TM-06

The use of Markov optimization models in the economic and ecological management of forested landscapes under risk

Buongiorno, J. (jbongio@wisc.edu)
Zhou, M.
University of Wisconsin-Madison

ABSTRACT: Markov chains and Markov decision process models are very powerful approaches to simulate or optimizing forest systems under risk. The method consists first in transforming the initial system, possibly represented with a complex stochastic simulator, in a table of transition probabilities, as in a Markov chain, and then bringing the power of optimization to this simplified model. Markov chain models are tables of probabilities signifying the chances that a particular system changes from one state to another within a specified amount of time. They have wide and effective applications in forestry. Even the simplest results of Markov chains can give insights on forest growth dynamics. In particular, they can help predict the effects of natural or human disturbances on forest landscapes. They can also be used to project the evolution of a forest stand over time, through specific succession phases. The results of Markov chain theory, such as mean recurrence time and mean residence time help clarify the dynamics of forest stands, and its consequences for landscape diversity. Markov chains are also useful to predict the effects of management policies under risk, for both economic and ecological criteria. Markov decision process models introduce decision making in forest systems that evolve according to a Markov chain. A policy is a rule that specifies a decision fore each stand state. Mathematical programming can be used here to optimize the present value of expected returns from a stand state over an infinite horizon. Decisions that maximize a long-term expected value criterion, such as the long-term expected biodiversity of a stand, or the long-term expected periodic income, can also be found. We report on an application of these methods to the mixed loblolly pine (*Pinus taeda* L.) and hardwood forests in the southern United States. The results showed that natural catastrophes enhanced the diversity of the landscape, but impaired the tree diversity. Following current management would generate high landscape diversity, but low timber productivity. A highly diverse landscape could be maintained while keeping the tree diversity near the achievable maximum. But managing to maximize tree size diversity or species diversity would much decrease landscape diversity. The opportunity cost of preserving a highly diverse landscape was high in terms of foregone timber production.

KEYWORDS: Markov chain, decision making, decision process, landscape management, diversity, risk, catastrophe

INTRODUCTION

The present study explored Markov decision process models (MDP) to manage for diversity of landscape, with consideration for other ecological and economic objectives. MDP models are very effective in formulating and solving forest management problem with uncertainties (Lembersky and Johnson, 1975; Rollin et al., 2005).

With the MDP approach, the landscape diversity was measured from the probability distribution of stand states. We then optimized the landscape diversity, determined a landscape with a preferred distribution of stand states and calculated the trade-off between landscape objectives, biodiversity, stand composition and economic returns.

We used the mixed loblolly pine-hardwood forest of the southern United States as the case study. Loblolly pine is one of the most important species in this area. It dominates a forest of about 12 million ha. This forest was represented by permanent plots in Alabama, Arkansas, Louisiana, Mississippi, Tennessee, and Texas (Slide 2).

MARKOV MODEL OF STAND GROWTH

The stand state was defined by the basal area of trees in six classes of tree size and species: pine pulpwood (12.7 cm ≤ DBH < 22.99 cm), pine small sawtimber(22.9 cm ≤ DBH < 38.1 cm), pine large sawtimber (38.1 cm ≤ DBH), hardwood pulpwood (12.7 cm ≤ DBH < 27.9 cm), hardwood small sawtimber (27.9 cm ≤ DBH < 38.1 cm), and hardwood large sawtimber (38.1 cm ≤ DBH). For each tree class, the basal area was low (0) or high (1). The threshold was the mean basal area per ha on the sample plots. Each stand state was designated by a string of six digits such as 010110 where the first three digits stood for the basal area of pulpwood, small sawtimber, and large sawtimber of pines, and the last three digits for hardwoods. There were 64 possible stand states.

The matrix of transition probabilities between stand states, T, was obtained by simulation with a non-linear stochastic growth model (Zhou and Buongiorno 2004):

$$y_{t+1} = G(y_t)y_t + Ry_t + u_{t+1} \qquad (1),$$

where $y_t = [y_{ijt}]$ is the number of live trees per hectare of size j and species i (pines, soft hardwoods, hard hardwoods) in year t. G and R are matrices of parameters, and u_{t+1} is a vector of random shocks.

