EVALUATION OF THE PRIVATE FORESTLAND OWNERSHIP PARCELIZATION AND ITS EFFECTS ON THE FOREST LANDSCAPE IN THE SOUTHEASTERN MISSOURI OZARKS

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A candidate for the degree of Doctor of Philosophy

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ABSTRACT

The recent increase in forestland ownership parcelization has stirred worries for its unknown effects in the forest landscape. Particularly, under parcelized ownership, management activities from forestland owners can result in fragmented harvest events, which may influence the composition, structure and spatial pattern of the forest landscape in the future. Due to the complexity of the related processes and the broad spatial and temporal scale involved, a tool such as forest landscape simulation models is required to properly investigate the ecological consequences of such change.

First, a computer model was developed for the spatial representation of the parcelized forestland ownership patterns. FLOSS – A Forest Land Ownership Spatial Simulator – is a landscape pattern generator designed to create forestland ownership patterns that are strongly characterized by the shape of the underlying Public Land Survey System (PLSS) structure. FLOSS simulates ownership patterns based on the actual parcel size distributions. Model performance is evaluated by comparing with the actual ownership pattern, and is applied for simulating forestland ownership patterns of various parcelization levels.

Second, a transition matrix model is used to characterize the recent change in forestland ownership parcelization. A transition probability matrix for parcel size change was developed based on the plat books of 1930 and 2000. The results from the transition matrix model suggest a strong tendency towards further parcelization, characterized by parcel size classes smaller than 100 ha, and reveals the significant contribution from large

scale purchases from private entities, such as the Pioneer Forest, to the current status of the ownership parcelization.

Third, the harvest regimes characterized by a parcelized ownership landscape are spatially implemented for LANDIS to evaluate its effects on forest composition, age structure, and spatial pattern. The effects from parcelization level and harvest intensity are evaluated from LANDIS simulation results by using a 2×2 factorial design for short-, mid-, and long-term effects. The results predict that the change in forest landscape will be dominated by the successional process, with significant but limited effects from parcelization levels and harvest intensities. In particular, the spatial pattern of age structure will be affected by the highly limited extent of the harvest intensity associated with the small ownership types, creating age patches with simpler shapes and relatively greater aggregation level compared to those created from purely successional regeneration in the absence of significant disturbance events. The implications and limits of the application are discussed.

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Chapter I. Introduction

A. Problem identification

With approximately 160 million hectares of forest privately owned in the United States, about 59 % of the private owners are known to be the non-industrial private forest (NIPF) owners (Birch 1996). The state of Missouri, like the rest of the United States, experienced dramatic parcelization in the recent decades. Recent studies show that nonindustrial private forestland owners hold 82% of Missouri's timberland (4.6 million ha), and more than half of the parcels in this area are smaller than 40 ha (100 acres) (Moser et al. 2003, USDA 1989). The extent, intensity, and pattern of ongoing human influences are identified as a set of major factors that will determine the future status of forest landscapes (Kittredge Jr. et al. 2003). Consequently, understanding the interaction of forest management practices with the parcelization of forest ownerships is of great importance in understanding the future of the forest landscape. The magnitude of parcelization process has raised concerns due to the largely unknown ecological consequences resulting from this phenomenon.

The concerns regarding the highly parcelized ownership are generally based on the following assumptions: (1) forest management practices in a highly parcelized landscape will result in a highly fragmented forest landscape due to the spatial configuration of the harvest events characterized by the underlying ownership pattern (Gustafson et al. 2000); (2) greater number of landowners and their diverse motives can result in management fragmentation, which may reinforce the effects from the fragmented harvest events; and (3) forest products output may decline due to the lower proportion of participation in forest management and timber harvest operations, which is known to be associated with smaller parcel sizes (DeCoster 1998). On the other hand, it is also possible that the lower level of management associated with smaller parcel sizes may result in increasing amount of forest stands with larger interior area, which may have beneficial ecological effects (Temple and Cary 1988).

In light of these concerns and our limited knowledge of the consequences from the parcelized ownership, the purpose of this dissertation is to improve our understanding by: (1) characterizing the ownership parcelization process; (2) developing a method that can represent the parcelized ownership patterns characterized by its shape and size distribution; and (3) applying the harvest regimes of a parcelized ownership to a landscape simulation model to investigate the responses from the forest landscape, based on two watersheds – Black River and St. Francis River – located in the southeastern Missouri Ozarks (Figure II-1).

B. Approach

The fact that forest landscape processes operate at multiple temporal and spatial scales makes the related research a more challenging task (Levin 1992). The long-lasting legacy of natural and human disturbances in the forest landscape is one example of the magnitude of the spatial and temporal scales involved in the forest landscape (Foster et al. 1998, Walling et al. 1994). Consequently, the approach for the investigation of changes in the forest landscape in response to the relationships of the changing ownership parcelization and other related forest landscape processes must consider spatial and temporal scales accordingly.

The spatially interactive nature of the processes that characterize forest dynamics is in the domain of landscape ecology (Turner 1989, Urban et al. 1987). In addition, the scope of forest dynamics in this study requires the incorporation of extensive spatial and temporal scales and the interactions between ecological processes, in which human intervention plays one of the key roles in the landscape dynamics. Landscape ecology, as a systematic approach that integrates human- and ecological processes in multiple spatial and temporal scales, provides a valuable framework for addressing the questions asked in this study (Forman and Godron 1986, Gardner et al. 1987).

In particular, forest modeling has proved to be a useful tool for landscape ecology, because it allows researchers to compare alternative scenarios and provide quantitative evaluation of the responses from the landscape over large spatial and temporal scales. Especially with the recent advance in computer and GIS technology, spatial modeling, which previously had limited scope and application due to intensive computational requirements and lack of reliable spatial data input, is now widely used for research related to complicated landscape dynamics that involve natural and anthropogenic disturbances. Most of all, modeling can help managers and policy makers test and evaluate alternative forest management strategies that involve interaction of multiple spatial processes over a long period of time, most such alternatives are impossible to evaluate with field studies.

Historically, a number of forest models have been developed to simulate the forest change. Gap models, such as JABOWA/FORET, that can simulate species interactions at scales from a tree-size plot to stand sized grid (0.01-100 ha), have been extensively used for simulating forest change by applying life history parameters of tree species and site conditions (Botkin et al. 1972, Shugart 1984). Although gap models best describe the processes occurring at a small spatial scale, an entire forest stand simulation has been demonstrated by applying multiple singe plot runs. However, the lack of spatial interaction and disturbances, as well as the tremendous computational load when applied to large areas, limits its use for forest landscape modeling.

Individual tree-based models, such as SORTIE (Pacala et al. 1993), are able to simulate stand-level regeneration, succession, disturbance, and ecosystem processes in a spatially explicit manner. However, the high cost in data preparation, parameterization, and computational need limits its utility in a regional context. Disturbance models, such as DISPATCH (Baker et al. 1991), focus on spatially dynamic disturbances by modeling long-term fire disturbances in forest landscapes over large areas. For example, DISPATCH simulates fire occurrence and spread based on cover types as a state variable representing the fire probability. However, such models are limited by the static nature of the forest cover types over time, as well as the simplified state variables that define the landscape. Therefore, these models are not capable of simulating the spatially interactive processes that changes the vegetation types and age structures, which may in turn affect the disturbance regime.

LANDIS (He and Mladenoff 1999, Mladenoff and He 1999), a spatially explicit and stochastic forest landscape model, uses the interactions of tree species life history characteristics, site conditions, and natural and anthropogenic disturbances to simulate succession and disturbance dynamics. Being a raster based simulation model, LANDIS can adapt to a range of spatial scale of interest by adjusting the cell size, and by tracking the absence/presence of tree species age cohort in each cell, the model provides a representation of the forest dynamics in a landscape scale while retaining computational efficiency. LANDIS simulates multiple spatially dynamic processes, such as harvest events, fire and wind disturbances, and biological disturbances (He and Mladenoff 1999, Gustafson et al. 2000, Sturtevant et al. 2004). LANDIS has moderate requirements for input parameters, and produces moderately detailed results at landscape scales (over 10,000 ha), and over long periods of time (up to 500 years).

However, no single modeling approach can handle the entire ecological processes involved in forest landscape dynamics across all spatial and temporal scales. Therefore, a forest landscape model is usually selected based on how well it can deal with the particular questions being asked. For this study, LANDIS is a suitable tool for the spatial scales (two watersheds, > 780,000 ha) and temporal scales (> 100 years) involved, as well as the questions related to forest succession, disturbance dynamics and the effects from human induced disturbances in the forest landscape.

In addition, evaluating the effects of private ownership parcelization requires better understanding of the nature of the parcelization process itself. For example, a parcelized ownership landscape can be characterized by the shape, size distribution, and the spatial pattern of the ownership parcel, which can significantly affect the spatial distribution of the management practices on a landscape. In addition, the harvest methods and intensities associated with parcel size class can also substantially influence the forest landscape.

To address these issues, this dissertation uses a modeling approach to explore the ownership parcelization and its effects on the forest landscape. Various methods are used to characterize and develop a model to represent parcelized private ownerships and the associated forest management practices. Fidings related to parcelization and to forest management practices are combined in a forest landscape model, LANDIS, to investigate their joint effects and interactions.

C. Chapter outline

This dissertation is comprised of three major chapters, each of which addresses different issues regarding the process of the private ownership parcelization and its effects on the forest landscape in the Black- and St. Francis River watersheds.

Chapter 2 presents a method for generating landscape-scale patterns of parcelized ownership. A stochastic pattern generator, Forest Land Ownership Spatial Simulator (FLOSS), is developed to create ownership boundary maps characterized by parcel shape and parcel size distribution. The performance of the model is evaluated by comparing the generated patterns with the actual boundary patterns. Then an application of the model is demonstrated based on a future projection of parcelization.

Chapter 3 presents an analysis of past trends in ownership parcelization in the study area. The process of ownership parcelization is strongly affected by the underlying PLSS structure, which is characterized by unique parcel size distributions. Therefore, a single statistic, such as mean parcel size or a single probability distribution, is often unable to represent the complexity of the parcelized ownership landscape. Furthermore, identifying the trend in the parcelization process across the entire range of parcel size classes can facilitate identifying particular parcel size classes that may be more vulnerable to further parcelization. A Markovian transition probability matrix model is used to identify the strongest trends in parcel size changes and to calculate the stable stage distribution. In addition, the large amount of land acquisition by a particular private landowner, the Pioneer Forest, is identified as a special case, and its influence on the parcelization process is evaluated.

In chapter 4, the effects from harvest events in a parcelized ownership landscape, accompanied by potential changes in harvest intensities, are investigated by using a forest landscape model LANDIS. Simulation scenarios are constructed using a 2×2 factorial design based on two levels of ownership parcelization and two levels of harvest intensity levels, and analyzed by multivariate analysis of variance (MANOVA). Quantitative measures are made of the total area and landscape metrics (area-weighted fractal dimension and aggregation index) for each of the 4 dominant species groups (maple, white oak, red oak, and shortleaf pine group) and 4 age classes (1–30 years; 31–60 years; 61–100 years; and ≥ 101 years), aggregated into 3 different temporal stages (short-term effect: 10-50 years; mid-term effect: 60-100 years; and long-term effect: ≥ 110 years) for the analysis.

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Chapter II. Simulating spatial patterns of parcelized private forestland ownership in the Missouri Ozarks, USA.

A. Introduction

Increasing parcelization of forestland ownership has been a national trend in the United States over the past several decades (Yaffee et al. 1996). A similar trend has also occurred in Missouri, where the number of non-industrial private forestland owners increased from 81,000 in 1978 to 300,000 in 1993. Among the latter, 45% of the owners had properties that were smaller than 4 ha (10 acres) and 79% owned properties smaller than 20 ha (50 acres) (Birch 1996, Hahn and Spencer 1991). Currently nonindustrial private forestland owners hold 82% of Missouri's timberland area (4.6 million ha), and more than half of the parcels comprising this acreage are smaller than 40 ha (100 acres) (Moser et al. 2003, USDA 1989). Such a high degree of forestland ownership parcelization raises concerns in light of studies indicating that human influence is one of the most significant factors affecting forest landscape dynamics, and that the management practices from different landowners can result in complex ecological impacts that are difficult to predict (Botkin 1990, Spies et al. 1994, Turner et al. 1996, Liu 2001). In addition, a large number of landowners with a diversity of interests can result in a maze of uncoordinated management practices, which can deepen the uncertainty of future forest composition and structure by introducing complex forest management regimes at the landscape scale that vary in extent, intensities, and spatial implementations.

While numerous studies have been conducted regarding the effects of habitat fragmentation on biodiversity, wildlife habitat value and wildlife behavior (Bancroft et al. 1995, Debinski and Holt 2000, Fahrig 1997, Radeloff et al. 2000, Tinker et al. 1998, Trzcinski et al. 1999, Villard et al. 1999), little is known about the effects of land ownership parcelization on forest landscape dynamics (Kurttila et al. 2002, Mladenoff et al. 1995, Wallin et al. 1994).

To properly evaluate the effects of ownership parcelization, it is imperative to establish a reliable simulation capability for land ownership patterns. However, analyzing the effects of ownership parcelization is subject to many of the same challenges faced by other landscape scale studies, including empirical and experimental limits due to the enormous spatial and temporal scales involved (Hargrove and Pickering 1992). In particular, obtaining accurate ownership boundary maps over a large region can be an extremely expensive process, involving labor intensive digitizing and GIS processing. Even when a reliable land ownership boundary map is readily available, it can be argued that such a map does not provide sufficient information, given that reliable inference regarding the effects of land ownership patterns cannot be obtained when a sample is limited to a single realization of a certain spatial extent (Fortin et al. 2003). The particular land ownership pattern that is observed is merely a single case of the various possible patterns, and therefore incapable of demonstrating the range of variability needed for modeling. The use of real land ownership pattern is, therefore, insufficient for evaluating the effects of ownership parcelization due to the inability to obtain the required number and range of possible patterns.

A neutral model can provide a useful tool for generating spatial and temporal variations in land ownership patterns. Neutral landscape pattern models have been developed in the past two decades to facilitate interpreting real landscape patterns (Gardner et al. 1987, Gardner et al. 1991, O'Neill et al. 1992, Hargis et al. 1998, Saura and Martínez-Millán 2000). These neutral models are designed to generate neutral ('null') landscape patterns that do not reflect any specific process, so that they can be used to test the existence of meaningful patterns in actual landscapes (Gardner et al. 1987). Such models are based on simple random maps where occupation in a two dimensional landscape is randomly determined by probability *p* (Gardner et al. 1987). Further development of neutral models has incorporated: (1) a hierarchical structure to reflect scale-dependent relationships in the landscape (O'Neill et al. 1992); and (2) a midpoint displacement fractal algorithm for multifractal maps at specified levels of aggregation (Gardner 1999). Another variant such as SIMMAP (Saura and Martínez-Millán 2000) uses a MRC (modified random cluster) method, which is a combination of simple percolation and clustering of neighboring pixels. On an overall basis, therefore, and in contrast to the simple neutral model, the more recent neutral models are capable of generating 'realistic' landscape patterns that resemble natural landscapes.

A simulation model for land ownership pattern should be able to reproduce the variability of actual ownership patterns with respect to the spatial characteristics of composition and configuration. The output from such a model could also subsequently be used as an input to other forest landscape models for evaluating the effects of land ownership parcelization on forest landscape dynamics. Ideally such capability would enable a better assessment of the impact of ownership parcelization by simulating the full range of variability of the forest landscape responses according to various levels of land ownership parcelization.

Although existing neutral models provide a solid framework for analyzing various landscape patterns, they generally fall short in generating realistic land ownership patterns. First, ownership patterns are likely to display different levels of aggregation among different ownership types (e.g. private and public owners occupying a single landscape). The limited transactions, various applicable regulations, and contiguous government acquisitions generally result in publicly-owned forestland being much less fragmented in terms of ownership than are private forestlands. However, existing neutral models (e.g. RULE and SIMMAP) are not capable of simulating separate levels of aggregation among different patch types in a single landscape. In these models control of aggregation level in a landscape is limited to a single parameter that is applied over the entire landscape. For example, actual land ownership patterns are usually comprised of private forestland with many small parcels and fewer large parcels, and industrial or public forestland with many larger parcels and fewer small parcels intermingled together in a single landscape. However, this kind of combined ownership landscape cannot be generated using a single aggregation parameter such as that applied by the existing neutral models. In addition, land ownership patterns may exhibit different shape characteristics compared to natural landscapes. In particular, we presume that most of the forest ownership parcels in the United States have rectilinear shapes (especially in the Midwest and the Western United States) because of their original creation in accordance with the public land survey system (PLSS) adopted by the federal government. The PLSS has been used as a method for managing the surveying, sales, and settlement of the land in the public domain since the Land Ordinance of 1785 (White 1983). The basic unit in the PLSS is a 10 km(6-mile) square township, which is divided into 36 2-km (1-mile) square sections (260 ha, 640 acres). Sections are further divided into half-, quarter-, half-of-quarter-, and quarter-of-quarter sections, with areas of 130, 65, 32, and 16 ha (320, 160, 80, and 40 acres), respectively.

The PLSS has played a formative role in the land ownership patterns in the United States, given that the spatial layout of most homesteads granted to settlers and subsequent land transactions were based on this system (White 1983). This reflects a more general historical relationship between the shape characteristics of PLSS and the actual patterns of land ownership. On an overall basis, it may be recognized that although the later variants of neutral models have improved their capabilities for generating more 'realistic' natural landscape patterns, they still do not accurately reflect the actual patterns of land ownership. Due to these limitations, the existing neutral models and their variants are limited in their ability to represent the aggregation levels among land ownership types or to approximate the shape characteristic of ownership parcels imposed by the PLSS structure.

In light of the above, a model was developed to simulate land ownership patterns, including the capacity to apply multiple aggregation levels and create parcels with PLSS-like shapes. The goal was to develop a tool that can realistically generate ownership patterns within the framework of neutral models, thus facilitating its use in generating numerous land ownership pattern realizations for analysis and modeling.

The objectives of this chapter were to: (1) develop a computer simulation tool – Forest Land Ownership Spatial Simulator (FLOSS) – that is capable of stochastic simulation of forest land ownership patterns in Missouri and possibly elsewhere in the United States; (2) evaluate how well FLOSS represents actual patterns of the land ownership; and (3) demonstrate the ability of FLOSS to generate land ownership patterns characterized by varying degrees of parcelization.

B. Materials and Methods

1. Model description

FLOSS is a raster-based model designed to simulate a variety of land ownership patterns, especially those based on the PLSS structure. The program uses a recursive algorithm to generate land ownership parcels. The model generates landscape patterns by controlling the aggregation level of separate ownership types. In particular, the aggregation level control is implemented by specifying the patch size distribution of each patch type that is to be generated. Given that the patch size distributions are not identical among different ownership types (e.g., public ownerships tend to have much larger parcels than private ownerships, see Figure II-1 and Figure II-2), the model is designed to be capable of generating a combination of several ownership types with different patch size characteristics. The shape control in the algorithm reflects our observation that PLSS-based ownership parcels generally manifest simple rectilinear shapes across all patch sizes and ownership types. It should be noted that FLOSS is developed as a pattern generator, which is not capable of modeling temporal sequences, e.g. changes in land ownership patterns over time.

The user provides a parameter in ASCII text format that is comprised of a patch ID number, a patch size, and the number of parcels to be generated by the given patch ID and patch size (Table II-1). Since there is virtually no limit to the number of input patch types, a potentially unlimited assortment of combinations of ownership type and size distributions may be used.

In generating a particular patch, FLOSS determines the location of an initial pixel based on random placement and a target patch size. The model first randomly selects a pixel that is not already assigned to any other patch type and uses a recursive algorithm to check whether the empty patch in which the pixel is located is large enough to allow the patch to grow to its target size. For example, when generating a 500-pixel patch on the landscape, the model ensures that the ‘empty patch’ including the randomly selected pixel is greater than 500 pixels in size. If not, the model will reject the pixel and look for an alternative initial selection. To avoid an infinite recursive loop in the event there are no empty parcels of requisite minimum size in the landscape, a limit is imposed on the search for an initial pixel with an acceptable ‘empty patch’ – up to the number of pixels in the landscape, e.g. 1 million searches for a 1000×1000 pixel landscape. Then FLOSS will use the largest ‘empty patch’ available to create the patch and proceed to the next patch creation request, and this creation is recorded in a log file for future reference. It should be noted that this algorithm may yield unrealistic results under specific circumstances. The algorithm works well in landscapes with a diversity of patch sizes, such as those with both large public land parcels and numerous smaller private parcels. However, if the user is trying to create a landscape consisting primarily of large parcels, the simulation can result in greater number of smaller parcels than expected.

Once the initial pixel has been selected, FLOSS will ‘grow’ the patch to its target size as dictated by the parameter file. In order to generate PLSS-based patch shapes, the growth algorithm of FLOSS was designed to maintain patch shape simplicity (Figure II-3). The growth is a pixel-by-pixel process in which a new adjacent empty pixel is randomly selected and added in any of the four-neighbor directions. However, only the pixels that are closest to the initial pixel can be selected to ensure a simple patch shape (Figure II-3). Although simple, this rule – together with the underlying raster geometry – was very effective in maintaining PLSS-like patch shape characteristics such as relatively straight borders and rectilinear geometry. The cell selection and patch growth processes are iterated until the target frequency of the specific patch type and size is fulfilled (Table II-1), and then the next parameter input line is processed. FLOSS will generate a particular number of parcels with ID and size based on the order furnished in the input parameter (Table II-1). The final output is an ASCII text raster map, which can be converted directly to various GIS formats for analysis and various applications. The overall flow diagram for FLOSS is shown in Figure II-4.

FLOSS processes the input parameter file in a line-by-line manner; thus the parcels that appear earlier in the parameter file are also created earlier. This requires the user to decide on a patch generation order. Given that FLOSS creates parcels by 'growing' them, it was discovered in developing the model that the creation of smaller parcels in earlier stages of the simulation process may not leave 'empty parcels' of sufficient size to accommodate the growth of larger ownership parcels, thus leading to landscape patterns in which patch size distribution is skewed towards the smaller end. To address this problem, parcels were created in the order from larger to smaller size for this study.

C. Model parameterization

1. Estimating patch size distributions

The model was tested in the Black and St. Francis River watersheds in the Ozark highlands of southeastern Missouri, where an increasing degree of parcelization in the ownership of forest land has been observed over the past 30 years (Figure II-2). To quantify the current level of ownership parcelization, we randomly selected 15 sample blocks (4.8×4.8 km) from the combined watershed area and utilized plat books to digitize boundaries of all property tracts that were at least partly included within the selected sample blocks (Anonymous 1999, 2000a, 2000b, 2001a, 2002b). All tracts, including those owned by the same individual or group, were individually identified as parcels. Each digitized property tract as shown in the plat books was also categorized by landownership type as either private non-industrial, private industrial, or public (Figure II-2). A total of 1306 parcels (i.e., tracts) were identified and digitized in the sample blocks. Of these, 1239 were under private non-industrial ownership, 14 were owned by private industrial entities, and 53 were under public ownership. Patch sizes ranged from 1 to 4345 ha, with the mean size of 56 ha and median of 16 ha. Only 61 parcels were larger than 200 ha, resulting in an extremely skewed patch size distribution (Figure II-5).

The patch size probability distributions for private and public land ownerships acquired from the digitized plat books were directly used as FLOSS input parameters. However, in order to derive different patch size distributions for comparing different levels of ownership parcelization, we estimated the Weibull probability function parameters based on the sizes of the digitized property parcels to represent the tract size distribution of private and public ownership types. The Weibull distribution was used because it is simple to fit, while also versatile and powerful enough to provide various continuous probability distributions (Dubey 1967, Evans et al. 1993).

The Weibull probability density function for random variable X of the two-parameter model is:

$$f(x) = \left(\frac{cx^{c-1}}{b^c}\right)\exp\left[-\left(\frac{x}{b}\right)^c\right](b > 0, c > 0)$$

where b is the scale parameter and c is the shape parameter (Evans et al. 1993). With only two variables, the Weibull distribution can display a variety of probability distributions. The curve follows a reverse-J shape when $c < 1$, and an exponential shape when $c = 1$. When $1 < c < 3.6$ and $c > 3.6$, the curve shows a unimodal distribution with positive and negative skewness, respectively; and when $c \approx 3.6$ the curve resembles a normal distribution.

We used the maximum-likelihood method in the MASS package of R (version 1.7.1) to estimate the shape and scale parameters $\hat{c}$ and $\hat{b}$, respectively, which are simultaneous solutions of the following equations (Wu 2002):

$$\frac{\sum_{i=1}^{n} x_i^{\hat{c}} \ln x_i}{\sum_{i=1}^{n} x_i^{\hat{c}}} - \frac{1}{\hat{c}} - \frac{1}{n}\sum_{i=1}^{n} \ln x_i = 0$$

$$\hat{b} = \frac{\sum_{i=1}^{n} x_i^{\hat{c}}}{n}$$

where x is a quantile and n is the number of quantiles. Since the land ownership patch size distributions in this study area were extremely skewed toward smaller patch sizes, we used the natural log of patch size as quantiles for parameter estimation. The patch size distribution generated a natural log range from 0 to 8.5, and we decided to use 17 quantiles by using a .5 natural log interval. Although somewhat arbitrary, a natural log interval was determined so that the major variations in the distribution could be well represented without complicating the parameterization procedure. A log interval of .5 provided sufficient resolution for representing the overall shape of the patch size distribution.

One noticeable feature of the patch size distribution is the high peak in the 6th quantile in both land ownership types (Figure II-6). We believe this is a result of the underlying history of the PLSS structure. The peak in the 6th quantile (approximately 400 acres) corresponds to the size between a 'half-section' (320 acres) and a 'section' (640 acres). From a historical perspective, limited pressure for further subdivisions in sections with low resource and economic value, in conjunction with parcel consolidation by timber companies during the lumber era may have caused this peak in the 6th quantile (Dr. Walter Schroeder and Dr. Mark Cowell, University of Missouri-Columbia, personal communication). Such a peak, while meaningful, can distort the Weibull parameter estimation of the patch size distribution if used directly, which in turn can lead to gross overestimation of smaller parcels. Therefore, we decided to use the mean frequency of the 5th and 7th quantile as the frequency for 6th quantile for the Weibull parameter estimation, while keeping a record of the ratio of this modification. After the Weibull estimation of patch size distribution was completed, we used the inverse of the ratio of the modification to introduce the frequency peak of the 6th quantile, and use it for FLOSS simulation.

Another problem associated with the use of a Weibull estimation arises from the different sample sizes for each land ownership type (private: n = 1253; public: n = 53), which can result in biased shape parameter values. We used the bootstrap method to simulate a sample size for public lands equivalent to that observed for private lands and in the process eliminate the distortion in the estimated Weibull shape parameter. The bootstrap method is used in statistical inference by creating an arbitrary number of replicates $\hat{\theta}^*$ (Efron and Tibshirani 1993) which, in our case, is the number of private land ownership parcels. Given that there were 1253 private (industrial and non-industrial) parcels, we used the bootstrap method to create $\hat{\theta}^* = 1253$ for the public land ownership type. We made 10,000 iterations of bootstrap sampling for the modified public patch size distribution, which was used to estimate the Weibull shape and scale parameters by using maximum-likelihood fit (Venables and Ripley 2002).

2. Estimating land ownership type proportion

For comparison of the simulation results to the actual landscape, we generated a 'combined' landscape including both private and public parcels. This required an estimate of the proportions of the entire landscape occupied by private and public ownership parcels. However, the proportions from our sample blocks could not be used directly because they overestimated the proportion of the public ownership parcels. The larger size of most such parcels that were digitized extended beyond the boundaries of the small sample cells (4.8×4.8 km) exaggerated the proportion of public land in the landscape to approximately 60% (Figure II-2). Therefore, we used the proportion of public land from the entire study area, including all lands owned by the Missouri Department of Conservation, United States Forest Service, and the Missouri State parks (Figure II-1), which was approximately 24% of the landscape.

3. Parameterizing future land ownership parcelization

A pilot study of evaluating FLOSS behavior under different parcelization levels was conducted to represent possible future private land ownership parcelization. Simple linear regression was used to project future land ownership patch parcelization. This was based on the decreasing mean property size per landowner (not the mean patch size as measured in our study area) from 59.9 ha in 1978 to 18.2 ha in 1993 (Birch 1996):

$$MPS(t) = 59.9 - 2.78t$$

where *MPS(t)* is the mean property size at year *t*. This is obviously a simplification of the reality, since the rate of parcelization may change over time and may also be different among different patch sizes. Ideally, this projection should be based on the historical change over multiple temporal phases in the full distribution of patch sizes. However, a source of such data was not available at a reasonable cost.

In addition, mean property size was interpreted as mean patch size for the future projection. Although it is not unusual for a single landowner to own multiple parcels of properties, the dramatic increase in the number of landowners (nearly 4-fold in 15 years) and the decrease in mean property size (Birch 1996) suggests that the parcelization is mainly due to new owners with small-sized properties. Therefore, using change in ownership size as a surrogate for change in patch size was deemed reasonable for this study.

Based on an initial estimate, private land mean patch size for ownership was 56 ha, future mean patch sizes were projected as 42, 34, and 28 ha for 5, 8, and 10 years, respectively. Since only mean patch sizes were utilized, it was assumed that the size distribution would maintain its shape in the future. Therefore, for the Weibull fit of the future distribution, this involved moving the current ownership patch size distribution towards the smaller end of the distribution by one quantile, and then estimating the shape and scale parameters with a zero base for the respective mean patch sizes (Figure II-7). We then modified the value of the 6^{th} quantile to represent the peak that was discussed above. It is important to emphasize that a realistic patch size distribution can only be estimated from the change in the full distribution of patch sizes as mentioned above. Nevertheless, due to the limited patch data available, the procedure described above was necessary.

