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# Modelling and mapping agricultural output values using farm specific details and environmental databases

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***Abstract***

*Ongoing concerns regarding the economic losses associated with the CAP and the negative environmental impacts of present land-use have led to calls for land use change and consequent efforts to identify areas which are, from both a financial and social perspective, most appropriate for such conversion. This paper develops and applies an output value modelling methodology in which site specific biophysical factors are combined with farm level data in order to predict input usage and, subsequently, farm profit. The spatial analytic capabilities of a geographical information system (GIS) are used to combine the variety of data employed to permit analysis of a large study area (the entirety of Wales) and yield models of both the market and shadow value of output from the two principal agricultural sectors of the area: dairying and sheep farming. The GIS is then used to produced readily interpretable maps of these values across the study area. The resulting maps are highly compatible both with value maps of alternative land uses given in the recent literature and with approaches to policy formulation currently under development by a range of UK agencies. Such maps may be used to assist estimation of the extent and location of farming response to land use policy change.*

# Modelling and mapping agricultural output values using farm specific details and environmental databases

## 1. INTRODUCTION

The economic losses (Anderson and Tyres, 1991; Josling, 1993) associated with the CAP and the widespread overuse of land for agricultural purposes (North, 1990), combined with long-standing concerns regarding the negative environmental impacts of present land-use (Body, 1982; Hodge, 1990; Fuller, 1996; Dobson, 1997), have led many commentators to consider the possibility of reorienting support away from conventional production measures and towards a more holistic agri-environmental system where both food and amenity become recognised and remunerative farm outputs (Blunden and Curry, 1988; DoE, 1988; Colman, 1993). Policy response to these pressures has come from both the EU (e.g. the MacSharry Reforms) and the national level (e.g. nitrate sensitive areas). A number of these initiatives have promoted moves out of conventional agriculture and into alternative land uses. Within these policies there have been increasing efforts to identify areas which are, from both a financial and social perspective, most appropriate for such conversion. An interesting and relevant recent example is provided by joint proposals from the Countryside and Forestry Commissions (1996; and more recently Forestry Commission, 1998) concerning potential conversions to woodland wherein planning will be guided by a series of forthcoming maps indicating optimal planting areas[1]. Clearly, in order to identify the economically optimal areas for conversion we also need to know the value of land under current, agricultural, production.

To address this requirement, this paper models farm gate income and its shadow value equivalent for major farm sectors within a large study area, namely the entirety of Wales, UK. An innovative methodology is developed utilising a geographic information system (GIS) to integrate and relate a variety of spatially referenced data concerning individual farm costs and revenues, with further data concerning the biophysical characteristics of each farm. The GIS is then used to extrapolate predictions from the resultant models to yield agricultural value maps for the entire study area for use within policy appraisals such as those outlined above. The maps are consistent with others produced by the authors detailing values for alternative land-use values, in particular the timber, recreational and carbon-storage values generated by multi-purpose woodlands (Bateman, 1996; Bateman and Lovett, 1998; Bateman et al., 1999).

Section 2 of the paper outlines the GIS-based methodology and the data are discussed in section 3. For modelling purposes, farms in the sample were clustered into distinct groups as explained in section 4

[1] Policy interest in this field has also been expressed by the Scottish Office whose recently announced Development and Testing of Land Use Methodologies programme will run for 3 years with a total budget approaching £1 million.

which also reviews definitions of farm gate and shadow value of production. Thereafter, the results of the modelling exercise for both sheep and dairy farming are discussed in section 5 and the consequent GIS maps are presented in section 6. Section 7 provides a summary and conclusions, including consideration of future extensions to the methodology developed here.

## 2. DEVELOPING A GIS-BASED MODELLING METHODOLOGY

Despite the considerable potential of utilising the spatial analytic capabilities of a GIS for modelling in agricultural economics, to date such systems have only been used to a limited extent (Moxey, 1996). However, whenever there are economic issues with a spatial dimension (e.g. changing patterns of land use; policy measures which are area sensitive; etc.) then the ability to overlay and integrate spatial data (relating, say to land characteristics) with economic data (which might relate to the farm business), means that a GIS provides the opportunity for much greater realism, comprehensiveness and relevance in modelling. The current paper adopts exactly that approach in order to generate estimates of farm gate and shadow values of agricultural output which could then be used, *inter alia*, to model changing patterns of land use.

Following a review of the literature (Bateman, 1996), it was decided to make an analysis of farm profitability the basis of our modelling methodology. This is both a common approach (e.g. Chambers and Pope, 1994) and accords with that adopted by the UK study which most closely resembles the present research, namely the NERC/ESRC Land Use Modelling Programme (NELUP) at the University of Newcastle upon Tyne (O'Callaghan, 1995, 1996)[2]. Both the present and NELUP studies use a GIS to integrate the physical environment into an analysis of farm profitability (Moxey and Allanson, 1994; Watson and Wadsworth, 1996). However, unlike our own study, the NELUP model does not have access to individual farm-level data[3] (discussed below) but has instead to depend upon aggregated Parish level agricultural census information collected by the Farm Business Survey (Allanson et al., 1992). This is a substantial drawback as it limits the scope for using the analytical capabilities of a GIS to relate the input-output situation of a particular farm to the characteristics of its biophysical environment.

The analytical framework which we present in this paper was developed iteratively as a result of empirical investigation. An initial single model attempting to relate farm income measures to a variety of input intensity measures (e.g. livestock per hectare), environmental factors (e.g. soil type)

[2] Another important ongoing study is the Land Use Allocation Model (Jones et al., 1995) currently under development at the University of Reading. This linear programming model also uses FBS data although, as per the NELUP model, this is aggregate rather than farm level. Consequently many of our comments regarding NELUP could also be applied to the LUAM model.

[3] Note that a small farm level study of 10 farms has been conducted under the NELUP programme (Oglethorpe and O'Callaghan, 1995).

and what we refer to as modification variables (e.g. fertiliser per hectare), proved to be overly simplistic for two reasons[4]. First, farm output decisions and hence incomes are subject to institutional rules (most noticeably, in the study area, whether or not a given farm holds a milk quota) to the extent that farms cannot be considered a homogeneous group. Second, investigations indicated that, even within a homogeneous sub-group of farms, a single model did not adequately describe the farmers decision process with regard to how the farm environment influences input and output decision making and hence income (Bateman and Lovett, 1992).

In order to address the first of these issues, farms were classified into broadly homogenous groups or sectors (using a cluster analysis described subsequently) within which policy constraints were roughly similar. The second issue was tackled through a two stage modelling procedure where in stage 1 income values were determined by the array and intensity of inputs utilised; while in stage two, the inputs employed were dependent on the prevailing biophysical characteristics and possible modifications of these characteristics. Cross-section regression analysis was then used to estimate the parameters of the stage one and two relationships within each sector. The stage 1 profit - input relationship was each sector is specified by:

$$\pi_{ij} = f_j(I_{1ij}, I_{2ij},,,, I_{pij},,,, I_{kij}) \tag{1}$$

where

$\pi_{ij}$ is the profit level of the ith farm (i = 1, , , n) on the jth sector (j = 1, , , m)
$I_{pij}$ is the intensity of use of the pth input (p = 1, , , k) on the ith farm in the jth sector

The stage 2 input – biophysical environment relationship for each input in each sector was specified by:

$$I_{pij} = g_{pj}(B_{1ij}, B_{2ij},,,, B_{hij},,,, B_{zij}, M_{1ij}, M_{2ij},,,, M_{rij},,,, M_{vij}) \tag{2}$$

where
$B_{hij}$ is the level of the hth biophysical variable (h = 1, , , z) on the ith farm in the jth sector
$M_{hij}$ is the level of the rth biophysical modification variable (r = 1, , , v) on the ith farm in the jth sector

The biophysical variables were stored on a grid cell (raster) basis within the GIS for the entire extent of the study area (see discussion of data below). Therefore by holding the modification variables at appropriate levels for the farm sector under consideration, we could use the regression parameters of

[4] The single equation approach was also hampered by multicollinearity between input and biophysical variables (Bateman and Lovett, 1992). This multi-stage approach to addressing multicollinearity owes much to Smith and Desvousges (1986).

