LARGE-SCALE FOREST LANDSCAPE MODEL, DESIGN, VALIDATION, AND APPLICATION IN MANAGEMENT OF OAK DECLINE

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LARGE-SCALE FOREST LANDSCAPE MODEL, DESIGN, VALIDATION, AND APPLICATION IN MANAGEMENT OF OAK DECLINE

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ABSTRACT

Forest landscape models (FLMs) have increasingly become important tools for exploring forest landscape changes by predicting forest vegetation dynamics over large spatial scales. However, two challenges confronting FLMs have persisted: how to simulate fine, site-scale processes while making large-scale (landscape and regional) simulation feasible, and how to fully take advantage of extensive U.S. Forest Service Inventory and Analysis (FIA) data to initialize and constraint model parameters. In this dissertation, first, a new FLM, LANDIS PRO was developed. In LANDIS PRO, forest succession and dynamics are simulated by incorporating species-, stand-, and landscape-scale processes by tracking number of trees by species age cohort. Because stand-scale resource competition is achieved by implementing rather than simulating the emergent properties of stand development, LANDIS PRO is computationally efficient, which makes large-scale simulation feasible. Since model parameters and simulation results are comparatively straightforward to forest inventory data, current intensive forest inventory data can be directly applied for model initialization and to constrain model parameters.

Validation of FLMs is essential to ensure users' confidence in model predictions and achieve reliable management decision making. To date, validation of FLMs has been

limited due to lack of suitable data. However, recent advances in FLMs, together with increasingly available spatiotemporal data make FLM validation feasible. In this dissertation, second, I proposed a framework for validating forest landscape projections from LANDIS PRO using Forest Inventory Analysis (FIA) data. The proposed framework incorporated data assimilation techniques to constrain model parameters and the initial state of the landscape by verifying the initialized landscape and iteratively calibrating the model parameters. The model predictions were rigorously validated against independent FIA data at multiple scales, and the long-term natural successional pattern was also verified against empirical studies. Results showed model predictions were able to capture much of the variation overtime in species basal area and tree density at stand-, landtype- , and landscape-scales. Subsequent long-term predictions of natural succession patterns were consistent with expected changes in tree species density of oak-dominated forests in the absence of disturbance.

Lastly, I used LANDIS PRO, a forest landscape model that includes stand-scale species density and basal area to evaluate the potential landscape-scale effects of alternative harvest methods (thinning, clearcutting and group selection) on oak decline mitigation. Projections indicated that forest harvesting can be effective in mitigating oak decline. Group selection and clearcutting were the most effective methods in the management of oak decline in the short-term (20 years) and mid-term (50 years), respectively. However, in the long-run (100 years), there was no significant difference predicted among the three methods.

Chapter I. Introduction

1. Research problem

Concerns about global climate change, disturbance, and ecosystem management have increasingly required predictions of vegetation dynamics at regional scales (Purves and Pacala 2008, Morin et al. 2007, Moorcroft 2006, Clark and Gelfand 2006, Frelich and Reich 2009). However, studies at these scales are challenging because conducting and replicating field experiments at these scales are logistically intractable (Urban 2000, Schmolke et al. 2010, He 2008). Thus, modeling has become an efficient and indispensable approach for supporting management and decision-making by addressing the potential response of tree species to climate change and management over large spatial and temporal extents (Luo et al. 2011, Clark 2001, Coreau et al. 2009, Thuiller 2007).

Generally, niche-based models and process-based models are the primary tools for projecting vegetation dynamics at regional scales (Morin and Thuiller 2009, Keenan et al. 2011). However, they have not incorporated the spatial interactions of forest landscape processes. Forest landscape models (FLMs) are explicitly designed to simulate forest landscape processes. However, two challenges confronting FLMs have persisted: how to simulate fine, site-scale processes while making large-scale (landscape and regional) simulation amenable, and how to fully take advantage of extensive U.S. Forest Service Inventory and Analysis (FIA) data to initialize and constrain model parameters.

Numerous approaches have been attempted to simplify site-level processes in FLMs to achieve the capability of simulating forest landscape processes. Most FLMs use rules defined through species vital attributes or succession pathways to simulate stand-level processes. However, such simplification may not be adequate for landscapes where the effects of disturbance are relatively weak; under such circumstances site-level processes are critical determinants of forest composition and dynamics. Accordingly, FLM are needed, which are capable of (1) incorporating the key mechanisms determining stand-scale resource competition while making large-scale simulation amenable, and (2) directly employs forest inventory data to initialize and calibrate model parameters.

To ensure the users' confidence in the FLMs predictions and achieve reliable management decision making, the validation of FLMs, which is to quantify the accuracy of the predicted results, has become essential (Rykiel 1996, Gardner and Urban 2003, Schiegg et al. 2005, Gordon et al. 2004, Prisley and Mortimer 2004, Reynolds and Ford 1999, Bellocchi et al. 2010, Shifley et al.2009, Peterson et al. 2003). Result validation of FLM is usually accomplished through comparison of the models' predicted outcomes with independent spatiotemporal data observed for the simulated area (Gardner and Urban 2003, Shifley et al. 2009, Clark et al. 2001, Moorcroft 2006). However, due to the lack of such spatiotemporal data and the inherent stochasticity in FLMs, coupled with the incompatibility of the models predictions with forest inventory data, validation of FLMs is challenging (He 2008, He et al. 2011). Recent advances in FLMs, together with increasingly available spatiotemporal data make it feasible to conduct result validation for some FLMs.

2. Objectives

The objectives of my research are to (1) develop a new FLM, LANDIS PRO based on over a decade of development and testing of the original LANDIS model, (2) propose a framework for the result validation of LANDIS PRO using Forest Inventory Analysis (FIA) data, (3) apply this new FLM, LANDIS PRO, to evaluate the long-term landscape effects of forest management on mitigation of oak decline. These three objectives correspond to my three chapters in my dissertation.

3. Chapter outline

Chapter II presents the design of the LANDIS PRO forest landscape model. In LANDIS PRO, forest succession and dynamics are simulated by incorporating species-level, stand-level, and landscape-level processes. The new model can estimate tree density and basal area by size class and by species for all forest sites on a modeled landscape. This makes the model highly compatible with FIA data. Thus, the model can be directly initialized from FIA data as well as calibrated and validated against FIA data. I demonstrate that the model can be initialized from a historic FIA inventory (1978), calibrated with a prior time-series of sequential FIA inventories (1978 to 2003), with modeled projections (1978 to 2008) validated against a corresponding interval of FIA data. I also demonstrate that the model can be applied on a forest landscape 10^7 ha in extent, a spatial extent which has rarely been attempted in the past. Finally, I show how results validation and model evaluation can be conducted in a rigorous fashion not previous demonstrated for FLM applications.

Chapter III proposes a framework for the result validation of LANDIS PRO using Forest Inventory Analysis (FIA) data. The proposed framework incorporates DA (data assimilation) techniques to constrain model parameters and initial state by verifying the initialized landscape and iteratively calibrating the model parameters. The model predictions are rigorously validated against independent FIA data at multiple scales, where a variety of processes are encompassed that influence the forest succession and dynamics. The long-term natural successional pattern is also verified against empirical studies.

Chapter IV evaluates the long-term landscape scale effectiveness of three harvest methods (e.g. clear-cut, thinning, and group-selection) on mitigating oak decline. Specifically, I applied LANDIS PRO to simulate the forest succession and dynamics under three forest harvesting scenarios (thinning, clear-cut and group-selection) and no harvesting (only with natural succession). The potential risk sites for oak decline were quantified using simulated results involving the basal area of red oak species and land type. These two factors were associated with predisposing factors attributing to oak decline and the quantification captured both biotic and abiotic causes (Johnson et al. 2009, Fan et al. 2011).

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Chapter II. A large scale forest landscape model incorporating multi-scale processes and utilizing forest inventory data

Abstract

Over the past two decades, there has been remarkable progress in the development of forest landscape models (FLMs). However, two challenges confronting FLMs have persisted: how to simulate fine, site-scale processes while making large-scale (landscape and regional) simulation amenable, and how to fully take advantage of extensive U.S. Forest Service Inventory and Analysis (FIA) data to initialize and constraint model parameters.

In this study, we present the design of a new FLM, LANDIS PRO. LANDIS PRO has benefited from the recent advances in individual-based models that scale up individuals to retain the density and size structure, which are the key mechanisms of resource competition determining forest dynamics. In LANDIS PRO, forest succession and dynamics are simulated by incorporating species-scale, stand-scale, and landscape-scale processes by tracking number of trees by species age cohort. Stand-scale resource competition is quantified by a measure of the amount of growing space occupied (GSO) estimated by summing the minimum growing space required to support the total trees on the site. GSO is derived from Reineke stand density index (SDI) and Maximum SDI. Competition-caused mortality is simulated using -3/2 self-thinning theory. Due to the dynamics of establishment and mortality, resource availability varies among different stand development stages. In LANDIS PRO, the simulation of stand development patterns is governed by growing space occupied and follows the well documented stages

of stand development: stand initiation stage, stem exclusion stage, understory reinitiation stage, and old-growth stage.

Because stand-scale resource competition is achieved by implementing rather than simulating the emergent properties of stand development, LANDIS PRO is computationally efficient. Owning to the availability of density and size information, key stand parameters such as basal area, stocking, and importance value can be derived for each species. These features of model input and output make model parameters and simulation results are comparatively straightforward to forest inventory data. Therefore, current intensive forest inventory data can be directly applied for model initialization and to constrain model parameters.

We demonstrate that the model can be initialized from a historic FIA inventory (1978), calibrated with a prior time-series of sequential FIA inventories (1978 to 2003), with modeled projections (1978 to 2008) validated against a corresponding interval of FIA data. We also demonstrate that the model can be applied on a forest landscape 10^7 ha in extent. Finally, we show how results validation and model evaluation can be conducted in a rigorous fashion not previously demonstrated for FLM applications. Since LANDIS PRO outputs carry considerable quantitative information (e.g., density, basal area and stocking), it is more relevant to forest management, and may significantly improve the simulation of forest disturbance (e.g. harvest, fire, climate change). Through this study we have demonstrated a more complete framework for forest landscape model simulation including initial landscape verification, model calibration, and model validation.

Keywords: forest landscape processes, forest landscape model, species level processes, stand level processes, landscape level processes, model initialization, model calibration, result validation, LANDIS PRO, northern Arkansas, oak-pine forest ecosystems

1. Introduction

Forest landscapes change as the results of multi-scaled interactions ranging from stand-scale resource competition, forest landscape processes (FLPs) to regional-scale progresses (e.g. climate change). Forest landscape models (FLMs) have increasingly become important tools for exploring these changes by predicting forest vegetation dynamics over large spatial scales (landscape and regional) (Keane et al. 2004, Perry and Enright 2006, Scheller and Mladenoff 2007, He et al. 2008, Taylor et al. 2009). Over the past two decades, there has been remarkable progress in the development of FLMs. FLMs have been widely used to examine the effects of wildfire (e.g., Keane et al. 2008, Yang et al. 2004, Sturtevant et al. 2009), prescribed fire (e.g., Syphard et al. 2011), harvest (e.g., Gustafson et al. 2000), insect outbreaks (e.g., Sturtevant et al. 2004) and climate change (e.g. Scheller et al. 2005, Gustafson et al. 2010, Schumacher and Bugmann 2006, Thompson et al. 2011) on forest dynamics at various spatial scales. Despite their wide usefulness, a fundamental challenge has persisted since the inception of FLMs: how to simulate fine, stand-scale processes while making large-scale simulation amenable. (how to simulate fine, stand-scale processes within a large-scale simulation framework)

In a FLM, the forest landscape is divided into raster cells (polygons for some models). Site-level processes such as forest succession and competition are simulated in each cell, and FLPs are simulated over a subset of spatially continuous cells. Site-level processes contain species- and stand-level processes. Species-level processes simulate species growth, establishment, and mortality. Stand-level processes simulate inter- and intra-species competition for resource availability (e.g. light). Stand-level processes regulate species-level processes, such as competition-caused mortality (Oliver and Larson 1996). FLPs also interact with species-level processes through disturbance-induced mortality. Because the computational load for FLMs increases exponentially with increasing site-level complexity and number of cells simulated, FLMs typically simplify species- and stand-level processes in order to simulate relatively large landscapes (Mladenoff 2004).

For early FLMs, site-level species information is aggregated as absence/presence of species age cohorts in LANDIS (Mladenoff and He 1999) or forest type in LANDSUM (Keane et al. 2002) and SIMPPLLE (Chew et al.2004) in lieu of tree density and size. Species-growth in many FLMs is simplified as age increment (e.g., Li et al. 2001, Gustafson and Crow 1999) rather than DBH and crown increment as simulated in gap models as a function of competition for resources, particularly light with neighbors (Pacala et al. 1996, Deutschman et al. 1999). The modeled stand-scale resource competition is either simplified using species vital attributes so that higher shade-tolerant species outcompete shade intolerant species (e.g. LANDIS), or simplified using succession pathways so that late-successional forest types replace early-successional forest types by a predefined transition probabilities (Chew et al. 2004, Keane et al. 2004). The simplifications of site-level processes in the early FLMs make them applicable to the strongly disturbed landscapes (e.g. clearcut or stand replacing fire), thereby, site-level processes can be strongly influenced or overridden by FLPs (Romme et al. 1998, Schumacher et al. 2004, Turner 2010). However, the simplified FLMs have not incorporated the important stand-scale mechanisms (e.g. density, size, height structure) of resource competition determining forest dynamics (Moorcroft et al. 2001, Purves et al. 2008). Thus, they may not be adequate for landscapes where the effects of disturbance are relatively weak, because under such circumstances site-level processes are critical determinants of future forest composition and dynamics (Schumacher et al. 2004, Bohlma et al. 2012).

Recent FLMs have advanced in incorporating species-level quantitative information (e.g. tree number, biomass), thereby, improving the formulation of stand-scale resource competition. For example, in LANDIS II, biomass was added to each species age cohort (Scheller and Mladenoff 2004, Scheller et al. 2007). It uses a ratio of actual biomass to potential biomass for a site (land type or ecoregion) to quantify resource availability (growing space), assuming species-age cohort biomass implicitly incorporates density information. Potential biomass is assumed as 30-fold of maximum ANPP for each species, which is estimated from ecosystem models, e.g., PnET II (Aber et al. 1995). Besides simulating biomass dynamics, LANDIS II implemented ecosystem processes such as nutrient cycling in each cell, which expanded scope of traditional FLMs (Scheller et al. 2011). LANDCLIM tracks number of trees and biomass by species age cohort. It is unique in that it introduces gap model dynamics into simulating site-scale dynamics by including the interactions of abiotic variables (terrain, soil, and climate) and biotic variables (tree size, density, and biomass). Stand-scale resource competition is determined by growth- and density-dependent mortality driven by maximum stand biomass (Schumacher et al. 2004). Because of the additional computer memory required for simulating the greater complexity at each cell, simulation capacity of these models is limited, for example, 10^4–10^5 cells in Schumacher and Bugmann (2006); 10^4 cells in Scheller et al. (2011), 10^6 cells in Thompson et al. (2011). In terms of simulation capacity, these models have not demonstrated substantial improvement compared to a decade ago, for example, 10^6 cells in He and Mladenoff (1999).

Another challenge is that FLMs have not fully take advantage of the available extensive forest inventory data to initialize and constrain model parameters. Currently, many FLMs usually utilize tree species occurrence and frequency imputed across the landscape (e.g., Zhang et al. 2009, Thompson et al. 2011). This is because model input parameters such as absence/presence, biomass and ANPP are not comparatively straightforward to derive from traditional inventory data, which usually directly involves the number of trees and stem diameters (Pacala et al. 1996, Moorcroft et al. 2001). Meanwhile, for the first time, millions of observations of individual trees are available benefiting from advances in inventory data collection procedures (Woodall et al. 2010). It provides a new opportunity for FLMs to be directly initialized from, and calibrated against available inventory data to constrain model parameters and initial forest condition, as well as rigorously validated against these data to improve the future model predictions. The rigorous validation of FLMs is an area which has not been fully explored (He et al. 2011).

All of the above add up to an innovative approach to substantially improve the FLMs, by incorporating the key mechanisms determining stand-scale resource competition while making large-scale simulation amenable, and directly employing forest inventory data to initialize and calibrate model parameters. Although individual-based models (IBMs) naturally capture these key mechanisms, and are comparatively easier to parameterize and validate against inventory data (Pacala et al. 1996), applying them for spatially explicit simulation of landscape processes over a large scale would require immensely computational loads (Moorcroft et al. 2001, Urban 2005, Seidl et al. 2012). To solve this problem, what is needed is to scale up individuals to retain only individual-level mechanisms– resource competition without simulating every tree. Recent progress in IBMs to scale up individuals by using mean density and size structure of species offers a possible resolution to tackle the challenges confronting FLMs (Strigul et al. 2008). Besides, size structure, age structure and functional type composition, which are major stand detail considerably, determine the ecosystem subsequent dynamics (Moorcroft et al. 2001). Because density and size information is available, Reineke stand density index (SDI) can be used to quantify resource competition at stand scales (Reineke 1933), and Yoda's self-thinning line (-2/3 rule) (Yoda et al. 1963) can be applied to simulate resource competition-caused mortality. Since density and size structure are comparatively straightforward to estimate from forest inventory data, the formulation of a FLM incorporating mean density and size structure can directly use current accumulated intensive inventory data to constrain model structure and parameters.

In this paper, we present a new design of the forest landscape model, LANDIS PRO. In LANDIS PRO, forest succession and dynamics are simulated by incorporating species-, stand-, and landscape-scale processes by scaling up individual information through tracking the number and size of trees by species age cohort. Species-scale processes including growth, establishment and mortality are regulated by stand-scale resource competition as a function of environmental heterogeneity and resource availability. These processes, in combination with landscape disturbance and seed dispersal largely determine the species composition, forest structure and long-term dynamic of forest landscape. The new FLM model is highly compatible with FIA data, thus, the model can be directly initialized from FIA data, as well as calibrated and validated against FIA data. Specifically, we demonstrate that the model can be directly initialized from a historic FIA inventory (1978), calibrated with a prior time-series of sequential FIA inventories (1978 to 2003), with model projections (1978 to 2008) validated against FIA data. We also demonstrate that the model can be applied on a forest landscape 10^7 ha in spatial extent. Finally, we show how results validation and model evaluation can be conducted in a rigorous fashion not previously demonstrated for FLM applications.

2. Methods

2.1 The overall design and structure of LANDIS PRO

LANDIS PRO is a raster-based FLM evolved from over 15 years of development and applications of the LANDIS model (Mladenoff et al. 1996, He and Mladenoff 1999, Mladenoff 2004). LANDIS PRO simulates forest landscape change over large spatial (~ 10^7 ha) and temporal (~10^3 years) extents with flexible spatial (10-500 m pixel size) and temporal resolutions (1-10 years). Within each raster cell, the model records number of trees by species age cohort (Figure 1), and size (e.g., DBH) for each age cohort is derived from empirical age-DBH relationships (e.g., Lowenstein et al. 2000). Thus, number of trees by species age cohort is the only parameter for the landscape initialization. Due to the available density and size information, key stand parameters such as species composition, basal area, density, stocking, and importance value can be derived for each species. Biomass and carbon for individual species or for the cell can also be calculated using published empirical equations (Jenkins et al. 2003, Woodall et al. 2011). Taken together, these features of model input and output make model parameters and simulation results comparatively straightforward to apply with forest inventory data, thereby, current intensive forest inventory data can be directly apply to model initialization, constrain model parameters.

Compared to the previous versions of LANDIS models, number of trees is the only integer added to the original LANDIS model data structure, which requires one-fouth of the memory overhead compared to adding a biomass variable (Schumacher et al. 2004, Pennanen et al. 2004, Scheller et al. 2007). LANDIS PRO uses a sorted linked list to store number of trees occurring by species age cohort in sequential order (e.g. sorted by value or name) (Figure 2), thereby, this data structure enhances memory efficiency and making regional-scale simulation possible (Yang et al. 2011).

In LANDIS PRO, forest succession and dynamics are designed to incorporate species-, stand-, and landscape-scale processes (Figure 1). Species- and stand- scale processes are simulated within each cell, and landscape-scale processes are simulated across the whole landscape. In the model, the processes at these three scales interact with each other. Species-scale processes are regulated by stand-scale resource competition and FLPs. Stand-scale resource is occupied by species-scale seedling establishment, and got released by disturbance- and reaching longevity-caused mortality. Species-scale processes include tree growth, seedling establishment, stem resprouting, and mortality. These are simulated using species' vital attributes (Mladenoff and He 1999) and empirical growth equations such as age-DBH relationships (Lowenstein et al. 2000).

Stand-scale processes include competition for resources (e.g. light, water, and nutrients), which controls competition-caused mortality and seedling establishment. The competition intensity is quantified by the amount of growing space occupied (GSO) (Oliver and Larson 1996) within each cell. GSO is estimated by summing the total minimum growing space required to support all trees on this site; minimum growing space per tree is derived from Reineke stand density index (SDI) and maximum SDI (Reineke 1933). Competition-caused mortality is simulated using Yoda's self-thinning (Yoda et al. 1963), and seedling establishment is determined by available growing space, species shade tolerance and species establishment probability. Due to the dynamics of establishment and mortality, resource availability varies among different stand development stages. In LANDIS PRO, the simulation of stand development patterns is governed by GSO and follows the well documented stages of stand development (Peet and Christensen 1987, Oliver and Larson 1996).

Landscape-scale processes simulated in LANDIS PRO include seed dispersal (exotic species invasion), fire, wind, insect and disease spread, forest harvesting, fuel treatments and silvicultural treatments. These disturbance processes release growing space on one or more stands on the landscape, thereby, disturbance often reset the development stage of affected stands (Oliver and Larson 1996).

To reflect environmental heterogeneity caused by factors such as topography, soil type, and land use, the heterogeneous landscape is stratified into relatively homogeneous units called land types (Figure 1). Within a land type, similarity in species establishment probabilities (SEP) and maximum growing space occupied (MGSO) is assumed. SEP is the same parameter as used in previous LANDIS models (Mladenoff and He 1999), LANDIS II (Scheller and Mladenoff 2004), and LANDCLIM (Schumacher et al. 2004). It is a number from 0.0-1.0, reflecting how different environmental conditions favor a particular species in terms of its seedling establishment (He et al. 1999). The second source of heterogeneity is landscape disturbance and management. In this paper, we focus only on species- and stand-level processes. The simulation of FLPs (e.g. harvest, fire) in LANDIS PRO is described in other papers (e.g., Fraser et al. 2012).

2.2 Seed dispersal

In LANDIS PRO, seed dispersal is a spatial process. A dispersal kernel for the parent tree is determined by species-specific effective and maximum dispersal distance. The dispersal probability of seed arriving a given cell from the parent cell is calculated using a negative exponential decay function described by He and Mladenoff (1999b). The number of seeds reaching a given cell at a given distance from the parent tree is the product of dispersal probability and annual total number of seeds, which have potential to germinate produced by one sexually mature parent tree. The total number of seeds for each species reaching a given cell is derived by accumulating estimated contributions from all available parent trees of this species within the dispersal kernel. The average number of seeds having potential to germinate that a mature tree can produce per year, which can be derived from (Burns and Honkala 1990) is a new parameter added in LANDIS PRO. It can be calibrated to ensure the number of trees per area unit simulated in LANDIS PRO matches that recorded in forest inventory data.

2.3 Stand-scale processes

2.3.1 Resource competition quantified by growing space occupied (GSO)

To quantify stand-scale resource competition, the Reineke stand density index (SDI) can be applied to pure stands using the quadratic mean stand diameter and number of trees (Reineke 1933, Stage 1968; Long and Daniel 1990, Curtis 1982, Shaw 2000). However, SDI estimation for the mixed stands has been an ongoing debate because of the differences in growing space requirements among species and variation caused by uneven or irregular stand age structures (Torres-Rojo 2000, Woodall et al. 2002). To avoid accounting for the differences in growing space required by different species, stand-scale resource competition is quantified using GSO. GSO is estimated by summing of the total minimum growing space required for total trees. The minimum growing space required for each tree at a given species and size is derived from Reineke stand density index (SDI) and maximum SDI. Maximum SDI is defined as the maximum number of 10-inch diameter trees per hectare, and has already been reported for many species (Reineke, 1933, Long 1985).

To calculate GSO, number of trees by species age cohort (DBH) (Figure 3a) is converted into the corresponding number of 10-inch diameter trees also called number of standard trees (NST_i) using Reineke SDI (Figure 3b, Equation 1); Minimum growing space required for each 10-inch diameter tree per species ($MinGS_i$_standard) is calculated using the inverse of Maximum SDI for given species (Equation 2); the total growing space is sum of total minimum growing space occupied by all 10-inch diameter trees; the GSO for the cell is calculated as the percentage of total growing space against cell size (Figure 3c, Equation 3). Since this percentage is a summation of values associated only with tree DBH and density, GSO is independent of site quality, and can be computed and compared for stands with mixed species and age classes as well as for even-aged monocultures.

(Equation 1)

(Equation2)

(Equation 3)

Where $DBHi_{ij}$ (in *cm*) and NT_{ij} (in stems) are the mean diameter and number of trees for j^{th} diameter class of species *i;* $MaxSDI_i$ is the maximum (indexed) number of trees with 10-inch diameter per hectare for species *i*; raster_area represents the area for each raster in the model in m^2.

2.3.2 Stand development patterns

Four stand development stages are included in LANDIS PRO stand development: (1) stand initiation stage, (2) stem exclusion stage, (3) understory reinitiation stage, and (4) old-growth stage (Oliver and Larson 1996). Four specific thresholds of GSO are user-defined by landtype to regulate seedling establishment at stand initiation and stem exclusion stage (Figure *4*). These are (1) open grown ($0\text{-}GSO_1$), (2) partially occupied ($GSO_1\text{-}GSO_2$), (3) crown closure ($GSO_2\text{-}GSO_3$), (4) fully occupied ($GSO_3\text{-}MGSO$). MGSO represents the maximum growing space that can be occupied. Once stands exceed MGSO, self-thinning is initiated and stands are presumed to reach stem exclusion stage.

An open, recently disturbed forest site enters the stand initiation stage characterized by widespread establishment of primarily shade intolerant species and rapid growth of advance reproduction (Franklin 2002). As the stand is progressively filled and occupied, only seedlings of shade-tolerant species can become established. When the growing space becomes fully occupied through a combination of tree establishment and growth, the stand is considered fully stocked, thereby, entering the stem exclusion stage of development. Once stands reach stem exclusion stage, self-thinning is initiated and continues to the following understory reinitiaion and old-growth stages (Oliver and Larson 1996).

