Empirical evidence for the diffusion of knowledge in land use change

Calum Brown*,[1], Peter Alexander[2,3], Mark Rounsevell[1,2]

*Corresponding author. Email: calum.brown@kit.edu, telephone: +49 8821 183161

[1]Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research, Atmospheric Environmental Research (IMK-IFU), Kreuzeckbahnstr. 19, 82467 Garmisch-Partenkirchen, Germany

[2]School of Geosciences, University of Edinburgh, Drummond Street, Edinburgh EH8 9XP, UK

[3]Global Academy of Agriculture and Food Security, The Royal (Dick) School of Veterinary Studies, University of Edinburgh, Easter Bush Campus, Midlothian, EH25 9RG, UK

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Competing interests

The authors declare no competing interests

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Abstract

Changes and innovations in land management have been hypothesised to spread through knowledge diffusion between land managers. Such diffusion can occur directly between neighbours or, in recent years, through various forms of information technology. Land system models and policy initiatives do not generally account for this process, partly because of a lack of empirical studies of its spatial and temporal properties. We look for evidence of the existence and form of diffusion in UK agriculture and forestry between 1968 and 2015, using logistic models of spatial dependencies in the uptake of new crops and subsidies. Strong evidence is found of spatial diffusion, with no clear evidence that its form has changed systematically over recent decades. We conclude that improved understanding of diffusion is necessary to replace 'one size fits all' representations in land use policy-making and modelling, so that appropriate account can be taken of the spatial aggregations and time lags that appear to remain general characteristics of uptake of new management practices.

Keywords: land management, uptake, adoption, innovation, social network, climate change adaptation

Introduction

Diffusion of knowledge, practices, and attitudes has been recognised as a component of land use change since the seminal works of Rogers (Rogers 1962) and Hägerstrand (Hagerstrand 1968), and has been the focus of a great deal of empirical and theoretical research over several decades (Feder and Umali 1993; Marra et al. 2003; Knowler and Bradshaw 2007). Diffusion has been detected through statistical models, e.g. (Allanson 1994; Isham 2002; Genius et al. 2013), process-based models, e.g. (Berger 2001; Kiesling et al. 2011; Alexander et al. 2013), and surveys (Feder et al. 1985; Wu and Pretty 2004; Xiong et al. 2016b). However, empirical studies of diffusion in land use change have become rarer in recent years, especially outside developing countries, and are not generally used to inform land system policy-making. This may indicate a mismatch between diffusion-dependent land system dynamics in the real world and their conceptual counterparts, with potentially serious implications for the anticipation and management of land use changes.

Particularly significant are the spatial and temporal characteristics of diffusion, and their impacts on the pattern and rate of land use change. These characteristics largely depend upon the ways in which land managers interact with one another, with neighbour-to-neighbour interactions or imitation expected to produce easily-detectable signals of gradual, local change (Hagerstrand 1968). However, the rapid development of mass communication, digital resources and social media has fundamentally altered communication processes. In agriculture, novel technologies have often been used to disseminate information (sometimes in innovative ways, such as the use of radio ‘entertainment-education’ programmes to spread agricultural knowledge (Heong et al. 2008)), as well as allowing direct communication between distant practitioners. Indeed, there is evidence that land managers have become increasingly reliant on digital technology for information about their land use choices, e.g. (Wheeler 2008; Jansen et al. 2010). This has the effect of breaking geographical dependencies, potentially favouring rapid and spatially unstructured diffusion (Lichter and Brown 2011). Conversely, there is evidence that farmers still value the local, trusted and context-specific information that neighbours can provide, wether through communication or simple observation (Llewellyn 2007).

Partly as a consequence of the uncertainty about the processes by which diffusion in land use now occurs (or matters), the dominant assumption in land system modelling and governance is that land managers have perfect or near-perfect knowledge and foresight of the management options available to them, even where these rely on new practices or technology (Heistermann et al. 2006; Brown et al. 2017). This implies effectively instantaneous and complete uptake of appropriate options and rejection of inappropriate options, both of which misrepresent the gradual, experimental nature of land use change in general and climate adaptation in particular (Moser and Ekstrom 2010; Naess 2013; Zehr 2015). Some models do allow for spatio-temporal autocorrelation in land use change that match historical observations (e.g. (Overmars et al. 2003; Meiyappan et al. 2014)). However, this generic autocorrelation can represent patterns of productivity, accessibility, culture or opportunity costs as well as diffusion, and the exact role of each usually remains unspecified. As such, approaches of this kind are misleading where rapid changes disrupt existing processes or introduce new ones, for example where climatic thresholds in productivity are crossed, or where radically new technologies emerge (Marra et al. 2003; Gornall et al. 2010).

In areas with limited communications infrastructure, well-studied forms of diffusion between neighbouring land managers can be expected to retain considerable influence (Feder et al. 1985; de Graaff et al. 2008). However, even in areas with well-developed mass communication and digital technology, spatio-temporal patterns have been detected, for example, in the spread of organic agriculture (Wollni and Andersson 2014; Allaire et al. 2015), and also in socio-technical systems that can intersect with land use (e.g. (Vespignani

2012)). Conversely, other studies have found little or no evidence of spatial influences between neighbouring farmers (Schmit and Rounsevell 2006). Generalising from these cases is difficult because data with sufficient spatio-temporal detail are scarce while contrasting theories of social diffusion are common. This often forces researchers and policy-makers to choose between discredited 'universal' mathematical descriptions that ignore social, cultural and environmental contexts, and unworkably specific descriptions suggested by social research that focus on these contexts rather than any overarching behavioural consistencies (Mahajan and Schoeman 1977; Ruttan 1996; Strang and Soule 1998; Brown et al. 2016a). Additional empirical research is therefore needed not only to establish the importance of knowledge diffusion, but also to identify the general assumptions that can and cannot be made about its form when projecting future land use change and designing policies.

This work explores three case studies to assess the extent to which spatial diffusion between land managers is still a meaningful process. Using records of uptake of subsidy schemes and crops, we apply logistic regression models to test for the occurrence of diffusion between neighbouring land managers. The case studies are all drawn from the UK agriculture and forestry sectors to assess the existence, form and development of diffusion in broadly-relevant European settings. Data used span the period 1968-2015, covering the development of the internet, social media, and other forms of modern information technology, allowing for a tentative assessment of their impact. A further aim of this study is to stimulate further analyses of new datasets as part of a comprehensive assessment of diffusion in diverse settings to support land system modelling and governance.

Materials & methods

Three datasets were analysed using logistic regression models in the *R* package *arm* (Gelman and Hill 2007) (details below). These datasets described the uptake of new crops (Oilseed Rape) and government subsidy schemes (the Scottish Woodland Grant Scheme and the English Energy Crops Scheme) in the UK over the combined period 1968 to 2015. These three datasets are either derived from agricultural censuses (Oilseed Rape data) or subsidy payment records (Woodland Grant and Energy Crops schemes). These data give locations and times of uptake that are either approximate (Oilseed Rape; within 2km grid cells and periods of two to eight years) or precise (Woodland Grant and Energy Crops schemes). All three cases were adopted over a number of years, with relative rates of uptake differing especially between Oilseed Rape and the subsidy schemes, but the temporal form of uptake being notably similar in all three cases (Figure 1). Uptake (a binary dependent variable) was modelled as a function of case-specific explanatory variables and previous uptake in local- to large-scale 'neighbourhoods' (described below and in Table 1). In some cases, data were too sparse to robustly estimate effects of all explanatory variables, and so analysis was conducted both with and without these variables in these cases. Results summaries presented below include explanatory variables, while full model results with and without explanatory variables are presented in the SI.

Dataset	Dependent variable	Explanatory variables	Data sources
Oilseed Rape	First uptake of Oilseed Rape (binary response)	Proportion of neighbouring cells with first uptake at last census Area of agriculture, livestock farming, crops, owned and rented land within cell (hectares) Number of land holdings within cell Number of part time farmers and number of workers within cell	Agricultural census data (gridded, 2km) for England and Wales (EDINA 2012)
Woodland Grant Scheme	First uptake of Woodland Grant Scheme (binary response)	Number of neighbouring instances of uptake at each preceding year Category of land holding / land owner: corporate investor, personal investor, family estate, farm, farm woodland or other agricultural holding, industrial, mainly woodland, mixed estate, private residence, public building, public ownership, recreation, traditional estate, other (categories recorded 1989-1991). Industrial, mainly woodland, mixed estate, private residence, public building, recreation, crofting common grazings, crofting in-bye land, personal occupier, public ownership, voluntary organisation, other (categories recorded 1992-1999)	Subsidy payment records (Forestry Commission Scotland 2017)
Energy Crops Scheme	First uptake of Energy Crops Scheme subsidy (binary response)	Number of neighbouring instances of uptake at each preceding year Agricultural grade of land (1-5 categorical scale) Miscanthus productivity (Mg ha^{-1})	Subsidy payment records (Natural England 2015) Agricultural grade and Miscanthus productivity (Hastings et al. 2014)

Table 1: Dependent and explanatory variables modelled for each dataset, along with their source and measurement unit. Proportions and numbers of neighbours are calculated within spatial and temporal extents of 2-500km and 1-4 years, respectively, except in the case of Oilseed rape where temporally variable census intervals were used (see main text). Full model results are presented in the SI.

