Accuracy Assessment for a Simulation Model of Amazonian Deforestation

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This article describes a quantitative assessment of the output from the Behavioral Landscape Model (BLM), which has been developed to simulate the spatial pattern of deforestation (i.e. forest fragmentation) in the Amazon basin in a manner consistent with human behavior. The assessment consists of eighteen runs for a section of the Transamazon Highway in the lower basin, where the BLM's simulated deforestation map for each run is compared to a reference map of 1999. The BLM simulates the transition from forest to non-forest in a spatially explicit manner in 20-m × 20-m pixels. The pixels are nested within a hierarchical stratification structure of household lots within larger development rectangles that emanate from the Transamazon Highway. Each of the eighteen runs derives from a unique combination of three model parameters. We have derived novel methods of assessment to consider (1) the nested stratification structure, (2) multiple resolutions, (3) a simpler model that predicts deforestation near the highway, (4) a null model that predicts forest persistence, and (5) a uniform model that has accuracy equal to the expected accuracy of a random spatial allocation. Results show that the model's specification of the overall quantity of non-forest is the most important factor that constrains and correlates with accuracy. A large source of location agreement is the BLM's assumption that deforestation within household lots occurs near roads. A large source of location disagreement is the BLM's less than perfect ability to simulate the proportion of deforestation by household lot. This article discusses implications of these results in the context of land change science and dynamic simulation modeling. *Key Words: behavioral landscape model, change, land, pattern, scale.*

Deforestation in the Amazon basin demonstrates one of the most important ways that humans transform landscapes. The implications of such land changes are enormous and varied (Myers 1980; Ojima, Galvin, and Turner 1994; Gutman et al. 2004). They include consequences that are important to social stability (Schmink and Wood 1992; Simmons 2004), economic structure (Hecht and Cockburn 1990; Walker and Homma 1996; Pfaff 1999), national security (Hecht and Cockburn 1990; Schmink and Wood 1992), climate change (Fearnside 1996; Labraga 1997), water quality (Boischio and Henshel 2000), species extinctions (Vandermeer and Perfecto 1995), and even mercury exposure (Boischio and Henshel 2000). Therefore, there are numerous reasons why it is important for geographers to understand and to explain the processes of land change in the Amazon basin.

Eugenio Arima and Marcellus Caldas were affiliated with Michigan State University during the time the work reported in this article was done.

The Modeling Approach

There could be an infinite number of possible explanations for Amazonian deforestation, depending in part on the philosophical orientation of the geographer. Therefore, it is important for geographers to have methods to distinguish those explanations that have weaker explanatory power from those that have stronger explanatory power. One way to design such a method is to express the explanations in terms of quantitative models, then to measure the explanatory power of the models vis-à-vis reference data. This article takes such an approach.

To date, modeling in the Amazon Basin has been mostly of an econometric nature, similar to Pfaff (1999) who attempted to explain county-level deforestation with regression models. This approach has been followed by others such as Andersen et al. (2002). More recently, hierarchical models have been employed as well, and interest has intensified from aggregate measures of deforestation to spatial pattern (Pan et al. 2004). Predictive modeling has been less frequently applied, and

Annals of the Association of American Geographers, 97(4), 2007, pp. 677–695
Initial submissions, February 2006; revised submissions, September and October 2006; final acceptance, October 2006
Published by Blackwell Publishing, 350 Main Street, Malden, MA 02148, and 9600 Garsington Road, Oxford OX4 2DQ, U.K.

includes efforts addressing smallholder behavior (e.g., Dale et al. 1994; Walker 2003) as well as approaches using agent-based simulations (Evans et al. 2001; Deadman et al. 2004). The Behavioral Landscape Model (BLM) extends the agent-informed household models to landscapes beyond the lot of an individual farm (Walker et al. 2004). The BLM is the model that this article assesses, as applied to a section of the Transamazon Highway (BR-230) in the state of Pará, Brazil.

The BLM focuses on processes that explain the quantity, location, and pattern of deforestation. Many geographers are familiar with the fishbone pattern of deforestation as seen via remote sensing from above parts of Pará and Rondônia (highways BR-230 and BR 364, respectively). For this article's application, the "spine" of the fish is the Transamazon highway (BR-230) and the bones are the secondary roads that extend from and perpendicular to the highway. Settlers are the proximate agents of deforestation. Many of these settlers are following the official plans for settlement designed by the government. The plans call for the immigrants to settle in a landscape that is stratified by large development rectangles, so-called *glebas*, situated along the highway and secondary roads (Figure 1). The main highway runs generally east and west through the middle of Figure 1. Each secondary road has one large development rectangle to its east and one to its west, thus the secondary roads are situated between pairs of development rectangles that run generally north and south. These large development rectangles are substratified in 100-ha lots (Figure 2). Typically, each family occupies a lot—that is, a substratum. One of the family's first activities on a lot is usually to convert some of the land near the road from forest to non-forest to stake a claim and to begin agriculture (Walker 2003).

The BLM is an expression of our empirical, theoretical, and conceptual understanding of the land transformation process. The BLM simulates the process by assigning stochastically a proportion of deforestation to each substratum, then placing the specified amount of simulated deforestation in pixels that are as close as possible to the road within each substratum. The smallest areal units in the analysis are 20-m $\times$ 20-m pixels nested within the substrata. Three parameters determine the statistical distribution from which the proportion of deforestation per substratum is selected randomly. Therefore, each run of the BLM generates a different simulated map that has a different quantity and

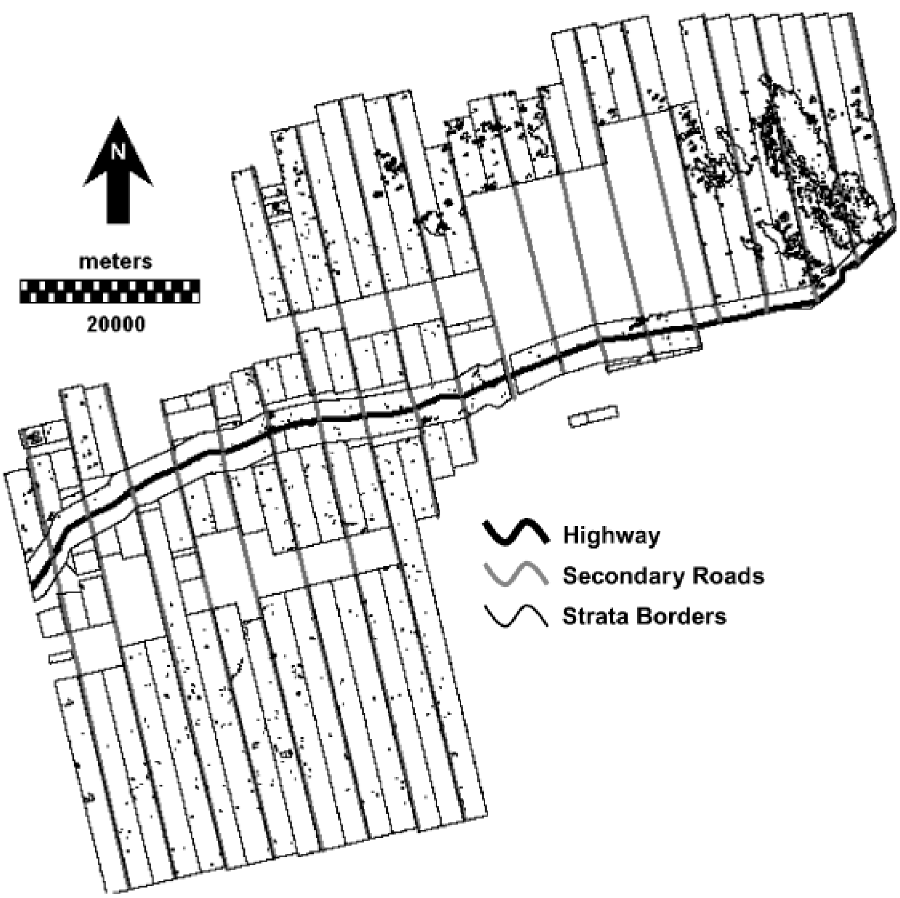

Figure 1. Large development rectangles (i.e., strata) of the Uruará study area where the irregular patches are clouds and shadows that are masked from the analysis.

