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An indicator of forest dynamics using a shifting landscape mosaic

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ABSTRACT

The composition of a landscape is a fundamental indicator in land-cover pattern assessments. The objective of this paper was to evaluate a landscape composition indicator called 'landscape mosaic' as a framework for interpreting land-cover dynamics over a 9-year period in a 360,000 km^2 study area in the southern United States. The indicator classified a land parcel into one of 19 possible landscape mosaic classes according to the proportions of natural, developed, and agriculture land-cover types in a surrounding 4.41-ha neighborhood. Using land-cover maps from remote sensing, the landscape mosaics were calculated for each 0.09-ha pixel in the study area in 1996 and 2005. Mosaic transition matrices estimated from the pixel change data were then used to develop two Markov chain models. A "landscape mosaic" model was a temporal model of the shifting landscape mosaic, based on the probability of landscape mosaic change for all pixels. A "forest security" model was the same, except that the Markov states were defined by both the landscape mosaic and the land-cover of each pixel, which allowed interpreting forest land-cover dynamics in the context of a shifting landscape mosaic. In the forest security model, the overall percentage of forest decreased from 33% in 2005 to 17% at steady-state, and there was little change in the relative distribution of existing forest area among landscape mosaic classes. In contrast, the landscape mosaic steady-state was reached later, and indicated that a maximum of 10% of total area was available for forest. The implication was that forest security depended ultimately on the dynamics of the landscape mosaics that contained forest, not on forest dynamics within those landscape mosaics.

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1. Introduction

The composition of a landscape is a fundamental indicator of patterns within that landscape (O'Neill et al., 1988; Li and Reynolds, 1994), if only because few other pattern indicators are interpretable independent of landscape composition (Gardner et al., 1987; Gustafson, 1998). Pattern indicators for large-area ecological assessments from land-cover maps must include composition indicators that are applicable to all land-cover types and interpretable with respect to many societal and ecological concerns like biodiversity, urban sprawl, and water quality. Establishing a foundation for using those indicators requires testing them with neutral models, examining their statistical properties, and learning how to interpret them (Turner et al., 2001). The objective of this study was to lay part of the foundation for a landscape composition indicator

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called 'landscape mosaic' through analysis and interpretation of land-cover changes from 1996 to 2005 in a study area along the south coast of the United States.

The landscape mosaic indicator comes from the 'landscape pattern type' indicator (Wickham and Norton, 1994) which has been adapted for large-area pattern assessments using land-cover maps derived from remote sensing (Riitters and Wickham, 1995; Jones et al., 1997; Riitters et al., 2000). The indicator classifies a land-cover pixel according to the land-cover composition in a fixed-area neighborhood surrounding that pixel, and a map of landscape mosaics may be constructed by classifying every pixel on the land-cover map. A map of landscape mosaics can help to visualize 'interface zones' (e.g., the 'forest–urban interface') and other spatial gradients of land-cover composition across a region (e.g., Riitters et al., 2000), but more work is needed to develop the indicator as a framework for interpreting land-cover dynamics.

To evaluate the landscape mosaic as a framework for interpreting pixel-level forest dynamics, we defined forest security as the likelihood that a pixel of forest remained as forest over time, which depended on the landscape mosaic that contains a forest pixel. In a dynamic landscape, land-cover change at the pixel level also changes the mosaic at the landscape level, so that the security of a particular pixel of forest can change over time even if that pixel remains as forest. One example is urban sprawl at the forest–urban interface. Forest clearing to build a house is likely within the forest–urban interface because of infrastructure such as roads and water service. Forest removal (a pixel-level change) changes the forest–urban interface (a landscape-level change) by altering its composition and ultimately shifting its location. Additional forest clearing in the same neighborhood may become more or less likely in the future, and the likelihood of forest clearing in new neighborhoods may change as the forest–urban interface itself moves. If forest security depends on forest location relative to a forest–urban interface, then forest security changes when the forest–urban interface moves.

The modeling problem in our study was to link forest change at the pixel level with mosaic change at the landscape level. Gustafson (1998) noted that the conceptual model of a shifting landscape mosaic (Bormann and Likens, 1979) has been useful for describing landscape dynamics, but that the temporal component of that conceptual model needed more development. In contrast, Markov chain models have a long history in temporal analysis of landscape change, but most implementations are not spatial models (see reviews by Baker, 1989; Brown et al., 2004). For Markov models, the most common spatial approach has been to estimate pixel-level transition probabilities based on the spatial attributes or context of each pixel, such that the probabilities of transitions among Markov states can change over time (Brown et al., 2004). An alternate approach to incorporate spatial information was used by Flamm and Turner (1994) in a 'patch' transition model. In that study, the transition probabilities were held constant, and the Markov state of a patch was defined by enumerating its spatial attributes such as soil type, land ownership, and vegetation cover type. We used a similar approach at the pixel level in this study, whereby the Markov state of a pixel was defined both by its land-cover and by the landscape mosaic that contained it. We considered two implementations of that basic model, including a temporal model of the shifting landscape mosaic for all land-cover types, and a model that distinguished between forest and nonforest pixels. The first model was used to characterize the long-term or steady-state distribution of all pixels among landscape mosaics, and the second model allowed interpreting forest dynamics and steady-state distributions of forest in the context of a shifting landscape mosaic.

