Structural Agricultural Land Use Modelling

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Contributed Paper prepared for presentation at the International Association of Agricultural Economists Conference, Beijing, China, August 16-22, 2009

Abstract

This paper develops a structural econometric model of agricultural land use and production based on the joint multi-output technology representation introduced by Chambers and Just (1989). Starting from a flexible specification of the farm profit function we derive land use allocation, input applications, crops yield and livestock number equations in a joint and theoretically consistent framework. We present an empirical application using fine-scale spatial data covering the entirety of England and Wales and including the main economic, policy and environmental drivers of land use change in the past 40 years. To account for the presence of censored observations in this micro-level data we estimate the model as a system of two-limits Tobit equations via Quasi-Maximum Likelihood. We finally compare the forecasting ability of our approach against an established benchmark: the land use share logit model.

JEL classification: Q15, Q53, C34.

Keywords: Land Use, Structural Econometric Modelling, Agro-Environmental Policy, System of Censored Equations, Multivariate Tobit, Quasi-Maximum Likelihood.

Quantifying the response of agricultural land use and production to changes in market conditions, policies and environmental factors has fundamental economic and policy relevance. Agricultural land use decisions, whilst private, have often significant public implications, generating both external costs, such as non-point pollution, changes to wildlife habitats, deforestation and wetland degradation, and external benefits, like the provision of recreational opportunities and biodiversity. The study of the causes of agricultural land use change and its effect on the environment have motivated a wide spectrum of applied economic analyses, encouraging the development of empirical land use models estimated on spatially explicit data (for recent reviews see Irwin and Geoghegan, 2001; Plantinga and Irwin, 2006). The framework proposed here diverges from previous econometric models of land use. Rather than developing a reduced form, empirical approach to investigate land use allocation choices, the present paper places agricultural land use decisions in a theoretically consistent, econometric structure including also crop and livestock production, input applications and profits. In doing so it builds upon the dual multi-product profit function approach introduced in Chambers and Just (1989).

Previous econometric land use models

According to the underpinning assumptions and the data required for estimation, econometric land use models can be classified into two broad categories: (a) *parcel* models and (b) *share* models.[1] Parcel models (e.g. Chomitz and Gray, 1996; Wu et al., 2004; Lubowski et al., 2006; Langpap et al. 2008) require data on the contiguous spatial pattern of land use, typically sampled through geographic information system (GIS) techniques. Adopting the classic Von Thünen (1826) assumption that land will be put to the use that maximizes profits, the addition of an appropriate error structure allows empirical specification as a discrete choice model. This approach considers the decision-making in each parcel (land data point) as an independent optimization problem. For this reason parcel models are best suited to the appraisal of broad land use categories, distinguishing, for example, between agriculture, forestry and urban areas. However, they are less appropriate for analyzing more refined agricultural land use types, (e.g. modelling choices amongst diverse types of arable crops) where interdependencies between cultivation decisions in neighbouring fields cannot be ignored. Indeed, pressures concerning crop rotation, efficient allocation of machinery and labor and the presence of fixed but allocatable inputs imply that agricultural activities are typically joint in production (Shumway et al., 1984; Ball, 1988; Chambers and Just, 1989).

Joint production decisions have been investigated via land use share models, introduced by Lichtenberg (1989) and Wu and Segerson (1995) and further developed by Plantinga (1996),

[1] Econometric modelling is only one of the strategies proposed in the literature to analyze land use change. For a comprehensive review, including also other methodological approaches, see Irwin and Geoghegan (2001).

Plantinga et al. (1999), Plantinga and Ahn (2002) and Chakir (2009) amongst others. These approaches analyze the proportions of different agricultural land uses using data aggregated over regions or counties. Assuming constant returns to scale allows the researcher to model production decisions by treating these large areas as unique, macro-farms. In the resulting specification, typically based on a logistic function, land use shares depend on the environmental and climatic characteristics of the region and on the prices of all possible outputs and inputs.

These studies have identified the main drivers of agricultural land allocation decisions, capturing that spatial dimension which is critical to adequately assess the economic and environmental consequences of land use change (for a review see Plantinga and Irwin, 2006). However, as explicitly acknowledged in most of these contributions, both parcel and share models are essentially empirical frameworks, which cannot be related to farm profits or welfare. Furthermore, as they focus solely upon switches between land use types, they cannot encompass changes in land use intensity, such as alterations in crop output levels, input application rates (e.g. fertilizer use) and, in particular, changes in livestock numbers which, if included in the analysis, are considered in a completely separate model (e.g. Chomitz and Thomas, 2003; Seo and Medelsohn, 2008). However, as emphasized within the conceptual framework for modelling agro-environmental policies proposed by Just and Antle (1990), both extensive and intensive margin elasticities are of considerable policy and stakeholder interest (Arnade and Kelch, 2007) and critical to assess the impact of agricultural production on the environment. This paper addresses these issues developing a theoretically consistent structural framework and presenting an empirical application concerning policies to reduce diffuse agricultural pollution using fine-scale spatial data covering the entirety of England and Wales.

Distinguishing features of this analysis

Compared with the approaches outlined previously, which directly model the land allocation equations and leave the farm profit function un-specified, this study is distinguished by underpinning all the analysis on a flexible specification of the profit function itself. As shown in Section 2, this allow us to derive, in a coherent and structural framework, not only land use decisions, but also input and output intensities (including both crop yields and livestock numbers) and welfare measures. In doing so, we build upon farm modelling theory, and in particular on the dual joint (in-inputs) multi-outputs profit function introduced by Chambers and Just (1989). Our approach is very flexible, and can be implemented on different types of data, including farm cross-section or panel data, regional aggregated data, or data sampled at fine-scale spatial resolutions. Approaches based on a flexible specification of the farm multi-output profit function have been already implemented to model agricultural production and land allocation decisions (Guyomart et al., 1996; Oude Lansink and

Peerlings, 1996; Ball et al., 1997; Sckokai and Moro, 2005; Arnade and Kelch, 2007). However, these prior contributions are based either on national or on farm level data and, therefore, cannot address the spatial nature of land use change or include those refined climatic and physical factors which are crucial in determining the observed pattern of land use and its impact on the environment.

In contrast, our empirical analysis is highly spatially explicit, being implemented on a large panel of $2km^2$ grid square data covering the entirety of England and Wales, which is discussed in detail in Section 3. This micro-level data is essential to capture the diversity of climatic and economic drivers influencing land use change and to adequately assess its environmental consequences (e.g. Just and Antle, 1990; Chomitz and Thomas, 2003; Wu et al. 2004; Chakir, 2009). The disadvantage of using such a detailed spatial resolution is that no information on profits is available at this fine-scale. For this reason, in the present empirical analysis we do not include welfare considerations, focusing instead upon those equations included in the structural model which deal with land use and livestock numbers. Since these are the two main determinants of farms' environmental impact, our empirical illustration is both a policy relevant analysis and an effective yardstick to compare our strategy against established, empirically-driven land use modelling approaches.[2]

Such a fine-scale spatial analysis requires an estimation technique which deals with the presence of censored observations: a distinguishing feature of micro-level data arising from corner solutions in the production decisions. Recent contributions have addressed this issue within the analysis of household demand systems (e.g. Yen et al., 2003; Dong et al., 2004; Meyerhoefer et al., 2005) but, to our knowledge, censored systems of equations have never been implemented to model land use decisions. Section 4 presents our empirical model, the estimation technique and the results, comparing the forecasting performance with that of the established land use share model. Section 5 concludes.

[2] As showed, for example, in Arnade and Kelch (2007), whilst an aggregated dataset allows the estimation of profit and yield equations, it would also reduce the empirical analysis to a mere illustration. Our chosen approach, therefore, conforms to the exhortations of Just (2000), who advocates using micro-level data in applied agricultural economic analyses, "rather than continue to demonstrate points and methodology with aggregate data simply because they are available".

