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ECOMOD-6211; No. of Pages 8

ARTICLE IN PRESS

Ecological Modelling xxx (2011) xxx–xxx

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

An innovative computer design for modeling forest landscape change in very large spatial extents with fine resolutions

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ARTICLE INFO

Article history:
Received 26 November 2010
Received in revised form 25 March 2011
Accepted 29 April 2011
Available online xxx

Keywords:
Forest landscape model
Simulation extent
Data structure
Scaling
LANDIS PRO

ABSTRACT

Although forest landscape models (FLMs) have benefited greatly from ongoing advances of computer technology and software engineering, computing capacity remains a bottleneck in the design and development of FLMs. Computer memory overhead and run time efficiency are primary limiting factors when applying forest landscape models to simulate large landscapes with fine spatial resolutions and great vegetation detail. We introduce LANDIS PRO 6.0, a landscape model that simulates forest succession and disturbances on a wide range of spatial and temporal scales. LANDIS PRO 6.0 improves on existing forest landscape models with two new data structures and algorithms (hash table and run-length compression). The innovative computer design enables LANDIS PRO 6.0 to simulate very large (>10^8 ha) landscapes with a 30-m spatial resolution, which to our knowledge no other raster forest landscape models can do. We demonstrate model behavior and performance through application to five nested forest landscapes with varying sizes (from 1 million to 100 million 0.09-ha cells) in the southern Missouri Ozarks. The simulation results showed significant and variable effects of changing spatial extent on simulated forest succession patterns. Results highlighted the utility of a model like LANDIS PRO 6.0 that is capable of efficiently simulating large landscapes and scaling up forest landscape processes to a common regional scale of analysis. The programming methodology presented here may significantly advance the development of next generation of forest landscape models.

1. Introduction

Forest landscape models (FLMs) are broadly defined as computer programs that simulate change on forest landscapes over broad spatio-temporal scales (Mladenoff, 2004). More specifically, a forest landscape model is one that simulates spatio-temporal characteristics of at least one forest landscape processes (e.g., fire, insect outbreak, seed dispersal, forest harvest) in a spatially interactive manner (He, 2008). Because of large spatial (10^2–10^7 ha) and long temporal (10^1–10^3 years) scales involved in forest landscape processes, it is often infeasible to evaluate cumulative effects of these processes through empirical studies or field experiments (Mladenoff, 2004). Thus, FLMs are increasingly used by forest researchers and managers to assess vegetation change in response to natural and anthropogenic disturbances, forest management, and climate change over large areas and long time periods (Perry and Enright, 2006).

Although FLMs have benefited greatly from ongoing technological advances; one fundamental challenge that has persisted since the inception of FLMs is balancing realistic simulation of ecological processes at broad spatial scales with computing capacity (He et al., 2011). Early FLMs developed two decades ago were able to simulate raster grids of 100 cells × 100 cells. Now it is common for FLMs to simulate raster grids as large as 1000 cells × 1000 cells due to the advances in computing capacity. With the spatial resolution usually 30 m (0.09 ha), as is the resolution of widely used Landsat TM imagery, the size of landscapes that can be simulated has increased from 10^3 ha to over 10^5 ha. This increase has greatly helped to expand the scope of applications of FLMs (Table 1). However, when modeling landscapes at the scale of 10^6 ha, contemporary computing capacity soon becomes a bottleneck that forces modeling applications to use a coarser spatial resolution (e.g., 1 ha in Perera et al., 2003; 9 ha in Wimberly, 2002; and 14 ha in Fall et al., 2004). The difference on spatial resolution inevitably affects simulation results because landscape patterns and processes are scale-dependent and their response to changing scale is often nonlinear (Wu et al., 2002). For example, with increasing cell size, rare forest types will be replaced by dominant forest types; and

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doi:10.1016/j.ecolmodel.2011.04.032

Table 1
Selected exemplary application of forest landscape simulation models (FLMs). The table shows that suitable landscape size, spatial resolution, and level of vegetation detail represented in the FLMs vary among these models. It is evident that the large majority of FLMs are raster models.

