UK National Ecosystem Assessment Follow-on

Work Package Report 3:

Economic value of ecosystem services

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Abbreviations and acronyms

AIC	Akaike Information Criterion
AONB	Area of Outstanding Natural Beauty
ARIES	Artificial Intelligence for Ecosystem Services
BAU	Business As Usual
BBS	British Bird Survey
BSFP	British Survey of Fertiliser Practice
CAP	EU Common Agricultural Policy
CCC	Committee on Climate Change
CEH	Centre for Ecology and Hydrology
CFT	Cool Farm Tool
CNCDR	UK Centre for Natural Capital Decision Making
CROW	Countryside and Rights of Way Act 2000
CSERGE	Centre for Social and Economic Research on the Global Environment
DECC	Department of Environment and Climate Change
DEFRA	Department for Environment, Food and Rural Affairs
DEM	Digital Elevation Model
DLUA	Developed Land Use Areas
EBM	Ecosystem-Based Management
ECM	Export Coefficient Modelling
EEA	European Environment Agency
EH	English Heritage
ERSA	Economic Report on Scottish Agriculture
ESA	Environmentally Sensitive Areas
ESC	Ecological Site Classification model
ESRC	Economic and Social Research Council
EU	European Union
FAO	UN Food and Agriculture Organisation
FC	UK Forestry Commission
FIAP	Forest Investment Appraisal Package
FGM	Farm Gross Margin
GB	Great Britain
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
GQA	Environment Agency General Quality Assessment
HA	Hydrometric Areas
HWP	Harvested Wood Products
HWSD	Harmonized World Soil Database
IHDTM	Integrated Hydrological Digital Terrain Model
INVEST	Integrated Valuation of Environmental Services and Tradeoffs
IPCC	Intergovernmental Panel on Climate Change
IPF	Independent Panel on Forestry
JAC	June Agricultural Census
LCA	Landscape Character Area
LNR	Local Nature Reserve
LSOA	Lower Super Output Area

LUCI	Land Utilisation and Capability Indicator
MA	UN Millennium Ecosystem Assessment
MAE	Mean Absolute Error
MENE	Monitor of Engagement with the Natural Environment
MIMES	Multi-scale Integrated Models of Ecosystem Services
ML	Maximum Likelihood
MNL	Multinomial Logit Model
MV	Market Value
NCC	UK Natural Capital Committee
NERC	Natural Environment Research Council
NGO	Non-Governmental Organisation
NML	Nested Multinomial Logit Model
NNR	National Nature Reserve
NPV	Net Present Value
NRFA	National River Flow Archive
NVZ	Nitrate Vulnerable-Zones
OS	Ordnance Survey
OSM	Open Street Map Project
POK	Pedunculate Oak
QML	Quasi Maximum Likelihood
RP	Revealed Preference
RSPB	Royal Society for the Protection of Birds
RUM	Random Utility Model
RWB	River Waterbodies
SC	Soil-Climate
SCCAN	System Cynorthwyo Cynllunio Adnoddau Naturiol (Welsh for Natural Resource Planning Support System)
SDA	Severely Disadvantaged Area
SEER	Social and Environmental Economic Research
SOM	Soil Organic Matter
SP	Stated Preference
SPS	Single Payment Scheme
SS	Sitka Spruce
SSSI	Site of Special Scientific Interest
STW	Sewage Treatment Works
SV	Social Value
TEEB	The Economics of Ecosystems and Biodiversity
TIM	The Integrated Model
TN	Total Nitrogen
TP	Total Phosphorus
UKCP09	UK Climate Projections 2009
UK NEA	UK National Ecosystem Assessment
UK NEAFO	UK National Ecosystem Assessment Follow-on
UNESCO	UN Education, Scientific and Cultural Organisation
WFD	Water Framework Directive
YC	Yield Class

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Key Findings

For decisions to be both robust and efficient, they should avoid appraising pre-determined options, instead, allowing the characteristics and corresponding values of the real-world to determine the best use of scarce resources. Many decision analyses assess a small number of pre-determined options. In the case of land use, such appraisals might typically consider around half a dozen options, each described in terms of a different end point. A major weakness of such approaches is that they are not 'robust', i.e. the decision-maker has no way of knowing whether the best option is included in the analysis. Consequently, the chosen option may not be 'efficient' because it may not offer the best value for money. More practically, such analyses give no indication regarding which policies might be required to attain a desired end point (or even if that end point is feasible). To avoid these problems, the UK NEAFO presents The Integrated Model (TIM): a programmed system that links a series of modules together to assess both the drivers and consequences of land-use change (for instance, the agricultural production module links changes in drivers, such as government policy, prices, costs, soils, climate, etc., to changes in farm outputs).

Decisions need to take into account all of the major drivers of, and impacts from, the changes they are considering. Changes in natural capital-related goods can be driven by many factors at the same time. For example, shifts in policy and ongoing climate change may simultaneously affect land use. In turn, such changes in land use may have a variety of impacts, all of which need to be analysed in order to assess the true consequences of alternative policies. Appraisals can incorporate many of the drivers of land-use change, in particular, paying close attention to the impacts of changes in both climate and policy. They provide extensive assessments of the impacts of such changes, including agricultural outputs and incomes for all farm types, water quality, greenhouse gases, recreational visits, forest outputs, and biodiversity (represented in the UK NEAFO by the indicator of bird species richness).

Many of the services provided by the natural environment can be robustly assessed using economic values, which are then readily incorporated within decision-making systems. Assessing environmental public goods in terms of their economic value permits the even-handed comparison of gains and losses in both market and non-market goods. The UK NEAFO builds on previous work to significantly extend the robustness of economic values for non-market environmental goods. The valuations the UK NEAFO presents should be applicable to a wide variety of decision-making challenges, as well as being compatible with the rigorous requirements of TIM, which requires appraising a broad array of possible policy changes (i.e. options that may cause minor or major increases in the supply of ecosystem services). The UK NEAFO recognises cases where current valuation and modelling techniques do not provide robust values for certain aspects of natural capital (e.g. the non-use existence values associated with biodiversity), so presents approaches which focus on incorporating such natural capital within conventional decision-making via the estimation of the costs of ensuring specified levels of provision (e.g. ensuring no net loss in biodiversity).

Leaving the uptake of subsidies to market forces alone is likely to result in poor value for money for the taxpayer. When subsidies are made available, but not tied to the value of public goods produced ('untargeted'), their effectiveness may be poor. In such cases, the uptake of subsidies will be determined by the private profits they support rather than the social value they generate. With regards to land use, this effect can be seen in the historic failure of EU Common Agricultural Policy (CAP) set-aside payments – put in place to reduce the overproduction of agricultural output, in reality, they mainly removed only the poorest quality land from use.

Targeted policies deliver greatly improved value for money from available resources. Working with, rather than in ignorance of, the natural environment allows the decision-maker to see how the alternative implementation of a policy can significantly enhance value for money. The UK NEAFO offers a methodology that can spatially 'target' resources (e.g. CAP payments) to almost any scale, from very small areas, up to the whole of Great Britain. Our use of this methodology shows that such targeting greatly improves the generation of environmental (and other) public goods and, therefore, benefits society. Such resource-efficient approaches are of particular importance during periods of financial austerity.

A UK NEAFO case study, relevant to current policy questions, examines the potential for establishing new forests in England, Scotland and Wales. This analysis, which was prompted by government announcements of the intention to expand forestry in all three countries, assesses land use at a maximum 2 km resolution for the entirety of Great Britain during the period 2014 to 2063. It considers the impact of any land use change on all of the various systems: agriculture, timber, water quality, greenhouse gases, recreation and biodiversity. Key outputs of this analysis include three scenarios developed by the project:

- Investigation of a 'Business As Usual' (BAU) baseline in which no new afforestation policies are implemented. This assessment provides a counterfactual for the other policy change analyses. Furthermore, it reveals the impact of forecast climate change on all the aforementioned systems during the appraisal period.

- Investigation of a 'Market Value' (MV) driven planting policy in which TIM is employed to consider all feasible locations for afforestation, selecting those which maximise the net value of market-priced agricultural and forestry outputs alone, while ignoring potential societal benefits. This simulates the consequences of announcing a general, untargeted planting policy and results in forestry being confined to remote upland areas of marginal agricultural value. Such locations are far from human populations, which limits the recreational values new forests might generate. Planting under this scheme also occurs on organic soils, which become degraded and emit large volumes of greenhouse gases. This approach to decision-making ends with negative overall value to society. Hence, it is not only poor value for money for the taxpayer, but actually results in net losses for society.

- Investigation of a targeted 'Social Value' (SV) driven planting policy in which TIM selects planting locations that take into account the full sweep of benefits and impacts generated by afforestation. The targeting process accounts for both market-priced goods (including timber and the costs of displaced agriculture) and those non-market goods for which we can estimate robust economic values (e.g. greenhouse gas emissions and storage, and recreation). This results in woodlands being located away from vulnerable organic soils and close to areas that yield higher recreational values. Analysis of the impacts on non-market goods which could not be given robust economic values (e.g. biodiversity and water quality) shows that water quality and woodland bird species richness are also enhanced when the value of all goods and services are considered in choosing planting locations.

3.1 Summary

3.1.1 Background and motivation

At its most fundamental, this report addresses one simple question: What is the best use of land?

The simplicity of this question is not matched by its answer, which turns out to be surprisingly complex. This complexity ultimately derives from the fact that we do not live in a world of either infinite resources or unbounded opportunities; if we did then decisions could be made without consideration of either direct costs, or the opportunity costs of foregone alternatives. However, in a world of scarce resources and limited opportunities such decisions are very unlikely to be optimal.

Of course the very notion of optimality requires that we have some objective that we are trying to optimise. Typically this objective would be taken as attempting to use those scarce resources in the best way possible. But how might we identify the best use for resources? At least two issues need to be addressed in any search for optimal land use allocations.

First, decision makers need to consider the different ways in which those resources could be used. Decisions which only examine a single option, or even a small number of pre-set alternatives, are unlikely to identify the underlying optimal use of those scarce resources. This problem is compounded when decision makers consider sets of artificially constructed scenarios of future land use. While such analyses are potentially useful provided that the set of options is firmly grounded in reality, often there is no prior check on the physical, social and economic feasibility of competing scenarios. Comparisons across possibly infeasible outcomes are potential barriers to good decision making, raising unrealistic expectations. Related to this, a focus upon future outcomes, even if they are feasible, is unhelpful if there is no clear path to attaining those outcomes. The focus on future outcomes, characteristic of much scenario analysis, ignores the fact that policy makers need to make decisions now and have to know the consequences of changing the policy, economic or social levers at their disposal. Furthermore, any decision support analysis needs to incorporate the context of a steadily changing and increasingly uncertain world. Forces such as on-going climate change mean that there is no steady and constant baseline to work from; Business as Usual will not yield an unchanging world in such contexts. Therefore identification of optimal uses of land resources cannot be based either upon assessments of pre-set groups of future scenarios or ignore exogenous drivers. It needs to start from the present day situation, incorporate on-going environmental, economic and social trends, and consider the impact of multiple feasible changes in all available policy levers.

Identification of the best use of resources also requires that we address a second issue; to appraise all of the major consequences of each available option. Of course no appraisal of a complex system such as land will ever be absolutely complete. Similarly, a modelling exercise will always be, to some extent, an abstraction from reality. The criterion here is not to attain a perfect replication of reality, but rather to deliver a robust analysis that reliably captures the major drivers of change and their associated trends, and which supports a significant improvement in decision making. However, a more fundamental question concerns who it is that we are assessing the best use of resources for? An assessment for a private sector business will typically only consider those market priced expenditures and revenues directly accruing to that business. This is a useful analysis to undertake as it is often the case that the key resources necessary for any option to be realised are owned by private business. So, in our land use case, farmers and landholders own the vast majority of land resources. While their decisions might not solely be driven by market returns on these assets, empirical analyses show that such returns are major determinants of land use[1]. Therefore analyses of the market value of land use options are important inputs to any decision analysis as they indicate the likely response to changes in policy, economic or other levers. However, particularly in the case of land use, a given decision will indirectly generate a wider set of gains and losses (some market priced, others not) which are external to private businesses and instead fall across society. These externalities need to be brought into the analysis if we wish to assess the full social value (i.e. private and public) of changing land use.

A useful extension of this latter issue would be to consider the precise distribution of benefits and costs within and across society, as this is unlikely to be even, impinging upon some groups more than others. We set down and implement a methodology for considering this issue elsewhere (see Bateman *et al.*, 2011a; Perino *et al.*, 2013). However, the present study focuses upon the issue of resource use efficiency on the grounds that this determines the scale of net benefits available for subsequent redistribution. There is always some trade-off between the efficiency of resource use and the distribution of the costs and benefits which that use generates and different objectives regarding the latter generate differing impacts upon the former. Indeed, many would argue that attempting to intertwine concerns regarding resource efficiency and objectives regarding redistribution within a single policy is likely to be to the joint detriment of both. Such an argument would seek to raise efficiency so as to increase the resources available for redistribution and then design specific policies to deliver the latter. In effect the present project adopts this stance although in subsequent work we will investigate the application of techniques such as those referred to above to examine the potential for and trade-offs inherent in redistributing the net benefits of alternative land use policies.

While we set issues of distribution to one side, as far as possible we seek to examine all of the impacts, both positive and negative, which any particular change in land use generates. Such an analysis attempts to advance the 'ecosystem services' approach to decision making developed through the Millennium Ecosystem Assessment (2005), the various TEEB analyses (2009) and the UK National Ecosystem Assessment (2011)[2]. These 'system' based analyses have set a new standard in comprehensiveness, bringing together the plethora of effects generated by changes to the natural environment. However, they also share a philosophical approach which is essentially anthropocentric, recognising that real world decisions reflect those concerns which are of value to humans. As such they are highly compatible with economic approaches to decision making. Using economic terminology, such assessments include all of the 'goods' (literally anything which generates value) arising from a project, irrespective of whether these are in the form of either market priced or non-market sources of value. Such appraisals embrace the 'use values' that people obtain from both direct and indirect use of goods (e.g. the direct value of food production and the indirect value of ecosystem services which enhance water quality)[3]. These analyses also seek to include 'non-use values' such as the pleasure which humans obtain from the knowledge that species of conservation interest continue to exist or that pristine wilderness is not degraded (although we discuss the practical difficulties of assessing such values below)[4].

[1] Recent examples of such studies include Arnade and Kelch (2007), Irwin et al., (2009), Brady and Irwin (2011), Fezzi and Bateman (2011) and Lacroix and Thomas (2011).

[2] As per the UK NEA (2011), the focus of our assessment is upon valuation of the ecosystem services generated by natural capital stocks. Elsewhere we have highlighted the need to also consider the sustainability of those underlying stocks (Bateman et al., 2011b; Natural Capital Committee, 2013). While this is an important extension it goes beyond the remit of the present study.

[3] Note that, as per UK NEA (2011), we take care to avoid double counting problems by focussing upon the final point at which value is generated.

[4] Note that we avoid the term 'intrinsic value'. The word 'intrinsic' is defined by the Merriam-Webster dictionary as "belonging to the essential nature or constitution of a thing". Therefore the intrinsic value of

This link through to economic values makes such assessments compatible with conventional decision making systems as set out in official guides to project appraisal such as the H.M. Treasury (2003) 'Green Book' guide to appraisal and evaluation for the UK Government. However, as that guide recognises, incorporating non-market values into decision making is often challenging. In the case of land use change the variety of goods generated are most naturally measured through a variety of different units. Of course common unit assessment of the market value of change is, by definition, readily provided via the market price of inputs (e.g. fertilizer) and outputs (e.g. food). However, many of the externalities generated by land use (including say the impacts of that fertilizer upon water quality, but also wider effects such as greenhouse gas emissions, open access recreation, impacts on wild species habitat and hence biodiversity, etc.) do not have market prices. They are assessed in physical or bio-physical units (e.g. mg/l, tCO_2e, numbers of visits, biodiversity indices, etc.) and leave decision makers with the unenviable challenge of identifying optimal trade-offs between incomparable measures. For instance, how does one assess a land use option which reduces the use of fertilizers and hence improves water quality yet increases farm production of greenhouse gases? What it the correct trade-off between mg/l nitrate concentrations and tC/ha greenhouse gas emissions? The lack of comparable units inhibits the decision maker's ability to identify which options deliver the greatest net benefits to society.

In fact all but the simplest decisions involve trade-offs across multiple units and the way that this is achieved is to impose some commensurability across those units. In effect decision makers evaluate changes occurring in one unit against changes arising in another. This valuation can either be explicit (where the decision maker states the trade-off, or value, of changes in one unit against another) or implicit (where that trade-off is not stated but can be inferred from the decision made). In all cases the decision maker is using values in making the decision whether or not they choose to overtly acknowledge that this is the case. Indeed valuation is the very essence of all decision making and to pretend otherwise is either disingenuous or suggests a lack of understanding.

Given that some form of valuation is inevitable, what is the best approach to this element of all decision making? There is a long established literature showing that failure to make values explicit almost inevitably leads to inconsistencies across decisions (Tengs *et al*., 1995; Dobes and Bennett, 2009; Ergas, 2009). Therefore whichever approach to valuation is adopted, explicit values are preferred to implicit as they are more readily scrutinised and less liable to cross-decision inconsistencies.

If we seek to allocate scarce resources fairly and efficiently then the drive for consistency needs to be extended not just beyond the individual decision but even beyond the realm of similar projects. This is particularly the case where there is a suspicion that certain categories of project (say those with a concern for the natural environment) might be accorded a lower priority than others (say those supporting the financial sector). From the perspective of economics a unit of value should be treated identically irrespective of its origin. Given that public sector decision makers are seeking to allocate limited fiscal resources across a wide range of possible investments ranging from environmental improvements to provision of a health service, policing, maintenance of national infrastructure, etc., then it is important that approaches to decision making (and budget allocation) are even handed across all sectors. Given that money is the common unit of assessment across all of these other sectors then this gives a strong argument for the use of this same common unit of comparison for assessments concerning the natural environment.

say a particular bird belongs to that bird and cannot be defined by another entity such as a human. Of course humans can and do hold values for birds including the use values held by bird-watchers and the non-use values which a wider group hold for the continued existence of many species. However, these are anthropocentric values (see also discussions in Bateman et al., 2011b).

Given the various advantages which economic valuation of non-market benefits change brings to land use decision making we make this a cornerstone of the present research. In pursuing this aim we draw upon the rich literature regarding the economic valuation of non-market externalities which has developed in recent years[5] and progressively been incorporated within both analyses of land use change and wider ecosystem service assessments. However, our use of valuation techniques is, we argue, discerning regarding the robustness of values that are likely to be derived. For example, we remain sceptical regarding the use of stated preference techniques to estimate individuals' willingness to pay for goods with which they have little familiarity and hence vague definitions. The case in point which we highlight subsequently is that of the non-use existence value of biodiversity. Because this is a non-use value there are no behavioural data from which we can reveal valuations (unlike say, the use value of watching wild animal species where observations regarding the time and direct costs individuals incur provide the base data needed to infer values). Therefore economists are forced back upon survey based stated preferences as the basis for valuations. While such approaches may produce defensible values for well understood, high experience goods, the concept of biodiversity is somewhat nebulous for many survey respondents. Furthermore, as there are generally no coercive mechanisms through which researchers can force such respondents to pay for biodiversity, hypothetical survey scenarios lack the incentive compatibility vital to ensuring that respondents cannot deliberately misrepresent their true preferences (Carson and Groves, 2007). This confluence of factors undermines the robustness of stated preference estimates of non-use existence values for wild species.

We respond to the problem of non-robust values for biodiversity within our initial 'Proof of Concept' case study in Section 3.3 of this report. Here we develop a 'conservation constraints' approach to incorporating wild species diversity within economic decision making. This applies the requirement that, in any area, we reject any land use change option which reduces biodiversity. The opportunity cost (e.g. foregone increases in agricultural production) which such a rule imposes, while not in any way a valuation of the biodiversity conserved, nevertheless provides an input to the decision process which could, for example, be used to trigger 'Payments for Ecosystem Services' or similar compensation to those who have lost income as a result of this constraint. This apparently simple approach has one weakness in that there is the possibility of disproportionate costs[6] arising from such constraints and is only justified in cases where robust benefit estimates are not available and there is a clear mandate against biodiversity loss[7]. Failure to impose these requirements could easily result in the stultification of potentially beneficial land use. However, just such conditions apply to biodiversity in the UK where H.M. Government (2011) has explicitly announced its intention to halt loss of wild species (and indeed to deliver net improvements in the natural environment). If these dual conditions do not hold then the constraints approach cannot be justified.

The research presented in this report seeks to contribute to the existing literature on land use decision making by developing a methodology which addresses all of the above issues. Our fundamental question – what is the best use of land? – remains throughout, and our inquiry is firmly

[5] Examples include Champ et al. (2003), Freeman (2003), Heal et al. (2005), Hanley and Barbier (2009), Bateman et al. (2011b).

[6] The term 'disproportionate costs' is obviously open to interpretation and is used as per the EU Water Framework Directive (EC, 2000). This has generated extensive work on the definition of disproportionality (Lago et al., 2006; Martin-Ortega et al., 2011).

[7] While not an absolute requirement, it is important that such a biodiversity constraints approach should be applied using as finer a spatial resolution to the analysis as feasible in order to minimise opportunity costs. To show why this is necessary consider two assessments, one operating at the resolution of the single farm while the second takes as its minimum unit 100 farms. Supposed that in a given set of 100 farms just one would induce biodiversity loss on its land if a given policy, which boosts agricultural output, were implemented. Using the farm scale analysis only that single farm will be prevented from adopting this land use. In contrast the coarser assessment would prevent all 100 farms from undertaking this change.

grounded in environmental economics. We consider a mix of land uses to be optimal when there is no alternative mix which could increase the net value that society derives from its land. Thus, the best mix of land uses is one that maximises society's net benefits. At a fundamental level, economics is the science of constrained optimisation: constrained because of the scarcity of resources at our disposal; and optimisation because we wish to extract the greatest possible net benefit from them. Thus defined, achieving the best use of land – extracting the greatest benefit from scarce resources – is simply an economic exercise in constrained optimisation.

3.1.2 A modular environmental-economic approach

Given the background motivation set out above, the research starts by rejecting the common use of pre-set end-point scenarios in favour of an attempt to model the numerous physical and economic processes which characterise land, its use and the consequences of that use. These individual analyses become the 'component modules' of an integrated assessment which begins with readily observable present-day realities and models the impacts of changes over time to yield analytically defined end points. Analyses are performed for any user specified period. At present, analyses operate on an annual basis although future work will seek to reduce this interval[8]. Dynamic effects are in-built in that each period takes the end of the previous interval as its starting position.

The individual component modules and their linkages are programmed together through a custom built software system discussed subsequently. An immediate advantage of having an integration system which is linked to but distinct from the component modules is that this permits development of the overall system to evolve even when work is focussed upon just a single module. More fundamentally, modularity raises the potential for other users to substitute alternative models of a given element (e.g. other water quality models) to take advantage of the remainder of the integrated system. The system is being constructed in open source code wherever possible with the intention being to move towards an entirely open-source system which we would share freely so as to enhance general use of the research and its modelling.

The component modules are constructed so as to simulate the effect of changes in the diverse environment, policy, economic and social forces which drive each system. Furthermore, each component module is linked to the others such that changes any given driver(s) (e.g. an alteration in farm subsidies in conjunction with on-going climate change) impacts both directly upon the relevant immediate component (e.g. agricultural land use and consequent farm produce) and indirectly upon linked components (e.g. changes in competing land uses such as forestry, changing greenhouse gas emissions, altering diffuse pollution and hence water quality, impinging upon recreation and biodiversity, etc.). As far as possible[9] these direct and indirect impacts are translated into common unit economic values (specifically, pounds). Appraisals are then made of both the market value and social values of changes; the former indicating the likely response of land owners in the absence of incentives such as payments for ecosystem services; while the latter indicates the potential wider value of changes (and hence the scope for funding such compensation payments).

Development of the individual component modules built for this analysis drew upon a number of data sources. These provided data which were spatially referenced and covered an appropriate time period sufficient to allow the incorporation of both location and temporal change effects within models of land use decision making. Full details of these data are provided in the Appendices to this

[8] Although shorter time-steps increase the computational demands of the system they permit analysis of short period events such as weather extremes.

[9] As discussed subsequently, we argue that economic assessments of the non-use, existence value of biodiversity are insufficiently robust to be admitted alongside other economic benefit values. We therefore use an approach which examines the economic costs associated with conserving biodiversity.

report, but in summary these included spatially and temporally disaggregated climate variables including average temperature and accumulated rainfall during the growing season obtained from the UK Met Office website[10] and interpolated to match the resolution of our land use data. Estimates of future weather variables were obtained from the UKCP0 (2009a, 2009b) climate change scenarios. We also include other measures of the physical environment (such as urban extent) from Ordnance Survey (OS) sources which also provided topographic variables from their Digital Terrain Model, while soil characteristics were derived from the 1km master library of the European Soil Database (Liedekerke *et al*., 2005). A summary of the various component modules developed for this analysis and their specific source datasets is as follows:

- Farm module: Describes farm level decisions regarding agricultural production and hence land use, and estimates resultant market priced returns. This module draws upon a unique database established by Fezzi and Bateman (2011), which integrates multiple sources of information dating back to the late 1960s. The resulting data, collected on a 2km grid square (400ha) basis, cover the entirety of England, Wales and Scotland (Great Britain, GB). Data taken from the Agricultural Census[11] detail the area of each agricultural land use (e.g. various cereals, oilseeds, different root crops, various grassland types, etc.) and numbers of various types of livestock (cows, beef, sheep, etc.). A variety of sources yield data on spatially and temporally disaggregated policy, area designations (e.g. National Parks, Nitrate Sensitive Areas and Environmentally Sensitive Areas), prices and costs (our data recording variation in these latter factors only across time, as they are assumed to be equal across location). Data on yield and profits are not available at the detailed spatial resolution required to link this analysis to the physical characteristics of each grid square. Given this, estimates of the market value of agricultural production are calculated as output revenues minus variable input costs to yield 'Farm Gross Margin' (FGM) values.

- Timber module: Describes timber production decisions, detailing choices regarding tree management (e.g. the 'thinning' of poorly performing trees early on in a plantation 'rotation') and felling. This analysis was developed in collaboration with the team members based at the UK Forestry Commission (FC) and utilizes their Ecological Site Classification model (ESC, 2013). This is a well-established decision model developed by (Pyatt et al., 2001) and is based on a synthesis of multi-criteria analysis (Ray *et al*., 1996) and fuzzy-set theory (Ray *et al*., 1998). Timber valuation is achieved through linkage with the FC and the flow of costs and revenues arising from timber production.

- Farm greenhouse gas (GHG) module: Describes the net GHG emissions resulting from agricultural activities. This analysis utilises the Cool Farm Tool (CFT, 2013) developed by the team members based at the University of Aberdeen. The analysis includes direct and indirect changes in carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4) emissions arising from agricultural activities, including use of machinery, arable production including fertilizer use and the major emissions originating from livestock systems. Valuation is achieved through reference to the extensive literature on the damage costs avoided by reduction of GHG emissions as well as UK Government official estimates of this value. As these values diverge substantially, alternative analyses are produced for each value estimate.

- Forestry GHG module: Describes the net GHG emissions resulting from forestry activities. Here GHG flux is dominated by carbon dioxide (CO_2) storage in livewood, storage or emission from soils (dependent upon soil type) and emissions from felling waste and timber products

[10] *www.metoffice.gov.uk*
[11] Obtained from EDINA; www.edina.ac.uk.

(which have varying lifespans). This analysis utilises the CARBINE model (Thompson and Matthews, 1989), developed by team members based at the Forestry Commission. Valuation is achieved as per the farm GHG module.

- Recreation module: This module develops a new Random Utility Model (RUM)[12] to analyse and value the impact of changes in land use on individuals' recreational choices and their associated travel costs, accounting for both the number and value of recreational visits. Crucially, the model captures the impacts of substitute availability upon the number and value of visits, including the dynamic effects of progressive land use change over time. So, for example, the provision of a new woodland recreation site in a certain location is assessed taking into account the impact of all other substitute sites (both woodland and other habitats). Furthermore the provision of that site is then taken into account when assessing the value of any further new recreational site. This avoids the over-estimation of values which would arise if these substitution and dynamic effects were ignored. Observations of recreational visits were taken from the Monitor of Engagement with the Natural Environment (MENE) (Natural England, 2010), which to date has surveyed recreation behaviour in nearly 150,000 households in England annually, sampling continuously around the year and providing data on outset and destination for a randomly selected trip. This is easily the best source of economically relevant recreation data in the UK. Further data is taken from a variety of sources to detail road infrastructure, its quality, travel speeds, the location of actual and potential recreational sites and substitute availability, etc. After allowing for these various determinants of visits, valuations of recreation are obtained by examining behaviour and observing the trade-offs individuals make between the time and travel costs of trips and the decision regarding where to visit or indeed whether to make any trip at all.

- Water quality module: Describes the hydrological processes that link land use to nutrient concentrations and ecological status in rivers. This analysis initially applies nutrient export coefficient modelling (ECM) to information on the inputs-to and flow-from catchments. This information is then fed into structural statistical models of river water quality drawing upon Environment Agency General Quality Assessment data (which provides measures of phosphate and nitrate concentrations in rivers for 2000 and 2009) and the Water Framework Directive (WFD) Ecological Status classification of UK rivers for 2010. Making allowance for sewage inputs reveals highly significant relationships between land use and nutrient concentrations. Further statistical analyses reveals that because nutrient concentrations are only one of many factors determining ecological status, changes in land use may have only marginal impacts on WFD classifications of UK rivers. Economic valuation of the impact of changes in water quality considered two issues: (i) the changes in costs of treating water abstracted for drinking purposes induced by changes in diffuse pollution due to alterations in land use and (ii) changes in the value of water related recreation. Despite extensive contacts with Defra and various water companies, no firm estimates of treatment cost changes were established (indeed these investigations suggested that such abstraction treatment costs were minor and that, while capital investment costs associated with the treatment of sewage were substantial, no clear linkage with the nutrient content of water upstream from sewage discharges could be identified). Consequently while the impacts of land use change upon water quality are quantified and presented in the main report, values are not presented in respect of item (i) above. Given this lack of robust values we exclude impacts upon water quality from our subsequent optimisation analysis although we feel that this is an area where further research could establish reliable values and hence allow this

[12] The seminal work on RUM analyses is provided by McFadden (1974) for which he received the Nobel Prize in economics in 2000.

decision to be reversed. Turning to item (ii), the valuation of water quality impacts upon river recreation was achieved through a new study undertaken for UK NEAFO through the SEER project. To avoid double counting with the recreation values generated from our analysis of MENE data for the general consequences of land use change (discussed above) we present results and valuation estimates from our focused water quality exercise in an Annex to this report and do not include these with our wider recreation value estimates.

- Biodiversity module: There is no single, generally accepted measure of the impact of land use upon wild species and there is considerable tension between assessments of the fundamental ecosystem processes supporting such species and measures of species themselves. There is further debate about whether assessments should consider measures of biodiversity, supporting ecosystem services, species of conservation concern, or species of popular interest. The latter are more relevant from the perspective of general preferences and economic values yet the supporting measures are those governing sustainability. Given this, we have chosen a measure which is, we accept, open to debate, but has the available information quality necessary to support development of the methodology by providing excellent spatial and temporal data coverage. The British Bird Survey (BBS) (BTO, 2011) provides such data and allows the modelling of a long-established and generally accepted measure of diversity (Simpson, 1949). Our models link BBS data to corresponding land use to allow estimation of the consequnces of change in the later upon the former. Note then that strictly speaking this provides a measure of bird species richness and our subsequent use of the term biodivesity is a shorthand for this which we accept is open to criticism but is, in the absence of a superior measure which is also backed by a comparable quality of spatial and temporal data, defencible as a means for permitting development of our overall methodology. If superior and more comprehensive measures of biodiversity are made available they should be substituted for that used here. Valuation of biodiversity and wild species conservation raises further challenges. The use value of wild species as providers of pest control and pollination services is, in principle, straightforward provided that natural science assessments of the impact upon the production of market priced agricultural produce can be established (see, for example, UK NEA, 2011). Similarly, one could in principle assess the contribution of wild species to related recreation values or tourism (Molloy, 2011). However, the non-use, existence values associated with biodiversity are less readily assessed as these are not well reflected in behaviour[13]. In principle, associated values might be estimated via stated preference valuation surveys. However, as argued by Bateman *et al*. (2011b), the general lack of familiarity of individuals with concepts such as biodiversity, combined with the lack of any obvious, incentive-compatible payment mechanism means that respondents in such surveys face both an unfamiliar good and payment vehicle; a combination which undermines the robustness of resulting responses. Specifically, a number of reviews have found that values elicited in such circumstances are sensitive to objectively irrelevant changes in the framing of valuation questions. By definition, robust decision making methods have to exclude such information. Given this we exclude monetary assessments of biodiversity response from the optimisation of land use. However, within our Proof of Concept analysis (Section 3.3) we demonstrate the applicability of our previously discussed 'constraints' approach to the incorporation of biodiversity concerns within land use decision making. In this application we use a simple 'no-loss' approach applied at a local level across the whole of Great Britain demonstrating that the opportunity costs incurred by such an imposition are relatively modest once the other non-market environmental consequences of land use change are considered. A number of alternative constraints might be envisaged including those that requeies an overall net gain in environmental quality;

[13] One possible exception is via legacies and donation, although (as discussed in UK NEA, 2011) these are liable to be significant under-estimates of underlying values.

possibilities which are particularly timely given the Government's recently announced policy intention to introduce biodiversity offsetting within England (Defra, 2013).

3.1.3 The Integrated Model (TIM)

The individual component modules and their linkages are programmed together through our custom built software system; The Integrated Model (TIM). This programmed linkage allows the analyst to examine the consequences of any desired change in multiple drivers. For example, TIM allows the analysis to examine the consequence for land use of say a new farm subsidy regime at the same time as a shift in precipitation and temperature arising from climate change. TIM traces the consequences of these changes through the component modules to yield estimates of both direct impacts in terms of land use and agricultural produce, and indirect effects upon alternative land uses (e.g. a reduction in woodlands), changes in GHG emissions, water quality, recreation and biodiversity. All of these effects are assessed in quantitative terms and all except for biodiversity are measured in terms of economic values.

However, the real advantage of TIM and the major contribution of this research to the literature, is not in terms of the assessment of the effects of some user-specified policy change, useful though that is. Rather, the major innovation here is the potential which TIM affords to identify the optimal way in which to implement such a policy change[14]. This is achieved by using TIM to interrogate all the component modules simultaneously to examine the consequences of any specified change in some land use driver occurring at any location and at any time over a specified period. Through an optimisation routine TIM identifies those solutions which maximise and user-defined objective. In the illustrative case study discussed below we optimise two objectives (a) maximising the market value of a land use policy and (b) maximising the social value of that policy. In so doing the analysis illustrates a 'spatial targeting' approach to decision making which allocates scarce resources to those locations which maximise the specified objective (here either market or social value). This approach avoids the problem of specifying pre-set end points through a conventional scenario analysis and ensures that the best value for money given available resources is achieved. As the component modules all reflect the underlying variation of the natural environment and its consequences for economic costs and benefits, this approach genuinely incorporates the natural world into economic decision making.

An overview of the operation of TIM is provided through our case study, which we summarise below.

3.1.4 Case Study: Planting new forests in Britain

3.1.4.1 Overview: Motivation, analysis and deliverables

In order to motivate the development of the present system and simultaneously address a question of considerable contemporary policy interest, we applied our optimising TIM methodology to the issue of extending the area of forestry across Great Britain. Within England this policy goal stems in considerable part from the work of the Independent Panel on Forestry (IPF, 2012) which has been endorsed by Defra (2012, 2013) and the UK Natural Capital Committee (NCC, 2012). Separate

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14 Indeed the long term potential is to use TIM not only to identify optimal implementation strategies but also to design optimal policies, i.e. to define those policies which deliver the best possible use of all land throughout Great Britain. This requires that we quantify all feasible policies and search across these to find that combination which yields the highest social value. However, this goal will not be attained within the UK NEAFO timescale.

initiatives to promote afforestation have also been adopted by both the Scottish and Welsh devolved parliaments (Scottish Government, 2012a; Welsh Assembly, 2012). All three legislatures seek to deliver a substantial level of new forestry planting sustained over a considerable period. During 2012 we undertook direct discussions with a number of these bodies and on the basis of these determined to examine a policy context in which each country decides to plant 5,000ha of new woodland per annum for each year between 2014 and 2063 yielding an overall increase in forest extent of 750,000 hectares across Great Britain over the full assessment period.

As discussed previously, our methodology rejects the commonly used approach of comparing across a limited selection of pre-set scenarios to see which provides the best outcome. Instead we start from the initial policy aim, which here is to increase woodland coverage by the desired amount and rate, and then utilise our system of integrated component modules to evaluate the optimal location for that level of woodland expansion.

As per any analysis, we begin by first defining a 'Business As Usual' (BAU) baseline for land use against which any subsequent analysis results can be compared. Here we do not have any policy change (including no afforestation). However, land use does not stay constant over the analysis period as climate change drives alterations in agricultural activities. Our two alternative objectives are then defined to serve as the policy options open to decision makers:

- a 'Market Value' (MaxMV) option[15]. in which the desired new afforestation is located so as to maximise the net benefits in terms of the market priced goods concerned (agricultural outputs and forest timber values); and
- a 'Social Value' (MaxSV) option in which new forests are located so as to maximise the net benefits in terms of all the economic values (market and non-market values) covered in this report (agricultural outputs, forest timber values, agricultural GHG flows, forestry GHG flows, and recreation).

Each option is assessed against the BAU baseline to reveal the changes induced by optimising each objective. In both cases we calculate both the market and social values resulting from the planting that occurs (i.e. we know how a switch towards social value optimisation affects market values and vice versa).

These various assessments provide decision makers with the necessary information to determine whether a given policy, even when optimised, is worth undertaking. For example, if social values are negative under both options, then we may be better off remaining with the no-policy BAU situation[16]. In contrast if the social value from the MaxSV option is positive then its excess over the social value from the MaxMV option quantifies the loss that would be incurred if the policy was guided solely by market forces (equivalent to the net gains of adopting a social optimisation approach). The MaxSV assessment is of particular interest in cases where the optimisation of social values depresses market values relative to the BAU as comparison of the two indicates the level of compensatory incentives (e.g. payments for ecosystem services) required to induce private land owners to change land use, as well as the net social benefits of implementing such payments.

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15 Note that, in libertarian terms, none of these options convey a pure market outcome as government intervention in land use has both a long history and is continuing.

16 Of course this is only true to the extent that we have truly encapsulated all values within our analysis. The underlying objective of this research is to contribute to the development of methodology for which the forestry case study is illustrative. While we feel that empirical results are defensible, these were not the over-riding focus of our study and we would suggest that there is room for some improvement before applied findings are used as the basis of policy change.

3.1.4.2 Defining the objective to be optimised

Our illustrative application considers two objective functions: maximising the market value of afforestation (MaxMV), and maximising its social value (MaxSV). An initial issue is to acknowledge that this assessment involves a variety of impacts which naturally occur over very different timescales. So, for example, while it is reasonable to think about the annual value of agricultural production, the economic assessment of forestry only makes sense if we consider at very least a full rotation from planting to felling which other processes, such as changes in soil carbon, can take even longer periods. To allow for this we consider these 'natural' time periods for each process, calculate the net present value of the corresponding stream of costs and benefits over those periods and then calculate the annualised equivalent (the 'annuity') of that discounted stream of values. Therefore, when we refer to our assessment period of 2014 to 2063, we are actually referring to an annuity which may be calculated over a much longer period but is then considered for that common 50 year timespan (e.g. the annuity for a 200 year soil carbon process is calculated, entered for each of the 50 years of the assessment and compared to the annuity for agriculture over the latter period). This allows a fair comparison across very differing activities.

Considering the various value streams concerned, let us start with those that yield market values: agriculture and timber production. In converting any particular agricultural land area to woodland, value flows are changed in a number of ways. Since the land is no longer used for agricultural production, the flow of benefits over time from food output is lost. To measure the value change resulting from ceasing agricultural production then, as outlined above, we calculate the net present value of that stream of costs and benefits (valued using the market prices of foregone farm produce) for 50 years from the year of conversion (which may be any year from 2014 to 2063). We then convert that net present value into an equivalent annual annuity[17]; that is to say, we calculate the value which, if realised for each of the 50 years following conversion, would result in the exact same net present value. Let us call that annuity value v^{Farm}. Notably, in our analysis this value happens to be negative for every instance in which farmland is converted into forest. This reflects the high market priced returns to agriculture relative to forestry.

Considering our other market value, timber, as mentioned above our 50 year assessment period, while adequate for agricultural value streams, will not capture the major revenues associated with timber production as the time from planting to felling (a 'rotation') exceeds this period for all but the fastest growing softwood species. To allow for this, our appraisal of timber production is extended to encapsulate the rotation length for even the slowest growing broadleaf species. As before, annualisation will make the net benefits of timber production comparable with those for the other values assessed in the analysis. We denoted the resulting annual equivalent annuity value as v^{Timber}.

We can now calculate the market value of land use change for any given location, indexed j, as simply the sum $v_j^m = v_j^{Farm} + v_j^{Timber}$. Furthermore, for the first year of our assessment period, we can optimise the objective of maximising market value by simply calculating this sum for all locations across each country and ordering these from highest to lowest and planting the top 5,000ha with new woodland. We can then repeat this exercise for the second year of the assessment and so on until our appraisal period is completed. Such an assessment has considerable merit in that it encapsulated the impact of the diversity of the natural environment upon these market values. However, our analysis seeks to go much further than this. In particularly we can now begin to

17 The use of annuities allows us to compare activities which have differing lifecycle lengths; in this instance agriculture and forestry.

consider the social value of planting (both to see the social consequences of the maxMV planting strategy; and to use this to guide planting in our maxSV objective).

Recall that, for reasons explained previously, while we quantify the impact of each planting strategy upon water quality we do not monetise these and therefore, within the present study, they play no part in determining the location of forest planting. However, the impact of land use change upon greenhouse gases is both monetised and included within the optimisation procedure. The alternations in land use induced by afforestation is likely to induce multiple changes upon the balance of greenhouse gasses emitted from or stored at any planted location. There are a number of elements to consider here, including changes in farm emissions of CO_2, N_2O and CH_4; emissions and sequestration of CO_2 from forestry operations (including emissions from machinery, storage in livewood and delayed emissions from post-felling wood products); and changes in soil carbon[18]. These effects are converted into CO_2 equivalents, monetised[19] and annuitized to yield the value v^{GHG}.

We can now calculate a partial approximation to social value which extends beyond market value to include greenhouse gas impacts but, for the moment excludes the value of recreation. We can calculate this partial social value as the sum $v_j^{sg} = v_j^{Farm} + v_j^{Timber} + v_j^{GHG}$. Again we can optimise this objective by calculating v_j^{sg} at each location across each country and choosing those that give the highest value in the first year of our assessment and then repeating this for subsequent years. We can of course also calculate v_j^{m} for the planting locations identified when we locate forests by maximising v_j^{sg}, a comparison which tells us about the impact upon the private sector of including GHG within our decision making process. If, as is likely, this results in a decline in market values relative to the maxMV approach to planting then that difference could be used to identify the compensation needed by the private sector in order to make them indifferent between the two planting regimes. If this compensation is less than the extra value of GHG storage then this would suggest that such payments are justified from a social perspective.

Each of the values of conversion, v^{Farm}, v^{Timber} and v^{GHG} are spatially independent. That is to say, the value of conversion of one cell has no impact of the value of conversion of any other cell. Unfortunately, the relatively simple optimisation routines which can be implemented when all values are spatially independent are insufficient in the presence of spatially dependent values. This situation arises in our present analysis because of the likelihood that the creation of a new multi-purpose woodland may provide new recreational opportunities. Of course, the closer a household is to the new woodland, the more value it will realise from the new recreational site. However, at the same time, if that household already enjoys a large number of outdoor recreational opportunities in their area, and particularly if those recreational sites are woodlands, then the addition of more woodland is likely to offer relatively little additional recreational value. Accordingly, the recreational values generated by planting new woodlands are not spatially independent of one another. While each cell in an area may offer substantial recreational values if planted independently, as soon as one cell contains woodland, the additional recreational benefits of planting more woodland on any other cell in that area are very much reduced. As a result, when we attempt to include the benefits of woodland recreation, the simple strategy of evaluating the benefit from conversion of each cell and then choosing the highest valued cells will not work. Rather, we need to evaluate the

[18] A further incomplete value stream here concerns changes to soil carbon for certain soil types, most particularly peat soils where transition periods between equilibria can be very long (see discussion of the economics of soil carbon arising from conversions from agriculture to forestry in Bateman et al., 2003). We adopt an extended evaluation approach as per timber revenues and calculate annuities accordingly.

[19] As mentioned previously, because there is significant debate over the value of sequestered and emitted carbon, we have used a range of values in our subsequent analyses.

simultaneous conversion of sets of sites and choose the specific set which offers the maximum value: a considerably harder problem. The introduction of spatially dependent values does make the identification of optimal locations considerably more complex. Section 3.12 sets out the details of the approach used to address this issue but in essence we use well established routines and commercial software (the IBM CPLEX solver) to solves this problem and identify the consequences of different planting regimes for our recreational value v^{Rec}. This in turn allows us to identify our comprehensive social value as the sum $v_j^S = v_j^{Farm} + v_j^{Timber} + v_j^{GHG} + v_j^{Rec}$.

Alongside our value estimates, the land use mosaic defined by each optimization is fed into both the water and biodiversity modules to examine consequences for both water quality and wild species diversity, both of which are assessed quantitatively allowing the decision maker to examine both the direction and magnitude of changes induced under each optimisation rule.

3.1.4.3 Findings

The key objective of our research is methodological development, and our major findings reflect this. Further discussion of each of the following points is given in the 'Key Findings' of this report. These identify five generally applicable key messages as follows:

- for decisions to be both robust and efficient they should avoid appraising pre-determined options and instead allow the characteristics and corresponding values of the real-world to determine the best use of scarce resources;
- decisions need to consider all of the major drivers and impacts of the changes they are considering;
- many of the services provided by the natural environment can be robustly assessed using economic values which are then readily incorporated within decision making systems;
- leaving the uptake of subsidies to market forces alone is likely to result in poor value for money to the taxpayer; and
- targeted policies deliver greatly improved value for money from available resources.

Our policy relevant case study to examine the potential for establishing new forests in England, Scotland and Wales provided a number of key outputs including:

- a 'Business As Usual' (BAU) baseline which reveals the impact of forecast climate change upon land use in each country across the appraisal period;
- a 'Market Value' (MV) driven planting policy which results in forestry being confined to remote upland areas of marginal agricultural value. Such locations are far from populations which limits the recreational values generated and greenhouse gas values are ignored; and
- a 'Social Value' (SV) driven planting policy where the values of agriculture, timber production, greenhouse gases and recreation are all considered. This moves planting away from carbon rich organic soils and towards areas which displace agricultural greenhouse gases and generate recreation values.

The message of the case study is clear: using market values alone to direct public spending on afforestation yields relatively poor value for money for taxpayers. Using the integrated modelling approach to include the economic value of other non-market goods significantly improves the social value of public spending. The approach developed in this research provides decision makers with the ability to direct public funds to those areas of the country which will maximise value for money for the UK taxpayer.

3.1.5 Section Synopses

Here we provide a brief synopsis of each section and their contributions to the integrated model (TIM) and the report as a whole.

Key Findings from UK NEAFO Work Package 3a: Economic values of ecosystem services

This Section distils the primary 'take home messages' from throughout the report.

Section 3.1. Summary: UK NEAFO WP3a: Economic values of ecosystem services

Gives an overview of what the research hopes to achieve, as well as why and how this was accomplished. Here, we lay out the motivation for TIM and introduce its component modules. Key terms and concepts are also introduced and defined.

Section 3.2: Literature review: Ecosystem service decision support tools

Places the current study within the context of the extant literature, and by comparison reveals the unique contributions offered in this report.

Section 3.3. Proof of concept: Can spatially targeted policies increase land use efficiency? Extending the UK NEA scenario analysis

Demonstrates the potential gains to society's wealth and well-being arising from the adoption of spatially targeted policies. Graphic and numerical results from a 50 year simulation of land use and climate change under various policy options are presented for the UK. As such, this Section serves as a proof of concept and provides the rationale for pursuing the spatially explicit optimality analyses throughout the report.

Section 3.4. The agricultural production module

Presents a spatially explicit, structural econometric model of UK agricultural land use which ultimately provides the farm module in TIM. This module embraces the market, policy and environmental drivers of land use decisions related to crop and livestock production, and estimates the profits thereof. It incorporates stocking intensities for the major livestock types (dairy cows, beef cows and sheep) and the seven major agricultural land uses (cereals; oilseed rape; root crops; temporary grassland; permanent grassland; rough grazing; and other agricultural land).

Section 3.5. The farm greenhouse gas (GHG) module: GHG emissions and sequestration on agricultural land

Provides a spatially and temporally explicit modelling of GHG emissions and sequestration associated with predicted changes in agricultural land use. This model ultimately serves as the farm GHG module in TIM. GHG flows are calculated as a function of soil type, land use and assumed farm management data to enable spatial projections.

Section 3.6. Timber production module: Tree growth, timber yield and climate change

Models variation in growth rates, timber yield class, and timber profits for a variety of physical environmental conditions across the UK, taking into account the effects of unavoidable climate change. This model predicts timber costs and benefits for different tree species across locations, climate scenarios and a common silvicultural management regime, and ultimately forms the forestry production module in TIM.

Section 3.7. The forestry greenhouse gas (GHG) module: GHG flows from forestry activities

Estimates the annual GHG flows arising from the afforestation of land and ultimately forms the forestry carbon module in TIM. This Section employs the Forest Research CARBINE tool to model carbon exchanges between the atmosphere, forest ecosystems and the wider forestry sector as a result of tree growth, mortality and harvesting. It incorporates the net annual carbon flows in livewood stands, harvested wood products, deadwood and forest soils, for representative conifer (Sitka spruce) and deciduous (Pedunculate oak) species'.

Section 3.8. Water quality module part 1: Export coefficient modelling

Describes an export coefficient modelling exercise for estimating the rate and annual levels of nitrate and phosphate nutrient exports from land use into water-bodies. This provides one of the empirical inputs to the spatially explicit modelling of nutrients and ecological status described in Section 3.9. Together, Sections 3.8 and 3.9 describe the impact of land use change upon various aspects of water quality and are linked to TIM through Section 3.9.

Section 3.9. Water quality module part 2: Spatially transferable modelling of nutrients and Water Framework Directive ecological status

Describes models estimated to establish the link between land use and the ecological status of river bodies. Using data on observed nitrate and phosphate concentrations in rivers in England and Wales, statistical models are estimated that relate nutrient inputs on land (primarily from agriculture and sewage) to concentrations in rivers. Subsequently, using data on the ecological status of river bodies in the UK, the statistical relationship between ecological status and nutrient concentrations is established. Results show highly significant relationships between land use, nutrient concentrations and on to ecological status.

Section 3.10. The recreation module: Impact of land use changes upon recreation values

Describes the analysis of recreational visits and corresponding values derived from applying a random utility modelling approach to the MENE data. The module takes into account the status quo situation in terms of the spatial distribution of both the population and relevant aspects of the natural environment, specifically the array of available substitute recreational resources and the transport infrastructure (and quality thereof) determining accessibility and travel times. The analysis then assesses the net consequences of changes in land use (e.g. the planting of new forests) and estimates resultant recreational benefit values.

Section 3.11. The biodiversity module

A model of bird diversity was developed using BTO/JNCC/RSPB Breeding Bird Survey (BBS) data collected at a 1km square resolution between 1999 and 2011. These data were related to land use data from this period, together with various other predictors. Whilst some estimates lacked precision, patterns emerged with regard to the impacts of land use upon biodiversity. This ultimately forms the biodiversity module in TIM, and in future research it could operate as a binding constraint on land use change if, for example, there was a legal requirement for no net loss in biodiversity.

Section 3.12. Applying The Integrated Model (TIM): Planning Britain's new forests

This section introduces The Integrated Model (TIM) to consider the interactions and relationships between each of the individual component modules and the output they derive. The integration of the component modules is described and TIM is run for three scenarios (described in **Section 3.12.3**). It describes the afforestation policies selected in order to motivate the research and discusses the case study illustration of the methodology developed throughout the report, presenting results for the market value and social value optimisations.

Section 3.13. Conclusions

This section presents conclusions from the overall body of research, highlighting the potential value of this work to UK decision making and indicating future directions for research.

Section 3.14. Annex 1: Land use, land cover, and livestock data

This Annex provides details of the dataset we compiled for this research. To our knowledge, it is the most comprehensive definition of the physical stock of land types in Great Britain for the purposes of ecosystem assessment. This data underpinned each component module as well the final integrated model, TIM.

Section 3.15. Annex 2: Supporting data

This section describes the supporting data underpinning the research in this report. An internal digital data depository was established, providing access to a suite of datasets that described the spatially and temporally explicit components of natural and human systems at the 2 km base resolution (unless otherwise stated). These provide Great Britain-wide descriptors for natural environment and socio-economic phenomena, a common spatial unit for analysis, and facilitate the testing of models that seek better understanding of natural and human systems which are related to land use.

Section 3.16. Annex 3: The recreational value of changes in water quality

This section examines the relationship between ecological quality of rivers, the characteristics of associated potential recreation sites, and the preferences of individuals in evaluating the 'use' and 'non-use' value of such sites. Using a bespoke random utility model, evidence is presented which supports established findings (Eom and Larson, 2006; ENDS, 1998; Moran, 1999; and Bateman *et al.*, 2006) that utility from the 'use' of natural resources declines with distance from an individual's home, and that the nature of values emanating from river quality attributes differ with regard to 'use' and 'non-use' categorisations.

Section 3.17. Annex 4: Carbon values

This section briefly reviews the challenges involved in estimating carbon values, the methods employed in current best practice, and justifies the values used throughout this report. We use the carbon values published by the UK Committee on Climate Change (2008, 2013) and the UK Department of Environment and Climate Change (DECC, 2009, 2013) for use in UK policy appraisal, and the mean estimate from a recent metastudy of the social cost of carbon (Tol, 2013). This gives us three separate estimates of carbon prices, which facilitates sensitivity analysis.

3.2 Literature review: Ecosystem service decision support tools

The United Nations Millennium Ecosystem Assessment (MA, 2005) mainstreamed the concept of ecosystem services, defined as the benefits people derive from ecosystems, into policy and decision making. A rapidly growing body of research and modelling initiatives seeks to identify, characterise, and value ecosystem goods and services, drawing from diverse fields including economics, ecology, geography, systems theory and social sciences. Although models combining process descriptions, valuations and usable decision support frameworks are still in their infancy (Jackson *et al*., 2013), a variety of decision support tools have recently emerged to facilitate integrated modelling and holistic ecosystem services assessments for informing decision making. They range from simple spreadsheet applications to complex software packages, and vary in their approaches to economic valuation, spatial and temporal representation of services, and incorporation of existing biophysical models (Bagstad *et al*., 2013). They differ in their ability to handle multiple spatial and temporal scales, data scarcity, computational constraints, and methodological and philosophical approaches to balancing conflicts between users, science, and data (van Delden *et al*., 2011). Beyond the simple spreadsheet models, most decision support tools seek to support scenario analyses using simplified underlying biophysical models or "ecological production functions" (Daily *et al*., 2009) by quantifying services and their trade-offs (in monetary or non-monetary units) at a landscape scale. They take in spatial data and produce maps displaying results in biophysical units, to which monetary values are sometimes applied (Bagstad *et al*., 2013).

3.2.1 The motivation for economic valuation

The desirability of ecosystem service valuation is the subject of on-going, intense and controversial debate (e.g. Monbiot, 2012; Costanza *et al*., 2012; as discussed in Robinson *et al*., 2013). Although economic valuation offers the most obvious way of translating ecosystem services and land use impacts into comparable units, it still encounters significant opposition. In keeping with this debate, the frameworks reviewed here undertake differing approaches to valuation: some explicitly avoiding provision of monetary values; some translating everything into monetary values, either as key outputs or for input into optimisation or trade-off analysis; and others attempting a hybrid approach. Hybrid approaches largely fall into one of two categories. The first provides both monetary and non-monetary values for all services, along with means to explore their interactions from both monetary and non-monetary perspectives. The second values some services in monetary terms, while others are reported only in their 'natural', biophysical units (e.g. a requirement for water quality to lie within certain chemical and/or biological thresholds, or for there to be no net losses in biodiversity indices).

While we accept that many other land use decision making strategies exist, we adopt an environmental economic approach for several reasons, and describe these in detail below. In doing so, we adopt the latter strategy outlined above, reporting in monetary terms all ecosystem services and land use impacts for which robust economic valuations can be obtained: the resulting values become inputs in an optimisation routine. However, because valuations of biodiversity are not robust (Bateman *et al*., 2011b, 2013; UK NEA, 2011), biodiversity becomes an external constraint on the optimisation procedure. Simply stated, our justification for environmental valuation is that **only a strategy firmly grounded in environmental economics can simultaneously facilitate straightforward comparisons between multiple trade-offs and reliably identify those policies which offer society the greatest value for money.**

Optimisation delivers an explicit, formal procedure for evaluating trade-offs between competing options. Land use decision makers are faced with multiple trade-offs: land devoted to agriculture cannot also be dedicated to residential development, and land that is converted to motorway cannot also support livestock production. Moreover, land use policies have multiple direct and indirect impacts, and associated with each is yet another stream of trade-offs. For example, restrictions on fertiliser use affect crop selection and farm profitability, but also bird species diversity and downstream river quality. The question faced by policy makers thus becomes 'which stream of direct and indirect impacts delivers the greatest gains to society?'

This question is particularly challenging when each stream of impacts is measured in different natural units. Changes in water quality may be measured in pollutant concentration, agricultural production in tonnes of output, greenhouse gas (GHG) flows in tonnes of CO_2e (CO_2 equivalent), recreation in number of visits, and bird species diversity by Simpson's Diversity Index. Optimal decision making requires the comparison of trade-offs and the identification of options which deliver the greatest net benefits; however these 'natural' physical units do not facilitate such comparison. For example, exactly how many tonnes of wheat production should society trade for an extra tonne of CO_2e sequestration, and what is the appropriate conversion factor for trading off kilograms of beef this year against recreational visits in 5 years? To make the best decisions, and to maximize net gains from land use, decision makers must have information about these trade-offs in comparable units.

Ideally, the common unit for comparison would satisfy several criteria. First, it must be sufficiently robust and reliable to inform decision making from the individual farm to the national policy arena. Therefore, it must also be familiar to and readily understood by stakeholders at all levels, and from any industry or discipline. Third, it must be able to distinguish clearly between superior and inferior outcomes, as well as identify outcomes which are of equal benefit. Finally, it must be flexible and sensitive to changes over time, and able to incorporate continuously changing policy, economic, and biophysical relationships.

None of the 'natural units' in which land use impacts and ecosystem services are typically measured satisfy these criteria, meaning an alternative common unit is necessary to support optimal decision making. Only economic values satisfy all of the above criteria. As such, the ecosystem services and land use changes for which robust economic values can be obtained should be reported in monetary terms. In some instances, this is uncontroversial; for instance, the monetisation of agricultural and timber output is already commonplace. In others, valuation is more difficult, but still possible, as is the case with valuing GHG flows (see Annex 4). Finally, as we argue in Bateman *et al*. (2011b, 2013) and in the UK NEA (2011), contingent valuations of biodiversity are not robust, and as such impacts on biodiversity are reported, but are not part of the optimisation in The Integrated Model (TIM) developed here. In future work, biodiversity constraints (see Section 3.11.7) could be incorporated.

3.2.2 UK Ecosystem service mapping tools

In the UK, as elsewhere, the ecosystem service concept has gathered significant momentum. This is demonstrated by the variety of tools and mapping endeavours documented on the Natural Environment Research Council's (NERC) Biodiversity and Ecosystem Service Sustainability (BESS) mapping gateway[20], which serves as an information portal pointing to various UK projects. It indicates a wide range of on-going ecosystem service mapping initiatives ranging from local to national scale. The projects' core objectives vary from informing local decision making to developing conceptual frameworks for mapping economic values of services and benefits pertaining to social, cultural and health impacts. They utilise a broad range of data, including, for example: administrative boundaries, biological monitoring, habitat or land cover, habitat quality and or condition, human census, infrastructure, land use, protected or designated areas, and presence and condition of rivers.

[20] http://www.nerc-bess.net/ne-ess/

A typical example is the SCCAN (System Cynorthwyo Cynllunio Adnoddau Naturiol / Welsh for Natural Resource Planning Support System) project, which the Countryside Council for Wales and Environment Systems has been developing since 2010. Its aim is to deliver an ecosystem service mapping system that can assist interested parties, including local stakeholders, policy makers, conservationists and private companies in taking an ecosystems approach in their decision making. SCCAN brings together data from a wide range of sources and scales, converts these into a common grid structure, and evaluates and sets priorities using a rule based approach which determines which data are useful in describing a service, and how to weight them when combined using expert judgement. The aim is to provide the best mix of services, meeting society's needs while maintaining ecological resilience and options for future use.

In practice, many of these mapping tools layer geographic information system (GIS) data. They identify overlaps and thus potential hotspots of service delivery, but also potential conflict areas where trade-offs are apparent. Their most frequent use is to encourage participatory engagement with the community to develop an agreed shared future, and ensuring decisions are operationally viable.

3.2.3 Generic, integrated ecosystem service models

In addition to these mapping tools, a range of more comprehensive integrated models have been developed. The fundamental difference between these mapping approaches and a new emergent set of more integrated, holistic modelling tools such as InVEST, LUCI, MIMES, and The Integrated Model (TIM) developed in this report, is that the latter generate production functions exploiting fundamental biophysical models linking inputs to outputs from our best scientific understanding. This enables generation of outputs beyond current data availability which constrains many simpler mapping approaches. Furthermore, outputs can be expressed in service specific, physical units (e.g. kgC, runoff, yield), and if required, valued economically. Interactions between services are also implicitly modelled, enabling a greater understanding of the importance of spatial context and the inter-dependence of ecosystem function and service delivery. The challenge is to organise the wide array of existing ecosystem process models for single ecosystem functions in a meaningful and transparent way. However, in a recent review exploring modelling options for use in Natural England's Ecosystem Services Pilot Catchments, Bellamy *et al*. (2011) concluded that such an approach was not feasible, owing to inherent complexity, data and computational requirements, uncertainty, and challenges with interpretation. Instead, they recommend a Bayesian Belief Networks approach within a GIS framework for modelling the effects of land use and land management changes on ecosystem services. Whilst the Bayesian Belief Network approach indeed seems valuable, and is adopted, for example by the ARIES model, integrated tools such as TIM, LUCI and InVEST suggest that the mechanistic biophysical approach does have significant potential and can deliver meaningful outcomes for land and water managers.

Internationally, two of the best known ecosystem service frameworks are the InVEST tool (Tallis *et al*., 2013) and ARIES (Bagstad *et al*., 2011). InVEST currently considers water quality, soil conservation, carbon sequestration, biodiversity conservation, aesthetic quality, coastal and marine environment vulnerability, hydropower production, pollination services and values of selected market commodities. It considers both marine and terrestrial environments. Its models are biophysical, and include explicit economic valuation of all services. The most recent release of ARIES includes carbon sequestration, flood regulation, water supply, sediment regulation, fisheries, recreation, aesthetic viewsheds, and open-space proximity value. It is designed to be extremely flexible and can include biophysical models where desired, but generally uses empirical neural networks/Bayesian statistical approaches to extract relationships between inputs and outputs, along with agent based modelling.

Other tools gaining interest in the international literature are MIMES, LUCI and Co$ting Nature. MIMES is a systems model which represents the dynamics and feedback loops between physical, social and economic processes in detail (although to date the physical process feedbacks are further developed and better integrated than the social and economic components). It seeks to be a truly integrated model, and represents an ambitious effort to take integrated modelling forward to match or extend the state of the art of meteorological and climate modelling. LUCI is an extension of the Polyscape framework for weighing land management and ecosystem service trade-offs described in Jackson *et al*. (2013). It is highly spatially explicit, with resolution of 5 meter grid squares within the UK and at worst 50 by 50m globally. It is therefore applicable at any spatial scale, and can consider the cumulative impacts of small interventions such as riparian planting at national scale. It currently considers agricultural productivity, flood regulation, carbon sequestration, sediment regulation, habitat connectivity, and water quality. It has a simple approach to considering trade-offs between services, classifying individual service provision at its native spatial resolution into “existing good”, “potential to improve”, or negligible existing or potential provision”. It then layers those categorised services to identify parts of the landscape where trade-offs versus win-win situations exist, and where management interventions could enhance or protect multiple services. Finally, Co$ting Nature uses global datasets to estimate and value water yield, carbon storage, nature-based tourism, and natural hazard mitigation services, aggregating these into a “service index” accounting for not only provision but also beneficiary location. Although it is less flexible and modular than the other frameworks, it is significantly easier to apply (and access).

Numerous further tools are emerging. Conducting a literature review and interviews with 77 colleagues across academic, public, private, and NGO sectors, Bagstad *et al*. (2013) identified numerous “ad-hoc” ecosystem service mapping efforts and “ecosystem-based management tools.” For example, as of November 2012 the Ecosystem-Based Management (EBM) Tools database contained 183 tools (Ecosystem-Based Management Tools Database, 2012). Bagstad *et al*., (2013) identified 17 tools (including the five described above) with an explicit focus on multiple ecosystem services. Many of these developing tools include estimation of monetary values by supplying a per-unit market, social, avoided, or replacement cost (Bagstad *et al*., 2013). The review excluded tools specifically developed for conservation planning or optimization, integrated models not explicitly linked to ecosystem services and “one-time applications”.

3.2.4 TIM in context

Because many of the models discussed here remain in their infancy, a comprehensive comparison is difficult. Documentation is often sparse and they all are undergoing rapid changes in further development. A distinction must also be made between what each model currently achieves, and what its likely capabilities in the medium and long term. Acknowledging this, **Table 3.1** attempts to summarise some of the key differences and similarities between six leading frameworks, considering only the current to medium term.

Table 3.1. Overview of integrated modelling frameworks

	ARIES	Co$ting Nature	InVEST	LUCI	MIMES	TIM
Model approach	Bayesian belief network and agent based modelling; flexible framework	Web-enabled model with globally available data using simple empirical models.	Detailed biophysical models and economic valuation of all services	Simplified biophysical models with fine spatial detail; fast running for scenario exploration	Detailed physics & integration of environmental, economic and social drivers	Biophysical modules with robust economic valuation and formal optimisation
Spatial scale of analysis [resolution of individual elements in brackets if applicable]	Flexible, but generally regional scale	Flexible, has global coverage [1km^2 or 1ha]	Regional – component models not suited for local scale application	Sub-field to national [typically 5x5m 50x50m]	In theory flexible, to date regional to global	Medium catchment to national [2km grid square]
Temporal scale of analysis	Flexible	Steady state	Annual, sub-annual in development	Steady state and annual, sub-annual in development	In theory flexible; data requirements currently limiting.	Annual but could be sub-annual
Data gathering effort required by user	Heavy for new applications (existing applications will be made available via web portal)	Negligible; data pre-loaded and available via web portal	Heavy	Moderate; "first tier" suite of models work with widely available national data	Very heavy	Negligible; data is pre-loaded and available within the TIM software
Parameterisation effort required by user	Theoretically low – data driven model approach; but models need to be trained on data	Negligible; default parameters provided although can be tweaked by user	Heavy – detailed biophysical models requiring parameterisation	Light- default parameters provided although user is encouraged to modify/consider them	Very heavy	Economic valuation of services & analysis of their inter actions
Flexibility/modularity	Very high	Low	High	High	N/A – fully integrated systems model, component processes could be modularised but not services.	High, with built-in constrained optimisation procedure
Economic valuation provided?	No	No	Yes	No	In theory; due to type of model perhaps not fully yet.	Yes.
Types of trade-offs considered	Biophysical & via analysis of service flow from provision to beneficiaries	Services categorised & flow to beneficiaries considered	Biophysical and monetary units traded against each other	Biophysical; "win-win" vs. trade off analysis of categorised services	Economic valuation of services & analysis of their inter actions	Trade-offs analysed by explicit economic valuation of all services
Optimisation?	Through scenario optimisation; although Bayesian framework potentially enables robust optimisation and uncertainty analysis.	Through scenario optimisation only	Through scenario exploration only	Through scenario exploration, some guidance on optimisation given via maps showing regions where preservation or change desirable		Yes, constrained optimisation procedure is part of framework
Unique Features	Sophisticated modelling of flows to beneficiaries, source and sink, flexibility, Bayesian & agent based modelling.	Globally available, simple to use, data pre-loaded for user	Most established/ advanced suite of biophysical models, explicit economic valuation	Designed to work with nationally available data, spatial scale scans sub-field to national, fast running to enable real time stakeholder exploration	Full systems approach, truly integrated model	Constrained optimisation procedure; explicit economic valuation; increased integration via coupling linkages between services

TIM is unique in being the first application of an integrated modular ecosystem service framework covering the whole of the UK and using detailed UK-specific data (we discount “global” applications, using coarser global data, such as MIMES and Co$ting Nature). However, when compared to the established suite of ecosystem service models, it becomes apparent that TIM’s novelty lies in the introduction of formal optimisation alongside robust ecosystem service valuation. Crucially, because services are values in common economic units, trade-offs and comparisons can be drawn and their impacts can be readily interpreted by a diverse audience of varying specialist backgrounds. This is particularly useful in land use policy as decision makers are expected to maximise net returns from scarce resources, accounting for a broad range of biophysical and economic impacts and responses. Although InVEST also applies economic valuation, it stops short of formal optimisation and lacks the 2km grid square resolution of TIM in the UK.

3.3 Proof of concept: Can spatially targeted policies increase land use efficiency? Extending the UK NEA scenario analysis [21]

3.3.1 Objective

The objective in this section is to demonstrate that a new approach to policy making which abandons the use of uniformly applied policies selected from a set of arbitrarily predetermined end-points can significantly improve decision making in the UK.

3.3.2 Summary

The UK NEA (2011) made a clear case for the potential gains in wealth and human well-being from valuing ecosystem services and incorporating these values into economic analyses and policy. The valuation component of this has received significant attention, and whilst more work in that area is necessary, this report focuses instead on the crucial question of how best to incorporate these values into the policy making process. Two features of the conventional approach to land use decision making render it un-fit for purpose. The first entails attempts to choose 'the best' policy from a set of arbitrarily predetermined options. Policy makers are often presented with an arbitrary and limited set of policy options from which they must select the best. Moreover, when these predetermined options lack economic valuation, they are forced to compare incomparable units and make policies without knowing the potential values resulting from each option. This restricts the choices available to decision makers and offers no guarantee that the policies which would maximise net benefits even enter into land use policy discussions. The second shortcoming entails the uniform application of these policies across the entire UK. This ignores the spatial differentiation in the biophysical, economic and demographic characteristics which underpin human-environment interactions throughout Great Britain and is therefore inconsistent with evidence based policy.

The novelty of this research is in the way we address these two shortcomings. In addition to maximising the sum of market and non-market benefits, the approach to designing and implementing land use policies presented here explicitly models and actively takes advantage of local environmental and economic conditions. That is, we examine the underlying human, economic, and ecological conditions for every 2-km grid square in Great Britain, and select different policies for different locations in order to maximise society's net returns from land use. This entails a fundamental change in decision making practice, and enables us to move away from the conventional approach of choosing 'the best' among a set of uniformly applied and arbitrarily predetermined options and towards policies which are strategically designed to take advantage of spatial variation and local conditions.

3.3.2.1 Choosing from a set of arbitrarily determined policy options

Conventional decision making entails comparing the costs and benefits of several potential options and selecting the one which maximises net benefits. Although considerable effort is expended in researching and vetting the options that are eventually compared, this approach has several shortcomings in that:

[21] The work for this chapter was carried out as part of the UK NEAFO WP3a program, and elements have been published in Bateman et al., (2013).

- there is no formal, systematic method of ensuring that the best option (i.e. the one which maximises net benefits) is actually on the table for comparison;
- it is not always clear that the options considered are actually feasible in practice; and
- once an option is selected, and if it is in fact feasible, there may still be no clear strategy for identifying the most resource efficient way to implement it.

3.3.2.2 Uniformly applied policies

Given the extent of heterogeneity in biophysical processes and the natural environment across the UK, as well as the varied ways in which humans interact with them, it is unlikely that any single policy could simultaneously be optimal in every location. As such, spatially differentiated policies which are specifically designed to take advantage of this variation could lead to substantial efficiency gains in environmental-economic decisions (Bateman *et al*., 2013). We illustrate this with a simple example concerning land use policies in the UK (for greater detail, see Bateman *et al*., 2013).

3.3.3 Potential benefits from spatially targeted land use policies in the UK: A case study

The following case study demonstrates how selecting and applying spatially specific land use policies in accordance with local environmental-economic conditions can significantly increase the net value of land to society.

The initial analysis conducted examined the consequences of policy-driven land use change for the ecosystem services provided by the following:

- agricultural production;
- greenhouse gases (emissions and sequestration);
- open-access recreational visits;
- urban green space; and
- biodiversity conservation (proxied by wild bird species diversity).

Each of these was considered within the context of unavoidable climate change, and models were run for the 50 year period from 2010-2060.

3.3.3.1 Data

Raw data were compiled from multiple sources (for greater detail, see Bateman *et al*., 2013, and supplementary material) to develop a 40-year dataset with a spatially disaggregated resolution of 2-km grid squares (400 ha) across all of Great Britain. This created more than 500,000 spatially referenced, time-specific, land use records.

