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Forest Ecology and Management 217 (2005) 266–274
Forest Ecology and Management
www.elsevier.com/locate/foreco

# Is forest fragmentation driven by the spatial configuration of land quality? The case of western Oregon

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Received 25 May 2005; received in revised form 10 June 2005; accepted 13 June 2005

**Abstract**

We investigated spatial configuration of economic returns, to enhance models of forest fragmentation for western Oregon and western Washington. Drawing from spatial land rent theory, economic drivers of forest fragmentation at the landscape level include land quality comprised of attributes such as soil fertility or the distance of urban plots to amenities. We included the spatial configuration of land quality as independent variables in regressions for western Oregon. Results indicate that land quality fragmentation is a significant determinant of forest fragmentation. This holds both for a model using a forest fragmentation index composed of three fragmentation metrics, and separate models for each component or metric: percent non-forest, percent edge, and interspersion. Including land quality fragmentation as an explanatory variable increases the fit of the regressions by more when the dependent variable represents spatial pattern (e.g., percent edge) rather than aggregate land use (e.g., percent non-forest). Variables capturing the spatial configuration of soil quality improve the fit of all specifications and have some effect in terms of bias of other parameter estimates. Improved understanding of key determinants will aid in designing land conservation policies that provide a mechanism for aligning private incentives with broader public goals.


*Keywords:* Fragmentation; Land quality; Land rent; Spatial configuration

## 1. Introduction

Land-use conversion is a primary determinant of environmental change in terrestrial ecosystems. Projections are for more than 50 million acres of U.S. forest to be converted to developed uses (e.g., parking lots) over

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doi:10.1016/j.foreco.2005.06.007

the next 50 years (Alig et al., 2004; Alig and Plantinga, 2004), as the population grows by more than 120 million people. Land use change can lead to forest fragmentation—the transformation of a contiguous patch of forest into disjunct patches. Forest fragmentation is widely considered to be a primary threat to terrestrial biodiversity (Armsworth et al., 2004), and a recent GIS analysis of the fragmentation of continental U.S. forests indicates that fragmentation is so pervasive that edge effects potentially influence ecological processes on most forested lands (Ritters et al., 2002). Although the ecological effects of forest fragmentation have received substantial attention, an understanding of the economic drivers of fragmentation is less developed.

Fragmentation concerns are now being reflected in the design of conservation policies in the most recent U.S. Farm Bill. For example, reducing forest fragmentation is a primary goal in the Wildlife Habitat Incentives Program (WHIP) as administered by several states. Likewise, many wildlife conservation plans adopted by non-governmental agencies such as Partners-In-Flight have explicit goals related to the reduction of forest fragmentation. However, the efficient design of land-use policies to address forest fragmentation must account for the economic drivers that cause fragmentation.

A recent paper published in this journal quantifies the effects that various socio-economic drivers have on forest fragmentation at the census tract level in the Pacific Northwest (Butler et al., 2004). Three separate fragmentation metrics used in ecological studies were investigated in Butler et al.: percent of the landscape in non-forest uses, percent of the landscape as edge forest, and an interspersion index. The socio-economic drivers included various proxies for aggregate returns to various land uses, such as population density, income, and percentage of the landscape as agriculture. Fragmentation was regressed on the socio-economic drivers by first combining the three metrics into one metric. Second, the three metrics were used in three separate regressions on the socio-economic drivers. The model fit was significantly higher when the dependent variable was an aggregate land use measure (e.g., percentage of the landscape in non-forest) rather than a measure of the spatial configuration of land use (e.g., percent edge, interspersion). If economic returns are heterogeneous within a landscape, then the spatial configuration of returns to land will drive the spatial configuration of land use (Wu and Plantinga, 2003). However, the independent variables in Butler et al. (2004) are proxies for aggregate land use returns rather than proxies for the spatial configuration of returns. Therefore, not including a variable measuring the spatial configuration of returns may represent an omitted variable bias and be a potential explanation for the reduced fit of the model when explaining spatial land use measures rather than aggregate land use measures.