The observed shocks were the differences between the number of trees predicted by the deterministic part of model (1) and the actual number of trees on the plots. We used bootstrapping, drawing randomly from the observed shocks with replacement. From a random initial condition, y^0_t, model (1) was used to predict the condition of the stand in the following year, y^0_{t+1}, and thus calculate the probability of transition between states.

In addition, in the region of interest, hurricanes have been the most typical and destructive natural catastrophes. We estimated the probability of catastrophic hurricanes in the hurricane-prone area at $h= 0.025\ y^{-1}$. Hurricanes increased the probability that a one-hectare stand moved from state s to state 000,000 in a year.

A part of the stand probability transition matrix is in Table 1. There was a high probability that a stand would stay in the same state over one year, as reflected by the main diagonal of the matrix. Most of the probabilities of moving to state 0000 were equal to 0.025, the probability of a hurricane.

Table 1. Partial matrix of transition probabilities between stand states.

State at *t*[1]	**State at *t*+1**						
	000,000	**000,001**	**000,101**	**…**	**111,101**	**111,110**	**111,111**
000,000	0.797	0.027	0	…	0	0	0
000,001	0.025	0.782	0.064	…	0	0	0
000,010	0.025	0	0	…	0	0	0
…	…	…	…	…	…	…	…
111,101	0.025	0	0	…	0.842	0	0.034
111,110	0.025	0	0	…	0	0.847	0.05
111,111	0.025	0	0	…	0	0	0.89

[1] Basal area in pulpwood, small sawtimber, and large saw timber of pines (first three digits), or hardwoods (last three digits) 1= higher than current average, 0= lower than current average.

During the simulation we computed the expected size and species diversities for each state, as well as the expected volume and basal area by tree class and basal area level. State 000,111 with the high basal area in hardwoods had the highest species diversity, while state 111,000 with the high basal area in softwoods had the lowest. Three states had the smallest size diversity: 000,000; 100,000; and 100,100, they all had low basal area in the small and large sawtimber. The highest size diversity occurred in states 111,011 and 111,111, which had high basal area in most tree classes.

MARKOV MODEL OF PRICES

Steady state predictions

Given the transition probabilities between stand states, T, the steady state probabilities P* were obtained by solving:

$$P^* = P^* \times T \quad (2),$$

where P*=[p*s] and p*s was the probability of stand state s (s=1,…,64) in the long run. Changing T, for example to reflect different frequencies of natural catastrophes, led to different steady states. This procedure was also used to predict the steady state that would result from continuing the current policy, revealed by the harvest pattern on the observed plots in the time between the last two inventories.

According to equation (2), without catastrophe or human intervention, about 90% of the forest land would have stands with high basal area in large sawtimber of both pines and hardwoods (Fig. 1). The landscape diversity was much lower than the one observed at the last inventory. Defining old growth as the most likely states in the absence of major disturbance, the frequency of old-growth in such forests was 83%. The old-growth forest would have very large pines and hardwoods trees, along with many mid-sized hardwood trees, and some young saplings of pines and hardwoods, a plausible climax state given the shade tolerance of hardwoods. The expected adjustment time to approach the steady state was 92 years, and the residence time of old-growth was the sum of the residence times of these states, 55 years, and the average recurrence time of old-growth was 9 years. This result suggests that the old-growth stage of a loblolly pine and hardwood forest was quite dynamic. These changes may be due to frequent forest fires, as fire, “a major and frequent influence affecting the developing of old-growth pine forests in the region of interest, is critical for maintaining pine abundance, especially on better quality sites” (Bragg, 2004).