As there is a significant amount of public land in this study area, we included the simulation of public land based on the proportion of the area of private- and public land. The same patch size distribution was used for simulating future public land, as no significant change in public land ownership was assumed for the period of our projection. Based on the current public land map, the simulation was conducted with the current proportion of private and public land – 76% of private and 24% of public ownership area – with their respective patch size distributions.

4. FLOSS simulations

One hundred replications of FLOSS simulations were undertaken for each patch size distribution scenario (current and three future parcelization levels). Simulations were generated on a raster grid of 1000×1000 pixels. The pixel size was determined using the size of a 'quarter subsubsection' in the PLSS system (201×201 m = 4 ha = 10 acres). Although there are no restrictions on landscape or pixel size for FLOSS simulations (except for hardware limitations such as lack of physical memory or restricted memory allocated for stack size by the operating system), it was decided not to simulate the smallest property patch size observed (≈ 1 ha). The decision was based on the limited number of such parcels observed (only 140 digitized parcels were smaller than 4 ha in the study sample blocks) and the dramatically reduced computing intensity required for the simulation.

5. Evaluation of simulation results

Landscape indices measure both spatial and aspatial characteristics of landscape patterns in a quantitative perspective (Turner 1990). Among the variety of indices available, patch density, area-weighted mean shape index (McGarigal and Marks 1994), fractal dimension index (Milne 1988, O'Neill et al. 1988), and aggregation index (He et al. 2000) were utilized to evaluate area, shape, and configuration-related characteristics, respectively. We used FRAGSTATS (version 3.3, McGarigal and Marks 1994) to calculate the above landscape indices at both landscape- and class-level. Landscape-level indices represent the overall spatial characteristic of the entire landscape regardless of the patch type present, while class-level indices show the spatial characteristic with each patch type explicitly recognized (McGarigal and Marks 1994).

In this study, patch size classes for each land ownership type were used for class-level analysis. Each of the landscape indices was calculated for simulated and actual landscapes. However, it can be difficult to compare real and simulated landscapes directly due to differences in scale (Turner et al. 1989). For example, while sample blocks encompassed an area of 4.8×4.8 km, the extent of the simulated landscape was 201×201 km, which is more than 1700 times the area of a sample block. Therefore, it is likely that results will be strongly affected by the scale differences incorporated in calculating landscape indices. For that reason we decided to calculate the landscape-level indices from randomly selected windows that are the size of sample blocks (4.8×4.8 km), which would produce results covering identical spatial areas. The same window size was also applied to the sample blocks for FRAGSTATS calculation to match the analysis extent. The digitized sample blocks were converted to grids with 30×30 m resolution, and the simulated landscapes were resampled to the same cell size to match the resolution scale. It should also be noted that FRAGSTATS uses all available parcels present in the landscape regardless of patch type when calculating landscape-level indices. Thus, both private and public ownership types were included for the landscape-level comparisons. However, given that public land ownership was assumed to remain constant for future projections, we limited our comparison to private ownership patterns for the class-level landscape indices.

Patch density (PD) is an area-related landscape index equal to the number of parcels divided by total landscape area. Thus, landscape-level PD reflects the total number of parcels in the entire landscape, while class-level PD can indicate how well FLOSS generated the parcels after the given size distribution for each patch type. However, it should be noted that multiple parcels of the same type that are adjacent to one another are regarded as a single patch, which may result in underestimation of PD values that were actually created in the simulation.

To measure the patch shape complexity, area-weighted mean shape index (AWMSI) was used for landscape-level analysis, and fractal dimension (FD) was used for class-level analysis. Shape index is based on the relationship of the actual perimeter and the minimum perimeter for the given patch size (number of pixels). The value ranges from 1 for a maximally compact patch, i.e., square, with higher values without limit with increasing shape complexity. However, since it is well known that shape index is highly dependent on the scale of the analysis, comparing shape indices of different patch size classes may be problematic. Therefore, fractal dimension (FD) was used for class-level analysis of patch shape complexity. Fractal dimension represents the complexity of the patch shape based on the perimeter-area fractal analysis of the patch (Milne 1988, O'Neill et al. 1988). The index value ranges from 1 to 2, approaching 2 with greater shape complexity, and approaching 1 with simple shape such as a Euclidean geometry (e.g., square, circle). Although fractal dimension is known to be relatively independent of the scale of the analysis, this is only accurate when certain pattern-process relationships are held within particular scale domains (Wiens 1989). Therefore, although each patch size class incorporate parcels of similar size, the interpretation of the FD comparisons should be carefully made.

Aggregation index (AI) is a raster-based configuration index which quantifies the aggregation level of each patch type (class-level) or all parcels throughout the landscape (landscape-level) (He et al. 2000). AI is calculated from an adjacency matrix, which is based on the number of shared edges of the parcels from each patch type in the landscape. AI indicates if certain patch types are placed side by side (aggregated) or are situated apart from one another (dispersed) in the landscape. AI reaches 100 when the pixels of the specific patch type are sharing the most possible edges (thus forming a single large patch), and the index reaches 0 when pixels of the given type are completely dispersed as separate single pixels throughout the landscape.

All comparisons for the landscape-level indices are conducted using one-way ANOVA tests, and for the class-levels indices means and standard error bars are presented in the result figures.

D. Results

1. Comparison of actual and simulated land ownership patterns

The Weibull function, aided by the bootstrap sampling approach, produced a reasonably good fit for the actual patch size distribution for land ownership (Figure II-6). The fitted patch size distribution characterized the more fragmented private land ownership pattern somewhat more accurately than the public land ownership parcels. For the private ownership distribution, smaller patch sizes ($< 10^1$ ha) were slightly underestimated, while larger parcels ($\geq 10^1$ ha) were slightly overestimated, but overall the fit was good. However, because of the relatively irregular shape of the parcels, the fit for the public ownership distribution was not as close as that for privately owned lands. It is clearly evident, for example, that the very low value at quantile 10 did not fit well through the use of a single Weibull distribution function given that the actual distribution of the public land ownership is almost bimodal in form. This indicates the limit of using a single function probability distribution to represent landscapes with complicated patch size distributions, such as landscapes with a small number of large parcels dominated by public land.

The shape and scale parameters for private land ownership distribution were 2.469 and 3.184, respectively, which were lower than those of 3.121 and 5.150 of public ownership. Chi-square tests indicated no significant difference between the observed and the estimated patch size distributions for both private ($\chi^2 = 0.0014$, $df = 15$, $p \approx 1$) and public ($\chi^2 = 0.0021$, $df = 14$, $p \approx 1$) land ownership, indicating a good fit.

For the projected 5-, 8-, and 10-year scenarios for future parcelization of private land ownership, the estimated Weibull shape parameters were 2.042, 1.814, and 1.633, respectively; and scale parameters were 2.765, 2.400, and 2.200, respectively. The resulting patch size distributions represented the increasing numbers of smaller parcels that characterize more highly fragmented landscapes (Figure II-7). FLOSS input data consisting of patch size distributions for each future parcelization level was based on single estimated Weibull probability distributions (Table II-1). However, results show that using the unimodal form of a single Weibull distribution function can result in failure to include the largest parcels, since they tend to be placed at the tail of the distribution, thereby resulting in near to zero probability. Furthermore, the extremely large public land parcels in the focal watersheds (Figure II-1) suggest that using the Weibull function is limited for estimating the public land ownership patch size distribution on a regional scale.

The simulated patterns of land ownership (Figure II-8.a) were visually similar to the actual ownership patterns in the sample study cells (Figure II-1). The mean patch size of the simulated patterns was slightly smaller than that of actual ownership patterns, but the difference was not significant ($p > 0.5$). Landscape-level patch density was significantly higher for simulated patterns than for the real patterns ($p < 0.05$) (Table II-2) which was possibly caused by the greater level of dispersion of the parcels. Higher patch dispersion of the simulated patterns was a prevalent phenomenon, and will be discussed in detail later in this study. Class-level PD levels showed similar patterns between actual and simulated land ownership patterns (Figure II-9.a). However, it is clear that PD values of smaller parcels are overestimated in the simulation results. We suspect that the main reason for this discrepancy is the tendency of the smaller parcels to be located contiguous to one another in the actual land ownership pattern (Figure II-2), which directly relates to the level of aggregation of the parcels. Highly aggregated parcels may result in lower patch density, as identical contiguous parcels are considered to be a single patch, which is often the case in the actual ownership landscape. In contrast, since FLOSS generates parcels of the same type in a more dispersed way because of its random placement algorithm in selecting the initial pixel, the simulated patterns resulted in lower aggregation and thus greater PD values.

Landscape-level area-weighted mean shape index (AWMSI) was slightly higher in the simulated ownership patterns than the actual patterns (Table II-2), although the difference was not significant ($p > 0.5$). Overall, such low values suggest that the simulated parcels generally have relatively simple shapes, reflecting the PLSS-based rectangular shapes of the actual land ownership parcels. Class-level FD indicated that FLOSS tends to oversimplify the shape complexity of the largest and smallest parcels, while slightly increasing the shape complexity of intermediate-sized parcels (from 10 to 100 ha) (Figure II-9.b). A possible explanation for this phenomenon may lie in the patch generation order. Since larger parcels were generated earlier in the simulation, they tended to have simpler shapes due to less constraints associated with patch growth. However, once the landscape starts to become occupied by parcels, the growth of subsequent parcels often becomes constrained as they are ‘squeezed’ into the remaining empty space, resulting in relatively greater shape complexity. This may start occurring abruptly during the simulation as evidenced by the sudden increase of variability in the patch size class right below 1000 ha. As the model generates smaller parcels, FD variability gradually diminishes, indicating that such spatial constraint becomes less of a problem in the generation of smaller parcels. Then, since the smallest parcels are made from very few pixels (e.g. patch size class 15, 16 and 17 are made of 3, 2, and 1 pixels, respectively), the shape complexity becomes limited thus resulting in lower FD values and small variability (Figure II-9.b).

The simulated landscapes had a significantly lower aggregation index (AI) than did the sample blocks at the landscape-level ($p < 0.01$) (Table II-2) and most of the size classes at the class-level (Figure II-9.c). The overall trend of lower AI values for smaller patch size classes was expected, because the AI is based on the number of shared edges of the same type of pixels in the patch (He at al. 2000). It is interesting that the difference of AI between the actual and simulated patterns increases towards the smaller patch size classes. This is due to the difference in the arrangements of the smaller parcels between actual and simulated ownership patterns. The smaller parcels from the actual ownership patterns are often found right next to one another, since many of them were created by further division of a single large tract by new private landowners purchasing small tracts of land (Figure II-2), resulting in higher AI values. In contrast, the smaller parcels in the simulated patterns were dominantly influenced by the simple random placement algorithm, which was further emphasized by the absence of growth algorithm. This created a highly dispersed pattern of the smaller parcels in the simulated ownership patterns, which resulted in lower AI values compared to the actual ownership patterns (Figure II-8).

2. Future land ownership parcelization

Mean patch sizes were significantly smaller in ownership patterns with higher parcelization ($p < 0.01$) (Table II-2). Landscape-level patch density (PD) was slightly higher in the simulated land ownership patterns with higher parcelization ($p < 0.05$) (Table II-2). At the class-level, PD values across most of the patch size classes were similar across all parcelization levels (Figure II-10.a). However, smaller parcels (< 10 ha) in higher parcelization levels showed higher PD values, possibly caused by the relationship between the percentage of land cover and the actual number of parcels that were generated for each of the patch size classes. Specifically, for patch size classes smaller than 10 ha, the differences in the percentage of land cover (Figure II-6) are amplified because of the smaller patch sizes – it requires more smaller parcels to fill the given area – resulting in substantially different number of parcels to be generated, which in turn produced the significant differences in PD values.

Landscape-level area-weighted mean shape index (AWMSI) values were slightly lower with higher parcelization levels ($p < 0.05$) (Table II-2). Class-level fractal dimension (FD) patterns were very similar among all parcelization levels, where the largest and smallest patch size classes exhibited very low shape complexity (Figure II-10.b). However, for the smallest patch size classes (< 10 ha), the FD values from higher parcelization levels were slightly greater than those from lower levels. This may be related to the aggregation level of the parcels, which will be discussed later in more detail. The pattern of gradually decreasing variability of FD towards the smaller parcels, which was discussed when comparing the actual and the simulated patterns, was again observed in all parcelization levels (Figure II-10.b). In addition to this observation, it is interesting that the variability within the same patch size class (for parcels approximately from 100 to 1000 ha) was smaller in lower parcelization levels. We believe this is partly caused by the FLOSS algorithm. In particular, in simulating lower parcelization levels, the remaining empty space rapidly decreases as the landscape is quickly occupied by larger parcels in the earlier stage of the simulation, exerting greater spatial constraints – thus greater shape complexity – on the subsequent parcels even in the same patch size class, which in turn results in greater variability. On the contrary, in higher parcelization levels with numerous smaller parcels, there is smaller variability in shape complexity because of the lack of spatial constraints.

Landscape-level aggregation index (AI) values were significantly different among different parcelization levels ($p < 0.01$), but the extent of the differences was nearly negligible (Table II-2). For all parcelization levels, class-level AI values were lower at the smaller size classes, and the curves were very close to one another among almost all patch size classes (Figure II-10.c). AI values were greater for the 5- and 10-year future landscapes at the smallest patch size classes (< 10 ha), which is also observed in the FD curves (Figure II-10.b). Such correlation between the shape complexity (FD) and the aggregation level (AI) was also observed when the actual and simulated ownership patterns were compared previously (Figure II-9.b, c). This phenomenon reflects the indirect effects of the input parameter (patch size distribution) on the resulting shape and aggregation characteristics of the simulated patterns. For example, in FLOSS, the shape of the parcels cannot be directly controlled by the user, but instead is determined by the patch growth algorithm designed to maintain the rectangular PLSS structure. Meanwhile, the input parameter exerts indirect control over the aggregation level of the parcels to be simulated. The interaction of these two creates a strong structural bias in the resulting patterns, such as a strong trend of shape complexity or aggregation levels in particular patch size classes as shown in these results.

Results suggest that FLOSS simulated different levels of ownership parcelization with respect to its aggregation level. However, the strong emphasis on the patch shape control – PLSS structure – in FLOSS algorithm, in conjunction with the input parameter – patch size distribution – created results that clarify the advantages and disadvantages of FLOSS. The lack of shape control by the user limits the use of FLOSS for generating patterns with strong PLSS structure. Therefore, the application of FLOSS is limited to areas with strong historical influences from the PLSS, or with similar highly rectangular patterns. Also, results indicate that shape and aggregation characteristics of the simulated ownership patterns can be sensitive to particular patch size distributions, e.g., landscapes heavily dominated by extremely large parcels. Results also show the potential of FLOSS application for landscapes with highly fragmented ownership patterns, such as those in the Missouri Ozarks. The caveat is to ensure whether the simulated ownership patterns do provide realistic representation of the actual landscape. Efficient and realistic representation of various levels of land ownership parcelization is important when considering the application of FLOSS. Since harvest or management practices can be assigned to individual parcels identified from the FLOSS-generated patterns, sophisticated combinations of forest management scenarios can be implemented in a spatially explicit framework. This in turn would greatly benefit the potential application of forest landscape models capable of simulating harvest disturbances.

E. Discussion

FLOSS was effective in creating land ownership patterns of the Missouri Ozarks that strongly reflects the underlying PLSS structure. Results suggest that FLOSS was able to reproduce the given patch size distribution without seriously compromising the spatial characteristics (e.g., shape, configuration) of the PLSS structure. The performance of FLOSS demonstrates its usefulness in specific geographical locations in the United States, in particular those characterized by extensive land ownership parcelization with patterns strongly related to the PLSS structure. FLOSS was also capable of simulating a combination of different land ownership types across different levels of parcelization. With increasing effort in scenario-based landscape modeling that ventures to answer questions from a resource management perspective, FLOSS may be a valuable tool, especially since it is capable of spatially arranging forest management units in a meaningful and realistic way.

However, it should be noted that the way FLOSS was parameterized is specific to the observed patch size distribution in the study area. Using the Weibull distribution may not be a proper solution for landscapes with extremely large parcels. The Weibull distribution will place large parcels at the tail of the distribution; therefore they will have extremely low probabilities that ultimately will result in an inaccurate representation. Examples of such landscapes include those in which a small number of extremely large parcels of public land ownership exist, such as is characteristic of much of the Western United States. In this case, we advise that input parameters be derived directly from the patch distribution rather than estimated from specific probability distribution functions.

Also, strictly applying a specific probability distribution, or using a single probability distribution function, may not be a viable approach in many areas. For example, the pattern of public land ownership in our study shows that patch size distributions with more than one mode may overestimate certain patch size classes. Also, as shown in the peak of 6th quantile in both private and public ownership distributions, there may be unusually high or low values for a particular patch size class, and each case should be carefully considered based on any historical factors that may have contributed to the development of the ownership pattern.

In addition, the FLOSS algorithm does not take geographical constraints such as topography or hydrological features into account which may affect the spatial pattern or organization of ownership parcels. In this case, the user could utilize a base map to mask out specific areas or better depict spatial constraints so that the patch generation becomes limited in certain areas. This limitation should also be considered for the application of FLOSS to other geographical areas where ownership patterns experienced different historical influences in the past. Especially in the Eastern United States, private land ownership patterns are strongly controlled by metes and bounds, which is highly dependent on geographical constraints. In such case, users should be aware that the design of FLOSS algorithm, which specifically aims to reproduce rectangular parcels strongly related to the PLSS structure, will not be able to accurately represent the ownership patterns.

FLOSS also showed strong structural bias, especially from its growth algorithm, but also from the growth order of the parcels and the resolution applied to the simulation. For example, we suspect that FLOSS-simulated landscapes reflect the spatial constraints imposed from using a specific ‘growing’ order with the given growth algorithm, which influenced the FD measure for small and large parcels. We expect that this effect can be reduced if the largest public parcels are pre-defined on the landscape, assuming the persistent nature of the public land ownership patterns. Also, the resolution will play a critical role in the patch shapes, especially those which are smaller in size. This is inevitable given that single pixels are used as basic growth units in the simulation. Using a resolution the size of the smallest patch did not pose a serious problem in our case since the smallest parcels usually resembled a simple square or rectangular form. However, users should be careful when using FLOSS for areas where the smallest parcels exhibit a certain degree of shape complexity; this may require using a more detailed resolution than the smallest patch size.

In summary, FLOSS is a tool that may be used to create numerous realizations of land ownership patterns for modeling as well as to overcome obstacles often encountered when using actual ownership data in natural resource management applications, especially when such data is unavailable or unreliable. However, it is important to keep in mind the structural bias imposed by the model in making meaningful and reliable simulations. The user should be aware of the strong PLSS structure and the effects of resolution imposed by the model, which may apply to geographical locations in the United States where PLSS played a significant historical role in the formation of private ownership patterns. Spatially explicit landscape models can benefit by using FLOSS to generate large-scale land ownership patterns and to spatially apply a variety of management scenarios. Such applications will likely prove useful for decision-making in resource management involving a wide spectrum of land ownership and management policies.

F. Tables

Table II-1. Sample information required for a FLOSS input parameter. The information is based on the estimated Weibull probability distribution of the patch size distribution of public and private land ownership type. The parameter from this information will fill a 1000×1000 pixel landscape. The actual parameter file will have line entries comprised of patch ID, patch size in number of pixels, and number of parcels in each line.

Patch ID	Patch size (pixel)	Number of parcels	Patch ID	Patch size (pixel)	Number of parcels
public01	3828	1	private01	3828	0
public02	2322	1	private02	2322	2
public03	1408	3	private03	1408	4
public04	854	7	private04	854	3
public05	518	18	private05	518	10
public06	314	40	private06	314	37
public07	191	74	private07	191	122
public08	116	122	private08	116	351
public09	70	316	private09	70	949
public10	43	206	private10	43	2249
public11	26	453	private11	26	4708
public12	16	578	private12	16	8664
public13	9	666	private13	9	13960
public14	6	671	private14	6	19353
public15	3	553	private15	3	22127
public16	2	312	private16	2	18486
public17	1	56	private17	1	6181

Table II-2. Selected landscape-level indices ($\bar{x} \pm SE$) of FLOSS-simulated land ownership patterns (Current: FLOSS simulation based on current land ownership parcelization level; 5, 8, 10-year: FLOSS simulation based on equivalent future projection years). The results were analyzed by the random moving windows method. Since simulated landscapes had greater spatial extent than the sample blocks, moving windows of a size equivalent to sample blocks were randomly selected and used for analysis. Abbreviations are as follow: MPS: mean patch size; PD: patch density; AWSI: area-weighted shape index; AI: aggregation index.

Landscape Indices	Actual [1]	Current	5-year	8-year	10-year
MPS	56.1 ± 3.92	53.9 ± 1.24	43.9 ± 0.84	36.3 ± 0.20	32.9 ± 0.15
PD	1.13 ± 0.35	1.78 ± 0.14	1.90 ± 0.15	2.13 ± 0.13	2.18 ± 0.34
AWSI	1.57 ± 0.22	1.70 ± 0.09	1.68 ± 0.08	1.66 ± 0.06	1.63 ± 0.06
AI	97.8 ± 0.6	95.6 ± 0.0	95.4 ± 0.0	95.0 ± 0.0	94.7 ± 0.0

[1] Results from the sample study blocks.

G. Figures

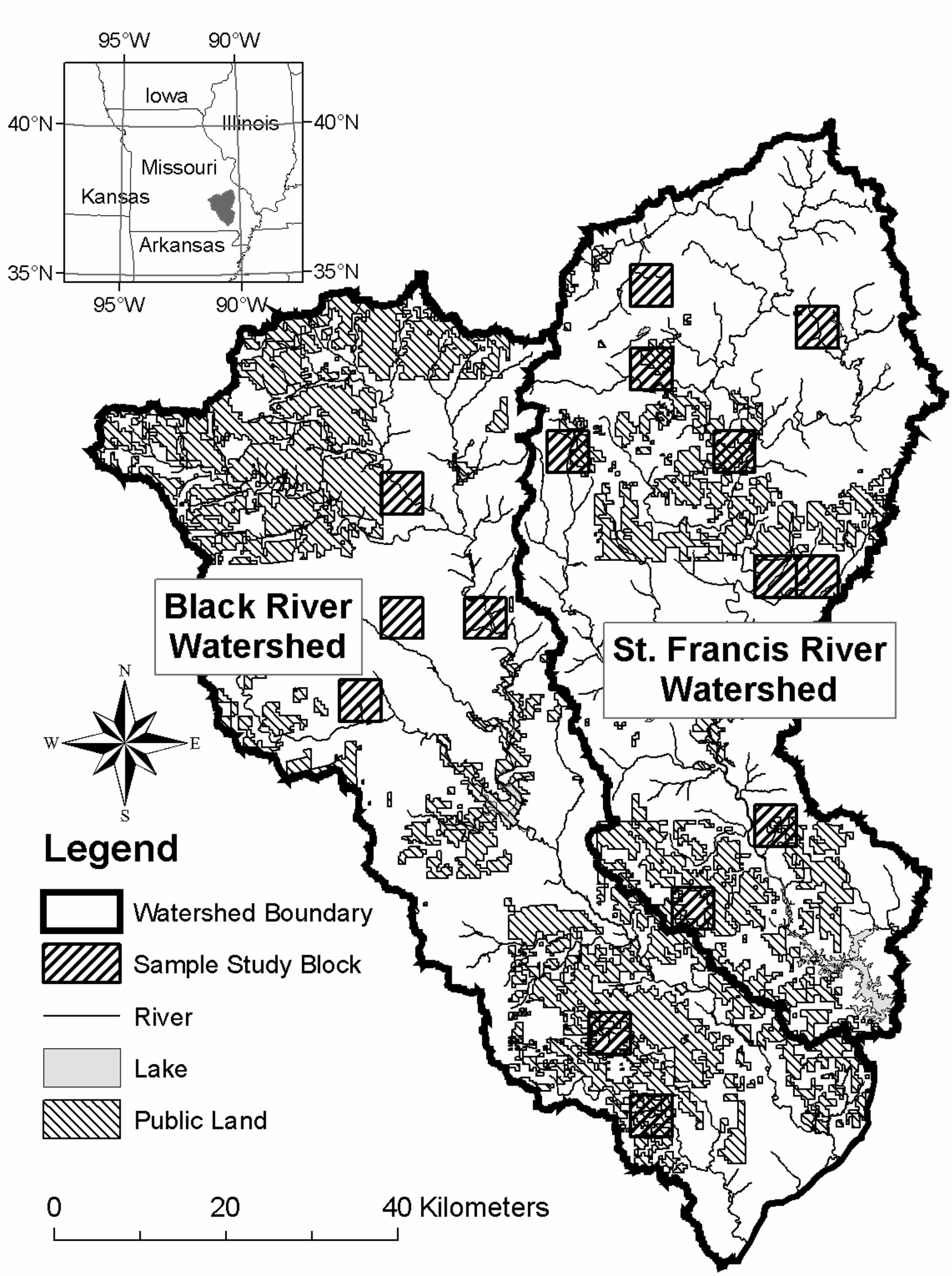

Figure II–1. Figure caption is on the following page.

Figure II-1. Map and location of the study area in the Black and St. Francis River watersheds of the Missouri Ozarks. Locations of the randomly selected 15 sample blocks (4.8×4.8 km) and their ID numbers are indicated.

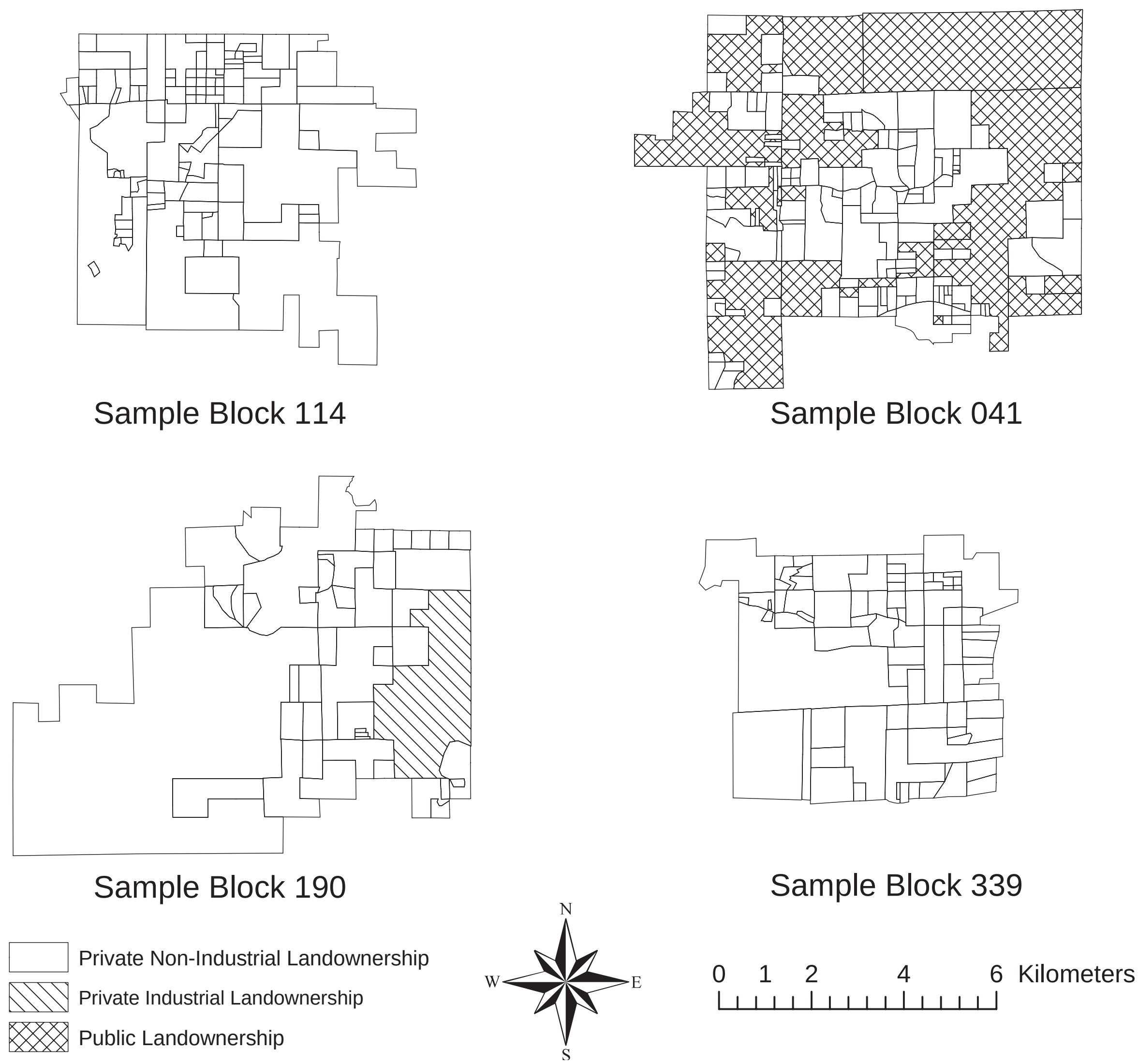

Figure II-2. Land ownership boundaries in selected sample blocks. Digitized ownership parcels were categorized by private non-industrial, private industrial, and public ownership designations. Patch boundaries were often extended beyond the sample block boundary as some entire parcels which were not entirely contained in the sample blocks (See Figure 1 for the sample block locations).