The purpose of this paper is to augment ecological investigations with economic theory to further our understanding of drivers of forest fragmentation at the landscape level, and to then test it empirically in western Oregon. Although variables representing the spatial configuration of returns to land within regions are typically not available, we can exploit spatial information regarding land quality as a proxy. In theory, land quality is a general term that represents parcel-specific attributes affecting the economic returns to various uses of that parcel. For example, land quality can include attributes such as soil fertility or the distance of urban plots to amenities. Econometric analysis on aggregate land use has shown that the amount of forestland in a region is a function of the amount of land with low soil quality[1] (Plantinga, 1996; Lubowski, 2002). We extend the Butler et al. approach by testing economic theories that together provide a means for investigating the spatial relationships involving forest fragmentation on the landscape. For example, we test the configuration of land quality as a determinant of forest fragmentation in western Oregon. We use GIS information on soil quality and calculate the spatial configuration of low quality land with fragmentation indices, and examine the effects on model fit when the dependent variable represents the spatial pattern of land use rather than aggregate land use.

## 2. The theory of the spatial configuration of land use

The usual starting point for considering land use allocation is Ricardo's and von Thunen's land rent

[1] Soil quality is commonly quantified with the land capability class index (LCC).

theories (van Kooten and Folmer, 2004), which state that land use is allocated to maximize the present value of the flow of net revenue (or rent) from a land parcel $i$ of particular quality $q$. Land quality, $q$, is an all-encompassing term that can include many factors that would influence the value of land in different uses. For example, parcels that are further from urban centers are generally considered to be of lower quality for urban development than parcels that are close to urban centers. Likewise, parcels with high soil fertility and moderate slopes are generally considered to be more suitable for agricultural production than parcels with low soil fertility and steep slopes.

Suppose there are $j = 1, \ldots, M$ possible uses of land. Each use $j$ has associated with it a net market returns function $R^j$, which is a function of exogenous market prices of products from use $j$ and exogenous land quality $q$. $R^j$ has the following properties:

$$R^j = R(p^j, q); \quad \frac{\partial R^j}{\partial q} \geq 0; \quad \frac{\partial R^j}{\partial p^j} \geq 0; \quad \frac{\partial^2 R^j}{\partial q^2} \leq 0; \quad \frac{\partial^2 R^j}{\partial p^{j^2}} \leq 0$$

Thus, if land quality is homogeneous within parcels, then a profit-maximizing landowner will allocate parcel $i$ to use $k$ if $R^k(p^k, q_i) > R^j(p^j, q_i), \forall j \neq k$. Now, suppose that $R^k(p^k, q_i) > R^j(p^j, q_i), \forall j \neq k$ on land parcels with land quality in the following range: $q_i \in [q', q'']$. Therefore, all land with quality in this range will be allocated to use $k$.

Suppose that we are interested in the spatial configuration of land in use $k$ on a particular landscape. Define a landscape as a one-dimensional collection of spatially related land parcels (indexed $i = 1, \ldots, N$), each of which has a given level of land quality $q_i$, $L = \{q_1, q_2, \ldots, q_N\}$, where parcel 1 is adjacent to parcel 2, which is adjacent to parcel 3, and so on. Next, define $\delta_i$ as an indicator value that equals 1 if land quality $q_i \in [q', q'']$ and equals 0 otherwise. Thus, if relative prices are constant across the landscape, each parcel $i$ will be devoted to either use $k$ ($\delta_i = 1$) or some alternate use ($\delta_i = 0$) and the spatial configuration $S$ of use $k$ on landscape $L$ will be defined as $L_k^S = \{\delta_1, \delta_2, \ldots, \delta_n\}$. The spatial configuration of use $k$ could be quantified with a fragmentation index. For example, suppose use $k$ indicates a forested use, and define a core forest parcel as a forested parcel bordered on both sides by forest. Thus, the amount of core forest ($C$) on landscape $L$ would be defined as follows: $C = \sum_{\delta_i \in L} \delta_i \delta_{i-1} \delta_{i+1}$. So, by defining the land quality range in which use $k$ is the economically optimal use, an index that quantifies the spatial configuration of such land quality should correspond directly with the spatial configuration of land in use $k$.