Model	Exemplary application	Landscape size	Spatial resolution	Level of vegetation detail	Source
BFOLDS	Predicting spatial extent and locations for old-growth forest in response to fire disturbance, Ontario, Canada	1.8×10^6 ha	1 ha	Forest cover type and cover age	Perera et al. (2003)
DISPATCH	Effects of altered fire/harvest regime on the structure of a generalized temperate-zone forested landscape	4.0×10^4 ha	1 ha	Vegetation type	Baker (1995)
EMBYR	Simulating spatial patterns and effects of wildfires through a heterogeneous landscape in Yellowstone National Park, USA	6.3×10^4 ha	0.25 ha	Fuel class	Hargrovea et al. (2000)
FIN-LANDIS	Interactive effects of fire spread, seed dispersal, and forest succession for the Ulvinsalo nature reserve in Finland	2.5×10^3 ha	0.04 ha	Presence/absence of age-cohorts	Pennanen and Kuuluvainen (2002)
FIRE-BGC	Effects of fire on ecosystem characteristics such as NPP, ET, and leaf area index for a landscape in Glacier National Park	5.0×10^4 ha	NR		Keane et al. (1996)
FRESCAPE	Relative importance of fuel mosaics on reducing fire risk in south-west Tasmania, Australia	1.8×10^6 ha	1 ha		King et al. (2008)
LADS	Simulating pre-settlement forested landscape dynamics in the Oregon Coast Range	2.3×10^6 ha	9 ha	Forest structure class	Wimberly (2002)
LANDCLIM	Assessing the relative importance of climate effects, wildfires and management for future forest landscape dynamics in the Swiss Alps	2.4×10^3 ha	0.0625 ha	Biomass of age cohorts	Schumacher and Bugmann (2006)
LANDIS	Examining spatial controls of occurrence and spread of wildfires in the Missouri Ozark Highlands, USA	1.3×10^5 ha	0.09 ha	Presence/absence of age-cohorts	Yang et al. (2008)
LANDIS-II	Simulation of forest change in the New Jersey Pine Barrens under current and pre-colonial fire regimes	6.5×10^5 ha	1 ha	Biomass of age cohorts	Scheller et al. (2008)
LANDSUM	Quantifying the historical range and variability of landscape composition and structure for landscape in Montana, USA	1.0×10^5 ha	0.09 ha	Potential Vegetation types	Keane et al. (2008)
SELES	Evaluating consequences of various ecosystem management strategies and fire cycles on age-class structure and harvest in a boreal forest landscape, Quebec, Canada	3.5×10^6 ha	14 ha	Vegetation type	Fall et al. (2004)
SEM-LAND	Assessing the influence of potential climate change on fire regime and forest landscape dynamics for a lodgepole pine forest in Alberta, Canada	7.0×10^3 ha	1 ha	Vegetation type	Li et al. (2000)
SIMPPLLE[a]	Simulating vegetation change and the interaction between vegetation patterns and disturbance processes for a number of landscapes within Montana and Idaho, USA	1.0×10^4 ha–7.0×10^5 ha	NR	Vegetation type	Chew et al. (2004)
TELSA[a]	Exploratory landscape scenario analyses for generic landscapes	1.0×10^4 ha–2.0×10^5 ha	2 ha	Forest cover type	Kurz et al. (2000)

NR: not reported in the reference paper.
[a] Polygon based models.

some important fine-scale processes such as selective harvesting and windthrow, which could impact wildlife habitat, cannot be explicitly modeled (Shifley et al., 2008).

One solution to simulating very large spatial extents without sacrificing spatial resolutions is to split a large landscape into many smaller tiles, run the simulation for each tile, and mosaic the results from individual tiles to represent the whole landscape. Although this approach does not demand further simulation capacity, it imposes a great burden to the users in post-modeling analysis. In addition, this approach may lead into unrealistic spatial patterns because it creates artificial barriers that restrict landscape processes such as fire and seed dispersal to be simulated within a single tile, while in reality these processes can spread across tile boundaries.

We have developed LANDIS PRO 6.0, a forest landscape model that is capable of simulating forest change over very large (10^6–10^8 ha) landscapes at 30-m resolution. LANDIS PRO 6.0 is an offspring of the LANDIS model (Mladenoff, 2004; He et al., 2005), which has been one of the most predominant FLMs for more than 10 years (Perry and Enright, 2006). The LANDIS model (version 1.0–5.0) tracks the presence and the absence of tree species by age cohorts in each cell during the simulation. It uses a bit-wise array (64 bits/8 bytes) data structure to represent tree species age cohorts, which is arguably the most efficient in terms of computer memory usage to store species age cohorts at cell level (He et al., 1999). However, computing capacity is still a primary limiting factor when applying the LANDIS model to very large landscapes. For example, if simulating 10 tree species on a landscape represented by a raster grid of 10,000 × 10,000 cells, the total memory requirement for LANDIS to store species age cohorts is 8 GB (i.e., 8 bytes × 10 tree species × 100 million cells), which is clearly above the physical memory limit (3 GB) of a contemporary 32-bit personal computer. In order to mitigate this memory usage problem, the LANDIS PRO 6.0 model employs data structures of hash tables and run-length compression to store species age cohorts more efficiently at grid level. This innovative computer design makes it possible to expand the forest landscape simulation to regional scales, examine forest ecological processes across scales (Rastetter et al., 2003; Urban, 2005), link landscape dynamics with regional-scale wildlife conservation (Shifley et al., 2008; Rittenhouse et al., 2011), and jointly assess the cumulative effects of multiple (e.g., federal, state, and private) ownerships on a large landscape as a whole (Shinneman et al., 2010).