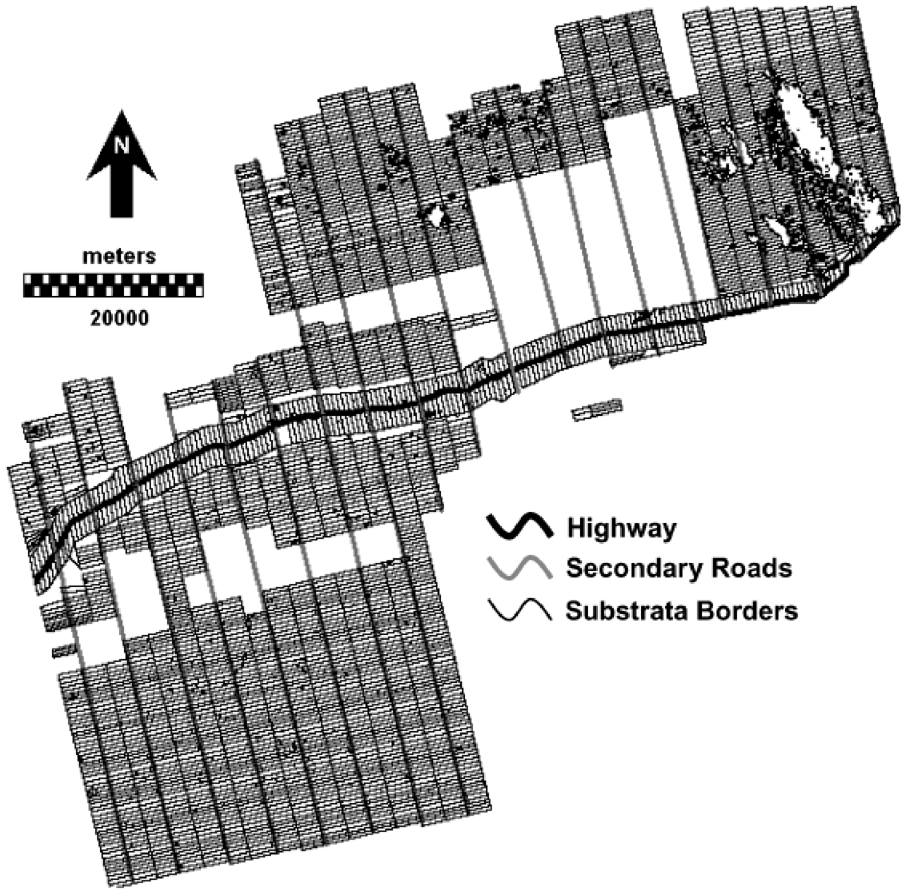

Figure 2. Household lots (i.e., substrata) of the Uruará study area where the irregular patches are clouds and shadows that are masked from the analysis.

location of non-forest, depending on the particular run's parameters and the random selection. Substrata closer to the highway have a larger probability of having a higher proportion of deforestation than those substrata farther from the highway, according to the BLM. The Methods section gives more details of the BLM.

Purpose of Model Assessment

A primary goal of this article is to measure the consistency between empirical observations and the model's resulting expression of the land transformation process; therefore we compare reference data to the model's outputs. Such an exercise is useful if it enables learning. An intelligently designed assessment exposes information concerning a variety of important issues because there are several reasons why the output from any particular run of a simulation model would have some level of agreement and some level of disagreement with reference data. These reasons range from the conceptual to the technical. In the context of land change modeling, the reasons include (1) the stability of the land transformation process, (2) the modeler's understanding of the land transformation process, (3) the compatibility among scales of the various components of the analysis, (4) the simplification of the model's assumptions, (5) the translation of the model's concepts to mathematics and computer code, (6) the model's stochasticity, (7) the accuracy of the input data, and (8) the accuracy of the reference data. No single assessment procedure can tackle all of these aspects simultaneously.

This article's assessment focuses on those aspects that can be measured quantitatively by comparing the reference map to maps from the BLM simulation runs. Even with this restriction, there are an infinite number of ways to approach this type of assessment because there are an infinite number of ways to compare maps. Some measurements of map comparisons can be useful; many are not.

A useful measurement communicates clearly the reasons for the levels of both agreement and disagreement between the reference map and model's simulation maps. For the assessment exercise to accomplish this, it must compare the maps in a manner that relates to both the land transformation process and the model. For example, the nested stratification structure is an important aspect of both the Amazonian land transformation process and the BLM; therefore the assessment procedure should express the results in a manner that is meaningful in terms of the nested stratification structure. The pixels are an aspect of the BLM because pixels are the format of the reference data, and the BLM simulation adopts this format. However, pixels are not an important aspect of the land transformation process because humans do not manage landscapes in terms of pixels. Pixels are an artifact of the computer technology that stores the data. Therefore a useful assessment process should compare the maps in a manner that is insensitive to this artifact of the data format.

This article presents an approach to assessment that addresses five important issues. First, this article expresses components of agreement and disagreement in terms of hierarchical concepts that are relevant to both the land transformation process and the land transformation model. Second, the approach examines the consequences of variation in three important model parameters in order to show which parameters are relatively influential. Third, the procedure compares the model results to three other simpler models, in order to quantify the added value, if any, of the BLM's complexity. Fourth, the procedure compares the maps at multiple resolutions in order to examine the distances over which location disagreements occur and to test the sensitivity of the assessment to variation in the resolution of the pixels. Fifth, the approach presents each measurement in a graphical manner that is intellectually accessible to a nonmathematical audience, even while some of the underlying mathematics are nontrivial. An assessment should have these characteristics so that readers can grasp the most important aspects of the model's performance and so that researchers can establish the next most important steps in the research agenda, which is what this article does.

Methods

Data

The BLM is based on three types of data including a cadastral coverage of individual holdings, a map of land cover, and information from interviews with agents of change. This subsection describes each in sequence.

Figure 2 shows the cadastral coverage for colonization in the vicinity of Uruará, a small town on the Transamazon Highway (BR-230) in the lower Amazon basin. This coverage derives from the early years of colonization in the 1970s, but still represents the appropriate delineation of present property boundaries given the long-run inertia in the settlement scheme.

Figure 3 shows the reference map of land cover for 1999 in terms of 20-m × 20-m pixels, where each pixel is classified as either forest or non-forest. In order to produce this map, four Landsat ETM+scenes were preprocessed for atmospheric effects, mosaicked, and initially classified into forty unsupervised ISODATA classes. These classes were then grouped according to mean spectral signatures into: forest, non-forest, mixed forest/non-forest, water, cloud, and shadow. A histogram slice was performed on the mixed pixels to reclassify them as forest or non-forest. The no-data category was created as the union of water, clouds, shadows, and some rectangular patches that are not part of the smallholder settlement process that the BLM simulates. Ultimately, the final land cover map shows three categories: forest, non-forest, and no data. Accuracy of classifications such as these is usually around 70–80 percent at the pixel-level scale (Mausel et al. 1993; Lambin 1997; McCracken et al. 1999). We did not undertake rigorous quantitative accuracy assessment, and instead relied on our prior knowledge about the location of forested and deforested areas to conclude that the classification was consistent with our ground-based knowledge. The lot boundary layer was georegistered to the image using the Transamazon highway as reference by first-order datum translation and found to be within two pixels. The extent of the lot boundaries was used to clip the mosaicked images to generate the base map. The original 30-m pixels were converted to 20-m pixels so that there would be 2,500 pixels in each 100-ha plot, which facilitates simulation modeling.

Walker, Moran, and Anselin (2000) and Walker, Perz, et al. (2002) conducted interviews in 1993 and 1996 with agents of deforestation, specifically smallholders who had colonized the area. The 1993 survey was a pilot study, followed up three years later with a concentrated effort to collect data on 261 smallholder properties. Walker, Perz, et al. (2002) and Caldas et al. (2007) give details concerning the sample. The agents interviewed were subsistence-oriented farmers growing both food and commercial crops, and maintaining small cattle herds (Walker 2003). The focus of both the surveys and the BLM modeling framework is on small-scale agriculture, not large commercial operations. Large operations are obviously important to the rate of deforestation, but land use decisions of largeholders are different from those of subsistence-oriented households (Walker 2003). The large properties found in the study region are masked in the cadastral and model output, where they appear as rectangular patches of no data (Aldrich et al. 2006).

Figure 3. Reference map with 26 percent deforestation.

One hundred hectares is the size of each substratum (i.e., lot), which is the land unit originally designated for occupation by individual families by Brazil's colonization agency (INCRA). Some land consolidation has occurred, yielding an average lot size of 133 ha (Caldas et al. 2007). Nevertheless, more than 80 percent of the lots remained 100-ha properties in 1996, and changes in size of holdings were negligible as of 2002 (Aldrich et al. 2006). Settlers may obtain second lots in undisturbed forest as investments for children. These lots are not farmed until the children mature and begin their own activities. Thus, most active agriculture practiced by the smallholder population occurs on 100-ha holdings. In 1996, the household head was typically male with an average age of 49 years. At that time, properties had been occupied for about fourteen years. These properties were occupied by owners and usually had one family in residence (the average number of families in residence was 1.3 per property). Deforestation rates in the 1990s averaged about 1 ha per year on individual holdings (Walker, Wood, et al. 2002), although rates can be appreciably more in some cases (Walker et al. 1997).

Behavioral Landscape Model Simulation Runs

The BLM simulates incremental deforestation for each year and ultimately produces a map of total cumulative deforestation. The initial year of the simulation is 1974, the approximate time that the actual deforestation process began, and the final year is 1999, the year of the reference data. Therefore, there are twenty-five iterations of the annual time step in the simulation. At each iteration, the BLM simulates at most one deforestation event in each lot, where a deforestation event is defined as the conversion of a cluster of pixels from forest to non-forest within a 100-ha household lot. The cluster of pixels is located as close as possible to the adjacent road. The BLM does not simulate conversion of non-forest to forest because its purpose is to examine the loss of primary forest. As time progresses, deforestation events are allowed to occur in lots that are farther from the main highway. The final simulated deforestation map shows the pixels that have experienced deforestation during the course of the simulation.