2. Methods

2.1. Study area and land-cover data

The 360,000 km^2 study area (Fig. 1) was the southern coastal region of the U.S. from the country of Mexico to the State of Georgia. Included were parts of seven ecoregion provinces (Bailey, 1995) from the Southwest Plateau and Plains Dry Steppe and Shrub province in the west to the Outer Coastal Plain Mixed Forest province in the east. The Mississippi River floodplain and delta bisected the region, and the largest cities in the region were Houston and New Orleans. The study area experienced substantial land-use and land-cover changes over the past several decades (USDA Natural Resources Conservation Service 2000). Some parts of the study area (e.g., near Houston) experienced extensive urban development resulting in permanent loss of forestland. Other parts of the study area contained some of the most productive forestland in the United States where forest was both lost (harvest) and gained (re-growth) over relatively short (30–60 years) time intervals (Smith et al., 2004). Forest was much less abundant, but relatively more stable in the western portion of the study area where natural landscapes were dominated by shrubs and grasses.

Land-cover maps for the years 1996 and 2005 were obtained from the National Oceanic and Atmospheric Administration, Coastal Change Analysis Program (C-CAP; http://www.csc.noaa.gov/crs/lca/ccap.html). The maps were derived principally from Landsat Thematic Mapper images and they showed 21 land-cover classes (Dobson et al., 1995) at a spatial resolution of 0.09 ha per pixel, with an overall accuracy goal of 85% (C-CAP; ibid). There were minor differences in total land area (e.g., beach erosion) between 1996 and 2005, and we used the 1996 map to define the study area. To employ the landscape mosaic model (see below), we generalized the 21 land-cover classes to three classes: (1) 'developed', including the original developed open space class and the low, medium, and high intensity developed classes; (2) 'agriculture', including cultivated land and pasture/hay, and; (3) 'natural,' including grassland, forest, scrub/shrub, wetland, shore, bare land, open water, and aquatic bed. To examine forest dynamics in particular, the original maps were generalized a second time, to forest and nonforest land-cover, with the forest class comprised of the deciduous, evergreen, and mixed upland forest classes, and the palustrine and estuarine forested wetland classes.

2.2. Landscape mosaic indicator

The landscape mosaic indicator classified a pixel into one of 19 possible landscape mosaic types according to the percentages of (generalized) natural, developed, and agriculture land-cover

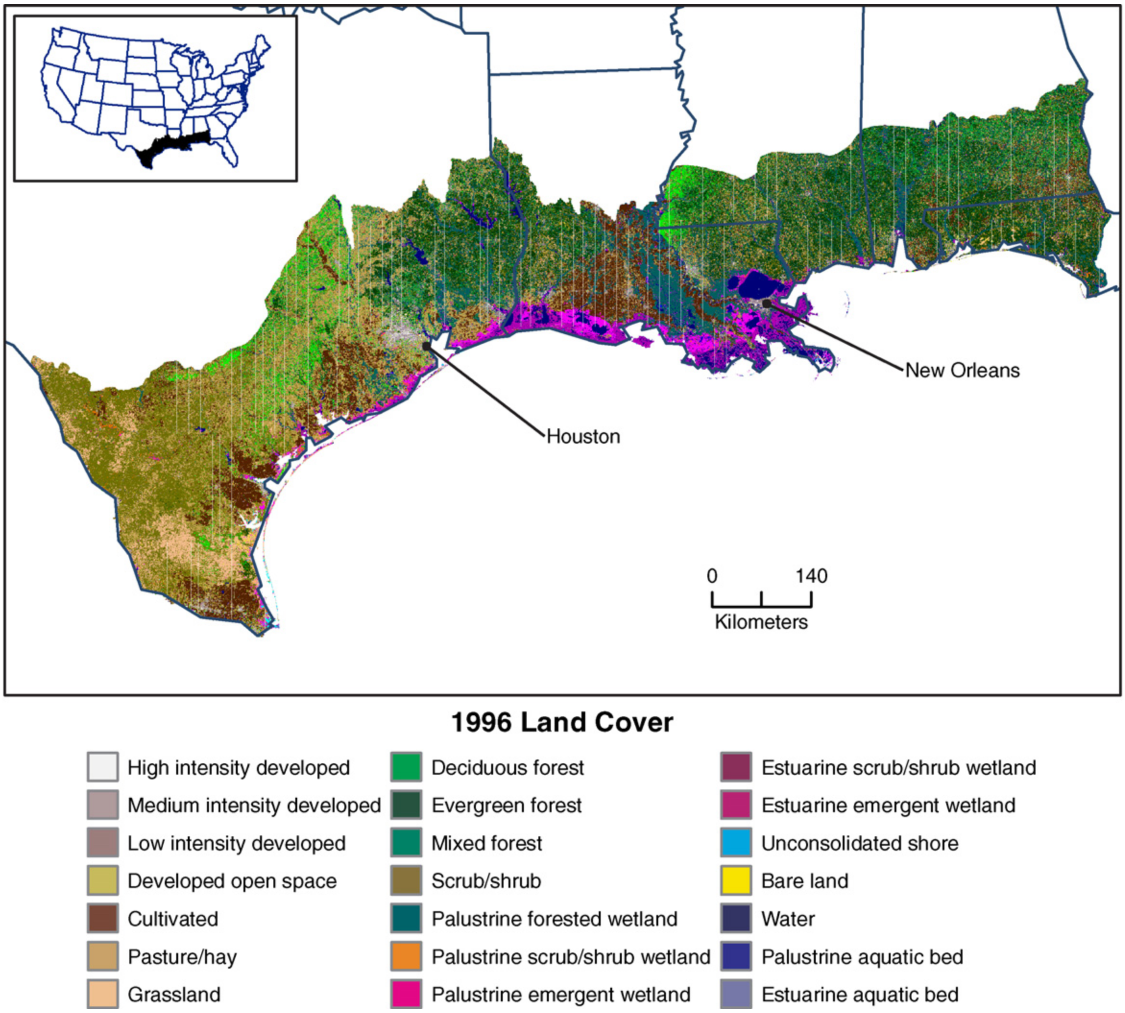

Fig. 1 – The location of the study area is illustrated with the original 21-class land-cover map in 1996. The map contains approximately 399 million pixels.