Oilseed Rape data

Oilseed rape expanded substantially across the UK following the country's entry to the European Economic Community in 1973 and the introduction of subsidies for its production, with rapeseed production rising from 60,000 tonnes in 1975 to 1.2 million tonnes by 1995 (Scarisbrick et al. 1989; Alexander et al. 2013). Agricultural census data used here describe Oilseed Rape crop areas and yields across England and Wales from 1969 to 1997 at intervals of two to eight years (from 1969, 1972, 1976, 1979, 1981, 1988, 1993, 1994, 1995, 1996, 1997), and at 2 km grid scale (EDINA 2012). Data were converted to presence/absence of the crop within each grid cell at each timestep, but further data manipulation was avoided – in particular, the resolution was not altered because the existing 2km scale exceeded the average size of agricultural holdings in the UK (presently ~0.8 km^2) (European Commission 2017). This large grid cell size biases the analysis against detection of diffusion between neighbouring farms rather than towards misinterpretation of expansion within single farms. It has previously been demonstrated that an agent-based model including diffusion can match spatio-temporal characteristics of these data (Alexander et al. 2013), but statistical tests of this process have not to our knowledge been carried out. As a result, it remains unclear whether diffusion-based explanations are necessary or merely adequate, with the tests used here providing a new robust assessment.

We modelled the spread of Oilseed Rape grown for oilseed (whether in spring or winter), as this was the only consistent category throughout the agricultural censuses. At each timestep, we modelled uptake as the presence of the crop in cells where it had previously been absent (i.e. cells where the crop had been recorded at earlier timesteps were excluded from the analysis except as possible sources of diffusion). Uptake was modelled as being dependent upon explanatory variables including the extent of livestock and crop farming in each cell, the number of farm workers, the number of part-time farm workers, the number of holdings, whether agricultural land was rented or owned, and the total agricultural area (except after 1993, when only total agricultural area data was available) (Table 1). The temporal scale of analysis was not varied due to the lengthy and inconsistent gaps between the original censuses, but the relationship between census gap length and apparent neighbourhood effects was checked.

Scottish Woodland Grant Scheme

The Scottish Woodland Grant Scheme was established to support the creation of new woodland and management of existing woodland (Forestry Commission Scotland 2017), and ran in three phases between 1988 and 2004. The scheme required an application to the (national) Forestry Commission, which then approved schemes, distributed funding and checked progress. The scheme was publicised without apparent spatial dependencies that could confound the detection of local-scale diffusion.

Data for the Woodland Grant Scheme include the time and location of each new scheme, allowing accurate modelling of spatial and temporal dependencies in uptake. This made it necessary to ensure that multiple schemes within single land holdings were not interpreted as instances of diffusion (especially given the large size of many Scottish estates), and so records of land holding identities were used to exclude all but the first instance of uptake within each holding, with later instances kept only as potential sources of diffusion. The use of consultants for applications to the scheme introduced a further potential mechanism of diffusion between estates. Therefore, models were run without considering consultant identity in the first case, and then re-run with all but the first application by each consultant excluded, as with land holding identities. This was not done for the first Woodland Grant Scheme (1988-1991) because consultant names were not recorded. Further available explanatory variables were the land type (defined in categories of 'mainly woodland', 'mixed estate', 'public building', 'recreation', and 'private residence') (again except between 1988 and 1991) and the owner type ('personal occupier', 'public', 'voluntary organisation', 'private residence', and 'other') (Table 1). Entries with missing or inaccurate information (e.g. years outside the range of the scheme, coordinates outside Scotland) were excluded from all analyses (64 entries, 1.1% of the total). Spatial explanatory variables measured the previous uptake of the scheme at each of the preceding 4 years (i.e. the number of neighbouring schemes initiated 1, 2, 3 or 4 years prior to each instance of uptake). Models were not run where the number of new schemes fell below 100 per year (from 2000 onwards, following trimming by consultant identity).

English Energy Crops Scheme

The English Energy Crops scheme was established to encourage bioenergy production by farmers in England through the payment of grants during the period 2002-2015 (Natural England 2006, 2015). The crops included were Miscanthus, and willow or poplar for short rotation coppice. Like the Scottish Woodland Grant Scheme, these data provide the boundaries of schemes along with their year of establishment, but without other information.

While this made it impossible to control for large land holdings containing multiple schemes, the smaller size of agricultural land holdings in England makes this less of a concern than with the Woodland Grant Scheme in Scotland. Furthermore, neighbouring schemes with the same date of initiation were excluded from the analysis to avoid possible double-counting of schemes within the same land holding (this step removed 25.8 % of the total, strongly biasing against the detection of genuine diffusion). The data were further trimmed to remove schemes misplaced on land classified as urban, non-agricultural or unproductive, with land types derived from land cover and productivity data (Hastings et al. 2014); this led to the exclusion of a further 12.5% of the schemes. These same productivity data were used to provide explanatory variables for the agricultural grade of land (a measure of the versatility and suitability of land for crops) and productivity for Miscanthus (Table 1). Spatial explanatory variables were constructed for different time periods in the same way as for the Scottish Woodland Grant Scheme. Due to the low number of schemes recorded (375 in total following exclusions), models were run for every year in which 20 or more schemes were initiated (2005, 2006, 2007, 2008, 2010, 2013).

Statistical analysis

Regressions models were fitted for each dataset and over a range of neighbourhood radii and timescales. From these models, those with the 'best' fit were selected using Akaike Information Criterion (AIC), to identify at what spatial and temporal scales evidence of diffusion was strongest. Details of the statistical analysis are given below.

A potential confounding factor in spatial analyses of this kind is spatial variation in suitability for the crops or trees being grown, making it likely that instances of uptake will be aggregated even in the absence of any form of diffusion. Given a general lack or inadequacy of data describing land suitability for the cases included here, we chose to exclude all records in which the crops or schemes were not adopted at some point during the timespan of the datasets, and therefore to model only spatial effects on the timing of uptake. As a result, models only included locations that grew Oilseed Rape or took part in the subsidy schemes at some point, meaning that at each timestep the ‘zeros’ (lack of uptake) in the models included only those places still to adopt (and therefore excluding the final year of each dataset from the analyses, because all remaining locations adopted at that point). We therefore make the assumption that there was no temporal change in the suitability of land for the crop and schemes studied.

This approach substantially reduced the number of data available to the models, while making the analyses more balanced (and hence reliable) in terms of the relative numbers of uptake and non-uptake recorded (Tables S1-S3). It also introduced a strong bias against the detection of diffusion by assuming that a lack of adoption was always due to unsuitability rather than absence of diffusion. In the absence of comprehensive suitability data, this assumption ensures that results provide a conservative estimate of potential diffusion and so a robust test of its presence, if not its exact form. This also precluded the detection of general differences in uptake between types of land holding, given that all recorded holdings took up the crop or scheme at some point in time. Similarly, we did not attempt to account for autocorrelation in explanatory variables because those remaining have no obvious role in driving changes in uptake over time, and spurious associations could have obscured genuine signals of diffusion.

Because spatial errors in model results could be affected by suitability as well as diffusion (i.e. errors occurring because diffusion was not properly accounted for and because of variations in land suitability would be indistinguishable), we did not analyse these to look for signals of diffusion, but instead constructed neighbourhood-based measures of uptake at preceding timesteps. Variable spatial and temporal resolutions were used to allow assessment of which, if any, spatio-temporal scales showed patterns in uptake, and whether these scales changed over the period analysed. To compare spatial scales, the nearest-neighbour distances between instances of uptake were recorded, as well as the number of instances within circular neighbourhoods of differing radii (2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 25, 30, 35, 40, 45, 50, 100 and 500km; with larger scales used to allow for unexplained large-scale effects not meaningfully linked to a neighbourhood). To compare temporal scales, neighbouring instances of uptake initiated 1, 2, 3, and 4 years prior to the focal year were recorded (except in the case of Oilseed rape and years near the start of each dataset, where data for preceding years were not available). Changes in the speed and extent of diffusion would therefore be expected to be detectable through changes in the neighbourhoods contained in the best-fitting models. In every case, the dependent variable was a binary measure of uptake or lack of uptake (1/0).

Dedicated models of spatial diffusion processes were not applied because these include more rigid asumptions about the size and form of neighbourhoods, which would have necessitated very extensive testing while potentially excluding valid alternatives, and while also being more challenging to define in the absence of suitability data. Instead, the range of unweighted neighbourhoods described above were used to account for potentially varied spatial influences, from which forms of diffusion (or other effect, where possible) may be inferred. Each dataset was analysed using two-tailed binomial logistic regression models of change (adoption) or lack of change (non-adoption) using all available explanatory variables (both including and excluding the spatial proximity of previous changes). These models assume that a binary response (adoption (1) or non-adoption (0)) can be linked via a logistic function to a series of explanatory variables that may be categorical and/or continuous in nature, with the explanatory variables (and observations) being independent from one another. Because models are fitted by maximum likelihood estimation, results from small datasets are less reliable than those from large datasets.

Here we carried out model selection through comparison of AIC (Akaike's Information Criterion; (Akaike 2011)) values, which summarise the comparative fit of the models to the data while penalising for complexity. Models minimising the AIC values (or within the conventional range of 2 of the minimum value taken to indicate equivalently good-fit; (Symonds and Moussalli 2011)) were identified for each case study, with odds ratios and the areas under the receiver operating characteristic curves (AUC) subsequently used to draw conclusions about the effects of individual terms. Wherever possible, potentially confounding factors were accounted for using separate data and model design, as described above. Finally, models were treated as indicative of any potential presence of diffusion in uptake rather than definitive tests of the temporal and spatial scales over which such diffusion occurs. The numbers of data and models on which findings are based are given below and in the SI.