Trees that are small, shade intolerant, or approaching their species' longevity can be outcompeted first via self-thinning (Westoby 1984, Reynolds and Ford 2005, Commes and Allen 2007). As the mean size of trees in the stand increases, larger canopy gaps are created by the death of trees. During the understory reinitiaion stage, these gaps are refilled by establishment of new seedlings or the lateral growth of adjacent of trees. Continued tree growth and mortality in the absence of exogenous disturbance moves the stand into the old-growth stage of development where old trees die as they reach their species' longevity, creating large canopy gaps that promote tree regeneration and move the stand into an uneven-aged condition.

The definitions of the four GSO thresholds by the user provide flexibility for simulating different forest ecosystems. For example, a savanna system may only have first development stage and have a low GSO_1 threshold; and a woodland system may never reach the crown closure stage and may have low GSO_1 and $GSO_{2;}$ MGSO thresholds for south-facing land types may be lower than those for north-facing land types because of the higher moisture and nutrient availability (Oliver and Larson 1996, Kabrick et al. 2008, Johnson et al. 2009).

2.3.3 Self-thinning

In LANDIS PRO, resource competition-caused tree mortality is simulated as self-thinning, which is a natural process caused by limited growing space and less shade tolerance (Zeide 2005, Shaw 2006, Monserud et al. 2005). Specifically, once the growing space on a stand is fully occupied, self-thinning is initiated. The associated tree mortality is characterized by the decrease of number of trees with increasing average tree size in the stands. The pattern is considerably predictable and typically follows the -3/2 rule (also referred as Yoda's self-thinning line) (Yoda et. al 1963).

In LANDIS PRO, MGSO (the maximum growing space that can be occupied) is defined to identify the trajectory of the self-thinning line. When stands approach or exceed MaGSO (the upper limit of the available growing space), the model initiates stand-scale self-thinning. Specifically, four quarterly age ranges for thinning are created based on species longevity. Self-thinning will be performed progressively through these four age ranges until sites converge with self-thinning line. In each age range, growing space occupied for one standard tree by species age cohort first ranks based on the growing space occupied. Following the rank, the mortality by species age cohort is determined as a function of age and shade tolerance of the species. In general, higher shade tolerance species have lower thinning percentage, because they are more shade tolerant and can survive longer period of suppression (Adler 1996, Reynolds and Ford 2005). Thus, stand development trajectories converge with the self-thinning line and move along the self-thing line from lower right to upper left (Figure 4).

2.4 Species-scale processes

Species-scale processes in LANDIS PRO include growth, seedling establishment, sprouting, and sexual mortality. Species-scale processes are modeled using species vital attributes including species age of maturity, longevity, maximum DBH, and average number of seeds per mature tree per year (Table 1). Tree growth is simulated by age and DBH increment by species age cohort. Age increment is determined directly from the model time step. DBH increment is modeled using empirical log normal distribution for errors (Condit et al. 2006), or calibrated locally (Murphy et al. 1998, Loewenstein et al. 2000).

Since LANDIS PRO tracks the total number of seeds and simulates seed dispersal, the number of arriving seeds is known for each species per cell. Seed germination and establishment is regulated by the number of available seeds, GSO and species shade tolerance (Table 1) in combination with species establishment probability (SEP). The SEP values vary among ecological landtypes and reflect differences in species establishment associated with topography, moisture regime, and site quality (Mladenoff and He 1999). These values also can be modified to model expected changes in tree reproduction associated with exogenous factors such as climate change.

Sprouting is simulated for trees with capability for vegetative reproduction following exogenous disturbances such as harvesting, wind, and fire. Species-specific sprouting probabilities are age dependent and specified as part of each species' vital attribute data (Table 2).

Tree mortality in the model contains four subunits: (1) natural mortality due to reaching species longevity, (2) background mortality caused by unknown or unspecified factors (Hamilton and Edwards 1976), (3) stand-scale resource competition-caused mortality (self-thinning), and (4) landscape disturbance and management-caused mortality. Compared to the previous versions of LANDIS, the latter two forms of mortality simulation are new and are tree-based as opposed to age cohort-based (i.e., rather than modeling the death of an entire age cohort as a single entity, individual trees or subsets of trees within a cohort can die). This new feature increases the simulation realism for disturbance and competition, which often remove only part of age cohort. The background mortality allows for customizing an empirical function estimating the mortality caused by exogenous factors such as climate change and extreme (Hamilton and Edwards 1976, Johnson et al. 2009).

2.5 Study area

The study area was approximately 10^7 ha comprised of 4100× 3200 cells, each with a resolution of 90 m (0.81ha). Boundaries correspond to FIA Survey Unit 5 in Arkansas (Figure 5). This study area included the entire Ozark and Boston Mountains in Arkansas. It is characterized as deeply dissected and rugged, with elevations ranging from 213 m in valley bottoms to 762 m at the highest ridge crests. The average annual temperature and precipitation ranged from 14 to 17 ^{0}C, and 1150 to 1325 mm, respectively; the majority of precipitation occurred in the spring and fall. The area was mostly hardwood forest characterized as mixed hardwood-pine dominated by oak (*Quercus* spp.), hickory (*Carya* spp.) and shortleaf pine (*Pinus echinata Mill.*). The dominant hardwood species include white oak (*Quercus alba* L.), post oak (*Quercus stellata* Wangenh.), chinkapin oak (*Quercus muehlenbergii* Engelm.), black oak (*Quercus velutina* Lam.), northern red oak *(Qurecus rubra* L.), blackjack oak (*Quercus* *marilandica* Muenchh.), southern red oak (*Quercus falcate* Michx.), pignut hickory (*Carya glabra* Sweet), and black hickory (*C. texana* Buckl.). Species composition and distribution were significantly altered since European settlement (Hulting 2006; Spetich and He, 2008). A large portion of the current forest cover regenerated after extensive timber harvest in the early 1900s and today the age of dominant and codominant oaks typically ranges from 60 to 90 years. The stem density has greatly increased reaching full stocking due to nearly a century of fire suppression (Heitzman 2003). .

To initialize landscape conditions, calibrate LANDIS PRO, and validate the model projections, we derived the number of trees and basal area by species at 1978, 2003 and 2008 from FIA data by land type and for the entire landscape. Since only forest growth and succession were simulated in this study, only undisturbed FIA plots (no logging, insects, disease and fire since the last measurement) were used. For each FIA plot, tree ages were estimated using empirical age-DBH equation (Loewenstein et al. 2000), and then the number of trees and basal area by species age cohort per plot and per hectare were aggregated based on tree expansion factors recorded in FIA (Jenkins et al. 2001). Stratum expansion factors, which are an area expansion factors in FIA, were used to scale-up FIA plot inventory to the landscape scale to estimate number of trees and basal area by species age cohort by landtype and for the whole landscape.

2.6 Landscape initialization

2.3.1 Species vital attributes and land types

The species vital attributes used in LANDIS PRO and presented in Table 2 were derived from existing data sets for the Boston Mountains (Spetich and He, 2008) and Silvics of North America (Burns and Honkala 1990). Tree species in this study were grouped into six functional species groups accounting for 90% of total basal area: white oak (white oak and post oak), red oak (northern red oak and southern red oak), black oak, hickory, pine (shortleaf pine and loblolly pine (*Pinus taeda* L.) and maple (red maple (*Acer rubrum* L.) and sugar maple (*Acer saccharum* Marsh.)).

The land type map is derived from the Ozark-St.Francis National Forest Ecological Classification System (ECS) and Land Type Associations (LTAs) (Figure 5). In this study area, there are five LTA classes based on slope position and aspect. SEP for each land type was derived from existing forest inventory data for the Boston Mountains, Arkansas (Spetich and He, 2008). Four values of GSO (GSO_1, GSO_2, GSO_3 and GSO_thinning) by landtype were defined and calibrate against FIA data.

2.3.2 Species composition map

We created a digital forest species composition map (1978) for the study area containing number of trees by species age cohort in each cell from the FIA data for inventory year 1978 (Figure 6a). This was done using software called Landscape Builder developed specifically for LANDIS PRO (Dijak 2012). Combined the FIA unit map, national forest type map, national forest size class map, land cover map and landform map, a stochastically selected, representative FIA plot was assigned to each of the raster-based cell representing species composition on the initial landscape (Figure 7). Then, we calculated the number of trees and basal area by species age cohort for the representative FIA plot based on the raster size and FIA area expansion factors (Woodall et al. 2011). To verify the landscape initialization algorithms and ensure the initialized landscape matched 1978 FIA data, we compared basal area and number of trees by species age cohort from the 1978 initial species composition map with the summarized 1978 FIA data at both the landscape and landtype scales.

2.7 Data-splitting for model calibration

Model calibration is an iterative process of adjusting the model input parameters until the simulated results for a given landscape over a specified time period are acceptably close to observed results for the matching time period. It is widely accepted that model validation is conducted using independent data. However, independent spatial and temporal data at a landscape scale are not often available. In this study, since only 30 years' time period data (1978-2008) were available, data-splitting approach was used to avoid 'resubstitution' in which the data for model calibration are also used to model validation. Specifically, 50% of FIA plots at 2003 were used for model calibration, and rest of 50% FIA plots at 2003 and 100% of FIA plots at 2008 were used for model validation. Some degree dependence may exist given that data were recorded in two periods of time only 30 years apart. However, this data did provide a rare record of observed change over several decades, which allows direct comparison between observed with simulated results for a forest landcape.

The calibrated parameters in the models include species growth rates and annual total number of seed that have potential to germinate produced by one sexually mature parent tree. The calibration of species growth rates was achieved through adjusting species growth curves during the process of landscape initialization verification by comparing initialized species basal area with FIA data at 1978 at landscape scale and landtype scale. We then used the initialized landscape conditions directly from FIA data at 1978 as the starting point and simulated forest succession and dynamics without disturbance until 2003. The annual total number of seeds produced by one sexually mature parent tree, which have potential to germinate, was calibrated by comparing the simulated number of trees by species at 2003 against the observed number of trees directly derived from 50 percent of the FIA plots at 2003.

2.8 Results validation

We validated simulation results by comparing LANDIS PRO model predictions to observed changes for a time period not included during model calibration. After calibrating the model using 50 percent of the FIA plots at 2003, we simulated landscape from 1978 to 2008 and compare the predicted results (30 years) was compared against the observed changes in the FIA inventory for same time period. Specifically, we compared the simulated basal area and tree density by species at 2003 (25^{th} year) against rest half of 2003 FIA data that were held in reserve; we compared the simulated results at 2008 (30^{th} year) against the 2008 FIA data at landscape and landtype scales.

2.9 Long-term results verification

We performed an additional long-term model evaluation to verify that the theories and underlying assumptions regulating stand dynamics in the LANDIS PRO model are correct, or at least biologically reasonable. We used the calibrated model to simulate forest landscape change without disturbance for 150 years. Previous research about upland Missouri old-growth forests (Richards et al. 1995, Shifley et al. 1995) was used as the best available information about long-term forest patterns of development and succession to evaluate the simulated long-term forest succession, because, in absence of disturbance, our model is meant to predict potential natural succession. We then used Gingrich (1967) stocking charts and Reineke (1933) density diagrams to evaluate stand development dynamics--specifically the relationship between basal area, density and quadratic mean diameter over time.

3. Results

3.1 Landscape initialization verification

3.1.1 Forest composition for initial landscape

Our model verification indicated the digital map of tree composition constructed with Landscape Builder from FIA data for 1978 captured the species composition of oak-dominated forests at 1978 reasonably well. There was no significant difference in species density (χ^2=1.93, *df* = 5,P=0.86) or basal area (χ^2=1.40, *df* = 5,P=0.92) at the landscape scale nor by land type (south and west: χ^2=2.55 *df* = 5,P=0.77; χ^2=1.48, *df* = 5,P=0.92; north and east χ^2=2.82, *df* = 5,P=0.73; χ^2=1.18, *df* = 5,P=0.95) (Figure 8). The white oak group (consisting of white oak and post oak) was the predominant species group across the landscape, comprising 35 percent of the total basal area. The red oak group (northern red oak, southern red oak) and black oak groups together included another 30 percent of the total basal area. Hickory was consistently abundant across the landscape, making up 20 percent of the basal area. Pine and maple followed in abundance with 10 percent and 5 percent of the total basal area, respectively.

3.1.2 Forest structure for initial landscape

There was no significant difference between the initialized 1978 landscape conditions and the FIA data at the landscape scale for number of trees by age classes (χ^2=3.23, *df* = 9, P=0.95;) or for basal area by age classes (χ^2=1.07, *df* = 9, P=0.98) for all species combined (Figure 9). This illustrates that the landscape initialization process was capable of capturing characteristics of the forest structure. The age class distribution (estimated from the DBH distribution) for each species had a reverse J-shape both for the initialized landscape and for the FIA data. In 1978, species in the white oak and the red oak groups were dominant in the overstory, hickory was of intermediate abundance, and maple was predominantly an understory species group.

3.2 Model calibration

Prior to site-specific LANDIS PRO calibration for the study region, the simulated species density and basal area per acre projected from 1978 to 2003 were significantly different from observed values reported in the 2003 FIA field inventory. Thus, we made iterative adjustment to model parameters controlling DBH-age relationships and annual total number of seed to ensure model predictions from 1978 to 2003 matched observed values for the half of the FIA data used in model calibration. Following this calibration, there was no significant difference in species density (landscape: χ^2=1.85, *df* = 5,P=0.87*;* south and west land types: χ^2=1.04, *df* = 5,P=0.96*;* north and east land types: χ^2=2.68, *df* = 5,P=0.75) nor in basal area (landscape: χ^2=2.61, *df* = 5,P=0.76*;* south and west land types: χ^2=3.70, *df* = 5,P=0.59; north and east land types: χ^2=1.85, *df* = 5,P=0.87) between simulated results from LANDIS PRO and observed FIA estimates for 2003.

3.3 Results validation

Following model calibration based on data from 1978 and 2003, we validated model predictions against observed FIA data for the period from 2003 to 2008. The predicted landscape conditions were consistent with the observed FIA data in 2008 at the landscape scale (χ^2=2.82, *df* = 5, P=0.73) and land type scale (south and west land types: χ^2=3.13, *df* = 5, P=0.68; north and east land types: χ^2=2.87, *df* = 5,P=0.72*;* χ^2=2.16, *df* = 5,P=0.83). Model estimates of basal area by species group also were consistent with the

2008 FIA inventory results at the landscape scale (χ^2=2.01, *df* = 5,P=0.85) and the land type scale (south and west land types: χ^2=2.58, *df* = 5,P=0.76; north and east land types: χ^2=2.27, *df* = 5,P=0.81) (Figure 6b, Figure8) Although, validation results showed acceptable predictive performance when compared to FIA data, differences between simulated results and FIA data at the land type scale were larger than at the landscape scale.

3.4 Long-term results verification

3.4.1 Forest composition and structure

This phase of model evaluation focused on verification that the long-term, cumulative landscape changes were consistent with established theories of forest stand development. This evaluation was accomplished by simulating landscape change from 1978 to 2128 without any exogenous disturbances (harvest, wildfire) (Figure10). As expected, the density of white oak, red oak, black oak, hickory and pine decreased dramatically over the 150-year period as a consequence of self-thinning associated with forest maturation and increasing mean tree size. The lack of simulated disturbance favored establishment of shade tolerant species, and the predicted maple density gradually increased from 5% in 1978 to 20% in 2128. Simulated basal area, biomass and carbon increased from 1978 to a peak at 2098, followed subsequently by slight declines. This outcome is primarily attributable to simulated trends that have a large proportion of trees in the red oak and black oak species groups dying as they reach their maximum longevity around 2098 and being replaced by young cohorts of regenerating trees.

Predicted basal area reached a maximum of 100 ft^2/acre on southwest landtypes and 120 ft^2/acre on northeast landtypes. These values are consistent with the basal area estimates of 102-120 ft^2/acre reported by Shifley et al. (1995) and Richards et al. (1995) for mature, undisturbed forests in the Ozark Highlands. Also, in 2128 (Figure 6c), species basal area, biomass and carbon were concentrated in large, old trees; this pattern was associated with the shift in age distribution due to continued diameter growth of trees in the absence of exogenous disturbances. In year 2128 the age distribution of trees greater than 96 years old approaches a bell-shape with ten or fewer trees per acre in younger diameter classes (Figure 9). In upland oak forests in the Central Hardwood region, competitive oak regeneration is highly dependent on disturbance, such as, fire and thinning. Without disturbance, oak-dominated forests frequently are successionally replaced by a gradually increasing population of shade-tolerant species (e.g. sugar maple, red maple, sweetgum) (Figure 10). This is one of the most pervasive problems associated with sustaining oak-dominated forests, particularly on mesic sites (Dey et al.2008, Spetich et al. 2002).

3.4.2 Successional dynamics

Our model predictions indicated that without disturbances white oaks would continue to dominate the landscape for the next 150 years (Figure 6c, Figure 10). The red oaks and especially black oak declined in basal area after 2080 as many trees of those species groups reached their maximum longevity and died. Maple gradually increased over the next 150 years. The absolute increases in number of maple trees, basal area, or biomass per acre were small, but the increases relative to the corresponding initial values for maple in 1978 were huge. These predicted trajectories of forest change were consistent with our expectations for oak-dominated forests in the study region. In absence of disturbance, mixed oak forests typically transition to a greater proportion of longer-lived white oak species and shade-tolerant species such as maple increase in abundance (Johnson et al. 2009).

Gingrich (1967) stocking charts for upland oak forests indicate combinations of mean stand diameter, basal area per acre, and number of trees per acre at which a forest stand is considered fully stocked (i.e. capable of fully occupying but not exceeding the available growing space) (Ernst and Knapp 1985) (Figure 11). The upper limit of stand occupancy is indicated by the line for 100 percent stocking (often termed the A-line). The minimum conditions at which the trees on the site can fully occupy the growing space occur at approximately 58 percent stocking (often termed the B-line). In theory, an undisturbed oak-hickory stand at a stocking level less than 100 percent would gradually increase in basal area and decrease in number of trees at rates that would move the stand toward but not consistently above 100 percent stocking. Figure 11 plots the trajectories from 1978 to 2128 for mean stand conditions for the entire landscape and by land type. Trajectories remain within the fully stocked zone (between 58 and 100 percent). Mean stocking percent increases over time, as would be expected without exogenous disturbances. Also as expected, on north and east land types mean stocking per acre increases more rapidly and the mean number of trees decreases more rapidly than on south and west slopes which typically have lower site quality and slower tree growth. At year 2128 of the simulation period, the mean stocking percent per acre reached 90% for north and east land types and 75% for south and west land types. These predicted stocking percents are consistent with the stocking percentages of 80%-95% reported by Shifley et al. (1995) for mature and old-growth upland oak forests the adjacent Ozark Highlands.

Reineke (1933) density diagrams, which are algebraically analogous to the Gingrich stocking guides (Curtis 1970), provide another graphical framework to examine trajectories of mean stand conditions over time with respect to available growing space (Figure 12). The Reineke density diagrams illustrate the increase in mean diameter and decrease in number of trees per acre associated with self-thinning as stands grow undisturbed at landscape and land type scales.

3.4.3 Landscape heterogeneity

Initial landscape heterogeneity is captured in differences among land types that arise during landscape initialization using FIA data. Projected changes in landscape heterogeneity occur from differences among land types in the estimated growth rates (captured in the age-diameter equations by land type) and in differential species establishment rates among land types (captured in the seeding algorithms). In our study, south and west land types and north and east land types presented large differences in physical environments which are reflected in differential rates of forest change among land types. Our predicted results showed that the total density, basal area, biomass and carbon for north and east land types were on average higher than those for south and west land types (Figure 10). The maximum stocking percent reached at north and east land type was also higher than for south and west land types (Figure 11). Thus, user-defined parameters were able to capture the effects of the landscape heterogeneity in species composition, biomass, and carbon.

4. Discussion

4.1 Design implications

We have presented a new FLM, LANDIS PRO, which is capable of predicting forest succession and dynamics that emerge as the results of interaction of species-scale processes, stand-scale resource competition, and FLPs. In LANDIS PRO, species-level processes such as mortality and seedling establishment are regulated by stand-scale resource competition, and by landscape disturbance and management. Stand-scale growing space is occupied through seedling establishment and released via competition- and age-caused mortality. Since the landscape variation in resource availability and the environmental heterogeneity are encapsulated by land types, the model is able to predict the forest composition and distribution dynamics across heterogeneous landscapes. In addition, landscape heterogeneity was revealed not only in differences in species establishment probabilities by land type (as were done for prior LANDIS family models) but also in the varying total basal area and biomass by land types, which were emergent properties of the model. Verification of long-term simulation results showed that simulated succession trajectories followed the patterns generally observed in central hardwood forests (Abrams 2003, Jonson et al. 2009, Dey et al.2010), in that, with the absence of the fire oak-dominated forests were predicted to be successionally replaced by mesic, shade-tolerant species (e.g., maples).

LANDIS PRO has benefited from the recent advances in IBMs that scale up individuals through simulating number of trees and size by species age cohort while carrying the key mechanisms of resource competition without simulating every tree (Strigul et al. 2008, Moorcroft et al. 2001). This is achieved by implementing rather than simulating the emergent properties of stand development, analogous to the concepts of macroscopic equations used to scale up individual tree level information to stand scales (Strigul et al. 2008). Stand-scale resource competition is quantified by GSO estimated using minimum growing space required for all trees in a cell. This estimation is based on Maximum SDI using density and size related information, which are acknowledged as the primarily determinants of resource competition driving forest dynamics. Because values of GSO are only associated with tree DBH and density, GSO is independent of site quality. This makes GSO computable and comparable not only for even-aged monocultures but for stands with mixed species and age classes. Resource competition regulates seedling establishment and self-thinning (competition-caused mortality) with consideration of resource availability at different stand development stages, which follow well-accepted theories of stand development including stand initiation, stem exclusion, understory reinitiation, and old growth.

LANDIS PRO finds a balance between stand-scale complexity and computation capacity. Our simulation demonstrated that the LANDIS PRO makes large scale simulation possible with added stand-scale complexity. Simulating forest landscape change at large scales is necessary to incorporate great environmental heterogeneity. For example, Yang et al. (2011) demonstrated that species abundance and composition differed significantly when changing the spatial extent of simulation from $10^3 \times 10^3$ cells to $10^4 \times 10^4$ cells with 30 m resolution in Missouri hardwood forests. This simulation capacity is equivalent to 10^8 ha at 90 m resolution, which covers a large region of Central Hardwood Forests containing Arkansas, Missouri, Illinois, and Indiana on a high-end personal computer. Simulating at such large scale is particularly valuable for comparing

FLM predictions to those made from niche and (biogeochemical and biogeographical) process models. Currently, niche and process models are the primary tools for projecting the future climate effects on forest composition and distribution at regional scales (Morin et al. 2008, Beaumont et al.2007, Morin and Thuiller 2009, Scheiter and Higgins 2008), whereas FLMs have contributed little to this type research due to their inability to simulate sufficiently large landscapes. Recent studies have shown that FLPs may exert greater effects on forest landscape change than direct vegetation change caused by climate warming (Schumacher and Bugmann 2006, Gustafson et al. 2010). The improved simulation capacity may allow regional-scale simulation of disturbance and management effects and reduce prediction uncertainties in niche or process models (Purves and Pacala 2008, Iversion et al. 2011, Matthews et al. 2011).

With incorporating the density and size information, the model is formulated at a scale consistent with field studies. The model therefore is comparatively easier to parameterize and compare with field data. Consequently, forest inventory data can be directly used to initialize, constrain model parameters, and validate model's predictions in forest composition, structure, and successional trajectory. This should open new opportunities in FLMs.

4.2 Data assimilation (DA), result validation, and model verification

Data assimilation (DA) is increasingly important in improving ecological forecasting and estimates of uncertainty (Luo et al. 2011, Williams et al. 2005, Hobbs and Ogle 2011). DA procedures call for informative initial conditions and calibrated model parameters so that the modeled results match the observed data as closely as possible before predicting the future state of an ecosystem. In our study, verification of historical landscape initialization results and model calibration based on observed landscape change were conducted before predicting future landscape dynamics. We have shown that the initialized 1978 landscape from FIA data reasonably represented the historic forest structure and composition. The model calibration was achieved through a DA process by systematically adjusting model parameters.

Results validation and model validation are critical processes in ecological modeling to quantify the reliability and confidence of model prediction (Rykiel 1996, Shifley et al. 2009, Clark et al. 2001). In our study, the predicted forest structure and composition following 30 years of simulation has been statistically validated against FIA data. FIA data used in our study have a relatively short time span (e.g., 1978–2010 for our study area) and thus temporal autocorrelation (Araújo et al. 2005) may limit the effective use of FIA data to validate vegetation change for long projection periods. Nevertheless, FIA data provide rare spatial time series that cover a wide area from which various forest successional stages across space may mediate the relatively short survey time span. Finding truly independent landscape-scale calibration and validation data sets is problematic. However, over time longer series of repeated FIA measurements will accumulate and at least partially alleviate this concern. Likewise a limited number of landscape-scale experiments that measure tree-, stand-, and landscape-scale change over time (e.g., Shifley and Kabrick 2002, Hardwood Ecosystem Experiment 2012), will gradually provide independent data suitable for validating landscape model predictions in detail over multiple decades.

Even though the model is more mechanistic compared to previous versions of LANDIS, it uses empirical relationships to simulate tree growth, mortality, and stand development. Such empirical relationships need validation. Empirical studies of old-growth, and second-growth oak forests have been used to verify that the long-term predicted results are ecologically reasonable. Gingrich stocking charts and Reineke density diagrams have been used to validate the model design including stand development and patterns of succession. The overall model evaluation showed that the model realistically predict patterns of succession, and old-growth forest structure and composition. Simultaneously, the underlying model theories and design have been evaluated. The validation and evaluation efforts using FIA data and other inventories to test LANDIS PRO projections over time is a level of scrutiny that has not previously been attempted for FLMs applied over such a large a spatial extent.

The capacity to perform such detailed validation testing is largely due to the new design of LANDIS PRO and its compatibility with FIA data. Through this study we have demonstrated a more complete framework for forest landscape model simulation including initial landscape verification, model calibration, and model validation. This may become a standard protocol for future FLM predictions (He et al. 2011).