The objectives of this paper are to present the computer design of the LANDIS PRO 6.0 model, which we believe can mitigate the bottleneck effect of computing capacity on the development of raster based forest landscape models; and to assess the capability of LANDIS PRO 6.0 in simulating forest change on large landscapes with desirable fine spatial resolutions. We compared the modeling performance and behavior of the newly developed LANDIS PRO 6.0 model against its predecessor LANDIS model (version 4.0) on five nested landscapes with varying sizes in the southern Missouri Ozark Highlands. Specifically, we examine how (1) the innovative design can improve the maximum spatial extent of forest landscape modeling, (2) the run time efficiency of the LANDIS and LANDIS PRO models respond to the landscape size, and (3) changing spatial extent can affect the simulated results of forest succession patterns in the Ozark region.

2. Materials and methods

2.1. Study area

The Ozark Highlands is an ancient plateau that covers much of the southern half of Missouri, as well as portions of northern Arkansas and southwestern Illinois, USA. The Ozark Plateau is dissected by a dense stream network that has created ridges and valleys, some with steep slopes. The vegetation of the Ozarks is an oak and oak-pine forest matrix juxtaposed with patches of open woodlands and grasslands. Dominant tree species include white oak (*Quercus alba* L.), post oak (*Q. stellata* Wangenh.), black oak (*Q. velutina* Lam.) and shortleaf pine (*Pinus echinata* Mill.). The abundance of shortleaf pine is much lower than it was prior to the heavy logging that occurred in the late 19th and early 20th centuries (Batek et al., 1999). Red maple (*Acer rubrum* L.) and sugar maple (*Acer saccharum* Marsh.) have increased in abundance, due to their shade tolerance and decades of fire suppression. The landscape includes large areas of mature and aging forest due to the prior heavy harvesting and subsequent natural regeneration and forest regrowth.

The Mark Twain National Forest (MTNF) is located in this region. It consists of nine administrative districts that collectively cover approximately 1.2×10^6 ha of area (about half the land within MTNF district boundaries is privately owned). Previous applications of LANDIS only examine one district ($\sim 10^5$ ha) at a time due to computing limitations (Shifley et al., 2008). LANDIS PRO 6.0 presents us opportunities to examine the interaction of spatial pattern and landscape processes over all nine districts including the private lands within and between each unit. The sizes of five nested landscapes (Fig. 1) we simulated are, in increasing order, 9×10^4 ha (1000 by 1000 cells), 3.6×10^5 ha (2000 by 2000 cells), 1.44×10^6 ha (4000 by 4000 cells), 2.25×10^6 ha (5000 by 5000 cells) and 9×10^6 ha (10,000 by 10,000 cells). In each case the cell size is 30 m by 30 m.

2.2. LANDIS PRO model

LANDIS PRO 6.0 preserves the ecological design of LANDIS v4.0 (He et al., 2005). It is developed to simulate the cumulative effects of forest succession, various disturbance processes (e.g., fire, windthrow, insect outbreak, and forest harvesting), and their interactions on spatial patterns of forest composition and age structure at landscape and regional scales. Details about ecological design of LANDIS can be found from other sources (Mladenoff and He, 1999; He et al., 2005), and hence only the modules related in this study (succession and seed dispersal) and the new data structures developed for LANDIS PRO (Hash table and run-length compression) are presented in this paper.

2.2.1. Succession and seed dispersal

In LANDIS PRO 6.0, succession is simulated as a non-spatial competitive process driven by species life history attributes at cell level. Succession dynamics are simplified as regeneration, growth, and mortality acting on species age cohorts. The mortality process is simulated based on species longevity. Age cohorts that approach to the species longevity have higher mortality probability during the simulation. The birth (sexual regeneration) and vegetative reproduction (asexual regeneration) processes are simulated base on species establishment probability (SEP) and vegetative sprouting probability (He et al., 2005), respectively. Asexual regeneration is triggered by disturbance- or age-related mortality. Sexual regeneration is simulated whenever there is seed establishment event, which is driven by seed dispersal and SEP. LANDIS stratifies the heterogeneous landscape into land types based on climate, soil and terrain attributes (Mladenoff and He, 1999). SEP, which describes the relative suitability of each species to establish itself under open-canopy scenarios provided there are abundant seeds on a site, is defined at the land type level.