The BLM simulates the amount of additional deforestation at each time step within each household lot as a random variable. The distribution of the random

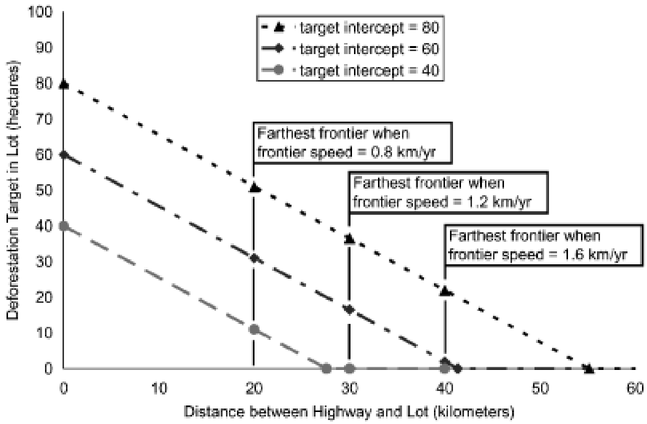

Figure 4. Deforestation target versus distance to highway for three levels of target intercept. The three vertical lines show the farthest extent of the deforestation frontier when the simulation runs for twenty-five years for three levels of frontier speed.

variable is dictated by three parameters: (1) target intercept, (2) frontier speed, and (3) maximum duration (Walker et al. 2004).

The target intercept parameter determines the targeted total cumulative quantity of simulated deforestation, where higher parameter values correspond to higher targeted amounts of simulated deforestation. The simulated deforestation target in each lot is the quantity of deforestation that the simulation would produce if it were allowed to run for a sufficient number of time iterations. It is common for the simulation to reach its final year before the target is attained, in which case the total quantity of simulated deforestation is less than the target. The target intercept parameter is the y-intercept of a negatively-sloped linear relationship between the simulated deforestation target in a lot and the distance between the main highway and the lot (Figure 4); thus, the units of the target intercept parameter are hectares of non-forest per lot. Each lot is assigned a simulated deforestation target based on the linear relationship plus a normally distributed error term. The negative slope of the linear relationship is based on regression analysis using the 1999 lot-level reference data, which shows that lots closer to the main highway have larger amounts of cumulative deforestation in 1999 (Walker, Perz, et al. 2002). The 1999 data help to parameterize the regression component of the model and also serve as reference data to assess the model's output maps; therefore we use the word "simulation" rather than "prediction" to describe the BLM (Pontius, Huffaker, and Denman 2004; Pontius and Pacheco 2004). The BLM uses the reference data to help to determine a single overall general linear relationship for the entire study area. This model is less likely than more elaborate algorithms (e.g., neural networks) to become over fit to the reference data because the BLM uses only three parameters and lacks automated iterative procedures to determine nonlinear relationships for the values of spatially-explicit parameters at fine scales within the study area. This article tests for sensitivity to the target intercept parameter by examining three levels of it: 40, 60, and 80. The simulated deforestation approaches the target gradually over time. The other two parameters control how gradually the simulated deforestation process occurs.

The frontier speed parameter (i.e. the speed of the frontier advance) dictates how quickly the frontier of simulated deforestation recedes from the main highway. Higher parameter values allow deforestation to spread more quickly farther from the main highway into the forest. Specifically, the frontier speed parameter is the annual increase in number of kilometers between the main highway and the frontier of allowed simulated deforestation. Empirically, this reflects the sequential nature of land occupation, in that latecomers must move beyond already settled land to find a vacant lot, thereby advancing the agricultural frontier. As soon as a lot is between the frontier and the highway, the lot begins its simulated deforestation process in annual events in order to approach its target. Consequently, larger parameter values result in higher amounts of total cumulative simulated deforestation because larger values allow distant lots to begin the deforestation process earlier in the simulation, so those lots can reach their deforestation targets before the end of the simulation. If the simulation ends before the frontier reaches a particular lot, then that lot never attains its deforestation target. For example, Figure 4 shows that if the number of simulated years is 25 and the frontier speed is 0.8 km per year, then lots that are farther than 20 km from the highway never have an opportunity to begin the simulated deforestation process. This article tests for sensitivity to the frontier speed parameter by examining three levels of it: 0.8, 1.2, and 1.6.

The maximum duration parameter is the other parameter that influences how fast the simulated deforestation process occurs because it dictates the number of years between the beginning and the completion of the simulated deforestation process in a lot, so it is equal to the number of deforestation events during the simulation (Walker 2003). Lower parameter values result in deforestation target being attained faster. Specifically, the maximum duration parameter is the maximum number of years required for a lot to attain its deforestation target, after the lot's deforestation process begins. The simulated deforestation begins in the year that the frontier reaches the lot and accumulates annually until the deforestation target is attained. The simulated number of years for any particular lot is selected from a uniform distribution between one and the maximum duration parameter. The amount of additional deforestation per year in each lot is the deforestation target in each lot divided by the randomly selected number of years in each lot. If the simulation ends before the deforestation target is attained, then the total cumulative simulated deforestation will be less than the target. Consequently, higher maximum duration parameter values are associated with slightly lower amounts of cumulative deforestation. Survey data serve to guide the choice of values for the number of years for the deforestation process in a typical lot (Walker et al. 1997; Walker 2003). This article tests for sensitivity to the maximum duration parameter by examining two levels of it: 6 and 3.

We analyze eighteen model runs, where each run has a unique combination of the three parameters. There are three levels of target intercept, three levels of frontier speed, and two levels of maximum duration. Therefore, the number of runs is equal to the number of combinations of these parameters, which is $3 \times 3 \times 2 = 18$. Figure 5 shows the run that simulates the smallest quantity of non-forest, Figure 6 shows the run that simulates the most accurate quantity of non-forest, and Figure 7 shows the run that simulates the largest quantity of non-forest.

Figure 8 summarizes the eighteen runs of the BLM. The vertical axis is the percentage of the study area and the horizontal axis shows the parameter combination, while each bar represents one of the simulation runs. The bars are ordered along the horizontal axis according to first the target intercept parameter, then the frontier speed parameter, and finally the maximum duration parameter. This ordering leads to a nearly perfect sequence of increasing percent of simulated non-forest. Each bar is a vertical Venn diagram where the union of the bottom two segments is the non-forest area in the reference map, the union of the top two segments is the non-forest area in the simulation map, and the intersection in the middle segment is the agreement between the reference non-forest and simulated non-forest. Thus the middle segment is the deforestation that the BLM run simulates correctly, while the other two segments are error. The Results section describes the statistics that derive from Figure 8.

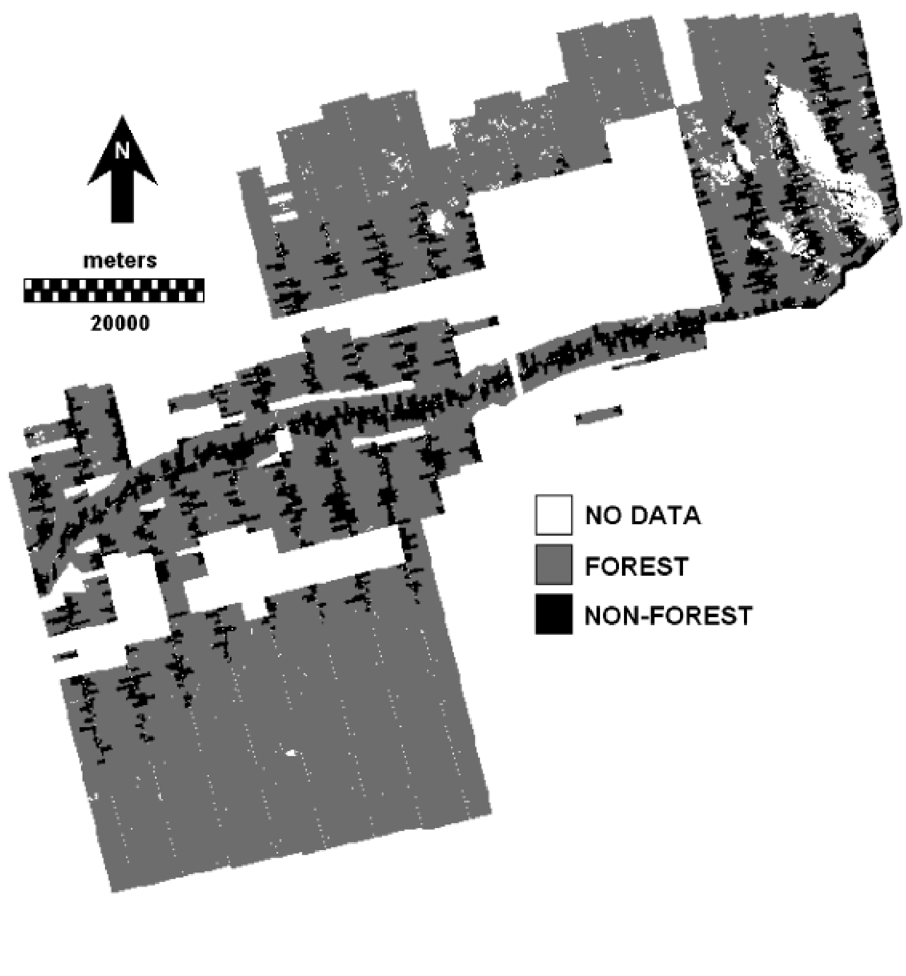

Figure 5. Behavioral Landscape Model (BLM) simulation map with 15 percent deforestation that results when target intercept = 40, frontier speed = 0.6, and maximum duration = 6.

