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The physical, economic and policy drivers of land conversion to forestry in Ireland

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Abstract

Land use change is fundamentally a product of the interaction of physical land characteristics, economic considerations and agricultural and environmental policies. Researchers are increasingly combining physical and socio-economic spatial data to investigate the drivers of land-use change in relation to policy and economic developments. Focusing on Ireland, this study develops a panel data set of annual afforestation over 2811 small-area boundaries between 1993 and 2007 from vector and raster data sources. Soil type and other physical characteristics are combined with the net returns of converting agricultural land to forestry, based on the micro-simulation of individual farm incomes, to investigate land conversion. A spatial econometric approach is adopted to model the data and a range of physical, economic and policy factors are identified as having a significant effect on afforestation rates. In addition to the financial returns, the availability and quality of land and the implementation of environmental protection policies are identified as important factors in land conversion. The implications of these factors for the goal of forest expansion are discussed in relation to conflicting current and future land use policies.

Keywords: Afforestation, Land-use change, policy conflicts, spatial panel model

1. Introduction

Land use change modelling requires combining both physical and economic spatial data if it is to be used to understand policy developments and predict future land-use changes (Seto and Kaufmann, 2003). In the absence of data concerning the economic implications of land-use decisions, interpreting historic change, particularly in relation to policy developments, poses a significant challenge (Bockstael, 1996). Although physical drivers of land conversion may be identified, the causal relationship between characteristics and change may be less clear (Irwin and Geogheghan, 2001). This is perhaps of most relevance in enterprises where state and regional policies have a defining and widespread impact, such as agriculture and forestry. Despite the recognition of the importance of including economic data in spatial models researchers may be constrained by the existence of data or the scale at which data is available. In agricultural research, spatial data on farm incomes at the individual or local level may be limited. One approach to overcoming this issue is to simulate individual farm data from broader regional or national data (O'Donoghue et al., 2012).

Increasing forest cover is a common goal internationally and has been supported within European agricultural policy for a number of decades (Nijink and Bizikova, 2008). Land conversion to forestry is a complex issue that is influenced by social, economic and environmental factors that policy-makers should account for in the development of forest policy and the setting of targets (Beach et al., 2005). Thus, understanding afforestation requires combining multiple sources of data within a modelling approach that ideally accounts for both the spatial and temporal nature of the phenomenon. Spatial econometric models offer the potential to investigate and quantify the effects of these factors on land conversion while explicitly addressing the spatial nature of the data (Radeloff et al., 2012).

1.1 Land conversion to forestry

Afforestation is increasingly valued for its potential to enhance ecosystem services and is being actively promoted in many countries through state policy and support (Kanowski, 2010). Forest cover expansion is included as a source of carbon dioxide emission reduction under the Kyoto Protocol, which is a significant factor in the promotion of forest expansion policies (Nijnk and Bizikova, 2008). Similar to many countries, Ireland has sought to increase its forest cover for some time with rural employment and economic diversification benefits being important drivers in the 20th Century and ecosystem services being increasingly recognised in modern forest policy (Department of Agriculture, Food and Forestry, 1996; OCarroll, 2004).

Ireland offers a particularly interesting example of forest expansion policy as it possesses one of the lowest areas of forest cover in Europe, despite possessing excellent growing conditions for commercial forestry, and a history of ambitious afforestation policies (OCarroll, 2004). Current forest cover stands at 10.9% with the majority of this area composed of plantation forests established in the last hundred years. The goal of state policy is to increase forest cover to 17% by the year 2030 through private planting (Department of Agriculture, Food and Forestry, 1996). Historical afforestation policies and establishment in Ireland have a distinctive locational bias defined by the quality of the underlying land (Upton et al., 2012). Initial efforts by the state to expand forest cover were enthusiastic but poorly planned and resulted in relatively low levels of planting (OCarroll, 2004). Planting was limited to sub-marginal land, often at higher elevations with peat soils. Although grants for planting by private land-owners were available, private afforestation was limited until the late 1980s when annual premiums were introduced under the Western Package Scheme which was co-funded by the EU (EU Regulation No. 1820/80). These payments compensated private landowners, for a limited period of time, for lost agricultural income as forests developed. This resulted in a significant increase in afforestation by private landowners (Figure 1). Supports for planting by state agencies were removed in the mid-1990s, which essentially saw the end of public planting. Initially policies for private planting specifically targeted agriculturally disadvantaged parts of Ireland. Since 1992 a consistent policy of grants and annual premiums for 20 years open to all private land-owners, but with higher rates for farmers, has been in place. Ireland benefited from funding for afforestation by the EU under the Community aid scheme for afforestation from 1992 (Council Regulation (EEC) No 2080/92) and under support for rural development from 2000 (Council Regulation (EC) No 1257/1999). The availability of grants and premiums make forestry a financially attractive enterprise for many farmers but particularly those engaged in extensive livestock rearing (Breen et al., 2010). However, annual afforestation rates have been variable and declining since 2005.