types in a surrounding 4.41-ha neighborhood. Because those percentages summed to 100%, it was convenient to use a tri-polar chart (Fig. 2) to illustrate the model and to serve as a map legend. Thresholds at the 100, 60 and 10% levels along each axis partitioned the tri-polar space into 19 landscape mosaic categories. The classification of a pixel was obtained by locating that pixel in the tri-polar space according to the observed land-cover percentages in that pixel's neighborhood.

The landscape mosaic map legend (Fig. 2) labeled the 19 mosaic classes by the letters 'A' (or 'a'), 'N' ('n'), and 'D' ('d') that referred to agriculture, natural, and developed, respectively. An upper-case letter was interpreted as 'at least 60% but less than 100%,' a lower-case letter meant 'at least 10% but less than 60%,' and the absence of a letter implied 'less than 10%.' At the three corners of the tri-polar chart, double upper-case letters referred to neighborhoods containing 100% of a generalized land-cover type. To simplify the map legend, we portrayed the 19 landscape mosaic classes by 19 colors (see inset in Fig. 2) where the intensities of the three colors red, green, and blue were proportional to the percentages of the three land-cover types (developed, natural, agriculture, respectively) in a landscape mosaic class. For example, landscape mosaics dominated by agriculture appeared in different shades of blue depending on the presence of developed (more red) or natural (more green) land-cover.

We classified and mapped the landscape mosaic separately for each pixel on the land-cover map, by defining a unique fixed-area neighborhood around each pixel. A moving window algorithm was used to perform the landscape mosaic classification and mapping using square windows of size 7 pixels by 7 pixels (4.41 ha). Application to the land-cover maps from 1996 to 2005 yielded two maps of landscape mosaics at a spatial resolution of 0.09 ha per pixel. When viewed over the entire study area (Fig. 3, top), a landscape mosaic map portrayed regional patterns in land-cover dominance by agriculture (blue), developed (red) and natural (green) land-cover types (compare to Fig. 1). Local detail of landscape mosaics emerged with magnification of a smaller region (Fig. 3, bottom) where it was easier to see the influence of non-dominant land-cover types on landscape mosaic. For example, the influence of the road network appeared as a network of landscape mosaics that contained at least 10% developed

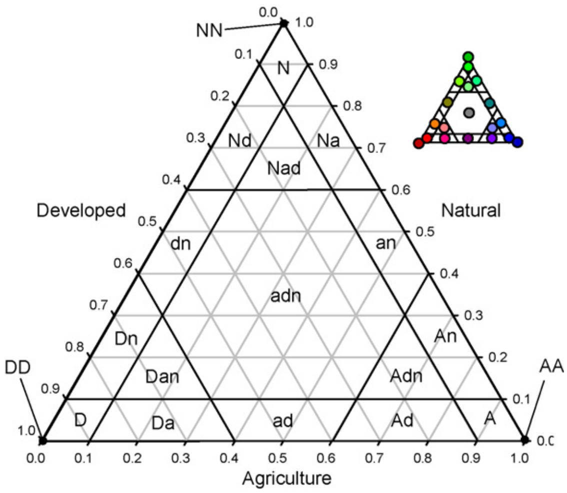

Fig. 2 – Tri-polar chart illustrating the definition of landscape mosaic classes from the proportions of developed, agricultural, and natural land-cover. The inset chart shows the colors used to render maps of landscape mosaics in Fig. 3.

land-cover, set against landscape mosaics characteristic of the larger region not near roads.

The thresholds of 10, 60, and 100% that were used to partition the tri-polar space must be considered to be arbitrary because any classification model is at least partly arbitrary. Our selection of thresholds distinguished between landscape mosaics on the basis of the presence (10% threshold), dominance (60%), and exclusivity (100%) of the three generalized land-cover types. Similar thresholds have long been used for community classification based on species composition. Gagné and Fahrig (2007) classified landscapes based on land-cover composition; they used a 50% threshold to classify 'urban' and 'forested' landscapes, and a 70% threshold to classify 'agricultural' landscapes. One of the motivations for the present study was to see if our heuristic choice of thresholds yielded meaningful results in a modeling framework. If so, that would increase confidence in those thresholds but it would not guarantee that they were optimal.

2.3. *Markov chain models*

We used discrete time, finite-state, homogeneous (stationary) Markov chain models for this study. Suppose that a map legend has s classes and let those classes define the s possible Markov states of a pixel at times $t = 1$ and 2 (here, the years 1996 and 2005). Let $\mathbf{P}$ be a $s \times s$ matrix of transition probabilities (P_{ij}) where column i indicates the 1996 Markov state, row j indicates the 2005 Markov state, and P_{ij} is the probability that a pixel in state i in 1996 was in state j in 2005. Each column of $\mathbf{P}$ sums to unity, and a diagonal element P_{ii} is the probability of no state change for pixels in state i. If $\mathbf{X}_t$ is the $1 \times s$ vector of probabilities that a pixel is in state i at time t, then $\mathbf{X}_{t+1} = \mathbf{P}\mathbf{X}_t$, which is the essential feature of a discrete time, finite state Markov model.

