Measuring Allocation Errors in Land Change Models in Amazonia

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Abstract. *Top-down land change models use computer simulation to allocate demands for change over the spatial region under study. This paper presents a metric to estimate the goodness of fit of land change models. It focuses only on changed areas, preventing inflated goodness of fit values due to large fractions of the landscape remaining unchanged. We use the proposed metric to evaluate land change models for Amazonia. Despite large quality differences between them, all models have problems to predict new frontiers and expansion areas. The best model considered in this paper only performs slightly better than a simple model that predicts a cell's deforestation based on the deforestation in neighboring cells.*

1 Introduction

Changes in land use and land cover have increased worldwide substantially in the second half of the 20th century, mostly as part of the economic growth of emerging nations such as China, India, Brazil and Indonesia. Land cover is the biophysical state of the earth's surface; land use is the purpose for which humans use the land [1]. Forest and cropland are examples of land cover and agricultural and pasture is an example of land use. We use the term "land change" to refer to land use and land cover change. Land changes result from people acting on ecosystems, based on demographic, social, and economic factors. Planners and policy makers need models that represent how humans change the land [2]. Despite the challenges involved in building them, these models have an important role, as they serve as tools to understand human-environment interactions and to help public policy making.

Many papers on land change models make strong policy recommendations based on their results [3, 4]. Thus, measuring the quality of land change models is important to assess the likelihood of the scenarios expressed by the models. The problem is of course that these models project future changes and therefore testing them is unattainable at the moment when the model is conceived. What can be done is an *ex-post analysis*: looking at the past from the future. Some years later, we can compare the model projections with the reality. To do this comparison properly, we need a metric that expresses differences between the model projections and the facts.

This paper evaluates the results of several models of deforestation in the Brazilian Amazon in an ex-post analysis. We propose a goodness of fit metric extending the works of [5] and [6]. The metric uses a multi-resolution approach to account for the scale-dependency of spatial patterns. Using this approach, we aim at better understanding the strong points and the flaws of the different models and their underlying conjectures. To do this, we also compared the models to a simple model based on the previous year's deforestation as the only explaining variable.

2 Review of current goodness of fit metrics for spatial models

There are two complementary views on the literature on the issue of measuring the goodness of fit of land change models. One of them is the multiple resolution approach proposed by Costanza [5] to evaluate land change models [7, 8]. In his paper, Costanza proposes a method to compute the goodness of fit for categorical data. Arguing that simple cell-by-cell comparison is misleading because allocation of change can occur at neighboring cells, he proposes comparing the two maps at several resolutions, using moving windows. He starts with a window whose size is a single cell. For each window position, he computes a goodness of fit metric. After moving the window over the whole map, he gets the average of this metric and uses it as the goodness of fit measure at the window's resolution. Then, he doubles the window size and evaluates the metric again. The result is a set of metrics, one for each window resolution.

A second view in the literature argues for taking persistence into account when computing model goodness of fit. In land change modeling, the primary interest is finding out whether the cells representing land change were correctly placed. As Pontius et al. [6] point out, in most land change models a lot of areas remain the same from one time step to another. Usually, the changes are a small proportion of the total area. Thus, to properly assess goodness of fit in land change models, we have to account for persistence and should only consider the areas where change occurred. To compare different models, Pontius et al. [9] propose the metric "figure of merit" to compute the ratio of the area that was correctly predicted as change and all the areas that were observed or modeled as change:

$$FM = \frac{Change_{correct}}{Change_{correct} + Change_{ref} + Change_{mod} + Change_{wrongcat}}$$

Where

$Change_{correct}$ = Area that is change in both the model result and the reference map

$Change_{ref}$ = Area that is change in the reference map, but not change in the model result

$Change_{mod}$ = Area that is change in the model result, but not change in the reference map

$Change_{wrongcat}$ = Area that is change in both the model result and the reference map, but was predicted a wrong category of change.