Given a set of exogenous market prices for each of the $j$ land uses ($p^j$), the spatial configuration of land quality $L$ determines the spatial configuration of land in use $j$, while the market price of $p^j$ relative to all other prices will determine the aggregate amount of land in use $j$. Therefore, we can define the spatial configuration $S$ of use $k$ on landscape $L$ as a function of market prices to each use $j$ ($p^j$) and the spatial configuration of land quality $L$:

$$L_k^S = f(p^1, p^2, \ldots, p^J, L). \tag{1}$$

Equation (1) will serve as the theoretical basis for specifying the empirical model of forest fragmentation in section 3.

## 3. Model specification

We build on the linear regression model presented in Butler et al. (2004) to quantify the relationship between the spatial configuration of land quality and forest fragmentation. A forest fragmentation index composed of three fragmentation metrics is calculated for western Oregon and regressed on a series of independent variables, following the theoretical specification presented in (1). The model is estimated both with and without a variable measuring the spatial configuration of land quality and separate models are run for the composite index and each of the components of the index.

Butler et al. (2004) use a composite forest fragmentation index (ffi), consisting of three selected measures: percentage non-forest cover (pnf), percentage edge (pe), and interspersion (in). All fragmentation indices were calculated from the Oregon National Land Cover Data (NLCD) map, produced by a consortium of governmental agencies from 1990 Thematic Mapper satellite imagery (Vogelmann et al., 2001).[2] To efficiently combine the metrics into a single unified index, all metrics must have similar

[2] The NLCD is a raster data set with 30m pixels.

ranges and similar relationships to fragmentation. Thus, the metrics were calculated to range from zero to one and defined such that they were all positively correlated with fragmentation.

For both the current study and Butler et al. (2004), the index of percentage non-forest cover (pnf) is the proportion of each census tract that is not in a forested use. Percentage edge (pe) is the percentage of the forested pixels in each county that is bordered on at least one side by a human land use. Interspersion is a measure of the number of dissimilar (i.e., human land use) neighbors (using the adjacent eight cells) to each forested pixel, normalized to a percentage for each census tract as a whole. The metrics are then combined into one composite forest fragmentation index (ffi), where each index is weighted equally:

$$\text{ffi} = \frac{\text{pnf} + \text{pe} + \text{in}}{3}$$

For a more in-depth description of the calculation of each of the fragmentation indices, see Butler et al. (2004).

Building off our theoretical model of the determinants of the spatial configuration of land use, we define a land quality variable that determines forestland and quantify its spatial configuration in a similar way to the forest fragmentation indices above. We quantified land quality with the widely used land capability class index (LCC) that ranges from 1 (highest quality) to 8 (lowest quality) and is based on a ranking of twelve different soil characteristics that are critical for crop production. The overall LCC score consists of the lowest ranking given to any of these twelve soil features. Several studies on the allocation of land to forest and agriculture have shown that soil quality, as quantified by the widely used land capability class (LCC) measure, is a major determinant of land use to these two major uses (Plantinga, 1996; Hardie and Parks, 1997). In addition, Lubowski (2002) found that the probability of urban development on parcels with low LCC ratings was lower than on parcels with higher LCC ratings. Thus, we define land quality through the LCC index.

Generally, an LCC ranking of 1 or 2 indicates few limitations for agriculture, while an LCC ranking greater than 4 is not suitable for agriculture. LCC rankings of 3 and 4 have limitations to agriculture and would be considered marginal farmland relative to LCC rankings of 1 and 2. Likewise, LCC rankings of 5–8 are generally considered more suitable to forested uses of land. Using the LCC rankings, we define low land quality as land with an LCC greater than 3 and high quality as land with an LCC of 3 or less.[3] Thus, we would expect forest to be found on low quality land and agriculture and urban uses to be found on high quality land.[4] Furthermore, Equation (1) indicates that the spatial configuration of this low quality land should be a strong determinant of the spatial configuration of forestland. Thus, we use GIS layers describing LCC's for Western Oregon from the USDA National Resources Conservation Service (NRCS) and calculate fragmentation indices for low quality land. As guided by theory, the same three ecological indices from Butler et al. (2004) are calculated: percentage of high quality land (phq), percentage of edge low quality land (pelq), and an interspersion index for low quality land (inlq). To match the NLCD data, the GIS soil quality layers are converted from vector to raster format with 30 m pixels and each of the fragmentation indices is calculated identically to the forest fragmentation indices. Fragmentation indices are calculated using the software FragStats Version 3.3 (McGarigal et al., 2002).