Hill et al. (2004) comprehensively described the properties and analysis of discrete time, finite state, and homogeneous Markov chain models. We used only a few of the possibilities and the reader may refer to Hill et al. (2004) for details and references. The asymptotic, steady-state (equilibrium) probability distribution of $\mathbf{X}_t$, denoted as $\mathbf{X}^*$, was estimated by the dominant eigenvector of $\mathbf{P}$, normalized to sum to unity. The rate of convergence to that asymptote was measured by the damping ratio, $\rho = \lambda_1/|\lambda_2|$, where λ_1 and λ_2 were the first and second eigenvalues of $\mathbf{P}$ and smaller values of ρ indicated slower convergence to $\mathbf{X}^*$. Since each time step equaled 9 years, the expected residence time of a pixel in state i was estimated by turnover time, $\mathbf{T}_i = 9/(1 - P_{ii})$. The entropy of a steady-state column i of $\mathbf{P}$ was $\mathbf{H}_i = -\sum_j (P_{ij} \times \log(P_{ij}))$, the entropy of the Markov chain for all s states in a stationary community was $H(P) = \sum_i (\mathbf{X}_i^* \times \mathbf{H}_i)$, and the normalized [0,1] entropy was $H'(P) = H(P)/\log(1/s)$. Values of $H'(P)$ closer to zero indicated a more deterministic Markov chain and values closer to one indicated a more random Markov chain.

Discrete time, finite-state, homogeneous Markov chain models assumed spatial–temporal stationarity of transition probabilities and we made that assumption as a heuristic device (Baker, 1989) to evaluate the utility of the landscape mosaic indicator for interpreting land-cover dynamics. The steady-state concept implicit in a Markov chain model was scale-dependent (Turner et al., 1993) and we used one measurement scale to illustrate the application of the modeling approach to the landscape mosaic indicator.

To investigate the temporal dynamics of the shifting landscape mosaic, we constructed a 'landscape mosaic' Markov chain model (Model 1) which considered transitions ($\mathbf{P}_1$) of all pixels between the Markov states defined by the 19 landscape mosaics. To investigate the temporal dynamics of forest in relation to landscape mosaic, we constructed a 'forest security' Markov chain model (Model 2) that also considered all pixels in the transition matrix ($\mathbf{P}_2$), but defined the Markov states on the basis of forest versus nonforest land-cover in addition to landscape mosaic. In Model 2, all pixels that were not forest were labeled by a new 'nonforest' Markov state, and the forest pixels (only) were labeled according to the landscape mosaics of those forest pixels. Note that in Model 2, two of the 19 landscape mosaics from Model 1 (AA, DD) were infeasible for a forest pixel, and that a new nonforest Markov state was added, so that $s = 18$ in comparison to $s = 19$ for Model 1.

It was possible to interpret Model 2 as an expansion of a classical 'from–to' land-cover change analysis of a forest/nonforest map. In a classical analysis there would be two possible pixel states (forest, nonforest) and four possible pixel transitions between 1996 and 2005: (1) forest → forest; (2) forest → nonforest; (3) nonforest → forest; (4) nonforest → nonforest. Model 2 expanded the descriptions of the transitions involving forest pixels (transition types 1, 2, and 3) by incorporating their landscape mosaic states at different times. In the transition matrix ($\mathbf{P}_2$) for Model 2, the new nonforest row showed the probability that a forest pixel in 1996 was nonforest in 2005, given its landscape mosaic in 1996 (transition type 2). The new nonforest column showed the probability that a nonforest pixel was converted to a forest pixel as part of a 2005 landscape mosaic (transition type 3). In the square sub-matrix of $\mathbf{P}_2$ that did not include the nonforest row or the nonforest column, the diagonal elements represented the probability of a stable landscape mosaic for a persistent forest