Equation (2) to produce maps of predicted levels for all inputs for that sector. Subsequently a map of predicted income for the study area could be derived by applying the regression parameters of Equation (1) to the maps of predicted input levels.

The approach taken characterises farm decision making as a process in which the farmer first considers the institutional rules and constraints within which the farm must operate[5]; then assesses the physical environment of the farm and the extent to which it may be modified (as described in Equation (2)); before finally deciding the type and level of inputs to use which in turn determine outputs and farm profitability (as per Equation (1)). We recognise and fully acknowledge the fact that, from a sociological perspective, such a model remains naïve. In particular the writings of the Wageningen school (Van der Ploeg, 1993; Röling, 1993, 1994) show that many economic models of farm decision making omit consideration of factors such as farmers mindset, intrinsic knowledge base, personal and social experience, risk aversion (and its interaction with former factors), access to and quality of the local community knowledge base, etc. These are important influences which we do not deny and recognise as a limitation of our model.

## 3. THE DATA

The models detailed above require individual farm-level data on both biophysical characteristics and the variety of input, output and related variables which define a farm. The Farm Business Survey of Wales (FBSW) provided the necessary farm level cost and revenue data, while biophysical characteristics were taken from the LandIS database compiled by the Soil Survey and Land Research Centre (SSLRC, Cranfield) and other sources[6]. These data are briefly reviewed below.

During the 1989/90 study period the FBSW interviewed and obtained full accounts data for a representative sample of 571 farms across Wales[7]. Farms were geographically referenced according to the location of the farmhouse and for the purposes of this analysis these points were used to assign each farm to a 1km grid square. Access to the full FBSW dataset was permitted, although interviews with surveyors, who had visited each of the farms concerned, showed that many of the farms in the dataset were unsuitable for inclusion in the present study either because the farmhouse was not located on the land managed or the farm itself covered a diversity of environments, e.g. both lowland and upland areas affording winter shelter and summer grazing. Retention of such farms within the sample risked

[5] One further fundamental constraint is the difficulty for the farmer of moving from one farm to another. Often the farmer may face insurmountable problems in undertaking such a change.
[6] See acknowledgements to this paper.
[7] This is a routine, annual survey which typically interviews samples of this size. Farms are obliged to join the sample when selected.

confounding the relation between farm performance and biophysical characteristics, thus negating the fundamental research objective of producing models of the output value of a given area of land under a specified usage[8]. The latter value can directly be incorporated in land use planning systems such as those discussed at the start of this paper. Such mixed environment farms were therefore excluded along with those with large non-agricultural incomes leaving a final sample of 240 farms. The FBSW dataset is based upon full details of the annual accounts of the sample (which by law have to be surrendered, upon demand, to the FBSW). It is consequently a highly detailed and rich dataset.

The SSLRC land information system (LandIS) was complied for the Ministry of Agriculture, Fisheries and Food to facilitate "land use planning and national resource use" (Rudeforth et al., 1984). It represents the most comprehensive and detailed source of information on the biophysical characteristics of land across England and Wales. One part of LandIS is a database containing long term averages for a variety of agroclimatic variables at a 5km grid cell resolution. A summary of the variables selected for use in this study is given in Table 1. Further details regarding the compilation of the agroclimatic database and the geostatistical procedures used to interpolate measurements onto a 5km resolution grid are given by Jones and Thomasson, 1985; Ragg et al., 1988 and Hallett et al., 1996.

To supplement the characteristics extracted from LandIS, measures of elevation and associated variables were generated from the Bartholomew 1:250,000 digital map database for the UK. Contours and spot heights were processed within the GIS to produce a digital elevation model (DEM)[9] of Wales and estimates of elevation, slope angle and aspect were then calculated at a 500m resolution and subsequently averaged to provide values for 1km grid cells across the study area.

Integrating the farm and biophysical variables involved linking databases of varying resolutions. The approach taken was akin to a point-in-polygon method (Burrough and McDonnell, 1998) with the grid reference of each farmhouse being used to select values from the 1km resolution grids of topographic variables and the 5km cells of the LandIS agroclimatic measures. Characterisation of the biophysical environment facing each farm business was therefore a little generalised, but thought to be appropriate given the nature of the data sources available and the size of the study area. It also should be emphasised that the geographical matching of farm and environmental variables in this study is considerably more meaningful in previous research reliant on agricultural census data aggregated to parishes.

[8] Note that the exclusion of such farms means that our models are not designed for predicting the incomes of farms which straddle differing environments. However, as made clear here, our objective is to value differing land uses in differing locations, rather than farms per se.

[9]The authors are grateful to Julii Brainard of the School of Environmental Sciences, UEA, for assistance in creating the DEM.

## 4. FARM SECTORS AND FARM INCOME

Initial investigations revealed some substantial contrasts between different groups of farms, most noticeably in terms of principal activity and resultant income levels (Bateman and Lovett, 1992). Ignoring this issue could have led to the underestimation of standard errors and exaggeration of the degree of explanation of any single model applied across all farms. Rather than adopt *ad hoc* rules for sectoral definition, a two stage classification process was implemented. Firstly, a principle components analysis (Norusis, 1985) was undertaken using farm-level data concerning the proportion of total revenue derived from each of six groups of output activities. Farms were subsequently grouped on the basis of their scores on the six components using a hierarchical agglomerative technique based on the Ward Error Sum of Squares (ESS) statistic (Ward, 1963). Scrutiny of the output of this analysis (particularly the ESS increments in the agglomeration schedule) suggested that a six cluster solution was the most appropriate[10]. Table 2 lists activity and income level statistics for each cluster.

It was decided that sample sizes were insufficient to justify further analysis of clusters 3 to 6. This left the two principal agricultural sectors for Wales; farms in cluster 1 specialising in sheep production with substantial production of beef cattle (hereafter referred to as 'sheep' farms) and; farms in cluster 2 specialising in dairying (hereafter referred to as 'milk' farms). As a final test of sectoral homogeneity, standard diagnostic tests for outliers were employed (Minitab, 1992). This identified one outlier amongst cluster 1 and three amongst cluster 2 and these farms were omitted to leave a final sample of 85 sheep farms and 104 milk farms. The most striking difference between these two clusters was a wide disparity in income levels with mean net income per hectare on milk farms being nearly six times that on sheep farms.

An issue which proved more complex than expected was the definition of appropriate measures of what the farmer perceives as his/her annual net income (which we term farm gate income: FGI) and of the shadow value equivalent of this (note that to permit comparability between farms of differing size all values referred to subsequently are adjusted to a per effective hectare basis[11]). An immediately appealing measure in the FBSW dataset is the 'Net Farm Income' (NFI) variable[12]. However, following initial investigation (Bateman and Lovett, 1992) this variable was found to be unsuitable for general modelling requirements because, while its output value minus input value part (denoted 'Farm

[10] Note that these are reasonably similar to those defined by the FBSW. However, unlike the latter they do not further subdivide farms according to their size as this may be (and subsequently proved to be) a significant determinant of per hectare farm income.

[11] This adjustment was at the individual farm level using FBSW data on effective farm area (the latter omits land under roads, buildings, etc.) This applies to all regression models and results reported subsequently.

Surplus' in FBSW publications) is, as expected, positively correlated with the quality of the biophysical farm environment (the variables $B_{1ij}, B_{2ij}, , , B_{hij}, , , B_{zij}$ in equation (2)), for sheep farms the opposite relationship occurs with respect to the 'Subsidies and Grants' constituent of NFI[13]. This tends to suppress the link between environmental adversity and overall income levels which is a substantial focus of interest in this study.

The definition of the correct measure of farm income is inherently problematic and is itself the subject of research (Sturgess, 1996). Following conversations with Tim Jenkins (FBSW Director, Aberystwyth) it was decided to base statistical investigations of agricultural value upon the Farm Surplus variable with subsequent adjustments of predicted values to estimate FGI. An appropriate definition was agreed with FBSW as per equation (3):

$$\text{FGI} = \text{Farm Surplus} + \{\text{Subsidies and grants - Rent and rates - Depreciation}\} \qquad (3)$$

To obtain FGI requires an estimate of {.} in (3). Actual observations on {.} can be used to define an adjustment variable, ADJFGI, which is the absolute difference (in £/ha.) between FGI and Farm Surplus. This variable was defined for both the sheep and milk sectors (producing variables ADJFGIS and ADJFGIM respectively). ADJFGIS was generally positive and found to vary according to the biophysical environment (increasing with environmental adversity); accordingly a simple regression model was used to predict its value.[14] In contrast a simple flat rate of £95 was found to be adequate for ADJGFIM.