Seed dispersal is a spatial process simulated at the landscape level. The seed dispersal distance is modeled as a function of effective and maximum dispersal distances. The effective disper-

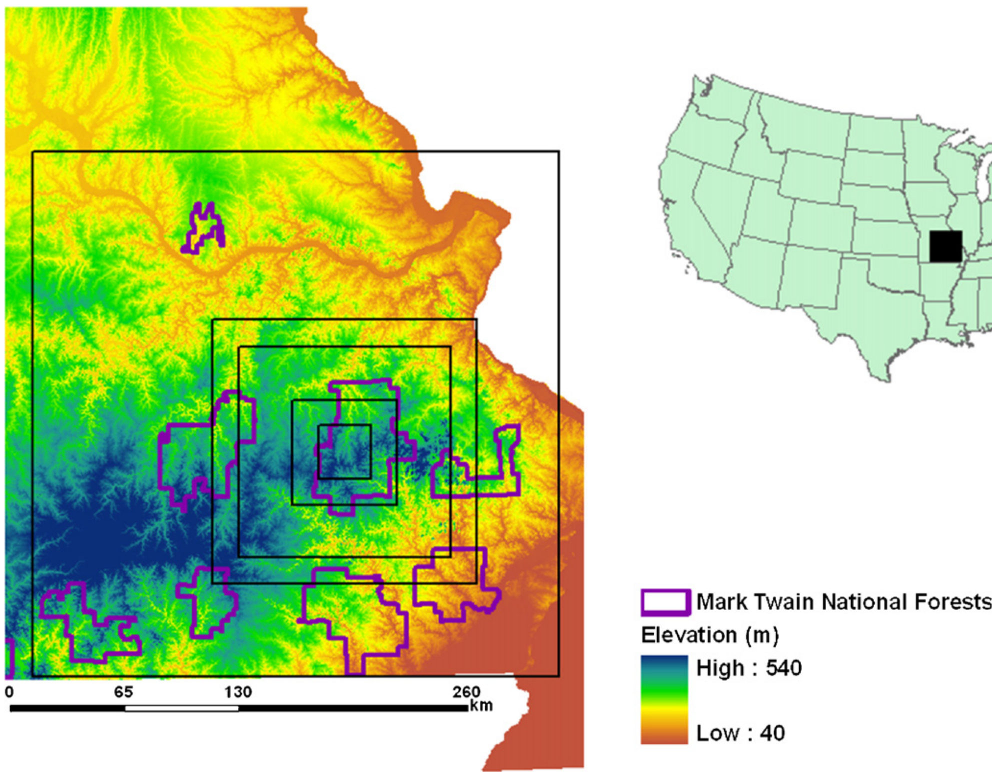

Fig. 1. Five nested landscapes with varying sizes (9×10^4 ha, 3.6×10^5 ha, 1.44×10^6 ha, 2.25×10^6 ha, and 9×10^6 ha) located in Missouri Ozark Highlands.

sal distance is that for which seed has the highest probability ($p > 0.95$) to reach a site; while the maximum dispersal distance is that beyond which seed has near zero probability ($p < 0.001$) of reaching a site (He and Mladenoff, 1999). Seed can theoretically disperse from any cell on the grid that contains sexually mature age cohorts. Whether the seed will successfully establish on a different cell depends on distance from seed source, the characteristics of trees already at the site, the shade tolerance of the dispersing species, and the land type (Gustafson et al., 2000).

2.2.2. *Hash table*

Hash table is a data structure that associates keys with values. It is in essence a lookup table that can efficiently find the corresponding data value for a given key (Weiss, 2006). The premise for using a hash table in LANDIS PRO 6.0 is that many cells on a landscape have the same data value. Instead of allocating each of those cells a different chunk of memory space to store the same species age cohorts, LANDIS PRO 6.0 stores an integer key (4 bytes) for each cell, and uses a hash table to link the key with its corresponding age cohorts (Fig. 2). The size of hash table is determined by the number of unique species composition and age structure classes that are *present* on a landscape within an iteration, as each unique class corresponds to only one unique key in a hash table. The memory usage for storing an integer key (4 bytes) in a cell is much less than that for representing species age cohorts in a cell. For simulating 10 tree species on a large landscape with 100 million (10,000 by 10,000) cells, this method can reduce the memory usage from 8 GB to only 0.4 GB and still store the same age cohort information at a grid level.

The use of hash table in forest landscape modeling can also improve computational efficiency. One of the most basic succession processes simulated in LANDIS model is the growth function, which involves incrementing existing tree age cohorts to older ages as the simulation moves to the next time step. The original LANDIS simulates this process by iterating every individual cell on the landscape, even though many cells have identical age cohorts and hence identical growth outcomes. LANDIS PRO 6.0, however, keeps the key of every cell unchanged. It updates only the corresponding species age cohort matrix to which each key associates. The computational cost is greatly reduced since one update of corresponding age cohorts in the hash table is equivalent to simulating growth process on all cells with the same key.