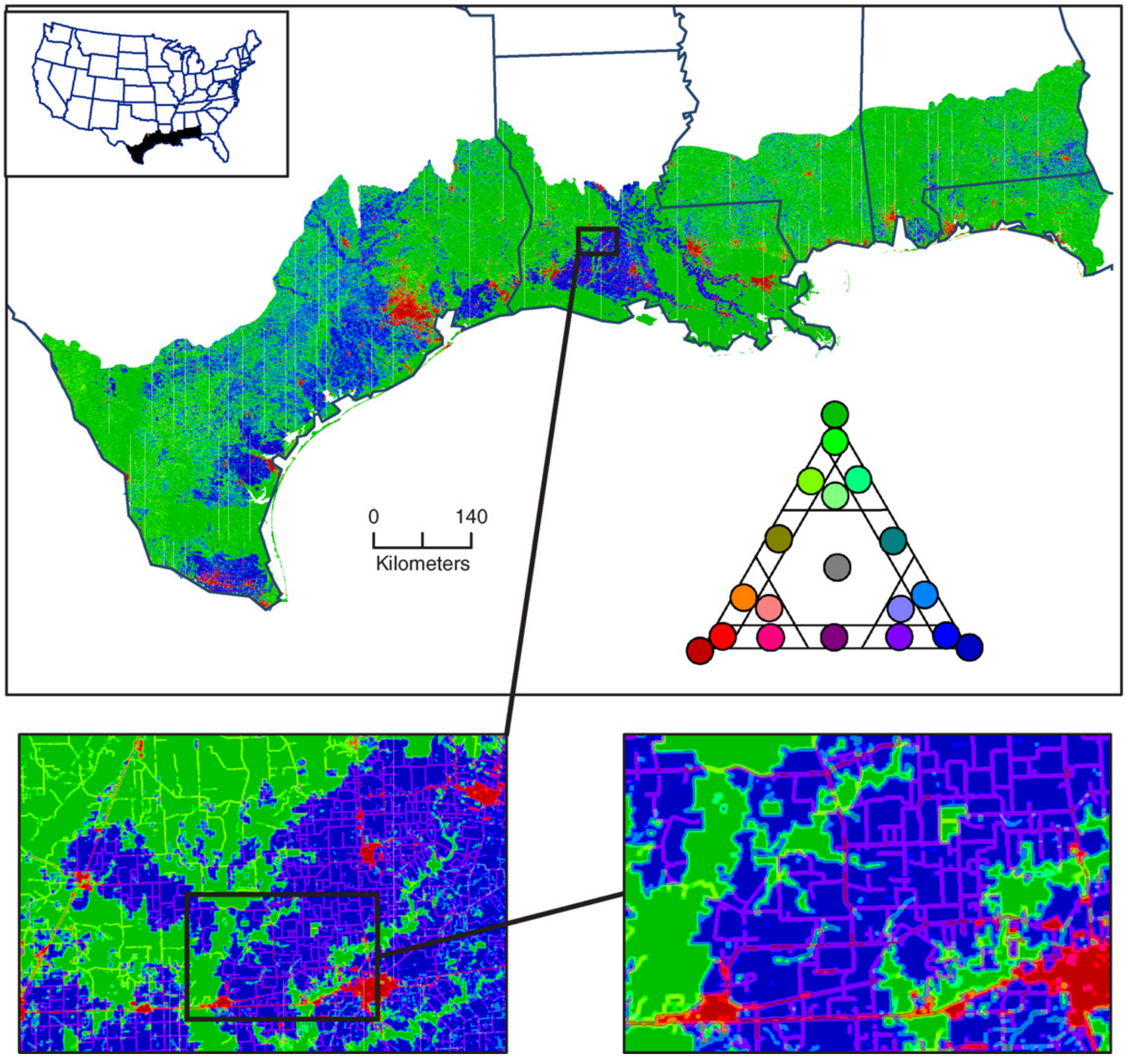

Fig. 3 – The regional distributions of landscape mosaics (top map) mimic the regional distributions of dominant land-cover types (compare to Fig. 1). Magnification of small sub-regions (bottom left and bottom right) makes it possible to see the full range of landscape mosaic classes, many of which are manifest over small areas. See Fig. 2 for definitions of landscape mosaic classes from the inset color chart.

pixel, and the off-diagonal elements represented the probabilities that the landscape mosaic changed for a persistent forest pixel (transition type 1). To estimate $\mathbf{P}_2$, the subset of forest 'gain' pixels was intersected with the 2005 landscape mosaic map to estimate probabilities in the nonforest column, and the subset of forest 'loss' pixels was intersected with 1996 map to estimate probabilities in the nonforest row of $\mathbf{P}_2$. The subset of pixels that was forest at both dates was used to estimate probabilities in the square sub-matrix of $\mathbf{P}_2$ corresponding to the stable (diagonal elements) and shifting (off-diagonal elements) landscape mosaics. The subset of pixels that was nonforest at both dates was used to estimate probabilities the remaining cell of $\mathbf{P}_2$ (transition type 4).

3. Results

Observed land-cover changes from 1996 to 2005 provided background for interpreting the results of the Markov models. Overall, the percentage of agriculture land-cover remained constant at 22.8% while the percentage of developed land-cover increased from 4.5 to 4.9% and the percentage of natural land-cover (including forest) decreased from 72.7 to 72.3%. The 0.4% decrease of natural land-cover included a 4.2% net loss of forest (from 37.0 to 32.8% overall). The gross forest loss was 16.9% of the *forest* area, the gross forest gain was 3.4% of the *nonforest* area, and the net forest loss was 11.2% of the *forest* area.

The transition probabilities for all pixels in the study area from 1996 to 2005 were as shown in Table 1 (Model 1; $\mathbf{P}_1$) and Table 2 (Model 2; $\mathbf{P}_2$). The diagonal elements of both transition matrices were typically large in comparison to the off-diagonal elements, reflecting the fact that only 5.7% of the pixels in the study area experienced a change of landscape mosaic from 1996 to 2005. In general terms, the largest off-diagonal elements in $\mathbf{P}_1$ (Table 1) appeared in rows and columns that were probably indicative of urbanization as the most important land-use change in the region. For example, for the landscape mosaic D in 1996, the probability of change to DD by 2005 was 0.172, and the

Table 1 – The transition matrix P_1 for the 'landscape mosaic' model (Model 1 in text) shows the probability of a pixel transition from 1996 landscape mosaic (columns) to a 2005 landscape mosaic (rows)