Equation (1) states that the spatial configuration of land use is a function of the spatial configuration of land quality and relative net returns from different uses of land. Thus, we follow Butler et al. (2004) and include proxies for relative returns to different land uses. Based upon previous research findings and data availability, we include population density, income, proximity of urban areas and highways, agriculture and federal land ownership, and slope variables in our empirical model. Log and arcsin square root transformations were used for the population density and slope variables, respectively, to produce linear relationships with the dependent variable. Because the log of zero is undefined and zero is a valid value for the population density in an analysis unit, all tracts with zero population densities were assigned values of the next lowest population density value.

[3] Defining the lower limit of low quality land at 5 rather than 4 does not produce qualitatively different results in the regression analysis.

[4] Lands with a soil type defined as urban were categorized as high quality land.

We used a standard multiple linear regression model to quantify the relationships between the forest fragmentation index and the explanatory variables. The regression models were weighted by the area of each analysis unit to adjust for unequal analysis unit sizes. This is an artifact of using analysis units that were designed for a population census and defined to have similar numbers of people in each analysis unit. Regression models were run both with and without the land quality fragmentation indices to understand the effects of including this variable and to test the theory in Equation (1). To check for collinearity, the variables were first examined from a theoretical perspective and all explanatory variables that appeared redundant or were highly correlated ($\rho > 0.65$) with other variables were removed. Two interaction terms, log(population density) × highway distance and percentage federal ownership × arcsin(slope)$^{0.5}$, were added to the model to correct for unexpected signs for the highway distance and percentage federal ownership variables.

## 4. Results

The model was estimated with 555 observations for Census tracts in western Oregon by ordinary least squares. First, we created a regression model using the composite forest fragmentation index (Table 1). Second, a model was estimated by splitting the composite index into its three components: percent non-forest (Table 2), percent edge (Table 3), and interspersion (Table 4). Each representation of the dependent variable was estimated both with (model 1) and without (model 2) the variable depicting the fragmentation of land quality, giving a total of eight regression equations presented in Tables 1–4.

Results for the composite index (Table 1) indicate that land quality fragmentation is a strongly significant determinant of forest fragmentation. The coefficient is positive and significantly different from zero, with a relatively high partial $r^2$. The adjusted $r^2$ improves from 0.87 to 0.91 upon inclusion of this variable into the model. Of the remaining variables, population density and percent agricultural land are positive determinants of forest fragmentation and significantly different from zero in both models. The following are negative determinants of forest fragmentation and significantly different from zero in both models: distance to highway, distance to urban center, and log(population density) × distance to highway. The coefficient for average income is negative and significantly different from zero in model 1 but not model 2. An $F$-test strongly rejects the hypothesis that the coefficient on land quality fragmentation should be restricted to be zero at any reasonable confidence level. In terms of any potential bias from this restriction, the coefficients for two key variables clearly differ from model 1 to model 2. The

Table 1
Coefficients of the forest fragmentation index linear regression model with (model 1) and without land quality fragmentation (model 2)

| Variable | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Coefficient | $t$-Value | Partial $r^2$ | Coefficient | $t$-Value | Partial $r^2$ |
| Intercept | 10.752* | 6.045 | | 15.948* | 7.752 | |
| Log(population density) | 12.668a,* | 14.956 | 0.291 | 19.045a,* | 22.192 | 0.474 |
| Distance to highway | −0.270* | −2.370 | 0.010 | −0.457* | −3.418 | 0.021 |
| Average income | −0.128* | −2.560 | 0.012 | −0.096 | −1.623 | 0.005 |
| Distance to urban center | −0.018 | −1.756 | 0.006 | −0.038* | −3.169 | 0.018 |
| Percent agricultural land | 0.318a,* | 21.840 | 0.467 | 0.436a,* | 30.566 | 0.631 |
| Percent federal land | −0.036 | −0.659 | 0.001 | −0.018 | −0.276 | 0.000 |
| Arcsin(slope)$^{0.5}$ | 0.148 | 0.403 | 0.000 | 0.213 | 0.490 | 0.000 |
| Log(population density) × distance to highway | −0.635* | −5.348 | 0.050 | −0.981* | −7.142 | 0.085 |
| Percent federally owned × arcsin(slope)$^{0.5}$ | 0.143 | 0.959 | 0.002 | 0.105 | 0.595 | 0.001 |
| Land quality fragmentation | 0.383* | 14.680 | 0.283 | | | |
| Complete model adj. $r^2$ | 0.91 | | | 0.87 | | |

$N = 555$.
[a] Significantly different across models at the 5% level.
* $P < 0.05$.