2.2.3. *Run-length compression*

The premise of using run-length compression is based on local-scale homogeneity. That is, cells with the same value are often spatially connected and form small homogeneous patches on a large-scale heterogeneous landscape. Taking advantage of this spatial pattern, we use a run-length compression algorithm and data structure to further reduce memory usage. Runs are linear strings of consecutive cells that have identical data values. The run-length compression algorithm stores each run as a single 2-tuple, which contains two components: length (i.e., counts of cells) and the data value for each of the consecutive cells, rather than a repeated string of identical value (Fig. 3a).

There is, however, a great disadvantage when using run-length compression in forest landscape modeling. That is slow query operation. Unlike the conventional grid representation, run-length compression does not store data values cell by cell. Therefore, the geographical location of a cell is no longer spatially explicitly stored in the run-length data structure. When retrieving the data value for a given cell (i,j), the algorithm must visit each data run in order from the beginning to calculate the cumulative length and determine the specific run associated with cell (i,j). For the worst case scenario (i.e., the given cell belongs to the very last run), every data run on a gridded landscape must be visited. To solve this problem, we added a new array M as retrieval markers, in which element M_k stores a pair of integers (2×4 bytes). The first integer (run index) indicates which run the 10kth cell belongs to, and the second integer shows the cumulative length of the corresponding run (Fig. 3b).

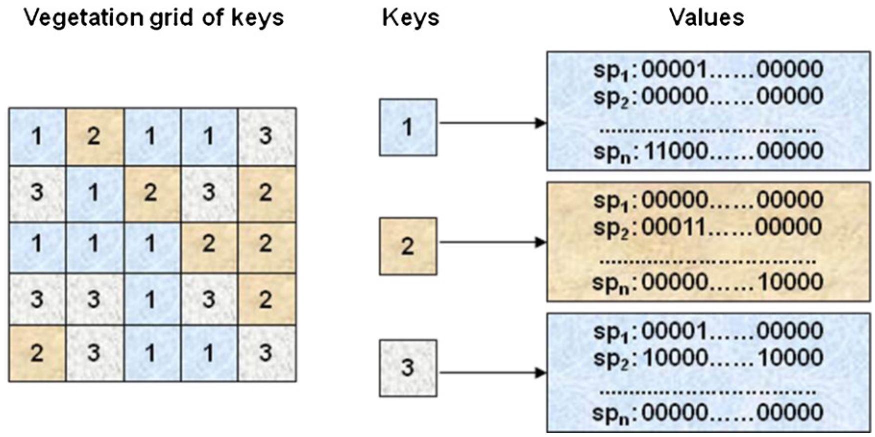

Fig. 2. Use of a hash table in LANDIS PRO 6.0. Instead of storing age cohort matrix by species for each cell, LANDIS PRO 6.0 only stores a hash table key, which takes much less memory space. Each key (1, 2, or 3 in this example) is associated with its corresponding data values (species age cohort matrix) stored in the hash table and can be used to readily find the values for a given cell.

The size of array *M* is one tenth of the size of landscape. For a landscape with 10,000 by 10,000 cells, the memory usage for this array is only 80 MB. With help of the retrieval markers, we are able to shrink the search range down to 10 cells and significantly improve the query efficiency with relatively little additional memory usage.

2.3. Model parameterization

To simulate forest succession, the LANDIS family of models (LANDIS v4.0 and LANDIS PRO 6.0) requires life history attributes of each included tree species, a raster-based land type map, and an initial forest composition map that represents the presence of tree species by age classes on every cell. There were five species groups tracked in the simulations: white oak (assembly of white oak and post oak), black oak (assembly of black oak and scarlet oak), shortleaf pine, sugar maple (assembly of red maple, sugar maple and associated mesic tree species), and a generic grass species on associated pastures and other open land. Life history attributes for each species group (Table 2) were parameterized in previous studies (Shifley et al., 2000, 2006; Shang et al., 2007; Yang et al., 2008).

We used DEM, soil, and land use map layers to derive a digital land type map. The map includes six land type classes: grassland or other open land, northeast slopes, southwest slopes, ridge tops, upland drainages, and bottomland or mesic sites. Grassland is actually a combined land type and land use category for sites that remain open and covered by grass species. Species establishment probabilities were determined based on the relative species abundance in undisturbed old-growth and relatively undisturbed mature second-growth stands (Shifley et al., 2000).