2005 Landscape Mosaic	1996 Landscape mosaic																		
	A	D	N	Ad	An	Dn	Da	Na	Nd	Adn	Dan	Nad	ad	an	dn	adn	NN	AA	DD
A	0.936			0.001	0.002			0.001		0.001			0.001	0.002				0.009	
D	0.001	0.825		0.002		**0.077**	**0.099**		0.002	0.002	**0.056**	0.001	0.020		0.014	0.005			
N	0.001		0.876		0.003			0.025	0.002					0.006			0.024	0.001	
Ad	0.005			0.967	0.003		0.001			**0.063**		0.001	0.005			0.004		0.001	
An	0.021		0.002		0.935			0.007		0.002				0.044				0.005	
Dn		0.002	0.001			0.859	0.006		0.008	0.002	**0.130**	0.003	0.002		**0.101**	0.013			
Da		0.001		0.002		0.001	0.717			0.001	**0.066**		0.041			0.005			
Na	0.003		0.035		0.008			0.907				0.001		0.033			0.005	0.001	
Nd			0.039	0.001		0.001		0.002	0.944	0.002		**0.051**			0.003	0.006	0.003		
Adn				0.009	0.005					0.875		0.002		0.001		0.013			
Dan						0.003	0.006			0.001	0.708	0.001	0.002		0.002	0.008			
Nad			0.001	0.001				0.006	0.011	0.003		0.838		0.001		0.010			
ad				0.006			0.001			0.001			0.878			0.008			
an	0.003		0.003		0.016			0.031						0.892		0.001	0.001	0.001	
dn			0.001			0.001			0.024			0.004	0.001		0.851	0.009			
adn			0.001	0.006	0.002		0.001	0.004	0.005	0.045	0.001	**0.096**	0.018	0.012	0.013	0.914			
NN	0.001		0.040		0.002			0.016	0.001					0.004			0.965	0.001	
AA	0.026				0.005		0.001	0.001					0.001	0.001				0.980	
DD	0.001	**0.172**		0.004		**0.058**	**0.168**		0.002	0.002	0.037	0.001	0.032		0.014	0.005			0.998

Bold values indicate off-diagonal values that are larger than 0.05; values less than 0.001 are excluded for readability.

Table 2 – The transition matrix P_2 for the 'forest security' model (Model 2 in text) shows the probability of a pixel transition from 1996 landscape mosaic (columns) to a 2005 landscape mosaic (rows)

2005 Landscape mosaic (forest pixels only)	1996 Landscape mosaic (forest pixels only)																	
	A	D	N	Ad	An	Dn	Da	Na	Nd	Adn	Dan	Nad	ad	an	dn	adn	NN	Nonforest
A	0.782				0.002													
D		0.875		0.001		0.013	**0.200**				0.023		0.027		0.001			
N			0.739		0.001			0.023	0.001					0.003			0.014	0.004
Ad	0.001			0.828						0.009			0.001					
An	0.016				0.793									0.011				
Dn		0.001				0.793	0.011		0.001	0.001	**0.147**		0.002		0.038	0.007		
Da				0.001			0.585				0.013		0.022					
Na	0.001		0.026		0.004			0.803				0.001		0.029			0.002	0.002
Nd			0.022					0.001	0.790			0.042			0.002	0.005	0.001	0.001
Adn				0.016	0.001					0.743						0.002		
Dan						0.001	0.011				0.573		0.001			0.002		
Nad			0.001					0.003	0.006	0.001		0.705				0.011		
ad				0.007			0.001						0.789					
an	0.002				0.017			0.012						0.773				
dn									0.015		0.001	0.003	0.001		0.761	0.014		
adn				0.007	0.001			0.001	0.002	0.033	0.001	0.043	0.018	0.004	0.006	0.748		
NN			0.036					0.011						0.002			0.813	0.026
Nonforest	**0.197**	**0.123**	**0.176**	**0.140**	**0.180**	**0.193**	**0.192**	**0.145**	**0.185**	**0.211**	**0.242**	**0.206**	**0.137**	**0.178**	**0.192**	**0.210**	**0.169**	0.966

All but the last column and last row pertain to forest pixels only. Bold values indicate off-diagonal values that are larger than 0.05; values less than 0.001 are excluded for readability.

combined probability for all other possible changes was only 0.003. In contrast, the off-diagonal elements of $\mathbf{P}_2$ (Table 2) generally indicated that for forest pixels, direct forest loss (i.e., conversion from forest to nonforest) was more much more likely than any change of landscape mosaic between 1996 and 2005. In particular, the entry in the 'nonforest' row of $\mathbf{P}_2$ (Table 2) was larger than the sum of all other off-diagonal elements of the corresponding column, indicating that the probability of a transition from forest to nonforest was higher than the combined probabilities for all possible landscape mosaic changes for persistent forest during that time period. The 'nonforest' column of $\mathbf{P}_2$ showed that if forest was gained between 1996 and 2005, it was almost certain to have appeared in landscape mosaics that were already dominated by natural land-cover types (landscape mosaics NN, N, Na, and Nd).

Considering Model 1 first, approximately 70% of all pixels in the study area resided in a landscape mosaic dominated by natural land-cover types in 1996 and 2005, and another 20% appeared in agriculture-dominated landscape mosaics (Table 3). In the steady-state distribution, 90% of all pixels would reside in the DD landscape mosaic, implying that they would also be in the developed land-cover type. The long-term

Table 3 – Summary of landscape mosaic and forest statistics from Model 1 and Model 2 (see text)