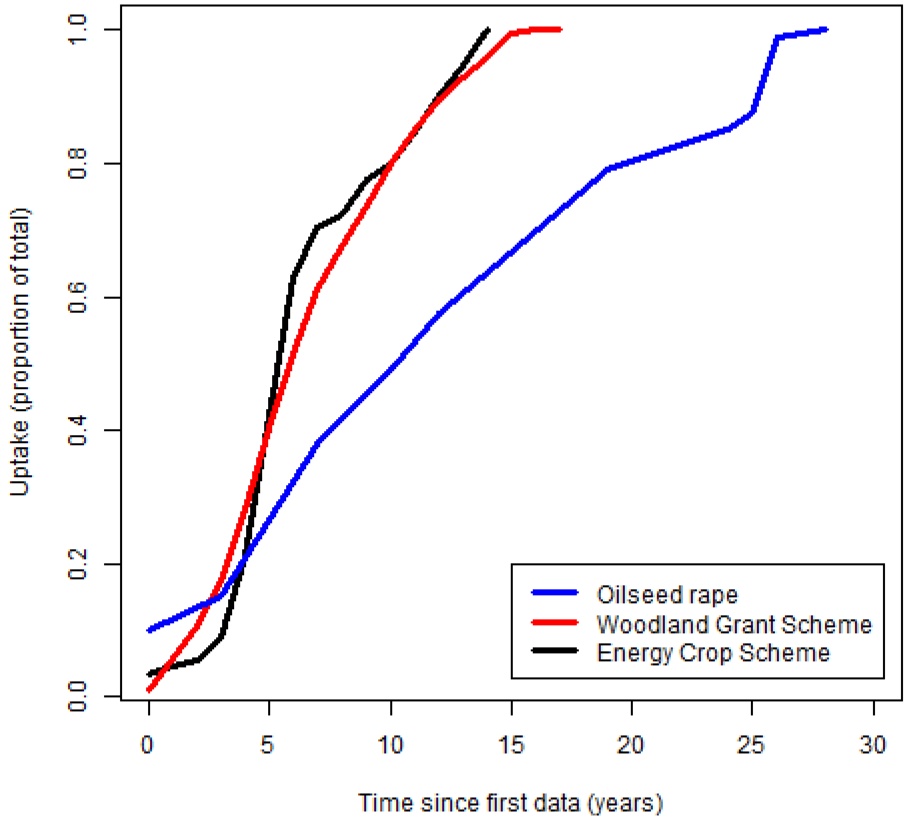


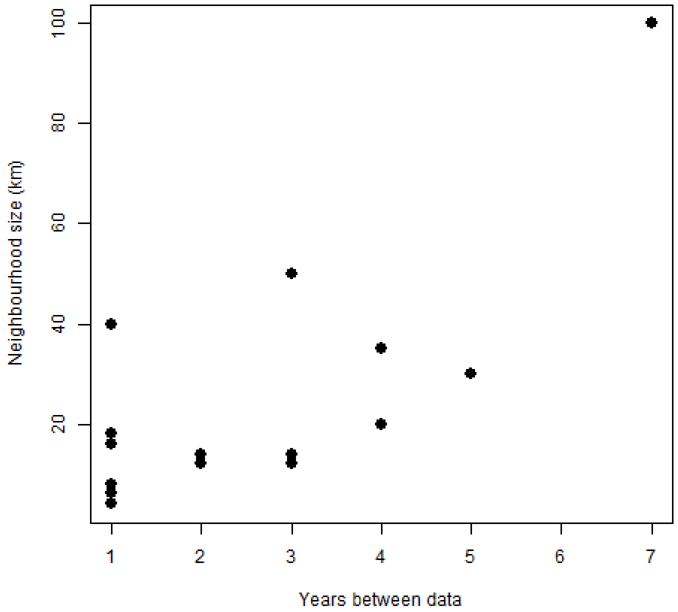
Figure 1: Cumulative uptake of Oilseed Rape 1969-1997, Scottish Woodland Grant Scheme 1992-2004 and Energy Crops Scheme 2002-2015. A value of 1.0 for uptake represents the final extent of uptake recorded, rather than the maximum possible, and so similar absolute rates of uptake over time do not necessarily overlap.

Results

Oilseed Rape

Results of the oilseed rape analysis were broadly consistent across years in terms of the effects of the explanatory variables. Particularly consistent were the effects of the terms capturing the spatial proximity of previous uptake, which had a positive and substantial effect on uptake (except for the last two censuses analysed, where relatively few records of non-uptake remained, and effects were negative). Of the neighbourhoods tested, those with radii of up to 20km minimised AIC scores in most years (Figure 2), suggesting that these neighbourhoods contributed most to modelling subsequent uptake. There was no clear systematic change in the size of the best-performing neighbourhood over time or when other explanatory variables were excluded, but there was a trend in the size of the best-performing neighbourhood over different census gaps, with increasingly long gaps between censuses correlating with the detection of effects of increasingly large neighbourhoods (Figure 2).

Based on AIC scores, fifteen models were identified as providing the best fits to the data (1-3 per year of analysis). The effects of all explanatory variables in the model with the lowest single AIC score in each year showed further common effects (Table 2, with full results and numbers of data available in Table S1). These suggested that cells with larger agricultural areas and more individual holdings were more likely to include the crop for the first part of the time span analyses, while livestock farms, part-time farmers and those with more workers were far less likely to adopt the crop at first. These results were replicated in other models with higher AIC scores and different neighbourhood measurements.



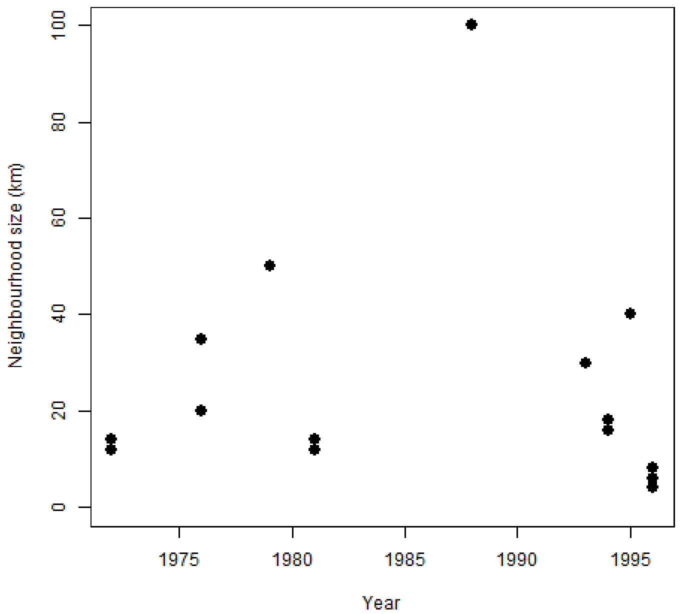


Figure 2: The neighbourhood sizes (radii) contained in models with the minimum AIC (within a range of 2) for each year of the Oilseed Rape uptake analysis (a) and for each of the gaps (years) between datasets (b). Points are shown only where the neighbourhood had a non-zero effect on uptake (Table S1).

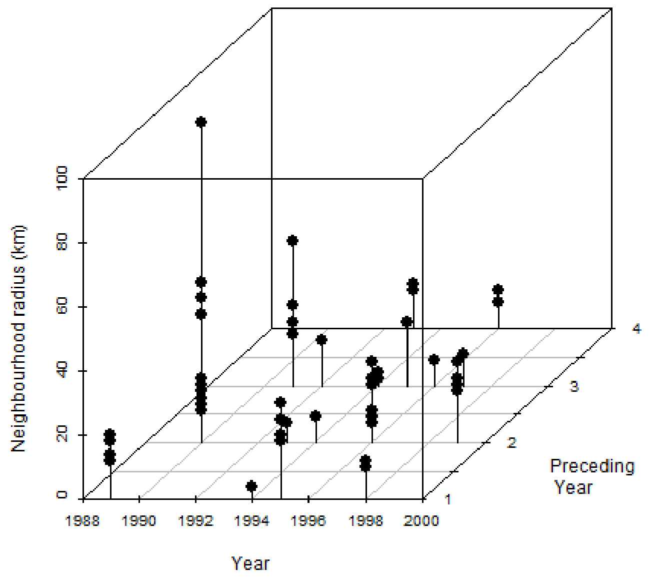
	1972	1976	1979	1981	1988	1993	1994	1995	1996
Neighbourhood	+ (12km)	+ (20km)	+ (50km)	+ (14km)	+ (100km)	+ (30km)	+ (16km)	- (40km)	- (6km)
Livestock	+	-		-	-				
Crops		-	+						
Part-time		-			-				
No. holdings	-	+	-		+				
Total agricultural area		+			+	+	+		
Area rented		-			-				
Area owned		-			-				
No. workers		-		-	-				

Table 2: The effects of explanatory variables on uptake of Oilseed Rape taken from the model with the lowest AIC value for each year of the analysis. Grey cells indicate the exclusion of variables from some models (due to lack of data). 'Neighbourhood' refers to the number of instances of uptake within the neighbourhood of given radius at the preceding census; 'Livestock' refers to the area farmed for livestock production; 'Crops' refers to the area farmed for crop production; 'Part-time' refers to the area occupied by part-time farmers; other 'no…' and 'area….' variables refer to the number or area within each cell. Full results and effect sizes are available in Tables S1a-n.