4.3 Model implications, potentials, and future research

LANDIS PRO has numerous potential applications. First, the model provides more quantitative information than before, which can be applied to address the critical questions regarding species abundance, forest composition, biomass accumulation, carbon sequestration and biodiversity. These questions increasingly concern scientists and society under the future climate change and ecosystem management (Frelich and Reich 2009, Thuiller 2007). Second, by explicitly incorporating the effects of climatic factors on seedling establishment and background mortality, it can be suitable for addressing the impacts of climate change on forest dynamics. Third, by simulating the number of trees and DBH by species age cohort, LANDIS PRO can improve simulating natural disturbance and forest management scenarios, which greatly affect forest structure and dynamics. For example, varying fire severity can be simulated by modeling the proportion of killed trees by species age cohort (rather than removing an entire age cohort as required in previous versions of LANDIS). Harvest can be simulated in greater detail with silvicultural prescriptions based on density, basal area, or stocking percent of the current and/or the residual stand (Fraser 2012). Fourth, because of the greater level of tree- and stand-scale detail carried in the model (e.g., number of trees and basal area by species group and landtype), standard stand-scale measurements (e.g. Reineke density diagram and Gingrich stocking chart) can be used to analyze the simulation results. This makes simulation results more relevant to forest management and planning.

The additions to LANDIS PRO of competition-caused mortality, of stocking control per unit area, and of growing space-regulated seedling establishment continue the evolution of FLMs that incorporate greater detail and realism at stand scales. Limits on computation capacity and data for model development and landscape initialization have constrained faster progresses in integration of species-, stand-, and landscape-scale processes in one simulation model. Nevertheless, we envision the day when a future variant of LANDIS could model stand-scale dynamics in much greater detail. For example a future LANDIS model might simulate tree and stand-scale forest change by invoking an established individual- tree-based simulation model such as the Forest Vegetation Simulator (Dixon 2002) for each raster at each time step. Forest growth and yield modelers who work primarily at the tree and stand scale have been simultaneously striving to incorporate landscape-scale processes within their modeling systems (e.g. Crookston and Stage 1991, Falkowski et al. 2010, Landscape Management System 2012). Further integration of existing tree-, stand-, and landscape-scale modeling expertise seems inevitable and highly desirable for addressing complex forest management issues. Although landscape-scale forest modelers have often worked independently from tree- or stand-scale modelers (e.g., those focused on timber growth and yield; see Weiskittel et al. 2011), greater collaboration is likely to be beneficial in developing robust, multi-scale models.

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Tables

Table 1. SeedlingS establishment in stand initiation stage determined by species shade tolerance and growing space occupied

Stand development stages	Seed germination
Open grown stands (0~GSO1)	Seedlings of all species can become established except for those in the most shade tolerant class
Partially occupied (GSO_1~GSO2)	Seedlings of all species can become established
Crown closure (GSO2 ~ GSO3)	Seedlings can become established only if the species' shade tolerance class is greater than that of any species currently on the raster
Fully occupied (GSO3 ~ MGSO)	Only species seedlings in the most shade tolerant class can become established
Self-thinning (GSO> MGSO)	No species seedlings can become established

Table 2. Species life history (vital attribute) parameters utilized for application of LANDIS PRO in Northern Arkansas

Species group name	Longevity (years)	Mean maturity (years)	Shade tolerance (class)	Fire tolerance (class)	Effective seeding distance(m)	Maximum seeding distance(m)	Vegetative reproduction probability	Minimum sprouting age(years)	Maximum sprouting age (years)	Maximum DBH (cm)	Maximum SDI (trees/ha)	Potential germination seeds per parent tree
Pine	200	20	3	4	40	200	0.5	1	47	60	990	50
Black oak	120	20	3	3	60	200	0.4	10	70	60	570	90
Red oak	150	20	3	3	60	200	0.4	10	70	60	570	90
White oak	300	20	4	4	60	200	0.5	10	50	65	570	90
Hickory	250	20	3	3	325	200	0.5	10	70	60	570	30
Maple	200	20	5	1	100	200	0.3	10	70	60	570	90

Figures

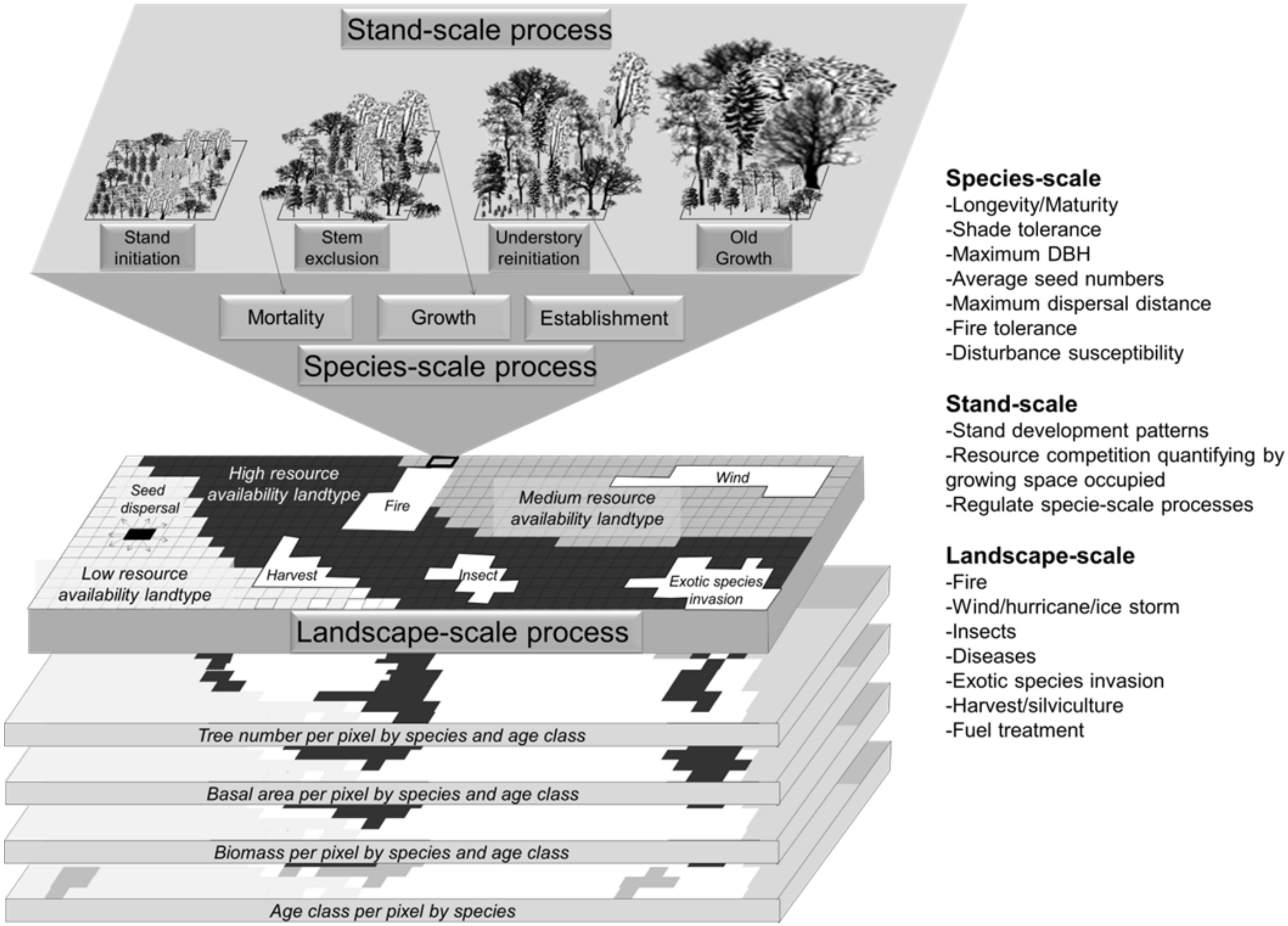

Figure 1. The conceptual design of LANDIS PRO

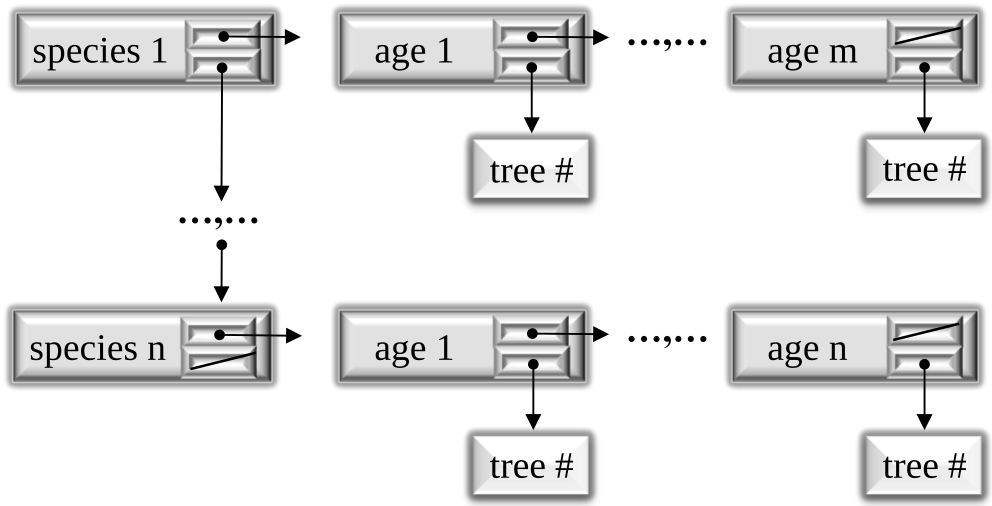

Figure 2. LANDIS PRO (sorted linked list) data structure for the representation species age-cohorts and number of individual trees in each cell

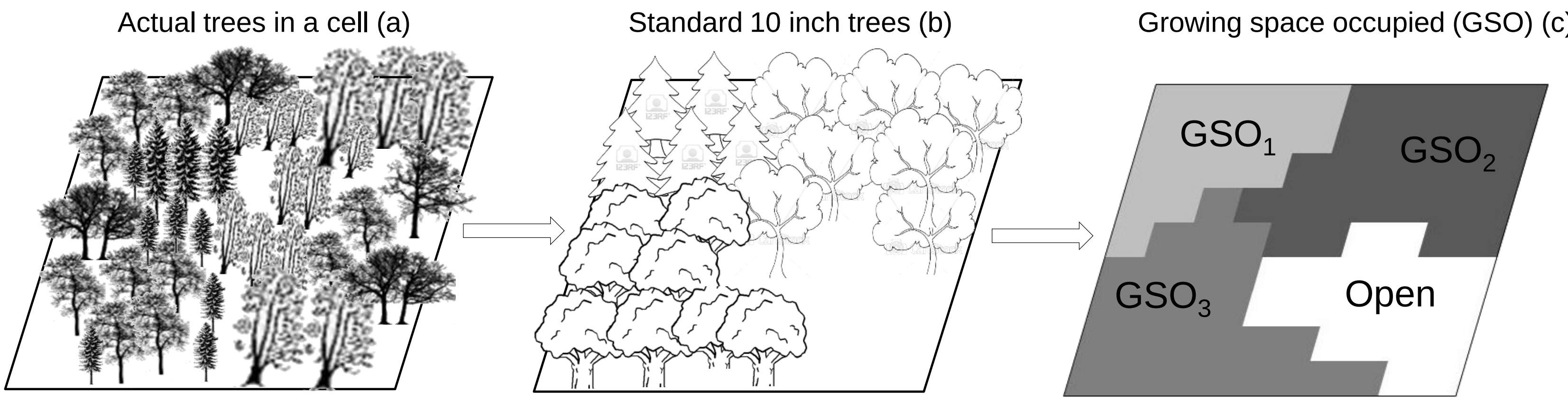

Figure 3. Procedures to estimate growing space occupied (GSO) using Reineke stand density index (SDI) and Maximum SDI

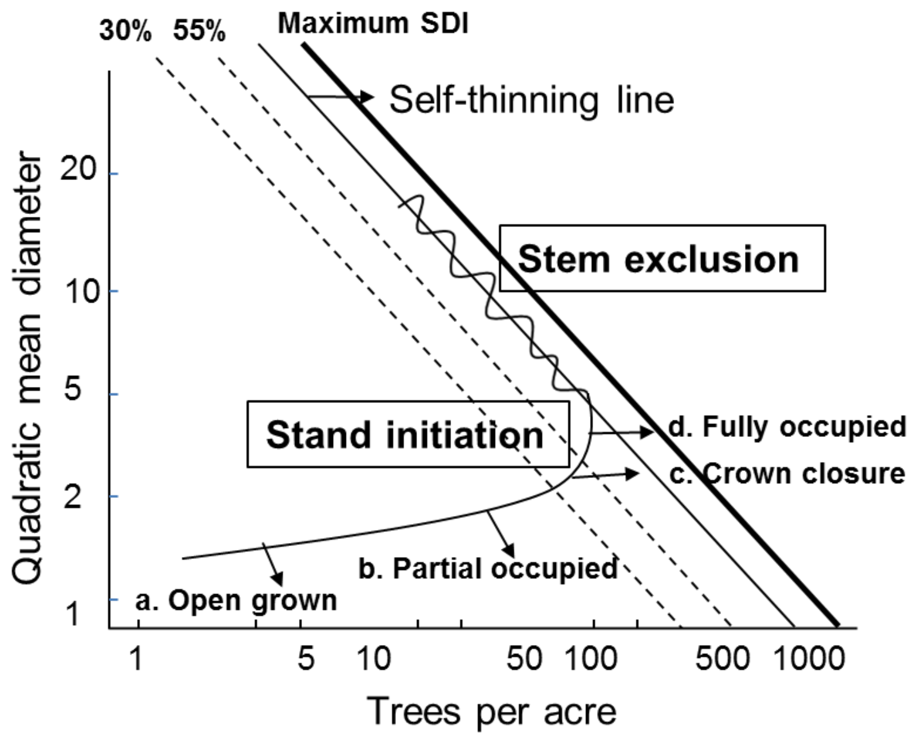

Figure 4. Stand development regulated by growing space occupied

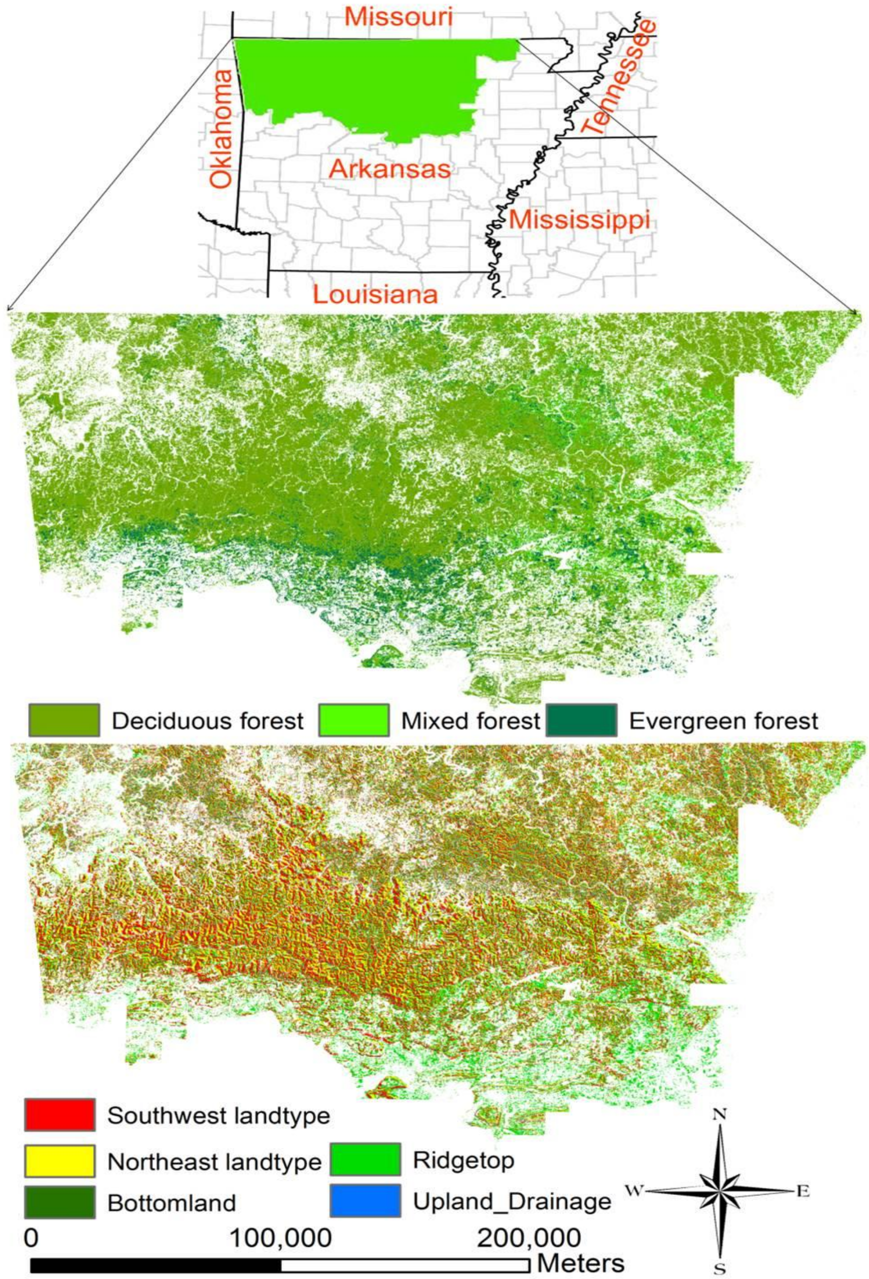

Figure 5. The 10^7 ha study area is located in Northern Arkansas within FIA survey unit 5 as indicated by the green area on the top panel. The study area is dominated by oak forest, with a variety of landtypes.

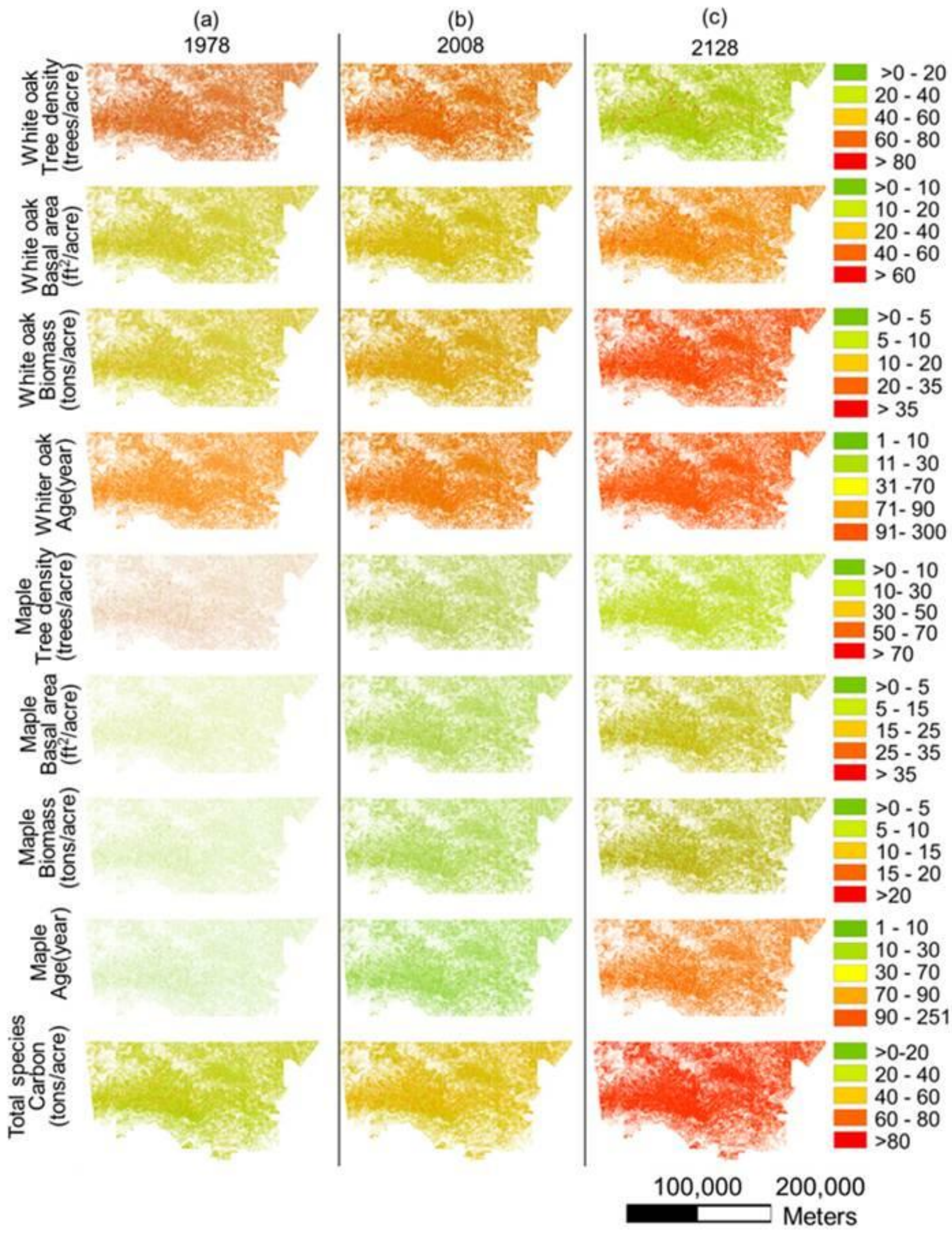

Figure 6. Tree density, basal area, biomass for white oak and maple, carbon of total species at 1978(a), 2008(b) and 2128(c)

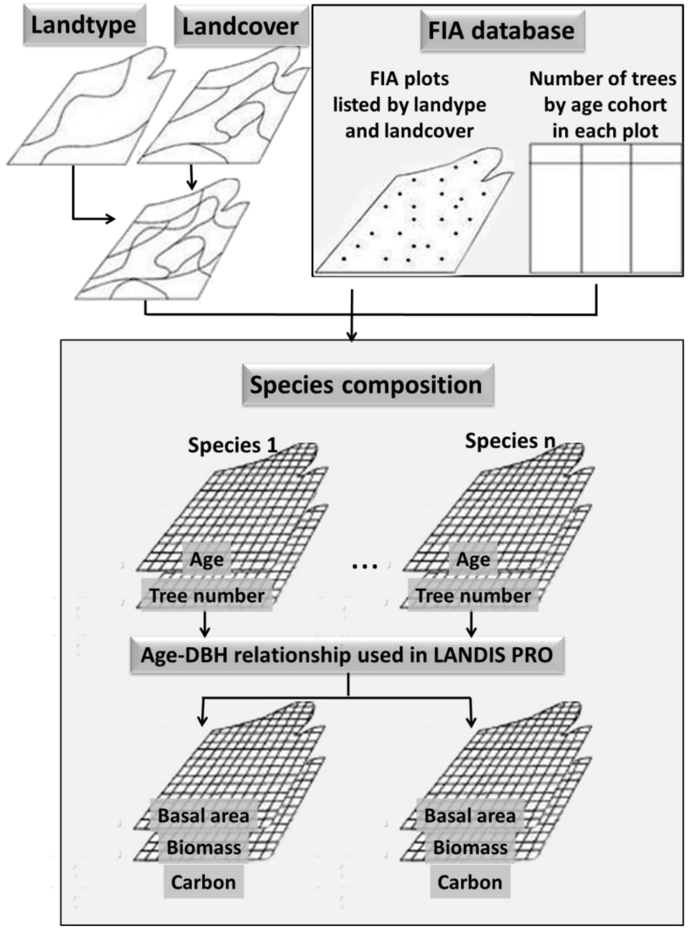

Figure 7. Flow chart of the landscape initialization using FIA data

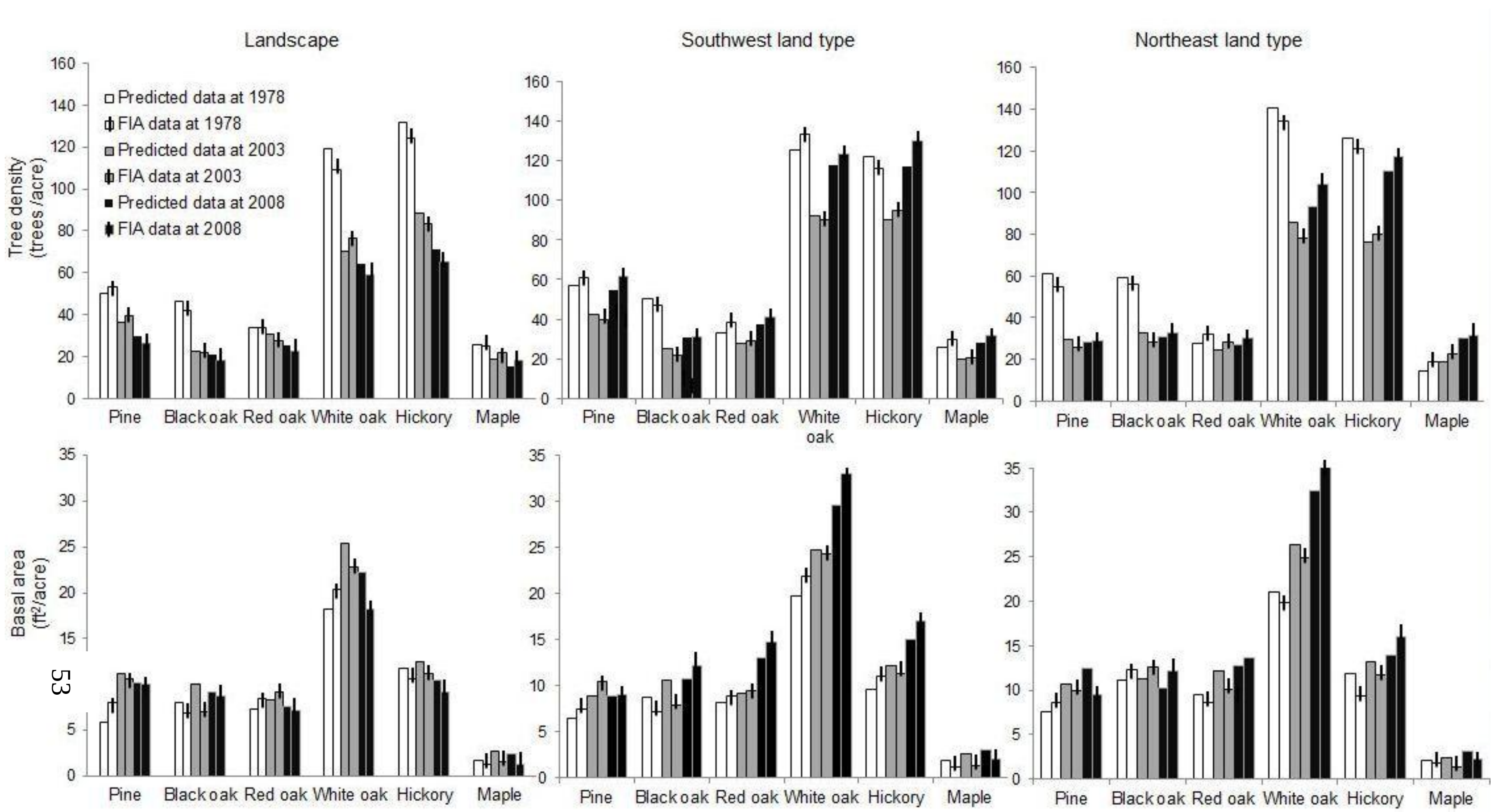

Figure 8. Comparison by species group of simulated tree density and basal area with FIA data at 1978, 2003 and2008 at landscape and landtype scales

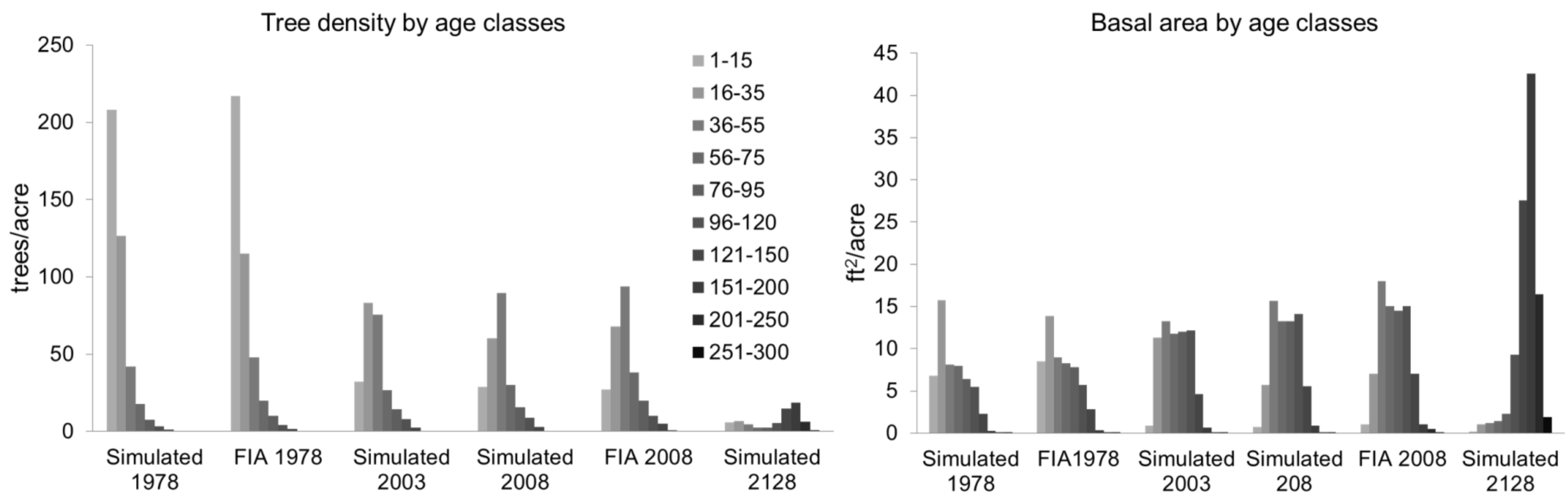

Figure 9. Simulated combined species age class distribution by number of trees and basal at 1978, 2003, 2008 and 2128, and combined species age distribution of FIA data at 1978.