In our work, we combine Costanza's multi resolution metric [5] with Pontius et al. [9] "figure of merit". We extend Costanza's metric for cell spaces where the cells have numerical values, as described in the next section. Constanza's metric accounts for misallocation of cells with change and the Pontius extension avoids inflated large goodness of fit value due to large amounts of unchanged area.

3 A metric for goodness of fit in land change models

Top-down land change models usually have three sub-models: *demand*, *potential*, and *allocation* [7, 10, 11]. The demand depends on the underlying causes of change and represents how much change will happen. Usually, it is calculated externally by tools that consider economic, demographic and social trends. The demand is then spatially allocated based on the potential for change of each cell. For example, increase in global food consumption results in greater demand for agricultural areas.

Each place has a *potential for transition* between land cover classes. This potential depends on the relative importance of driving forces of change in that place. The potential represents the proximate causes, which are the factors directly linked to the locations. It combines data from different sources, such as distance to roads, soil quality, and protected areas to estimate the possibility of change from one given land cover to another. The result identifies the areas more likely to change. Finally, the *allocation* combines the demand and the potential to simulate where land change will take place. Given the demand is usually external to the model, modelers need to estimate the transition potential well so their simulations get closer to reality.

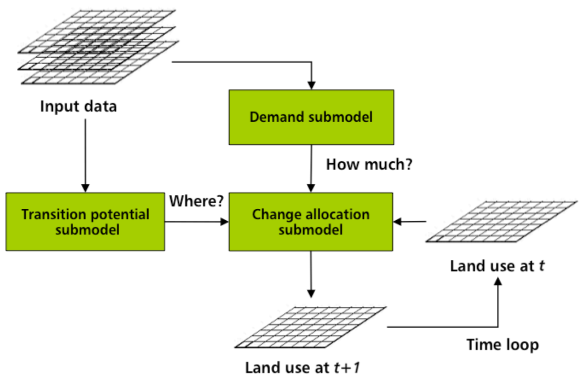

Figure 1: general view of top-down land change models. Source: Adapted from [12].

We propose a metric for evaluating goodness of fit in land change models that focuses on change and accounts for persistence. The metric takes Costanza's multiple resolution approach and restricts it to the areas of actual or projected change. This approach is consistent with the *figure of merit* metric proposed by Pontius, as discussed in section 2. Since our goal is to evaluate the potential and allocation procedures and not the correctness of the demand, the demand for change to be allocated in both cell spaces has to be the same.

We developed a metric for the case where one land cover transition is possible, e.g., from forest to deforested area. The metric can be extended to the case of multiple land cover classes. For a single land cover transition, the metric is computed by the following equation:

$$F_w = 1 - \frac{\sum_{s=1}^{t_w} \left[\left| \sum_{i=1}^{w^2} a_{refi} - \sum_{j=1}^{w^2} a_{modj} \right| \right]_s}{2 \sum_{u=1}^{num} a_{refu}}$$

F_w = Goodness of fit at resolution *w*.

t_w = Number of sampling windows at resolution *w*.

w = Resolution (a sampling window has w^2 cells).

a_{refi} = Percent of change in land cover in cell *i* in the reference cell space.

a_{modj} = Change in land use/land cover in cell *j* in the model cell space.

i, j = Cells inside a sampling window.

u = Cells inside the cell space.

s = A sampling window.

num = Number of cells in the cell space ($t_w * w^2$)

For each window size, we get a goodness of fit metric by moving the window over the whole cell space and finding out the average value of the fit. The cell space is repeatedly traversed using sampling windows of increasing size (r). For each sampling window, we get the difference between quantity of change in the reference cell and quantity of change in the model cell space. We divide this difference by 2 to avoid double counting, since an increase in one location leads to a decrease by the same amount in another location. The error term is then summed over all windows and divided by the total change in the whole map. Subtracting it from one provides the goodness of fit.

The metric is appropriate to compare two cell spaces with the same spatial resolution and extent where the amount of change is the same in both. Using it, we find the degree of agreement between the cell spaces. The result is independent of the total area of the examined map. Therefore, including more (unchanged) cells (e.g. the cells outside the study area in a square map) in the computation does not alter the result.