The determinants of land use considered in this analysis included:

- physical environmental characteristics (spatially variable factors such as soil characteristics and slope, as well as spatio-temporal climate variables such as growing season temperature and precipitation);
- agricultural and environmental policy (taxes, subsidies, and land use constraints);
- market forces (prices and costs); and
- technology (incorporated as changes in costs).

3.3.3.2 Assumptions and policy options

Accounting for 74.8% of the total surface area, agriculture dominates land use in the UK. The models used here assume that farmers determine land use in order to maximise long-run profits, subject to the various policy, price, and physical-environmental conditions they face in a given location and time. The analysis examined how policy-driven land use change would affect net social benefits from land over the period 2010-2060. We use the six potential policy scenarios described in the UK NEA (2011). These include both spatially focused and spatially unfocused policies and are summarised in **Table 3.2**.

Table 3.2. Summary of land use change policy scenarios.

Policy option	Environmental regulation and planning policy relative to current	Spatial focusing of changes
Go with the flow (GF)	**Similar:** Policy and regulatory regime as today. Existing patterns of countryside protection relaxed only where economic priorities dominate.	**Unfocused:** Similar spatial constraints on land use change as today. No expansion of the protected area network.
Nature at work (NW)	**Stronger:** Policy and planning emphasize multi-functional landscapes and the need to maintain ecosystem function.	**Focused:** Greening of urban and peri-urban areas to enhance recreation values.
Green & pleasant land (GPL)	**Stronger:** Agri-environmental schemes strengthened with expansion of stewardship and conservation areas.	**Focused:** Increased extent of existing conservation areas. Creation of functional ecological networks where possible.
Local stewardship (LS)	**Stronger:** Agri-environmental schemes strengthened with expansion of stewardship and conservation areas.	**Unfocused:** No strong spatial component to changes but protection of areas of national significance continues.
National security (NS)	**Weaker:** Emphasis on increasing UK agricultural production. Environmental regulation and policy is weakened.	**Unfocused:** Some land use conversion into woodland occurs in areas of lower agricultural values
World markets (WM)	**Weaker:** Environmental regulation and policy is weakened unless they coincide with improved agricultural production.	**Focused:** Losses of greenbelt to urban development, resulting in loss of recreational values. Weaker protection of designated sites and habitats.

Source: adapted from Bateman et al., (2013)

3.3.3.3 Results

The high-resolution spatially explicit model enabled us to evaluate the outcomes of each policy scenario for every 2km grid-square in Great Britain, and to select the policy which maximised a given objective in that cell. Three objectives were considered: maximising market values only, maximising all monetary values, and maximising all monetary values subject to a biodiversity conservation constraint. That multiple colours are visible in **Figures 3.1A**, **C, E** proves that no single policy scenario was optimal in all locations.

The results in **Figure 3.1** show that when the objective is to maximise only market values (**Figures. 3.1A**, **B**), largely unfocused policies that prioritise agricultural land use (NS and WM) dominate. However, these policies ultimately reduce overall values (including those from other ecosystem services) from the landscape in many parts of the country (**Figure 3.1B**); notably in upland areas (where agricultural intensification results in substantial net emissions of GHG) and around major cities (where losses of greenbelt land lower recreation values). In comparison, **Figures 3.1C**, **D** pursue the objective of maximising the net of all monetary values, including those from non-market ecosystem services (excluding biodiversity for now). For this objective, spatially focused policies which emphasise multifunctional landscapes and ecosystem function (NW) tend to dominate, yielding net benefits in almost all areas, with the greatest gains in areas of high population (**Figure 3.1D**). Crucially, this demonstrates that due to biophysical and economic heterogeneity, the value that Great Britain derives from its land use is maximised only when differentiated policies are matched to differentiated local conditions.

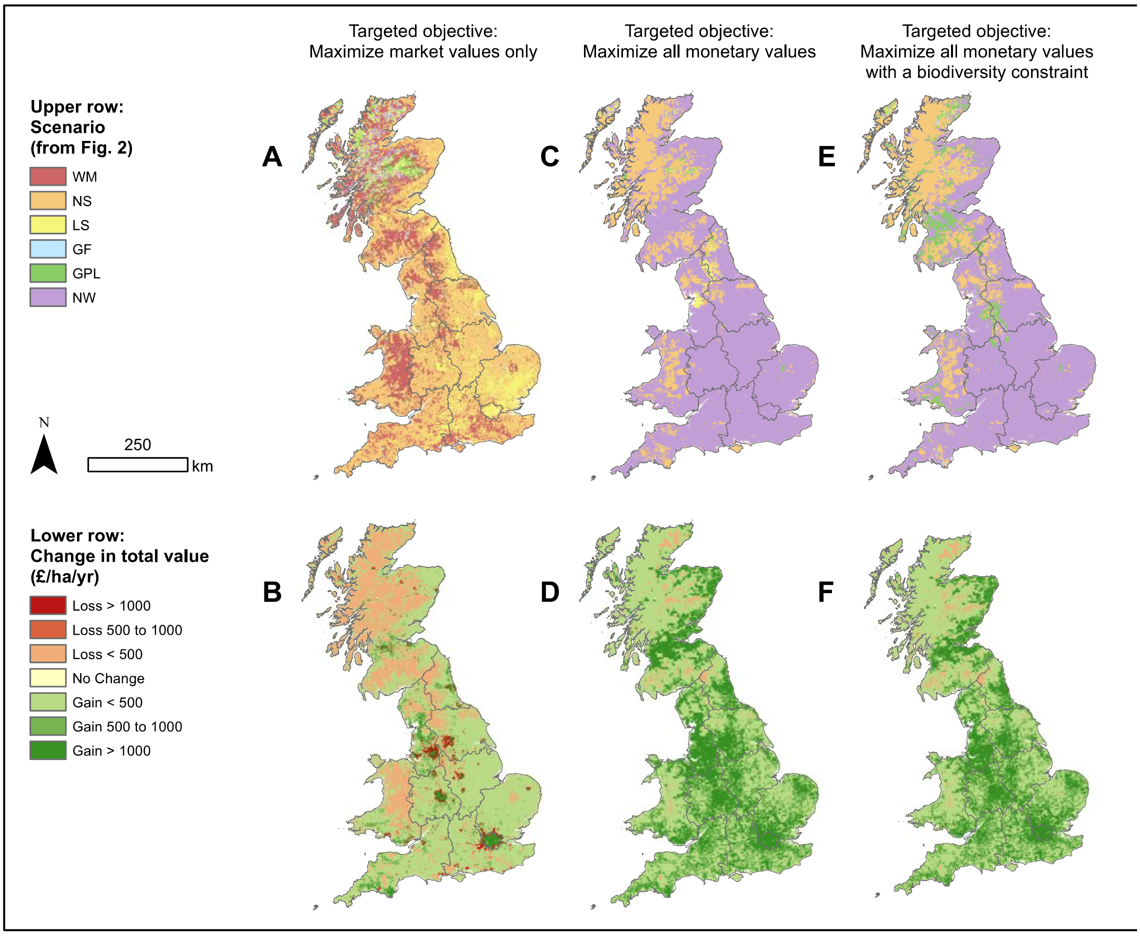

Figure 3.1. Optimal scenarios and changes in value. Optimal scenarios (A, C, and E) for each 2-km grid square and corresponding changes in value from 2010-2060 (B, D, and F) in Great Britain under three alternative targeted objectives: (i) conventional approach to maximising market values only (A and B); (ii) maximising the value of all those ecosystem services that can be robustly monetised (C and D); (iii) maximising all ecosystem service values but with a constraint so that no policy option that gives a net loss of wild bird diversity is permitted in the area affected (E and F) [all analyses assume low GHG emissions, climate change from Jenkins et al., (2009).
Source: Bateman et al., (2013).

Decisions based on all ecosystem services for which robust economic values can be derived (**Figures. 3.1C,D**) unambiguously deliver greater net benefits to society than those designed to maximise only market values (**Figures 3.1A,B**). However, because the value of biodiversity cannot be reliably estimated, it has hitherto been excluded from the analysis. In **Figures 3.1E,F**, we now incorporate measures of change in wild bird species diversity by introducing a simple constraint stipulating that any policy which reduces the species diversity index in a given area is rejected for that area. The similarity to **Figures 3.1C,D** shows that, when applied in a targeted manner, this constraint has relatively little impact upon which scenario delivers the greatest net benefits to society; i.e. the 'opportunity cost' of imposing a species conservation constraint is relatively minor. Nevertheless, comparison of **Figures. 3.1C**,**E** shows that, in certain areas, the biodiversity constraint causes a shift from policy NW, which focuses on the enhancement of greenbelt areas for recreation, to policy GPL, which focuses on extension of existing areas of conservation value.

For concreteness, **Table 3.3** presents the monetary results from the analysis shown in **Figure 3.1**. It shows that spatially targeted policies can increase net benefits relative to their unfocused, uniformly applied counterparts even when market values alone are considered, but that the gains are much greater when all monetary values are taken into account. These results are primarily driven by changes in non-market recreation and non-market urban green space.

Table 3.3. Change in values across Great Britain from the present day (2010) to 2060 achieved by the targeting of policy scenarios under three decision rules.

Decision component	Maximize market (agricultural) values only (Figs.3.1A&B)	Maximize all monetary values (Figs. 3.1C&D)	Maximize all monetary values with biodiversity constraint (Figs. 3.1E&F)
Market agricultural value	971	-448	-455
Non-market GHG emissions	-109	1,517	1,510
Non-market recreation	2,550	13,854	12,685
Non-market urban greenspace	-2,520	4,683	4,352
All monetary values	892	19,606	18,092

All data in £millions p.a.; real values in £2010; UKCIP low emission scenario throughout
Source: Bateman et al. (2013)

3.3.4 Conclusions and next steps

The example presented here clearly articulates the potential for significant increases in net benefits to society arising from the design and implementation of spatially targeted policies that actively and deliberately take advantage of the environmental-economic and biophysical heterogeneity observed across Great Britain. This was shown with respect to the ecosystem services as listed at the beginning of Section 3.3.3..

Our unique contribution is to show that due to the spatial heterogeneity of biophysical and ecological conditions across Great Britain, no single uniformly applied land use policy is likely to maximise the total economic value of land. We demonstrate this by looking across the six UK NEA policy scenarios to identify and assign the optimal scenario for each cell of a 2-km square grid of the entire UK. The analysis showed that no single policy dominated, and as such significant gains can be realised simply by matching spatially explicit environmental policies to spatially explicit environmental-economic conditions.

The subsequent sections of this report extend the analysis in several ways. First, the set of ecosystem services considered is expanded to include forestry and water quality. Second, models are developed for each ecosystem service related good and described in the following sections. Although each model can be used in isolation, our primary contribution derives from the fact that ecosystem services are valued and subjected to a formal optimisation procedure in The Integrated Model (TIM).

3.4 The agricultural production module

3.4.1 Summary

This section presents a spatially explicit, structural econometric model of UK agricultural land use. This model embraces the market, policy and environmental drivers of land use decisions related to crop and livestock production, and estimates the profits thereof.

3.4.2 Objective

To model and quantitatively parameterise spatially explicit (2km grid square resolution) determinants covering the entirety of Great Britain for:

- stocking intensities for the major livestock types: dairy cows, beef cows and sheep; and
- shares within each grid cell of the seven major agricultural land uses: cereals; oilseed rape; root crops; temporary grassland; permanent grassland; rough grazing; and other agricultural land.

3.4.3 Data

We utilise a number of datasets including TERRAIN (2012), the June Agricultural Census (JAC, 2013), SOIL (2012) and CLIMATE (2012), which are briefly described below. These were combined to form a truly unique database covering the whole of Great Britain at a 2km grid square (400 ha) level. The resulting dataset incorporates information from the late sixties to the present on the following variables: land use shares and livestock numbers; environmental and climatic determinants; and policy and other drivers. Yield and profit data are not available at the detailed spatial resolution required, so we employ the farm gross margin (FGM) (Defra, 2010) measure of farm output value instead. For further details on our constructed dataset, see Section 3.14.

The agricultural data were extracted from JAC (2013), and includes the number of hectares of farm land in use, head-counts for livestock (dairy cows, beef cows and sheep) and crop types (cereals, oilseed rape, root crops, temporary grassland, permanent grassland and rough grazing, and other). Together the first six land use types mentioned account for more than 88% of the total agricultural land within GB and represent the *h*-1 land uses which we will explicitly model later in Equation 5.6. We include the remaining 12% in an “other” land use category encompassing horticulture, other arable crops, woodland on the farm, set-aside, bare, fallow and all other land (e.g. ponds and paths). These data covers Great Britain for fifteen unevenly spaced years between 1969 and 2006. This yields about 60,000 grid-square records for the entire spatial extent, amounting to over 600,000 sets of grid-square records for overall analysis (note that not all years include information for both Wales and Scotland).

UKCP09 (2009a) contains variables on potential environmental and climate related drivers of agricultural land use covering the growing season (April-September), including average temperature and accumulated rainfall at a 5km resolution (see Section 3.15.3.3)[22]. Other environmental and

[22] While common in the literature, our definition of growing season is only an approximation. The exact definition of the thermal growing season is the longest period within a year that begins at the start of a period of five successive days where the daily-average temperature is greater than 5.0°C and ends on the day before of a period of five successive days when the daily-average temperature is less than 5.0°C. While this latter is more precise, it would be impractical to calculate a different growing season for each location and year in our sample as we only have monthly maximum and minimum temperatures, rather than daily information. In

topographic variables which may influence farmers' decisions, including characteristics and texture types of soil, were obtained from SOIL (2012). Finally, data for mean altitude and slope on a farm-by-farm basis, are both derived via GIS analysis from the two datasets: TERRAIN (2012) and Defra (2009a), at 2km resolution.

Regarding the policy determinants, we include the share of each grid square designated as National Park, Nitrate Vulnerable-Zones (DESIG, 2012), Environmentally Sensitive Areas (ESA) (DESIG, 2012), Greenbelt (GREENBELT_S, 2013; and GREENBELT_EW, 2012) (see Section 3.15). ESAs, introduced in 1987 and extended in subsequent years, are intended to conserve and enhance areas of particular landscape and wildlife significance. Participation in ESA schemes is voluntary and farmers receive monetary compensation for engaging in environmentally friendly farming practices, such as converting arable land to permanent grassland or establishing hedgerows. NVZs were introduced after 1990 with the intention of reducing nitrate levels in selected aquifers and ground waters used for public water supply. NVZ participation is compulsory and the scheme has been extended since its initial introduction. Finally, farms located within the boundaries of National Parks can benefit from direct payments if they manage their land for environmental enhancement and undertake various low-intensity activities.

Finally, a lack of information on the spatial variation of market input and output prices and technology dictates that we do not model these explicitly at any spatial level. Instead such effects are controlled for as fixed effects via yearly dummies. This approach allows us to parsimoniously control for all time-varying omitted factors and to isolate the effect of climate and other environmental variables on land use decisions. We also control for transportation costs including the distance to the closest major market, defined as an urban centre with more the 300 thousand inhabitants (TRAVEL_CITY, 2012; see Section 3.15).

3.4.4 Methodology

We present only a brief overview here; for a more detailed discussion of the methodology, see Fezzi and Bateman (2011). At its most basic level, our method assumes that farm-level decisions regarding land allocation and livestock intensity are driven by a profit motive, and models historical farming behaviour accordingly. This can be readily extended to accommodate a more general utility representation. We assume that each farmer maximises profits per unit of land by solving the following constrained optimisation problem:

Equation 3.4.1:

$$\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \max_{s_1,\ldots,s_h}\{\pi(\mathbf{p},\mathbf{w},\mathbf{z},L,s_1,\ldots,s_h) : \textstyle\sum_{i=1}^{h} s_h = 1\} \cdot$$

where $\pi^L(.)$ is a dual (indirect) profit function per unit of land,
p is the vector of prices of the *m* outputs,
w is the vector of costs of the *n* inputs,
s is the vector of *h* land share allocations,
L is the total land available and
z is the vector of *k* other fixed factors (which may include physical and environmental characteristics, policy incentives and constraints, etc.).
This dual profit function is positively linearly homogenous and strictly convex in input and output prices. By using Hotelling's Lemma we can derive the output supply ($\mathbf{y}^L$) and input demand ($\mathbf{r}^L$)

addition, our data wants to represent a climate, i.e. an average for 30 years weather, and not the yearly effect of weather, so our definition represents well the quantity of interest, i.e. the amount of temperature and precipitation received by the crops during their growth period on average during a 30 years period.

equations per unit of land (hereafter we will refer to these quantities as input and output *intensities* as per Deaton and Muellbauer (1980).

Equation 3.4.2:

$$y_i^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \frac{\partial \pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L)}{\partial p_i} = \frac{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial p_i}$$, with *i*= 1,...,*m*,

and

Equation 3.4.3:

$$r_j^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \frac{\partial \pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L)}{\partial w_j} = \frac{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial w_j}$$, with *j* =1,...,*n*,

The superscript on *s* indicates the optimal shares, i.e. those shares which satisfy Equation 5.1. The optimal land use shares are defined by first order conditions of Equation 5.1:

Equation 3.4.4:

$$\frac{\partial \pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial s_i} = \lambda$$ for *i* = 1,..., *h*.

The Lagrange multiplier λ corresponds to the land shadow price, or marginal rent (Chambers and Just, 1989), and is assumed to be equal across all land uses. When a corner solution exists (i.e. not all crops are cultivated on all farms) this equation still holds for all crops receiving non-zero allocation (Chambers and Just, 1989). When these equations are linear in the optimal land allocations, then including the constraint that the sum of the shares needs to be equal to unity leads to a linear system of *h* equations in *h* unknowns which can be solved to obtain the optimal land allocation as a function of **p**, **w**, **z** and *L* (Fezzi and Bateman, 2011).

For estimation purposes, the empirical profit function per unit of land can be specified via a number of flexible functional forms. For example, (Fezzi and Bateman, 2011) adopt a Normalized Quadratic (NQ) form, where:

w_n is the numeraire good;
$\boldsymbol{x} = \left(\frac{\boldsymbol{p}}{\boldsymbol{w_n}}, \frac{\boldsymbol{w}}{\boldsymbol{w_n}}\right)$ is the vector of normalized input and output (netput) prices;
$\bar{\pi}^L = \frac{\pi^L}{w_n}$ is the normalized profit per unit of land;
$\boldsymbol{z}^* = (\boldsymbol{z}, \boldsymbol{L})$ is the vector of fixed factors including policy and environmental drivers and the total land available: *L*.

such that the NQ profit function is defined as:

Equation 3.4.5:

$$\bar{\pi}^L = \alpha_0 + \sum_{i=1}^{m+n-1} \alpha_i x_i + \frac{1}{2}\sum_{i=1}^{m+n-1}\sum_{j=1}^{m+n-1} \alpha_{ij} x_i x_j + \sum_{i=1}^{h-1} \beta_i s_i + \frac{1}{2}\sum_{i=1}^{h-1} \gamma_i s_i^2 ,$$

Profits in each cell are, therefore, a quadratic function of prices and land use shares. This representation includes only *h*-1 land use shares, since one of these can be obtained via the additivity constraint and is therefore redundant. Symmetry is imposed by assuming $\alpha_{ij} = \alpha_{ji}$ whereas linear homogeneity is ensured by construction. Input and output intensities can be derived via Hotelling's Lemma. For instance, if x_i indicates the normalized price of cereals, the equation corresponding to cereal yield (y_{iL}) can be derived as:

Equation 3.4.6:

$$\frac{\partial \bar{\pi}^L}{\partial x_i} = y_i^L = \alpha_i + \sum_{j=1}^{m+n-1} \alpha_{ij} x_j \ ,$$

In addition, we allow the parameter α_i to be a function of the environmental, climatic and physical characteristics of the farm (i.e. the fixed factors in Equation 5.4) as:

Equation 3.4.7:

$$\alpha_i = \alpha_{i0} + \sum_{n=1}^{k} \alpha_{ij} z_j^*$$

The optimal land use shares are defined by fixed order conditions in Equation 5.4 which can be solved to derive the land use share equations as:

Equation 3.4.8:

$$s_i = \frac{\beta_i}{\gamma_i} + \frac{1}{\gamma_i}\lambda \ \text{, for } i = 1,...,h\text{-}1,$$

We also specify the intercept of this equation as a function of the environmental and climatic factors characterising the farm.

3.4.4.1 Estimation

In the following discussion we retain the NQ specification discussed above. However, a number of alternative specifications were investigated and the final approach is discussed below.

As noted previously, micro-data on land use are often characterised by corner solutions (not all farms cultivate all possible crops). Therefore imposing normal disturbances and implementing Maximum Likelihood (ML) estimation techniques will yield inconsistent estimates of the land use share and input and output intensity equations (Amemiya, 1973). We address this issue by specifying a Tobit system of equations (Tobin, 1958) in which the latent shares s_i* are defined as in Equation 3.48 plus additive normal residuals.

Observed shares are specified as: $s_i = 0$ if $s_i^* \leq 0$, $s_i = 1$ if $s_i^* \geq 1$ and $s_i = s_i^*$ otherwise. This transformation can be interpreted by recalling that the fixed order conditions of the profit maximization problem are equal to the land shadow prices. For this reason, censoring from below (above) implies that the corresponding land use shadow price is lower (higher) than those of alternative uses. One concern arising from this specification is that the adding-up restriction (i.e. the sum of all land use shares needs to be equal to one) is not satisfied for the observed shares. Following (Pudney, 1989), we address this issue by treating one of the shares as a residual category and estimating the remaining h–1 equations as a joint system. Note that this multivariate Tobit specification does not take into account the role of virtual prices when goods are not consumed (Lee and Pitt, 1986). However this should not be a major issue in this analysis since, as shown in the next section, we do not model prices explicitly but rather control for their effect via yearly dummy variables.

When more than three equations are used the ML estimation of a Tobit system requires the evaluation of multiple Gaussian integrals, which is computationally extremely intensive. To address this issue, we follow the approach suggested by Yen *et al*., (2003), who propose an approximation of the multivariate Tobit via a sequence of bivariate models, deriving a consistent Quasi Maximum Likelihood (QML) estimator. More precisely, we implement the algorithm proposed by Fezzi and

Bateman (2011), which extends the Yen *et al*. (2003) approach to the two-limit Tobit model by including censoring from above and by allowing the standard errors to vary across observations as a function of a vector of exogenous variables. This QML estimator is consistent, allows the estimation of cross-equation correlations and the imposition of cross-equation restrictions. We implement the same QML approach to estimate the system of output Equations 3.46 to 3.48, but clearly we neither discard one of the equations nor apply any censoring from above.

We implement the QML approach to estimate two censored Tobit systems:

- a livestock intensity equation system using three categories: dairy cows; beef cows; and sheep; and
- a land use share system with six categories: cereal; oilseed rape; root crops; temporary grassland; permanent grassland; and rough grazing.

To control for spatial autocorrelation we estimate the model using only a fraction of our data, selected via spatial sampling (e.g. Carrión-Flores and Irwin, 2004; Fezzi and Bateman, 2011). This is defined by randomly extracting one grid square and then sampling every fourth grid cell along both latitude and longitude axes (i.e., considering only the corners in a four by four square of cells), leaving a subsample of roughly 33,000 observations.

We illustrate findings using results from logarithmic specification with interactions for the climatic determinants in Equation 3.4.7. Furthermore, since omitted cell-specific factors can be present, we correct the variance-covariance matrix allowing the residuals to be correlated among observations pertaining to the same cell in different years (Williams, 2000).

As an illustration, **Table 3.4** reports the most important estimated coefficients of three selected land use equations, namely those of cereals, root crops and rough grazing. Estimated effects are consistent with our expectations. For example, considering the environmental determinants of land use, favourable conditions for crop growth (deeper soils, flatter land, etc.) increase the share of arable land. However, effects are non-linear and the temperature and precipitation interactions are highly significant, consistent with the literature on plan physiology (e.g. Morison, 1996) and previous findings Fezzi and Bateman (2011). Considering the policy variables, National Parks and ESAs decrease the share of intensive land uses (cereals and root crops), which are substituted for un-fertilized pastures (rough grazing).

Table 3.5 evaluates the fit and predictive ability of our model by reporting the mean absolute error (MAE) statistics for the land use share and the livestock equations. These are calculated as the mean absolute value of the difference between the predictions and the actual (JAC, 2013) data, for the whole of GB in 2003 (this being the most recent year for which we have data covering the entire nation). Since only 5% of these data are used for estimation, this test consists of mainly out-of-sample forecasting. Our approach is able to capture a significant proportion of the variability of the endogenous variables, with, for example, the MAE for cereals being less than one-third of the standard deviation. The best predictions are for rough grazing, with the MAE being less than $1/4$ of the standard deviation of the variable. Finally, the MAEs for the livestock equations are also adequate, being less than $1/2$ of the standard deviation (livestock counts can be highly variable in the JAC, 2013, data because of the methodology used to collect the data and to assign them to grid squares; see Section 3.14).

Table 3.4. Results for parameter estimates for selected land use share equations.

Variable	Cereals	Root crops	Rough grazing
Altitude	-1.93 ***	-0.03***	1.08 ***
Log Temperature	514.18 ***	41.03 ***	972.81***
Log Precipitation	159.79	13.69 ***	429.62 ***
Log Precipitation * Log Temperature	-93.53 ***	-6.37 ***	-163.82 ***
Slope	-0.62 ***	-0.003	0.64 ***
Share of National Park	-0.04 ***	-0.001	0.04
Share of ESA	-0.02 **	-0.002 **	0.02 **
Share of greenbelt	-0.02 **	0.002 **	0.01 *
Distance to the closest urban centre > 300k habitants	-0.02 ***	-0.001 ***	0.02 ***
Share of soil defined as gravelly	-5.41 ***	-0.61 ***	-1.00
Share of soil defined as stony	-1.42*	0.001	-3.61 **
Share of soil defined as peaty	-10.22 ***	1.94 ***	4.07 **

Yearly fixed effects and heteroskedastic error component parameters included in the model but not reported in the table to preserve space. Standard errors corrected for cell-specific autocorrelation as in Williams (2000). Significance p-value: *p< 0.05; **< 0.01; ***<0.001.

Table 3.5. Predictive performance.

Dependent variable	St. dev. of variable	MAE
Cereals	63.25	20.15
Oilseed rape	14.77	5.35
Root crops	14.08	4.95
Temporary grassland	20.61	10.52
Permanent grassland	82.26	39.20
Rough grazing	120.45	32.12
Other	41.07	32.66
Dairy cattle	82.95	37.06
Beef cattle	124.92	64.04
Sheep	771.19	339.06

Forecasting performance tested on GB data in year 2003 (53,837 observations).
This is an out of sample forecast test

The ability of the agricultural module to predict out of sample is graphically demonstrated in **Figure 3.2**. Here, on the left hand side, we map the observed (actual) intensity of wheat production (in hectares per 2km square). This is compared, on the right hand side, with the values predicted by the data when modelled on data excluding the prediction period. As can be seen both the spatial pattern and intensity of production are well captured by the model. When combined with the formal tests provided in **Table 3.4** this confirms the ability of the model to robustly estimate quantities and spatial location of agricultural production as well its capabilities to generate forward forecasts.

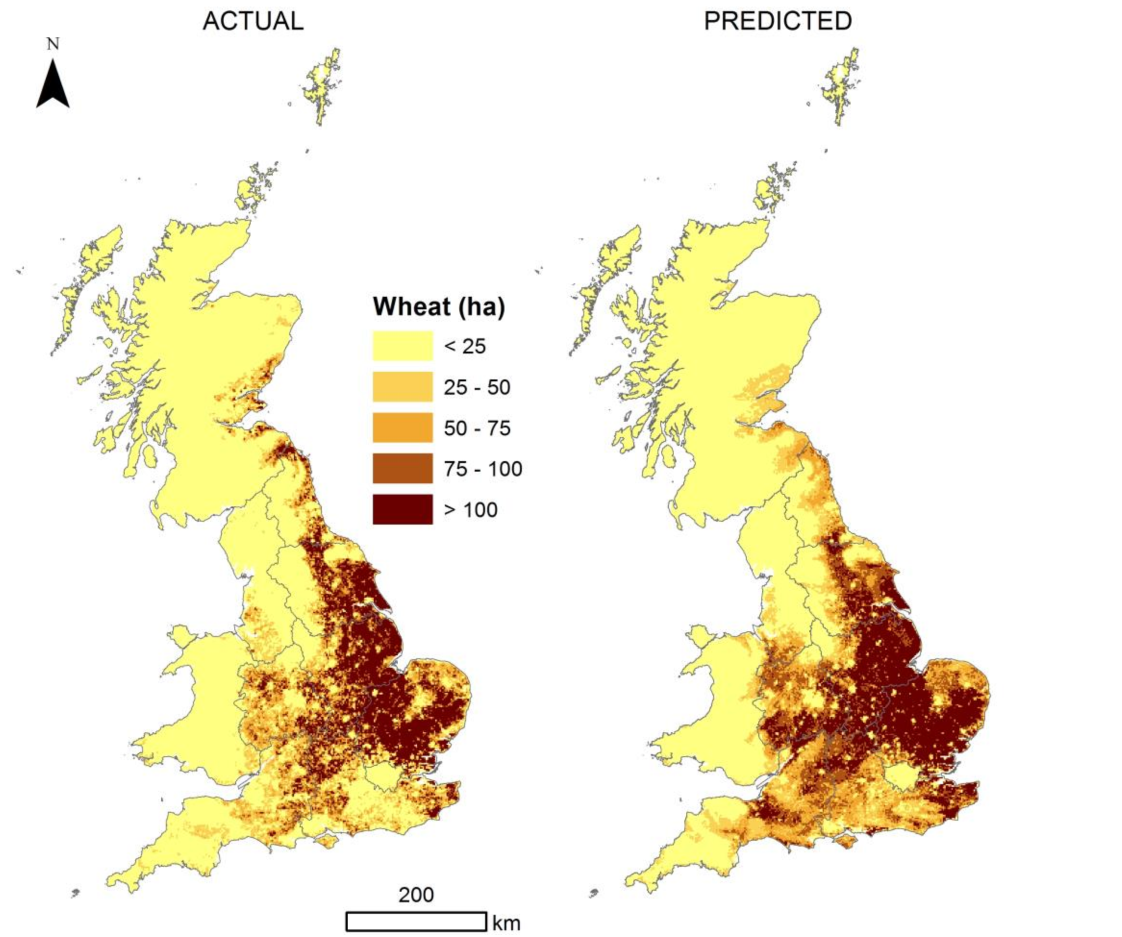

Figure 3.2. Distribution of actual (left) versus out of sample predicted (right) hectares of wheat per 2km square (maximum = 400 ha) for 2010.

For details of the methodology used to collect the data and to assign them to grid squares; see Section 3.15 Annex 2: Supporting data.

3.4.5 Limitations of our approach

Several caveats need to be taken into account when considering the results produced by this agricultural modelling approach.

First, this framework is essentially static and looks at equilibrium, long-run relations. While this is an essential feature for examining long-term impacts such as climate change, it does not investigate inter-temporal aspects of agricultural production decisions. For instance, we assume equilibrium in the land market with land shadow prices equal across all land uses. However, in the short-run other factors such as levels of existing capital (e.g. buildings) could bring disequilibrium in the land market.

Second, the issue of land tenure, which can be important in shaping agricultural land decisions, is not addressed in this work. For example traditional agricultural tenancies guarantee lifetime security of tenure in most circumstances, with the considerable prospect of succession for two more generations. Such tenancies traditionally include a clause restricting the land to agricultural use, reserving existing trees to the landlord, and preventing tree planting on any scale by the tenant farmer.

Third, we assume that farmers are risk neutral and profit maximisers, while other factors besides mere profit maximization can influence farmers' decisions. For instance, previous research as shown that farmers can exhibit a significant level of risk aversion.

Fourth, the research here focuses on the impact of changes in temperature and precipitation on land use decisions, but does not account for other factors which might be affected by climate change. For example, increased CO_2 fertilization could improve crop yields, however there may be a quantity versus quality trade-off as these could be offset by declining nutritional value. Further potential effects of climate change include impacts on pollinators and the transmigration of new crop pests and diseases. Finally, although we considered the impact of changing average temperature and precipitation, we did not consider potentially significant impact extreme events.

Fifth, we do not account for the potential introduction of new crops, technologies or farming practices.

3.5 The farm greenhouse gas (GHG) module: GHG emissions and sequestration on agricultural land

3.5.1 Summary

This section discusses the spatially and temporally explicit modelling of greenhouse gas (GHG) flows associated with predicted changes in agricultural land use. There are a range of models available to estimate emissions as a function of land use and site management, from the IPCC Tier 1 methods (IPCC, 2006) to more detailed process-based models such as DNDC (Li *et al*., 1992), RothC (Coleman and Jenkinson, 1996), or DAYCENT (Parton *et al*., 1993). These models vary with regard to the data requirements, computational intensity, and time required for interpreting the output. Within this project we chose to use the Cool Farm Tool (CFT, 2013) as a model of intermediate complexity which requires as inputs general activity data and site characteristics provided by the other components of this project. Data inputs and section linkages are described in more detail below.

3.5.2 Objectives

The aim is to calculate the GHG flows associated with agricultural land use change described elsewhere in this report. GHG flows are calculated as a function of soil type, land-use, and assumed farm management data to enable spatial projections. Further details regarding the caveats relating to emissions excluded from this calculation are given in the methodology Section 3.5.4.

3.5.3 Data

Many soil based emissions from agriculture depend on certain soil characteristics as well as management practices. Bouwman *et al*. (2002), for example, incorporate such characteristics within an empirical model of soil based nitrous oxide (N2O) and nitric oxide (NO) emissions as described in 3.5.4.1. To populate this model, the following variables were obtained for the UK from the Harmonized World Soil Database (HWSD) (FAO/IFA/IIASA/ISRIC-WSI/ISSCAS/JRC, 2013): soil texture, soil organic matter (SOM), soil moisture, soil drainage, soil pH bulk density, and direct and indirect N_2O emissions were estimated accordingly. The inputs are presented in more detail in **Table 3.6**.

Predicted land use information was obtained from the agricultural model describing the seven land use categories for farmland as follows: oilseed rape; cereals; root crops; grassland with rough grazing; permanent grazing; temperate grazing and other.

Table 3.6. Categories for soil parameters as used in CFT.

Soil parameter	Classes
Soil texture	(i) coarse (sand, loamy sand, sandy loam, loam, silt loam, silt) (ii) medium (sandy clay loam, clay loam, silty clay loam) (iii) fine (sandy clay, silty clay, clay)
SOM	SOM<= 1.72 1.72 <= SOM <= 5.16 5.16 <= SOM <= 10.32 SOM>=10.32
Soil moisture	moist dry
soil drainage	poorly drained - for fine soils good drained - for medium and coarse soils
soil pH	pH <= 5.5 5.5 <= pH <= 7.3 7.3 <= pH <= 8.5 pH >= 8.5
Bulk density	values from Harmonised World Soil Database (source below)

Soil parameters from the Harmonized World Soil Database (HWSD) were categorized for soil texture, soil organic matter (SOM), soil moisture, soil drainage, soil pH and bulk density to give background information for calculating GHG.
Source: (FAO/IFA/IIASA/ISRIC-WSI/ISSCAS/JRC, 2013).

3.5.4 Methodology

Agriculture is a substantial emitter of GHGs through for example, machinery use, mineral and organic fertiliser use, ruminant livestock, effects of both biomass and soil carbon stocks. Major carbon pools on land persist in living biomass (forests, perennials and tree-cropping systems), in addition to soil carbon.

Since most agricultural produce is for consumption within a period of months to a few years it is common practice (e.g. GHG protocol - GHG, 2013) not to account for photosynthetically fixed carbon in plant biomass or agricultural produce. The soil organic carbon (SOC) pool can be a substantial source or sink for emissions, although, except in the case of organic soils the SOC pool tends to equilibrate under fairly constant land use Jenkinson (1990). As a consequence, the major sources of emissions not related to energy use are nitrous oxide (N_2O) and methane (CH_4). N_2O emissions arise due to the mineralisation of nitrogen in organic matter (in the soil or for example in animal manures), and through the use of synthetic nitrogen fertilisers. Major sources of methane are from ruminant livestock (a function of dry matter intake) and manure management. Since dry matter intake is roughly proportional to animal size the key variables affecting GHG emissions are nitrogen fertiliser for field crops (e.g. Hillier *et al*., 2011), and number of head for a given livestock species. These were thus the critical input variables required for the GHG modelling component.

Based on the outputs of Section 3.4 agricultural land is classified into seven categories in this project. For each category a representative management regime is identified with specific fertiliser rates and machinery use characteristic of the UK. GHG emissions associated with livestock were incorporated into the analysis implementing the emission factors reported by (IPCC, 2006).

3.5.4.1 Cool Farm Tool (CFT)

The Cool Farm Tool was employed to calculate GHG flows from agricultural land. This tool was originally developed for farmers to estimate the carbon footprint of crop and livestock products. It was designed to be both simple enough for general agricultural use, but scientifically robust for calculating carbon emissions. The CFT has been tested and adopted by a range of multinational companies who are using it to work with their suppliers to measure, manage and reduce GHG emissions in an effort to mitigate global climate change. The calculation of emissions is done at farm-level based on land use and related information and takes all relevant data on production processes, fertiliser use, energy and transport into account. The tool identifies hotspots and makes it easy for farmers to test alternative management scenarios, revealing those that will have a positive impact on net GHG emissions.

Methodologically the CFT sits between calculators using simple emission factor approaches IPCC (2006, Tier 1) and Process-Based models that require a greater level of data input and training to interpret IPCC (2006, Tier 3). The tool is divided into seven input sections as follows:

- General Information (location, year, product, production area, climate);
- Crop Management (agricultural operations, crop protection, fertilizer use, residue management);
- sequestration (land use and management, above ground biomass);
- livestock (feed choices, enteric fermentation, N excretion, manure management);
- Field Energy Use (irrigation, farm machinery, etc.,);
- Primary Processing (factory, storage, etc.,); and
- Transport (road, rail, air, ship).

CFT (2013) has been engineered in Microsoft Excel and is currently being adapted for online use.

The CFT employs a multivariate empirical model of Bouwman *et al*. (2002) to estimate NO and N_2O emissions from fertiliser applications. The model is given as follows.

Equation 3.5.1:

$$\mathrm{N_2O} = e^{\mathrm{const}} + \sum_{1}^{n=i} \mathrm{Factor\ class}\ (i)$$

Where factor the classes are; fertiliser type x fertiliser application rate, crop type, soil texture, soil organic carbon, soil drainage, soil pH, soil cation exchange capacity, climate type, and application method. Factors were determined by statistical analysis and are given in Bouwman *et al*. (2002). The model for ammonia (NH_3) emissions differs marginally.

Equation 3.5.2:

$$\mathrm{NH_3} = \mathrm{FA} \cdot e \sum_{1}^{n=i} \mathrm{Factor\ class}\ (i)$$

,where FA is the amount of fertiliser applied. The model is described in FAO/IFA (2001).

Emissions from the production of nitrogen fertilisers are generally comparable in magnitude to field N_2O emissions. These emissions are often attributed to industry, although since they are produced for agricultural use it is often considered appropriate to incorporate these emissions in agricultural assessments and product carbon footprinting. Embedded emissions in other agro-chemicals are incorporated on a unit active ingredient using figures derived from the Audsley (1997) harmonisation life cycle assessment.

Other embedded emissions (for example in machinery manufacture) are not included. Although this is somewhat inconsistent from a scoping point of view, there is no consensus on how to incorporate these emissions although they are acknowledge to be insignificant relative to other agricultural emissions sources (Whittaker *et al*., 2013)

For the present analysis we use the first two of the seven inputs for the CFT described earlier; the "General Information", and "Crop Management," programmed into MATLAB (2013) to calculate carbon emissions from agriculture for the UK. Therefore, representative management regimes include fertilizer use and emissions for machinery in six of the seven land use categories as shown in **Table 3.7**. For the land use category "other" (derived from the June Agricultural Census – JAC, 2013 - , whose method was described earlier in Section 3.4) we assume the following approximate breakdown into other land use classes: (i) cereals - 10%, (ii) horticulture - 20%, (iii) other agriculture - 45%, and (iv) woodland - 25%. Woodland is covered in Section 3.7 and so is not considered here. For the horticulture subclass we assumed management as for root crops. For the "other agriculture" subclass we assumed 15% of the 45% to be fallow (no emissions). For the remaining 30% of this subclass we assumed emissions to be an average of those from all other main land use classes.

For land management practices (**Table 3.7**) fertiliser use and general management of agricultural land were considered as typically used in the UK (St. Clair *et al*., 2008; Haverkort and Hillier, 2011; Defra 2011a). Fertiliser applications were estimated from Defra (2011a) and were weighted for the typical crops used in the UK.

Currently between 5 to 10% of the farms in the UK are considered to be organic Jones and Crane (2009). To reflect this in the study, we reduced all fertiliser use by 5% (**Table 3.7**) to accommodate a 5% minimum coverage as organic farms.

Emissions of CH_4 and N_2O from livestock (dairy and beef cows, and sheep) were estimated from (IPCC, 2006). The factors are summarised in **Table 3.8**. The calculation refers to a typical average weight of animals in the UK.

Table 3.7. Management practices including fertilizer use for different land uses.

Land use	Fertiliser	Fertiliser (organic)	Management
Oilseed rape	N = 191 kg ha^{-1} P_2O_5 = 58 kg ha^{-1} K_2O = 65 kg ha^{-1} CaO = 4400 kg ha^{-1}	N = 172 kg ha^{-1} P_2O_5 = 52 kg ha^{-1} K_2O = 58.5 kg ha^{-1} CaO = 3960 kg ha^{-1}	Ploughing Discing Fertiliser spraying Harvesting
Cereals	N = 146 kg ha^{-1} P_2O_5 = 54 kg ha^{-1} K_2O = 64 kg ha^{-1} CaO = 4000 kg ha^{-1}	N = 131 kg ha^{-1} P_2O_5 = 48.6 kg ha^{-1} K_2O = 57.6 kg ha^{-1} CaO = 3600 kg ha^{-1}	Ploughing Harrowing Gain drilling Roller harrowing Fertiliser spraying Harvesting Baling
Root crops	N = 129 kg ha^{-1} P_2O_5 = 95 kg ha^{-1} K_2O = 165 kg ha^{-1}	N = 116 kg ha^{-1} P_2O_5 = 85.5 kg ha^{-1} K_2O = 148.5 kg ha^{-1}	Ploughing Field Cultivating/ridging Rotary hoeing/bed Tilling Planting Tine harrowing/seed handling & transport Fertiliser spraying Potato harvesting
Grassland with grazing	-	-	-
Permanent grazing	N = 85 kg ha^{-1} P_2O_5 = 21 kg ha^{-1} K_2O = 25 kg ha^{-1} CaO = 4300 kg ha^{-1}	N = 76.5 kg ha^{-1} P_2O_5 = 18.9 kg ha^{-1} K_2O = 22.5 kg ha^{-1} CaO = 3870 kg ha^{-1}	Ploughing Fertiliser Spraying Harvesting
Temporary grazing	N = 118 kg ha^{-1} P_2O_5 = 27 kg ha^{-1} K_2O = 41 kg ha^{-1} CaO = 4600 kg ha^{-1}	N = 106 kg ha^{-1} P_2O_5 = 24 kg ha^{-1} K_2O = 36.9 kg ha^{-1} CaO = 4140 kg ha^{-1}	Ploughing Fertiliser Spraying Harvesting

Depicts typical land management practices for fertiliser use and general management of agricultural land as found in the UK. Fertilizer amounts are given for conventional practices for a mix of 95% conventional, 5 % organic.
Source: derived from St. Clair et al. (2008), Haverkort and Hillier (2011), Jones and Crane (2009) and DEFRA (2011a).

Table 3.8. Emission factors for CH_4 and N_2O from livestock.

Emissions	Dairy cows (600 kg)	Beef cows (300kg)	Sheep (65 kg)
CH_4 from fermentation *(kg CH_4 head^{-1} yr^{-1})*	117	57	8
CH_4 from manure due to annual temperature (T=13°C) *(kg CH_4 head^{-1} yr^{-1})*	27	8	0.19
N excretion rate *(kg N (1000 kg animal mass)$^{-1}$ day^{-1})*	0.48	0.33	0.85
N_2O from manure *(factor)*	0.02	0.02	0.01

Emissions factors per head for livestock
Source: (IPCC, 2006)

3.5.5 Validation and caveats

Using the management assumptions for the seven land uses, we obtain a total value for UK nitrate fertiliser use of around 1,331,286 t N/yr. It is noteworthy that the figure for nitrogen use figure somewhat exceeds the total synthetic N use figure from (FAO/IFA, 2001) which is approximately 1,000,000 t/yr, but both numbers are close. The difference can be partly explained by the fact that – for simplicity - we consider synthetic N to be the source of all N in our calculations. In reality a significant proportion of N comes from animal manures sources, for which soil N_2O should still be accounted but production emissions not. This may also lead to a slight overestimate of emissions in our case, however given the uncertainty in the fate of N in the soil (particularly for organic N sources) and consequently N_2O emissions this is unlikely to substantially impact results. The differences may also result from the assumptions we made regarding the seven land use classes. The fertiliser amounts used per ha follow recommendations from and for farmers (Defra, 2009b, 2011a; St. Clair *et al*., 2008; Haverkort and Hillier, 2011) but these generally focus on ideal production scenarios and thus may overestimate inputs when taking into account less productive sites or regions. In summary, possible reasons for overestimation of the total amount of fertiliser:

- estimated fertiliser use does not consider organic farms. Calculations of fertiliser and emissions in the model with organic farms will be less;
- the classification of agricultural land into just seven land use categories required simplified assumptions regarding management, and an overestimation of fertiliser may have resulted; and
- most farms in the UK (70% - Defra, 2011a) use a type of manure that reduces the general use of chemical fertilisers. In the current estimation we do not consider such uses.

The main reasons for uncertainties in estimations of direct and indirect N emissions from managed soils are related to the certainty of the emission factors, natural variability, partitioning fractions, lack of coverage of measurements and spatial aggregation (IPCC, 2006). Depending on the handling of these uncertainties the calculated N emissions can differ in various studies

Management of crop residues such as straw and other non-harvested crop biomass was not considered in the current study with the assumption that residue is exported from the site. (“Export from farm”). Although management of such residual biomass can be a substantial source of emissions (e.g. IPCC, 2006) it is in practice very difficult to account for. This is due both to a lack of data regarding common practice for its management and attribution or allocation between agricultural sectors. For example, if straw is used in the livestock sector for animal bedding the allocation livestock and cropping system is based on whether it is regarded as a bi-product or co-product of the cropping. In other cases the residue could have a direct influence on the total emissions, mostly by increasing the GHG emissions. The worst case scenarios are burning the residue, composting it or leaving it on the farm, but these are ignored for now.

We also did not include emissions due to the oxidation of organic (e.g. peat and fen) soils. Organic soils contain high densities of C, accumulated over many centuries, because decomposition is suppressed by the absence of oxygen under flood conditions. In order to use this land for agriculture, these soils need to be drained, which aerates the soil, favouring decomposition and therefore high fluxes of CO_2 and N_2O. The global warming potential (GWP) of N_2O over a 100 year time horizon is 298 (IPCC, 2007b) (i.e. effectively meaning that over a 100 year period 1 molecule of N_2O has the same global warming effect as 298 molecules of CO_2). Taking this into consideration, the GHG emissions from the Norfolk and Lincolnshire fens, for example, are probably underestimated. In such cases the possible consequence of exploitation for agricultural purposes is GHG emissions an order of magnitude higher than for mineral soils. Thus, our approach may substantially underestimate GHG emissions in these specific regions.

3.5.6 Results

Per hectare estimated emissions for each land use class for an example soil type are shown in **Table 3.9**. For grazing land there are substantial differences between rough grazing land and improved pasture – with the former being essentially unmanaged except by grazing animals and the latter often receiving substantial fertiliser treatments in addition to other management activities, such as mowing and seeding. It should be noted that this table does not include the emissions from the livestock themselves, as this is a function of stocking rate rather than area per se. Emissions from the animals themselves are treated later. Here rough grazing is assumed - with no fertiliser or pesticides – which results in low emissions from the site (excluding livestock). Agrochemical use is highest for root crops. The “field energy use” reflects the machines used in the process and assuming that the diesel is used.

3.5.6.1 GHG emissions in CO_2e ha^{-1} yr^{-1}

The GHG emissions per hectare vary as a function of farming system. Lowest values are for rough grassland – predominantly in the Scottish Highlands – on which agricultural production is limited and of relatively low intensity. Those areas in which the bulk of our cereal and field crops are grown have GHG emissions of the order or 1000-2500 kg CO_2e ha^{-1} yr^{-1} in which cases GHG emissions are mostly a function of nitrogen fertiliser use. However, it is worth stating that nitrogen use is generally controlled in the UK, and in good practice nitrogen is efficiently used so that inputs are matched to plant uptake.

Per hectare emissions from the “other” land use class results from (i) 208 kg CO_2e ha^{-1} yr^{-1} (10% cereal emissions), (ii) 279 kg CO_2e ha^{-1} yr^{-1} (20% horticulture/root crops), (iii) 460 kg CO_2e ha^{-1} yr^{-1} (30% of averaged emissions of the other 6 land uses and 15% bare soil with no emissions) and (iv) 0 kg CO_2e ha^{-1} yr^{-1} (25% wood – not considered). So, as a result, the total estimated GHG emissions for “other” land use are 947 kg CO_2e ha^{-1} yr^{-1}.

By considering 5% of all farms to be organic, the results show a clear reduction in the GHG emissions (**Table 3.9**) compared to the high fertiliser input for non-organic, intensive grazing grassland. Emissions from livestock are considered separately from the other land management emissions. Average emissions for dairy cows, beef and sheep were obtained by multiplying the (per head) emission factors below by the number of animals in each class within each grid cell. Based on the emission factors (**Table 3.8**) from (IPCC, 2006) we calculated the following general GHG emissions for an annual mean temperature of 13°C:

- dairy cow (600 kg) = 4585 kg CO_2e/head/ yr;
- beef cow (300 kg) = 1963 kg CO_2 e/head/ yr; and
- sheep (65 kg) = 299 kg CO_2 e/head/ yr.

Table 3.9. GHG emissions in CO_2e ha^{-1} yr^{-1} for different land use and management regime for one soil type.

		All data in kg CO_2e ha^{-1} yr^{-1}				
Land use	**Fertiliser production**	**Background direct and indirect N_2O**	**Fertiliser induced field emissions**	**Agro-chemicals**	**Field energy use**	**Totals**
Oilseed rape	1451 (1306)	164.2 (164.2)	669 (581)	102.5 (102.5)	113.2	**2450 (2267)**
Cereals	1248 (1123)	164.2 (164.2)	471 (413)	41 (41)	152.1	**2076 (1893)**
Root crops	531 (478)	164.2 (164.2)	404 (356)	164 (164)	130.4	**1394 (1293)**
Grassland with grazing		49.3				**49.3**
Permanent grazing	1090 (981)	48.1 (48.1)	167 (150)	123 (123)	44.4	**1473 (1347)**
Temporary grazing	1253 (1127)	48.1 (48.1)	238 (212)	123 (123)	44.4	**1707 (1555)**

Example of GHG emissions of CO_2e ha^{-1} yr^{-1} for land use and management as in Table 6.2 of the following soil type: soil texture: medium, SOM: 1.72 – 5.16, soil moisture: moist, soil drainage: good, soil pH: 5.5 – 7.3. Emissions in parentheses are for a 95% conventional 5% organic mix.

Model simulations were performed to examine the plausibility of estimates obtained from the analysis. Simulations for crops and grass reflected agricultural land use, yielding estimates of high GHG emissions for regions with intensive cropping or for grasslands with high stocking densities. In the north of the UK (Scotland) and in the west (Wales) rough grazing is the dominant land use with low emissions from soil and plants. The highest GHG emissions for crops go up to 2750 kg CO_2e ha^{-1} yr^{-1}. The GHG emissions from livestock show a different picture with highest emissions in intensive grazed regions (Wales, most of Scotland and north western England). Together, these result in total emissions up to 7700 kg CO_2e ha^{-1} yr^{-1} for intensively grazed regions. The lowest emissions are shown in east Scotland, for unmanaged grassland with a very low grazing intensity.

In general, higher emissions of GHGs results from regions in which there is substantial livestock production. The higher values of emissions (around 7700 kg CO_2e ha^{-1} yr^{-1}) result from areas of permanent grassland (which we have assumed to be improved and thus receive significant fertiliser inputs), where there is intensive dairy, beef, or sheep production. This is often in southern and western parts of GB on lands which are not generally suitable for cereal production. The assumptions regarding input use may influence the magnitude of the emissions from these areas. However, the general effect is robust given the outputs of the land use model, since ruminant livestock are known to be significant sources of GHGs from farming.

The current level of total emissions were calculated to be 51 Mt CO_2e per annum for crop land and livestock in England, Wales and Scotland. Defra (2011c) calculated 49 Mt CO_2e for the agricultural sector in the UK in 2009. The close agreement of these numbers is felt to be acceptable given slight differences in the scope of these calculations (our number includes around 5% for energy use and machinery but does not include Northern Ireland.

3.5.7 Discussion and Conclusion

The MATLAB coding used by the CFT calculates GHG emissions for the seven land uses by assuming corresponding typical management systems. These are generalisations to provide estimates of GHG emissions transferable across the entire country.

Livestock are a major contributor to total GHG emissions, and in particular, the total emissions are highly sensitive to stocking rates particularly for cattle and sheep, which are an important source of CH_4 from both enteric fermentation and from manure, and GWP of CH_4 is 25 times that of CO_2 (IPCC, 2007b).

The inclusion of organic farms reduces GHG emissions due to reduced fertiliser use. Less fertiliser use means lower GHG emissions, which is good in terms of reducing total GHG emissions. But with reduced fertiliser there is often a trade-off in the yield, which has consequences for food production, and may create a driver for land use change if any loss in production is to be compensated for by exploiting lands currently not under agricultural use. There is still a lot of research needed to find the ideal environmental optimum N rate by crop and region to compare with the current economic optima.

3.6 Timber production module: Tree growth, timber yield and climate change

3.6.1 Summary

This section is developed in response to the objective associated with the analysis of timber profits under current and future climate changes. It is arranged in two parts: In Section 3.6.3 'Yield class and profits', we discuss the methodology used to calculate profits from tree volumes under current climate conditions; In Section 3.6.4 'Impact of climate change on forestry growth', we estimate the impact of climate change on forest growth using changes in yield class (YC), as a function of local and climatic characteristics, modelled with flexible functional forms. In each part we describe the data, methodology and results.

3.6.2 Objectives

- To model variation in growth rates and timber yield class for representative commercially grown tree species for a variety of physical environmental conditions across Great Britain.
- To incorporate into this analysis the influence of climate change upon growth rates and timber yields.
- To predict timber costs and benefits and hence profitability for different tree species across locations, climate scenarios and a common silvicultural management regime.

3.6.3 Yield class and profits

3.6.3.1 Data

In determining the suitability of sites for forest growth we rely on several constructed databases derived from modelling advice throughout in collaboration with experts in the UK Forestry Commission (FC). Expected forest growth is established in the FC Ecological Site Classification model (ESC, 2013). This is a well-established decision model developed by Pyatt *et al*. (2001) and is based on a synthesis of multi-criteria analysis Ray *et al*. (1996) and fuzzy-set theory Ray *et al*. (1998). A schematic overview of the model is presented in **Figure 3.3**.

The ESC model provides an analysis of timber yield which is sensitive to the suitability of land (in terms of soil, moisture, elevation, temperature, etc., (ESC, 2013), and incorporates the judgment of experts who assign characteristics into two macro-classes: climate and soil. Each macro-class is further organised into sub-classes (e.g. accumulated temperature, and soil moisture regime). One output of the model is predicted C, which is the mean annual volume of tree growth under optimal management measured in cubic metres per hectare per year (m^3/ha/yr), for each GB 250m grid cell (ESC, 2013). This output resolution was converted to the common 2km grid used for the wider analysis ESC_SEER (2012). A quantitative summary of the data for the two representative species: Sitka Spruce (SS) for coniferous and Pedunculate Oak (POK) for broadleaf, referred to in this section are presented in **Table 3.10**.

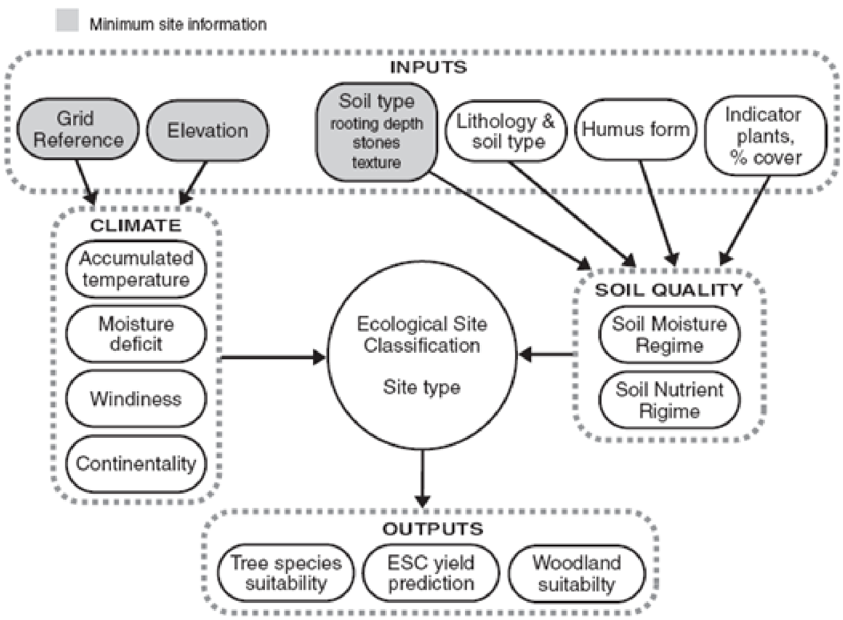

Figure 3.3. Schematic diagram of the ESC model. Source: BVCM Report Matthews (2011).

Table 3.10. ESC results: main yield class characteristics.

Tree type	Mean Esc score (st.dev)	Min	Max
Sitka Spruce (SS)	13.23 (3.81)	0	21
P.Oak (POK)	3.82 (1.95)	0	8

Yield class statistics for Sitka Spruce and Penduculate Oak across GB by 2km grid cells.
Source: ESC_SEER (2012)

The YC in ESC is represented by a continuous variable which assumes value zero where soil and climatic factors are unsuitable for planting; such as in urban areas. The average ESC YC values are subsequently rounded to the nearest even number as is conventional in forestry studies. The resulting averages in YC terms are: 14, for SS and 4, for POK, these will be used both in this analysis and in the analysis that follows in Section 3.7.

3.6.3.2 Methodology

Timber profits are obtained by multiplying tree volume by their corresponding market price, incorporating relevant management costs. To obtain tree volumes the ESC rounded YC values were then fed into the CARBINE model (Thompson and Matthews, 1989), described in Section 3.6.4, which produces tree volume for a variety of management regimes. For the purposes of modelling in both this section and in Section 3.7 we only consider the management regime: ‘thinning and felling. The rate of growth and volume of timber output from SS is both faster and more plentiful than that of POK, with five rotations for only two of POK. A comparison of the average YC timber volume for SS and POK is illustrated in **Figure 3.4**.

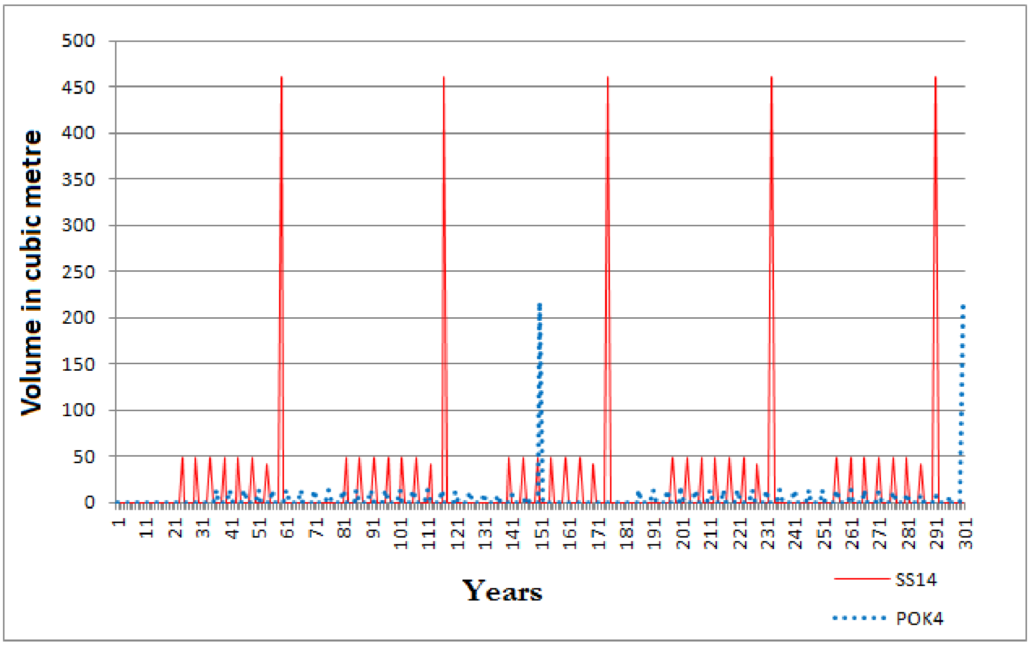

Figure 3.4. Timber volumes over multiple rotations: Sitka Spruce (yield class 14) and Pendunculate Oak (yield class 4). Shows the volume of timber harvested over a three hundred year period (five rotations of YC14 Sitka Spruce (SS) and two rotations of yield class 4 Penduculate Oak (POK)). Source: Derived from CARBINE model (Thompson and Matthews, 1989).

To obtain market values, the CARBINE tree volume is combined with the FC Forest Investment Appraisal Package (FIAP, 2013) to calculate the economic profitability of forests. This linkage brings in timber prices (Lavers and Moore 1983) to allow analysis of revenues and comparison with management costs to yield estimates of profitability. FIAP provides price-size curves (price per m^3) for SS and POK and average management costs (for activities such as mounding, planting, staking, insurance, drainage, weeding, spraying etc.,) under a variety of silvicultural systems. The price-size curves (otherwise regarded as timber prices) are perpetually monitored by the FC and are expected to remain constant in real terms throughout the period of the analysis. These curves are illustrated in **Figure 3.5**.

Figure 3.5 shows that price per m^3 is not a constant variable, but rather increases with volume. Both curves increase sharply and remain steady after they reach a maximum. This relationship can be explained by considering that when a cubic metre of wood is composed of small volume trees this has a restricted set of end-uses (e.g. fence posts, pulpwood, etc.) reflected in the price. Whereas, when a cubic metre is composed of high volume wood it commands a higher price because it has multiple end-uses (e.g. floor boards, construction materials, furniture, etc.). Once the volume reaches roughly floorboard size it will have a constant price, as shown in **Figure 3.5**.

The maximum price for SS is £22 for trees with a volume exceeding $0.4m^3$/ha and the maximum for POK is £30 when the volume reached exceeds $1.60m^3$/ha. Differences between species are also reflected in management costs. For example, on average managements costs for POK YC 4 in the first 10 years are £560/ha whereas they are only £230/ha for SS YC 14.

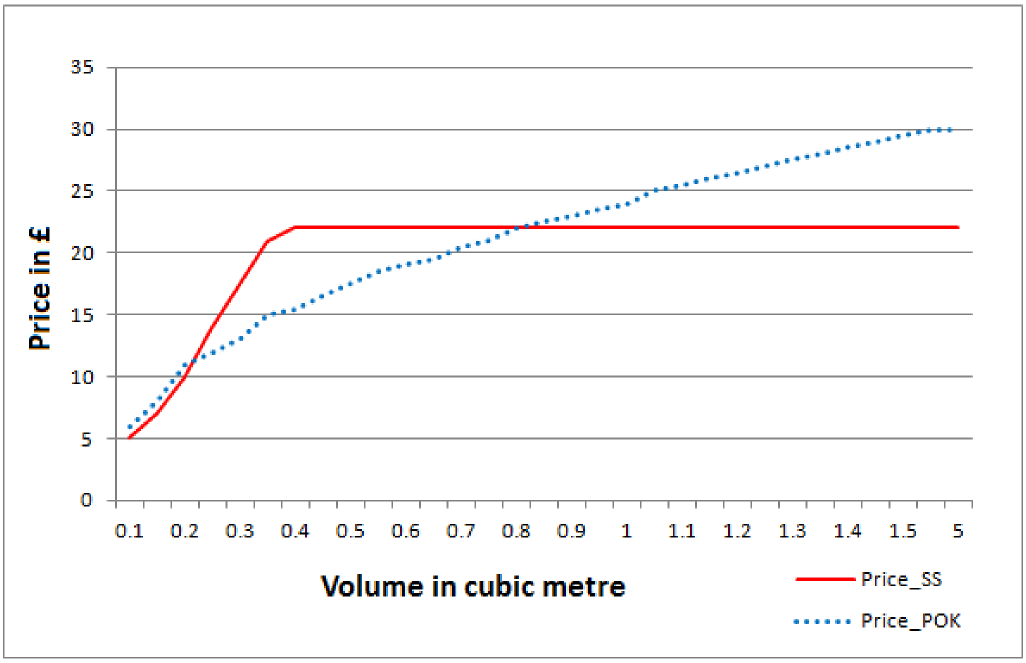

Figure 3.5. Price-Size Curves for Sitka Spruce and Penduncluate Oak. Comparison of price-size curves (price by volume per cubic metre) for Penduncluate Oak and Sitka Spruce. Source: Derived from FIAP (2013).

Relevant management costs refer only to variable costs and exclude fixed costs such as fencing, consultancy advice, etc., which are expected to be significant only in the early years of land use conversion. Further, in keeping with the shadow pricing approach (Gregersen and Contreras, 1979, 1992), adopted for the treatment of agriculture, we exclude forestry grant schemes on the grounds that these represent transfer payments. This allows us to inspect the social value of land use conversions but *will differ* from the market value assessments to which private land owners will respond.

Profits are finally calculated as the difference between revenues and costs. However, given the delays between revenues and costs, profits are calculated in Net Present Value (NPV) terms, using a constant social discount rate of 3.5%, and are reported in **Table 3.11** with annuity equivalents for each species and YC.

With the exception of the higher YC SS forests the findings in **Table 3.11** show that in a number of cases the financial returns are negative. This is the case even under social (as opposed to higher market) discount rates, and with the exclusion of other externalities, such as recreation, and carbon sequestration. Such poor financial performance explains the low prevalence of commercial woodland across the majority of Great Britain.

Table 3.11. NPV and annuity values for Sitka Spruce (SS) and Penduculate Oak (POK).

Species	Yield Class	Net Present Value	Annuity
SS	6	-2262	-84
SS	8	-1865	-71
SS	10	-1336	-51
SS	12	-813	-31
SS	14	-243	-10
SS	16	299	12
SS	18	884	35
SS	20	1278	53
POK	2	-6485	-221
POK	4	-6340	-218
POK	6	-6159	-209
POK	8	-5750	-196

Comparison of current expected profitability of Sitka Spruce and Penduculate Oak under thinning and felling management regime and a constant social discount rate of 3.5%.

3.6.3.3 Results

Figure 3.6 presents projected estimates of the distribution of the baseline tree population by YC score for SS (in the left panel) and for POK in the right one, under current climatic conditions. Reviewing these maps we see that the more suitable regions for growing SS are generally in the west of GB, the north Pennines and in central Scotland. In the right panel we see that suitable regions for POK lie to the north of London, in the Wye Valley and along the Northumbrian coastline (north-east England).

The figure illustrates the current forest baseline in the left panel and the projected current climatic conditions and profits. Once these are integrated into the whole model we discuss the resulting maps which illustrate different plantation scenarios (see Section 3.12).

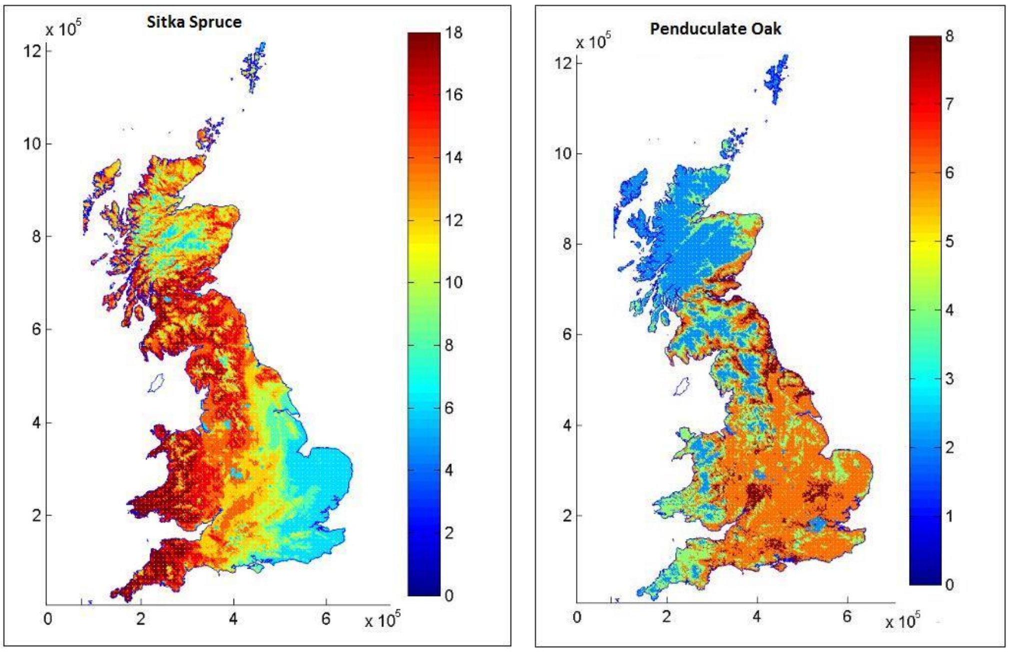

Figure 3.6. Timber volumes over multiple rotations based on average yield class (YC) values: Sitka Spruce (YC 14) and Penunculate Oak (YC 4). Maps of expected forest growth for Sitka Spruce and Penduculate Oak under current climatic conditions.
Source: ESC_SEER (2012).

3.6.4 Impact of climate change on forestry growth

Historically, forests have been fairly resilient to the effects of short run variation weather patterns. However, evidence of climate change shows that winters are getting wetter, which contributes to soil erosion, and windier which affects the altitude at which some species can thrive, and summers drier impacting on growth rates (Broadmeadow and Nisbet, 2012; Broadmeadow, 2002; Broadmeadow and Ray, 2005). There is also a spatial element associated with erratic weather patterns, such that we cannot model the effects using non-spatially specific variables.

3.6.4.1 Data

From a practical point of view, the ESC database provides expected YC values under climate change scenarios. However, direct outputs from ESC cannot be used for some aspects of our modelling being insufficient to meet the expectations our objectives as outlined in Section 3.6.2. For this reason we derive estimates of YC (ESC_SEER, 2012) and combine these with local and climatic factors taken from the following datasets CLIMATE (2012), SOIL (2012), TERRAIN and (2012), whose derivations are described in Section 3.15.

Ultimately, one of the objectives of this report (Section 3.1) is to develop linkages between constituent models, which we do in the integrated model (TIM) discussed in Section 3.12**.** To feed into that model, unfortunately**,** direct outputs from ESC are not replicable within TIM. For this reason a new model was developed to determine the impact of climate change on forest growth. Results were generated from a cross-sectional analysis of the co-dependencies of variables taken from the datasets mentioned. Hence factors drawn from the dataset have been selected to be as similar as possible to the input variables used in ESC. The key variables in the model are:

- mean temperature and precipitation during the growing season over the period 1961 to 1990. These are the key variables to be modified in analysing the effect of future climate change;
- average slope and elevation of the cell, which are further determinants of the YC;
- Easting and Northing. These variables are ancillary to the description of the YC changes but we expect that they will capture spatial correlation in other explanatory factors not explicitly mentioned here; and
- soil characteristics defined in (SOIL, 2012), are set out as a series of binary variables:
  - **Water regime**, this variable measures the dominant annual soil water regime which is determined by the number of months at a particular water-table level. The variable takes value 1 if the soil is defined as not wet (e.g. water-table is not wet within 80cm for 3 or more months per annum); 0 otherwise.
  - **pH**: if higher than 5.5 this is considered by FC to be a rich or very rich soil type (Pyatt *et al*., 2001, p.14). This variable takes value 1 if pH > 5.5; 0 otherwise.
  - **Water capacity**, this variable refers to water storage capacity expressed as millimetres per meter (mm/m). It takes value 1 if water in soil > 75mm; 0 otherwise.
  - **Carbon in soil**, this variable describes the soil health; healthy soil is where the percentage of organic carbon in top and sub-soil is within a range: > 1.2% and < 25%, where it takes the value 1 in our model; 0 otherwise.

