Evaluating the Impact of Distance Measures on Deforestation Simulations in the Fluvial Landscapes of Amazonia

Maria Salonen, Eduardo Eiji Maeda,
Tuuli Toivonen

Received: 26 February 2013 / Revised: 23 April 2013 / Accepted: 7 October 2013 / Published online: 29 October 2013

Abstract Land use and land cover change (LUCC) models frequently employ different accessibility measures as a proxy for human influence on land change processes. Here, we simulate deforestation in Peruvian Amazonia and evaluate different accessibility measures as LUCC model inputs. We demonstrate how the selection, and different combinations, of accessibility measures impact simulation results. Out of the individual measures, *time distance to market center* catches the essential aspects of accessibility in our study area. The most accurate simulation is achieved when *time distance to market center* is used in association with *distance to transport network* and additional landscape variables. Although traditional *Euclidean measures* result in clearly lower simulation accuracy when used separately, the combination of two complementary *Euclidean measures* enhances simulation accuracy significantly. Our results highlight the need for site and context sensitive selection of accessibility variables. More sophisticated accessibility measures can potentially improve LUCC models' spatial accuracy, which often remains low.

Keywords Accessibility · Distance · LUCC modeling · Deforestation · Peruvian Amazonia

INTRODUCTION

Methodologies and tools for spatial simulation of land use and land cover change (LUCC) have experienced rapid

development during the past few decades (Hibbard et al. 2010). Despite these advances the level of uncertainty regarding the location and the amount of change in LUCC simulations remains high (Pontius et al. 2008). Moreover, data availability, quality, and suitability continue to be acute questions for the selection of spatial variables used for simulations and for the overall reliability of the models (Veldkamp and Lambin 2001).

In terms of environmental data we are doing rather well: High resolution global data on environmental systems have become widely available through remote sensing and extensive global environmental monitoring efforts (e.g., Achard et al. 2007; Batjes 2009). Data on commonly used biophysical variables in LUCC modeling (elevation, slope, soils, precipitation, etc.) are thus relatively easy to obtain. Challenges of scale, quality, and interoperability of such global datasets have been widely examined (e.g., Verburg et al. 2011b). In contrast to these directly observable biophysical variables, corresponding consistent information on human systems is much harder to find (Veldkamp and Lambin 2001; Verburg et al. 2011a). Human systems are more difficult to quantify than biophysical variables and the relevance of different anthropogenic surrogate variables often remains unexplored.

Physical accessibility is one of the most commonly used surrogates for human pressure on the environment. It is regarded as one of the strongest predictors of the location of land changes: proximity to transport network, particularly roads, is seen to explain changes resulting from new infrastructure investments (Kirby et al. 2006) and proximity to urban centers is considered to explain changes related to population pressure and market influence (Alvarez and Naughton-Treves 2003).

Despite the evident importance of accessibility, there is no clear consensus on how to conceptualize and quantify it

Electronic supplementary material The online version of this article (doi:10.1007/s13280-013-0463-x) contains supplementary material, which is available to authorized users.

for modeling purposes (Geurs and van Wee 2004). The methodological development around accessibility measures has mainly happened in the fields of transportation and urban geography and the methods developed have only partially been adopted by LUCC modelers. Travel time and other cost distance measures have for some time been proposed as realistic surrogates for accessibility (e.g., Ingram 1971; Verburg et al. 2011a), and there are examples of LUCC models that employ time distance or transport cost as accessibility inputs (e.g., Cropper et al. 2001; Verburg et al. 2004a; Merry et al. 2009; Mann et al. 2010; Bowman et al. 2012; Schirpke et al. 2012). Nevertheless, in many LUCC models, accessibility is still quantified as straight-line distances to a transportation network, to population and/or market centers and to previously changed areas (e.g., Laurance et al. 2002; Chomitz and Thomas 2003; Mas et al. 2004; Viña et al. 2004; Jasinski et al. 2005; Kirby et al. 2006; Soares-Filho et al. 2006; Pan et al. 2007; Kim 2010; Thapa and Murayama 2011).