Plantation forests can achieve high productivity rates even on poorly drained mineral soils (Farrelly et al., 2011), giving forestry a greater competitive advantage on poorer quality soils. Nonetheless, farmers have been reluctant to plant forestry due to a range of factors, including the non-pecuniary costs, related to a change in land use and lifestyle. Although the Irish public support and value afforestation greatly, farmers may view forestry as a less desirable land use (Upton et al., 2012). Land conversion to forest by private land-owners is a complex issue with multiple underlying causes, including, but not limited to, the incentives and restrictions of state policies (Beach et al., 2005). The effects of policy changes and market conditions on afforestation rates in Ireland have been explored using time-series and panel data (McKillop and Kula, 1987; McCarthy et al., 2003). In general such studies find that the profitability of agriculture and forestry are significant factors in determining afforestation rates. Researchers have examined afforestation in Ireland on the county level but failed to account for the spatial nature of the data in the modelling process or the physical characteristics of the land (McCarthy et al., 2003). Examinations of private afforestation in Ireland have shown that land quality is a defining aspect of the decision-making process by farmers (Ni Dhubhain and Gardiner, 1994; Howley et al., 2012). Land quality underlies the productivity and profitability of alternative land uses, making it an essential element in understanding land conversion. In addition, forestry has been recognised as an enterprise only "suitable" for the worst quality land by land-owners (O'Leary et al., 2000). This may be driven by the belief that land should be used for the production of food if at all possible rather than an aversion to forestry per se (McDonagh et al., 2010). However, strong negative views of afforestation have been identified in parts of Ireland, particularly those that saw a rapid expansion of forest cover over a relatively short time-period (O'Leary et al, 2000).

It has been suggested that conservation policies related to protected habitats or species have reduced annual afforestation rates and discouraged applications from relevant areas (Collier et al., 2002). The EU habitats (92/43/EEC) and birds (79/409/EEC) directives resulted in the identification of special areas of conservation and special protection areas, which complemented the Irish specification of natural heritage areas. Habitats and species related to these areas are given legal protection and applications for afforestation funding within these areas require approval from the Irish National Parks and Wildlife Service. Forests can increase soil acidity through their capacity of trees to scavenge industrial air pollutants or sea-salts (Dunford et al., 2012). Where this occurs on soils with poor buffering capacity adjacent water-ways may become acidified. The Forest Service in Ireland has identified areas that are considered at risk of acidification due to the poor buffering capacity of the soil and afforestation is controlled in these areas.

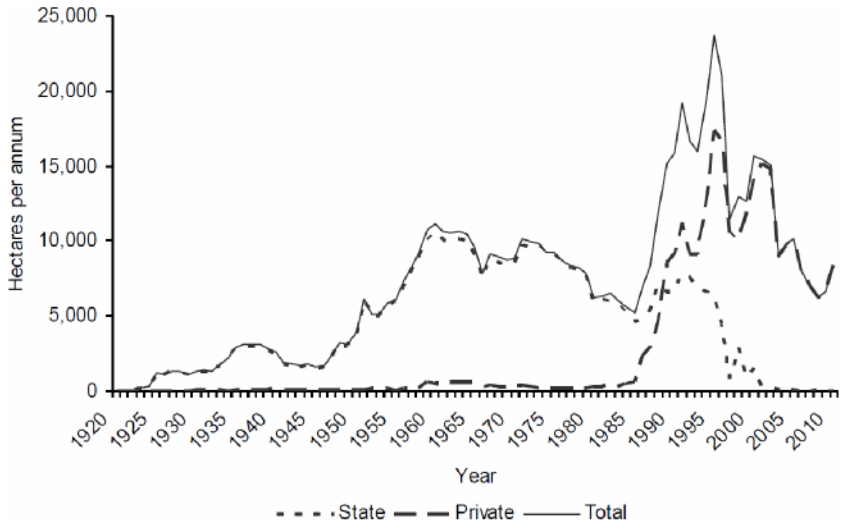

Figure 1 Annual afforestation rates in Ireland 1923 -2010

1.2 Spatial models of land conversion

Spatial models of land-use change are employed to gain greater insight into the drivers of change, the effectiveness of policies and to predict future land conversion (Lubowski et al., 2008). Land-use change studies have been conducted on a diverse range of issues including urban expansion (Seto and Kaufmann, 2003), deforestation (Wyman and Stein, 2010) and afforestation (Clement et al., 2009). Land quality, related to factors such as soil, elevation and slope, is one of the essential determinants of private land-use decision-making given its underlying effect on productivity and should be incorporated into spatial models (Lubowski et al., 2008). Soil type and other physical characteristics have been identified as significant factors in land use change models (Fu et al., 2006; Chakir and Parent, 2009). Ultimately, however, the financial implications of land-use change should be included in models if the decisions made by private land-owners are to be understood within an economic framework (Bockstael, 1996).