4 Goodness of fit of Brazilian Amazon deforestation models

We applied the proposed goodness of fit metric to evaluated two models that try to predict deforestation in the Brazilian Amazon: The SimAmazonia model, developed by Soares-Filho et al. [3], and the model developed by Laurance et al. [4].

We evaluated model projections for the year 2011, taking the PRODES data provided by INPE (Brazilian National Space Research Institute) as the reference for observed deforestation. PRODES uses wall-to-wall mapping to get yearly data on the location and extent of the deforestation by clear cuts in the Brazilian Legal Amazon, an area of 5 million km^2. It uses remote sensing data with 20 to 30 meter resolution and produces deforestation maps in the 1:250.000 scale. Since 2003, INPE makes PRODES data freely available in the internet. The scientific community takes PRODES to be the standard reference for ground truth in Amazonia deforestation [13, 14].

SimAmazonia projects the deforestation in Amazonia in 2050, based on data from 2001. We estimated its results for 2011 using data provided by its authors. It has different submodels for 47 subregions of Amazonia, with modules considering socioeconomic factors and spatial factors (e.g. infrastructure projects). For our assessment, we took the Business-as-usual scenario (BAU) and the Governance scenario (GOV). Their main difference between BAU and GOV scenarios is the greater extent of government intervention in the latter case. The GOV scenario has more protected areas whose effectiveness is guaranteed.

The model by Laurance et al. projects deforestation in the Brazilian Amazonia in 2020 based on the data for 2000. It assumes a heavy impact of infrastructure projects that would lead to deforestation in Amazonia of 28% (optimistic scenario) or 42% (non-optimistic scenario) in 2020. The non-optimistic scenario assumes larger degraded areas close to roads and rivers and more deforestation in conservation areas. We could not get access to the original data, despite requests to the authors. Thus, we used input data and estimation methods as similar as possible to the author's description to simulate both scenarios for 2011.

We also used a neighborhood model as an example of the simplest possible land change model for Amazonia. The model has a single assumption: the potential for change in one year is the average deforestation of the neighboring cells for the previous year.

The demand for deforestation in all models is the actual total deforestation given by PRODES. The first two models originally projected higher demand compared to the PRODES estimates. We reimplemented such models in order to take into account the differences in the demand. The three models were implemented using TerraME toolkit [15]. Results for the goodness of fit at the highest resolution are shown in Figure 2. Both SimAmazonia models and the neighborhood model have goodness of fit values above 50%, which means that less than half of the demand was allocated in wrong places.

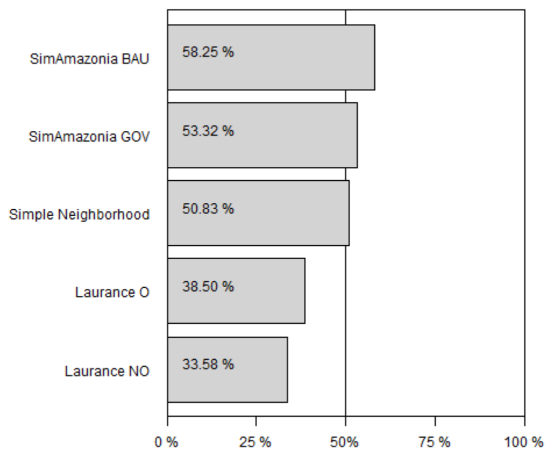

Figure 2: Bar chart of the goodness of fit at the finest resolution (pixel-wise comparison of reference and model result cell space). Laurance O and NO stand for the optimistic and the non-optimistic scenario.

Figure 3 shows the goodness of fit plotted against sampling window size. We see the differences between the model performances persist over many resolutions. The goodness of fit values increase slowly with increasing window size (note the logarithmic scale of the x axis). The steeper the increase of the fit curve, the more near-distance errors exist in the data. Near-distance errors occur when the mechanism allocates the change in a wrong location, but spatially close to the correct one. Thus, by increasing the window size, this misallocation gets smoothed out.