The farm gate price received by farmers for their produce tells us the financial value (to farmers) of that output but it does not necessarily correspond to the wider social value of that output. In order to move closer to the latter we adjust for the following factors:

1. *Market price support;* The Organisation for Economic Co-operation and Development produce annual estimates both of the value of output and the value of market price support disaggregated for all major farm products in each member nation (OECD, 1992). Using this information, a rate of market price support can be calculated and subtracted from the market price of the goods concerned.

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[12] For precise definition of this and subsequent FBSW terms see FBSW (1990).

[13] This is in itself interesting as it shows that, at least on sheep farms, subsidies and grants do compensate for environmental adversity. Further complexity arises because the unpaid labour element of NFI is positively correlated with such adversity; i.e. farmers attempt to combat poor physical environments by devoting relatively more labour to the farm.

[14] See Bateman (1996) and subsequent discussion of Table 4.

2. *Direct subsidies and grants;* OECD (1992) also gives values for the amount of direct subsidies and grants paid to farmers. However, unlike our market price support calculation, such a rate of support cannot be said to be a reasonable approximation of the direct payments received by each farm. Fortunately the FBSW data supplied for this research details individual farm direct subsidies and grants disaggregated to three headings: cattle; sheep; and miscellaneous. Consequently individual payments can be directly subtracted from the total output value of each farm.

3. *Input subsidies;* Rates of input subsidy for each output heading were calculated from data given in OECD (1992). Ideally we would wish to allocate costs to individual outputs and remove input subsidies from these different cost portions. However, given that the same inputs are used on a variety of outputs, such an allocation of costs was not possible. An alternative approach is to calculate input subsidy values for each output by applying relevant input subsidy rates to the value of each output. These can then be added to total input costs.

4. *Levies;* These are in effect negative market price supports and can be treated in the same manner. Whereas adjusting for market price support will lower shadow value (with respect to market price), adjusting for levies (where applicable) will reverse the direction of movement (although the value of levies is invariably far below that of market price support).

5. *Impacts of the above upon world price levels:* The policy instruments above have had a considerable and depressing impact upon world market prices for agricultural produce which needs to be considered in our shadow pricing exercise (Rosenblatt et al., 1988). Roningen and Dixit (1989) provide estimates of the rates of world price increase of various farm products resulting from a general liberalisation of agricultural policy as implied by adjusting for the above instruments[15].

The resulting value (which we will refer to as an undistorted or shadow value and denote SV) is not the full social value of agricultural output as we ignore non-market externalities. However, such externalities may well be better evaluated explicitly and a range of techniques for such valuation now exist (Bateman, forthcoming).

The SV corresponding to Farm Surplus was calculated by adjusting the recorded financial values of outputs and inputs to estimated world price equivalents for the sample year. Two steps were involved in this calculation. First, output values were adjusted for market price support and co-responsibility levies and input values were adjusted for input subsidies.[16] Second, the adjusted output value for each farm product was multiplied by a trade liberalisation coefficient which attempted to capture the effect of multilateral agricultural trade liberalisation on the world price of that product. For ease of computation a combined shadow value adjustment factor for sheep and milk farms (SVadjs and SVadjm) allowing for all of these elements was calculated. Results from this analysis indicate that the SV of output was around 55% of Farm Surplus for the milk farms, a figure that rose to about 60% for the sheep farms in our sample.

We have now established definitions whereby we can identify both FGI and SV. Both of these are derived from Farm Surplus which we now define as $\pi_{ij}$ in equation (1); one set of equations (1) and (2) being estimated for each of the two farm sectors under consideration.

## 5. MODELLING FARM SURPLUS

Regression analysis proceeded in line with the principles described by Lewis-Beck (1980), particular attention being paid to problems of multicollinearity. Referring back to the modelling terminology defined in section 2; we first estimated the 'stage 1' value function (equation (1)) which defines the input-profit relationship. This identified the explanatory input variables which were best able to predict Farm Surplus and which subsequently formed the dependent variables in the 'stage 2' equation set (equation (2)) which defined the input – biophysical environment relationship.

The dataset was extensively investigated with a variety of specifications and functional forms being tested. Table 3 reports the best fitting stage 1 model of Farm Surplus per effective hectare for the sample of sheep farms and milk farms.

Given their cross-sectional nature, both models have a relatively high degree of explanatory power.[17] Examining the model for sheep farms we can see that Farm Surplus increases with livestock intensity (\$live/eh), with the efficiency of that livestock (lamb/ewe) and with the amount of labour a farmer and/or

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[15] Taken from Roningen and Dixit (1989, page 16, table 5). The trade liberalisation adjustment attempts to remove the distortions inherent in actual world prices stemming from policy intervention in the agricultural sectors of the main developed countries in the late 1980s.

[16] All adjustments made were based on data from OECD (1992); further details are given in Bateman (1996).

[17] There is debate as to what is an acceptable value for adj. $R^2$ in cross sectional studies. Hanley (1990) recommends a value of 0.2 while Mitchell and Carson (1989) suggest 0.15. The current study relies primarily on the former, more demanding, rule. Note also that the F ratio is significant in all cases and the null hypothesis of zero coefficient of determination is rejected at 1% significance for all our results.

spouse devotes to the farm ($f&sLab/h). However, increased revenue dependency upon direct payments (grants %) is synonymous with relatively lower levels of Farm Surplus.

The stage 1 model for milk farms performs even better than that for sheep farms achieving a very satisfactory degree of explanation given that this is a cross-sectional analysis. As before we find positive relationships between Farm Surplus and input intensity ($live/eh, genC/h). Similarly farm efficiency is a clear determinant of Farm Surplus which increases with the value of milk produced per cow ($mlk/cow)[18] and falls as more paid labour is required per hectare (pLab/h). Finally, we have two variables showing that where milk farms have to increasingly rely upon lower margin, non-core activities such as sheep and cattle (gShep%TO, catt%FR) so Farm Surplus values tend to decline.

The second stage of the modelling process entails the estimation of predictive models for each of the stage 1 explanatory variables for both types of farm. Thus, stage 2 models are concerned with predicting the relationship between biophysical characteristics and agricultural inputs. Table 4 presents the results of the stage 2 models for sheep farms.

Given their cross-sectional nature, the models have reasonable explanatory power with the possible exception of the model for labour inputs. Inspection of the lamb/ewe model shows that the value of this input efficiency measure is lower for soils prone to waterlogging (lnFCdays) but improves where modification leads to better forage availability (Silag%, $crop/h). Consideration of these variables leads to a problem regarding how they should be treated when using the model to predict lamb/ewe for the entire study area. We have full coverage for all of the biophysical variables (i.e. a raster layer for lnFCdays can readily be created within the GIS) but the same was not true of the modification variables. A typical approach to such problems is to hold such variables at defensible constant values[19]. An analysis of the distribution of both modification variables showed them to be somewhat skewed and so, for the purposes of prediction, both were held at their median values ($crop/h = 19.50; Silag% = 0.145).

Livestock intensity ($live/eh) is well predicted by the next model, being negatively related to increased susceptibility to waterlogging (lnFCdays) and positively related to improved access to the land (SprMWD^2) and forage availability (Silag%), the latter being treated as before in generating predictions of $live/eh. The third model shows farmer and spouse labour input rising in more waterlogged areas (Endwet) and following a negative quadratic with respect to accessibility (SprMWD, SprMWD^2) suggesting that as accessibility declines so does labour input but at a declining rate indicative of some minimum level below which labour input will not fall. However, the strongest relationship is with farm

[18] This is analogous to the lamb/ewe variable in the stage 1 model for sheep farms.
[19] See, for example, Garrod and Willis (1992).

size with small farms exhibiting significantly higher levels of farmer and spouse labour input. Again for predictive purposes this variable was held at its median value (<140eh = 1).