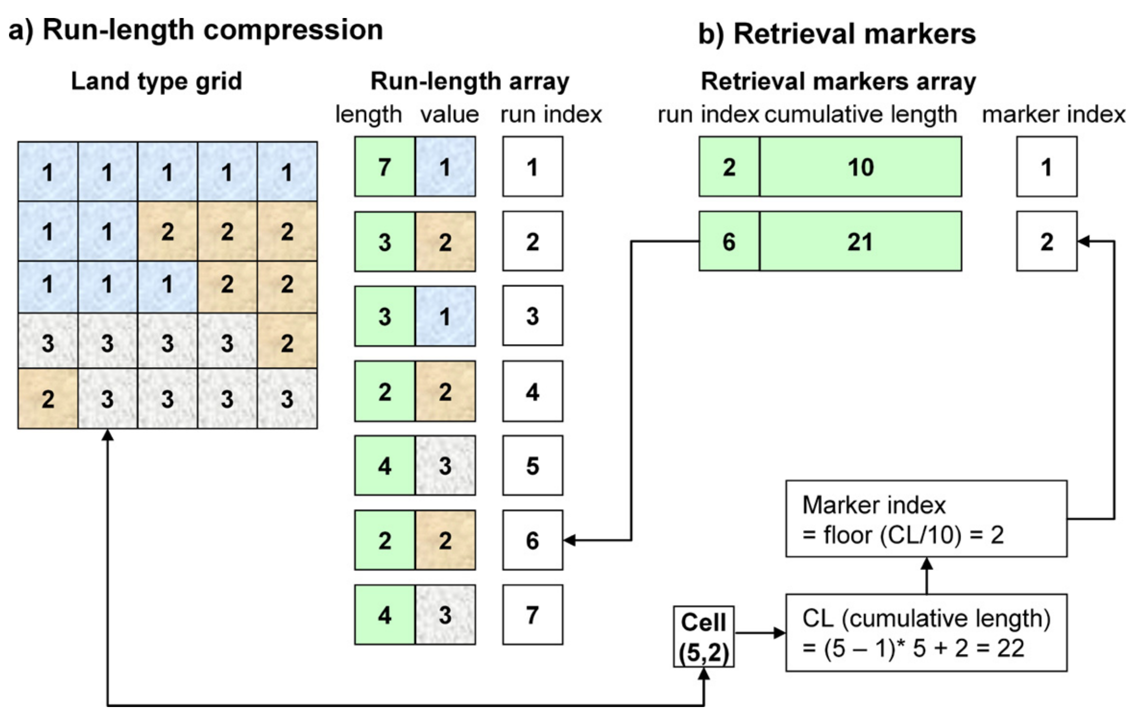

Fig. 3. (a) Run-length compression. The example land type grid (25 cells) is compressed into a run-length array with 7 runs. Each run is represented as a 2-tuple: length and data value. The array is interpreted as seven cells valued 1, three cells valued 2, three cells valued 1, etc. In this example, the run-length data structure reduces the memory usage into approximately half of that represented by the original grid data structure. (b) Illustration of how retrieval markers can facilitate a fast query. For a given cell, the algorithm determines the retrieval marker whose cumulative length is closest to the cell's cumulative length. Then the run-length algorithm starts searching for the values associated with the run indicated by the chosen marker.