Figure 6. Behavioral Landscape Model (BLM) simulation map with 24 percent deforestation that results when target intercept = 60, frontier speed = 0.8, and maximum duration = 3.

Mathematical Notation

This subsection gives the mathematical notation that this article uses to compare the reference map (R) to a BLM simulation map (S), where the 100-ha household lots are the substrata, which are nested within larger strata. The notation is general, so it applies to other cases where a scientist needs to compare two maps that share a categorical variable while taking into consideration a nested stratification structure, such as towns within counties within states. It follows the notation of Pontius (2000, 2002) and Pontius and Suedmeyer (2004). Let us define the following:

d = index for a stratum = 1, . . . , D
D = number of strata = 43
e = index for a substratum in stratum d = 1, . . . , Ed
Ed = number of substrata in stratum d
n = index for a pixel within substratum e in stratum d = 1, . . . , Nde
Nde = number of pixels within substratum e in stratum d
j = index for a category = 1, . . . , J
J = number of categories = 2
$Rdenj$ = membership to category j for pixel n within substratum e in stratum d of map R
$Sdenj$ = membership to category j for pixel n within substratum e in stratum d of map S.

For this article's case study, there are two categories: forest ($j = 1$) and non-forest ($j = 2$). Each $Rdenj$ and each $Sdenj$ is either 0 or 1 because each pixel of each map has complete membership to exactly one category for the 20-m resolution data. Equations (1), (2), and (3) use dot notation to denote the proportion membership to category j at the level of the substrata, strata, and study area, respectively, for the reference map (R). A dot replaces a subscript at the position that indicates the level of averaging. For example, Equation (1) shows that $Rde \bullet j$ denotes the average membership to category j for substratum e in stratum d for map R. Specifically,

$$Rde \bullet j = \frac{\sum_{n=1}^{Nde} Rdenj}{\sum_{n=1}^{Nde} 1} \tag{1}$$

$$Rd \bullet \bullet j = \frac{\sum_{e=1}^{Ed} \sum_{n=1}^{Nde} Rdenj}{\sum_{e=1}^{Ed} \sum_{n=1}^{Nde} 1} \tag{2}$$

$$R \bullet \bullet \bullet j = \frac{\sum_{d=1}^{D} \sum_{e=1}^{Ed} \sum_{n=1}^{Nde} Rdenj}{\sum_{d=1}^{D} \sum_{e=1}^{Ed} \sum_{n=1}^{Nde} 1} \tag{3}$$

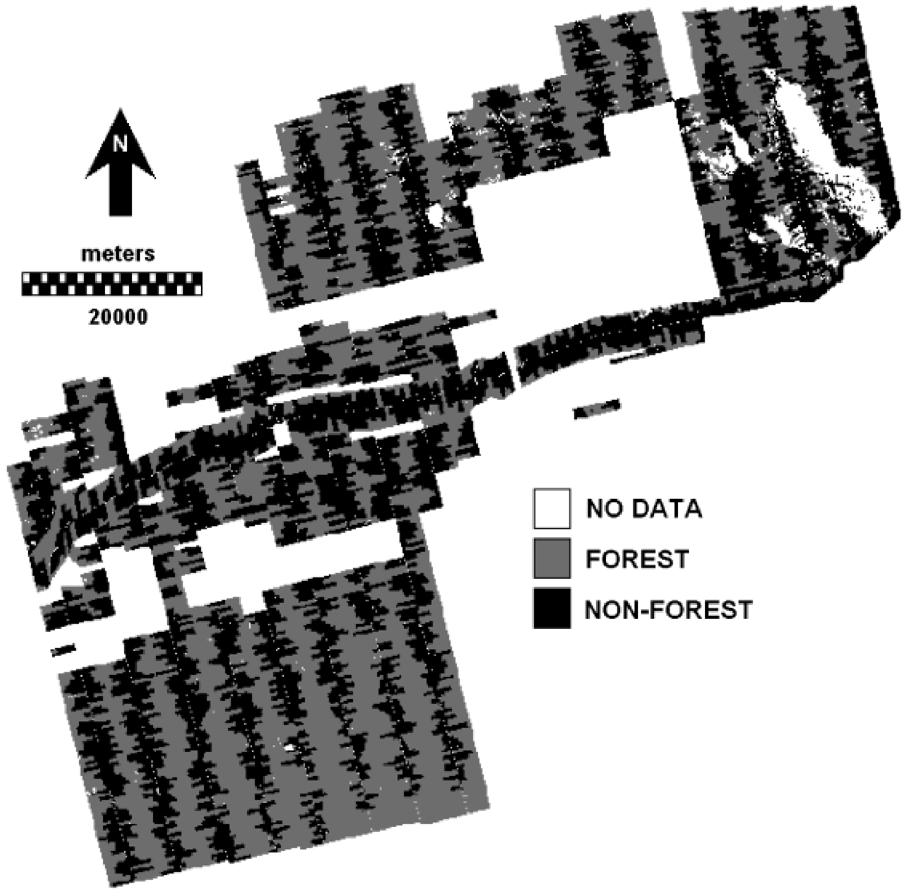

Figure 7. Behavioral Landscape Model (BLM) simulation map with 49 percent deforestation that results when target intercept $= 80$, frontier speed $= 1.6$, and maximum duration $= 3$.

Analogous equations exist for the simulation map (S). Respectively,

$$Sde\bullet j = \frac{\sum_{n=1}^{Nde} Sdenj}{\sum_{n=1}^{Nde} 1} \tag{4}$$

$$Sd\bullet\bullet j = \frac{\sum_{e=1}^{Ed}\sum_{n=1}^{Nde} Sdenj}{\sum_{e=1}^{Ed}\sum_{n=1}^{Nde} 1} \tag{5}$$

$$S\bullet\bullet\bullet j = \frac{\sum_{d=1}^{D}\sum_{e=1}^{Ed}\sum_{n=1}^{Nde} Sdenj}{\sum_{d=1}^{D}\sum_{e=1}^{Ed}\sum_{n=1}^{Nde} 1} \tag{6}$$

Equation (7) gives the proportion agreement between the reference map (R) and a BLM simulation map (S) at a single pixel n within substratum e in stratum d. Equation (7) makes sense when each pixel belongs to exactly one category. In particular, Equation (7) yields 1 if the pixels are either both completely forest or both completely non-forest, and yields 0 if the pixels completely disagree. Equation (7) makes sense also when the pixels have partial (mixed or fuzzy) membership to more than one category, which is necessary for the multiple-resolution methods of map comparison that this article uses (Pontius 2002; Pontius and Cheuk 2006). Equation (8) gives the proportion agreement between map R and map S for the entire study area by using the pixel-level concept that Equation (7) expresses:

$$\text{proportion agreement at pixel } den = \sum_{j=1}^{J} MIN(Rdenj,\ Sdenj) \tag{7}$$

$$\text{proportion agreement between maps } R \text{ and } S = \frac{\sum_{d=1}^{D}\sum_{e=1}^{Ed}\sum_{n=1}^{Nde}\sum_{j=1}^{J} MIN(Rdenj, Sdenj)}{\sum_{d=1}^{D}\sum_{e=1}^{Ed}\sum_{n=1}^{Nde} 1} \tag{8}$$

Hierarchical Stratification

Figure 9 gives a sequence of nine mathematical expressions that quantify the agreement between the reference map and another map that displays various possible types of information. Table 1 helps to describe the nine expressions of Figure 9. Table 2 then uses the nine expressions to define components of agreement and disagreement between the reference map and a particular simulation map. Figure 10 displays the components of Table 2 for each of the eighteen BLM simulation runs in a manner that considers explicitly the maps' hierarchical stratification structure. This mathematical approach is similar to that of Pontius (2002) and Pontius