Woodland Grant Scheme

Two distinct analyses of the Woodland Grant Scheme data (without and with consideration of consultant identity, respectively) produced results that were strongly consistent in the early years of the scheme's operation. Models of uptake in 1989, 1990 and 1991 that accounted for the locations of the first instances of uptake (in 1988) invariably outperformed other models, minimising AIC values and including positive neighbourhood effects. Results suggest increased uptake around the sites of initial adoption within neighbourhoods of radii 0-20km (over one year), 20-40km (over two years) and 40-60km (over three years) (Figure 3). Following this, repeated evidence of increased uptake within neighbourhoods of radii 40km and less around sites of adoption over the four preceding years was found using the full dataset (Table 3), and intermittent evidence of short-term, small-scale neighbourhood effects was found using the dataset trimmed by consultant identity. This difference was most likely due to the substantially decreased number of data in later years following trimming, but may also indicate spatial structure in the usage of consultants. Once again no systematic differences in neighbourhood effects were found when other explanatory variables were excluded.

Based on AIC scores, 48 models were identified as providing the best fits to the data (with no trimming by consultant identity). Other explanatory variables had clear effects through time, with particularly strong evidence of delayed uptake of the scheme amongst estates owned by personal occupiers, public bodies and voluntary organisations, or those used for recreation or industry, but earlier adoption amongst mixed estates, wooded estates and those incorporating a public building (Table 3, with full results and numbers of data available in Table S2). No estate or owner types were found to be more likely to adopt the scheme in its early years (though data on owner types were not available for the first Woodland Grant Scheme, 1988-1991).



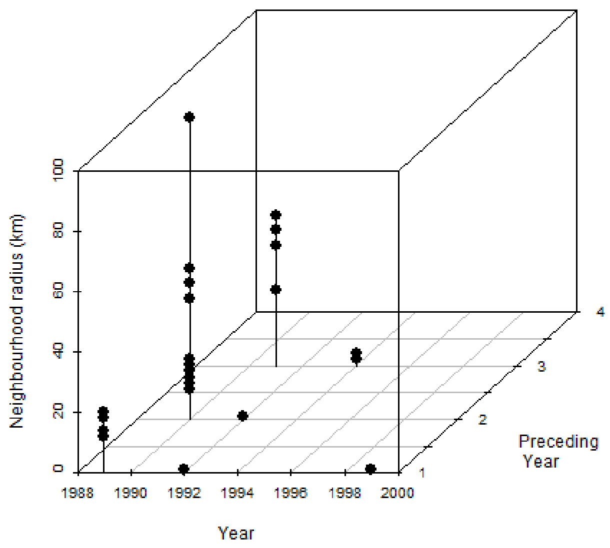


Figure 3: Spatial and temporal extents (radii, years) of neighbourhoods contained in models with the minimum AIC (within a range of 2) for each year of the Scottish Woodland Grant Scheme uptake analysis. Plot (a) shows results where consultant identity is not considered, and plot (b) shows results with only the first scheme per consultant included. Points are shown only where the neighbourhood had a non-zero effect on uptake (Table S2).

	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Neighbourhood	+ (14km, 1 year)	+ (100km, 2 years)	+ (25km, 3 years)	+ (14km, 3 years)	+ (6km, 2 years)	+ (4km, 3 years)	+ (25km, 1 year)	+ (8km, 4 years)	+ (10km, 3 years)	+ (12km, 1 year)	+ (18km, 2 years)
Estate type: mixed		-		+		+		+			
Estate type: mainly woodland				+	+	+					
Estate type: public building				+	+						
Estate type: recreation				-	-		+	+	+		
Estate type: private residence					-						
Estate type: industrial					-		+	+			
Owner type: personal occupier				-	-	-					
Owner type: public ownership				-			-				
Owner type: voluntary organisation				-	-	-	-	-			
Owner type: other				+	+						

Table 3: The effects of explanatory variables on uptake of the Scottish Woodland Grant Scheme taken from the model with the lowest AIC value for each year of the analysis. Results from equally well-supported models (AIC within 2 of minimum value) are not shown here, but contain further (positive) effects of neighbourhoods as shown in Figure 3. Grey cells indicate the exclusion of variables from some models (due to lack of data). 'Neighbourhood' refers to the number of instances of uptake within the neighbourhood of given radius at the given preceding year. 'Min. dist.' refers to the distance to the closest instance of preceding uptake. Only variables that have non-zero effects (with 95% confidence intervals) in at least one year are shown here. Full results are available in Tables S2a-v.

Energy Crops Scheme

The analysis of the English Energy Crops Scheme suggests that neighbourhood effects may have existed in each of the years for which sufficient data were available (2005, 2006, 2007, 2008, 2010 and 2013). Based on AIC scores, 29 models were identified as providing the best fits to the data. In 13 of these cases, the distance to the closest preceding uptake of the scheme, or the number of preceding instances of uptake within neighbourhoods of 40km radius or less, had positive effects on subsequent uptake (Figure 4). These effects were most substantial in the first year of analysis, with only limited evidence of spatial diffusion between neighbouring and/or nearby adoptions of the scheme following this (full model results and numbers of data are given in Table S3). Effects were most commonly detected over a period of 1 year, but results from 2007 suggest a lingering effect of earlier distributions of the schemes. The other available explanatory variables, the agricultural grade of land and the productivity for Miscanthus, had effects in several cases (Table S3), all of which suggested that schemes were more likely to be initiated on land with low agricultural grade or Miscanthus productivity in 2006, 2007 and 2013. Although these results are less clear than those for the Scottish Woodland Grant Scheme, they are consistent with a similar form of spatial diffusion around sites of early adoption, and have a strikingly similar temporal pattern (Figure 1).

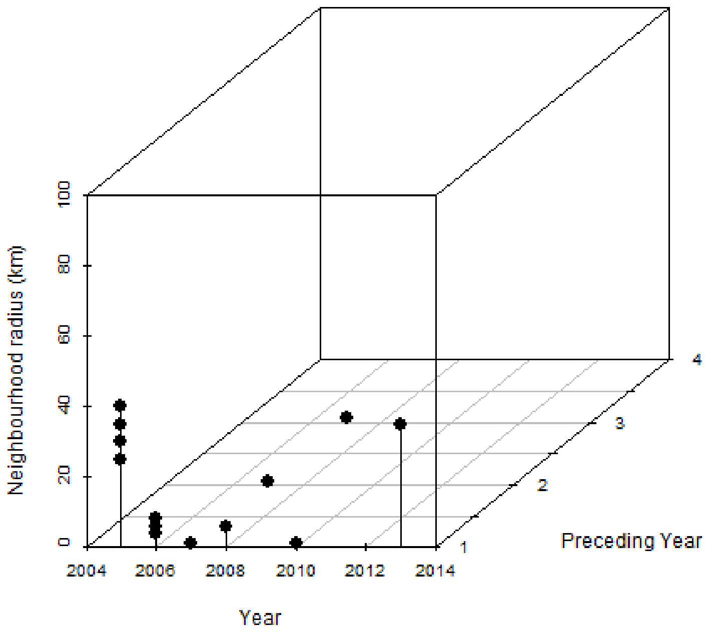


Figure 4: Spatial and temporal extents (radii, years) of neighbourhoods contained in models with the minimum AIC (within a range of 2) for each year of the English Energy Crop Scheme uptake analysis (analyses were carried out only for 2005, 2006, 2007, 2008, 2010 and 2013). Points are shown only where the neighbourhood had a non-zero effect on uptake (Table S3).

Discussion and conclusions

The analysis of crop and subsidy adoption between 1969 and 2015 in the UK suggests that the diffusion of knowledge and practices between land managers remains a strong, if complex, determinant of land use change. The consistency with which variables describing spatial diffusion improved the fit of our models indicates that the process almost always played a substantial role in shaping the uptake of new practices, and that it usually operated within distances of 40km or less, year-to-year.

Notwithstanding these general findings, variation within the results may be attributable to the context-dependent social factors that inevitably affect diffusion (Strang and Soule 1998; Maertens and Barrett 2013). Different individuals and groups may have different levels of communication, risk aversion and adaptability over time, altering the apparent scales over which diffusion occurs. Different forms of land management also imply different spatial and temporal scales of decision making, as in the case of Scottish estates that vary dramatically in size and management purpose (Primmer and Karppinen 2010). Biophysical constraints related to topography, or socio-cultural constraints related to social groupings or norms, may prevent neighbourhood diffusion. Conversely, personal long-distance diffusion can occur through population movements, family connections or contact through interest groups. Consultants and advisory bodies are also likely to play a role in diffusing innovations over large distances (which we cannot directly test for here), given their importance in UK agriculture and forestry and their frequent dedication to this very process (e.g. (MFP 2017; SRUC 2017).