In developing spatial models of land-use change, researchers generally employ satellite imagery from different time-periods and explore change at the single land-parcel or pixel level over a set period (e.g. Radeloff et al., 2012). Alternatively, researchers may examine total changes across administrative boundaries which can facilitate the incorporation of economic data more readily (Seto and Kaufmann, 2003). In modelling spatially derived data researchers should test for spatial autocorrelation amongst the observations, which can lead to biased estimations (Anselin, 2010). Spatial dependence amongst the observations is considered one of the primary problems with employing spatially explicit panel data and a number of approaches to dealing with this potential source of bias have been developed (Elhorst, 2003). One approach is to specify a spatial lag variable that accounts for the interaction of the dependent variable in related observations. This requires the specification of the spatial relationship between observed units, which can be expressed in a spatial weights matrix.

1.3 Study aim

Understanding the drivers of afforestation should assist in explaining afforestation patterns and help to inform meaningful forest policy. Afforestation by private land-owners may be affected by a combination of market drivers, policy variables, owner characteristics and land conditions (Beach et al., 2005). In the context of this study, it is hypothesised that the underlying characteristics of the land, the financial implications of conversion and the constraining effects of conservation policies influence afforestation. Thus, the primary aim of the study is to test the nature of these effects in explaining afforestation in Ireland and their significance to forest and broader land use policies. Geographic information system (GIS) analysis, the micro-simulation of farm-level incomes and financial analysis techniques are employed to build a panel data set to explore the importance of physical, economic and policy related factors in explaining annual afforestation in Ireland between 1993 and 2007. A random effects and a spatial autoregressive random effects model, that accounts for the spatial correlation of observations, are employed to model the data.

2. Methodology

The boundaries of electoral divisions (EDs) were employed as the spatial unit in which observations would be specified as they represent the smallest spatial unit for which economic data is available. Ireland is divided into 3,440 EDs in total but those which occur within cities and those for which agricultural data were not available were removed, resulting in a sample of 2,811 (Figure 2(a)). Employing a GIS these boundaries were intersected with available spatial data, including grant-aided afforestation, to produce a panel dataset describing the physical characteristics of the areas and the annual afforestation occurring within them. Rather than rely on data from satellite imagery, this study employed vector data supplied by the Forest Service that details forest cover in Ireland derived from aerial photography and applications for grant-aid. These data cover all forests in 2007 including most grant-aided plantations from 1990. Given their connection to financial supports these data are considered to be of high quality and offer the distinct advantage of identifying the date of forest establishment, thus facilitating the development of a detailed data set of annual afforestation. As data for some early years were incomplete the study focuses on the years 1993 to 2007. It should be noted that this dataset consists of private grant-aided afforestation only and thus forest establishment by state agencies or non-funded private planting is not captured.

Using the digital soil map of Ireland (Fealy et al., 2009) it was possible to identify the area of different soil types in each ED. Great soil groups were grouped into peats, poorly drained minerals and well-drained minerals representing the most significant divisions from a forestry and agriculture perspective (Table 1). Other areas consisting of unplantable areas such as water, artificial surfaces and bare rock were also grouped as a single category. Figure 2(d) displays the mapped divisions.

Table 1 Soil divisions and their associated great soil groups

Soil description	**Great Soil Group**
Well-drained mineral soils	Acid Brown Earths, Brown Podzolics, Grey Brown Podzolics
Poorly-drained mineral	Surface water Gleys, Ground water Gleys, Peaty Gleys, Podzols
Peat	Blanket Peats, Basin Peats

The standard measure of the profitability of investing in forestry is the land expectation value (LEV) (Klemperer, 1996). In this study the LEV per hectare included the costs of management, future timber revenues and the supports offered by the state, in addition to the opportunity cost of converting agricultural land. Thus the LEV for each ED, n, was calculated as the sum of discounted revenues and costs:

=1

Where R is revenues from thinning and clearfell, C are costs related to replanting, maintenance (from year 6), insurance (years 5 to 20) and inspection paths, P are premium payments paid in years 1-20 only, A is the ED average market margin for cattle systems, r is the discount rate of 5%, t is the rotation of 40 years and y is the relevant year.

In the analysis, it was assumed that a plantation containing 80% Sitka spruce and 20% Japanese larch, which is the most commonly planted species combination in Ireland, was established. A yield class of 20 $m^3ha^{-1}yr^{-1}$ and a rotation of 40 years were specified, which is reflective of average growth rates in the private forest estate. Predictions of timber output were based on the yield tables of the UK Forestry Commission (Edwards and Christie, 1981). The relevant annual premium payments for this combination for the year of establishment were included for the first twenty years. Timber sales from thinnings and clearfell were included and it was assumed that timber prices did not change in real terms over the time-period, which follows the assumptions of previous authors (e.g. Clinch, 1999). State supports cover the initial cost of forest establishment and were thus excluded from the valuation, however reforestation costs at the end of the rotation were included.