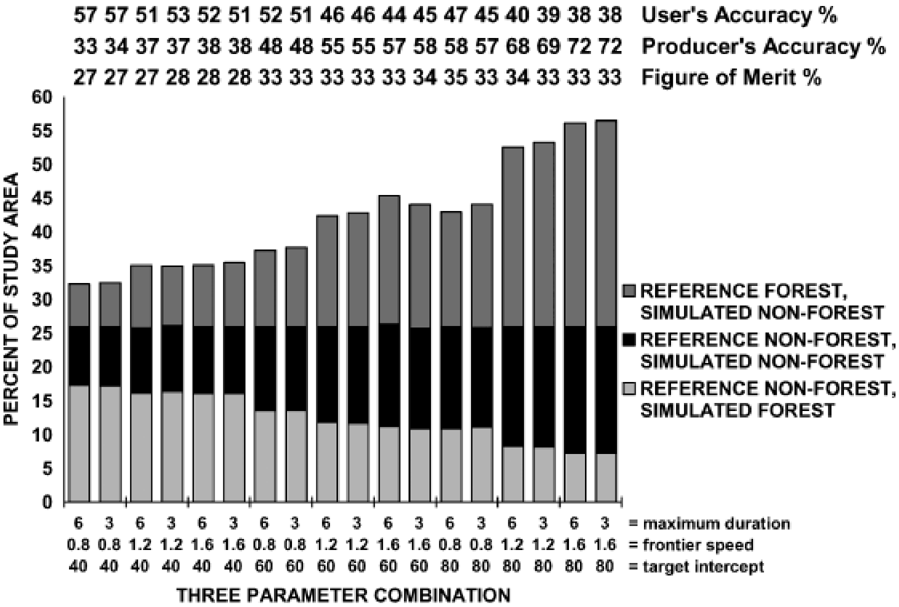

Figure 8. Vertical Venn diagram of reference non-forest and simulated non-forest for each Behavioral Landscape Model (BLM) simulation run. The reference map has 26 percent non-forest.

and Suedmeyer (2004), however this article marks the first time these techniques have been used to assess a land change model for a nested stratification structure.

Each of the nine expressions in Figure 9 has the form of Equation (8) in order to show clearly the differences among the expressions, although some of the expressions in Figure 9 could be simplified. Each expression gives the proportion agreement between the reference map and another map that has a particular combination of information. An expression's position within the space of Figure 9 defines the particular combination of information displayed in the map that is compared to the reference map. The space of Figure 9 is defined by two axes that show two major types of information: information of quantity and information of location (Pontius 2000).

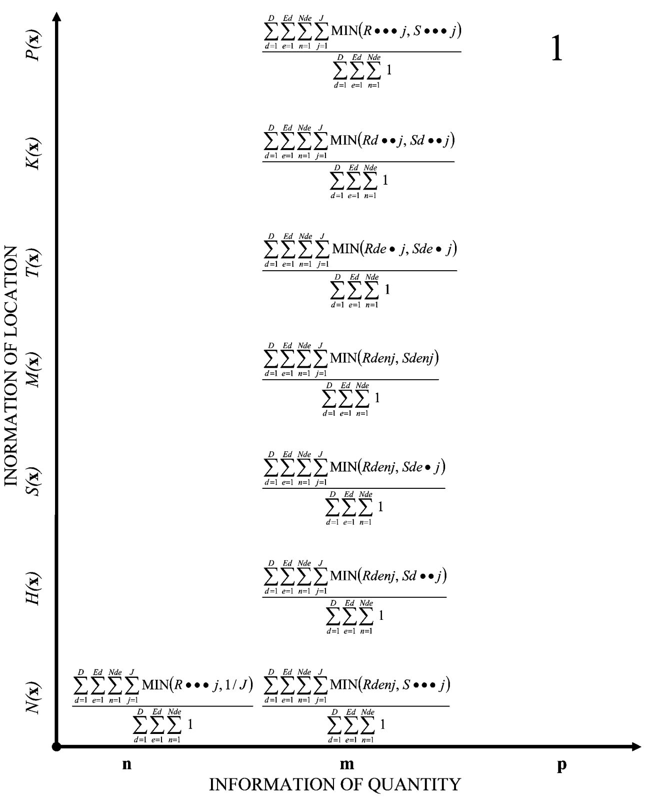

Figure 9. Mathematical expressions described in Table 1, then used in Table 2 to compute the components of agreement and disagreement shown in Figure 10.

Information of quantity refers to the possible simulated amounts of non-forest and forest. Information of quantity has three levels: no information, medium information, and perfect information, denoted respectively as **n**, **m**, and **p**. No information of quantity expresses a case where a map has half non-forest and half forest. Medium information of quantity expresses a case where a map has the amounts of non-forest and forest shown by the particular BLM simulation run of interest. Perfect information of quantity expresses a case where a map has the amounts of non-forest and forest shown in the reference map.

Information of location refers to possible simulated spatial allocations of non-forest and forest. Information of location has seven levels: no, uniform within strata, uniform within substrata, specified by pixel, perfect within substrata, perfect within strata, and perfect global, denoted respectively as $N(\mathbf{x})$, $H(\mathbf{x})$, $S(\mathbf{x})$, $M(\mathbf{x})$, $T(\mathbf{x})$, $K(\mathbf{x})$, and $P(\mathbf{x})$. There are nine important combinations for the information of quantity and information of location that make the sequence of $N(\mathbf{n})$, $N(\mathbf{m})$, $H(\mathbf{m})$, $S(\mathbf{m})$, $M(\mathbf{m})$, $T(\mathbf{m})$, $K(\mathbf{m})$, $P(\mathbf{m})$, and $P(\mathbf{p})$.

Table 1. Specification of the quantities and locations of forest and non-forest in the map that is compared to the reference map for each expression in Figure 9

Expression	Distribution of non-forest and forest
$P(\mathbf{p})$	Same quantities as the reference map, allocated the same as in the reference map.
$P(\mathbf{m})$	Same quantities as the simulation map, allocated as accurately as possible in the study area.
$K(\mathbf{m})$	Same quantities as the simulation map in each stratum, allocated as accurately as possible in each stratum.
$T(\mathbf{m})$	Same quantities as the simulation map in each substratum, allocated as accurately as possible in each substratum.
$M(\mathbf{m})$	Same quantities as the simulation map in each substratum, allocated the same as in the simulation map.
$S(\mathbf{m})$	Same quantities as the simulation map in each substratum, allocated uniformly in each substratum.
$H(\mathbf{m})$	Same quantities as the simulation map in each stratum, allocated uniformly in each stratum.
$N(\mathbf{m})$	Same quantities as the simulation map, allocated uniformly in the study area.
$N(\mathbf{n})$	Half non-forest and half forest, allocated uniformly in the study area.

Note: The values of the expressions depend on the particular simulation map of interest.

For each expression in the sequence, Table 1 describes how the non-forest and forest is distributed in the map according to the particular combination of the information of quantity and information of location. Each subsequent expression in the sequence quantifies the agreement between the reference map and another map that usually has increasingly accurate information, therefore the value of each subsequent expression is usually larger than the value of its preceding expression. For example, starting at the bottom of Table 1, $N(\mathbf{n})$ is 50 percent at the 20-m resolution of the raw data because it is the agreement between the reference map and a map that has half non-forest and half forest distributed uniformly across the entire study area. In the middle of Table 1, $M(\mathbf{m})$ is the agreement between the reference map and the BLM simulation run of interest, which is identical to Equation (8). At the top of Table 1, $P(\mathbf{p})$ is always 100 percent because it is the agreement between the reference map and a map that has the same quantity of deforestation as the reference map and the same spatial allocation of deforestation as the reference map.

Table 2 uses the sequence of nine expressions in Table 1 to define a sequence of five components of agreement and four components of disagreement. These components sum to 100 percent of the study area, as Figure 10 illustrates. Each component quantifies the additional agreement or additional disagreement between the maps, given the sum of the previous components of information in the sequence from bottom to top. Table 2 explains the conceptual source and mathematical

Table 2. Components of agreement and disagreement that use expressions in Figure 9 to produce Figure 10

Component	Conceptual source	Mathematical expression
Disagreement due to quantity	Less than perfect simulation of quantities	$P(\mathbf{p}) - P(\mathbf{m})$
Disagreement due to strata location	Less than perfect allocation to strata within the study area	$P(\mathbf{m}) - K(\mathbf{m})$
Disagreement due to substrata location	Less than perfect allocation to substrata within strata	$K(\mathbf{m}) - T(\mathbf{m})$
Disagreement due to pixel location	Less than perfect allocation to pixels within substrata	$T(\mathbf{m}) - M(\mathbf{m})$
Agreement due to pixel location	Better than uniform allocation to pixels within substrata	$\mathrm{MAX}[M(\mathbf{m}) - S(\mathbf{m}), 0]$
Agreement due to substrata location	Better than uniform allocation to substrata within strata	If $\mathrm{MIN}[H(\mathbf{m}), S(\mathbf{m}), M(\mathbf{m})] = H(\mathbf{m})$, then $\mathrm{MIN}[S(\mathbf{m}) - H(\mathbf{m}), M(\mathbf{m}) - H(\mathbf{m})]$, else 0
Agreement due to strata location	Better than uniform allocation to strata within the study area	If $\mathrm{MIN}[N(\mathbf{m}), H(\mathbf{m}), S(\mathbf{m}), M(\mathbf{m})] = N(\mathbf{m})$, then $\mathrm{MIN}[H(\mathbf{m}) - N(\mathbf{m}), S(\mathbf{m}) - N(\mathbf{m}), M(\mathbf{m}) - N(\mathbf{m})]$, else 0
Agreement due to quantity	Better than uniform simulation of quantities	If $\mathrm{MIN}[N(\mathbf{n}), N(\mathbf{m}), H(\mathbf{m}), S(\mathbf{m}), M(\mathbf{m})] = N(\mathbf{n})$, then $\mathrm{MIN}[N(\mathbf{m}) - N(\mathbf{n}), H(\mathbf{m}) - N(\mathbf{n}), S(\mathbf{m}) - N(\mathbf{n}), M(\mathbf{m}) - N(\mathbf{n})]$, else 0
Agreement due to chance	Complete uniformity of both quantity and location	$\mathrm{MIN}[N(\mathbf{n}), N(\mathbf{m}), H(\mathbf{m}), S(\mathbf{m}), M(\mathbf{m})]$

Note: The conceptual source describes the reason a Behavioral Landscape Model (BLM) run generates the component in terms of the run's specification of the quantities and locations of the simulated forest and non-forest.