3.6.4.2 Methodology

The relationship between YC and local characteristics can be represented by very complex non-linear functions. Therefore using a simple linear regression model or other parametric specifications for the YC will almost certainly result in biased outcomes due to uniformed assumptions made by researchers. It is for this reason that we rely on semi-parametric regression models which enable the distribution of explanatory variables to be kept flexible, changing in accordance with the data. The SS and POK are separately modelled and both are analysed using the generalized additive model approach developed by (Wood, 2003). This approach compares favourably with previously tried semi-parametric approaches as it allows estimates of the degree of non-linearity directly from the data without any need for further assumptions. The initial model is set to explore non-linearities in all continuous variables as a smooth function: s(.). Note that smooth functions cannot be applied to non-continuous variables, such as dummy variables, which need to be included in a parametric form. Informed by the results of the model, the subsequent semi-parametric model includes the climatic variables as step functions and keeps all the other variables as non-linear. To preserve the complex, non-linear effect of climatic variables on YC, the set of step functions used to capture the effect of temperature and rainfall are given generically by:

Equation 7.1:

$$Temp_1 = \begin{cases} 0 & \text{if Temperature} \leq K \\ (\mathrm{SEER}_{MT_{6190}} - \mathrm{K}) & \text{if Temperature} > K \end{cases}$$

$$Temp_2 = \mathrm{SEER}_{MT_{6190}}$$

$$Rain_1 = \begin{cases} 0 & \text{if Rain} \leq J \\ (\mathrm{SEER}_{MP_{6190}} - \mathrm{J}) & \text{if Rain} > J \end{cases}$$

$$Rain_2 = \mathrm{SEER}_{MP_{6190}}$$

The values for the thresholds *K* and *J* are chosen following the results of the smooth functions for temperature and rainfall estimated by the model with all continuous variables as non-linear functions (for graphs illustrating these functions see: Section 3.6.6, Appendix A). The temperature threshold (K) differs for each and is set to 12^{o}C for SS and 9^{o}C for POK. For rainfall the threshold (J) is set to 400mm for both species. This threshold refers only to the average rainfall quantity in the growing season.

The generic model, used to estimate values for SS and POK, is given in Equation 3.6.2 and is estimated separately for SS and POK and the results are given in **Table 3.12**.

Equation 3.6.2

$$YC = \alpha + \beta_1 Wr + \beta_2 pH + \beta_3 Wc + \beta_4 Carbon + \beta_5 s(slope) + \beta_6 s(elevation) + \beta_7 s(easting, northing) + \beta_8 Temp_1 + \beta_9 Temp_2 + \beta_{10} Rain_1 + \beta_{11} Rain_2 + \beta_{12} Temp_1 Rain_1 + \beta_{13} Temp_1 Rain_2 + \beta_{14} Temp_2 Rain_1 + \beta_{15} Temp_2 Rain_2 + \varepsilon$$

where ε is the normally distributed error term; dummy variables: *Wr* is the water regime, *pH* is the soil-pH level, *Wc* is water capacity, and *carbon* is carbon in soil; variables in the smooth functions, s(.) are: *slope*, *elevation*, and *Easting* and *Northing*; and variables in the parametric step functions are: *average temperature* and *precipitation*. Equation 3.6.2 introduces climatic factors as linear terms which enable the integration in TIM to be performed faster.

3.6.4.3 Results

Table 3.12. Predicted timber yield class (YC) for Sitka Spruce and Pendunculate Oak as a function of cell characteristics for all 2km GB grid cells.

Parameter	Description	SS	POK
		Flexible functions	
		edf(std.err)	***Edf(st.err)***
S(Easting, Northing)	Ancillary variable (captures non-focal local variation)	28.80(29.00)***	28.91(29.0)***
S(slope)	Average slope of the cell	8.40(8.90)***	8.38(8.90)***
S(elevation)	Average elevation	8.88(9.00)***	8.44(8.91)***
		Fixed factors	
		Coeff (st.err)	***Coeff (st.err)***
Water regime (Dummy variable)	Annual dominant soil water regime. 1= if water-table is not wet i.e. is within 80cm for 3 or more months; 0=otherwise	0.0589(0.0108)***	0.1237(0.0061)***
Water capacity (Dummy variable)	Water storage capacity expressed as millimetres per meter (mm/m). 1= water in soil > 75mm/m 0=otherwise	-0.0284(0.0131)*	0.0610(0.0076)***
pH (Dummy variable)	Soil Health. 1= Non-acid soils (pH>5.5); 0= otherwise	0.0306(0.0160)	0.2837(0.0089)***
Carbon	Carbon in soil (% of organic carbon in top soil). 1= if between 1.2% & 25%; 0=otherwise	-0.088(0.0114)***	-0.0291(0.0070)***
Temp1	Temperature threshold : >K K=12°C for SS. K=9 °C for POK	4.669(0.293)***	0.6330(0.0630)***
Temp2	Temperature (°C)	-4.935(0.007)***	0.1836(0.0186)***
Rain1	Rainfall threshold: > J J=400mm for SS and POK	0.1358(0.0065)***	-0.0542(0.0038)***
Rain2	Rainfall (mm)	-0.137(0.0065)***	-0.1370(0.0065)***
Temp1Rain1	(Temperature threshold: > K) *(Rainfall threshold >J)	0.0194(0.0009)***	-0.0039(0.0005)***
Temp2Rain1	(Temperature) * (Rainfall threshold: > J)	-0.0132(0.001)***	0.0055(0.00045)***
Temp1Rain2	(Temperature threshold: >K)*(Rainfall)	-0.0163(0.001)***	0.0013(0.0003)***
Temp2Rain2	(Temperature) * (Rainfall)	0.0130(0.006)***	-0.0033(0.0003)***
Constant (α)		66.36(2.60)***	-0.0567(0.0090)***
N	Number of cells	56,366	50,766
Log-likeilhood		-42264	-42105
R^2Adj		0.93	0.89

Significance p-value: *p<0.05; **p<0.01; ***p<0.001.

The semi-parametric specification enables the distribution of continuous explanatory variables to be kept flexible, changing in accordance with the data. This approach compares favourably with parametric approaches as it allows estimates of the degree of non-linearity without any need for further assumptions.

In the upper part of the table the “effective degree of freedom -edf” reports the estimated level of non-linearity for the slope, elevation and easting and northing variables. In the second half of the table, coefficients of linear parameters describe their effect on YC.

The results presented in **Table 3.12** are given in two stages: in the first stage we report the "*effective degree of freedom -edf*" of the smooth functions which explain the estimated level of non-linearity for the slope, elevation and easting and northing variables; in the second we report the coefficients of linear parameters such as dummies variables; and rainfall and temperature expressed as a step-function.

All the variables modelled as smooth function are highly non-linear, in fact the higher the *edf*, the more "non-linear" the estimate: s(.). For example, an *edf* equal to one means that the best approximation for that variable is linear. In our data, all variables are better represented by a non-linear function. The parametric variables are all highly significant and with the expected sign. The impact of pH and water regime dummies is positive on YC for both species, indicating that yield increases in response to increases in these factors. Whereas, water capacity is negative for SS and positive for POK, indicating that a rise in water capacity leads to a fall in the yield for SS, but a rise in it for POK. This finding is consistent with other work such as (S. Broadmeadow & Nisbet, 2012). The temperature effect is positive under the threshold and negative above for SS, however, the opposite is true for the YC for POK, which is always positive, but the effect found above the threshold (9^{o}C) is one third of that below it. The interaction between rainfall and temperature is always positive when both variables are below or above the threshold for SS. This implies that SS benefits either when temperature is below 12^{o}C and rainfall below 400mm or temperature is above 12^{o}C and rainfall above 400mm. However, dry weather with increased temperature has a negative impact on SS forest growth. POK presents opposite climatic effects: when both rainfall and temperature variables are below or above the threshold level YC for POK, here this is expected to decline, whereas, POK will benefit from dry weather and increased temperature and vice versa. These results are consistent with expectations of YC values for SS and POK and are illustrated in **Figure 3.6,** where we see that POK performs better in the south-east of England with dry warmer weather and SS is more suitable for colder and wetter climates found in the north-west of England.

The results for SS and POK are both highly satisfactory with R-square above 85% (see **Table 3.12**). The SS model explains 92% of YC variation and the average Mean Square Error (MSE) is 1.01 (median 0.3) which implies that the predicted YC (rounded to the nearest even number) is generally very well-determined. The POK model explains approximately 89% of YC variation with a mean MSE of 0.31 (median 0.11).

3.6.5 Conclusion

The results we present are also consistent with FC findings (FC, 2002) revealing that temperature and precipitation are important factors for tree growth. Changes in tree volume are expected to occur under different climate change scenarios. However, climatic factors are not constant across space, and local factors can smooth these impacts. We expect that productivity of SS will increase in the south-west of Scotland and in north Wales mainly as a result of warmer temperatures, and is likely to decrease in the south-east of England mainly due to reduced summer rainfall and longer periods of drought. POK productivity is also expected to increase in all areas of GB with the exception of the west of England which as we have explained, will not be suitable for commercial broadleaf tree production.

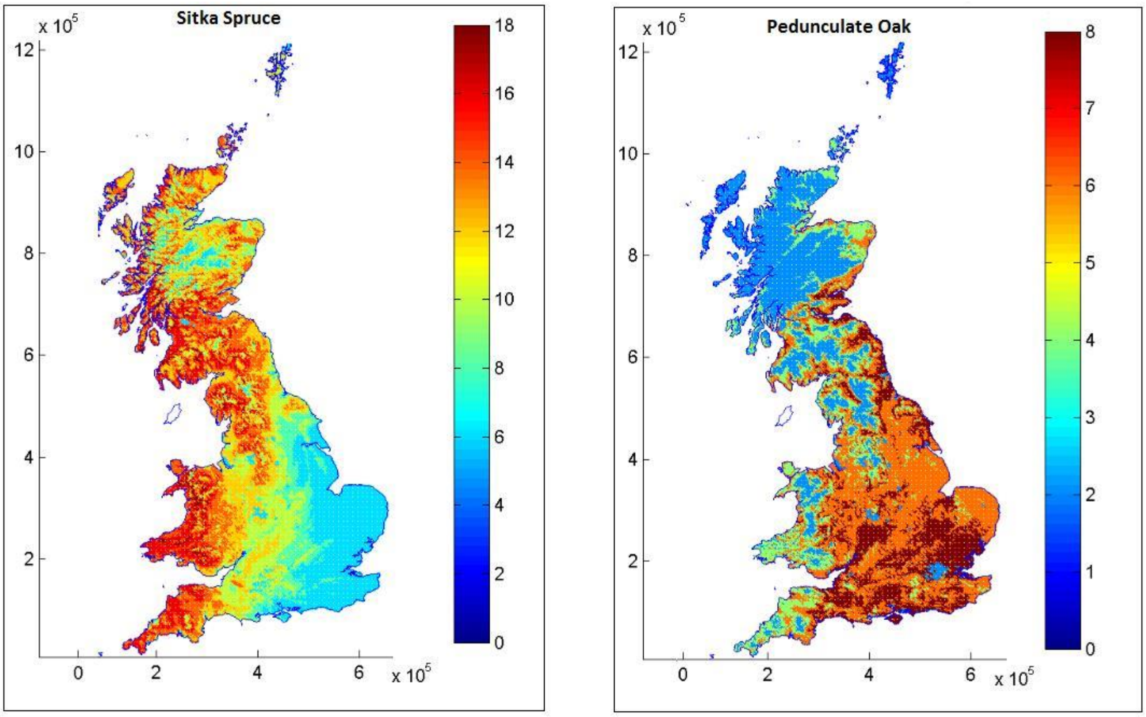

Figure 3.7. The estimated forests suitability for Sitka Spruce and Pendunculate Oak under the future climatic conditions from our semi-parametric model coefficients. Maps report the estimated forest growth for Sitka Spruce and Pendunculate Oak under 2060 climate conditions. Changes predicted are significant for both species. Source: TIM (Section 3.12)

Converting our semi-parametric coefficients into spatial data points we are able to map the outcome as shown in **Figure 3.7**. These maps illustrate the predicted planting pattern that results for SS in the left panel and POK in the right one. Both species will face significant changes guided by a combination of warmer and drier seasons with significant spatial variation. The effects depicted will be relevant for policy makers considering commercial afforestation or management of existing forest stands, as well a guide for single farmer production choices. Estimates of related profits derived from TIM are given in Section 3.12.

3.6.6 Appendix A: Interaction effects and expected non-linearity between climate variables and timber productivity

The semi-parametric model with all continuous variables as smooth functions (s(.)) describes significant interaction effects between mean temperature and precipitation for both Sitka Spruce (**Figure 3.8**) and Pedunculate Oak (**Figure 3.10**). Further the relationship between climatic variables and Yield class is non-linear and single smooth functions depict the expected non-linearity (**Figures 3.9** and **3.11**). Building on this evidence from several semi-parametric models we define the model and step-functions reported in earlier in this report**.**

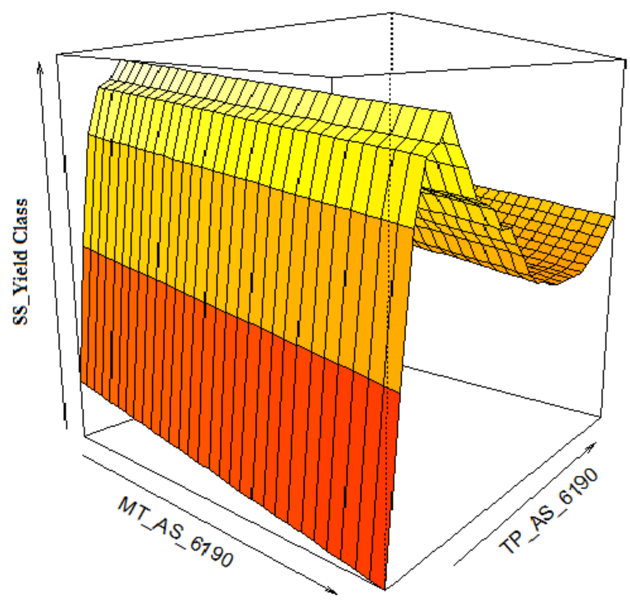

Figure 3.8. Sitka Spruce: smooth function for both temperature and precipitation variables. Shows the interaction effect of temperature and precipitation on SS productivity

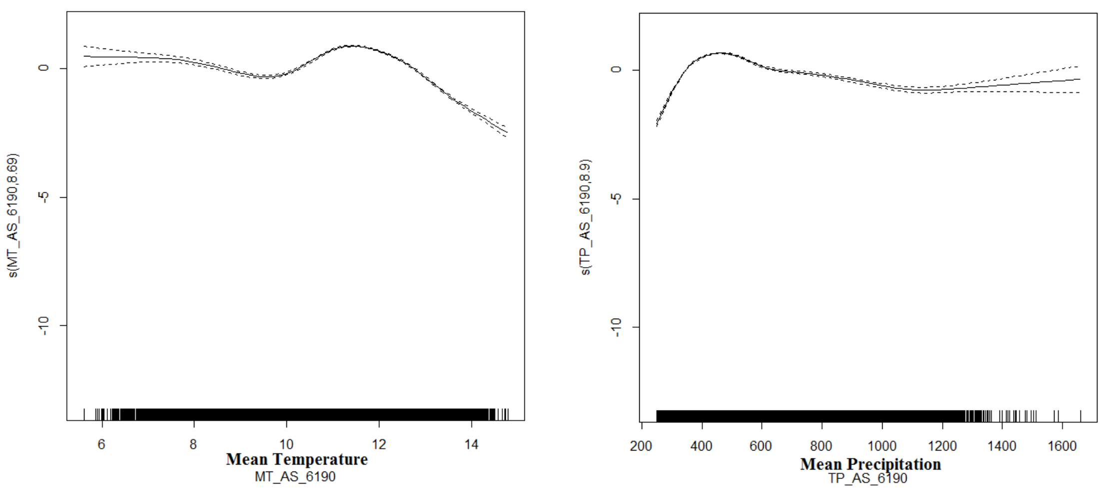

Figure 3.9. Sitka Spruce: single smooth function for temperature and precipitation. Shows the non-linear function for temperature and precipitation. Both graphs have been used for the definition of the step-functions in Forestry section (Equation 3.6.2)

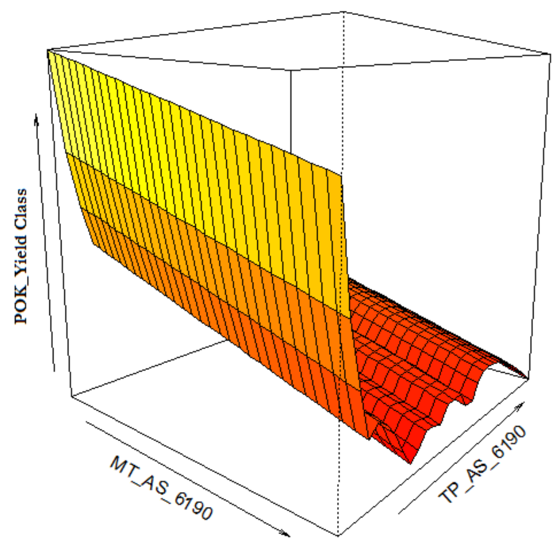

Figure 3.10. Penduculate Oak: smooth function for temperature and precipitation variables. Shows the interaction effect of temperature and precipitation on POK productivity.

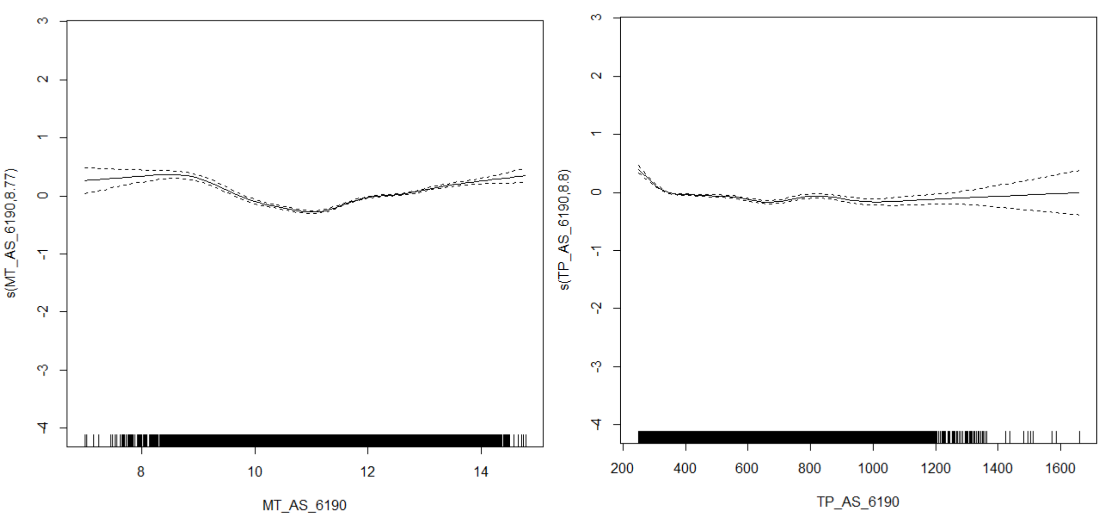

Figure 3.11. Penduculate Oak: single smooth function for temperature and precipitation. Shows the non-linear function for temperature and precipitation. Both graphs have been used for the definition of the step-functions in Forestry section (Equation 3.6.2).

3.7 The forestry greenhouse gas (GHG) module: GHG flows from forestry activities

3.7.1 Summary

This section describes research that estimates the annual GHG flows arising from the afforestation of land, accounting for the emissions and sequestration associated with standing trees, harvested wood products (HWP), deadwood (litter) and soil. These flows vary with the chosen forest management regime, which in our analysis entails 'thinning and felling', referring to a combination of felling at the end of a rotation (the lifetime of a tree crop) and 'thinning' of a proportion of trees at various points within the rotation (thus maximising overall timber revenues). This analysis is coherent with the Woodland Carbon Code guideline (2013) which requires permanent land-use changes and conversion of no-forest land. All carbon measures are expressed as tCO_2 equivalent and are directly comparable with Woodland Carbon Units. Our analysis is underpinned by the Forest Research CARBINE model (Thompson and Matthews, 1989), which is employed in a wide range of forest decision applications (Matthews and Broadmeadow, 2009), however its use here is confined to the estimation of GHG flows.

3.7.2 Objective

To estimate the effect of new planting on net annual carbon flows in livewood stands, harvested wood products (HWP), deadwood and forest soils, for representative conifer (Sitka spruce) and deciduous (Pedunculate oak) species.

3.7.3 Data

When applied in a spatially explicit manner, the CARBINE model uses inputs regarding tree growth rates derived from the Ecological Site Classification (ESC) decision support system developed by (Pyatt *et al*., 2001). Drawing upon the yield tables provided by Edwards and Christie (1981), the ESC (2013) model provides site specific estimates of potential timber yield class (YC) at the 2km grid cell resolution across the entirety of Great Britain (as described in Section 3.6.3.1). Specifically, ESC predicts the maximum mean annual increment in timber volume by yield class (YC; measured in m^3/ha/yr) for new plantations, taking into account the local characteristics of planting sites.

These estimates provide the basic input to the CARBINE analysis of GHG sequestration and emissions associated with livewood, harvested wood products (HWP), deadwood (including litter) and soil carbon.

For newly created forest areas tree species, year of planting and age are set as analyst-controlled variables in addition to variables relating to management regime and rotation period (in years assuming a clearfell regime), which form the initial data inputs into CARBINE. In our analysis we adopt 2013 as the initial year of planting and following assumptions:

- no genetic or agronomic improvements;
- no pests or disease impact; and
- no fertilization or irrigation.

As stated, in this analysis we focus on a single management regime: 'thinning and felling'. Thinning involves the removal of wood at prescribed stages during the lifecycle of the stand. Thinning is assumed to start several years after planting (varying across species and YC) and then occurs at regular periods (e.g. every 5 years). Felling ages similarly vary by species and growth rates. The present analysis assumes species representative stands and tree density (on planting or regeneration) of 2,500 trees per hectare. The spatially explicit nature of the analysis allows the calculation of species-specific carbon sequestration in livewood. Stem volumes (in units of cubic metres over bark per hectare) for both 'standing' and 'removed' wood are assessed for the chosen management regime. Stem biomass estimates are obtained by multiplying the species-specific stem volume (from Edwards and Christie, 1981) by a species specific value of wood density expressed as oven dry tonnes of mass per cubic metre of 'green' timber volume Lavers and Moore (1983). In the case of SS and POK these values are 0.33 odt/m^3 and 0.56 odt/m^3 respectively as shown in **Table 3.13**.

Table 3.13. Tree species, growth rates represented in the CARBINE model.

Tree species	Growth rate* (m^3/ha/yr)		Basic density† (odt/m^3)	Allometric coefficients‡	
	Lowest	Highest		fR	fB
Sitka spruce	6	24	0.33	0.45	0.35
Oak	2	8	0.56	0.50	0.80

* Growth rate is defined as the maximum average rate of cumulative volume production over a rotation. (The average rate of production will vary with the specified rotation.)
† Basic density is defined here in units of oven dry mass per 'green' cubic metre.
‡ The allometric coefficient fR is used to determine the quantity of root wood, whilst fB is used to determine the quantity of branch wood and foliage combined.
Source: CARBINE model (Thompson and Matthews, 1989)

The figures reported in **Table 3.13** summarise the rate of growth (YC), density of wood and allometric coefficients for the two species under consideration. Here fR and fB are species-specific coefficients assumed to be constant with respect to tree age, size and growth rate. The values assumed for different tree species are based on interpretation of summary estimates of root, branch, foliage and stem biomass using the Forestry Commission forest stand biomass model BSORT (Matthews and Duckworth, 2005).

3.7.4 Methodology

CARBINE is an analytical model of carbon exchanges between the atmosphere, forest ecosystems (trees, deadwood, litter and soil) and the wider forestry sector as a result of tree growth, mortality and harvesting (Thompson and Matthews, 1989; Matthews, 1991). Carbon sequestered in harvested wood of merchantable quality is allocated to HWP using a dynamic assortment forecasting model that accounts for variation in product out-turn specific to tree species and size classification of stem wood at the time of harvest (Rollinson and Gay, 1983). HWP are further categorised as long-lived and short-lived sawn timber, particleboard and paper. Each of these classes of wood products is modelled in terms of their service life and the consequent time profile of carbon emissions. So, for example, long-lived timber products have a much more delayed emission profile than say paper products. Emission profiles are set so as to emit all stored carbon over the lifetime of the relevant HWP. Carbon not sequestered in HWP is treated as waste and conservatively assumed to rapidly emit all stored carbon.

CARBINE consists of various sub-models, each estimating different aspects of forest carbon flows by calculating the stock levels at different points in time. The sub-models used in this analysis are:

- carbon sequestered in and GHG emitted from livewood;
- carbon sequestered in and GHG emitted from HWP;
- GHG sequestered in and GHG emitted from deadwood (litter); and

- GHG associated with a range of soil types.

Note that a further CARBINE sub-model analysing the GHG implications of substituting timber for fossil fuels is not incorporated within the present analysis (although obviously such substitution raises the potential for afforestation delivering further net reductions in GHG emissions). The sub-models for livewood and deadwood each consist of four elements assessing stems, branches, foliage and roots. Total tree volume is converted to oven dry biomass using the values of wood density described in **Table 3.13** with a presumed carbon content of 0.5 tC per oven dry tonne of biomass (Matthews, 1993). Although the carbon content of woody dry matter is assumed to be constant, different tree species exhibit very different patterns of carbon sequestration because the dry matter content per unit volume (i.e. the wood basic density) is species-specific, as are relationships between crown, root and stem biomass (see **Table 3.13**). An overview of the structure of the CARBINE model is provided in **Figure 3.12**.

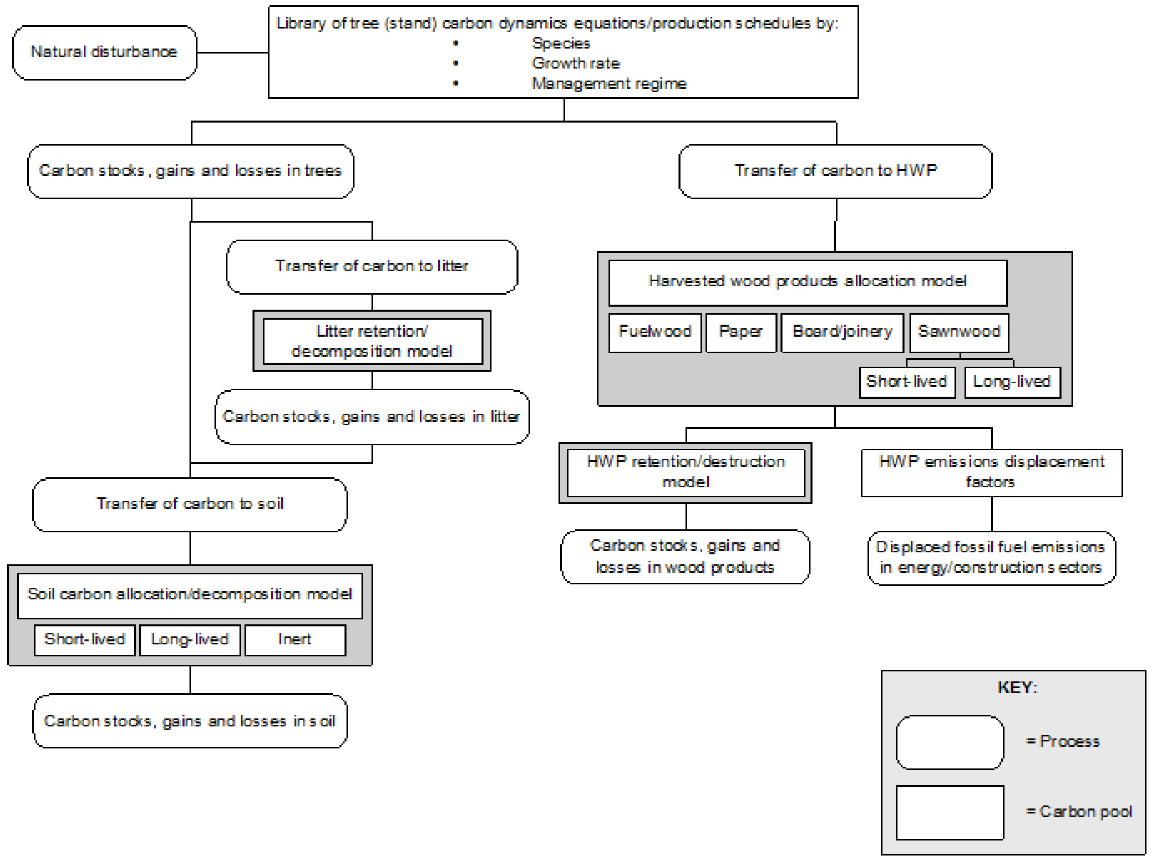

Figure 3.12. Overview of the structure of the CARBINE model. This provides an overview of the structure of the model, illustrating the processes and the various points of associated emissions. Source: Matthews (2011).

To obtain estimates of carbon and biomass in tree roots, branches and foliage the model relies on simple allometric relationships with stem wood, as defined by Equations 3.7.1 and 3.7.2 respectively.

Equation 3.7.1:

Root carbon or biomass = fR × Stem carbon or biomass

Equation 3.7.2:

Branch + foliage carbon or biomass = fB × Stem carbon or biomass

Figure 3.13 illustrates the CARBINE approach to allocating harvested wood between forest litter and primary products. Branchwood from harvested trees is assumed to be either used as wood fuel or left on site as part of the litter pool. The proportions allocated to be left on site or harvested for fuel are determined by simple partition coefficients, η_1 and η_2 (**Figure 3.13**). These coefficients are both set to 50%. The first step in the ultimate allocation of harvested stem wood to primary products involves an initial allocation to waste wood left as litter in the forest and to three 'raw' stem wood categories of 'bark', 'small roundwood' and 'sawlogs'. The proportion of stem wood allocated to litter is determined by a partition coefficient, η_3, which is set to a standard value of 10% FC_stats (2013). The allocation of the remaining stem material to bark, small roundwood and sawlogs (otherwise known as a product assortment) is determined respectively by the partition coefficients η_4, η_5 and η_6, which depend on the size and shape of the harvested trees. In turn, tree size and shape depend on many factors but notably tree species, growth rate and the relevant management regime (Matthews and Mackie, 2006). The specific definitions used for small roundwood and sawlogs also influence these allocations.

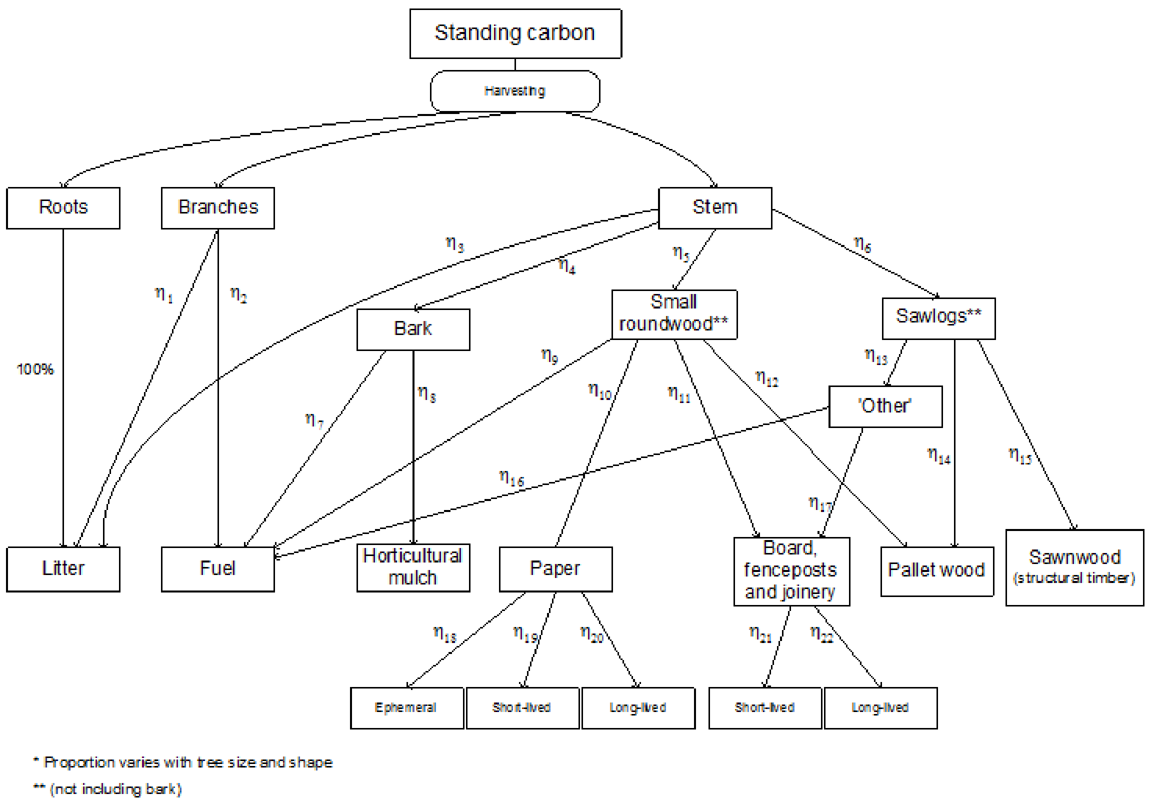

Figure 3.13. The allocation of harvested wood inherent in the CARBINE model. Source: Matthews (2011).

Assumptions regarding sawlog size are taken from previous applications of CARBINE and the calculation of bark, small roundwood and sawlog partition coefficients (η_4, η_5 and η_6) is based on standard tables given in Matthews and Mackie (2006) and Edwards and Christie (1981). However, some modelling of these results is necessary to enable the values in the tables to be accessed by variables available in CARBINE. The general form of the equations for estimating η_4, η_5 and η_6 expressed as percentages is given by Equations 8.3, 8.4 and 8.5.

Equation 3.73:

$$\eta_5 = 100 \times (1 - \eta_4 - \eta_6)$$

Equation 3.74:

$$\eta_4 = 100 \times (1 - fUB\ (dbh))$$

where fUB (dbh) is a function for estimating underbark stem wood volume (or biomass or carbon) as a fraction of overbark stem wood volume (or biomass or carbon) and dbh is taken as the quadratic mean of the diameter breast height of the harvested trees (Matthews and Mackie, 2006). The parameter η_6 is defined as:

Equation 3.75:

$$\eta_6 = 100 \times (fUB\ (species, dbh) \times fSAWLOG\ (dbh))$$

where fSAWLOG (dbh) is a function for estimating overbark sawlog volume (or biomass or carbon, for conifer or broadleaf sawlogs as defined above) as a fraction of overbark stem wood volume. Parameterization of fUB (dbh) and fSAWLOG (dbh) relies on piecewise relationships with respect to the quadratic mean dbh of harvested trees (for a fuller explanation the reader is directed to the work of Matthews and Mackie, 2006, and Edwards and Christie, 1981). These relationships also depend on tree species (or species group) and whether the stand has been thinned or not. The values assigned to other relevant partition coefficients are described in **Table 3.14**.

Table 3.14. Partition coefficients for allocation of 'raw' harvested wood material to primary wood product categories.

Timber species group	Species-specific partition coefficients								
	Small roundwood				Sawlogs			'Other'	
	η_9	η_{10}	η_{11}	η_{12}	η_{13}	η_{14}	η_{15}	η_{16}	η_{17}
Spruces	20	20	35	25	70	0	30	43	57
Oak	80	20	0	0	80	15	5	56	44

Source: Matthews and Mackie (2006).

Finally, the soil carbon sub-model runs concurrently with the forest sub-model. Initial soil carbon is estimated based on land use/cover (e.g. arable, pasture, etc.) and soil texture (sand, loam, clay or peat). The structure and parameterisation of the soil carbon sub-model is based qualitatively on the Roth-C agricultural soil carbon model (Coleman and Jenkinson, 1996).

3.7.5 Results

In this section we summarise certain key results from the CARBINE analysis of the GHG impacts of afforestation. **Figure 3.14** illustrates carbon sequestration (t CO_2eq/ha) in livewood for an area planted with Pedunculate oak (POK) growing at YC4. The two lines shown illustrate the livewood storage occurring in each year and the cumulative storage for each rotation (with felling clearly shown where the cumulative curve returns to zero and the per annum (marginal) curve records a major negative value as stored carbon is transferred from livewood to HWP or waste forms). The shape of the cumulative storage graph indicates that maximum marginal storage is reached about two-thirds of the way through the rotation. The graph also underlines the long term nature of rotations for deciduous species, with felling arising some 150 years after planting in this instance. **Figure 3.8.4** illustrates comparable curves for Sitka spruce (SS). While exhibiting similar marginal/cumulative relationships, SS rotations are typically much shorter (e.g. 58 years for YC14 SS).

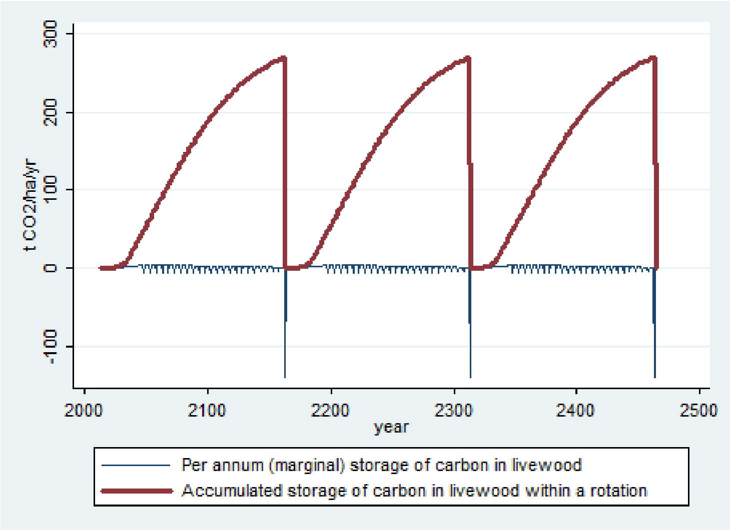

Figure 3.14. Carbon (t CO_2/ha) in penduncluate oak (YC4) livewood per annum (marginal) and accumulated within a rotation, over three rotations. Source: CARBINE.

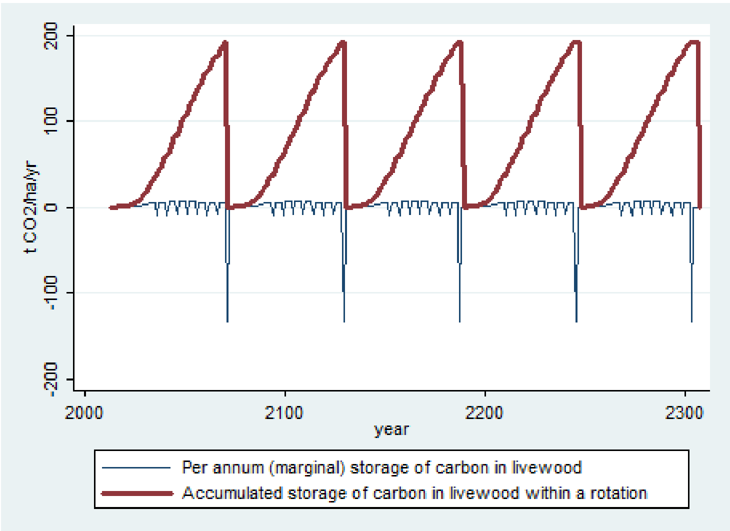

Figure 3.15. Carbon (t CO_2/ha) in Sitka spruce (YC14) livewood per annum (marginal) and accumulated within a rotation, over five rotations. Source: CARBINE.

Continuing with the POK example, **Figure 3.16** graphs the marginal (per annum) and cumulative curves for the storage of carbon in HWP. This slowly increases over the first rotation and peaks immediately after felling. However, this peak is quickly reduced due to wastage and then more slowly erodes as we move further into the future as longer lived products slowly emit their stored carbon back into the atmosphere. This relationship is repeated for successive rotations. A somewhat similar pattern of build-up and then release is observed for carbon in forest litter.

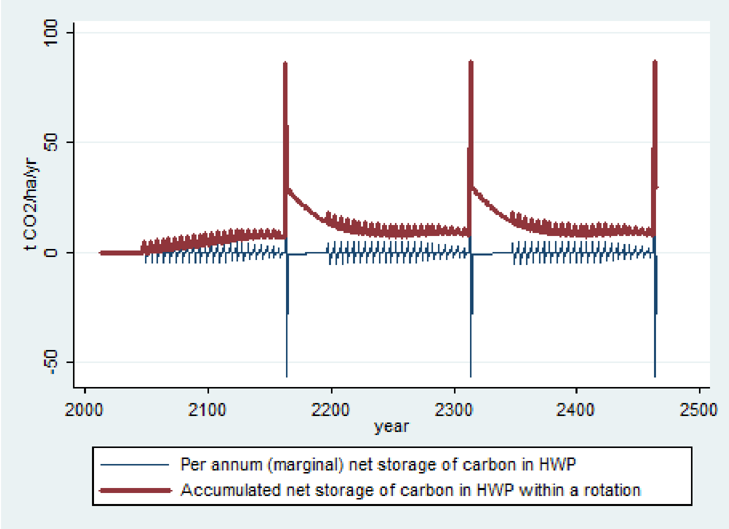

Figure 3.16. Carbon (t CO_2/ha) in penduncluate oak (YC4) harvested wood products (HWP) per annum (marginal) and accumulated within a rotation, over three rotations. Source: CARBINE

Key to any forecasts of the soil carbon contribution to net GHG flow is the ability to take into account the land-use prior to afforestation. This is differentiated according to whether prior soil use was either classified as disturbed or undisturbed. Still considering POK, **Figure 3.17** provides carbon profiles for both organic (peat) and clay soils, each being considered for both prior disturbed or undisturbed land use.

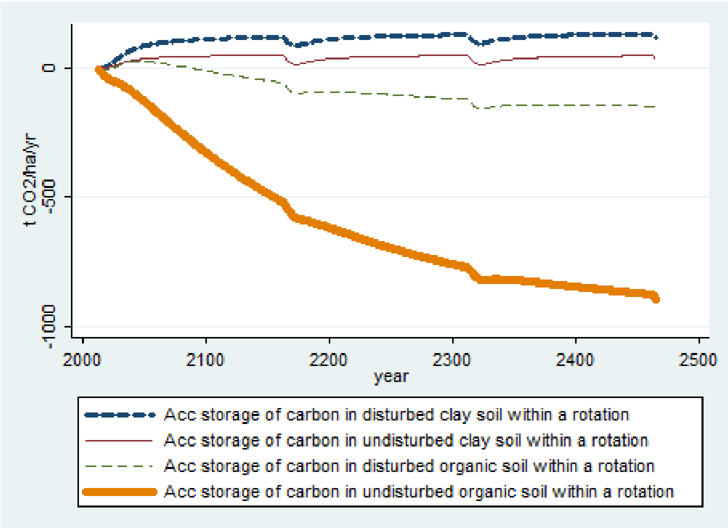

Figure 3.17. Carbon (t CO_2/ha) in penduncluate oak (YC4) accumulated or lost over three rotations for soil types: undisturbed clay; disturbed clay; disturbed organic; and undisturbed organic. Source: CARBINE.

The most striking feature of this graph is the strong reduction in soil carbon which occurs when trees are planted on previously undisturbed organic soils (e.g. peatland). **Table 3.15** reports the quantity of carbon accumulated or lost over one rotation for different soil types. The negative values for organic soils confirm as in the Woodland Carbon Code guideline (2013) that the woodland creation on organic soil cannot be an eligible activity as it is associated to high quantity of carbon lost. This occurs because afforestation causes peats to dry out and release their previously stored carbon. As peatlands are superb stores of carbon the potential losses can be dramatic. In comparison afforestation of previously disturbed peatlands results in a much smaller level of losses – although this merely reflects the fact that previous disturbance will have already lead to drying out and carbon release. In contrast, the afforestation of most other soils results in an increase in carbon storage. Here the change is greatest for previously disturbed soils (such as arable areas subject to regular ploughing) which are likely to have suffered prior depletion of their natural carbon stocks.

Table 3.15. Carbon (t CO_2/ha) in pendunculate oak (YC4) accumulated or lost over one rotation for soil types: undisturbed clay; disturbed clay; disturbed organic; and undisturbed organic.

Period	Disturbed mineral clay	Undisturbed mineral clay	Disturbed organic	Undisturbed organic
2013-2023	17.59	7.71	-1.58	-47.02
2024-2033	54.67	23.76	19.14	-69.14
2034-2043	77.37	33.40	26.44	-102.46
2044-2053	90.87	39.11	25.44	-141.70
2054-2063	99.26	42.58	20.16	-183.00
2064-2073	104.85	44.84	12.89	-224.18
2074-2083	108.87	46.44	4.79	-264.20
2084-2093	111.95	47.63	-3.53	-302.59
2094-2103	114.43	48.52	-11.79	-339.17
2104-2113	116.48	49.19	-19.85	-373.90
2114-2123	118.19	49.66	-27.67	-406.83
2124-2133	119.62	49.94	-35.21	-438.02
2134-2143	120.84	50.11	-42.44	-467.51
2144-2153	121.91	50.19	-49.32	-495.37
2154-2163	117.80	45.17	-60.92	-526.71
2164-2173	88.79	15.29	-96.99	-581.37

Source: CARBINE

Similar patterns of soil carbon change occur for coniferous afforestation.

3.7.6 Discussion and conclusion

The models described in this section are incorporated within our integrated modelling system as described subsequently in this report permitting assessment of the consequences of afforestation upon the sequestration and emission of GHGs. This assessment is comprehensive in that it embraces GHG in livewood, waste and forest litter, products and soil carbon.

3.8 Water quality module part 1: Export coefficient modelling

This section describes an export coefficient modelling exercise intended to obtain estimates of the rate and annual levels of nutrient exports from land use into water-bodies. This provides one of the empirical inputs to the subsequent spatially explicit modelling of nutrients and ecological status described in the next section of this report. Together these analyses provide models examining the impact of land use change upon various aspects of water quality. These are linked to the overall analysis of policy change impacts presented subsequently in this report.

3.8.1 Summary

Numerous water quality models have been developed using many different approaches, ranging from simple empirical models to complex distributed physically-based ones (Chen *et al*., 1996; Keller *et al*., 2007; Makarewicz *et al*., 2013; McIntyre *et al*., 2003; Polus *et al*., 2011; Saleh *et al*., 2000; Saleh and Gallego, 2007; and Somura *et al*., 2012). A common problem with the complex (physically-based) models is that they have high data requirements and are relatively difficult to calibrate on a large scale. Yet, these models sometimes give only as much or less information compared to simpler models. For this reason in this project, we adopt the export coefficient modelling approach to predict the nutrient loading from UK catchments (across a national scale) with reasonable accuracy whilst retaining low and readily available input requirements.

3.8.2 Objective

To develop a simple model to quantify the nutrient exports from a catchment/region to surface water bodies, using readily available information on the inputs-to and flow-from the catchment. To achieve this, an export coefficient modelling (ECM) approach is adopted.

3.8.3 Data

We use a number of datasets which are described in the Sections 3.14 and 3.15 these are: LCUAP2 (2000, 2010), Livestock2 (2000, 2010), Casweb (2013), GROfS (2013) and UKBorders (2013). These datasets principally provide information on various determinants of nutrient inputs including measures of livestock (e.g. stocking levels by type), coverage (in ha) for different land use categories, and population location data. Two further datasets are also used: Annual fertiliser input data (for nitrogen and phosphates) for England and Wales, obtained from the British Survey of Fertiliser Practice (BSFP, 2013); and for daily mean water flow quality data (fortnightly interval) we used the Environment Agency water quality data: EA-AfA194 (2012) and SEPA (2012a).

3.8.4 Assumptions

Motivated by the need for an efficient method to model nutrient exports, and taking account of limited data availability, the following assumptions are made with respect to the input variables:

- land use, livestock and population are assumed to be uniformly distributed across a 2km^2 cell in a given catchment;
- fertiliser application rates for each crop type are assumed to be same across England and Wales;
- the total population that falls within a developed land use area GIS polygon and the surrounding 250m buffer was assumed to be the population connected to a sewage treatment works; and

- catchments in a given soil-climate class share a similar set of nutrient export characteristics.

3.8.5 Methodology

The ECM approach is based on models used in the literature that have been developed, tested and widely accepted at various spatial and temporal scales to predict delivery of nutrients under changing land use scenarios: Beaulac and Reckhow (1982), Ding *et al*., (2010), Haygarth *et al*. (2003), Johnes *et al*. (1996), Johnes and Heathwaite (1997), Matias and Johnes (2012), Omernik (1976), Shi *et al*. (2006) and Worrall *et al*. (2012). ECM is a simple yet useful approach that can also be used in sensitivity analysis requiring minimal data to provide estimates of the impact of land-change-use patterns on water quality.

ECMs are usually constructed on a catchment basis using the available information on: a) distribution of land use/land management and fertiliser application to each; b) the number and distribution of livestock and their nutrient inputs; c) the number and nutrient inputs from human population; and d) and the inputs of nutrients through N fixation and atmospheric deposition.

An export coefficient of a specific land use type is a measure of the rate of export of nutrients from a specified source area to a downstream water body. Therefore, given the land use proportions in a catchment and the nutrients exported per unit area from each, it is possible to estimate total annual nutrient loads using the following formula (Johnes, 1996):

Equation 3.8.1:

$$L_E = \sum_{i=1}^{n} E_i\,[A_i(I_i)] + p$$

where,
L_E - estimated nutrient load;
E_i - export coefficient for nutrient source *i* ;
A_i - area of catchment occupied by land use type *i*, or number of livestock type *i*, or of people;
I_i - input of nutrient to source *i*;
p - input of nutrient from precipitation.

3.8.5.1 Soil-Climate (SC) classes

Work such as Haygarth *et al*. (2003) has reported that export coefficient values can vary widely between different geoclimatic regions. Therefore, to improve the predictive power of the ECM used in this study, a distribution of five soil-climate (SC) classes (shown in **Figure 3.18**) were defined to represent major landscape units with broadly similar climate, soil type, hydrogeology and farming applications and, therefore, have broadly a similar capacity of nutrient export/retention potential. The soil-climate classes derived and their predominant catchment characteristics are listed in **Table 3.16**.

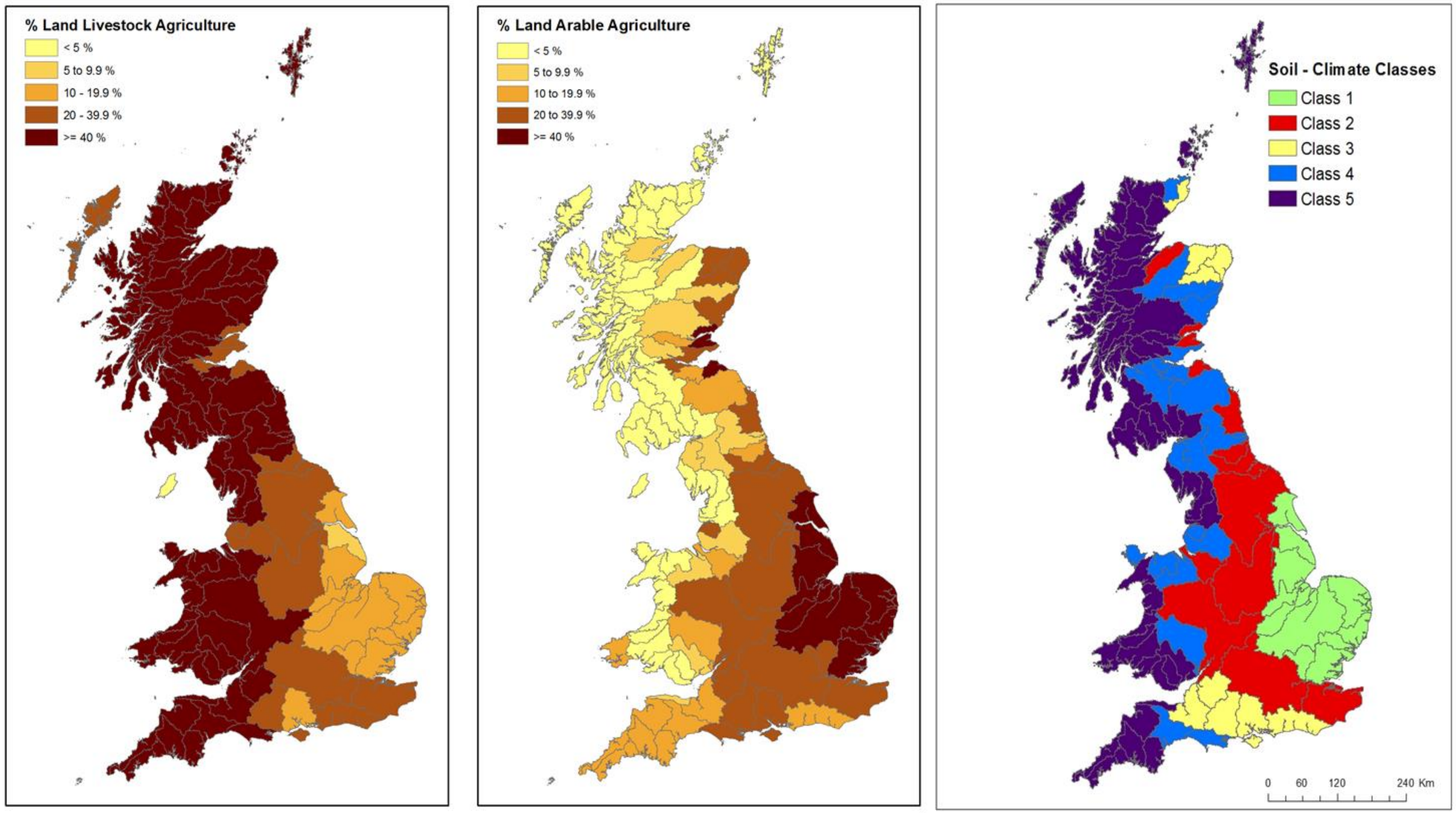

Figure 3.18. Distribution of percentage of land under agriculture and different soil-climate classes. Maps generated using AgCensus data and cluster analysis on percentage of area covered by different soil-climate zones. Source: Morton et al. (2011); JAC (2013); FAO/IFA/IIASA/ISRIC-WSI/ISSCAS/JRC (2009).

Table 3.16. Description of the five soil-climate classes defined (shown in Figure 9.1) and the predominant catchment characteristics.

Soil-Climate Class	Predominant Catchment Characteristics
Class 1 (Region 1: Anglia)	Low precipitation and medium or fine textured soils; Intensive arable (>40%) regions; Areas with essentially no groundwater or high/moderate productivity aquifers with low permeability cover.
Class 2 (Region 2: NE, Midlands & SE of England)	Low or medium precipitation and medium or fine textured soils; Mixed arable (>20%)/dairying (>30%) regions; High/Moderate productivity aquifers with low to high permeable cover.
Class 3 (Region 3: Southern England)	Medium precipitation and medium or fine textured soils; Mixed arable (20 - 40%)/dairying (10 - >40%) regions; Areas with high/moderate productivity aquifers with permeable cover.
Class 4 (Region 4: East & SE of Scotland, NW of England, and regions between midlands and the west coast)	Medium or high precipitation and medium or fine textured soils; Predominantly livestock farming (>40%) regions; Areas with low to high productivity aquifers with low permeability cover.
Class 5 (Region 5: Western fringe of the UK)	High precipitation and medium or fine textured soils; Extensive livestock (>40%) regions; Areas with low productivity aquifers with permeable/ low permeability cover.

Classes generated using AgCensus data and cluster analysis on percentage of area covered by different soil-climate zones. Source: Land Cover Map 2007, AgCensus data & Harmonized World Soil Database (HWSD).

3.8.6 Derivation of nutrient inputs, export coefficients and loadings

3.8.6.1 Nutrient Inputs to the catchment

For each catchment land use hectare, livestock numbers and population numbers were extracted from the EA-AfA186 (2012) and SEPA (2012b) datasets (see Sections 3.14 and 3.15) for the both study periods. Annual fertiliser inputs for each land use category were obtained from British Survey of Fertiliser Practice (BSFP, 2013) for 2000 - 2011. Annual input of nutrients to a catchment from different sources was calculated as follows.

Equation 3.8.2:

$$I_{lu} = \sum_{i=1}^{n} A_i \times I_i$$

Equation 3.8.3:

$$I_{ls/p} = \sum_{j=1}^{m} N_j \times I_j$$

where,
I_{lu} - nutrient input from the land use,
A_i - area covered by land use type *I*,
I_i - fertilizer input to land use type *i*,
$I_{ls/p}$ - nutrient input from livestock or population,
N_i - number of livestock type *j,* or number of people connected to sewage treatment type *j*, and
I_j - nutrient input from livestock or population sources of type *j*.

Estimating nutrient inputs from human sources within a catchment is challenging given the limited availability of data detailing the location of septic tanks and the number of people connected to sewage treatment works (STW). Consequently access to data on the amount and composition of any effluent from these sources and the subsequent amount of nutrient exported to a stream/river is also limited (Dudley and May, 2007). To address this issue studies typically adopt an indirect method to estimate nutrient inputs from human sources (May *et al*., 1996; May *et al*., 1998; Weller, 2000; Hall, 2001; Withers *et al*., 2012). In this study, nutrient inputs from humans were estimated using available population data. A GIS was used to generate a 250m buffer zone around each of the Developed Land Use Areas (DLUA) obtained from OS (2013b). It was assumed that all the population that live within the DLUA is connected to mains sewage and hence to mains sewage treatment works (STWs). The population served by septic tanks was estimated by subtracting the estimated population connected to STWs from the total population in a catchment as detailed in the dataset SEWAGE (2013; see Section 3.15). Although this is a simple approach, it was expected to approximately differentiate exports from STWs and those from septic tanks and take into account the different types of treatment. This was considered superior to studies where a single export coefficient (kg nutrient lost per head) for the whole population is assumed irrespective of the treatment the sewage had undergone (e.g. Johnes, 1996). Nutrient inputs from atmospheric sources (dry/wet deposition) were derived from the literature (e.g. Owen, 1976; Söderlund *et al*., 1982; Royal Society, 1983; Johnes, 1996; Cape *et al*., 2001).

3.8.6.2 Export coefficients

Ideally, export coefficients used in such a modelling are derived from field scale experiments (literature) that are then calibrated for catchment outlets. Although, such an approach of up scaling from a field scale to catchment scale may lead to some uncertainty, the model still provides an effective and inexpensive means of evaluating the impact of land-use and land management practice on water quality (Shi *et al*., 2006).

The soil climate classes defined in this model are similar to the geoclimatic regions defined by Johnes *et al*. (2007) and Haygarth *et al*. (2003). For example, Class 3 (see **Figure 3.18** & **Table 3.16**), characterised as regions with medium precipitation and predominant fine/medium textured soils, is similar to the mixed arable/dairying and permeable group defined by Johnes *et al*. (2007). Similarly, Class 1 (Anglia region) is similar to the 'intensive arable regions' group in the above studies. Since the export coefficients used in Haygarth *et al*. (2003) and Johnes *et al*. (2007) were well calibrated and validated (on 47 river basins) and the geo-climatic regions used in those studies are similar to the classes being used in the current project, it was decided to use the coefficients from these studies for this modelling routine.

3.8.6.3 Water Framework Directive

Nisbet *et al*., (2011) use data for 4,837 river waterbodies (RWBs) (RWBs, 2013) in England from the WFD Cycle 1 assessment WFD (2008). Similar boundaries for Wales and Scotland were obtained with assistance from the Environment Agency and SEPA (SEPA, 2012a), resulting in 8,169 RWBs with a range of WFD status variables (RWBs, 2013).

From the available WFD status variables the following characteristics (as assessed for 2009) were used as a basis for the woodland planting prioritisation exercise:

- ecological status (graded from bad to high);
- soluble Reactive Phosphorous or Phosphate status (graded from bad to high);
- dissolved Oxygen status (graded from bad to high);
- pH status (graded from bad to high);
- specific Pollutants status (graded pass/fail which is equivalent to good or not); and
- Nitrate Vulnerable-Zones (NVZ) status (based on intersecting RWBs with NVZ boundaries as of 2010).

Several of these variables were similar to those used in the Nisbet *et al*., (2011) assessment but it was not possible to identify suitable data for sediment and pesticide risks. Specific pollutant status was used instead because this covered some pesticides. Dissolved oxygen was added because it is a good general indicator of environmental conditions (EA, 2011). The six variables were subsequently used to derive a priority score as follows:

- the phosphate, dissolved oxygen and specific pollutant attributes were coded as 1 if the status was less than good and 0 otherwise;
- the NVZ attribute was similarly coded with 1 if the RWB intersected an NVZ and 0 otherwise;
- these four scores were added together so that each RWB had a resulting value ranging from 0 to 4. Of the 8,169 RWBs there were 47 % with a score of at least 1 and 14 % with a score of 3 or more. The nitrate and phosphate variables were the two where codes of 1 were most common, the former occurring in 37 % of RWBs and the latter in 24 %;
- any RWBs with a pH status less than good or an ecological status of high or good were screened out by setting the score variable to 0. This ensured that priority was focused on areas with less than good ecological status and where woodland planting would not accentuate any acidification problems.

The result of these calculations was to leave 38 % of RWBs with a score of at least one and 14 % with a score of 3 or more. The polygon values were then interpolated onto the 57,230 points in the national 2km mesh distribution by assigning each point with the score of the polygon closest to it. **Figure 3.19** shows the resulting distribution of values, with a concentration of higher scores in lowland England, particularly parts of East Anglia, the Midlands, the North West and South East.

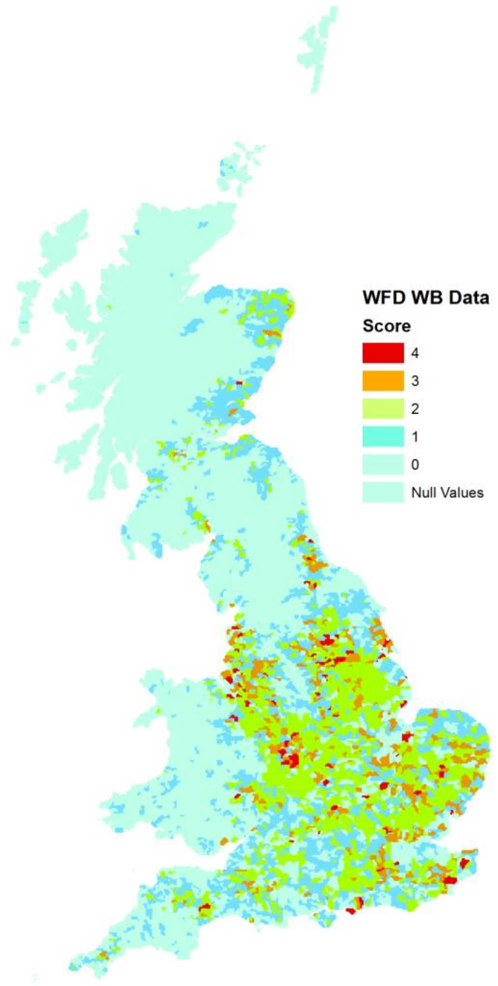

Figure 3.19. Distribution of suitable planting site if the water framework directive criteria is used as the policy driver. Source: RWBs (2013).

3.8.7 Results

In this section we have set out a model that enables us to estimate the nutrient runoff from land into stream waters. This export coefficient model (ECM) is widely used in several studies to make predictions about the impacts of land use change on nutrient exports.

We now report four tables of results which follow from this method, due to time constraints, some of them are not directly derived but obtained from similar models described in the literature. As described in the previous section, a set of export coefficients for nitrate and phosphate for each soil-climate class were chosen from the literature (Haygarth *et al*., 2003; Johnes *et al*., 2007; Shi *et al*., 2006;), and are given in **Table 3.19**. Briefly we describe what is presented. There are 18 land use categories, four livestock categories, two population categories (based on sewage treatment) and a category that represents wet/dry atmospheric deposition, used in the model (as listed in **Tables 3.17 – 20**). Many of these variables are already familiar to the reader but in order to be in a position to make informed decisions about land-use, definitions used are more precise that one might expect. For example, land covered in grass is differentiated into permanent grassland, temporary grass; and rough grazing, and cereals into wheat, winter barley, spring barley, maize and other cereals.

Fertiliser inputs for each land-use (BSFP, 2013), and inputs from livestock and humans (Haygarth *et al*., 2003; Johnes *et al*., 2007; Shi *et al*., 2006) for the period 2000-2011 are as listed in **Tables 3.17** and 3.**18**.

In addition, as the export coefficients reported in the literature are for total nitrogen (TN) and total phosphorus (TP), export coefficients for nitrates and phosphates were estimated assuming that the nitrate load was 50% of TN and phosphate load was about 40% of the total phosphorus (TP) load, a similar approach was adopted by Johnes *et al*. (1996). The estimated export coefficients for nitrates and phosphates are listed in **Tables 3.19** and **3.20**.

Glancing at the results, reading across both nitrates and phosphates we see that the annual nutrient load lost per hectare is consistently high for potatoes, sugar beet, oilseed rape and other crops, followed by cereals, grasslands rough grazing and woodlands etc. Such variability could be mainly due to the differences in the nutrient treatment (inputs) they receive throughout a year. Among the livestock categories, nutrient exports from cattle (per head) are relatively large. Nitrate export from human sources connected to sewage treatment works (STWs) is about 14% less than that from population served by septic tanks. Similarly, phosphate export from the population on STWs is about 40% less than that from population served by septic tanks.

When the nutrients lost per hectare are compared across the five soil-climates regions as found in **Table 3.20**, exports from the Anglia region are found to be relatively low, which reflects the low annual precipitation and runoff in this region, and for region 4 (NW England and regions between midlands and the west coast) high levels of loses of nitrate and phosphates per annum are detected, which may be due to the slope and runoff in this region. Although at this stage, it is difficult to interpret the results as the model does not take into account the variability in topographical, rainfall, and runoff. The export coefficients estimated in this modelling are presented in **Table 3.20***,* are subsequently used as some of the inputs to the integrated nutrient and ecological status model which is described and estimated in Section 3.9 of this report. The spatially explicit model of nutrients described in that section provides for a more sophisticated treatment of the way in which water is affected by parameters such as precipitation, slope, distance from the water body and other additional variables. Hence, the results derived from the integrated model (TIM) are anticipated to provide not only more insights into nutrient exports from the five soil-climate classes but through interactions with the other land-use change models reflect on overall impacts on water quality throughout Great Britain.

3.8.7.1 Limitations

The major source of uncertainty in this model is the water quality data. Annual mean concentrations estimated from two-weekly/monthly data can lead to under/over estimates depending on the flow conditions at the time of sampling. For example, for determinants like phosphorus, which tend to increase in concentration with increasing flow, regular but infrequent sampling will be biased towards periods of relatively low total flux (Littlewood, 1992). This can be overcome with increased sampling frequency, however on a regional/national-scale this is difficult to achieve.

As there is no direct method to estimate the population connected to STWs and septic tanks, the indirect and simpler method adopted here may introduce some uncertainty in the model. However, this method would at least help differentiate exports from STWs and septic tanks and to some extent take into account any treatment the sewage may have received.
It is worth noting that the export coefficients used in this study were calibrated by previous studies only for the rivers used to derive the coefficients and not for the entire region. Therefore, the load estimates from this model are only relative indications.

Table 3.17. Annual nitrate inputs for 2000 - 2011.

Land use	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Permanent Grassland	135	131	123	119	115	113	111	106	94	98	104	99
Temporary Grass	187	167	177	166	156	157	139	135	126	117	134	126
Rough Grazing	10	10	10	10	10	10	10	10	10	10	10	10
Non-farm Grass & heath	4	4	4	4	4	4	4	4	4	4	4	4
Farm Woodland	20	20	20	20	20	20	20	20	20	20	20	20
Non-farm woodland	20	20	20	20	20	20	20	20	20	20	20	20
Wheat	159	165.5	167	157	156	148	164	136.5	131	165	162	151
Winter Barley	149	143	153	149	143	140	139	139	137	142	145	143
Spring Barley	115	109	111	111	109	105	108	102	102	107	105	105
Total Barley	132	126	132	130	126	122.5	123.5	120.5	119.5	124.5	125	124
Maize	62	57	52	51	55	55	56	56	46	49	49	52
Other Cereals	120	93	110	93	86.5	91.5	112	80.5	83	102	90	72
Potatoes	175	170	176	159	168	178	157	142	166	179	149	170
Sugar beet	114	113	116	113	105	104	109	102	96	104	103	99
Total Oilseed Rape	164.5	181.5	165	173	174	180	189	163	158	155	165	170
Other crops	49	88	68	49	38	61	47	71	52	41	40	42
Horticulture	70.3	71.3	86.7	92.3	77	77	48	93	64	69	85	67
Other Farmland	4	4	4	4	4	4	4	4	4	4	4	4
Cattle	70.2	70.2	70.2	70.2	70.2	70.2	70.2	70.2	70.2	70.2	70.2	70.2
Pigs	18.8	18.8	18.8	18.8	18.8	18.8	18.8	18.8	18.8	18.8	18.8	18.8
Sheep	10.1	10.1	10.1	10.1	10.1	10.1	10.1	10.1	10.1	10.1	10.1	10.1
Poultry	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Pop on Septic Tanks	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9
Population on STW	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9	3.9
Wet/dry deposition	20	20	20	20	20	20	20	20	20	20	20	20

Values shown as kg ha^{-1} yr^{-1} for land use and as kg ca^{-1} yr^{-1} for livestock and human sources. Source: BSFP (2013), Johnes (1996), Shi et al. (2006).

Table 3.18. Annual phosphate inputs 2000 – 2011.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Permanent Grassland	*16*	*16*	*16*	*15*	*14*	*14*	*13*	*11*	*7*	*6*	*8*	*7*
Temporary Grass	29	20	29	21	23	20	18	18	14	12	13	11
Rough Grazing	0	0	0	0	0	0	0	0	0	0	0	0
Non-farm Grass & heath	0	0	0	0	0	0	0	0	0	0	0	0
Farm Woodland	0	0	0	0	0	0	0	0	0	0	0	0
Non-farm woodland	0	0	0	0	0	0	0	0	0	0	0	0
Wheat	35	31.5	28.5	27.5	26.5	26.5	23	17	16.5	13	23.5	23
Winter Barley	45	44	44	38	42	39	35	33	32	20	31	28
Spring Barley	37	30	27	29	32	30	28	25	23	16	22	21
Total Barley	41	37	35.5	33.5	37	34.5	31.5	29	27.5	18	26.5	24.5
Maize	42	30	43	43	41	37	41	38	32	29	30	27
Other Cereals	44	31	35	31.5	31.5	33	23	15.5	14.5	11	18	19
Potatoes	165	148	127	128	127	151	123	104.5	136	153	139.5	78
Sugar beet	39	36	43	34	36	37	35	41	31	20	29	26
Total Oilseed Rape	35	36	37	31.5	36.5	31.5	28.5	18	38.5	15	24.5	23.5
Other crops	31	23.1	29.4	26.6	25.6	23.3	17.1	22.1	20.9	15.6	20.4	17.4
Horticulture	37	33	32.8	29	48.8	40	31.8	51.3	33.3	33.5	21.8	44
Other Farmland	0	0	0	0	0	0	0	0	0	0	0	0
Cattle	39.8	39.8	39.8	39.8	39.8	39.8	39.8	39.8	39.8	39.8	39.8	39.8
Pigs	12.7	12.7	12.7	12.7	12.7	12.7	12.7	12.7	12.7	12.7	12.7	12.7
Sheep	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4
Poultry	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Pop on Septic Tanks	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6
Population on STW	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6
Wet/dry deposition	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5

Values shown as kg/ha/yr or land use and as kg/ca/yr^{-} for livestock and human sources. Source: BSFP(2013), Johnes (1996), Shi et al (2006).

Table 3.19. List of export coefficients for nitrate and phosphate by soil-climate classes.

	Nitrate					Phosphate				
Region	1	2	3	4	5	1	2	3	4	5
Permanent Grassland	0.86	4.24	4.24	10.58	5.29	0.012	0.047	0.047	0.169	0.084
Temporary Grass	1.08	5.1	5.1	16.54	8.27	0.014	0.113	0.113	0.379	0.162
Rough Grazing	0.02	0.05	0.05	0.05	0.05	0.008	0.008	0.008	0.008	0.008
Non-farm Grass & heath	0.02	0.05	0.05	0.05	0.05	0.008	0.008	0.008	0.008	0.008
Farm Woodland	0.02	0.1	0.1	0.1	0.1	0.008	0.008	0.008	0.008	0.008
Non-farm woodland	0.02	0.1	0.1	0.1	0.1	0.008	0.008	0.008	0.008	0.008
Wheat	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Winter Barley	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Spring Barley	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Total Barley	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Maize	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Other Cereals	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Potatoes	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Sugar beet	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Total Oilseed Rape	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Other crops	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Horticulture	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Other Farmland	0.02	0.05	0.05	0.05	0.05	0.008	0.008	0.008	0.008	0.008
Cattle	5.85	5.54	5.54	5.57	5.54	0.123	0.207	0.207	0.414	0.207
Pigs	1.57	1.33	1.33	1.34	1.33	0.04	0.059	0.059	0.119	0.059
Sheep	0.84	0.84	0.84	0.84	0.84	0.011	0.019	0.019	0.037	0.019
Poultry	0.04	0.04	0.04	0.04	0.04	0.001	0.002	0.002	0.005	0.002
Pop on Septic Tanks	1.22	1.22	1.22	1.22	1.22	0.157	0.157	0.157	0.157	0.157
Population on STW	1.05	1.05	1.05	1.05	1.05	0.095	0.095	0.095	0.095	0.095
Wet/dry deposition	11.76	11.76	11.76	11.76	11.76	0.083	0.083	0.083	0.083	0.083

Regions: 1=Anglia; 2=NE, Midlands & SE England; 3= Southern England; 4= East and SE Scotland, NW England and regions between midlands and the west coast 5= Western fringe of the UK.
Values shown as kg ha^{-1} yr^{-1} for land use and as kg ca^{-1} yr^{-1} for livestock and human sources. Source: BSFP (2013), Johnes (1996), Shi et al (2006).

Table 3.20. List of export coefficients for nitrate and phosphate by soil-climate classes.