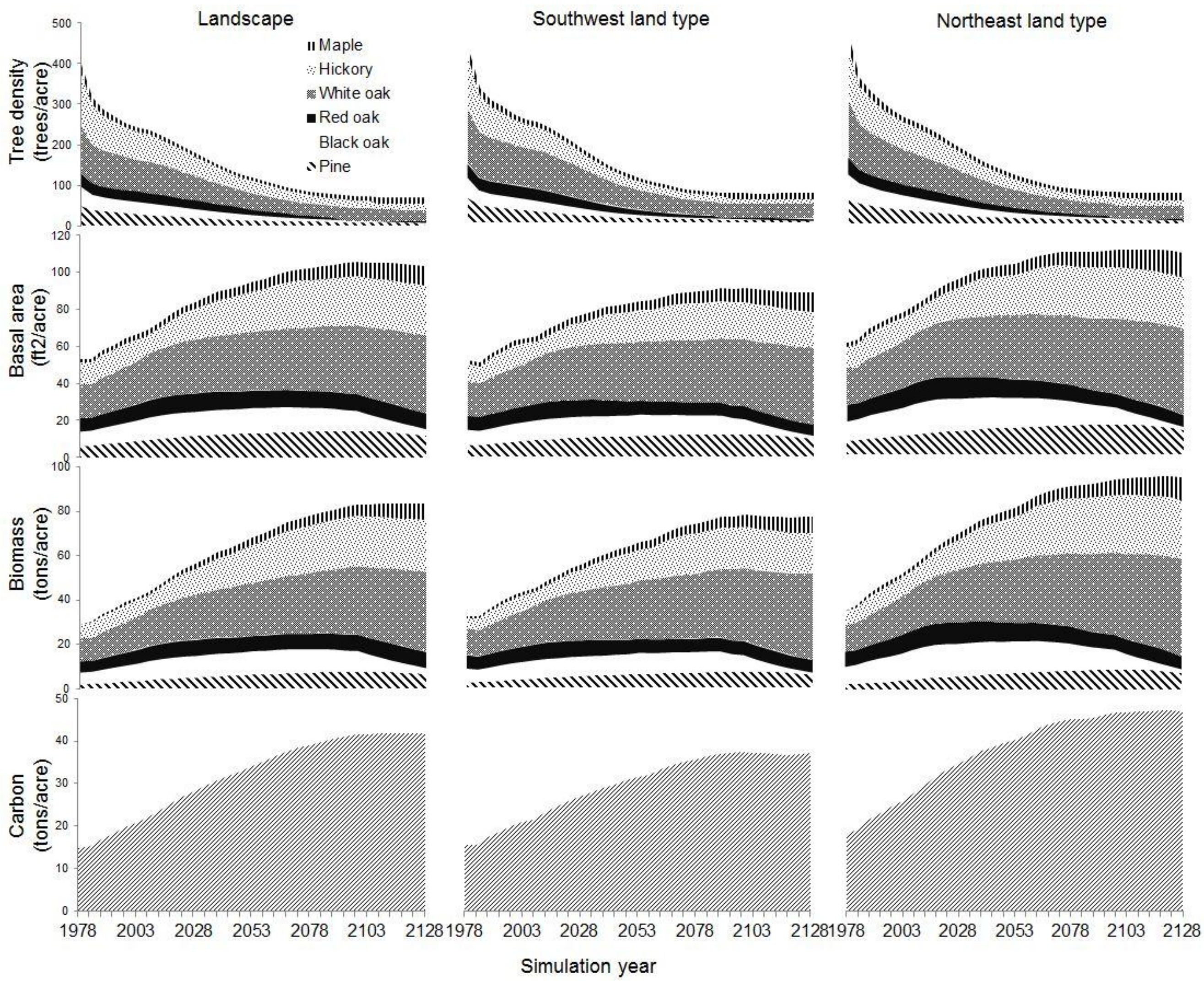

Figure 10. Simulated tree density, basal area and biomass by species group, and carbon for total species at landscape and lantype scales over 150 years

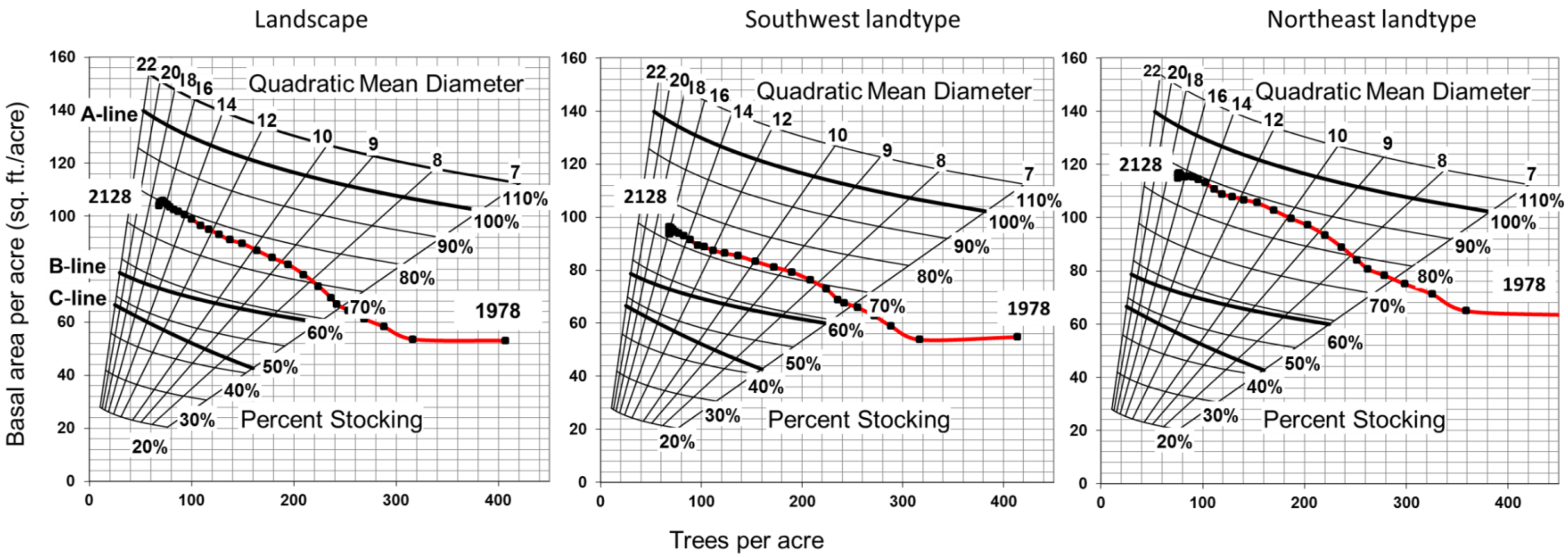

Figure 11. Gingrich stocking charts showing mean stand trajectories from 1978 to 2128 (150 simulation years) at landscape and landtype scales

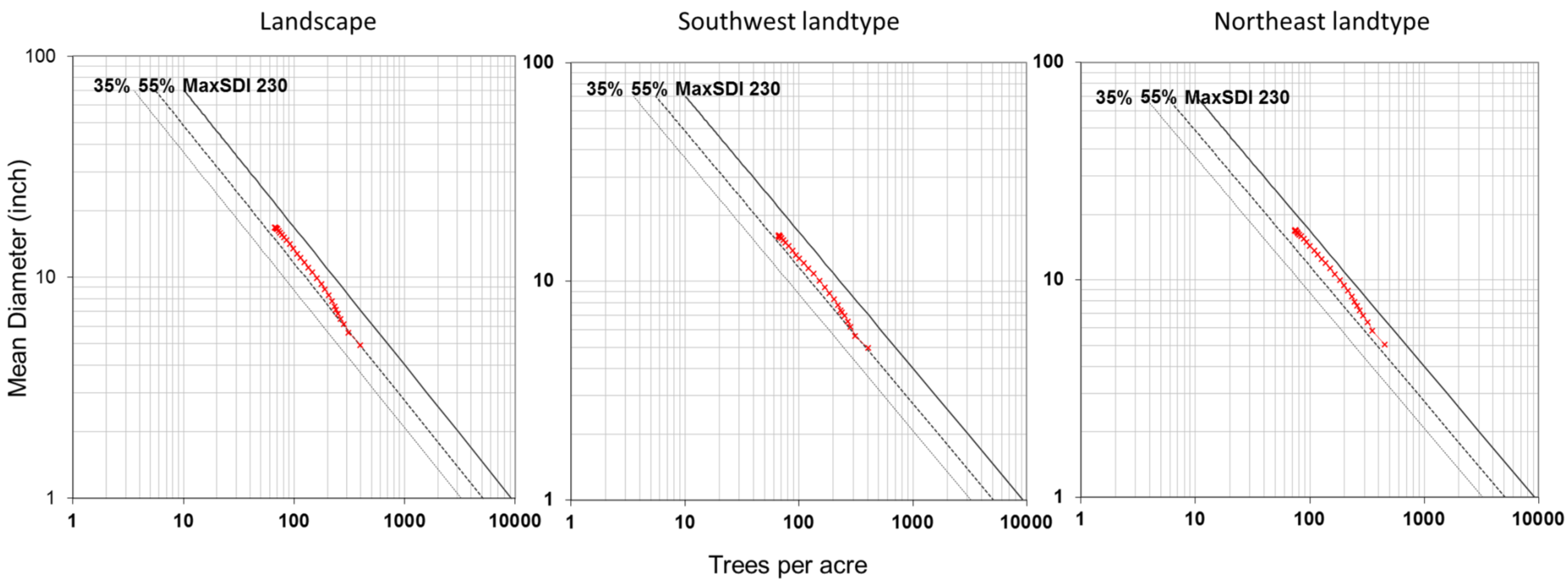

Figure 12. Reineke density diagrams showing mean stand trajectories from 1978 to 2128 (150 simulation years) at landscape and landtype scale

Chapter III. Validating a forest landscape model using forest inventory data

Abstract

Forest landscape models (FLMs) are increasingly used for predicting vegetation dynamics at landscape scales to aid ecosystem management planning and decision making. Validation of FLMs is essential to ensure users' confidence in model predictions and achieve reliable management decision making. Validation is usually accomplished through comparison of models' predictions with independent spatiotemporal data for the simulated area. To date, validation of FLMs has been limited due to lack of suitable data and the inherent stochasticity in FLMs. However, recent advances in FLMs, together with increasingly available spatiotemporal data make FLM validation feasible in some situations. Here, we propose a framework for validating forest landscape projections from LANDIS PRO using Forest Inventory Analysis (FIA) data. The proposed framework incorporates data assimilation techniques to constrain model parameters and the initial state of the landscape by verifying the initialized landscape and iteratively calibrating the model parameters. The model predictions are rigorously validated against independent FIA data at multiple scales, where a variety of processes are encompassed that influence forest succession and dynamics. The long-term natural successional pattern is also verified against empirical studies.

Results showed that the landscape initializations realistically represented conditions on the forest landscape, and the projected landscape change over time for calibrated forest landscape model was consistent with observed changes over time for the FIA data. Model predictions were able to capture much of the variation overtime in species basal area and tree density at stand-, landtype- , and landscape-scales. Subsequent long-term predictions of natural succession patterns were consistent with expected changes in tree species density in the absence of disturbance: oak-dominated forests will eventually transition to forests with greater proportion of long-lived white oak and shade-tolerant maple. This proposed validation framework represents a first attempt to validate forest landscape predictions at multiple scales. Insights gained through this study provide a credible basis for the use of this model as an aid in decision-making. Such a framework may provide a reference for future FLM validation efforts.

Key words: forest landscape models (FLMs), LANDIS PRO, result validation, model calibration, FIA data, data assimilation (DA), species, stand, and landscape scale

1. Introduction

Spatially explicit forest landscape models (FLMs) are increasingly used for predicting vegetation dynamics at landscape scales to aid ecosystem management planning and decision making (Shifley et al. 2009, Zollner et al. 2008, Mladenoff 2004, He et al. 2011). The utility of FLMs largely depends on the suitability of the predicted results for their intended purpose (Luo et al. 2011, Coreau et al. 2009, Clark et al. 2001, Clark 2005, Moorcroft 2006, Cramer et al. 2001). Potential FLM applications vary in accuracy requirements, and suitability of a particular FLM is often judged in the context of whether or not it is better than the available alternatives.

FLMs have numerous sources of uncertainty associated with model structure, parameter estimates, data inputs, and stochastic components in the models. Model uncertainties may affect the reliability of predictions (Xu et al. 2010, 2009, Clark 2003, Cressie et al. 2009). This makes model validation, which is used to quantify accuracy of model predictions, indispensable for the FLMs (Rykiel 1996, Gardner and Urban 2003, Schiegg et al. 2005, Gordon et al. 2004, Prisley and Mortimer 2004, Reynolds and Ford 1999, Bellocchi et al. 2010, Shifley et al.2009, Peterson et al. 2003). Systematic validation of FLM predictions is required to ensure that results can be relied upon for forest management decision making.

Model validation includes conceptual validation and operational validation (Rykiel 1996). The latter is also known as result validation. Conceptual validation is a process to determine that the theories and assumptions underlying the design of the model are reasonable, or at least justifiable. This process is usually conducted at the model development stage by identifying, incorporating, and verifying the operation of modeled processes against the underlying theories of ecology, forest succession dynamics, and empirical knowledge (Schiegg et al. 2005). Conceptual validation is usually completed when it has been demonstrated that the model provides scientifically acceptable explanations of the cause-effect relationships and results have been published via the peer review process. However, the validity of conceptual design does not ensure that models can make credible predictions (Rykiel 1996, Oreskes et al., 1994, Shifley et al.2009). Thus, validation of prediction results becomes particularly important if a model is to be applied in decision making for real landscapes. Results validation is the process of quantifying the accuracy of predictions, and this is accomplished through comparison of model predictions to observed data (Gardner and Urban 2003, Shifley et al. 2009, Clark et al. 2001, Moorcroft 2006). This is an essential step in determining the suitability of a FLM for a specific application.

Results validation of FLMs has been hindered by the following difficulties. First, FLM predictions involve spatial time series data, yet independent spatiotemporal data for results validation are rarely available (Araújo 2005, He 2008, Coreau et al. 2009, Schiegg et al. 2005, Shifley et al. 2009, Rykiel 1996, Gordon et al. 2004, Luo et al. 2011, Purves and Pacala 2008). Second, FLM predictions include the inherent stochasticity of forest landscape processes such as fire, wind, insects, disease, and harvesting (Mladenoff 2004, He et al. 2011), which lead to spatial and temporal variation (stochasticity) in predictions across the landscape (Mladenoff 2004, Chew et al. 1995). Addressing this stochasticity in landscape predictions is particularly daunting for the validation of FLMs that are compared against a known landscape (Scheller and Mladenoff 2004, Mladenoff and Baker 1999). Third, most prior FLMs have used utilized broad, categorical estimates of forest conditions such as absence/presence of age cohorts in LANDIS (6.0 and the previous versions) (He and Mladenoff, 1999) or forest types in LANDSUM (Keane et al. 2002) and SIMPPLLE (Chew et al. 2004) for model evaluation rather than quantitative estimates of metrics such as tree species composition, tree size class, stand density, stand basal area, stand biomass or other common quantitative forest inventory metrics. However, recent research with LANDIS II (Scheller and Mladenoff 2004) and LANDCLIM (Schumaker et al. 2004) has moved in that direction with evaluation of estimated biomass and annual net primary productivity at the stand scale.

For example, LANDIS-II demonstrated reasonable predictions of above ground net primary productivity and species biomass at the landscape scale through comparisons with reported values in published literature (Scheller and Mladenoff, 2004). The total aboveground biomass and tree species composition predicted by LANDCLIM were tested against other models' predictions and values reported in published literature at landscape scale and stand scale (e.g. Schumacher et al. 2004).

With increasing demand for simulation realism and quantitative information (e.g., aboveground biomass and carbon), there has been a trend to incorporate additional quantitative attributes in FLMs to improve simulation realism of stand-level processes (He et al. 2011). For example, in LANDIS PRO, model realism is enhanced by incorporating stand-scale estimates of available growing space that regulate growth and reproduction dynamics of cohorts of trees that differ by species and age class. The improved simulation realism significantly improves the comparability of predicted forest conditions with quantitative forest inventory data. The underlying data structure in LANDIS PRO is tree density and basal area by species cohort defined by age class and diameter class. Consequently model estimates are highly compatible with traditional forest inventory data. Thus, LANDIS PRO can be directly initialized from forest inventory data as well as calibrated and validated using repeated forest inventory measurements over time (Wang et al. in review).

Benefiting from increasingly available forest inventory data, data assimilation (DA) which combines observational data with ecological models to constrain parameters and the initial system state before predicting the future state of an ecosystem, is increasingly important to advance model prediction (Luo et al. 2011, Williams et al.2005, Hobbs and Ogle 2011). Thus, FLMs initialization, verification, and calibration may be needed to achieve informative initial conditions and calibrated model parameters in that the simulated results can match the observed data as closely as possible before yield simulation.

Validation of FLMs may need to be conducted at multiple scales since a FLM often involve site level, stand level, and landscape level processes (Shifley et al.2009, He et al. 2011, Moorcroft 2006, Schumacher et al. 2004, He, 2008). Thus, the scales of available independent data should match the scale at which the validation is conducted (Renschler 2003, Moorcroft 2006, Shifley et al. 2009). Since the underlying mechanisms in FLMs are different at different scales, validation criteria should be specified varying with scales (Rykiel 1996, Shifley et al. 2009). For example, at the stand scale, the conceptual and operational validation should show FLMs are capable of portraying the key stand-level processes, which vary in simulation mechanisms among FLMs. Examples include successional pathways in LANDSUM (Keane et al. 2002) and SIMMPPLLE (Chew et al. 2004), site dynamics regulated by species vital attributes in

LANDIS (Mladenoff and He 1999), or stand development driven by growing space available in LANDIS PRO (Wang et al. in review). At the land type scale, the forest succession and dynamics influenced by varying land type suitability should be captured by FLMs. The validation of FLMs at the landscape scale should account for the spatial heterogeneity caused by physical environment and disturbance.

In this paper, we propose a rigorous framework for the validation of LANDIS PRO through comparison of the model predictions with independent forest inventory data. The proposed validation framework incorporates data assimilation (DA) techniques (Luo et al. 2011), and multi-scales concerning model formulation and available independent forest inventory data. Our proposed validation framework represents a first attempt to validate forest landscape predictions at multiple scales. Such a framework may provide a reference for future FLM validation efforts.

2. Study area

Our study area (10^7 ha) includes the entire Ozark Mountains and Boston Mountains of Northern Arkansas. The boundaries correspond to FIA Survey Unit 5 in Arkansas (Figure 1). The topography in the study area is deeply dissected and rugged, with elevations ranging from 213 m in valley bottoms to 762 m at the highest ridge crests. The main soils are Udults. The average annual temperature and precipitation range from 14 to 17 0C, and from 1,150 to 1,325 mm, respectively, with the majority of precipitation falling in the spring and fall.

Most of this area is hardwood forest characterized as mixed hardwood-pine dominated by oak (*Quercus* spp.), hickory (*Carya* spp.) and shortleaf pine (*Pinus* *echinata Mill.),* that regenerated after extensive timber harvesting in the early 1990s (Heitzman et al. 2007). The dominant species include white oak (*Quercus alba* L.), post oak (*Q. stellata* Wangenh.), chinkapin oak (*Q. muehlenbergii* Engelm.), black oak (*Q. velutina* Lam.), northern red oak (*Q. rubra* L.), blackjack oak (*Q. marilandica* Muenchh.), southern red oak (*Q. falcate* Michx.), pignut hickory (*Carya glabra* Sweet), and black hickory (*C. texana* Buckl.). Other species including red maple (*Acer rubrum* L.), sugar maple (*A. saccharum Marsh.),* sweetgum (*Liquidambar styraciflua* L.), blackgum (*Nyssa sylvatica* Marsh), dogwood (*Cornus florida* L.) are also represented.

3. Approaches and Methods

A modeling process involving temporal predictions typically includes model initialization, calibration, verification, and validation (Figure 2). The model is often initialized at a past time t_0, and verification of the initialized model may require iterative changes to model parameters to ensure that the initial conditions are as closely as approximate the data available. This process is also known as data assimilation (DA) (Luo et al. 2011). Model verification at time t_m using independent data is essential to ensure the modeled dynamics are correctly simulated within the timeframe t_0 to t_m. This process may require multiple iterations of model calibration until satisfactory results are achieved. The well calibrated model can then be used to simulat from t_0 to time t_{m+n}, providing an quantitative model validation against a new data set for the period t_m to t_n (Figure 2). If the validation results are acceptable for the model's intended purpose, projections may be made for future years beyond t_n.

In our study, we used the LANDIS PRO forest landscape model to predict the forest composition, structure and species distribution dynamics from 1978 to 2128. The initialized landscape for LANDIS PRO including number of trees by species age cohort for each cell can be directly parameterized from Forest Inventory and Analysis (FIA) data in combination with land form (derived from DEM) and land cover (identifying forest types). The initial landscape conditions were parameterized at 1978 because it is the earliest FIA inventory available digitally in our study area. The initialized forest composition for the modeled landscape was verified against FIA data of 1978 and model parameters were calibrated to ensure the best possible match of the initialized forest composition to FIA data. We then ran the model for 25 years to 2003, and compared simulated tree basal area and density by species with the recorded values in FIA inventory at 2003. We iteratively recalibrated model parameters to achieve a close match between predicted and observed changes from 1978 to 2003. Finally, we used the well-calibrated LANDIS PRO to simulate change for the entire study area for 150 years using a five-year time step.

LANDIS PRO is scale dependent and is formulated to include species-, stand- and landscape-scale processes. Specifically, forest successional dynamics emerge as the result of the species growth, mortality and recruitment governed by competition for resource availability at stand-scale, and landscape heterogeneity is revealed by the interaction of tree species establishment coefficients and available growing space among landtypes (Wang et al. in prep). In this study, LANDIS PRO was validated through comparing model's prediction with FIA data at stand-, landtype- and landscape-scale. Specifically, after model calibration based on the 1978 and 2003 forest inventories, the predicted basal area and density by species at 1988, 1995 and 2008 year were compared against FIA data at each of those inventory years across the three scales for model validation. The stand-scale dynamics were validated by using Gingrich stocking charts (1967) and Reineke density diagrams (1933). The long-term (> 100 years) predicted successional trajectories, which do not have long-term field data to support direct validation based on comparison with observed long-term changes, were verified against results conditions observed fro old-growth forests in this region. In particular, we were interested in knowing how well does LANDIS PRO model perform for the calibration period and for new inventory periods at stand-, land type- and landscape-scales.

3.1 FIA data

We used Forest Inventory and Analysis (FIA) data in the same study area between 1978 -2008 to perform model initialization, verification, calibration, and validation. Specifically, the FIA data at 1978 and 2003 were used for landscape initialization, verification, and calibration. The FIA data at 1988, 1995 and 2008 were applied for model validation. The 1988 and 1995 are separate inventories within the calibration period and the 2008 inventory is outside the calibration period. These data constitute a rare record of observed forest succession allowing direct comparison between model prediction and inventory data. The unprecedented quality of these data allows us to explore predictive credibility of a FLM, with a level of quantitative detail that has not yet been addressed in previous research.