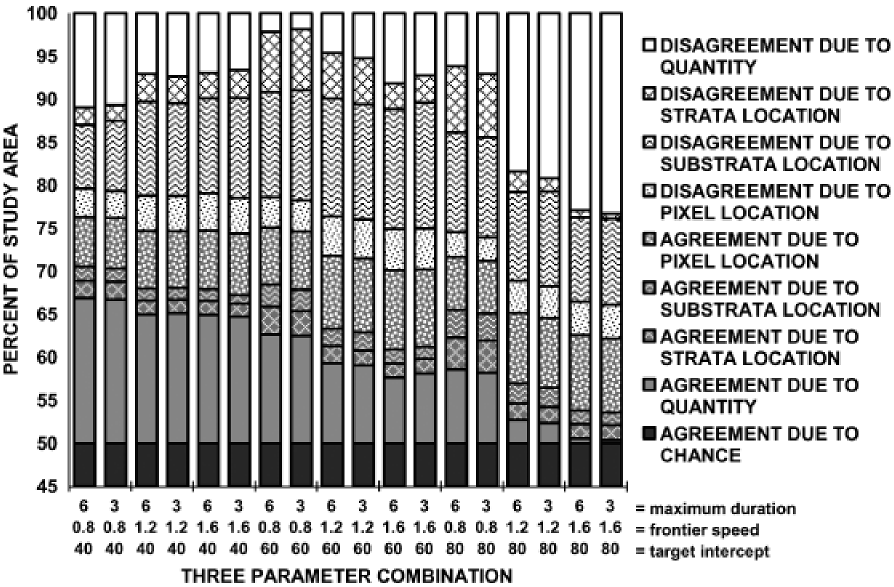

Figure 10. Components of agreement and disagreement between the reference map and the simulation map for each of eighteen Behavioral Landscape Model (BLM) simulation runs.

expression for each component, which Figure 10 shows for each of the eighteen model runs.

We derived the mathematical expressions in Figure 9 and Table 2 specifically for this application of the BLM to the Amazon. We imagine that the equations will be useful for other cases where a researcher needs to compare two maps that share a categorical variable with respect to a nested hierarchical stratification structure. Although there is a plethora of spatial pattern metrics that could be used to compare maps of a categorical variable, it is helpful to use our method of map comparison to assess the BLM runs because the stratification structure is fundamental to both the process of land change and the design of the model. Consequently, our method can detect distinguishing spatial aspects of the fishbone pattern. For example, starting from the top of Table 2, the component of disagreement due to quantity is small when the model accurately portrays the overall quantity of deforestation, which occurs when the model accurately portrays the overall size of in the fishbone pattern. The component of disagreement due to strata location is small when the model accurately portrays the spatial variation of deforestation among strata, which occurs when the model accurately portrays the variation in size among the ribs in the fishbone pattern. The component of disagreement due to substrata location is small when the model accurately portrays the spatial variation of deforestation among substrata nested within the strata, which occurs when the model accurately portrays how the ribs are wider nearer the main highway and narrower farther from the spine in the fishbone pattern. The component of disagreement due to pixel location is small when the model accurately portrays the spatial variation of deforestation within the substrata, which occurs when the model accurately portrays how the deforestation is near the roads such that it defines the ribs in the fishbone pattern.

Persistence, Uniform, and Highway Models

The quantity of simulated non-forest constrains the accuracy of the simulation. The solid lines of Figure 11 show these mathematical constraints. The vertical axis is the percentage of the study area for which the simulation agrees with the reference map, and the horizontal axis of Figure 10 is the percentage of the study area that a model run simulates as non-forest. If the model were to simulate 26 percent non-forest, then it would be mathematically possible for the simulation to attain 100 percent agreement, which would occur if the model were to allocate the non-forest at the perfectly correct locations. If the model does not simulate 26 percent non-forest, then it is mathematically impossible for the simulation to attain complete agreement with the reference map because the model's accuracy would be constrained by the solid boundary at the top of Figure 11. Similarly, there is a lower bound on the accuracy shown by the solid line in the lower part of Figure 11. Consequently, the accuracy of any simulation is constrained to be within the diagonally-oriented rectangular area defined by the solid lines in Figure 11. We compare each BLM simulation run to corresponding runs of three simpler models: the Persistence model, the Uniform model, and the Highway model. Figure 11 plots the accuracy of these three models with respect to the BLM.

The Persistence model simulates complete persistence of the initial state. We assume the initial state is complete forest, thus a Persistence model simulates 0 percent

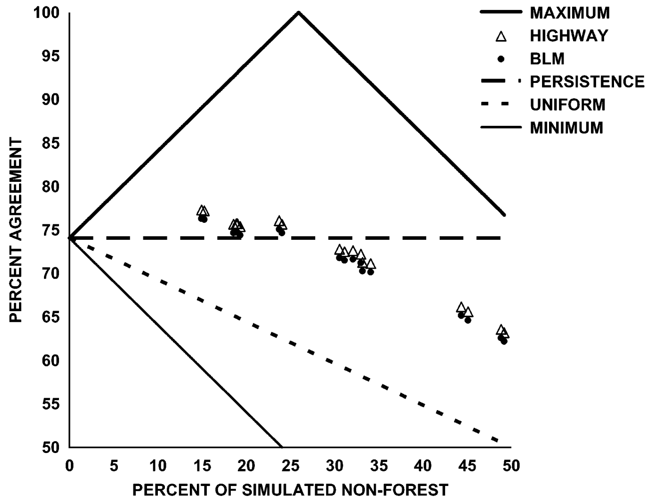

Figure 11. Accuracy for each of eighteen Behavioral Landscape Model (BLM) simulation runs with respect to mathematical constraints and the Persistence, Uniform, and Highway models.

non-forest. The left side of Figure 11 shows that if a model were to simulate 0 percent non-forest (i.e., complete forest), then it would have 74 percent agreement with the reference map because the reference map has 74 percent forest. The horizontal dashed line in Figure 11 shows the accuracy of the Persistence model with respect to the other models.

The Uniform model allocates the categories uniformly in space, given the simulated quantity of non-forest. Thus every pixel from the Uniform model has identical membership $S\bullet\bullet\bullet j$ to category j. The accuracy of a Uniform model is $N(\mathbf{m})$ given in Figure 9. The downward sloping dotted line in the middle of Figure 11 shows the accuracy of the Uniform model, which is equal to the expected accuracy of a model that allocates the categories randomly in space, given the simulated quantity of non-forest.

The Highway model allocates the non-forest category as close to the main highway as possible while ignoring the secondary roads, given the simulated quantity of non-forest. Therefore, each run of the Highway model corresponds to a run of the BLM, where each Highway model run uses the same quantity of simulated non-forest as the corresponding BLM run. There are eighteen Highway model runs, which correspond to the eighteen BLM simulation runs. Figure 11 compares each BLM run to its corresponding Highway model run.

Multiple Resolutions

A multiple resolution procedure compares the reference map to each BLM simulation map similar to the method of Pontius (2002) and Pontius, Huffaker, and Denman (2004). An aggregation rule converts the 20-m × 20-m raw pixels into coarser pixels by computing the proportion of forest and non-forest raw pixels within each coarser pixel. Each finer resolution is nested within each coarser resolution such that the side of each coarser pixel is a multiple of the side of a raw pixel, and the multiples progress in a geometric sequence as 1, 2, 4, 8, . . . , 4,096. Figure 12 expresses the pixel resolution as the length of the side of the coarse pixels, which is 20 m times the aggregation multiple. The pixel aggregation process can cause each coarse pixel to have partial membership to both the non-forest and forest categories, so it is appropriate to use Equation (7) to compute the agreement between the corresponding pixels of the reference map and a BLM simulation map. Agreement between the maps increases up to a limit as the resolution becomes coarser, because the pixel aggregation procedure resolves disagreement due to location, but does not influence disagreement due to quantity. Figure 12 portrays each BLM simulation run as a column of symbols that rise as resolution becomes coarser. The upper limit that bounds the accuracy is the mathematical constraint that previous subsection describes and that Figures 11 and 12 show. The rate at which the agreement rises relates directly to the similarity of the spatial pattern in the reference map and the simulation map. When the simulation map has only minor location errors over small distances, the reference pattern and simulation pattern appear visually similar and the agreement between the two maps rises quickly as the resolution becomes slightly coarser. When the simulation map has major location errors over large distances, then the reference pattern and simulation pattern appear visually dissimilar and the agreement between the two maps rises only as the resolution becomes very coarse.