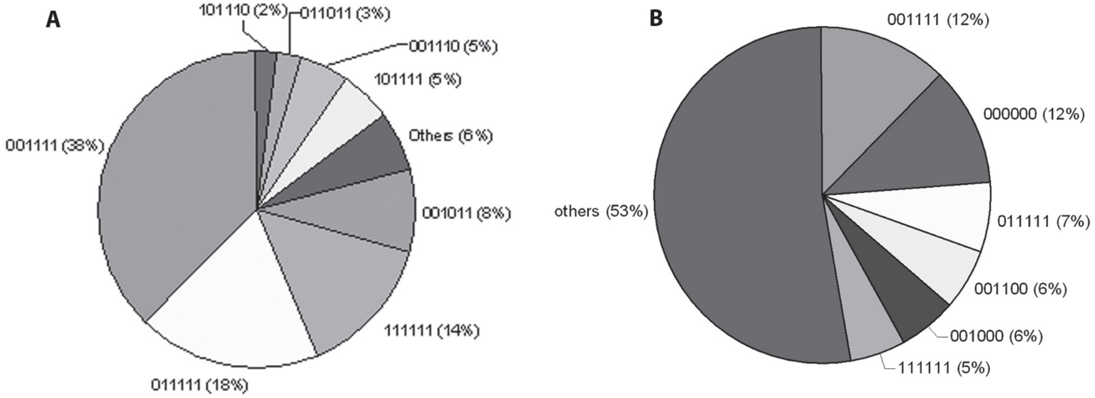

Figure 1. Distribution of stand states without hurricanes (A) and without hurricanes (B). Old forest is 84% of the landscape in A and 29% of the landscape in B.

Hurricanes completely changed the steady state landscape. All 64 stand states were present, so that the landscape was much more diverse than without catastrophe. The occurrence of hurricanes reduced the diversity of tree size and tree species, the average basal area, and the frequency of old-growth, compared to the undisturbed steady state. The current landscape was even more diverse than the steady-state landscape with hurricanes, but the tree diversity and basal area were lower, and old growth was much less frequent.

Decisions and management criteria

Decisions were defined as changing a stand from one state to another by harvesting at a given frequency. Thus, equation (2) gave the steady state probability of each stand state for any policy (Lin and Buongiorno, 1998).

For a large forest area, the steady state probabilities P* were also the distribution of various stand states that would result in the long run from pursuing a particular policy. Landscape diversity was measured with Shannon's index (Pielou 1977), based on the frequency of each state in the landscape.

Decisions also changed the size and species composition of the trees in the forest, as well as the basal area and the timber production per unit of land. The diversity of tree species was also computed with Shannon's index, based on the frequency of trees by species group and size class.

The timber production due to a decision was the difference in volume between the pre-harvest and post-harvest state.

The expected diversity, basal area, and volume in each stand state were obtained with the simulation based on model (1), simultaneously with the calculation of transition probabilities between stand states described above.

Predicting the effects of the current management

The current management was represented by a decision matrix Dc =[*dc*(*s*, *s'*)], where [*dc*(*s*, *s')*] was the probability that a stand in state s was cut to state s' within a period of n years. The matrix of n-year transition probabilities under current management was then:

$$T_c = [p_c(i, j)] = D_c * T^n \qquad (3),$$

which with equation (2), gave the vector of steady-state probabilities of the stand states under current management, P_c^*. This then led to the expected species, size, landscape diversity, basal area, old-growth frequency, and harvest under current management. The expected annual harvest was assumed to be *1/n* of the expected harvest over *n* years.

Managing for landscape diversity

To maximize landscape diversity in the sense of equation (3), we noted that when decisions were taken into account, the probability of a stand state ps could also be written as:

$$p_s = \sum_d z_{sd} \qquad (4),$$

where z_{sd} was the probability of making decision d in state s. Then, the maximum diversity was obtained by solving the following nonlinear program:

$$\begin{aligned}
&\underset{z_{sd}}{Max}\ H_L = -\sum_s \Big(\sum_s z_{sd}\Big) \ln \sum_s z_{sd} \\
&s.t. \\
&\sum_d z_{s'd} - \sum_s \sum_d z_{sd}\, p(s' \mid s, d) = 0 \qquad s' = 1, \ldots, 64 \\
&z_{sd} \geq 0 \qquad \forall s, d \\
&\sum_s \sum_d z_{sd} = 1
\end{aligned} \qquad (5),$$

where p(s'|s,d) was the probability of finding a stand in state s' at t+1 after starting in state s and making decision d. The first set of constraints kept the probability of each stand state constant over time (steady state). The other constraints expressed the fact that the variables zsd were probabilities, thus non-negative, and adding up to unity.