	Nitrate					Phosphate				
Region	1	2	3	4	5	1	2	3	4	5
Permanent Grassland	0.86	4.24	4.24	10.58	5.29	0.012	0.047	0.047	0.169	0.084
Temporary Grass	1.08	5.1	5.1	16.54	8.27	0.014	0.113	0.113	0.379	0.162
Rough Grazing	0.02	0.05	0.05	0.05	0.05	0.008	0.008	0.008	0.008	0.008
Non-farm Grass & heath	0.02	0.05	0.05	0.05	0.05	0.008	0.008	0.008	0.008	0.008
Farm Woodland	0.02	0.1	0.1	0.1	0.1	0.008	0.008	0.008	0.008	0.008
Non-farm woodland	0.02	0.1	0.1	0.1	0.1	0.008	0.008	0.008	0.008	0.008
Wheat	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Winter Barley	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Spring Barley	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Total Barley	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Maize	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Other Cereals	1.54	10.23	10.23	19.72	9.47	0.038	0.272	0.272	0.458	0.458
Potatoes	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Sugar beet	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Total Oilseed Rape	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Other crops	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Horticulture	3.29	17.15	17.15	17.4	17.4	0.15	0.365	0.365	1.834	1.834
Other Farmland	0.02	0.05	0.05	0.05	0.05	0.008	0.008	0.008	0.008	0.008
Cattle	5.85	5.54	5.54	5.57	5.54	0.123	0.207	0.207	0.414	0.207
Pigs	1.57	1.33	1.33	1.34	1.33	0.04	0.059	0.059	0.119	0.059
Sheep	0.84	0.84	0.84	0.84	0.84	0.011	0.019	0.019	0.037	0.019
Poultry	0.04	0.04	0.04	0.04	0.04	0.001	0.002	0.002	0.005	0.002
Population on Septic Tanks	1.22	1.22	1.22	1.22	1.22	0.157	0.157	0.157	0.157	0.157
Population on sewage treatment works (STWs)	1.05	1.05	1.05	1.05	1.05	0.095	0.095	0.095	0.095	0.095
Wet/dry deposition	11.76	11.76	11.76	11.76	11.76	0.083	0.083	0.083	0.083	0.083

Regions: 1=Anglia; 2=NE, Midlands & SE England; 3= Southern England; 4= East and SE Scotland, NW England and regions between midlands and the west coast 5= Western fringe of the UK.
Values are shown as kg/ha/yr for land use and as kg/ca/ yr for livestock and human sources.

These values were estimated assuming that nitrate load was 50% of total nitrogen (TN) load and phosphate load was 40% of the total phosphorus (TP) load.

Source: Johnes (1996); Haygarth et al. (2003); Shi et al. (2006) and Johnes et al. (2007).

3.9 Water quality module part 2: Spatially transferable modelling of nutrients and Water Framework Directive ecological status

3.9.1 Summary

This section describes models estimated to establish the link between land use and the ecological status of river bodies in Great Britain. The approach used is one of structural statistical modelling in which observations of real world data are used to establish the nature of the relationships between cause and effect. The modelling proceeds through two key steps. First, using data on observed nitrate and phosphate concentrations in rivers in England and Wales, statistical models are estimated that relate nutrient inputs on land (primarily from agriculture and sewage) to concentrations in rivers. Subsequently, using data on the ecological status of river bodies in the UK compiled under the Water Framework Directive (WFD), the statistical relationship between ecological status and nutrient concentrations is established. Our statistical modelling exercise shows highly significant relationships between land use, nutrient concentrations and on to ecological status. It is evident, however, that nutrient concentrations are only one of many factors determining ecological status, so changes in nutrient concentrations may have only marginal impacts on ecological status.

3.9.2 Objective

To estimate the relationship between changing land use, nutrient concentrations in rivers and, ultimately, the ecological status of river water bodies. Those ecological statuses feed directly into the Water Recreation Model described in Section 3.16, where they are seen to be a key determinant of the economic values that individuals derive from river sites.

3.9.3 Data

The fundamental units of analysis used in the water quality modelling are the cells of the 2km grid established for Great Britain that is used throughout the report. In this section, we refer to those cells as *Land Cells,* as we are interested in the land use on those cells and how that land use impacts on water quality in rivers.

A 2km resolution Digital Elevation Model (DEM) was developed using the grid and a flow accumulation algorithm used to define cells to which at least 25 other cells drain. All cells meeting that criteria are defined as *River Cells* and those cells form a rough approximation to the river network in GB. Note that a River Cell is also a Land Cell insomuch as land use patterns at the cell level can impact on the quality of water in the river that runs through it.

Water quality data for the modelling described in this section were obtained under license from the Environment Agency. These data consist of two key data sets; the General Quality Assessment (GQA) data which provides measures of phosphate and nitrate concentrations in rivers for 2000 and 2009 and the Water Framework Directive (WFD) Ecological Status classification of UK rivers for 2010. As shown in **Table 3.21**, both data sets are categorical in nature.

Table 3.21. Categorical data definitions for water quality data sets used in the analysis.		
GQA Phosphate Concentration Categories	**GQA Nitrate Concentration Categories**	**WFD Ecological Status Classifications**
Grade 1 : <5 mg NO_3/l	Grade 1: <0.02 mg P/l	High
Grade 2: >5 to 10 mg NO_3/l	Grade 2: >0.02 to 0.06 mg P/l	Good
Grade 3: >10 to 20 mg NO_3/l	Grade 3: >0.06 to 0.1 mg P/l	Moderate
Grade 4: >20 to 30 mg NO_3/l	Grade 4: >0.1 to 0.2 mg P/l	Poor
Grade 5: >30 to 40 mg NO_3/l	Grade 5: >0.2 to 1.0 mg P/l	Bad
Grade 6: >40 mg NO_3/l	Grade 6: >1.0 mg P/l	

The analysis described in this section draws heavily on the work described in the previous section establishing best estimates of nutrient loads resulting from different activities on land (particularly agriculture and sewerage infrastructure). To implement the analyses, the scale of those different activities on each land cell was required for both 2000 and for 2009/2010. As described in more detail in Section 3.15 those datasets were compiled from a variety of sources.

3.9.4 Nutrient Models

Our statistical model begins from the assumption that the nutrient concentration in any river cell must result in part from nutrients that run-off from the land and in part from other sources. Accordingly,

Equation 3.91:

$$Nutrient\ Concentration_s = \frac{Nutrient\ Land_s + Nutrient\ Other_s}{Flow_s} \qquad (s = 1, 2, \dots, S)$$

where $Nutrient\ Land_s$ is the annual quantity of nutrients entering river cell *s* from land sources, $Nutrient\ Other_s$ is the annual quantity from other sources and $Flow_s$ measures the annual flow of water through *s*.

For the purposes of our model we assume that nutrients from land sources can be calculated as a function of the nutrients exported from each land cell. Building on the work reported in Section 3.8, we calculate that quantity by multiplying data on a land cell's agricultural and sewerage infrastructure by the export coefficients appropriate for that cell's soil climate category. Accordingly, a first estimate of the nutrients available for export from a land cell is given by;

Equation 3.92:

$$z_i = \boldsymbol{x}_i \boldsymbol{\gamma}_{sc_i} \quad (i = 1, 2, \dots, M)$$

where $\boldsymbol{x}_i$ is the vector of land use and sewerage data for land cell i, and $\boldsymbol{\gamma}_{sc_i}$ are the export coefficients for cell i's soil climate category.

Of course, not all of the nutrient exported from a land cell will end up in a river. Rather we would expect that a proportion of z_i will be lost through a variety of decay processes that occur as the nutrient is transported first over land and then in the river before contributing to the nutrient concentration measured in a river cell. We assume that those decay processes are a function of the distance from land cell i to a river cell s over land $d^L_{i,s}$ and in the river $d^R_{i,s}$ and use a power function specification with parameters λ^L and λ^R to capture rates of distance decay. Accordingly, our first cut estimate of the nutrient reaching a river cell from a particular land cell in its catchment is given by:

Equation 3.9.3:

$$\sum_{i \in C_s} Nutrient\ Land_{i,s} = z_i {d^L_{i,s}}^{\lambda^L} {d^R_{i,s}}^{\lambda^R}$$

Observe that should $\lambda^L = 0$ then our data would be indicating that there is no decay in nutrients as they are transported over land, likewise should $\lambda^R = 0$ the data indicate no in-river decay in nutrients. Our prior expectations are that both λ^L and λ^R will be negative.

Naturally, the relationship in Equation 10.3 ignores the fact that there exists considerable variation in the features of land sites and the path over which nutrients migrate from land to measurement location. Aided by the repeat measure nature of our land and nutrient concentration data, we capture that variability through the inclusion of a land cell-specific scaling parameter, β_i. Our final specification of the quantity of nutrients reaching river cell s from land cells in its catchment, C_s, is given by:

Equation 3.9.4:

$$Nutrient\ Land_s = \sum_{i \in C_s} \beta_i z_i {d^L_{i,s}}^{\lambda^L} {d^R_{i,s}}^{\lambda^R}$$

We assume that β_i must be non-negative so that at least some (perhaps very small) proportion of the nutrients deposited on a land cell must reach the measuring point in a river. In contrast, we entertain the possibility that our export coefficients, $\boldsymbol{\gamma}_{sc_i}$, only approximate the true export coefficients up to some scale transformation such that β_i might actually be greater than zero. Accordingly, in estimating the parameters of the model we assume that $\beta_i \sim Lognormal(\beta, \sigma_\beta)$ with parameters β (the location parameter of the distribution) and σ_β (the scale parameter of the distribution) to be estimated from data.

To complete the model we require some specification for $Nutrient\ Other_s$, the contribution to river nutrient concentrations from other sources. We assume those sources include groundwater and human activities other than agriculture and sewerage. To capture contributions from those sources we introduce a river cell specific element to the model

Equation 3.9.5:

$$\frac{Nutrient\ Other_s}{Flow_s} = \alpha_s \qquad (s = 1, 2, \ldots, S)$$

We assume that $\alpha_s \sim Normal(\alpha, \sigma_\alpha)$. It follows that our final statistical specification

Equation 3.9.6:

$$Nutrient\ Concentration_s = \alpha_s + \frac{\sum_{i \in C_s} \beta_i z_i {d^L_{i,s}}^{\lambda^L} {d^R_{i,s}}^{\lambda^R}}{Flow_s} \qquad (s = 1, 2, \ldots, S)$$

Since our GQA data only identifies nutrient concentrations within classes bounded by specified concentrations, we make the assumption that $Nutrient\ Concentration_s$ is a lognormally distributed random variate and estimate the parameters of the model using techniques of simulated maximum likelihood.

The model in Equation 10.6 was estimated using repeat-measure GQA data for England and Wales for the years 2000 and 2009. Parameter estimates for models of Nitrate concentrations and Phosphate concentrations are reported in **Table 3.22**.

The parameter estimates for both models generally concur with prior expectations with regards to sign and most parameters are deemed statistically significant at the 95% level of confidence or higher. Notice the significance of the β parameter that for both cases confirms that there is a significant statistical relationship between nutrient loadings on land with those observed by rivers (the negative coefficient on β in the phosphate model is explicable by the lognormal distribution of this parameter – the modal value of β lies between zero and one).

Table 3.22. Parameters of the Nutrient concentration models for Nitrates and Phosphates.

Parameter	**Nitrate**		**Phosphate**	
	Coeff (std err)	*p*-value	Coeff (std err)	*p*-value
Other Nutrients				
Location: α	2.2372 (0.0527)	<0.0001	-2.7284 (0.0753)	<0.0001
Scale: σ_α	1.0794 (0.03)	<0.0001	1.5463 (0.0493)	<0.0001
Land Nutrient Scaling:				
Location: β	-1.5655 (0.0717)	<0.0001	1.6175 (0.2282)	<0.0001
Scale: σ_β	0.3727 (0.0259)	<0.0001	0.1909 (0.0553)	0.0003
Distance Decay:				
Land: λ^L	-1.9045 (0.2022)	<0.0001	-0.7858 (0.2249)	0.0002
River: λ^R	-0.0002 (0.0027)	0.464	0.0042 (0.0055)	0.2194
Concentration Distribution:				
Scale: σ	0.2035 (0.0097)	<0.0001	0.6137 (0.0226)	<0.0001
N	1184		1884	
Log Likelihood	-3198.83		-3255.29	

Most interestingly we observe highly significant negative estimates for the decay parameters on land distance, λ^L, but not river distance, λ^R. Our models hence suggest that there is a relatively rapid decay in nutrients in their movement across land to the river course but no discernible further decay in river. Moreover, the smaller absolute value of the land distance decay parameter for the phosphate model suggests greater mobility for phosphate than nitrate.

As might be expected given the inclusion of land cell-specific (β_i) and river cell-specific (α_s) parameters, the model does very well at predicting nutrient classifications within sample. 75.6% of observation classifications are correctly predicted by the nitrate model, with an equivalent figure of 69.9% for the phosphate model.

To assess the responsiveness of nutrients to the planting of woodland, we calculated the proportion of river sites (not already in the lowest concentration category) that would move to a lower concentration category in the event of all land cells adjacent to rivers being planted with new woods. For the nitrate model we found 40.9% of the river cells improved by one or more categories under such a planting regime while the equivalent figure for the phosphate model was 22.6%. The difference between the two reflects the difference predicted in distance decay over land for the two nutrients. While planting all river courses with woodland does not represent a realistic policy scenario, the exercise demonstrates that by reducing nutrient applications on land, our models are capable of predicting changes in nutrient concentrations in rivers.

3.9.5 Nutrient Transfer Models

A major problem with applying the phosphate and nutrient models to the prediction of nutrient concentrations in rivers across the UK, is the fact that the GQA data used in the estimation of those models were limited to England and Wales. In particular, the data provide no direct information on the values of the land cell-specific parameter, β_i, and river cell-specific parameters, α_s, for rivers outside the original sample. Moreover, the models reported in **Figures 3.10.1** and **3.10.2** below only relate the population distribution of those parameters, not the specific values for any particular land or river cell.

To overcome that problem we apply the method described by Revelt and Train (1999). Using Bayes theorem, we predict the most likely values of β_i for each land cell in the data given the population distribution and the observed data for that cell. Recall those parameters reflect a cell specific scaling parameter that estimates the proportion of nutrient load on a particular cell that is exported to the river. Variation in β_i may reflect inaccuracies in the export coefficients used in the calculation of cell nutrient loads and other features of the land cell such as its hydrogeological characteristics and soil climate type. Accordingly, in a secondary analysis we regress the estimated $\beta_i$on an array of variables describing various features of the land cell. **Table 3.23** reports the coefficients from that analysis for the Nitrate and Phosphate models. Observe that the models describe around 48% of the variation of β_i across land cells for nitrates and 47% for phosphates.

We use those models to predict values of β_i across all land cells in the UK. Those predictions are depicted in the maps shown in **Figure 3.20**. Observe the strong regional trends in the β_i parameters across the country. In particular, the models suggest that generally higher levels of export are observed in the relatively hilly areas of Wales and Scotland with lower values typifying large areas of lowland southern England.

Table 3.23: Parameters of the β transfer models for Nitrates and Phosphates.

Parameter	Nitrate		Phosphate	
	Coeff (t-stat)	p-value	Coeff (t-stat)	p-value
Constant	0.2049 (68.1976)	<0.001	4.8133 (145.9791)	<0.001
Land Use				
Permanent Grassland	0.0001 (7.0232)	<0.001	-0.0016 (-7.4963)	<0.001
Temporary Grassland	0.0005 (8.4365)	<0.001	0.0022 (3.4631)	0.001
Rough Grazing	0.0004 (29.2643)	<0.001	0.0015 (10.4593)	<0.001
Other Grassland	0 (-2.9504)	0.003	0.0013 (8.6065)	<0.001
Farm Woodland	-0.0001 (-3.5628)	<0.001	0.0009 (2.7017)	0.007
Other Woodland	0.0002 (19.2744)	<0.001	0.0018 (16.5066)	<0.001
Wheat	0 (-1.9213)	0.055	-0.0024 (-10.6795)	<0.001
Winter Barley	0.0002 (4.2416)	<0.001	0.003 (5.3685)	<0.001
Spring Barley	0.0004 (9.8031)	<0.001	0.0108 (22.2218)	<0.001
Other Barley	-0.0014 (-6.7092)	<0.001	0.0041 (1.7453)	0.081
Maize	-0.0002 (-3.4917)	<0.001	-0.0036 (-5.9879)	<0.001
Other Cereals	-0.0005 (-6.368)	<0.001	-0.0043 (-4.7072)	<0.001
Potatoes	0.0007 (8.0877)	<0.001	0.0142 (14.4181)	<0.001
Sugar Beet	-0.0002 (-2.9791)	0.003	0.0063 (8.4505)	<0.001
Oil Seed Rape	0.0001 (1.988)	0.047	0.0066 (16.1351)	<0.001
Other Crops	-0.0006 (-14.3437)	<0.001	0.0001 (0.2389)	0.811
Horticulture	-0.0002 (-2.5361)	0.011	-0.0022 (-2.9924)	0.003
Other Farm	-0.0002 (-4.5399)	<0.001	-0.003 (-7.497)	<0.001
Livestock				
Cows	-0.0002 (-22.5085)	<0.001	-0.0002 (-2.251)	0.024
Sheep	0 (17.8187)	<0.001	0.0005 (29.8322)	<0.001
Pigs	0 (8.4988)	<0.001	0 (1.2113)	0.226
Poultry	0 (-17.2356)	<0.001	0 (-14.3142)	<0.001
Sewerage Infrastructure				
On Septic Tanks	0 (-11.5682)	<0.001	-0.0004 (-23.8317)	<0.001
On Mains Sewerage	0 (0.3512)	0.725	0 (0.8308)	0.406
Soil Climate Class				
Class 1:	0	baseline	0	baseline
Class 2	0.0059 (4.0599)	<0.001	-0.0115 (-0.7199)	0.472
Class 3	0.0416 (25.514)	<0.001	0.5273 (29.4696)	<0.001
Class 4	0.0533 (30.6801)	<0.001	0.6325 (33.1879)	<0.001
Class 5	-0.0169 (-9.102)	<0.001	-0.1359 (-6.6647)	<0.001
Hydrogeological Class				
Class 1	0	baseline	0	baseline
Class 2	0.0085 (7.76)	<0.001	-0.0279 (-2.3258)	0.02
Class 3	-0.0113 (-10.7939)	<0.001	0.0815 (7.1109)	<0.001
Class 4	0.0039 (1.9263)	0.054	-0.0566 (-2.5479)	0.011
Class 5	0 (-0.0172)	0.986	-0.0739 (-5.6931)	<0.001
N	30,838		30,838	
k	33		33	
R^2	0.4819		0.4696	

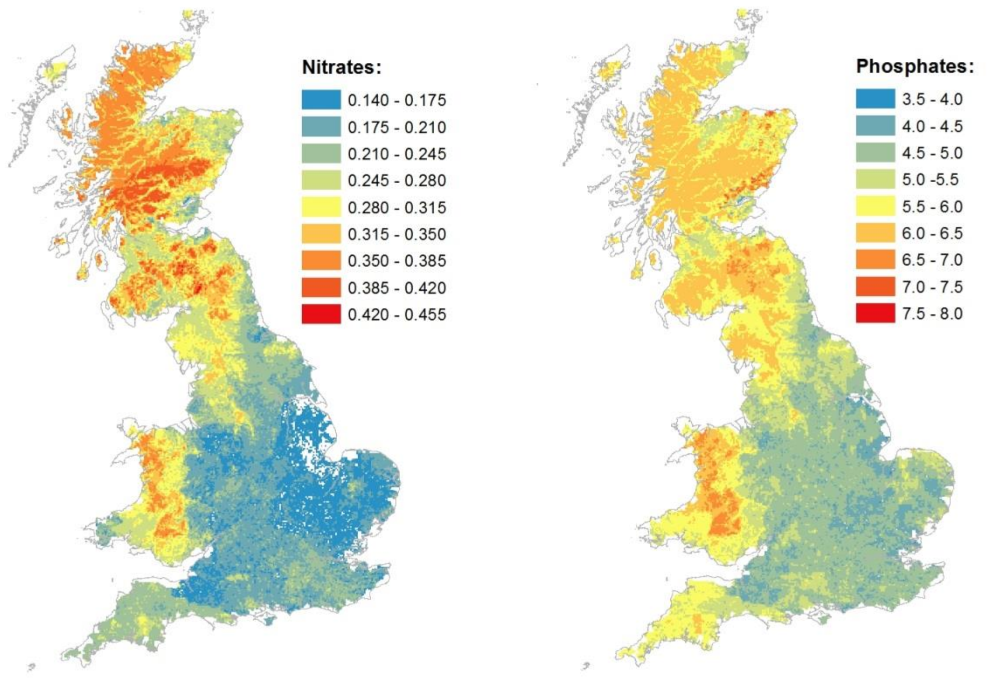

Figure 3.20. Predicted β parameters for Nitrates and Phosphates.

Table 3.24 reports on parameter estimates for a similar analysis carried out for the river cell-specific α_s parameters. Recall these parameters capture the contribution to river nutrient concentrations from other sources. We assume those sources include groundwater and human activities other than agriculture and sewerage. For the purposes of this regression, we assume that variation in α_s is determined in part by characteristics of the river at a river site and the land use in its environs. We also include variables describing the soil climate class and hydrogeological class of a river cell's catchment. Observe that the models describe around 45% of the variation of α_s across river cells for nitrates and 39% for phosphates.

Table 3.24. Parameters of the α transfer models for Nitrates and Phosphates.

Parameter	Nitrate		Phosphate	
	Coeff (*t*-stat)	*p*-value	Coeff (*t*-stat)	*p*-value
Constant	3.1308 (21.7405)	<0.001	-1.9698 (-9.385)	<0.001
Land Use				
Coast	0.0105 (1.3402)	0.18	-0.0087 (-0.7635)	0.445
Urban	-0.0086 (-6.5055)	<0.001	-0.0066 (-3.4398)	0.001
Temporary Grassland	0.1215 (9.4662)	<0.001	0.1133 (6.0592)	<0.001
Other Grassland	-0.0299 (-15.5119)	<0.001	-0.026 (-9.2385)	<0.001
Woodland	-0.0185 (-7.1415)	<0.001	-0.0236 (-6.2452)	<0.001
River Characteristics				
Canal	0.0785 (1.155)	0.248	0.1844 (1.8618)	0.063
Pipe	0.0903 (0.4896)	0.625	0.2446 (0.9105)	0.363
Baseflow	-0.0427 (-8.8189)	<0.001	-0.0228 (-3.2275)	0.001
Sewerage Infrastructure				
On Septic Tanks	0.0003 (3.9228)	<0.001	0.0007 (6.068)	<0.001
Soil Climate Class				
Class 1:	0	baseline	0	baseline
Class 2	0.0287 (0.3013)	0.763	0.0507 (0.3649)	0.715
Class 3	-0.454 (-4.0651)	<0.001	-0.8354 (-5.132)	<0.001
Class 4	-0.6 (-5.2256)	<0.001	-0.7068 (-4.2233)	<0.001
Class 5	0.4352 (3.7851)	<0.001	0.2899 (1.7302)	0.084
Hydrogeological Class				
Class 1	0	baseline	0	baseline
Class 2	0.1195 (0.9526)	0.341	0.4112 (2.2484)	0.025
Class 3	0.3401 (4.2476)	<0.001	-0.2481 (-2.1265)	0.034
Class 4	0.2877 (1.2045)	0.229	0.5899 (1.6947)	0.09
Class 5	0.205 (1.8842)	0.06	0.4616 (2.9104)	0.004
N	1,184		1,184	
k	18		18	
R^2	0.4513		0.3899	

Figure 3.21 plots out predicted values for α_s across all river sites in the UK. Again the data tend to show distinct regional patterns with apparently larger contributions from other nutrient sources being experienced across lowland England and relatively lower contributions in more mountainous rivers in Scotland and Wales.

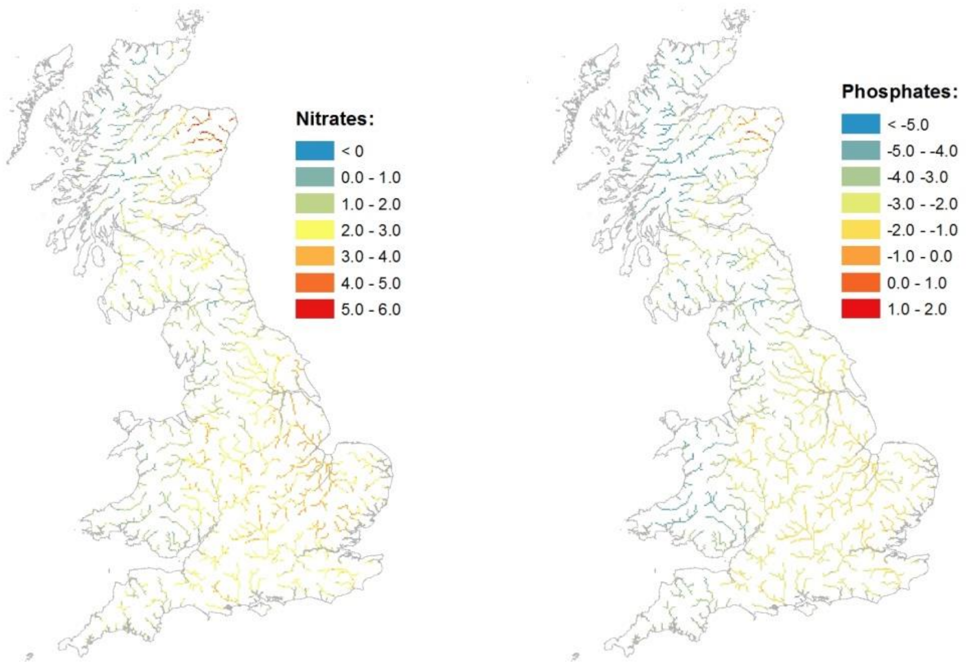

Figure 3.21. Predicted α parameters for Nitrates and Phosphates.

3.9.6 WFD Classification Model

The ultimate objective of the water quality analysis is to allow for the prediction of changes in ecological status in rivers that might result from changes in land use (in our case study the planting of new woodland) that change nutrient concentrations in rivers. The Environment Agency, classifies the ecological status of all surface water bodies in the UK under the Water Framework Directive (EA, 2013). That classification includes the identification of ecological status on a five point scale from Bad through Poor to Moderate to Good to High. Nutrient concentrations play a role in establishing ecological status both directly in that the classification depends on a series of chemical and physic-chemical quality elements of a river (including nutrient concentrations) and indirectly through the role nutrient concentrations play in determining the biological quality of a river. The particular method used by the environment agency implies that the WFD ecological status classification revolves primarily around worse-performing elements; for example a key determining factor is the lowest classed physico-chemical quality element. To reflect that classification methodology we use our models to predict phosphate and nitrate categories in each WFD river water body. Subsequently, we regress the WFD classification in that body against the worst performing nutrient category: that is to say, our regressor captures the concentration category of whichever of nitrates or phosphates is found to be in the highest concentration in a WFD river water body. We call that regressor the *Nutrient Category*.

Since the data only provides an ordinal categorisation of ecological status, we employ an ordered probit model (Greene, 2003) to perform the statistical analysis. The results of that analysis are reported in **Table 3.25**.

Table 3.25 Parameters of water framework directive categories.

Parameter	Coeff (*t*-stat)	*p*-value
Category Boundaries:		
Low boundary, κ_1	-2.0524 (-26.899)	<0.001
Middle boundary, κ_2	-1.1041 (-16.179)	<0.001
Upper boundary, κ_3	0.561 (8.625)	<0.001
Nutrient Category:		
Category 1	0	baseline
Category 2	-0.0396 (-0.518)	0.3022
Category 3	-0.3225 (-4.096)	<0.001
Category 4	-0.5695 (-7.868)	<0.001
Category 5	-0.5489 (-7.568)	<0.001
Category 6	-0.5159 (-6.827)	<0.001
N	5,282	
Log Likelihood	-5,365.4	

The ordered probit assumes that the ranking of river bodies by ecological status can be modelled as being determined by some underlying index; higher values of the index imply a higher probability of being in a better ecological status category. The first three parameters in **Table 3.25** record the estimated boundary points of the index where river cells jump between the five ecological status categories. The remaining parameters in **Table 3.25** describe the impact on ecological status classification of being in different nutrient categories. Recall that a higher nutrient category corresponds to a higher concentration of either phosphate or nitrate and hence we would expect it to lead to an increased likelihood of being classified in a lower ecological status category. The parameters in **Table 3.25** confirm that expectation. We observe that there is little difference in ecological status classification for rivers with the lowest two categories of nutrient concentration. Moving to nutrient category 3 and on to categories 4 , 5 and 6 significantly lowers the underlying index and increases the probability that a river will fall in a lower ecological status category.

3.9.7 Conclusions

Using the parameters presented in **Table 3.25** it is possible to predict the probability that a river body, currently in some particular WFD ecological status class, will switch to some other class as a result of a change in nutrient category. Those probabilities are used in the integrated model. The logic proceeds as follows. As land use changes in the catchment of a river cell, the nutrient concentrations in that river cell change and we can predict those changes using our phosphate and nitrate models. In turn, those changes in concentration may precipitate changes in nutrient category which feed into the WFD classification model and can be used to predict the probability of changes in ecological status. Our investigations suggest that, while being a significant determinant of ecological status, changes in nutrient concentrations tend to only marginally effect ecological status classification; for example, even reasonably large falls (or increases) in nutrient concentrations are unlikely to change the ecological status of a river body by more than one point on the classification scale.

3.10 The recreation module: Impact of land use changes upon recreation values

3.10.1 Summary

A key consideration in the expansion of woodland planting in Great Britain is the possibility that new woodlands will provide increased opportunities for recreation. To estimate the magnitude of the benefits that might be realised by those increased recreational opportunities and to understand how those values might differ across planting locations requires the estimation of a recreational demand model. The structure of that model must be such that it allows estimation of the welfare benefits of new woodlands in monetary terms: that is to say, in terms that might be directly compared to the other costs and benefits of planting. Also, that model must capture fundamental realities of the welfare that might be realised from recreational woodlands: particularly, that the benefits an individual enjoys from a recreational woodland decline both with increasing distance to that woodland and also with the increasing availability of alternative outdoor recreational opportunities. In this section, we report on the building of a recreational demand model that fulfils those criteria.

3.10.2 Theory and Economic Modelling

Our approach to estimating a recreational demand model adopts the long-established random utility framework first developed by McFadden (1974). That framework characterises recreational decisions as discrete choices in which, on any particular choice occasion, an individual has the opportunity to visit one of an array of sites each offering different opportunities for outdoor recreational activities. In essence, the modelling approach seeks to establish the value of the recreational opportunities offered by sites by observing data recording which particular sites individuals chose to visit given the set of sites that they could have possibly visited.
More formally, imagine a dataset that records the outdoor recreational choices of a sample of individuals, indexed $i = 1,2, \dots, N$, on a particular day. Each member of that sample enjoys a set of possible sites that they might visit, indexed as $j = 1,2, \dots, J_i$, and the data records which particular site is chosen for a visit. The choice as to which site to visit will depend on a number of factors, but two important considerations are the quality of the recreational experience offered by a site and the cost in time and money of visiting that site. In our model, the quality of recreational experience offered by site j is determined by the vector of site characteristics $\boldsymbol{x}_j$ and the costs of making a trip to site j by the travel costs tc_{ij}.

To construct our model, we first need to posit a function which describes the utility an individual will enjoy if they decided to visit site j. In line with the vast majority of the literature we choose the simple linear approximation;

$$v_{ij} = \alpha_j + \boldsymbol{x}_j\boldsymbol{\beta} + \gamma\left(I_{i,t} - tc_{ij}\right) \qquad (j = 1, 2, \dots, J_i \text{ and } \forall i)$$

where, $I_{i,t}$ is individual i's per period income, α_j is a site-specific utility element, $\boldsymbol{\beta}$ is the vector of coefficients describing the marginal utilities of site qualities and γ_i is the marginal utility of income. Alternatively, an individual may choose not to make an outdoor recreational trip. We give that "no trip" option the index $j = 0$, and specify the utility from that option as;

$$v_{i0} = \alpha_0 \qquad (\forall i)$$

Since the scale on which utility is measured is not known, we can make any arbitrary decision as to what quantity represent zero. For the purposes of this analysis we set α_0, the utility of the "no trip" option to zero such that the utility of other options is measured in comparison to the utility provided by this baseline option.

Adopting the familiar random utility framework, we develop our econometric specification from (1) by constructing the conditional indirect utility function;

$$u_{ij} = v_{ij} + \varepsilon_{ij} \qquad (j = 0, 1, \dots, J \textit{ and } \forall i)$$

where ε_{ij} is an econometric error term introduced to capture the divergence between our model of utility (v_{ij}) and the individual's experienced utility (u_{ij}). Following standard practice, the error terms are assumed to be distributed $IID\ EV(0,1)$; that is to say, as independent draws from a standard Type I Extreme Value distribution.

In making recreational trip decisions it is assumed that individuals choose from the set of options $j = 0, 1, \dots, J_i$, selecting that option which gives them the highest utility. Accordingly, the probability of observing individual i choosing to visit site k can be written as;

$$\begin{aligned} P_{ik} &= Prob\left[u_{ik} > u_{ij} \ \ \forall\, j \neq k\right] \\ &= Prob\left[v_{ik} + \varepsilon_{ik} > v_{ij} + \varepsilon_{ij} \ \ \forall\, j \neq k\right] \\ &= Prob\left[v_{ik} - v_{ij} \ > \varepsilon_{ij} - \varepsilon_{ik} \ \ \forall\, j \neq k\right] \end{aligned}$$

Given the distributional assumptions regarding the error terms, (3) results in an econometric expression for the probability of observing a particular recreational choice that takes the familiar multinomial logit (MNL) form;

$$P_{ik} = \frac{e^{v_{ik}}}{\sum_{j=0}^{J_i} e^{v_{ij}}} \qquad (\forall i, k)$$

Given data on the recreational choices of the N individuals, it follows from (4) that the log of the likelihood of observing those choices is;

$$ln\, L(\boldsymbol{\alpha}, \boldsymbol{\beta}, \gamma) = \sum_{i=1}^{N} \sum_{j=0}^{J_i} Y_{ij}\, ln\, P_{ik}$$

Where Y_{ij} is a dummy variable which takes the value 1 if individual i chose recreational option j, or zero otherwise and $\boldsymbol{\alpha}$ is the vector of utility elements specific to the different recreation trip options containing elements α_j $(j = 0,1, \dots, J_i)$. The parameters of the model can be estimated using maximum likelihood methods by optimising (5) with respect to the parameters of the utility function $\boldsymbol{\alpha}, \boldsymbol{\beta}, \gamma$.

The MNL is perhaps the simplest of the large class of econometric models that might be used to model recreational choices in the random utility framework. The MNL is adopted for the purposes of this research for a number of reasons. First, the datasets constructed for the purposes of estimating a recreational choice model for UK NEAFO are extremely large: they need to be to provide a representative analysis of outdoor recreation decisions for GB. The simplicity of the MNL likelihood function (4) allows the maximum likelihood routines to return estimates in timescales of several hours rather than the several days that would be required for more complex specifications. It would not have been practical to estimate those more complex models within the timescales of this project. More importantly, the MNL provides an expression for the expected welfare values that are derived from access to a set of recreational sites that takes a particularly convenient form;

$$E[W|J_i] = \frac{1}{\gamma} ln \left(\sum_{j=0}^{J_i} e^{v_{ij}} \right)$$

In simple terms, given the assumptions of the MNL model, equation (6) describes the analyst's best estimate of the maximum welfare, in money terms, that a respondent will enjoy from the J_i recreational activities open to them on any one choice occasion. The purpose of the UK NEAFO analysis is to understand how that welfare might be enhanced by the provision of new recreational opportunities in the form of open access woodlands. So, for example, imagine a new woodland were added to an individual's recreational choice set, then from (6) the expected value of that new woodland to individual i would be;

$$E[\Delta W] = \frac{1}{\gamma} ln\left(\sum_{j=0}^{J_i} e^{v_{ij}} + e^{v_{iJ+1}}\right) - \frac{1}{\gamma} ln\left(\sum_{j=0}^{J_i} e^{v_{ij}}\right)$$

Notice that the log form of (7) implies that as the number and quality of recreational opportunities available to an individual increases (i.e. the size of $\sum_{j=0}^{J_i} e^{v_{ij}}$ goes up) the smaller the additional welfare benefits enjoyed from the addition of the new woodland. In other words, individuals well-endowed with recreational opportunities will value an additional woodland less than those with relatively few recreational opportunities.

Now, imagine that there existed M locations in which new woodlands might be planted and we faced the problem of choosing N $(N < M)$ locations in which to plant in order to maximise recreational welfare values. Any particular planting decision could be described by a vector $\boldsymbol{d}$, where $\boldsymbol{d}$ has M elements, one for each potential planting location, and in which the m^{th} element, d_m, records a 1 if planting occurs at that site and a 0 otherwise. Clearly, the elements in $\boldsymbol{d}$ will sum to N. In this case, the welfare benefits of a particular planting decision for individual i will be given by;

$$E[\Delta W] = \frac{1}{\gamma} ln\left(\sum_{j=0}^{J_i} e^{v_{ij}} + \sum_{m=1}^{M} d_m e^{v_{im}}\right) - \frac{1}{\gamma} ln\left(\sum_{j=0}^{J_i} e^{v_{ij}}\right)$$

It turns out that the expression in (8) has a number of important features with respect to the argument $\sum_{m=1}^{M} d_m e^{v_{im}}$: that is to say, with respect to the element of (8) that reflects our planting decisions. First, it is montonically increasing in that argument and second it evaluates to zero when that argument takes a value of zero. Those two features mean that (8) can be linearised in a way that allows the use of relatively simple methods of integer programming to select the optimal set of planting locations. This is discussed in greater detail in Section 3.12 and the annex to TIM and data simulation.

Use of the MNL does, however, entail accepting some limitations to the realism of the model. In particular, the MNL does not allow for particularly realistic patterns of substitution between options. In particular, the model does not allow for the fact that the certain elements of the choice set might be much closer substitutes than others. So for example, imagine two individuals, one with a choice set replete with woodland another with a choice set with very few opportunities for woodland recreation. For the sake of argument, however, assume that both individuals enjoy approximately identical welfare values from the recreational opportunities afforded by their different choice sets. Now imagine we were to extend both individuals' choice sets by adding additional woodland. Intuition informs us that that additional woodland would offer much greater welfare gains to the individual lacking in woodland recreational activities.

Observe from (7), however, that the MNL would prescribe that both individuals enjoy the same welfare gain from that addition to their choice set.

Models exist that would provide much more realistic substitution patterns. A relatively simple extension would be to estimate a Nested Multinomial Logit Model (NMNL) which can be specified to allow for groups of similar types of site to exhibit much closer substitution relationships. Unfortunately, moving to a NMNL specification would introduce complexity in using the recreational model in the identification of optimal planting strategies. Accordingly, that extension is the focus of future research endeavours.

3.10.3 Data

The estimation of a discrete choice recreational demand model requires the compilation of a dataset that details two key items of information:

- *Choices:* the recreational decisions made by a sample of households: that is to say, a dataset which describes whether a household chose to make an outdoor recreational trip on a particular occasion and, if they choose to make such a trip, where they decided to visit; and
- *Choice Sets*: details of the set of outdoor recreational sites that each of those households might potentially have chosen to visit: that is to say, households' recreational choice sets.

Constructing such a dataset for the purposes of the UK NEAFO project presents two unique challenges. First, the UK NEAFO project is pursued at the scale of a nation, the vast majority of previous recreational modelling exercises focus on a considerably smaller spatial scale. Second, most of those previous modelling exercises focus on one particular form of outdoor recreation; most frequently fishing trip or trips to beaches. The UK NEAFO project requires a model which can distinguish the benefits that come from woodland recreational sites in the context of <u>all</u> alternative outdoor recreation opportunities. Accordingly, the development of a dataset for the UK NEAFO recreational model has necessitated the creation of a recreational choice dataset of unprecedented scope and detail and required the use of advanced software applications capable of processing and manipulating enormous datasets.

3.10.3.1 Outdoor Recreation Activity Data

At the core of the UK NEAFO recreational choice dataset is data collected from Natural England's national survey entitled the *Monitor of Engagement with the Natural Environment* (MENE). Similar surveys are undertaken in Scotland and Wales, but the unique feature of MENE is that it records the exact destination of recreational trips taken by respondents. While it may be possible to extract useful information from the Scottish and Welsh surveys, since they do not record information on recreational destination the data they provide is not immediately amenable to recreational demand modelling.

In its present form, the MENE survey began in 2009-10 with surveys being undertaken each year through to 2012-13. In total, the MENE dataset records between 9,000 and 10,000 respondent interviews each year: a total of 37,571 observations. Each observation provides details of the outdoor recreational activities of a household member over the course of the last week. If the respondent has involved themselves in such activities, then one particular trip is chosen at random. The MENE dataset records information on the activities undertaken on that trip, the nature of the outdoor location visited and its approximate geographic location. The MENE dataset is provided with weights that allow analysts to derive nationally representative statistics from the data.

Outdoor Recreation Site Data

Perhaps the greatest challenge in constructing the UK NEAFO recreation data set has been identifying a comprehensive, spatially-referenced catalogue of outdoor recreational sites in Great Britain. No such dataset currently exists. From the outset, we defined three qualitatively different forms of outdoor recreational site:

- *area features (Parks)*: These recreational sites are prescribed by some well-defined boundary. Recreational activity is allowed across most, or all, of the site and the provision of recreational services is often the primary, or sole, purpose of the site. Good examples of area features include municipal parks, nature reserves and recreational woodlands. We use the generic term parks to refer to sites of this type;

- *linear features (Paths)*: These recreational sites are prescribed by linear rights of way, usually in the form of footpaths or bridleways. Often used for walking or hiking, these rights of way may pass through agricultural land, along rivers or coastlines or over areas of semi-natural land. In their use of these linear features, recreational users will usually not deviate from the path into the surrounding countryside and indeed may not have the right to do so. We use the generic term path to refer to sites of this type; and
- *beaches*: With characteristics of both linear and area features, we include beaches as a separate category for the purposes of our analysis.

Data on area features were compiled from an array of geographical information system (GIS) resources. Detailed information on those data sources is provided in Annex 2 (supporting data). In brief, accessible recreational woodlands in GB were identified from the Woodland Trust's *Woods for People* project and the characteristics of those woodlands (primarily whether broad-leafed or coniferous) were determined by cross-referencing with the Forestry Commission's inventory of the UK's woodland estate. Data regarding the location of national and local nature reserves, as well as country parks, National Trust properties and doorstep and millennium greens were compiled from a variety of mainly government sources. The type of habitat characterising those recreational sites was determined through overlaying CEH's *Landcover* dataset, allowing sites to be categorised as primarily semi-natural grassland, wetlands or mountains, moors and heaths. Likewise, recreational sites were categorised as being lake or river sites if those features dominated the site. One major category of outdoor recreational site not represented in those datasets is that of municipal parks, recreation grounds and commons (often termed urban greenspace). Since, no GB dataset exists for such sites, their locations were determined from interrogation of the rich resource provided by the Open Street Map (OSM) project.

OSM was also instrumental in defining linear features. The GB network of public access paths and bridleways (from now on just paths) was extracted from OSM. Paths in urban areas or in recreational parks were extracted leaving just those that passed through natural areas and through agricultural land. Notice that many of the recreational opportunities afforded by the UK's national parks were captured by way of their paths network. A single 'path' recreational site was identified as a contiguous network of connected paths. The characteristics of each of those paths was established according to the type of habitat they passed through and by their proximity to rivers, lakes and coasts. Beaches were identified through reference to a variety of sources documented in the data annex.

Table 3.26 documents the types and number of outdoor recreational sites identified in the construction of the UK NEAFO recreational choice dataset.

Table 3.26. Recreational Sites.

Site Type	Num Sites	Num Size Categories
Beach:		
Beach	505	1
Area Features:		
Municipal		
Parks	7,307	3 (≤25ha, >25ha&≤75ha, >75ha)
Recreation Grounds	5,031	3 (≤25ha, >25ha&≤75ha, >75ha)
Commons	1,399	3 (≤25ha, >25ha&≤75ha, >75ha)
Woods		
Broad Leaf	13,209	3 (≤50ha, >50ha&≤150ha, >150ha)
Coniferous	4,375	3 (≤50ha, >50ha&≤150ha, >150ha)
Rural		
Semi-Natural Grassland	1,042	2 (≤50ha, >50ha)
Wetland	118	1
Mountains, Moors & Heaths	228	1
Country Park	589	1
National Trust	125	1
Coastal	51	1
Water:		
Rivers	506	1
Lakes	144	1
Linear Features (Paths):		
Natural:		
Mountains, Moors & Heaths	1,024	2 (≤5km and >5km)
Woodland Broad Leaf	1,149	2 (≤5km and >5km)
Woodland Coniferous	499	2 (≤5km and >5km)
Farm and Grassland		
Farm	15,486	2 (≤5km and >5km)
Semi-Natural Grassland	2,066	2 (≤5km and >5km)
Water		
Coastal	523	2 (≤5km and >5km)
Estuary	203	2 (≤5km and >5km)
Rivers	1,469	2 (≤5km and >5km)
Lakes	186	2 (≤5km and >5km)
Total	57,224	43

Choice Sets
The recreational site dataset was used to identify a choice set for each respondent in the MENE survey data. That data identified the lower super output area (LSOA) of each respondent's home. Accordingly, the outset location for recreational trips for each respondent was taken as the population weighted centroid of the LSOA in which they reside.

Using a UK roads dataset provided by the OS, a GIS roads network was constructed for the UK in which the driving time along every stretch of road was established from average driving speeds on roads of different categories. Access points to recreational parks or paths were taken at points at which those paths are parks intersected the roads network (except where those intersections were on motorways or dual carriageways). Accordingly, large parks or extensive paths are often characterised by a large number of access points.

To create a choice set for each respondent, the 23 recreational site types described in **Table 3.26** were further subdivided by size (see final column of **Table 3.26**) to generate 42 different categories of recreational site. For each respondent in the dataset GIS software was used to locate the 10 nearest sites of each type. Accordingly, each respondent's choice set was taken to comprise that array of 430 sites. Two additional options were added to each respondent's choice set: the option to not take a trip ("no trip" option) and the option to take a trip to a site not present in their choice set ("other trip" option).

Finally, the GIS network software was used to record the travel time and travel distance to each of the sites in a respondent's choice set through the roads network. Travel times and distances were converted to travel costs by using an approximation to each respondent's cost of time calculated as a third of their after tax hourly income and adding on a cost of travel calculated as £0.25 per kilometre travelled.

Since, 883 respondents to the MENE survey indicated that they had not started their trip from their home, the travel costs calculated in this way would not be correct. Accordingly, those observations were excluded from the data. All the same, the final dataset used in the analysis contained information on almost 15 million respondent-site choice options.

3.10.4 Matching Choices to Sites

The next step in constructing the UK NEAFO recreational dataset was to establish which particular site each respondent had chosen to visit for a recreational trip. Of the 37,571 observations in the MENE dataset, some 22,562 respondents had not taken an outdoor recreational trip over the course of the last seven days. Those individuals were catalogued as choosing the "no trip" option.

The MENE dataset failed to record the destination location for a further 2,258 respondents. As a crude approximation, those respondents were categorised as choosing the "other site" option. Given more time, those choices could be handled in a more realistic manner, particularly accounting for the fact that those respondents might actually have chosen one of the options in their choice sets.

A further set of observations were attributed to the "other trip" option on account of the information in the MENE dataset suggesting that they had not visited a site identified in the UK NEAFO recreational site dataset. In particular, trips described as being to an "allotment" or to a "village" were handled in this manner.

For the remaining observations, the MENE dataset records answers to a series of questions that provide insights as to the nature of the recreational site the respondent visited. For example, the survey records whether the respondent went for a walk on a path or took part in an activity involving water, the data also records whether the respondent visited a wood or a beach or a municipal park. That array of information was used in identifying which particular recreational site the respondent had visited. As a first step, GIS software was used to identify the 50 closest path sites, 50 closest park sites and 50 closest beach sites to each respondent's destination location as recorded in the MENE data. Then a scoring system was devised in which the characteristics of each site were compared to the description of the visited site recorded in the MENE data. The closer the site matched the description provided in the data, the higher its score. Finally, each sites score was inverse-weighted by its distance from the MENE-recorded destination location. The chosen site was taken to be that site with highest distance-weighted score.

Where the distance-weighted score exceeded a threshold level, it was determined that the actual site visited had not been found in the UK NEAFO recreation site dataset either because that site had not been identified in compiling that dataset or because the destination location in the MENE dataset was incorrectly recorded.

Table 3.27 reports the breakdown of trips in the data set that were made to sites of different types. Notice how almost half of the trips taken by respondents in the data are to municipal parks and recreation grounds. Importantly, for the purposes of the UK NEAFO analysis, trips to woodlands are also shown to be an important recreational destination.

As a final step, the site identified as a respondent's chosen destination was searched for in each respondent's choice set. For the majority of observations, the visited site was identified. For those observations where the site was not found in a respondent's choice set, that respondent was characterised as choosing the "other trip" option. A better approach would have been to add the identified destination to the respondent's choice set, but for technical reasons and for lack of time that extra processing step was not undertaken.

Table 3.27. Proportion of respondents making an outdoor recreational trip visiting different types of site.

Site Type	Percentage of Respondents
Beach:	7.99%
Area Features:	
Municipal	
Parks & Rec. Grounds	43.33%
Commons	2.88%
Woods	
Broad Leaf	15.32%
Coniferous	1.77%
Rural	
Wetland	0.50%
Mountains, Moors & Heaths	0.11%
Semi-Natural Grassland	2.12%
Country Park	7.58%
National Trust	0.79%
Water:	
Rivers & Lakes	1.87%
Linear Features (Paths):	
Natural:	
Mountains, Moors & Heaths	0.44%
Woodland	0.81%
Farm and SNG	
Farm and Grassland	11.68%
ln(length of path)	
Water	
Coastal	0.78%
River or Lake	2.01%

3.10.5 Modelling Results

A multinomial logit model of the form described above was estimated using specially written code which employed a number of programming tricks in order to speed up execution with extremely large datasets. The model was specified using a relatively simple specification for the utility function (1). In particular, a constant was included for each type of recreational site and the value of the recreational benefits coming from sites of different types allowed to vary according to the natural log of the area (park sites) or length (path sites) of the site. The estimated parameters of the model are shown in **Table 3.28**.

One item of immediate note from **Table 3.28** is that each and every parameter in the dataset is significant at higher than the 0.1% level of confidence. Of course, such an outcome is not unexpected given the fact that the model is estimated on a dataset comprising 34,653 observations. Also, recall that the baseline level of utility in the model is taken to be that provided by the “no trip” option. Since a sizeable majority of respondents did not choose to take a trip to an outdoor recreational sites it is not altogether surprising that the model estimates that the utilities derived from trips to such sites are significantly lower than that offered by the “no trip” option.

Examination of the estimated parameters suggests a broad consistency with prior expectations. Utility is decreasing in travel costs, such that respondents’ behaviour suggests a preference for nearer recreational sites over more distant ones. The utility of those recreational sites is significantly increasing with the log of size and this is true across the range of outdoor recreational sites examined in the model. Parks in general (that is to say, sites defined as a specified recreational area) tend to command greater utility values than paths, with municipal parks, commons and recreation grounds offering the highest recreational values of all sites. Woodland recreational sites tend to fall somewhere in the mid-range of recreational values with no significant differences between the recreational values ascribed to broad-leaf woodland as compared to coniferous woodland.

Table 3.28. Parameter estimates from a multinomial logit model estimated on the UK NEAFO recreational choice dataset.

Parameters	Coefficient	Robust s.e.	t-stat	p-stat
Travel Cost	-0.3353	0.0049	-68.4377	<0.001
No Trip (Baseline)	0			
Other Sites	-1.3179	0.0149	-88.4484	<0.001
Beach:				
Beach	-5.3490	0.3345	-15.9909	<0.001
Area Features:				
Municipal				
Parks & Rec. Grounds	-4.1898	0.1330	-31.5024	<0.001
Commons	-4.5799	0.1500	-30.5327	<0.001
ln(area)	0.0676	0.0125	5.4091	<0.001
Woods				
Broad Leaf	-5.1707	0.1882	-27.4742	<0.001
Coniferous	-5.1605	0.2021	-25.5342	<0.001
ln(area)	0.1296	0.0172	7.5362	<0.001
Rural				
Wetland	-5.7419	0.3586	-16.0120	<0.001
Mountains, Moors & Heaths	-7.1961	0.4171	-17.2526	<0.001
Semi-Natural Grassland	-6.8321	0.2943	-23.2149	<0.001
Country Park	-6.0077	0.3266	-18.3948	<0.001
National Trust	-6.0448	0.3454	-17.5007	<0.001
ln(area)	0.2856	0.0239	11.9491	<0.001
Water:				
Rivers & Lakes	-4.7912	0.5657	-8.4695	<0.001
ln(area)	0.1992	0.0473	4.2114	<0.001
Linear Features (Paths):				
Natural:				
Mountains, Moors & Heaths	-6.2508	0.3221	-16.814	<0.001
Woodland	-7.4496	0.3053	-21.429	<0.001
ln(length of path)	0.4411	0.0317	13.295	<0.001
Farm and SNG				
Farm and Grassland	-6.8321	0.2489	-25.498	<0.001
ln(length of path)	0.4377	0.0278	15.145	<0.001
Water				
Coastal	-7.5609	0.6157	-11.096	<0.001
River or Lake	-8.3692	0.5994	-12.642	<0.001
ln(length of path)	0.5982	0.0679	8.704	<0.001

3.10.5.1 Predicting Recreational Welfare

For the purposes of examining optimal planting decisions, the model parameters shown in **Table 3.28** were used to predict recreational welfare values across GB. First, the distribution of population across GB was simplified by ascribing the population in each lower super output area (LSOA; see Section 3.15.3.6) to the 2km grid cell within which its central point falls. That procedure resulted in the identification of just over 11,500 population locations. For each population location a choice set of 432 recreational options was constructed in exactly the same way as described for the UK NEAFO recreational data set. Finally using the estimated parameters and those choice sets, equation (6) was evaluated to establish the current levels of welfare being enjoyed at different population locations across the UK. The geographic distribution of those annual recreational welfare values per year is illustrated in **Figure 3.22**.

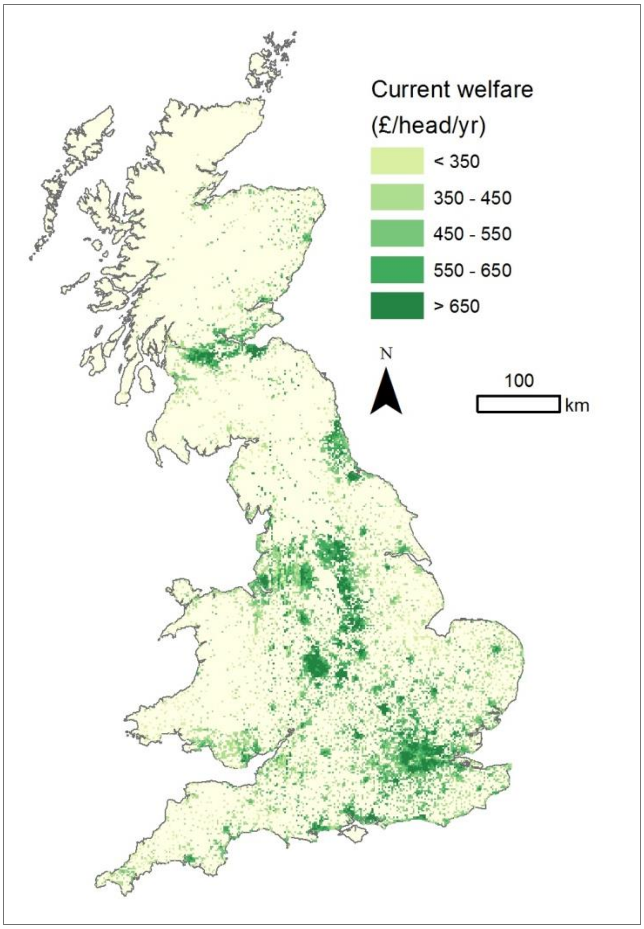

Figure 3.22. Annual welfare benefits from access to current set of outdoor recreation opportunities.

While a detailed discussion of the distribution of current welfare values is not the focus of this investigation, it is interesting to note that significant difference occur across GB with values ranging from a low of £258 to a maximum of £959 and that in part those difference reflect differences in the availability of recreational opportunities across GB.

To gain a better understanding of how the planting of new woodlands might impact on recreational welfare values a further investigative analysis was undertaken. In particular, using (7) the welfare gains realised by individuals in each population location were estimated in the event of a 100 ha broad-leaf woodland being planted within 10 minutes one-way drive time of that location and within 20 minutes. The results of that analysis are illustrated in **Figure 3.23**.

Consider first, the top row of **Figure 3.23** which illustrates the welfare benefits from a 100 ha woodland planted at 10 minutes distance, first in values per head and then in values for everyone living within a population location. The annual welfare benefits of such a woodland would average

£3.02 per head per year, but again considerable geographical variation exists in this value partly as a result of differences in the availability of recreational opportunities across GB. For example, the per head welfare gains appear to be relatively lower in London than they are in areas of north-west England or South Wales. That information on its own might suggest that the latter areas represent a preferred planting location to the former.

Now observe the right hand figure in the top row. That figure shows the same data but now multiplied up by the size of the population in each population. The important thing to note here is that the weight of population in each location matters. Now the greatest gains in welfare are achieved by planting close to the heavily populated urban regions in, for example, London and Birmingham. Accordingly, in choosing planting locations, we expect to find that recreational benefits will be optimised not only by planting in locations where individuals enjoy the greatest welfare gains from new woods but, at least as importantly, in locations where many people can be advantaged by access to the new recreational resource.

The bottom row of maps in **Figure 3.23** shows an equivalent analysis but this time for a new 100ha woodland planted at a distance of 20 minutes drive time from each population location. Comparing with the previous analysis, it is evident that the benefits of a new recreational woodland decline rapidly with increasing travel distance. At 20 minutes distance the average per head annual welfare gains fall to £0.29. The clear message is that in choosing optimal planting locations, recreational values will exert a powerful influence to plant close to heavily populated areas.

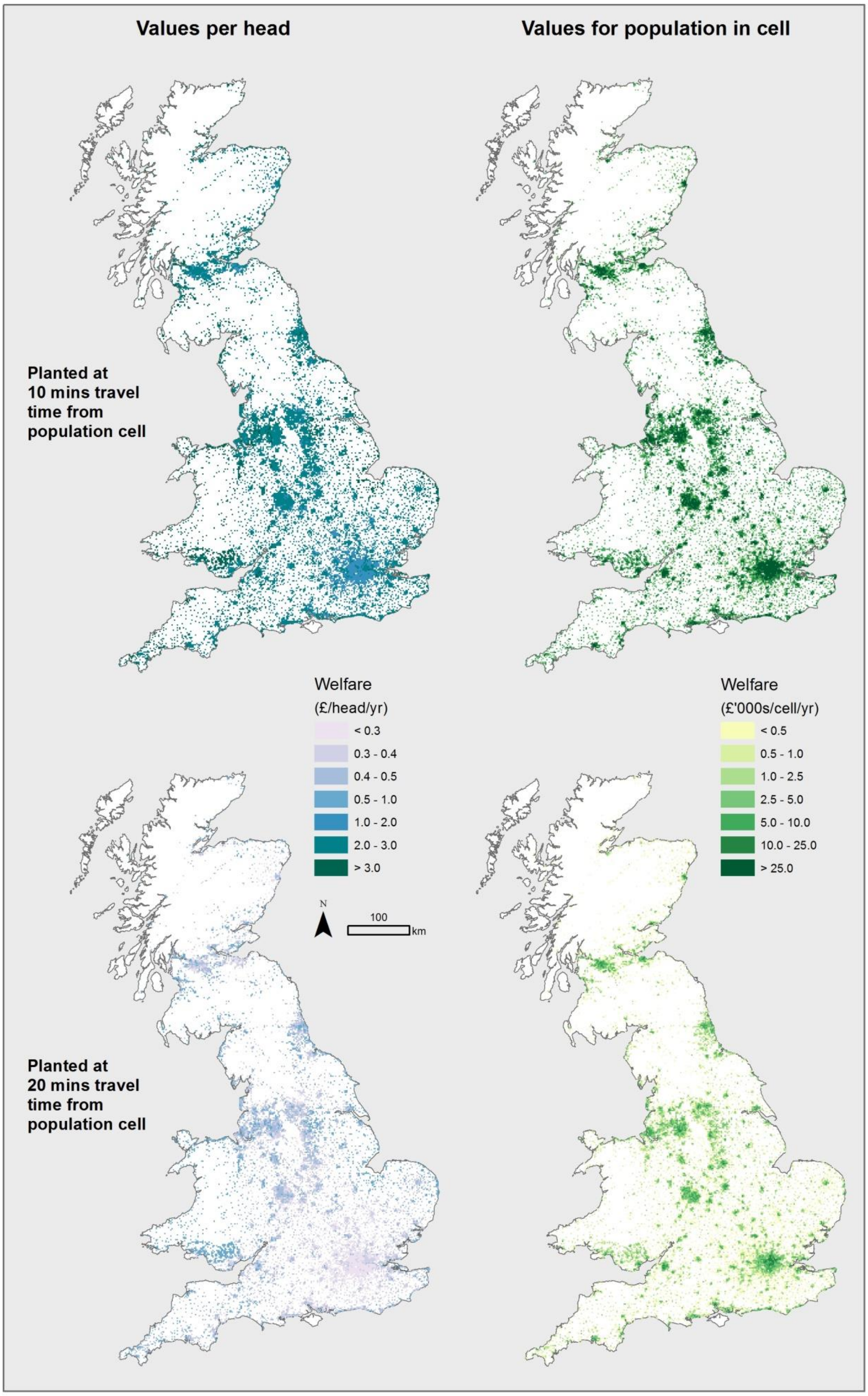

Figure 3.23. Recreational welfare benefits from the planting of a 100ha broad-leafed woodland.

3.10.6 Concluding Remarks

The recreation model described in this section provides a means of estimating the welfare values that might arise from complex patterns of new woodland planting across GB. Those welfare values are calculated in money terms and our analyses suggest the magnitudes of the welfare gains estimated by the model are of intuitively appropriate proportions: the planting of a substantial 100ha forest at 10 minutes driving distance, for example, results in an average individual welfare gain of £3.02 per year. In addition, that recreational demand model predicts that those welfare gains are lower the more distant the newly planted woodland: at a distance of 20 minutes driving time that same 100ha woodland only yields average individual welfare gains of £0.32 per year. Finally, intrinsic to the structure of the model is the fact that the welfare gains from a new woodland are less substantial the greater the availability of alternative recreational opportunities: the same 100ha forest planted at 10 minutes driving distance, for example, offers an annual welfare gain of £4.65 for each individual in the worst endowed area and only £1.14 in the best endowed area.

Much of the effort in constructing the recreational demand model has been in compiling a suitably comprehensive dataset of outdoor recreational sites. That enormous undertaking has resulted in perhaps the richest dataset of recreational choices ever compiled for the UK, indeed, perhaps the most comprehensive constructed anywhere in the world. Within the time constraints imposed by the UK NEAFO, we have only been able to exploit a tiny fraction of that richness and the possibility exists to develop truly exceptional recreational demand models based on this initial effort.

3.11 The biodiversity module

3.11.1 Summary

A model of bird species richness was developed using Breeding Bird Survey (BBS)[23] data collected at a 1km square resolution during the period 1999 –2011. These data were related to land use data from this period, together with various other predictors. Diversity was modelled for various categories of birdlife: (i) all species; (ii) farmland birds (of particular interest given declines in this group); (iii) woodland and upland habitat birds; (iv) birds on the red and amber lists of conservation concern (Eaton *et al*., 2009); (v) birds on the green list (those not of conservation concern). Various combinations of these categories were also considered (e.g. red and amber list farmland species). Whilst some estimates lacked precision, patterns emerged with regard to the impacts of land use upon bird species richness. Habitat-specific constraints for upland, farmland and woodland areas are suggested.

As stated in the introduction to this report, we recognise the ongoing debate regarding the definition and assessment of biodiversity. Furthermore we fully acknowledge that our measure of bird species richness is open to criticism as not encompassing the true depth of biodiversity. We adopt our measure purely as a means of incorporating some measure of the impact of land use change upon wild species which is backed by a high quality spatial and temporal dataset. While it concerns species of considerable conservation interest and utility, if superior and more comprehensive measures of biodiversity are made available they should be substituted for that used here. Furhermore the reader should be aware throughout that our use of the term 'biodiversity' might more strictly be replaced by the label 'bird species richness'. However, it is the underlying need to include wild species impacts within decision making which is the principle we are seeking to implement here.

3.11.2 Objective

The objective is to develop a model of the impact of land use on the diversity of breeding birds across Great Britain. This is used to examine the impact of land use change and constraints upon measures of biodiversity.

3.11.3 Data

The Breeding Bird Survey (BBS) is a line-transect survey of a random sample of 1km squares, collected annually by volunteers on behalf of the BTO, JNCC and the RSPB. Sample squares are chosen as a random sample, stratified by observer density: Regions with larger numbers of potential volunteers are thereby allotted a larger number of squares, enabling more birdwatchers to become involved in these areas. The analysis is weighted appropriately to take the differences in regional sampling density into account, as described below. Observers make two early morning visits to a given sample square between April and June, recording all birds encountered while walking two 1-km transects across the square. Birds are recorded in three distance categories, or as 'in flight'. The aim is for each volunteer to survey the same square (or squares) every year (Risely *et al*., 2012).

BBS data for the years 1999 – 2011 were obtained (BTO, 2011) to correspond with the earliest and latest years for which land use data were available (*c.* 2000 and *c.* 2010). There are no BBS data

[23] The BBS is jointly funded by the British Trust for Ornithology (BTO), the Joint Nature Conservation Committee (JNCC) and the Royal Society for the Protection of Birds (RSPB).

available for 2001 due to access restrictions arising from the foot-and-mouth outbreak. Dictated by available records for agricultural land use data, analyses were conducted with respect to “early land use”, using bird data from 1999 to 2005, and “late land use” using bird data from 2006 to 2011. Analyses focused, therefore, on two ranges of years, referred to hereafter as “early” and “late”. **Figure 3.24** shows the distribution of BBS 1km squares surveyed in Great Britain during the period considered. Land use data at the 1km resolution for the same locations were also used in the analyses (LCUP1, 2000, 2007; LCUAP1, 2000, 2010; Livestock1, 2000, 2010). Further details of these datasets can be found in Section 3.14.

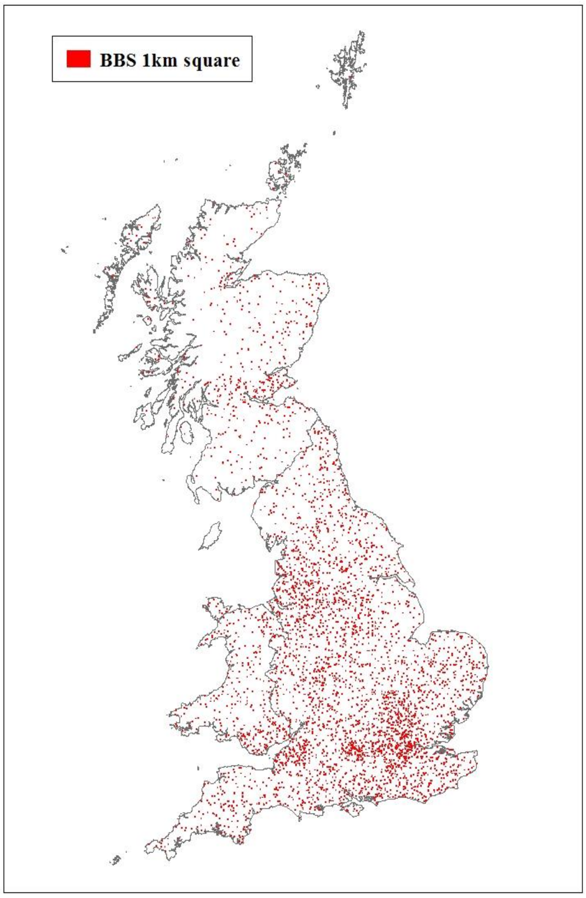

Figure 3.24. Distribution of Breeding Bird Survey (BBS) 1km squares surveyed between 1999 and 2011 with available 1km land use data.

3.11.4 Methodology

BBS count data were processed in order to extract the most robust summary of the breeding bird community present in each 1km survey square. Breeding birds are easier to survey repeatedly due to territoriality and/or close association with nesting locations. Non-breeding birds, either wintering populations or young yet to reach breeding age, are much less predictable in numbers, aggregation and location in the landscape, requiring both different survey methods and different analytical approaches for spatio-temporal variation to be assessed. For these reasons, there is no analogue of the BBS for non-breeding birds. In the context of this report a breeding bird focus is appropriate because model robustness and, therefore, reliability is maximized, and because it makes efficient use of the datasets available for analysis. It is possible that future analyses may be able to incorporate data from other surveys, taking into account non-breeding and wintering bird populations in wetlands, for example.

Bird data were summarized within each of the early and late year ranges in order to minimize possible effects of stochasticity in annual counts from these low-intensity sample surveys. For example, an uncommon or cryptic bird species may be present but not detected in some years, so treating consecutive years as repeat samples and summarizing annual diversity indices across them will provide a more representative measure of actual local bird communities.

Records of birds in flight were discarded, as these individuals were not closely associated with the habitat within the cell. This helps to ensure that data contributing to the diversity indices were more likely to reflect direct influences of the habitat within the squares in question, such that changes in these habitats are reflected more accurately in the predictions. Squares with data from only one year within the 1999-2011 time periods were discarded, as were records of bird species that were recorded on fewer than 40 BBS squares across the country and full time period. For each species, the maximum count across both visits in a year was extracted. *Laridae, sub-order Lari* (gulls), were excluded because the majority of records in terrestrial habitats will have consisted of aggregations of immature and sub-adult birds away from breeding sites.

Any unusually high, outlier bird counts (totals of birds not recorded as in flight) for each square-species combination were excluded because they probably represented non-breeding flocks. Flocks were identified and excluded as follows for all species: if a species had a ratio of maximum to median count of over 20, taking early and late visit counts into account across the whole BBS dataset, the counts greater than the 99th percentile were flagged. If one of the two counts from a given year were flagged in this way, the other, lower count was used and the flagged value discarded. If both counts were greater than the 99th percentile, then the lower value was used, unless both counts were greater than twice the value of the 99th percentile, in which case no count for that species was included for that square in that year (note that the latter occurrence was extremely rare). This process aimed to exclude records that were unreliable as indices of local breeding densities whilst retaining genuine extreme values that are likely to be informative of bird communities in unusual habitats. After this process, the maximum of the remaining early and late counts for a given square in a given year was taken as the count for that square and year.

The composition of the bird community represented by the presence and abundance of all remaining bird species in each survey square and year range was summarized using Simpson's Diversity Index (*D*) (Simpson, 1949), calculated in each year following Equation 12.1.

Equation 3.11.1:

$$D = \frac{1}{\sum_{i=1}^{S} p_i^2}$$

where *S* = number of bird species recorded at a focal site in that year, p_i = proportion of birds of species *i* relative to the total number of birds of all species.

The maximum value of *D* was calculated for each square across all years within each year range in which that square was surveyed. This became the dependent variable in the models. The maximum of these annual counts within a year range was then taken as the "early range" or "late range" count for that square, as appropriate.

In order to observe the effect of land use on different elements of the community of birds found in a 1km square, Simpson's diversity index was calculated using: (i) all species, (ii) only species which are known to occur on farmland and farmland borders, (iii) those deemed to be woodland specialists or generalists (Gibbons *et al*., 1993), (iv) those species found in upland habitats, (v) those species that are red- or amber-listed and thus of conservation concern, (vi) those green-listed so not deemed to be of conservation concern (Eaton *et al*., 2009). A further four species groups were produced by sub-dividing the latter two categories further into the farmland or woodland species on the red and amber, or green, lists.

For each 1km BBS grid square, the land use, land cover and livestock datasets dictated the possible explanatory variables. The variables used were based on: a) expert knowledge of bird habitat preferences; b) limiting variables with uneven reporting rates across Great Britain (e.g. seasonality in agricultural data, see Section 3.14); and c) reducing the presence of correlated variables (e.g. cattle and sheep were highly correlated with permanent grassland). Additionally, coastal habitat was rare on BBS squares and was dropped due to low sample size. Due to the large, known differences in bird communities between deciduous and coniferous woodland the distinction between these was incorporated by using the deciduous and coniferous cover variables found in the input datasets LCUP1 (2000, 2007).

In Great Britain, there are local area differences in the composition of bird communities which do not always relate to the presence or absence of a particular habitat (at least to the extent that such habitat is distinguishable using this land use definition). *Sitta europaea* (Eurasian nuthatch), for example, has a northern limit to its distribution which does not match the availability of deciduous woodland, which is its preferred habitat within its range (Baillie *et al*., 2012), and species such as *Phoenicurus phoenicurus* (Common redstart) and *Phylloscopus sibilatrix* (wood warbler) are more numerous in western deciduous woodland than in eastern deciduous woodland. Following the approach used in UK NEA (201), to avoid the spurious relationships with particular habitat categories that such broad spatial patterns might produce, the 100km Ordnance Survey grid square corresponding to each BBS square was included in the model as a factor. Due to the paucity of BBS 1km squares in a number of 100 km squares, some adjacent grid squares were combined so that each level of this control variable contained at least 15 BBS squares.