Table 2
Coefficients of the percent non-forest index with and without land quality fragmentation

| Variable | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Coefficient | $t$-Value | Partial $r^2$ | Coefficient | $t$-Value | Partial $r^2$ |
| Intercept | 27.064* | 11.590 | | 31.779* | 13.181 | |
| Log(population density) | 18.573[a,*] | 16.889 | 0.344 | 23.329[a,*] | 23.197 | 0.496 |
| Distance to highway | 0.056 | 0.374 | 0.000 | −0.094 | −0.600 | 0.001 |
| Average income | −0.404* | −6.189 | 0.066 | −0.351* | −5.092 | 0.045 |
| Distance to urban center | −0.032* | −2.396 | 0.010 | −0.053* | −3.773 | 0.025 |
| Percent agricultural land | 0.656[a,*] | 30.909 | 0.637 | 0.777[a,*] | 46.441 | 0.798 |
| Percent federal land | 0.056 | 0.782 | 0.001 | 0.100 | 1.310 | 0.003 |
| Arcsin(slope)$^{0.5}$ | −0.242 | −0.506 | 0.001 | −0.201 | −0.396 | 0.000 |
| Log(population density) × distance to highway | −0.435* | −2.812 | 0.014 | −0.701* | −4.354 | 0.034 |
| Percent federally owned × arcsin(slope)$^{0.5}$ | −0.177 | −0.910 | 0.002 | −0.305 | −1.478 | 0.004 |
| Percent high quality land | 0.226* | 8.484 | 0.117 | | | |
| Adj. $r^2$ | 0.94 | | | 0.93 | | |

$N = 555$.
[a] Significantly different across models at the 5% level.
* $P < 0.05$.

coefficients on log(population density) and percent agricultural land are significantly different between model specifications at the 5% level. Thus, the omission of land quality fragmentation from this model appears to have some effect on bias in the other parameters as well as on the overall fit of the model.

Results for the non-forest index (Table 2) indicate that the percentage of the tract in high quality land is a positive and highly significant determinant of the amount of non-forest land in the tract. However, the change in adjusted $r^2$ is much lower between model 1 and model 2 for this index than for the composite index. As for the composite index in Table 1, the coefficients on log(population density) and percent agricultural land are significantly different between model specifications at the 5% level. Thus, the omission of the share of land in high quality land appears to affect the fit of the model and influence the bias concerning coefficients to a small degree.

Where percent edge was measured, percentage of low quality parcels measured as edge is a positive and highly significant determinant of the percentage of forest edges, at the 5% level (Table 3). In addition, the partial $r^2$ for this variable is much higher than the

Table 3
Coefficients of the percentage edge index with and without land quality fragmentation

| Variable | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Coefficient | $t$-Value | Partial $r^2$ | Coefficient | $t$-Value | Partial $r^2$ |
| Intercept | 1.671[a] | 0.759 | | 7.166[a,*] | 2.656 | |
| Log(population density) | 10.891[a,*] | 10.418 | 0.166 | 19.743[a,*] | 17.544 | 0.361 |
| Distance to highway | −0.461[a,*] | −3.228 | 0.019 | −0.789[a,*] | −4.494 | 0.036 |
| Average income | 0.091 | 1.454 | 0.004 | 0.120 | 1.550 | 0.004 |
| Distance to urban center | −0.014 | −1.139 | 0.002 | −0.030 | −1.883 | 0.007 |
| Percent agricultural land | 0.198[a,*] | 11.330 | 0.191 | 0.348[a,*] | 18.587 | 0.388 |
| Percent federal land | −0.095 | −1.371 | 0.003 | −0.106 | −1.234 | 0.003 |
| Arcsin(slope)$^{0.5}$ | 0.368 | 0.802 | 0.001 | 0.552 | 0.971 | 0.002 |
| Log(population density) × distance to highway | −0.786[a,*] | −5.289 | 0.049 | −1.319[a,*] | −7.324 | 0.089 |
| Percent federally owned × arcsin(slope)$^{0.5}$ | 0.341 | 1.830 | 0.006 | 0.417 | 1.805 | 0.006 |
| Percent edge low quality land | 0.483* | 17.113 | 0.350 | | | |
| Adj. $r^2$ | 0.84 | | | 0.76 | | |