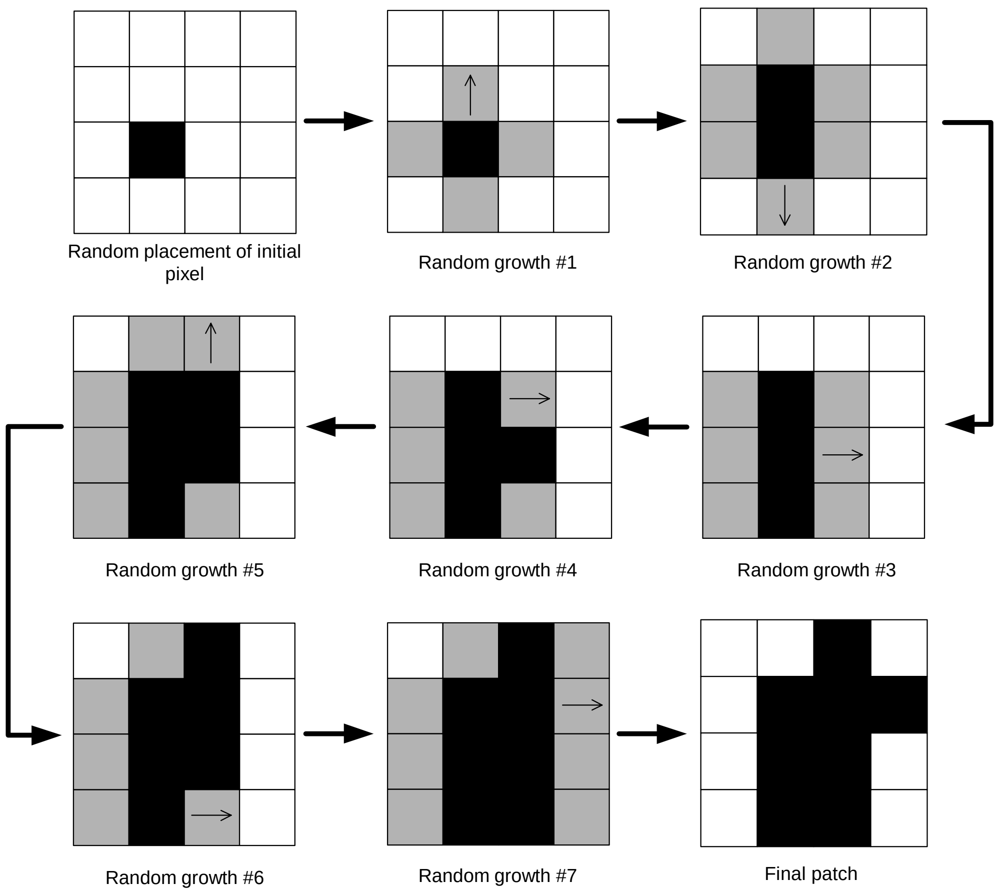

Figure II-3. A demonstration of a FLOSS simulation for an 8-pixel sized parcel in an empty 4×4 pixel landscape. The procedure depicts the random placement of the initial pixel and the subsequent random growth by the 4-neighbor rules. The shade of the pixel depicts the following in the simulation: ■: pixels selected for growth; □: Potential pixels that can be selected for growth; ⟶ : selected growth direction. Potential pixels are determined in each growth step so that they are adjacent to the existing patch but are also closest to the initial pixel, which ensures that the patch retains its simple geometric form. Then the growth direction is randomly determined, and one pixel is randomly selected from the potential pixels in the growth direction to create a single pixel growth. This process is iterated until the target size of the patch is met. It should be noted that this procedure does not simulate a temporal sequence of a particular land ownership landscape. FLOSS is designed to reproduce neutral patterns based on strong underlying PLSS structure.

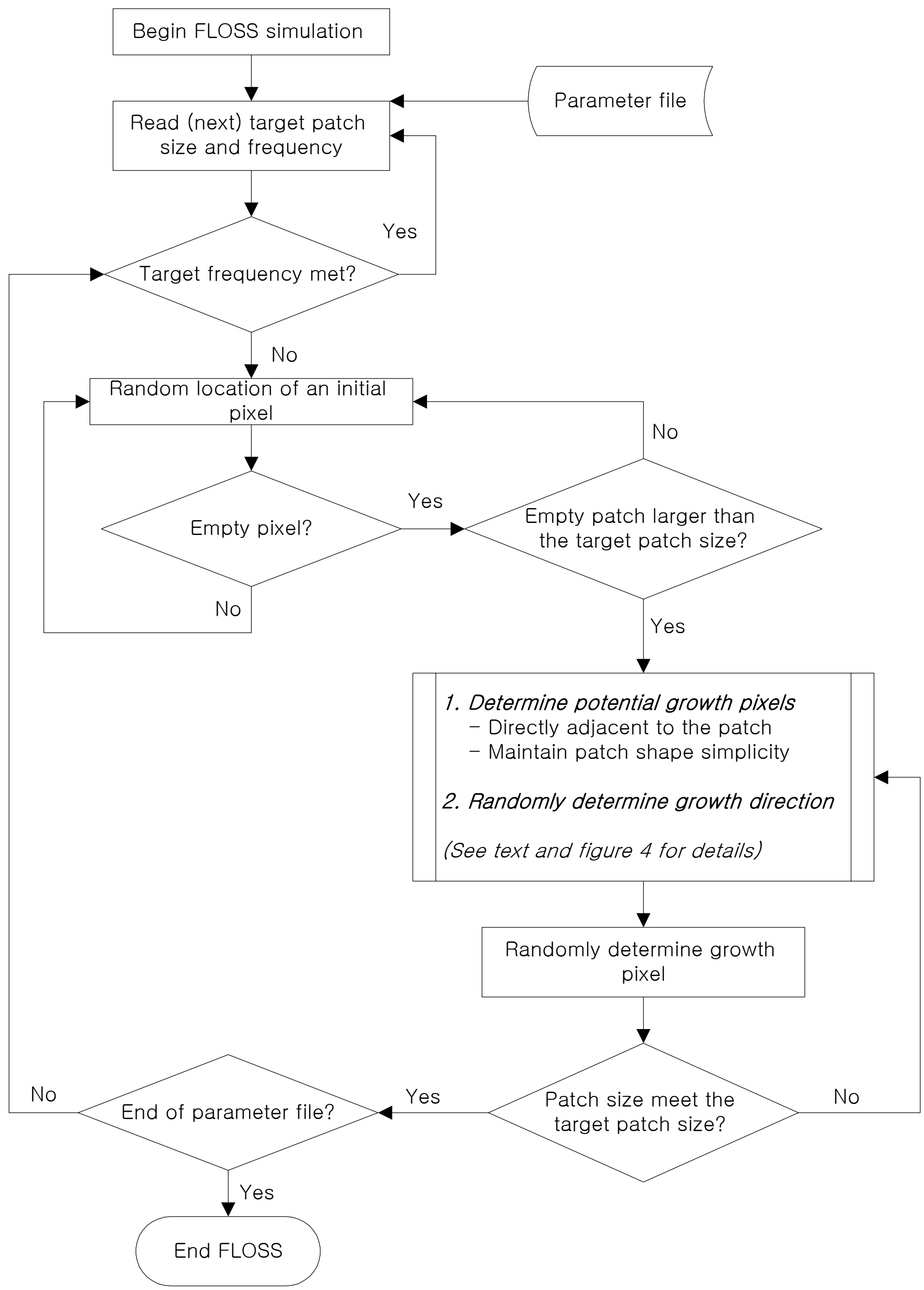

Figure II-4. Logical flow diagram of FLOSS. See figure 3 and text for details of the patch growth module.

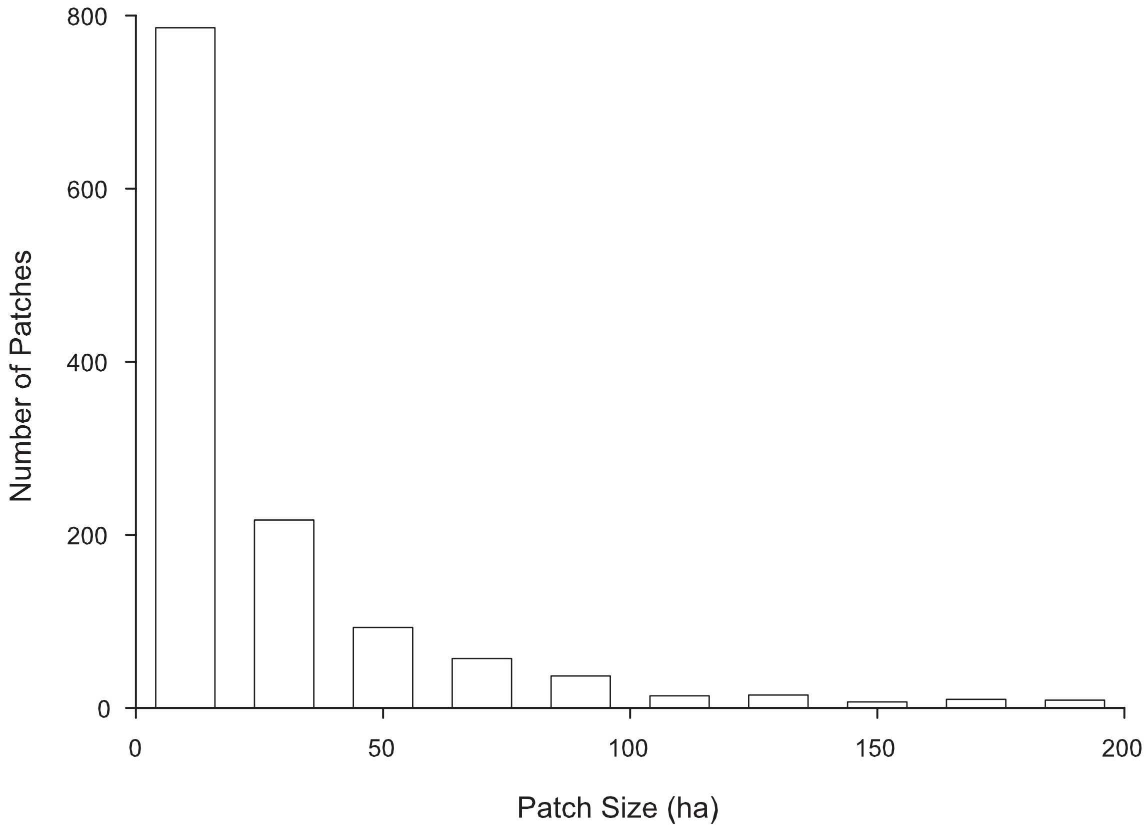

Figure II-5. Land ownership patch size distribution of the digitized ownership parcels (n = 1306) from the 15 sample blocks. Parcels smaller than 200 ha were used (there were only 61 parcels larger than 200 ha).

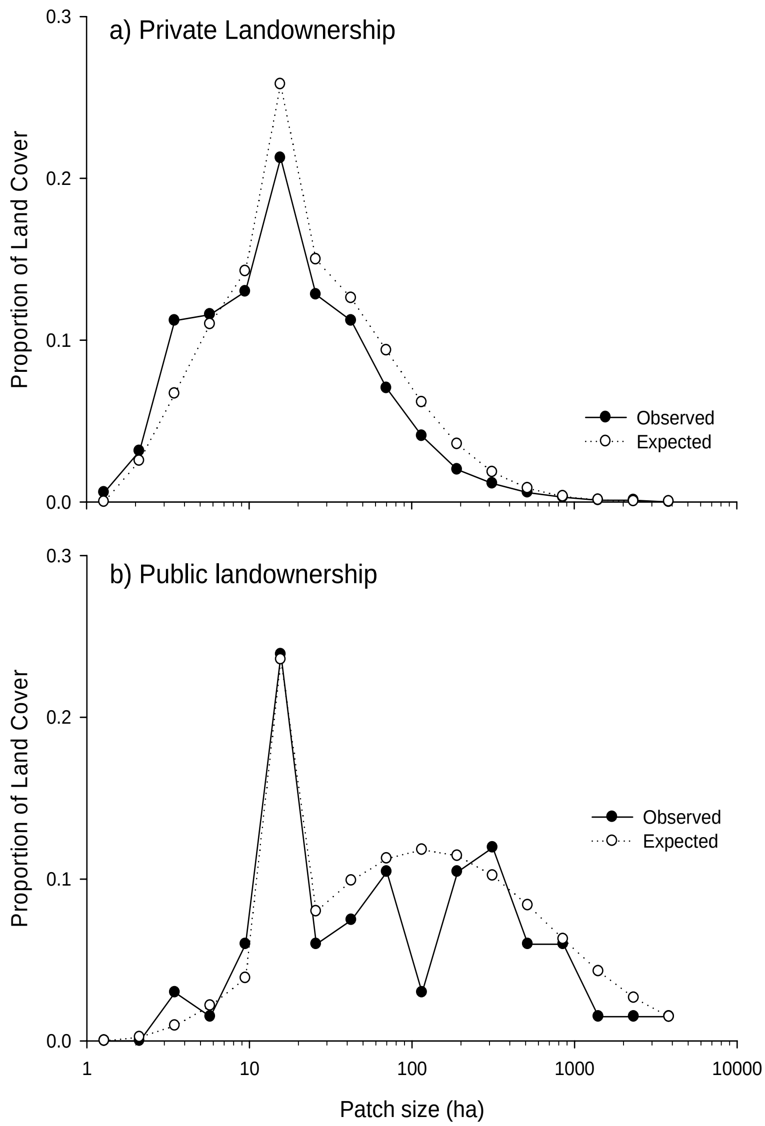

Figure II-6. Observed and simulated patch size distributions of private (a) and public (b) land ownership. Observed distributions were calculated from actual ownership patch size measured from the sample blocks. Simulated distributions were generated by bootstrap sampling, Weibull probability function fit, and FLOSS simulation. The peak of the 6th quantile is a modified value adjusted after the Weibull fit, necessitated by the unusually high initial value being associated with the size of a ‘quarter section’ (129.50 ha, 320 acre) of the underlying Public Land Survey System (PLSS) structure (See text for detail).

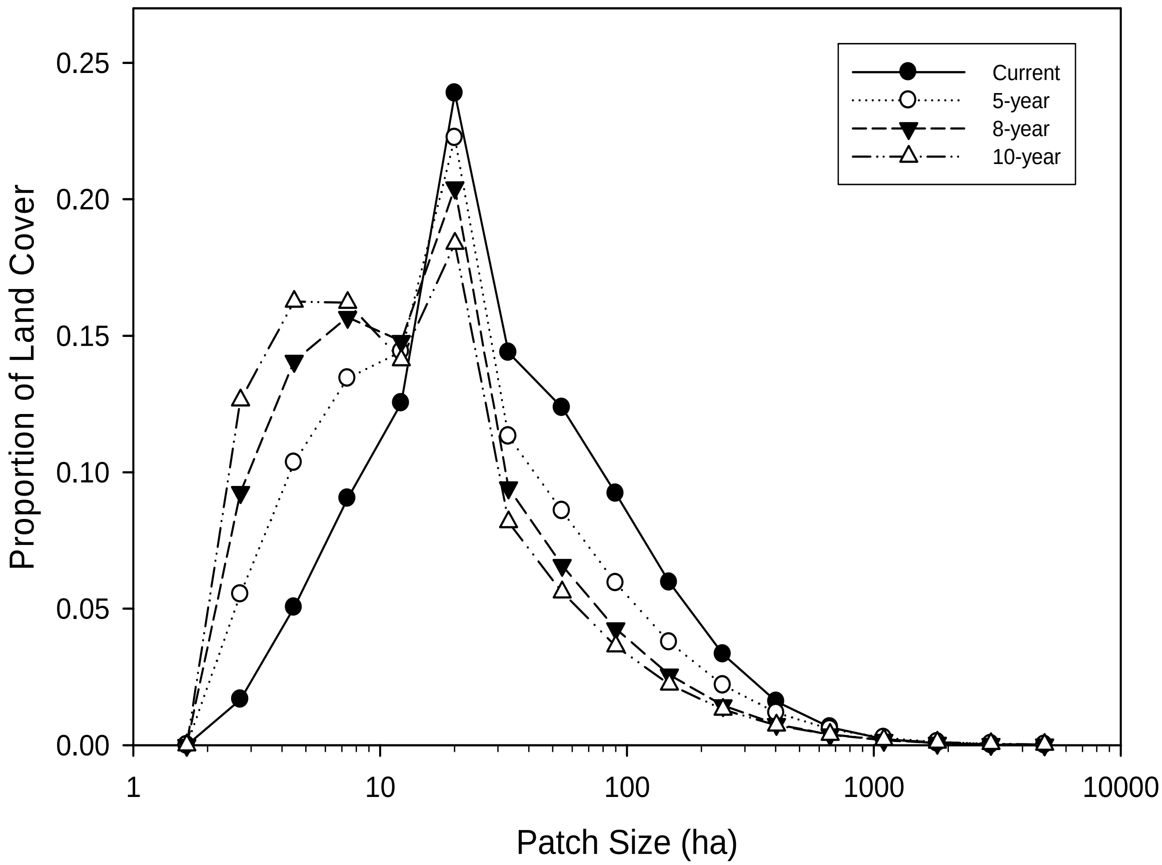

Figure II-7. Projected future land ownership patch size distribution. Projection is based on the estimated future mean patch size derived from the property size decrease rate in the state of Missouri from 1978 to 1993. The estimated mean patch size was used for the Weibull probability function fit and future patch size distributions. For FLOSS simulations, the values of the 6th quantile were modified to reflect the peaks (see text and Figure 5 caption for details).

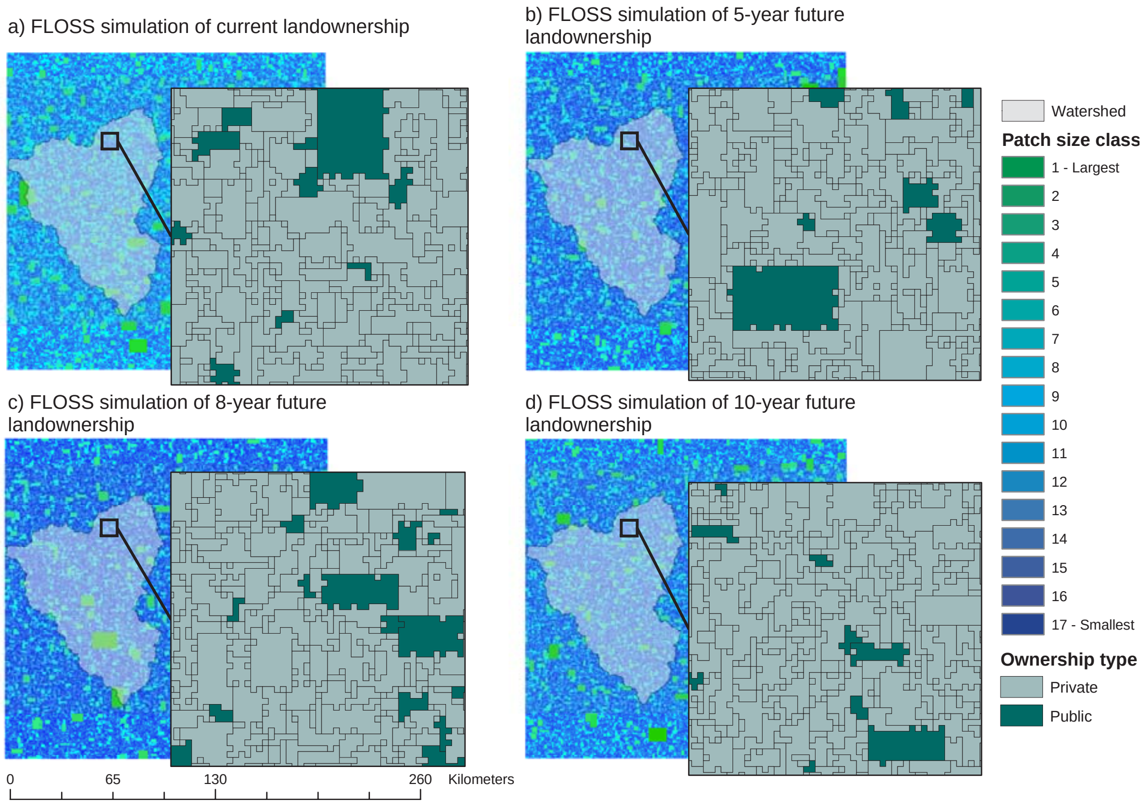

Figure II-8. FLOSS simulation of private (a) and public (b) land ownership parcels in a 1000 by 1000 grid for the current and projected patch size distributions. The boxed areas are equivalent to the size of a sample block (4.8×4.8 km), and the ownership type (private or public) and patch size class are shown in detail.

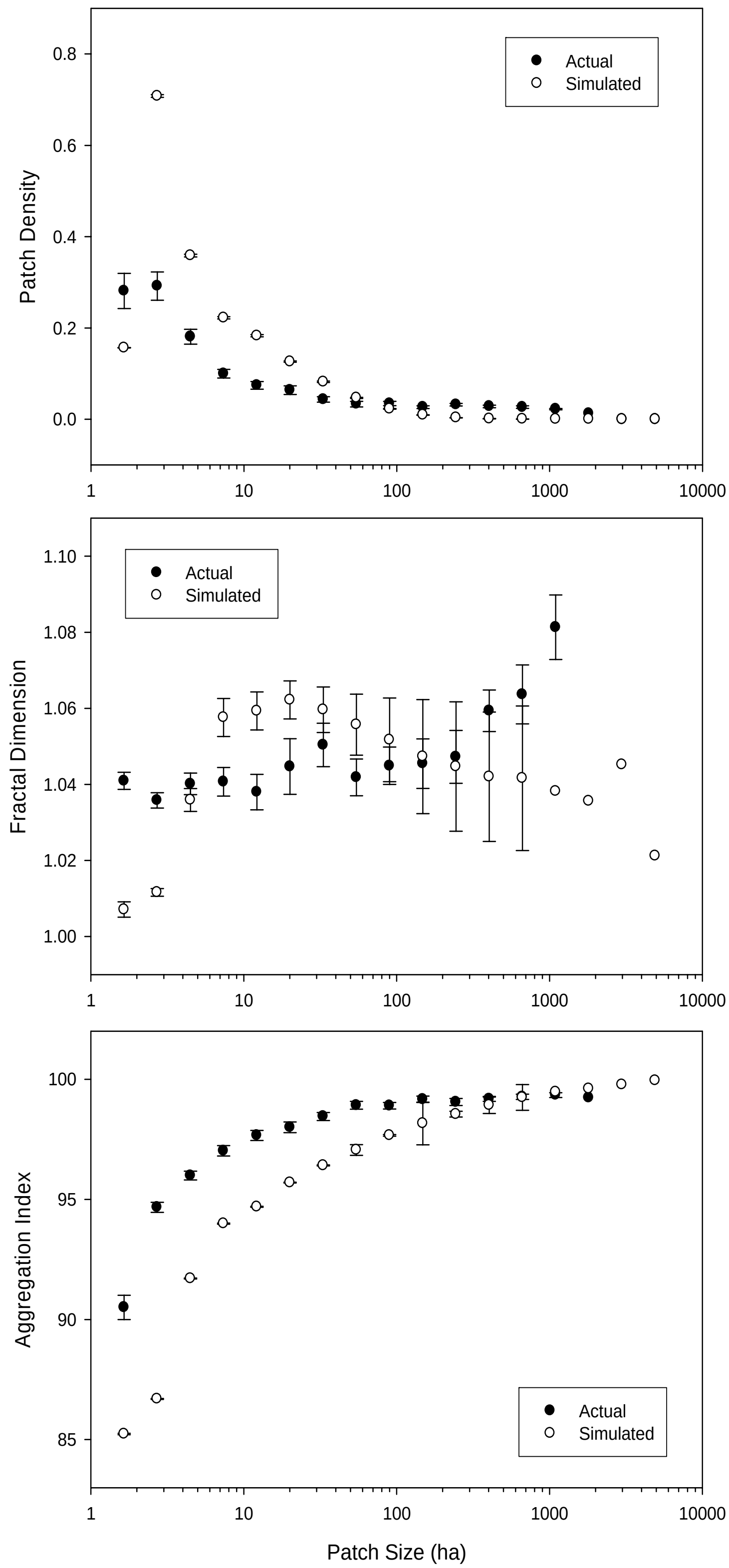

Figure II–9. Figure caption is on the following page.

Figure II-9. Selected landscape-level landscape indices ($\bar{x} \pm SE$) calculated from sample blocks (actual) and FLOSS simulation (simulated).

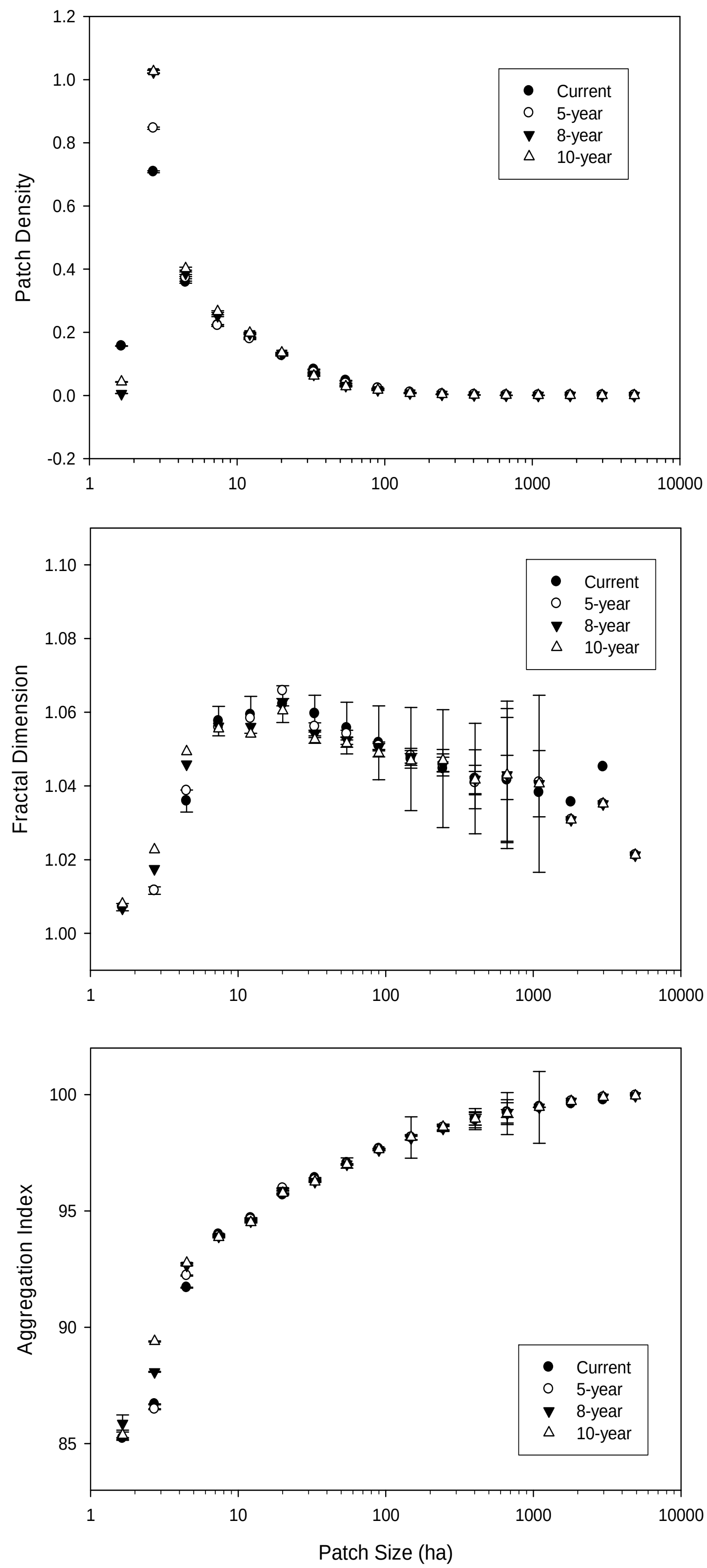

Figure II–10. Figure caption is on the following page.

Figure II-10. Selected class-level landscape indices ($\bar{x} \pm SE$) of the simulated landscape patterns of future parcelization levels.

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Chapter III. Characterizing the process of private forestland ownership parcelization in the Missouri Ozarks, USA, from 1930 to 2000.

A. Introduction

Approximately 160 million hectares of forest is privately owned in the United States, while about 59 % of the private owners are known to be the non-industrial private forest (NIPF) owners (Birch 1996). Non-industrial private forest (NIPF) owners are referred as those who do not have the capability to commercially process the wood in their forestland (Mehmood and Zhang 2001). However, although the NIPF owners do not own processing mills, it is usually known that they grow and sell the majority of wood consumed in the U.S.

In addition to the extensive NIPF ownership, the parcelization of private forestland has also been intensifying in the recent years (Yaffee et al. 1996). Parcelization occurs as individual landowners are replaced by multiple landowners with smaller holdings. This trend is influenced by a number of social and demographic forces; e.g., inheritance, economics, urbanization, geographical locations, tax, and income level (Sampson and DeCoster 2000, Mehmood and Zhang 2001). As a result, the number of private forestland owners is increasing while the average size of the forest property parcels is decreasing.

Ownership parcelization of forestland is not a new phenomenon. This has been occurring in the last few decades, with such an intensity that studies project 95 % of the privately owned forest parcels will be smaller than 40 hectares (100 acres) by the year of 2010 (Yaffee et al. 1996, DeCoster 1998). It is generally known that the forest property parcel size has a positive relationship with the timber supply (Greene and Blatner 1986, Romm et al. 1987), which indicates that the increasing parcelization poses a threat to stumpage supplies.

Furthermore, ownership parcelization is also a warning sign for conservation-related aspects of the forest resources. Management practices from various landowners can result in complex ecological interactions that are difficult to predict (Botkin 1990, Spies et al. 1994, Turner et al. 1996, Liu 2001). For example, habitat quality may be directly influenced by certain management practices or their absence conducted by the owners that may change the forest composition and/or structure, or completely convert a forest into a different land cover type. This is particularly of interest because studies have shown that such influences from ownership parcelization is one of the strongest driving forces for forest fragmentation and early sign of further urban development (Sampson and DeCoster 2000, Thorne and Sundquist 2001). Also, forestland parcelization can potentially affect the habitat quality since parcelized private forestlands are known to be highly vulnerable to developmental pressure (LaPierre and Germain 2005). Last but not least, a diversity of interests from the landowners can result in uncoordinated management practices, which can complicate pursuit of management objectives that require large areas to implement (e.g. conservation of certain avian species or large mammals).