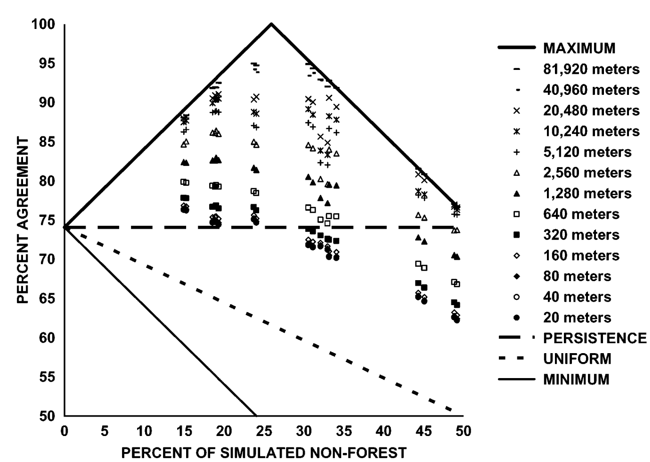

Figure 12. Accuracy for each of eighteen Behavioral Landscape Model (BLM) simulation runs at multiple resolutions with respect to mathematical constraints and the Persistence and Uniform models.

Results

All BLM runs are substantially more accurate than the Uniform model and are consistently less accurate than the Highway model when assessed vis-à-vis the 1999 reference data on a pixel-by-pixel basis at the 20-m resolution of the raw data (Figure 11). The BLM is more accurate than the Persistence model when the BLM simulates less than the amount of deforestation in the reference map, and the BLM is less accurate than the Persistence model when the BLM simulates more than the amount of deforestation in the reference map at the 20-m resolution. There is a strong correlation between the amount of deforestation in the simulation and the accuracy of the simulation. When the BLM simulates more deforestation, it becomes less accurate in terms of percentage agreement. Consequently, the model parameters that have large influence on the quantity of simulated deforestation also have large influence on the accuracy of the simulation. The largest potential for improvement in model accuracy is improvement in the way the model simulates the quantity of deforestation at the substratum level—that is, the 100-ha household lot level. The remainder of this section examines the details of the results in terms of Figures 8, 10–12.

Figure 8 assesses the eighteen BLM simulation maps at the 20-m resolution in a manner that relates to the three model parameters. The target intercept parameter has the most influence over the quantity of simulated deforestation, since the amount of simulated deforestation is the sum of the middle and top bar segments. Larger values of the target intercept parameter values correspond to larger amounts of simulated non-forest. For any particular target intercept value, larger frontier speeds cause more simulated non-forest. The maximum duration parameter has very little influence on the results as seen by the pairing of the nearly identical adjacent bars for the two levels of the maximum duration parameter, given a particular combination of the other two parameters. The parameter combination of target intercept = 60, frontier speed = 0.8, and maximum duration = 3 yields 24 percent simulated non-forest (Figure 6), which is closest to the 26 percent non-forest in the reference map (Figure 3).

Figure 8 shows that the amount of error is greater than the amount of correctly modeled deforestation for all simulation runs, since the sum of the top and bottom segments of the bar is greater than the middle segment. The figure of merit statistic is the ratio of the length of the middle segment to the length of the entire bar; therefore the figure of merit indicates model accuracy on a scale from 0 percent to 100 percent. If there is no overlap between the reference non-forest and simulated non-forest, then the figure of merit is zero. If there is perfect correspondence between the reference non-forest and the simulated non-forest, then the figure of merit is 100 percent. In Figure 8, the figure of merit ranges between 27 and 28 percent for the first six bars that show cases where the BLM simulates less non-forest than the amount of reference non-forest. The figure of merit ranges between 33 and 34 percent for the other twelve bars that show larger amounts of simulated non-forest. A recent survey of thirteen land change modeling applications found a range for the figure of merit from 1 to 59 with a median of 21 percent (Pontius et al. 2008).

Figure 8 contains information to visualize two common statistics: user's accuracy and producer's accuracy. The user's accuracy is the proportion of pixels that are non-forest in the reference map, given that the BLM simulates non-forest. In Figure 8, the user's accuracy is the ratio of the middle segment to the sum of the middle and top segments. The results show that the user's accuracy is greater than 50 percent if and only if the BLM simulates less non-forest than the amount of non-forest observed in the reference map. This means that the BLM is more accurate when it simulates deforestation closer to the highway, since the runs that have smaller amounts of simulated deforestation are the runs that locate the simulated deforestation closer to the highway. The producer's accuracy is the proportion of pixels that the BLM simulates as non-forest, given that the reference map shows non-forest. In Figure 8, the producer's accuracy is the ratio of the middle segment to the sum of the middle and bottom segments. The results show that the producer's accuracy is greater than 50 percent if and only if the BLM simulates more non-forest than the amount of non-forest in the reference map. If the percentage of simulated deforestation were to grow toward 100 percent, then the producer's accuracy would approach 100 percent and the user's accuracy would approach 26 percent, since 26 percent is the quantity of non-forest in the reference map.

Figure 10 shows the results concerning the components of agreement and disagreement for the various levels of stratification at the 20-m resolution of the raw data. The vertical axis shows percentage of the study area; each bar is one of the BLM runs. The bars are ordered along the horizontal axis in the same sequence as in Figure 8.

It is useful to focus first on the components of disagreement starting at the top of each bar in Figure 10. The disagreement due to quantity is a function purely of the correspondence between the quantity of non-forest in the simulation map and the quantity of non-forest in the reference map. This component is the difference between 100 percent and the mathematical constraint shown by the solid line at the top of Figures 11 and 12. The other three components of disagreement relate to location information and indicate how accurately the BLM simulates deforestation in space. The disagreement due to strata location varies across the BLM runs; it tends to be larger when the BLM simulates the overall quantity accurately and smaller when the BLM simulates the overall quantity inaccurately. It indicates how well the BLM simulates the deforestation in terms of regional location as defined by the large development rectangles. Next is the disagreement due to substrata location, which is the largest component of location disagreement for every BLM run. This means that the largest portion of the model's location disagreement is associated with its less than perfect assignment of the deforestation to the substrata. This type of disagreement would be rectified if the BLM were to simulate the proportion of non-forest within each 100-ha household lot more accurately. Disagreement due to pixel level location is fairly stable among the BLM runs, accounting for about 4 percent of the study area, which means that the model's assumption concerning the placement of the deforestation near the road within each household lot is not a large source of error.

Now we focus on the components of agreement from the middle to the bottom in Figure 10. Three components of agreement are associated with location information. In every BLM run, the largest component of agreement due to location is pixel level location, which accounts for 7 percent of the study area on average. This indicates that an important source of location agreement is attributable to the assumption that settlers deforest near the road within their substratum lots. The components of agreement due to substrata location and the agreement due to strata location are small and similar, as there is less than one percentage point difference between the two components within each BLM run. The fact that these components are positive indicates that the BLM produces a better than uniform allocation of deforestation among the substrata within the strata and among the strata within the study area. The agreement due to quantity indicates how much better the quantity of simulated non-forest is with respect to a uniform distribution of equal amounts of non-forest and forest, thus it varies substantially among BLM runs. The agreement due to quantity is the difference between 50 percent and the downward sloping dotted line in Figures 11 and 12. All BLM runs have 50 percent agreement due to chance because a completely random allocation of forest and non-forest would be 50 percent correct, since each 20-m pixel of the reference map is one of two categories.

Figure 11 summarizes the results at the 20-m resolution in a manner that compares the BLM to the Persistence, Uniform, and Highway models. Most importantly, there is an obvious linear trend that shows how percentage agreement decreases as the amount of simulated deforestation increases ($R^2 = 0.95$). The BLM is more accurate than the Persistence model if and only if the BLM simulates less than the amount of non-forest shown in the reference map, since the closed circles are above the horizontal dashed line if and only if they are on the left side of the figure. Figure 11 shows also that each run of the BLM is substantially more accurate than the Uniform model, since each closed circle is far above the downward sloping dotted line. The symbols in Figure 11 show that each run of the BLM is slightly less accurate than the corresponding run of the Highway model, since each closed circle is slightly below its corresponding open triangle. The points in Figure 11 are arranged in pairs, where each pair reflects the two levels of the maximum duration parameter, given each particular combination of the other two parameters. This indicates that the maximum duration parameter has very little influence on the results.

Figure 12 summarizes the results at multiple resolutions. The accuracy of the simulation increases as resolution becomes coarser, so Figure 12 shows a vertical column of symbols for each BLM run. Eight of the eighteen BLM runs are more accurate than the Persistence model at the 20-m resolution of the raw data, since eight of the closed circles are above the horizontal dashed line. The open squares show that fourteen of the BLM runs are more accurate than the Persistence model at a resolution of 640 m, which is 32 times coarser per pixel side than the raw data. The crosses show that all the BLM runs are more accurate than the Persistence model at resolutions coarser than 5.12 km, as more than half of disagreement due to location is resolved at that resolution.