Given a solution of (4), the best policy, expressed as the probability Xsd of making decision d given a stand state *s* was:

$$X_{sd} = \frac{z_{sd}}{\sum_{d} z_{sd}} \qquad (6).$$

Another definition of a diverse landscape had the largest minimum frequency of any state. With this maxmin criterion, the problem was linear:

$$\begin{aligned}
&\underset{z_{sd}}{Max}\ A_{\min} \\
&s.t. \\
&0 \le A_{\min} \le \sum_{d} z_{sd} \qquad\qquad s = 1,\ldots,64
\end{aligned} \qquad (7),$$

where Amin was the smallest frequency of any stand state. Thus, the theoretical maximum of Amin was 1/64 = 1.6%. Like the theoretical maximum of Hs, it was achieved when each state occupied an equal fraction of the landscape. The other constraints were as in (4).

A third way to manage landscape was to achieve a desirable distribution of stand states. This problem was formulated by goal programming:

$$\begin{aligned}
&\underset{z,D}{Min}\ \sum_{d} (D_s^{-} + D_s^{+}) \\
&s.t. \\
&\sum_{d} z_{sd} - D_s^{-} + D_s^{+} = \phi_s \qquad s = 1,\ldots,64 \\
&\sum_{d} z_{s'd} - \sum_{s}\sum_{d} z_{sd}\, p(s' \mid s, d) = 0 \qquad s' = 1,\ldots,64 \\
&z_{sd} \ge 0 \qquad \forall s, d \\
&\sum_{s}\sum_{d} z_{ik} = 1 \\
&D_s^{-}, D_s^{-} \ge 0 \qquad \forall s
\end{aligned} \qquad (8),$$

where Øs was the desired fraction of the landscape in state s, and D_s- and D_s+ were the deviations from Øs.

In managing landscapes, especially forest conditions, old-growth in particular has become of much interest from the point of view of biological conservation (e.g., Zenner, 2004; Aldrich et al., 2003). The management policy that would maximize the probability of old-growth or any other desirable set of states, Ω (equivalently maximizing the sum of frequencies of these states in the landscape), was obtained by solving the following linear program:

$$\begin{aligned}
&\max_{z} \sum_{s \in \Omega}\sum_{d} z_{sd} \\
&s.t. \\
&\sum_{d} z_{s'd} - \sum_{s}\sum_{d} z_{sd}\, p(s' \mid s, d) = 0 \qquad j = 1,\ldots,64 \\
&z_{sd} \ge 0, \\
&\sum_{s}\sum_{d} z_{sd} = 1
\end{aligned} \qquad (9).$$

Given solutions of (7), (8), or (9), the corresponding best policy was obtained with equation (6).

Dealing with tree diversity and forest productivity

In practice, and as recognized by the models above, landscape management is carried out by manipulating stands. These interventions affect the tree composition of the forest, and its productivity. We explored these effects by taking expected diversity of tree species, size, and harvest volume, as objective functions, or constraints. For example, the management that maximized the expected tree species diversity, tree size diversity, or harvest volume was obtained by solving (Manne 1960):

$$\begin{aligned}
&\max_{z_{sd}} \sum_{s}\sum_{d} R_{sd} \cdot z_{sd} \\
&\boldsymbol{s.t.} \\
&\sum_{d} z_{s'd} - \sum_{s}\sum_{d} z_{sd}\, p\left(s' \mid s, d\right) = 0 \qquad j = 1, \ldots, 64 \\
&z_{sd} \geq 0, \\
&\sum_{s}\sum_{d} z_{sd} = 1
\end{aligned} \qquad (10),$$

where Rsd was species diversity, size diversity, or harvest volume per ha per year given stand state s and decision d. Model (14) was also used to measure the trade-off between these objectives and landscape diversity by adding a constraint on landscape diversity:

$$-\sum_{s}(\sum_{s} z_{sd}) \ln \sum_{s} z_{sd} = H_L^{*} \qquad (11),$$

where HL* was a lower bound on landscape diversity.