Apart from the purpose of ownership, various parcel sizes may also indirectly reflect the management goals of the owner, as smaller forestland parcels are economically less viable to operate and manage for generating profits from timber products. Some forest management practices may only be practical on forestland parcels larger than a particular size, regardless of the motivation of the owners, which is apparent when related to the economic viability of the operations involved.

On the other hand, despite the overall trend of greater ownership parcelization, large amount of forestland acquisitions by non-industrial private entities (e.g., the Pioneer Forest) have also occurred in the past. The Pioneer Forest, which now owns nearly 160,000 acres of forestland in Missouri, is a good example how a single private entity can dramatically change the ownership structure at a regional scale. It is important that such acquisitions usually end up aggregating numerous small ownership parcels into one large parcel. However, existing studies are often focused on the trend of the parcelization and such acquisitions are seldom considered.

Although numerous studies call for greater attention and more research devoted to private forestland parcelization, few studies have actually investigated the details and effects of the phenomenon. Often 'mean property size' or 'mean parcel size' are used to characterize the degree of forestland parcelization, but these may not be meaningful indicators of the dynamics that may result from the ownership parcelization.

Using a single statistic to describe the level of parcelization limits our understanding of the potential differences in the management approaches among landowners who owns parcel of different sizes. Ownership of different parcel sizes may result from different purposes of ownership; forestland owners with smaller parcels may have different motives for the ownership compared to those with larger parcels, and may adopt drastically different forest management practices, including the lack of any actual management activities. Therefore, instead of a single statistic, a distributional quantitative measure is more versatile in describing with the phenomena.

This study uses a modeling approach to characterize the ownership parcelization across the entire range of existing parcel sizes in the landscape by using a transition matrix model. Transition models use transition probabilities to describe the changes in the state variables. They have been broadly applied to a variety of system to evaluate population structure and viability (Lefkovitch 1965, Huenneke and Marks 1987, Horvitz and Schemske 1995, Bierzychudek 1999, Knight 2004), model vegetation changes (Enright and Ogden 1979, Usher 1981), and analyze land use and land cover change (Muller and Middleton 1994, Bourne 1969, Brown et al. 2000, Burnham 1973, Bell 1974, Turner 1987). State variables that have been employed included life stage of organisms, vegetation types, or land use and land cover types.

This study uses a transition matrix model to describe the ownership parcelization process in the southeastern Missouri Ozarks. The effects from large-scale private acquisitions, such as those from the Pioneer Forest, are also evaluated as a separate scenario. Specifically, the objectives of this study are to:

(1) characterize the parcelization process in association with the existing parcel size classes in the landscape by using a transition matrix model;

(2) evaluate the effects of aggregative acquisitions of a particular private ownership – the Pioneer Forest – in the parcelization process; and

(3) delineate any strong tendencies in particular parcel size classes resulting from the parcelization of aggregation process.

B. Materials and methods

1. Transition matrix model

Transition matrix models describe the probabilistic relationship between the attributes of the variable and the position of this variable in a time sequence (Bourne 1969). The state transitions are treated as random Markovian processes which are only affected by the condition on the initial state. The transition matrix model is in the form of

$$\begin{vmatrix} P_{11} & P_{12} & P_{13} & \cdots & P_{1j} \\ P_{21} & P_{22} & P_{23} & \cdots & P_{2j} \\ P_{31} & P_{32} & P_{33} & \cdots & P_{3j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ P_{i1} & P_{i2} & P_{i3} & \cdots & P_{ij} \end{vmatrix} \times \begin{vmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ \vdots \\ y_{it} \end{vmatrix} = \begin{vmatrix} y_{1t+1} \\ y_{2t+1} \\ y_{3t+1} \\ \vdots \\ y_{it+1} \end{vmatrix}, (i = j)$$

where *i* and *j* is the number of classes of the state variable, *Pij* is the transition probability of the state variable at class *i* changing into class *j*, the vector of $y_{1t},\ldots,y_{it}$ is the state variable distribution at time *t*, and the vector of $y_{1t+1},\ldots,y_{it+1}$ is the state variable distribution at time $t+1$. The probability matrix *Pij* has latent roots with the maximum number of the state variable classes in the model. The latent root of largest absolute value is designated λ_1, which is the dominant eigenvalue of the matrix. Given so, an arbitrary state variable class distribution of the vector $y_{1t},\ldots,y_{it}$ will approach a vector which is called the 'stable stage distribution', given that *Pij* is square, nonnegative, and irreducible (Gourley and Lawrence 1977).

For the transition matrix used in this study, the state variables are defined as the patch size classes and transition probabilities are defined as the probability of an individual parcel of size class *i*, changing into other size class *j* or remaining at the same size class *i*, representing further parcelization or aggregation, or unchanged status of ownership parcel size class. Therefore, the vector of stable stage distribution, in this case, will be the asymptotic state of the relative frequency of each parcel size classes (Bierzychudek 1982). The advantage of the transition model is in the capability of characterizing the parcelization process across the entire range of parcel sizes, by using parcel size classes as the state variable.

Several assumptions are implied in the use of the transition matrix model for the purpose of prediction; 1) the probability of the transition is solely dependent on the current state of the variable with no consideration to the processes involved, therefore no causality can be implied in the model, and 2) the transition rates for each of the state variables are stationary; that is, the transition probabilities are assumed to be constant over time (Bierzychudek 1982). However, both assumptions are practically unrealistic regarding the dynamic nature and the related factors that affect the parcelization process, therefore the use of the model in this study is limited as an exploratory tool to describe and characterize the parcelization process, but not as a way to predict the future parcelization level. Consequently, using the transition matrix model holds its value for our purpose to describe and characterize the parcelization process by delineating the intensity of both decreasing and increasing trends in particular parcel size classes.

2. Study area

This study was based in the Black and St. Francis River watersheds in the Ozark highlands of southeastern Missouri (Figure III-1). Most of the study area is dominated by mixed oak-hickory forest (> 75 %), and approximately 13 % is dominated by shortleaf pine (*Pinus echinata*) and shortleaf pine–oak mixed forest. Much of the shortleaf pine forests prior to the 20th century are now replaced by oaks and hickories as a result of extensive clearcutting and burning by settlers and logging industries in the early 1900s (Guyette and Larsen 2000). As with most forestland in Missouri, the study area has been under the pressure of ownership parcelization in the last few decades (Birch 1996, Hahn and Spencer 1991).

3. Materials

In order to calculate the transition probabilities of parcels sizes in the study area, we used parcel size information acquired from the plat books from two temporal sequences, one from 1930 (Anonymous 1930) and the other around the year of 2000 (Anonymous 1999, 2000a, 2000b, 2001a, 2001b). Fifteen sample blocks (4.8×4.8 km) from the combined watershed area were selected to measure the parcel size transition probabilities, and digitally scanned plat book images were acquired for each of the sample blocks. The plat books for the year of 1930 were acquired from the collection of digital library archive at the University of Missouri-Columbia. For the plat books of the year around 2000, actual plat books were acquired and then digitally scanned. An image manipulation program GIMP (GIMP documentation team 2001) was used to match the scale of the scanned plat book images from both temporal sequences.

4. Constructing transition probability matrices

Each of the individual ownership parcels, being separate spatial entities, could not be directly counted as a sample state variable to measure the parcel size changes. A single ownership parcel cannot provide a unique single case of a parcel size transition, since it may be divided into many parcels, or vice versa. Therefore, systematic point-grids were randomly overlaid to the 1930 plat book images of the sample block areas and then were georeferenced to 2000 plat book images so that individual points were at the same locations for both 1930 and 2000 (Figure III-2). Then all pairs of the parcel sizes and ownership types at each point for both temporal sequences were recorded. Several ownership types were classified and recorded: public ownership type, such as those owned by the United Stated Department of Agriculture Forest Service; private industrial ownership type; and private non-industrial ownership type.

A considerable number of acquisitions were observed that resulted in aggregations of small parcels into large parcels by a single owner, Leo Drey, the owner of the Pioneer Forest. These transitions were separately recorded and were used to create an alternative scenario of parcel size change. This is due to the unusual objective and management practices exercised from the Pioneer Forest. Although the Pioneer Forest is a for-profit organization, timber management of the Pioneer Forest is not geared towards maximum economic gain. It is rather focused on the restoration of high quality oak-hickory forests by exclusively using single tree selection harvest method (http://www.pioneerforest.com). Consequently, the acquisitions from the Pioneer Forest can be considered as a unique phenomenon that can result in larger non-industrial private ownership type, and were parameterized later for an alternative scenario for the transition matrix model.

The frequency distributions of size class point counts of the private non-industrial parcels for each of the temporal sequences were derived from the recorded parcel size frequency table. These were used to compare the distributions and to determine the number of quantiles of parcel size class for transition matrix construction. A log-normal conversion was applied to the parcel sizes because of the extremely skewed distribution towards the smaller end; parcel sizes in a linear scale would not be able to represent much variability in the distribution.

The number of quantiles was determined so that the variability of the distribution is well retained while keeping the matrix at a manageable size. Because of the large range of the parcel sizes and the highly skewed distribution, a relatively large number of quantiles had to be used compared to other transition matrix studies. This was necessary in order to differentiate meaningful parcel size classes and their transition probabilities. However, the number of quantiles could not be too large because of the sporadic distributions of parcel sizes for both years; although a large number of quantiles may provide greater resolution in parcel size differentiation, many size classes would be empty and eventually result in a distorted transition matrix that will prevent any meaningful results.

Once the number of quantiles was determined, transition matrices were constructed from the pairs of the parcel size changes from the year 1930 to 2000. To compare the effects from the aggregative acquisitions from the Pioneer Forest, we constructed two transition matrices for the purpose of this study to apply two scenarios: (1) a matrix based on all privately owned parcel size changes, including the aggregative acquisitions from the Pioneer Forest; and (2) a matrix based on all privately owned parcel size changes except those from the acquisitions by the Pioneer Forest.

5. Confidence intervals

In order to provide confidence intervals for the stable stage distributions of parcel size classes, a bootstrap resampling method was utilized. The bootstrap method is used to provide statistical inference by creating an arbitrary number of replicates (Efron and Tibshirani 1993) in case the underlying distribution of the sample is unknown. Bootstrap transition tables were created by sampling individual pairs of observations with replacement from the pairs of parcel size transitions for each of the scenarios. The resulting sample size of the bootstrap transition table was identical to the number of transitions used for each of the scenarios. We created a total of 1000 bootstrap transition tables for each of the scenarios, from which the stable stage distributions of parcel size classes were calculated. These were then analyzed to calculate the 95% confidence intervals for each of the parcel size classes in the stable state distribution. We used MATLAB (2001) for the bootstrap procedure and the calculation of the stable stage distributions for each of the scenarios.

C. Results

1. Parcel size point counts of 1930 and 2000

A total of 1771 pairs of private non-industrial parcel measurements of their sizes and the transition types were used for the analysis in the year of 1930 and 2000. The acquisitions from the Pioneer Forest comprised approximately 9.7% of total measurements (n = 171). A total of 10 quantiles were used to derive the distributions of the frequency of the recorded parcel sizes of both temporal sequences (Figure III-3). Any smaller number of quantiles was not able to retain the variations of the distributions. In contrast, although using more quantiles may increase the resolution of the distribution, the extremely skewed and sporadic nature of the distributions can create numerous classes without any parcels, and cause unrealistic results from the transition matrix model.

It should be noted that these distributions are not the actual 'parcel size frequency distributions' *per se*, for the given sample years. As discussed in the methodology, the observations were made at all measurement points throughout the plat book for the purpose of deriving the transition probabilities between parcel sizes. Consequently, the frequency distributions are generally overestimated for larger parcels and underestimated for smaller parcels, as larger parcels include a greater number of sampling points, and the measurements were not made on an individual patch basis.

Significant differences were observed between the distributions of 1930 and 2000 ($\chi = 2475.907$, $df = 289$, $p < 0.001$). Overall, the number of smaller parcels increased and larger parcels decreased in 2000 compared to 1930. However, there were very high records of parcel sizes at the 5th (midpoint: 116.8 ha) and 10th (midpoint: 1429.4 ha) quantiles in 2000, showing the aggregation of private parcels at particular parcel sizes classes. Specifically, the increasing number of parcels at the 10th quantile exclusively resulted from the acquisitions from the Pioneer Forest. In addition, while as the parcel sizes in 1930 shows a bimodal distribution with modes at the 4th and 6th quantiles, with midpoints of 70.8 ha and 193.5 ha respectively, in 2000 the distribution shows a lower plateau in the mid-size range and higher values at either end of the distribution.

2. Transition probability matrices

One thousand transition probability matrices for each of the two scenarios were constructed by bootstrap resampling method, which were then used to quantify the future ownership parcelization levels (Table III-1). The effects of excluding the acquisitions from the Pioneer Forest can already be observed in the transition matrix of the scenario without the Pioneer Forest acquisitions, as all transition probabilities to the largest parcel size classes are significantly smaller (Table III-1).

3. Stable stage distributions

Stable stage parcel size distributions from the scenario with all parcel transitions showed considerably higher abundance in the first quantile, suggesting further level of ownership parcelization in the future (Figure III-4). In the mid-range, the stable stage distribution of the all parcel transition scenario somewhat resembled the bimodal shape with modes that was observed in the parcel size distribution in 1930 (Figure III-3). However, the modes moved towards the smaller end, from the 4th and 6th quantile in 1930 to 3rd and 5th quantile in the stable stage distribution. In addition, the higher mode among the two was the one at the smaller size class in the stable stage distribution, but vice versa in the 1930 distribution. Interestingly, despite the results suggesting higher level of parcelization, the model showed that the abundances in the largest parcel size classes (quantiles 8, 9 and 10, ≥ 528.5 ha) would remain in the stable stage distribution when all parcel transitions were considered.

Stable stage distribution was significantly altered when the acquisitions by the Pioneer Forest were removed from the transition matrix (Figure III-4). The results suggest mixed outcomes, as the abundances of mid- to small-sized parcel size classes (midpoint: ≤ 193.5 ha) all increased, and those of larger size classes (midpoint: ≥ 528.5 ha) significantly decreased. Most noticeably, removing the Pioneer Forest acquisitions caused a dramatic shift in the largest size class, which was completely removed from the stable stage distribution. At the other extreme, the smallest size class (midpoint: 6.3 ha) significantly increased. The mid-sized parcel size classes increased to a smaller extent, which is most noticeable in the 5th quantile (midpoint: 116.8 ha).

D. Discussion

The dramatic changes in the parcel size distribution observed from 1930 to 2000 (Figure III-3) suggest that the parcelization has been a strong process in the southeastern Missouri Ozarks that characterizes the current private forestland ownership. In particular, some of the distribution patterns in particular parcel size classes may be associated with the structural bias caused by the Public Land Survey System (PLSS). Since the Land Ordinance of 1785, PLSS has provided the basic spatial units for the survey, sales, and settlement of public domain land in the United States (White 1983). The system starts from a 6-mile square basic unit called township, which is divided into 36 1-mile square sections with the size of 640 acres (259.0 ha). Sections are further divided into quarter-, quarter-half, and quarter-quarter sections, with areas of 160, 80, and 40 acres, respectively. Consequently, PLSS played a significant role in the creation of the spatial layouts of homesteads granted to the pioneer settlers, as well as the subsequent land transactions later in the United States history (White 1983), and may be affecting the current parcelization process. The strong underlying structure of the PLSS can still be found in the rectangular and square shaped parcel shapes in the southeastern Missouri Ozarks and in other Midwest region of the United States (Figure III-2).

The size class of the 4th, 6th and 7th quantiles (midpoints: 70.8, 193.5, and 320.5 ha, respectively) closely matches with the PLSS unit of quarter-section (160 acres, 70.8 ha) and section (320 acres, 259.0 ha), which indicates the strong tendency of ownership parcel sizes in such PLSS units in 1930. This was also observed on the plat books used in our study, as numerous cases of an entire section owned by a single individual. However, many of these entire section parcels 1930 were removed from the landscape as they were divided into smaller parcels in 2000.

The point counts increased by almost two-fold in the smallest parcel size class (6.3 ha) from 1930 to 2000 (Figure III-3). Regarding that these point counts are negatively correlated with parcel size, as smaller parcels are being under-represented, the actual increase is estimated to be even greater than that shown in the measurement. This dramatic increase in parcel sizes smaller than 10 ha are most likely involved with expanding residential development in the area.

On the other extreme, the point counts for the largest parcel class increased by more than three-fold from 1930 to 2000, which shows the nature of the new acquisitions. Most of the new parcels in the largest classes were purchased by the Pioneer Forest. Often, an entire section – sometimes more than one section – was purchased by the Pioneer Forest. These acquisitions resulted in the aggregation of small parcels with various owners into one large parcel. Some of the purchases were extremely large that the resulting parcel owned by the Pioneer Forest extended across a few sections, as the largest point count parcel size was measured at 1826 ha.

The stable stage distribution calculated from the transition matrix model with all parcel transitions showed the continuing trend of parcelization in each of the parcel size classes. Specifically, the smallest parcel size class maintained its increasing trend, reaching a relative abundance close to 13% of the landscape. The decreasing trend in the 4th and 6th quantile observed in Figure III-3 also continued, resulting in lower levels of relative abundance than the 3rd and 5th quantile. Although the 7th quantile further decreased in the stable stage distribution, model estimated that the large parcels at quantiles 7, 8, 9 and 10 (≥ 320.5 ha) to occupy a considerable part of the ownership landscape (13.6 %) under the current parcel size transition rate. These results agree with DeCoster (1998) who observed increase in mid-sized parcels (100 – 499 acres, or 40.5 – 202.0 ha), persistence of large parcels (≥ 500 acres, 202.4 ha) and increase in the smallest parcels (< 100 acres, 40.5 ha).

The results suggested that the acquisitions from the Pioneer Forest have played a significant role in shifting the stable stage distribution. For example, without the Pioneer Forest acquisitions, the model results suggested mixed trends, with a strong decreasing trend at the largest parcel size classes (8^{th}, 9^{th} and 10^{th} quantiles, midpoint: ≥ 528.5 ha), with the largest parcel size class (midpoint: 1429.4 ha) completely eliminated, and a strong increasing trend at the smaller parcel size classes. Notably, such change would induce even greater level of ownership parcelization than simply portrayed as parcel size class abundance. For example, although increase in the smallest parcel size class of 1.2 % may seem minimal, the associated impact on the spatial characteristic of the ownership landscape can be surprisingly high because of the small parcel size, resulting in thousands of new parcels with extremely small sizes. The resulting distribution also suggests the strong tendency of the acquisitions of the Pioneer Forest towards the largest parcel size classes; although this is an important part of the process, however, it should be noted that such acquisitions are rarely made.

The particular shape of the stable stage distributions can provide insights as to which particular parcel size classes are more vulnerable or resistant to the parcelization process. In particular, a strong tendency towards parcel sizes of 1^{st}, 3^{rd} and 5^{th} quantiles are observed in the stable stage distributions regardless of the Pioneer Forest acquisitions.

In comparison, the stable stage distribution suggests the exceptional vulnerability of the largest parcels of the 9th and 10th quantiles with the lack of the large scale acquisitions from the Pioneer Forest, while the decrease in the 6th, 7th and 8th quantiles were relatively insensitive to the scenario without the Pioneer Forest acquisitions.

The results from the transition matrix models in this study should be considered in light of the limits involved with the assumptions of the model. The major limitations of the transition matrix models associated with this study are based on the assumptions of stationarity in transition rates and the transitions being dependent only on the current stage of the state variable. The assumption of stationarity in transition rates rarely holds true for the process of ownership parcelization, since transition rates in particular parcel size classes can change over time. Using the two scenarios is an indirect way to cope with this assumption, as the scenario without the Pioneer Forest is based on the premise that parcel size transitions from such acquisitions may not occur in the future. Nevertheless, it should be noted that the stable stage distribution cannot be regarded as future prediction of landownership parcel size distributions, but as measures that show the trends in the parcelization process.

The assumption of no causality also limits this study as changes in parcel sizes do not occur as an isolated process, but are associated with certain economic or demographic forces that plays a significant role for a landowner to decide the size of the parcel they purchase or sell (Decoster 1998). This assumption of non-causality also relates back to the stationarity assumption, mostly due to the dynamic nature of the socio-economic processes associated with the ownership parcelization process (Gobster and Rickenbach 2004).

In addition, the implications of this study should be regarded in light of the fact that only two temporal stages have been utilized. Using multiple temporal stages can better reveal the dynamic nature of the transition rates that has occurred in the recent years. For example, using a more recent temporal stage is likely to show greater transition probabilities into the smallest parcel size classes, while the aggregative transitions, such as those from the Pioneer Forest, are most likely to be very weak.

As ownership parcelization intensifies, understanding the dynamics of the process will assist in evaluating the potential ecological impacts, developing well informed forest management practices, and eventually bringing more private land owners to be involved in forest management. This could also help agencies for developing effective educational or incentive programs to better target private forestland owners for sustainable forestry in the future.

Besides, although it may be obvious that ownership parcelization is occurring and affecting the land use pattern in the landscape, there are still very limited studies on how this will affect the landscape structure in a more comprehensive context (Croissant 2004). For example, one can fear that the potential impact from the highly parcelized ownership landscape may be devastating for ecological conservation, given that the dispersed management activities can result in highly fragmented habitats. On the contrary, however, if most of the forestland owners with small parcels are not engaged in active management, the highly parcelized ownership landscape may not have any significant impact to the habitat quality of the landscape.

By characterizing the forestland ownership parcelization across the entire range of parcel sizes, this study may also be useful in assisting research related to the evaluation of the impacts from the changing intensities and spatial arrangements of forest management practices, especially considering the development of the recent forest landscape models that are capable of simulating various forest management schemes in a spatially explicit manner (Baker and Mladenoff 1999, He et al. 2003, Gustafson et al. 2000, Zollner et al. 2005). By associating varying forest management practices and intensities with the distributional characteristics of existing ownership parcels, this study presents the opportunity to formulate the level of ‘management fragmentation’ for realistic applications of harvest practices for such landscape models.

E. Tables

Table III-1. Transition probability matrices for each of the scenarios from all observations, with all parcel size transitions included (A) and transitions without the acquisitions from the Pioneer Forest (B). The parcelizing and aggregating transition probabilities are shaded in light blue and light orange, respectively, to assist the readability of the table. For the construction of transition probability matrices, bootstrapping with replacement for the sample size of the observations were used, which was then iterated 1000 times to calculate the confidence interval.

	Size class	Size class To										Midpoint
	From	1	2	3	4	5	6	7	8	9	10	size (ha)
A.	1 (6 ha)	0.44	0.05	0.19	0.12	0.13	0.04	0.01	0.03	0.00	0.00	6
All	2 (26 ha)	0.20	0.20	0.20	0.20	0.13	0.07	0.00	0.00	0.00	0.00	26
	3 (43 ha)	0.12	0.05	0.37	0.10	0.18	0.09	0.05	0.01	0.01	0.02	43
	4 (71 ha)	0.06	0.04	0.14	0.35	0.16	0.16	0.05	0.01	0.01	0.02	71
	5 (117 ha)	0.06	0.03	0.16	0.16	0.36	0.15	0.04	0.01	0.02	0.00	117
	6 (193 ha)	0.08	0.05	0.11	0.09	0.12	0.45	0.06	0.02	0.01	0.02	193
	7 (321 ha)	0.07	0.05	0.09	0.15	0.15	0.13	0.25	0.06	0.01	0.04	321
	8 (528 ha)	0.03	0.01	0.07	0.07	0.07	0.04	0.00	0.42	0.00	0.29	528
	9 (871 ha)	0.10	0.15	**0.32**	0.00	0.10	0.00	**0.32**	0.02	0.00	0.00	871
	10 (1429 ha)	0.00	0.00	**0.38**	0.00	0.00	0.00	0.00	**0.43**	0.19	0.00	1429
B.	1 (6 ha)	0.44	0.05	0.19	0.12	0.13	0.04	0.01	0.03	0.00	0.00	6
no	2 (26 ha)	0.23	0.23	0.23	0.08	0.15	0.08	0.00	0.00	0.00	0.00	26
PF	3 (43 ha)	0.13	0.05	0.40	0.11	0.19	0.05	0.05	0.01	0.01	0.00	43
	4 (71 ha)	0.07	0.04	0.13	0.36	0.17	0.16	0.05	0.01	0.00	0.00	71
	5 (117 ha)	0.06	0.03	0.16	0.16	0.36	0.15	0.04	0.01	0.02	0.00	117
	6 (193 ha)	0.08	0.05	0.11	0.09	0.12	0.45	0.06	0.02	0.01	0.00	193
	7 (321 ha)	0.07	0.05	0.10	0.16	0.16	0.13	0.26	0.06	0.01	0.00	321
	8 (528 ha)	0.04	0.01	0.11	0.09	0.07	0.05	0.00	0.63	0.00	0.00	528
	9 (871 ha)	0.10	0.15	**0.32**	0.00	0.10	0.00	**0.32**	0.02	0.00	0.00	871
	10 (1429 ha)	0.00	0.00	**0.47**	0.00	0.00	0.00	0.00	**0.53**	0.00	0.00	1429
	Midpoint size (ha)	6	26	43	71	117	193	321	528	871	1429	

F. Figures

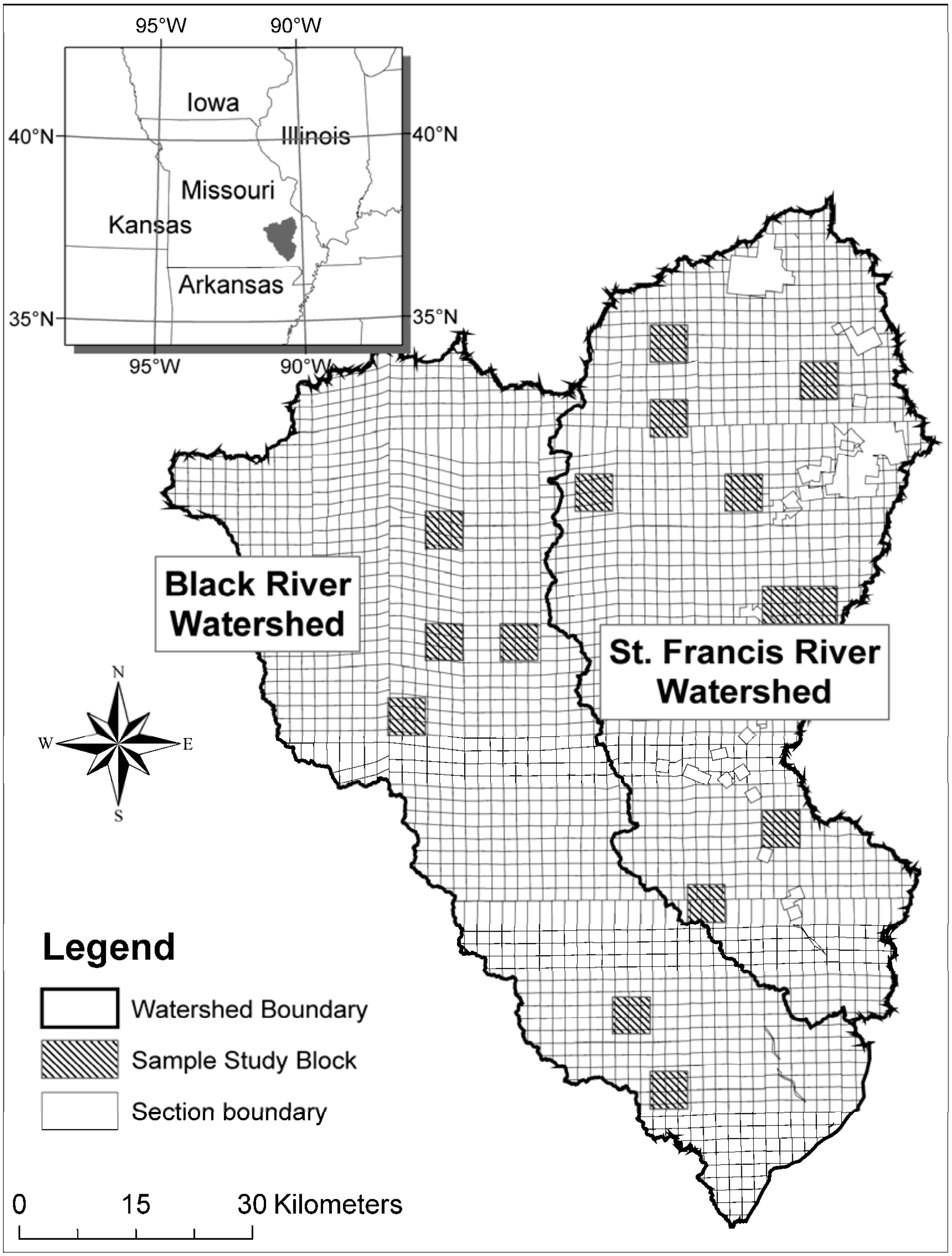

Figure III-1. Map showing the location of the study area of Black and St. Francis River watersheds. Locations of the 15 sample study blocks and section boundaries (under PLSS system) are shown.