In this study, LANDIS PRO model predictions were validated under natural succession, so FIA inventory plots if they had been obviously disturbed were omitted. In particular, all plots meeting the following conditions were included in the sample: (1)

classified as forest, (2) no evidence of disturbance including logging, insects, disease and fire since the last measurement. Using these guidelines, 5,941, 5,968, 6,002, 5,525 and 5,518 plots were used at 1978, 1988, 1995, 2003 and 2008, respectively.

3.2 LANDIS PRO model description and parameterization

3.2.1 Model description

LANDIS PRO is a new generation of FLM based on over 10 years of development and testing of the original LANDIS model (Mladenoff et al. 1996, Mladenoff and He 1999, He and Mladenoff, 1999a). It has the capacity to simulate of forest dynamics with or without natural (e.g. fire, wind, and disease) and anthropogenic disturbances (e.g. harvest and fuel treatment). In LANDIS PRO, the simulated landscape is divided into equally sized raster cells. For each cell, tree species are recorded by age cohorts and the number of trees associated with each age cohort. The number of years between successive age cohorts can be from 1 to 10 years and must correspond to the time step to be used in model. Tree ages can be converted to and from tree diameters based upon known age-size relationships in the study area (e.g., Loewenstein et al.2000). The tree size information along with number of trees in a cell can be further summarized to estimate the proportion of the total growing space that is occupied (Wang et al. in review).

Succession dynamics at each cell are simulated by species-level processes and stand-level processes. The modeled species-level process are recruitment, sprouting, growth and mortality; these are based on species life history attributes including longevity, age of sexual maturity, maximum age of vegetative reproduction, sprouting probability, and reproduction establishment coefficients.

Stand-scale processes for a given site simulate competition for resources such as light and nutrients. Competition at a given point in time is estimated from the available growing space at each cell based on the number of trees and quadratic mean DBH by species and age cohort for each cell. Growing space is estimated by Reineke's stand density index (SDI), which describes stand (or cell) density relatively to the maximum SDI (MaxSDI) for a stand. This within-stand competition as determined by available growing space in LANDIS PRO is linked to the well documented stages of stand development (Peet and Christensen 1987, Oliver and Larson 1996) including stand initiation, stem exclusion, understory reinitiation, and old-growth.

Specifically, an open, recently disturbed forest site enters the stand initiation stage characterized by widespread establishment of primarily shade intolerant tree species, growth of advance tree reproduction, and basal sprouting from tree root systems surviving from the prior stand. As the site is progressively filled and occupied, only seedlings of shade-tolerant species can become established beneath the canopy of existing trees. When the growing space becomes fully occupied through a combination of tree establishment and growth, the stand is considered fully stocked (Reineke 1933, Gingrich 1967) and enters the stem exclusion stage of development. Self-thinning (Yoda et al. 1963) occurs during this stage when trees that are at a competitive disadvantage are crowded out and release growing space to the remaining trees. Trees that are small, shade intolerant, or approaching their species' longevity succumb first via self-thinning (Commes and Allen 2007, Reynolds and Ford 2005, Franklin 2002). During the understory reinitiaion stage of stand development large canopy gaps created as trees die will be refilled by establishment of new seedlings or the lateral growth of adjacent of trees. Continued tree growth and mortality in the absence of exogenous disturbance moves the stand into the old growth stage of development where old trees die as they reach their species' longevity, creating large canopy gaps that promote tree regeneration and move the stand into an uneven-aged condition.

The landscape-level processes include disturbance, seed dispersal, and establishment. To reflect landscape heterogeneity, the study landscape is stratified into relatively homogeneous units called land types reflecting variation in the physical environment due to factors such as topography, soil type, temperature regime and moisture regime. Within a land type, similarity in species establishment probabilities and disturbance regime is assumed and modeled using a combination of species establishment probabilities (SEP) and growing space availability (relative maximum stand density that can be reached). Since SEP and disturbance vary spatially and temporally, they are capable of reflecting the landscape heterogeneity in space and time, even within a single land type.

At the landscape scale, besides the varied SEP and disturbance regimes among different landtypes, maximum resource availability by landtype was included to reflect the landscape heterogeneity and regulate the competition for resources at the stand scale. Overall, within LANDIS PRO, forest dynamics emerge as the result of natural tree growth, mortality and recruitment at the species-level, competition for resource availability at the stand-level, and landscape heterogeneity at the landscape-level.

3.2.2 Model parameterization

In this study, tree species were grouped into six functional species group accounting for 90% of total basal area. The groups are white oak (white oak and post oak), red oak (northern red oak and southern red oak), black oak (black oak and blackjack oak), hickory (*Carya* spp.), pine (shortleaf pine and loblolly pine [*Pinus taeda* L.]) and maple (red maple and sugar maple). The species vital attributes, landtype map and species establishment probabilities by landtype were compiled based on an existing data set for the Boston Mountains (Spetich and He, 2008) and Silvics of North America (Burns et al. 1990).

A forest composition map including number of trees by age cohort in each cell was directly initialized from FIA data recorded in 1978. This initialization process was conducted using the Landscape Builder software developed specifically for LANDIS PRO (Dijak 2011, *in revision*). Specifically, in each FIA plot, tree diameters were converted to tree age cohorts using published age-DBH equations (Gompertz 1825, Loewenstein et al. 2000). The number of trees by species-age cohort for each FIA plot was determined based on the raster size and FIA tree expansion factor (Woodall et al. 2011). Then, based on a raster map combining land cover and landform, FIA forest plots with the corresponding land cover and landform were stochastically assigned to each pixel for a statistically representative mapping of forest species composition by age class for the initial landscape. Species composition and land type maps were rasterized to a 90 m× 90 m cell size resolution.

3.3 Experimental design of LANDIS PRO validation at multiple scales

3.3.1 Stand scale

Stand-scale validation was stratified into cells (sites) of southwest and northeast landtype groups. Then, for simulation years corresponding to 1978, 1988, 1995, 2003, and 2008 a random sample of 15000 cells was pulled from each of the two strata (Figure3b). In each cell, basal area (ft^2) and tree density (trees) by species group were directly derived from model simulation results representing stand-scale predicted results.

For the same years, the undisturbed FIA plots included in the validation data set were first classified into landtypes based on slope, aspect, physiographic class, and forest type (Dijak 2011). For the northeast and southwest landtypes, individual trees were aggregated into five species functional groups corresponding to those simulated in LANDIS PRO. Basal area (ft^2/acre) and tree density (trees/acre) by species functional group were calculated for each FIA plot. To compare these FIA plots at a scale appropriate for LANDIS PRO model predictions at stand scale (cell), we aggregated the estimated basal area and tree density by species functional group at each plot to the LANDIS PRO model 90m cell size by using the tree expansion factor (Figure3a).To validate stand scale development, 300 subsamples were randomly selected from these 15000 samples for both southwest and northeast landtypes. Time series data from 1978 to 2128 involving the predicted total trees and basal area were derived for these 300 cells. Then, tree density (trees/acre), basal area (ft^2/acre) and quadratic mean diameter (Dq, inch) were calculated for each cell to compute the corresponding Gingrich (1967) stocking estimates and the Reineke stand density index as a graphic representation of stand-scale development.

3.3.2 *landtype scale*

Landtypes are suitable ecological units for aggregating FIA data by relatively homogenous environmental conditions. Landtypes are delineated according to their relatively homogeneity of soils, terrain and weather pattern (He et al. 1998). In the FIA database for the plots within each landtype polygon randomly selected for validation, mean tree density (trees/acre) and basal area (ft^2/acre) by species group were computed for inventory years from 1978 to 2008 (Figure 3c).

To derive the landtype-scale data from LANDIS PRO for comparing with FIA data, two groups of polygons representing southwest and northeast landtypes were randomly selected. Within each selected landtype polygon, the number of trees (trees/acre) and basal area (ft^2/acre) by species group was calculated by as the sum over all LANDIS cells within a landtype polygon divided by total area of landtype polygon (Figure 3d).

3.3.3 *Landscape scale*

In the FIA database, all undisturbed FIA plots were used for landscape-scale comparison with model predictions (Figure 3e). In each FIA plot, the number of trees and basal area by species group were scaled to the corresponding quantities for the modeled 90m cell size in LANDIS using FIA tree and area expansion factors. In LANDIS PRO, a large group of cells (30,000) were randomly selected from the entire landscape (Figure 3f).

To validate forest succession and dynamics, time series of basal area, tree density and percent landscape cover for each species group were generated from 1978 to 2128 to verify against previous old-growth studies of oak forests and empirical knowledge (Shifley et al. 1995, Richards et al. 1995).

3.4 Statistical analysis

Model validation involves rigorous statistical comparison of predicted and observed results (Moorcroft 2006, Bayarri et al. 2007, Oreskes et al., 1994). A variety of statistical approaches have been proposed to perform model validation. These include graphical comparisons, statistical tests of differences, and goodness-of-fit (Yang et al. 2004, Miehle et al. 2006, Bellocchi et al. 2010). The use of these statistical approaches has generated much debate (Yang et al. 2004). For example, Yang et al. (2004) argued that the application of statistical tests (e.g. t-test, χ^2test) in model validation is largely uninformative and of limited utility; model validation should examine how well a model fits independent data rather than use simple pass/fail statistical hypothesis tests attempting to answer whether or not a model is correct.

We employed several goodness-of-fit measurements to quantify how well model simulations compared to the actual FIA data. These included residuals-based (the relative mean error of prediction), ¯% (Eq. 1); the relative mean absolute error, MAE% (Eq. 2), the relative root mean square error of prediction RMSE% (Eq. 3) and an association-based measure, the Nash-Sutcliffe index of model efficiency, ME (Eq. 4)).

The relative mean error of prediction, ¯%, compares the predicted values and observed values to estimate the mean bias and the accuracy of model predictions. MAE% and RMSE% measure the prediction accuracy using absolute prediction errors on an individual level. Since RMSE% is based on squared prediction errors, RMSE% is thus more sensitive to outliers than MAE% which is a linear function of the errors. Therefore, the greater the difference between MAE% and RMSE% is, the greater is the likelihood of significant prediction errors (Miehle et al. 2006, Blanco et al. 2007, Walter and Moore 2005). ME examines the agreement of individual predicted and observed values compared to a 1:1 line which would indicate perfect agreement between plotted pairs of observed and predicted values. The closer the value of ME to +1 the better (Nash and Sutcliffe 1970, Miehle et al. 2006).

(Equation 1)

(Equation 2)

(Equation 3)

(Equation 4)

where O_i is the observed values for model comparison, Pi is the predicted values, and n is number of paired-values for comparison between observed values and predicted values.

With built-in stochastic components, the FLMs are not designed to predict the occurrence of a given event at a single real location (Mladenoff and He, 1999). Thus, only aggregated statistical properties can be estimated reliably across broad spatial and temporal scales (Levin et al. 1997). In our study, the mean of samples was used to conduct statistical comparisons.

4. Results

4.1 Landscape initialization verification

To verify the landscape initialization algorithms and ensure the initialized landscape conditions used with LANDIS PRO for 1978 closely approximated those reflected in inventory data, we quantified the prediction error of basal area and tree density by species functional group from the 1978 initial species composition map with the summarized 1978 FIA data at stand-, landtype- and landscape scales, as well as by species group across the whole landscape. The verification showed that differences in predicted and observed species basal area and tree density were less than 5% for ¯%, MAE% and RMSE% and the value of ME approximated 1 at these three scales (Figure 4, 7, and 8). Thus, the initialized landscape captured the species composition of oak-dominated forests at 1978 reasonably well.

4.2 Model calibration

The initialized landscape was simulated for 25 years from 1978 to 2003 to calibrate the species age and size relationships that regulate basal area and the annual number of potentially germinating seeds that affect density. This iterative calibration process was accomplished through comparing the predicted species basal area and number of trees with observed values for FIA data at 2003 and adjusting model parameters as required. In general, the final calibration results showed that the differences in predicted species basal area and tree density was small (¯% < 5%) and values of MAE% and RMSE% were similar and small in magnitude. Model predictions were accurate with an ME of approximately 1, although slight larger discrepancies exist for maple and pine (Figure 4, 7, and 8). Thus, we judged the model to be calibrated to predict reasonable outcomes.

4.3 Model validation

The calibrated model was run for 150 years of simulated landscape change. The predicted species basal area and tree density at 1988, 1995 and 2008 at stand-, landtype- and landscape-scale were validated against the observed FIA data at each corresponding year.

4.3.1 Stand scale

At stand scale, the differences in model prediction of species basal area and tree density at 1988, 1995 and 2008 were small. The minor difference between MAE% and RMSE% indicated there were no extreme prediction errors at 1988, 1995 and 2008. ME was close to 1, revealing a reasonable level of predicted accuracy. Specifically, there was smaller bias and better accuracy at stands on the northeast landtype than stands on the southwest landtype, as well as smaller bias and better accuracy of predicted species tree density than species basal area. The comparison of bias and accuracy of model predictions at 1988, 1995, and 2008 showed that there was bigger bias and less accuracy at 1995 than at that at 1988 and 2008 (Figure4).

We randomly selected 300 predicted stands (from 1978 to 2128) to graph on Gingrich stocking charts and Reineke density diagrams to verify the stand development process. Those stands were classified into three typical groups representing stand development governed by available growing space: group I, group II, group III in Figure 5 and Figure 6. Specifically, group I represented stands beginning with the stand initiation stage typically characterized by fewer trees, lower basal area and lower stocking, although the mean diameter was higher. As the simulated succession proceeded, more seedlings become established in the available growing space resulting in an increase of trees per acre, a decrease of the mean diameter and a slight increase in basal area. Once stands reached the stem exclusion stage, self-thinning resulted in a rapid decrease of trees per acre. The remaining live trees increased in diameter, so basal area continued to increase while the number of trees remained relatively constant.

Group II stands started at the stem exclusion stage characterized by a higher number of trees and higher basal area than group I. Almost immediately density dependent mortality began as shown by the decreasing number of trees while the basal area showed the only slight increase. Continued tree growth resulted in a rapid increase in mean diameter and basal area.

Group III referred to stands starting with late stand initiation stage with high stocking but with the smallest mean diameter. Since the stands started above the maximum stocking line on Gingrich stocking charts and Reineke density diagrams, there were higher mortality rates arising from intense self-thinning associated with competition for growing space. Once growing space was released, the subsequent tree growth contributed to the rapid increase of basal area and mean diameter.

4.3.2 Landtype scale

At landtype scale, there was small difference in prediction within 10% of ¯%, and accuracy within a range from 10% to 20% of MAE% and RMSE%. The small difference between MAE% and RMSE% indicated an absence of extreme prediction outliers. Values for ME were close to 1. Specifically, the predicted accuracy on the northeast landtype was higher than on the southwest landtype. The prediction accuracy of tree density was higher than for basal area. In addition, the prediction accuracy at 1988 and 1995 was higher than at 1995 (Figure 7).

4.3.3 *Landscape scale*

The differences between model predictions at the landscape scale compared to the FIA data were also small (¯% <5%, MAE%, RMSE% <10%). The value of ME approximated 1 with small difference between MAE% and RMSE %. The predicted accuracy of tree density was slightly higher than basal area. Likewise, the model predictions at 1988 and 2008 were slightly better than those at 1995 (Figure 8).

Species-level validation at the landscape scale showed reasonable prediction of tree density for all species groups, and basal area for white oak group, red oak group, black oak and hickory were within 10% of the FIA data (Table 1). The discrepancies between predicted tree density and basal area of maple and pine were somewhat higher but within 15% of the FIA data.

Simulated species basal area, tree density and species abundance (percentage of landscape coverage for each dominant species) indicated that without disturbances white oak group would continually dominate landscape from 1978 to 2128. The red oak group and especially black oak declined in basal area after 2080 as many trees established in the early to mid1900's were predicted to reach their longevity and die. Because no fire was simulated, maple was predicted to gradually increase from 1978 to 2128. Likewise, pine declined slightly in trees per acre because pine is a fire-dependent species. However, shortleaf pine has a relatively long longevity (200 years). Consequently, most pine survived for the 150- year duration of the simulation, and both basal area and percentage cover remained stable (Figure 9).

These predicted successional trajectories were consistence with previous studies in oak-dominated forest and empirical knowledge. In absence of disturbance, these oak-dominated forest typically transition to a greater proportion of longer-lived white oak species, and shade-tolerant species such as maple increase in abundance (Johnson et al. 2009).

Overall, model validation showed a reasonable level of predicted accuracy at stand-, landtype- and landscape-scale. Specifically, the best predicted accuracy was at the landscape scale, followed by landtype- and stand-scale. There were more predicted discrepancies in species basal area than tree density, and better accuracy for dominant species including white oak, red oak and black oak compared to maple and pine. The predicted accuracy at 1988 and 2008 were better than those at 1995.

5. Discussion

This study makes a first attempt to rigorously validate the simulation results of a FLM. The framework incorporated DA techniques that constrain model parameters and the initial state to advance model prediction by combining increasingly available forest inventory data and forest landscape model. The initialized landscape was verified against FIA data to constrain the initial forest landscape. The verification results suggested that the landscape initialization realistically represents the historical forest landscape. A well-calibrated model was achieved by iteratively adjusting the model input parameters so predictions closely matched observed changes for the 25-year period from 1978 to 2003. We have shown that the predictions by the calibrated forest landscape were well consistent with observed changes in the FIA data for the same period. Then, the well-verified and calibrated model was applied to predict the future state of forest for 150 years. This spanned two additional FIA inventories in 1988 and 1995 within the range of the calibration data, an additional FIA inventory outside the range of the calibration data in 2008, and long–term predictions of forest change in the absence of exogenous disturbances.   The predicted results were rigorously validated against the FIA data to quantify models' predictive performance, which has not been previously attempted at this level of detail in forest landscape modeling.

The proposed framework for validating FLMs contains multiple scales because FLMs incorporate multi-scale processes from site (stand) to landscape. In this study, LANDIS PRO was validated at stand-, landtype- and landscape-scales. Collectively, that approach encompass a variety of processes that influence forest succession and dynamics. The model predicted results were rigorously validated by employing four measures (¯%, MAE%, RMSE% and ME) to quantify the bias and accuracy of model prediction. The validation results indicated that LANDIS PRO predictions were unbiased with high predicted accuracy among stand-, landtype- and landscape scales. However, the model performance varied by scales. Overall, the predicted accuracy was best at landscape scale, followed by landtype- and stand-scale, which was consistent with our expectations because the variance in model prediction decreased as observations were aggregated into to lager spatial units (Guisan et al. 2007). We also found that the predicted accuracy is greater for northeast landtypes than southwest landtypes. This may be because there is more variation in the observed FIA data for the lower quality the southwest landtypes than for the higher high quality northeast landtypes (Gordon et al. 2005). Furthermore, our results showed that LANDIS PRO predicted reasonable patterns of long-term natural species successional in the absence of exogenous disturbance. As generally observed in oak-dominated in Central Hardwood ecosystems, in absence of disturbance, oak-dominated forests are successionally replaced by mesic, shade-tolerant species (e.g. maple) (Johnson et al. 2009).

Our results also showed that the predicted accuracy was higher at 1988 (10^{th} year) than at 1995 (15^{th} year). This is because the predicted error caused by uncertainties (e.g. parameter uncertainty, algorithm stochsticity) were accumulated through time (Xu et al. 2004, 2009.), leading to larger error at 1995 than at 1988. However, the predicted accuracy at 2008 was not higher than that at 1995. This is because the model was calibrated at 2003. This calibration processes constrained the model parameters and decreased the parameter uncertainties (Shifley et al.2009). Therefore, benefiting from the increasingly available inventory data, model calibration and short-term predicted validation were recommended for future prediction.

Our results showed that the predicted accuracy of tree density was better than species basal area. This is because the prediction of tree density was largely determined by a single parameter estimating the number of seeds per species per year in the model. Modeled estimates of basal area over time are additionally affected by species growth rates and age-size relationships (Loewenstein et al. 2000) that introduce additional uncertainty into species basal area estimates.

The prediction accuracy varies among species with better accuracy for dominant and common species (e.g. white oak, red oak) than for less common species (e.g. hickory), understory species (e.g. maple) and site-specific species (e.g. pine). This result was consistent with other studies where species intrinsic ecological characteristics such as commonness, range size, niche width, and niche position influence model performance, (Guisan et al. 2007, Kadmon et al. 2003). Their influence on model performance is achieved through affecting sample size and sampling prevalence (Mcpherson et al. 2004). For instance, with the same total sample size and prevalence, we can achieve a better sample of dominant species and common species (e.g. white oak) characteristics than locally distributed species and sparsely distributed species. Consequently, the sample estimates are typically more precise for dominant species than intermediate species and understory species. This poses challenges to any statistical analyses and results in decreased predictive accuracies for species with relatively few observations (Hernandez et al. 2006). Such better species samples can generate much reliable and acceptable initialized landscape and model parameters, thus, leading to less uncertainty and better predictive accuracy (Clark 2003, Xu et al. 2011).

Stocking charts and stand density diagrams are practical tools commonly used by forest managers and planners to quantify forest condition (Gingrich 1967, Reineke 1933, Ernst and Knapp 1985, Jack and Long 1996, Long 1985, Vacchiano et al. 2008, Larsen et al. 2010). Our study is unique in using the Gingrich stocking chart and Reneike stand density diagram to verify the long-term trajectories of stand-level development simulated by a FLM. Our results showed that the predicted stand-level development conformed well, but not perfectly, when compared to theories and empirical knowledge of long-term stand dynamics measured jointly by changes in tree density and basal area (Oliver and Larson 1996, Johnson et al. 2009). This provided valuable information about our design and our modeled implementation of stand-scale processes in LANDIS PRO, which incorporates resource availability quantified by available growing space. Results show that stand- and site-scale dynamics within the landscape can produce realistic results that conform to established knowledge about forest stand dynamics. This represents a significant advance in forest landscape modeling.

We have used the difference between model predictions and observed FIA forest inventory to quantify the expected prediction accuracy for this study area from the stand to the landscape scale and from minor to dominant species groups. Quantification of such differences is essential to an understanding of the utility of the model for scenario analyses. The impracticality of conducting landscape-scale forest ecosystem experiments in the forest has resulted in increasing use of scenario modeling to analyze the effects of different management actions on focal forests (Mladenoff and Baker 1999). Model scenarios are generally created by altering input parameters to reflect changes in climate, disturbance, and/or management while the other calibrated model relationships remain unchanged (He 2008, Coreau et al. 2009, Schmolke et al. 2010). Thus, quantifying the agreement between model output and the real world data through validation is the basis to separate whether a response is due to the different simulated scenarios or inherent uncertainty in the model. Only if we quantify and understand the uncertainties in the initial conditions, model internal algorithms, and stochastic modeling components can we legitimately analyze the effects of different model scenarios.

In this study we conduct model validation only on forest succession in the absence of major disturbances. Because FLMs simulate succession, disturbance, and their interactions, the modeling results should also be evaluated on disturbance effects on stand development (e.g., fire-induced mortality, post-fire regeneration), and spatial and temporal heterogeneity of disturbance patterns and interactions among disturbance agents (He 2008). However, few studies have actually measured disturbance effects on succession at landscape scales. Most FLMs employ a distribution based approach to simulate disturbance and disturbances are simulated stochastically, which makes validation of disturbance even more difficult. New approaches are yet to be developed in this front.