Given such complications, it is notable that we find substantial consistency in both temporal and spatial patterns of uptake. In particular, we find no convincing evidence that the nature of diffusion in land management has changed systematically over the past four and a half decades in the UK. Due to the limited availability of appropriate data, as well as the focus on the UK, broader conclusions can only be drawn tentatively. However, the absence of the expected decay in spatial diffusion as digital technologies grew is notable (such decay would primarily be expected between datasets and within the Energy Crops Scheme, given the periods covered). Instead, we find that patterns and rates of uptake in our examples were relatively consistent, regardless of the time periods over which they occurred. Oilseed Rape seems to have spread through neighbourhoods of ~10-20 km radii between censuses; the Woodland Grant Scheme from sites of initial adoption and then in successive 'waves' through neighbourhoods of 10-40km radius, and the Energy Crops Scheme through a more localised form of diffusion, often between neighbouring or near-neighbouring farms. It is likely that these signals would have been stronger if we had been able to account more accurately for differences between farm types in levels of uptake, but further studies are clearly necessary to investigate the generality of these findings. At the same time, some unexplained large-scale spatial effects are apparent (i.e. across distances of 50-100km, and primarily for the Woodland Grant Scheme), and while we find no evidence that these are due to patterns in suitability or other explanatory variables, they appear unlikely to have been caused by direct communication or imitation.

Particularly striking is the similarity in temporal patterns of uptake, especially between the two subsidy schemes (and between these and the first 15 years of Oilseed rape uptake) (Figure 1). This similarity suggests that if distinct processes of diffusion occur, they do not necessarily lead to distinct aggregate rates of uptake. Nevertheless, it is hard to link characteristics of these examples to their form of diffusion; Oilseed Rape is the most visible of the three (and also the case covering the largest geographical area), while new management of existing woodlands under the Woodland Grant Scheme would potentially be very hard to detect in the absence of direct communication. It is important to note, though, that the findings are potentially consistent with a more constant form of year-to-year, neighbour-to-neighbour diffusion that is hinted at by the Energy Crops Scheme results but, perhaps, hidden by long, varying gaps between Oilseed Rape censuses and the large, varying sizes of estates involved in the Woodland Grant Scheme. In any case, direct influence between neighbouring land owners appears to affect land use decisions despite any additional, indirect or spatially unstructured communication through, for example, social media and the internet.

Inevitably, these conclusions remain subject to some uncertainties, largely as a result of a shortage of comprehensive data that would allow robust isolation of the signals of diffusion. Perhaps most significantly, our assumption that suitability for each of the three case studies was limited to those locations that participated in the scheme at some point introduces a strong bias against the detection of diffusion. The shortage of data describing suitability further limits our ability to check for its independent effects on uptake, although findings from the Energy Crops Scheme suggest that these are limited. Where diffusion does occur, we are not able to determine whether it results from communication or observation, and the time periods spanned by the case studies used here do not permit a rigorous comparison with the development of digital technologies (which was most substantial during the period covered by the Energy Crops Scheme). Finally, we can not exclude the possibility of unconsidered factors being responsible for the spatial signals we identify. Spatial diffusion appears the most parsimonious explanation for our findings, but confirmation requires considerably more data and analysis.

Outlook

The strength of spatial diffusion processes found here has clear policy-relevance. In particular, it suggests that failing to consider diffusion may generate highly misleading expectations by precluding anticipation of the spatial aggregations and time lags that appear to be general characteristics of uptake of new management practices (see also e.g. (Alexander et al. 2013; Wollni and Andersson 2014; Allaire et al. 2015; Brown et al. 2016b)). This, in turn, would suggest that changes would be unrealistically fast, general, and amenable to simplistic policy interventions; a particular shortcoming for climate mitigation or adaptation (Brown et al. 2017). Instead, policies may need to promote information availability, establish exemplars and encourage early adoption of beneficial innovations by actors, or in locations, that will maximise the subsequent rate and extent of uptake (Darr and Pretzsch 2008).

More detailed knowledge of information dissemination between land managers is likely to substantially benefit policy-making for food security, sustainability and climate adaptation, all of which rely heavily on changes in established practices and the spread of innovations. Generating this knowledge is challenging given the lack of relevant data covering long time periods and at high spatial resolution. There is, however, a substantial body of work from several different disciplines that can and should be considered when designing models of diffusion (e.g. (Wejnert 2002; Knowler and Bradshaw 2007; Xiong et al. 2016a). There are also several recent examples of agent-based models intended to explore imitation, diffusion or the effects of social networks (e.g. (Berger et al. 2006; Gotts and Polhill 2009; Alexander et al. 2013; Brown et al. 2016b)). These could be complemented by use of statistical models of diffusion to test for the best-fitting types and forms, perhaps revealing previously hidden characteristics of diffusion processes. Finally, we suggest that establishing a body of evidence based on diverse case studies would be invaluable to understanding not only diffusion but also other basic processes of land use change. Although this work contributes to this effort, further case studies that allow fuller understanding of these processes in a variety of contexts are needed. These could build on the increasing availability of high-resolution remote sensing data, records of public funding to land managers, and social survey outcomes that can complement statistical data analysis. Access to data is a key concern here, as is recognition of the role that empirical analyses can play in informing modelling studies and policy formulation, and in gradually improving our knowledge of the complex processes involved in land use change.

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Empirical evidence for the diffusion of knowledge in land use change – Supporting Information

Table S1: Series of sub-tables giving results of models that minimised AIC scores for each year of the Oilseed Rape analysis, in terms of odds ratios and 95% confidence intervals of the fitted model, as well as area under the receiver operating characteristic (ROC) curve (AUC). Intercepts are omitted. The neighbourhood term here is labelled as 'OSRnghbrs' and the radius of each neighbourhood is given above each sub-table. Because the 'OSRnghbrs' term refers to the proportion of neighbouring cells with uptake at the previous census, its value is often very low, producing very high fitted values. Where explanatory variables were available only in some years, models were defined both with and without those variables, with all results presented below. Explanatory variables are defined in Table 1 and labelled as: 'livestock' = area of livestock farming within cell (ha), 'crops' = area of crops within cell (ha), 'part.time' = number of part-time farmers within cell, 'no.holdings' = number of land holdings within the cell, 'area' = total agricultural area within cell (ha), 'rented' = area of rented land within cell (ha), 'owned' = area of owned land within cell (ha), 'workers' = number of farm workers within cell.

Table S1a: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1972 (based on 23884 cells without uptake; 1497 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 12km. AUC = 0.6737

		2.5 %	97.5 %
OSRnghbrs	358.36767560	212.68850666	601.76982626
livestock	1.14453484	1.01981163	1.28287350
crops	1.09857223	0.97301249	1.23931428
part.time	1.09158731	0.96492825	1.23453865
no.holdings	0.88729063	0.79167607	0.99481006
area	0.97422130	0.92574821	1.02248455
rented	1.02810845	0.97959595	1.08192440
owned	1.02834660	0.97980018	1.08219839
workers	0.99443841	0.98675754	1.00117251

Table S1b: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1972 (based on 23884 cells without uptake; 1497 with uptake) with trimmed explanatory variables. The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 12km. AUC = 0.6675

		2.5 %	97.5 %
OSRnghbrs	421.18094298	253.02569358	698.64926795
area	1.00139562	1.00103364	1.00175582

Table S1c: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1976 (based on 17509 cells without uptake; 6375 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 20km. AUC = 0.7215

		2.5 %	97.5 %
OSRnghbrs	103.1259008	64.7464338	164.4565360
livestock	0.5156222	0.4746347	0.5596387
crops	0.8495849	0.7877045	0.9153628
part.time	0.7028395	0.6447146	0.7657663
no.holdings	1.3546173	1.2473932	1.4718965
area	1.9721562	1.0760829	3.6154683
rented	0.5086527	0.2774607	0.9322106
owned	0.5091785	0.2777468	0.9331773
workers	0.9889481	0.9848756	0.9928843

Table S1d: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1976 (based on 17509 cells without uptake; 6375 with uptake) with trimmed explanatory variables. The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 35km. AUC = 0.6433

		2.5 %	97.5 %
OSRnghbrs	1456.1559594	845.49772448	2510.9770852
area	1.0024922	1.00226414	1.0027220

Table S1e: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1979 (based on 14317 cells without uptake; 3192 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 50km. AUC = 0.7869

		2.5 %	97.5 %
OSRnghbrs	96.7924772	70.37524549	133.34665763
livestock	1.0022201	0.82336069	1.20983750
crops	1.4333640	1.17377359	1.73707671
part.time	1.2048498	0.98223755	1.46722880
no.holdings	0.7768060	0.64074351	0.94892695
area	1.5207332	0.65481259	3.53285045
rented	0.6593328	0.28381186	1.53124018
owned	0.6597260	0.28398224	1.53214782
workers	0.9972116	0.99367293	1.00064874

Table S1f: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1979 (based on 14317 cells without uptake; 3192 with uptake) with trimmed explanatory variables. The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 50km. AUC = 0.7631

		2.5 %	97.5 %
OSRnghbrs	438.65803204	333.66604126	577.99458266
area	1.00214682	1.00186971	1.00242711

Table S1g: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1981 (based on 11986 cells without uptake; 2331 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 14km. AUC = 0.8046