2. The economic framework

The theoretical model

This section illustrates the theoretical framework underpinning our structural land use modelling strategy, which builds upon the farm profit maximization problem in the presence of fixed allocatable inputs illustrated by Chambers and Just (1989). For simplicity we consider land to be the only fixed allocatable input. Furthermore, we indicate with **y** the vector of *m* outputs, with **r** the vector of *n* inputs, with **p** the vector of strictly positive output prices, with **w** the vector of strictly positive input prices, with **l** the vector of *h* land use allocations, with *L* the total land available and with **z** the vector of *k* other fixed factors (which may include physical and environmental characteristics, policy incentives and constraints, etc.). Since we are also considering livestock outputs, we generalize Chambers and Just (1989) framework allowing the number of possible land uses *h* to be different from the number of possible outputs *m*. The multi-output profit function, given a fixed land allocation can be written as:

$$(1)\ \pi(\mathbf{p},\mathbf{w},\mathbf{z},l_1,...,l_h) = \max\{\mathbf{p'y} - \mathbf{w'r} : \mathbf{y} \in Y(\mathbf{r},\mathbf{z},l_1,...,l_h)\}$$

where Y (**r**, **z**, l_1, ..., l_h) indicates the producible output set for a given land allocation[3]. This profit function is positively linearly homogenous and convex in input and output prices. In such a framework, one can derive the profit maximizing input demand and output supply given a fixed land allocation via the Hotelling's lemma (Chambers and Just, 1989). Furthermore, the profit function associated with the optimal land allocation can be written as:

$$(2)\ \pi(\mathbf{p},\mathbf{w},\mathbf{z},L) = \max_{l_1,...,l_h}\{\pi(\mathbf{p},\mathbf{w},\mathbf{z},l_1,...,l_h) : \textstyle\sum_{i=1}^{h} l_h = L\}.$$

The farm profit maximization problem can be expressed, without any loss of generality, in terms of profit maximization per unit of land. Indicating with **s** the *h* land use shares corresponding to the land use allocations *l*, and with $\pi^L(.)$ the profits per unit of land, we can re-write the optimal land use allocation problem as:

[3] This framework assumes the farmers to be risk neutral. However, empirical analyses (e.g. Chavas and Holt, 1990; Pope and Just, 1991) show that farmers decisions may present some degree of risk aversion. The approach outlined in this paper is, however, flexible enough to allow departures from risk neutrality. These could be encompassed following, for instance, Coyle (1999) or Skokai and Moro (2005).

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

This expression, whilst written in terms of land use share and profit per area, is equivalent to (2) and does not assume constant returns to scale. In fact, profit per area is a function of *L* and, therefore, the profit-maximizing shares depend on the total land available. Since the profit per area function is positively linearly homogenous and strictly convex in input and output prices, using the Hotelling's lemma one can derive the output supply (y^L) and input demand (r^L) per area (hereafter we will refer to these quantities as input and output *intensities*) as:

(4.a) $y_i^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \dfrac{\partial \pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L)}{\partial p_i} = \dfrac{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial p_i}$, and

(4.b) $r_j^L(\mathbf{p},\mathbf{w},\mathbf{z},L) = \dfrac{\partial \pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L)}{\partial w_j} = \dfrac{\pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial w_j}$,

where the superscript on *s* indicates the optimal shares, i.e. the shares that satisfy (3). The equations describing the optimal land allocations can be derived by recognizing that land is allocated to the different uses in order to equalize their marginal rent or shadow prices[4]. In terms of optimal land use shares this can be written as:

(5) $\dfrac{\partial \pi^L(\mathbf{p},\mathbf{w},\mathbf{z},L,\bar{s}_1,\ldots,\bar{s}_h)}{\partial s_i} = 0$, for $i = 1,\ldots, h$.

When these equations are linear in the optimal land allocations, including the constraint that the sum of the shares need to be equal to one 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*.[5] For empirical estimation, these relations can be translated into a unifying framework encompassing land use share allocation, input and output intensities and profits per area by directly specifying the profit function per area as one of the flexible functional forms available in the literature (for some examples see Chambers, 1988).

[4] Even if corner solutions arise, this condition still holds for all land uses receiving a non-zero allocation (see Chambers and Just, 1989).

[5] More precisely, these results are valid also if the equations are linear in a monotonic transformation of the optimal land use shares (e.g. the logarithm transformation). This is true if profit per area is specified as a quadratic function of this monotonic transformation, as in most established flexible functional form such as the translog and the normalized quadratic. However, prices and other fixed factors can enter the profit function and the derived land allocation equations in any desired functional form.

The empirical specification

We specify the profits per area as a Normalized Quadratic (NQ) function. This functional form has been widely applied in agricultural economics for modelling joint (in input) multi-output production processes (Moore et al. 1994, Oude Lansink and Peerlings 1996, Guyomard et al. 1996, Sckokai and Moro 2005, Arnade and Kelch 2007). Some of the desirable properties of the NQ profit function are that it is locally flexible, self dual and its Hessian is a matrix of constants (i.e. convexity holds globally). Furthermore, it allows negative profits (losses) which cannot be included in other specifications, such as the translog. Defining with w_n the numeraire good, indicating with $\mathbf{x} = (\mathbf{p}/w_n, \mathbf{w}/w_n)$ the vector of normalized input and output (netput) prices and with $\mathbf{z}^*=(\mathbf{z}, L)$ the vector of fixed factors including policy and environmental drivers and also the total land available L, the NQ profit function can be written as:

$$(6)\ \bar{\pi}^L = \alpha_0 + \sum_{i=1}^{m+n-1}\alpha_i x_i + \frac{1}{2}\sum_{i=1}^{m+n-1}\sum_{j=1}^{m+n-1}\alpha_{ij}x_i x_j + \sum_{i=1}^{h-1}\beta_i s_i + \frac{1}{2}\sum_{i=1}^{h-1}\sum_{j=1}^{h-1}\beta_{ij}s_i s_j + \sum_{i=1}^{k+1}\gamma_i z_i^* +$$

$$+\frac{1}{2}\sum_{i=1}^{k+1}\sum_{j=1}^{k+1}\gamma_{ij}z_i^* z_j^* + \sum_{i=1}^{m+n-1}\sum_{j=1}^{h-1}\delta_{ij}x_i s_j + \sum_{i=1}^{m+n-1}\sum_{j=1}^{k+1}\phi_{ij}x_i z_j^* + \sum_{i=1}^{h-1}\sum_{j=1}^{k+1}\varphi_{ij}s_i z_j^*,$$

where $\bar{\pi}^L = \pi/w_n$ is the normalized profit per unit of land. This profit function is linearly homogeneous by construction, and symmetry can be ensured by imposing $\alpha_{ij} = \alpha_{ji}$, $\beta_{ij} = \beta_{ji}$ and $\gamma_{ij} = \gamma_{ji}$. Only h–1 land use shares appear in the profit function since the last one can be computed by difference and it is therefore redundant. Input and output intensities can be derived as in (4.a) and (4.b). For instance, if x_i is a normalized output price, the corresponding output intensity can be written as:

$$(7)\ \frac{\partial\bar{\pi}^L}{\partial x_i} = y_i^L = \alpha_i + \sum_{j=1}^{m+n-1}\alpha_{ij}x_j + \sum_{j=1}^{h-1}\delta_{ij}s_j + \sum_{j=1}^{k+1}\phi_{ij}z_j^*\ ,$$

which contains the same structural parameters of the profit function. Furthermore, optimal land use shares can be derived by solving the following system of h–1 equations:

$$(8)\ \frac{\partial\bar{\pi}^L}{\partial s_i} = \beta_i + \sum_{j=1}^{m+n-1}\delta_{ij}x_j + \sum_{j=1}^{h-1}\beta_{ij}s_j + \sum_{j=1}^{k+1}\varphi_{ij}z_j^* = 0 \quad \text{(for } i = 1,\dots, h-1\text{), with}$$

$$\sum_{j=1}^{h} s_j = 1.$$

This system contains (h–1) (m + n + k + h/2 + 1) structural parameters that are also included in the profit function. Solving the system for the optimal land use shares leads to h reduced form equations:

(9) $s_i = \theta_i + \sum_{j=1}^{m+n-1} \theta_{ji} x_j + \sum_{j=1}^{k+1} \eta_{ji} z_j^*$, for i = 1,...,h,

with $\boldsymbol{\theta}$ and $\boldsymbol{\eta}$ being the vectors of the parameters to be estimated, which are non linear combinations of the structural parameters in (8). This reduced form system contains h (m + n + k + 1) parameters and m + n + k + 1 restrictions:

$\sum_{i=1}^{h} \theta_i = 1$;

$\sum_{i=1}^{h} \theta_{ji} = 0$, $j = 1,...,m+n-1$;

$\sum_{i=1}^{h} \eta_{ji} = 0$, $j = 1,...,k+1$;

which need to be satisfied to ensure that the sum of the shares equals one. This leaves only (h–1) (m + n + k + 1) free reduced form parameters, which are not enough to recover all the structural parameters in (10). However, equations (9) represent a flexible specification embedded in the structural economic model, in which optimal land use shares depend upon all the netput prices and all the fixed factors quantities, including the physical and environmental characteristics of the farm. Depending on the available data and on the objective of the empirical analysis, one can estimate the complete model or focus solely on particular equations. If data on profits, input and output quantities and land use areas are available, the full model consisting of equations (6), (7) and (9) can be jointly estimated. Given the lack of high resolution profit data and our interest on the environmental and hence spatial aspects of land use, in the subsequent empirical analysis we focus on the land use and livestock number equations, while maintaining the model's structural foundation and its clear underpinning assumptions

3. Data, sources and descriptive statistics

In order to correctly assess the financial, policy and environmental drivers of land use change, this analysis employs a unique database, which integrates multiple sources of information dating back to the late 1960s. The resulting data, collected on a 2km^2 grid square (400ha) basis, cover the entirety of England and Wales and encompass, for the past 40 years: (a) land use shares and livestock number,

(b) environmental and climatic determinants, (c) input and output prices, (d) policy and other drivers. However, as already mentioned, we do not include yield and profits data, since the necessary information is simply not available at the disaggregated level required by this analysis. The different data sources are described in detail throughout the remainder of this section.

Agricultural land use data. Data on agricultural land use hectares and livestock numbers, derived from the June Agricultural Census (JAC) on a $2km^2$ (400 ha) grid square resolution are available on-line from EDINA (www.edina.ac.uk), which aggregates information collected by the Department of Environment, Food and Rural Affairs (DEFRA), and the Welsh Assembly. These data cover the entirety of England and Wales for seventeen, unevenly spaced, years between 1969 and 2006 (in years 2005 and 2006 only Welsh data is available). This yields roughly 38,000 grid-square records each year.

Regarding livestock numbers, we distinguish between dairy cows, beef cows and sheep. Dairy cows also include those heifers less than 2 years old which are not in milk production, but are classified as being part of the dairy herd in the JAC statistics, whereas with the term beef cows we refer to all cattle not classified as dairy. Concerning agricultural land use types, we explicitly model cereals (including wheat, barley, oats, etc.), oilseed rape, root crops (potatoes and sugar beet), temporary grassland (grass being sown every 3 to 5 years and typically part of an arable crop rotation), permanent grassland (grassland maintained perpetually without reseeding) and rough grazing. These six land use types together cover more than 88% of the total agricultural land within the country. We include the remaining 12% in an "other" land category encompassing horticulture, other arable crops, woodland on the farm, set-aside, bare, fallow and all other land (ponds, paths, etc.). As described on the EDINA web-site, grid square land use estimates are derived from parish summaries or DEFRA estimates, taking into account potential land use capability. These statistics can sometimes overestimate or underestimate the amount of agricultural land within an area since their collection is based on the location of the main farm house. For example, when a farm's agricultural land belongs to more than one parish, all the land use is assigned to that parish in which the main farm is registered.[6] For this reason the recorded areas of certain extensive land uses, in particular rough grazing and permanent grassland, can sometimes exceed the total amount of land within a grid square (400 ha). We correct this feature by rescaling the sum of the different agricultural land use areas assigned to each grid square to match with the total agricultural land derived from the Agricultural Land Classification

[6] For a more detailed description see http://edina.ac.uk/agcensus/agcen2.pdf (accessed on the 7th April 2009).

(ALC) system published by DEFRA and the Welsh Assembly.[7] This rescaling process, while ensuring consistency, has no direct influence on the model estimation, which is based on share data.

[TABLE 1 about here]

Descriptive statistics, land uses (ha) and livestock numbers (heads) per 2km^2 grid square

Descriptive statistics for the agricultural land use types and livestock numbers are reported in Table 1 for three illustrative years and for the total dataset. These figures refer only to grid squares in which there is at least some land classified as agriculture according to the ALC. As shown in the Table, whereas the total land devoted to farming has only changed slightly over the last 40 years, its allocation between the different agricultural land uses has transformed considerably. In particular, the area of oilseed rape has increased substantially, driven by the soaring prices and the targeted support payments included in various reforms of the European Union (EU) Common Agricultural Policy (CAP). In contrast, root crop shares have been decreasing somewhat, as their relative prices have fallen. However, because of their relatively higher revenues, their cultivation continues to be primarily limited by soil and climatic factors. Cereals are consistently the main arable crops in the country, although changes in technology, prices and area payments have induced variability in their area allocations. Temporary grassland has been steadily decreasing, whereas the areas devoted to rough grazing and permanent grassland have remained fairly constant. Land included in the category "other" has significantly increased, particularly since the 1990s because of the introduction of set-aside and various grants encouraging farm woodland. In contrast, the last 15 years have seen a decline of the livestock sector with challenges such as the outbreak of the Bovine Spongiform Encephalopathy (BSE) disease and decreasing prices, leading to a considerable reduction in stocking rates. Finally, with concerns regarding the empirical specification in mind, it is important to note all variables are obviously censored from below at zero while the most extensive land uses (e.g. grassland) are also censored from above at the grid square size (400ha).

Physical environment and climatic data. For each 2km^2 grid square we consider a detailed specification of the environmental determinants influencing farmers' decision making. These small size aggregation units allow us to fully represent the heterogeneity which characterizes the UK

[7] This data is described in detail at http://www.defra.gov.uk/farm/environment/land-use/pdf/alcleaflet.pdf (accessed on the 7th April 2009). It is based on a series of surveys carried on from the late 1960s to the late 1980s and distinguishes agricultural land from urban and other non-agricultural lands. To account for urban area increases since the last survey, we augment this data using Land Cover Map 2000 information (Centre of Ecology and Hydrology, http://www.ceh.ac.uk/sections/seo/lcm2000_home.html, 7th April 2009). However, in the United Kingdom the growth of urban areas has been relatively modest, while the total amount of land devoted to agriculture has remained fairly constant over the last two decades (see DEFRA statistics at http://www.defra.gov.uk/environment/statistics/land/alltables.htm, 7th April 2009).

farming system. For each grid square, we extract, from the National Soil Resources Institute LandIS database[8]: average annual rainfall (denoted *aar*), autumn machinery working days (*mwd,* a measure of the suitability of the soil for arable cultivation), mean potential evapotranspiration (*pt,* indicating the amount of water that, if available, can be evaporated and transpired), median duration of field capacity (*fc*, reflecting water abundance in the soil), total number of degree days in the growing season (*dd*, from April to September) and mean elevation (*alt*). We also include the share of agricultural land with slope higher than 6 degrees (*smore6*) derived via GIS analysis from the Ordnance Survey, Digital Terrain Model[9]. The descriptive statistics, reported in Table 2, highlight the significant spatial variability which characterizes these variables.