The role of accessibility in land change processes is particularly interesting in Amazonia. Vast deforestation is typically associated with the Brazilian Amazon where state settlement programs have encouraged the populating of what had previously been poorly accessible areas. This development has involved extensive infrastructure building, typically followed by increasing deforestation rates (Kirby et al. 2006). A contrasting example is provided by north-eastern Peruvian Amazonia which has remained more sparsely populated and relatively poorly accessible. There transportation and movement are largely based on rivers and deforestation rates are considerably more moderate than in neighboring regions (Imbernon 1999).

In this paper, we systematically test the effect of different accessibility measures on a LUCC model that simulates deforestation dynamics in north-eastern Peruvian Amazonia. Region-specific specialties in transport systems, such as fluviality in our case, are a typical challenge for accessibility analyses in the tropics. We carry out a retrospective modeling exercise (from no deforestation to the present day deforestation pattern) and focus particularly on two questions: (i) What is the impact of different accessibility input variables on LUCC modeling results? and (ii) Which accessibility measure(s) together with other landscape variables yield the most reliable deforestation simulations? The general considerations on different accessibility measures provided by our examples are applicable in any context. Moreover, this particular case study provides concrete inputs for LUCC models in the fluvial landscapes of Amazonia where LUCC is a particularly important topic, given the local and global significance of the region (Cochrane and Laurance 2008).

MATERIALS AND METHODS

Study Area

Our case study area is located in the Loreto Region, north-eastern Peruvian Amazonia (Fig. 1). The area is a biodiversity hotspot and even today it is still among the most inaccessible regions in the world (Nelson 2008). There are very few roads in Loreto but the region is well connected by branching and highly meandering rivers that form the backbone of regional transportation. As a majority of transportation within the region is fluvial, the dynamic river network shapes patterns of accessibility between the regional core and the hinterland (Salonen et al. 2012). Meandering channels are the dominant river channel type in the area (Puhakka et al. 1992), and the high sinuosity of the channels implies that travel routes may end up being much longer than straight-line distances (Toivonen et al. 2007). Apart from Iquitos (the main market center of the region with circa 400 000 inhabitants) and a few secondary towns, the population is sparse and located along river courses.

Agriculture and forestry are among the most important economic activities in Loreto (Kvist and Nebel 2001) and agricultural expansion is the main cause of deforestation in the region (MINAM 2009). Forests in Loreto are well preserved in comparison to other regions in Peruvian Amazonia: although in absolute numbers Loreto ranks third in regional comparison of deforested area, the relative share of deforestation in Loreto is among the smallest (MINAM 2009).

Study Design

In order to assess the influence of different accessibility measures on deforestation simulations, we made a comparison of independent LUCC model runs, each run having a different set of input variables. The starting point of the simulations was a hypothetical situation where no deforestation had occurred in the landscape and the reference situation was the deforestation observed in the year 2000. Although we acknowledge the importance of independent validation (Kok et al. 2001), we performed the simulation for the calibration period and used the same dataset of year 2000 for calibration and validation. This was done, because we were interested in assessing the success of landscape pattern simulations as such rather than in future projections (see Mas et al. 2012 for a similar approach). The analysis focused solely on deforestation, without regarding forest regeneration. A total of 11 input dataset combinations were tested (Table 1; Fig. 2), as follows: First we tested the isolated influence of each accessibility variable by running the model with four different accessibility measures as the only inputs for the model (4 runs). Secondly, in order to demonstrate the effect of the other variables, simulations

Fig. 1 Our study area is located in the Loreto region in north-eastern Peruvian Amazonia. Approximately one-third of the region is a seasonally inundated flood plain and the transportation network is largely fluvial. Photographs © Maria Salonen