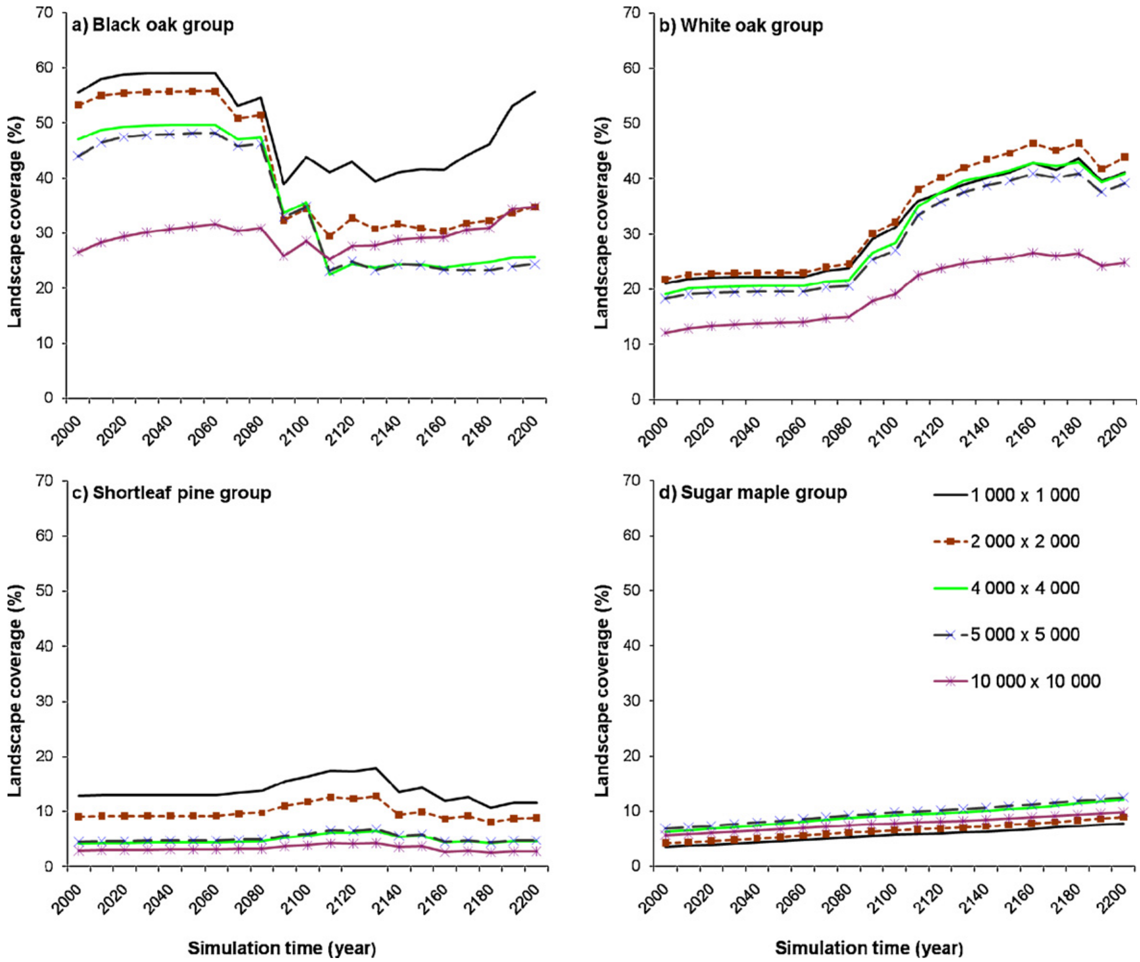

Fig. 4. Simulated species abundance (i.e., percentage of landscape coverage of each dominant species) change over 200 years of simulation for varying landscape sizes (from 1000 by 1000 cells to 10,000 by 10,000 cells).

We used plot-level Combined Data Systems (CDS) data collected by the Mark Twain National Forest (MTNF) and the Forest Inventory and Analysis (FIA) data collected during 1990s to derive initial (at calendar year 2000) species and age structure conditions on these landscapes. CDS data contain stand polygon maps with the associated stand-scale attributes. The combination of stand age and forest cover type was used to assign species and age cohort classes to each cell, based on the probabilities of occurrence observed from nearby cells for which species-level inventories had been previously conducted. Additional details about this procedure and initial species and age maps can be found in Zhang et al. (2009). Each simulation started at calendar year 2000 and ran for 200 years. All of the simulations were performed on a PC with an Intel Core2 Duo dual-core processor, two gigabytes of RAM, and running the Windows XP 32-bit operating system.

Table 2
Major life history attributes parameterized for the Ozark Highlands of Missouri for use in the LANDIS PRO model.

Species group	LONG	ST	ED	MD	VP
Black oak	150	3	40	800	0.8
White oak	250	3	40	800	0.5
Shortleaf pine	200	3	50	80	0.5
Maple	200	5	100	200	0.3
Generic grass	20	−1	10	80	1.0

LONG: longevity (years); ST: shade tolerance (categorical classes 1–5, as class 5 indicates most tolerant); ED: effective seeding distance (m); MD: maximum seeding distance (m); VP: vegetative resprouting probability (0–1).

3. Results and discussion

The Ozark forest successional dynamics exhibited some general characteristics that were independent of spatial extent (i.e., size of test landscapes). For example, black oak group showed a substantial decline in abundance at simulation year 2090 at all spatial extents (Fig. 4a) due to increased age-related mortality. A large proportion of black oak sites were 50–60 years old at the start of the simulation in 2000 and reached longevity (150 years) at year 2090. White oaks and to a lesser degree shortleaf pines increased in relative abundance as these sites regenerated beginning in simulation year 2090 (Fig. 4b and c). Shortleaf pine subsequently declined in relative abundance as pines on many sites approached their longevity (200 years) beginning in approximately 2130. Unlike the other three species, sugar maple showed a steady increase in abundance over the simulation time period (Fig. 4d) due to its high shade tolerance.

However, there were also significant and variable effects on the species abundance trajectory and species composition associated with changing the spatial extent of the simulation. The landscape of 9×10^6 ha (10,000 by 10,000 cells) produced a smaller decline in black oak abundance at simulation year 2090 and subsequently, a smaller increase of abundance of white oak and shortleaf pine than those from other simulation sizes. Black oak was initially the most dominant species on all five landscapes (Fig. 4a). After 200 years of simulation white oak was the most abundant species for the intermediate landscape sizes of 4×10^6 ha, but not for larger and smaller landscapes (Fig. 4b). The two minor species (shortleaf pine and sugar maple) responded to the change of spatial extent differently.