[TABLE 2 about here]

Descriptive statistics, environmental and climatic determinants

Agricultural inputs and outputs price data. The analysis requires detailed information regarding the main agricultural output and input prices during the past 40 years. There is not a unique source which supplies such a comprehensive database for the United Kingdom. Therefore, we produce our database by extracting time series data from a variety of different sources, linked by using data in the common years. Cereals price is based on the simple average of wheat, barley and oats prices, derived from DEFRA (2006), MAFF (1982) and Mitchell (1988). Root crops price is given by the average of potatoes and sugar beet prices, extracted from DEFRA (2006), MAFF (1982) and Office of National Statistics (ONS, 1974-85), the same sources being used for the oilseed rape price. Milk, dairy cows, beef meat (per cow) and lamb meat (per sheep) prices are based on DEFRA (2006) and ONS (1974-85). Fertilizer price is derived from Defra (2006) and ONS (1974-85), oil price from the British Petroleum Statistical Review of Word Energy[10] and milk quota (leased) prices from Ian Potters Associates (www.ipaquotas.com). Crop and livestock prices incorporate subsidies and levies, including arable area payments. Input prices are on a national level, whereas output prices are converted to a regional level using the agricultural output regional price statistics extracted from the UK Farm Business Survey for years 1982-2000.[11]

[8] For more details see http://www.landis.org.uk/gateway/ooi/intro.cfm (7th April 2009).
[9] For details see http://www.ordnancesurvey.co.uk/oswebsite/ (7th April 2009).
[10] See http://www.bp.com/productlanding.do?categoryId=6929&contentId=7044622 (7th April 2009).
[11] The Farm Business Survey (FBS) provides detailed information regarding the financial performance and physical and economic characteristics of UK farming enterprises. Its sampling covers more than 2000 farms per year and is designed to inform policy decisions on matters affecting farm businesses and enable analysis of policy impacts. The main publication from the FBS data analysis is the report on Agriculture in the United Kingdom (DEFRA, 2009).

Policy and other determinants. Policy changes, and in particular the several reforms which the CAP has undergone, have shaped the UK rural environment, influencing significant changes in farming practices, cultivation and livestock management. Apart from the subsidies directly linked to specific crop or livestock productions (e.g. arable area payments, intervention prices, beef premium) which are already included in the output prices, we also consider the compulsory rate of set-aside and more general and spatially heterogeneous policy measures. In particular, we calculate the share of each grid square designated as National Park, Nitrate Vulnerable Zone (NVZ) and Environmentally Sensitive Area (ESA).[12] NVZs, established in 1996 and extended in 2003 and 2008, have been designed to reduce surface and groundwater nitrate contamination in compliance with the EU Nitrate Directive (European Council, 1991). The range of measures enforced in NVZs does not go beyond good agricultural practice and, therefore, while being mandatory and uncompensated, these are not expected to significantly change agricultural land use shares. ESAs, introduced in 1987 and undergone various extensions in subsequent years, were launched to safeguard and enhance areas of particularly high landscape, wildlife or historic value. 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, establishing hedgerows, etc. Finally, we include in the model the distance to the closest sugar beet factory, to capture transportation costs, and the share of urban area within a square.

4. The agricultural land use model for England and Wales

Estimation

The model presented in Section 2 is estimated using the England and Wales 2km^2 grid square panel database introduced in the previous section. Effectively, we model each 2km^2 grid square as a single farm. Since the average farmed land in each square is roughly 300ha and the average size of a full-time cropping or mixed farm in the United Kingdom is about 150ha and increasing steadily over time, this assumption does not appear unreasonable. To address the possibility of spatial autocorrelation in the residuals we estimate the model using only a fraction of the data, defined by sampling one grid square every four along both the latitude and longitude axes, leaving a sub-sample comprising of roughly 6% of the original data. Recalling the discussions of Section 3, we further omit squares in which rescaling would be too substantial, defined as cases were (*a*) the difference between the sum of the agricultural land use areas from the JAC and the total agricultural area according to the ALC

[12] Digital boundaries at a field level for National Parks, NVZs and ESAs have been downloaded from MAGIC (www.magic.gov.uk).

system is higher than 400ha, and (*b*) the ratio of these two agricultural areas is higher than 4 or smaller than 1/4. This corresponds to roughly 7% of the remaining observations, leaving about 2,200 grid cells in each year which correspond to approximately 30,000 observations in total.

For the model estimation we consider the seven agricultural land use shares and three livestock types illustrated in Table 1. Regarding the **x** vector of exogenous netput prices, we include those for cereals, oilseed rape, root crops, milk, dairy cows, beef meat, lamb meat, fertilizer, milk quota and energy (oil) described in Section 2, with the latter as the numeraire. Since the land use decisions taken by farmers are based on their expectations on the output prices for the forthcoming year, for estimation we substitute the actual output prices with the prices predicted by an autoregressive model with trend.[13] The vector of fixed factors **z** includes a trend to represent technological change and variation in husbandry practice across years (we allow the trend to change after 1988, the year corresponding to the outbreak of the BSE), the rate of compulsory set-aside, the spatially targeted policy drivers (shares of each grid square included into National Parks, NVZs and ESAs) and the environmental and climatic determinants illustrated previously in Table 2, embedded in a full quadratic specification (i.e. squared terms and interactions) to model non-linear effects. In a preliminary analysis we also observed how permanent grassland is rapidly replaced by rough grazing in upland areas. To model this highly non-linear relation, within just these two land use equations we allow the effect of elevation to change after a threshold altitude of 200m. Finally, the distance to the closest sugar beet factory and the share of urban area within a grid square are also included in **z**.

In absence of corner solutions (censoring), the livestock intensities and land use shares equations (7) and (9) can be specified with additive, normal disturbances. Under this assumption, the livestock equations can be estimated jointly via Generalized Least Squares (GLS) or Maximum Likelihood (ML), imposing the symmetry restrictions implied by the profit function (6). However, this approach cannot be implemented for the estimation of the *h* equations included in the land use share system. In fact, in each square, shares must sum to one and, therefore, error terms must sum to zero, implying that the residual covariance matrix is singular. The solution is simply to drop one equation and estimate the system with ML, obtaining estimates which are invariant to which equation is dropped (Barten, 1969).

However, observed shares are also bounded between zero and one. If this feature can be safely ignored with data aggregated on a national or regional level, it creates a significant amount of

[13] Several approaches have been used to estimate farmers' expected prices. Some examples are provided in Wu et al. (2004). Our strategy corresponds to the one implemented by Wu and Segerson (1995) and De Pinto and Nelson (2009).

censored observations on micro-level data (as shown previously in Table 1). In such a case, assuming normal disturbances and implementing ML leads to inconsistent estimates (Amemiya, 1973). This issue can be addressed specifying a Tobit model (Tobin, 1958), in which the latent shares s_i^* are defined as in (9) plus additive normal residuals, and observed shares are: $s_i = 0$ if $s_i^* \leq 0$, $s_i = 1$ if $s_i^* \geq 1$ and $s_i = s_i^*$ otherwise. This framework can be interpreted by recalling that agricultural land is allocated to different uses according to their associated shadow prices. Therefore, in each grid square, 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, though the adding-up restriction holds for the latent equations, it is not satisfied for the observed shares. We address this issue following Pudney (1989), who suggests treating one of the shares as a residual category, defined by the identity:

(10) $$s_h = 1 - \sum_{j=1}^{h-1} s_j ,$$

and estimating the remaining $h - 1$ equations as a joint system. This approach has been implemented in applied demand analysis for the estimation of censored system of equations using household data (Yen and Huang, 2002; Yen et al., 2003). In our study, the share of land devoted to "other" agricultural uses arises naturally as the obvious choice for the residual category, this being a composite bundle of highly heterogeneous and marginal land uses.[14]

When the number of equations is higher than three the ML estimation of a Tobit system requires the evaluation of multiple Gaussian integrals which is computationally extremely intensive. The recent literature on censored demand system estimation has proposed various approaches to address this issue: two-step estimation (Shonkwiler and Yen, 1999), minimum distance estimation (Perali and Chavas, 2000), simulated maximum likelihood (Yen and Huang, 2002; Yen et al., 2003), maximum entropy (Dong et al., 2004) and generalized method of moments (Meyerhoefer et al., 2005). In this paper we follow the practical and computationally feasible solution proposed by Yen et al. (2003), who suggest approximating the multivariate Tobit with a sequence of bivariate models, deriving a consistent Quasi Maximum Likelihood (QML) estimator. Considering two equations i and j, and observation t, indicating with $\mathbf{q_t} = [\mathbf{x_t} \; ; \; \mathbf{z^*_t}]$ the vector of explanatory variables, with $\boldsymbol{\delta}_\mathbf{i}$ and $\boldsymbol{\delta}_\mathbf{j}$ the vectors of parameters to be estimated, with $\sigma_{i,t}$ and $\sigma_{j,t}$ the residual standard errors of the latent

[14] The resulting parameter estimates are not invariant to which equation is dropped. This is not a significant problem for our analysis, since the exclusion of the category "other" is the logical choice according to the land use shares definition. When parameter invariance is a crucial issue, other estimation techniques can be implemented (e.g. Dong et al., 2004; Meyerhoefer et al., 2005).

variables, and defining $e_{i,t} = (s_{i,t} - \boldsymbol{\delta}_\mathbf{i}^{'}\mathbf{q_t}) / \sigma_{i,t}$ and $e_{j,t} = (s_{j,t} - \boldsymbol{\delta}_\mathbf{j}^{'}\mathbf{q_t}) / \sigma_{j,t}$, the likelihood of the bivariate Tobit model censored between 0 and 1 can be written as:

$$(10)\ L_{i,j,t} = [\Psi(e_{i,t}; e_{j,t}; \rho_{ij})]^{I(e_{i,t}=0;e_{j,t}=0)} [\sigma_{i,t}^{-1}\sigma_{j,t}^{-1}\psi(e_{i,t}; e_{j,t}; \rho_{ij})]^{I(0<e_{i,t}<1;0<e_{j,t}<1)} [\Psi(-e_{i,t}; e_{j,t}; -\rho_{ij})]^{I(e_{i,t}=1;e_{j,t}=0)} \times$$
$$[\Psi(e_{i,t}; -e_{j,t}; -\rho_{ij})]^{I(e_{i,t}=0;e_{j,t}=1)} [\sigma_{i,t}^{-1}\phi(e_{i,t})\Phi[(e_{j,t} - \rho_{ij}e_{i,t})/(1-\rho_{ij}^{\ 2})^{0.5}]^{I(0<e_{i,t}<1;e_{j,t}<0)} \times$$
$$[\sigma_{j,t}^{-1}\phi(e_{j,t})\Phi[(e_{i,t} - \rho_{ij}e_{j,t})/(1-\rho_{ij}^{\ 2})^{0.5}]^{I(e_{i,t}<0;0<e_{j,t}<1)}\ ,$$

where $\phi(.)$ and $\Phi(.)$ indicate the density and the distribution function of the standard normal, $\psi(.\,;.\,;.)$ and $\Psi(.\,;.\,;)$ the density and the distribution function of the standard bivariate normal and *I(.)* is an indicator function assuming value 1 when the argument condition is satisfied and 0 otherwise. In Tobit specifications un-modelled heteroskedasticity is a serious problem, causing all parameter estimates to be biased. Therefore, we account for possible heteroskedasticity in the error term allowing the standard errors to vary across observations as a function of a vector of exogenous variables $\boldsymbol{v}$ (which include: total amount of agricultural land within the square, trend, elevation, machinery working days and dummies identifying the region in which the grid square is located) and a vector of parameters $\boldsymbol{\zeta}$. Specifically, for observation t and equation i:

$$(11)\ \sigma_{j,t} = \exp(\boldsymbol{\zeta}_i{}'\mathbf{v}_{i,t})\,.$$

Considering the land use share system which excludes the *h*th land use share, the likelihood maximized by the QML estimator can be written as:

$$(12)\ L = \prod_{t=1}^{T}\prod_{i=1}^{h-1}\prod_{j=i+1}^{h-1} L_{i,j,t}\,,$$

with T = total number of observations within the sample. This QML estimator is consistent, allows the estimation of cross-equation correlations and the imposition of cross-equation restrictions. However, since the quasi-likelihood is different from the likelihood of the true model, the parameters covariance matrix needs to be estimated using the robust procedure introduced by White (1982). The same QML approach can be implemented to estimate the system of livestock equations (7), but clearly neither discarding one of the equations nor applying any censuring from above.

Results and forecasting performance

We implement the QML approach (12) to estimate two censored Tobit systems: the 3 livestock intensity (dairy cows, beef cows, sheep) equation system (7) and the 6 land use shares (cereal, oilseed rape, root crops, temporary grassland, permanent grassland, rough grazing) system (9). Selecting as starting values the parameter estimates of univariate, heteroskedastic Tobit models, and using the Newton-Raphson method as the maximization algorithm, the QML approach converges in a convenient length of time for both systems.[15] We discard from the model the non-significant normalized price parameters (but always retain the own price and fertilizer price) to improve the estimates of the remaining ones, since the agricultural price variables in our sample, as in most studies, are characterized by a high degree of correlation.

[TABLE 3 about here]

Land use share equations parameter estimates

Table 3 reports the final parameter estimates of the land use share equations. The sign and magnitude of the coefficients are consistent with our expectations. In particular, focusing on the economic determinants, in the upper part of the table, the own output price effects are always positive and the cross-price effects negative. Considering potential policies to address diffuse pollution, an increase in fertilizer price decreases the optimal shares of nutrient-intensive crops, in particular oilseed rape and cereals, which are converted into more extensive land uses such as temporary grassland and rough grazing. On the other hand, there is no significant effect on root crops, which are profitable even with high fertilizer prices, their cultivation being restricted primarily by environmental determinants. Considering other policy drivers, as expected, significant conversion out of arable land follows an increase in the rate of set aside. Similarly, ESA payments encourage significant switching from arable land to extensive grassland types (permanent grassland and rough grazing), but are typically not high enough to foster conversion of root crops. In National Parks, the optimal shares devoted to arable land and to grassland receiving fertilizer applications are also reduced, being replaced by land in the "other" category (e.g. woodland) and rough grazing. Considering the environmental determinants of land use, reported in the lower part of the Table, favourable conditions for crop growth (e.g. more machinery working days, flatter land, etc.) increase the share of arable land, in particular of root crops. However, effects are highly non-linear, as highlighted in Figure 1, which represents the relationship between the land use shares predicted by our model and machinery working days, with all other variables held constant at their 2004 sample mean values. The non-linear effects are particularly noticeable for the cereals share, which peaks at around 120 *mwd* and then slowly declines, being

[15] We estimate the model using the function ml in Stata 10.1 and a 1.86 GHz Intel Core 2 Duo processor, with 2GB RAM. The 6 equations land use shares system converges in about 372 minutes, whereas the 3 equations livestock system requires only 10 minutes.

replaced by more profitable crops, such as potatoes and sugar beet. Finally, the parameters of the variance equations (not reported in Table 3 to preserve space) are highly significant, suggesting a heteroskedastic residual component, which, if ignored, would have biased parameter estimates.