The final stage 2 equation for sheep farms, predicts the proportion of total farm revenue derived from subsidies and grants (grants%). Here the dependent variable is purely predicted by biophysical variables which provide a good degree of explanation. As discussed previously sheep farm grants are a function of environmental adversity, in this case modelled by increased waterlogging and slope.

Table 5 presents the stage 2 models for milk farms. The model for predicting livestock intensity ($live/eh) on milk farms fits the cross-sectional data well. Livestock intensity declines in areas of higher waterlogging risk (lnEwet) and rises in areas considered suitable for delicate crops (lnAWpot). There is also a positive general association with lowland relief areas (Lowrelif). Farmers can also improve the ability of the farm environment to support livestock both directly through the use of fertilisers (Fert/h) and indirectly through inputs of concentrates (pConc/h). As with our sheep models, for predictive purposes data on the biophysical variables (here lnEwet, lnAWpot and Lowrelif) are available for the entire study area. However, as before we hold the modification variables (here Fert/h and pConc/h) at representative constant values. In the livestock intensity model both modification variables exhibit a slightly skewed distribution and so are held at their median values (pConc/h = 241.2; Fert/h = 88.36).

In the model predicting the percentage of farm total output value derived from direct payments for sheep (gShep%TO), the dependent variable exhibits a quadratic relationship with the waterlogging measure (Enddry), falling at a declining rate as the end of field capacity period increases. This model is relatively weak compared to previous stage 2 models. Nevertheless it does satisfy our theoretical validity criteria. (adj. $R^2 > 0.2$). However, this is not true of the next model which predicts the general farm costs per hectare input intensity measure (genC/h) and accordingly we have grounds for doubting the validity of using such a model to predict the value of this input in the stage 1 model for milk farms. However, inspection of genC/h showed it to be reasonably normally distributed across farms and so it was decided to hold it at its mean value (85.23) in the stage 1 equation[20]. This is clearly not ideal but it is a recognised and unbiased way of addressing such a problem.

The explanatory power of the best fitting model for the input efficiency measure $mlk/cow (the value of milk produced per cow) for our milk farm sample is rather better, although a collinearity problem between the two variables Awcer^2 and SprMWD (both of which are related to soil moisture) makes their interpretation problematic. Nevertheless, these variables were retained on the grounds that they

[20] So in the stage 1 model we multiply the coefficient on genC/h by the mean value of the variable, i.e. 1.6977 * 85.23 = 144.7.

substantially improved prediction of the dependent variable, which is the prime purpose of the stage 2 models. Other variables are more straightforward to interpret. Soil classes 2 and 3 refer to some of the best (brown earth) soils found in the study area[21] while the variable Lowrelif indicates lowland areas. As expected both are positively related to milk yields as is higher levels of concentrate usage (pConc/h)[22]. Interestingly, and in contrast to sheep farms, higher levels of labour input on milk farms seem to be an indicator of inefficiency and consequent lower yields. This seems reasonable and is backed up by the negative sign on paid labour input in the stage 1 milk farm model. It seems that whereas low income levels mean that sheep farmers have no option but to devote additional unpaid labour to their farms, milk farms are generally operating at a much higher level of efficiency where profit maximisation can often be enhanced through cost reductions.

As before the modification variables are held as constants when the stage 2 models are used for predictive purposes. Here both f&sLab/h and pConc/h were found to have somewhat skewed distributions and so were held at median values of 135.6 and 241.2 respectively.

The next model considers another input efficiency measure, namely the value of paid labour per hectare on milk farms (pLab/h). Analysis of this model shows that the level of paid labour employed on farms is lower in areas of relative environmental adversity (indicated by high values of the Rain^2, MdefCerl and Elev^2 variables) and higher in areas were the environment is more benign (high values for Grazseas and Enddry^2). It is perhaps not surprising to find that the amount of paid labour on farms is inversely related to the farmer and spouse labour input, suggesting that as a farmers income increases so he/she substitutes paid labour for personal effort. For predictive purposes f&sLab/h is again held at its median value.

Finally the last stage 2 model is concerned with predicting catt%FR, an indicator of a particular, lower margin, non-core activity on our milk farms. This model fails our criterion of theoretical validity. However, catt%FR was approximately normally distributed and was consequently set to its mean value (0.1107) for predictive purposes within the stage 1 equation for milk farms[23].

The various stage 1 and 2 models provide empirical estimates of the relationship between the biophysical environment, levels of inputs and resultant output values on our sheep and milk farms. These estimates can now be applied to the prediction of FGI and SV for both sectors across the entirety of the study area thereby yielding vital information concerning the potential for land use change and policy impact within the area.

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[21] See Bateman (1996) for further details.
[22] Tests revealed no significant multicollinearity problem.
[23] So in the stage 1 model we multiply the coefficient on catt%FR by the mean value of the variable, i.e. -460.6 * 0.1107 = -50.99.

## 6. MAPPING MARKET AND SHADOW VALUES FOR FARMS

An initial attempt to implement our GIS based methodology revealed that the range of certain biophysical variables across the full extent of the study area was somewhat greater than that of the sample farms. This was most noticeable amongst the milk farm sample which lacked substantial upland observations. In general there was not a problem across the vast majority of the study area, but it was at the extremes, particularly in very mountainous areas, that models were effectively being used to predict outside the range of available data.

In effect, two solutions are feasible for such a problem (Altman and Gardner, 1989): either we can refrain from prediction in such areas or we can truncate each biophysical variable to some level represented in our farm sample data. The latter course of action was preferred as it was felt that having holes in the final map of predicted values would be confusing. Affected cells were set to the upper or lower limit of the farm sample data as appropriate. For our sheep farm models over 90% of the 20563 1km square land cells constituting the entire surface of Wales suffered no truncation of any variable, 8% of cells had one variable truncated and less than 2% of cells suffered further truncation. However for our milk sample these proportions were 74%, 10% and just over 15% respectively. The reason for this difference is simple, namely that there are relatively few milk farms in extreme upland areas. Consequently we have to be circumspect about predictions of milk farm values in such locations.

Farm Surplus values can now be estimated by running the various stage 2 models (using truncated biophysical variable surfaces as appropriate) to predict the input variables for the stage 1 models from which Farm Surplus values were then estimated. Table 6 details these values for both sectors, emphasising the highly significant difference in profitability between the two sectors. This difference becomes more extreme if we recall that there are relatively fewer milk than sheep farms in areas of environmental adversity, i.e. those cells at the lower end of the distribution of predicted Farm Surplus probably refer to very few (if any) real world milk farms.

The adjustment factors were then applied as detailed previously to estimate focus values of FGI and SV. By applying the adjustment factors (ADJFGIS and SVadjs for sheep farms and ADJFGIM and SVadjm for milk farms) to the estimates of Farm Surplus the predicted market and shadow values of output for each sector can be obtained. Considering the sheep farm sector first, Figure 1 shows the resulting GIS generated map for predicted farm gate income (FGIs) while Figure 2 illustrates predicted shadow value (SVs).

The distribution of predicted values of FGIs and SVs is similar and conforms strongly to prior expectations. Values are lowest in the Snowdonia, Cambrian and Brecon mountains and increase with movement into lowland areas. Localised variation due to soil quality and related impacts can also be detected. The somewhat blocky nature of parts of these figures is primarily these latter effects as the LandIS variables are at a 5km resolution whilst the other biophysical measures are recorded on 1km grid cells[24]. Given this, the overall picture provided by these results seems highly plausible.

This analysis was repeated for milk farms and Figure 3 shows the map for predicted farm gate income (FGIm) while Figure 4 details predicted shadow value (SVm).

As both the adjustment factors ADJFGIM and SVadjm are constants applied to predicted Farm Surplus values, the maps of FGIm and SVm only differ in terms of absolute values. For both we can see strong topographic and soil effects (see for example the band of poorer soils extending down the centre of the Pembroke peninsula). As before the predicted values conform strongly to prior expectations.

Comparing Figures 1 to 4, it is clear that for each sector shadow values lie substantially below farm gate income levels. However, the most stark contrast is between sectors, with milk values very much higher than their sheep equivalents (note the scale at the bottom of each figure). Table 7 illustrates this contrast by summarising frequency distributions for all four variables. This table quantifies the very wide disparity in both farm gate income and shadow value levels between the sheep and milk sectors. As noted with respect to Farm Surplus, this disparity becomes even sharper when we recognise that milk farms tend to be concentrated upon better land, i.e. the lower say 10% of milk values will, in reality, contain very few actual milk farms.