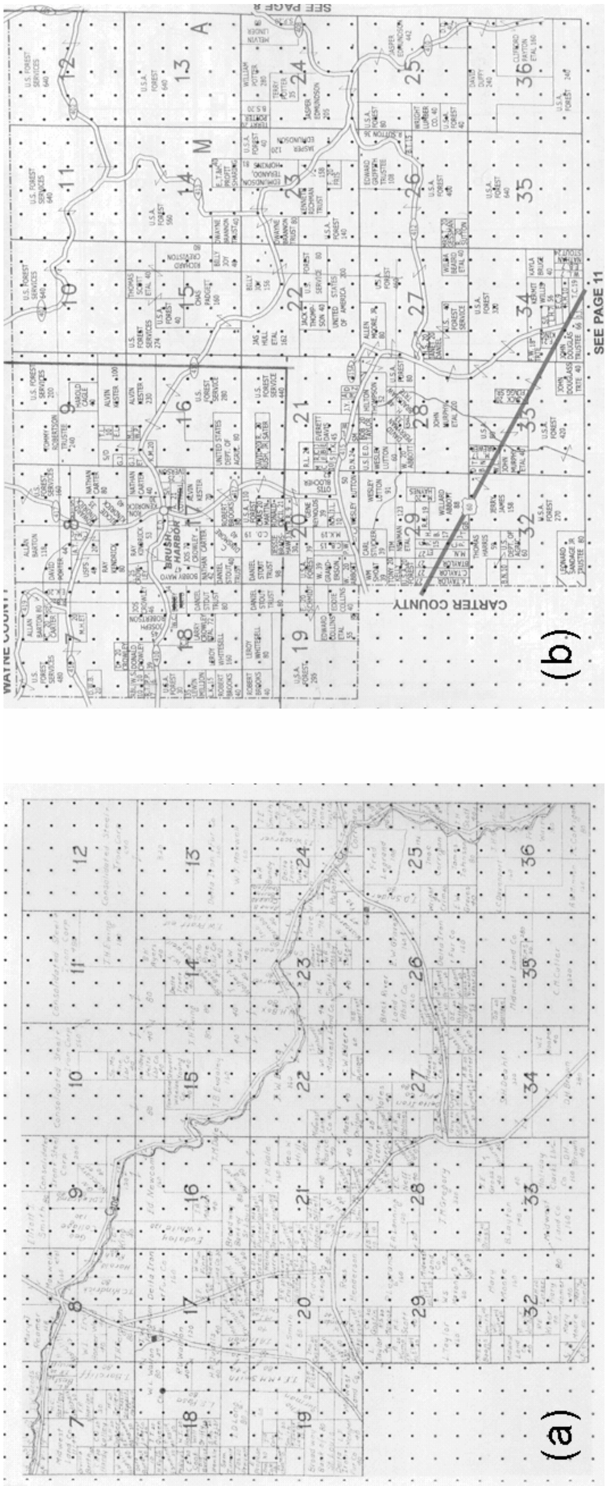

Figure III-2. Sample plat book images from the year (a) 1930 and (b) 2000 used in the study, shown with the overlaid point grid. The points on the image designate the locations at which parcel sizes were measured and parcel ownership types were recorded. These measurements were repeated for all 15 sample study plots shown in Figure III-1.

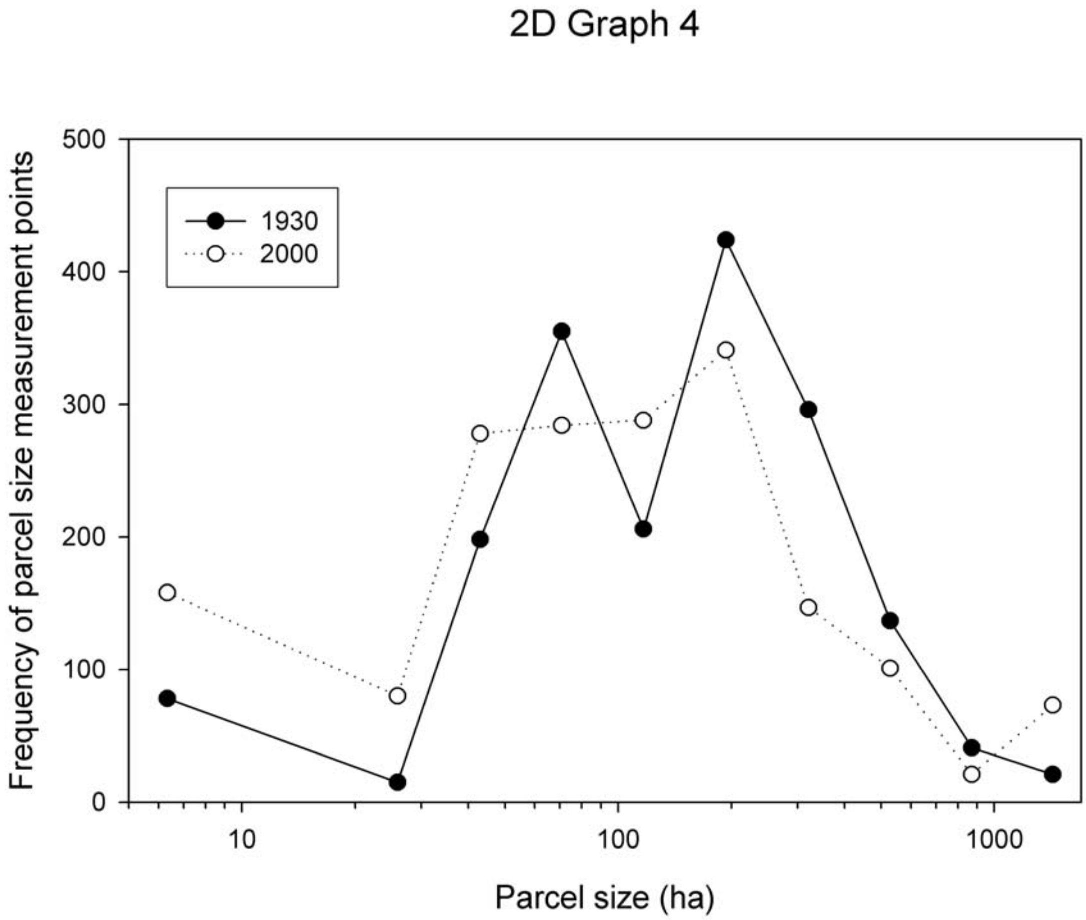

Figure III-3. Frequency of recorded parcel sizes from the plat books of 1930 and 2000. The frequencies are based on records of size and ownership type of the parcels counted at the points from the point-grid overlaid to the plat books, as shown in Figure III-2. Note that the parcel size axis is in log-scale due to the extremely skewed distribution towards the smaller end.

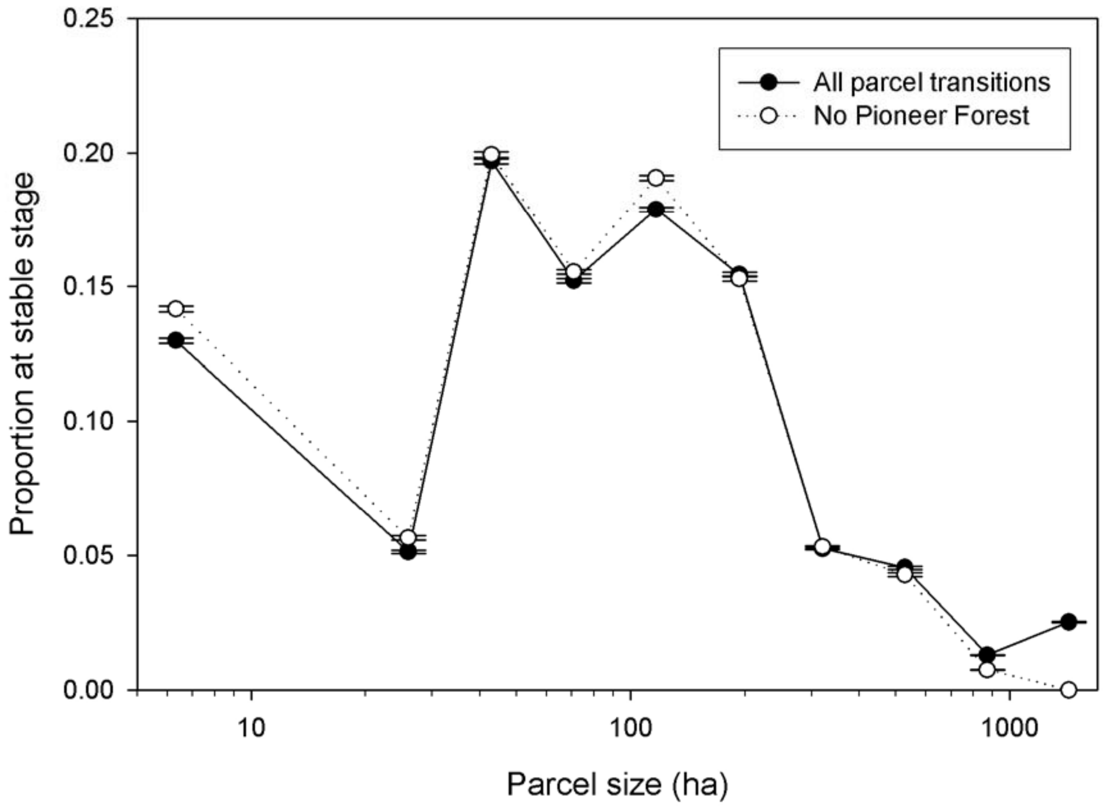

Figure III-4. The proportion of parcels in each of the parcel size classes at stable stage distribution. Stable stage parcel size class distributions are generated from transition probability matrices constructed based on the two different scenarios: all parcel transitions counted; and transitions without the acquisitions from the Pioneer Forest. Error bars indicate 95% confidence intervals that were calculated from 1000 bootstrap data sets of the transition probability matrices for each of the scenarios.

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Chapter IV. The effects of ownership parcelization on the forest landscape in the Missouri Ozarks, USA.

A. Introduction

The recent phenomenon of parcelization of privately-owned forestland in the United States has raised concerns because of its potential negative ecological impacts and the potential reduction in forest product supply (Mehmood and Zhang 2001). In the state of Missouri, as a result of the parcelization, nonindustrial private forestland (NIPF) owners now hold 87 percent (11.3 million acres) of Missouri's timberland area, with more than half of the owned parcels smaller than 100 acres (USDA 1989). Such highly parcelized ownership structure in Missouri is a relatively recent phenomenon as portrayed in the changing number of NIPF owners, dramatically increasing from 81,000 in 1978 to 300,000 in 1993, with 79% of those owning parcels smaller than 50 acres (Birch 1996, Hahn and Spencer 1991).

The complexity of the situation comes from the diverse interests and objectives of the numerous landowners (Turner et al. 1996, Rickenbach and Gobster 2003, Gobster and Rickenbach 2004). Coupled with the higher level of parcelization, the diversity of the landowners' interests and motives may result in fragmented management practices applied to the forest landscape, making an integrated landscape management approach a challenging task (Kurtz and Lewis 1981, Bailey 1996, Raedeke et al. 2001). Recent studies have demonstrated how various ownership types and management practices can affect the forest landscape in a variety of ways (Campbell and Kittredge 1996, Crow et al. 1999, Gustafson et al. 2000, Zollner et al. 2005). However, the ecological effects on the forest landscape caused by the highly parcelized private ownership is seldom investigated, which is in sharp contrast compared to numerous studies on the effects of habitat fragmentation on biodiversity, wildlife habitat quality and wildlife behavior (Bancroft et al. 1995, Tinker et al. 1998, Villard et al. 1999, Radeloff et al. 2000).

Although it is generally known that higher ownership parcelization is likely to result in reduced intensity in forest management, several studies have indicated potentials for the opposite. For example, Bourke and Luloff (1994) showed that non-industrial private forestland owners in Pennsylvania shared common concerns with the general public with respect toward forest management policies. In addition, private owners, once educated and informed of the possible forest management policies, are more likely to be involved in programs for forest management (Creighton et al. 2002). Coupled with the increasing interest in ecosystem management and forestry co-operatives from private owners with small parcels, these suggest the possibility of increasing harvest intensity even in a highly parcelized ownership landscape (Padgham 2002).

Ownership parcelization can affect the landscape in a variety of ways. It is known that owners with different parcel classes have different management strategies, mostly affected by the motives of ownership (Haymond 1998, Kittredge et al. 2003, Richter 2005). First, owners with smaller parcels tend not to target their management efforts towards stumpage, with limited participation in any of the forest management activities. In contrast, those with larger parcels are more likely to be engaged in managing production of wood products, either directly through timber harvest or indirectly by conducting intermediate operations such as stand improvement or thinning of the stand. Therefore, greater level of parcelization can reduce the intensity of harvest operations – as disturbance events – in the landscape, leading to less impact on the forest successional dynamics, such as species composition and age structure of the forest.

However, greater parcelization implies that forest management practices are conducted in a spatially fragmented way, which may influence the spatial pattern of the forest even with the low level of harvest intensity. A number of studies showed that harvest strategies in various spatial configurations, with the same area or amount of timber harvested, can efficiently affect the amount of interior habitat for particular species, (Crow and Gustafson 1997, Zollner et al. 2005). In addition, parcel shape characteristics occurring from the ownership parcelization, which strongly reflects the underlying PLSS structure characterized by straight, rectilinear boundaries with high proportion of particular parcel size classes (chapter 2), may affect the spatial configuration of harvest events, and eventually the forest landscape, such as leading to patterns with lower patch shape complexity.

As forest succession, ownership parcelization and disturbance regimes occur and interact in a large spatial and temporal scale, the resulting ecological impacts can be extremely complicated. Therefore, a forest landscape simulation model, particularly one that can simulate both the ecological processes and the forest management practices in a spatially explicit way, becomes an effective tool for such inquiries. In addition, the difficulty in conducting actual experiments landscape response over a long term in a vast spatial scale, forest landscape simulation modeling is an effective tool that can be used to compare and evaluate various scenarios. For these reasons, LANDIS, which has been extensively used, calibrated, and applied in the hardwood forests of southeastern Missouri Ozarks, was used for the purpose of this study (Gustafson et al. 2000, Shifley et al. 2000, He et al. 2004).

Nevertheless, even with the help of forest landscape model, simulating harvest events characterized by highly parcelized ownership landscape is difficult to implement. To properly evaluate the effects of ownership parcelization, a reliable representation of the land ownership pattern is necessary. However, obtaining accurate ownership boundary maps over a large region can involve labor intensive digitizing and GIS processing, resulting in extremely high cost. Even with an actual land ownership boundary map, it can be argued that reliable inference cannot be obtained when the sample map is limited to a certain spatial extent (Fortin et al. 2003). Although neutral models can be a potential tool for creating landscape patterns (Gardner et al. 1987, Gardner et al. 1991, O'Neill et al. 1992, Hargis et al. 1998, Saura and Martínez-Millán 2000), these are not the ideal models to simulate highly artificial ownership patterns characterized by rectilinear boundaries, for the following reasons: (1) the models are designed to generate neutral ('null') landscape patterns that do not reflect any specific process (Gardner et al. 1987); (2) the more recent variants are used to generate realistic 'natural' landscape patterns (Saura and Martínez-Millán 2000); and (3) all existing neutral models are not capable of generating patterns with a specific parcel size distribution. Therefore, for the spatial implementation of harvest events in a highly parcelized landscape, selection of a model that can reproduce the variability of actual ownership patterns with respect to the spatial characteristics of composition and configuration is important. For these reasons, a Forested Land Ownership Spatial

Simulator (FLOSS) is a promising model for the purpose of this study (chapter 2), as it is designed to generate landownership patterns with strong PLSS structure, and is capable of creating parcels with the specified parcel size distribution.

This study evaluates the long-term influences and interactions from forest management practices conducted by private forestland owners with varying degrees of parcelization, harvest intensity, and fire regimes in a forested landscape. A forest landscape model was used to simulate the changes reflected by tree species composition, age structure and their respective spatial patterns. Specifically, the objectives are to investigate the direct effects and their interactions in various temporal terms (short-, mid- and long-term) caused by different levels of parcelization and harvest intensities to a forest landscape in the southeastern Missouri Ozarks by evaluating the following components: (1) response of species abundance of four dominant tree species groups (white oak, red oak, shortleaf pine, and maple); (2) changes in the age structure of the forest landscape; and (3) changes in the spatial patterns of the four major tree species and age classes.

B. Methods

1. Study area

The study area is located at the southeastern part of the Ozark Highlands in Missouri, including two watersheds – the Black River and St. Francois River watersheds (Figure IV-1). As part of the Ozark central hardwood region, the total area covers over 780,000 ha. Most of the area is heavily forested by mixed oak-hickory forest. The forests in this area are dominated with white oak (*Quercus alba*), scarlet oak (*Q. coccinea*), black oak (*Q. velutina*), post oak (*Q. stellata*), and pignut hickory (*Carya glabra*), mockernut hickory (*C. tomentosa*), and black hickory (*C. texana*), with scattered stands of shortleaf pine (*Pinus echinata*) / shortleaf pine-oak mixed forest (USDA 1989, MoRaP 2000, Nigh and Schroeder 2002). However, much of the shortleaf pines acreage that existed prior to 1900 was replaced by oaks and hickories as a result of clearcutting and burning in the early 1900s (Cunningham and Hauser 1989). Based on the land type association (LTA), the area mostly consists of oak-pine woodland/forest hill (49%) and igneous knobs (23%), along with pine-oak woodland/dissected plains (9%), dolomite glade/woodlands (7%), and forested rugged hills and breaks (7%) (Bailey 1996, USGS 1996).

Elevation ranges from 97 to 540 m, with slopes typically ranging from 0 to 30 degrees. The climate of the study area is humid and continental. Precipitation averages approximately 1,100 mm per year, with more than 350 mm of precipitation occurring in April, May and June, while January being the driest month with mean precipitation of 50 mm (Baldwin 1973). Annual mean temperature is 11C$^{\circ}$, with July being the warmest month with a 25C° mean temperature and January the coldest with 1.2C°. The soil of the study area is mostly alfisols and ultisols, which are formed from old granites and Paleozoic limestones and sandstone to Pleistocene loess and alluvium (Unklesbay and Vineyard 1992).

Historically, forest management in the Ozarks since the early 20th century was based on fire control, resulting in mid-canopy filled with shade tolerant species (Dey et al. 1996, Larsen et al. 1997, Rebertus and Burns 1997, Guyette and Larsen 2000, Guyette and Dey 2000,). Therefore, as many oak forests are reaching their maturity, studies suggested that the oak forests may be replaced by more shade tolerant tree species such as hickories and red maple (*A. rubrum*) in the future (Dwyer et al. 1995, Dey et al. 1996).

2. Approach

Parcelization level

In this study, two levels of ownership parcelization were used: (1) the current level of parcelization; and (2) an estimated higher level of parcelization based on the current trend in parcel size changes in the study area. The higher level of parcelization was estimated based on the transition matrix model specified by the changes in pairs of parcel size classes between the year of 1930 and 2000, which is described in chapter 3 in detail. Based on the resulting parcel size distribution of the transition matrix model, a forestland ownership boundary pattern simulator, FLOSS, was used to generate the resulting spatial pattern of ownership parcels (chapter 2). FLOSS is a stochastic pattern generator that is designed to simulate ownership patterns with strong PLSS shape characteristics, which uses a user-specified parcel size distribution as input parameter.

The design, operation, and performance of FLOSS are discussed in detail in chapter 2. The generated ownership patterns can then be used for the spatial implementation of harvest events in a parcelized ownership landscape.

Harvest intensity

Harvest intensity can be characterized by harvest rotation rate, which depicts the amount of harvest area per unit time (e.g. percent per year). The reciprocal if this value is the harvest rotation year, the amount of time required to harvest the area equivalent to the entire landscape of interest (e.g., 10% harvest / decade = 100 rotation year). It was determined that two levels, 7% and 15% per decade, were appropriate to reflect the low and high level of harvest intensity in private forestland, based on the survey results, previous empirical studies on NIPF landowner’s harvest practices, and the general management intensities used for moderate level of silvicultural treatment (USDA 1986, Kittrege et al. 2003, Richter 2005).

Forest landscape simulation model

A spatially explicit forest landscape model, LANDIS, was used to simulate the tree species dynamics (dispersion, establishment and competition), disturbances (i.e., fire and harvest events). By simulating spatial interactions between forest succession and various disturbance events, and LANDIS makes it possible to investigate the forest landscape response to the various scenarios (Mladenoff and He 1999, He and Mladenoff 1999, Gustafson et al. 2000). LANDIS operates on a raster grid, in which each pixel (or ‘site’ in LANDIS terminology) contains information of tree species, age cohorts, and environmental variables that affect the regeneration, succession, and survival of the species / age cohorts and natural disturbances. LANDIS is designed to capture the spatial interactions of the processes occurring over long temporal periods (hundreds of years) over large landscapes (10^4 to 10^6 ha) in 10-year time steps.

In LANDIS, succession is simulated as a competitive process of existing tree species with the combination of life history attributes (e.g., shade and fire tolerance, seed dispersal, longevity, maturity age) and the suitability of the landtype to particular species. This is dynamically related to natural disturbances and harvest events that eliminate particular species and / or age classes, which in turn affects the successional dynamics (He and Mladenoff 1999). For example, species-specific fire tolerance and age of the tree species interacts with the intensity of fire events, and determine whether particular age classes and tree species are to be eliminated by a particular fire event.

Fire and wind disturbances are simulated as stochastic natural disturbance events. Fire disturbance is modeled as bottom-up process, thus killing younger age cohorts first, while wind disturbance is a top-down process, where older age cohorts are first eliminated. The fire related tree mortality in LANDIS is also dependant on the fire intensity based on the species-specific fire tolerance characteristics. The improved fire module of LANDIS in the newest version (version 4.0) simulates fire occurrences as a hierarchical process (Yang et al. 2004).

The fire module simulates fire events based on the following steps: (1) a number of ignition events are generated based on the ignition density; (2) for each ignition event, it is determined it can successfully initiate a fire event; (3) for each fire initiation, fire size is determined from a lognormal distribution specified by mean fire size and its standard deviation; and (4) fire spread is simulated by various methods as specified by the user:

simple, modified percolation, or the simplistic method based on random wind direction, fire size, and fire probability (Gardner et al. 1999, Wimberly et al. 2000, Hargrove et al. 2000, Yang et al. 2004). The fire ignition, spread, and intensity can be based on time since last fire, or on the fuel module, in which the intensity of a fire event is based on the coarse and fine fuel load at the particular location.

Environmental factors that affect natural disturbances are represented as fire and wind disturbance parameters, and can be parameterized for each landtype (or as a separate fire regime map for the newer fire module). Such parameters control disturbance return interval and size distribution, as well as fire ignition and probability coefficients.

Seed dispersal is spatially simulated by an exponential distribution following the effective and maximum seed dispersal distance specified for each tree species. Establishment coefficient, shade tolerance, and existing vegetation determine whether a particular tree species can successfully regenerate at a particular site (Mladenoff and He 1999). For example, a tree with lower shade tolerance cannot establish on a site where an age class of a tree species with higher shade tolerance exists. Asexual regeneration in LANDIS is simulated based on the vegetative propagation coefficient specified for each species, which is used to determine the probability of reestablishment after a disturbance.

Harvest module of LANDIS simulates disturbances caused by harvest activity in the landscape (Gustafson et al. 2000). The harvest module of LANDIS is capable of simulating a variety of harvest activities for even-aged, uneven-aged, regeneration- and intermediate harvests, i.e. clearcut, shelterwood, thinning, and group selection. The harvest module is extremely flexible by offering numerous options for the management events, such as selective removal of age classes and tree species, various temporal combinations of harvest events, and others. The temporal combinations can be implemented as single-entry, two-entry, and periodic-entry prescriptions of harvest events.

Management areas are specified by a single or combinations of such harvest activities that characterizes the management objectives in a specific area. Management areas are further divided into stands that are used as spatial units in which the management activities are conducted, and can be prioritized by stand ranking algorithms specified by the user. Succession in the site after the harvest event is simulated by the regeneration process discussed above.

3. LANDIS parameterization

Input parameters and maps for LANDIS were created from various sources based on existing spatial data sets and previous LANDIS applications applied to southeastern Missouri Ozarks and from a forestland ownership pattern model, FLOSS (Shifley et al. 1997, Shifley et al. 2000, He et al. 2004, chapter 2).

Species map and attribute

Forest composition map specifies the spatial distribution of tree species and the associated age classes, and is used for the initial forest map for LANDIS simulation. Forest composition map was created based on the Land Use Land Cover Map (LULC) of Missouri (MORAP 2000), Forest Inventory Analysis database (FIA), and the Land Type Association (LTA) (USDA 1989, Bailey 1996). FIA database was used as the data source as it provides age information of trees at known plots. For each of the plot, which represents an area of 1 acre, FIA database includes records of forest type, timber volume/acre, stand size, stand density, stand age, ownership, DBH, species, growth rate, and timber quality.

There were 625 FIA plots included in this study area, and the information in the given plots was used to determine the dominant species, modified species importance value (the summation of the relative density and relative dominance (Curtis & McIntosh 1951)) and the associated age class. Relative frequency was dropped in calculating the species importance value since the value was the same for all species in the same plot.

Based on these data, a number of GIS processing was conducted in Arc/Info to derive the species composition map. First, the LULC map was reclassified based on the represented forest types for four major species groups – red oak, white oak, maple, and shortleaf pine –, and then was spatially combined with the LTA types so that a combination of both types could be identified. Second, FIA points were spatially joined with each of the combination, from which the importance value and age classes could be calculated. The specified abundance and age classes for each combination were randomly distributed accordingly, and used as forest types for initial forest composition map and to provide age class information.

Tree species life attributes are parameters that control the regeneration (seed dispersal and establishment) and succession in LANDIS, which in turn interacts with environmental variables and disturbances. Species life-history and landtype attributes were derived from previous LANDIS studies in the region (Shifley et al. 2000). Species life-history is comprised of parameters of longevity, maturity age, shade and fire tolerance, effective and maximum seeding distance, vegetative propagation coefficient, and minimum age to resprout, and were specified for four major species group in the study area (Table IV-1).

Red oak group is characterized by mid-longevity, with moderate shade and fire tolerance and high probability of sprouting. White oak group has greater longevity and fire tolerance than red oak group, but with relatively lower sprouting probability. Shortleaf pine group has mid-longevity, and moderate shade tolerance; and shares the same fire tolerance as white oak group but with very limited sprouting ability. Maple group has mid-longevity, but has the highest shade tolerance and lowest fire tolerance among all species group, and relatively limited sprouting ability.

Landtype

Land type map represents the environmental characteristics of the area that is specified by species establishment coefficients. This enables LANDIS to simulate the interaction of the environmental conditions and ecological characteristics of tree species in response to various disturbance events. Land type map was created from the digital elevation model (DEM), geology and soil data based on the landtype models used for previous LANDIS studies close to the study area (Shifley et al. 1997, Shifley et al. 2000). The specific landtypes used for this study includes: south and west slopes, north and east slopes, ridge tops or upland flats, upland waterways, floodplains or low terraces, side slopes on limestone, or glades.

Disturbance

The fire disturbance was simulated by using a hierarchical process for fire initiation and the simplistic method for fire spread (He and Mladenoff 1999, Yang et al.

2004). Fire regime maps used were the same as landtype maps, and fire disturbance attributes were based on fire intensity curves to characterize the effects of environmental condition to fire regimes, which were derived from previous LANDIS studies in the region (Table IV-3) (Shifley et al. 1997, Shifley et al. 2000). In addition, each fire regime unit is characterized by parameters such as fire return interval (time required to burn the entire landscape), fire density and ignition coefficients (determines the number of fire ignitions and the probability of successful fire initiation).

Fire return interval is the mean number of years required for fires to burn the entire area, and controls the fire probability of the given cell. Under the fire suppression policy in Missouri, current fire return interval ranges from 300 to 415 years (Westin 1992), while previous studies on the historical fire regime in the Missouri Ozarks suggests greater frequency during the pre-European settlement, with fire return intervals generally ranging under 100 years (Guyette 1995, Guyette and Day 1997a, Guyette and Dey 1997b). For this study, continuing high fire suppression level (fire return interval 300 years) was used for the simulation.

Harvest regime

The harvest regimes were determined based on the survey results from the private landowners in the study area (Richter 2005). Since the survey did not include questions regarding detailed harvest practices, three ‘management types’ were identified based on particular questions related to past and potential harvest practices: sawlog; pulpwood, and firewood management. For each of these ‘management types’, the commonly used harvest methods associated with the respective management types were applied: sawlog management type divided into identical proportions of clearcut, shelterwood, and group selection method; pulpwood management type with clearcut method, and firewood management type with clearcut method (Table IV-4). For the clearcut, group selection, and pulpwood method, all species across all age cohorts were eliminated. Harvest events in a shelterwood method occur in two stages: (1) a stand is initially harvested by the specified species and age cohorts; and (2) the stand is revisited later after specified decades and the remaining cohorts are removed. In this study, all age cohorts of maple and shortleaf pine species groups, and 1-30 and 31-60 year age group stands of both oak species groups were harvested during the first visit, and the remaining age cohorts (≥ 61 years) of the oak species were harvested during the second visit after 2 decades.

The proportions of each harvest method for a set of ownership parcel size classes (< 20 ha; 21-41 ha; 42-88 ha; 89-205 ha, and > 206 ha) were also calculated based on the survey, which were used as the basis for generating stand maps to demonstrate varying parcelization levels (Table IV-5). A random stand ranking algorithm was used, as harvest events from NIPF private owners are known to show spatially random pattern, and are strongly affected by ownership size class (Kittredge et al. 2003).

In essence, spatial implementation of harvest events in LANDIS was represented by using stand maps with two different levels of parcelization characteristics, as stand maps depict the spatial unit in which a harvest event is applied. Due to the limited number of stands that can be processed in LANDIS, the ownership boundary maps generated from FLOSS were reclassified based on the harvest methods (Figure IV-2). The proportions of harvest methods in each of the parcel size class (Table IV-5) were used to determine the proportions in each of the combination of parcel size classes and harvest methods. Unique ID numbers were assigned for each individual parcel, which were then used as stand maps for the harvest module in LANDIS.