Although the Irish Census of Agriculture describes the general characteristics of farms in EDs it does not include data on farm incomes at this level. However, micro-simulation models have been developed that derive spatially explicit simulated farm level income data based on the National Farm Survey (NFS), a detailed annual survey of farm economic activity from a representative sample of Irish farms. Data from the NFS is assigned to simulated farms in EDs following a quota sampling approach based on farm characteristics, including farm size, farm system, soil quality and whether a farmer is part-time or not. The micro-simulation model, called SMILE, is outlined in O'Donoghue et al. (2012). As forestry is most competitive with cattle enterprises (Breen et al., 2010) and cattle farmers are more likely to plant forestry (Howley et al., 2012) the average market margin for this enterprise in each ED was included to account for the opportunity cost of land conversion. Thus it was possible to generate the average LEV per hectare for a move from agriculture into forestry per ED and year. It was assumed that farmers, who qualify for higher rates of premiums, undertook all afforestation as it was not possible to distinguish between private planters from the spatial data. However, Forest Service statistics suggest that farmers made up approximately 90% of private planting during the period.

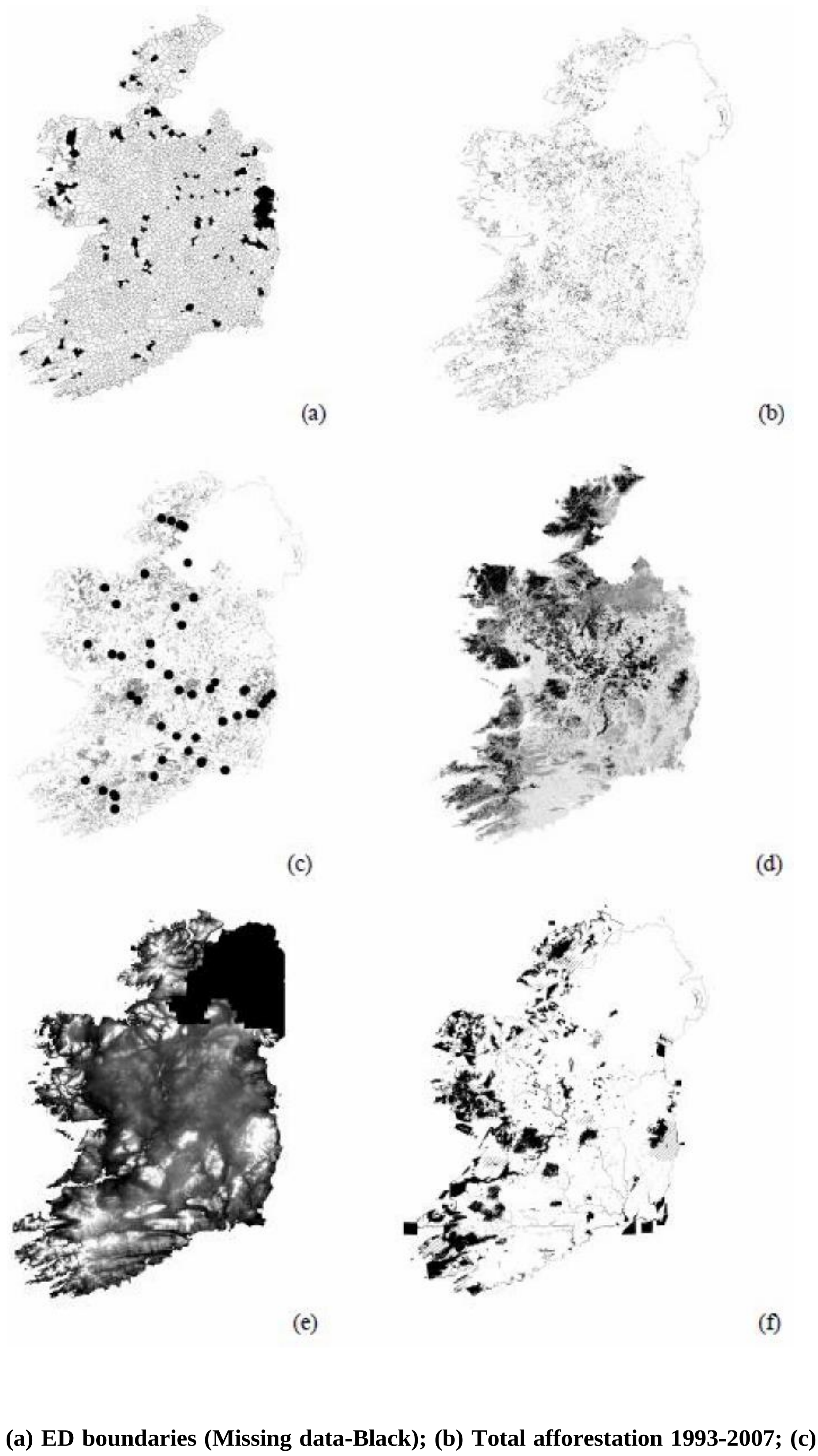

Figure 2: (a) ED boundaries (Missing data-Black); (b) Total afforestation 1993-2007; (c) Forest cover pre-1993 and location of sawmills; (d) Soil type - Peat (Black), Poorly drained mineral (Light grey), Well-drained mineral (Dark grey); (e) DEM of Ireland; (f) SAC/SPA/NHA (Black) and acid sensitive areas (Hatched). Sources: Forest Service - (b), (c), (f); EPA - (e); Teagasc - (d)

As elevation can play an important role in agricultural and forest productivity the average elevation in metres across each ED was calculated from a digital elevation model of Ireland. The distance from the centroid of each ED to the nearest sawmill was included to investigate the effect of available markets and local commercial forest activity on planting rates. Land prices are an important factor in changes in land use, however there currently exists no reliable source of land price data for Ireland over the period of interest and regional data is particularly sparse. The NFS collects self-reported farm valuations, which were used to generate per hectare land values across eight regions over the time-period and were considered a reliable proxy for market data. Figure 2 displays the primary spatial data employed in the analysis.

Figure 2(b) displays the area afforested between 1993 and 2007 and suggests that spatial clustering of afforestation may be present. Spatial correlation between annual afforestation in EDs was tested using Moran's I and found to be significant, although relatively small, in each year (Table 2). The results suggest that ED afforestation may be spatially clustered. Correlation amongst the dependent variable in a model invalidates the assumption of independence and may lead to biased estimates. This correlation can be accounted for by employing a spatial autoregressive (SAR) model (Elhorst, 2003). The SA R model accounts for the correlation in the dependent variable explicitly by estimating a spatial lag parameter that describes the effect of the extent of the dependent variable in surrounding observations.

Table 2 Moran's I test for spatial correlation amongst ED afforestation per year

Year	**Moran's I**	**P>z**