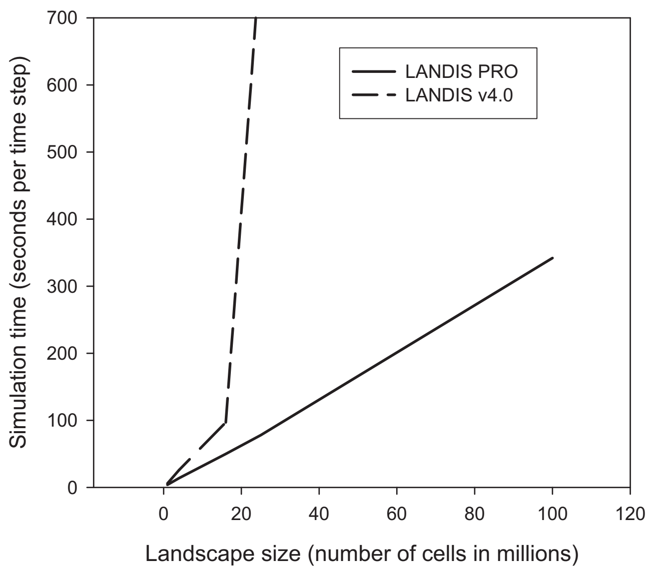

Fig. 5. Run time efficiency varied by landscape size for forest change simulation measured by computational time over one simulation time step for models LANDIS PRO and LANDIS 4.0.

Shortleaf pine showed a decrease in abundance with the increase of landscape size. In contrast, sugar maple generally increased in abundance with increasing landscape size. This is because with the increasing simulation extent, the proportion of areas suitable for shortleaf pine to establish decreased; while that for sugar maple to establish increased. In all cases the differences in initial species abundance were associated with differences in initial landscape conditions for landscapes of different sizes. The simulated changes of species abundances differed with spatial extent mainly due to differences in the proportion of the various land types with the associated species establishment probabilities and species shade tolerance.

Run time efficiency is linearly proportional to the number of cells for both models, but the slope for LANDIS v4.0 is much steeper than LANDIS PRO 6.0 (Fig. 5). LANDIS PRO 6.0 is substantially faster than LANDIS v4.0, especially for large landscape sizes. When landscape size reached 5000 by 5000 cells (25 million cells), computations within the LANDIS v4.0 model broke down because the physical memory was exhausted. Our case study application simulated only five tree species. Many LANDIS applications track more tree species and would exacerbate memory limitations. For example, Syphard et al. (2006) used the LANDIS model to simulate 19 species in a southern California Mediterranean landscape. Memory usage and simulation time of LANDIS are a function of both grid size and the number of tree species tracked. In contrast, memory usage of LANDIS PRO is a function of grid size only. When increasing the number of tracked species, LANDIS PRO will become more advantageous to simulate large landscapes than current LANDIS models.

4. Conclusions

LANDIS PRO 6.0 simulates spatially explicit ecological patterns and processes on a wide range of spatial scales (10^3–10^8 ha). Our understanding of a forest landscape is dependent on spatial extent, as demonstrated in our case study model application. The location and extent of the analyzed landscape should always be matched to the specific management, policy, or scientific questions of interest. A larger landscape is not always more appropriate. However, when landscapes with large extents are needed for analyses—and that is a common occurrence—it is important to have the capacity to efficiently analyze them.

We present two new data structures and algorithms (hash table and run-length compression) for improving computational efficiency and memory usage of raster based forest landscape models. The new computer design shifts the focus from cell-level memory compression to grid-level memory compression. Consequently, the model implemented with the new computer design can simulate much larger landscapes with a faster computational speed than previous forest landscape models. Although programming methodology does not change the essence of ecological modeling, it does modify data storage and access and improve model application scopes. The ability to work with large landscapes and fine spatial resolutions is critical to future applications of complicated ecological models such as LANDIS PRO. The methods presented here can significantly expand the scope of suitable applications for forest landscape modeling and may prove adaptable to other forest landscape simulation models that are highly demanding in computational resources for simulating a finite number of vegetation states at each cell over a large raster grid.

Acknowledgements

Funding support for this research came from the U.S. Forest Service Northern Research Station, Chinese Academy of Sciences (CAS; Grant No. 09YBR211SS), and the Project KZCX2-YW-444. We thank William Dijak for his help in GIS data processing and Dr. Robert Keane and anonymous reviewer for their constructive comments that have greatly improved this manuscript. LANDIS PRO 6.0 can be downloaded at http://web.missouri.edu/~umcsnrlandis/.

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Please cite this article in press as: Yang, J., et al., An innovative computer design for modeling forest landscape change in very large spatial extents with fine resolutions. Ecol. Model. (2011), doi:10.1016/j.ecolmodel.2011.04.032