Table 1 Metadata on the spatial datasets used in the analyses

<i>Spatial determinants of deforestation</i>	<i>Model runs</i>											<i>Original scale / resolution</i>
	1	2	3	4	5	6	7	8	9	10	11	
<i>Accessibility measures</i>	A 1-4				L	Groups A1L-A4L						
A1 Euclidean distance to center	x					x				x		Salonen et al. (2012) 30 m
A2 Euclidean distance to network		x					x			x		Salonen et al. (2012) 30 m
A3 Network distance to center			x					x				Salonen et al. (2012) 30 m
A4 Time distance to center				x					x			Salonen et al. (2012) 30 m
<i>Landscape features (Group L)</i>												
Geology and soil formations					x	x	x	x	x	x	x	Geological map of Perú (INGEMMET 1999) 1 : 1000000
Protected areas					x	x	x	x	x	x	x	Map of protected areas (SERNANP 2012) 1 : 1900000
Indigenous areas					x	x	x	x	x	x	x	Map of indigenous communities (GOREL 2009) 1 : 1200000
Digital elevation model					x	x	x	x	x	x	x	Shuttle Radar Topography Mission (SRTM) 3 arc-seconds
<i>Data in the initial and final landscapes</i>												
River network	x								x			IIAP / BIODAMAZ (2004) 1 : 100000
Flooded area		x							x			Ecological systems classification (Josse et al. 2007) 1 : 250000
City of Iquitos			x									IIAP (2004) ca. 1 : 100000
Deforestation year 2000									x			Deforestation map of Peruvian Amazonia 2000 (MINAM 2009) 1 : 100000

^a INGEMMET - Instituto Geológico Minero y Metalúrgico, 1999, Mapa geológico del Perú. 1 : 1000000. / SERNANP - Servicio Nacional de Áreas Naturales Protegidas por el Estado, 2012. Mapa de áreas naturales protegidas. 1:1900000. / INEI = Instituto Nacional de Estadística e Informática; GOREL = Gobierno Regional de Loreto; IIAP = Instituto de Investigaciones de la Amazonia Peruana; BIODAMAZ = Proyecto Diversidad Biológica de la Amazonia Peruana; MINAM = Ministerio del Ambiente

Fig. 2 Flowchart illustrating the workflow of this study. Modeling steps (i–iv) are presented in more detail in “Model Inputs” and “The LUCC Modeling Procedure” sections

were performed using only a group of landscape variables without any data on accessibility (1 run). (The results of these first 5 runs are presented in Figs. S1 and S2, Electronic Supplementary Material.) Thirdly, the model was run using each individual accessibility variable together with the landscape variable group (4 runs). Finally, the joint influence of the two possibly complementary accessibility measures (distance to transport network and distance to center) was tested by running the model with a combination of the landscape variable group and the two accessibility measures (distance to center tested both as Euclidean distance and as time distance) (2 runs).

Model Inputs

The model received three datasets as inputs: (1) a map describing the land cover at the beginning of the modeling period (hereafter the *initial landscape*), (2) a map presenting the real deforestation pattern at the end of the modeling period (hereafter the *final landscape*), and (3) a set of explanatory variables that potentially influence the spatial distribution of deforestation (hereafter *spatial determinants of deforestation*). All the inputs were tiff images with a cell size of 100 m.

The exact study area was delineated as a rectangle (covering approximately 200 000 km² of Loreto) around the city of Iquitos (see Fig. 1). This delineation was applied in order to capture the deforestation patterns within the influence area of Iquitos and to restrict the influence of other cities, such as Pucallpa, in the neighboring Ucayali region.

Initial and Final Landscape Maps

The initial and final landscape maps contained three land cover classes: floodplain, forest, and non-forest. The flood plain included the river network and inundated areas as defined in the Ecological Systems classification (Josse et al. 2007) (Table 1). The forested area covered everything except for the flood plain and the deforested area.

As the initial landscape map described a situation where no deforestation had occurred around Iquitos, the deforested area was represented with a single non-forest spot indicating the location of the city. The final landscape map, in turn, represented the deforestation pattern in the year 2000 outside the flooded areas (Table 1). The difference in deforested area between the initial and the final landscapes was 3376 km² which represents 1.7 % of the study area.