1993	0.09	0.000
1994	0.14	0.000
1995	0.20	0.000
1996	0.15	0.000
1997	0.14	0.000
1998	0.10	0.000
1999	0.09	0.000
2000	0.18	0.000
2001	0.25	0.000
2002	0.19	0.000
2003	0.16	0.000
2004	0.14	0.000
2005	0.12	0.000
2006	0.12	0.000
2007	0.10	0.000

The data primarily relate to the characteristics of the EDs and are thus time-invariant limiting the options for modelling the full data-set. A random effects model assumes no individual specific effects and can thus incorporate time-invariant characteristics as independent variables. The basic model took the form of:

Where i is the individual ED, t is the time period, Y is the rate of afforestation, X are the characteristics of ED, β are the coefficients to be estimated, α is the constant term, μ is the time invariant individual specific random effect and e is the error term. To account for the identified spatial correlation a second model was specified that took the form of a spatial autoregressive random effects model, which incorporates a spatial lag of the dependent variable;

Where W is the spatial weights matrix (SWM) that describes the relationship between the observed ED and those surrounding it and λ is the associated coefficient to be estimated. In this study the correlation of afforestation rates may stem from a number of sources that are not accounted for in the model, such as the influence of additional physical site characteristics, land-owner interactions and local industry and state promotional and advisory agents. Thus a binary contiguity spatial weights matrix, where EDs that share a boundary are identified as related, was considered most appropriate. Each matrix row was standardized so that the binary effect was divided between neighbours equally. Dummy variables representing time periods and the Counties in which EDs are located were included in the model to account for time and general spatial effects but are excluded from the reported results for brevity. Both models were simulated using maximum likelihood estimation. The SAR model was estimated using the splm package in R (Millo and Piras, 2012). As the size of the ED may bias the area related variables, the percentage of afforestation and percentages of soil type, forest cover and protected areas were modelled rather than the area. Summary statistics for the model variables are contained in Table 3. The afforestation variable was highly skewed and was therefore log-transformed before model estimation. As the log of zero is not defined afforestation of 0.001ha replaced zero observations before transformation.

Table 3 Summary statistics of model variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Afforestation (%)	42165	0.17	0.45	0.00	12.02
Peat soils (%)	42165	15.63	19.52	0.00	92.66
Poorly drained mineral soils (%)	42165	25.79	22.37	0.00	95.93
Well-drained mineral soils (%)	42165	42.64	28.37	0.00	99.99
Elevation (m)	42165	99.89	61.28	0.00	453.10
Distance to sawmill (km)	42165	19.94	12.25	0.06	64.51
Private forest cover (%)	42165	3.22	3.44	0.00	31.57
Public forest cover (%)	42165	4.55	7.47	0.00	73.95
SAC/SPA/N HA (%)	42165	6.80	15.91	0.00	100.00
Acid sensitive (%)	42165	5.46	21.32	0.00	100.00
Average farm size (ha)	42165	35.63	14.79	12.21	153.47
Reported land value (1,000s €)	42165	11.83	4.48	6.76	40.50
Forest LEV (1,000s €)	42165	2.74	2.85	-9.09	17.51

3. Results

Correlation between the independent variables is generally low except between the soil variables, which is expected given that they are proportional to each other (Table 4). Thus, multi-collinearity was not deemed to be a significant issue in the models.