General Linear Models were run using the GENMOD procedure in SAS (2008). Data from both year ranges were included together in single models. This could have introduced a degree of pseudo replication and inaccurate estimates of variance with greater precision than was justified by the data. As a conservative estimate, therefore, standard errors were derived as the maximum standard error for each parameter from models run using either only early or only late range data. Models were fitted using every possible combination of the 12 land use variables; squared terms were always fitted with the corresponding linear term. The 100km square identity variable was included in every model. In order to account for the variable survey effort across the UK introduced by the stratification of the BBS sample and, thus, to ensure that the model results were equally applicable to all parts of the UK, an appropriate weighting variable was included in every model, as follows. The country was divided into the standard regions used in the organisation of the BBS (N=80), the total number of BBS squares surveyed during each year being divided by the number of squares surveyed in that region during the same year to provide an annual weight value for each square surveyed. The weight value for each square used in the models was then the mean weight value across the years in which that square was surveyed for each range of years, either between 1999 and 2005 or 2006 and 2011.

The Akaike Information Criterion (AIC) value was calculated for each model, with the lowest value across models showing the most parsimonious model, balancing explanatory power against the number of parameters. Akaike weights were calculated for each variable and model-averaged parameter estimates calculated for each variable, squared term, level of the 100km factor and intercept along with model averaged standard errors, as per Burnham and Anderson (2002, 2004).

3.11.5 Results

Akaike variable weights are shown in **Table 3.29** for the diversity of all birds, with 1 representing the variables given the highest ranking in calculating model averaged parameter estimates. Values were similar for the other diversity variables. The weights show that all the variables, with the exception of potatoes, horticulture and, other crops, were important in explaining the variation in bird diversity nationally. “Other crops” may have been too heterogeneous in composition to have a consistent effect over large spatial scales, while the same might be true of potatoes and horticulture they may still be influential land-uses locally.

Table 3.29. Model averaged Akaike weight for land use variables, overall Simpson’s diversity index.

Variable	Model averaged Akaike weight
Deciduous woodland	1.000
Coniferous woodland	1.000
Fresh water	0.982
Urban	1.000
Permanent grassland	1.000
Rough grazing	1.000
Non-farmed grassland	1.000
Wheat	1.000
Barley	1.000
Other cereal	0.201
Potatoes	0.687
Horticulture	0.562

Model fits were acceptable, although lower than would be ideal to support the use of the models for predictions: observed-to-predicted-value correlation coefficients varied from 0.53 to 0.70 (0.60 for the diversity of all birds). This indicates that the models have considerable predictive value but that they also leave a significant proportion of the variation in diversity unexplained.

The model averaged parameter estimates and associated standard errors are shown in **Tables 3.30** to **3.32** for all Simpson’s diversity indices for the intercept and all land use variables. For illustration, **Table 3.33** in the appendix to this section shows the parameter estimates and standard errors for the 100 km square factor for the diversity of all birds. High standard errors, suggest that regional effects on diversity, independent of land-use differences, were weak in most cases. The limited importance of the potatoes, horticulture and other crops variables is reflected in the high model-averaged standard errors relative to the parameter estimates for these three variables (**Tables 3.30**, **3.31** and **3.32**).

Table 3.30. Land use variable model-averaged parameter estimates for models with pooled data and standard errors as maximum of early or late range data, dependent variables are Simpson's diversity indices with different bird species communities.

Model averaged parameter estimate (SE)				
Variable	**All species**	**Farmland species**	**Farmland red- and amber- list species**	**Farmland and green- list species**
Intercept	16.4301 (1.7469)	10.5509 (1.1634)	5.8858 (0.5639)	6.9949 (0.5530)
Deciduous	0.1224 (0.0217)	0.0773 (0.0136)	0.0189 (0.0072)	0.0612 (0.0075)
Deciduous^2	-0.0019 (0.0003)	-0.0012 (0.0002)	-0.0004 (0.0001)	-0.0009 (0.0001)
Coniferous	-0.0461 (0.0139)	-0.0240 (0.0091)	-0.0017 (0.0061)	0.0080 (0.0061)
Coniferous^2			-0.0002 (0.0001)	-0.0003 (0.0001)
Fresh water	0.0902 (0.0547)	-0.0213 (0.0325)	0.0053 (0.0162)	-0.0503 (0.0173)
Fresh water ^{2}	-0.0022 (0.0013)	-0.0000 (0.0007)	-0.0006 (0.0005)	0.0008 (0.0004)
Urban	0.0442 (0.0183)	0.0211 (0.0114)	-0.0005 (0.0056)	0.0250 (0.0056)
Urban^2	-0.0011 (0.0001)	-0.0006 (0.0001)	-0.0003 (0.0001)	-0.0005 (0.0001)
Perm grassland	0.0320 (0.0249)	0.0173 (0.0172)	0.0111 (0.0085)	0.0028 (0.0111)
Perm grassland^2	-0.0006 (0.0002)	-0.0003 (0.0001)	-0.0002 (0.0001)	-0.00005 (0.0001)
Rough grazing	-0.1297 (0.0152)	-0.0726 (0.0097)	-0.0313 (0.0043)	-0.0462 (0.0042)
Rough grazing ^{2}				
NF grassland	-0.0931 (0.0175)	-0.0548 (0.011)	-0.0096 (0.0089)	-0.0352 (0.0057)
NF grassland^2			-0.0004 (0.0002)	
Wheat	0.0016 (0.0381)	0.0592 (0.0249)	0.0460 (0.0126)	0.0304 (0.0118)
Wheat^2	-0.0010 (0.0005)	-0.0013 (0.0004)	-0.0011 (0.0002)	-0.0008 (0.0002)
Barley	-0.0295 (0.0379)	0.0238 (0.0272)	0.0247 (0.0140)	-0.0212 (0.0160)
Barley^2	-0.0007 (0.0009)	-0.0014 (0.0007)	-0.0009 (0.0004)	-0.0001 (0.0004)
Other cereal	0.0187 (0.1790)	0.0768 (0.1231)	0.0044 (0.0544)	0.0605 (0.0758)
Other cereal^2	-0.0017 (0.0216)	-0.0043 (0.0129)	-0.0005 (0.0072)	-0.0035 (0.0078)
Potatoes	-0.0610 (0.1471)	-0.1012 (0.0853)	0.0045 (0.0418)	-0.0645 (0.0456)
Potatoes^2	-0.0002 (0.0101)	0.0010 (0.0065)	-0.0006 (0.0037)	-0.0004 (0.0040)
Horticulture	-0.0325 (0.0564)	-0.0044 (0.0292)	-0.0002 (0.0215)	-0.0161 (0.0223)
Horticulture^2	0.0005 (0.0013)	0.0002 (0.0009)	0.00002 (0.0006)	0.0005 (0.0006)

NF = non-farm

Table 3.31. Land use variable model-averaged parameter estimates for models with pooled data and standard errors as maximum of early or late range data, dependent variables are Simpson's diversity indices with different bird species communities.

Model averaged parameter estimate (SE)			
Variable	**Woodland species**	**Woodland red and amber- list species**	**Woodland and green- list species**
Intercept	7.1114 (0.7466)	3.128 (0.3404)	5.7328 (0.4988)
Deciduous	0.1462 (0.0093)	0.0357 (0.0041)	0.1205 (0.0069)
Deciduous^2	-0.0015 (0.0002)	-0.0004 (0.0001)	-0.0013 (0.0001)
Coniferous	0.0706 (0.0079)	0.0059 (0.0036)	0.0546 (0.0055)
Coniferous^2	-0.0006 (0.0001)	-0.00005 (0.00003)	-0.0004 (0.0001)
Fresh water	-0.0185 (0.0290)	0.0027 (0.0058)	-0.0203 (0.0201)
Fresh water ^{2}	0.0007 (0.0007)		0.0006 (0.0006)
Urban	0.0244 (0.0072)	0.0056 (0.0033)	0.0162 (0.0052)
Urban^2	-0.0004 (0.0001)	-0.0001 (0.0000)	-0.0003 (0.0000)
Perm grassland	0.0265 (0.0138)	0.0010 (0.0060)	0.0147 (0.0105)
Perm grassland^2	-0.0002 (0.0001)	-0.000002 (0.0001)	-0.0001 (0.0001)
Rough grazing	-0.0412 (0.0056)	-0.0111 (0.0029)	-0.0303 (0.0040)
Rough grazing ^{2}			
NF grassland	0.0081 (0.0123)	0.0064 (0.0062)	0.0005 (0.0091)
NF grassland^2	-0.0007 (0.0003)	-0.0003 (0.0002)	-0.0004 (0.0002)
Wheat	0.0285 (0.0174)	-0.0015 (0.0069)	0.0274 (0.0129)
Wheat^2	-0.0007 (0.0003)	-0.0002 (0.0001)	-0.0006 (0.0002)
Barley	0.0098 (0.0256)	-0.0035 (0.0085)	0.0063 (0.0185)
Barley^2	-0.0002 (0.0006)	0.00001 (0.0002)	-0.0002 (0.0004)
Other cereal	0.1419 (0.0897)	0.0005 (0.0272)	0.1256 (0.0615)
Other cereal^2	-0.0103 (0.0092)	0.0001 (0.0033)	-0.0097 (0.0061)
Potatoes	-0.0725 (0.0552)	-0.0374 (0.0128)	-0.0379 (0.0429)
Potatoes^2	-0.0004 (0.0050)		-0.0008 (0.0040)
Horticulture	0.0031 (0.0128)	-0.0010 (0.0052)	0.0022 (0.0070)
Horticulture^2			

Table 3.32. Land use variable model-averaged parameter estimates for models with pooled data and standard errors as maximum of early or late range data, dependent variables are Simpson's diversity indices with different bird species communities.

Model averaged parameter estimate (SE)			
Variable	**Upland species**	**Red and amber list species**	**Green list species**
Intercept	2.0959 (0.316)	8.3375 (0.7996)	10.6097 (0.8992)
Deciduous	-0.0072 (0.0029)	0.0064 (0.0120)	0.1110 (0.0123)
Deciduous^2		-0.0004 (0.0002)	-0.0015 (0.0002)
Coniferous	-0.0121 (0.0037)	-0.0014 (0.0089)	0.0169 (0.0100)
Coniferous^2	0.0001 (0.00004)	-0.0004 (0.0001)	-0.0005 (0.0001)
Fresh water	0.0449 (0.0094)	0.064 (0.0235)	0.0069 (0.0142)
Fresh water ^{2}	-0.0008 (0.0003)	-0.0014 (0.0005)	
Urban	-0.0095 (0.0027)	-0.0126 (0.0080)	0.0509 (0.0094)
Urban^2		-0.0003 (0.0001)	-0.0008 (0.0001)
Perm grassland	0.0157 (0.0044)	0.0248 (0.0113)	0.0094 (0.0154)
Perm grassland^2	-0.0002 (0.0000)	-0.0005 (0.0001)	-0.0002 (0.0002)
Rough grazing	0.0213 (0.0043)	-0.0596 (0.0059)	-0.0738 (0.0069)
Rough grazing ^{2}	-0.0003 (0.00004)		
NF grassland	-0.0031 (0.0039)	-0.0109 (0.0127)	-0.0556 (0.0093)
NF grassland^2		-0.0006 (0.0003)	
Wheat	-0.0312 (0.0075)	-0.0138 (0.0178)	0.0255 (0.0193)
Wheat^2	0.0004 (0.0001)	-0.0004 (0.0003)	-0.0010 (0.0004)
Barley	-0.0190 (0.0084)	0.0072 (0.0212)	-0.0522 (0.0227)
Barley^2	0.0002 (0.0002)	-0.0005 (0.0006)	0.0003 (0.0006)
Other cereal	-0.0157 (0.0349)	-0.0015 (0.0795)	0.0299 (0.1090)
Other cereal^2	0.0007 (0.0033)	-0.0005 (0.0112)	-0.0021 (0.0137)
Potatoes	-0.0280 (0.0304)	0.0039 (0.0615)	-0.0921 (0.0740)
Potatoes^2	0.0029 (0.0030)	-0.0003 (0.0061)	-0.0005 (0.0064)
Horticulture	-0.0200 (0.0116)	-0.0048 (0.0295)	-0.0042 (0.0168)
Horticulture^2	0.0002 (0.0003)	-0.0000 (0.0009)	

3.11.6 Discussion and conclusions

Considering results for the overall diversity index (**Table 3.30**), deciduous woodland has one of the largest estimated effects of land use upon bird biodiversity. The substantial positive linear effect combined with the smaller negative squared term suggest that increasing such woodland raises diversity although the rate of increase flattens off at higher levels. There is a negative linear effect for coniferous woodland, emphasising the importance of the difference between woodland compositions for bird diversity. Freshwater displays a similar shaped relationship to that of deciduous woodland (although at a lower effect size). A wider array of waterbirds will occur where fresh water is present in an area, alongside other habitats that will provide for a broad range of terrestrial species, although higher areas of fresh water will generally have less of the species-rich edge habitat that is particularly rich in resources for birds. Urban habitats show a positive polynomial trend, perhaps aided by the presence of garden habitat. Permanent grassland shows a similar trend, albeit with a rather high standard error. Negative estimates for rough grazing and non-farmed grassland may be related to the prevalence of these habitats at higher altitudes where diversity tends to drop off. The presence of such correlations implies that parameters should be interpreted with some care and not unduly extrapolated out of sample. Estimates for wheat and barley are quite low and have high associated standard errors, reflecting the species-paucity of large tracts of arable land, despite the presence there of significant numbers of species of conservation concern.

The results for farmland birds illustrate the complexity in interpreting broad patterns in a summary index such as diversity. Estimates for barley are quite low and with high standard errors, indicating no positive effect of this crop despite its common use in less intensive farming regimes that are typically beneficial to farmland birds. Conversely, there appears to be a positive relationship with wheat, albeit dropping off where it becomes most common, despite this crop being indicative of intensive arable cropping. This pattern is still observed whether species are of conservation concern or not. This apparent contradiction probably reflects the fact that, despite long-term declines, farmland birds are still most common in regions dominated by farmland, while more extensive systems are now mostly found in marginal farming areas where factors such as climate and non-cropped habitats may have more influence on the presence of farmland birds. Relevant non-cropped habitats include the hedgerows found in much arable farmland, versus the dry stone walls often found in more marginal areas.

Woodland species are more diverse in deciduous woods and this trend is stronger, with smaller standard errors indicating more certainty in the conclusion, than it is for diversity as a whole. However, coniferous woodland also shows a positive relationship for this category of species, indicating the importance of this tree community for a largely distinct group of bird species. However, while this trend is positive, it is curvilinear and peaks at an intermediate level of conifer area, showing that the benefits for diversity are maximized when it is found in combination with other habitats. The pattern is also strong only for overall woodland bird diversity and species on the green list, not for those considered of conservation concern, i.e. the effects mostly concern common species.

Upland bird diversity has a negative relationship with deciduous woodland and predominantly negative relationships, becoming less steep at higher areas, with coniferous woodland, wheat and barley. These effects show negative associations with land-uses not found in the uplands, while predominantly positive associations with fresh water and rough grazing (which is correlated with the mountains, moorlands and heathland land cover variable) reflect the habitat preferences of upland species.

When all birds on the red or amber list are considered, fresh water and permanent grassland appear predominantly to influence diversity positively, although the relationships level off at higher area cover values. Birds of conservation concern include such grassland species as *Alauda arvensis* (Eurasian skylark) and *Vanellus vanellus* (Northern lapwing) and the positive effect of permanent grassland probably reflects habitat availability for these species. Other variables, including deciduous woodland, show less clear effects on birds of conservation concern, but, for birds on the green list, deciduous woodland still shows the greatest effect on diversity, as found for the overall diversity index. However, such patterns should be interpreted with caution, because land-use variables may actually only be correlated with the true drivers of variation, rather than causal factors, and diversity are complex composite variables that will be influenced in multiple ways.

All of the results described above and, ultimately, used in maps illustrating effects on biodiversity (see Section 3.12), concern changes in the Simpson's diversity index for breeding birds. Although the method for calculating this index is described in the methodology (Section 3.11.4), the absolute figures for the index do not have an easily visualized meaning. To illustrate what any predicted changes in diversity might actually mean in terms of real changes in the bird community, an example follows considering the diversity for one hypothetical high-diversity, lowland square in south-east England and one hypothetical low-diversity, upland square in Scotland. Altering the bird numbers shows the effect of such changes on the diversity index. The lowland square has 26 species, including 15 blackbirds, one blackcap, eleven chaffinches, 16 great tits and 37 wood pigeons, giving a diversity index of 9.087. Removing the blackcap results in a reduction of 0.123 in the index, removing all eight species with only one individual result in a reduction of 0.953, removing one chaffinch reduces the index by 0.043 and redistributing the total number of individuals as if all 26 species had been recorded in equal numbers increases the index by 16.913. The upland square has four species, comprising six golden plovers, 24 meadow pipits, one red grouse and two skylarks, giving a diversity index of 1.765. Removing the red grouse reduces the index for the upland square by 0.103, removing one of the golden plovers reduces the index by 0.075, removing one of the meadow pipits reduces the index by 0.0351 and removing 14 meadow pipits reduces the index by 0.795.

3.11.7 Constraints and caveats

The production of multiple indices allows for the possibility of a more nuanced approach to biodiversity constraints, sensitive to the dominant species and habitats of the area in question. The bird communities in uplands, for example, may change with encroachment of farmland or woodland leading to a rise in overall diversity, but this might mask a reduction in the diversity of more specialist upland birds, which would not be desirable from a conservation viewpoint. Equally, where a landscape is dominated by farmland, then maintenance of farmland bird diversity might be a target, and if there are substantial areas of woodland, woodland bird diversity is likely to be more important than a simple, overall diversity index. With this in mind, we suggest the following rules for land use constraints, which would be spatially specific, defined in respect of landscape type. We would propose that a "change" (in all cases below, "*falls*") would be defined as having to be significant, i.e. with 95% confidence limits excluding zero. In each case below, we suggest an appropriate constraint that could be defined from the data analysis described above for a particular landscape type, defined by default at the 1km square scale. If, on predicting bird diversity responses from land-use change and the models described here, the response would violate the constraint described, the land-use change concerned would be deemed unacceptable:

- in uplands, defined as where mountain, moors and heathland (MMH) constitute 50% or greater of the land cover of an area, neither upland diversity nor overall diversity of red- and amber-listed birds should *fall*;
- in farmland, defined as where total farmland (farmland plus improved grassland) constitutes 50% or greater of the land cover of an area, then neither farmland diversity nor overall diversity of red- and amber-listed birds should *fall*;
- in woodland, defined as where total woodland (deciduous plus coniferous woodland) constitutes 15% or greater of the land cover of an area, then neither woodland diversity nor overall diversity of red- and amber-listed birds should *fall*;
- in lowland mosaic landscapes, defined as where total woodland constitutes 15% or greater and total farmland constitutes 50% or greater of the land cover of an area, none of farmland diversity, woodland diversity and overall diversity of red- and amber-listed birds should *fall*; and
- where none of the above applies, then neither overall diversity nor diversity of red- and amber-listed birds should *fall*.

If any of the above diversity losses are predicted to apply within an area following land use change, then the value of the lost economic activity from imposing the constraint which avoids those losses provides us with an estimate of the 'opportunity cost' of maintaining biodiversity. The option which minimizes those opportunity costs is referred to as the cost-effective solution.

3.11.7.1 Caveats

A number of caveats should be taken into account when interpreting the maps, (Section 3.12) the models presented and the summaries of bird diversity predicted under each scenario. These are summarised below considering the source data and the model used.

BBS survey design and data handling

BBS surveys focus on terrestrial breeding birds, so coastal and estuarine birds tend to be under-recorded and make up only a small proportion of the diversity modelled here. Effects of scenarios on bird diversity in these habitats are likely to be underestimated by the models and are likely to be greatest in winter, when UK wetlands host large flocks of *Charadrii* (waders) and *Anaidae* (waterfowl).

Birds which are normally observed in flight, such as *Apodidae* (swifts) and *Hirundinidae* (swallows and martins), are likely to be under-recorded as these observations are discarded from this analysis. In addition, birds such as *Cinclus cinclus* (White-throated dipper) and *Alcedo atthis* (Common kingfisher) which are associated with linear waterways, tend to be under-recorded by area-based surveys such as the BBS.

The number of BBS squares covered in upland habitats is limited due to problems of accessibility for volunteers, so the results for these areas are based on fewer data points than those for the lowlands. However, key birds breeding on upland such as *Lagopus lagopus* (red grouse), *Anthus pratensis* (meadow pipit), *Alauda arvensis* (skylark), *Pluvialis apricaria* (golden plover) and *Numenius arquata* (Eurasian curlew) were all included in diversity indices and the data were sufficient for a specific upland diversity index to be calculated. Given the conservation importance of retaining upland bird communities rather than allowing generalists (common species which inhabit multiple environments) to colonise the uplands, which could increase overall diversity, we have retained this index for use in the constraints.

The number of species contributing to the diversity index was limited to those that were recorded in 40 or more squares. This was done in order to limit the presence in the data of uncommon non-breeding species, which could increase noise in the data and distort the diversity index calculation, but some rare breeders will also have been excluded, making the diversity index more conservative.

Variations in the detection probability between species and habitats were no accounted for in the analyses described here. Therefore variation in diversity may be underestimated if it involves more cryptic species (less easily detected further from the transect line). This is especially relevant in habitats such as woodlands where detection probability drops more steeply with increased distance from the observer. It would be possible to estimate "true diversity by first converting BBS counts to estimated densities using distance analysis (Buckland *et al*., 2001) but this is not a simple process and involves a number of assumptions about the nature of the survey data.

Consistency of habitat relationships with scale

Birds may differ in their habitat preferences depending on the scale of the change in habitat. A change at the 1km square scale may differ to a change at the 10km square or regional scale. A bird that depends on a matrix of deciduous woodland and farmland being present may react positively to an increasing percentage of woodland in a 1km square, for example, but may be less common in a 10km square with a high percentage of woodland. The model derived here, as it stands, is assessing only the effect of habitat cover at the 1km square scale, but the larger effect sizes of the 100km square variable suggests that larger-scale factors may be more important; however, the standard errors for the 100km effects were large and further investigation is required. The scale at which diversity is measured must be considered if it is to be used to underlie management decisions: aiming to maximize diversity at a local scale will very often give rise to different recommendations to maximizing it at larger scales. The percentage cover of habitats determining the constraints may have to be adjusted at different scales and this could be a focus of future research.

Subtle changes and other drivers

Important effects on biodiversity could easily occur through subtle changes in land-use which are not included in these models. For example changes in the character of the landscape could occur through changes in cropping of arable land (both in terms of the nature and timing of agricultural operations and of the choice of crops) which have not been included here due to standardization across the differences in data available between constituent countries of the UK.

Whilst it is important to assess the effect of land use change on bird communities, hence the use of diversity indices here, there will be important sensitivities at species-level which will be missed in this analysis due to the lumping of effects for multiple species. This may potentially lead to management which might be good for a community of birds overall but bad for particular species, which may be of conservation concern themselves. Future work intends to look in more detail at species-level effects.

Finally, the analysis here models only the effect of land use change on bird species diversity. Direct effects of climate, for example, could have major impacts on bird distribution independent of their effects on land-use. There is some evidence, for example, of changes in bird community composition as a result of climate change (e.g. Gregory *et al*., 2009). Otherwise, good data to support such relationships are sparse, so they are not included in the model.

Model fit

The models of Simpson's diversity index described here explain reasonable proportions of the observed variation, but less than would be ideal. It is likely that this is because diversity is a complex, multi-faceted variable that is influenced by assemblage composition and the relative abundances of all species present, as well as the coarse nature of the land-use variables used. As a result, caution should be used in interpreting predictions of changes in diversity resulting from applications of the models. On-going work is investigating the models based on the abundance of individual species and the use of less amalgamated and enhanced land-use data (including input data informing about the intensity of farming, for example). These models will be used to construct diversity indices as a secondary product and are expected to provide greatly improved predictive power.

3.11.8 Appendix: Regional effects on bird species richness

Table 3.33. Model-averaged estimates for levels of 100km square class, Simpson's diversity for all birds.

Ordnance Survey 100km Square merged region descriptions	Model averaged parameter estimate (SE)
AB	-1.5548 (1.2386)
AR	-0.7253 (1.2079)
CO	-0.4816 (1.4215)
CU	0.0762 (1.2291)
DY	-0.7001 (1.2267)
GL	-0.4303 (1.1546)
OH	-3.1689 (1.3261)
OS	-1.1752 (1.3274)
NC	-0.4483 (1.2249)
NG	-0.9245 (1.2531)
NH	-0.5495 (1.2104)
NN	-0.6337 (1.2155)
NO	-1.0614 (1.2117)
NS	-1.3374 (1.1810)
NT	-0.6208 (1.2039)
NU	0.4162 (1.6096)
NY	-0.7187 (1.1895)
NZ	-0.1999 (1.2037)
SD	0.3606 (1.1924)
SE	-0.5415 (1.1743)
SH	-1.0573 (1.2618)
SJ	0.3337 (1.1756)
SK	0.0360 (1.1508)
SO	-0.0577 (1.1764)
SP	-0.8994 (1.1529)
SS	-1.0692 (1.3072)
ST	-0.0263 (1.1687)
SU	-0.7647 (1.1388)
SX	-0.5799 (1.2273)
SY	-0.1932 (1.4505)
SZ	-1.4332 (1.7712)
TA	-1.6052 (1.2173)
TF	-1.1068 (1.1848)
TG	0.2882 (1.3868)
TL	-0.0432 (1.1586)
TM	-0.8741 (1.2631)
TR	0.000 (0.0000)

3.12 Applying The Integrated Model (TIM): Planning Britain's new forests

3.12.1 Objective

This Work Package presents a new approach to land use decision making based on analyses conducted with The Integrated Model (TIM). This brings together economic and natural science knowledge regarding the consequences and values generated by changes in land use. Specifically, TIM allows the decision maker to examine which options deliver the best value for money for the private individual and for society as a whole. The use of this approach is illustrated through its application to the issue of planting new British woodlands, the focus of much popular interest and recent policy announcements. We show how a limited focus on, for instance, displaced agriculture alone can result in decisions which represent very poor value for the taxpayer, while a more comprehensive assessment of the wider benefits of land use change can identify new ways of applying policy which generate major gains across society.

3.12.2 Overview of TIM

Achieving the above stated objective requires an examination, from a social perspective, of the costs and benefits associated with various policies and their real-world implementation. However, this analysis must recognise the role of private land owners in determining land use, and acknowledge that their decisions are driven by market prices. Consequentially, prevailing land use patterns are driven by narrowly defined private sector market returns. This presents opportunities for efficiency gains (that is, society can extract greater value from its scarce resources) wherever the market and social values of land use diverge.

To give a holistic view of how land use change affects the environment and economy, TIM incorporates several component modules, accounting for agricultural and timber production, GHG flows, recreation, water quality and biodiversity. These are described in detail in previous sections of the report, and are summarised below. To begin, let us imagine that we have at our disposal a set of outcomes derived from these modules; in each of these a picture of the world emerges. However, any given area of land may have competing potentials in timber, agricultural, or even recreational use and, as a result, the component modules must be able to interact. For example, in the timber production module, planting sites are selected to maximise timber profits, while in the agricultural module, farmers seek to maximise farm gross margins. This of course means that both farmers and foresters may wish to use the same plot of land for different ends. If their interests are considered in isolated analyses, then we may well fail to extract the maximum potential benefits from land use in terms of the social values it can generate in either the present period or in the future. In reality, one land use can preclude another, potentially for very long periods of time.

This quick example serves to illustrate the importance of an integrated approach to modelling land-use and its potential change. TIM draws in the elements of each module, identifying complementarities and substitutions, dependencies and mutually exclusive relationships. Through this process, the analysis seeks to make recommendations about the best use of land. Of course, the definition of 'best' depends upon the objective that one wishes to optimise. While private individuals might seek to maximise their personal returns, social decision makers have a variety of objectives, ranging from a similar desire to maximise the value of marketed goods, to adding in concerns about greenhouse gas emissions, to seeking to optimise across a range of market and non-market goods. Therefore, there is no single optimum outcome; rather there are outcomes which are optimal given a specific objective. So, in the case study discussed in this report, we consider a mix of alternative feasible objectives covering the range described above. This approach accords well with the fundamental definition of economics as the science of constrained optimisation: constrained by the scarcity of resources at our disposal; optimised to extract the greatest possible benefit from them given a clearly defined objective. Thus defined, achieving the best use of land – extracting the greatest benefit from scarce resources – is simply an economic exercise in constrained optimisation. TIM's capacity for constrained optimisation is one of its distinguishing features.

As per any economic analysis of a change in policy or any other drivers, TIM first provides a "Business As Usual" (BAU) baseline. This models the impact upon resource use of unavoidable changes. Thus, in our land use change example, the BAU baseline reflects the impacts of unavoidable climate change in the absence of policy or any other change. That baseline is then used to evaluate the consequences of say a policy change which the decision maker or other research user is interested in.

The component modules underpinning TIM analyse all feasible permutations of the chosen policy, considering land use change in every possible location[24] across each country and at all possible points in time throughout the entire assessment period. All of these analytic parameters (such as the area to consider, the period of analysis and of course the specifics of the policy change) can be varied to cater for the interests of the decision maker. Crucially, TIM also allows the decision maker to determine which output measures are of interest. So, in the case study presented below, the decision makers may be interested in maximising the value of the marketed goods produced by alternative land uses. Alternatively they may additionally want the value of non-market goods such as greenhouse gases or recreation to be taken into consideration and that sum maximised. Or they may wish to examine which spatial and temporal pattern of land use will optimise the social value sum of all these various impacts. Furthermore, in each case TIM informs the decision maker about the consequence of each optimising solution for those goods which we do not have reliable economic values for, such as biodiversity. By examining these various permutations, TIM allows the decision maker to examine the trade-off between these various monetised and non-monetised benefits[25].

Figure 3.25 summarises TIM, and with it our empirical approach to optimising user defined objectives. The figure explains the process in a linear fashion running from left to right and uses the illustrative case study to demonstrate how the various component modules are brought together in the TIM approach. This starts with the various drivers of change. These are categorised as: variation in the physical environment (both between locations and across time due to processes such as climate change); policy drivers (both pre-existing and changes occurring over the analysis period); and market forces (prices, costs, etc.). TIM enables the analyst to adjust the drivers of land use change, for instance by introducing various policy options, and see how these affect economic values and objectives over a chosen period of time.

The various TIM modules (agricultural, timber, GHG, recreation, water quality and biodiversity) utilise prior data to obtain estimates of both the baseline conditions of each production system and their responsiveness to changes in the drivers. That is, the modules predict how changes in these drivers will affect land use into the future, and allow the analyst to compare this to a relevant baseline. Of course, such land use changes will affect the type, quantity, and distribution of

[24] Given the very high values associated with urban areas, for simplicity we omit these from any possible land use change, confining ourselves instead to the very large majority of Great Britain which is, in at least some form, used for agriculture.

[25] Future permutations of TIM could impose the no-loss biodiversity constraints used in our Proof of Concept analysis (?Work Package? 4), or investigate the implications of more stringent constraints requiring improvements in wild species diversity and conservation (as discussed in Section 3.11.6).

ecosystem goods and services (dark blue boxes in **Figure 3.25**) produced (or lost). Some of these goods and services are traded in private markets and have reliable market values (e.g. food and timber). Others, such as greenhouse gasses and recreation lack market prices, but may still be robustly valued in monetary terms. Where consistent, reliable values can be obtained, these are fed into an optimisation routine which can identify land use mixes that satisfy our various optimisation objectives. For instance, the analyst can maximise market values alone, or incorporate the full range of market and non-market values to maximise society's net benefit from land use. Unfortunately, values for some ecosystem services, such as water quality and biodiversity, cannot be estimated robustly, and therefore cannot enter into the optimisation routine. Instead, they could act as external constraints: for instance, the analyst may seek to maximise society's net benefits from land use, subject to the constraint that there is no net loss in biodiversity.

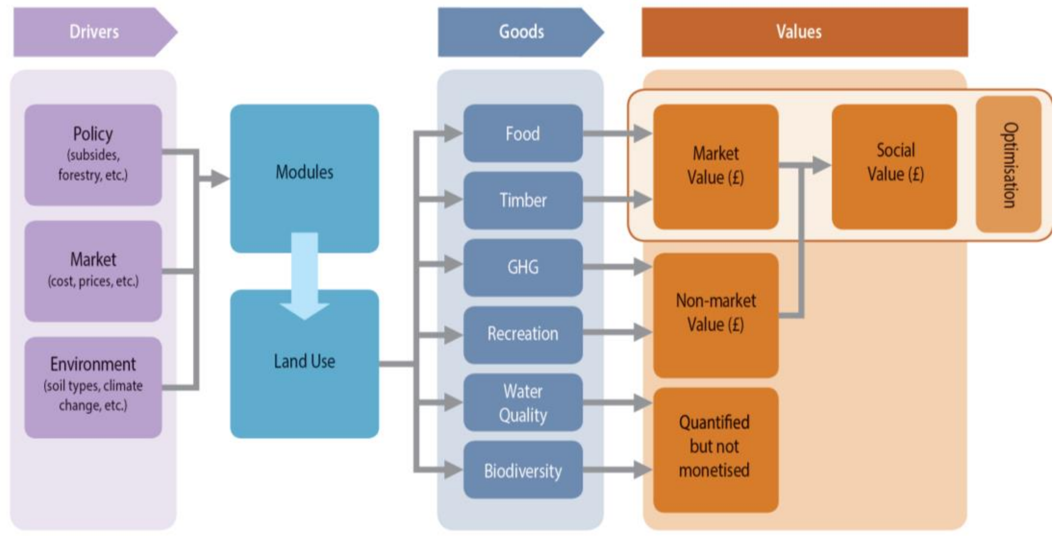

Figure 3.25. The Integrated Model (TIM): A schematic overview.

3.12.3 An integrated modular approach

TIM's agricultural production module captures the market value of agricultural land use. However, as we are also interested in capturing social values (taking into account externalities), TIM contains modules that describe the non-market externalities resulting from greenhouse gas (GHG) flows and recreational visits, as well as impacts on water quality (though water quality is not valued in monetary terms). Finally, TIM includes a biodiversity module that captures a non-monetary measure of the impact of land use on bird species diversity.

The timber production module captures variation in growth rates, timber yield class, and timber profits for a variety of physical environmental conditions across the UK, taking into account the effects of unavoidable climate change. This model predicts timber production costs and benefits for different tree species across locations, climate scenarios and a common silvicultural management regime, and ultimately forms the forestry production module in TIM.

The agricultural GHG module in TIM evaluates, for each 2km grid cell, the carbon dioxide equivalent (in tonnes; tCO_2e) GHG flows from agricultural land use, taking into account the temperature and soil characteristics of the cell. Based on the tried-and-tested Cool Farm Tool software, the model includes the calculation of emissions from machinery use, fertiliser application and livestock which are specific to the production decisions made by the farmer in each location. Carbon emissions in a cell are spatially and temporally independent in the model, with annual emissions in any year being determined solely by the characteristics of the cell in that year.

The forestry GHG module estimates annual GHG flows arising from the afforestation of land, capturing the CO_2e GHG impacts of planting new woodland. The module employs the Forest Research CARBINE tool to model GHG exchanges between the atmosphere, forest ecosystems and the wider forestry sector as a result of tree growth, mortality and harvesting. Specifically, the module incorporates the net annual carbon flows in livewood stands, harvested wood products, deadwood and forest soils, for representative conifer (Sitka spruce) and deciduous (Pedunculate oak) species.

The recreational module develops a new application of the Random Utility Model (RUM)[26] approach to impacts of land use change individuals' visitation choices and associated recreational values. The model captures the impacts of substitute availability upon the number and value of visits, including the dynamic effects of progressive land use change over time. So, for example, the provision of a new woodland recreation site in a certain location is assessed taking into account the impact of all other substitute sites (both woodland and other habitats). Furthermore the provision of that site is then taken into account when assessing the value of any further new recreational site. This avoids the over-estimation of values which would arise if these substitution and dynamic effects were ignored. Observations of recreational visits were taken from the Monitor of Engagement with the Natural Environment (MENE, Natural England, 2010), which to date has surveyed recreation behaviour in nearly 150,000 households in England annually, sampling continuously around the year and providing data on outset and destination for one randomly selected trip per household. A second recreational analysis is undertaken regarding the specific issue of the value to visitors of changes in river water quality arising from land use change. However, to avoid the risk of double counting values with those associated with our MENE based study we do not include our water quality recreation results within the TIM analysis. Results from our water quality recreation study are presented in an Annex to this report.

The water quality module describes the hydrological processes that link land use to nutrient concentrations and ecological status in rivers. This analysis initially applies nutrient export coefficient modelling (ECM) to information on the inputs-to and flow-from catchments. This information is then fed into structural statistical models of river water quality drawing upon Environment Agency General Quality Assessment (GQA) data, which provides measures of nitrate concentrations in rivers for 2000 and 2009. Making allowance for sewage inputs reveals highly significant relationships between land use and nutrient concentrations. A lack of robust economic assessments of the benefits of changing nutrient levels in abstracted waters means that we quantify but do not place monetary values upon changes in water quality.

The biodiversity module provides a model of bird diversity using Breeding Bird Survey (BBS) data collected at a 1km square resolution during the period 1999 - 2011. These data were related to land use data from this period. Diversity was modelled for four categorisations of birdlife: (i) all species; (ii) farmland species; (iii) woodland and upland habitat species; (iv) species on the red and amber lists of conservation concern (Eaton *et al*., 2009).

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[26] The seminal work on RUM analyses is provided by McFadden (1976) for which he received the Nobel Prize in economics in 2000.

3.12.4 Case Study: Planting new forests in Britain

3.12.4.1 Overview: Motivation, analysis and deliverables

In this section we apply the optimising TIM methodology to address a question of considerable contemporary policy interest: the issue of extending the area of forestry across Great Britain. Within England this policy goal stems, in considerable part, from the work of the Independent Panel on Forestry (IPF, 2012) which has been endorsed by Defra (2012, 2013) and the UK Natural Capital Committee (NCC, 2012). Separate initiatives to promote afforestation have also been adopted by both the Scottish and Welsh devolved parliaments (Scottish Government, 2012a; Welsh Assembly, 2012). All three legislatures seek to deliver a substantial level of new forestry planting sustained over a considerable time horizon.

During 2012 we undertook direct discussions with a number of these Government bodies, and on the basis of these determined to examine a policy context in which each country decides to plant 5,000 hectares of new woodland per annum for each year between 2014 and 2063, yielding an overall increase in forest extent of 750,000 hectares across Great Britain over the full 50 year assessment period.

As discussed previously, our methodology rejects the commonly used approach of comparing across a limited selection of pre-set scenarios to see which provides the best outcome. Instead we start from the initial policy aim, which here is to increase woodland coverage by the desired amount and rate, and then utilise our system of integrated component modules to evaluate the optimal location for that level of woodland expansion.

As per any analysis, we begin by first defining a 'Business As Usual' (BAU) baseline for land use against which any subsequent analysis results can be compared. Here we do not have any policy change (including no afforestation). However, land use does not stay constant over the analysis period as climate change drives alterations in agricultural activities. Our two alternative objectives are then defined to serve as the policy options open to decision makers:

- a 'Market Value' (MaxMV) option[27] in which the desired new afforestation is located so as to maximise net benefits in terms of the market priced goods concerned (agricultural outputs and forest timber values); and
- a 'Social Value' (MaxSV) option in which new forests are located so as to maximise the net benefit of all the economic values (both those market values accruing to private land users and the non-market values distributed across society) covered in this report (agricultural outputs, forest timber values, agricultural GHG flows, forestry GHG flows, and recreation).

Each option is assessed against the BAU baseline to reveal the changes induced by optimising each objective. In both cases we calculate both the market and social values resulting from the planting that occurs (i.e. we know how a switch towards social value optimisation affects market values and vice versa).

These various assessments provide decision makers with the necessary information to determine whether a given policy, even when optimised, is worth undertaking. For example, if social values are negative under both options, then we may be better off remaining with the no-policy BAU

[27] Note that, in libertarian terms, none of these options convey a pure market outcome as government intervention in land use has both a long history and is continuing.

situation[28]. In contrast if the social value from the MaxSV option is positive then its excess over the social value from the MaxMV option quantifies the loss that would be incurred if the policy was guided solely by market forces (equivalent to the net gains of adopting a social optimisation approach). The MaxSV assessment is of particular interest in cases where the optimisation of social values depresses market values relative to the BAU, as comparison of the two indicates the level of compensatory incentives (e.g. payments for ecosystem services) required to induce private land owners to change land use, as well as the net social benefits of implementing such payments.

3.12.4.2 Defining the objective to be optimised

As outlined above, our illustrative application considers two objective functions: maximising the market value of afforestation (MaxMV), and maximising its social value (MaxSV). An initial issue is to acknowledge that this assessment involves a variety of impacts which naturally occur over very different timescales. So, for example, while it is reasonable to think about the annual value of agricultural production, the economic assessment of forestry only makes sense if we consider at the very least a full rotation from planting to felling, while other processes, such as changes in soil carbon, can take even longer periods. To allow for this, we consider these 'natural' time periods for each process, calculate the net present value of the corresponding stream of costs and benefits over those periods, and then calculate the annualised equivalent (the 'annuity') of that discounted stream of values. Therefore, when we refer to our assessment period of 2014 to 2063, we are actually referring to an annuity which may be calculated over a much longer period, but is then considered for that common 50 year timespan (e.g. the annuity for a 200 year soil carbon process is calculated, entered for each of the 50 years of the assessment and compared to the annuity for agriculture over the latter period). This allows a fair comparison across very differing activities. Details of the annuity calculations are presented in Appendix 1 of this section.

Considering the various value streams concerned, let us start with those that yield market values: agriculture and timber production. In converting any particular agricultural land area to woodland, value flows are changed in a number of ways. Since the land is no longer used for agricultural production, the flow of benefits over time from food output is lost. To measure the value change resulting from ceasing agricultural production, as outlined above, we calculate the net present value of that stream of costs and benefits (valued using the market prices of foregone farm produce) for 50 years from the year of conversion (which may be any year from 2014 to 2063). We then convert that net present value into an equivalent annual annuity[29]; that is to say, we calculate the value which, if realised for each of the 50 years following conversion, would result in the exact same net present value. Let us call that annuity value v^{Farm}. Notably, in our analysis this value happens to be negative for every instance in which farmland is converted into forest. This reflects the high market priced returns to agriculture relative to forestry.

Now consider our other market value, timber. As mentioned above, our 50 year assessment period, while adequate for agricultural value streams, will not capture the major revenues associated with timber production as the rotation time from planting to felling exceeds this period for all but the fastest growing softwood species. To allow for this, our appraisal of timber production is extended to encapsulate the rotation length for even the slowest growing broadleaf species. As before,

[28] Of course this is only true to the extent that we have truly encapsulated all values within our analysis. The underlying objective of this research is to contribute to the development of methodology for which the forestry case study is illustrative. While we feel that empirical results are defensible, these were not the over-riding focus of our study and we would suggest that there is room for some improvement before applied findings are used as the basis of policy change.

[29] The use of annuities allows us to compare activities which have differing lifecycle lengths; in this instance agriculture and forestry.

annualisation will make the net benefits of timber production comparable with those for the other values assessed in the analysis. We denoted the resulting annual equivalent annuity value as v^{Timber}.

We can now calculate the market value of land use change for any given location, indexed j, as simply the sum $v_j^m = v_j^{Farm} + v_j^{Timber}$. Furthermore, for the first year of our assessment period, we can optimise the objective of maximising market value by simply calculating this sum for all locations across each country and ordering these from highest to lowest and planting the top 5,000ha with new woodland. We can then repeat this exercise for the second year of the assessment and so on until our appraisal period is completed. Such an assessment has considerable merit in that it encapsulated the impact of the diversity of the natural environment upon these market values. However, our analysis seeks to go much further than this. In particular, we can now begin to consider the social value of planting (both to see the social consequences of the maxMV planting strategy; and to use this to guide planting in our maxSV objective).

Recall that, for reasons explained previously, while we quantify the impact of each planting strategy upon water quality we do not monetise these and therefore, within the present study, they play no part in determining the location of forest planting. However, the impact of land use change upon greenhouse gases is both monetised and included within the optimisation procedure. The alterations in land use induced by afforestation are likely to induce multiple changes upon the balance of greenhouse gasses emitted from or stored at any planted location. There are a number of elements to consider here, including changes in farm emissions of CO_2, N_2O and CH_4; emissions and sequestration of CO_2 from forestry operations (including emissions from machinery, storage in livewood and delayed emissions from post-felling wood products); and changes in soil carbon[30]. These effects are converted into CO_2 equivalents, monetized[31] and annuitized to yield the value v^{GHG}.

We can now calculate a partial approximation to social value which extends beyond market value to include greenhouse gas impacts but, for the moment excludes the value of recreation. We can calculate this partial social value as the sum $v_j^{sg} = v_j^{Farm} + v_j^{Timber} + v_j^{GHG}$. Again we can optimise this objective by calculating v_j^{sg} at each location across each country and choosing those that give the highest value in the first year of our assessment and then repeating this for subsequent years. We can of course also calculate v_j^m for the planting locations identified when we locate forests by maximising v_j^{sg}, a comparison which tells us about the impact upon the private sector of including GHG within our decision making process. If, as is likely, this results in a decline in market values relative to the maxMV approach to planting, then that difference could be used to identify the compensation needed by the private sector in order to make them indifferent between the two planting regimes. If this compensation is less than the extra value of GHG storage then this would suggest that such payments are justified from a social perspective.

Each of the values of conversion, v^{Farm}, v^{Timber} and v^{GHG} are spatially independent. That is to say, the value of conversion of one cell has no impact of the value of conversion of any other cell. Unfortunately, the relatively simple optimisation routines which can be implemented when all values are spatially independent are insufficient in the presence of spatially dependent values. This

[30] A further incomplete value stream here concerns changes to soil carbon for certain soil types, most particularly peat soils where transition periods between equilibria can be very long (see discussion of the economics of soil carbon arising from conversions from agriculture to forestry in Bateman et al., 2003). We adopt an extended evaluation approach as per timber revenues and calculate annuities accordingly.

[31] As mentioned previously, because there is significant debate over the value of sequestered and emitted carbon, we have used a range of values in our subsequent analyses.

situation arises in our present analysis because of the likelihood that the creation of a new multi-purpose woodland may provide new recreational opportunities. Of course, the closer a household is to the new woodland, the more value it will realise from the new recreational site. However, at the same time, if that household already enjoys a large number of outdoor recreational opportunities in their area, and particularly if those recreational sites are woodlands, then the addition of more woodland is likely to offer relatively little additional recreational value. Accordingly, the recreational values generated by planting new woodlands are not spatially independent of one another. While each cell in an area may offer substantial recreational values if planted independently, as soon as one cell contains woodland, the additional recreational benefits of planting more woodland on any other cell in that area are very much reduced. This diminishment of additional values becomes progressively more important as time progresses and successive waves of planting are undertaken. As a result, when we attempt to include the benefits of woodland recreation, the simple strategy of evaluating the benefit from conversion of each cell and then choosing the highest valued cells will not work. Rather, we need to evaluate the simultaneous conversion of sets of sites and choose the specific set which offers the maximum value: a considerably harder problem. The introduction of spatially dependent values does make the identification of optimal locations considerably more complex. Appendix 2 of this report sets out the details of the approach used to address this issue, but in essence we use well established routines and commercial software (the IBM CPLEX solver) to solve this problem and identify the consequences of different planting regimes for our recreational value v^{Rec} in a manner which allows us to identify that set of planting which maximises any optima involving recreation values. Given this, we can now identify our comprehensive social value as the sum $v_j^{s*} = v_j^{Farm} + v_j^{Timber} + v_j^{GHG} + v_j^{Rec}$.

With our recreational value v^{Rec} defined we can of course readily calculate a further sum $v_j^{sr} = v_j^{Farm} + v_j^{Timber} + v_j^{Rec}$. This tells us the social value of planting if we choose to ignore greenhouse gas implications. Taken together this provides the research user with a variety of policy relevant valuation measures for each planting option. Furthermore, alongside our value estimates, the land use mosaic defined by each optimization is fed into both the water and biodiversity modules to examine consequences for both water quality and wild species diversity, both of which are assessed quantitatively allowing the decision maker to examine both the direction and magnitude of changes induced under each optimisation rule.

3.12.4.3 Summarising the case study

Our empirical analysis considers various optimisations: for the Business As Usual (BAU) baseline, maximising market values (MaxMV) and maximising social values (MaxSV). Indeed we also consider various intermediate objectives as summarised in **Table 3.34**. All analyses (including the baseline) cover the common assessment period (2014 – 2063) and encompass land use change driven by unavoidable climate change.

The TIM approach allows the decision maker to consider a number of assumptions and parameters. TIM is specifically designed to make these assumptions explicit and to offer considerable flexibility for end users to customise the model. For example, carbon values, discount rates, base years and periods of analysis can all be varied. The research presented here uses annuitized versions of the three CO_2e values described in Annex 4 to this report, the HM Treasury's constant discount rate for policy appraisal of 3.5%, a base year of 2013, and a period of analysis from 2014-63. Because these are coded as variables they can be easily changed, for instance, during robustness checks and sensitivity analyses.

A number of other settings can be adjusted, such as whether to calculate value on a per hectare basis (default) or by 2km x 2km grid square. The fine spatial resolution of the analysis means that the study area can also be adjusted from the default of all of Great Britain (with explicit considerations of England, Scotland and Wales) or to any user-desired area (e.g. regions, counties, etc.). The planting policy can also be adjusted, in terms of the minimum area of agricultural land per cell for planting eligibility (default = 20ha per 2km x 2km square cell), but also in terms of how strictly the constraint is defined. That is, the policy could entail planting the agricultural area in a set number of 2km x 2km square cells per annum per country, or planting between lower and upper bounds on the number of hectares per annum per country (default; min=4,800ha yr^{-1}, max=5,200ha yr^{-1}). Finally, tree species considered for planting can be varied. At present TIM is set up to allow for planting of either Pedunculate oak or Sitka spruce (chosen as representative broadleaf and coniferous trees), but others could be added and data has been obtained on provided for beech and Scots pine with our Forestry Commission partners holding information for a wide range of species.

Another user-defined decision is whether or not to include or exclude Single Payment Scheme (SPS) subsidies to farmers. These are transfer payments from taxpayers to farmers and therefore there is an economic argument that these should adjusted for if we wish to see the underlying value of changes affecting agriculture. The data used to value agricultural output are obtained from the Farm Business Survey (http://www.farmbusinesssurvey.co.uk/index.html) via the UK Data Archive (http://www.data-archive.ac.uk/) and includes information regarding historic subsidies such as the Single Farm Payment and its contemporary successor the Single Payment Scheme (SPS). Annual SPS rates currently range from £258.50/ha for the majority of the UK that lies outside Severely Disadvantaged Area (SDA) designations, falling to £207.72/ha for SDA areas and £36.29/ha for the relatively small areas classified as SDA Moorland. In the present analysis we use a simple flat rate of £210/ha (an average confirmed by Savills, 2013). A useful extension to this analysis might be to incorporate digital maps of the SDA and SDA Moorland boundaries to adjust SPS levels to those specific to each area. However, as the average value is representative for the vast majority of land such an extension is unlikely to substantially alter results.

Agricultural output, timber production arising from the afforestation policy, GHG flows and recreation are all valued in GB pounds (at 2013 values) and are annuitized to facilitate comparisons across very different time scales. Timber values are annuitized over the first full rotation, with planting starting at any point between 2014 and 2063. Because the land uses considered here entail sequestering GHGs for varying lengths of time, GHG annuities are calculated with respect to the duration of each flow. Annuities for agricultural GHG flows, including those from machinery, soils, crops, fertilisers, and livestock are calculated for 2014-63. For carbon in forest livewood, deadwood and products (including emissions therefrom), the annuity is calculated over the first full rotation with planting starting at any point between 2014-63, but extended to the end of the second rotation (to capture emissions from deadwood and wood products). Finally, for GHGs in forest soils, the annuity is calculated for two rotations from planting, starting at any point during the 2014-63 period.

Table 3.34 summarises our analyses. Only those values reported in shaded cells are incorporated in the optimisation routine; un-shaded cells do not influence the specific optimisation. As noted, water quality (in terms of nitrate concentrations) and impacts on bird species diversity (measured by Simpson's Index) are quantified for each case, but are not monetised.

We report on five optimisation rules, encompassing increasingly comprehensive measures of value as one moves down the table. Specifically, the optimisation rules are:
1. BAU – Business as usual baseline. This includes agricultural values, no policy change, and accounts for unavoidable climate change. Notably, the value of additional timber output is zero because there is no afforestation in the baseline.
2. MaxMV – Maximising market values. This includes values from agricultural and timber output, and accounts for unavoidable climate change.

3. $MaxSV^g$ – Maximising social values net of GHG flows, but excluding recreation. Equivalent to MaxMV, but includes values from GHG flows, and accounts for unavoidable climate change.
4. $MaxSV^r$ – Maximising social values net of recreation, but excluding GHGs. Equivalent to MaxMV, but includes values from recreation, and accounts for unavoidable climate change.
5. MaxSV – Maximising social values. This includes values from agricultural production, timber output, GHG flows, and recreation, and accounts for unavoidable climate change.

Table 3.34. Summary of case study analyses: Optimisation objectives and derived measures.

Optimisation rule	Agricultural output	Timber output	GHG	Recreation	Water quality	Biodiversity impact
BAU	£	n/a	£	£	✓	✓
MaxMV	£	£	£	£	✓	✓
MaxSV^{g}	£	£	£	£	✓	✓
MaxSV^{r}	£	£	£	£	✓	✓
MaxSV	£	£	£	£	✓	✓

uded in assessment
narket value

Included in the assessment of social value

Notation:

= Shaded cells indicate values incorporated within the optimisation process i.e. these values influence the location of forest planting (unlike unshaded cells).

£ = Assessed in terms of economic values (£ ha^{-1} yr^{-1}; annuity values)

✓= Assessed quantitatively but not in terms of economic values (Water quality assessed as nitrate concentrations; Biodiversity assessed as Simpson's Index)

n/a = For BAU the timber annuity value is zero as there is no conversion of agricultural land to woodland.

Baseline = 2013; Common assessment period: 2014-63

Annuity periods:

- Agricultural outputs: Annuity calculated for 2014-63
- Timber: Annuity calculated over the first full rotation from planting starting at any point during the 2014-63 period
- For Recreation: Annuities calculated for 2014-63
- Carbon:
    - For farm carbon (machinery, soils, crops, fertilisers, etc.): annuity for 2014-63
    - For carbon in forest livewood, deadwood and products (including delayed emissions from the latter): the annuity is calculated over the first full rotation from planting starting at any point during the 2014-63 period but extended (to allow for the emission of carbon from deadwood and products) to the end of the second rotation.
    - For carbon in forest soils: the annuity is calculated for two rotations from planting starting at any point during the 2014-63 period.

Analysis extensions:

- Three carbon prices
- Values calculated by 2km square grid cell or by hectare (default)
- Excluding or including (default) Single Payment Scheme (SPS)
- Discount rate (user specified, any level; default = 3.5%)
- Planting the agricultural area in a set number of 2km square cells per annum per country or planting between a lower and upon bound on number of hectares per annum per country (default; min=4,800ha/yr, max=5,200ha/yr)
- Minimum area of agricultural land for planting eligibility (default = 20 ha/2km square cell)
- Assessment starting year (default = 2013) and assessment period (default = 2014-63)
- Tree species (at present either Pedunculate Oak or Sitka spruce; others can be added, data supplied for beech and Scots pine).

3.12.5 Results

This research seeks to bring both economic analysis and the real-world complexities and variation of the natural environment into land use decision making. Results therefore reflect both factors. While readers may be familiar with the economic concepts underpinning this work, the specifics of the British environment may be less familiar to some readers. Given that variation in the natural environment significantly determines results from our analysis, it is useful to provide some contextual information regarding the study area.

Figure 3.26 presents a map of Great Britain which indicates the location of many of those features which influence findings from the TIM analysis. As can be seen the country is highly varied. Indeed one of the major determinants of land use (and the response to any afforestation policy) is elevation. Upland areas dominate central and western Scotland, the borders area south of Glasgow and on into north-western England down to areas around Sheffield. Similarly Wales is dominated by upland areas with the exception of southern and south western areas. Almost all of the remaining areas are lowland, including the majority of middle, eastern and southern England, although the south west is a patchwork of lowland and upland areas. Generally, upland areas are colder, subject to heavy rainfall and characterised by poorer soils which makes them more limited in terms of the agricultural production options available to them than are lowland regions. Consequently, when we consider the impacts of afforestation, lowland areas will entail high opportunity costs in terms of foregone agriculture which will be only partially defrayed by potentially higher timber revenues in such areas. Turning to consider greenhouse gas consequences, while some upland areas are characterised by organic soils whose carbon stores may be lost as a consequence of afforestation, nevertheless the high stock densities of upland areas mean that afforestation away from peat soils may reduce GHG emissions substantially if they displace livestock. However, while these latter factors mitigate towards planting on upland (but non-peat) areas, woodlands can be major sources of recreation benefits, but only if they are located near to population centres. As **Figure 3.26** shows, these are mainly located in lowland areas which would tend to 'bring forests down the hill' towards urban fringes. One issue here is that the substantially larger size of English cities may well impinge upon the location of forests outside the country, most obviously in Wales where the comparatively lower population density, particularly in the north of the country, means that forests may be dragged towards the border with England. An extension to this research might be to recalculate the value of each nation's forests solely to the citizens of the country undertaking the planting. However, in the present analysis we do not differentiate the value of forests according to who receives the benefits they provide (an approach which accords with H.M. Treasury (2003) guidelines which require that assessments are undertaken across the entire nation).

Water quality effects of afforestation are expected to be generally positive irrespective of location as they avoid relatively high agricultural fertiliser applications. However, biodiversity impacts are more difficult to predict as they can vary substantially across numerous ecosystems. The one clear expectation here is that planting new woodlands will benefit those species which favour such environments.

This diversity of impacts and values shows that, while we can make predictions regarding the direction of impacts for many of the effects of afforestation, without an analysis on the scale of that proposed here it is difficult to determine the overall net value of afforestation, let alone answer the highly complex question of where Britain's new woodlands should be located. These are the questions which TIM sets out to address.

Figure 3.26. The study area – Great Britain.

3.12.5.1 The Business as Usual (BAU) baseline

Our case study addresses how the introduction of an afforestation policy in Great Britain will affect land use changes over the 50-year period from 2013 to 2063. Moreover, it demonstrates how various policy objectives, such as maximising market versus social returns, affect planting decisions and overall land use. In order to fully understand the implications of each policy objective (or optimisation rule, from **Table 3.34**), we must first establish a baseline against which they may be compared. This holds policy constant (i.e. there is no afforestation) and only examines the impact of unavoidable drivers of change over the assessment period; in this case the impact of climate change which, irrespective of current climate policy, will still occur.

Figure 3.27 shows climate change induced changes in mean temperature (first row) and total monthly precipitation (averaged over the growing season months; second row) during the April-September growing season for the period 2014-2063. The left (2014) and central (2063) columns depict the first and final years of the assessment period, respectively, and the right column (2014-2063) depicts the change over time. As can be seen, the entire country becomes warmer, with temperature gains increasing in intensity as one moves from north to south, and with the highest temperatures concentrated largely in the southeast.

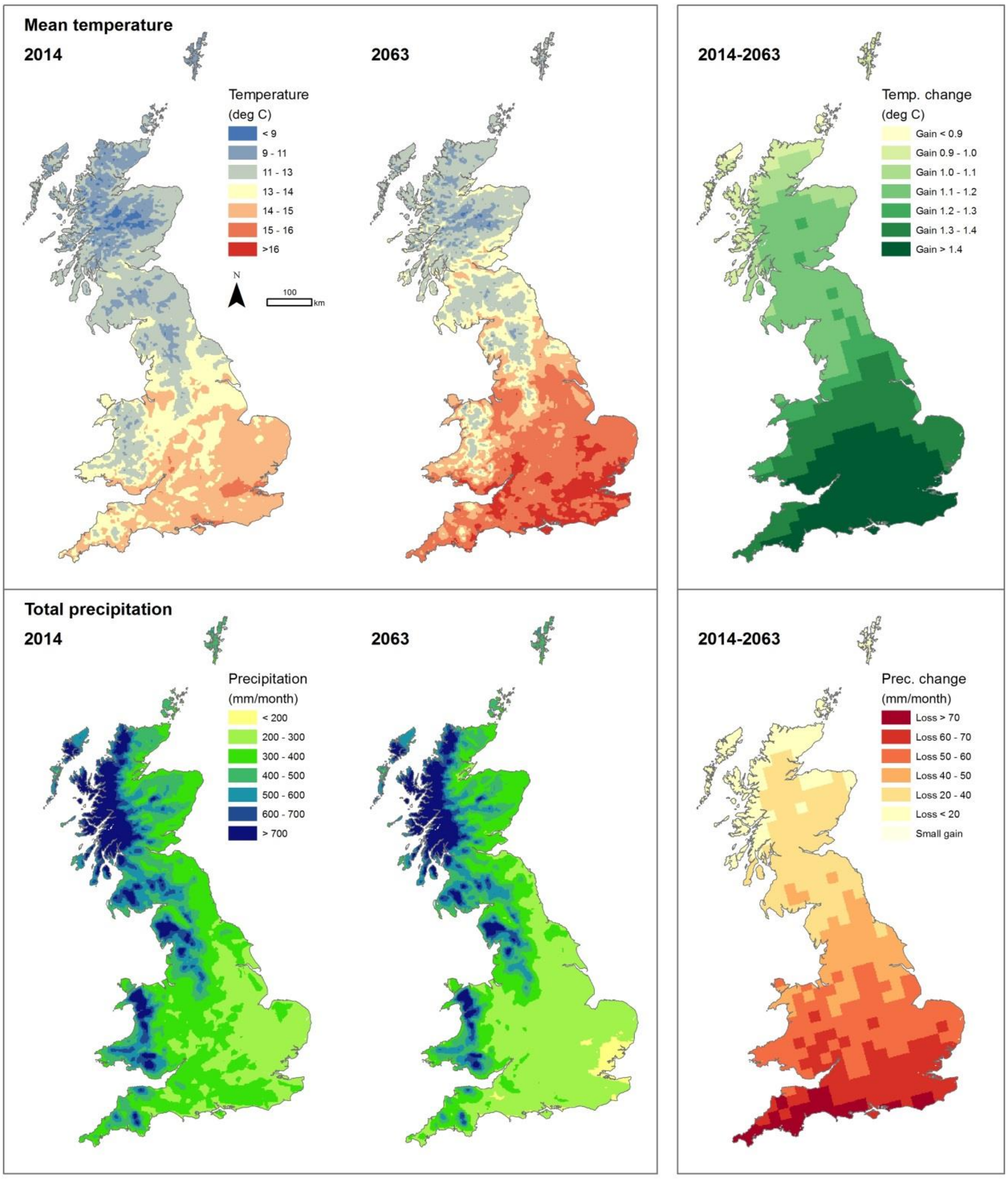

Figure 3.27. Climate change impacts over the 2014-63 assessment period: Mean growing season (April-Sept.) air temperature and total monthly precipitation. Based on UKCP09 medium emissions scenario (data originally at 5km resolution; see data annex). The figure depicts changes in mean temperature (first row) and total monthly precipitation (averaged over the growing season months; second row) during the April-September growing season for the period 2014-2063. The left (2014) and central (2063) columns depict the first and final years of the assessment period, respectively, and the right column (2014-2063) depicts the change over time.

BAU: Implications of climate change for UK agricultural land use

These changing temperature and precipitation patterns (depicted above) drive shifts in agricultural land use, even in the BAU baseline where there is no policy change. Such effects are to be expected and indeed are likely to impinge upon the agricultural system worldwide. These consequences however will differ dramatically around the world. Overall, there is likely to be considerable dislocation of supply which, compounded by forecast increases in demand due to both population increases and an unevenly distributed rise in affluence, is likely to cause price instability and overall rises in the absence of substantial technological improvements (Garnett, *et al*., 2013). Given our heavy reliance upon imports, this is likely to pose a substantial challenge to food security within the UK (*ibid.*) However, compared to much of the globe, the UK is a relatively cool (if not cold) and damp country. Therefore, our research shows that the generally warmer temperatures induced by climate change will, on the whole, boost UK agricultural production (Fezzi *et al*., 2013). While it is still very much an open empirical question as to the extent to which this increase in domestic supply might offset import insecurities (our suspicion is that the net effect will be to lower UK food security), from the perspective of UK farming, warmer local temperatures will generally enhance production possibilities.

Our analysis reflects this increase in baseline production conditions and forecasts that farmers will generally respond by moving towards more profitable activities. So, for example, in lowland areas we see movements away from pastoral farming and towards higher income arable production. This tends to further concentrate lower value livestock activities towards more disadvantaged upland areas who take advantage of higher temperatures to increase the intensity of grassland operations resulting in high stocking rates for livestock. Even on the more challenged uplands we forecast increases in livestock intensities. This raises the value of agricultural output under the BAU option. However as we show subsequently, there are a number of downsides to these trends as the conversion of unimproved rough grazing areas to more intensively used grasslands induce reductions in our biodiversity measures and some catchments experience a reduction in water quality.

Turning to consider specific forecasts of agricultural response to climate change under the BAU option, **Figure 3.28** shows how the area of land (measured in hectares per 2km square cell) devoted to cereal crops increases between 2014 (left hand map) and 2063 (centre map) in response to climate change induced rises in temperature for a crop whose varieties are moderately resistant to accompanying reductions in rainfall[32]. Increases in both intensity and extent occur throughout lowland Britain (as clearly shown in the right hand panel).

[32] Note, however, that this analysis shows the expected effects of average trends in temperature and rainfall. They should not be taken as implying resilience to an increase in the frequency and intensity of short term weather extremes such as intense droughts. As the frequency of such events is forecast to increase (Pall et al., 2011; Coumou and Rahmstorf, 2012; Rahmstorf and Coumou, 2011) then a useful extension to this research would be to incorporate such effects.

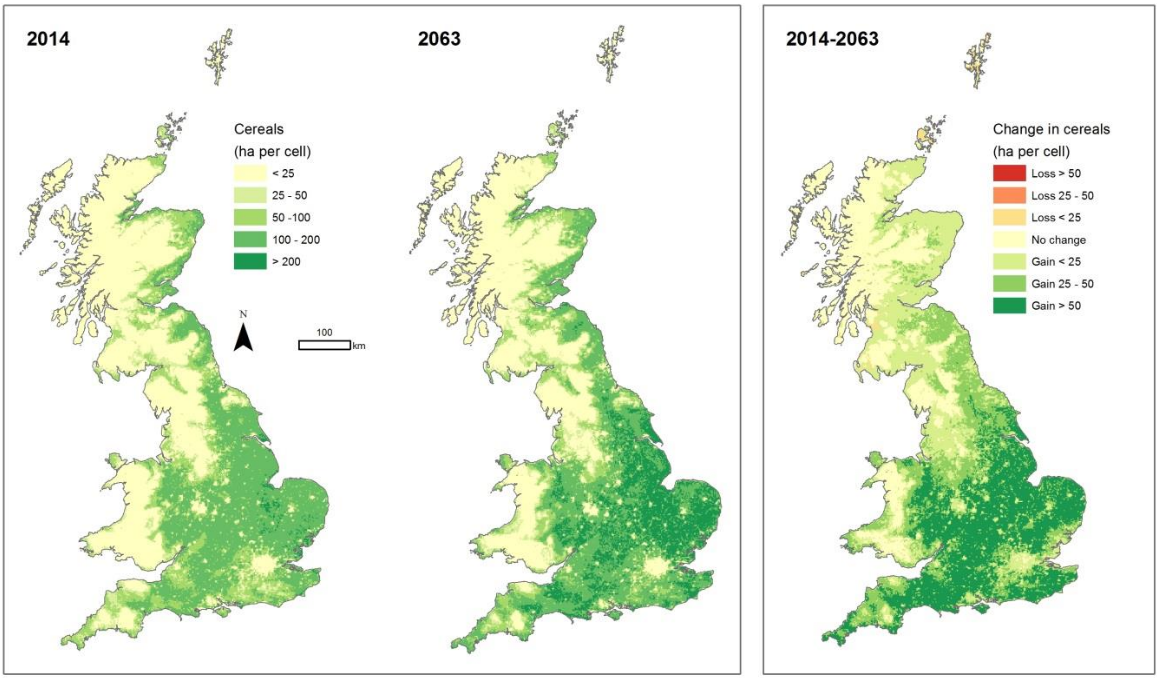

Figure 28. BAU area of land devoted to cereals production (hectares per cell). Figure depicts the area of land in each 2 km cell that is devoted to cereal crops, and how this changes with climate. The left (2014) and central (2063) columns depict the first and final years of the assessment period, respectively, and the right column (2014-2063) depicts the change over time.

Figure 3.28 measures changes in cereals production in terms of *hectares per 2km square cell*. As an aside, these changes could be measured *per hectare of agricultural land*, as is shown below in **Figure 3.29**. For clarity, **Figures 3.28** and **3.29** utilise the same data, and differ only in that the former depicts changes in terms of hectares per 2km square cell, while the latter depicts changes as a proportion of agricultural land. Comparing the two figures demonstrates that this adjustment makes very little difference to the results: the trend is similar, and as such subsequent results are reported in terms of hectares per 2km square cell, as in **Figure 3.28.**

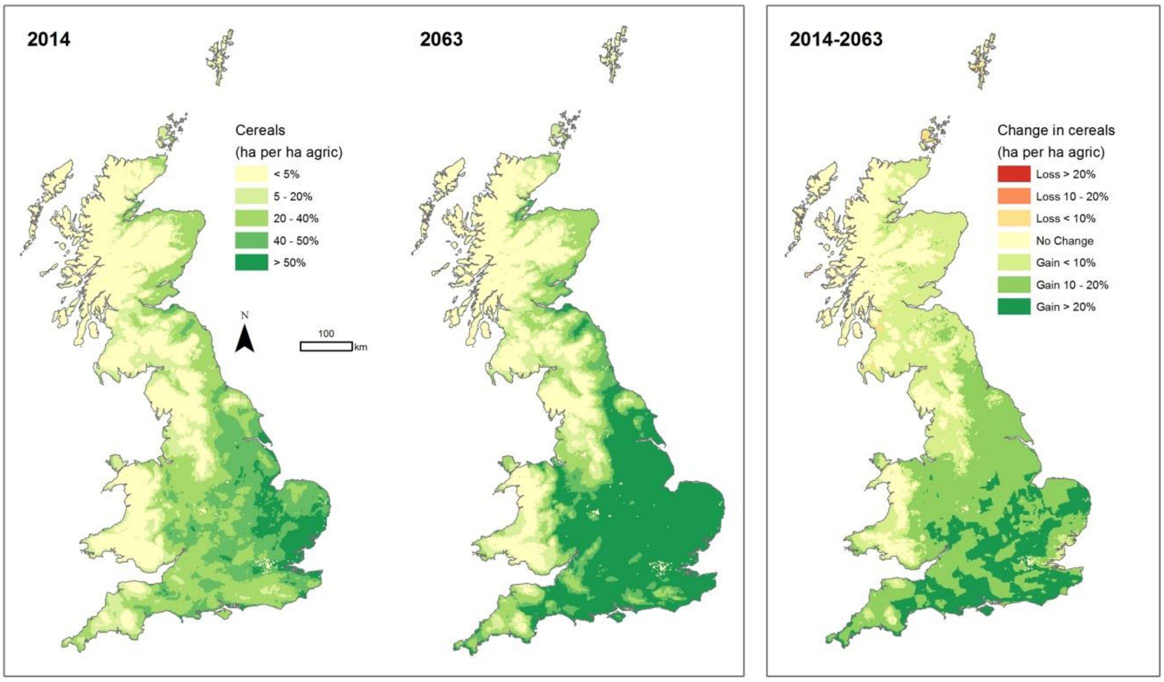

Figure 3.29. BAU area of land devoted to cereals production (per hectare of agricultural land).
Figure depicts the area, per hectare of agricultural land that is devoted to cereal crops, and how this changes with climate. The left (2014) and central (2063) columns depict the first and final years of the assessment period, respectively, and the right column (2014-2063) depicts the change over time.

Figure 3.30 shows how the area of land (measured in hectares per 2km cell) devoted to oilseed rape changes in response to climate change. Gains occur in northeast England, and increase moving south through the midlands and the east and south of England. Although, as today, oilseed rape production remains well below that of cereal output, these increases nevertheless represent significant gains in farm income over the assessment period.

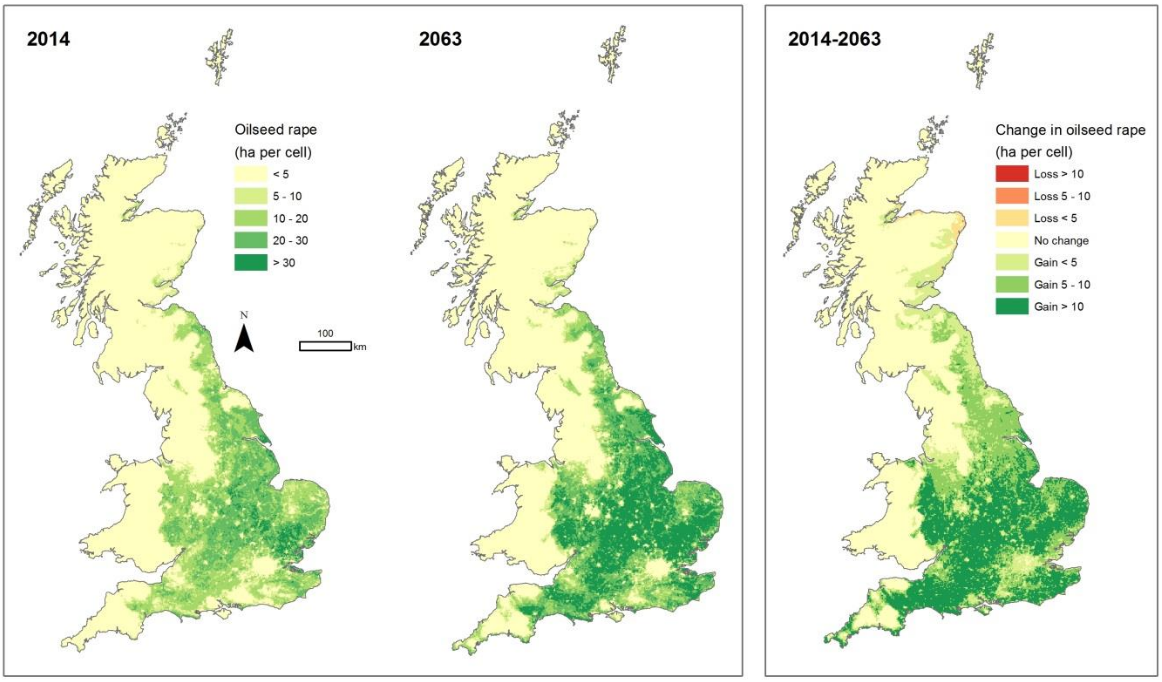

Figure 3.30. BAU area of land devoted to oilseed rape production (hectares per cell). Figure depicts the area of land in each 2 km cell that is devoted to oilseed rape production, and how this changes with climate. The left (2014) and central (2063) columns depict the first and final years of the assessment period, respectively, and the right column (2014-2063) depicts the change over time.