Landscape mosaic	1996[a]	2005[a]	Steady state[a]	Residence time (years)
Model 1—Landscape mosaic				
NN	51.9	50.5	1.0	257
N	7.5	8.1	0.4	72
Na	7.4	7.4	0.4	96
Nd	3.0	3.4	0.8	160
Nad	0.4	0.4	0.1	56
DD	1.1	1.4	90.4	5607
D	0.6	0.6	0.5	52
Da	0.2	0.2	0.1	32
Dn	0.8	0.9	0.5	61
Dan	0.1	0.1	<0.1	31
AA	6.7	6.8	2.4	461
A	3.9	3.9	0.7	140
Ad	1.2	1.2	1.0	275
An	8.2	8.0	0.7	139
Adn	0.5	0.5	0.2	72
ad	0.2	0.2	0.1	74
an	4.4	4.4	0.3	83
dn	0.6	0.6	0.2	61
adn	1.4	1.5	0.5	104
Landscape mosaic that contains forest	**1996[a]**	**2005[a]**	**Steady state[a]**	**Residence time (years)**
Model 2—Forest security				
NN	28.2	24.7	11.9	48
N	3.7	3.4	2.0	34
Na	2.8	2.5	1.3	46
Nd	1.0	1.0	0.8	43
Nad	0.1	0.1	<0.1	31
D	<0.1	<0.1	<0.1	72
Da	<0.1	<0.1	<0.1	22
Dn	0.1	0.1	<0.1	43
Dan	<0.1	<0.1	<0.1	21
A	<0.1	<0.1	<0.1	41
Ad	<0.1	<0.1	<0.1	52
An	0.2	0.2	<0.1	43
Adn	<0.1	<0.1	<0.1	35
ad	<0.1	<0.1	<0.1	43
an	0.6	0.5	0.3	40
dn	0.1	0.1	0.1	38
adn	0.1	0.1	0.1	36
Nonforest	63.0	67.2	83.4	268

The percent of total area in each landscape mosaic class is as observed in 1996 and 2005, and as predicted for a steady-state equilibrium. Residence time is the expected time that a pixel will remain in the indicated landscape mosaic class. Note that for Model 2, the 'DD' and 'AA' landscape mosaics are not applicable, and that for Model 1 the 'nonforest' entry is not applicable (see text for explanation).
[a] Percent of total study area.

Table 4 – Summary of the distributions of existing forest area among landscape mosaic classes as observed in 1996 and 2005, and as predicted by Model 2 (see text) at steady-state equilibrium

Landscape mosaic that contains forest	1996[a]	2005[a]	Steady state[a]
NN	76.4	75.3	72.0
N	9.9	10.4	11.8
Na	7.5	7.7	7.7
Nd	2.8	3.1	4.7
Nad	0.3	0.3	0.5
D	<0.1	<0.1	0.1
Da	<0.1	<0.1	<0.1
Dn	0.2	0.2	0.2
Dan	<0.1	<0.1	<0.1
A	<0.1	<0.1	<0.1
Ad	<0.1	<0.1	<0.1
An	0.6	0.6	0.4
Adn	<0.1	<0.1	<0.1
ad	<0.1	<0.1	<0.1
an	1.6	1.6	1.5
dn	0.4	0.4	0.6
adn	0.3	0.4	0.5

The values differ from those shown in Table 3 because the percentages here are of total forest area rather than of total area.
[a] Percent of total forest area.

transition from dominance by natural and agricultural to developed landscape mosaics was additional evidence that urbanization was the dominant land-use trend between 1996 and 2005. Typical expected residence times were highest in the landscape mosaics that were exclusively developed (DD; 5607 years), agriculture (AA; 461 years), or natural (NN; 257 years). In contrast, residence times ranged from 31 to 61 years in landscape mosaics that were not all developed but that contained at least 60% developed land-cover in 1996 (D, Da, Dn, Dan). Overall, the percentage of pixels in the all developed (DD) landscape mosaic was not large in 1996 (1.1% of total area), but it increased by approximately 25%, to 1.4% of total area by 2005. The rate of convergence (ρ) for Model 1 was 1.01 and the normalized entropy ($H'(P)$) was 0.015.

For Model 2, 28.2% of all pixels were forest and resided in an exclusively natural (NN) landscape mosaic in 1996 and that percentage decreased to 24.7% by 2005 (Table 3). The remaining forest pixels were found mainly in the four other landscape mosaics dominated by natural land-cover (N, Na, Nd, Nad) at both dates. Relatively small percentages of total area consisted of forest land-cover in the other landscape mosaics, and the nonforest pixels comprised 63.0 and 67.2% of total area in 1996 and 2005, respectively. In the steady-state distribution for Model 2 (Table 3), forest area decreased by 16.2% of total area after 2005 (as nonforest increased from 67.2 to 83.4%). Most of the expected residence times for forest in a given mosaic (Model 2) were shorter than for all land-cover types in that mosaic (Model 1), implying that a landscape mosaic was more likely to change for a forest pixel than for a nonforest pixel. For Model 2, the rate of convergence (ρ) was 1.14, which implied a faster convergence rate than was obtained for Model 1. The normalized entropy ($H'(P)$) was 0.086, which implied a less deterministic Markov chain in comparison to Model 1, yet the normalized entropy values for both models were relatively small in comparison to a value of 1.000 that would be obtained for a completely random Markov chain.

Another perspective of the dynamics of forest in relation to landscape mosaic was obtained by expressing the distributions of forest area in 1996, 2005, and at steady-state (Model 2) as percentages of total forest area at each time (Table 4) instead of as percentages of total area (Table 3). That enabled comparisons of forest distribution among landscape mosaic classes without confounding by the differences in total forest area over time. There was not much change in the distributions of forest among landscape mosaics from 1996 to 2005, and even as the overall percentage of forest in the study area decreased by 48% (from 33 to 17%) at steady-state, forest remained concentrated in the five landscape mosaics dominated by natural land-cover types (NN, N, Na, Nd, Nad).