Expected cutting cycle, recurrence, residence and adjustment time of stand states

The interval between harvests for any policy was a random variable. For a particular policy k*, the expected cutting cycle, *C*(*k**) was the expected interval between states that called for harvest. Using *p*(*i, k**) to denote the steady state probability of being in state i under policy k*, then the probability of being in any states that call for harvest, *p*(*k**) was:

$$p(k^{*}) = \sum_{i \in S(k^{*})} p(i, k^{*}) \qquad (12),$$

where *S*(*k**) was the set of all states that call for harvest when policy k* was followed. Then,

$$C(k^{*}) = \frac{1}{p(k^{*})} \qquad (13)$$

was the time needed for the stand to return to a state that calls for a harvest, given that it started from such a state, when policy k* was followed (Kaya and Buongiorno, 1989).

With the steady state probability, *p*(*i, k**), we also derived the expected residence time of being in state i, defined as the average time that a stand remained in the same state sequentially, under policy k*:

$$m(i, k^{*}) = \frac{1}{(1 - \mathrm{p}(i, i, \mathrm{k}^{*}))} \qquad (14),$$

where *p*(*i,i,k**) was the one-step probability that state started and remained in the same state i under policy k*.

And the expected recurrence time, denoted by *r*(*s, k**), was the average time it took for a stand in a state s to return to the same state after exiting it, which is the inverse of the steady-state probability of the state:

$$r(s,k^*) = \frac{1}{\mathrm{p(s,k^*)\ )}} \qquad (15).$$

The expected adjustment time was defined as the average time it took to approach closely to steady state with a particular, starting from the initial stand condition. Let Pt denote the vector of stand probability distribution at time t, D the decision matrix and T the stand transition matrix, then, without management,

$$P_{t+1} = P_t \times T \qquad (16),$$

and with management,

$$P_{t+1} = P_t \times D \times T \qquad (17).$$

With successive matrix multiplication (Hoel et al., 1987, pp47-49), we calculated the time it took till the maximum change of all the elements in P is less than 0.001 and used it as an approximation of the expected adjustment time. This information helped to decide whether management policy could accelerate the process of convergence to a desired state.

Single management objectives

To compare management regimes, the diversity indices were expressed relative to the steady-state diversity in unmanaged forests with high-frequency shocks and catastrophes.

This study shows the effects on the steady state forest of pursuing different single objectives, as well as the effects of continuing the current management policy. The highest landscape diversity predicted with model (5) was 13.2% higher than the landscape diversity achievable without management. The expected adjustment time to approach the steady state was 18 years, much shorter than that without management (45 years). Thus, management accelerated the convergence to a highly diverse landscape. Maximizing the smallest state frequency as in model (6) produced similar results in all respects, which are not shown in the tablet to save space.

The management to maximize old-growth frequency, obtained with model (9) increase the frequency predicted without management by four percent, but led to a lower landscape diversity, while giving similar tree size and tree species diversity.

Maximizing the diversity of tree size or stand basal area, with model (10), had similar effects, except that maximizing tree size diversity produced a much higher frequency of old growth. Both required very long cutting cycles, 177 and 53 years, respectively. Maximizing species diversity called for intense harvesting and induced low landscape diversity and basal area, and less than 2% frequency of old growth. The expected cutting cycle of this policy was only nine years. Maximizing sawtimber harvest gave the lowest landscape diversity and basal area and eliminated old growth. And it required the shortest cutting cycle, seven years.

The estimated current annual harvests of sawtimber and pulpwood were 2.04 and 0.62 m^3/ha, respectively. This study shows the steady state probabilities of stand states if current policy was followed. The current policy gave diversities of landscape, species, and size that were close to those of an unmanaged forest, but there was less old-growth. Productivity was one third the maximum that could be obtained, and 83% of what it would be by maximizing landscape diversity.

Trade-off between landscape diversity and other objectives

Figure 2 shows the effects of maximizing species or size diversity with model (10) with a constraint on landscape diversity (11). As the constraint on landscape diversity increased from 30% to 60% of its level in an unmanaged forest, the maximum achievable species and size diversity increased rapidly, along with the decreasing of expected annual harvest. Thus, within that range there was no conflict between landscape diversity and diversity of tree species or size. Beyond a landscape diversity requirement of 75%, tree size diversity decreased slightly, but stayed near its level in an unmanaged forest. The expected annual harvest decreased till the landscape diversity requirement was 103% and then increased slightly. Meanwhile, the maximum achievable species diversity decreased significantly, but stayed nevertheless above its level in an unmanaged forest, during which the expected annual harvest continuously decreased.