		2.5 %	97.5 %
OSRnghbrs	27.81542185	21.95383575	35.28260567
livestock	0.67646717	0.53967503	0.84478341
crops	1.04740385	0.83348958	1.31216794
part.time	0.80293787	0.63603478	1.01093838
no.holdings	1.21107103	0.96619418	1.52240932
area	0.52144203	0.19366839	1.40348050
rented	1.92449582	0.71501923	5.18160245
owned	1.92338349	0.71460617	5.17860345
workers	0.98676020	0.97990152	0.99323095

Table S1h: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1981 (based on 11986 cells without uptake; 2331 with uptake) with trimmed explanatory variables. The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 18km. AUC = 0.7871

		2.5 %	97.5 %
OSRnghbrs	77.54843030	63.08702507	95.50057211
area	1.00256328	1.00223597	1.00289523

Table S1i: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1988 (based on 5902 cells without uptake; 6084 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 100km. AUC = 0.834

		2.5 %	97.5 %
OSRnghbrs	518.3690475	377.9157507	713.8590469
livestock	0.5407497	0.4625372	0.6303823
crops	0.9209370	0.7780283	1.0876078
part.time	0.5560038	0.4712825	0.6542960
no.holdings	1.6095136	1.3717043	1.8934366
area	2.5554457	1.0686710	6.1158213
rented	0.3928666	0.1641565	0.9394376
owned	0.3926975	0.1640862	0.9390307
workers	0.9857408	0.9791451	0.9920065

Table S1j: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1988 (based on 5902 cells without uptake; 6084 with uptake) with trimmed explanatory variables. The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 30km. AUC = 0.826

		2.5 %	97.5 %
OSRnghbrs	885.8623923	671.449165	1174.8998895
area	1.0019451	1.001581	1.0023138

Table S1k: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1993 (based on 4163 cells without uptake; 1739 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 30km. AUC = 0.8067

		2.5 %	97.5 %
OSRnghbrs	88.496142	67.86522862	115.945830
area	1.000401	1.00007638	1.000769

Table S1l: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1994 (based on 3506 cells without uptake; 657 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 16km. AUC = 0.836

		2.5 %	97.5 %
OSRnghbrs	262.29669954	169.0799055	412.07831434
area	1.00089752	1.0001843	1.00163668

Table S1m: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1995 (based on 336 cells without uptake; 3170 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 40km. AUC = 0.8878

		2.5 %	97.5 %
OSRnghbrs	2.539026e-04	1.148283e-04	5.382924e-04
area	1.000122e+00	9.992492e-01	1.000974e+00

Table S1n: Results of the best-fitting model (lowest AIC) for the Oilseed Rape analysis for 1996 (based on 151 cells without uptake; 185 with uptake). The neighbourhood within which the term 'OSRnghbrs' was calculated had a radius of 6km. AUC = 0.5966

		2.5 %	97.5 %
OSRnghbrs	0.2934832	0.1191364	0.7091707
area	1.0001949	0.9996581	1.0009531

Table S2: Series of sub-tables giving full results of models that minimised AIC scores for each year of the Woodland Grant Scheme analysis, with no trimming for consultant identity, in terms of odds ratios and 95% confidence intervals of the fitted model, as well as area under the receiver operating characteristic (ROC) curve (AUC). The neighbourhood term is here labelled as ‘nghbrs’, and its spatial and temporal scale in each model given in each sub-table legend. In contrast to Table S1 (Oilseed Rape analysis), the neighbourhood term here represents a simple count of neighbouring instances of scheme uptake at previous points in time, making fitted values relatively low. Models were defined both with and without explanatory variables to check for effects of data scarcity on overall model fit. All results are presented below, with intercepts omitted. Explanatory variables describe estate ownership or usage as defined in Table 1 and are labelled as: ‘typeCorporate Investor’ = corporate investor ownership, ‘typeFamily Estate’ = family estate ownership, ‘typeFARM’ = farm, ‘typeFarm Woodland/Agricultural holding’ = farm woodland or other agricultural holding, ‘typeINDUSTRIAL’ = industrial ownership, ‘typeMAINLY WOODLAND’ = mainly woodland, ‘typeMIXED ESTATE’ = mixed estate, ‘typeOTHER’ = other ownership, ‘typePersonal Investor’ = personal investor ownership, ‘typePRIVATE RESIDENCE’ = private residence, ‘typePUBLIC BUILDING’ = public building, ‘typePublic Ownership’ = public ownership, ‘typeRECREATION’ = recreation, ‘typeTraditional Estate’ = traditional estate, ‘owner_typeCROFT COMMON GRAZINGS’ = crofting common grazings, ‘owner_typeCROFTING IN-BYE LAND’ = crofting in-bye land, ‘owner_typePERSONAL OCCUPIER’ = personal occupier ownership, ‘owner_typePUBLIC OWNERSHIP‘ = public ownership, ‘owner_typeVOLUNTARY ORGANISATION’ = voluntary organisation ownership, ‘owner_typeOTHER’ = other ownership.

Table S2a: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1989 (based on 7991 instances of no uptake and 848 instances of uptake). The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 14km and included instances of uptake 1 year previously. AUC = 0.9246

		2.5 %	97.5 %
typeCorporate Investor	1.020731e+00	3.121045e-01	3.583115e+00
typeFamily Estate	7.497728e-01	2.353425e-01	2.571562e+00
typeFARM	1.578760e-09	7.541280e-156	3.117424e-138
typeFarm Woodland/Agricultural Holding	7.613337e-01	2.392924e-01	2.607843e+00
typeINDUSTRIAL	1.633164e-09	0.000000e+00	0.000000e+00
typeMAINLY WOODLAND	1.662221e-09	3.624529e-189	9.500885e-169
typeMIXED ESTATE	1.621808e-09	1.171517e-170	9.642355e-150
typeOther	4.188637e-01	1.232422e-01	1.517181e+00
typePersonal Investor	1.161062e+00	3.595604e-01	4.030809e+00
typePRIVATE RESIDENCE	1.608949e-09	0.000000e+00	0.000000e+00
typePUBLIC BUILDING	1.578913e-09	0.000000e+00	0.000000e+00
typePublic Ownership	6.883054e-01	1.937073e-01	2.590892e+00
typeRECREATION	1.637428e-09	0.000000e+00	0.000000e+00
typeTraditional Estate	9.040578e-01	2.807574e-01	3.129944e+00
nghbrs	1.032506e+00	1.013705e+00	1.051672e+00

Table S2b: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1989 (based on 7991 instances of no uptake and 848 instances of uptake) with only the neighbourhood term included. The term ‘nghbrs’ was calculated as the distance to the nearest instance of uptake 1 year previously. AUC = 0.5733

		2.5 %	97.5 %
mindist_1yrs	0.9662637	0.9572413	0.9749014

Table S2c: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1990 (based on 7125 instances of no uptake and 866 instances of uptake). The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 100km and included instances of uptake 2 years previously. AUC = 0.9674

		2.5 %	97.5 %
typeCorporate Investor	1.874796e+00	3.919677e-01	9.972811e+00
typeFamily Estate	2.534007e+00	5.488950e-01	1.306353e+01
typeFARM	1.509617e-09	7.049781e-121	8.336514e-118
typeFarm Woodland/Agricultural Holding	1.861824e+00	4.042994e-01	9.576550e+00
typeINDUSTRIAL	1.365632e-09	0.000000e+00	0.000000e+00
typeMAINLY WOODLAND	1.572407e-09	9.608628e-141	1.906431e-140
typeMIXED ESTATE	6.549405e-04	2.848787e-05	6.262079e-03
typeOther	4.089590e+00	8.377618e-01	2.219979e+01
typePersonal Investor	1.531671e+00	3.251526e-01	8.037702e+00
typePRIVATE RESIDENCE	1.551477e-09	5.422462e-307	2.317654e-302
typePUBLIC BUILDING	1.402265e-09	0.000000e+00	0.000000e+00
typePublic Ownership	8.155574e-01	1.578791e-01	4.625449e+00
typeRECREATION	1.455207e-09	0.000000e+00	3.258088e-313
typeTraditional Estate	2.110015e+00	4.506796e-01	1.101358e+01
nghbrs	1.002146e+00	1.000356e+00	1.003946e+00

Table S2d: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1990 (based on 7125 instances of no uptake and 866 instances of uptake) with only the neighbourhood term included. The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 14km and included instances of uptake 1 year previously. AUC = 0.5842

		2.5 %	97.5 %
count14_1yrs	1.01545705	1.01139770	1.01952264

Table S2e: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1991 (based on 6520 instances of no uptake and 605 instances of uptake). The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 25km and included instances of uptake 3 years previously. AUC = 0.9769

		2.5 %	97.5 %
typeCorporate Investor	5.529037e-01	6.418109e-67	4.763124e+65
typeFamily Estate	6.024691e-01	6.835982e-69	5.634901e+71
typeFARM	3.749719e-12	NA	Inf
typeFarm Woodland/Agricultural Holding	5.548975e-01	1.862282e-61	1.789252e+58
typeINDUSTRIAL	6.176664e-19	0.000000e+00	2.111315e+140
typeMAINLY WOODLAND	3.729752e-12	NA	Inf
typeMIXED ESTATE	7.174596e-12	NA	Inf
typeOther	7.359004e-01	2.918747e-69	1.855417e+68
typePersonal Investor	6.330977e-01	8.757715e-66	4.576681e+64
typePRIVATE RESIDENCE	6.437813e-19	0.000000e+00	1.695322e+138
typePUBLIC BUILDING	1.449224e-11	NA	Inf
typePublic Ownership	5.522066e-01	5.920987e-69	5.150022e+67
typeRECREATION	6.501058e-19	0.000000e+00	1.775823e+138
typeTraditional Estate	5.358854e-01	1.003393e-65	2.862020e+64
nghbrs	1.066237e+00	1.042319e+00	1.090705e+00