$N = 555$.
[a] Significantly different across models at the 5% level.
* $P < 0.05$.

Table 4
Coefficients of the interspersion index with and without land quality fragmentation

| Variable | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | Coefficient | $t$-Value | Partial $r^2$ | Coefficient | $t$-Value | Partial $r^2$ |
| Intercept | 5.618* | 3.149 | | 8.900* | 4.397 | |
| Log(population density) | 9.959[a],* | 12.441 | 0.221 | 14.063[a],* | 16.657 | 0.337 |
| Distance to highway | −0.441* | −3.835 | 0.026 | −0.490* | −3.717 | 0.025 |
| Average income | −0.040 | −0.795 | 0.001 | −0.055 | −0.949 | 0.002 |
| Distance to urban center | −0.018 | −1.784 | 0.006 | −0.031* | −2.660 | 0.013 |
| Percent agricultural land | 0.152* | 12.122 | 0.212 | 0.184* | 13.115 | 0.240 |
| Percent federal land | −0.038 | −0.681 | 0.001 | −0.049 | −0.757 | 0.001 |
| Arcsin(slope)$^{0.5}$ | 0.308 | 0.828 | 0.001 | 0.287 | 0.672 | 0.001 |
| Log(population density) × distance to highway | −0.756* | −6.377 | 0.069 | −0.923* | −6.831 | 0.079 |
| Percent federally owned × arcsin(slope)$^{0.5}$ | 0.160 | 1.060 | 0.002 | 0.202 | 1.167 | 0.003 |
| Interspersion for low quality land | 0.388* | 13.111 | 0.240 | | | |
| Adj. $r^2$ | 0.75 | | | 0.67 | | |

$N = 555$.
[a] Significantly different across models at the 5% level.
* $P < 0.05$.

partial $r^2$ for the other variables, indicating that land quality fragmentation accounts for a large amount of the variation in forest fragmentation when measured with edge parcels. The overall adjusted $r^2$ increases from 0.76 to 0.84 upon inclusion into the model of the variable representing percent low quality edges. This is a much larger increase than for either the composite index or the percent non-forest index. In terms of omitted variable bias, once again, the coefficients on log(population density) and percent agricultural land are significantly different between model specifications at the 5% level, and in addition so are those for the distance from a highway and interaction between distance to highway and log(population density) variables. Thus, omission of percent edge of low quality land from this model appears to have a large effect on the fit of the model and some effect on bias of the other parameters.

Table 4 presents results for the interspersion index of forest fragmentation. The interspersion index of low quality land is a positive and highly significant determinant of the interspersion index of forest fragmentation at the 5% level. In addition, the partial $r^2$ for this variable is high relative to the partial $r^2$ for the other variables in the model. The overall adjusted $r^2$ increases from 0.67 to 0.75 upon inclusion of the interspersion index of low quality land. Coefficients on the log(population density) variable are significantly different across specifications at the 5% level. Thus, omission of the interspersion index of low quality land from this model appears to have a large effect on the fit of the model and a relatively small effect on the bias of the other parameters.

## 5. Discussion

Equation (1) builds on Ricardo's and von Thunen's theories of land rent to develop the theory that landscape spatial configuration is a function of relative land rents to different uses of land as well as the spatial configuration of land quality. Empirical results explaining variation in the composite forest fragmentation index and the individual components of that index strongly support the theory in Equation (1). Variables capturing the fragmentation of land with low soil quality are used to proxy for the spatial configuration of land quality and are strongly significant in all models presented here.