[FIGURE 1 about here]

Relationships among predicted land use shares and machinery working days

The estimated coefficients of the livestock intensity equations are reported in Table 4.[16] Again, own price effects are always positive and significant, whereas cross-price effects, in particular between beef and sheep, are negative. Interestingly, the coefficient of milk quota price is significantly higher (in absolute value) than the one of milk price in the dairy cow equation. This suggests the presence of significant transaction costs and uncertainties associated with the milk quota market (for a detailed analysis of the inefficiencies in the EU quota system sees, for example, Boots et al., 1997). Furthermore, different grassland types are associated with very diverse optimal numbers of livestock. Again model estimates confirms prior expectations: dairy cows are reared primarily on intensive grasslands, beef enterprises are located on all types of pasture and sheep are grazed mainly on less improved land, such as permanent grassland and rough grazing. In addition, an increase in the price of fertilizer, which is strongly related to grass growth and animal intake, reduces the intensity of all the livestock enterprises considered. Also the share of land under special designation (NVZs, ESAs, National Parks, etc.) influences to some extent the average stocking density, both directly and by changing the proportions of land uses. Finally, the strong impact of the BSE outbreak on the whole industry emerges in the estimates, with the trend in each livestock equation (particularly that for beef cows) decreasing significantly after 1988.

[TABLE 4 about here]

Livestock intensity equations parameter estimates

We evaluate the fit and predictive ability of our structural model by comparing its forecasting performance against that of an established benchmark: the logit land use share model introduced by Lichtenberg (1989), Wu and Segerson (1995) and Plantinga (1996) and applied extensively thereafter.

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[16] Note that in the livestock equations the land use shares are modelled as exogenous, assuming that farmers maximize profits in a two-step process and, therefore, treat land use allocations as fixed factors in the netput equations. This is the same approach employed by Arnade and Kelch (2007) and stems directly from the Chambers and Just (1989) profit function maximization. Using univariate Tobit models we empirically compare two estimation approaches: the standard ML which assumes that the land use shares are exogenous and a ML with instrumental variables to model land use shares as endogenous. The first strategy provides significantly superior out-of-sample performance for each of the three livestock equations. This suggests that, at least in our sample, land use allocation choices are planned on a longer run basis and can be considered as fixed when evaluating livestock intensity decisions.

Table 5 reports the Mean Absolute Error (MAE) statistics for the land use share and the livestock equations calculated as the mean absolute value of the difference between the predictions and the actual JAC data, for the whole England and Wales in 2004, this being this the most recent years for which we have JAC data covering the entire country.[17] Despite the constraints placed upon our model due to its structural underpinnings, our approach still yields results which are superior for cereals, oilseed rape, root crops and temporary grassland shares. The logit model performs slightly better for permanent grassland and rough-grazing. However, JAC data is very noisy for these two land use categories, particularly in the recent years, because of the parish level data collection approach and the grid square assignation methodology. Therefore, the resultant forecasting comparisons have to be interpreted cautiously. The logit only clearly outperforms the structural model with respect to the "other" category. This is not surprising since in our approach this class is not directly modelled but estimated as a difference, as shown in equation (10). Overall, these results indicate how the predictive ability of the structural model is comparable or even moderately superior to the one of the benchmark. This is somewhat unexpected, as the logit share model is an empirical-driven approach, specifically designed to describe and predict land use shares. In contrast, our model is based on a flexible specification for the farm profit function, from which not only land use equations but also input and output intensities are derived in a coherent framework. This ensures a comprehensive and theoretically consistent representation which, as shown but these results, does not sacrifice empirical predictive accuracy. Furthermore, in this application the obvious drawback of the logit approach is that it cannot include livestock numbers and, therefore, cannot consider one of the most significant sources of agricultural pollution.

[TABLE 5 about here]

Forecasting performance (MAE): structural model and logit share model

[FIGURE 2 about here]

Cereals in 2004: JAC data and model predictions

In order to analyze the spatial forecasting ability of our model, Figure 2 maps actual and predicted shares of cereals in 2004. The model performance is highly satisfactory with the two maps showing essentially the same spatial patterns of land use. However, some minor differences can be seen (e.g. in the South of England and in the West Midlands) and the actual data results in being somehow blockier than the predicted ones, with some grid squares with high cereal shares shown right next to grid

[17] Since only 6% of the 2004 data are used to estimate the model, this consists of mainly out-of-sample forecasting. Therefore it is an appropriate yardstick to compare models performances avoiding the risk of preferring an over-fitted specification.

squares with very low shares. This is not likely to be a shortcoming of the model, but is more probably a drawback of the raw JAC data, resulting from the parish level record allocation and collection procedure and the subsequent grid square conversion procedure. This feature is even more evident in extensive land use types, such as grasslands, as showed in Figure 3. Whilst the patter of land use is essentially the same in the predicted and actual data, the predicted temporary grassland is much smoother than the one in the JAC records.

[FIGURE 3 about here]

Temporary grassland in 2004: JAC data and model predictions

5. Concluding remarks

The approach proposed in this paper diverges from existing spatially explicit, econometric land use models since, instead of focusing only on reduced form, land use allocation equations, it develops a structural approach encompassing agricultural land use decisions, livestock numbers, crops yields, inputs applications and profits in a coherent and unifying framework. The underpinning theoretical model builds upon the joint multi-output profit function introduced by Chambers and Just (1989) and is translated into an empirically tractable system of equations by directly specifying the profit function as one of the flexible functional forms available in the literature. The resulting applied specification is very flexible, and can be implemented on different types of data, ranging from aggregated national or regional data to farm-level information.

In our empirical application estimates the model using a 2km^2 grid square panel dataset covering the entirety of England and Wales for the past 40 years, including all the major policy, market and environmental drivers of agricultural land use. The fine-scale nature of this data allows us to include a detailed specification of the physical environment determinants, which is critical to assess the economic and environmental consequences of land use change. Whilst this micro-level data are necessary to capture the relevant spatial heterogeneity, they are also characterized by the presence of censored observations, which considerably complicate the econometric estimation. In this paper we address this issue by extending to land use modelling the QML estimator recently developed by Yen et al. (2003) for systems of censored demand equations.

The findings of this research could be extended in several directions. First, in the empirical application we did not estimate all the structural parameters of the model and, therefore, did not derive the welfare implications of land use change. Farm-level data on profits and yield could be used to address this limitation and jointly estimate the entire system of equations (6), (7) and (9). The obvious drawback of this approach would be loss of the spatial dimension of the analysis, which could be at least partially maintained by knowing the location of the farms and linking it to the environmental characteristics. Secondly, our approach is general enough to be implemented in a variety of empirical contexts. Given the refined specification of the climatic variables, an obvious candidate is the prediction of the effects of global warming on agriculture. Finally, our framework is essentially static: an important extension would be to formulate a dynamic econometric specification to investigate the inter-temporal aspects of agricultural production decisions.

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Appendix: Tables and Figures

TABLE 1

Descriptive statistics, land uses (ha) and livestock numbers (heads) per 2km^2 grid square

	1969	1988	2004		Total			
	$\bar{x}$	$\bar{x}$	$\bar{x}$		$\bar{x}$	$\hat{s}(x)$	Min	max
Cereals	87.8	94.6	76.4		83.0	77.4	0	347.2
Oilseed Rape	0.1	8.5	13.3		6.9	12.3	0	124.7
Root crops	10.1	9.5	7.5		9.1	18.7	0	186.8
T. grassland	41.1	28.8	22.6		29.3	28.7	0	349.5
P. grassland	116.7	115.6	112.7		113.0	97.0	0	400
Rough grazing	47.1	39.6	40.5		44.0	100	0	400
Other	22.8	26.6	45.7		37.8	45.6	0	400
Tot. land	*325.6*	*323.2*	*318.7*		323.1	96.9	1.25	400
Dairy	87.1	71.5	62.0		74.1	99.1	0	1128
Beef	151.4	149.8	89.9		144.9	123.8	0	1221
Sheep	472.2	784.1	323.8		693.6	899.0	0	11289

Notes: only grid squares containing some agricultural land (according to the ALC) are considered, $\bar{x}$ indicates the sample mean, $\hat{s}(x)$ the sample standard deviation.