4. Discussion

In recent decades, urbanization has been the dominant process affecting land-cover change in the study area. That process was evident not only in the observed transition matrix for Model 1 (Table 1) but also in the steady-state distribution of landscape mosaics (Table 3) which indicated that urbanization will lead eventually to an almost completely developed study region with at least 90% developed land-cover. Of course, it was not really expected that 90% of the study area would be so converted in the real world, if only because of biophysical and legal constraints on land development. Nevertheless, confidence in the Markov chain model increased because the landscape mosaic transitions were robust to a known process and yielded logical results in the long term.

Forest security (Model 2) presented a much more interesting set of dynamics to interpret in relation to landscape mosaic. The nonforest column in Table 2 indicated that the overall probability of forest gain (conversion from nonforest to forest) was approximately 0.03 for a nonforest pixel, and that forest gains were almost certain to have occurred as transitions to the landscape mosaics that were already dominated by natural land-cover types. That pattern of forest gain was plausibly a result of silvicultural processes of forest regeneration following harvest of relatively small forest tracts embedded within larger forest tracts. In contrast, the probability of forest loss (conversion from forest to nonforest; the nonforest row in Table 2) was between 0.123 and 0.242 depending on landscape mosaic in 1996. The highest rates (>0.200) of forest loss occurred in the most heterogeneous landscape mosaics (Dan, Adn, Nad, adn).

The interpretation of forest security was relatively simple in this example. Apart from silvicultural operations, forest dynamics were driven mainly by direct forest loss, probably resulting mainly from urbanization. The forest that did persist over time was likely to occur in roughly the same proportions across landscape mosaics as it did in 2005, only there would be less of it. Short-term forest security was lowest in relatively heterogeneous landscape mosaics that probably represent transition zones ('interfaces') between undeveloped and developed portions of the region, and forest loss in those zones was likely an indication that the urbanization process was proceeding across the landscape. For the (rare) forest pixel that persisted after urbanization occurred around it, long-term security became relatively high, probably because it became part of a green infrastructure that was either preserved (e.g., parks) or not suitable for development (e.g., riparian forest) within highly developed landscape mosaics.

There was an apparent conflict between the steady-state distributions of Model 1 and Model 2 that may be interpreted as a tension between landscape-level and pixel-level land-cover dynamics. The conflict arose because at steady state, Model 1 indicated that 90% of the study area would be developed land-cover, while Model 2 indicated that 17% of the study area would be forest land-cover. Furthermore, the entropies of both Markov chains were so low that there was not much doubt about either steady-state condition. The key to resolving that conflict was to note that while both conditions could not be true at the same time, they could both be true at *different times*. A comparison of the convergence rates indicated that steady-state was reached ten times faster for Model 2 than for Model 1. Thus, it would be feasible to achieve the Model 2 steady-state, but that steady-state would not be sustained when the Model 1 steady-state was reached later. In real-world terms, the conflict arose because it would not be possible to continue to gain forest in mostly natural landscapes (Model 2) if there were no mostly natural landscapes (Model 1). In other words, forest security ultimately depended on landscape-level land-cover dynamics and not on pixel-level forest dynamics.

That comparison of model results was justified because the two models used exactly the same data, and therefore, any differences in the results could be attributed to differences in the models. Since Model 1 was a landscape mosaic model and Model 2 was a combined forest land-cover and landscape mosaic model, it was natural to interpret the observed differences in terms of either a landscape perspective or a forest sector perspective on land-cover dynamics. Recognizing difficulties inherent in comparing model results, the comparison of the steady-state distributions was probably the least contentious comparison that could have been made. The subsequent examination of convergence rates was to explain the conflict between the steady-state distributions of the two models. However, the conceptual resolution of the conflict was not the same as an analytical resolution which would require linking the two models together. For example, the temporal dynamics of forest pixels (Model 2) might have been expected to have proceeded at a faster rate (and, as a result, to have converged sooner) than the dynamics of landscape mosaics for all pixels (Model 1) because a Markov state transition could have been produced by a forest to nonforest change to only one pixel, whereas a state transition in Model 1 typically required changes to more than one pixel to change the landscape mosaic. Analytical linkage of pixel- and landscape-level dynamics using Markov models remained an interesting question for future research.

The simple modeling framework that we used could be easily adapted to other circumstances and assumptions. For example, the spatial scale of the landscape-level analysis was defined by the size of the neighborhood that was used to evaluate the landscape mosaic indicator. That spatial scale could be purposefully selected to 'tune' the analysis. Larger neighborhood sizes would be more sensitive to lower (spatial) frequency variance of landscape mosaics, and smaller sizes would be more sensitive to higher frequency variance. Our choice of neighborhood size was based on the requirements that it had to be sufficiently large to reliably measure landscape mosaic, and sufficiently small to capture relatively rare and high frequency land-cover changes. Preliminary analyses suggested that a longer time series of land-cover data or more land-cover change during the same time period was needed to usefully employ larger neighborhood sizes. The definition of landscape mosaic could also be changed by re-partitioning the tri-polar space to either ignore or highlight different aspects of what could be considered to be a continuous landscape mosaic. Focal land-cover classes other than forest could be examined, either alone using Model 2, or together using a complete enumeration of the 399 Markov states obtained by intersecting all 21 land-cover classes with 19 landscape mosaic classes. In summary, by demonstrating that land-cover changes could be interpreted in terms of landscape mosaic changes, this study laid part of the foundation for using landscape mosaic as a composition indicator in large-area land-cover pattern assessments.

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