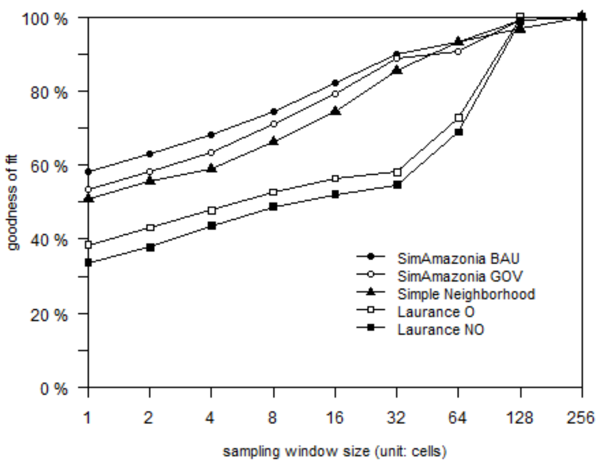

Figure 3: The goodness of fit of the different models plotted against sampling window size (logarithmic scale). The largest window is 256 by 256 cells. As it covers the whole cell space, which is 134 by 104 cells large, the goodness of fit is inevitably 100%.

The models allocate a lot of change in wrong regions. Both SimAmazonia models have a similar performance. Using a normalized demand, the allocation procedure is more realistic in the BAU scenario. The Laurance scenarios project most of the change in the wrong places. Even with sampling windows of size of 32 by 32 cells (800 by 800km), the Laurance models have a fit of only approximately 50%. The neighborhood model performs almost as well as the SimAmazonia models and much better than the Laurance models.

5 Discussion

The results presented in the previous section show that even the best model considered in our study allocates only about 60% of the change correctly. To understand the possible causes of allocation errors, we use the results of the neighborhood model. This model has a simple and restricted allocation procedure, which places all changes close to already deforested areas. We should expect that such a model reproduces the local extensions of existing areas correctly, but fails to account for new deforestation frontiers. Since the SimAmazonia models and the neighborhood model have a similar goodness of fit, we take that SimAmazonia models are not able to find out where the new frontiers of Amazonia are.

To explore further the factors that lead to modeling errors, we compare cell spaces of the deforestation as predicted by the models with the PRODES dataset in Figure 4. Because of their over-reliance on road infrastructure as the main factor for deforestation, the Laurance models allocate much change in the wrong places. Laurance et al. consider the impact of roads in the more remote areas to be the same as those closer to the markets of Belém (a in Figure 4), Cuiabá (b) and the Brazilian Southeast. Therefore, public policies that would use these models for planning would be limited to avoiding road building. As the PRODES results show, some roads are much more relevant as drivers of deforestation than others. Capturing the relative importance of roads is thus important for models that could guide public policy making. Laurance et al. also underestimate the effectiveness of protected areas. Recent studies show that protected areas in Amazonia have very low deforestation and thus are an important part of forest protection policies [16].