Spatial Determinants of Deforestation

The spatial determinants of deforestation consisted of different accessibility measures and selected landscape features reflecting environmental conditions and land use restrictions in the study area (Table 1). As our focus was on the accessibility measures (called A1, A2, A3, A4, as defined later), we used the landscape variables as one group (Group L), without analyzing the individual role of these variables. Variable groups where each accessibility measure was used together with the landscape variable group L are called A1L (accessibility measure A1 + landscape variable group L), A2L (measure A2 + group L), A3L (measure A3 + group L), and A4L (measure A4 + group L). We also tested the combination of two possibly complementary accessibility measures (distance to urban center and distance to transport network) together with the landscape variables, in order to see whether the two accessibility measures together performed better than each of them alone. These variable groups are called A1A2L (accessibility measures A1 and A2 and the landscape variable group L) and A4A2L (measures A4 and A2 and group L).

Accessibility Variables We tested four different accessibility measures, all of them computed with Spatial Analyst Tools in ArcGIS 9.3.1 (ESRI, Redlands, CA, USA). *Euclidean distance to center* (variable A1) was measured as a straight-line distance from each cell to Iquitos, without regarding the transportation network. Similarly, *Euclidean distance to network* (A2) was measured as a straight-line distance from each cell to the closest river or road network cell. *Network distance to center* (A3) was calculated with a cost distance algorithm, using impedance values that corresponded to actual distances in meters. Consequently, the final cell values represent realistic travel distances from each cell to Iquitos, along the transportation network. Finally, *time distance to center* (A4) was calculated with a cost distance algorithm and the impedance values were defined based on GPS-measured travel speeds along different rivers. The observed navigation speeds ranged from 7.0 to 21.3 km h⁻¹, larger rivers generally receiving smaller impedance values (indicating faster movement) and smaller rivers larger impedance values (indicating slower movement). Driving speed along the one existing road (100 km long, between Iquitos and Nauta) was defined as 60 km h⁻¹ and the speed of traveling on land areas was set at 3 km h⁻¹, corresponding to a relatively slow walking speed. The final cell values reveal travel times from the cell center to Iquitos, along the river network. For a more detailed description of the data and methodology for calculating the different accessibility measures, see Salonen et al. (2012).

The spatial appearance of all accessibility variables is shown in the upper left box in Fig. 2.

Landscape Variables: Environment and Land Tenure The topography of the study area was depicted by SRTM data and the geological map of Peru was used to determine different geological formations (Table 1). Floristic patterns in Amazonia are strongly associated with underlying geological patterns (Tuomisto et al. 1995) and, thus, the geological entities and their edaphic properties were used as a model input instead of a soil map that was only available at a very coarse resolution. Naturally, both the topography and the geological formations reflect the patterns of the floodplain and the river network.

Other abiotic environmental variables occasionally used in LUCC modeling, such as precipitation and temperature, were omitted from the analysis, given their minimal variation and uniform distribution across the study area.

Land tenure was represented with two spatial variables known to have an effect on land use patterns in Amazonia (see Oliveira et al. 2007): protected areas and indigenous territories. In the year 2000 there were three protected areas in the study area. The largest of these, Pacaya-Samiria (south-west of Iquitos), was already established as a national reserve, while the two other areas (Allpahuayo-Mishana in the proximity of Iquitos and Pucacuro further north-west close to the Ecuadorian border) had the status of a “reserved zone” (SERNANP 2012). *Indigenous territories* are areas titled to or used by indigenous groups in Loreto. These vary in size and shape and are located mainly along rivers.

The spatial appearance of all landscape variables is shown in the upper right box in Fig. 2.

The LUCC Modeling Procedure

Land change simulations were done using Dinamica EGO (version 1.6.2), which is a cellular automata model initially developed for simulation of Amazonian landscape dynamics (Soares-Filho et al. 2002). Dinamica has been widely applied to explore different LUCC processes in many parts of the world, ranging from tropical deforestation (e.g., Maeda et al. 2010, 2011; Fuller et al. 2011) to urban growth dynamics (Thapa and Murayama 2011).

The LUCC simulation procedure in Dinamica can be divided into a series of distinct phases (see Fig. 2): (i) estimation of land change rates based on historical data on change rates in the landscape, (ii) quantification of land transition probability and its spatial distribution based on the Bayesian Weights of Evidence (WoE) method (Bonham-Carter 1994; Soares-Filho et al. 2009), (iii) spatial allocation of changes, and (iv) model performance

assessment and validation. The model is calibrated by modifying the share of pixels allocated through two complementary allocation algorithms (*expander* and *patcher*) and by defining the mean patch size, patch size variance, and patch isometry of the simulated deforestation patches.