Root crops also increase in line with temperatures as shown in **Figure 3.31**. Again the trend is for increases to be widespread across all lowland areas of Britain, although in absolute extent these are minor compared to those for say cereals.

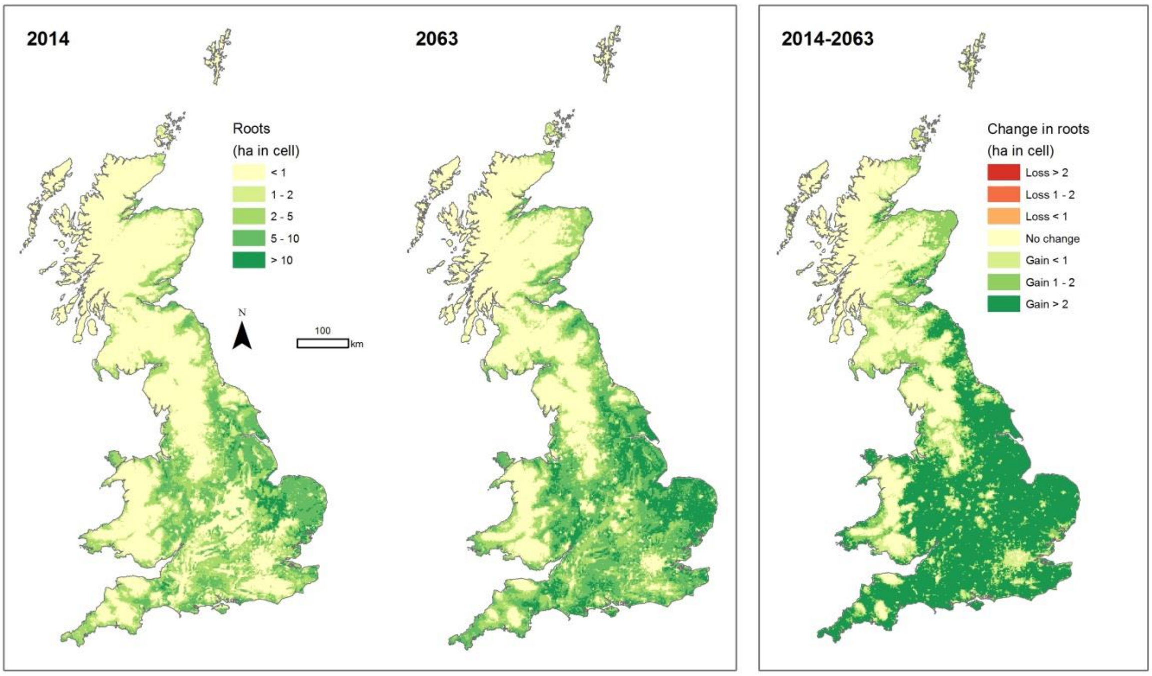

Figure 3.31. BAU area of land devoted to root crop production (hectares per cell). Figure depicts the area of land in each 2 km cell that is devoted to root crop production, and how this changes with climate. The left (2014) and central (2063) columns depict the first and final years of the assessment period, respectively, and the right column (2014-2063) depicts the change over time.

The changing temperature and precipitation patterns depicted in **Figure 3.27** mean that land which is of marginal agricultural value in 2014 will be able to support higher value agricultural activities by 2063. This is illustrated by **Figure 3.32** in which a clear pattern of converting relatively low value rough grazing into increasingly high value temporary and even permanent grasslands emerges. Maps A, B, and C in the right hand column show changes over the assessment period for rough grazing (1st row), temporary grassland (2nd row), and permanent grassland (3rd row). Map A shows that higher temperatures and drier weather support a transition away from rough grazing across upland areas of Wales, the northwest of England, and Scotland (the apparent gains in lowland areas are from a very low base and should not be over-interpreted). The losses of rough grazing shown in the upland areas of Map A transition into higher output temporary grassland in Map B or even permanent grassland in Map C. This suggests major increases in livestocking rates (which we investigate subsequently). Similarly, in Maps B and C we see losses of temporary and permanent grasslands in the lowlands as these transition into the gains in cereals and other arable crops shown in **Figure 3.28** to **3.31**. Therefore in both the upland and lowland areas of Britain we see patterns of climate induced land use change through which farmers take advantage of improved weather conditions to move into higher income activities. This yields an increase in the overall value of British agriculture which we quantify subsequently.

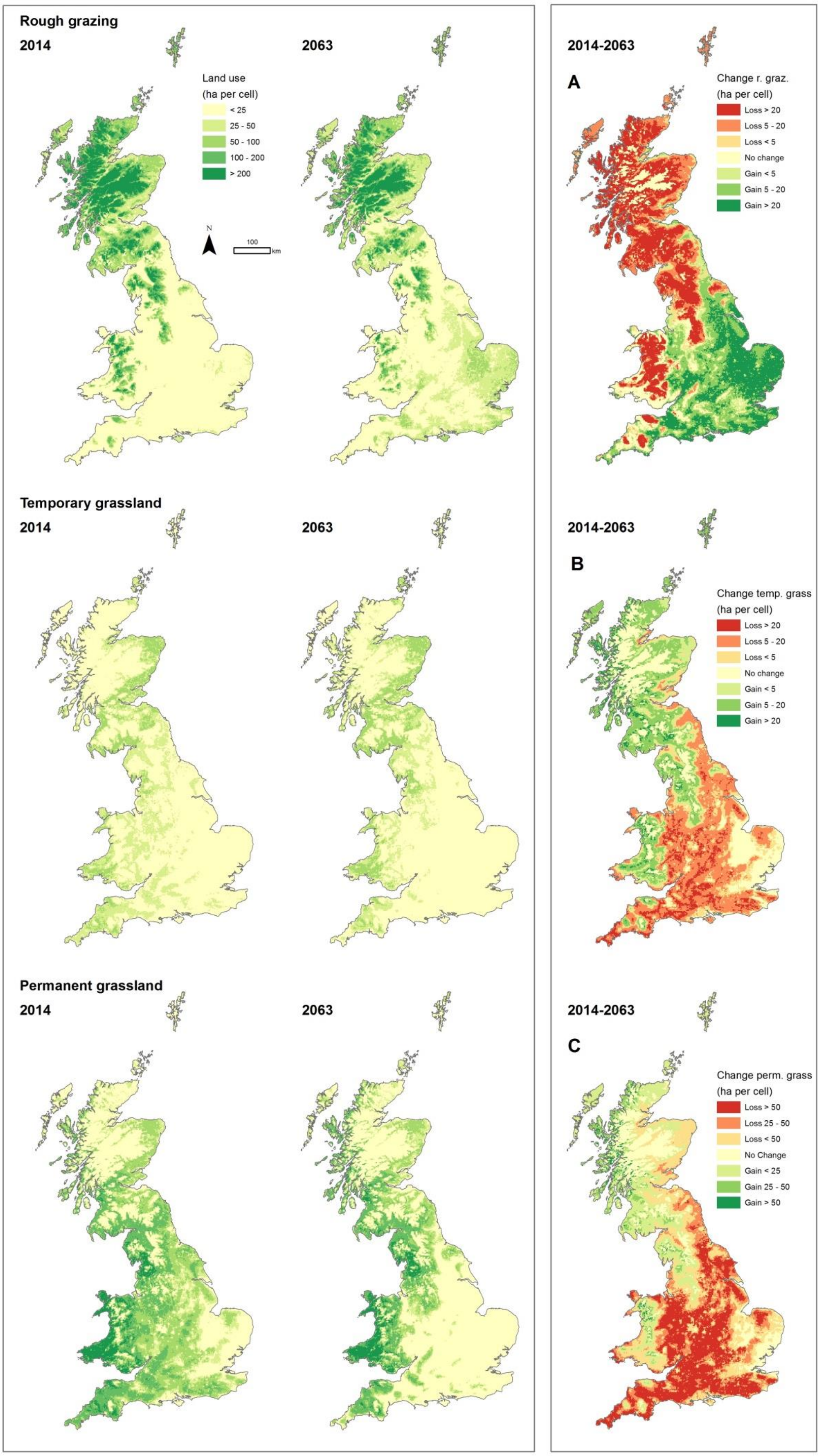

Figure 3.32. BAU area of land devoted to rough grazing, temporary grassland and permanent grassland production (hectares per cell). Figure depicts changes in grazing and grassland. Left and central columns depict the first (2014) and final (2063) years of analysis, and the right column (2014-2063) depicts the change over time.

Figure 3.33 shows how the change in grazing and grassland resulting from climate change affects the distribution of beef and dairy production across Great Britain. The increased potential for lowland arable production shown in **Figure 3.28** results in widespread reductions in stocking density across much of England. However, the improvements in upland areas shown by the transition from rough grazing to temporary and permanent grassland in **Figure 32** permit a substantial increase in livestock numbers in Wales, Scotland and upland England.

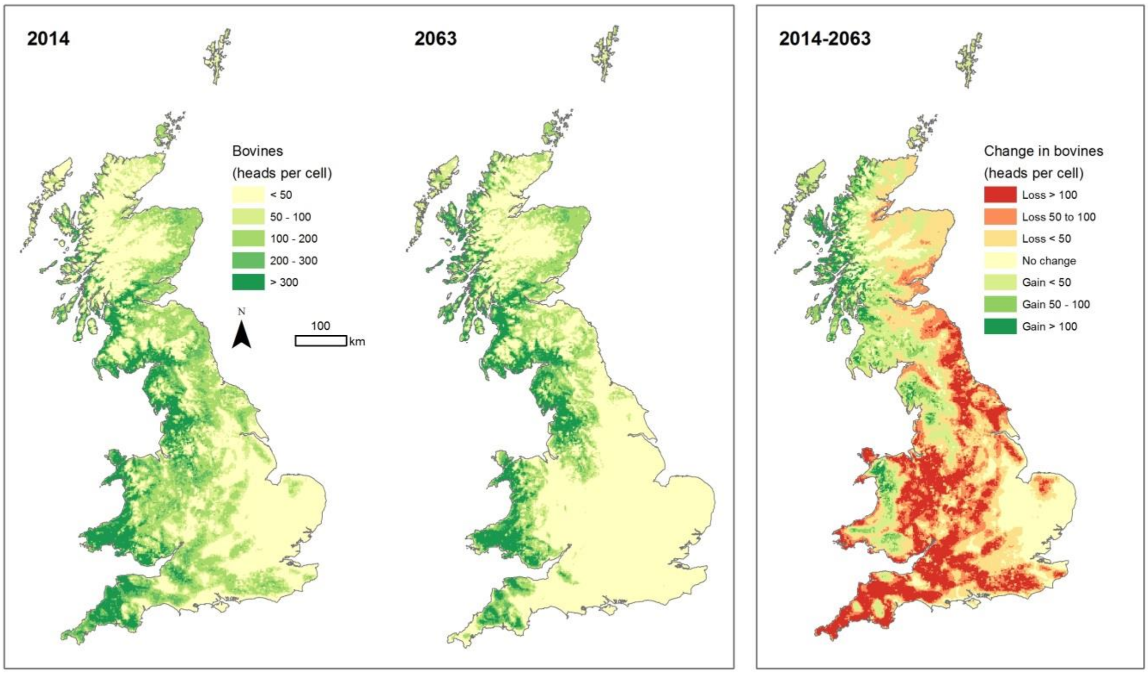

Figure 3.33. BAU beef and dairy production (heads per cell). Figure depicts the distribution of beef and dairy production. The left and central columns depict the first (2014) and final (2063) years of the assessment period, respectively, and the right column (2014-2063) depicts the change over time.

Given that livestock (particularly beef and dairy cattle) yield much higher emissions of GHGs than do arable systems, the pattern of changes in livestock intensity shown in **Figure 3.32** are directly reflected in changes in agricultural emissions of GHGs. **Figure 3.34** shows the change in average annual agricultural greenhouse gas emissions ($tCO_2e\ ha^{-1}\ yr^{-1}$) from 2014-63. In northwest England and Scotland, increased emissions are driven in part by increased livestock and in part by increased crop production.

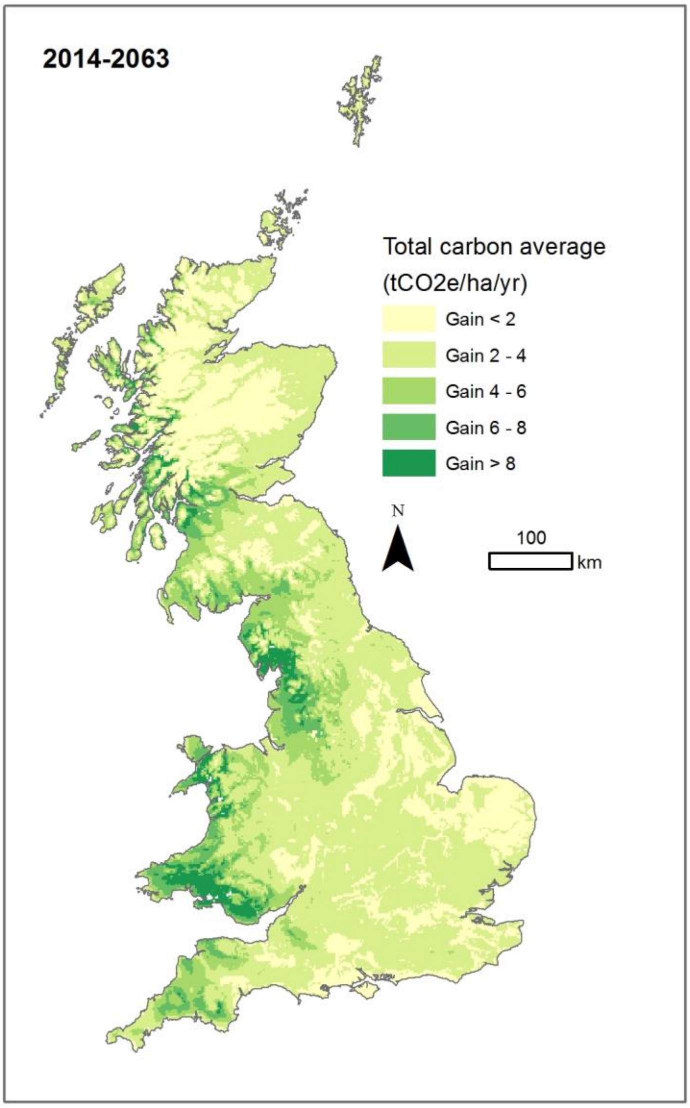

Figure 3.34. Average annual CO_2e emissions from agriculture ($tCO_2e\ ha^{-1}\ yr^{-1}$). Figure depicts the distribution of average annual CO_2e emissions ($tCO_2e\ ha^{-1}\ yr^{-1}$) from agriculture in the BAU baseline.

BAU: Implications of climate change for UK forestry

Although there is no afforestation policy under the BAU baseline, unavoidable climate change has consequences for tree growth which we need to assess and incorporate into our subsequent policy analyses. Yield class is a measure, in cubic meters per hectare per year ($m^3\ ha^{-1}\ yr^{-1}$), of the rate of tree growth, and is affected by a range of factors, including temperature and precipitation. **Figure 3.35** shows how baseline yield classes for Pedunculate Oak (POK) and Sitka Spruce (SS) change over the assessment period. The right hand column indicates that warmer, drier conditions benefit POK throughout central and southern England, whereas yield class falls for SS in lowland areas (where declining precipitation becomes a limiting factor) and rises at higher altitudes (where, in the absence of water constraints, SS benefits from increasing temperatures).

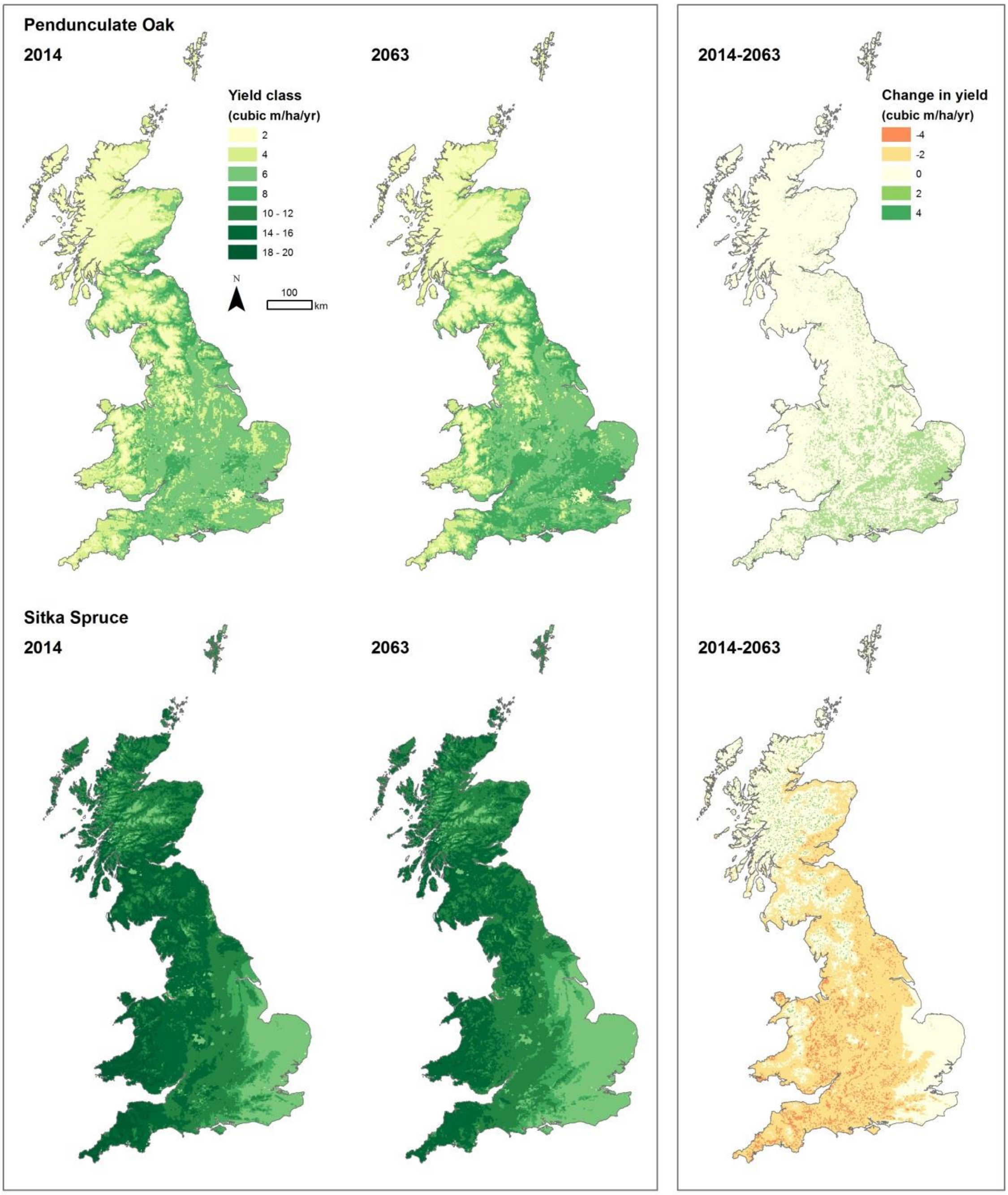

Figure 3.35. Annual tree growth rates (yield class; m^3 ha^{-1} yr^{-1}). Figure depicts changes in tree growth rates (yield class; m^3 ha^{-1} yr^{-1}) as a result of climate change: Pedunculate Oak (upper row) and Sitka spruce (lower row).

The final element required to complete the BAU baseline is an examination of how biodiversity changes over the assessment period. **Table 3.35** measures how, in the absence of any new afforestation, climate change induced shifts in agricultural land use impact upon bird biodiversity over the 2014-63 assessment period. Impacts are measured using Simpson's Index of bird diversity (as discussed in Section 3.11; our biodiversity module); positive (negative) values indicate increases (decreases) in diversity.

Table 3.34. Changes in bird biodiversity (Simpson's index) under the BAU (2014-2063).

Measure of biodiversity change	Mean*	S.E. Mean	Lower 95% CI	Upper 95% CI	St. Dev.
All Birds	-0.248	0.006	-0.260	-0.236	1.420
Wood Birds	-0.034	0.004	-0.041	-0.027	0.839
Farm Birds	-0.032	0.004	-0.039	-0.025	0.873
Red/Amber Birds	-0.092	0.002	-0.097	-0.088	0.573

Table. 13.3 Measures BAU changes in bird biodiversity for 2014-63, using Simpson's index of bird diversity. Positive (negative) values indicate increases (decreases) in diversity.
N = 57,230 for all GB level analyses (the number of 2km x 2km squares in Great Britain)
95%CI = 95% confidence interval around the mean
St. Dev. = Standard deviation
*All means are significantly different from zero at p<0.01 (nonparametric test applied due to significant skew in data)

Results, detailed in **Table 3.35**, reveal that the mean change in diversity across bird groups is small, but in all cases negative and statistically significant. A troubling background is provided by the BAU analysis (shown in the first block of four rows in the table) which envisages no new planting of woodland and therefore reveals the underlying impact on bird diversity measures arising from the expected impact of climate change upon agricultural land use. Here, all four measures of bird diversity reveal declines between 2014 and 2063. This reflects the forecast increase in the intensity of agricultural production over this period and suggests that Britain's bird biodiversity will decline generally as a result of this trend.

Figure 3.36 reveals the distinct spatial pattern which, to a considerable extent, characterises all of all the above changes. Using the example of woodland birds we observe biodiversity losses in the lowlands and gains in the uplands. This reflects the pattern of increasing intensity of lowland arable production shown in **Figure 3.28** to **3.32** and also suggests that the concentration of livestock in the uplands is not deleterious to bird biodiversity[33].

[33] This contrasting pattern may well explain the diverse mixture of improvements and degradations to water quality observed in Table 13.2.

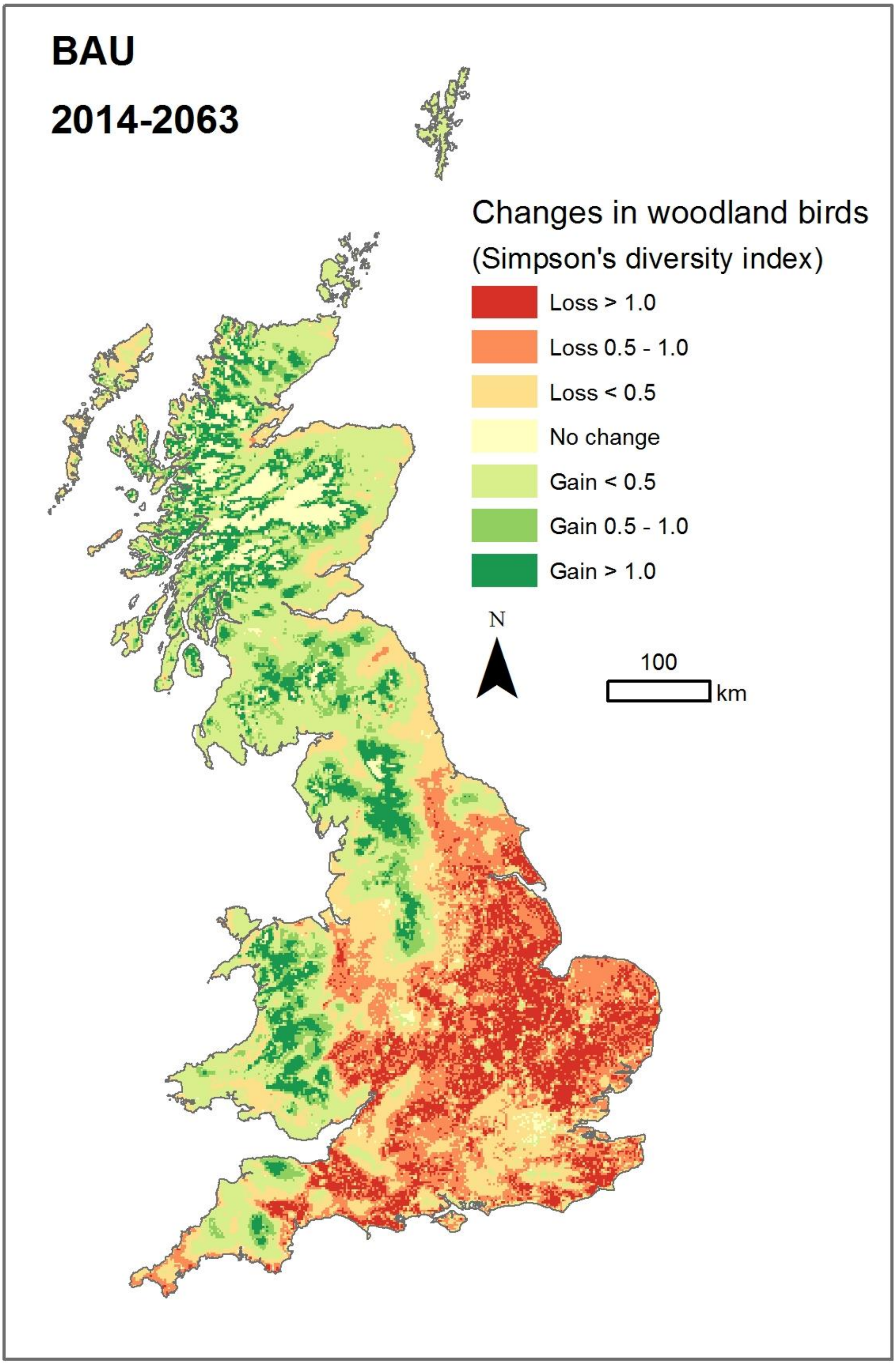

Figure 3.36. BAU baseline changes in woodland birds. Figure depicts change in biodiversity (measured by Simpson's diversity index) under Business as Usual (BAU).

3.12.5.2 Britain's New Forests: Optimal policy implementation for alternative objectives

With our baseline firmly defined and explored we can now proceed to the main focus of our case study and investigate the options for planting Britain's new forests. As summarised in **Table 3.36**, we consider the planting strategies arising from a variety of objectives, each being determined according to the extent that they consider or disregard the various values generated by afforestation. In effect each objective corresponds to a different forestry policy. In each case we use TIM to identify the precise implementation across all GB locations and across the 50 year time horizon which maximises value as defined in the corresponding objective. In this section we present results for our four policies/objectives as follows:

- MaxMV – Maximising market values: Includes values from agricultural and timber output only;
- $MaxSV^g$ – Maximising the sum of market values (agriculture and timber) plus GHG values but no other afforestation impacts;
- $MaxSV^r$ – Maximising the sum of market values (agriculture and timber) plus recreation values but no other afforestation impacts; and
- MaxSV – Maximising social values as the sum of market values (agriculture and timber) plus GHG values plus recreation values.

In all cases we calculate changes in value away from the BAU baseline, i.e. we present values which are net of the underlying impact of unavoidable climate change.

For simplicity we open our discussion of results by examining the two most conventional of the above measures, the market value (MV) and the social value (SV) of the afforestation project with the latter defined to embrace all of the effects of planting for which we have robust economic values. **Table 3.36** presents values for these two measures disaggregated across the nations of Great Britain. Recall that in both cases our TIM methodology has identified that pattern of planting across space and time which maximises the value of the measure being investigated. Given this, the results of **Table 3.36** are startling. If we exclude non-market externalities from the assessment of optimal planting locations (i.e. the maxMV strategy) then the social value generated by the resulting forestry strategy is not just low, it is actually negative. In other words, such an approach to decision making, simply providing tax funds for planting and leaving the decision about where that planting should occur up to the market actually generates net costs of over £65million per annum to the UK taxpayer; society would be better off not planting any new forests than following such a course of action. Conversely, if we allow the value of GHG and recreation generated by forests to influence the location of planting then the optimal location results in a very substantial positive value for society of nearly £550million per year. Indeed this value is a lower bound as it is calculated using our lowest value for GHG (C1); we return to explore this point subsequently.

Table 3.35. The social value of new forests (£ million per annum) located according to two alternative decision rules; social values calculated using H.M. Treasury cost-benefit rules and lowest carbon price (C1).

Optimisation rule	Values included in planting decision	GB	England	Scotland	Wales
MaxMV	Market values (agriculture + timber) only	-£66	-£30	-£3	-£33
MaxSV	Market values + GHG + Recreation	£546	£461	£64	£21

Table reports the social value of 750,000 hectares of new forest, divided evenly between England, Scotland and Wales and planted between 2014-63 using two alternative planting strategies: (i) to maximise market values (ii) to maximise social values. Results assume planting is with broadleaves (Pedunculate Oak). Note that figures in red indicate negative social values.

The very substantial difference in social values generated by the two approaches to decision making is graphically illustrated in **Figure 3.37**.

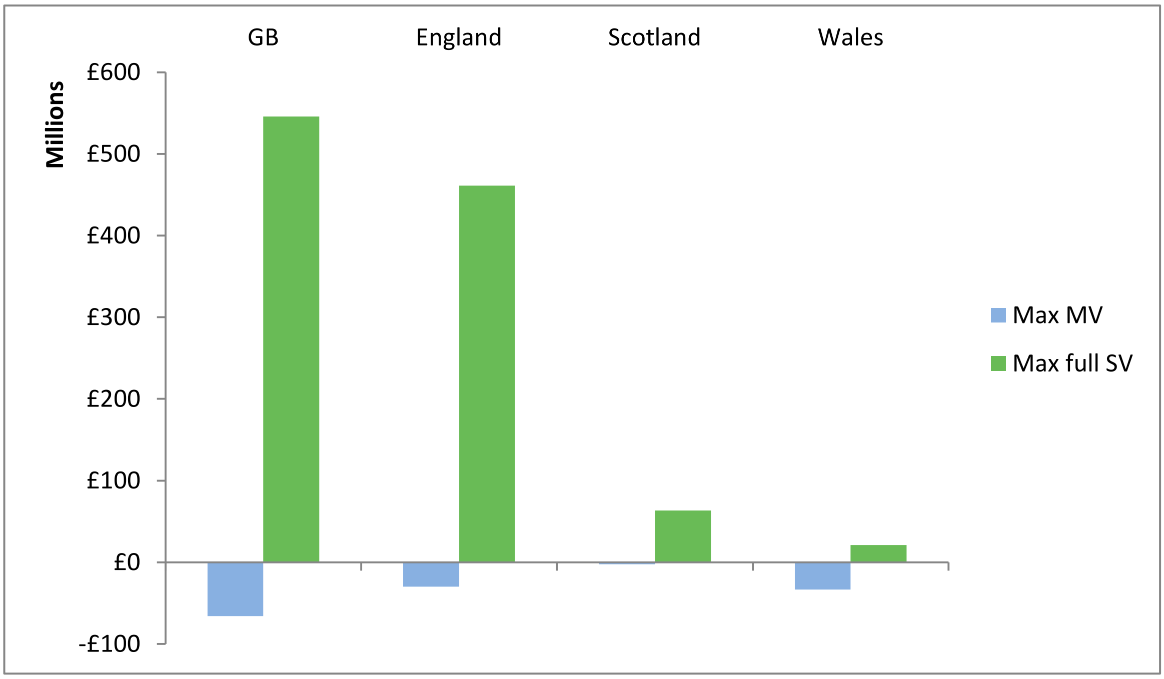

Figure 3.37. The social value of new forests (£ million per annum) located according to two alternative decision rules; social values calculated using H.M. Treasury cost-benefit rules and lowest carbon price (C1). Figure graphs the social value of 750,000 hectares of new forest, divided evenly between England, Scotland and Wales and planted between 2014-63 using two alternative planting strategies: (i) to maximise market values (ii) to maximise social values. Results assume planting is with broadleaves (Pedunculate Oak).

Perhaps even more interesting than the overall values generated by the various approaches to decision making are the very different locations for planting which they imply. These are revealed in **Figure 3.38** which shows planting locations for all four of our maximisation rules.

The first of these maps (top row, left hand) show the best possible location for planting under a decision making approach which focuses solely upon market values (agricultural output and timber production). The negative values generated through the focus on market values in the maxMV strategy reflects the fact that, in almost all locations a standard economic assessment would find the displaced value of agriculture exceeds that of timber (indeed using standard Treasury discount rates, as here, the net present value of timber production is negative, reflecting the long time between planting and felling). Therefore the market merely seeks to minimise this loss by placing these new forests on the most marginal and lowest agricultural value land available. Therefore in each of the three countries under consideration we find forestry banished to the extreme uplands where agricultural values are lowest. So in England planting is focussed upon the northern Cumbrian mountains and Cheviots next to the Scottish border. Within Scotland forestry is consigned to the agriculturally even more disadvantaged areas of the central Highlands. While in Wales it is the central spine of the Cambrian Mountains which becomes the repository for these new forests. Throughout it is the objective of minimising market value losses that drive planting although, as **Table 3.36** has already revealed, resultant social values are negative implying a major loss for the public purse as taxpayers foot the bill of this highly inefficient approach to decision making.

The SV^g map (top, right) in **Figure 3.38** shows the substantial shift in planting locations which occurs if we take GHG implications into account. Almost all forests shift substantially from their previous locations. Two factors are driving this move; soil carbon and the potential for displacing GHG emissions from livestock. The first of these factors is illustrated in **Figure 3.39** which shows the location of high-carbon soils across Britain. Planting trees on such soils, particularly when they have not been previously depleted of their carbon by ploughing, results in carbon emissions to the atmosphere as tree planting and growth dries out the soils and liberates stored carbon. This affects many of the mountainous areas planted under the maxMV rule. However, away from peat soils, woodlands can produce net sinks of carbon compared to the major emissions of GHG associated with livestock. Therefore, the SVg map shows forests also moving into those high livestock intensity areas identified in **Figure 3.33**, thereby reducing the associated high emissions shown in **Figure 3.34**.

A further major shift in planting locations occurs if we move to a SV^r planting rule (bottom, left of **Figure 3.38**). Here we ignore GHG but now add recreation values to those provided by market goods. The movement in planting locations is again dramatic as the hills and remote livestocking areas are left behind and woodlands are located as near as possible to Britain's cities. Within England we see major woodlands established around London, Birmingham, Manchester, Liverpool, Leeds, Sheffield, Newcastle, etc. Even smaller centre such as Norwich, Plymouth and Southampton are all well served by this policy. As highlighted in our recreation module (Section 3.10) these woodlands near to be located close to populations to maximise these values. Turning to consider Scotland a similar pattern is clear with the majority of new woodlands being focused upon the central belt between Glasgow and Edinburgh although as before other smaller centred, such as Aberdeen, are again well served by this strategy. Results for Wales also reflect the majority distribution of population with woodlands thronging the southern centres of Swansea and Cardiff, although it is likely that the latter locations also reflect the ease of access for nearby populations in England. This aspect of the results is most clearly demonstrated in the north of the country which, despite having a lower population density than the south, nevertheless becomes a repository for quite substantial planting as a result of the ease of access to the large populations just across the border in England (indeed a clear border effect, and the impact of good road links along the north coast of Wales, can clearly be seen). It is likely that, if the Welsh Government chose to ignore such trans-national spill-over benefits then this density of planting may diminish (although it is also likely that these non-market benefits would be associated with tourism revenue values which might be a useful source of revenue for the area).

The final map of **Figure 3.38** (lower, right) shows optimal planting locations for the maxSV rule which considers market goods, GHG and recreation values. As we will detail subsequently, the market values are actually one of the smaller elements of the overall values generated by afforestation. Therefore it is not surprising to find that we find socially optimal planting locations reflect a mix of both the GHG and recreation narratives, with woodlands both located near to cities to boost recreation values and on high livestocking areas to avoid associated GHG emissions. However, the contrast with the initial maxMV map is startling; the maxSV approach to decision making retains almost none of the locations which would be chosen if the government simply made taxpayer funds available but left the planting decision to the market.

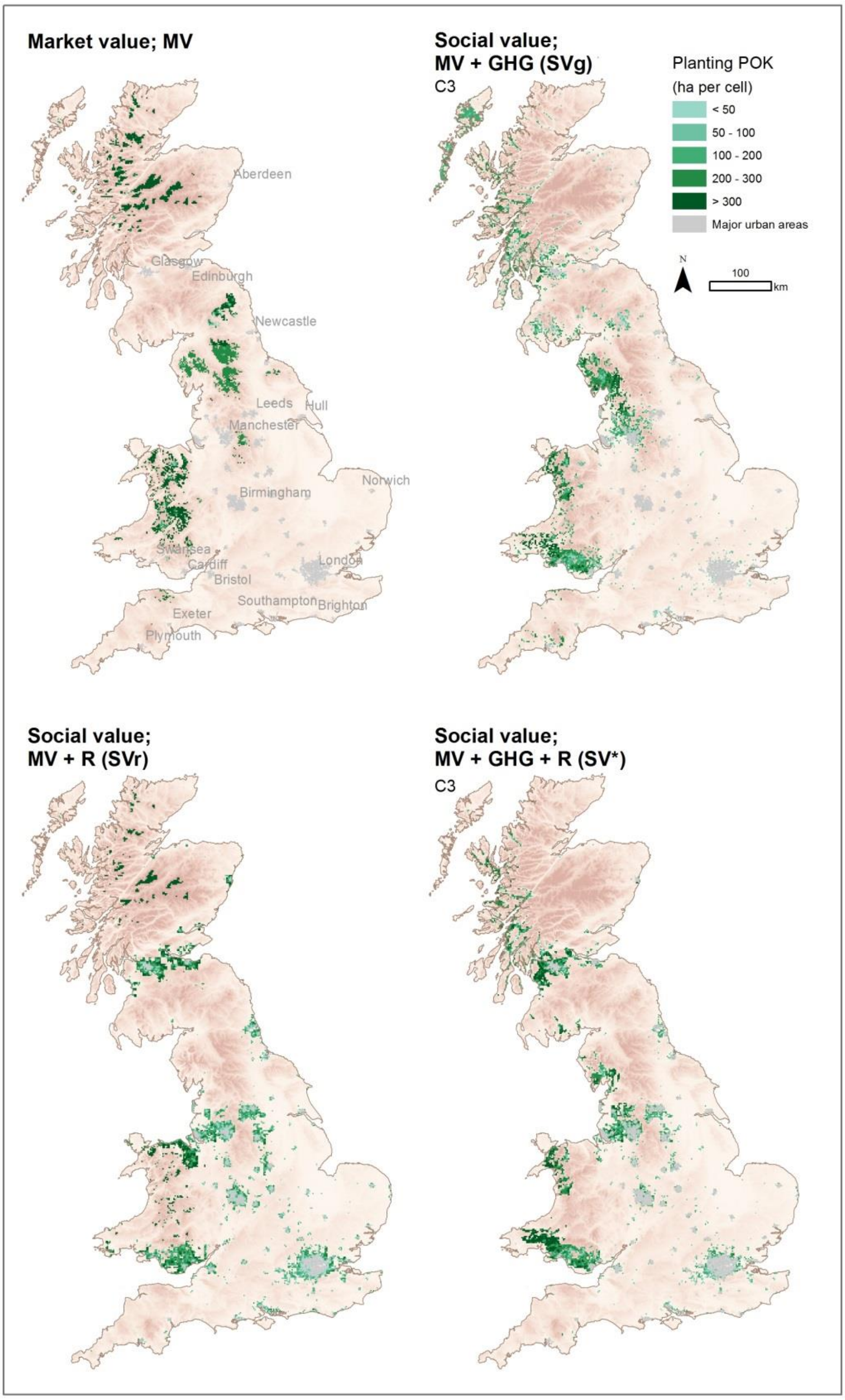

Figure 3.38. Optimal location for Britain's new woodlands under four approaches to decision making. Optimal location for Britain's new woodlands under four approaches to decision making: (top, left) maximising market values only; (top, right) maximising market and GHG values; (bottom left) maximising market and recreation values; (bottom right) maximising market, GHG and recreation values. Assumes POK planting throughout, 750,000 hectares planted, divided evenly between England, Scotland and Wales between 2014-2063.

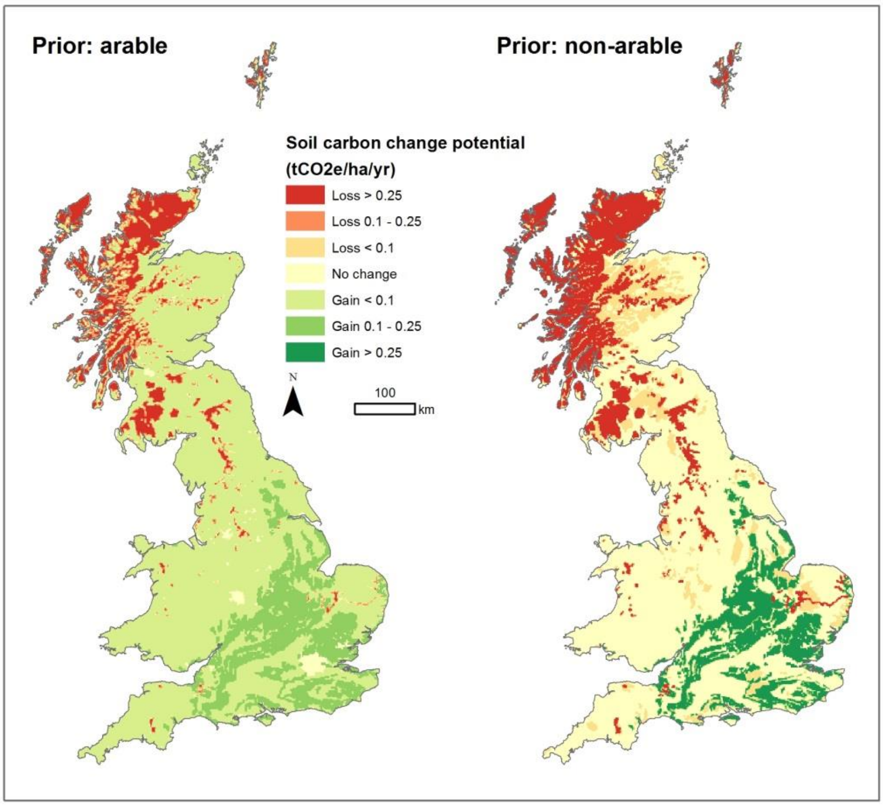

Figure 3.39. Potential changes in soil carbon storage induced by afforestation. Potential changes in soil carbon storage induced by afforestation, taken as the average change per soil type (including sand, loam, clay, and organic) across both SS and POK for all yields.

The relative size of values under the maxMV and maxSV decision making strategies is detailed in **Tables 3.37** and **3.38** , mapped in **Figure 3.40** and graphed in **Figure 3.41** (note the very different scales used on the two panels given in the latter figure; the MV values are simply too small to register on a graph of the SV values). Taken together these results not only confirm the very poor value for money (indeed losses) induced by adopting the MV approach to planting new woodlands, but also the vital importance of including non-market values within our assessments. These overwhelm the size of the market values confirming what has been known for a long time; that forestry is essentially a public good rather than a private investment opportunity[34].

[34] This assumes that the historic tax-haven status of forestry as a way of avoiding income tax is not resurrected.

Table 3.36. The social value of new forests (£ million per annum) located according in order to maximise the market value of afforestation (agricultural plus timber values) only. Planting using Pedunculate Oak.

Annuity Values: Difference from BAU (in 2013 £'s) maxMV POK					
		GB	**England**	**Scotland**	**Wales**
Market Values	Agricultural Profits	-£71,840,422	-£31,662,357	-£1,688,067	-£38,489,998
	Timber Profits	-£62,405,227	-£20,907,001	-£20,966,024	-£20,532,202
	Total Market Value	-£134,245,649	-£52,569,357	-£22,654,091	-£59,022,200
Non-Market Values	Agricultural Carbon	£5,705,719	£2,065,195	£353,488	£3,287,036
	Forest Carbon	£5,160,790	£1,444,746	£1,224,895	£2,491,149
	Recreation	£2,031,942	£522,000	£12,058	£1,497,884
	SPS (transfer to farmers)	£55,560,616	£18,521,317	£18,521,462	£18,517,837
	Total Non-Market Value	£68,459,067	£22,553,258	£20,111,902	£25,793,907
Social Value	**Total Social Value**	-£65,786,582	-£30,016,099	-£2,542,189	-£33,228,294

Although GHG values play no part in determining planting under the maxMV approach, in calculating GHG values for the above assessment we use the lowest carbon price (C1). We discuss the impact of varying the carbon price subsequently.

Table 3.37. The social value of new forests (£ million per annum) located according in order to maximise the social value of afforestation (agricultural, timber, GHG and recreation values). Planting using Pedunculate Oak; GHG valued using carbon price C1 (lowest)

Annuity Values: Difference from BAU (in 2013 £'s) maxSV POK C1					
		GB	**England**	**Scotland**	**Wales**
Market Values	Agricultural Profits	-£226,343,767	-£87,102,808	-£62,731,327	-£76,509,632
	Timber Profits	-£61,047,422	-£20,519,393	-£20,272,634	-£20,255,395
	Total Market Value	-£287,391,189	-£107,622,201	-£83,003,961	-£96,765,027
Non-Market Values	Agricultural Carbon	£11,959,773	£3,099,222	£3,508,396	£5,352,155
	Forest Carbon	£8,810,168	£3,070,040	£2,745,912	£2,994,216
	Recreation	£755,758,469	£543,398,128	£121,352,158	£91,008,184
	SPS (transfer to farmers)	£56,856,956	£19,290,528	£18,900,709	£18,665,719
	Total Non-Market Value	£833,385,367	£568,857,919	£146,507,175	£118,020,274
Social Value	**Total Social Value**	£545,994,178	£461,235,718	£63,503,214	£21,255,247

GHG values are considered in determining planting under the maxSV approach. In the above assessment (and in the calculation of social values) we use the lowest carbon price (C1). We discuss the impact of varying the carbon price subsequently.

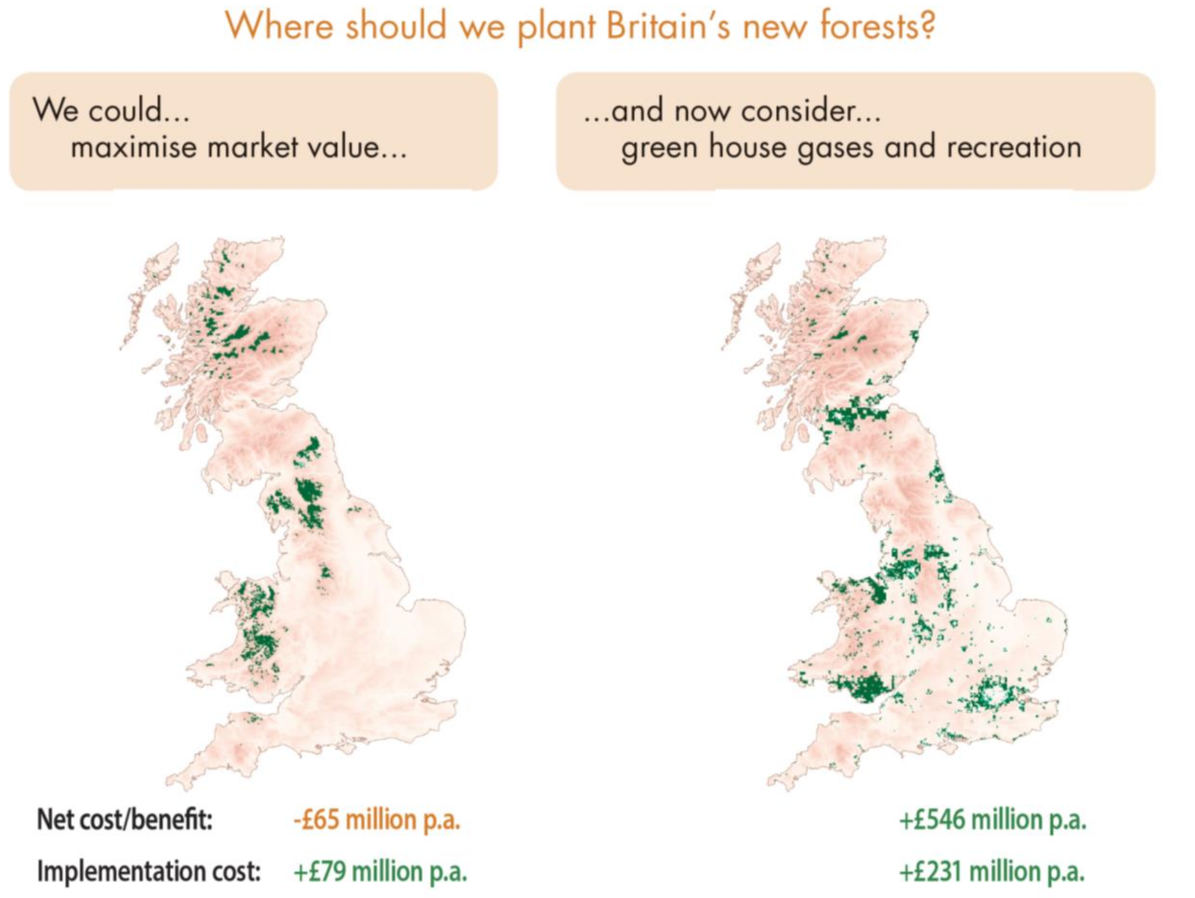

Figure 3.40. A comparison of the costs and benefits of different forest planting schemes showing the effects on where woodland would be planted, and the relative benefits and implementation costs incurred, when considering only the market values of timber versus a wider set of ecosystem services.

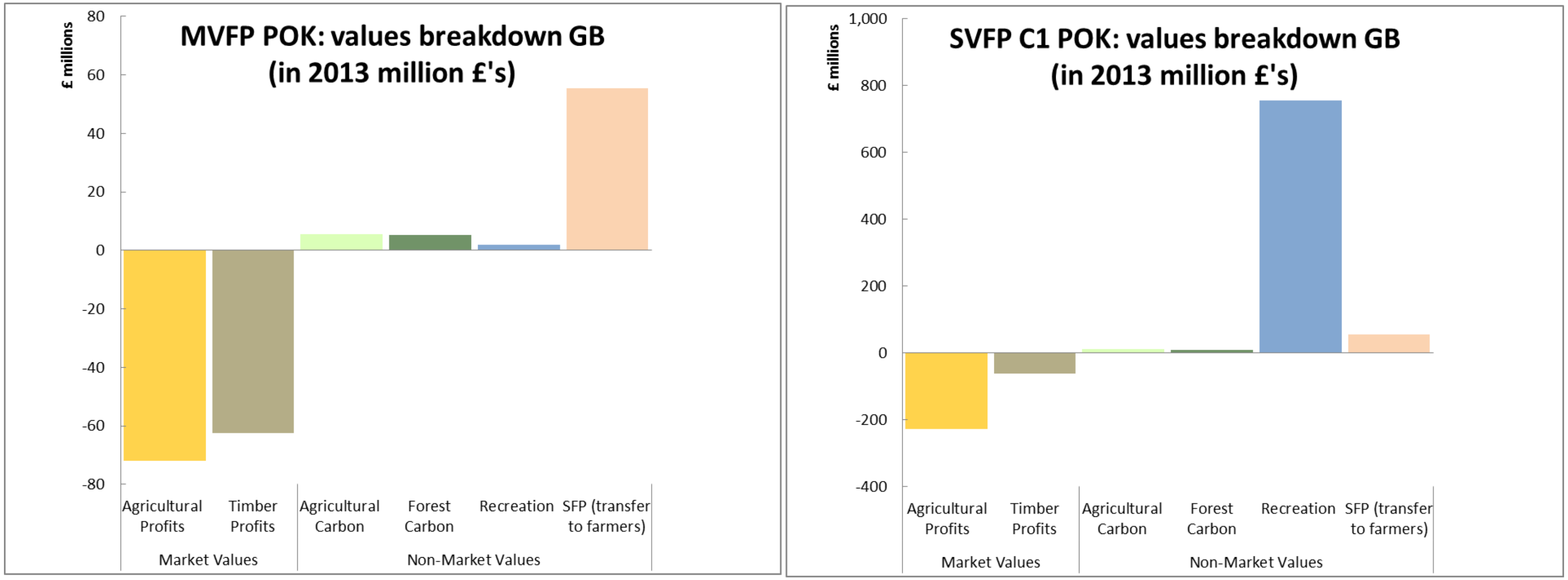

Figure 3.41. The social value of new forests (£ million per annum) located according to two alternative decision rules; social values calculated using H.M. Treasury cost-benefit rules and lowest carbon price (C1). Figure shows the social value of 750,000 hectares of new forest, divided evenly between England, Scotland and Wales and planted between 2014-63 using two alternative planting strategies: (i) to maximise market values (ii) to maximise social values. Results assume planting is with broadleaves (Pedunculate Oak). Social valuations use the lowest (C1) carbon price for assessing GHG values.

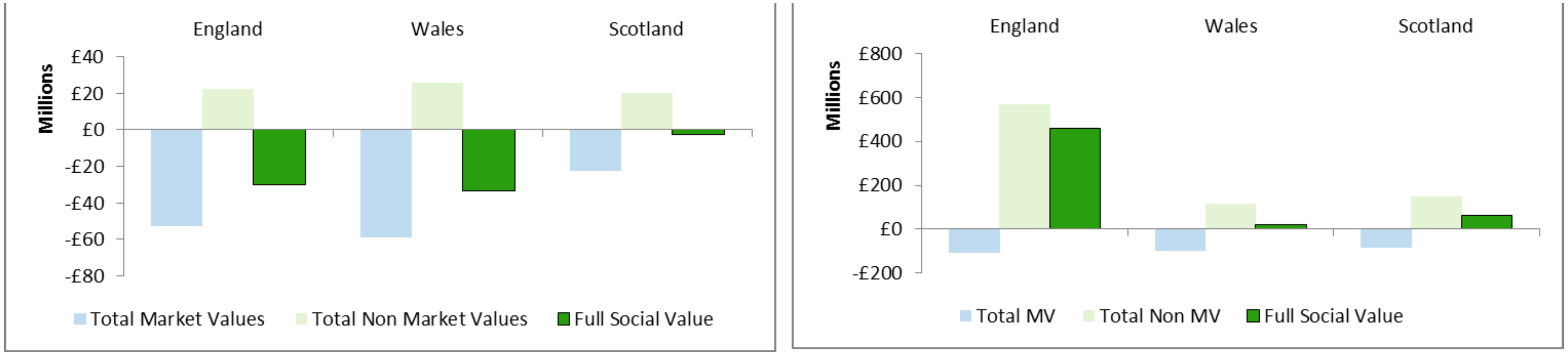

Figure 3.42. The social value of new forests (£ million per annum) located according to two alternative decision rules: (left hand panel) only considering market values; (right hand panel) considering market and non-market values. Figure shows the social value of 750,000 hectares of new forest, divided evenly between England, Scotland and Wales and planted between 2014-63 using two alternative planting strategies: (i) to maximise market values (ii) to maximise social values. Results assume planting is with broadleaves (Pedunculate Oak). Social valuations use the lowest (C1) carbon price for assessing GHG values.

Figure 3.31 graphs the market, non-market and aggregate social values at a country level for afforestation guided by the maxMV (left hand panel) and maxSV (right hand panel) decisions. Interestingly this highlights the very substantial losses to Welsh farmers resulting from decision making guided by market values alone.

Examining **Tables 3.37** and **3.38** and **Figures 3.41** and **3.42** we can see that the non-market value of recreation benefits generated by these new woodlands massively outweighs the opportunity cost of forgone agricultural output. As we have stressed elsewhere (Bateman *et al*., 2013) such a result in no way implies that the total value of recreation exceeds that of food production. Even at its full extent the proposed increase in woodland would only occupy just over 3% of Great Britain[35]. Such an extent does not seriously compromise the country's ability to produce food. Furthermore by targeting areas of particularly high recreational or GHG values we restrict forestry to areas where its marginal value exceed (by a substantial extent) that of agriculture.

The agricultural values reported in the above tables include subsidy payments from taxpayers to farmers. Therefore, in calculating the social value of any move out of agriculture and into forestry we need to credit back to taxpayers the value of subsidy savings, a transfer credit recorded in the lower half of **Tables 3.37** and **3.38**. The financial data used to value agricultural output is obtained from the Farm Business Survey (http://www.farmbusinesssurvey.co.uk/index.html) via the UK Data Archive (http://www.data-archive.ac.uk/) and includes subsidies such as the Single Farm Payment and its successor the Single Payment Scheme (SPS). Annual SPS rates currently range from £258.50/ha for the majority of the UK that lies outside Severely Disadvantaged Area (SDA) designations, falling to £207.72/ha for SDA farms and £36.29/ha for the relatively small areas classified as SDA Moorland. In the present analysis we use an average value of £210/ha (a mean which is confirmed by Savills, 2013). A useful extension to this analysis would be to incorporate digital maps of the SDA and SDA Moorland boundaries to adjust SPS levels to those specific to each area. However, as the average value is representative for the vast majority of land such an extension is unlikely to substantially alter results.

The tables also confirm our expectation that, using the standard Treasury discount rate (3.5%)[36] forestry accrues a negative value due to the long-delayed nature of felling benefits compared to the immediate costs of planting. However, the results in **Tables 3.37** and **3.38** are dominated by recreation values. In part this is due to the use of the lowest carbon price (C1) and so we now examine the consequences of switching to our higher price (C3).

Figure 3.43 illustrates the impact of varying the carbon price upon the optimal social value location for planting. Here the left hand panel repeats the planting map derived when we maximise social value defined as agricultural, timber, GHG and recreation values but using the lowest carbon price (C1); this then is a repeat of the final (lower right) map of **Figure 3.38**. On the right hand side of **Figure 3.43** we see the change in planting location when we retain the same maxSV decision rule, but apply the higher C3 carbon price to the GHG consequences of that planting. As can be seen the effect of this switch is substantial if not dramatic. Within England the very high population of its

[35] The area of England is 13,039,500 ha, Scotland measures 7,877,200 ha and Wales 2,077,900 ha making a total for Great Britain of 22,994,600 ha. This suggests that new afforestation of 750,000 hectares will take some 3.2% of the total area of Britain. If, as hypothesised in the present study all of that planting occurs on the 75% of the land area which is used for farming (ONS, 2011) then this would represent a reduction of about 4.3% of agricultural land.

[36] Note that it is arguably defensible to apply the Treasury long term declining discount rate (H.M. Treasury, 2003). However we note that this would imply an inconsistent variance of discount rates across differing value streams (as agricultural values would be discounted at the standard constant rate). This would produce a relative inflation of forestry values which we have resisted in the present analysis.

major cities means that recreation values overpower much of the additional value of GHG reductions and planting is relatively stable although the high livestocking areas of the north-west do attract a little more afforestation. The effect of the higher carbon price is more evident in Scotland where the higher value of displacing livestock emissions in the west attracts some forestry in that direction, somewhat reducing the recreational forest concentration around cities. However, it is in Wales where the most marked changes occur. The higher carbon price overpowers the recreational value of planting in the north east (a reflection that the predominantly English populations benefiting from that woodland are some distance from the Welsh border meaning that recreational values are considerably lower than for forests fringing their own cities). Instead this area moves sharply westwards to the coastal areas where it displaces livestock GHG emissions. A similar pattern occurs in the south of the country as the previous focus around Cardiff is now somewhat reduced (although far from removed) and more planting occurs to the west, again displacing livestock GHG emissions.

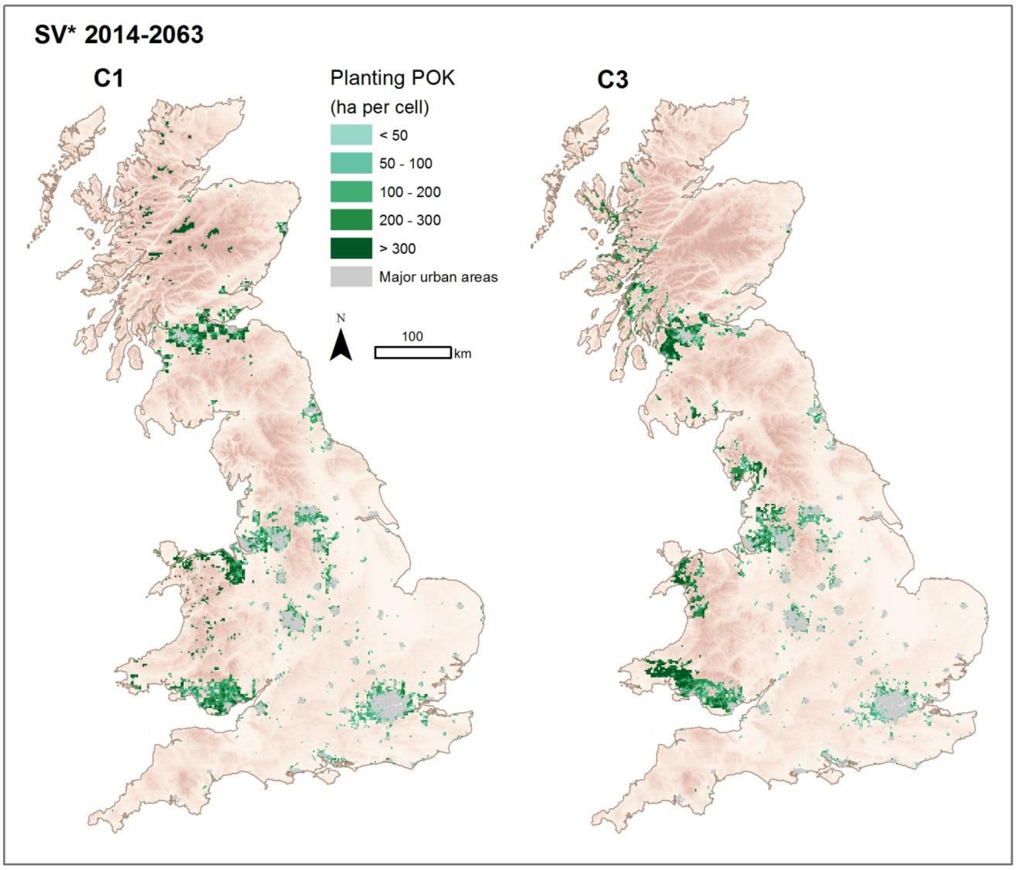

Figure 3.43. The impact of varying the carbon price upon the optimal social value location for planting (lowest carbon price on left; highest on right). Figure shows the optimal locations for planting forestry to maximise social value calculated using either the lowest (C1, left hand side) or the highest (C3, right hand side) carbon price.

The contrast with the social value of the maxSV strategy calculated using the two carbon prices is further detailed by comparing **Table 3.38** (which uses the lowest carbon price; C1) with **Table 3.39** (which uses the highest price; C3). Note that recreation values are still larger than those associated with GHG reductions, but now the difference is much smaller. Not surprisingly, overall national values are maximised when the higher carbon value is used.

Table 3.38. The social value of new forests (£ million per annum) located according in order to maximise the social value of afforestation (agricultural, timber, GHG and recreation values). Planting using Pedunculate Oak; GHG valued using carbon price C3 (highest).

Annuity Values: Difference from BAU (in 2013 £'s) maxSV POK C3					
		GB	**England**	**Scotland**	**Wales**
Market Values	Agricultural Profits	-£310,274,286	-£94,051,698	-£103,003,496	-£113,219,093
	Timber Profits	-£62,708,811	-£20,597,872	-£20,936,162	-£21,174,777
	Total Market Value	-£372,983,097	-£114,649,570	-£123,939,658	-£134,393,869
Non-Market Values	Agricultural Carbon	£331,295,150	£68,410,357	£113,462,461	£149,422,333
	Forest Carbon	£144,975,544	£49,850,253	£45,433,319	£49,691,972
	Recreation	£710,273,861	£528,173,024	£104,184,043	£77,916,795
	SPS (transfer to farmers)	£57,868,720	£19,290,452	£19,288,867	£19,289,401
	Total Non-Market Value	£1,244,413,275	£665,724,086	£282,368,689	£296,320,500
Social Value	**Total Social Value**	£871,430,178	£551,074,516	£158,429,031	£161,926,631

GHG values are considered in determining planting under the maxSV approach. In the above assessment (and in the calculation of social values) we use the highest carbon price (C3).

Figure 3.45 graphs out the substantial increases in national level social values under the three carbon prices studies. Note that the early convergence of the C2 and C3 price streams makes these two overall values very similar.

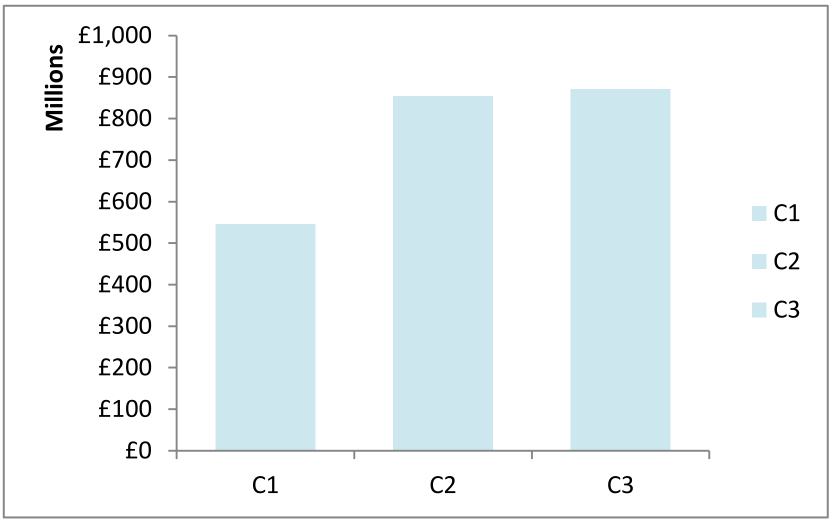

Figure 3.44. The impact of varying the carbon price upon the social value of afforestation (locations determined through the maxSV strategy).

Figure 3.**45** below shows the effect of considering of different carbon prices under the optimisation rule, aiming to maximise Full Social Value.

A final analysis is to examine the effect of switching the species used for afforestation from our representative broadleaf (Pedunculate Oak) to conifer (Sitka spruce). **Figure 3.45** illustrates resultant planting strategies while **Figure 3.46** shows effects on the size of social benefits generated. As can be seen, switching species makes very little difference to planting locations or overall social benefits although the shorter rotations of conifers do given them a marginal edge in terms of their economic value. That said the potential for wider effects (say beyond the biodiversity impacts on birds and the aesthetics of woodlands) may well mitigate in favour of broadleaves given the marginal difference in these values.

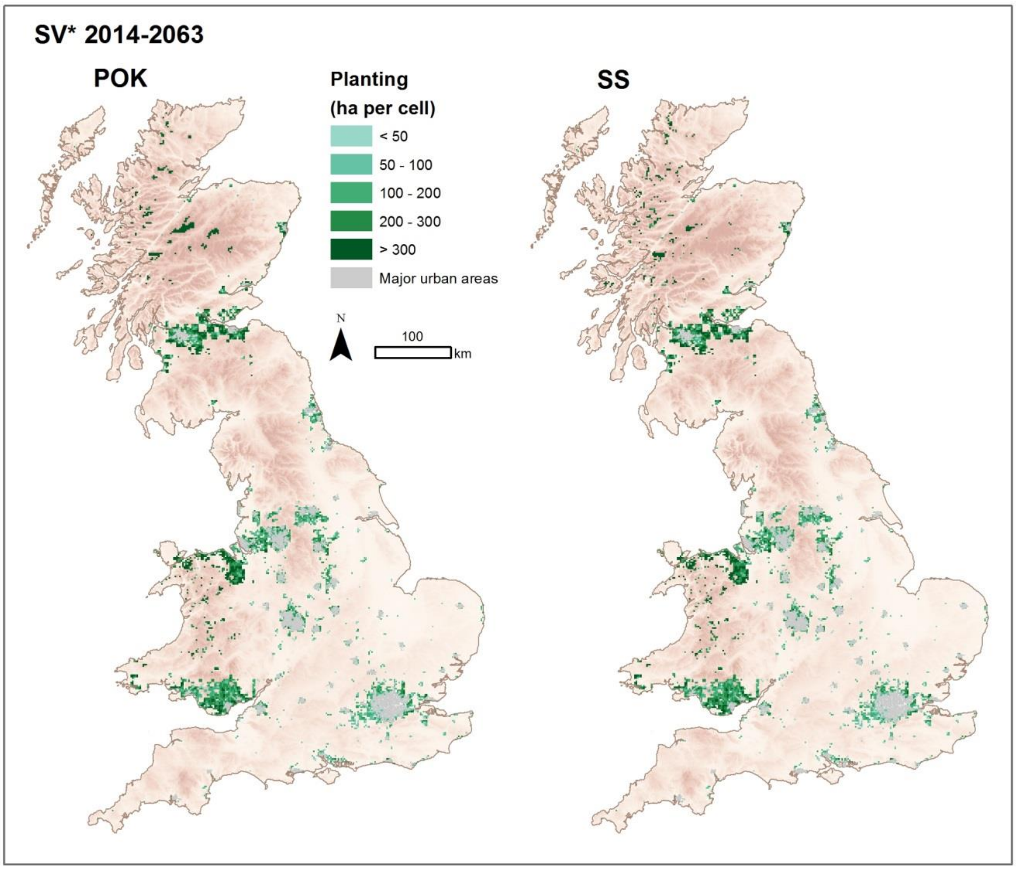

Figure 3.45. Variation in social value optimising locations of forestry across species: Pedunculate Oak (left hand map) and Sitka spruce (right hand map).

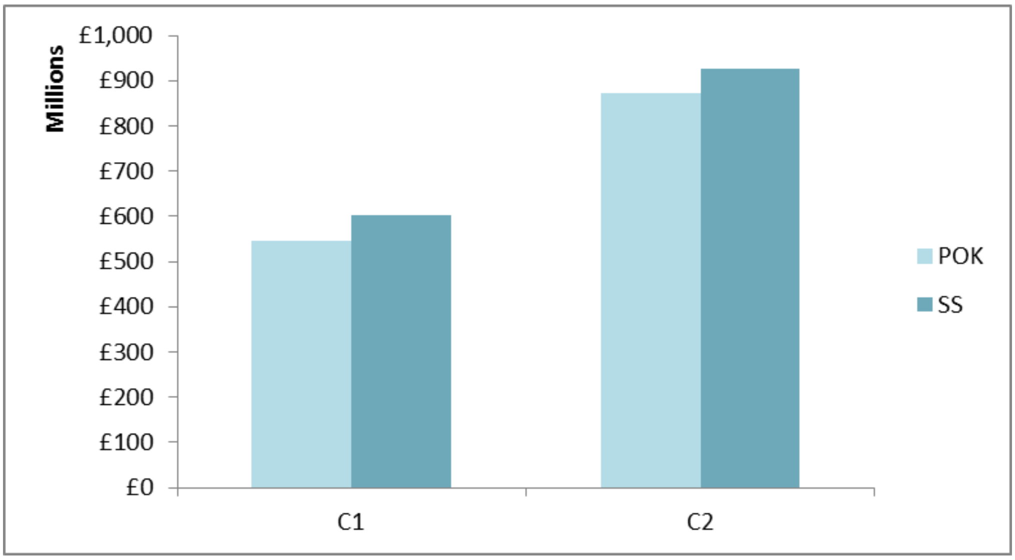

Figure 3.46. Variation in social value optimising locations of forestry across species: Pedunculate Oak (POK) and Sitka spruce (SS).

Changes in water quality

This section describes how afforestation affects water quality in river bodies under various optimisation rules and carbon prices.

Table 3.40 shows predicted changes in GQA nitrate concentration categories (relative to the baseline) if an afforestation policy plants Pedunculate oak (5,000ha yr^{-1} over the full assessment period in each of Scotland, England, and Wales) and optimisation covers only market values. The results show that planting improves water quality in all cases. This analysis adjusts for the underlying changes in water quality reflected in the BAU. Therefore, by contrast, the planting of trees uniformly improves water quality, a result which is repeated and intensified in subsequent analyses.

Table 3.40. Changes in nitrate class relative to BAU: planting Pedunculate oak and optimising market values only.

	Nitrate (N) class in 2064 under maxMV POK						
	GQA grade	1	2	3	4	5	6
N class in 2064 under BAU	mg NO_3/l	<5	5 to 10	10 to 20	20 to 30	30 to 40	>40 mg
	1	0	0	0	0	0	0
	2	9	0	0	0	0	0
	3	0	5	0	0	0	0
	4	0	0	13	0	0	0
	5	0	0	0	13	0	0
	6	0	0	0	0	8	0
Total	48						
Total	0						

Table shows changes in General Quality Assessment (GQA) categories as a result of changing nitrate concentrations in river water bodies if Pedunculate oak is planted and optimisation covers only market values. Planting improves water quality in all cases.