Table S2f: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1991 (based on 6520 instances of no uptake and 605 instances of uptake) with only the neighbourhood term included. The term ‘nghbrs’ was calculated as the distance to the nearest instance of uptake 2 years previously. AUC = 0.5855

		2.5 %	97.5 %
mindist_2yrs	0.9147169	0.8911230	0.9373871

Table S2g: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1992 (based on 5901 instances of no uptake and 619 instances of uptake). The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 14km and included instances of uptake 3 years previously. AUC = 0.7122

		2.5 %	97.5 %
typeINDUSTRIAL	1.947357e-07	3.070837e-127	1.100119e-123
typeMAINLY WOODLAND	1.337143e+00	1.056528e+00	1.690418e+00
typeMIXED ESTATE	1.277062e+00	1.034975e+00	1.576045e+00
typePRIVATE RESIDENCE	2.890910e-07	1.424031e-113	1.331938e-96
typePUBLIC BUILDING	6.340782e+00	3.371807e+00	1.210370e+01
typeRECREATION	1.040973e-01	2.535722e-02	2.815662e-01
owner_typeCROFT COMMON GRAZINGS	2.723460e-07	NA	8.321631e+13
owner_typeCROFTING IN-BYE LAND	2.861494e-07	NA	1.495951e+184
owner_typeOTHER	2.716612e+00	1.821720e+00	4.010011e+00
owner_typePERSONAL OCCUPIER	5.016441e-01	4.138421e-01	6.087386e-01
owner_typePUBLIC OWNERSHIP	5.098587e-01	2.682278e-01	9.148380e-01
owner_typeVOLUNTARY ORGANISATION	3.032213e-01	1.311697e-01	6.074670e-01
nghbrs	1.024603e+00	1.019515e+00	1.029721e+00

Table S2h: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1992 (based on 5901 instances of no uptake and 619 instances of uptake) with only the neighbourhood term included. The term ‘nghbrs’ was calculated as the distance to the nearest instance of uptake 2 years previously. AUC = 0.5822

		2.5 %	97.5 %
mindist_2yrs	0.9089528	0.883893	0.9332354

Table S2i: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1993 (based on 5028 instances of no uptake and 873 instances of uptake). The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 6km and included instances of uptake 2 years previously. AUC = 0.6698

		2.5 %	97.5 %
typeINDUSTRIAL	1.054281e-01	0.01722832	3.393449e-01
typeMAINLY WOODLAND	1.926710e+00	1.58515170	2.343066e+00
typeMIXED ESTATE	1.100172e+00	0.90776119	1.333056e+00
typePRIVATE RESIDENCE	5.054860e-01	0.30164718	7.994966e-01
typePUBLIC BUILDING	3.158710e+00	1.62414437	6.067477e+00
typeRECREATION	3.758693e-01	0.21267873	6.255953e-01
owner_typeCROFT COMMON GRAZINGS	2.502353e-06	NA	9.373384e-02
owner_typeCROFTING IN-BYE LAND	2.599385e-06	NA	9.398201e+36
owner_typeOTHER	2.746365e+00	1.75990376	4.253910e+00
owner_typePERSONAL OCCUPIER	5.609482e-01	0.47425102	6.641740e-01
owner_typePUBLIC OWNERSHIP	7.880954e-01	0.48696998	1.239545e+00
owner_typeVOLUNTARY ORGANISATION	2.707023e-01	0.13954772	4.789213e-01
nghbrs	1.051171e+00	1.03213932	1.070316e+00

Table S2j: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1993 (based on 5028 instances of no uptake and 873 instances of uptake) with only the neighbourhood term included. The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 10km and included instances of uptake 2 years previously. AUC = 0.5327

		2.5 %	97.5 %
count10_2yrs	1.0153940	1.0068842	1.0238470

Table S2k: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1994 (based on 4172 instances of no uptake and 856 instances of uptake). The neighbourhood within which the term 'nghbrs' was calculated had a radius of 4km and included instances of uptake 3 years previously. AUC = 0.60

		2.5 %	97.5 %
typeINDUSTRIAL	1.327722e+00	0.7360777	2.274710e+00
typeMAINLY WOODLAND	2.139614e+00	1.7390694	2.633192e+00
typeMIXED ESTATE	1.407051e+00	1.1624171	1.704235e+00
typePRIVATE RESIDENCE	9.028676e-01	0.6055112	1.309350e+00
typePUBLIC BUILDING	1.084266e+00	0.3556874	2.710992e+00
typeRECREATION	1.037520e+00	0.6821215	1.544732e+00
owner_typeCROFT COMMON GRAZINGS	2.717003e-06	NA	1.015966e-01
owner_typeCROFTING IN-BYE LAND	2.789378e-06	NA	1.007415e+37
owner_typeOTHER	1.526544e+00	0.8015840	2.763409e+00
owner_typePERSONAL OCCUPIER	7.988486e-01	0.6681287	9.571411e-01
owner_typePUBLIC OWNERSHIP	7.129382e-01	0.4397779	1.121197e+00
owner_typeVOLUNTARY ORGANISATION	5.575863e-01	0.3437609	8.699186e-01
nghbrs	1.050306e+00	1.0176664	1.083336e+00

Table S2l: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1994 (based on 4172 instances of no uptake and 856 instances of uptake) with only the neighbourhood term included. The neighbourhood within which the term 'nghbrs' was calculated had a radius of 2km and included instances of uptake 3 years previously. AUC = 0.5201

		2.5 %	97.5 %
count2_3yrs	1.0758550	1.0097783	1.1439548

Table S2m: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis fo r 1995 (based on 3487 instances of no uptake and 685 instances of uptake). The neighbourhood within which the term 'nghbrs' was calculated had a radius of 25km and included instances of uptake 1 year previously. AUC = 0.5802

		2.5 %	97.5 %
typeINDUSTRIAL	1.949973e+00	1.1097891	3.321560e+00
typeMAINLY WOODLAND	9.804660e-01	0.7648546	1.251102e+00
typeMIXED ESTATE	9.053723e-01	0.7370838	1.110604e+00
typePRIVATE RESIDENCE	7.302304e-01	0.4836743	1.070258e+00
typePUBLIC BUILDING	2.351275e+00	0.8730952	5.717112e+00
typeRECREATION	1.742300e+00	1.1803266	2.544064e+00
owner_typeCROFT COMMON GRAZINGS	9.800986e-07	NA	3.382254e+01
owner_typeCROFTING IN-BYE LAND	9.832273e-07	NA	1.426092e+64
owner_typeOTHER	7.677262e-01	0.2840371	1.747924e+00
owner_typePERSONAL OCCUPIER	9.391823e-01	0.7636898	1.159439e+00
owner_typePUBLIC OWNERSHIP	3.862289e-01	0.2158132	6.574623e-01
owner_typeVOLUNTARY ORGANISATION	4.176776e-01	0.2343174	7.024896e-01
nghbrs	1.004312e+00	1.0019890	1.006627e+00

Table S2n: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1995 (based on 3487 instances of no uptake and 685 instances of uptake) with only the neighbourhood term included. The neighbourhood within which the term 'nghbrs' was calculated had a radius of 500km and included instances of uptake 3 years previously. AUC = 0.5007

		2.5 %	97.5 %
count500_3yrs	1.008817e+00	0.9995315	NA

Table S2o: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1996 (based on 2963 instances of no uptake and 524 instances of uptake). The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 8km and included instances of uptake 4 years previously. AUC = 0.5807

		2.5 %	97.5 %
typeINDUSTRIAL	2.733385e+00	1.40502250	5.078359e+00
typeMAINLY WOODLAND	1.309006e+00	0.98157085	1.737472e+00
typeMIXED ESTATE	1.453881e+00	1.15354900	1.833891e+00
typePRIVATE RESIDENCE	1.191896e+00	0.78265218	1.769436e+00
typePUBLIC BUILDING	1.974474e+00	0.60492920	5.478309e+00
typeRECREATION	1.639560e+00	1.00653798	2.614435e+00
owner_typeCROFT COMMON GRAZINGS	1.464705e-06	NA	4.950800e+01
owner_typeCROFTING IN-BYE LAND	1.508110e-06	NA	2.166735e+64
owner_typeOTHER	1.507360e+00	0.59244155	3.363051e+00
owner_typePERSONAL OCCUPIER	1.117928e+00	0.87766395	1.433277e+00
owner_typePUBLIC OWNERSHIP	1.004800e+00	0.57538377	1.702118e+00
owner_typeVOLUNTARY ORGANISATION	4.977064e-01	0.25641634	8.953652e-01
nghbrs	1.024720e+00	1.00956590	1.039734e+00

Table S2p: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1996 (based on 2963 instances of no uptake and 524 instances of uptake) with only the neighbourhood term included. The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 14km and included instances of uptake 3 years previously. AUC = 0.5398

		2.5 %	97.5 %
count14_3yrs	1.0080495	1.0017127	1.0143723

Table S2q: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1997 (based on 2413 instances of no uptake and 550 instances of uptake). The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 10km and included instances of uptake 3 years previously. AUC = 0.5988