The landscape included both private (76%) and public (24%) lands. However, harvest regimes were only applied to one management area, specified by private management regime, because of several reasons: (1) the number of stands accepted by LANDIS is limited to 65536 based on the input format of the map file – 16-bit ERDAS GIS, and it was impossible to include public land with its own stands without exceeding this limit; and (2) the effects from the potentially higher management intensity in the public land (as high as 18.6% per decade) may obscure the main effects from the scenarios in this study. Consequently, the portions of public land in the study area were masked out and designated as a management area without any harvest regimes, and were excluded from the analysis.

4. Experimental design

A 2×2 factorial design was used with main factors of parcelization level and harvest intensity, with two factor levels each. Scenario with no harvest was also simulated, however it was excluded from the statistical analysis to maintain the complete factorial experimental design, as parcelization level cannot be applied under no harvest intensity. Instead, simulation results without harvest events were later used as a reference for the interpretation of the analysis results.

As discussed above, two levels of ownership parcelization – current and higher level – were implemented by using the FLOSS generated ownership maps as stand maps for the harvest module in LANDIS. Two harvest intensity factor levels of 7% per decade and 15% per decade were used, and from which the target harvest proportion and cell numbers for LANDIS simulation were determined (Table IV-5).

Each combination of parcelization and harvest intensity levels created 4 different scenarios, and each scenario was simulated with 20 iterations (200 simulation years) and 10 replicates. In addition, 2 additional scenarios excluding harvest-related factors (therefore both harvest intensity and parcelization level factor levels were excluded) were also simulated with 20 iterations and 5 replicates, for the purpose of reference. LANDIS outputs include maps of all age classes and for each species group, reclassified dominant species group, presence of each species group, fire event, and harvest event, for each of the 20 iterations. The overall diagram of the design of the simulation is presented in Figure IV-3.

5. Analysis

Three sets of response variables were measured for the analysis to evaluate the changes in forest succession and landscape patterns: (1) change in dominance in species group, measured by the total area of each species group; (2) change in age classes in the entire landscape, measured by the total area of reclassified age classes (1–30 years; 31–60 years; 61–100 years; and ≥ 101 years); and (3) change in spatial pattern of the overall landscape for age class and major species group, measured by landscape pattern metrics (area-weighted mean fractal dimension (Milne 1988, O'Neill et al. 1988), and aggregation index (He et al. 2000)). Measurements were aggregated for three separate temporal sequences to investigate the dynamic nature of the effects, specified by the following ranges in simulation years: (1) short-term: 10-50 years; (2) mid-term: 60-100 years; and (3) long-term: ≥ 110 years. FRAGSTATS (version 3.3, McGarigal and Marks 1995) and FIRESTATS (He et al. 2005) were used for all measurements and calculation of landscape metrics.

Fractal dimension represents the complexity of the patch shape based on the perimeter-area fractal analysis of the patch (Milne 1988, O'Neill et al. 1988). The index value ranges from 1 to 2, approaching 2 with greater shape complexity, and approaching 1 with simple shape such as a Euclidean geometry (e.g., square, circle).

Aggregation index (AI) is a raster-based configuration index which quantifies the aggregation level of each patch type (class-level) or all patches throughout the landscape (landscape-level) (He et al. 2000). AI is calculated from an adjacency matrix, which is based on the number of shared edges of the patches from each patch type. AI shows the level of how certain patch types are placed side by side (aggregated) or are located apart from one another (dispersed) in the landscape. AI reaches 100 when the pixels of the specific patch type are sharing the most possible edges (thus forming a single large patch), and the index reaches 0 when pixels of the given type are completely dispersed as separate single pixels. Because AI is calculated based on individual pixels, the results are relatively sensitive to the resolution of the landscape.

Multivariate analysis of variance (MANOVA) from the general linear model (GLM) in SPSS (version 12.0) was used to analyze the response variables aggregated for the short-, mid-, and long-term (10-50, 60-100, 110-200 simulation years), separately, to investigate the changing nature of the forest response, at the significance level of $\alpha = 0.01$. Pillai’s Trace statistic was used for hypotheses tests, because of its low sensitivity to the heterogeneity of variance assumption of MANOVA (Zar 1999).

Since there were only two factor levels for all main factors, post-hoc tests were not required. Instead, MANOVA significance test and descriptive statistics were used for various comparisons. In addition, as a complement to MANOVA analyses, the trajectories of all response variables were graphically projected for each temporal terms to evaluate the temporal changes and assist in interpreting the MANOVA results.

C. Results

1. Changes in species composition

In the absence of harvest events and fire suppression, the abundance of white oak species group continuously increased with a stabilizing trend in the end of the simulation, while short-lived red oak species group showed slight decrease and then increased throughout the remainder of the simulation (Figure IV-5). Abundance of the shade-tolerant maple species group showed a steady increase, and shortleaf pine species group showed a gradually increasing trend mostly caused by its limited extent in the initial condition. The relative abundance of the species presence can also be observed in Figure IV-5, in which the proportion of Figure IV-4 for each species is shown. The persistence of the oak species throughout the simulation reflects the tolerance to regionally dry conditions of the Missouri Ozarks, in particular, the xerophytic red oak species group (Johnson et al.2002, Batek et al. 1999). It should be noted that the oak decline in the Missouri Ozarks projected in the near future is usually accompanied by external factors, such as high infestations of oak borers and the occasional severe drought events (Dwyer et al. 1995, Law and Gott 1987), which has not been simulated in this study.

MANOVA tests showed that parcelization level, harvest intensity, and their interactions had significant effects in the short-, mid- and long-term on the species composition (Table IV-6.). The *F* statistics reveal that harvest intensity had the greatest contribution in explaining the variance in the species composition (Table IV-6.).

Individual ANOVA between-subjects tests show that harvest intensity had significant short-, mid- and long-term effects on the composition of all species groups, and parcelization level showed significant short-term effect on red oak, mid-term effects on maple and red oak, and long-term effect on maple species group (Table IV-7.). The effects from the interaction between parcelization level and harvest intensity was only significant for the maple species group composition in the long-term. During the short- and mid-term, composition of red oak species had the most contribution to the variance, which was replaced by the maple species groups in the long-term.

Despite the significance from the MANOVA and the individual ANOVA tests, the overall trajectories of species composition show that the changes incurred by the main factors were relatively minimal (Figure IV-6).

2. Changes in age structure

In the initial age structure, 61-100 year age class had the greatest abundance, followed by 31-60, 1-30, and ≥100 year age class. In the absence of harvest events and under fire suppression, the ≥100 year age group abundance rapidly increased and dominated the landscape towards the middle of the simulation, while the younger age groups decreased in the initial phase of the simulation as they moved up into older age groups without being replaced with younger age groups by the lack of regeneration (Figure IV-7). Such dominance from the older age group diminished in the later phase of the simulation as older age cohorts died from age, while the abundance of younger age groups gradually increased as regeneration started to actively take place.

MANOVA analysis indicated that harvest intensity had significant short-, mid-, and long-term effects on the abundance of age groups of the forest landscape (Table IV-8). Parcelization level showed significant effects only in the mid- and long-term age group abundance. *F* statistics showed that harvest intensity had the greatest contribution to the variance. The interactions between parcelization level and harvest intensity was not significant at any time of the simulation.

Individual ANOVA between-subjects tests showed significant effects of parcelization level for the 31-60 and ≥100 year age group abundance in the mid-term (Table IV-9). However, the significant parcelization effect observed from the MANOVA tests in the long-term was not found in any of the age groups in the individual ANOVA tests. Harvest intensity had significant effects on the abundance of 1-30 and 61-100 year age group in the short-term, and 1-30, 31-60 and ≥100 year age group in the mid- and long-term. *F* statistics indicated that the greatest contribution to the variance came from the harvest intensity effects on the ≥100 year age group abundance in the mid-term, which was replaced by the youngest 1-30 year age group in the long-term.

Overall, abundance of the youngest age group increased in response to higher harvest intensity, and ≥100 year age group decreased (Figure IV-8). 31-60 and 61-100 year age groups generally decreased in the mid-term, but gradually increased in the long-term. As indicated by the individual ANOVA tests, the most obvious differences in age group abundance were from the 31-60 and ≥100 year age group in the mid-term (Table IV-9). However, the overall difference was minimal despite the numerous significant test results, which was similar to the results from the species composition.

3. Spatial pattern of species distribution

MANOVA analysis for landscape-level area-weighted mean fractal dimension (AWMFD) and aggregation index (AI) of the species distribution showed that only harvest intensity had significant effect in the long-term (Table IV-10). Individual ANOVA tests indicated that only AI was significantly affected by harvest intensity in the long-term (Table IV-11).

The overall trend of AWMFD showed that species patch shapes became increasingly complex towards the later simulation years (Figure IV-9), which was accompanied by higher aggregation of species patches (Figure IV-10). Interestingly, shape complexity and aggregation level of species patches were the lowest under the absence of harvest events, and highest with higher parcelization level and harvest intensity.

4. Spatial pattern of age groups

MANOVA analysis of landscape-level AWMFD and AI indicated that parcelization level and harvest intensity had significant effects on the spatial pattern of age groups in all temporal terms, and that harvest intensity had the greatest contribution to the variance (Table IV-12). The interaction between parcelization level and harvest intensity on spatial pattern of age groups was only significant in the mid-term years.

Individual ANOVA tests indicated that AWMFD was significantly affected throughout all simulation years, while AI was only affected in the long-term (Table IV-13). In particular, AWMFD of age groups was significantly affected by harvest intensity in all simulation years, but was affected by parcelization level only during the mid-term. In contrast, AI of age groups was only affected by harvest intensity in the long-term. It is interesting to note that in the short- and mid-term, AWMFD had the greatest contribution to the variance, which was replaced by AI in the long-term.

The overall trends of AWMFD indicate that shape complexity of age group patches slightly increased in the mid-term and then substantially decreased in the long-term (Figure IV-11). The differences of shape complexity were minimal between parcelization levels, but were obvious between harvest intensity levels. Compared to the age patches without any harvest events, those created in scenarios with harvest events showed lower shape complexity. AI trends showed that the aggregation level of age patches showed dramatic changes by increasing in the mid-term, and then decreasing in the long-term (Figure IV-12). As indicated in the individual ANOVA tests (Table IV-13), AI of age patches did not show any differences from factor levels during short- and mid-term, but showed substantial differences in the long-term, especially from the harvest intensity levels. In particular, patches without harvest events were the most dispersed, while patches were more aggregated under higher level of harvest intensity (Figure IV-12).

D. Discussion

Previous studies have shown that the spatial dynamics of harvest practices can effectively influence the species composition, age structure, and the spatial pattern in the forest landscape (Franklin and Forman 1987, Gustafson 1998, Gustafson et al. 2000). However, the influence from the potentially changing spatial implementation of harvest events to the succession and patterns of the forest landscape has seldom been investigated. This study demonstrated that change in private ownership parcelization level and harvest intensity changes the resulting forest composition, age structure, and their landscape patterns with varying levels of effects. Overall, the changes in the landscape caused by parcelization level were minimal compared to harvest intensity, although the landscape patterns of age groups showed more sensitivity in their response. The strong successional process overwhelmed any effects from the harvest events, mainly due to the limited intensity associated with the dominance of smaller parcels under highly parcelized ownership landscape.

1. Parcelization and the limited harvest intensity

Higher harvest intensity resulted in significantly decreased abundance in maple group, and increased shortleaf pine and red oak group. In contrast, parcelization level did not have as much impact on the abundance of the species groups. However, regardless of the significance from the analysis of variance tests, the overall differences in the species composition were minimal (Figure IV-6). For example, even the most obvious difference in the composition of the red oak group in response to the harvest intensity level was <3%. Such limited responses from species composition were also demonstrated the spatial pattern of the species distribution: only one significant effect in the spatial pattern in response to harvest intensity in the long-term was observed in the MANOVA test (Table IV-10). This effect, however, failed to show any significant effect on the patch shape complexity or aggregation level from the individual ANOVA tests (Table IV-11).

This limited response from species composition and its spatial pattern is mostly caused by the restricted area that was 'harvestable', which is the result of the high proportion of non-management area in the smaller parcel size classes used to derive the harvest regimes for the simulation (Table IV-4). More importantly, under the same harvest intensity, the target harvest area for each of the parcelization levels was similar to each other (Table IV-5, Figure IV-13). Therefore, despite the differences in the spatial pattern of ownership parcels and the resulting harvest events, the similar level of harvest intensity under the same parcelization level, coupled with the extremely low level of harvest area, was not capable of substantially affecting the successional trajectory of the species composition. This greatly limited amount of harvest intensity also suggests that the ownership parcelization may not influence the reduction in the amount of forestry products as a result.

This demonstrates the effects from the extremely limited spatial extent for harvest events under highly parcelized ownership landscape; the simulated 7% per decade harvest intensity for the harvestable stands is equivalent to merely 1.61% per decade of the entire landscape, or 3.45% per decade even for the 15% per decade harvest intensity scenario. Considering that the parcelization process in the area is characterized by a strong tendency of transitions towards parcel sizes smaller than 50 ha (chapter 3), in which more than 70% of the forestland is subject to no management practices (Table

IV-4), the harvest events from private landowners may become even more limited in the future. Furthermore, such limit is likely to affect the nature of the harvest events even under higher harvest intensity; as more stands are harvested, the limit imposed may result in harvesting increasingly younger stands, which may add to the limited quantity with even lower value of stumpage. However, as reflected in the slightly higher harvest intensity in the higher parcelization level scenario in this study, the strong tendency of parcel size transitions towards particular parcel size classes may not necessarily result in reduced harvest intensity, even under greater ownership parcelization. Ironically, such changes suggest that the NIPF owners' participation in active forest management is becoming more critical in accomplishing sustainable forestry management at the regional scale (Kindscher and Scott 1997).

The abundance of age groups from all scenarios showed rapid transition into a forest landscape dominated by ≥100 year age groups towards the mid-term simulation years. However, with the increasing mortality from the older age classes and the increasing regeneration, the landscape age structure had more equally distributed age classes in the long-term (Figure IV-7, Figure IV-8). Similar to the results from the species composition, the age structure of the forest lacked the magnitude in their responses to the main factor levels from parcelization level and harvest intensity. Higher harvest intensity slightly reduced the abundance of ≥100 year age group in the mid-term while increasing the younger age groups (Figure IV-8). Higher parcelization level had similar significant effects in the mid-term, however with even smaller magnitude in comparison to the effects from harvest intensity level, which is most likely caused by the cumulative effects from the slightly higher harvest intensity from the higher parcelization level (Table IV-5).

2. Forest spatial pattern

Age group patches became more aggregated with greater shape complexity in the mid-term, which then disaggregated into smaller patches with lower shape complexity in the long-term. This sharp decrease is mostly caused by the dynamics from the successional process coupled with the continuing harvest events in the absence of significant disturbance events. In the short- and mid-term, the successional process created a landscape dominated by the ≥100 year age group, which creates a highly aggregated landscape pattern with moderate shape complexity. In the absence of large disturbance events, the ≥100 year age group dominance is decreasing, and is constantly being replaced by the small and young age groups, resulting in a more dispersed age group spatial pattern in the long-term. The harvest events, on the other hand, do not have enough intensity to change the successional trend as the forest transforms into a landscape with older forest stands in the mid-term. However, as the ≥100 year age group is replaced by younger age groups in the long-term, harvest events may interact with such change because of its spatial characteristics inherited from the parcelized ownership pattern. In particular, the harvest events can create new age cohorts with extremely simple shapes, but with relatively higher level of aggregation compared to age groups created from purely successional regeneration in the absence of disturbance events, since in such case the new cohorts occur in few number of pixels.

It is interesting to note the dynamics in the harvested area over simulation time, expressed by the greater amount of variation in the earlier simulation years and the decreasing harvested area from the group selection method in the later simulation years (Figure IV-13). This demonstrates that the highly parcelized harvest stands can limit the potential harvest methods that can be applied. Although the harvest regimes were parameterized for constant amount of harvest area per decade for each of the harvest intensity and parcelization scenarios (Table IV-5), the actual harvested area greatly fluctuated during the earlier simulation years, and remained considerably lower than specified in the parameter. This is mostly due to the characteristics of the group selection harvest method implemented in the harvest module of LANDIS: under group selection method, selected stands are revisited at a specified interval and harvested by a specified proportion throughout the entire simulation period (Gustafson et al. 2000). However, small stand sizes can prevent further harvest events from occurring in the stands for a long time, as proportions are limited by the size of the pixel; extremely small stands can be harvested by its entirety regardless of the specified proportion, and will not be harvested until the age cohort in the stand reaches minimum stand age regardless of the scheduled reentry. This condition resulted in the greatly reduced amount of group selection harvest area in the later simulation period, and effectively reduced the amount of the actual harvested area than specified in the harvest regime, indicating the limited harvest methods that can be applied in a severely parcelized ownership landscape.

3. Parcelization and the fire regime

Natural disturbance, such as fire, is a constant force affecting the forest landscape (Frelich and Lorimer 1991, Turner et al. 1994, Baker 1992, Mladenoff and He 1999). It is interesting to note that the highly suppressed fire regime used for the simulation may have also contributed to this outcome, as harvest events under highly parcelized ownership landscape and fire events under highly suppressed fire regime can share a number of characteristics: the current fire regime, characterized by relatively long fire return interval (fire return interval = 300 years), equivalent to the low harvest intensity; intense fires in the later simulation years, equivalent to near-clearcut harvest operations; the extremely small fire size (mean fire size = 8 ha), equivalent to highly parcelized harvest stands; and the random spatial distribution of the fire events characterized by the fire algorithm that was used (Yang et al. 2004), equivalent to the random stand ranking algorithm used for the harvest regimes. Therefore, the resulting fire events, especially in the later phase of the simulation, are essentially small stand replacing disturbance events occurring in a random spatial pattern, which shares its disturbance characteristics with the harvest events under highly parcelized ownership landscape.

4. Ecological implications

The ecological implications from the spatial heterogeneity in tree species and age groups can have both positive and negative for wildlife species of management interest, mostly because of the diversity of habitat requirements. For example, studies have showed that a number of breeding bird populations can be significantly affected by the spatial heterogeneity of the forest, such as stand type, age structure, size of openings, and the amount of edge area, which can result from a variety of harvest types (Annand and Thompson 1997, Chalfoun et al. 2002). However, extreme level of spatial heterogeneity is generally known to be harmful for most wildlife species, such as in the form of increased nest predation in edge areas or loss of interior habitat for area-sensitive species (Dunning et al. 1992, Herkert 1994). In addition, the considerable amount of variation in spatial patterns observed throughout the simulation emphasizes the importance of considering the change in landscape structure throughout the entire temporal scale involved. For example, negative changes in forest patterns, even over a relatively short time, may impose considerable pressure on the population viability for particular species if the change severely impairs the connectivity or reduces habitat to a critical level (With and King 1999).

5. Limitations

This study is limited by the imposed temporal and spatial stationarity in the level of landownership parcelization and the associated characteristics. As all input maps for LANDIS are fixed throughout the simulation, the level of ownership parcelization was assumed to be stationary throughout 200 years of simulation, which is most unlikely to be the case. The primary drivers of the level of ownership parcelization are social and economic forces (Gobster et al. 2000); therefore, the forestland ownership landscape is likely to experience constant changes in the future. In addition, since highly parcelized private ownership are more vulnerable to various development pressures (LaPierre and Germain 2005), there is greater potential of land cover type change that can fundamentally change the forest dynamics involved in particular locations, such as conversion to urban area. Furthermore, as harvest regime parameters are also fixed throughout the simulation, it was impossible to implement the dynamic characteristics associated to landowner's behavior or attitude that can be realized into changes in harvest regime.

The level of ownership parcelization and its transition rates may also depend on the spatial location in relation to the socioeconomic and demographic characteristics and other geographic features (Wang and Zhang 2001). Although it is likely that such effects would be limited in this study, because of the extremely limited harvest intensity from the

NIPF landowners, alternative approaches should be used for the application of parcelized ownership to forest landscape models in geographic locations in which human-induced landscape changes are more dynamic.

The simulation of potential interactions between the harvest-related events and fire disturbances is also limited in this study as the fuel module of LANDIS was not fully utilized. Such interactions are worthy of discussion, as they can generate complicated results because of the spatial interactions and the differences in the resulting conditions. The regeneration associated with a fire event is an ecological process, as younger age cohorts and species with lower fire tolerance are more likely to be eliminated, and species with higher fire tolerance, greater vegetative resprouting capability, and lower shade tolerance can benefit. In comparison, forest management practices are often targeted towards the value of the extracted wood products or a particular forest composition and structure for various management purposes, such as creating better habitat for game animals, improving visual aesthetics, or restoring a particular ecosystem. Also, the consumption of woody debris during fire events can significantly reduce the amount of coarse and fine fuel level on the forest floor, while for harvest events such effects will depend on the method of the harvest operation (Fule et al. 2001, He et al. 2004). In addition, fire events can limit the extent and location of a particular management practices, and may completely change existing management plans or even render them useless. On the contrary, harvest events, especially in the form of fuel management, may alter the fire regime by increasing or decreasing the fuel level or by imposing preference for particular species that may alter the fire susceptibility of the forest (Shang et al. 2004).

6. Summary

In summary, this study revealed various levels of effects from parcelization level and harvest intensity on species composition, age structure, and their respective landscape patterns in the forest landscape of the southeastern Missouri Ozarks. The effects from parcelization to species composition were generally minimal, although significant in some temporal terms, and even smaller when compared to the effects from harvest intensity level. The effects from parcelization and harvest intensity to species composition and age structure showed resemblance to the effects characterized by disturbance intensity, as higher level of both factors promoted younger stands and disturbance adapted species, such as shortleaf pine and red oak group. Overall, the forest landscape response showed dominant effects from the successional process, creating largely aggregated species patches.

In terms of landscape pattern, age group patches were more responsive to the harvest events in the later years of the simulation, creating slightly aggregated and simple-shaped patches, reflecting the spatial patterns of harvest events characterized by highly parcelized ownership. Parcelization levels, on the other hand, only showed limited effects to the forest landscape because of the extremely small differences in harvest intensities associated, suggesting that ownership parcelization may not be a significant factor in shaping the future forest landscape. In contrast, the more sensitive responses from harvest intensity levels suggest that the potential change in forest management participation by parcelized landowners has greater potential to create a large impact on the forest landscape, suggesting that the forest landscape change in accordance to changing ownership structure is strongly associated with management fragmentation and the related intensity, rather than the parcelized ownership *per se*. This also implies that the effects will be even more dramatic with greater level of forest management participation, as it will result in increased levels of both harvest intensity and the spatial extent of harvestable stands.

The highly parcelized ownership created small harvest stands, preventing particular harvest methods (i.e. group selection harvest method) from fulfilling the target harvest area, and generated greater variation in the earlier simulation years. In addition, the considerable amount of variation and dynamics in landscape structure during the simulation years revealed the difficulty in evaluating the ecological implications from changes induced by ownership parcelization.

E. Tables

Table IV-1. Species attribute parameters used for LANDIS simulation. The abbreviations are as follow: SLP – shortleaf pine; WOAK – white oak species group; ROAK – red oak species group; MAP – maple species group; LONG – longevity; MATUR – maturity; SHADE – shade tolerance; FIRE – fire tolerance; EFFD – effective seed dispersal distance (in meters); MAXD – maximum seed dispersal distance (in meters); VEGP – probability of vegetative propagation; SPAG – minimum age for a species to vegetatively sprout; RCLS – reclassification coefficient.

SPP.GROUP.	LONG.	MATUR.	SHADE.	FIRE.	EFFD.	MAXD.	VEG.P.	SP.AG.	RCLS.
SLP	200	20	3	4	40	80	0.5	10	0.700
WOAK	250	20	3	4	30	800	0.5	10	0.800
ROAK	150	20	3	3	30	800	0.8	10	0.525
MAP	200	20	5	1	100	200	0.3	10	0.500

Table IV-2. A sample of a landtype attribute parameter used for LANDIS simulation. The example shows the landtype characteristics associated with the southwest facing slope.

Parameters	Comments
SWSLOPE	# landtype name
70	# minimum age required for shade tolerance 5
400	# time since last windthrow
# species establishment coefficients	
0.7	# shortleaf pine
1	# whiteoak
0.9	# redoak
0.0058	# maple

Table IV-3. A sample of a fire regime attribute parameter used for LANDIS simulation. The example shows the landtype characteristics associated with the southwest facing slope.

Parameters	Comments
SWSLOPE	# landtype name
300	# mean fire return interval
0.005	# fire ignition coefficient
8	# mean fire size
10	# standard deviation of fire size
50	# last fire disturbance
10 30 60 90 150	# fire curve
3 3 3 3 3	# fire severity classes
10 20 60 80 100	# wind curve
4 3 3 3 3	# modified fire classes

Table IV-4. The proportion of the identified harvest methods from private landowner survey results calculated by parcel size classes. The abbreviations for harvest methods are as follows: No Mgmt – no management; Shelter – shelterwood; Group – group selection. These proportions were used as the basis to create combinations of harvest methods and parcel sizes classes, that were then used to parameterize FLOSS to generate stand maps for LANDIS simulation.

	Harvest methods					
	No Mgmt.	Sawlog			Firewood	Pulpwood
Size class		Clearcut	Shelter.	Group.		
< 20 ha	0.775	0.066	0.066	0.066	0.014	0.014
21-41 ha	0.842	0.032	0.032	0.032	0.063	0.000
42-88 ha	0.703	0.089	0.089	0.089	0.031	0.000
88-205 ha	0.745	0.055	0.055	0.055	0.091	0.000
> 206 ha	0.522	0.129	0.129	0.129	0.091	0.000

Table IV-5. The proportion and area designated for each harvest methods for the scenarios based on the parcelization and harvest intensity levels.

Harvest type	Harvest method	Stand.rank	Min.stand.age	Parcelization level			
				Current		High	
				Harvest intensity		Harvest intensity	
				7%/decade	15%/decade	7%/decade	15%/decade
Sawlog	Clearcut	random	80	0.42%	0.90%	0.46%	0.99%
	Shelter.	random	50	3277 ha	7022 ha	3584 ha	7680 ha
	Group sel.	random	50	2.35%	5.04%	2.57%	5.51%
Firewood	Clearcut	random	10	0.19%	0.41%	0.15%	0.32%
Pulpwood	Clearcut	random	30	0.05%	0.12%	0.08%	0.17%

Table IV-6. Multivariate analysis of variance (MANOVA) test results for the effects from parcelization level (PARCEL) and harvest intensity (HARVINT) and their interactions (PARCEL*HARV_INT) to the total area of major species groups, at short-, mid- and long-term (10-50, 60-100, and 110-200 simulation years, respectively).

Multivariate tests for species composition

TERM	Effect	Pillai's Trace	F	Hypothesis df	Error df	Sig.
SHORT-TERM	PARCEL	0.642	86.460	4	193	0.000
	HARV_INT	0.938	732.361	4	193	0.000
	PARCEL*HARV_INT	0.096	5.111	4	193	0.001
MID-TERM	PARCEL	0.429	36.253	4	193	0.000
	HARV_INT	0.965	1349.177	4	193	0.000
	PARCEL*HARV_INT	0.075	3.936	4	193	0.004
LONG-TERM	PARCEL	0.687	215.332	4	393	0.000
	HARV_INT	0.990	9795.640	4	393	0.000
	PARCEL*HARV_INT	0.094	10.157	4	393	0.000

Table IV-7. Results of individual ANOVA tests for the effects from parcelization level (PARCEL) and harvest intensity (HARVINT) and their interactions (PARCEL*HARV_INT) for each of the major species groups, at short-, mid- and long-term.

Individual ANOVA tests for species composition

YEAR	Source	Dependent variable	Type III SS	df	F	Sig.
SHORT-TERM	PARCEL	MAPLE	0.15	1	2.510	0.115
		REDOAK	2.84	1	15.128	0.000
		WHITEOAK	1.63	1	0.994	0.320
		SHORTLEAFPINE	0.31	1	0.665	0.416
	HARVINT	MAPLE	1.61	1	27.808	0.000
		REDOAK	50.31	1	268.407	0.000
		WHITEOAK	28.99	1	17.722	0.000
		SHORTLEAFPINE	7.58	1	16.439	0.000
	PARCEL*HARVINT	MAPLE	0.01	1	0.170	0.680
		REDOAK	0.34	1	1.833	0.177
		WHITEOAK	0.20	1	0.121	0.728
		SHORTLEAFPINE	0.05	1	0.108	0.743
	Error	MAPLE	11.34	196		
		REDOAK	36.73	196		
		WHITEOAK	320.65	196		
		SHORTLEAFPINE	90.33	196		
	Total	MAPLE	4791.42	200		
		REDOAK	98296.52	200		
		WHITEOAK	120828.55	200		
		SHORTLEAFPINE	27368.30	200		
MID-TERM	PARCEL	MAPLE	0.53	1	11.408	0.001
		REDOAK	19.80	1	39.867	0.000
		WHITEOAK	5.17	1	0.671	0.414
		SHORTLEAFPINE	2.09	1	1.129	0.289
	HARVINT	MAPLE	14.54	1	314.632	0.000
		REDOAK	334.90	1	674.348	0.000
		WHITEOAK	109.18	1	14.190	0.000
		SHORTLEAFPINE	48.91	1	26.389	0.000
	PARCEL*HARVINT	MAPLE	0.02	1	0.432	0.512
		REDOAK	1.28	1	2.577	0.110
		WHITEOAK	0.37	1	0.048	0.826
		SHORTLEAFPINE	0.22	1	0.118	0.732
	Error	MAPLE	9.06	196		
		REDOAK	97.34	196		
		WHITEOAK	1508.07	196		
		SHORTLEAFPINE	363.26	196		
	Total	MAPLE	6647.28	200		
		REDOAK	105398.73	200		
		WHITEOAK	200777.02	200		
		SHORTLEAFPINE	47501.96	200		

Table IV-7. (Continued)

YEAR	Source	Dependent variable	Type III SS	df	F	Sig.
LONG-TERM	PARCEL	MAPLE	1.73	1	144.655	0.000
		REDOAK	40.25	1	2.102	0.148
		WHITEOAK	6.63	1	0.923	0.337
		SHORTLEAFPINE	8.50	1	1.942	0.164
	HARVINT	MAPLE	88.94	1	7424.448	0.000
		REDOAK	854.96	1	44.654	0.000
		WHITEOAK	144.78	1	20.142	0.000
		SHORTLEAFPINE	203.09	1	46.391	0.000
	PARCEL*HARVINT	MAPLE	88.94	1	7.955	0.005
		REDOAK	854.96	1	0.145	0.704
		WHITEOAK	144.78	1	0.058	0.810
		SHORTLEAFPINE	203.09	1	0.297	0.586
	Error	MAPLE	4.74	196		
		REDOAK	7581.85	196		
		WHITEOAK	2846.43	196		
		SHORTLEAFPINE	1733.64	196		
	Total	MAPLE	15759.30	200		
		REDOAK	425163.29	200		
		WHITEOAK	743856.11	200		
		SHORTLEAFPINE	182359.11	200		

Table IV-8. Multivariate analysis of variance (MANOVA) test results for the effects from parcelization level (PARCEL) and harvest intensity (HARVINT) and their interactions (PARCEL*HARV_INT) to the total area of age groups, at short-, mid- and long-term.