Similarly, the highest achievable frequency of old-growth increased from zero to its highest possible level of 24% as landscape diversity was raised from 45% to 85% of its level in an unmanaged forest, at which point old growth frequency was near its level in an unmanaged forest. But the expected annual harvest decreased continuously. Beyond that, however, the frequency of old-growth decreased by four fifth as landscape diversity increased to its highest level. The expected harvest decreased to the lowest point when the landscape diversity was 97% and increased slightly as the landscape diversity requirement increased.

The constraint on landscape diversity had little effect on timber productivity as long as it was under 75% of its steady state level in an unmanaged forest. Beyond that, however, productivity dropped rapidly, and was cut by 2/3 when landscape diversity was at its highest possible level. The old-growth frequency continuously increased, from zero to 1.5%. Thus, there was a significant conflict between timber production and conservation of old-growth.

Other results

By using (8) without the goal variables D_s- and D_s+ we tried to maintain the distribution of stand states observed at the time of the last inventory. There was no feasible solution. However we did find a solution that minimized the sum of the deviations of the distribution of stand states compared to the last inventory distribution, while keeping the expected species and size diversity, basal area and landscape diversity above their current levels. It produced 3.9 $m^3ha^{-1}y^{-1}$ of sawtimber, 160% more than what the current policy would produce in the long run.

DISCUSSION AND SUMMARY

What is an optimal management regime for a forest landscape? There is no single answer to this question, because forest owners and managers hold different interests and expectations. But a good answer must reflect the biological growth of the forest type, minor and major disturbance in the landscape, desired levels of biotic components, and the harvesting of wood products (Franklin and Forman, 1987). In this paper, we incorporated these components into a set of models, centered on Markov processes, to determine management policies that best satisfied different objectives. The models were applied to the mixed loblolly pine-hardwood forests in the South of the United States.

Three types of disturbance were recognized: small-scale, high-frequency natural shocks, large-scale low-frequency catastrophic hurricanes, and harvests. Small-scale, high-frequency natural shocks benefit tree diversity in mixed loblolly pine forests (Zhou and Buongiorno, 2004). Hurricanes have a broad range of influences on species composition, structure, and natural succession (Myers and van Lear, 1998), as well as landscape patterns (Boose et al., 1994). The present findings suggested that catastrophic hurricanes reduced diversity of tree size and species but created a much more diverse landscape, as also found by Lin and Buongiorno (1998) for northern hardwoods. Catastrophic hurricanes generally remove all of the overstory, thus necessarily reducing tree size diversity. Boucher et al. (1990) find that survival of snapped-off pines is near zero after a very strong hurricane, inferring that shoot production capability of different species after clown loss may be a determinant for species survival. This helped to interpret the loss of species diversity in the loblolly pine-hardwood forest type by hurricanes. They also severely damage the understory (Myers and van Lear, 1998), preventing the development of stable climax ecosystems (Webb, 1958; Lugo et al., 1983; Boucher, 1990; Myers and van Lear, 1998), which explains the much lower frequency of old growth predicted by our model in the presence of hurricanes.

Optimizing MDP models with and without constraints led to inferences about the trade-off between landscape diversity and other management objectives. There were three major findings. First, managing for landscape diversity also promoted tree diversity, but increasing tree diversity alone did not enhance landscape diversity. As shown in this study, a highly diverse landscape could be maintained while keeping the tree diversity near the achievable maximum, but maximizing tree diversity only, especially species diversity, would compromise a great deal of the landscape diversity.

Secondly, the opportunity cost of preserving a highly diverse landscape was high in terms of timber harvests, and vice versa. The unique pursue of a diverse landscape only allowed some gentle thinning, cutting off almost two thirds of the maximal harvest. If the goal was only economic, the management plan would create a much less diverse landscape, as compared to the other policies. By increasing the preferred level of landscape diversity, the maximal harvest would decline rapidly.