		2.5 %	97.5 %
typeINDUSTRIAL	1.321240e+00	0.5513606	2.830900e+00
typeMAINLY WOODLAND	9.834200e-01	0.7361761	1.305813e+00
typeMIXED ESTATE	1.186258e+00	0.9419735	1.493226e+00
typePRIVATE RESIDENCE	1.011732e+00	0.6677808	1.498009e+00
typePUBLIC BUILDING	1.281270e+00	0.2790168	4.323314e+00
typeRECREATION	2.159183e+00	1.3706573	3.371671e+00
owner_typeCROFT COMMON GRAZINGS	1.239259e-06	NA	4.101847e+01
owner_typeCROFTING IN-BYE LAND	1.319490e-06	NA	1.892012e+64
owner_typeOTHER	2.229885e+00	0.9311629	4.965522e+00
owner_typePERSONAL OCCUPIER	1.196239e+00	0.9346382	1.541198e+00
owner_typePUBLIC OWNERSHIP	5.806370e-01	0.3033719	1.057000e+00
owner_typeVOLUNTARY ORGANISATION	1.050624e+00	0.6368961	1.690888e+00
nghbrs	1.028023e+00	1.0183699	1.037720e+00

Table S2r: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1997 (based on 2413 instances of no uptake and 550 instances of uptake) with only the neighbourhood term included. The neighbourhood within which the term ‘nghbrs’ was calculated had a radius of 500km and included instances of uptake 4 years previously. AUC = 0.465

		2.5 %	97.5 %
count500_4yrs	1.00250837	0.9993417	NA

Table S2s: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1998 (based on 1910 instances of no uptake and 503 instances of uptake). The neighbourhood within which the term 'nghbrs' was calculated had a radius of 12km and included instances of uptake 1 year previously. AUC = 0.5608

		2.5 %	97.5 %
typeINDUSTRIAL	5.072994e-01	0.14719227	1.335992e+00
typeMAINLY WOODLAND	9.561852e-01	0.70624874	1.286456e+00
typeMIXED ESTATE	1.165986e+00	0.91542311	1.484200e+00
typePRIVATE RESIDENCE	1.008222e+00	0.64370007	1.537733e+00
typePUBLIC BUILDING	1.180098e+00	0.30101137	3.838828e+00
typeRECREATION	1.517178e+00	0.90044763	2.518243e+00
owner_typeCROFT COMMON GRAZINGS	4.788728e-01	0.07521006	1.698797e+00
owner_typeCROFTING IN-BYE LAND	1.737918e-05	NA	7.838394e+10
owner_typeOTHER	1.001333e+00	0.28028688	2.825767e+00
owner_typePERSONAL OCCUPIER	1.056281e+00	0.82012017	1.368392e+00
owner_typePUBLIC OWNERSHIP	8.421712e-01	0.45176316	1.520000e+00
owner_typeVOLUNTARY ORGANISATION	9.126436e-01	0.52661530	1.533747e+00
nghbrs	1.011774e+00	1.00624420	1.017246e+00

Table S2t: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1998 (based on 1910 instances of no uptake and 503 instances of uptake) with only the neighbourhood term included. The term 'nghbrs' was calculated as the distance to the nearest instance of uptake 3 years previously. AUC = 0.5156

		2.5 %	97.5 %
mindist_3yrs	0.9883830	0.9714903	1.0015869

Table S2u: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1999 (based on 1413 instances of no uptake and 497 instances of uptake). The neighbourhood within which the term 'nghbrs' was calculated had a radius of 18km and included instances of uptake 2 years previously. AUC = 0.5744

		2.5 %	97.5 %
typeINDUSTRIAL	1.327582e+00	0.5709163	2.9179974
typeMAINLY WOODLAND	8.033313e-01	0.5830139	1.0990275
typeMIXED ESTATE	1.227953e+00	0.9538661	1.5802604
typePRIVATE RESIDENCE	1.235103e+00	0.7954311	1.8847604
typePUBLIC BUILDING	1.057432e+00	0.2832601	3.6327915
typeRECREATION	8.607774e-01	0.4672132	1.5399918
owner_typeCROFT COMMON GRAZINGS	5.821014e-07	NA	91.9219639
owner_typeCROFTING IN-BYE LAND	3.528896e+00	0.1380461	90.2134364
owner_typeOTHER	1.100069e+00	0.3006072	3.2646008
owner_typePERSONAL OCCUPIER	1.005570e+00	0.7735671	1.3135844
owner_typePUBLIC OWNERSHIP	1.618641e+00	0.8741411	2.9585609
owner_typeVOLUNTARY ORGANISATION	8.067361e-01	0.4365084	1.4312760
nghbrs	1.005805e+00	1.0019926	1.0095934

Table S2v: Results of the best-fitting model (lowest AIC) for the Woodland Grant Scheme analysis for 1999 (based on 1413 instances of no uptake and 497 instances of uptake) with only the neighbourhood term included. The term 'nghbrs' was calculated as the distance to the nearest instance of uptake 1 year previously. AUC = 0.5103

		2.5 %	97.5 %
mindist_1yrs	1.0026578	0.9842289	1.0205660

Table S3: Series of sub-tables giving full results of models that minimised AIC scores for each year of the Energy Crop Scheme analysis, using Miscanthus productivity (‘Misc.prod’) and agricultural grade of land (‘Grade’) as additional explanatory variables, in terms of odds ratios and 95% confidence intervals of the fitted model, as well as area under the receiver operating characteristic (ROC) curve (AUC). Neighbourhood terms are given last, and described as the count of schemes within a neighbourhood, by neighbourhood size (mindist = Distance to nearest previous instance of uptake, and other values are radii expressed in km) and temporal scale (years). Intercepts are omitted.

Table S3a: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2005 (based on 306 instances of no uptake and 48 instances of uptake) including agricultural grade of land. AUC = 0.6491

		2.5 %	97.5 %
Grade	0.926101139	0.6648909	1.28051017
count25_1yrs	1.950607895	1.4104709	2.60816182

Table S3b: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2005 (based on 306 instances of no uptake and 48 instances of uptake) including Miscanthus productivity. AUC = 0.6713

		2.5 %	97.5 %
Misc.prod	0.950177215	0.878940617	1.02364038
count25_1yrs	1.847540955	1.335000956	2.46657254

Table S3c: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2006 (based on 224 instances of no uptake and 82 instances of uptake) including agricultural grade of land. AUC = 0.5834

		2.5 %	97.5 %
Grade	0.77566433	0.603574207	0.9934093
count4_1yrs	4.72163762	1.904206522	9.5834735

Table S3d: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2006 (based on 224 instances of no uptake and 82 instances of uptake) including Miscanthus productivity. AUC = 0.6515

		2.5 %	97.5 %
Misc.prod	0.89783775	0.84662714	0.94988184
count4_1yrs	4.75705106	1.89129056	9.76468064

Table S3e: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2007 (based on 144 instances of no uptake and 80 instances of uptake) using agricultural grade of land. AUC = 0.623

		2.5 %	97.5 %
Grade	0.75255632	0.58180772	0.97102235
mindist_3yrs	0.99123332	0.98495391	0.99683480

Table S3f: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2007 (based on 144 instances of no uptake and 80 instances of uptake) using Miscanthus productivity. AUC = 0.6039

		2.5 %	97.5 %
Misc.prod	1.00514557	0.946946633	1.06430163
mindist_3yrs	0.99005182	0.983507692	0.99611499

Table S3g: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2008 (based on 115 instances of no uptake and 29 instances of uptake) using agricultural grade of land. AUC = 0.6579

		2.5 %	97.5 %
Grade	0.835255441	0.5367472136	1.28780361
count6_1yrs	6.314450179	3.2957844875	11.04315428

Table S3h: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2008 (based on 115 instances of no uptake and 29 instances of uptake) using Miscanthus Productivity. AUC = 0.6923

		2.5 %	97.5 %
Misc.prod	0.980134680	0.8922768513	1.071677562
count6_1yrs	6.471909620	3.3925986519	11.263839804

Table S3i: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2010 (based on 87 instances of no uptake and 21 instances of uptake) using agricultural grade of land. AUC = 0.757

		2.5 %	97.5 %
Grade	1.103722740	0.6368527309	1.89129751
mindist_1yrs	0.977456634	0.9643317177	0.98858314

Table S3j: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2010 (based on 87 instances of no uptake and 21 instances of uptake) using Miscanthus productivity. AUC = 0.7603

		2.5 %	97.5 %
Misc.prod	0.97984307	0.890601496	1.07450681
mindist_1yrs	0.97722518	0.963776529	0.98853744

Table S3k: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2013 (based on 38 instances of no uptake and 21 instances of uptake) using agricultural grade of Land. AUC = 0.6276

		2.5 %	97.5 %
Grade	6.124491e-01	0.375189987	9.924990e-01
count14_2yrs	6.193353e-07	NA	1.025989e+14

Table S3l: Results of the best-fitting model (lowest AIC) for the Energy Crop Scheme analysis for 2013 (based on 38 instances of no uptake and 21 instances of uptake) using Miscanthus Productivity. AUC = 0.6607

		2.5 %	97.5 %
Misc.prod	8.875837e-01	0.789590819	9.893862e-01
count14_2yrs	5.671520e-07	NA	1.033115e+14