## 7. SUMMARY AND CONCLUSIONS

Any attempt to influence patterns of agricultural land use requires an evaluation of the current usage of that land. This paper has developed a GIS-based methodology for the estimation of both the market and shadow values of current agricultural output for a large study area. This methodology permits explicit incorporation of biophysical data within the economic modelling of output values. The capacity to combine diverse spatially referenced data afforded by the use of a GIS allows such modelling to be undertaken at a highly disaggregated level, and yields readily interpretable maps of predicted values as well as more conventional quantitative analysis. These valuation maps are highly compatible with the decision making approaches currently being developed and employed by

[24] For full details see Bateman (1996).

agencies such as the Countryside Commission and Forestry Commission in their land use planning roles (see Introduction).

The application presented concerns a sample of farms across Wales. The study provides models and mapped estimates of both the market and shadow values of output of the two major farming sectors in this area; mainly sheep and mainly dairying farms. Results show that for both sectors the shadow values lie considerably below corresponding market values. Furthermore, sheep farm values were substantially lower than those enjoyed by the dairy sector. The spatial detail of information providing by the resultant GIS generated maps should permit analysts and policy makers to conduct a number of policy appraisals such as the assessment of both the likely extent and location of land use response to changes in policy parameters.

Ongoing and future work will consider the potential for incorporating alternative land uses within the methodological framework developed here. Research to date has shown the GIS-based approach to be particularly appropriate for assessment of the diversity of values (including timber yield, carbon storage, recreation and biodiversity) generated by multi-purpose woodlands (Bateman et al., 1996, 1997, 1999; Bateman and Lovett, 1997, 1998). Comparison of the market and shadow values of both woodland and conventional agriculture should provide a useful input to the ongoing debate concerning land use policy in the UK.

Table 1: Agroclimatic variables obtained from LandIS

| Variable name | Label | Definition |
|---|---|---|
| Accumulated temperature | Acctemp | Average annual accumulated temperature above $0^{o}C$ (in $^{o}C$) |
| Accumulated rainfall | Rainfall | Average annual accumulated rainfall (in mm) |
| Field capacity | Fcapdays | Average annual number of days where the soil experiences a zero moisture deficit (in days) |
| Return to field capacity | Retmed | Median measure from a distribution of the number of days between the date on which a soil returns to field capacity and $31^{st}$ Dec of that year (in days) |
| | Retwet | The upper quartile of the above distribution; a measure of return to field capacity in wet years (in days) |
| | Retdry | The lower quartile of the above distribution; a measure of return to field capacity in dry years (in days) |
| End of field capacity | Endmed | Median measure from a distribution of the number of days between the 31st Dec and the subsequent date on which field capacity ends (in days) |
| | Endwet | The upper quartile of the above distribution; a measure of the end of field capacity in wet years (in days) |
| | Enddry | The lower quartile of the above distribution; a measure of the end of field capacity in dry years (in days) |
| Available water | Avwatgra | Soil water available for a grass crop after allowing for gravity induced drainage; the difference between water content at field capacity and at permanent wilting point adjusted for grass rooting model (in mm) |
| | Avwatcer | As per Avwatgra but adjusted for a cereal crop (in mm) |
| | Avwatpot | As per Avwatgra but adjusted for potatoes (in mm) |
| | Avwatsb | As per Avwatgra but adjusted for sugarbeet (in mm) |
| Moisture deficit | Mdefgra | Difference between rainfall and the potential evapotranspiration of a grass crop (in mm) |
| | Mdefcer | As per Mdefgra but adjusted for a cereal crop (in mm) |
| | Mdefsbpt | As per Mdefgra but adjusted for a sugarbeet/potatoes crop (in mm) |
| Workability | Workabil | A seven point ordinal scale indicating the suitability of the land for heavy machinery work in spring and autumn (ordinal scale) |
| Spring machinery working days | SprMWD | Average number of days between 1st Jan and 30th Apr when land can be worked by machinery without soil damage (in days) |
| Autumn machinery working days | AutMWD | The average number of days between 1st September and 31st December when land can be worked by machinery without soil damage (in days) |
| Lowland relief region[1] | Lowrelif | Lowland topographic relief denoted as regions 4, 5 and 6 in Rudeforth et al., 1984 (dummy variable) |
| Soil type[2] | SoilX | SSLRC soil type classification code (various dummy variables for differing soils – specified in notes to regression models) |

NOTES FOR TABLE 1:

Note: All the variables listed in Table 1 are continuous unless specified otherwise. For further information on definitions and measurement see Jones and Thomasson, 1985, or Bateman, 1996, except for: [1] from Rudeforth et al.,

(1994) p.19 and; [2] from SSEW (1983) as re-categorised by Bateman (1996) and Bateman and Lovett (1998). Some variables were transformed (e.g. by taking natural logarithms) prior to regression analysis; all such transformations are detailed in notes to regression models.

Table 2: Farm cluster characteristics: average income and mean percentage of total revenue from specified activities in each cluster of farms

| Cluster | No. of Farms | Average Income (£/ha p.a.) | Mean percentage of total annual revenue from each activity | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Milk | Cattle | Sheep | Other Livestock | Crops | Misc. |
| 1 | 86 | 83 | 0.4 | 29.7 | 64.4 | 0.1 | 3.4 | 0.5 |
| 2 | 107 | 509 | 77.8 | 11.1 | 7.1 | 0.5 | 2.4 | 0.3 |
| 3 | 29 | 47 | 1.8 | 63.9 | 28.3 | 0.5 | 1.9 | 0.6 |
| 4 | 10 | 223 | 17.2 | 27.7 | 39.5 | 0.4 | 0.8 | 13.5 |
| 5 | 2 | 1145 | 0.0 | 18.2 | 7.8 | 74.6 | 1.1 | 0.1 |
| 6 | 6 | 58 | 5.1 | 20.1 | 14.3 | 0.9 | 56.6 | 1.2 |
| All | 240 | 283 | 35.9 | 25.1 | 31.7 | 1.0 | 4.1 | 0.9 |

Table 3: Best fitting stage 1 models of Farm Surplus/ha on sheep (cluster 1) and milk (cluster 2) farms

| Farm Surplus/ha for sheep farms | | Farm Surplus/ha for milk farms | |
|---|---|---|---|
| Constant | -207.77<br>(-3.35) | Constant | 4.80<br>(0.05) |
| Lamb/ewe | 180.87<br>(4.97) | $live/eh | 0.467<br>(7.38) |
| $live/eh | 0.151<br>(3.95) | gShep%TO | -3543.2<br>(-5.13) |
| $f&sLab | 0.010<br>(2.91) | genC/h | 1.680<br>(2.75) |
| grants% | -210.43<br>(-2.15) | $mlk/cow | 0.241<br>(2.67) |
| | | pLab/h | -0.510<br>(-2.63) |
| | | catt%FR | -460.6<br>(-2.43) |
| Adj. $R^2$ | 0.62 | | 0.67 |
| N | 85 | | 104 |

where:

| | | |
|---|---|---|
| lamb/ewe | = | No. of lambs reared per ewe per annum (efficiency measure) |
| $live/eh | = | Value of livestock per effective hectare (input intensity) |
| $f&sLab/h | = | Notional value of farmer and spouse labour input per hectare (input measure) |
| grants% | = | Total subsidies and grants (direct payments) expressed as a percentage of total farm revenue (grant dependency measure) |
| gShep%TO | = | Sheep grants expressed as a percentage of farm total output value (grant dependency measure) |
| genC/h | = | General farm costs (electricity, water and telephone charges, licences, insurance's, subscriptions, etc.) per hectare (input intensity) |
| $mlk/cow | = | The value of milk produced per cow (efficiency measure) |
| pLab/h | = | Value of paid labour per hectare (efficiency measure) |
| catt%FR | = | Value of cattle output expressed as % of total farm revenue (enforced diversity measure) |

Figures in brackets are t-values

Table 4: Best fitting Stage 2 Models for Sheep Farms

| Predictor | Dependent variable | | | |
|---|---|---|---|---|
| | Lambs/ewe | $live/eh | $f&sLab | grants % |
| Constant | 3.510 (5.99) | 2711.9 (4.38) | -791.0 (-0.29) | -1.292 (-4.94) |
| InFCdays | -0.452 (-4.30) | -410.0 (-3.70) | - | 0.272 (5.70) |
| SprMWD | - | - | -710.0 (-2.41) | - |
| SprMWD^2 | - | 1.421 (2.44) | 78.59 (3.27) | - |
| Endwet | - | - | 37.86 (2.60) | - |
| InSlope | - | - | | 0.032 (2.93) |
| Silag% | 0.59 (3.16) | 1035.8 (6.14) | - | - |
| $crop/h | 0.001 (2.57) | - | - | - |
| <140eh | - | - | 2191.4 (3.56) | - |
| Adj. $R^2$ | 0.37 | 0.45 | 0.25 | 0.39 |
| n | 85 | 85 | 85 | 85 |

where:

*Biophysical variables:*

lnFCdays = Natural log of the number of days pa. for which soil is at field capacity.
SprMWD = Number of spring machinery working days
SprMWD^2 = Square of number of spring machinery working days
Endwet = The end of field capacity period as measured in 'wet' years
lnSlope = Natural log of mean farm slope angle.