In phase (iii) the transitions are allocated in iterative steps, the number of which is determined by the user. The *expander* function expands already existing patches of a certain land cover class and thus exhibits feedback (spatial path dependence) over the allocation steps (see Brown et al. 2005). The *patcher* function, in turn, is designated to generate new deforestation patches through a seed formation mechanism (Soares-Filho et al. 2009). Both of these algorithms use a stochastic selecting mechanism which consists of scanning the initial landscape map to sort out the cells with the highest change probabilities (determined by the WoE method). When selecting cells for transition, the algorithms first arrange cells with the highest probabilities in a data array and then randomly select transition cells from the top to the bottom of the array. (For a full description of the methodology, see Soares-Filho et al. 2002, 2009.)

In this study the land change rates were inevitably correct in all the simulations as the calibration and validation periods were the same. Different settings were tested when calibrating the model and the final parameters used were the following: Ninety percent of the changes were allocated using the *patcher* algorithm and the remaining 10 % by the *expander*. The mean patch size was set to 1 ha/2 ha (*patcher/expander*, respectively), patch size variance to 5 ha and patch isometry to 1. Land changes were allocated in 20 iterative steps. Furthermore, we iterated each model run 16 times in order to see, how the stochastic component of the model affected the results. This number of iterations was sufficient to identify significant variations in the simulation results and an even number of iterations was convenient also for the visualization of the results. As outputs the model produced simulated landscape maps representing the predicted configuration of land cover classes in the landscape.

The fuzzy similarity index implemented in Dinamica EGO (Almeida et al. 2008; Soares-Filho et al. 2009) was used to compare the simulated landscape maps with the observed deforestation pattern (phase iv in Fig. 2). The method uses gradually expanding analysis windows, which is a useful approach when comparing maps that do not exactly match on a cell-by-cell basis but still have similar spatial patterns within a certain cell vicinity (Mas et al. 2012). The degree of similarity is expressed as an index ranging from 0 (total disagreement) to 1 (identical maps). The average similarity values of the 16 model iterations were visualized as a fuzzy similarity curve.

RESULTS

The Influence of Individual Accessibility Variables and Landscape Variables on Deforestation Simulations

The simulated landscape maps for groups A1L–A4L and the reference map are presented in Fig. 3. The different colors show how many times (out of the 16 model iterations) each pixel was classified to the respective land cover class. The model's stochastic allocation procedure results in slightly varying simulation results on a pixel-by-pixel level but the overall pattern stays rather stable over the iterations. In all groups more than 74 % of non-forest cells are allocated to same locations in at least eight model iterations out of the 16. Group A1L simulation depicts the change patterns around Iquitos well but ends up overplaying the vicinity of the city. Change patterns further away from the city are largely missed by this group. Group A2L simulation reveals a different pattern: The change pixels are allocated evenly along the river shores but the model does not distinguish between larger and smaller rivers. Thus, the river banks of the smaller tributaries are emphasized too much at the expense of the urban center. The Group A4L map allocates slightly more deforestation along the larger rivers (south-west of Iquitos) while the group A3L simulation places more emphasis on the smaller rivers in the proximity of the city. Although both of these simulations perform well around the city and along the main rivers, they miss the smaller deforestation patches further away from Iquitos.

The fuzzy similarity indices associated with these simulations are presented in Fig. 4. Each line represents the average of the 16 model iterations. Variation between the iterations was minor and thus the order of the curves would remain the same regardless of which model realizations were presented in the figure.