Table 4 Matrix of Pearson correlation coefficients of model variables

	Affor	Peat	P soil	W soil	Elev	Saw	Pr for	Pu for	SAC	Acid	Size	Price	LEV
Affor	1.00												
Peat	0.10	1.00											
P soil	0.13	-0.07	1.00										
W soil	-0.13	-0.52	-0.59	1.00									
Elev	0.11	0.09	0.06	-0.24	1.00								
Saw	-0.02	0.03	0.26	-0.22	-0.10	1.00							
Pr for	0.21	0.18	0.12	-0.23	0.21	-0.07	1.00						
Pu for	0.10	0.19	0.00	-0.20	0.50	-0.14	0.24	1.00					
SAC	-0.03	0.25	-0.07	-0.24	0.20	0.06	0.19	0.22	1.00				
Acid	-0.03	0.23	-0.14	-0.22	0.12	-0.03	0.08	0.12	0.20	1.00			
Size	-0.02	-0.23	-0.12	0.22	0.12	-0.14	-0.01	0.04	-0.05	0.02	1.00		
Price	-0.07	-0.13	-0.05	0.11	0.06	-0.08	0.13	0.01	0.05	-0.02	0.16	1.00	
LEV	0.02	0.31	0.14	-0.34	0.04	0.08	0.27	0.09	0.31	0.12	-0.19	0.39	1.00

All included variables had a significant effect on afforestation and there are no major changes in the sign or scale of coefficients between models (Table 5). However, the coefficient of the spatial lag is significant and positive indicating that afforestation in one ED is positively related to afforestation in adjacent ones. In addition the increase in the log-likelihood suggests that the spatial model performs better, which was confirmed with a likelihood ratio test (LR=1 166.98, P<0.001). It should be noted that the soil percentages are relative to the remaining area which is composed of unplantable land. Thus, although the percentage of well-drained mineral soils is negatively correlated with afforestation it has a small positive effect in the models.

Table 5 Results of random effects and spatial autoregressive random effects models

Log(afforestation%)	**RE Model**			**SAR RE Model**		
Variable	**Estimate**	**St. Er.**	**P>z**	**Estimate**	**St. Er**	**P>z**
Peat soils (%)	0.033	0.003	0.000	0.028	0.002	0.000
Poorly-drained mineral soils (%)	0.032	0.002	0.000	0.025	0.002	0.000
Well-drained mineral soils (%)	0.009	0.002	0.000	0.007	0.002	0.000
Elevation (m)	0.015	0.002	0.000	0.013	1.412	0.000
Sq. Elevation	-4.05E-05	5.04E-06	0.000	-3.35E-05	4.65E-06	0.000
Distance to sawmill (km)	-0.015	0.003	0.000	-0.011	0.003	0.000
Private forest cover (%)	0.210	0.019	0.000	0.200	0.017	0.000
Sq. private forest cover	-0.008	0.001	0.000	-0.008	0.001	0.000
Public forest cover (%)	0.035	0.009	0.000	0.029	0.008	0.000
Sq. public forest cover	-0.001	2.40E-04	0.001	-0.001	2.21E-04	0.000
SAC/SPA/NHA (%)	-0.011	0.002	0.000	-0.011	0.002	0.000
Acid sensitive (%)	-0.009	0.002	0.000	-0.007	0.002	0.000
Average farm size (ha)	-0.007	0.002	0.002	-0.005	0.002	0.008
Reported land value (1,000s €)	-0.049	0.009	0.000	-0.038	0.000	0.000
Forest LEV (1,000s €)	0.057	0.017	0.001	0.039	0.016	0.012
Constant	-10.414	0.324	0.000	-8.094	0.030	0.000
Spatial lag	-	-	-	0.239	0.007	0.000
Log likelihood	-115419.29			-114835.80		
N	42165			42165		

Given the combination of units in which the variables are expressed direct comparison of the scale of some coefficients is less meaningful. The random effects model was re-estimated with standardized independent variables and the coefficients can be interpreted in relation to a change in the standard deviation of the independent variables (Table 6). This standardized random effects (SRE) model highlights the importance of physical land characteristics in explaining the conversion of land to forestry and shows that the proportion of poorly drained mineral soil in an ED had the greatest relative effect. Conversely changes in the LEV had a relatively small effect.