*Modification variables:*

<140eh = Dummy for smaller farms (less than 140 effective hectares)
Silag% = Proportion of farm area put to silage.
$crop/h = Value of crops per hectare

Table 5: Best fitting Stage 2 Models for Milk Farms

| Predictor | Dependent variable | | | | | |
|---|---|---|---|---|---|---|
| | \$live/eh | gShep%TO | genC/h | \$mlk/cow | pLab/h | catt%FR |
| Constant | 468.0 (0.28) | 0.12787 (1.93) | 44.19 (3.47) | 481.0 (4.49) | 227.30 (2.65) | 0.092 (7.31) |
| InEwet | -736.8 (-2.72) | - | - | - | - | - |
| InAWpot | 804.6 (2.88) | - | - | - | - | - |
| Lowrelif | 140.24 (2.05) | - | - | 84.10 (2.29) | - | - |
| Enddry | - | -0.002 (-2.34) | - | - | - | - |
| EnddrySq | - | 0.00001 (3.06) | - | - | 0.032 (3.03) | - |
| AWgrSq | - | - | 0.002 (2.15) | - | - | - |
| AWcer^2 | - | - | - | 0.016 (3.27) | | - |
| SprMWD | - | - | - | -11.141 (-2.64) | | - |
| soil2&3 | - | - | - | 152.25 (3.86) | | - |
| Rain^2 | - | - | - | - | -0.0003 (-4.10) | - |
| MdefCerl | - | - | - | - | -4.802 (-4.58) | - |
| Grazseas | - | - | - | - | 1.0426 (3.17) | - |
| Elev^2 | - | - | - | - | -0.0006 (-2.54) | - |
| InSlope | - | - | - | - | - | -0.022 (-2.49) |
| sinAsp | - | - | - | - | - | -0.026 (-2.16) |
| pConc/h | 0.7432 (4.79) | - | - | 0.336 (4.03) | - | - |
| Fert/h | 2.2962 (3.69) | - | - | - | - | - |
| f&sLab/h | - | - | 0.081 (4.39) | -0.376 (-4.43) | -0.147 (-2.96) | - |
| ehaHay | - | - | - | - | - | 0.008 (3.38) |
| Adj. $R^2$ | 0.44 | 0.24 | 0.20 | 0.29 | 0.27 | 0.16 |
| n | 104 | 104 | 104 | 104 | 104 | 104 |

where:

*Biophysical variables:*

| | | |
|---|---|---|
| lnEwet | = | Natural log of the end of field capacity period as measured in ‘wet’ years |
| lnAWpot | = | Natural log of available water; measured for potato crop |
| Lowrelif | = | Farm in SSLRC relief regions 4, 5 or 6 (lowland) |
| Enddry | = | End of field capacity period as measured in ‘dry’ years. |
| EnddrySq | = | Enddry * Enddry |
| AWgrSq | = | Square of water availability for grass crop |
| soil2&3 | = | Farm located on soil types 2 (brown earths) and/or 3 (podzols) |
| Awcer^2 | = | Water availability for cereals |

SprMWD = Spring machinery working days
Rain^2 = Square of the average rainfall (mm pa.) on farm.
MdefCerl = Soil moisture deficit for cereals.
Grazseas = Length of grazing season (days pa.).
Elev^2 = Square of farm elevation (m) above sea level.
lnSlope = Natural logarithm of average slope on farm
sinAsp = Sine of aspect
*Modification variables:*
pConc/h = Value of purchased concentrates per hectare.
Fert/h = Value of fertiliser per hectare.
f&sLab/h = Notional value of farmer and spouse labour input per hectare
ehaHay = Effective hectares of farm put to hay

Table 6: Predicted Farm Surplus values for sheep and milk farms

| Farm Surplus (£/ha)[1] | Sheep farms | | Milk farms | |
|---|---|---|---|---|
| | No. of cells | % of all cells[2] | No. of cells | % of all cells[2] |
| 0.00 to 49.99 | 2483 | 12.1 | 7 | 0.1 |
| 50.00 to 99.99 | 6346 | 30.9 | 37 | 0.2 |
| 100.00 to 149.99 | 9492 | 46.2 | 248 | 1.2 |
| 150.00 to 199.99 | 1728 | 8.4 | 463 | 2.3 |
| 200.00 to 249.99 | 323 | 1.6 | 825 | 4.0 |
| 250.00 to 299.99 | 191 | 0.9 | 261 | 1.3 |
| 300.00 to 349.99 | - | - | 274 | 1.3 |
| 350.00 to 399.99 | - | - | 317 | 1.5 |
| 400.00 to 449.99 | - | - | 307 | 1.5 |
| 450.00 to 499.99 | - | - | 500 | 2.4 |
| 500.00 to 549.99 | - | - | 1295 | 6.3 |
| 550.00 to 599.99 | - | - | 2342 | 11.4 |
| 600.00 to 649.99 | - | - | 4845 | 23.6 |
| 650.00 to 699.99 | - | - | 5067 | 24.6 |
| 700.00 to 749.99 | - | - | 3171 | 15.4 |
| 750.00 to 799.99 | - | - | 543 | 2.6 |
| 800.00 to 849.99 | - | - | 61 | 0.3 |

Notes: 1. Categories chosen to facilitate easy comparison with values reported for woodland in Bateman and Lovett (1997).
2. There are 20563 1km square land cells.

Table 7: Predicted farm gate income and shadow values for sheep and milk farms

| Value (£/ha)[1] | Sheep farms | | | | Milk farms | | | |
|---|---|---|---|---|---|---|---|---|
| | FGIs | | SVs | | FGIm | | SVm | |
| | No. of cells | % of all cells[2] | No. of cells | % of all cells[2] | No. of cells | % of all cells[2] | No. of cells | % of all cells[2] |
| -100.00 to -50.01 | - | - | - | - | 3 | 0.1 | - | - |
| -50.00 to -0.01 | - | - | - | - | 37 | 0.2 | - | - |
| 0.00 to 49.99 | - | - | 7,414 | 36.1 | 219 | 1.1 | 32 | 0.2 |
| 50.00 to 99.99 | - | - | 12,389 | 60.3 | 418 | 2.0 | 364 | 1.8 |
| 100.00 to 149.99 | 8,296 | 40.4 | 728 | 3.5 | 887 | 4.3 | 1,184 | 5.8 |
| 150.00 to 199.99 | 11,506 | 56.0 | 32 | 0.2 | 264 | 1.3 | 452 | 2.2 |
| 200.00 to 249.99 | 527 | 2.6 | - | - | 251 | 1.2 | 468 | 2.3 |
| 250.00 to 299.99 | 234 | 1.1 | - | - | 336 | 1.6 | 734 | 3.6 |
| 300.00 to 349.99 | - | - | - | - | 284 | 1.4 | 2,640 | 12.8 |
| 350.00 to 399.99 | - | - | - | - | 479 | 2.3 | 7,510 | 36.5 |
| 400.00 to 449.99 | - | - | - | - | 1,186 | 5.8 | 6,566 | 31.9 |
| 450.00 to 499.99 | - | - | - | - | 2,231 | 10.9 | 613 | 3.0 |
| 500.00 to 549.99 | - | - | - | - | 4,582 | 22.3 | - | - |
| 550.00 to 599.99 | - | - | - | - | 5,228 | 25.4 | - | - |
| 600.00 to 649.99 | - | - | - | - | 3,467 | 16.9 | - | - |
| 650.00 to 699.99 | - | - | - | - | 608 | 3.0 | - | - |
| 700.00 to 749.99 | - | - | - | - | 83 | 0.4 | - | - |

Notes: 1. Categories chosen to facilitate easy comparison with values reported for woodland in Bateman and Lovett (1997).
2. There are 20563 1km square land cells.