TABLE 2

Descriptive statistics, environmental and climatic determinants

	Units	$\bar{x}$	$\hat{s}(x)$	min	max
aar	mm	888.4	360.5	509	3980
mwd	days	53.0	37.2	0	143
pt	mm	507.8	52.3	240	608
fc	days	114.7	21.7	80	230
dd	^{o}C	2290	169.2	1410	2641
alt	m	120.4	113.7	0	860
smore6	%	19.2	0.25	0	100

Notes: $\bar{x}$ indicates the sample mean, $\hat{s}(x)$ the sample standard deviation.

TABLE 3

Land use share equations parameter estimates

	Cereals	Oilseed rape	Root crops	Temp. Grassland	Perm. Grassland	Rough grazing
$P_{cereals}$	0.134 ***	--	--	-0.044 **	--	--
P_{rape}	--	0.148 ****	--	--	--	--
$P_{rootcrops}$	--	--	0.027 *	--	--	--
$P_{fertilizer}$	-0.111 ***	-0.283 ****	-0.017 *	0.067 ***	-0.018	0.036 *
Set aside rate	-0.425 ****	-0.114 ***	0.003	-0.009	-0.030	-0.025 *
ESA share	-0.033 ****	-0.008 ***	0.000	0.000	0.031 ***	0.032 ***
Park share	-0.019 ***	-0.006	-0.003 ***	-0.018 ***	-0.067 ***	0.041 ***
Urban share	-0.028 **	-0.003	-0.002	0.000	0.061 ***	0.010 *
smore6	-0.087 ***	-0.018 ***	0.000	-0.005	0.131 ***	0.052 ****
coast	-0.357	-0.505 *	-0.156	1.316 ***	-0.536	1.473 ***
alt	14.170 ****	3.048 ***	-2.693 ****	-0.787	#	#
atl^2	6.333 ***	1.337 **	-0.494 **	-0.834 *	#	#
alt < 200m	#	#	#	#	-0.057 ****	0.004
alt > 200m	#	#	#	#	0.085 **	-0.156 ***
I(alt > 200m)	#	#	#	#	-25.55 ***	21.96 **
mwd	4.174 ****	0.079	1.619 ****	0.956 ***	-8.455 ****	-0.582
mwd^2	-1.283 ***	-0.416 ***	0.681 ****	0.147	-1.346 ***	0.271 **
pt	6.727 ***	1.594 *	0.331 *	-3.419 ***	-23.95 ***	12.46 ***
pt^2	-2.773 **	-1.919 **	0.720 **	3.401 ***	3.969 *	-7.191 ***
fc	-4.794 *	-7.374 ***	-1.856 ***	0.482	7.165 *	4.394 *
fc^2	16.670 ***	-6.521 ***	2.896 ***	-7.498 ***	-22.22 ***	5.000 ***
dd	-4.228 ***	1.653 ***	-4.801 ****	4.271 ***	35.45 ****	-6.285 ***
dd^2	2.571 **	-0.233	1.592 ****	-1.506 **	-3.071 *	-1.179 *
aar	-3.726	-11.57 ****	6.056 ****	3.950 ***	-5.000	9.738 ***
aar^2	-1.269	-7.177 ***	1.701 ****	3.935 ***	-4.537 *	7.246 ***
Trend	0.015	0.282 ****	-0.015 ***	-0.155 ****	-0.101 ***	0.045 ***
Const	38.04 ****	-17.61 ****	6.677 ****	13.34 ****	36.18 ****	-0.884

Notes: to preserve space the residual correlations, the parameters corresponding to the variance equations, to the interactions of the environmental factors are not reported in the Table, but are available under request from the Authors. "--" = parameters non significant and therefore removed, "#" = parameter not included in the equation, "*" = t-stat > 2, "**" = t-stat > 3, "***" = t-stat > 4, "****" = t-stat > 10. All variables defined as in Table 1.

TABLE 4
Livestock intensity equations parameter estimates

	Dairy cows	**Beef cows**	**Sheep**
$s_{temp.grassland}$	1.427 ****	1.234 ****	1.814 ****
$s_{perm.grassland}$	0.438 ****	0.763 ****	2.400 ****
$s_{rough.grazing}$	0.041 **	0.296 ***	1.167 ****
P_{milk}	2.208 ***	--	--
P_{quota}	-3.034 ***	--	--
$P_{dairy\ cows}$	0.003	--	--
$P_{beef\ meat}$	--	0.084 ***	-0.209 **
$P_{sheep\ meat}$	--	-0.209 **	3.244 **
$P_{fertilizer}$	-0.261 **	-0.297 **	-1.090 *
ESA share	-0.047 ***	-0.169 *	0.091 *
NVZ share	-0.004	0.008 *	-0.147 ***
Park share	-0.007	-0.011	-0.282 ***
Urban share	0.077 ***	0.195 ****	-0.383 ***
L	0.013 ***	0.009 *	0.212
smore6	-0.113 ****	-0.067 ***	0.947 ***
coast	-1.480 *	1.460	11.52 **
alt	-12.99 ***	0.023	-41.38 ****
atl^2	-9.720 ***	4.566 **	-13.16
mwd	-1.574 **	1.116 **	-5.129 *
mwd^2	-2.089 ***	-2.735 ***	-11.01 ***
pt	9.334 ***	-21.79 ****	-73.98 ***
pt^2	-1.736	27.22 ****	14.42
fc	-5.250	-5.526 *	105.5 ***
fc^2	-6.054	-12.79 ***	32.97 *
dd	-5.263 ***	-14.68 ***	-15.59 *
dd^2	-1.155	2.709 *	0.445
aar	5.615 *	-6.729 ***	8.889
aar^2	3.534 *	0.930	68.08 ***
Trend	0.336 **	0.385 **	2.463 ***
$Trend_{BSE}$	-0.344 **	-0.895 ***	-2.542 ***
Const	-25.07 ***	19.02 ***	32.55 ****
$Dummy_{BSE}$	4.469 **	10.47 ***	60.89 ****
$\rho_{i,j}$			
Dairy cows	1		
Beef cows	0.238 ****	1	
Sheep	-0.201 ****	0.186 ****	1

Notes: to preserve space the parameters corresponding to the variance equations and to the interactions of the environmental factors are not reported in the Table, but are available under request from the Authors. "--" = parameters non significant and therefore removed, "*" = t-stat > 2, "**" = t-stat > 3, "***" = t-stat > 4, "****" = t-stat > 10. All variables defined as in Table 1.