If land quality fragmentation is not included as an explanatory variable (i.e., model 2), then the independent variables strongly resemble those from an aggregate land use model. Most aggregate land use models specify the proportions of land in forest/non-forest as functions of net-returns to different land uses (i.e., forest, agriculture, urban) and average levels of soil quality. It could be argued that the independent variables in model 2 represent proxies for urban returns—log(population density), distance to highway, distance to urban center, average income; agricultural returns—percent agricultural land; average soil quality—arcsin(slope)$^{0.5}$. Thus, it is clear that this specification fits percent non-forest (adj. $r^2 = 0.93$) better than fragmentation indices such as percent edge (adj. $r^2 = 0.76$) and interspersion (adj. $r^2 = 0.67$), because the independent variables in model 2 closely resemble the independent variables found in aggregate land use models. This is also clear because including land quality fragmentation as an explanatory variable increases the fit of the regressions by more when the dependent variable represents spatial pattern (e.g., percent edge, interspersion) rather than aggregate land use (e.g., percent non-forest).

By not including land quality fragmentation as an explanatory variable, the coefficients for two key variables – log(population density) and percent agricultural land – clearly differ from model 1 to model 2 in three of the four cases. In the fourth case of the interspersion index, only the coefficient for the population density variable reflects a significant difference between models. In general, omission of land quality fragmentation as an explanatory variable appears to have some effects on bias in terms of other parameter estimates across models.

## 6. Conclusions

We are interested in the future forest ecosystem setting, which will reflect the substantial further development of U.S. forests and a considerable exchange of land between forest and agricultural uses. Overall, more than 150 million acres of U.S. forest land are projected to be involved in changes among land uses over the next 50 years (Alig and Plantinga, 2004). In the case of Oregon, a recent ballot measure pertaining to property rights and amending the State's land law could potentially lead to increased conversion of forests to other uses. Given that such land use changes will materially affect forest ecosystems, including forest fragmentation, what policies should society be considering now? This study was designed to further our understanding of the economic drivers of forest fragmentation at the landscape level, using western Oregon as a case study. Improved understanding of key determinants will aid in designing land-use policies that provide a mechanism for aligning private incentives with broader public goals.

Land conservation policies are increasingly addressing forest fragmentation and further opportunities exist in future U.S. Farm Bills, other governmental planning, and conservation plans by non-governmental units. Our results indicate that accounting for economic drivers that cause forest fragmentation should be part of the efficient design of such land-use policies, including accounting for the spatial pattern of land quality.

The influence of the spatial configuration of land quality on forest fragmentation is consistent with economic theories and is strongly supported in this analysis. The inclusion of a variable representing the fragmentation of soil quality improves the fit on all specifications and alters the parameters on the other variables. This suggests that models which attempt to explain forest fragmentation without measures of the spatial configuration of land quality or other candidate independent variables, will have a reduced fit and a potential omitted variable bias, although the degree of bias is moderate in this paper. Admittedly, soil quality is only one possible component of the broader concept of land quality, and avenues for future research could explore alternative measures of the spatial configuration of land quality, particularly as pertains to urban development.

If policy makers wish to alter fragmentation trends, private landowner behavior and incentives are major considerations (Butler et al., 2004; Lewis and Plantinga, 2005). However, a complete understanding of designing policies to reduce fragmentation requires several research components. One is that there is little theoretical foundation for designing economic incentives to achieve spatial outcomes. Research is needed to identify the factors that will potentially affect efficiency. Another is the application of the methodology created in Lewis and Plantinga (2005) in a southern U.S. study to other regions to help understand regional differences in reducing fragmentation. Lewis and Plantinga (2005) find that the costs of reducing forest fragmentation vary greatly with initial landscape conditions (as influenced by land quality) and that a simple spatially uniform subsidy appears to perform well relative to more complicated spatially targeted policies.

Joint examination of ecological and economic aspects can enhance land conservation policies. For example, if economic efficiency is an important consideration in policy deliberations, then the desired ecological measure of forest fragmentation should be explicit. In general, this suggests the potential usefulness of a framework with linked ecological and economic analysis components for the broader case of coordinating multiple policies, such as in the case of the next national Farm Bill. Current multiple policy issues include climate change, open space, and forest fragmentation, with a view to increasing the efficiency of incentives for inducing land use changes to help address forest fragmentation and fostering other co-benefits of afforestation.

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