Figure 1: Predicted farm gate income for sheep farms (FGIs) (£/ha, 1990)

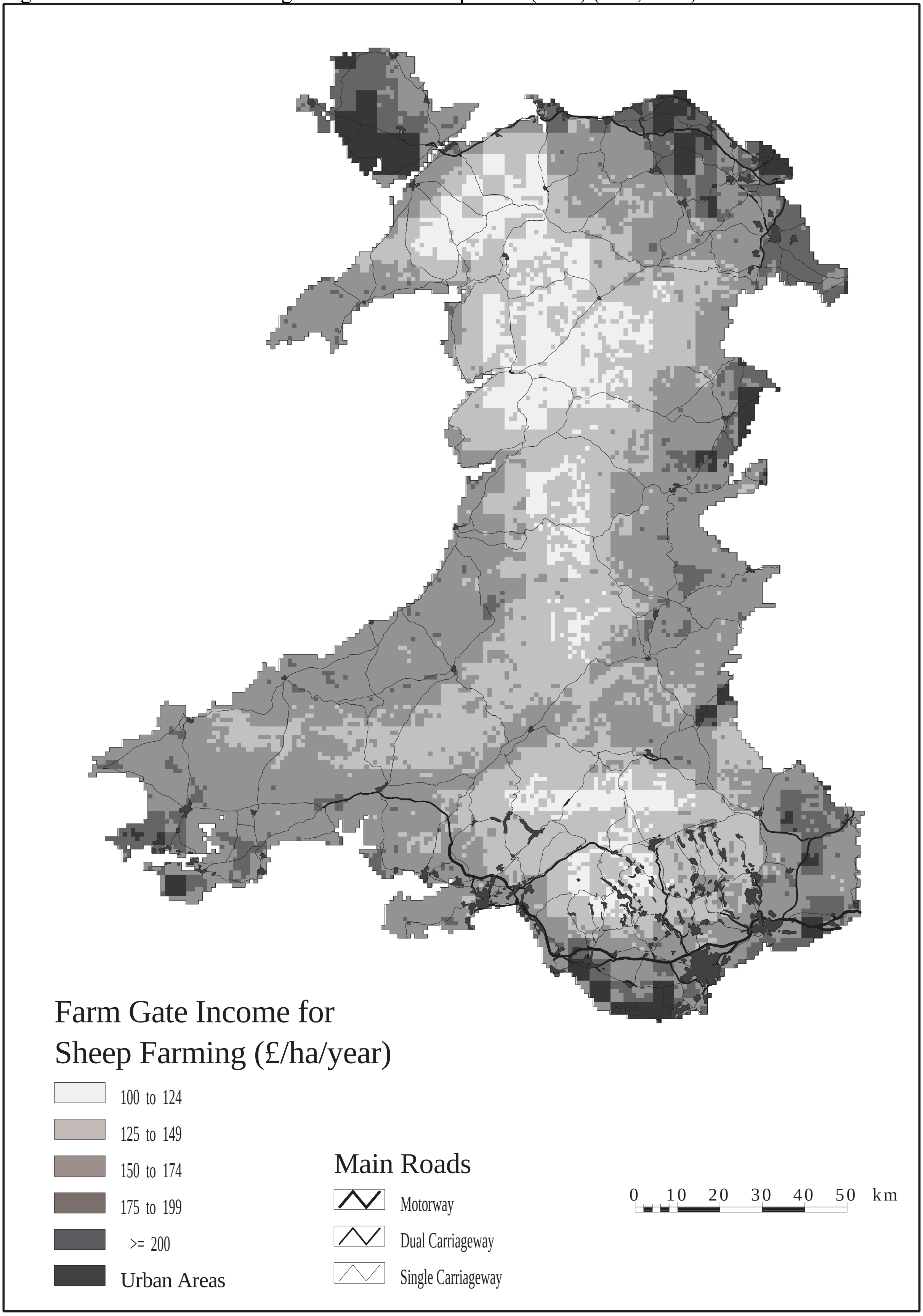


Figure 2: Predicted shadow value for sheep farms (SVs) (£/ha, 1990)

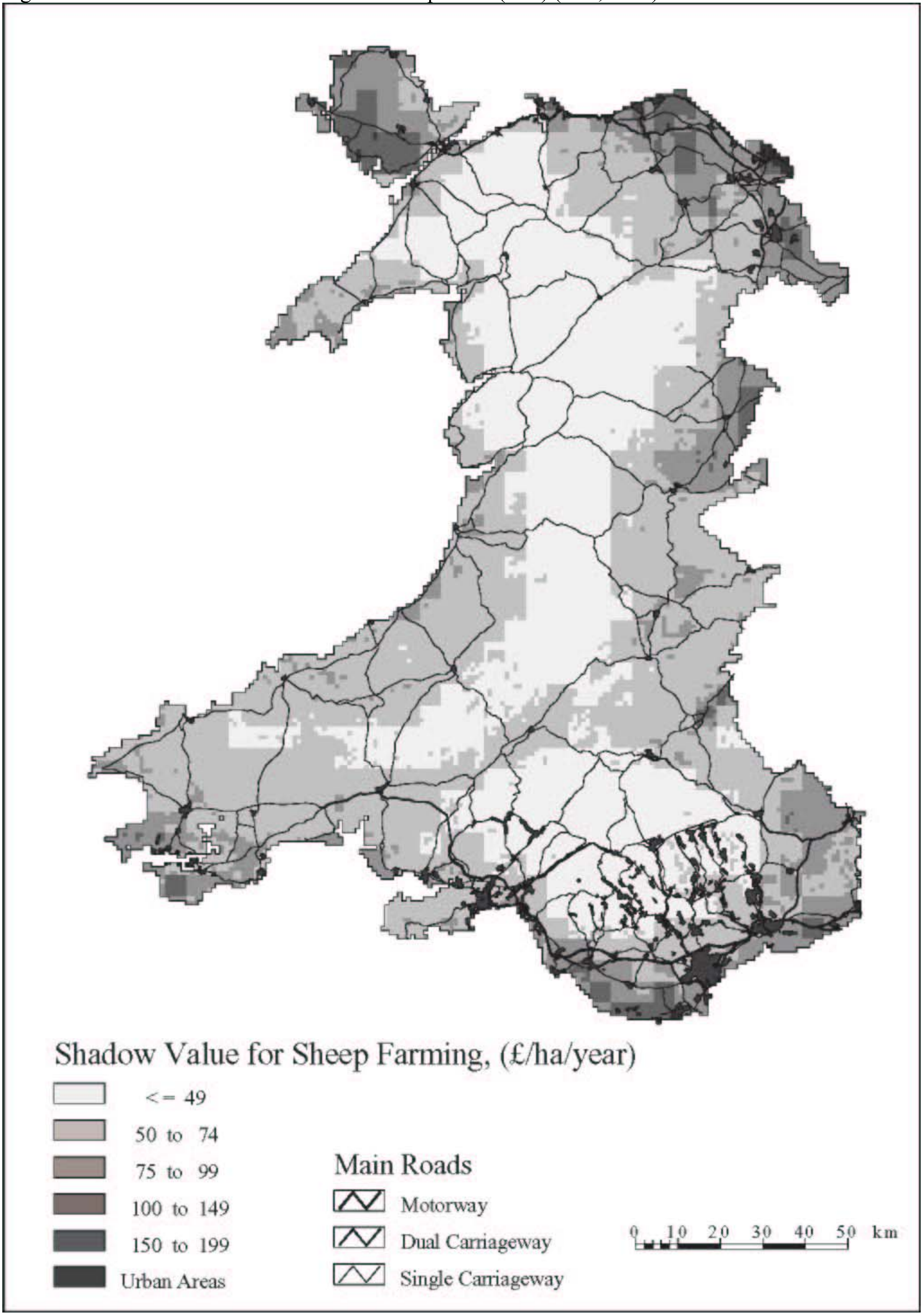


Figure 3: Predicted farm gate income for milk farms (FGIm) (£/ha, 1990)