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Tables

Table 1. The predicted error by species for species-level model validation at the landscape scale

	Basal area (ft^2/acre)					Density (trees/acre)				
	1978	1988	1995	2003	2008	1978	1988	1995	2003	2008
White oak	3.55	7.41	10.00	4.33	7.48	2.10	5.14	6.49	3.59	5.81
Red oak	3.38	8.68	9.94	4.77	8.24	2.95	4.37	7.84	3.77	6.37
Black oak	2.38	6.65	8.81	3.16	7.03	2.80	4.98	7.58	4.81	6.76
Hickory	5.03	8.58	10.53	5.78	9.63	2.72	5.71	7.59	3.15	7.51
Maple	7.74	10.43	15.97	7.90	12.19	3.20	8.88	12.98	5.03	9.13
Pine	6.28	9.55	12.62	6.22	10.87	3.77	6.30	9.72	4.78	8.62

Figures

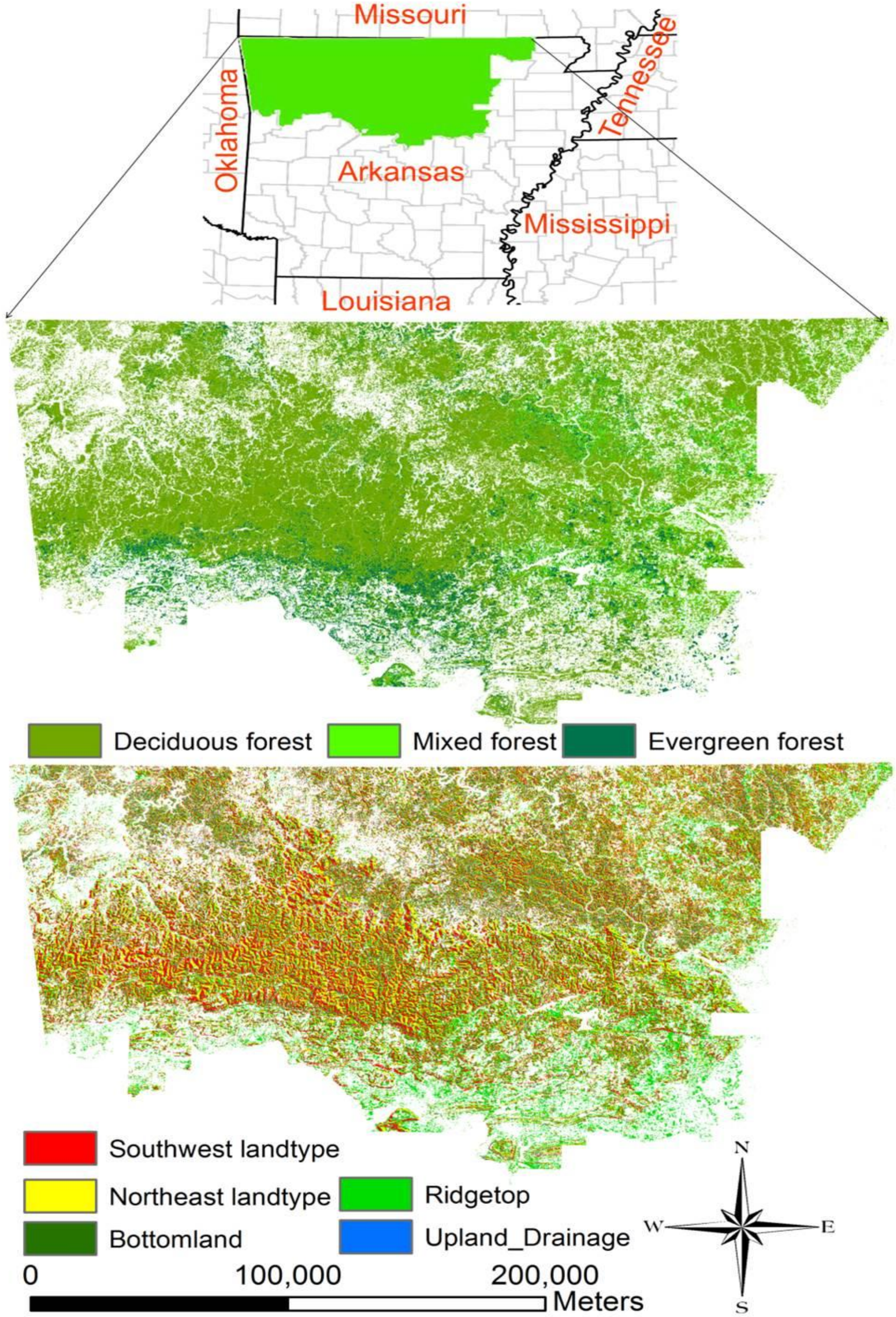

Figure 1. The 10^7 ha study area is located in Northern Arkansas within FIA survey unit 5 as indicated by the green area on the top panel. The study area is dominated by oak forest, with a variety of landtypes

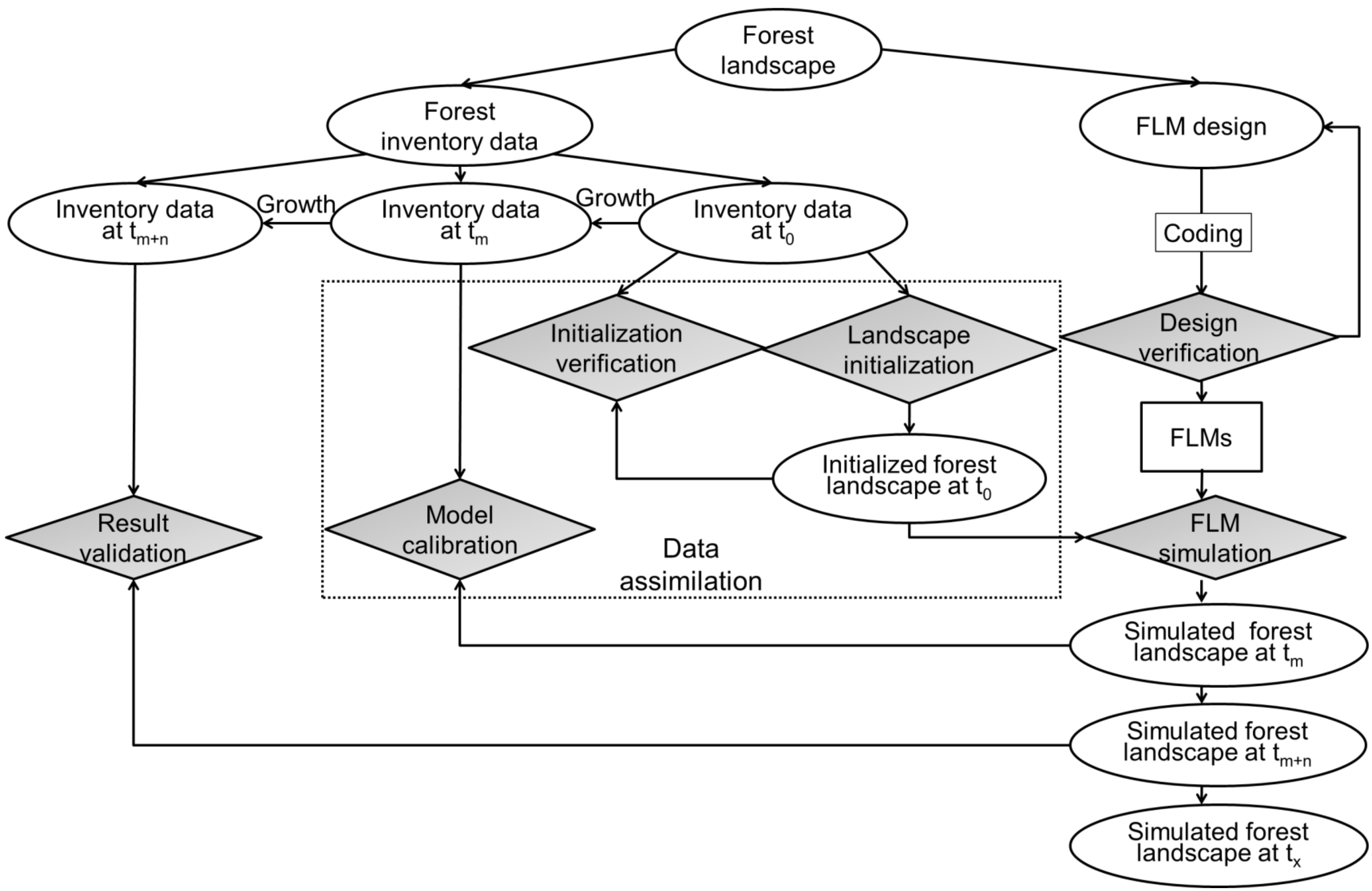

Figure 2. The proposed framework for validation of forest landscape models (FLMs)

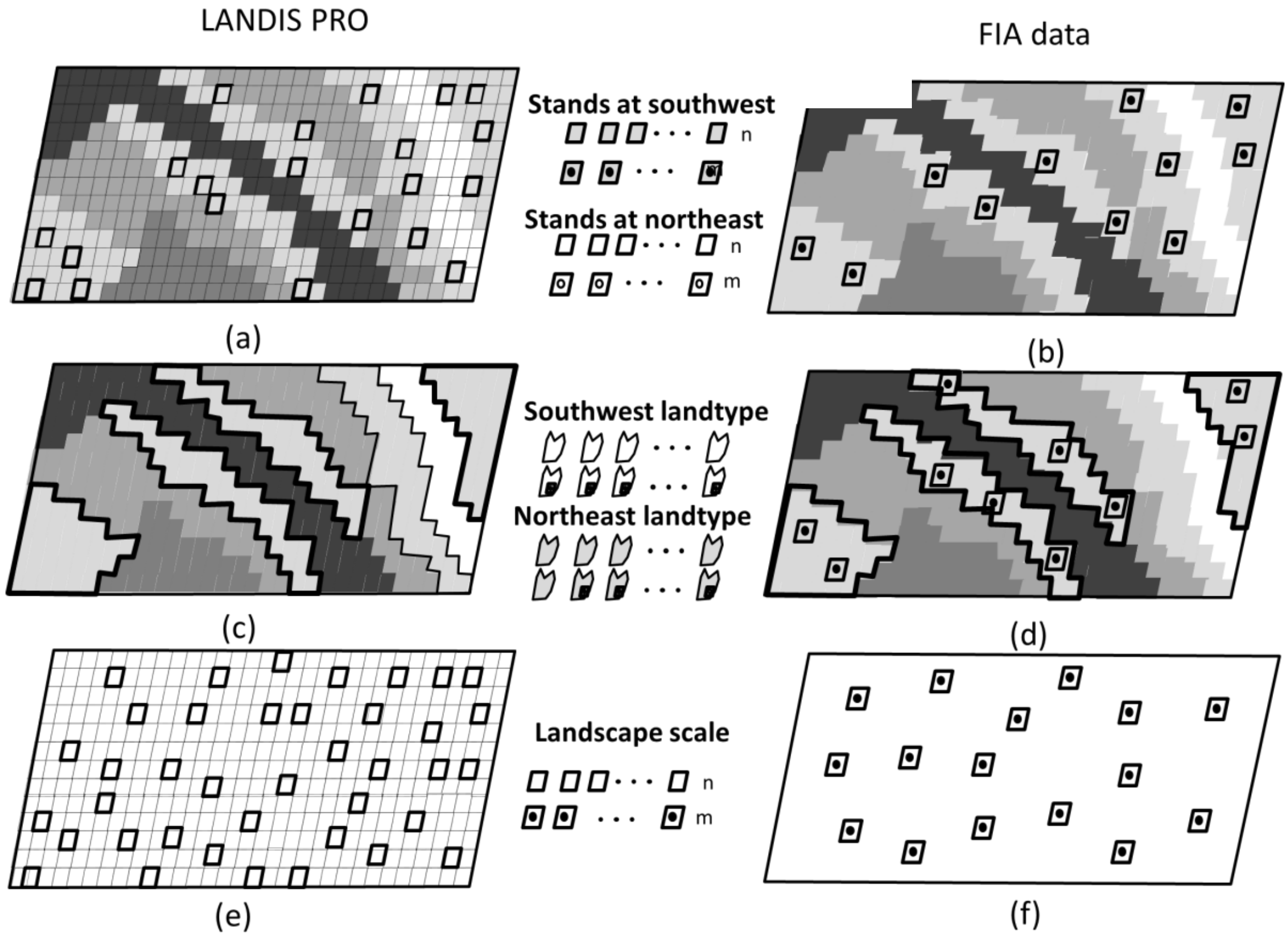

Figure 13. The sampling design for validation of LANDIS PRO model prediction against FIA data at stand scale ((a) randomly selected cells grouped landtype at the simulated landscape, (b) randomly selected plots grouped landtype from FIA database), landtype scale ((c) randomly selected landtype polygons at the simulated landscape, (d) randomly selected landtype polygons from FIA database), and landscape scale ((e) randomly selected cells at the simulated landscape, (d) randomly selected plots from FIA database).

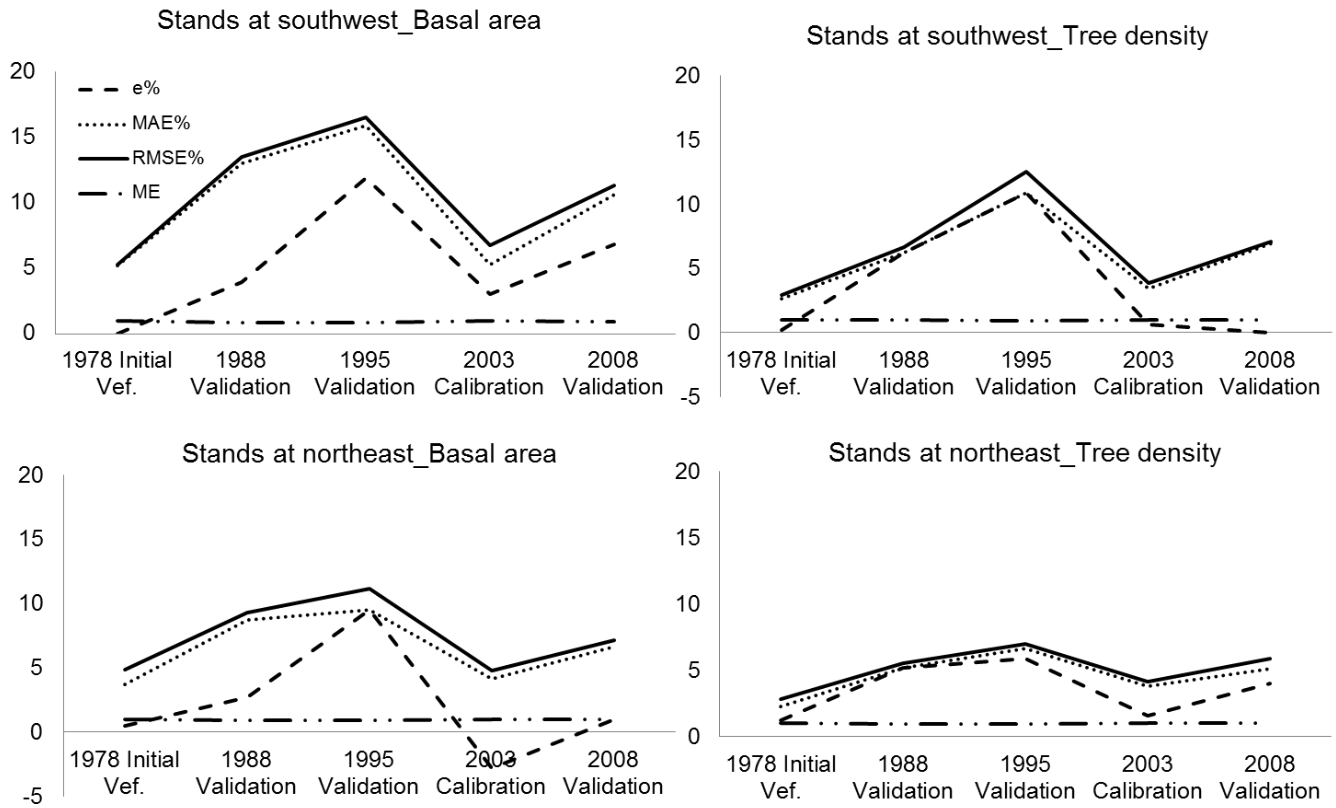

Figure 4. Results of comparison between FIA data and LANDIS PRO model predictions at the stand scale with different support: 1978 for initialization verification; 2003 for model calibration; and 1988, 1995 and 2008 for results validation.

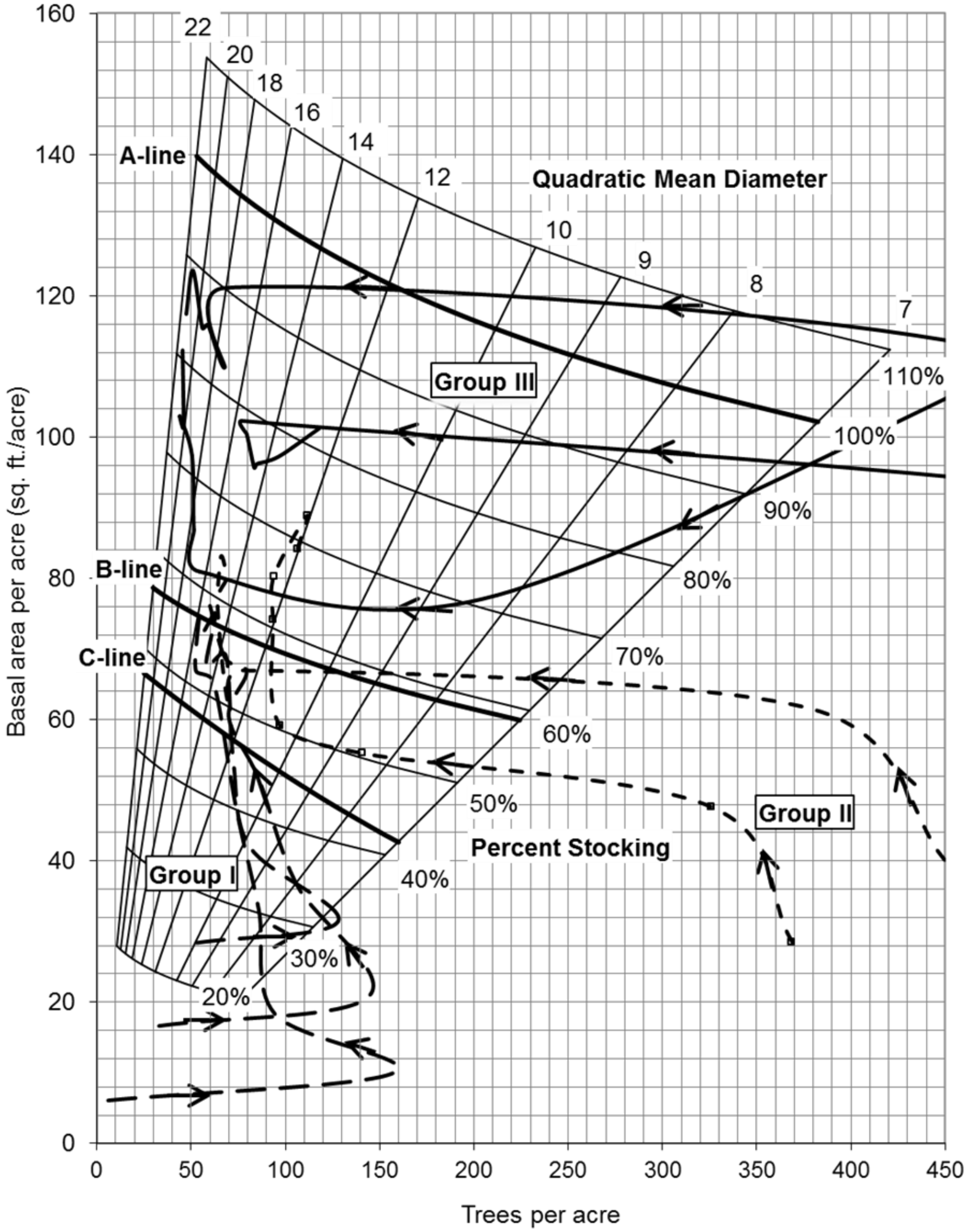

Figure 5. The Gingrich stocking chart showing modeled trajectories from 1978 to 2128 for 300 randomly selected stands

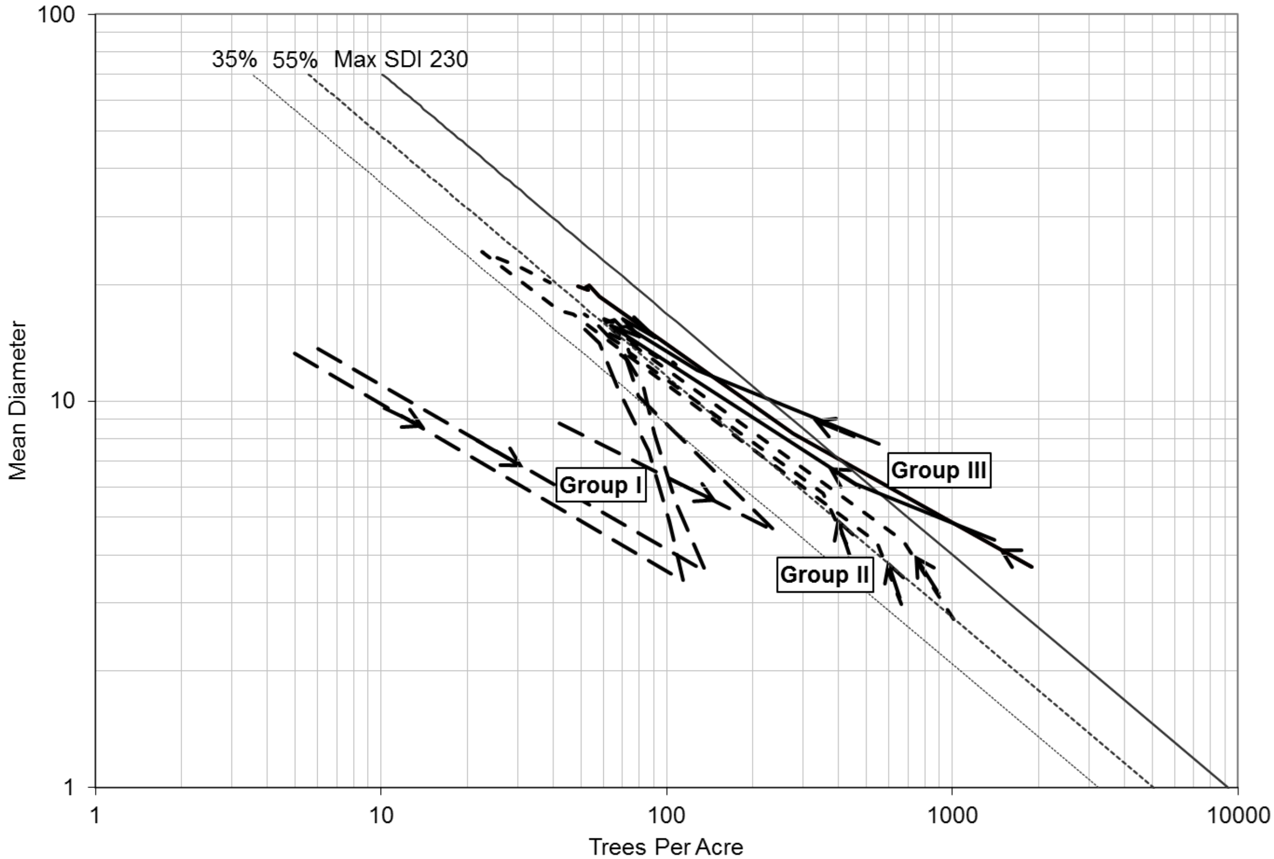

Figure 6. Reineke density diagrams showing modeled trajectories from 1978 to 2128 for 300 randomly selected stands

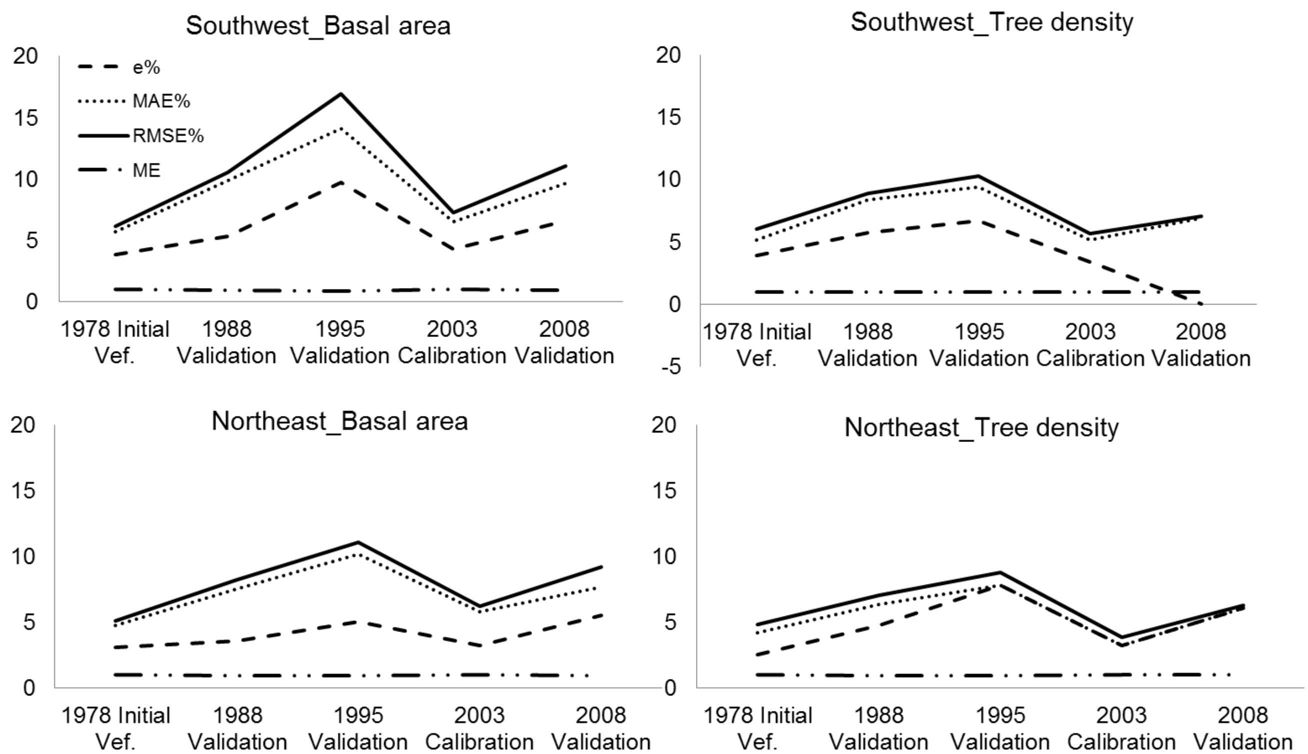

Figure 7. Results of comparison between FIA data and LANDIS PRO model prediction at the landtype scale with different support: 1978 for initialization verification; 2003 for model calibration; and 1988, 1995 and 2008 for results validation.

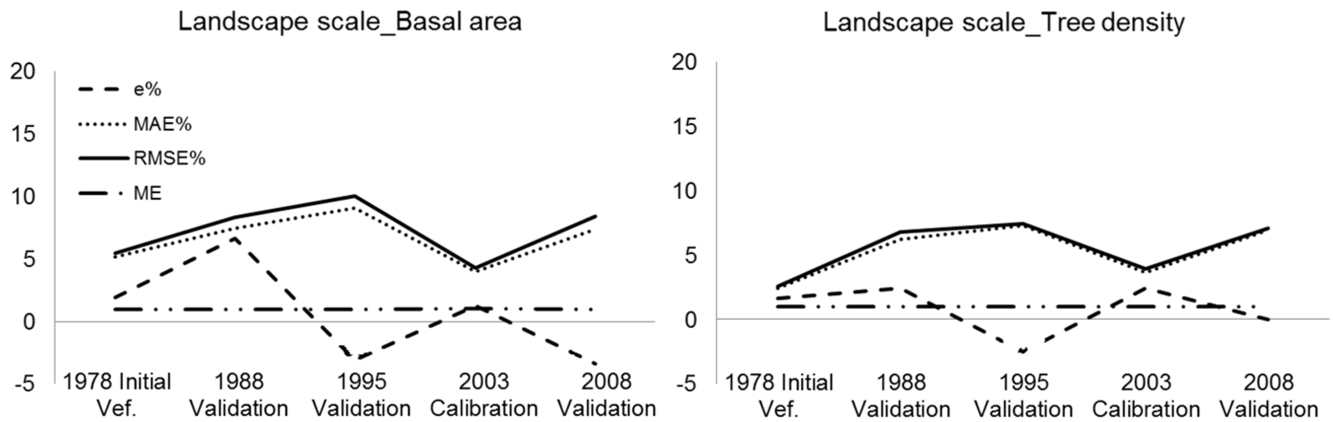

Figure 8. Results of comparison between FIA data and LANDIS PRO model prediction at the landscape scale with different support: 1978 for initialization verification; 2003 for model calibration; and 1988, 1995 and 2008 for results validation.