The order of the curves is clear: Groups A4L and A3L are the most successful in replicating the actual pattern of deforestation. When the maps are compared pixel-by-pixel (window size 1) both group A4L and group A3L simulations catch approximately 40 % of the actual pattern. With growing window size the similarity increases and at 2 km pixel size the similarity between group A3L and group A4L simulations and the reference map is nearly 0.79. At small window sizes, group A1L is close to the level of groups A4L and A3L but as the fuzziness of location is increased the difference between these groups becomes larger. At 2 km cell size, group A1L has a similarity value of 0.76. Group A2L is clearly less successful with its simulations. On a pixel-by-pixel scale the similarity of group A2L simulation to the actual pattern is 0.32 and at 2 km resolution it reaches a similarity of 0.73. For

Fig. 3 Simulated maps resulting from model runs with variable groups A1L–A4L and groups A1A2L and A4A2L. The reference map shows the true pattern of deforestation

Fig. 4 Multiple window fuzzy similarity indices obtained from the comparison between the reference map and the simulated maps using variable groups A1L–A4L and group L. Each line represents the average of the 16 model iterations

Fig. 5 Fuzzy similarity indices resulting from model runs with variable groups A1A2L and A4A2L [and groups A1L and A4L (in gray) for reference]. Each line represents the average of the 16 model iterations

comparison, the curve of Group L is also displayed. It runs clearly below the groups that contain data on accessibility.

The Influence of Complementary Accessibility Variables and Landscape Variables on Deforestation Simulations

The two maps at the bottom of Fig. 3 show the results of model runs where two accessibility measures (distance to network and distance to center as Euclidean distance and as time distance) were put together and analyzed with the landscape variables. A visual comparison suggests that the two simulated maps do not differ much; the most notable difference is that group A1A2L (accessibility to center as Euclidean distance) allocates slightly more change pixels to the study area's borders north-east and south-east of

Iquitos whereas group A4A2L (accessibility to center as time distance) avoids these areas that are in terms of time distant from Iquitos.

The fuzzy similarity indices (Fig. 5) confirm that, at small window sizes, differences in the accuracy of the simulations are small. For comparison, the fuzzy similarity curves of groups A1L and A4L are visualized too. As the analysis window grows, group A4A2L outperforms the other groups and is the most successful of all the 11 model runs. At 2 km cell size, the average similarity index of this group is 0.80. The simulations with group A1A2L are considerably more accurate than the simulations with groups A1L and A2L, which contained only one of the Euclidean measures. Furthermore, when the two Euclidean measures are put together, the accuracy of the simulations is much closer to the accuracy reached by the groups that contained more sophisticated distance measures: At 2 km analysis window size, the fuzzy similarity index of group A1A2L is 0.79 and finally, at 2.5 km window size, group A1A2L becomes slightly better than group A4L.

DISCUSSION

Quantification of Accessibility Makes a Difference

The need for better surrogates for human influence (that would for example take into account networks that guide the movement of people) was identified as a research priority among the LUCC community nearly 10 years ago (Verburg et al. 2004b). Since then, LUCC modelers have, to some extent, employed different accessibility measures—travel times, transport costs, and the like—as model inputs. Simple Euclidean measures are still very common—perhaps because they are easy and fast to compute—and in many cases no reasons or alternatives are presented for the selection of accessibility variables.

Based on our results it is nevertheless clear that using different accessibility measures as inputs for a LUCC model produce considerably different simulation results. The time distance measure shows the strongest performance in all the tests and seems to capture essential aspects of human pressure on the environment: when individual accessibility measures were tested in association with the landscape variables the best results were obtained with a variable group containing time distance to center. The most accurate simulated landscape maps resulted from the variable group that contained both time distance to center and distance to network together with the landscape variables.

Network distance measures perform nearly as well as time distance ones, which is not surprising given the similarity of these measures (see Salonen et al. 2012). In contrast, the most commonly used accessibility surrogates—Euclidean distance to center and Euclidean distance to

network—are less stable in their performance when they are used separately from each other. However, the simulation resulting from group L, which did not have any accessibility information, was clearly the least successful compared to the results from groups that had at least some measure of accessibility, indicating that even simple measures of accessibility can be useful and improve the accuracy of the model. Moreover, when put together the two simple measures complement each other and the joint effect of these two measures ended up being nearly as accurate as the effect of the single time distance measure.