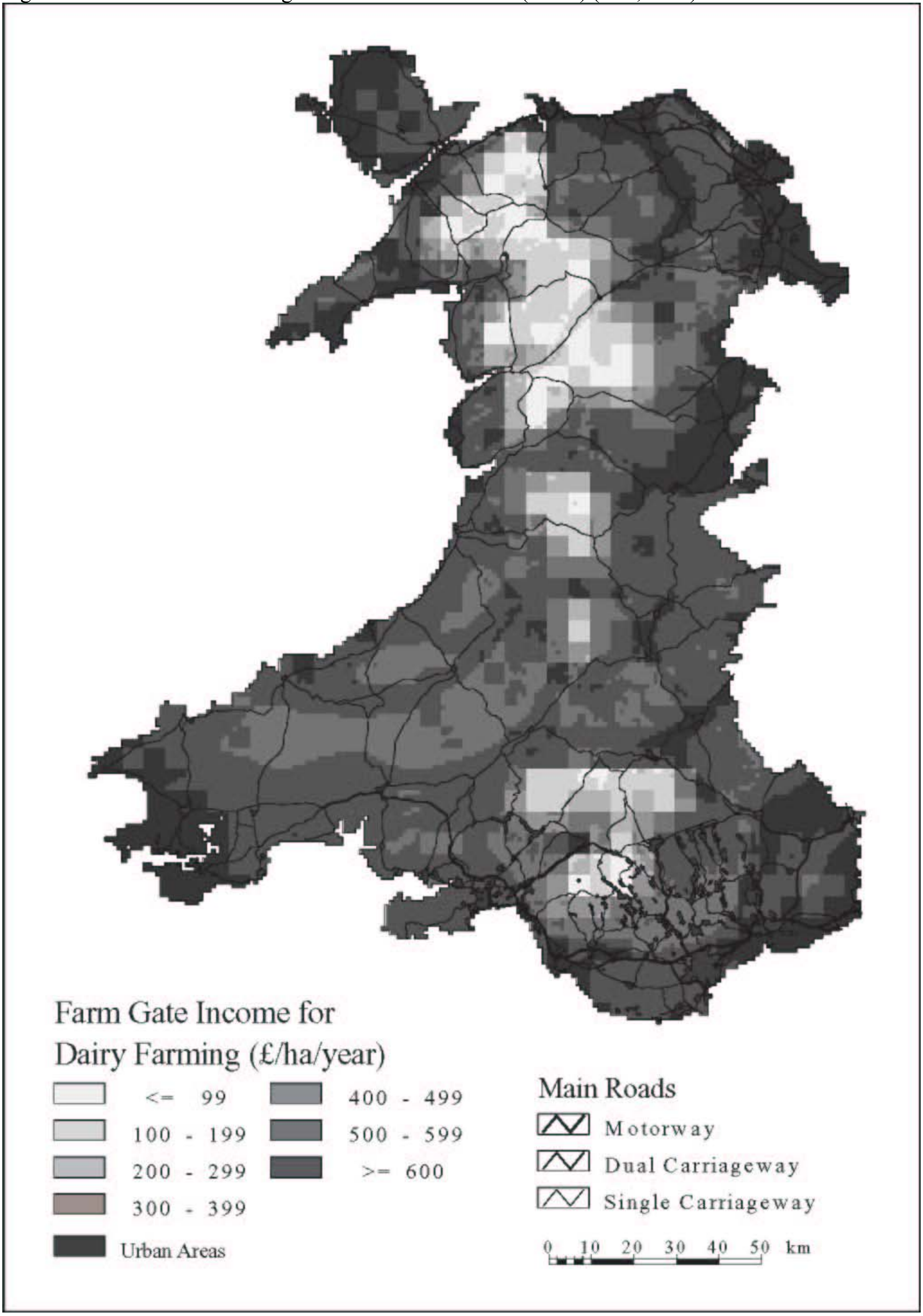
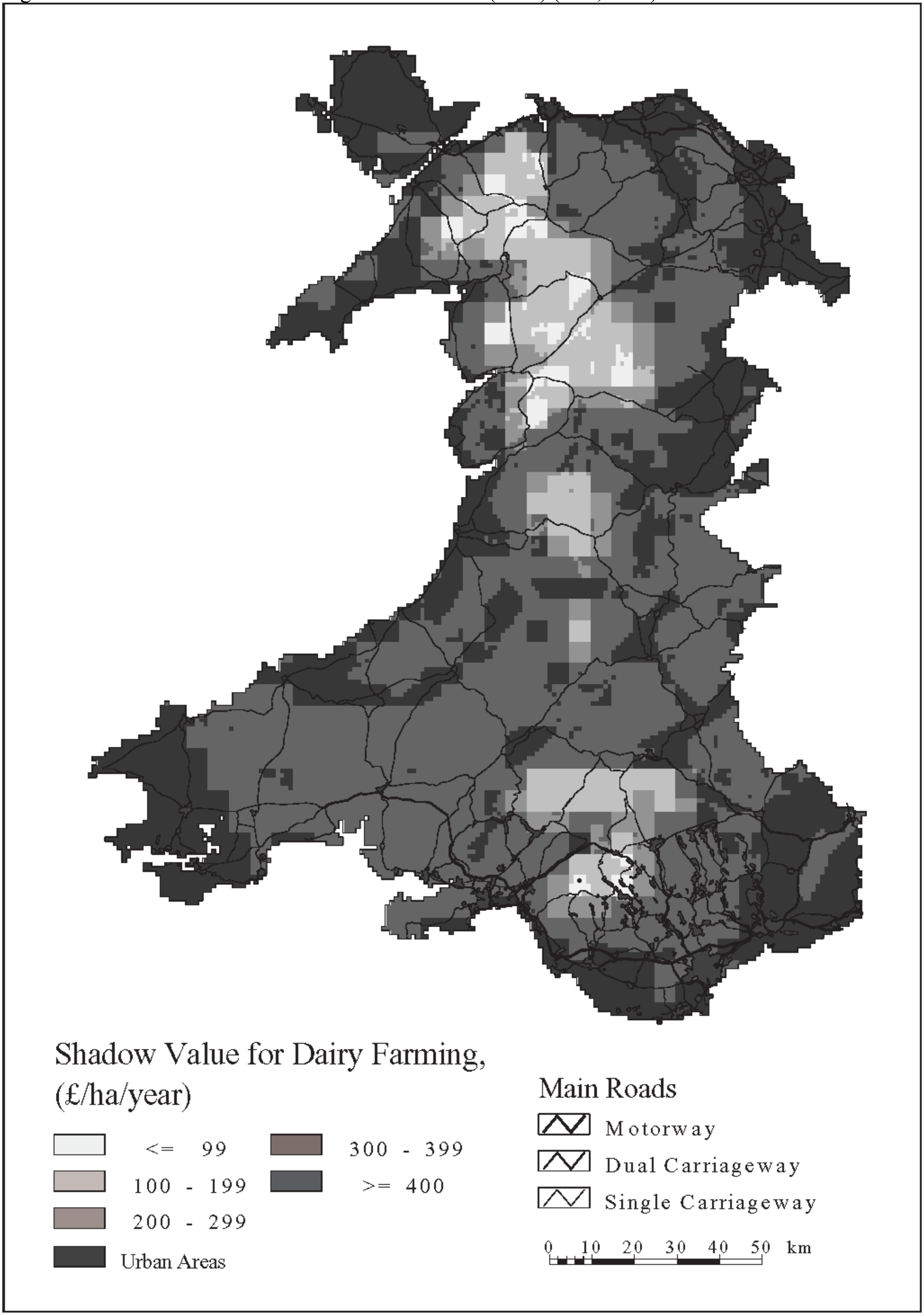


Figure 4: Predicted shadow value for milk farms (SVm) (£/ha, 1990)



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