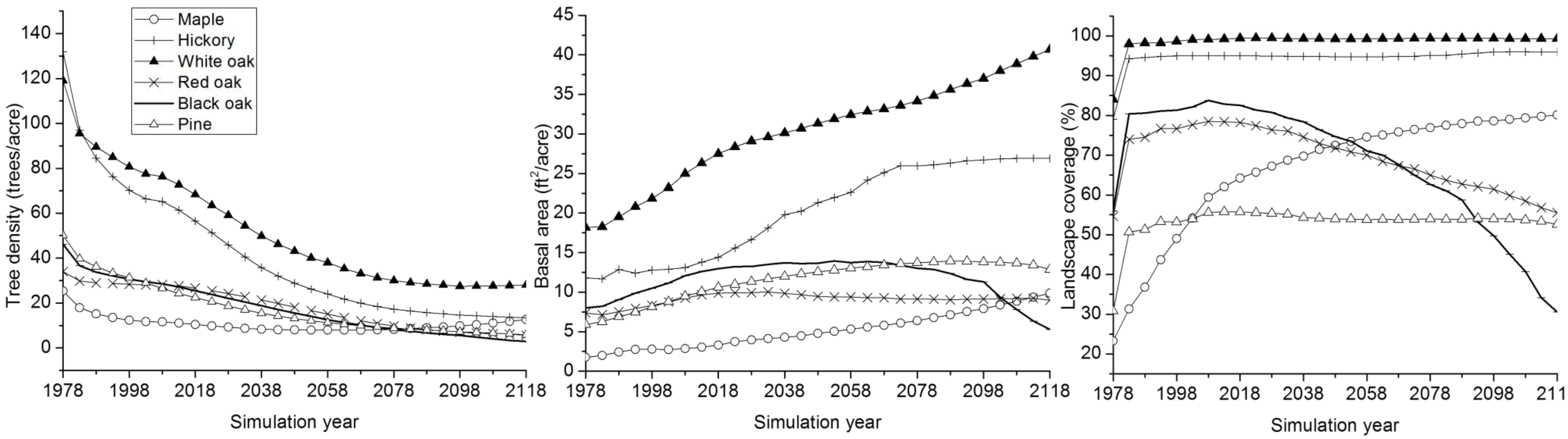

Figure 9. The simulated basal area (ft^2/acre), tree density (trees/acre) and abundance (percentage of landscape coverage) by species group over 150 years at landscape scale

Chapter IV. Evaluating the effects of forest harvesting on mitigating oak decline on a Central Hardwood Forest landscape

Abstract

Oak decline is a landscape process induced by the complex interactions of predisposing factors, inciting factors and contributing factors operating at tree, stand, and landscape scales. It has dramatically altered species composition and stand structure in affected area. Thinning, clearcutting and group selection have been widely adopted as harvest methods for reducing vulnerability of forests to oak decline. However, the long-term, landscape-scale effects of these methods are not well studied due to the limited availability of experimental data. In this study, we used LANDIS PRO, a forest landscape model that includes stand-scale species density and basal area to evaluate the potential landscape-scale effects of alternative harvest methods on oak decline mitigation. Since inciting factors such as drought or frost cannot be controlled, in this study, the rating system for oak decline risk was based on published literature associated with predisposing factors including three categories based on species composition, stand density, and site quality.

Projections indicated that forest harvesting can be effective in mitigating oak decline. The effectiveness of forest harvesting varied among the three harvest methods that were analyzed. Group selection and clearcutting were the most effective methods in the management of oak decline in the short-term (20 years) and mid-term (50 years),

respectively. However, in the long-run (100 years), there was no significant difference predicted among the three methods. As expected, forest harvesting reduced basal area and biomass. More basal area and biomass were harvested under the alternative with clearcutting, followed by group selection and thinning. The Thinning alternative accumulated the most standing biomass over time, followed by group selection and clearcutting.

Studying of the effects of harvest methods on the mitigation of oak decline has important implications for forest management. Considering the effects of harvest methods on mitigation of oak decline and accumulation of biomass, combined with the highly scattered distribution of high risk sites for oak decline, we found that the group selection harvest method may be the most feasible option to manage oak decline on highly vulnerable low quality sites. However, managers will need to also assess the economic and logistical constraints associated with the harvesting alternatives. Insights gained in this study will assist forest managers in developing effective and informed harvesting plans in the management of areas impacted by oak decline.

Keywords: Oak decline, LANDIS PRO, Forest landscape model, Oak forest, Forest harvesting, Central Hardwood Forest region

1. Introduction

Oak decline in the Eastern U.S is caused by the complex interactions of predisposing factors, inciting factors and contributing factors (Manion 1991, Heitzman et al. 2004, Poole et al. 2006, Starkey et al. 2004, 2006, Kabrick et al. 2004, Oak et al. 2004, Crook et al. 2004). Stands are predisposed to oak decline by factors, such as high stem density, species composition, advanced tree age, and shallow and rocky soils (Heitzman et al. 2003). Inciting factors including severe drought or insect defoliation can push stressed oak trees into a declining state. Contributing factors, such as secondary insects and pathogens, further stress trees and thereby can increase the rate of mortality (Starkey et al. 2004).

Red oak group species such as black oak (*Quercus velutina* Lam.), northern red oak (*Q. rubra* L.), and scarlet oak (*Q. coccinea* Muenchh.) have been much more susceptible to oak decline than the white oak group (Heitzman 2003, Kabrick et al. 2007, Voelkera and Muzika 2004, Shifley et al. 2006, Heitman et al. 2004). This is particularly true for trees of the red oak group that are physiologically mature and distributed on shallow, rocky soil ridges or south and west-facing slopes (Kabrick et al. 2004, 2007). During the early 1900s these low quality sites often favored the establishment of red oak group species following extensive forest harvesting and land use management (Kabrick et al. 2007). However, the older red oak trees that are growing on these draughty, low-quality sites become stressed when competing for limited water and nutrients. Trees in older age classes have less capacity to counteract stress and resume growth (Clatterbuck and Kauffman 2005). Consequently, oak decline is more prominent in older red oaks on low quality sites.

Since the late 1990s, the Ozark forests of Missouri, Arkansas and Oklahoma have undergone widespread oak decline which began with foliage wilt and browning followed by progressive branch dieback and mortality (Spetich 2004, Kabrick et al.2007, Heitzman et al. 2004). The most recent widespread oak decline event occurred from 1999 to 2005 and caused extensive mortality up to 12,000 ha of oak forests in Arkansas' Ozark National Forest alone (Starkey et al. 2004).

Oak decline in this area has dramatically altered species composition and stand structure, degraded timber values, reduced wildlife habitat, damaged aesthetics of forests, and increased fuel loads. In one of the most severely impacted forests of northern Arkansas, overstory basal area and density were reduced from 105 to 57ft^2/ac and from 156 to 89 trees/ac, respectively. Basal area and density of overstory red oak group species were reduced from 51 to 11 ft^2/ac, and from 60 to 11 trees/ac, respectively (Heitzman 2003). Heitzman and Muzika (2004) also found that shade tolerant species, such as red maple, blackgum (*Nyssa syvatica* Marsh.), and flowering dogwood (*Cornus florida* L.) increased in dominance on affected plots. Heitzman et al. (2007) further found that oak decline changed red oak stands to more mixed forests characterized by white oak (*Quercus rubra* L.), hickory (*Carya spp*.), red oak, blackgum and red maple. These changes are not desirable for maintaining oak forests. Therefore, because of the considerable economic importance and aesthetics, and wildlife value of oak forests, there is a need to identify active management regimes that reduce the risk and severity of oak decline, improve forest health, and maintain the sustainable oak forests.

Forest harvesting has been widely advocated to manipulate stand structure and species composition through removing susceptible species and declining trees, thereby, reducing stand stocking and tree composition, (Dwyer et al. 2007, Kessler 1992). Prior research has examined the effects of forest harvesting on oak decline at stand scales for relatively short timeframes (e.g. less than 20 years). The widely adopted harvest methods for reducing vulnerability to oak decline include even-aged (e.g. clearcutting) and uneven-aged management including group selection and thinning (Dwyer et al. 2007, Johnson et al. 2009). Burrill et al. (1999) showed that thinning (partial cutting) was useful in preventing future oak decline by increasing stand vigor and controlling species composition. Fan et al. (2008) showed that oak decline was typically found in stands which were at the understory reinitiation stage of stand development. They suggested that marking trees for harvest beginning with merchantable trees with a high probability of mortality should be an option for managing oak decline. Shifley et al. (2006) showed that tree crown class, diameter, and basal area of larger trees of other competitive species explained the most variability of red oak mortality. They recommended that large co-dominant trees in the red oak species group should be prioritized for harvesting if they have economic value, because they are more susceptible to future mortality from oak decline. Clearcutting may be a potential option to manage oak decline in stands that are largely comprised of red oak species. Group selection may also provide options to mitigate oak decline by removing patches of vulnerable trees or scattered declining trees (Johnson et al. 2009, Ward et al. 2005).

These stand level studies provide a scientific basis stand-scale for silvicultural treatments to mitigate oak decline. However, they may not be sufficient for addressing long-term cumulative effects at broad spatial and temporal scales. Oak decline is a spatially contiguous landscape process driven by a variety of processes operating from small site scales to landscape scales (Spetich and He 2008). At stand scale, succession of individual tree species and establishment of new species affect the dynamics of species composition and age structure, thereby, affecting the current and future dynamics of oak decline. At landscape scales, the shifting mosaic of species composition and age cohorts caused by fire, harvest and environmental heterogeneity (e.g. slope, aspect) will also affect the dynamics of oak decline. Spetich and He (2008) argued that the spatiotemporal pattern of oak decline provides the basis for where, when, how often, and what management alternatives should be used. Moreover, oak decline associated with tree age and species composition is spatially dynamic. Thus, the effects of forest management on oak decline should be addressed over the long term (Johnson et al. 2009). Although increasing attention has been paid to maintaining the long-term productivity and health of forest ecosystems at large spatial scales, little has been done to evaluate effectiveness of forest harvesting on mitigating oak decline at landscape scales.

The objectives of this study are to evaluate the long-term, landscape-scale effectiveness of three harvest methods (e.g. clearcutting, thinning, and group selection) on the mitigation of oak decline. The overall hypothesis is that forest management that combines stand scale silvicultural treatments with landscape scale considerations (e.g., site selection and allocation) will be effective in reducing mortality associate with oak decline. Specifically, we hypothesize that when harvest intensity (percent area harvested each year) is fixed because of limited fiscal and human resources, prioritizing high density red oak stands for harvest and harvesting older trees will be effective in mitigating oak decline. We used a spatially explicit forest landscape model, LANDIS PRO, to assess the spatial and temporal pattern of oak decline sites, as well as oak species composition and stand structure. Insights gained in this study can assist forest managers in designing effective harvesting plans for managing oak decline.

2. Methods

2.1 Study area

The study area is located in the Boston Mountains of Arkansas covering 427,660 ha (Figure 1). The Boston Mountains are the highest and southernmost part of Ozark highlands in Central Hardwood Forest region. This mountain area is deeply dissected and rugged, with elevation ranging from 275 m in valley bottoms to 762 m at the highest ridge crests. In this area, the average annual temperature and precipitation range from 14 to 17 ^{0}C, and from 1150 to 1325 mm, respectively, with the majority of rain falling in the spring and fall. The major soil in the region is characterized by Udults. The sharply rugged topography determines the land use of Boston Mountains and most of this area is hardwood forest. The dominant species are oaks including white oak, post oak (*Q. stellata* Wangenh.), chinkapin oak (*Q. muehlenbergii* Engelm.), black oak, northern red oak, blackjack oak (*Q. marilandica* Muenchh.), southern red oak (*Quercus falcate* Michx.) and scarlet oak, and hickory including pignut hickory (*Carya glabra* Sweet.), and black hickory (*C. texana* Buckl.).

In this area, it has been documented that the tree species composition and distribution have been significantly altered since European settlement (Foti 2004, Hulting 2006, Chapman et al. 2006). Red oak group species are more abundant than during the pre-settlement era because they regenerated following extensive timber harvest in the early 1900s. These red oaks are now maturing in stands with ages ranging from 60 to 90 years. Stem densities are relatively high because of decades of effective fire suppression.

The high tree density and maturing trees, in combination with a three-year drought from 1998 to 2000 and repeated insect defoliation, makes Arkansas' upland oak forests especially vulnerable to oak decline (Spetich 2004, Oak et al. 2004). Severe oak decline has dramatically affected the forest landscape. Spetich (2004) stated that during just one year, the basal area of snags increased from 1.8 m^2/ha to 4.4 m^2/ha, and the basal area of living trees decreased by 2.9 m^2/ha from 2000 to 2001. Consequently, management alternatives that can mitigate oak decline and improve forest health are of great importance in this region.

2.2 Forest harvesting alternatives

Key factors determining forest harvesting at the landscape scale include 1) treatment site selection and their spatial allocation, 2) tree species and age cohort selection, 3) harvest method including clearcutting, thinning, and group selection. For treatment site selection, existing studies suggest that management of oak decline should focus on low quality sites such as ridge tops and southwest facing slopes (Kabrick et al. 2007). To reflect the actual forest management, all three harvesting scenarios were applied to low quality sites, but thinning was applied only to high quality sites, where forest density and competition among trees for resource are both typically high (Table 1). High density stands are prioritized for harvesting because of intensive competition for resources. Red oak species and older age cohorts were given the highest priority for harvesting; because trees in red oak group, especially mature trees, are more susceptible to oak decline than other species and younger age groups (Fan et al. 2008).

The forest harvesting parameters including harvesting rotation and residual basal area were derived from the current management plan of Ozark- St .Francis National Forests (Table 2, Table 3, Table 4) (Forest Service Southern Region 2005).

The simulation experiment was designed with a single factor (harvest method) implemented at four treatment levels: (1) clearcutting, (2) group selection, (3) thinning, and (4) no harvesting (succession only). For each harvesting treatment, we simulated 100 years of succession and dynamics on the entire study area using 5 a year time step, and each alternative was replicated and simulated five times.

2.3 LANDIS PRO model

We simulate forest landscape dynamics using the spatially explicit forest succession and disturbance model, LANDIS PRO (Wang et al. 2012 in review). LANDIS PRO is a raster-based forest landscape model (FLM) evolved from over 15 years of development and applications of the LANDIS model (Mladenoff et al. 1996, He and Mladenoff 1999, Mladenoff 2004). It is designed for simulation of forest dynamics under natural (e.g. fire, wind, and disease) and anthropogenic disturbances (e.g. harvest and fuel treatment) over large spatial (~ 10^7 ha) and temporal (~10^3 years) extents with flexible spatial (10-500 m pixel size) and temporal resolutions (1-10 years). Within each raster cell, the species are recorded by number of trees by age cohorts, and tree size (e.g., DBH) for each age cohort is derived from empirical age-DBH relationships (e.g., Lowenstein et al. 2000).

In LANDSIS PRO, forest succession and dynamics are simulated by incorporating species-, stand-, and landscape-scale processes. The simulation of species-scale processes including tree growth, establishment, and mortality is achieved using species vital attributes (Mladenoff and He 1999) and empirical growth equations such as age-DBH relationships.

Stand-scale processes simulate resource competition (e.g. light and nutrients) quantified by the amount of growing space occupied (GSO). Within each cell, GSO is estimated by summing total minimum growing space to support all trees on a given site. The minimum growing space at a given species and size is derived from Reineke stand density index (SDI) and Maximum SDI (Reineke 1933). Competition-caused mortality is simulated using Yoda's self-thinning theory (Yoda et al. 1963). New seedling establishment is determined via algorithms that accounts for available growing space, species shade tolerance, and species-specific establishment probability. Due to the dynamics of establishment and mortality, resource availability varies among different stand development stages. In LANDIS PRO, stand development patterns are regulated by GSO in combination with the well documented stages of stand development (Peet and Christensen 1987, Oliver and Larson 1996) including stand initiation, stem exclusion, understory reinitiation, and old-growth.

The landscape-level processes include management, natural disturbance, and seed dispersal. To account for heterogeneity across the landscape, the study landscape is stratified into relatively homogeneous units called land types reflecting variation in the physical environment caused by factors such as topography, soil type, temperature regime and moisture regime. Within a given land type, similarity in species establishment probabilities (SEP) and resource availability is assumed and modeled using a combination of species establishment probabilities (SEP) and maximum resource availability (Maximum growing space occupied, MGSO) specific to that land type. Since

SEP and MGSO vary spatially and temporally, they are capable of reflecting the landscape heterogeneity in space and time, even within a single land type.

Using the harvest module of LANDIS PRO, the simulation of timber harvest is achieved by using a specific hierarchical management structure (Fraser 2012). First, the whole landscape was divided into broad management areas based on specific management goals. Second, each management area was gridded to stands each identified by a unique stand identification. In each time step, specific stands were prioritized for harvest based on user-specified ranking algorithms a including random function and basal area ranking. Two treatment types are currently available to simulate harvest. The first is a basal area based thinning, which is achieved by applying a user-specified residual basal area target for treated stands. With high residual basal area, this simulates thinning. With residual basal area zero, this simulates clearcutting. The second harvesting treatment is the group selection method which is designed to create canopy openings within a stand based on user-specified mean opening size (Fraser 2012). In both basal area based thinning and group selection, the total treatment area is specified as a percentage of management area.

Because LANDIS PRO includes quantitative stand attributes (density and basal area), it is especially useful in deriving the response variables used to quantify the risk of oak decline of each site. For instance oak decline is characterized based on species composition, stand density and quality sites.

2.4 FIA data for initializing predisposed landscape to oak decline

Eleven species are grouped into 5 functional species groups: white oak (white oak, post oak and chinkapin oak), red oak (northern red oak, southern red oak), black oak (black oak), shortleaf pine (*Pinus echinata* Mill), and maple (red maple and sugar maple (*Acer saccharum* Marsh. The species vital attributes (Table 5), landtype map and species establishment probabilities by landtype were compiled based on existing data sets for the Boston Mountains (Spetich and He 2008) and Silvics of North America (Burns et al. 1990).

The forest composition map including number of trees by age cohort in each cell was directly initialized from U.S. Forest Service Forest Inventory and Analysis data at 2008. This initialization process was conducted using Landscape Builder, software developed specifically for LANDIS PRO (Dijak 2012, *in review*). Specifically, in each FIA plot, tree diameters were converted to tree age cohorts using published age-DBH equations (Loewenstein et al. 2000). Number of trees by species age cohort for each representative FIA plot was computed based on the raster size and the FIA per hectare tree expansion factors (Jenkins et al. 2001). Then, for a given landform, FIA plots were stochastically populate initial conditions for each raster on the landscape map and define the forest species composition and tree size structure of the initial landscape. Species composition and land type maps were rasterized to a 90 m cell size resolution.

Eighteen management areas were parameterized on the modeled landscape based on management goals and site quality. Low quality sites are ridge tops and south-west facing slopes which are more susceptible to oak decline. High quality sites are floodplains and north-east facing slopes. These sites are characterized as less vulnerable to oak decline. All the input maps have been gridded to a 90 m cell size.

2.5 Oak decline risk rating synthesizing stand-scale studies

Since inciting factors such as drought or frost cannot be controlled, management efforts should concentrate on reducing exposure to predisposing factors (Johnson et al. 2009, Fan et al. 2011). Accordingly, predisposing factor should be considered to evaluate forest management plan. In this study, the rating system of oak decline risk was based on published literature associated with predisposing factors. This rating system included three categories based on land type and red oak basal area (Oak et al. 1996, Poole et al. 2006):

(1) High risk: stands on low quality sites including ridgetop, southwest facing slope having >6.9 m^2/ha of red oak species; or high quality sites including floodplain and northeast facing slope having >13.8 m^2/ha of red oak species,

(2) Moderate risk: stands on low quality sites including ridgetop, southwest facing slope having from 2.3 m^2/ha to 6.9 m^2/ha of red oak species; or high quality sites including floodplain and northeast facing slope having from 2.3 m^2/ha to 13.8 m^2/ha of red oak species,

(3) Low risk: stands with less than 2.3 m^2/ha of red oak species.

Oak decline risk sites were summarized as a percentage of the total landscape (number of pixels divided by the total number of pixels). Then, the three response variables quantifying oak decline are: percentage of high risk sites, moderate risk sites, and low risk sites. Because the three response variables varied through a 100 year simulation, we chose simulations years 20, 50 and 100 to represent short-term, mid-term and long-term response.

2.6 Data analysis

The effects of harvesting methods were analyzed using multivariate analysis of variance (MANOVA) technique. The global null hypothesis is that forest harvesting methods did not affect the risk of oak decline in the Boston Mountains, Arkansas. The MANOVA were conducted using PROC GLM in SAS. Pillai's Trace statistic was used due to it being the least sensitive to the heterogeneity of variance assumption. Next, separate individual ANOVA was conducted to analyze each response variable's sensitivity to the forest harvesting methods.

3. Results

3.1 The effects of forest harvesting method on oak decline

High oak decline risk sites dynamics mirror the trend of low risk sites in which high proportion of high risk sites correspond to low proportion of low risk sites, whereas medium risk sites are more variable depending on the tradeoff between low and high risk sites (Figure 2). High risk sites naturally decrease under the no harvesting and harvesting scenarios, particularly in the first 50 years. At simulation year 0 (at 2008), about 25% of initial landscape is quantified as high risk sites. There is an abrupt drop in of high risk sites and the corresponding increase of low risk sites in the first 5 years. This is because initial forests reached stem exclusion stage and LANDIS PRO implemented self-thinning to reduce stand density blow or equal to Yoda's self-thinning line. The rate of self-thinning, one model iteration in this case, implemented in LANDIS PRO may be faster than what would occur in the field. However, the long-term trends are stable indicating that the self-thinning algorithms work properly. In the first 20 years, high risk sites continue to decrease with about 50 percent reduction. Forest harvesting significantly reduced high oak decline risk sites. High risk sites have more variations in the first 50 years simulation than the last 50 years simulation, and more variation for high risk sites over 100 simulation years than in moderate and low risk sites. Overall, the tendencies of time series oak decline risk sites were similar among the three forest harvesting and no harvesting (natural succession) scenario.

The effects of harvesting methods on mitigating oak decline significantly differed at short-, mid-, and long-term (Figure 3, Table 6). Specifically, in short-term, group-selection was the most effective option in mitigating high risk oak decline followed by clear-cut and thinning. During the period of mid-term, high risk sites for oak decline decreased more under clear-cut than under those thinning and groups-selection. During 50-100 simulation years, high risk sites continued to change, although gradually with much smaller variation than that in the first 50 years. In the long-term, there was no striking variance in high risk sites among thinning, clear-cut and group-selection, although they are slightly lower under thinning than that under group-selection scenario and clear-cut scenario. With respect to mitigating moderate risk oak decline, clear-cut was the most effective method in the short-term and mid-term, but with the most effectiveness of thinning in the long-term.

3.2 The spatial distribution of high risk oak decline sites

The potential high risk oak decline sites were spatially delineated throughout the landscape. The simulated potential high risk oak decline maps also clearly demonstrated that the high risk sites significantly decreased throughout the landscape (Figure 4). At landscape scale, the spatial patterns under three forest harvesting methods were similar and scattered distributed across the landscape. These scattered patterns were largely determined by highly dissected topography and the cluttered distribution of red oak species. However, at a finer scale, there were smaller harvesting patches under thinning scenarios.

3.3 The effects of harvest methods on forest composition

In the initial oak-dominated forest, white oak group (white oak and post oak) were the predominant species across the landscape accounting for 30 percent of the total basal area (Figure 5-a1, a2). The red oak (northern red oak, southern red oak) and black oak were co-dominant, together comprising 40 percent of the total basal area. Understory species, hickory and maple were consistently abundant across the landscape, making up 10 percent and 5 percent of the basal area, respectively. Pine, a locally distributed species was comprised of 15 percent of total basal area.

Under the three forest harvesting scenarios and the scenario of no harvesting, there was a gradual increase in the basal area of white oak, pine, hickory and maple (Figure 5- a1, a2). The red oak and black oak continued to dominate with a slight decrease in basal area. The forest harvesting significantly affected forest composition. As expected, forest harvesting resulted in lower species basal area than that under natural succession; except that the basal area of white oak and maple associated with higher shade tolerance were slightly higher under the thinning scenario than that under the no harvesting scenario.

The response of species basal area to the three forest harvesting methods differed by species (Figure 5-a1, a2). As the understory species hickory and maple with the highest harvesting priority, their species basal areas are highest under thinning followed by clear-cut and group-selection. This tendency also existed in the low harvesting priority of dominant species such as white oak. When it comes to the dominant species red oak and black oak also with high harvesting priority, there was more basal area under group-selection followed by clear-cut and thinning. Pine, a low harvesting priority species, had the higher basal area under group-selection compared to that under the thinning and clear-cut scenario. In addition, the effects of forest harvesting on species basal area were markedly greater in the last 50 years than those in the first 50 years.

The species basal area harvested in each time step was specifically tracked. As expected, for all species, more basal area was harvested under clear-cut than those under group-selection and thinning (Fig 5- b1 b2). The trends of species basal area harvested were consistent with the trend of species basal area. Specifically, the basal area harvested decreases when species basal area decreases. Likewise, more basal area was harvested for a species when its basal area was high.

Since the direct positive association between basal area and biomass, thus, more biomass was harvested under clear cut and group selection than that under the thinning scenario (Figure 6). This result was consistent with the simulated total biomass. Apparently, cumulative forest harvesting reduced the biomass on the landscape. Among the three forest harvesting methods, biomass accumulated under thinning most approximates to that under the no harvest scenario.

4. Discussion

Long-term landscape effects of forest management are difficult to predict because of the spatial and temporal interaction among multiple ecological and anthropogenic processes. The large spatial extent and long temporal span make controlled field experiments insurmountable, and logistically impossible to replicate large-scale experiments (Turner et al. 1995, Urban 2000). Forest landscape models (FLMs) have become effective tools to evaluate the large-scale, cumulated effects of forest management and disturbance to aid forest management and decision making (Shifley et al. 2006, He 2008). The recent advances in FLM such as LANDIS PRO, which tracks density and basal area by species age cohort, makes it possible to derive the response variables directly related to oak decline. In this study, in order to evaluate the effects of three common forest harvesting methods on mitigating oak decline, we used LANDIS PRO to simulate the three forest harvesting scenarios (and no harvesting) and forest dynamics. The potential risk sites for oak decline were quantified using simulated results involving the basal area of red oak species and land type. These two factors were associated with predisposing factors attributed to oak decline and the quantification of potential risk sites captured both biotic and abiotic causes (Johnson et al. 2009, Fan et al. 2011).