Table 6 Results of SRE model of standardized independent variables

Log(afforestation%) Variable	Estimate	Stan. Er.	P>z
Std. peat soils	0.66	0.05	0.000
Std. poorly drained mineral soils	0.76	0.05	0.000
Std. well-drained mineral soils	0.25	0.06	0.000
Std. elevation	0.26	0.04	0.000
Std. distance to sawmill	-0.23	0.04	0.000
Std. private forest cover	0.29	0.03	0.000
Std. public forest cover	0.08	0.04	0.025
Std. SAC/SPA/NHA	-0.21	0.03	0.000
Std. acid sensitive	-0.18	0.04	0.000
Std. average farm size	-0.11	0.03	0.002
Std. reported land value	-0.22	0.04	0.000
Std. forest LEV	0.13	0.05	0.010
Constant	-8.36	0.24	0.000
Log likelihood	-115493.52		
N	42165		

It is important to note that the previous models ignore the dynamic effects of variables over time. For example, if interactions between soil type and 5-year time period (1998-2002 and 2003-2007) dummy variables are included in the original RE model it is evident that significant changes have occurred in the effect of soil type over the time period (Table 7). The influence of peat soils has declined over time while that of poorly drained mineral soils shows an increase. This can most likely be explained by the introduction of stricter environmental policies that recognised the value of bogs for carbon sequestration and biodiversity preservation. In addition, it may reflect an awareness of the lower productivity rates that can be achieved on such sites.

Table 7 Coefficients of soil and time-period interactions from RE model

Variable	Estimate	Stan. Err.	P>z
Peat (%)	0.039	0.003	0.000
Peat (%) 1998-2002	-0.004	0.003	0.197
Peat (%) 2003 -2007	-0.014	0.003	0.000
Poorly-drained mineral (%)	0.022	0.003	0.000
Poorly-drained mineral (%) 1998-2002	0.018	0.003	0.000
Poorly-drained mineral (%) 2003 -2007	0.013	0.003	0.000
Well-drained mineral (%)	0.006	0.003	0.030
Well-drained mineral (%) 1998-2002	0.001	0.003	0.594
Well-drained mineral (%) 2003-2007	0.009	0.003	0.002

4. Discussion

The results highlight the importance of underlying physical land characteristics in understanding afforestation. Physical site characteristics, such as soil and elevation, are essential factors in understanding the natural distribution of forests (Felicísimo et al., 2002) and have been shown to be important predictors of land-use change such as land abandonment (Sluiter and de Jong, 2002) and forest expansion (Fu et al., 2006). Such findings highlight the limitations imposed by site quality on both the range of land uses that can be practiced and their productivity and profitability. This study found that the percentage of poorer quality soil, both poorly drained mineral and peat, were found to be important variables in explaining annual afforestation in Ireland. Such soils are associated with lower levels of agricultural productivity but can result in relatively high growth rates for forestry depending on other factors and management (Farrelly, 2009). Thus forestry, as an enterprise, has a greater competitive advantage on such soils. Peat soils have been associated with afforestation in Ireland in the past but planting has been regulated in areas of acid sensitivity and lower yield classes to ensure forest productivity and to control potential effects of forest activity on water quality. This has resulted in significant decreases in peat afforestation in recent decades (Black et al., 2008). This was highlighted in Table 7 which demonstrated how the contribution of peat soils has declined over time while mineral soils show an increase.

Survey based studies have shown that farmers views on land quality and forestry can be a major factor in whether they establish forests or not. A common response from farmers is that their land is “too good” for forestry (Collier et al., 2002). Forestry is unlikely to compete financially on higher quality soils and farmers are unlikely to consider better quality sites for afforestation (Breen et al., 2010), thus it is unsurprising that well-drained mineral soils had the smallest effect amongst the soils and were found to be negatively correlated with afforestation in general. Elevation is also an important element in land productivity due to its links with physical and meteorological factors. Areas with higher average elevations are more likely to convert to forestry in the model. However, this relationship is non-linear which is likely to reflect limitations of any commercial land-use in high elevations.

As stated previously early afforestation efforts, particularly by the state, concentrated on upland, peat dominated sites which were considered sub-marginal for agriculture. More recently such areas have been increasingly valued for their role in the conservation of biodiversity. Predicting biodiversity changes as a result of land conversion to commercial forestry is difficult and may be either negative or positive depending on management and planning issues, however the most negative impacts are likely to occur in biodiversity rich habitats (Brockerhoff et al., 2008, Buscardo et al., 2008). The provision of environmental benefits is one of the goals of afforestation in Ireland and the recognition of the environmental sensitivity of some areas has resulted in the implementation of policies that attempt to counteract the potential negative impacts of afforestation. (Department of Agriculture, Food and Forestry, 1996). This includes controlling afforestation in areas which are deemed acid or environmentally sensitive. Applications for grant aided afforestation in special areas of conservation (SAC), special protection areas (SPA) or natural heritage areas (NHA) must be approved by the National Parks and Wildlife Service. The results of this study suggest that these areas have decreased afforestation rates in the EDs in which they occur.