Moreover, promoting landscape diversity from low to medium level would benefit old growth as well. But beyond that, there was a conflict between conserving old-growth and maintaining diversity of landscape. The policy that maximized the probability of old-growth led to a satisfactorily diverse landscape, but the probability would decrease significantly as we increased our expectation for diversity in landscape.

The "best" management policy depended on the main concerns of the landowners or forest managers and how much they would be willing to pay in terms of their secondary concerns. If the highest landscape diversity was a must, without compromising much of the tree diversity, we lost in both old-growth and economic interests. If a satisfactory level of landscape diversity, say, the level occurred in an unmanaged forest, was acceptable, we were always able to maintain very high tree diversity. Then forest landowners and managers needed to choose between old-growth conservation and economic interests to decide their "best" policy.

In this paper, MDP has shown several advantages in managing for landscape diversity under uncertainties. But limitations also existed, such as the compromise between the resolution of stand states and the solvability of the problems. Linking the decision on the stand state to harvesting a stand in practice was still not adequately straightforward. Future research would be also needed on considering the changing stumpage market and how this could impact the implementation of landscape management.

ACKNOWLEDGEMENTS

The research leading to this paper was supported in parts by McIntire-Stennis grant P879, by USDA-CSREES grant 2001-35108-10673, and by the School of Natural Resources, University of Wisconsin, Madison.

REFERENCES

Alrich, P.R., Parker, G.R., Ward, J.S., Michler, C.H., 2003. Spatial dispersion of trees in an old-growth temperate hardwood forest over 60 years of succession. Forest Ecology and Management 180: 475-491.

Barrett, T.M., Gilless, J.K., Davis, L.S., 1998. Economic and fragmentation effects of clear cut restrictions. For. Sci. 44 (4): 569 – 577.

Baskent, E.Z., Jordan, G.A., 1996. Characterizing spatial structure of forest landscapes. For. Chron. 67 (6): 610 – 621.

Baskent, E.Z., Jordan, G.A., 1996. Designing forest management to control spatial structure of landscapes. Landscape and Urban Planning 34 (1996): 55-74.

Boose, E.R., Foster, D.R., Fluet, M., 1994. Hurricane impacts to tropical and temperate forest landscapes. Ecological Monographs 64 (4): 369 – 400.

Borges, J.G., Hoganson, H.M., 1999a. Structuring a landscape by forestland classification and harvest scheduling spatial constraints. For. Ecol. Manage.

Borges, J.G., Hoganson, H.M., 1999b. Assessing the impact of management unit design and adjacency constraints on forest wide spatial conditions and timber revenue. Can. J. For. Res.

Boucher, D.H., Vandermeer, J.H., Yih, K., Zamora, N., 1990. Contrasting hurricane damage in tropical rain forest and pine forest. Ecology 71: 2022 – 2024.

Bragg, D.C., 2004. Composition, structure, and dynamics of a pine-hardwood old-growth remnant in southern Arkansas. J. of the Torrey Botanical Society 131 (4): 320 – 336.

Covington, W.W., Wood, D.B.,Young, D.L., Dykstra, D.P., Garrett, L.D., 1988. TEAMS: a decision support system for multi-resource management. J. For. 86 (8): 25 – 33.

Franklin, J.F., Forman, R.T.T., 1987. Creating landscape patterns by forest cutting: Ecological consequences and principles. Landscape Ecology 1: 5 – 18.

Gustafson, E.J., Crow, T.R., 1996. Simulating the effects of alternative forest management strategies on landscape structure. J. Environ. Manage. 46: 77 – 94.

Hoel, P.G., S.C. Port, C.J. Stone, 1987. Introduction to stochastic process. Waveland Press, Inc., IL. 203pp.

Kaya, I. and Buongiorno, J., 1989. A harvesting guide for uneven-aged northern hardwood stands. North. J. Appl. For. 2: 28 –31.

Kaya, I. and Buongiorno, J., 1987. Economic management of uneven-aged northern hardwood stands. North. J. Appl. For. 2: 28-31.

Kurttila, M. 2001. The spatial structure of forests in the optimization calculations of forest planning – a landscape ecological perspective. Forest Ecology and Management 142: 129 – 142.

Lembersky, M.R., Johnson, K.N., 1975. Optimal policies for managed stands: An infinite time Markov decision process approach. For. Sci. 21: 109-122.