Discussion

Setting Research Priorities

Figures 11 and 12 show how the overall quantity of deforestation that the BLM simulates places a substantial constraint on its ability to simulate accurately. If the model has substantial error in the overall quantity, then it is not mathematically possible for the BLM to simulate the categories accurately regardless of how those categories are arranged in space. If the model simulates the overall quantity accurately, then there is a large range for the model to allocate the location accurately or inaccurately in space. Therefore, readers must know the accuracy of the simulation of quantity in order to interpret the other aspects of the assessment. Future research with the BLM should focus on issues that influence the accuracy of the overall quantity of deforestation, which means the target intercept parameter merits more attention than the frontier speed.

Figure 10 shows that the BLM's assumption that deforestation occurs near the road within the substrata is an important systematic source of location accuracy and is never a large source of location disagreement. Therefore, it should not be a research priority to improve the simulation of the detailed spatial distribution of deforestation within the household lots. The assumption that deforestation occurs near the road should be kept, and future research should focus on more important sources of disagreement. Figure 10 shows that the largest source of location disagreement is misspecification of the location of non-forest within the strata, so future research should focus on explaining the spatial distribution of deforestation within the large development rectangles. In other words, we would likely see a substantial increase in the accuracy of the BLM if it were able to simulate more accurately the locations of the households that have very high amounts of deforestation versus those that have very small amounts of deforestation within the large strata. The BLM would accomplish this if it were to simulate more accurately the quantity of deforestation for each 100-ha household lot. If the model simulates the proportion of non-forest accurately for the lots, then it will simulate the correct overall quantity. Presently, the BLM assigns the target deforestation for each lot according to the linear relationship in Figure 4 combined with a randomly selected error term for each lot. Perhaps this allocation procedure could be improved by assigning error terms in a manner that takes into consideration spatial dependency and/or independent variables, such as land quality.

Selection of Metrics

As mentioned earlier, there are an infinite number of ways to compare maps in order to examine the correspondence between a reference map and a simulation map. Many investigators use pattern metrics, some of which are designed to measure patterns that the human eye can recognize easily (McGarigal and Marks 1995; Clarke and Gaydos 1998). Modelers frequently want models to simulate patterns that are similar to the reference pattern. However, it can be challenging to select an appropriate pattern metric because there are numerous pattern metrics and different metrics can give substantially different results. In this article, we have presented methods that focus on two important components of information in the maps: the quantity of each category and the location of each category. There are many reasons why we have taken this approach. First, the quantity of each category is the most obvious characteristic that is important for many applications. The quantity of each of the categories places hard constraints on many spatial and nonspatial metrics, as indicated by the lines in Figures 11 and 12. For example, if a landscape is covered nearly entirely by a single category, then it is not possible to have many patches compared to a landscape that has equal amounts of many categories. Therefore, it is necessary to understand the correspondence between the maps in terms of the quantity of each category in order to interpret the correspondence between the maps in terms of pattern metrics. After the specified quantity of each category in the reference and simulated maps is examined, our method then examines the specification of location as the next obvious aspect of a map comparison. If the correspondence in terms of location is high, then the agreement in terms of pattern must also be high. However, it is possible to have substantial disagreement in location but high agreement in general pattern. For example, if both the reference map and simulation map were chessboard patterns but misregistered by one row or column, then the location agreement at the pixel level would be zero but the pattern agreement would be perfect according to the human eye. Our multiple resolution method addresses this issue. If the spatial pattern in the reference map is similar to the pattern in the simulation map while the pixel-level agreement is low, then the multiple resolution method reveals this situation by showing a rapid increase in the overall agreement at early phases of the resolution coarsening process.

One distinct advantage of this article's metrics over pattern metrics is that our multiple resolution method works both when the pixels are pure and when the pixels are mixed. In other words, our method works when the pixels have full membership to exactly one category and also when the pixels have partial membership to multiple categories. This allows us to perform multiple resolution analysis while maintaining the quantity of each category in the maps. On the contrary, pattern metrics require that the pixels are pure, so the method to coarsen the pixels would need to use a rule to assign exactly one category to each coarse pixel in order to use popular pattern metrics at multiple resolutions. Such a rule corrupts the information in the maps because the rule can change the quantity of each category in the maps. Pontius and Cheuk (2006) explain this problem in depth and offer a solution, which is the basis for the methods used in this article.

This article's methods of multiple resolution analysis address how the accuracy assessment depends on scale. All of the model runs are performed at the single scale of the 20-m pixels, and then the results are analyzed at multiple scales. The results show that all the model runs are more accurate than the persistence model at a resolution of 5 km. This does not necessarily imply that the model would be more accurate than the persistence model if the base data were at a resolution of 5 km. Our recommended strategy is to run the model at the finest possible resolution based on the constraints of the data and computer resources, and then to assess the results at multiple scales. There exists evidence that the behavior of models can be scale dependent, meaning that models can perform differently when run at different scales (Dietzel and Clarke 2004; Evans and Kelley 2004).

Is the Model Good?

It would be convenient if there were a direct answer to the simple question "Is the model good?" However, there is not a single clear answer due the vagueness of the question. A definition of good requires a baseline for comparison. Our methods allow for three possible definitions of good because we analyze three alternative baselines that are designed to be easy to understand. If a researcher considers these baselines, then the BLM is not good according to the Highway model baseline, it is sometimes good according to the Persistence model baseline, and it is very good according to the Uniform model baseline. The baseline should be selected according to the purpose of the modeling application at an appropriate scale. A model can have numerous varied purposes for which additional baselines would be appropriate. The BLM is a prime example of such a model that could be called upon to address multiple objectives. Some of the desired uses for the model will become evident only after the model is fairly well developed and well known. For example, a researcher might be interested in using the BLM to simulate the pattern of deforestation for the sake of predicting the influence of land transformation on biodiversity (Menon et al. 2001). In this case, it would probably be important that the model be able to simulate the patchiness of the fishbone pattern, because the pattern of land cover is important for some species, especially those that need large patches of contiguous forest or those that thrive on the edges of patches. For such an application, the Highway model would be unacceptable because it simulates a uniform band of deforestation near the highway and never produces a patchy or fishbone pattern. However, if a researcher were interested in simulating deforestation for the sake of predicting the influence of land transformation on carbon dioxide emissions, then a simpler model that simulates the quantity of deforestation near the highway at a coarse resolution might suffice, especially if the initial distribution of terrestrial carbon is fairly uniform. Carbon scientists typically do not require precise information concerning the location of emissions, because the global warming effect derives from the total carbon dioxide concentration in the atmosphere, not the carbon dioxide's precise location of origin.

Land change modelers are constantly creating models that are important for a variety of reasons, and it is not easy to anticipate the precise tasks that will be asked of a particular model, because land transformation is crucial to so many phenomena. To serve the scientific community, land change modelers typically aim to create models that capture the process of land transformation, and then other applied scientists collaborate with the modelers to refine the models for particular applications. Scientists should evaluate the models at several points in the refinement process. This article presents general concepts that are likely to be relevant at several points in the refinement process, because our approach allows a scientist to measure a model's performance by measuring the model's accuracy at a variety of scales with respect to a variety of baselines.

Conclusions

This article describes the BLM as applied to a section of the Transamazon highway in the lower Amazon Basin within the State of Pará, and shows how to measure its performance in a manner that relates directly to the landscape's processes and the model's characteristics. The method of quantitative assessment articulates components of agreement and disagreement based on a philosophy of map comparison that separates explicitly the information concerning the quantity of deforestation from the information concerning the location of deforestation. Results have shown that one of the BLM's most helpful assumptions is that deforestation within household lots occurs near the main and secondary roads, and the largest consistent source of disagreement is the BLM's less than perfect ability to simulate the proportion of deforestation for each household lot. The BLM is consistently more accurate than a Uniform model that allocates deforestation uniformly across the landscape, but is consistently less accurate than a Highway model that simply places the simulated deforestation as close as possible to the main highway. The BLM's accuracy is within the range of accuracies that we have observed in other applications of land change models (Pontius et al. 2008). We have designed this article's statistical measurements so that they produce information that is helpful for other scientists whose goals are to communicate a model's performance and to set an agenda for future research.

Acknowledgments

The National Science Foundation supported this work via two projects: the Center for Integrated Study of the Human Dimensions of Global Change via a cooperative agreement with Carnegie Mellon University (SBR-9521914) and the grant entitled "Patterns and Processes of Landscape Change in the Brazilian Amazon" (BCS–0137020). In addition, the National Aeronautics and Space Administration's Large Scale Biosphere Atmosphere Experiment in Amazonia program supported this work under the project "A Basin-Scale Econometric Model for Projecting Future Amazonian Landscapes" (NCC5-694). We thank Kevin Denman for use of his program Assess10. Hao Chen of Clark Labs facilitated this work by creating the Validate module in the GIS software Idrisi®.

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