Table 3.41shows predicted changes in GQA nitrate concentration categories (relative to the baseline) under the same conditions (i.e. afforestation policy plants 5,000ha of Pedunculate oak in each of Scotland, England, and Wales each year over the full assessment period), however optimisation now covers social values.

Furthermore the three panels of this table vary carbon price in the targeting process and examine consequences for water quality. In comparison to the market value targeting of forestry detailed in **Table 3.40**, a shift to maximising overall social value further increases water quality. This improved if even further enhanced when we apply our higher carbon values (as they converge we find little difference in the effects of using C2 or C3 upon water quality; both lead to substantial improvements).

Taken together these results show that, while a lack of robust values means that we do not at present include water quality within our afforestation targeting strategies, nevertheless planting new woodlands have a consistently positive effect on water quality, an effect which appears positively correlated to the value accorded to the other non-market benefits of forestry.

Table 3.40 Changes in nitrate class relative to BAU: planting Pedunculate oak and optimising social values with various GHG emissions values.

Panel A: Lower bound estimate for value of GHG emissions (C1)

	Nitrate (N) class in 2064 under maxSV POK C1						
	GQA grade	1	2	3	4	5	6
N class in 2064 under BAU	mg NO_3/l	<5	5 to 10	10 to 20	20 to 30	30 to 40	>40 mg
	1	0	0	0	0	0	0
	2	11	0	0	0	0	0
	3	0	21	0	0	0	0
	4	0	0	18	0	0	0
	5	0	0	0	26	0	0
	6	0	0	0	0	11	0
Total	87						
Total	0						

Panel B: Central estimate for value of GHG emissions (C2)

	Nitrate (N) class in 2064 under maxSV POK C2						
	GQA grade	1	2	3	4	5	6
N class in 2064 under BAU	mg NO_3/l	<5	5 to 10	10 to 20	20 to 30	30 to 40	>40 mg
	1	0	0	0	0	0	0
	2	48	0	0	0	0	0
	3	0	28	0	0	0	0
	4	0	0	16	0	0	0
	5	0	0	0	18	0	0
	6	0	0	0	0	7	0
Total	117						
Total	0						

Panel C: Upper bound estimate for value of GHG emissions (C3)

	Class in 2064 under maxSV POK C3						
	GQA grade	1	2	3	4	5	6
Class in 2064 under BAU	mg NO_3/l	<5	5 to 10	10 to 20	20 to 30	30 to 40	>40 mg
	1	0	0	0	0	0	0
	2	48	0	0	0	0	0
	3	0	25	0	0	0	0
	4	0	0	15	0	0	0
	5	0	0	0	18	0	0
	6	0	0	0	0	7	0
Total	113						
Total	0						

Table shows changes in General Quality Assessment (GQA) categories as a result of changing nitrate concentrations in river water bodies if Pedunculate oak is planted and optimisation covers social values (using increasing estimates of the value of GHG flows). Planting improves water quality in all cases.

Impacts on biodiversity

The land use changes considered in this report, driven by climate change, afforestation policies and various optimisation objectives, have important impacts on biodiversity in the UK. This section presents results on how these drivers affect bird biodiversity (measured by Simpson's index of bird diversity, see Section 3.11) for various categories of birdlife: (i) all species; (ii) farmland birds (of particular interest given declines in this group); (iii) woodland and upland habitat birds; (iv) birds on the red and amber lists of conservation concern.

Table 3.42 measures of the impact of afforestation and climate change upon bird biodiversity (relative to the BAU baseline) over the period 2014-63, under various optimisation rules, tree species and carbon prices. Results are presented by bird group, with impacts reported over all of Great Britain and for changes in forests only. Positive (negative) values indicate increases (decreases) in diversity.

Table 3.42. Changes in bird biodiversity (measured by Simpson's index) relative to the baseline under various optimisation rules, tree species and carbon prices.

			Bird groups							
			All		Wood		Farm		Red/Amber	
		Area considered	all GB	forest only	all GB	forest only	all GB	forest only	all GB	forest only
Optimisation rule	Tree Species	Carbon price								
maxMV	n/a	n/a	0.067	1.446	0.104	0.323	0.031	-0.002	0.016	-0.001
maxSV	POK	C1 (low)	-0.087	0.456	0.050	0.662	-0.098	-0.794	-0.042	-0.263
maxSV	POK	C3 (high)	-0.148	-0.004	0.033	0.269	-0.119	-1.517	-0.062	-0.781
maxSV	SS	C3 (high)	-0.033	-0.002	0.090	1.004	-0.047	-0.587	-0.058	-0.738

Table measures changes (relative to BAU baseline) in bird biodiversity for 2014-63 (using Simpson's index of bird diversity), by bird group and area considered (all of Great Britain or forests only) under various optimisation rules, tree species, and carbon prices. Positive (negative) values indicate increases (decreases) in diversity.

All mean changes are significantly different from zero.
n= 57,230 for all GB level analyses (the number of 2km x 2km squares in Great Britain)
n= 4,483 (approx.) for all forest level analyses (the total number of 2km x 2km afforested under each scenario squares in Great Britain)
POK = Pedunculate Oak
SS = Sitka spruce

Table 3.42 adjusts for the climate change captured in the BAU scenario. These results therefore reveal the net impact of the various forestry planting options upon our biodiversity measure. Interestingly, almost all of the options where planting is guided by market forces alone result in gains in biodiversity. Given that we know that the MV optimisation objective mainly displaces agriculture in upland areas, this suggests that woodland is synonymous with higher biodiversity than currently characterises such areas. These gains are, not surprisingly, largest for the measure focussing upon woodland birds which gain most from afforestation.

The two middle rows present biodiversity index implications of planting Pedunculate oak trees so as to maximise net social benefits, taking into account market (agricultural and timber outputs) and the lower and upper bound estimates of greenhouse gas values. Here, the impacts on woodland birds are again positive, although when considered across all of Great Britain, they are now somewhat smaller than under the MV guided planting regimes. This is because incorporating GHG values into the optimisation drives afforestation away from high carbon soils. The second row shows impacts when planting is guided by social values using a low carbon price, and shows a significant gain for woodlands birds in forests when compared to the MV regime (row 1), but losses in farmland and red/amber species become larger. In the third row, the higher carbon price reduces the gains in woodland species diversity, though this is still positive, and losses in all other species are greater still.

Figure 3.**47** shows how different planting patterns resulting from incorporating different carbon values into the optimisation routine affect bird biodiversity. The left image is identical to **Figure** 3.36and is reproduced here simply for reference. The two right hand side figures show changes in Simpson's bird diversity index when POK is planted according to social value optimisation using a low (C1) and high (C3) carbon price. The low carbon value shows gains in diversity in the Scottish highlands, but when carbon emissions from disturbing organic soils are valued at a higher rate (as in the right most map, C3), planting, and therefore bird diversity gains are driven away from such high carbon soils.

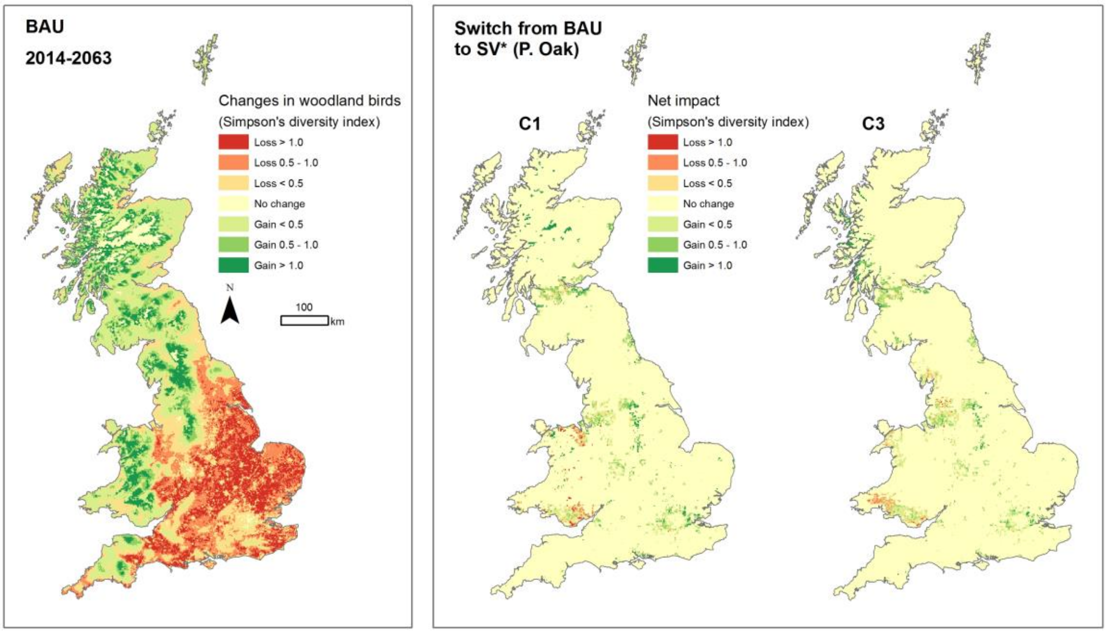

Figure 3.47. Impact of planting (POK) and carbon prices on bird biodiversity (measured by Simpson's index) relative to the baseline. Changes in bird biodiversity when Pedunculate oak is planted according to maximised social values under low (C1) and high (C3) carbon prices.

Returning now to consider **Table 3.42**, the final row shows impacts on bird diversity when Sitka spruce (rather than Pedunculate oak) is planted in accordance with maximising net social benefits using the high carbon price. Here again the impact on woodlands birds is positive, and is negative for all other bird groups (although these losses are generally smaller than for POK planting). Finally, it is worth noting that although planting benefits woodland birds in all cases, the negative impacts on farmland and Red/Amber list birds dominate when social values are considered across all of Great Britain.

These results indicate that the spatial interdependencies between different non-market externalities can be complex. We know that, in contrast to the maxMV targeting, the maxSV approach moves the location of woodlands away from remote upland sites and onto pastoral farmland, avoiding depletion of organic soil carbon and displacing the high greenhouse gas emissions of dairy and beef livestock systems. However, such locations are, at present, areas of high biodiversity and hence it is not particularly surprising to find that we now find relatively smaller gains in woodland birds here than in the upland locations favoured by the MV planting regime. Indeed it is noticeable that all the other bird biodiversity measures actually decline when we shift from MV to SVNR directed planting, due to this displacement of more biodiversity rich ecosystems. Indeed, analysis of tree species effects in **Table 3.42** shows that this displacement of prior biodiversity is highest when we plant using POK rather than SS, as the shorter rotation periods and higher timber returns of conifers are marginally more likely to displace higher intensity livestock areas (with lower levels of prior biodiversity) than are broadleaves.

Taken together, these results show that we would need to incorporate biodiversity directly into the planting targeting procedure (as per our 'Proof of Concept' application in Section 3.3) if we wish to deliver on official objectives to ensure no net loss (or even overall gains) in biodiversity. Subsequent analysis will use the biodiversity constraint approach of our earlier application (and also Bateman *et al*., 2013) to achieve this integration of biodiversity into the determination of planting locations.

The following section concludes our study and draws together key messages.

3.12.6 Appendix 1: Calculating the benefits and costs to make a planting decision – Annuity rules

In this Appendix we discuss how to translate a stream of values into the future into an annuity equivalent fixed payment. Initially we adopt the standard approach of considering a stream of annuity payments which are paid each year from tomorrow for a given number of years. Subsequently we show how to convert these into an annuity equivalent stream of fixed payments starting in the current period.

A glossary of notation is provided at the end of this Appendix.

3.12.6.1 Agricultural Income

The following discussion considers the process for a single cell (hence suppressing cell dependence) and only deals explicitly in the features of the cell (esc score (the growth rate of a tree, commonly referred to as its yield class and measured in m^3/ha/yr), soil, agricultural gross margin) and the year. In a given year, denoted *y*, the agricultural income of a cell is to be calculated as an annuity value representing the annuity equivalent of the income from agriculture over the next 50 years (to be programmed as a variable which can be altered).

Let us denote the period of time into the future over which the annuity is to be calculated as F_{AG}.

Let the agricultural revenue associated with the cell in year *t* be represented in functional notation by the function $R_{AG}(t)$.

The net present value of agricultural income for the cell in year y is calculated as,

$$NPV_{AGR}(y) = \sum_{t=0}^{F_{AG}} \frac{R_{AG}(y+t)}{(1+\delta)^t}$$

Where δ is the discount rate (3.5% in TIM but coded as a variable to allow for discount rate sensitivity analysis if required). Note that this summation includes the year y (t=0) and therefore covers $F_{AG} + 1$ years, this can be seen mathematically since,

$$\sum_{t=0}^{F_{AG}} 1 = F_{AG} + 1$$

To convert this to an annuity in year y we use the following equation,

$$A_{AGR}(y) = NPV_{AGR}(y) * \left(\frac{\delta}{1-(1+\delta)^{-(F_{AG}+1)}}\right)$$

3.12.6.2 Carbon from agriculture

The net present value of carbon emissions (or CO_2 equivalents) is also calculated as an annuity over the same period as agricultural incomes, $(F_{AG} + 1)$ years. The value of carbon emissions (measured in pounds per tonnes of CO_2 equivalents, £/t$CO_{2)}$ depends on the price of carbon at the time of emission, or sequestration, $P_C(t,i)$, where t is the year and i is an indicator relating to the specific carbon price series; we calculate the annuity using three carbon price series:

$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013)$. Let the emitted carbon from agriculture at time *t* be denoted as $C_{AG}(t)$.

The net present value of carbon emissions from agriculture for the cell in year *y* evaluated using carbon price series i is calculated as,

$$NPV_{AGC}(y,i) = \sum_{t=0}^{F_{AG}} \frac{C_{AG}(y+t) * P_C(y+t,i)}{(1+\delta)^t}$$

Again, to compute the annuity equivalent we use the formula,

$$A_{AGC}(y,i) = NPV_{AGC}(y,i) * \left(\frac{\delta}{1-(1+\delta)^{-(F_{AG}+1)}}\right)$$

3.12.6.3 Timber income and fixed costs

Unlike agriculture, timber income is a flow of differing values occurring at various times over the rotation period of the woodland. To deal with this we consider one cohort of trees planted in year *y* and calculate the annuity values associated with this cohort.

Firstly, since timber revenues are replicable across rotations we can consider one rotation length when calculating the annuity equivalent of timber incomes. Let us denote the yield class (*esc*) and species (*sp*) specific rotation length as $F(esc, sp)$.

Let the timber (*T*) revenue (i.e. R_T) equal the timber income minus associated costs such that at time *t* we have

$$R_T(t) = Q_T(t) * P_T(t) - KP(t) - KC(t).$$

Where $Q_T(t)$ is the quantity of timber harvested at time *t*, $P_T(t)$ is the price of timber harvested at time *t* (in real terms) and *KP(t)* are the one-off costs of land conversion and preparation occurring in the first year of the first rotation only (specifically these are the costs of 'mounding' and 'screefing' operations only) and *KC(t)* are other costs which are repeated for every rotation.

Assuming that the land conversion and preparation activities occur in the same year as planting then the rotation begins in year *y* and ends in year $(y + F(esc, sp) - 1)$. In this case, the net present value of timber revenue for the cell is calculated as,

$$NPV_{TR}(y, esc, sp) = \sum_{t=0}^{F(esc,sp)-1} \frac{R_T(y+t)}{(1+\delta)^t}$$

Note that this summation covers $F(esc, sp)$ years since $\sum_{t=0}^{F(esc,sp)-1} 1 = F(esc, sp)$.To compute the annuity equivalent we use the formula,

$$A_{TR}(y) = NPV_{TR}(y, esc, sp) * \left(\frac{\delta}{1-(1+\delta)^{-(F(esc,sp))}}\right)$$

Where we now have $F(esc, sp)$ rather than the $(F_{AG} + 1)$ period relevant to the agricultural revenue and carbon calculation.

3.12.6.4 Woodland Carbon: Trees, Products and Deadwood

We begin by summing the carbon quantities in timber and products (including deadwood) together into a total quantity $C_{TP}(t, esc, sp)$ standing for carbon in livewood, deadwood and timber products at time *t* from woodland species *sp* in a cell with a yield class equal to *esc*. As before, the value of carbon depends on the price of carbon at the time of emission, or sequestration, $P_C(t, i)$, where i is

an indicator relating to the specific carbon price series; we calculate the annuity using three carbon price series:
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013).$

Timber revenues are received over the *F*(*esc,sp*) years following planting. However, Forestry Commission estimates show that the carbon stored in livewood over that period takes a further rotation length to be re-emitted back to the atmosphere. Therefore the carbon storage and emission profile associated with a given cohort of trees is distributed over a two rotation period, i.e. over (2**F*(*esc,sp*)) starting in the current year. To make revenues and costs comparable we calculate the annuity equivalent of the carbon cost over the period *y* to *y* + *F*(*esc,sp*) - 1.

The net present value of total carbon from timber products in year *y* evaluated using carbon price series i is,

$$NPV_{CTP}(y, esc, sp, i) = \sum_{t=0}^{2*F(esc,sp)-1} \frac{C_{TP}(y+t, esc, sp) * P_C(y+t, i)}{(1+\delta)^t}$$

And the annuity equivalent over the period $y: y + F(esc, sp)$ is given by,

$$A_{CTP}(y, esc, sp, i) = NPV_{CTP}(y, esc, sp, i) * \left(\frac{\delta}{1-(1+\delta)^{-(F(esc,sp))}}\right)$$

3.12.6.5 Woodland Carbon: Soil

Soil carbon is the most complex of the carbon issues to deal with since the marginal amount of carbon stored in or released from the soil depends not only upon the *esc* and species type but also on the current rotation of planting, i.e. whether the cell was planted previously. To deal with this issue we calculate the net present value of carbon over two rotations (2**F*(*esc,sp*)). Let us denote the marginal quantity of carbon stored in the soil (*s*) in year *t* by woodland species *sp* on a cell with a yield class equal to *esc* and soil type denoted s as $C_S(t, esc, sp, s)$. As above, the value of carbon depends on the price of carbon at the time of emission, or sequestration, $P_C(t, i)$, where i is an indicator relating to the specific carbon price series; we calculate the annuity using three carbon price series:
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013).$

The net present value of total carbon from timber products in year y evaluated using carbon price series i is,

$$NPV_{CS}(y, esc, sp, s, i) = \sum_{t=0}^{2*F(esc,sp)-1} \frac{C_S(y+t, esc, sp, s) * P_C(Y+t, i)}{(1+\delta)^t}$$

The annuity equivalent of this is calculated as,

$$A_{CS}(y, esc, sp, s, i) = NPV_{CS}(y, esc, sp, s, i) * \left(\frac{\delta}{1-(1+\delta)^{-(2*F(esc,sp))}}\right)$$

Since this only depends on (*y, esc, sp, s, i*) it can be evaluated once within each year and assigned to each cell according to its *esc* and soil characteristics for a given species, *sp*.

3.12.6.6 Annuity payments starting today

The standard calculation of an annuity relates the net present value in the current year (y) to a series of future payments,

$$NPV(y) = \sum_{t=1}^{N} \frac{A}{(1+\delta)^t}$$

For example, consider a series of £100 payments over the next 50 years starting from tomorrow. This has a net present value of,

$$NPV(y) = \sum_{t=1}^{N} \frac{100}{(1+\delta)^t} = 2345.46$$

To translate this back to an annuity value of payments over the next N periods not including in the year y we use the formula,

$$A = NPV(y) * \left(\frac{\delta}{1-(1+\delta)^{-N}}\right) = 100$$

However, the net present value of these payments when an additional payment is made in the current year is different,

$$NPV_2(y) = A + \sum_{t=1}^{N} \frac{A}{(1+\delta)^t}$$

The annuity formula will tell you the annuity payment to be made over the next $N+1$ years, starting from tomorrow,

$$A_2 = NPV_2(y) * \left(\frac{\delta}{1-(1+\delta)^{-N+1}}\right)$$

Such that,

$$NPV_2(y) = \sum_{t=1}^{N+1} \frac{A_2}{(1+\delta)^t}$$

Technically this is not exactly what we want if we are interested in payments from today (year y) to year $y+N$. This requires a simple scalar multiplication of the annuity value,

$$A_3 = \frac{A_2}{1+\delta}$$

Such that,

$$NPV_2(y) = \sum_{t=0}^{N} \frac{A_3}{(1+\delta)^t} = \sum_{t=0}^{N} \frac{\frac{A_2}{1+\delta}}{(1+\delta)^t} = \sum_{t=1}^{N+1} \frac{A_2}{(1+\delta)^t}$$

Where $A_2$is the annuity equivalent of payments made from y+1 to y+N+1 and $A_3$is the annuity equivalent of payments made from today y to $y+N$. Since this multiplication occurs to all annuities it would not alter any planting decisions but we can include it for completeness.

Therefore, to convert the annuities calculated in sections 3.1-3.4 into annuity payments to be made starting in year y, we scale each annuity by the discount factor, that is,

$$A_{j,today} = \frac{A_j}{1+\delta}$$

Where $j = AGR, AGC, TR, CTP, CS$.

3.12.6.7 Changing ESC scores

The calculations given in sections 3.3 and 3.4 above are sufficient to calculate carbon associated with woodland provided that the *esc* score for a cell is unchanging. However, in the case where the *esc* score changes over time (as is an expected consequence of climate change) it is necessary to adjust the calculations. One way of doing this is to consider the *esc* score of a cell in any given year, t. Let **esc** be a vector of *esc* scores of length $(2 * F(esc(t), sp))$ for a given cell in year t for species sp.

First we calculate an average rotation length based on the average of the rotation lengths associated with the *esc* score of the cell in each of the $(F(esc(t), sp) + 1)$[37] years. Let $F(esc, sp)$ be the rotation length for species type *sp* and yield class *esc*. The average rotation period ($\bar{F}$) is calculated as,

$$\bar{F}(y, \boldsymbol{esc}, sp) = \frac{\sum_{t=0}^{F(esc(y),sp)-1} F(esc(y+t), sp)}{F(esc(y), sp)}$$

Rounded to the nearest integer.

The annuity value assigned to a cell in any given year, t, can be written as,

$$A_{j,today}(t, esc(t), sp, s, i)$$

For $j = TR, CTP, CS$ (soil only features in the annuity for soil carbon) and
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013)$.

These relate directly to the annuity values calculated above in sections 3.2, 3.3 and 3.4.

The net present value of each of these costs and benefits can then be calculated by constructing an "annuity of annuities" such that the net present value of a cell with changing *esc* scores, detailed in the vector **esc** when planted with species, *sp*, on soil type, *s* is,

$$\overline{NPV_j}(Y, \boldsymbol{esc}, sp, s) = \sum_{t=0}^{\bar{F}(Y,\boldsymbol{esc},sp)-1} \frac{A_{j,today}(y+t, esc(t), sp, s, i)}{(1+\delta)^t}$$

The equivalent annuity value with a variable *esc* score is then calculated as,

$$\overline{A_{J,}}(Y, \boldsymbol{esc}, sp, s, i) = \overline{NPV_i}(Y, \boldsymbol{esc}, sp, s, i) * \left(\frac{\delta}{1-(1+\delta)^{-(\bar{F}(Y,\boldsymbol{esc},sp))}}\right)$$

For $j = TR, CTP, CS$ and
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013)$.

Again to translate this into payments made from today we need to scale by the discount factor,

$$\bar{A}_{j,today}(Y, \boldsymbol{esc}, sp, s, i) = \frac{\overline{A_{J,}}(Y, \boldsymbol{esc}, sp, s, i)}{1+\delta}$$

For $j = TR, CTP, CS$ and

$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013)$.

[37] This could be chosen in many ways but one rotation covers the period for which changes in esc can be calculated using climate predictions.

The above calculations allow us to estimate the impact of climate change on tree growth and rotation length for the calculation of timber production over the first rotation. There is an issue of how climate change will affect rotation length over a longer term; this has relevance for our calculation of soil carbon which involves processes extending beyond the first rotation. Within the TIM calculations we assume that the yield class reached at the end of the first rotation is maintained thereafter. This assumption reflects the uncertainties and potential non-linear impact of climate change upon tree growth in the longer term.

3.12.6.8 Notation for annuity rules

y: Year in which the planting decision is being made and planting takes place

F_{AG}: Timeframe over which the agricultural income annuity is calculated

$F(esc, sp)$: Rotation length for species sp on a cell with yield class esc

δ: discount rate

$R_{AG}(t)$: Annual income from agriculture in the cell in period *t*

$NPV_{AGR}(y)$: Net present value of agriculture over the next 50 years, in year *y*

$A_{AGR}(y)$: Annuity equivalent of agricultural incomes (calculated over a 50 year period into the future)

$NPV_{AGC}(y, i)$: Net present value of agricultural carbon over the next 50 years, in year *y* for carbon prices series i, for
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013).$

$A_{AGC}(y, i)$: Annuity equivalent of agricultural carbon (calculated over a 50 year period into the future) for carbon prices series i, for
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013).$

$NPV_{TR}(y, esc, sp)$: Net present value of woodland of species *sp* growing at a rate *esc* over the next rotation, in year *y*

$A_{TR}(y, esc, sp)$: Annuity equivalent of timber income (calculated over a one rotation)

$NPV_{CTP}(y, esc, sp, i)$: Net present value of carbon stored in timber products over the next two rotations, in year *y* for carbon prices series i, for
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013).$

$A_{CTP}(y, esc, sp, i)$: Annuity equivalent of carbon stored in timber products (calculated over a one rotation) for carbon prices series i, for
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013).$

$NPV_{CS}(y, esc, sp, i)$: Net present value of carbon stored in soil over the next two rotations, in year *y* for carbon prices series i, for
$i = DECC\ central\ traded\ (2013), DECC\ central\ nontraded\ (2013), SCC\ TOL(2013).$

$A_{CS}(y, esc, sp, i)$: Annuity equivalent of carbon stored in soil (s) as calculated over a two rotations for carbon prices series i, for
$i = DECC\ central\ traded$ (2013), $DECC\ central\ nontraded$ (2013), $SCC\ TOL$(2013).

$A_{j,today}(y)$: Annuity equivalent with payments starting in year y for $j = AGR, AGC, TR, CTP, CS$.

$\bar{F}(y, \boldsymbol{esc}, sp)$: The average rotation period with changing *esc* score

$\overline{NPV_j}(Y, \boldsymbol{esc}, sp, s, i)$: The average net present value from source *j* in year y for $i = TR, CTP, CS$ and carbon price series i, for
$i = DECC\ central\ traded$ (2013), $DECC\ central\ nontraded$ (2013), $SCC\ TOL$(2013).

$\bar{A}_{j,today}(Y, \boldsymbol{esc}, sp, s, i)$: The annuity in year y (payments starting in year y) with changing *esc* scores for a cell with specified species, *sp*, and soil type, *s*, for $j = TR, CTP, CS$ and carbon price series i, for
$i = DECC\ central\ traded$ (2013), $DECC\ central\ nontraded$ (2013), $SCC\ TOL$(2013).

3.12.7 Appendix 2: Summary of the optimisation routine

To formalise this problem let us slightly simplify by noting that the requirement to plant 5,000 hectares of new forest in each country per annum equates to planting 12 cells each of 2km square (the minimum unit in the Agricultural Census data underpinning our farm model). Considering the set of such agricultural cells available for conversion to woodland in any particular year, let us define a dummy variable, x_j, that equals 1 if cell j is to be planted and 0 otherwise. Accordingly, any pattern of woodland planting can be described by setting 12 of the x_j's to a value of unity, such that $\sum_j x_j = 12$. It follows that the 'spatially independent' value of that planting strategy can be calculated as $\sum_j x_j v_j$. Now the recreational value of that pattern of planting to household i depends on both the set of recreational sites currently available to it, which we denote $\boldsymbol{K}$, and the set of new sites summarised in the vector describing the planting pattern, which we label $\boldsymbol{x}$. Accordingly, we can define a function $v_i^{Recreation}(\boldsymbol{K}, \boldsymbol{x})$ which describes the value of any particular planting pattern to household i. For completeness, we label the set of existing and potential recreational sites $\boldsymbol{R}$. Notice that the exact location and qualities of the sites in $\boldsymbol{K}$ and $\boldsymbol{x}$ are also arguments in that function but are suppressed for simplicity of presentation.

With the addition of woodland recreational values, the optimisation problem we have to solve in each time period in each country can be summarised as;

$$\max_{\boldsymbol{x}} W = \sum_{k=K+1}^{R} x_k v_k + \sum_{k=K+1}^{R} v_k^{Recreation}(\boldsymbol{K}, \boldsymbol{x})$$

$$subject\ to \sum_k x_k = 12$$

That is not a trivial problem particularly as a result of the nonlinearity of the recreational value change. Through a process of linear approximation, however, we are able to reformulate the problem as mixed integer linear programme, a type of mathematical programme that can be solved using commercial optimising software. The following sub-section overviews this process. This section requires some prior knowledge of the Random Utility Model (RUM) (McFadden, 1976) and can be omitted without any loss of general understanding of the results obtained from our analysis.

As outlined above, definition of an objective function and its optimisation is straightforward when we only consider spatially independent values such as farm production, timber and GHG. Linkage to the water quality and biodiversity consequences of such optimisation is also, in principle, relatively straightforward. However the introduction of spatial dependence in the form of recreational values necessitates the development of a novel approach to land use optimisation. We propose and implement an approach which builds from the complexities induced by such spatial dependence and subsequently adds in spatially independent values.

Given this, the optimisation routine starts from consideration of the impacts of land use change upon recreation values. We let K represent a set of existing recreation sites and R denote the set of all existing and potential recreation sites. Using the RUM (McFadden, 1976) with extreme type II errors we can derive expressions for the level of expected utility[38] provided by a set of existing sites for a representative individual at a particular location (taken as being a UK Census Lower Super Output Area; LSOA). Let us denote a particular LSOA by *i* and the total number of LSOAs by *i*, such that *i* =1,…, *i*,

[38] Note here that in taking expectations the error term simplifies out of the expression, $E(e^{\varepsilon_{i,j}}) = 1$.

$$U_{i|K} = ln \sum_{k=1}^{K} e^{v_{i,k}^{r}}$$

where

$$v_{i,k}^{r} = A_k - B * TC_{i,k}$$

and

A_k is a site specific utility component

$TC_{i,k}$ is the travel cost from LSOA i to site k.

Let us now define a base level of utility; that is, utility from an existing set of sites. Let us denote this set by k=1,…,K and order the set of sites in R such that the first K sites are the existing sites.

The baseline expected recreation utility is:

$$U_{i,k}^{0} = ln \sum_{k=1}^{K} e^{v_{i,k}^{r}}$$

Now consider a planting regime where we plant J additional new sites. Let **x** be a binary vector of length (R-K)[39] such that $\boldsymbol{x} = (x_{K+1}, x_2, \dots, x_R)$, representing all of the potential sites for planting. If a site *j* is planted then $x_j = 1$, otherwise $x_j = 0$.

The expected utility from planting J new sites according to **x** is calculated by:

$$U_{i,k+J} = \ln\left(\sum_{k=1}^{K} e^{v_{i,k}^{r}} + \sum_{j=k+1}^{R} e^{v_{i,j}^{r}} x_j\right)$$

Therefore, we can take the difference between the expected utility with new planting and the baseline expected utility to calculate the change in expected utility provided by a particular planting regime, **x** (which we want to optimise over) as follows:

$$\Delta U_{i,}(\boldsymbol{x}) = \ln\left(\sum_{k=1}^{k} e^{e^{v_{i,k}^{r}}} + \sum_{j=1}^{R-K} e^{v_{i,j}^{r}} x_j\right) - U_{i,k}^{0}$$

$$\Delta U_{i,}(\boldsymbol{x}) = \ln\left(\sum_{k=1}^{K} e^{e^{v_{i,k}^{r}}} + \sum_{j=K+1}^{R} e^{v_{i,j}^{r}} x_j\right) - ln \sum_{k=1}^{K} e^{v_{i,k}^{r}}$$

Let $\tilde{u}_i(K) = \sum_{k=1}^{K} e^{v_{i,k}^{r}}$ and $\tilde{u}_i(\boldsymbol{x}) = \sum_{j=K+1}^{R} e^{v_{i,j}^{r}} x_j$ such that,

$$\Delta U_{i,}(\boldsymbol{x}) = \ln(\tilde{u}_i(\boldsymbol{x}) + \tilde{u}_i(K)) - \ln(\tilde{u}_i(K))$$

The objective function that we wish to maximise is given by,

$$Max_{\boldsymbol{x}}\, W(\boldsymbol{x}) = \Sigma_{i=1}^{I} p_i(\Delta U_i(\boldsymbol{x})) + \Sigma_{j=K+1}^{R}(v_k^{Farm} + v_k^{GHG} + v_k^{Timber})x_j$$

where $\Sigma_{j=K+1}^{R}(v_j^{Farm} + v_j^{GHG} + v_j^{Timber})x_j$ is a term capturing the change in value through farm income, timber income, and greenhouse gas emissions, and p_i is the population in LSOA *i* and $\sum_{k=K+1}^{R} v_k^{Recreation}(\boldsymbol{K}, \boldsymbol{x}) = \Sigma_{i=1}^{I} p_i(\Delta U_i(\boldsymbol{x}))$ as per the maximisation equation immediately above.

[39] Where R is the total number of sites, both existing and potential, and K is the number of existing sites.

This objective function is maximised subject to a set of constraints,

$$\Sigma_{j=K+1}^{R} x_j = J$$

Where J is the number of cells to be planted.

This problem is non-linear since ΔU_i is non-linear. If ΔU_i were linear we could use a solver to maximise W(**x**) with respect to the planting regime x. As a solution we construct a piecewise linear approximation (meaning a series of straight lines that are joined together). We do this using the Tangent Line Approximation (TLA) Algorithm to produce a fitted linear approximation with known maximum error (known as α- approximation).

Using the approximation, for any given planting regime we can calculate $\tilde{u}_i(\boldsymbol{x})$ and use the straight line approximation to find a corresponding approximated value for $\Delta U_{i,}(\boldsymbol{x})$. The calculation of $\tilde{u}_i(\boldsymbol{x})$ is included as a constraint in the problem and fed into a solver,

$$\tilde{u}_i(\boldsymbol{x}) = \sum_{j=K+1}^{R} e^{v_{i,j}^{r}} x_j$$

The TLA outputs a set of points (c1, c2, …) and gradients (b1, b2, b3, …) which define the linear approximation (depicted in **Figure 3.A1**), these are used as inputs in the solver, such that,

$$\Delta U_i = f(x) = \begin{cases} a1 + b1 * \tilde{u}, & 0 < x \leq c1 \\ a2 + b2 * \tilde{u}, & c1 < x \leq c2 \end{cases}$$

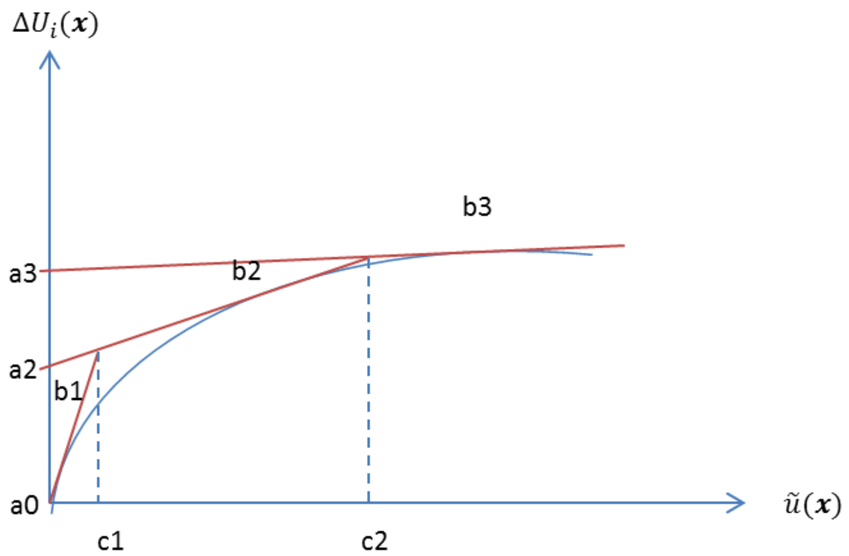

Figure 3.A1. Graphical depiction of the tangent line approximation method.

The IBM CPLEX solver uses a branch and bound algorithm to compute the global optimum by dividing the set of possible planting regimes into a series of smaller problems and computing an upper and lower bound for the value for the objective function within each region. This process enables the algorithm to avoid local optima.

3.13 Conclusions

The general objective of the research reported here is to contribute towards the improvement of decision making which involves natural capital resources and the ecosystem services and related goods they provide. As natural capital either directly or indirectly underpins virtually all economic activity and human wellbeing, this implies that the research has wide applicability to decision making within both the public and private sector.

The major contribution of the research is methodological. It significantly extends mainstream economic approaches to decision making, improving the incorporation of ecosystem services within such decisions and avoiding some of the more substantial shortcomings of conventional assessments. Given the strong inter-relationships between natural capital and land use we illustrate the methodological developments offered by this research through a case study application examining potential changes to Government policy in this area. Findings from the research highlight five generally applicable key messages and demonstrate the importance of each within decision making systems. These key messages are as follows:

- For decisions to be both robust and efficient they should avoid appraising pre-determined options and instead allow the characteristics and corresponding values of the real-world to determine the best use of scarce resources. Many decision analyses assess a small number of pre-determined options. In the case of land use, typically such appraisals might consider around half a dozen options, each described in terms of a different end-point. A major weakness of such approaches is that they are not *robust* to the charge that the decision maker has no means of knowing whether the best option is included in the analysis. Consequently the chosen option may not be *efficient* in that it may not offer best value for money. More practically, such analyses give no indication regarding which policies might be required to attain a desired end-point (or indeed if that end point is even feasible). To avoid these problems we develop The Integrated Model (TIM); a programmed system linking a series of modules which together assess both the drivers and consequences of land use change (e.g. the agricultural production module links changes in drivers such as government policy, prices, costs, soils, climate, etc., to changes in farm output). The high-speed computerised assessments afforded by TIM allow the analyst to appraise very large numbers of alternative land use change options, each considering a user-defined policy[40] (e.g. a certain subsidy payment) applied at a different location across Great Britain and each appraised in terms of the multiple consequences of that change (see below). TIM can compare these assessments against user-defined rules for determining which outcomes are considered best (or, in economic terminology, optimal). In our subsequent application we define the optimal policy as that which yields the highest net benefits from available resources. However, alternative objectives could be employed as desired by the research user.

- Decisions need to consider all of the major drivers and impacts of the changes they are considering. Changes in natural capital related goods can be driven by many factors at the same time. For example, shifts in policy and ongoing climate change may simultaneously affect land use. Furthermore, such land use change may in turn generate an array of impacts, all of which need to be analysed if we are to assess the true consequences of

[40] An interesting extension of this work would be to allow the system to identify the type of policy and level of its implementation which maximises a given, user-defined, objective. However, this is beyond the remit of the present research which places the user at the centre of the decision regarding which policy should be investigated.

alternative policies. Our research shows that appraisals can incorporate a wide range of the drivers of land use change (with particular attention being given to the impacts of changes in both climate and policies) and provide extensive assessments of the impacts of such changes (including agricultural outputs and incomes for all farm types; water quality; greenhouse gases; recreational visits; forest outputs; and biodiversity).

- Many of the services provided by the natural environment can be robustly assessed using economic values which are then readily incorporated within decision making systems. Assessing environmental public goods in terms of their economic value permits even handed comparison of gains and losses in both market and non-market goods. The present research builds on previous work to significantly extend both the remit and robustness of economic values for non-market environmental goods. The valuations presented here should be applicable to a wide variety of decision making challenges as well as being compatible with the rigorous requirements of the TIM system which entails values which are responsive to the wide array of possible policy changes being apprised (e.g. including options which vary from only a minor to very major increases in the supply of natural capital derived ecosystem services). However, we also recognise cases where the current state of the art does not provide robust values for certain aspects of natural capital (e.g. the non-use existence values associated with biodiversity) and present approaches which focus upon incorporation within conventional decision making via estimation of the costs of ensuring policy-specified levels of provision (e.g. ensuring no net loss in biodiversity).

- Leaving the uptake of subsidies to market forces alone is likely to result in poor value for money to the taxpayer. When subsidies are made available but not tied to the value of public goods produced ('untargeted') then their effectiveness can be poor. In such cases the uptake of subsidies will be determined not by the social value they generate but by the opportunity cost of foregone private market values of production. Within the area of land use this effect can be seen in the historic failure of EU Common Agricultural Policy (CAP) set-aside payments which were intended to reduce over-production of agricultural output but instead tended to remove only the poorest quality land from use. In our illustrative application we examine the impact of a policy intervention in which the uptake of a subsidy is determined by market forces alone; demonstrating the poor value for money generated by such an approach.

Targeted policies deliver greatly improved value for money from available resources. We show how working with, rather than in ignorance of, the natural environment allows the decision maker to see how alternative implementation of a policy can very significantly enhance value for money. Our research develops a methodology which can spatially 'target' resources (such as CAP payments) to almost any scale from very small areas up to the whole of Great Britain. This is used to show that such targeting greatly improves the generation of environmental (and other) public goods and hence social value. Such resource-efficient approaches are of particular importance during periods of financial austerity. In developing the research required to deliver the above general contributions, the work presented here undertook a policy relevant case study to examine the potential for establishing new forests in England, Scotland and Wales. This analysis, which was prompted by government announcements of an intention to expand forestry in all three countries, assessed land use at a maximum (and in many cases smaller) 2km resolution for the entirety of Great Britain over the period from 2014 to 2063. All analyses considered the impact of any land use change upon all of the various systems mentioned previously (agriculture, timber, water quality, greenhouse gases, recreation and biodiversity). Key outputs of this analysis include:

- Investigation of a 'Business As Usual' (BAU) baseline in which no new afforestation policies are implemented. This assessment provides a counterfactual for the other policy change analyses considered below. Furthermore, it also reveals the impact of forecast climate change upon all the above systems during the appraisal period.

- Investigation of a 'Market Value' (MV) driven planting policy where the integrated modelling system is employed to consider all feasible locations for afforestation, selecting those which maximise the net value of market priced agricultural and forestry outputs alone and ignoring the value of public goods generated. This simulates the consequences of announcing a general, untargeted planting policy. This results in forestry being confined to remote upland areas of marginal agricultural value. Such locations are far from human populations, which limits the recreational values generated. Planting under this scheme also occurs on organic soil areas which become degraded and emit large volumes of greenhouse gases. This approach to decision making generates negative overall social values and hence, not only poor value for money to the taxpayer, but in fact net losses for society.

- Investigation of a targeted 'Social Value' (SV) driven planting policy where the integrated modelling system selects planting locations taking into account the full sweep of impacts generated by afforestation. The targeting process accounts for both market priced goods (including timber and the costs of displaced agriculture) and those non-market goods which for which we can estimate robust economic values (here greenhouse gas emissions or storage and recreational values). This results in woodlands being located away from vulnerable organic soils and towards areas which yield higher recreational values. Assessment of impacts upon those environmental public goods which were not given economic values (impacts upon biodiversity and water quality) show that water quality and woodland bird biodiversity are also enhanced when we bring the value of other public goods into the determination of planting locations.

The message of the case study is clear: using market values alone to direct public spending on afforestation will yield poor value for money for taxpayers. Using the integrated modelling approach to include the economic value of other non-market goods significantly improves the social value of public spending. The approach developed in this research provides decision makers with the ability to direct public funds to those areas of the country which will maximise value for money for the UK taxpayer.

3.13.1 Future directions

The research discussed in this report adopts a relatively novel and, we would argue, useful approach to uniting both the economy and the natural environment within decision making concerning natural capital. Given that the approach developed here represents a somewhat distinct methodology there is, perhaps inevitably, many directions in which the work could be taken forward. Many of these extensions have been mentioned throughout the report and so we close by highlighting just a few possibilities which we feel may be of general interest:

- it is important to link the various changes in land use considered here to an analysis of wider food security in the face of increasing demands upon the world's production systems coupled with growing and more affluent populations, ongoing climate change and increases in extreme weather event;
- linkage to international markets needs to extend beyond food and related commodities to include the energy market which in turn influences the values of all goods in the economy and indeed affects non-market values;

- a further important linkage to develop is to investigate the macroeconomic consequences of land use change, in terms of both conventional measures of GDP, incomes, employment, etc. and with respect to developing environmental accounts;
- future extensions of this methodology should incorporate alternative biodiversity constraints such as those used in our Proof of Concept analysis (Section 3.3), or investigate the implications of more stringent constraints requiring improvements in wild species diversity and conservation. As part of such developments an analysis of the optimal targeting of new conservation areas is important in the light of the Lawton *et al*. (2010), "Making space for Nature" recommendations and ongoing initiatives concerning biodiversity offsetting;
- it is important to test and demonstrate further the potential advantages of the decision making methodology developed in this research in comparison with conventional approaches such as scenario analyses; and
- the transition of this methodology to a readily applicable tool to aid decision making has the potential to radically improve decision making in the UK. However, this cannot be treated as a merely technological challenge. To ensure suitability for purpose there has to be a process of co-development between decision makers and researchers.

All of the above extensions are embraced within a current proposal to the ESRC for a UK Centre for Natural Capital Decision Making (CNCDR).

3.14 Annex 1: Land use, land cover and livestock data.

3.14.1 Summary

A dataset describing classes of non-overlapping land use has been generated which has utility for research at a range of spatial scales. To our knowledge, it is the most comprehensive definition of the physical stock of land types in Great Britain for the purposes of ecosystem assessment.

Inconsistent correspondence between land cover and land use datasets and concerns over their thematic, temporal and spatial accuracy called into question the fitness of individual off-the-shelf datasets. In response, several datasets were combined to generate a custom product. In brief, satellite-derived land cover data and ancillary spatial data were used to locate areas that are likely to be functional e.g. used for agricultural production or urban activities. Results from agricultural survey data were used to refine the spatial distribution of arable and grassland and subdivide categorisation where appropriate. A Geographical Information System (GIS) was used to interrogate and integrate data to a base resolution of a 2km by 2km cell (a 1km resolution dataset was also produced for use in Section 3.11 only). The process was undertaken for two target years.

Rather than a complete land use definition, the resultant dataset is more adequately described as a high resolution database depicting potential land cover or land use area across Great Britain. Due to uncertainties with input data, there is greater confidence in relative magnitudes of areas (i.e. shares of land types) than absolute totals. However, as the level of spatial aggregation increases, the absolute area totals become more accurate. Also, as the timeframe of study increases, to say three to five years, data become more representative of that period, rather than a single target year.

Output from the agricultural production model (Section 3.4) was used to predict a baseline and changes in agricultural land use. The land use definition discussed here was used a) for estimation of models for other ecosystem components and b) as a baseline for non-agricultural land use.

3.14.2 Objectives

The land use dataset was developed to serve the following roles:

- to provide a complete picture of the spatial distribution of land use;
- to generate spatially consistent land use data across time (i.e. apply a reliable methodology);
- to include England, Scotland and Wales;
- to be fit for purpose at multiple levels: 2km, regional, hydrometric area, national-level;
- to be used in conjunction with other data to allow the derivation of trends and indicators of change;
- to be consistent with the demands of an interdisciplinary project; and
- to be used for the spatial re-distribution of other data e.g. heads of livestock.

3.14.3 Data

Data from multiple source geographies (**Table 3.A.1**) were translated into a common spatial unit which described general classes of non-overlapping land use and land cover. Two main data types were used: satellite-derived digital land cover maps and survey data on agricultural land use practices. Ancillary datasets (e.g. road networks and political boundaries) were employed to identify areas of non-agricultural land use to refine the classification. Using a GIS, data were integrated to a common spatial unit (2km × 2km cell), with this choice of resolution being a lowest common denominator given the highest detail at which agricultural land use data could be obtained.

Following initial scoping of data availability and temporal resolution, this was performed for two target years: 2000 and 2010.

The physical material at the surface of the earth, land cover, can be observed through field survey or via analysis of remotely sensed imagery. The Centre for Ecology and Hydrology (CEH) has produced Land Cover Maps for the UK: e.g. *LCM2000* (Fuller *et al*., 2002) and *LCM2007* (Morton *et al*., 2011). For each Land Cover Map, imagery taken over several years is reclassified on a pixel-by-pixel basis into land cover types (remotely sensed data were acquired between November 1996 and May 2001 for LCM2000 and between September 2005 and July 2008 for LCM2007). Land use reflects the functional dimension of Earth's surface. Land use in the UK is dominated by agriculture which accounts for 18.3 million hectares or 74.8% of the total surface area Defra (2011b). The June Survey of Agricultural and Horticultural Activity is a source of high quality land use data with national coverage. The June Survey is undertaken as a full census every ten years and as a sample survey in intervening years. The June Survey is undertaken independently in England, Scotland and Wales and results are released in aggregated spatial units. These data can either be obtained in the form of a regular grid known as the '*agcensus*' (available at 2km, 5km and 10km resolutions from JAC, 2013) or for administrative boundaries such as counties and regions (see details in **Table 3.A1.1**).

Due to protection against the disclosure of information on individual holdings, there are caveats associated with the use of these 'ready-made' datasets for spatially explicit research. Broadly speaking, agcensus data can be inaccurate at fine resolutions due to spatial reworking and re-distribution of holding data, and while statistics for administrative boundaries are more accurate, many data are suppressed to preserve anonymity or released at a higher level geography where the resolution is too coarse. To combat these shortfalls, both data formats were used.

3.14.4 Methodology

A GIS was used to interrogate and integrate land use and livestock data to a base resolution of a 2km by 2km cell (see Section 3.14.3 for a discussion of base unit). The process was undertaken for two target years and is summarised below. Further methodological detail, including a critical discussion of underlying methodological issues, can be obtained from the authors by request.

3.14.4.1 Overall land use

The stages of data integration can be summarised as:

- Stage 1: Reclassify existing Land Cover Maps and examine summary statistics;
- Stage 2: Augment reclassified Maps with other data pertaining to non-agricultural land cover and land use (e.g. urban or forestry);
- Stage 3: Test for correlation between agricultural land cover and land use data; and
- Stage 4: Perform redistribution of agricultural land use using available georeferenced data and statistics.

Table 3.A1.1: Raw data sources and temporal data available to describe target years 2000 and 2010.

Land cover and land use	Data description	Data type	Extent	Data source(s)	Target year 2000	Target year 2010
General land cover	Land Cover Map	25 m raster grid	GB	CEH	*c.*2000	*c.*2007
Coniferous or deciduous land cover	National Inventory for Woodland and Trees	GIS polygon file	GB	Forestry Commission	2002	2002
Urban and developed land use	Developed Land Use Areas	GIS polygon file	GB	OS Meridian	2009	2009
	Roads and railways	GIS polyline files	GB	OS Meridian	2009	2009
Agriculture	Processed June Agricultural Survey(s)	2 km *agcensus*	GB	EDINA	2004	2010
		Spreadsheet of county-level statistics	E	Defra	2000	2010
		Table for agricultural region statistics	S	ERSA	2001	2010
		Spreadsheet of Small Area statistics	W	National Assembly for Wales	2003	2010
	OS Open Data (county and region boundaries)	GIS polygon files	E & S	OS OpenData	2011	2011
	Small Area boundaries	GIS polygon file	W	National Assembly for Wales	2001	2001

Abbreviations used: CEH = Centre for Ecology and Hydrology; E = England; ERSA = Economic Report on Scottish Agriculture; GB = Great Britain; OS = Ordnance Survey; S = Scotland; W = Wales

Stages 1 and 2

Stages 1 and 2 enabled the creation of LCUP1 (2000, 2007) and LCUP2 (2000, 2007) datasets. First, the 25m resolution raster products for LCM2000 (Fuller *et al*., 2002) and LCM2007 (Morton *et al*., 2011) were used as raw land cover data for target years 2000 and 2010 respectively. Ten land cover categories, broadly corresponding to LCM2000 and LCM2007 Aggregate Classes and also consistent with habitat mapping as part of the first phase of UK NEA (2011), were created from combining subclasses of land cover (**Table 3.A1.2**). Next, a simple cross-tabulation was performed to look at land cover change on a cell-by-cell basis across the two time periods. Reasonable correlation with small changes in land cover were expected, e.g. due to development and small differences in the methodology between LCM2000 and LCM2007. However, the results of the comparison did not always perform as anticipated and there was considerable movement across many classes. To combat this, reclassified Land Cover Map data (for both target years) were augmented with Forestry Commission boundaries of existing woodland FC (2002), Ordnance Survey data on Roads and Railways and Developed Land Use Areas (OS, 2013b) (**Table 3.A1.1**). These updates enabled a more reliable indication of non-agricultural land use extent (e.g. LCUP2, 2000, 2007).

Table 3.A1.2: Classes of land cover (after Fuller et al., 2002; Morton et al., 2011).

Broad land cover class	LCM2000 subclass	code	LCM2007 subclass	code
Deciduous	Broad-leaved / mixed woodland	1.1	Broadleaved woodland	1
Coniferous	Coniferous woodland	2.1	Coniferous woodland	2
Enclosed Farmland	Arable cereals Arable horticulture Arable non-rotational Setaside grassland	4.1 4.2 4.3 5.2	Arable and Horticultural Land	3
Improved Grassland	Improved Grassland	5.1	Improved Grassland	4
Semi-natural Grass	Acid grassland Neutral grassland Calcareous grassland Fen, marsh, swamp (rush pasture)	8.1 6.1 7.1 11.1	Acid Grassland (Bracken) Neutral Grassland Calcareous Grassland Fen / swamp Rough Grassland	8 6 7 9 5
Mountains, moors and heaths	Bog (deep peat) Montane habitats Inland bare ground Dense dwarf shrub heath Open dwarf shrub heath Bracken	12.1 15.1 16.1 10.1 10.2 9.1	Bog Montane habitats Inland rock Heather Heather grassland	12 13 14 10 11
Coastal Margins	Saltmarsh Littoral rock Littoral sediment Supra-littoral rock Supra-littoral sediment	21.2 20.1 21.1 18.1 19.1	Saltmarsh Littoral rock Littoral sediment Supra-littoral rock Supra-littoral sediment	21 19 20 17 18
Freshwater, Wetlands	Water (inland)	13.1	Freshwater	16
Marine	Sea / Estuary	22.1	Saltwater	15
Urban and developed land	Continuous urban Suburban / rural developed	17.2 17.1	Urban Suburban	22 23

Stage 3

In some cases land cover classes may be synonymous with land use. Often, however, variability of land use is greater than the variability of land cover because one land cover can fulfil different functions, i.e. the relationship is not one-to-one (Gong and Weber, 2009). Nevertheless, land cover data can provide a useful framework within which to map agricultural land use (e.g. Posen *et al.*, 2011).

Initially, relevant land areas from land cover derived data were compared with national-level June Survey statistics for agriculture (SEERAD, 2001, and SGRPID, 2011). Considerable disparities in total areas were observed. For example, the total area of Temporary and Permanent grassland land use in the June Survey (SGRPID, 2011) was greater than the Improved Grassland land cover category (LCUP2, 2007); in contrast, Arable, horticulture & fallow (LCUP2, 2007, and SGRPID, 2011) was less than the Enclosed Farmland land cover (LCUP2, 2007).

A second round of correlation testing was performed to provide an indication of the strength of the relationship between land use and land cover at the 2km level (*agcensus*). The theory was that if a set of simple rules could establish the link between land cover and land use then there would be no real need to implement more sophisticated methodologies. A cell-by-cell comparison was performed for >2,000 randomly sampled cells across Great Britain. However, from this product, it is possible for observations of agricultural land to exceed the physical area of zones (see discussion in Comber *et al*., 2008; Posen *et al*., 2011). Our testing found particular problems in Scotland and Wales. For example, in 2010 (JAC, 2013) data for Scotland approximately a quarter of 2km cells are reported with an area > 400ha. We attribute this to sprawling grass and grazing land allocated to a single farm holding. Subsequent results and analyses informed the following decisions:

- the 2 km level *agcensus* data could be used to subdivide total arable land in a corresponding 2km cell into different types of crops (fine resolution data were used to maintain local cropping patterns); and
- higher level geographies (i.e. administrative-level) were needed to define the total arable land in a 2km cell and refine the distribution of types of grassland and grazing. Greater confidence was given to the administrative-level statistics as although these are aggregated for farms within an area, they are not subject to redistribution algorithms used in the production of the *agcensus*.

Further details are available from the authors on request.

Stage 4

Stage 4 enabled the creation of creation of LCUAP1 (2000, 2010) and LCUAP2 (2000, 2010) datasets. County- and Unitary Authority-level June Survey data for 2000 and 2010 were downloaded as a spreadsheet for England. Similar summaries were obtained for Welsh Agricultural Regions. Scottish regional data were obtained as PDF files from the Economic Report on Scottish Agriculture (ERSA) (ERSA, 2013). These administrative-level data were amalgamated into one dataset of 81 zones, each with six broad land use categories compatible in definition across time and for each country: Arable, horticulture & fallow; Temporary grassland; Permanent grassland; Sole-right rough grazing; Farm woodland; All other land on farm. Next, these tabulated data were joined to spatial boundary data in a GIS. At this stage, the implicit assumption was that the variables of interest (land use types) had a homogenous spatial distribution across source zones (administrative areas).

It was then necessary to redistribute the above source zone data within the locations constrained by appropriate land cover classes. In other words, the high resolution (25m × 25m grid) reclassified land cover data (used to create e.g. LCUP2) were used to restrict probable locations for agricultural land use within each administrative area. Geographic boundaries for the administrative areas were overlain on the land cover grid. Given that the area of land use in each source zone was known, we satisfied these observations by scaling the 25m resolution land cover-derived classes. Then, each broad land use type (at 25m resolution) was summed for a set of final target zones – a regular grid of 2km cells. Target zones of 1km were used for estimation of models in Section 3.11 only.

In the final step of processing, relevant crop types were extracted from the 2004 and 2010 *agcensus* (2km resolution) datasets. Total Arable, horticulture & fallow land in the 2km target zones were refined into different crop types using overlying *agcensus* data (by apply corresponding areal proportions). Therefore, the final dataset could be aggregated thematically or spatially to suit different research applications (e.g. LCUAP1, 2000; LCUAP2, 2000).

Definitions of the finest thematic resolution (25 classes) are provided in **Table 3.A1.3**. Further methodological details are available from the authors by request.

Table 3.A1.3: Disaggregated land use definitions (caveats/ restrictions in parentheses).

Name	Description
COAST	coastal margins
FWATER	freshwater
MARINE	sea and estuary
URBAN	urban and other developed land
PERMG	permanent grassland i.e. >5 yrs
TEMPG	temporary grassland i.e. <5 yrs
RGRAZ	rough grazing
GRSNFRM	semi-natural grass or mountains, moors and heaths where NOT used for farming
FWOOD	farm woodland
NFWOOD	woodland NOT used for farming
WHEAT	wheat
WBARLEY	winter barley (England and Scotland only)
SBARLEY	spring barley (England and Scotland only)
OTHCER	other cereals (includes oats and other cereals for combining)
POTS	potatoes
WOSR	winter oilseed rape (where available)
SOSR	spring oilseed rape (where available)
MAIZE	maize (Scotland 2004 is within 'othcrps')
SBEET	sugarbeet
OTHCRPS	other crops and bare fallow (includes oilseed rape for Wales; includes maize for Scotland 2004)
HORT	total horticulture
TBARLEY	total barley (Wales only)
TOSR	total oilseed rape (where seasonal data unavailable)
OTHFRM	other farmland e.g. roads, buildings, yards, ponds and, where appropriate, setaside
OCEAN	ocean (area that is not covered by land is given 'ocean' by default)

3.14.4.2 Distribution of livestock

The distribution of livestock was used as a proxy for the distribution of animal excreta and manures (Section 3.8).

Livestock were distributed over agricultural land using stocking densities at administrative-level (head counts of livestock are available from the June Survey via the sources described in the land use section and **Table 3.A1.1**). Initial analysis and a review of literature (e.g. see Lyons, 2010, and Posen *et al*., 2011) informed the following rules:

- cattle were distributed at administrative-level across grassland (Temporary and Permanent);
- sheep were distributed at administrative-level across grassland (Temporary and Permanent) and Sole-right rough grazing; and
- pigs and poultry were distributed at administrative-level across intensive agriculture (Arable, horticulture & fallow; and All other land on farm).

Then, each livestock type (at 25m resolution) was summed for the set of target zones – a regular grid of 2km cells (e.g. Livestock2, 2010).

We prepared poultry datasets to aid the estimation of nutrient export coefficients (Section 3.8); however, the agricultural model (Section 3.4) did not predict poultry numbers due to lack of temporal data. Indoor or outdoor distinction of pigs and poultry is important (e.g. for water quality, see Posen *et al*., 2011), but this was not possible due to a lack of spatial and temporal data.

3.14.4.3 Using an agricultural model to predict land use change

The land use definition (LCUAP2) was used to provide estimation data for models described in Sections 3.8 to 3.11. The agricultural model (Section 3.4) used aggregated classes of *agcensus* data over a greater time period. Other models (Sections 3.8 to 3.11) aggregated classes within LCUAP2 as appropriate.

The SEER agricultural model predicts, for an amount of farmland with a set of physical and environmental characteristics, the shares of likely land use given that a farmer will try to optimise profits (Section 3.4). The output land use share system has six categories: cereal; oilseed rape; sugar beet and potatoes; temporary grassland; permanent grassland; and rough grazing. A seventh category ‘other farmland’ included horticulture, other arable crops, farm woodland and set aside. Under changing scenarios (Section 3.12), these shares will change.

LCUAP2 (2010) was used to define the total agricultural area for the baseline year. The agricultural model (Section 3.4) provided the baseline for cropping under the seven shares above. Where other models required finer thematic resolution (e.g. amount of barley within cereals), land areas under analogous categories in target year 2010 (LCUAP2, 2010) at Landscape Character Area (LCA) level were used to proportionally adjust agricultural model output. Each LCA is defined by a unique combination of physical environment and social conditions and therefore their boundaries follow natural lines in the landscape rather than administrative areas (MAGIC, 2012; CCFW, 2012; Scottish Government, 2012b). Subdivision of the seventh land use category ‘other farmland’ was performed on a coincident cell-by-cell basis (farm woodland, within ‘other farmland’, was treated as a special case as the spatial distribution was frequently heterogeneous across a LCA). Further details are provided in Section 3.15.

Further adjustments required for amalgamation of the modelling components can be found in Section 3.15.

3.14.5 Results

Final output was a set of 2km x 2km raster grids representing a percentage of total area of each land type. Maximum thematic resolution of this dataset is 25 classes covering a spectrum of land use and land cover categories (**Table 3.A1.3**). This output was produced for each target year.

Due to the regular gridded nature of the dataset, each 2km grid cell can be assigned a geographic reference (e.g. British National Grid Easting and Northing for cell centroid) and exported to spreadsheet format for use outside of a GIS. Data can also be aggregated to be used at different spatial and thematic scales. In **Table 3.A1.4**, land use is aggregated to eleven broad categories at a national scale.

Table 3.A.1.4: Potential land use in the target years 2000 and 2010.

Land use	Area (ha) 2000	% 2000	Area (ha) 2010	% 2010	%change
Crops and bare fallow (including horticulture)	4,623,394	19.9	4,560,095	19.6	-0.3
Rough grazing (sole right)	4,211,367	18.1	3,913,729	16.8	-1.3
Permanent grassland (> 5yrs)	4,754,225	20.4	5,259,400	22.6	2.2
Temporary grassland (< 5yrs)	1,060,984	4.6	1,107,626	4.8	0.2
Farm woodland	492,743	2.1	764,063	3.3	1.2
Other farmland (roads, buildings, yards etc.)	648,298	2.8	492,424	2.1	-0.7
ESTIMATED TOTAL AGRICULTURAL AREA	15,791,011	67.9	16,097,337	69.1	1.2
Urban and developed land	2,607,465	11.2	2,747,848	11.8	0.6
Marine and coastal	352,306	1.5	382,222	1.7	0.2
Freshwater	211,833	0.9	248,539	1.1	0.2
Non-farm grass, mountains, moors and heath	1,709,945	7.3	1,658,405	7.1	-0.2
Non-farm wood	2,609,203	11.2	2,147,413	9.2	-2
TOTAL	23,281,763	100	23,281,763	100	

3.14.6 Discussion

Caveats associated with the land use dataset are briefly discussed.

3.14.6.1 Interpretation of the land use dataset

Disaggregation of source data into target zones potentially generates spatial distributions that are unrepresentative of real-world phenomena. This is known as the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984). Practically, the derived dataset has limitations for use at a very local scale due to the inherent uncertainties in the base data layers and the assumptions required during integration. Furthermore, assumptions have been made about the stability of land uses and land covers within the time periods for different data sources.

For these reasons, the land use definition is more adequately described as a dataset representing the potential distribution of land use and land cover for a particular timeframe. Confidence in the absolute values increases as the 2km resolution spatial data are aggregated to higher level geographies. Greatest confidence is given in the national-level summaries of broad land use categories (**Table 3.A1.4**).

The definition of land use can be manipulated easily into different thematic resolutions. While not entirely consistent with international standards (e.g. System of Environmental-Economic Accounting (SEEA), see details in Gong and Weber, 2009), the classification has maximised the suitability for Great Britain land use (with a possible extension to UK extent).

3.14.6.2 Integration of different systems

Flexibility in thematic resolution has meant that different model components were able to aggregate land use categories in different ways to improve fitness for purpose on an individual basis, thereby increasing confidence in the suitability of modelled variables (i.e. each modelled system was able to include the most significant variables, or combinations, and reduce error). However, this presented a difficulty for application of land use predictions governed by the agricultural model (Section 3.4). Further assumptions were needed to subdivide these seven broad categories.

Farm woodland was a special case. A lack of temporal data (and modelled insignificance in farmer decisions) meant that woodland on farms was subsumed within the 'other' land on farm category in Section 3.4. However, as this 'other' land changes under agricultural predictions, so does the amount of farm wood and hence total trees, which are important for other systems, e.g. water modelling. While the disparity of thematic resolution used by the different systems during modelling was not restricted to farm woodland, different assumptions were required to replicate the distinctiveness of the spatial distribution of this land use (i.e. cell-by-cell adjustments).

Broad land cover classes were often incompatible with (agricultural) land use. Grass and grazing land use was particularly problematic and led to the relinquishment of a mountains, moors and heaths habitat category (as used in the UK NEA, 2011). However, land cover was still used in the estimation of some modelled ecosystem components with the proviso that extra assumptions would be needed for prediction (e.g. Section 3.11).

Finally, every 2km cell was modelled as an individual farm (for further details see Section 3.4).

3.14.7 Summary

- Probable land use and cover has been estimated for the purpose of spatially explicit modelling of multiple ecosystem components.
- Inconsistencies between land use and land cover datasets, and issues regarding compatibility of data from different devolved administrations of England, Wales and Scotland, present problems for generating a national land use database.
- Assumptions are required to modify the spatial units.
- Adjustments were needed to agricultural land use predictions to meet differing demands of components of an interdisciplinary project.

3.15 Annex 2: Supporting data

3.15.1 Overview

An internal digital data depository was established, providing access to a suite of datasets that described the spatially and temporally explicit components of natural and human systems. Unless otherwise stated, these data were processed to a 2km base resolution. Following introduction of raw data sources, processing steps are discussed for the core datasets. A Geographical Information System (GIS) was used for spatial data handling and processing.
Where datasets have been used that were not developed exclusively for this project, references can be found in individual sections of this report.

3.15.2 Objectives

Supporting data serve a range of specific objectives and individual sections provide more detail. General objectives can be summarised:

- to provide Great Britain-wide descriptors for natural environment and socio-economic phenomena;
- to provide a common spatial unit for analysis; and
- to facilitate the testing of models that seek better understanding of natural and human systems which are related to land use.

3.15.3 Data

Spatial data were gathered from multiple sources to be processed in a GIS ESRI (2013). Often these were off-the-shelf, but in many cases agencies extracted bespoke datasets to cater to the needs of this ambitious project. Full details of all the main data sources are provided.

3.15.3.1 Elevation

Elevation data were gathered from the 50m resolution Integrated Hydrological Digital Terrain Model (IHDTM) licensed from the Centre for Ecology and Hydrology (CEH) (see Morris and Flavin, 1994, and IHDTM, 2002). This dataset, with a 0.1m vertical resolution, was originally derived from Ordnance Survey 1:50,000 mapping and vector data. This dataset was selected for its high quality and anticipated hydrological consistency.

3.15.3.2 Soil and underlying geology

The Harmonised World Soil Database (HWSD) is a 30 arc-second (approximately 1km resolution) raster (regular gridded) database with over 16,000 different soil mapping units. The HWSD is a composite dataset using existing regional and national updates of soil information with the information contained within the 1:5,000,000 scale FAO-UNESCO Soil Map of the World (FAO/IFA/IIASA/ISRIC-WSI/ISSCAS/JRC, 2009) Particularly relevant for a UK-based study, the areas covered by SOTER, including Central and Eastern Europe, are considered to have the highest reliability in the (World Soil and Terrain Digital Database project, which has an intended 1: 1,000,000 scale).

In practice, the HWSD is composed of a GIS raster image file linked to an attribute database in Microsoft Access format (freely accessible, subject to acknowledgement). There are three broad categories of data: (1) general information on the soil mapping unit composition; (2) information related to phases; (3) physical and chemical characteristics of topsoil (0—30cm) and subsoil (30—100cm). Example soil attributes include, but are not limited to, organic carbon, pH, water storage capacity, soil depth and textural class.

The ability to store and transport water through underlying rocks is important for determining the quantity of water (and ergo nutrients) that enter a river via groundwater. Spatial boundary data for superficial deposits and hydrogeology were taken from 1:625,000 scale national BGS data (BGS-DiGMapGB-625, 2013).

3.15.3.3 Climate

Baseline Climate Data

Climate variables were derived from 5km grid baseline data for UKCP09 held by the Met Office (UKCP09, 2009a, 2009b). Monthly data for total precipitation (mm) and mean air temperature (°C) and were acquired for 1961–1990. The datasets were provided as space-delimited text files and were available for scientific research, subject to registration.

Scenario Climate Data

Details of monthly mean daily maximum temperature mean daily minimum temperature and total precipitation projections from the UKCP09 project for the 2020s, 30s, 40s and 60s were obtained from UKCP09 (2009a, 2009b). The selected projections were for the medium emissions scenario and were on a 25km grid (2028 cells) aligned at an angle to the UK National Grid. The estimates extracted were 50% ‘change only’ values from a cumulative distribution function. This meant that there was a 50% probability of the change from the 1961-90 baseline being greater than the value specified (in °C or mm).

3.15.3.4 Water

Numerical and categorical quality and hydrometric data were gathered for a target period between 2000 and present. Unless otherwise stated, these raw data represent the finest spatial, temporal and thematic resolution data available.

River quality and water chemistry

General Quality Assessment (GQA) Headline Indicators of Water Courses (nutrients) were obtained for England and Wales under license from the Environment Agency (EA-AfA163, 2012; see also details in IfRR, 2012). These data are classified concentrations of nitrates (NO^3 mg/l) and phosphates (P mg/l) with grades from 1 (very low) to 6 (excessively high); grades thus represent ranges of concentrations, not absolute values (**Table 3.A2.1**). This project used data from 2000 and 2009 (most recent).

Table 3.A2.1: Environment Agency grading framework for GQA Headline Indicators of Water Courses.

	Nitrate (NO3) concentration (mg/l)	Phosphate concentration (mg/l)
Grade 1	<5	<0.02
Grade 2	>5 to 10	>0.02 to 0.06
Grade 3	>10 to 20	>0.06 to 0.1
Grade 4	>20 to 30	>0.1 to 0.2
Grade 5	>30 to 40	>0.2 to 1.0
Grade 6	>40	>1.0

Absolute concentration data were extracted by the Environment Agency for all sampling sites used for regular reporting for freshwater environments across England and Wales. These bespoke datasets, monthly resolution, included a range of determinants (e.g. NH4+, oxidised N, NO3-, NO2-, suspended solids, ortho-phosphate, TP, inorganic N, TN) and incorporated a time period from 2000 to the present day (EA-AfA194, 2012). Similar water chemistry data for Scotland were extracted for this project by the Scottish Environment Protection Agency (SEPA, 2012a).

A further set of categorical data were used as descriptors of river quality. The European Water Framework Directive (WFD, 2000) was transposed into UK law in 2003. Member States must aim to reach good chemical and ecological status in inland and coastal waters by 2015. Classification status and environmental objectives, for surface water bodies across England and Wales, have been published in the River Basin Management Plans and are publicly available from the Environment Agency (EA-WFD, 2011). Each water body had a unique identifier with attributes including a georeference and classification status (High, Good, Moderate, Poor, or Bad). Additionally, this project made use of spatial data for WFD waterbody catchments (a series of non-overlapping polygon catchments). These were obtained directly from the Environment Agency (EA-WFD, 2013) and SEPA

Flow data

National River Flow Archive (NRFA) hydrometric metadata and statistics are published in the UK Hydrometric Register (Marsh and Hannaford, 2008) for over 1,500 gauging stations. These data present an average of all samples held on the archive for the station over the full period of record (up to the end of 2005). This project made particular use of mean flow (m^3/s) and Base Flow Index (BFI). BFI is measure of the proportion of the river runoff that derives from stored sources; for example, the more permeable the rock, superficial deposits and soils in a catchment, the higher the base flow. The UK Hydrometric Register dataset was provided in spreadsheet format by CEH. Only open stations (correct as of 2005) were used.

Finer resolution, daily mean river flow data (EA-AfA186, 2012) were exported from the Environment Agency database for a range of catchments across England and Wales (196 sampling sites). Similar daily mean flow data were extracted by the Scottish Environment Protection Agency (SEPA, 2012b) for Scotland.

Freshwater boundary data

Hydrometric Areas, HA, (digital spatial boundary data licensed from the Centre for Ecology and Hydrology) are either integral river catchments having one or more outlets to the sea (or tidal estuary) or groupings of such catchments which have topographical similarity (Marsh and Hannaford, 2008). For convenience and consistency, these boundaries were used to define hydrologically similar areas (total = 97 in mainland Great Britain).