Results show that forest harvesting is significantly effective in mitigating oak decline especially in the short- and mid-term. The effectiveness of forest harvesting varied among thinning, clear-cut and group-selection. In general, group-selection is the most effective method to manage oak decline in the short-term (20 years) followed by clear-cut and thinning. At mid-term (50 years), clear-cut was the best method in mitigating oak decline. However, in the long-run (100 years), there was no significant difference among the three methods, only with slightly higher in group-selection and thinning than in clear-cut. These results were understandable because harvest intensity of group-selection and clear-cut was more intensive than in thinning. In this situation, the basal area of red oak species can be reduced much more in group-selection and clear-cut. The effectiveness of group-selection could be a result of targeted removal of scattered groups of trees accounting for the highly scattered distribution of high risk for oak decline sites (Spetich and He 2008), which was also an advantage over clear-cut

The variation of number of sites under three risk ratings for oak decline was lower in the last 50 years than the variation in the first 50 years. This may be attributed to stand development including self-thinning. At the beginning of the simulation, oak forests in this study area range from 60 to 90 years of age with extremely high stem density resulting from over a half century of fire suppression (Spetich 2004). Then, in the first 50 years, there was considerable high tree mortality arising from intense self-thinning for growing space. However, self-thinning is a non-linear process (Oliver and Larson 1996), combined with the non-linear forest harvesting, these two processes increased complexity of forest dynamics leading to high variation. In the last 50 years, oak forests were characterized by old-growth forests. In this old-growth oak forest, the tree growth was considerably slow and the intensity of self-thinning was reduced compared with its intensity in the first 50 years. Thus, the variation of oak decline was mainly caused by forest harvesting with self-thinning less of an influence.

Results show that the effects of harvest become less significant in the long-term than those for short- and mid-term. The significant decrease in high risk site for oak decline over time under natural succession with no harvesting was noteworthy. This result revealed that oak decline is a natural process, which has a natural cycle of development for predisposed oak stands (Manion and Lachance 1992, Johnson et al. 2009). This is due to predisposing factors including tree age and species composition which naturally change as a result of tree growth, seedling establishment and mortality caused by self-thinning. This trend may be significant to forest managers and planners when developing silvicultural prescriptions and long-term management plans.

Forest harvesting has a significant impact on species composition. In general, compared with the simulation under natural succession, the species basal area was reduced under forest harvesting scenarios, with the exception that the basal area of white oak and maple was slightly higher under thinning than that under natural succession. This higher basal area of white oak and maple under the thinning scenario is mainly due to their competiveness. Relatively high shade tolerant species such as white oak can establish once the growing space is released by thinning, which at the meantime prevents other relatively shade intolerant species to establish. However, under group-selection and clear-cut, more basal area is removed, which favors the seedling establishment process.

Our study has important implications for forest management. Forest harvesting is an effective management to mitigate oak decline. As expected, forest harvesting mostly affected species basal area harvested. In general, more species basal is removed under clear-cut, followed by group-selection and thinning. Also, the amount of basal area harvested followed a positive association with total basal area. This was because the basal area harvested was determined by the target residual basal area for harvesting and the current basal area on the stands. As expected, forest harvesting tended to reduce biomass. More biomass is removed under clear-cut and group-selection than under thinning. With increasing appreciation for the role of forests in carbon sequestration, effective forest management strongly argues for retaining aboveground forest carbon. Apparently, thinning was the most effective management method with respect to the accumulation of biomass, followed by group-selection and clear-cut. Considering the effects of forest harvesting methods on mitigating oak decline and accumulation of biomass, combined with the highly scatted distribution of high risk sites for oak decline, the group-selection may the feasible option to manage oak decline on low quality sites.

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Tables

Table 1. Forest harvesting scenarios on the low quality sites (applying thinning to high quality sites under three harvesting scenarios)

scenarios	Low quality sites	High quality sites
H0	No harvesting	Thinning
H1	Clearcutting	Thinning
H2	Group selection	Thinning
H3	Thinning	Thinning

Table 2. The thinning parameters

9	#Thinning#
8	#Management Area ID#
6	#Ranking algorithm#
5	#Entry year#
5	#Reentry year#
18.36	#Minimum stand harvest basal area(m^2)#
1	#remove largest tree first#
0.03	#Proportion of management area to harvest#
18.36	#Target stand basal area(m^2)#
#Species priority ranking for harvest#	
6	#Pine#
3	#Black oak#
4	#Red oak#
5	#White oak#
1	#Hickory#
2	#Maple#

Table 3. The clearcutting parameters

9	#Clear-cut#
6	#Management Area ID#
6	#Ranking algorithm#
5	#Entry year#
5	#Reentry year#
16	#Minimum stand harvest basal area(m^2)#
1	#remove largest tree first#
0.05	#Proportion of management area to harvested#
0	#Target stand basal area(m^2)#

Table 4. The group selection parameters

10	#Group-selection#
5	#Management Area ID#
6	#Ranking algorithm#
5	#Entry year#
5	#Reentry year#
5	#Minimum stand harvest basal area(m^2)#
3	#remove largest tree first#
0.15	#Proportion of management area to harvested#
0.2	#proportion of stand to be harvested#
1	#Mean group size#
1	#Standard deviation of group size#

Table 5. Species life history (vital attribute) parameters utilized for application of LANDIS in Boston Mountains, Arkansas

Species group name	Longevity (years)	Mean maturity (years)	Shade tolerance (class)	Fire tolerance (class)	Effective seeding distance(m)	Maximum seeding distance(m)	Vegetative reproduction probability	Minimum sprouting age(years)	Maximum sprouting age (years)	Maximum DBH (cm)	Maximum SDI (trees/ha)	Annual potential germination seeds per parent tree
Pine	200	20	3	4	40	200	0.5	1	47	60	990	50
Black oak	120	20	3	3	60	200	0.4	10	70	60	570	90
Red oak	150	20	3	3	60	200	0.4	10	70	60	570	90
White oak	300	20	4	4	60	200	0.5	10	50	65	570	90
Hickory	250	20	3	3	325	200	0.5	10	70	60	570	30
Maple	200	20	5	1	100	200	0.3	10	70	60	570	90

140

Table 6. MANOVA and individual ANOVA results for the short-, mid-, and long-term effects of harvest methods on oak decline

Harvesting method effects	Pillai's trace/type III SS	d.f.	F	Sig.
Short-term effects				
MANOVA global test of hypotheses				
Harvest Methods	1.99	6	7765.11	< 0.0001
Individual ANOVA l test of hypotheses				
High risk	0.96	2	8338.32	< 0.0001
Moderate risk	5.05	2	14499.80	<0.0001
Low risk	2.14	2	5043.88	< 0.0001
Mid-term effects				
MANOVA global test of hypotheses				
Harvest Methods	1.99	6	2057.73	< 0.0001
Individual ANOVA l test of hypotheses				
High risk	1.83	2	40.37	< 0.0001
Moderate risk	2.33	2	4.65	0.032
Low risk	17.78	2	13.75	0.0008
Long-term effects				
MANOVA global test of hypotheses				
Harvest Methods	1.74	6	24.98	< 0.0001
Individual ANOVA l test of hypotheses				
High risk	0.22	2	0.36	0.7037
Moderate risk	510.52	2	1027.90	<0.0001
Low risk	78.91	2	44.46	< 0.0001

Figures

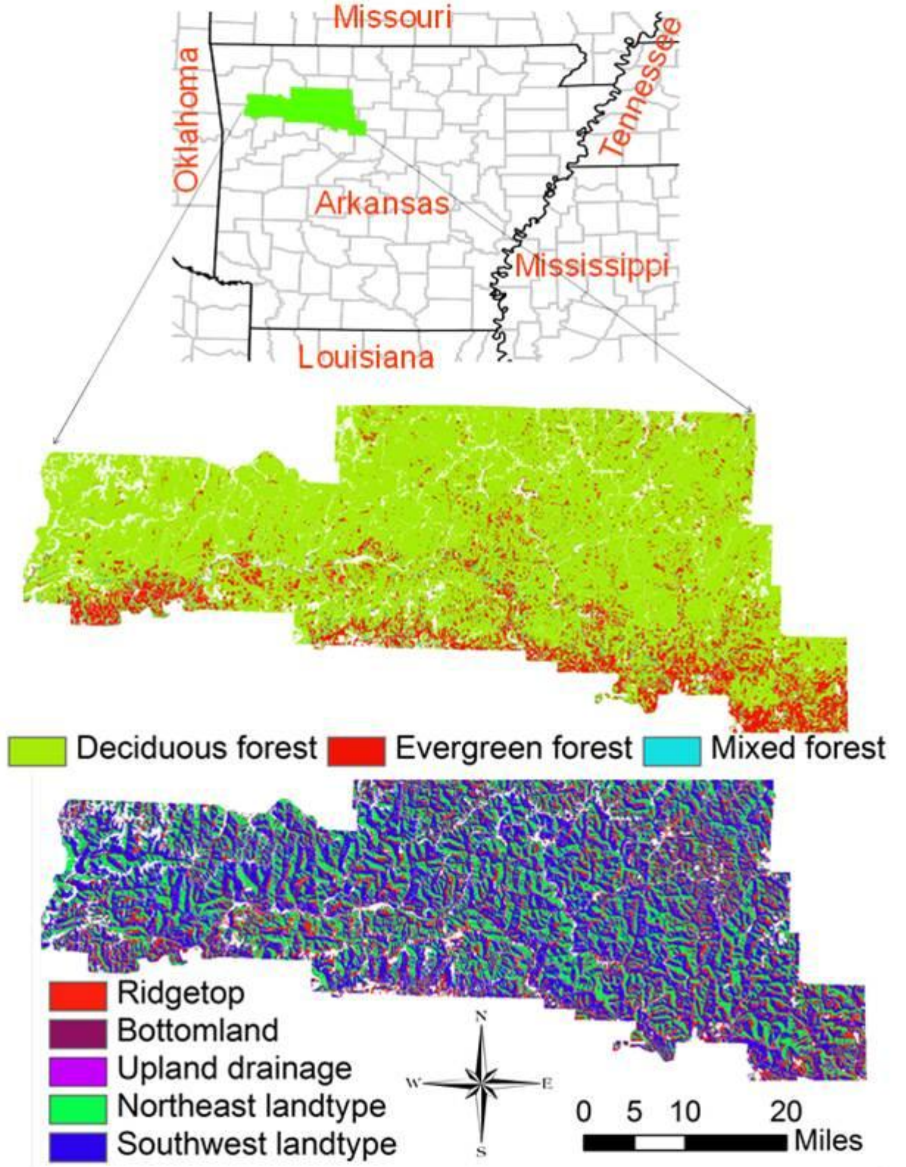

Figure 1. The study area is located in the Boston Mountains dominated by hardwood oak forests, and this area is highly dissected with a variety of landtypes

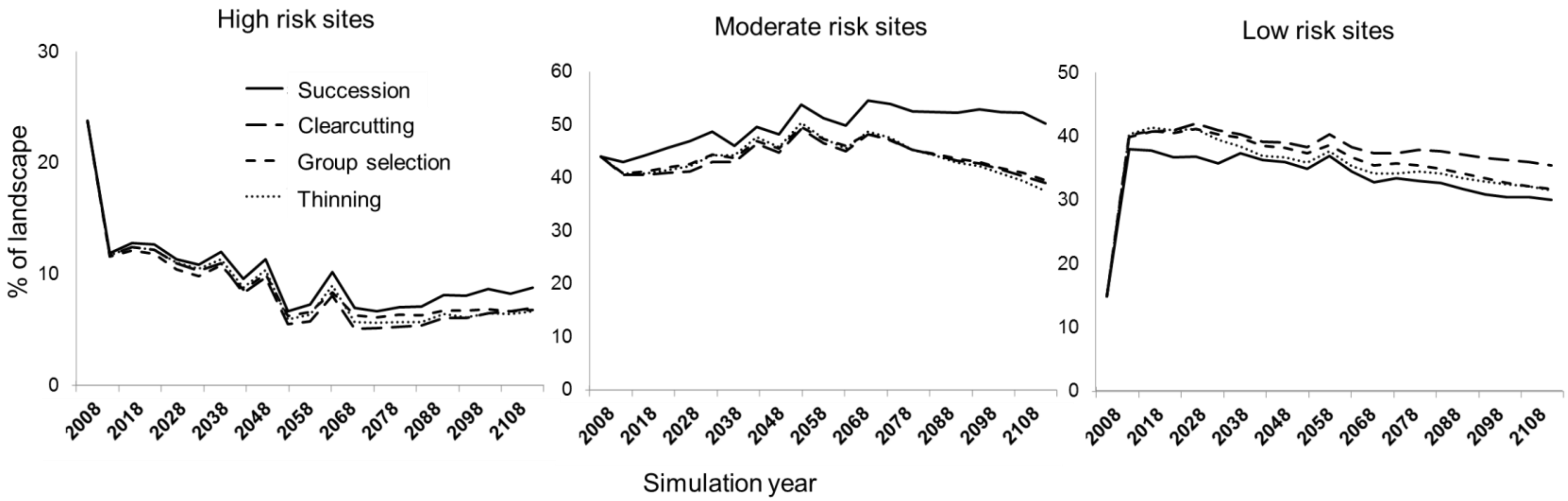

Figure 2. The potential high risk, moderate risk and low risk for oak decline under three forest harvesting scenarios and a no harvesting scenario with only natural succession

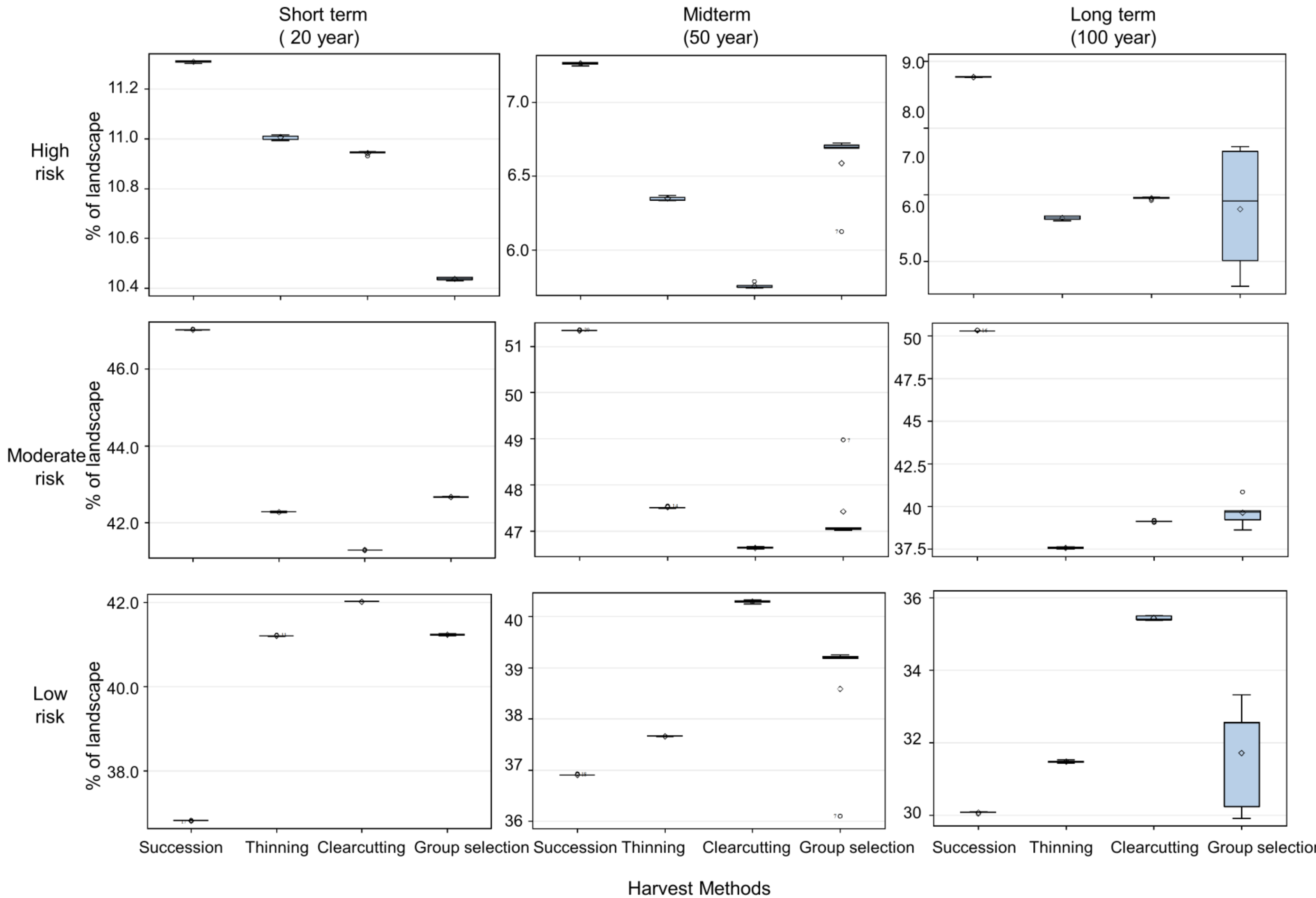

Figure 3. The potential high risk, moderate risk and low risk for oak decline under three forest harvesting scenarios and a no harvesting scenario with only natural succession at short-term, mid-term and long-term

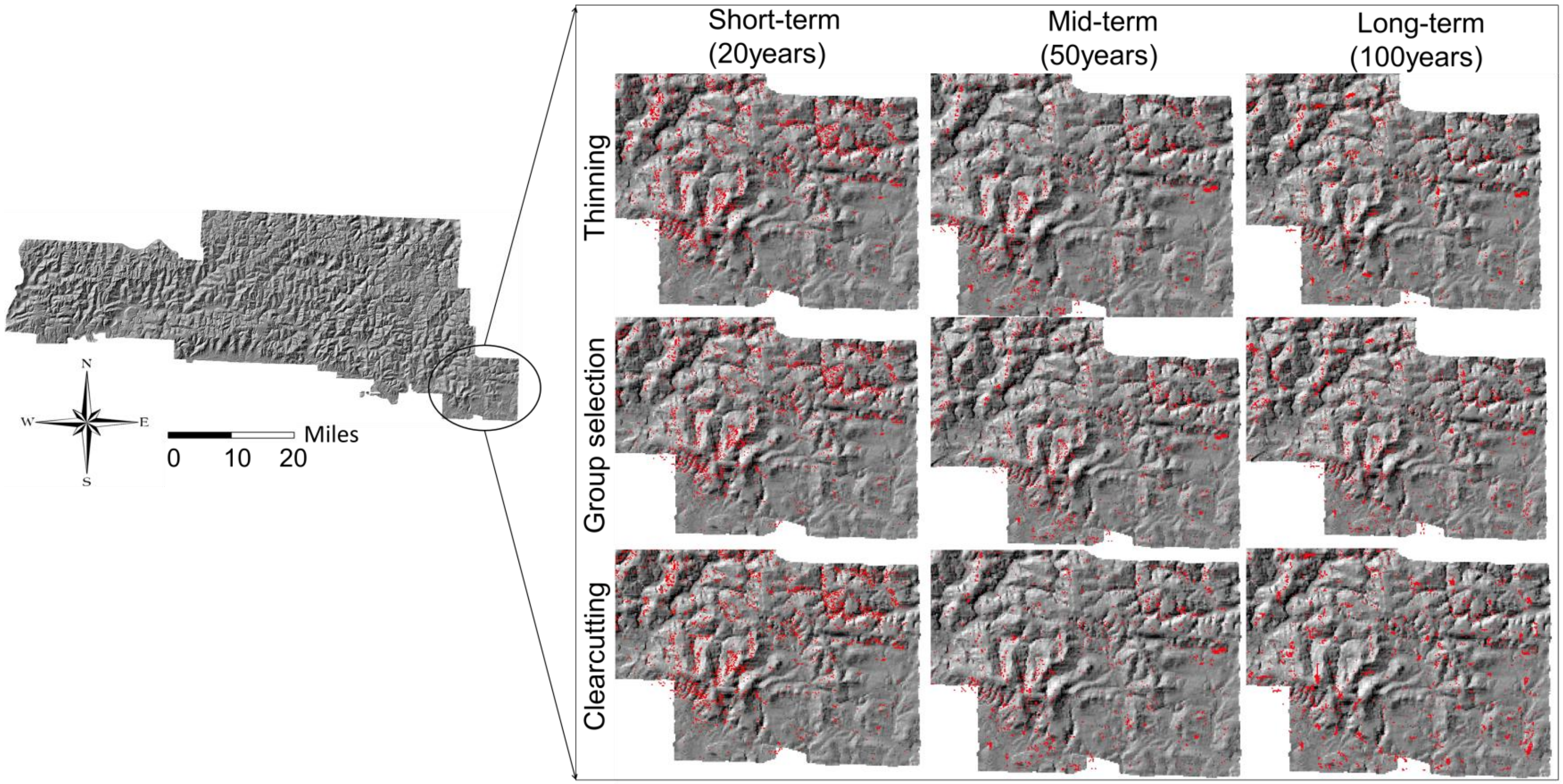

Figure 4. The simulated spatial distribution of potential high risk sites for oak decline under three forest harvesting scenarios

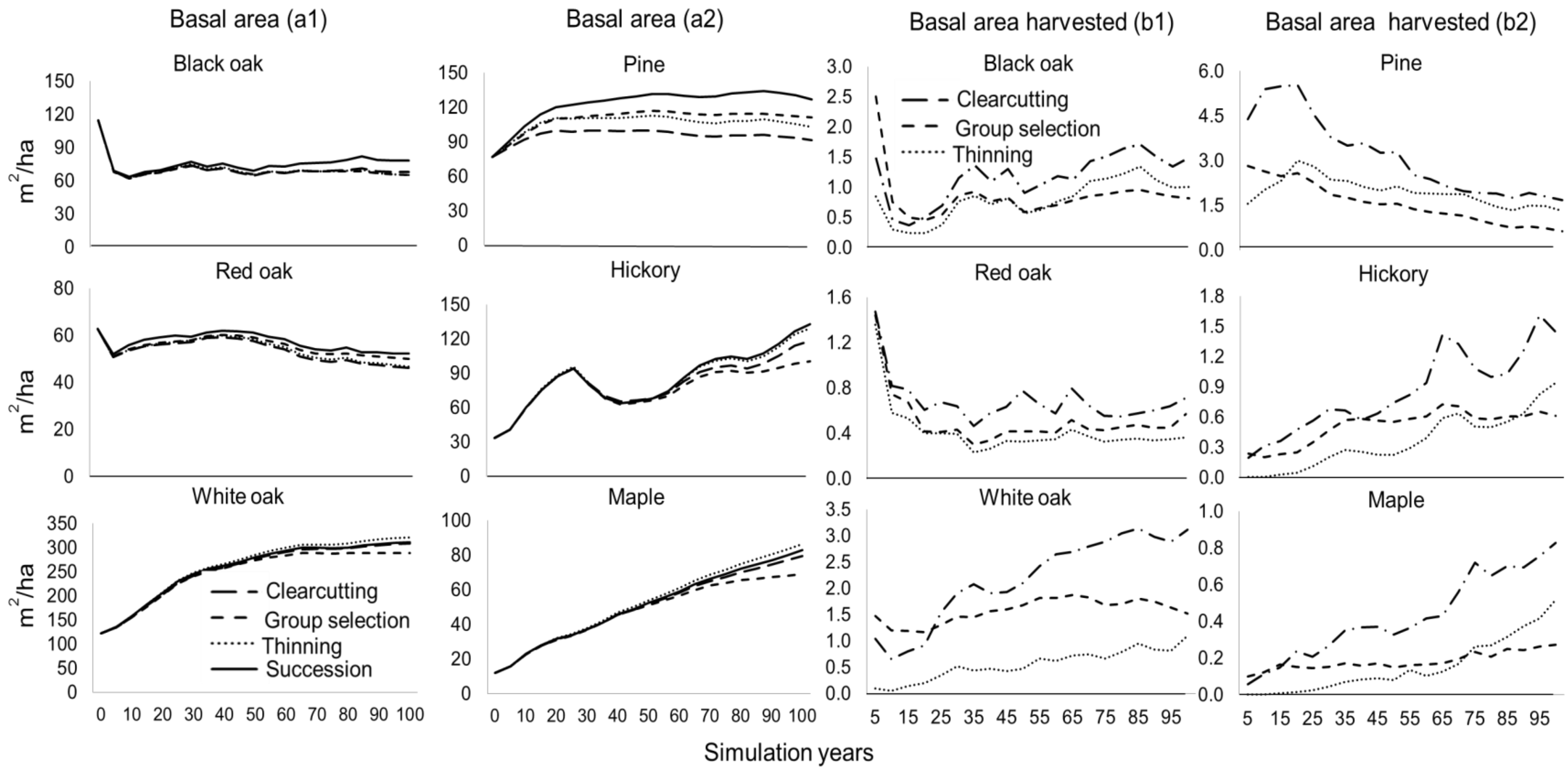

Figure 14. Simulated basal area (a1, a2) and harvested basal area by species (b1, b2) over 100 simulation years under the three forest harvesting scenarios and natural succession

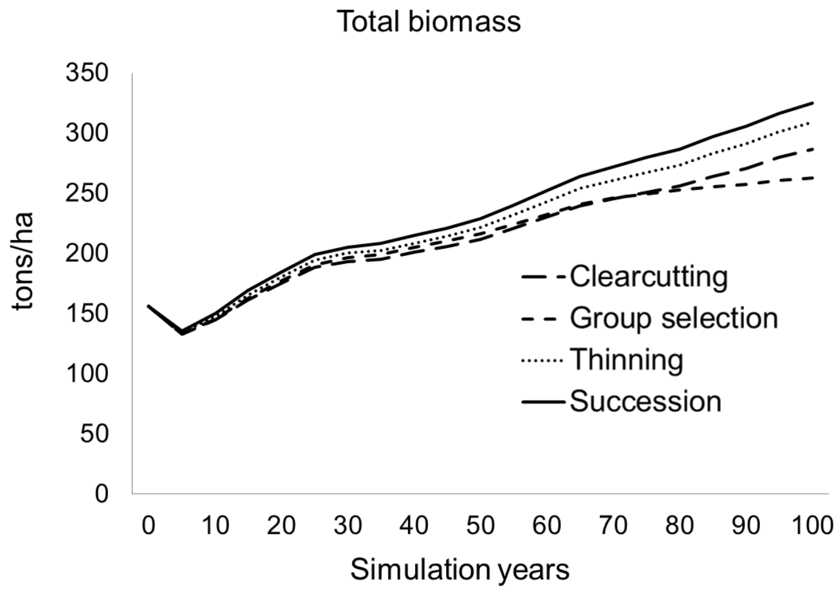

Figure 6. Simulated biomass of all species over 100 simulation years under three forest harvesting scenarios and natural succession

VITA

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