Multivariate tests for age group abundance

TERM	Effect	Pillai's Trace	F	Hypothesis df	Error df	Sig.
SHORT-TERM	PARCEL	0.052	2.660	4	193	0.034
	HARV_INT	0.554	59.881	4	193	0.000
	PARCEL*HARV_INT	0.003	0.135	4	193	0.969
MID-TERM	PARCEL	0.375	28.953	4	193	0.000
	HARV_INT	0.875	339.262	4	193	0.000
	PARCEL*HARV_INT	0.023	1.138	4	193	0.340
LONG-TERM	PARCEL	0.066	6.922	4	393	0.000
	HARV_INT	0.873	675.835	4	393	0.000
	PARCEL*HARV_INT	0.008	0.765	4	393	0.548

Table IV-9. Results of individual ANOVA tests for the effects from parcelization level (PARCEL) and harvest intensity (HARVINT) and their interactions (PARCEL*HARV_INT) for each of the age groups, at short-, mid- and long-term.

Individual ANOVA tests for age group abundance

YEAR	Source	Dependent variable	Type III SS	df	F	Sig.
SHORT-TERM	PARCEL	SEED/SAPLING	5.57	1	1.997	0.159
		POLE	0.27	1	0.014	0.908
		SAWLOG	1.38	1	0.428	0.514
		OLDGROWTH	2.84	1	0.084	0.773
	HARVINT	SEED/SAPLING	115.19	1	41.330	0.000
		POLE	0.31	1	0.016	0.901
		SAWLOG	36.36	1	11.296	0.001
		OLDGROWTH	28.00	1	0.825	0.365
	PARCEL*HARVINT	SEED/SAPLING	0.47	1	0.170	0.681
		POLE	0.09	1	0.005	0.946
		SAWLOG	0.21	1	0.066	0.797
		OLDGROWTH	0.28	1	0.008	0.928
	Error	SEED/SAPLING	546.27	196		
		POLE	3958.16	196		
		SAWLOG	630.93	196		
		OLDGROWTH	6655.11	196		
	Total	SEED/SAPLING	7461.45	200		
		POLE	30353.54	200		
		SAWLOG	110449.62	200		
		OLDGROWTH	46920.87	200		
MID-TERM	PARCEL	SEED/SAPLING	1.74	1	0.453	0.502
		POLE	5.95	1	8.096	0.005
		SAWLOG	1.68	1	0.124	0.725
		OLDGROWTH	22.03	1	17.442	0.000
	HARVINT	SEED/SAPLING	95.25	1	24.784	0.000
		POLE	81.98	1	111.588	0.000
		SAWLOG	11.88	1	0.875	0.351
		OLDGROWTH	446.66	1	353.679	0.000
	PARCEL*HARVINT	SEED/SAPLING	0.14	1	0.037	0.848
		POLE	0.20	1	0.273	0.602
		SAWLOG	0.29	1	0.021	0.884
		OLDGROWTH	1.61	1	1.272	0.261
	Error	SEED/SAPLING	753.29	196		
		POLE	143.99	196		
		SAWLOG	2659.75	196		
		OLDGROWTH	247.53	196		
	Total	SEED/SAPLING	15432.89	200		
		POLE	5352.62	200		
		SAWLOG	21242.70	200		
		OLDGROWTH	183439.92	200		

Table IV-9. Continued.

YEAR	Source	Dependent variable	Type III SS	df	F	Sig.
LONG-TERM	PARCEL	SEED/SAPLING	0.02	1	0.036	0.851
		POLE	0.03	1	0.019	0.892
		SAWLOG	1.04	1	0.124	0.725
		OLDGROWTH	0.40	1	0.042	0.837
	HARVINT	SEED/SAPLING	73.59	1	109.354	0.000
		POLE	23.36	1	15.77	0.000
		SAWLOG	31.37	1	3.731	0.054
		OLDGROWTH	259.78	1	27.461	0.000
	PARCEL*HARVINT	SEED/SAPLING	0.04	1	0.051	0.821
		POLE	0.05	1	0.033	0.855
		SAWLOG	0.03	1	0.004	0.951
		OLDGROWTH	0.13	1	0.013	0.908
	Error	SEED/SAPLING	266.49	196		
		POLE	586.60	196		
		SAWLOG	3329.15	196		
		OLDGROWTH	3746.20	196		
	Total	SEED/SAPLING	57026.26	200		
		POLE	45144.39	200		
		SAWLOG	47799.15	200		
		OLDGROWTH	172015.42	200		

Table IV-10. Results from the multivariate tests for landscape-level area-weighted mean fractal dimension (AWMFD) and aggregation index (AI) for species groups from the effects from parcelization level (PARCEL) and harvest intensity (HARVINT) and their interactions, at short-, mid-, and long term.

Multivariate tests for landscape metrics from species composition

TERM	Effect	Pillai's Trace	F	Hypothesis df	Error df	Sig.
SHORT-TERM	PARCEL	0.000	142.000	2	795	0.868
	HARV_INT	0.003	1.368	2	795	0.255
	PARCEL*HARV_INT	0.000	0.007	2	795	0.993
MID-TERM	PARCEL	0.001	0.257	2	795	0.773
	HARV_INT	0.008	3.223	2	795	0.040
	PARCEL*HARV_INT	0.001	0.201	2	795	0.818
LONG-TERM	PARCEL	0.000	0.067	2	1595	0.935
	HARV_INT	0.011	8.764	2	1595	0.000
	PARCEL*HARV_INT	0.000	0.032	2	1595	0.968

Table IV-11. Results from the individual ANOVA tests for landscape-level area-weighted mean fractal dimension (AWMFD) and aggregation index (AI) of species groups for the effects from parcelization level (PARCEL) and harvest intensity (HARVINT) and their interactions, at short-, mid- and long-term.

Individual ANOVA tests for landscape metrics from species composition

YEAR	Source	Dependent variable	Type III SS	df	F	Sig.
SHORT-TERM	PARCEL	AWMFD	0.00	1	0.165	0.685
		AI	17.53	1	0.093	0.760
	HARVINT	AWMFD	0.04	1	1.999	0.158
		AI	472.74	1	2.513	0.113
	PARCEL*HARVINT	AWMFD	0.00	1	0.013	0.908
		AI	2.59	1	0.014	0.907
	Error	AWMFD	15.79	796		
		AI	149746.60	796		
	Total	AWMFD	1226.32	800		
		AI	1078238.70	800		
MID-TERM	PARCEL	AWMFD	0.01	1	0.366	0.545
		AI	58.99	1	0.199	0.656
	HARVINT	AWMFD	0.11	1	4.354	0.037
		AI	1773.63	1	5.982	0.015
	PARCEL*HARVINT	AWMFD	0.00	1	0.088	0.767
		AI	2.76	1	0.009	0.923
	Error	AWMFD	19.73	796		
		AI	236008.89	796		
	Total	AWMFD	1305.16	800		
		AI	1699695.74	800		
LONG-TERM	PARCEL	AWMFD	0.00	1	0.064	0.800
		AI	55.35	1	0.102	0.749
	HARVINT	AWMFD	0.02	1	0.661	0.416
		AI	2154.54	1	3.989	0.046
	PARCEL*HARVINT	AWMFD	0.00	1	0.000	0.986
		AI	4.56	1	0.008	0.927
	Error	AWMFD	42.87	1596		
		AI	861964.13	1596		
	Total	AWMFD	2932.57	1600		
		AI	5753353.12	1600		

Table IV-12. Results from the multivariate tests for landscape-level area-weighted mean fractal dimension (AWMFD) and aggregation index (AI) for age groups from the effects from parcelization level (PARCEL) and harvest intensity (HARVINT) and their interactions, at short-, mid-, and long term.

Multivariate tests for landscape metrics from age groups

TERM	Effect	Pillai's Trace	F	Hypothesis df	Error df	Sig.
SHORT-TERM	PARCEL	0.123	13.722	2	195	0.000
	HARV_INT	0.663	192.064	2	195	0.000
	PARCEL*HARV_INT	0.011	1.105	2	195	0.333
MID-TERM	PARCEL	0.701	228.851	2	195	0.000
	HARV_INT	0.968	2924.750	2	195	0.000
	PARCEL*HARV_INT	0.192	23.145	2	195	0.000
LONG-TERM	PARCEL	0.052	10.813	2	195	0.000
	HARV_INT	0.652	369.319	2	195	0.000
	PARCEL*HARV_INT	0.002	0.456	2	195	0.634

Table IV-13. Results from the individual ANOVA tests for landscape-level area-weighted mean fractal dimension (AWMFD) and aggregation index (AI) of age groups for the effects from parcelization level (PARCEL) and harvest intensity (HARVINT) and their interactions, at short-, mid- and long-term.

Individual ANOVA tests for landscape metrics from age groups

YEAR	Source	Dependent variable	Type III SS	df	F	Sig.
SHORT-TERM	PARCEL	AWMFD	0.00	1	3.988	0.047
		AI	0.18	1	0.025	0.875
	HARVINT	AWMFD	0.03	1	45.767	0.000
		AI	0.20	1	0.028	0.866
	PARCEL*HARVINT	AWMFD	0.00	1	0.298	0.586
		AI	0.00	1	0.000	0.983
	Error	AWMFD	0.12	196		
		AI	1394.55	196		
	Total	AWMFD	327.25	200		
		AI	320908.90	200		
MID-TERM	PARCEL	AWMFD	0.00	1	33.514	0.000
		AI	4.95	1	1.491	0.223
	HARVINT	AWMFD	0.03	1	544.913	0.000
		AI	8.53	1	2.572	0.110
	PARCEL*HARVINT	AWMFD	0.00	1	3.489	0.063
		AI	0.43	1	0.130	0.719
	Error	AWMFD	0.01	196		
		AI	650.05	196		
	Total	AWMFD	349.52	200		
		AI	528336.67	200		
LONG-TERM	PARCEL	AWMFD	0.00	1	1.336	0.248
		AI	14.50	1	3.560	0.060
	HARVINT	AWMFD	0.03	1	12.439	0.000
		AI	792.32	1	194.483	0.000
	PARCEL*HARVINT	AWMFD	0.00	1	0.172	0.678
		AI	0.18	1	0.043	0.835
	Error	AWMFD	1.09	396		
		AI	1613.30	396		
	Total	AWMFD	563.72	400		
		AI	767352.38	400		

F. Figures

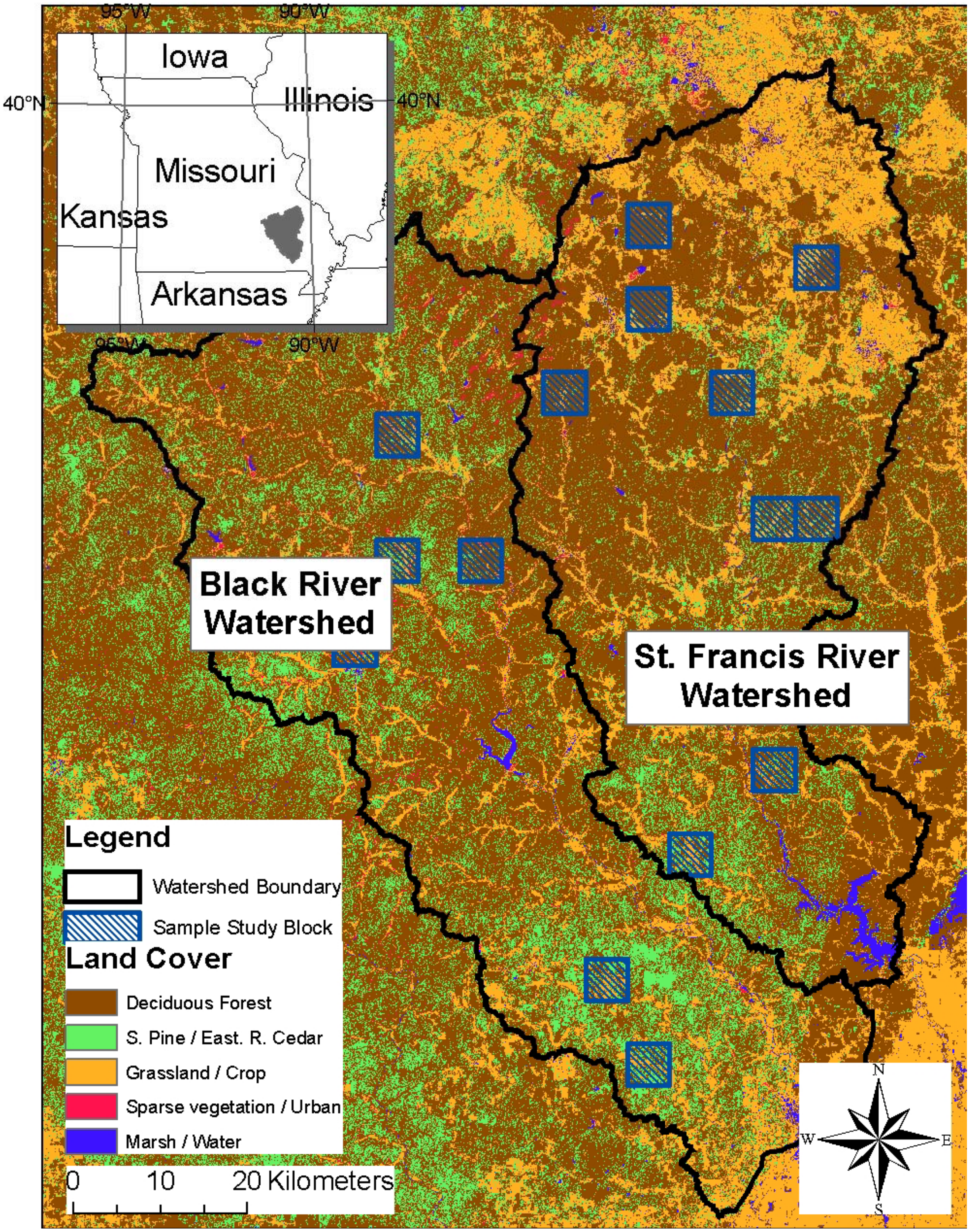

Figure IV-1. Map and land cover types of the study area in the Black and St. Francis River watershed, located in the southeastern Missouri Ozarks. Location of the sample study blocks, and the watershed boundary are shown.

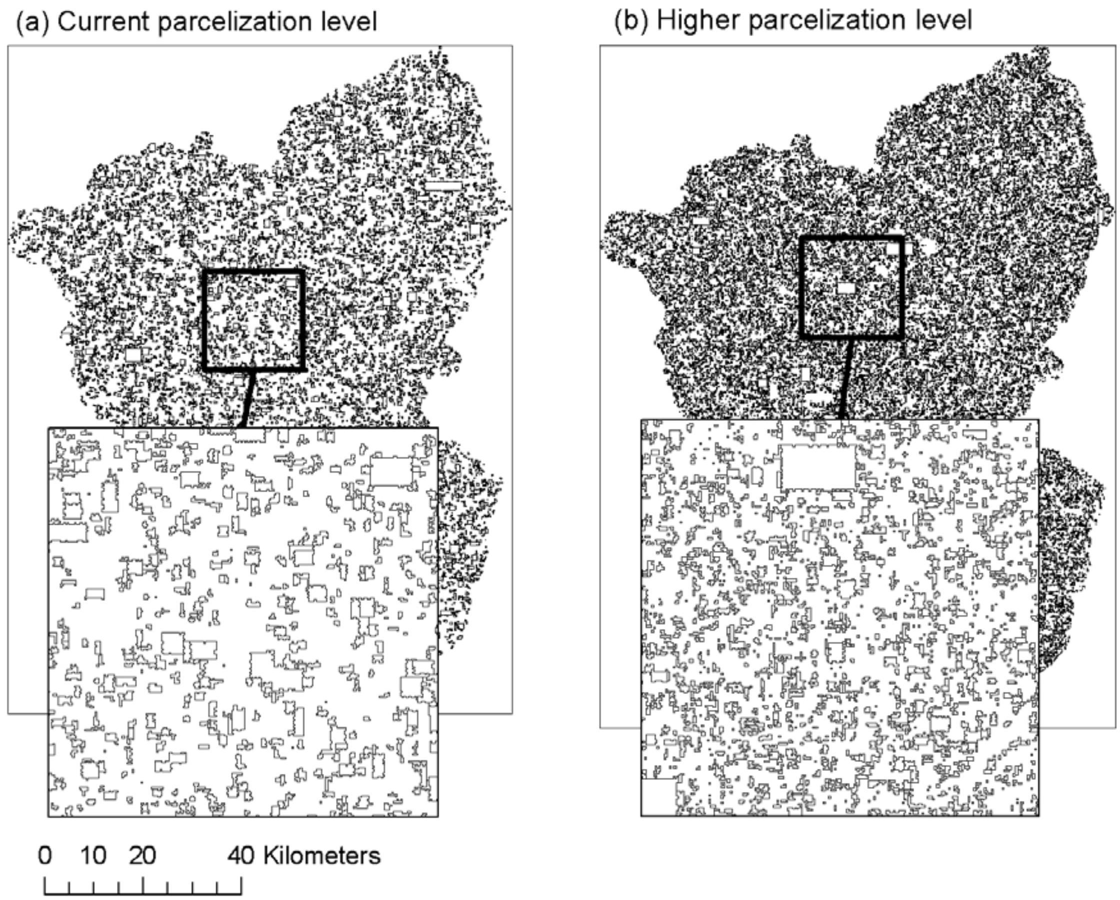

Figure IV-2. Stand maps used for LANDIS simulation of: (a) current parcelization; and (b) higher parcelization. See text for details on creating the maps.

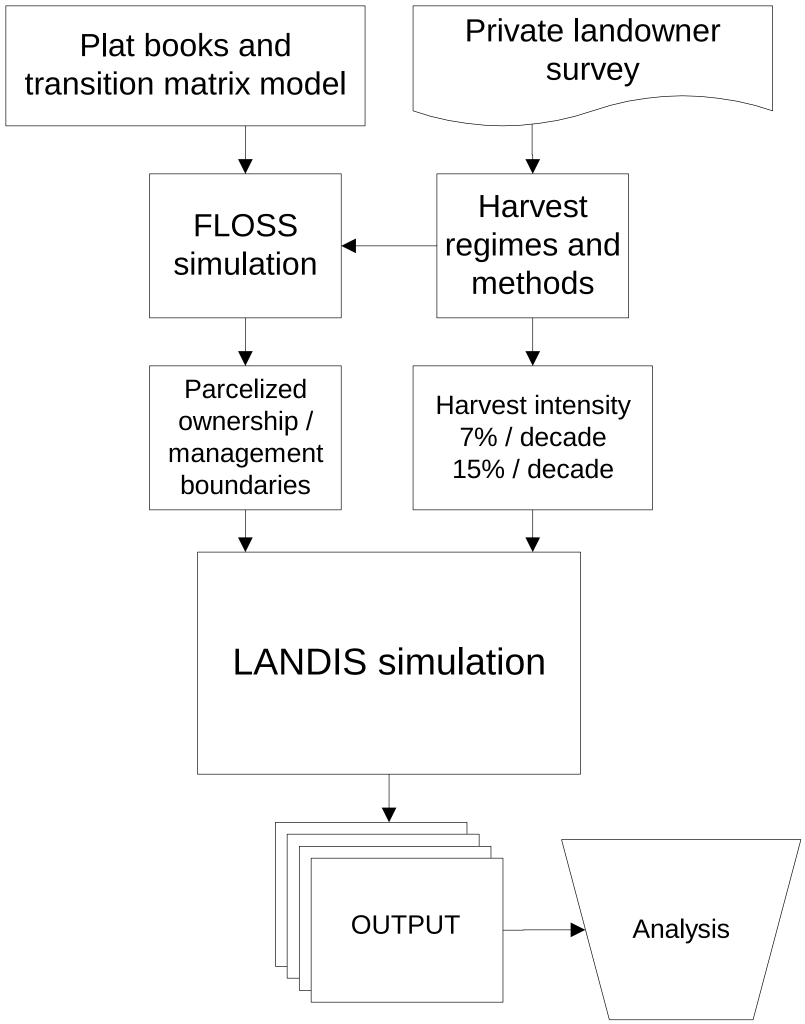

Figure IV-3. The diagram for the overall simulation approach.

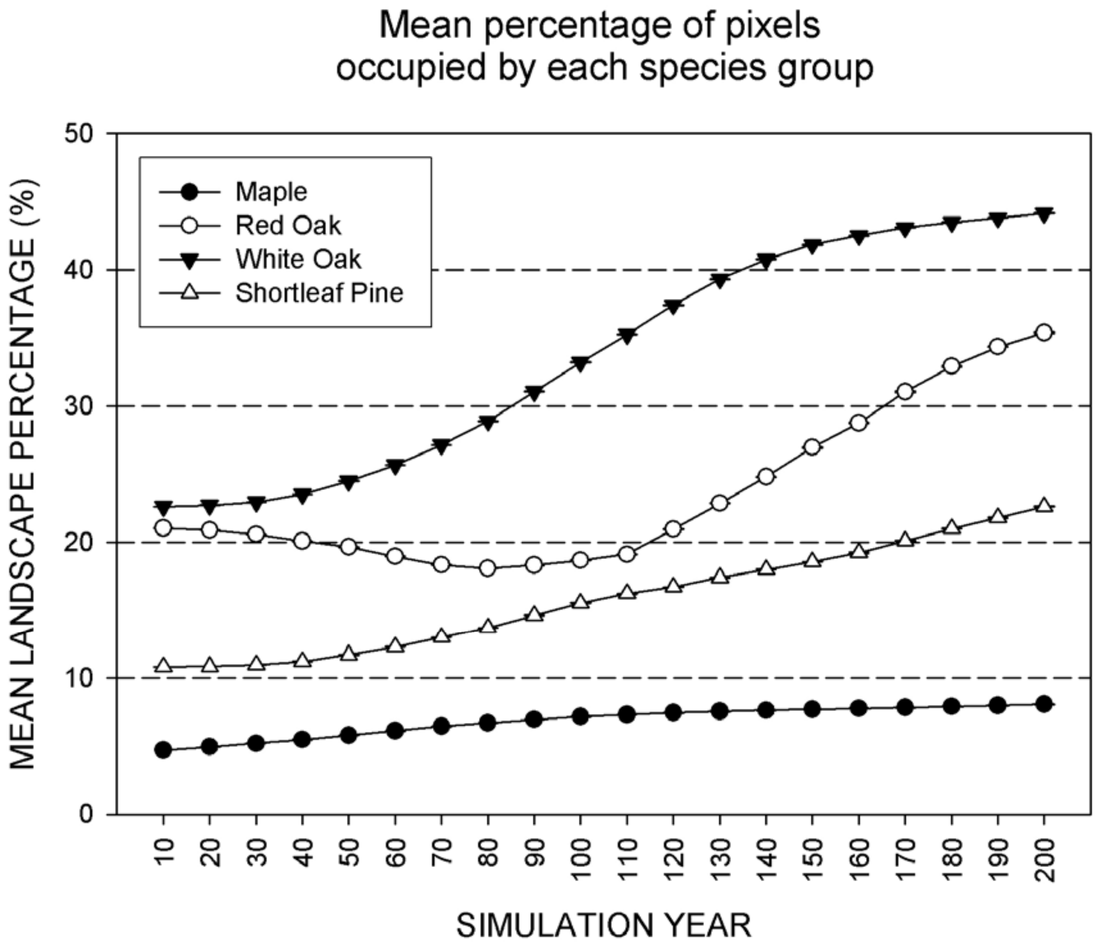

Figure IV-4. Mean landscape percentage occupied by the species groups over simulated years with no harvest events and under fire suppression (fire return interval = 300 years). The percentage is based on the presence / absence of each species groups, therefore in the later simulation years the sum can be greater than 100.

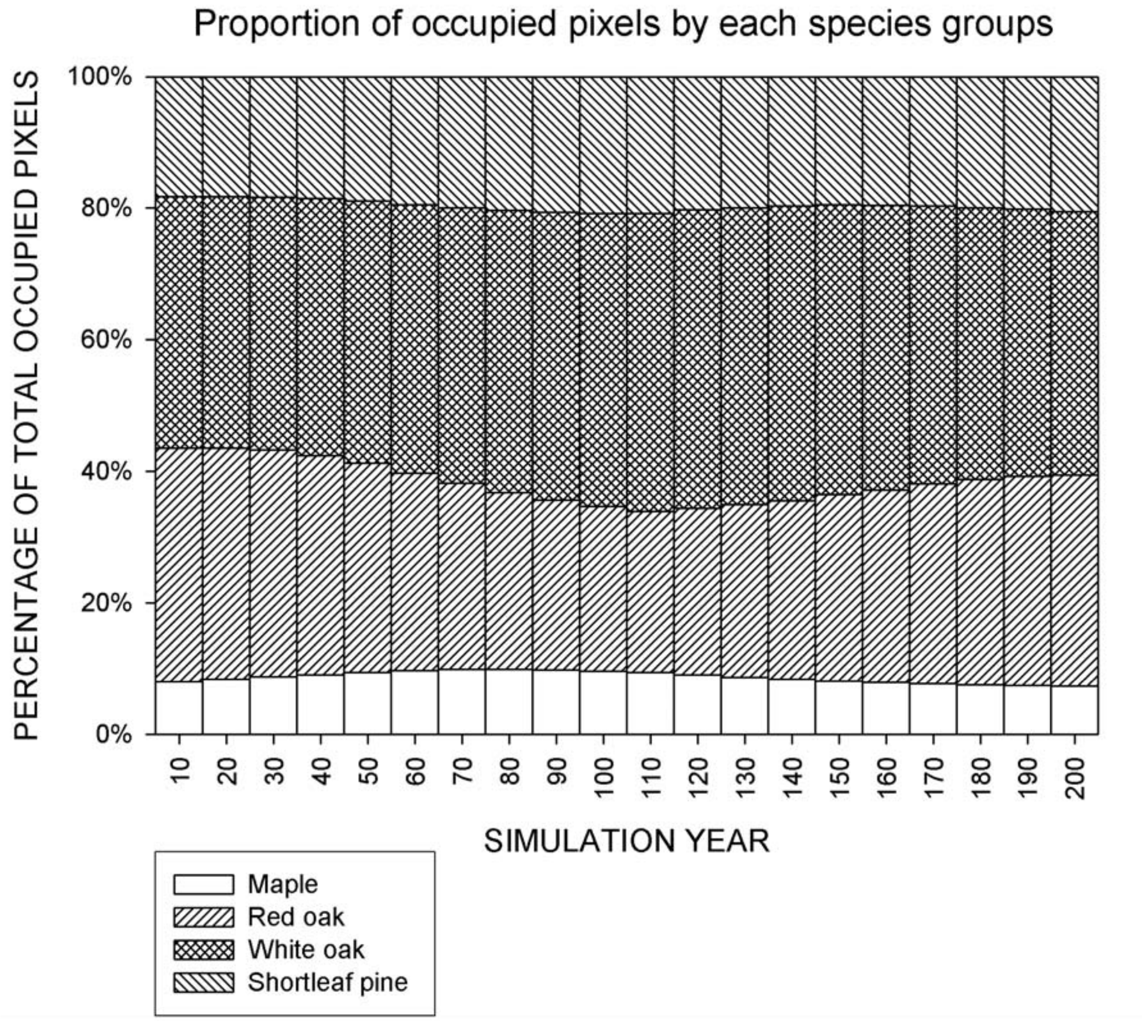

Figure IV-5. Mean proportion of the total number of pixels occupied by each species groups over simulated years with no harvest events and under fire suppression. This graph shows the relative abundance of the species groups presence, based on Figure IV-4.