CEH's 1:50,000 Watercourses were used to identify rivers, canals and surface pipes (man-made channels for transporting water e.g. aqueducts and mill leets) (CEH, 2012; Moore *et al*., 1994).

3.15.3.5 Land designations

Various different types of land designations (legal or less formal) were used by different modules of this research project during model development. Brief descriptions of the types of designation follow. Unless otherwise stated, digital boundary data were downloaded from: Natural England (MAGIC, 2012), Countryside Council for Wales (CCFW, 2012), SNH (2012) or (Scottish_Government, 2012). Temporally variable data were obtained where available and appropriate (i.e. new designations or changes to boundaries).

Conservation and land management legislation

National Parks are protected areas of the countryside and, although the land is often privately owned and worked (e.g. for agriculture), National Parks welcome visitors. Formal designation of land into National Parks has been staggered since the first Parks in the 1950s (see further details at Natural England, 2013a). There are currently 15 National Parks across Great Britain. English and Welsh spatial boundary data were downloaded from aforementioned sources; Scottish data were acquired from the Scottish Government (Scottish_Government, 2012).

An Area of Outstanding Natural Beauty (AONB) is an area of high scenic quality which has statutory protection in order to conserve and enhance the natural beauty of its landscape. AONBs have equivalent status to National Parks as far as conservation is concerned, but AONBs have more limited opportunities for extensive outdoor recreation. This research takes the Scottish equivalent of an AONB as the National Scenic Area (designated by Scottish Natural Heritage).

A Site of Special Scientific Interest (SSSI) is designated for its unique, varied and often threatened habitat, wildlife and/or geology. Public bodies own only about 20% of land designated as SSSIs and they are actively managed (and legally protected) to maintain their conservation interest. Many SSSIs provide opportunities for recreation, although this is not their primary purpose. Many SSSIs are also National Nature Reserves (NNRs) or Local Nature Reserves (LNRs) and these have greater recreational potential. An NNR is a site that is recognised for its wildlife and/or geology and is run by approved bodies, including Natural England, Scottish Natural Heritage, Forestry Commission, RSPB, and many Wildlife Trusts. Almost all NNRs are accessible and provide opportunities for people to experience nature. LNRs are sites for both people and wildlife and these are maintained by district and county councils. To qualify for LNR status, a site must be of importance for wildlife, geology, education or public enjoyment.

Public access, parks and gardens

Under the Countryside and Rights of Way Act 2000 (CROW), the public (England and Wales) can walk freely on mapped areas of mountain, moor, heath and down, and registered common land. Two datasets were obtained from Natural England for CROW: Access Layer Data, which consists of all conclusive open country and registered common land, and the Conclusive Register of Common Land. Spatial data for CROW land in Wales was unavailable. For Scotland, the Land Reform Act gives a right of responsible access to almost all land.

Country Parks are significant areas of accessible natural greenspace and were originally established as a result of the 1968 Countryside Act (England and Wales) and in Scotland under the Countryside (Scotland) Act 1967. They are primarily intended for recreation and leisure opportunities close to population centres and do not necessarily have any nature conservation importance. They typically deliver core facilities and services e.g. toilets and daily staff presence) but this is only a requirement for Country Parks with accredited status. There are over 400 Country Parks in England, 52 in Scotland and 35 in Wales. Due to the difficulty in obtaining a spatial dataset of Welsh Country Parks, they are excluded from the analysis.

Doorstep Greens and Millennium Greens are community-managed spaces which have received Lottery funding to create, improve or restore areas of green space close to population centres. The Doorstep Greens initiative ran from 2001 to 2006 and was the successor to Millennium Greens. These areas were designed to be ‘safe, secure and accessible to all’ (see Natural England, 2013b).

The Woods for People project (led by the Woodland Trust) has created a UK-wide inventory of accessible woodland (FC, 2012). This data source provides a good representation of recreational woodland sites. Other attributes about the type of trees and amenities Ancient Woodlands are areas that have had continuous woodland cover for at least 400 years. These woodlands are typically more ecologically diverse. The Ancient Woodland Inventory was available through MAGIC (2012), Forestry Commission (for Welsh data) (FC, 2013) and SNH (2012).

Spatial boundary files for Registered Parks and Gardens (England) were available from English Heritage (EH, 2013). Areas of land maintained by the National Trust and the National Trust for Scotland were identified using a National Trust point file (downloaded as a ‘points of interest’ file in Keyhole Markup Language form (GPSDT, 2013)).

Environmental land management and restrictions on development

Greenbelt is a policy for controlling urban growth. Spatial data for English greenbelt (c. 2011) were licensed by Defra from Ordnance Survey (OS, 2011). Presently, there is no national digital spatial boundary dataset for Scottish greenbelt. Each council was contacted for spatial information and PDF maps or ESRI shapefiles were received for all areas of Scottish greenbelt (present and historic). Additionally, there is currently one area of greenbelt in Wales; information on this was found in local development plans (i.e. Newport and Cardiff).

The Environmentally Sensitive Areas Scheme was introduced to offer incentives to encourage farmers to adopt agricultural practices which would safeguard and enhance parts of the countryside. Although the scheme is now closed, existing agreements can run until 2014. The agricultural production module of this project has used historic digital spatial data for Environmentally Sensitive Areas, these are zones in which farmers could apply for funding and do not therefore necessarily reflect agreements taken.

Nitrate pollution prevention regulations bring into force the European Commission nitrates directive (91/676/EEC). The regulations mean that all land which drains into waters polluted by nitrates is designated as a Nitrate Vulnerable Zone (NVZ) and farms within these areas must meet a set of NVZ requirements. For example, farmers must adequately store livestock manure, plan and produce a risk map for its redistribution as a fertiliser to comply with NVZ rules.

Descriptors: land type, cover and use

Land cover and land use in the UK have been described in a previous section of this report (Section 3.15).

Landscape can also be defined based on a unique combination of physical environment and social conditions. These natural areas are taken from National Character Areas in England (159), groupings of Landscape Character Assessment study areas in Scotland (25) and landscape character areas in Wales (48) (data sources were: MAGIC, 2012, SNH, 2012, and CCW, 2012 respectively). In this report, these natural areas are collectively referred to as 'Landscape Character Areas' (LCAs). Although they are regional-scale, the groupings are defined based on natural features of the landscape, rather than political boundaries.

3.15.3.6 Beaches, coast and coastal resorts

Under EC Directive 76/160/EEC, designated beaches are monitored for compliance to bathing water quality standards. Bathing water status for all popular UK bathing places beaches is available from the European Environment Agency (EEA, 2013). Additionally, the Environment Agency monitors and maintains a record of bathing waters in England and Wales and these data were downloaded via Open Government Licence (Geostore, 2013). Scottish designated bathing waters were available from Scottish_Government (2012). The locations and names of additional beaches visited by the public were extracted from: http://britishbeaches.info/.

Registers for Blue Flag status and Seaside Awards were used as indicators of beach quality or tourist appeal. Beaches are awarded the Blue Flag based on their conformity with 32 criteria covering: environmental education and information; water quality; environmental management; and safety and services (Blue Flag, 2013). The Blue Flag Programme is an international award scheme for labelling sustainable beaches and is maintained by a non-profit NGO. Fifty-five beaches in England were awarded Blue Flag status for the 2013 season. In Wales, 39 beaches were awarded the Blue Flag for the 2012 season (latest available data). Scotland had three Blue Flag beaches in 2012 and 2013. The UK national Seaside Award recognises and rewards beaches which achieve the highest standards of beach management (Keep Britain Tidy, 2013). There were 112 Seaside Awards presented in England in 2013 and 108 in Wales. Keep Scotland Beautiful's National Beach Award recognised 59 of Scotland's well-managed beaches in 2013 (Keep Scotland Beautiful, 2013).

Definitions for coastal resorts (or seaside towns) in England were taken from official government publications (Beatty *et al*., 2008; 2011; Humby, 2013) and from authors of the original reports. A seaside destination is any seaside settlement to which people travel for the beach and associated activities. Three tiers of resorts were distinguished based on their size: small (population below 10,000), medium (population 15,000 to 39,999) and large (population greater to or equal to 40,000). The spatial areas for these resorts were defined using Lower Super Output Area (LSOA) boundaries. A list of LSOA was provided for the former through personal communication with Sheffield Hallam University and LSOAs were defined from supplementary data provided by Humby (2013) for the latter two categories of resort. The definition of Welsh seaside towns came from Beatty *et al*. (2009) and represents coastal resorts with a population of approximately 1,500 to 66,000.

Ordnance Survey Open Data (Strategi) were used to define the coastline (high water) (OS, 2013c).

3.15.3.7 Recreational areas

The OpenStreetMap (OSM) project creates and distributes free geographic data (OSM, 2013). OSM data were used to provide an initial spatial definition of parks, paths, sports pitches, playgrounds, recreational lakes and recreational rivers (different to Section (water data)). There are several reasons for choosing OSM data for this research. First, these data are highly detailed, especially surrounding urban areas, and coverage across the UK is good. Second, the OSM project is an open-source resource and as such the (spatial-literate) public can upload data representing areas known to them. As such, the final product is likely to be updated frequently and a truer reflection of what is on the ground. However, as with any publicly sourced data, quality control is more sporadic.

3.15.3.8 Socio-economic and associated data

Socio-economic information was gathered to ascertain impact (or potential impacts) on human systems and natural systems. Key datasets are as follows:

- demographic data;
- a range of population summaries (e.g. total usual resident, adult, ethnic minorities, retired) were sourced from Census data (Casweb, 2013) or mid-year estimates (GROfS, 2013). These demographic data were taken at the intermediate geography level (i.e. aggregates of Census Output Areas, known as Lower Super Output Areas (LSOA) in England and Wales and Data Zones in Scotland). Corresponding boundary data were downloaded from UKBorders (2013);
- LSOAs are a geographic hierarchy designed to improve the reporting of small area statistics. They were designed in 2004 from groups of 2001 Output Areas (typically 4 to 6). LSOAs have a minimum population of 1,000 (with an average of 1,500) and a minimum resident household of 400 (with an average of 630) (ONS, 2013). There have been some (minor) changes in boundaries of LSOA from 2001 to 2011;
- higher-level geography (urban centre) population figures were taken from the ONS (2001) and GROfS (2001). Also, boundaries for DLUA were taken from the OS (2013b);
- household-level economic data;
- median household income was extracted from (Experian, 2008);
- travel/ connectivity data; and
- the Meridian 2 road network (OS, 2013b) and travel times from Jones *et al*. (2010) were used as raw data to derive travel times.

3.15.4 Methodology

Using a GIS, raw source data were translated into a common spatial unit for analysis.

3.15.4.1 Defining the extent of Great Britain

Great Britain includes all surfaces enclosed by inland borders. A definition of total area may be restricted to land only or include inland water in the littoral zone. The Extent of the Realm usually refers to the Mean Low Water Mark but in some cases boundaries extend beyond this to include offshore islands. A definition 'clipped to the coastline' (Mean High Water Mark) gives the Great Britain a more orthodox appearance; this area is over 23 million hectares (ONS, 2012). This total area can be subdivided into different geographical hierarchies, based on arbitrary zones, administrative or political areas, or based on natural land attributes.

The aforementioned spatial and spatio-temporal datasets, describing physical and social phenomena, originate from multiple source geographies. A common spatial unit was desirable for consistency across the different systems. Choice of this spatial unit (fitness for purpose) was a compromise between resolution, processing time and quality. The effects of scale and aggregation of spatial data (MAUP) have been introduced in Section 3.14 and further detail can be found in Openshaw (1984).

These data were integrated to a 2km grid, with this choice of resolution being a lowest common denominator given the highest detail at which agricultural land use data could be obtained. A non-overlapping continuous 2km grid across Great Britain encompasses approximately 57,000 individual cells.

When overlaying multiple spatial datasets, there will inevitably be some partitioning of grid cells. The following sections of the methodology discuss data interpolation and manipulation required to derive variables for the different models in this report. Where necessary, spatial data are re-projected to the standard OSGB 1936 British National Grid spatial reference system.

3.15.4.2 Elevation and slope

Elevation and slope variables were derived from the 50m resolution IHDTM (obtained as an ASCII raster and manipulated in a GIS). Average elevation for a 2km cell was simply the aggregate of all 1,600 elevation values in the corresponding IHDTM grid divided by the sum of cells.

Slope (degrees inclination) was calculated from the 50m IHDTM as the maximum rate of change in value from a cell to its eight neighbours. An average slope value was then taken for an entire cell.

Further to these two standard average-per-2km-cell variables, Section 3.4 required farmland-specific variables (here, farmland is inclusive and defined as all crops, grasses and other land on farms). Average elevation on farmland was calculated as a weighted average from a 25m resolution base definition of farmland (LCUAP2, 2010); in practice, this operation was calculated as a sum, for each 2km square cell, of the following: (elevation × (area farmland/area of land)). The approach was similar for slope. A final terrain variable was the proportion of land that is farmland and greater than six degrees inclination. All variables were calculated in a GIS and output as TERRAIN (2012). This dataset is used by models in Sections 3.4 and 3.6.

The 2km resolution average elevation data described above is further used to define a 2km resolution Digital Elevation Model (DEM). This DEM is used to calculate flow direction (path of steepest descent), flow length downstream and flow accumulation. In turn, flow accumulation defines a stream network (where number of cells draining to a cell > 25). The calculation of these variables is performed using standard hydrology tools in a GIS; however, it is also an iterative process in this case as minor modifications were made to the DEM to ensure that the river network and drainage basins showed reasonable correspondence with river and boundary data (Marsh and Hannaford, 2008, and CEH, 2012). Final variables were specifically developed for Section 3.9 (water quality; WATER, 2012).

3.15.4.3 Soil and hydrogeology

All soil variables were derived from HWSD (FAO/IFA/IIASA/ISRIC-WSI/ISSCAS/JRC, 2009) and pertain to the topsoil (0-30cm) unless stated otherwise. The source raster data was converted into vector format to allow the addition of an attribute table and the intersection of the 2km grid. Percentage total are in each class of interest in the 2km cell was then taken, or area-weighted averages were taken if more appropriate. Processing was carried out in a GIS and exported to MS Excel (SOIL, 2012). See variable descriptions in individual sections for further details.

Superficial deposits were reclassified into permeable (blown sand, Crag Group, glacial sand, landslip, raised marine, river terrace, other sand/ gravel) or low permeability (alluvium, Brickearth, clay-with-flints, Drift geology, lacustrine, peat, till). For hydrogeology, the Class 3 attribute was simplified (highly and moderately productive aquifers, low productivity aquifer and rocks with essentially no groundwater). Newly classified superficial deposits and hydrogeology layers were combined based on a classification scheme (**Table 3.A2.2**). The 2km grid was then overlain on the reclassified surface and the minimum value in a 2 km cell was taken.

Table 3.A2.2: Classification scheme for hydrogeology data.

Class	Rule
1	High/Moderate productive aquifer AND permeable cover
2	High/Moderate productive aquifer AND low permeable cover
3	low productivity aquifer AND permeable cover
4	low productivity aquifer AND low permeable cover
5	No groundwater

Observations for BFI originate from Marsh and Hannaford (2008) at gauging station level. Summary statistics are then taken at the HA-level (average and minimum BFI). The 2km grid was then overlain, taking the minimum BFI from summarised HA-level data if a 2 km cell crosses the boundaries of more than one HA.

Both hydrogeology and BFI variables can be found in GROUNDWATER (2013).

3.15.4.4 Climate

Baseline Climate Data

The grids were subsequently summed to create annual and growing season (April to September) totals for each 5km grid cells and these values were subsequently bilinearly interpolated to estimate values for each of the 57,230 points on the 2km resolution mesh covering Great Britain. Initially there were 239 points in coastal locations with missing data values for the climate variables so further processing was undertaken in ArcGIS to assign each of these points with the value of the closest point with complete estimates. None of these assignments involved using data from points more than 2,850m distant. The final dataset was stored as CLIMATE (2012).

Scenario Climate Data

Individual monthly values were further summarised in an Excel workbook as follows:

- calculate the average of the daily maximum and minimum temperature changes for each month;
- average these monthly mean values for the six growing season months in each year; and
- average the monthly precipitation change values for the six growing season months in each year.

These growing season totals were joined onto the polygon grid of 2,028 cells. Many of these had null values (e.g. areas of sea) so a second version was extracted with the 440 cells of ‘non-null’ values. A central point was then generated for each cell and the coordinates re-projected to the UK National Grid. Processing was then carried out in ArcGIS to assign each of the 57,230 points in the baseline

2km climate mesh with the change values for the nearest location in the 440 point scenario data. Once this integration had been achieved it was straightforward to calculate new absolute values of average growing season temperature (°C) and total precipitation (mm) for the for future decades (PROJECTIONS, 2013).

Figures 3.A2.1 and **3.A2.2** below show growing season mean temperature and precipitation for the 1961-90 baseline and 2030s and 2060s projections (PROJECTIONS, 2013). These maps imply that areas with < 300 mm precipitation are likely to expand to cover most of lowland England by the 2060s, with mean temperatures increasing to over 15°C. Upland areas of Britain are projected to be less impacted by changes in precipitation but mean growing season temperature increases of around 2°C are quite widespread. It is important to recognise that there is likely to be much annual variability around these middle point projections but changes of this magnitude would clearly have considerable implications for the suitability of different agricultural activities across Britain.

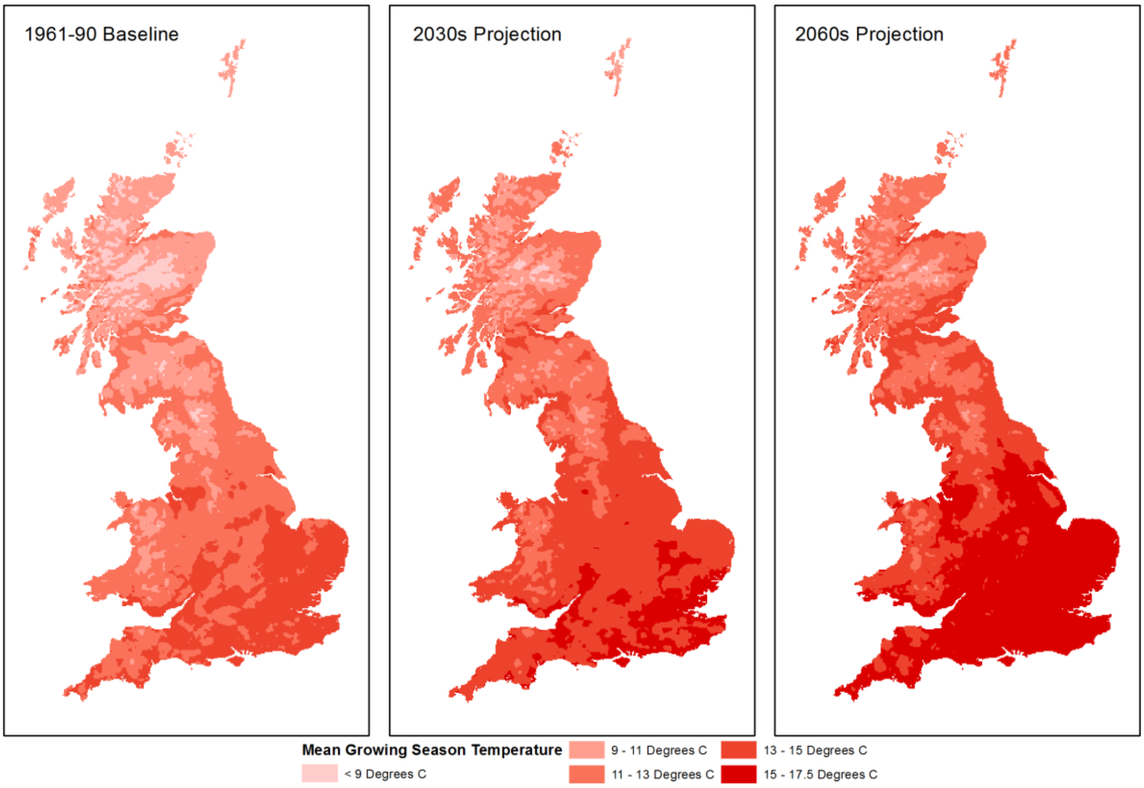

Figure 3.A2.1 Mean growing season temperature for the 1960-90 baseline, 2030s and 2060s projections.

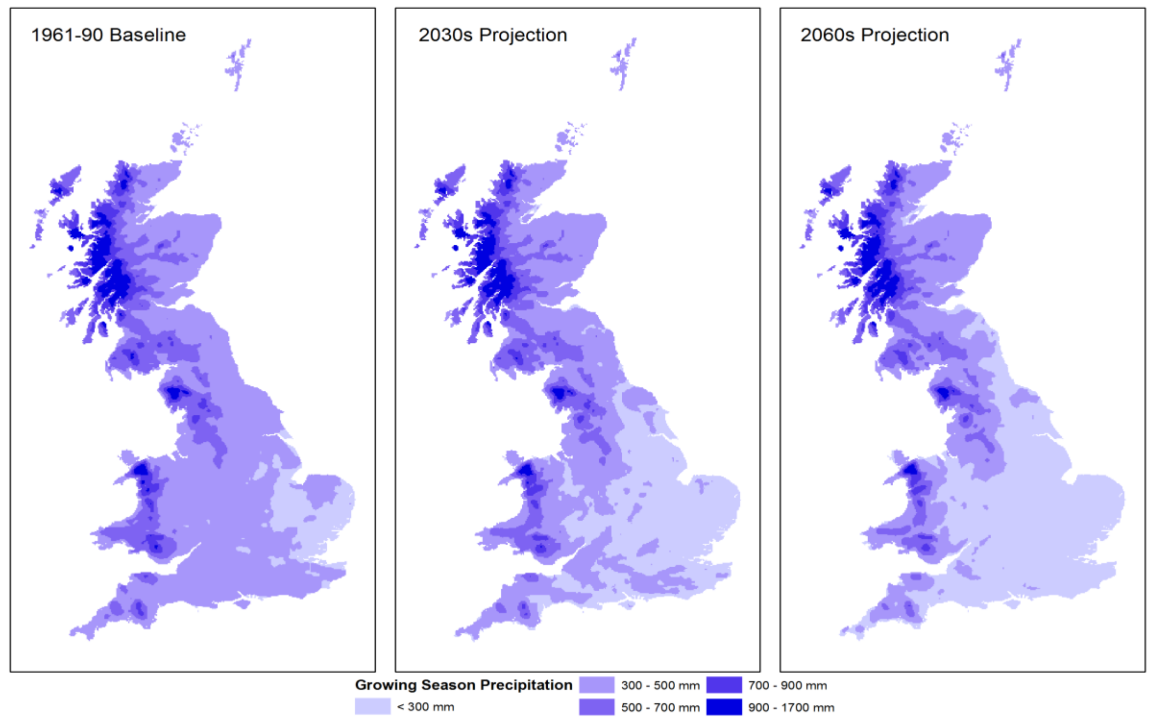

Figure 3.A2.2 Mean growing season precipitation for the 1960-90 baseline, 2030s and 2060s projections.

3.15.4.5 Water

The numeric water quality and hydrometric datasets were of a high quality, with fine temporal and spatial resolution. However, they required further sampling and post processing to be fit present purposes. For example, geographic references (sampling locations) for NRFA data and Environment Agency/ SEPA mean flow and water quality samples (described above) were not always consistent with each other or were ambiguous. Processing of water flow and quality observation data is described in the relevant section of this report (Section 3.9).

Categorical data were selected (sub-sampled) where they coincided with the derived 2km resolution stream network (in the case of GQA data) or within 5km of this network (WFD data). Adequate positioning of the observations on the river network was important; for example, sampling on a tributary must not be assigned to the main river channel at 2 km resolution. Any ambiguous points were removed from the observation dataset. Deviations were ascertained by a manual comparison of individual sample locations with centreline watercourse data (CEH, 2012).

In an initial test phase of The Integrated Model priority woodland was established based on WFD status variables. When these were combined it became apparent that there were many overlaps and sliver polygons on the England-Scotland border which required considerable editing in the ArcGIS software to correct. Another complication was that the WFD status assessment spreadsheets covering all of England, Wales and Scotland did not contain consistent attributes which limited the range of water quality characteristics that could be assessed. Ultimately, by linking the two sets of data using WB-ID codes it was possible to map 8,169 RWBs with a range of WFD status variables. Other water body polygons such as lakes and coastal locations were not assigned any status variables and coded as -1 (Null values) for the purposes of subsequent analysis (RWBs, 2013).

Additionally, physical response of a watercourse may be influenced by its morphology and this may be proxied by a descriptor of type. Therefore, presence of canal in 2km cell and presence of a surface pipe in a 2km cell were ascertained from CEH watercourse data (CANALS, 2012).

3.15.4.6 Land designations

Welsh greenbelt was digitised to clip to road and county boundaries using information found in Newport Unitary Development Plan (1996-2011)[41]. Scottish greenbelt PDFs were geo-referenced and digitised (scales typically ranging from 1:8,000 to 1:25,000). These national datasets were united with a simple shapefile for England to get total greenbelt in Great Britain. The 2km grid was then overlain and the percentage area of greenbelt in the cell was calculated from the intersection of the two datasets GREENBELT_EW (2012) and GREENBELT_S (2013).

Spatial boundary data for other land designations were available as ESRI shapefiles and the 2km grid was simply overlain.

3.15.4.7 Socio-economic and associated data

Raw demographic statistics, at LSOA-level, were assigned to a LSOA boundary or population weighted centroid (where appropriate, see individual sections for further details). Some statistics have not yet been released for intermediate-level geographies. In these cases, 2001 data were used.

Estimates for the population on mains sewerage, and those using septic tanks, were calculated using DLUA boundaries, LSOA (or Data Zone) boundaries and statistics for the total resident population. First, it was assumed that population was evenly distributed across a LSOA (or Data Zone). Each LSOA (or Data Zone) was given a population density. The DLUAs were then given a 250m buffer and it was assumed that all people within these areas were on mains sewerage, and by default those outside were on septic tank systems. Overlaying the population density surface with the mains sewerage area, and then the 2km grid, allowed an estimate of how the treatment of human effluent is shared in a 2km cell (SEWAGE, 2013). See Section 3.8 for further details.

3.15.4.8 Beaches, coast and coastal resorts

Beach and bathing data had geographic references and were added as points into ESRI's ArcGIS. Extra attributes were joined by name, where appropriate (e.g. possession of Blue Flag award). Any beaches which were noted in published statistics, i.e. as award winners, but were not otherwise part of spatial datasets were digitised manually.

The spatial extent of coastal resorts was defined by groupings of LSOAs. Where this information was not available (i.e. for Welsh resorts), resort names were matched to OS Meridian Developed Land Use Areas (OS, 2013b).

[41] Accessible at:
http://www.newport.gov.uk/stellent/groups/public/documents/plans_and_strategies/cont063489.pdf

3.15.4.9 Recreational areas

OSM data were downloaded using an open source software tool called 'Osmosis'. This is a command line Java application which can rapidly process OSM data, and it enables the user to selectively extract data based on elements (nodes, ways and relations) and their tags (keys and values). Data were subsequently converted into an ESRI shapefile format using a two-step importation and conversion process with POSTgreSQL (open source object-relational database system) and OpenGeo Suite (open source geospatial software for managing maps and data). Once in shapefile format, data were imported into ESRI's ArcGIS for further processing. First, they were re-projected in to the British National Grid (Projected Coordinate System) and they were then edited and combined with other data sources. Further details follow.

OSM data on parks were edited to remove the following: any areas with access restrictions, including all schools and their recreational grounds; sports clubs; any buildings or parking areas; and areas with a primary land use that would challenge recreational use (e.g. cemetery, allotments and farms). Additionally, very small 'parks' (< 10,000 m2) were removed if they did not contain a playground or were not given a name in OSM. This latter data cleansing process removed small areas that have been classified as a generic 'park' in OSM and are likely to be small community grassland features such as roundabouts or pedestrian areas.

As an intermediary step, the National Trust point file (see Section 3.15.3.5) was converted into shapefile format and re-projected. The points were overlain (with 150 m tolerance) on English Heritage's Registered Parks and Gardens dataset (see Section 3.15.3.5). Where selected National Trust-Parks and Gardens were also in the OSM-derived parks dataset, they were removed from the latter.

Next, multiple data sources were merged to obtain a spatial footprint of all major open-access recreation areas. These data sources were: the edited OSM-derived data on parks, National and Local Nature Reserves, Millennium and Doorstep Greens, Woods for People, Country Parks and National Trust properties (see descriptions in Section 3.15.3.5). Within each of the new recreational areas, the area of land and attributes (e.g. type of wood) under each of these categories were summarised. Additional attributes joined from processed OSM data were: area of pitches, area of playgrounds, length of rivers (inside recreational areas and within 25 m of the boundary), and lake area and perimeter. The amount of land under special types of designation was also calculated (e.g. National Parks, Areas of Outstanding National Beauty).

Finally, the habitat within each park was summarised according to the UK NEA definition (baseline year 2010; UK NEA, 2011). The UK NEA habitat shapefile (1 km resolution) was intersected with the parks layer using tools in Geospatial Modelling Environment (Beyer, 2013).

3.15.4.10 Recreational paths and walks

Connected OSM-derived paths were grouped by a process of applying a small buffer (10 m), dissolving the boundaries of overlapping polygons, assigning a unique ID to the polygons and then joining the polygon ID to each coincident line. Lines were then grouped by polygon ID. Resulting groups that had a total connected line length less than 1000 m were deemed minor places for recreation and were removed.

The terrain (habitat) traversed by each path was summarised by taking an intersection of the path data with the UK NEA habitat data (UK NEA, 2011). Spreadsheet-editing software was then used to calculate the length-weighted habitat. A similar intersection was performed to get the total path length in each National Park, in any Area of Outstanding National Beauty and in registered common land (CROW). The length of path beside a river or lake was calculated by taking buffers around these features (10, 50 and 100 m), dissolving their boundaries and taking an intersection with paths.

Additionally, a special category of paths were those along the coast. Buffers of 100 m and 500 m were applied to the coastline and paths were given a TRUE or FALSE indicator if they intersected these.

3.15.5 Discussion and summary

Discussion of supporting data and derived variables can be found in the relevant sections of this report (and references therein). However, general observations are as follows:

- together these datasets provide a broad set of physical and social descriptors; however, they are not exhaustive;
- for modelling purposes it is necessary to reduce the complexities of ecosystems and care must be taken to not over-simplifying phenomena;
- natural features cross artificial boundaries and therefore some spatial units are more appropriate than others; and
- due to a lack of alternatives, considerable simplifying assumptions were used for some of the variables (e.g. sewage).

3.16 Annex 3: The recreational value of changes in water quality

3.16.1 Summary

This section examines the relationship between ecological quality of rivers, the characteristics of associated potential recreation sites, and the preferences of individuals in evaluating the 'use' and 'non-use' value of such sites. Using a bespoke random utility model, evidence is presented which supports established findings (Eom and Larson, 2006; ENDS, 1998; Moran, 1999; and Bateman *et al.*, 2006) that utility from the 'use' of natural resources declines with distance from an individual's home, and that the nature of values emanating from river quality attributes differ with regard to 'use' and 'non-use' categorisations.

In particular, the model finds that although incremental improvement in the ecological status of rivers is associated within increasing 'non-use' utility, only an achievement of the *highest* ecological status was found to provide meaningful increases in 'use' utility. This suggests that 'non-use' utility may be a significant component of the welfare gains that arise from lesser improvements in the ecological status of rivers. Evidence also points to a new finding that values from 'non-use' decline at a rate approximately equal to the inverse of distance. Such empirical distance decay suggests that ignoring 'non-use' values may therefore significantly *understate* the welfare gains that might arise from river improvement initiatives. Finally, we find that the average annual welfare gain per person from a change in ecological quality from the poorest to the highest is valued in 2010 GB£ is estimated to be £12.71 (std. dev. £7.88), of which £11.03 (std. dev. £6.25) is derived in 'non-use' utility.

3.16.2 Objective

This work seeks to draw on and significantly extend existing methodologies (Whitehead *et al*., 2008; McFadden, 1994; Ben-Akiva and Morikawa, 1990; Hensher and Bradley, 1993; Adamowicz *et al*., 1994; Niklitschek and Leon, 1996; and Huang *et al*., 1997) to establish the welfare value of improvements in the ecological status of rivers in England, and in so doing to estimate values for ecological water improvements across Great Britain with respect to 'use' and 'non-use' recreational preferences.

3.16.3 Data

The data consists of two types; ecological status at river and site level; and household level survey data collected using a questionnaire incorporating both revealed preference (RP; travel cost method) and stated preference (SP; choice experiment approach) exercises.

In order to enhance the subsequent transferability of findings a study area was selected which incorporated both variation in surface water quality and variation in socio-economic characteristics. A region in the North of England encompassing Bradford, Leeds and Huddersfield was selected, as illustrated in **Figure 3.A3.1**.

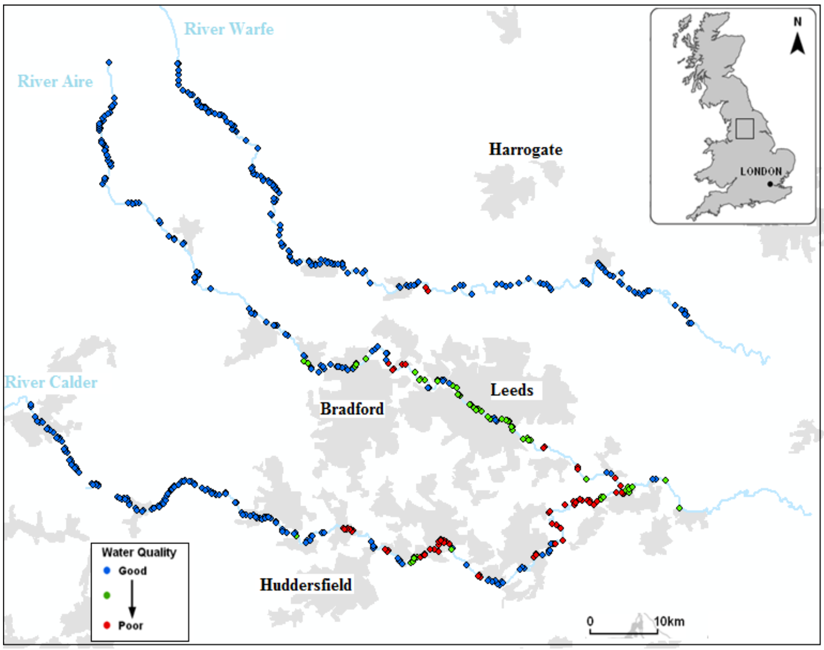

Figure 3.A3.1: Map depicts the location of the rivers in the study in the UK and the water quality. Source: Ferrini et al. (2008).

The transferability of the methodology was enhanced by using readily available Google Maps and GIS data to identify locations where the three major rivers in the region (the Calder, Aire and Wharfe; together covering a linear distance of about 125km) could be readily accessed by recreationalists either walking or driving to the sites (on site surveys verified the accuracy of these readily replicable approaches). This approach identified some 531 potential recreational sites. Further information on the physical-environmental characteristics of these sites was obtained using GIS, from the Ordnance Survey MasterMap (OS, 2013a) and Centre for Ecology and Hydrology (CEH, 2012) and Fuller *et al*. (2002) datasets. These also provide details of the predominant land use around each of the recreational sites, which were grouped into four broad categories: woodland; farmland; grassland; and urban (these categories being combinations of the wider categories used elsewhere in this research and the multi category classifications found in LCUAP2, 2000, 2010).

The current water quality at each of the recreational sites was calculated from Environment Agency long-term water quality monitoring data. Each river was then broken-down into several 3 km lengths, with each being categorised into one of four levels of ecological status: bad (red); poor (yellow); good (green); or excellent (blue), as shown in **Figure 3.A3.1**. The focus for this element of the exercise was to assess the ecological status of rivers in accordance with the classification system of the European Union's Water Framework Directive (WFD, 2012). The WFD requires that all EU member states are required to achieve good ecological status in rivers and lakes by 2015.

For the second dataset a large sample of over 2,000 households within the region were interviewed. The survey exercise was designed to by representative not only in terms of standard socioeconomic and demographic characteristics, but also with respect to distance from the rivers studied in the area (the latter objective ensuring that any distance decay in values was captured). Brief sample descriptive statistics were: average age 50 (s.d. 16); 44% males; average household size: 2.6; average number of children per family: 0.7; average net income in 2010 GB£: £22,496 (s.d. £12,347); job categories: 26% full time employed, 13% part-time employed, 33% retired, 7% self-employed.

The survey interview was conducted at the respondent's home address and administered using a custom designed computerised questionnaire which greatly simplified many of the questions required for both revealed preference (RP) and stated preference (SP) analyses. Using interactive maps respondents first located their home and then the various river sites they had visited over the previous 12 months (see **Figure 3.A3.2**). Additional demographic data was collected via a survey including: data on how frequently they had visited each of the sites; and the number of outdoor recreational trips they had taken to non-river sites. These responses provided the data required for an RP assessment of the use value of riverside recreational trips.

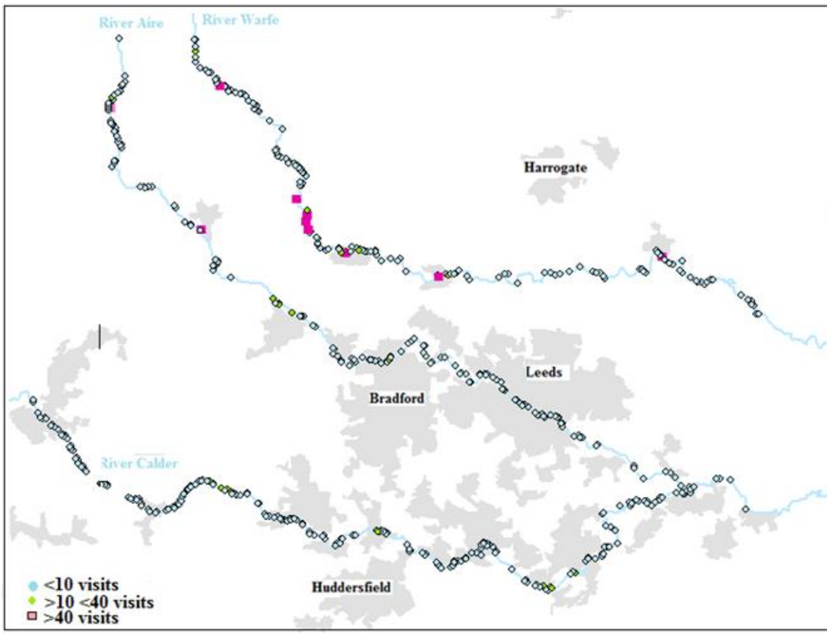

Figure3.A3.2: Map depicts the location of the study area and the number of recreational visits Source: Ferrini et al. (2008).

Although the exercise presented in this section utilises objectively measured water quality data, respondents assessments of sites were also elicited using a previously developed visual water quality ladder (Hime *et al*., 2009). This ladder was also used to convey potential changes in water quality within a subsequent map-based SP study in which choices between present and alternative future states (some of which involved costs) were offered to respondents. Responses to these options provided data for the SP estimates of willingness to pay for water quality improvements.

3.16.4 Methodology

Households are assumed to derive utility from the ecological status of rivers in two ways: first in how status enhances visits to recreational river sites ('use' value); second in how that status impacts on 'non-use' value. The model accommodates the fact that changes in water quality may impact on utility differently through each pathway. It also accommodates the fact that households regard recreational river sites as substitutes in 'use' but gain independent value from them in 'non-use'.

3.16.4.1 Structural model of utility difference arising from water quality changes

The structural model is defined as follows:

Equation 3.A3.1:

$$u_{i,t,s|j} = v_{i,t,s|j}^{use} + v_{i,t,s}^{non-use} \qquad (j = 1, 2, \dots, J + 2 \text{ and } \forall i, t, s)$$

where $i = 1,2, \dots, N$, represents people living in a region through which a number of rivers flow; $t = 1,2, \dots, T$ is the number of recreational choice occasions which are of equal length; $s = 0,1, \dots, S$ for states of the world in which the quality of river changes, this is mainly determined by the choice experiment design; and finally, $j = 1,2, \dots, J$ are the river site recreation options where $J + 1$ and $J + 2$ are respectively the option of not recreating or other non-river recreational options.

The structural model of the utility function comprises an element that captures value in 'use' and an element that captures value in 'non-use'. We construct a utility function to consider the value derived from rivers over the period of one year fixing T=365 and assuming that in each period an individual can make at most one recreational trip.

The econometric specification of model (1) is obtained by adding the error term $\varepsilon_{i,j,t,s}$ which captures the divergence between our model of 'use' utility $\left(v_{i,t,s|j}^{use}\right)$ and 'non-use' utility $\left(v_{i,t,s}^{non-use}\right)$ and the individual's experienced utility $\left(u_{i,t,s|j}\right)$. Following standard practice, the error terms are assumed to be $IID\ EV(0, \sigma^2)$; that is to say, as independent draws from a Type I Extreme Value distribution with location parameter zero and scale parameter σ^2.

3.16.4.2 Utility from use

In recreational choice period t, individual i, can choose to visit any of the J recreational river sites and it is assumed that 'use' utility is conditional on choosing to visit site j, can be modelled using the linear approximation:

Equation3.A3.2:

$$v_{i,t,s|j}^{use} = \alpha_{j,i,t} + \boldsymbol{x}_{j,t,s}\boldsymbol{\beta}_i + \gamma_i\left(I_{i,t} - tc_{i,j}\right) \qquad (j = 1, 2, \dots, J \text{ and } \forall i, t, s)$$

where, $I_{i,t}$ is individual i's per period income; $tc_{i,j}$ is the cost of travelling to and from site j for individual i; $\alpha_{j,i,t}$ is a site-specific utility element; $\boldsymbol{\beta}_i$ is the vector of coefficients describing the marginal use utilities of river site qualities and characteristics which are described by vector $\boldsymbol{x}_{j,t,s}$and γ_i is the marginal utility of income.

Alternatively, an individual may choose not to make an outdoor recreational trip, such an option is assigned to the index $J + 1$, and the utility associated from this option 'use' is specified as:

Equation 3.A3.3:

$$v_{i,t|J+1}^{use} = \alpha_{J+1,i,t} \qquad (\forall i, t)$$

or they may decide to take a trip to some alternative (that is, non-river) form of outdoor recreational site this option is assigned the index $J + 2$, and the utility associated from this option 'use' is specified as:

Equation 3.A3.4:

$$v_{i,t|J+2}^{use} = \alpha_{J+2,i,t} \qquad (\forall i,t)$$

Observe that since options $J+1$ and $J+2$ do not involve visiting a river site, the use utility associated with choosing either of those options does not change across scenarios.

3.16.4.3 Utility from non-use

Individuals also derive 'non-use' utility from rivers. To capture this the rivers are sub-divided into a series of consecutive but non-overlapping stretches of equal length, $m = 1,2, \dots, M$, and are assumed to remain identical over a stretch for the duration of a period. On the other hand, the qualities of river stretches differ across possible states of the world S which describe the qualities of rivers for the purposes of the choice experiment. We assume that the non-use utility derived from a particular stretch of river, stretch m, is a function of the qualities of that stretch weighted by the distance of that stretch from an individual's home. Accordingly, our model of the 'non-use' utility is derived from rivers is given by:

Equation 3.A3.5:

$$v_{i,t,s}^{non-use} = \sum_{m=1}^{M} {d_{i,m}}^{\lambda_i} \left(a_{m,i,t} + \boldsymbol{x}_{m,t,s}\boldsymbol{b_i}\right) + \gamma_i(-p_s/T) \qquad (\forall i,t,s)$$

where $d_{i,m}$ is the distance from individual i's home to the nearest point on stretch m; p_s is an annual cost associated with scenario s (with p_0, the cost in the current state of the world, being zero and that for each of the scenarios generated for the choice experiment, p_s $(s = 1,2, \dots, S)$, being greater than zero); $a_{m,i,t}$ is a stretch-specific element contributing to non-use utility, $\boldsymbol{b}_i$ is the vector of coefficients describing the marginal utilities of river site qualities from 'non-use' and λ_i is a parameter that establishes the rate of distance decay in 'non-use' utility. Note from comparison with (4) that unlike 'use' utility where an individual gains value in a period only from the site they choose to visit, 'non-use' utility is derived simultaneously from all river stretches and, as such, enters the utility function as a distance-weighted sum across all 'non-use' stretches. The use of a power function to describe that distance-weighting nests a number of plausible specifications; for example, $\lambda_i = 0$ suggests that 'non-use' utility does not decline with distance, while $\lambda_i < 0$ suggests a declining weight which asymptotes to zero with increasing distance.

To identify the parameters of the model we pursue an estimation strategy based on combining RP data with SP data. The RP data, recording day trips to recreational river sites, provides the primary source of identification for the parameters defining 'use' value.

3.16.4.4 Revealed preference data

In making recreational trip decisions in each period it is assumed that individuals choose from the set of options $j = 1, 2, \dots, J+2$, selecting that option which gives them the highest utility. Given the distributional assumptions regarding the utility error terms in Eq. 1 the probability of observing a particular recreational choice takes the familiar multinomial logit (MNL) form:

Equation 3.A3.6:

$$P_{i,k,t,0} = \frac{e^{v_{i,t,0|k}^{use}/\sigma_{RP}}}{\sum_{j=0}^{J+2} e^{v_{i,t,0|j}^{use}/\sigma_{RP}}} \qquad (\forall i,k,t)$$

where the scale of the error terms, σ_{RP}, is subscripted RP to allow for the fact that that scale may differ between actual recreational decisions observed in revealed preference data and those made in response to the hypothetical scenarios presented in the choice experiment.

3.16.4.5 Stated preference data

In the choice experiment exercise, individuals are presented with a series of questions, in each of which they have two scenarios to choose from, each differing in terms of the quality of the different river stretches and in terms of the annual cost. Respondents are assumed to choose the recreational option that provides them the highest level of utility. The utilities derived from those recreational options are assumed to be independent Type I Extreme Value distribution with equal variance. It follows that an individual's maximum utility in scenario s must also be an extreme value as:

Equation 3.A3.7:

$$u_{i,t,s} = \max_{j\in 1,..,J+2} u_{i,t,s|j} \sim EV\left(\sigma_s \ln \sum_{j=1}^{J+2} e^{\left(v_{i,t,s|j}^{use}+v_{i,t,s}^{non-use}\right)/\sigma_s}, \sigma_s\right) \qquad (\forall i,t,s)$$

where σ_s is the scale of the error terms relating to the utilities evaluated in response to scenario s. Since we have no reason to suspect that the error scales differ across scenarios, we impose the normalisation $\sigma_s = \sigma_{SP} = 1$ for all $s = 1, 2, \ldots, S$. Accordingly, our specification allows us to write the utility enjoyed by individual i in period t under scenario s as:

Equation 3.A3.8:

$$\begin{aligned} u_{i,t,s} &= \ln \sum_{j=1}^{J+2} e^{v_{i,t,s|j}^{use}+v_{i,t,s}^{non-use}} + \varepsilon_{i.t.s} \\ &= \ln \textstyle\sum_{j=1}^{J+2} e^{v_{i,t,s|j}^{use}} + v_{i,t,s}^{non-use} + \varepsilon_{i.t.s} \qquad (\forall i,t,s) \end{aligned}$$

where $\varepsilon_{i.t.s}$ is a standard Type I Extreme Value variate.

Of course, the choice experiment scenarios are framed as choices made over the duration of one year such that the final step derives the econometric specification for the utility from a particular choice experiment scenario, which is then summed over all periods;

Equation 3.A3.9:

$$\begin{aligned} u_{i,s} &= \sum_{t=1}^{T} \ln \sum_{j=1}^{J+2} e^{v_{i,t,s|j}^{use}} + \sum_{t=1}^{T} v_{i,t,s}^{non-use} + \sum_{t=1}^{T} \varepsilon_{i.t.s} \\ &= v_{i,s} + \sum_{t=1}^{T} \varepsilon_{i,t,s} \qquad (\forall i,s) \end{aligned}$$

In the choice experiment, individuals are presented with a series of tasks, $c = 1, 2, \ldots, C$ each of which asks them to state a preference over two particular scenarios, c_1 and c_2. In making that decision, an individual is assumed to choose the option providing the highest utility. From the analyst's point of view those utilities are, of course, random variables, such that the probability of observing individual i choosing option c_1 in choice task c, is given by:

Equation 3.A3.10:

$$
\begin{aligned}
P_{i,c} = Prob\left[Y_{i,c} = 1\right] &= Prob\left[u_{i,c_1} > u_{i,c_2}\right] \\
&= Prob\left[v_{i,c_1} + \sum_{t=1}^{T} \varepsilon_{i,t,c_1} > v_{i,c_2} + \sum_{t=1}^{T} \varepsilon_{i,t,c_2}\right] \\
&= Prob\left[v_{i,c_1} - v_{i,c_2} > \sum_{t=1}^{T} \left(\varepsilon_{i,t,c_2} - \varepsilon_{i,t,c_1}\right)\right] \\
&= Prob\left[v_{i,c_1} - v_{i,c_2} > \sum_{t=1}^{T} e_{i,t,c}\right] \qquad (\forall i, s)
\end{aligned}
$$

where $Y_{i,c}$ is a dummy variable that takes a value of 1 if individual i chooses option c_1 in choice task c or a value of 0 if they choose option c_2 and where, from a property of the Type I Extreme Value distribution, $e_{i,t} \sim Logistic(0,1)$. Observe that in differencing the utilities across the two scenarios any additive elements that are constant across scenarios are removed. For that reason, the data provides no means of identifying the stretch-specific utility elements: $a_{m,i,t}$. Likewise, it is not possible to identify non-use utility elements related to non-river recreational locations since these also remain constant across scenarios.

To evaluate the probability in of choosing c_1 in choice task c, we use a result from George and Mudholkar (1983) that shows how, as a convolution of standard logistic variates, the distribution of $\sum_{t=1}^{T} e_{i,t}$ can be very closely approximated by Student's *t* distribution. In particular;

Equation 3.A3.11:

$$
Prob\left[z > \sum_{t=1}^{T} e_{i,t,c}\right] \sim t_{5T+4}\left(0, \pi\left(\frac{15T + 12}{5T^2 + 2T}\right)^{-\frac{1}{2}}\right) \qquad (\forall i, c)
$$

where $t_{5T+4}(\cdot)$ is the cumulative density function of Student's *t* distribution with $5T + 4$ degrees of freedom.

Finally, the log likelihood function is defined as:

Equation 3.A3.12:

$$
\ln L(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma_0, \boldsymbol{b}, \boldsymbol{\lambda}) = \ln L^{RP}(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma_{RP}) + \ln L^{SP}(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{b}, \boldsymbol{\lambda})
$$

where:

Equation 3.A3.13:

$$
\ln L^{RP}(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma_{RP}) = \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{J+2} Y_{i,j,t,0} \ln P_{i,j,t,0}
$$

is the likelihood function from the RP data and $Y_{i,j,t,0}$ is a dummy variable which takes the value 1 if individual i chose recreational option j in period t, or zero otherwise, $\boldsymbol{\alpha}$ is the vector of utility elements specific to the different recreation trip options containing elements $\alpha_{j,i,t}$ $(j = 1, \dots, J + 2; i = 1, \dots, N; t = 1, \dots T)$, $\boldsymbol{\beta}$ is the vector of marginal utilities of river qualities comprising each $\boldsymbol{\beta}_i$ $(i = 1, \dots, N)$ and $\boldsymbol{\gamma}$ is the vector of marginal utility of income parameters with elements γ_i $(i = 1, \dots, N)$.

The log of the likelihood of SP choices is:

Equation 3.A3.14:

$$\ln L^{SP}(\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{b},\boldsymbol{\lambda}) = \sum_{i=1}^{N}\sum_{c=1}^{C} Y_{i,c}\ln P_{i,c} - \left(1 - Y_{i,c}\right)\ln P_{i,c}$$

where: $\boldsymbol{b}$ is the vector of marginal utilities of river qualities from non-use comprising each $\boldsymbol{b}_i$ $(i = 1, \dots, N)$ and $\boldsymbol{\lambda}$ is the vector of distance decay parameters with elements λ_i $(i = 1,2,..N)$.

The econometric specification is nonlinear in the structural preference parameters and allows for heterogeneity through a random parameters specification. Estimation is implemented through simulated maximum likelihood.

Verification of the structural model and its main characteristics was achieved using Monte Carlo simulation (available on request from the authors).

3.16.5 Results

For the purposes of estimating, with real world data, the parameters of the model outlined, we make a number of simplifying assumptions. Our data does not record changes in river qualities over time we therefore assume that those qualities remain constant over the period of one year. Consequently the vector of river qualities in the 'use' utility element of the utility function, $\boldsymbol{x}_{j,s}$, consists of a set of dummy variables capturing ecological status (with bad status being the baseline). A set of dummy variables captures the predominant land use at the site (with farmland being the baseline) and a variable measuring population density in the local area. Likewise, the vector of river qualities in the 'non-use' utility element of the utility function, $\boldsymbol{x}_{m,s}$, consists only of a set of dummy variables indicating the ecological status of the river stretch. Note that all other features of rivers are assumed to remain constant across scenarios and hence cancel out by differencing in the estimating Equation 17.12.

The heterogeneity in tastes across the sample is obtained by random parameters specification. In particular, we assume that the marginal utility of money parameter, the distance-decay parameter and the utility of the no-trip option are drawn from a normal distribution as specified.

In contrast, we constrain the utility of the other outdoor recreation trip and the taste parameters on river quality attributes for both 'use' and 'non-use' to be constant across individuals. Similarly, we constrain the parameters on the site-specific element of 'use' utility to be constant across individuals, but allow for unobserved differences in quality across sites by allowing those elements again to be drawn from a normal distribution.

Table 3.A3.1 reports estimated parameters which are all signed in accordance with prior expectations and generally statistically significant. The notable exceptions are the parameters on poor and good ecological status in the 'use' element of the utility function which are found to be insignificantly different from the baseline case of bad ecological status. In contrast the parameter on excellent ecological status indicates that individuals obtain a significant utility dividend from using rivers that are at the highest ecological status. It appears that in their 'use' of rivers for recreational activities, individuals only differentiate sites on the basis of whether or not they offer that highest level of ecological status. In effect, when visiting a river individuals are indifferent to an improvement from 'bad' to 'poor' status; only experiencing a significant enhancement to recreational use value when that river is improved to the highest ecological status. This appears to provide some support for the WFD objective of attaining that upper quality level.

In contrast, consider the parameters on the ecological status of rivers for the ‘non-use’ element of utility. Each of these parameters is statistically significant with a very high level of confidence being are ranked in a natural order with excellent status being preferred to good status and so forth therefore incremental improvements in river status are found only in ‘non-use’ utility.

Finally, it is worth noting that the distance-decay parameter on ‘non-use’ utility is significantly different from zero indicating that the ‘non-use’ utility an individual enjoys from a river declines with the distance that river is from their home. Indeed, the parameter value of -1.06 suggests the rate of decline to be approximately equal to the inverse of distance.

Taking the estimated parameters from the combined model, it is possible to carry out a welfare analysis that differentiates between changes in ‘use’ and ‘non-use’ value. To do this, we explore the average welfare gains that would be realised in our sample if all rivers in the region were improved from their current ecological status to excellent ecological status. We find that the average annual per person welfare gain from such a change is £12.71 (std. dev. £7.88), of which £11.03 (std. dev. £6.25) is derived in ‘non-use’ utility and £1.68 (std. dev. £1.85) in ‘use’ utility. Accordingly, our data suggest that the values of improvements in ecological status are relatively small in magnitude and come mainly from changes in ‘non-use’ utility.

Table 3.A3.1: Parameter estimates: Revealed and stated preference model.

	Parameter		Coeff. (std err.)
Use & non-use utility	$\left(\gamma_i \sim N\left(\gamma, \sigma_\gamma^2\right)\right)$		
Cost			
•	Location of Distribution	(γ)	-0.312 (0.022)***
•	Scale of Distribution	(σ_γ)	0.170 (0.010)***
Use Utility			
Recreational Trip Type:			
No Trip	$\left(\alpha_{J+1,i} \sim N\left(\alpha_{J+1}, \sigma_{\alpha_{J+1}}^2\right)\right)$		
•	Location of Distribution	(α_{J+1})	8.580 (0.398)***
•	Scale of Distribution	$(\sigma_{\alpha_{J+1}})$	2.236 (0.139)***
Other Outdoor Trip		(α_{J+2})	6.211 (0.419)***
River Trip	$\left(\alpha_j \sim N\left(\alpha, \sigma_\alpha^2\right)\right)$		
•	Location of Distribution	(α)	Baseline 0.0
•	Scale of Distribution	(σ_α)	3.419 (0.101)***
	River Site Qualities:		
	Ecological Status: Bad	(β_0)	Baseline 0.0
	Ecological Status: Poor	(β_1)	-0.137 (0.330)
	Ecological Status: Good	(β_2)	-0.061 (0.324)
	Ecological Status: Excellent	(β_3)	0.622 (0.277)
	Land Use: Farmland	(β_4)	Baseline 0.0
	Land Use: Urban	(β_5)	1.017 (0.262)
	Land Use: Grassland	(β_6)	0.857 (0.246)
	Land Use: Woodland	(β_7)	1.190 (0.269)
	Population Density	(β_8)	-0.350 (0.105)
Non-Use Utility	*River Site Qualities:*		
	Ecological Status: Bad	(b_0)	Baseline 0.0
	Ecological Status: Poor	(b_1)	3.078 (0.460)***
	Ecological Status: Good	(b_2)	6.754 (0.848)***
	Ecological Status: Excellent	(b_3)	8.120 (0.994)***
Distance Decay:	$\left(\lambda_i \sim N\left(\lambda, \sigma_\lambda^2\right)\right)$		
	Location of Distribution	(λ)	-1.060 (0.041)***
	Scale of Distribution	(σ_λ)	-0.379 (0.024)***
Relative Scale of CE		(σ_{SP})	0.519 (0.062)***
Log Likelihood		*-283,007.0*	
N		*1794*	

Estimated from Equation17.14. Standard errors in parentheses. Significance p-value:*p<0.05; **p<0.01; *** p <0.001.

3.17 Annex 4: Carbon values

The types of land use change considered in this report have significant impacts on greenhouse gas (GHG) emissions. To fully capture these effects, and to incorporate them into cost-benefit analyses, GHG emissions and sequestration resulting from land use change must be valued. Unfortunately, there is no nationally or globally agreed value for carbon (or CO_2 equivalent) emissions, and estimates range from -$6.6 to $2,400 per tonne (Tol, 2013). This section briefly reviews the challenges involved in estimating carbon values, the methods employed in current best practice, and justifies the values used throughout this report.

3.17.1 Approaches to estimating carbon values

There are many approaches to estimating the value of carbon emissions and sequestration, but two broad categories have come to represent current best practice:

- social cost of carbon (SCC); and
- target consistent marginal abatement costs (MAC)

3.17.1.1 Social cost of carbon

In a world of perfect information, cost-benefit analyses would use the social cost of carbon (SCC), defined as the cost of total global damages caused by an incremental unit of carbon emitted today, summed over its entire time in the atmosphere, and discounted to present value terms (Price *et al*., 2007). However, given the extent of uncertainty surrounding 'fat tails'[42] (Pycroft *et al*., 2011), environmental tipping points (Lenton *et al*., 2008; Weitzman, 2009), and the biosphere's precise response to atmospheric carbon (IPCC, 2007a), estimates of total damage vary widely. Moreover, given the timescales involved, estimates of SCC are particularly sensitive to the discount rate used, as well as a multitude of other assumptions regarding consumption growth rates, projected CO_2 emissions, the carbon cycle, and environmental sensitivity to CO_2 concentrations and temperature change. Tol (2013) analyses 588 estimates of the SCC from 75 reviews, finding that the mean estimate is $196 per metric tonne of carbon, while the mode is $49/tC (for emissions in 2010, expressed in 2010 US dollars). This suggests that the average values are driven by a few very large estimates. The wide range derives from different assumptions about the utility discount rate, also known as the pure rate of time preference[43] (see **Table 3.A4.1**). In short, the pure rate of time preference reflects an ethical decision about how much the present generation values future generations: a 0% pure rate of time preference treats all generations equally, while a positive rate discounts future generations' utility (Arrow *et al*., 2012; Heal, 2005).

[42] A 'fat tail' refers to the shape of the extreme edges, or 'tails' (and here, typically the right hand tail) of a probability density function (PDF). Usage of the term is somewhat arbitrary, leading to slight inconsistencies in definition, however, fat tails generally refer to PDFs that approach zero more slowly than the normal distribution (Calel et al., 2013). As explained by Weitzman (2011), "there is a race being run in the extreme tail between how rapidly probabilities are declining and how rapidly damages are increasing." Such fat tails are characterised by low (but crucially, non-negligible) probabilities of catastrophic events, the potential damages of which could push the SCC towards infinity, making mitigation efforts infinitely valuable (Weitzman, 2009).

[43] Crucially, this must not be confused (though it often is) with the consumption discount rate, which represents the relative weights placed on marginal increments of consumption (rather than utility) at different points in time. That is, it compares an extra dollar of consumption today with an extra dollar of consumption in the future. For a non-technical discussion, see NRC (2004), and for a formal treatment, see Heal (2005).

Table 3.A4.1: Summary Statistics of Social Cost of Carbon Estimates.

	All 588 estimates in sample	Pure Rates of Time Preference			Growth Rate
		3% ($/tC)	1% ($/tC)	0% ($/tC)	
Mean	196	25	105	296	2.3%
Mode	49	29	55	144	2.0%
Median	135	23	83	247	2.2%
Standard Deviation	322	22	128	309	1.3%

All values are for emissions in 2010 and expressed in 2010 US dollars. Sample composed of 588 estimates of the SCC from 75 studies analysed in Tol (2013). Source: Adapted from Tol (2013).

If cost-benefit analysis is to be meaningful, the values of GHG emissions and sequestration must be robust. However, the range of SCC estimates, and their sensitivity to arbitrarily determined parameters have led many to challenge their legitimacy for informing policy. A deeper and more fundamental problem is that the uncertainties extend beyond simple parameterisation and into the very structure of the underlying models used to estimate damages (Dietz and Fankhauser, 2010). This has sparked intense criticism of SCC estimates; see Pindyck (2013) and Stern (2013).

3.17.1.2 Target consistent marginal abatement costs[44]

Policy makers require robust cost-benefit analyses, which in turn need consistent, reliable, and accurate values for GHG emissions and sequestration. Given the wide range and inherent uncertainties surrounding the SCC (estimates span three orders of magnitude), there is justification for adopting alternative approaches. One such alternative entails setting an emissions cap or reductions target relative to some base level, and then estimating the cost of meeting it (Dietz and Fankhauser, 2010). Broadly, this is the marginal abatement cost (MAC) approach, where the MAC is the cost to polluters of reducing emissions by an incremental amount.

Of course, significant uncertainties exist here as well, not the least of which entail the changing costs and efficacy of abatement technologies; but the uncertainties surrounding MAC estimates are narrower than those around the SCC, perhaps by as much as an order of magnitude (see Dietz and Fankhauser, 2010). There are two primary reasons for this. First, MACs are typically grounded in observables, including currently available technologies with known market prices. Of course, these will change over time, but we can at least accept initial (short-term) estimates with relative confidence. Second, because the cost of abatement is independent of potential damages in the far-off future, estimates of the MAC exclude and are not affected by the uncertainties surrounding biophysical limits, carbon cycles, tipping points and temperature sensitivities which plague estimates of the SCC. However, MAC curves remain sensitive to assumptions regarding the lifetime of technologies, their investment and operating costs, and, of course, the appropriate discount rate (Kesicki and Ekins, 2011). Moreover, unlike the SCC, this approach obtains values implied by a specific target, but it cannot tell us anything about whether the chosen target (and its implicit price) is the 'right' one. That is, the MAC approach could yield carbon values that are well below (above) the 'true SCC', causing us to under (over) abate relative to the (unknown) true social optimum.

[44] This is the approach adopted by the UK Government for policy appraisals as of 2009 (DECC, 2009).

3.17.1.3 Top down vs. bottom up marginal abatement costs

There are two primary methods for creating marginal abatement cost curves: top down, and bottom up (Moran *et al*., 2011). Top down approaches begin by describing an economy (or sectors of an economy) in a computable general equilibrium (CGE) model with assumed production function(s), and use this to estimate costs of achieving specific targets. Moran *et al*. (2011) note that while this may be appropriate for sectors with relatively homogeneous production and abatement technologies spread over a small number of firms (e.g. energy production), it oversimplifies and misrepresents more atomistic sectors characterised by greater heterogeneity and regional diversity. This is particularly true of sectors such as agriculture, where production technologies vary significantly and abatement potentials are bounded by local biophysical characteristics.
Bottom up approaches attempt to address these shortcomings by taking stock of the full range of abatement technologies available in any sector and allowing for variations in implementation costs even within the sector. In the case of agriculture, for example, this would entail identifying all relevant abatement technologies and deploying them according to abatement potentials on individual farms or farm types across the country. While this has the potential to give a much richer view of abatement possibilities and costs, it is also more data intensive. For the purposes of this report, bottom up MAC curves for agriculture and forestry production would be ideal, but these are still under construction, and are not yet complete (see MacLeod *et al*., 2010; Moran *et al*., 2011).

3.17.2 Carbon values for UK policy appraisal

In 2009, the UK adopted a target consistent MAC approach to estimating carbon values for use in UK policy appraisal (DECC, 2009). Here, targets refer to artificial constraints on carbon emissions imposed by a regulatory authority (for example, the UK Government, EU, UN or other international agreement), and are commonly expressed in terms of quantity of emissions (as in the EU Emissions Trading Scheme; EU ETS) or percentage reductions relative to some base year (as in the UK Climate Change Act 2008; UK Parliament, 2008). In the UK context, there are separate carbon values for traded and non-traded sectors. This is justified by the fact that traded sectors are subject to the EU ETS, and thus face an implicit target determined by the cap on EU allowances, while the non-traded sectors fall outside the EU ETS and face targets set elsewhere, for example by the UK government.

Targets adopted in the UK were set out in the UK Climate Change Act (UK Parliament, 2008) and the first report of the Committee on Climate Change (2008) to the UK Government. They are consistent with the UK's EU and UN commitments, and entail reducing total UK emissions to 80% of their 1990 level by 2050, with interim targets of 26% and 12.5% reductions relative to 1990 levels by the years 2020 and 2012, respectively (the latter being the UK's Kyoto commitment). The Committee on Climate Change (CCC) is responsible for developing five-yearly 'carbon budgets' which help identify those sectors in which abatement efforts should be focused, and to monitor progress towards the targets (Committee on Climate Change, 2008, 2013). DECC (2013) reports separate values for GHG emissions (CO_2e) in traded and non-traded sectors, see **Table 3.A4.2**. Values in the traded sector are determined by the market prices of an EU emissions allowance (EUA), which permits the holder to emit 1 tonne of CO_2. Note that traded and non-traded sector prices converge in 2030, on the perhaps heroic assumption that a functional global carbon market shall be in operation by 2030[45] (DECC, 2009). Notably, these series peak between 2075 and 2078 and decline from 2079 onwards. This is a result of assumptions regarding fuel costs, global emissions trends, and most importantly,

[45] "… we assume that in the long run – from 2030 onwards - there will be a comprehensive global trading regime in place and therefore no distinction between the traded and non-traded sectors of the economy. Therefore, the traded-and non-traded sector carbon prices for use in appraisal will converge by 2030, to be replaced by an international carbon price derived from global abatement cost models." (DECC 2009: 32).

technological progress which underpin GLOCAF model used by DECC to forecast long run carbon prices (DECC, 2011b).

3.17.3 Carbon values used in this report

This report adopts the carbon values published by the UK Committee on Climate Change (2008, 2013) and the UK Department of Environment and Climate Change (DECC, 2009, 2013) for use in UK policy appraisal. Specifically, we use the DECC (2013) values which are based on the target consistent MAC approach explained above. However, for sensitivity analysis, we run the model using both the traded and non-traded sector values, as well as the $25/tC mean estimate of the SCC for studies using a 3% pure rate of time preference and a 2.3% growth rate from Tol (2013)[46] (see **Table3.A4.1**).

This gives us a range of carbon values with different price paths over time, and demonstrates the sensitivity of our results to alternative specifications of carbon prices. DECC (2013) provides carbon price projections to 2100, and we extend the SCC estimate to the same year. However, due to the long-term carbon flows associated with forestry, our analysis requires carbon values for each year until 2214. Owing to severe compounding over time, any projection that far into the future is inherently flawed. As such, we make the simplifying assumption that carbon values remain constant at their 2100 values. Though we admit that this is imperfect, the impact of this assumption is tempered by the effect of discounting into the very long-run.

For comparability, all values were converted to 2013 Great British pounds, using a constant long-run exchange rate of $1.587/£ provided by DECC (2013), and a GDP deflator provided by HM Treasury (2013). Finally, all units are reported in tonnes of CO_2 equivalent, rather than tonnes of carbon, using a conversion factor of 12:44. That is, the $25/tC (in 2010 US dollars) becomes £4.56/tCO_2 (in 2013 Great British pounds):

$$\frac{\$25}{tC} \times \frac{£1}{\$1.587} \times \frac{12C}{44CO_2} \times GDP\ Deflator = \frac{£4.56}{tCO_2}$$

The methods, approaches and prices described above represent the value of permanently sequestering 1 tonne of CO_2 from the atmosphere. However, in forestry and agriculture, carbon stored in soils and accumulated biomass is subsequently emitted when this matter decomposes. Thus, the carbon flows described in this report represent temporary, rather than permanent sequestration, and the values attributed to them must reflect this. Thus, for each year of analysis we calculated the value of sequestering one tonne of CO_2 in that year, for one year. Simply put, this amounts to the value of permanent sequestration in one year minus the discounted costs of permanent emissions in the next year, or

$$p_t - \frac{p_{(t+1)}}{(1+r)}$$

where p_t is the value of permanent carbon sequestration in year *t* and *r* is the discount rate. The quantity of carbon sequestered is then multiplied by the annualised value relevant to the year for which it is sequestered. **Table 3.A4. 2** shows the permanent values used in this report for carbon flows between 2010 and 2100.

[46] Specifically, we take the central traded and non-traded sector carbon values from DECC (2013). From Tol (2013), we take the $25/tC mean estimate from surveys adopting a 3% pure rate of time preference and assume that it grows at a constant rate of 2.3%.

Table 3.A4..2: Permanent and annual carbon prices 2010 – 2100 (£/tC0$_2$e).

	Permanent Values (2013 £/tC0$_2$e)				Permanent Values (2013 £/tC0$_2$e)		
	SCC 2.3% Growth	DECC Central Traded	DECC Central Non-traded		SCC 2.3% Growth	DECC Central Traded	DECC Central Non-traded
2010	4.56	12	57	**2056**	12.99	264	264
2011	4.67	11	57	**2057**	13.29	271	271
2012	4.78	6	58	**2058**	13.59	278	278
2013	4.89	3	59	**2059**	13.90	285	285
2014	5.00	4	60	**2060**	14.22	291	291
2015	5.11	4	61	**2061**	14.55	297	297
2016	5.23	4	62	**2061**	14.55	297	297
2017	5.35	4	63	**2062**	14.89	302	302
2018	5.47	4	64	**2063**	15.23	307	307
2019	5.60	5	65	**2064**	15.58	311	311
2020	5.73	5	66	**2065**	15.94	315	315
2021	5.86	12	67	**2066**	16.30	319	319
2022	5.99	19	68	**2067**	16.68	322	322
2023	6.13	26	69	**2068**	17.06	325	325
2024	6.27	33	70	**2069**	17.46	327	327
2025	6.42	41	71	**2070**	17.86	330	330
2026	6.57	48	72	**2071**	18.27	332	332
2027	6.72	55	73	**2072**	18.69	334	334
2028	6.87	62	74	**2073**	19.12	335	335
2029	7.03	69	76	**2074**	19.56	336	336
2030	7.19	76	76	**2075**	20.01	337	337
2031	7.36	84	84	**2076**	20.47	337	337
2032	7.53	91	91	**2077**	20.94	337	337
2033	7.70	98	98	**2078**	21.42	337	337
2034	7.88	105	105	**2079**	21.91	336	336
2035	8.06	112	112	**2080**	22.42	335	335
2036	8.24	119	119	**2081**	22.93	335	335
2037	8.43	126	126	**2082**	23.46	334	334
2038	8.63	134	134	**2083**	24.00	333	333
2039	8.82	141	141	**2084**	24.55	332	332
2040	9.03	148	148	**2085**	25.11	331	331
2041	9.23	155	155	**2086**	25.69	329	329
2042	9.45	162	162	**2087**	26.28	327	327
2043	9.66	169	169	**2088**	26.89	325	325
2044	9.89	176	176	**2089**	27.51	322	322
2045	10.11	183	183	**2090**	28.14	320	320
2046	10.35	191	191	**2091**	28.79	318	318
2047	10.58	198	198	**2092**	29.45	316	316
2048	10.83	205	205	**2093**	30.13	314	314
2049	11.08	212	212	**2094**	30.82	311	311
2050	11.33	219	219	**2095**	31.53	308	308
2051	11.59	227	227	**2096**	32.25	305	305
2052	11.86	234	234	**2097**	32.99	303	303
2053	12.13	242	242	**2098**	33.75	300	300
2054	12.41	249	249	**2099**	34.53	297	297
2055	12.70	257	257	**2100**	35.32	293	293

This table supports the DECC/HM Treasury Green Book guidance on valuing GHG emissions. The Low and High columns represent bounds for sensitivity analysis. These tables were last revised on 16 September 2013. Source: DECC (2013).

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