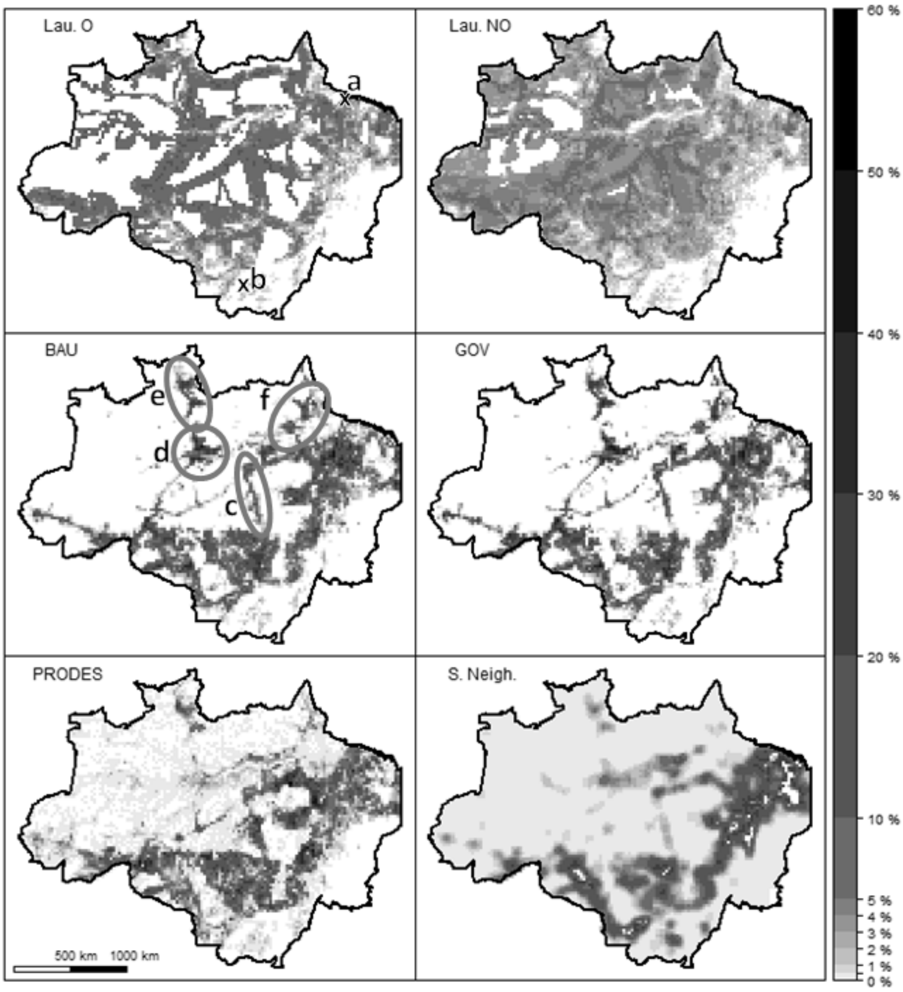

Figure 4: Maps of the area that was deforested in the years 2003-2011, according to PRODES data (lower left) and the model scenarios. The darker the cell's color, the higher the percentage of area deforested in that cell (values range from 0% to 60%). The letters a-f are explained in the text.

SimAmazonia captures most of the change close to existing deforested areas, but has a limited ability to predict how the frontier expands. It misses most of the deforestation around the Cuiabá-Santarém road (c) and predicted change close to

Manaus (d), in Roraima (e) and in the North of Pará (f) that did not happen. To fully understand the performance of the SimAmazonia model, a detailed analysis of its assumptions would be required, which is out of the scope of this paper. Our conjecture is that it is an effect of the 47 subregions used in the model. Breaking Amazonia into subregions is a sensible idea, since there are substantial differences inside the area. However, finding enough data to properly describe the factors that drive deforestation in each subregion is hard. Agricultural census data is available only at the municipality level. However, in Amazonia, municipalities have huge areas that make spatial allocation of driving factors extremely difficult. We presume that a better allocation of subregions in Amazonia could allow SimAmazonia to improve its goodness of fit.

6 Conclusion

This paper presents a metric to measure the quality of the transition potential and allocation methods of land change models. It uses a multi resolution method since spatial processes are scale-dependent. A model could have a low goodness of fit at detailed resolution, but could capture the general spatial pattern better than other models. The proposed metric focuses on changed areas and discards areas with no change. Thus, it prevents inflated goodness of fit values due to large fractions of the landscape remaining unchanged, as it often is the case in land change models.

We used the metric to compare several models that project deforestation in the Brazilian Amazon. Despite large quality differences between them, all the models have problems in predicting new frontiers and expansion areas. Because of this, the best model considered in this paper only performs slightly better than a simple model that predicts a cell's deforestation based on the deforestation in neighboring cells. We hope our results can motivate a new generation of deforestation models that better capture the socioeconomic factors underlying the decisions of the actors that carry out the deforestation.

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