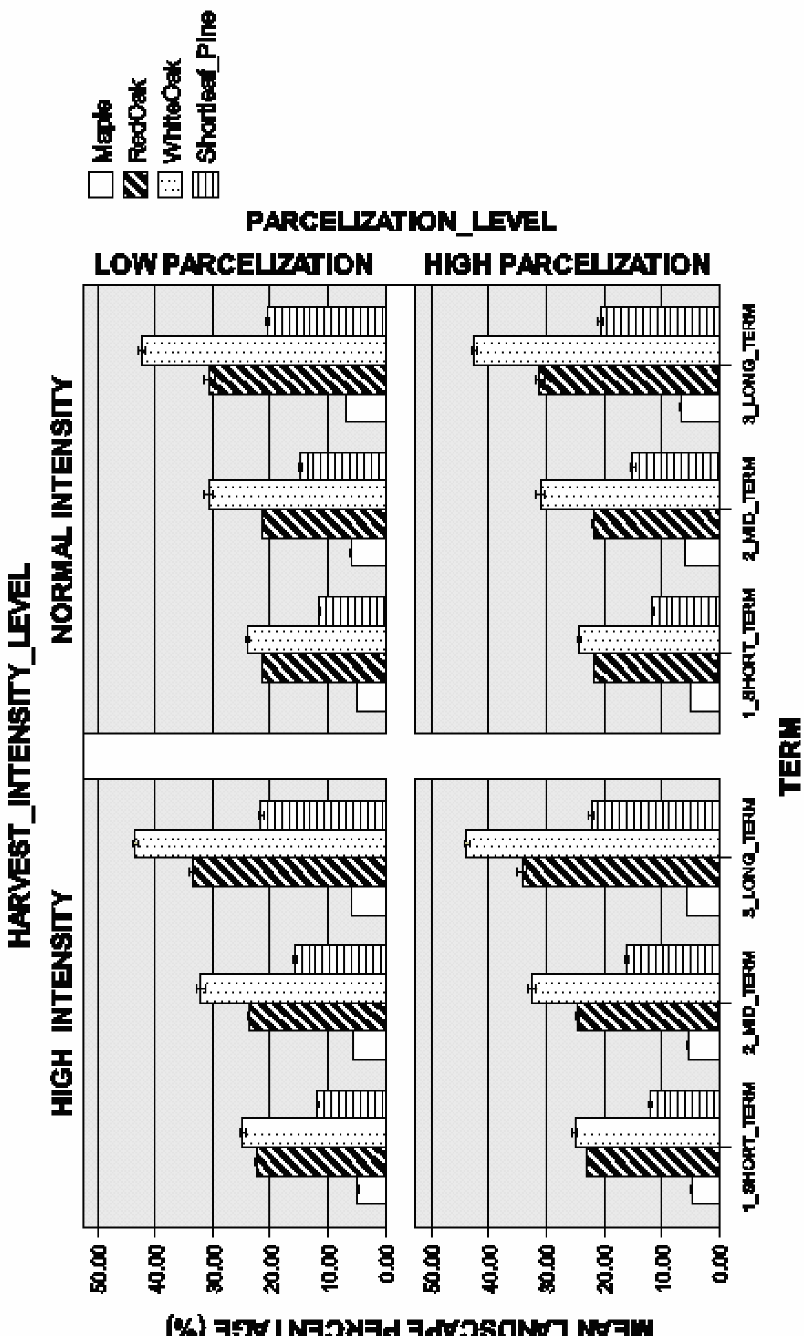

Figure IV-6. Mean landscape percentage occupied by the species groups for each of the scenarios at short-, mid- and long-term. The error bars represent the standard error of the mean.

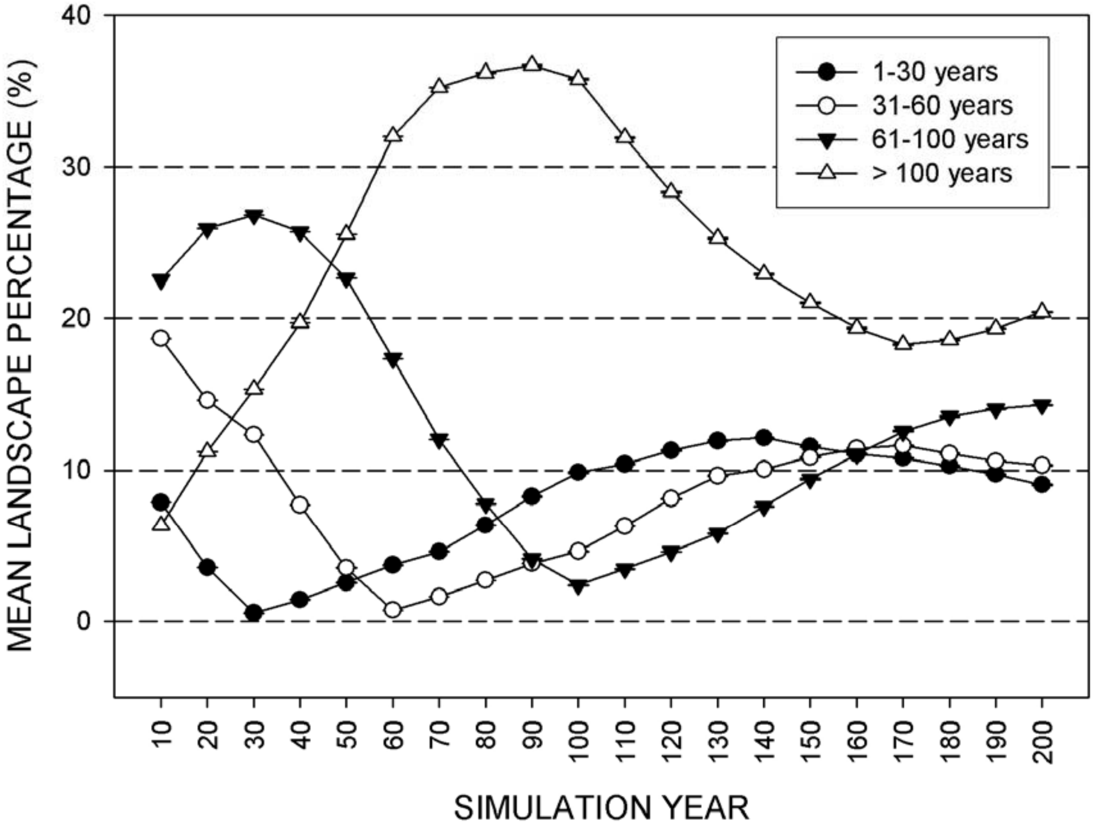

Figure IV-7. Mean landscape percentage occupied by reclassified age groups over simulated years under fire suppression with no harvest events. The error bars represent the standard error of the mean.

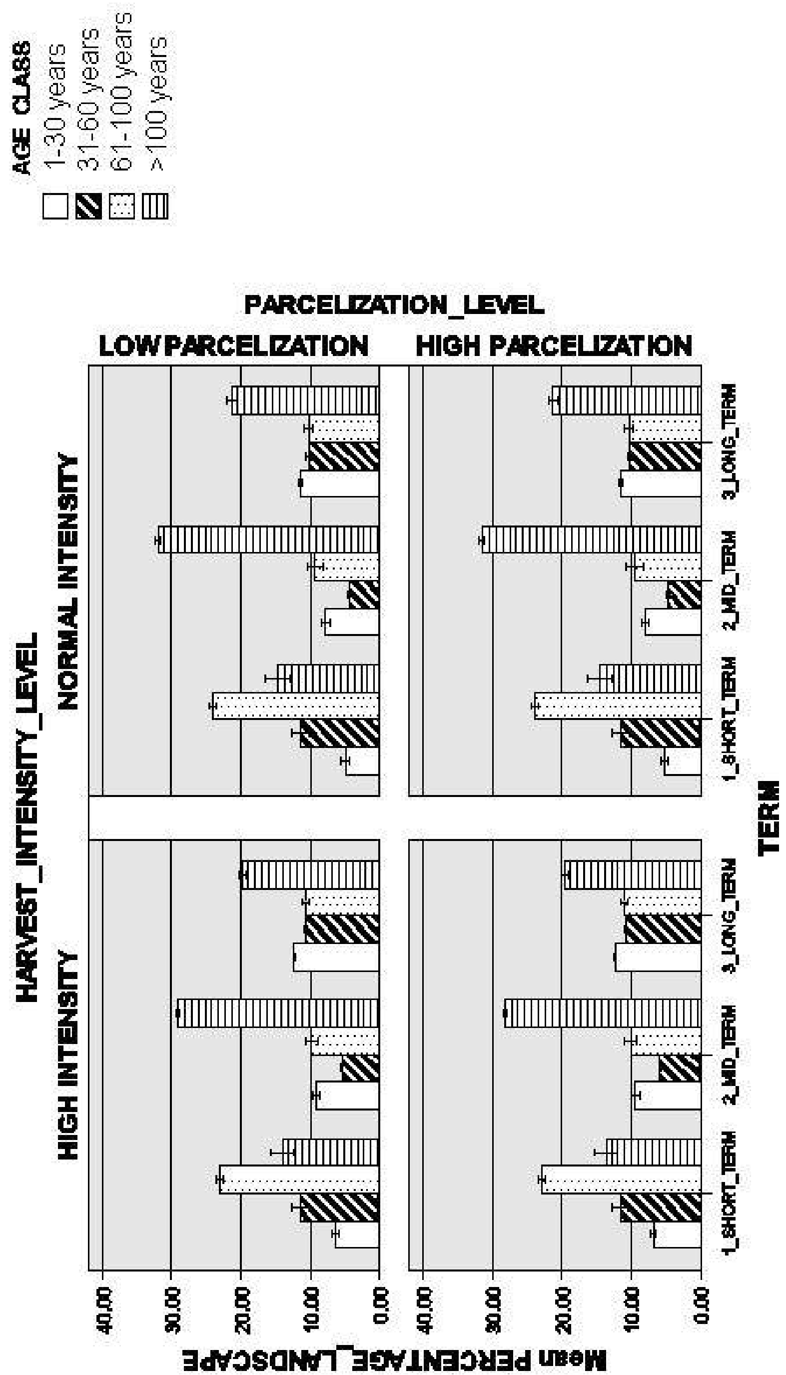

Figure IV-8. Mean landscape percentage occupied by the age groups for each of the scenarios at short-, mid- and long-term. The error bars represent the standard error of the mean.

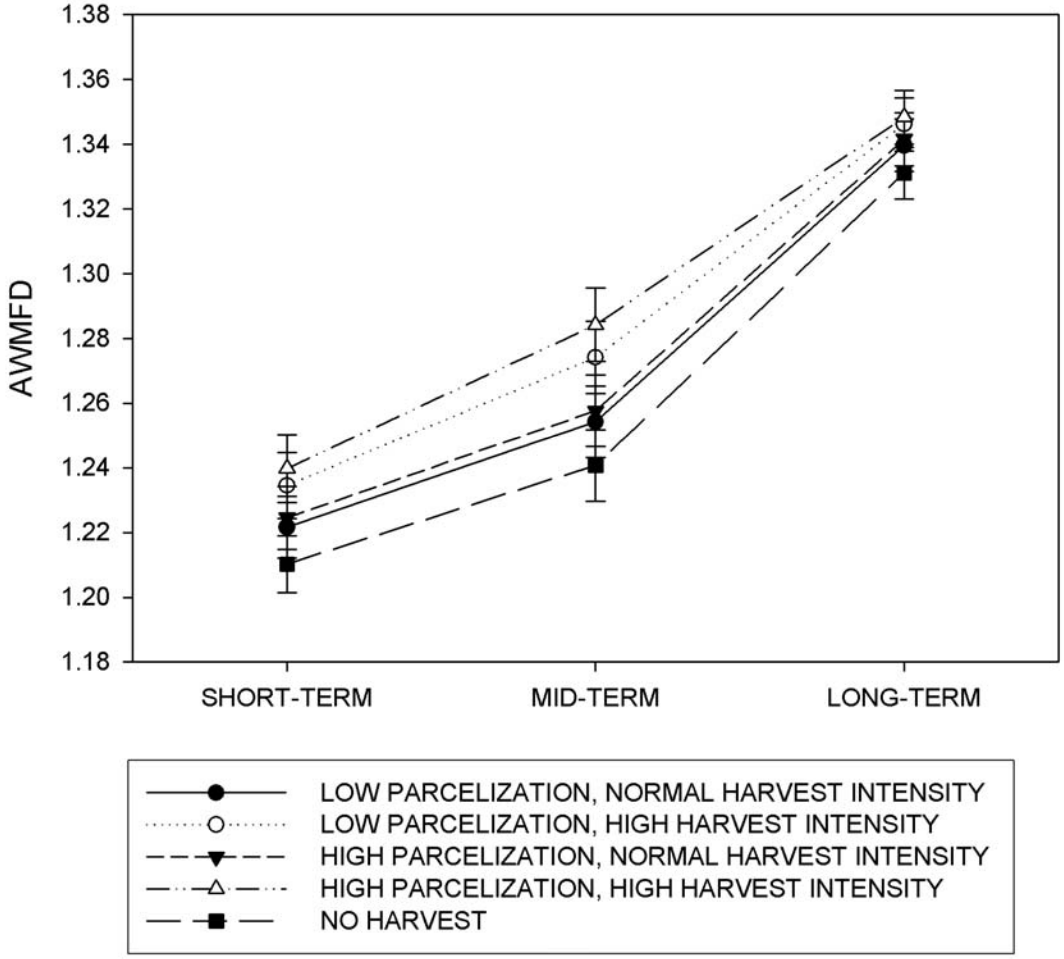

Figure IV-9. Landscape-level area-weighted mean fractal dimension (AWMFD) of the species groups at short-, mid-, and long-term for each of the scenarios. Scenarios with no harvest events are plotted together as reference. Error bars represent the stand error of the mean.

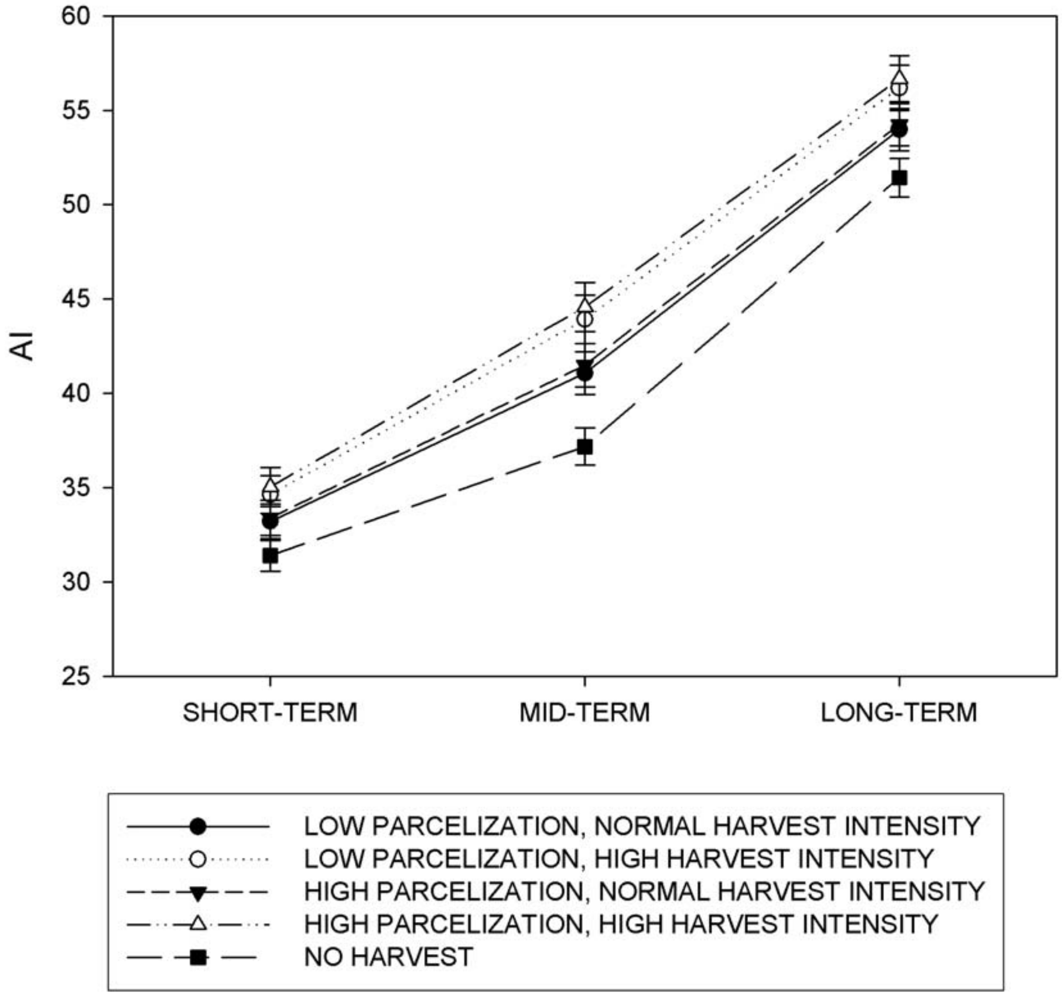

Figure IV-10. Landscape-level aggregation index (AI) of species groups at short-, mid-, and long-term for each of the scenarios. Scenarios with no harvest events are plotted together as reference. Error bars represent the standard error of the mean.

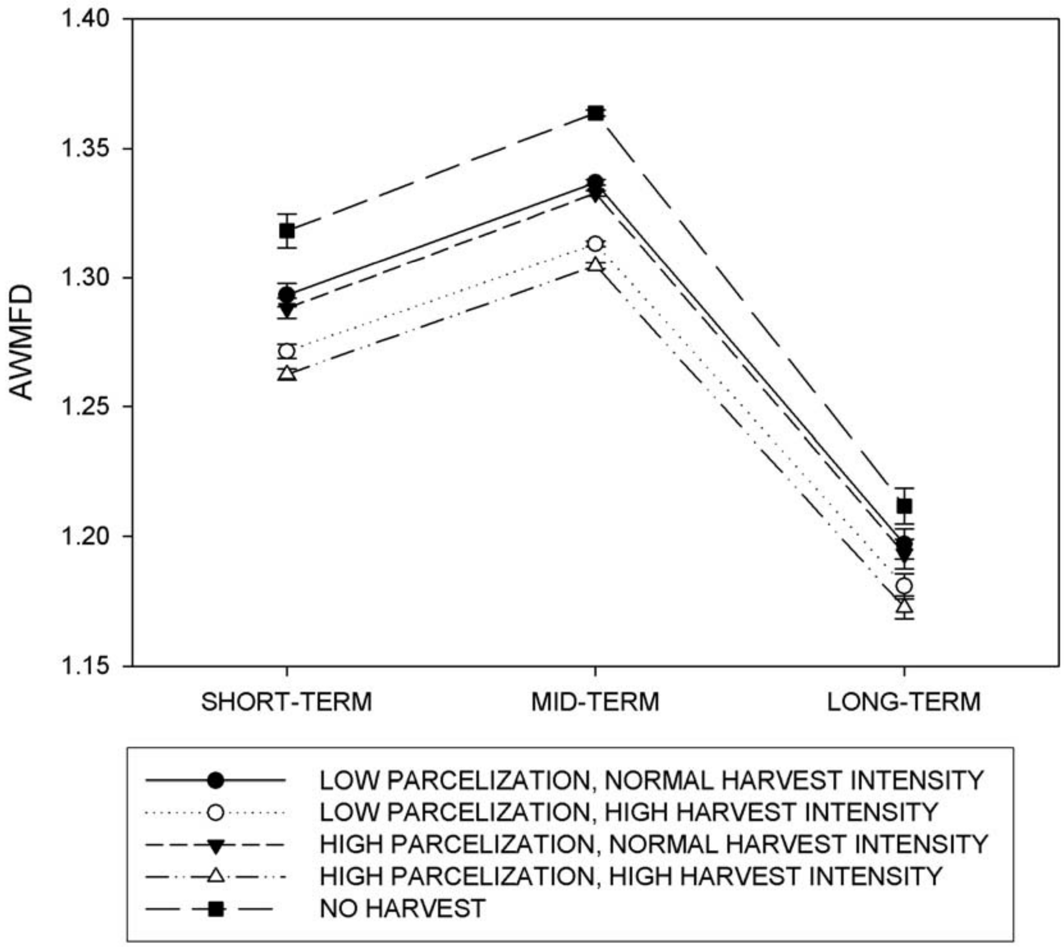

Figure IV-11. Landscape-level area-weighted mean fractal dimension (AWMFD) of age groups at short-, mid-, and long-term for each of the scenarios. Scenarios with no harvest events are plotted together as reference. Error bars represent the stand error of the mean.

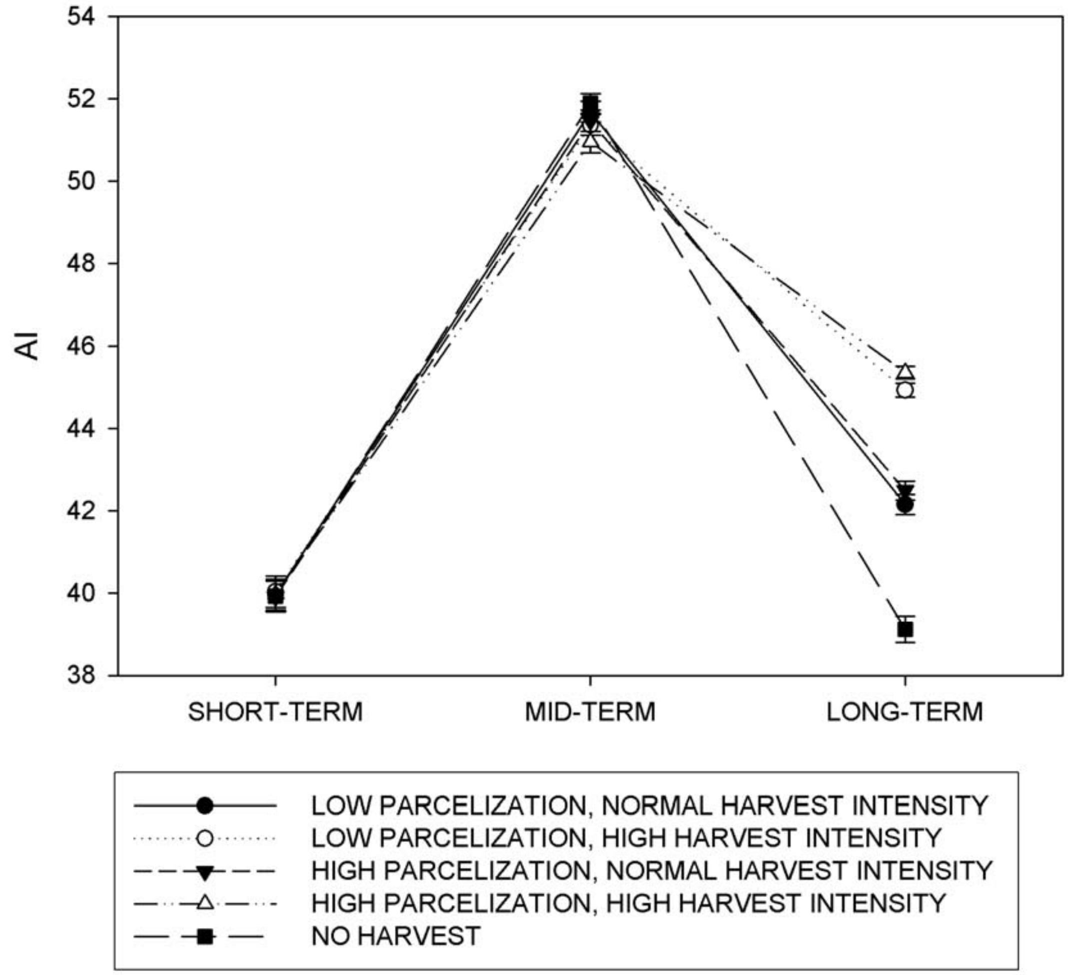

Figure IV-12. Landscape-level aggregation index (AI) of age groups at short-, mid-, and long-term for each of the scenarios. Scenarios with no harvest events are plotted together as reference. Error bars represent the standard error of the mean.

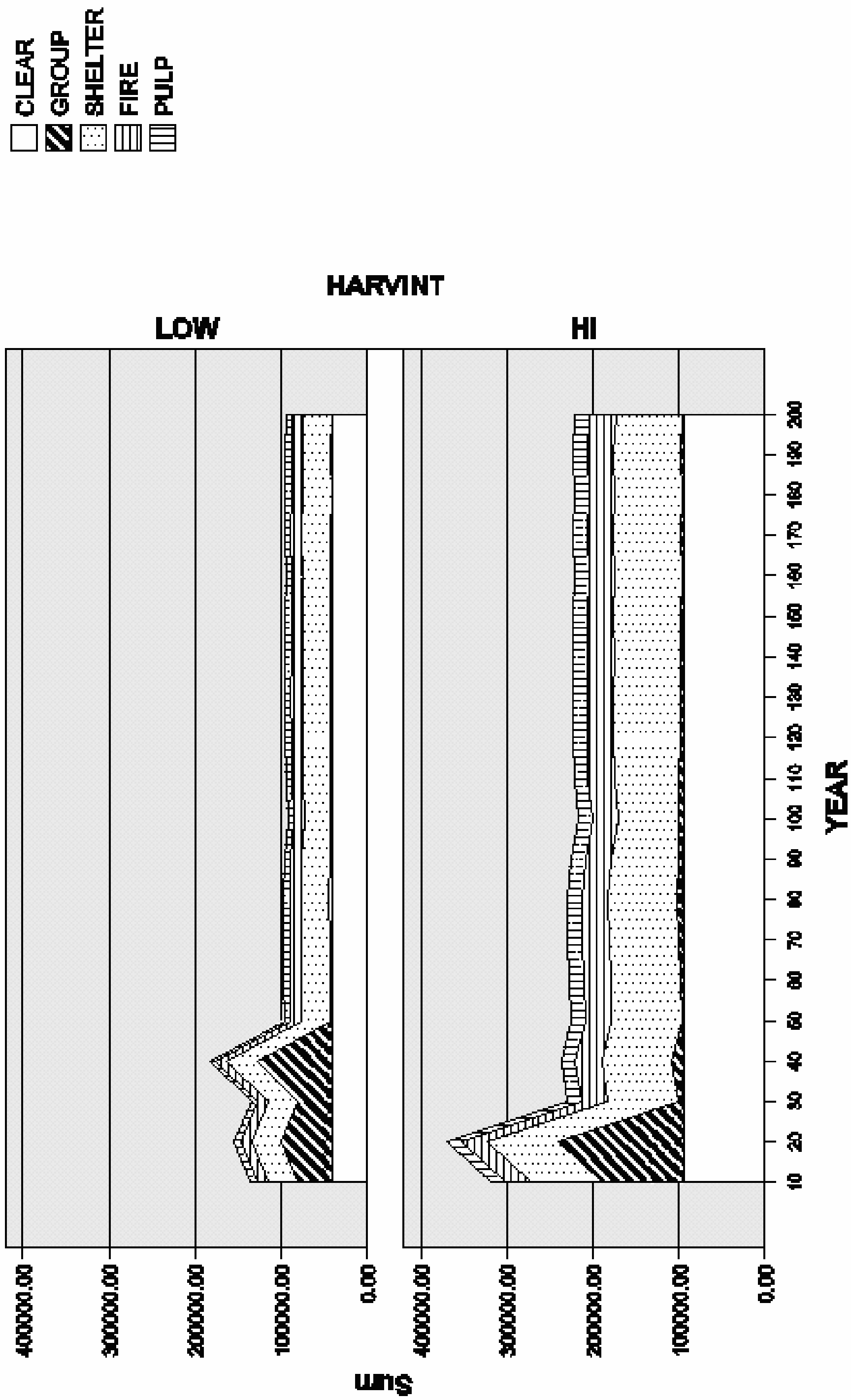

Figure IV-13. Mean harvested area from each of the harvest methods over simulated time for the two harvest intensity levels.

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Chapter V. Conclusions

This dissertation demonstrated methods to characterize the nature of ownership parcelization, and explored the potential changes in the forest landscape in response to the management practices in such parcelized ownership, based on the forest landscape of Black and St. Francis River watersheds in the southeastern Missouri Ozarks.

In particular, chapter 2 showed that the current ownership boundary in the study area is characterized by a landscape pattern that is different from those arising from natural processes, which strongly reflected the underlying Public Land Survey System (PLSS) structure. It also showed that the spatial characteristics among land ownership types – e.g., private, public land ownership – are different from each other, particularly regarding its parcel size distribution. An ownership pattern simulation model – the Fragmented Land Ownership Spatial Simulator (FLOSS) – was developed to generate land ownership patterns with similar shapes and parcel size distributions among different types of land ownership (e.g., private, public). The evaluation of the performance of FLOSS indicated that the model generated pattern with spatial characteristics similar to the actual ownership landscape, suggesting that it can effectively represent different levels of land ownership fragmentation. This allows FLOSS to serve as a feasible tool for evaluating forest management applications by spatially allocating various management scenarios in a realistic way.

In chapter 3, a transition probability modeling approach for characterizing the parcelization process of the private forestland ownership was presented. Two transition probability matrices were constructed; one based on all private ownership transitions and another without the transitions made by the Pioneer Forest, to investigate how the effects of the acquisitions from a unique private ownership, the Pioneer Forest. The transition matrix indicated a strong tendency towards parcel sizes smaller than 100 ha, suggesting that the private ownership can experience greater level of parcelization with the current transition rate. In particular, a strong tendency towards the parcel size classes with midpoints of 33 and 91 ha was discovered. The comparison with the matrix without the transitions caused by Pioneer Forest purchases suggests that without such large-scale acquisitions, the current trend of parcelization would even further intensify. Although this approach could not provide future estimates due to the limited time steps and the dynamic nature of parcel size transitions, the resulting stable stage distribution could be utilized as a reference that characterizes the current trend of parcelization.

Chapter 4 showed that the ownership parcelization landscape generated based on the results from chapter 2 and 3 could be successfully implemented for use in a forest landscape model – LANDIS – in order to simulate the effects from the parcelized ownership. The results of this chapter suggest that the low participation rate of owners with small-sized parcels limits the intensity of the harvest events under a highly parcelized ownership landscape. As a result, although significant, the parcelized ownership and harvest intensity levels did not cause substantial changes in the overall successional trajectories of the species composition, age structure, and the respective spatial patterns. However, in particular, the spatial patterns of age patches showed more aggregation and simple shapes with greater level of harvest intensity, but only marginally with greater parcelization level. The spatial constraint imposed on harvest events from the highly parcelized ownership landscape also limited particular harvest methods (e.g., group selection) from reaching its target harvest area. This also suggests that even with greater level of parcelization, the stumpage production may not be reduced because of the already low level of harvest intensity associated with forestland owners with small-sized parcels.

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