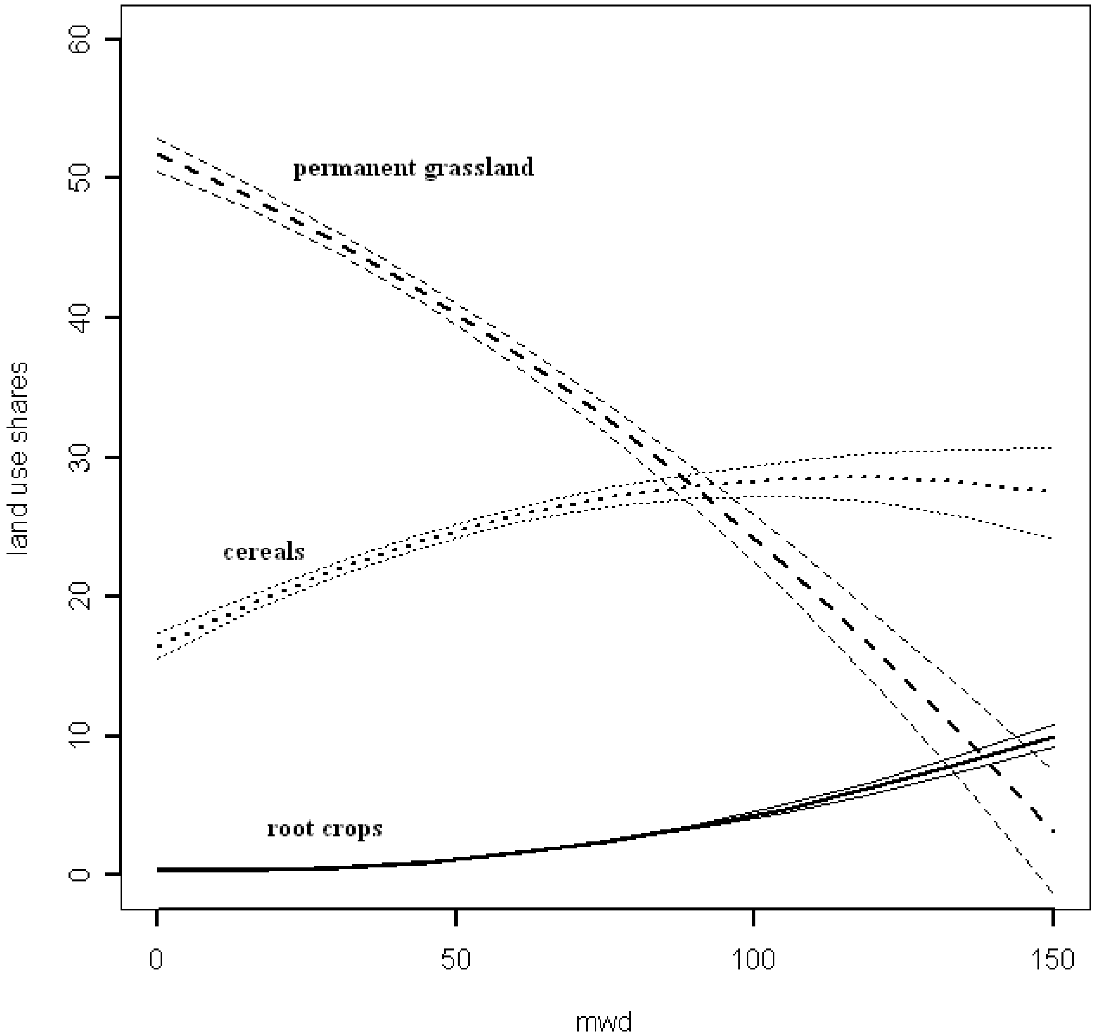
TABLE 5

Forecasting performance (MAE): structural model and logit share model

	Structural model	Logit
Land use (*ha*)		
Cereals	**24.5**	25.7
oilseed rape	**8.5**	9.7
root crops	**5.7**	6.0
temporary grassland	**12.1**	12.6
permanent grassland	41.1	**40.9**
rough grazing	19.0	**18.1**
other	24.3	**19.7**
Livestock (*heads*)		
dairy	47.0	--
beef	61.4	--
sheep	375.7	--

Notes: MAE for England and Wales in year 2004, total number of observations equal to 33283 (outliers excluded). Logit model specified including the same explanatory variables of the structural model and estimated following Zellner and Lee (1965).

FIGURE 1
Relationships among predicted land use shares and machinery working days



Notes: predicted shares and asymptotic 95% confidence intervals, all explanatory variables fixed at their average levels in year 2004.

FIGURE 2

Cereals in 2004: JAC data and model predictions

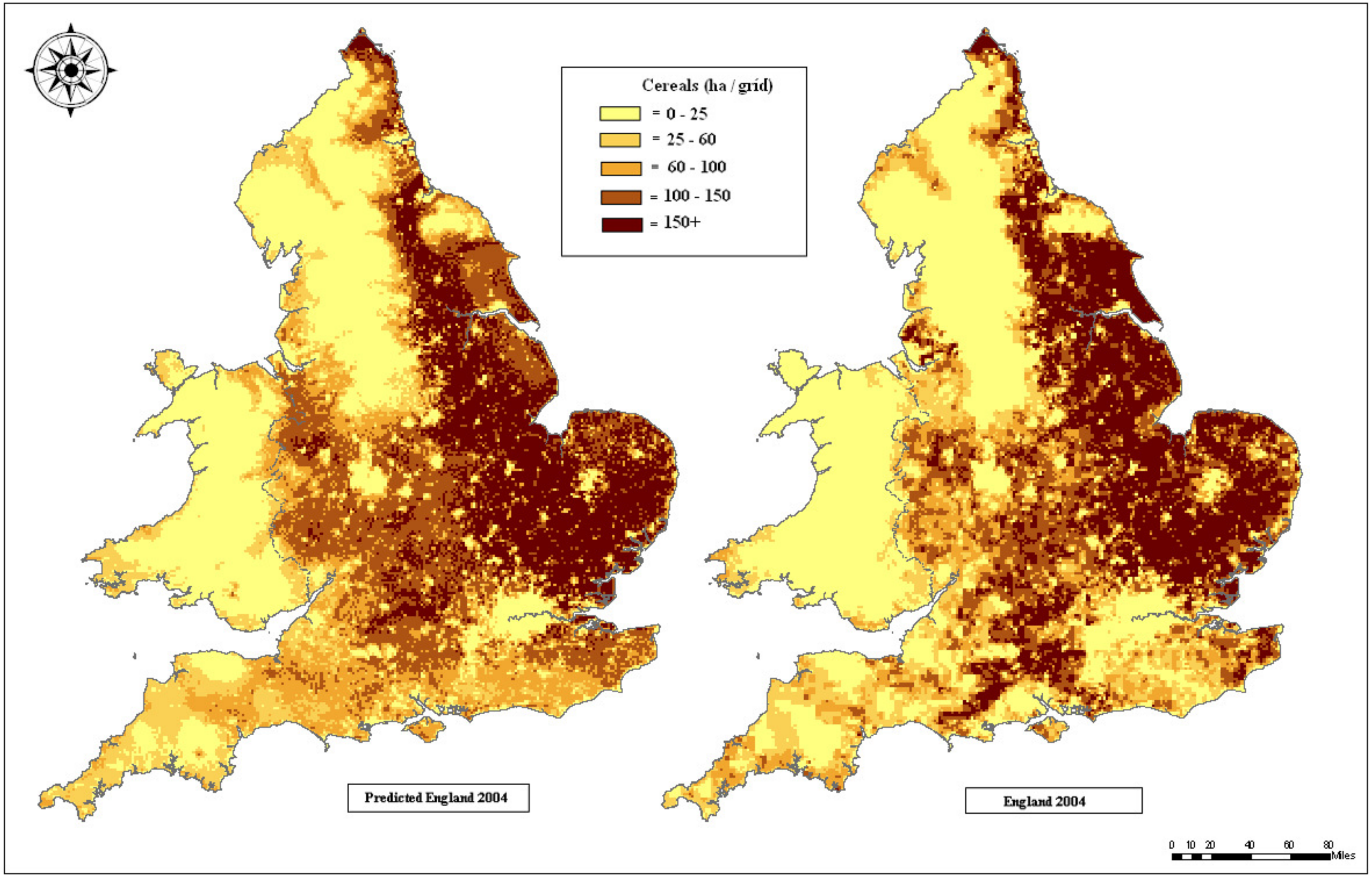


FIGURE 3

Temporary grassland in 2004: JAC data and model predictions