Lin, C.R., Buongiorno, J., 1999 a. Managing forests for tree and landscape diversity Part I: Predictions with Markov-chain models. P. 137-157 in Multiple use of forests and natural resources, F. Helles, P. Holten-Andersen, and L. Wichmann (eds.), Kluwer Academic Publishers, Dordrecht. 244 p.

Lin, C.R., Buongiorno, J., 1999 b. Managing forests for tree and landscape diversity Part II: Optimization with Markov decision process model. P. 158-174 in Multiple use of forests and natural resources, F. Helles, P. Holten-Andersen, and L. Wichmann (eds.), Kluwer Academic Publishers, Dordrecht. 244 p.

Lin, C.-R. And J. Buongiorno, 1998. Tree diversity, landscape diversity, and economics of maple-birch forests: implications of Markovian models. Management science. Vol. 44, No. 10: 1351 – 1366.

Lin,C.-R., Buongiorno, J., Prestemon, J., Skog, K., 1998. Growth Model for Uneven-Aged Loblolly Pine Stands: Simulations and management implications. FPL-RP-569. USDA ForServ., For. Products Lab., Madison, pp.13.

Lugo, A.E., Applefield, M., Pool, D.J., McDonald, R.B., 1983. The impact of Hurricane David on the forests of Dominica. Can. J. For. Res. 13: 201 – 211.

Manne, A.S. 1960. Linear programming and sequential decisions. Manage. Sci. 6 :259-267.

Myers, R.K., van Lear, D.H., 1998. Hurricane-fire interactions in coastal forests of the south: a review and hypothesis. Forest ecology and management 103: 265 – 276.

Nasset, E., 1997. A spatial decision support system for long-term forest management planning by means of linear programming and a geographical information system. Scan. J. For. Res. 12: 77 – 88.

Nalli, A., Nuutinen, T., Paivinen, R., 1996. Site-specific constraints in integrated forest planning. Scand. J. For. Res. 11: 85 – 96.

Ohman, K., Eriksson, L.O., 1998. The core area concept in forming contiguous areas for long-term forest planning. Can. J. For. Res. 28: 1032 – 1039.

Oliver, C.D. and Larson, B.C., 1990. Forest stand dynamics. McGraw-Hill, Inc. pp.467.

Pielou, E.C., 1977. Mathematical ecology. John Wiley & Sons, Inc. pp. 385.

Rollin, F., Buongiorno, J., Zhou, M., Peyron, J.-L., 2005. Management of mixed species, uneven-aged forests in the French Jura: from stochastic growth and price models to decision tables. Forest science 51(1):64-75.

Schulte, B., Buongiorno, J., Lin, C.-R.. Skog, K., 1998. SouthPro: a computer program for managing uneven-aged loblolly pine stands. U.S.D.A. General Technical Report FPL-GTR-112. Pp. 47.

Tarp, P., Helles, F., 1997. Spatial optimization by simulated annealing and linear programming. Scand. J. For. Res. 12: 390 – 402.

U.S. National Oceanic and Atmospheric Administration. http://www.noaa.gov/.

U.S.D.A. Forest Service, 1989. “Generic definition and description of old-growth forests.” Washington, D.C.

Webb, L.J., 1958. Cyclones as an ecological factor in tropical lowland rain forest north of Queenland. Aust. J. Bot. 6: 220 – 228.

Weintraub, A., Barahona, F., Epstein, R., 1994. A column generation algorithm for solving general forest planning problems with adjacency constraints. For. Sci. 40 (1): 142 – 161.

Wiens, J.A., Stenseth, N.C., Van Horne, B., Ims, R.A. 1993. Ecological mechanisms and landscape ecology. Oikos 66, 369 – 380.

Winer, B.J., 1991. Statistical principles in experimental design. 3rd Edition. New York: McGraw-Hill. Pp. 928.

Zhou, M., Buongiorno, J., 2004. Nonlinearity and noise interaction in a model of forest growth. Ecological Modelling 180:291-304.

Zenner, E.K, 2004. Does old-growth imply high live-tree structural complexity? Forest Ecology and Management 195: 243-258.