The LEV of moving from agriculture into forestry has a significant and positive effect on afforestation rates. Given the assumptions made in the calculation it is important to note that this effect is reflective of the relative changes to the forest premium rate and the market margin of cattle enterprises over space and time. The importance of state supports in achieving afforestation is recognised generally in the literature (Beach et al., 2005). Targeted supports have been found to be important explanatory factors in land use change in Europe (Serra et al., 2006). The average farm size in the ED has a negative effect, which may relate to the profitability of enterprises associated with larger farms. Land prices are recognised as having a significant effect on the attractiveness of afforestation, particularly given the long-term nature of the investment (Kula, 1992). In this study self-reported values were employed as actual sales data were lacking. The negative effect of land price is likely to reflect the perceived higher opportunity cost of planting when land prices increase.

The effect of existing forest cover and access to markets is particularly interesting from a planning perspective. Forest cover, both public and private, has a positive but non-linear effect on afforestation. In addition, distance to sawmills has a negative effect on afforestation levels which is likely to reflect a combination of factors including relative profitability due to lower transportation costs and economies of scale and an increasing awareness of forest benefits amongst residents. Clement et al. (2009) found a similar relationship and suggested that this was evidence that afforestation was driven by local timber demand. The presence of commercial forest activity also has the potential to increase landowner's awareness of the benefits of forestry as a profitable land use in addition to introducing a level of acceptability of forestry as a land conversion activity (O'Leary et al., 2000). At higher levels of forest cover the effect reverses and becomes negative, which may indicate an exhaustion of "suitable" forestry land in some EDs. As the competitiveness of forestry is strongly linked to land quality this suggests that the availability of poor quality land for forestry is limited in some areas. In addition, high levels of forest cover have been linked to negative attitudes amongst individuals where forests may be viewed as encroaching on agriculture, landscapes or communities (O'Leary et al., 2000; Carroll et al., 2011). Thus local landowners may view afforestation as a threat irrespective of its commercial benefits.

In addition to identifying the primary drivers of afforestation, this study highlights a significant challenge in land-use policy. Forest expansion is considered desirable for the provision of ecosystem services and rural economic diversification (Kanowski, 2010). However, this requires the replacement of an existing land-use. Traditionally, afforestation would occur on sub-marginal land but this is increasingly valued for biodiversity and recreation (Buckley et al., 2009; Bullock et al., 2012), which may be impacted negatively by afforestation (Buscardo et al., 2008). Such areas are therefore becoming less available for land conversion in general, including for afforestation. As shown in this study the relative profitability of forestry compared to agriculture also plays a role in annual afforestation rates. In the Irish context, policies to expand agricultural output significantly by 2020 are being developed (Department of Agriculture, Food and the Marine, 2010). If this results in increased profitability of competing agricultural enterprises, either through increased intensification or the expansion of more profitable enterprises, commercial forestry may lose competitiveness as a land-use option. Timber prices are generally stable and significant increases in forestry profitability through market activity are unlikely (Clinch, 1999). Increases in agricultural margins would, therefore, need to be counteracted by increases in state afforestation supports to offset the impact on planting rates. However, if agricultural intensification occurs only on the best quality land this could result in the availability of marginal land for alternative uses (Feehan and O'Connor, 2009). As shown in this study, conversion to forestry has been lower on better quality land in the past and so intensification in such areas should not significantly impact on achieved planting rates. Indeed such a scenario could offer opportunities for forest expansion on marginal land where forestry is a commercially attractive land-use assuming that land-use within such areas is not restricted by conservation measures, that land has not already been converted and that local land owners are willing to engage with an afforestation programme.

5. Conclusion

Afforestation by private landowners is generally seen as a function of agricultural commodity and timber prices, land prices and government subsidisation. However, fundamental to understanding this land use change is the influence of physical characteristics of the land, particularly soil quality. Commercial forestry is less reliant on site quality than other potential land uses and high productivity levels can be attained in areas considered marginal for agriculture. This study demonstrates the importance of physical site characteristics in understanding land conversion to forestry, with the proportion of poorer quality soils having a major effect on afforestation rates. The relative profitability of land conversion was found to have a significant effect but its influence on planting rates was relatively small. Conservation policies have impacted negatively on land conversion and limitations on land availability may be an important factor in some areas.

Overall this study highlights the potential for economic and physical spatial data to be combined in a meaningful way to understand spatial variations in annual land conversion to forestry. In addition, this study highlights the importance of land availability in policy development and of potential conflicts between policies with similar goals. When developing targets for forest expansion, policy makers should account for conflicting land use policies, the availability of land and the impact of changes to the profitability of alternative land uses if realistic targets are to be developed.

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