Indeed, the optimal representation of accessibility depends on the context. In areas where the transportation network around centers is regular and dense, the Euclidean distance to center may provide a good proxy for accessibility (e.g., Aparicio et al. 2008). Similarly, in areas where the influence of centers is minor, measuring distances to transport networks might be enough. In our case the combination of these measures provided much more accurate representation of access—even when both of these were measured as Euclidean distances.

In areas where the friction of movement cannot be considered homogeneous across the landscape, more sophisticated measures can increase the reliability of LUCC simulations. As our study shows, accessibility measures that incorporate spatial patterns and properties of the network may also provide added value for the LUCC analysis in the case of fluvial networks. Other studies conducted in completely different study areas confirm these findings: Nelson and Hellerstein (1997) tested their land change model of central Mexico with cost distance and Euclidean measures and found the former to work better. In mountainous areas of the Philippines, Verburg et al. (2004a) found that accessibility measured as travel time and travel cost were better predictors of agricultural land use patterns than simple Euclidean measures.

The phenomenon under study also affects the selection of the appropriate measure for representing accessibility. Land change—such as deforestation here—is a result of multiple processes. If land change is primarily driven by the commercial farming of perishable products, time distance to market logically is an important determinant of such changes (Salonen et al. 2012). In the case of non-perishable products, such as long-lasting fruit or timber, distance to transport network, transport costs, or agricultural rent might become the most critical components of accessibility, thus affecting the selection of the appropriate accessibility metrics (Verburg et al. 2004a; Mann et al. 2010).

Model Performance

Although simulated LUCC scenarios are widely accepted as an efficient way of communicating scientific results on

land change dynamics for decision makers and land users (Veldkamp and Lambin 2001; Fuller et al. 2011), the predictive power of LUCC models often remains low, both in terms of the location and the rate of change (Pontius et al. 2008). Whereas our best simulation reached a mean fuzzy similarity index of 0.8 at 2 km window size, the index at a similar resolution remained close to 0.5 in a case study conducted in the Mexican highlands (Guerrero et al. 2008) and under 0.6 in a case study of Brazilian Amazonia (Maeda et al. 2010). A case study of Bolivian Amazonia (Mas et al. 2012) reached a similarity of over 0.8 at 2 km resolution, and an urban land use simulation in Brazil reached 0.85 similarity at even smaller window sizes (Almeida et al. 2008). When comparing these results, it should be noted that the size of the study area, the rate of change, and the number of included land use/land cover classes differed between these studies. Thus, comparison of the fuzzy similarity values between different study settings should be viewed as tentative in nature.

Smaller deforestation areas far away from the center are poorly recognized by our models and accessibility does not explain these patterns. There are many possible explanations for this. First, unlike commercial farmers, groups living mainly in a subsistence economy are not sensitive to market access in their location decisions (Chomitz and Gray 1996). Moreover, the most remote areas might be subject to considerable pressure from illegal or non-resident extractors and loggers due to unclear property rights and highly valued natural resources (Viña et al. 2004).

Outside the scope of this paper but definitely worth further study is the influence of the scale and spatial extent of the analysis on the accuracy of the different accessibility measures.

CONCLUSIONS

This study demonstrates that a proper representation of accessibility is central for achieving more reliable LUCC simulations and that more consideration is needed regarding the selection of accessibility measures and the methods used to produce them. In our results, time distance to market center captured the most essential aspects of accessibility. Two complementary Euclidean measures together achieved a nearly similar degree of accuracy as that attained by the variable group where time distance alone represented accessibility. Based on these examples, we recommend that LUCC modelers test the effect of different accessibility variables and their combinations—paying attention to site-specific characteristics of the transport networks and the type of phenomenon analyzed. As we have shown, using more sophisticated measures of accessibility in LUCC modeling has the potential to

improve the spatial accuracy of models, reducing uncertainties and providing more reliable simulations for end users.

Acknowledgments The work described in this paper was financially supported by the University of Helsinki 3-Year Research Grants and ERC project GEDA. We would like to thank the Amazon research team at the University of Turku for valuable comments on data sources during the preparation of the manuscript. We also thank the anonymous reviewers for their comments.

REFERENCES

- Achard, F., R. Defries, H. Eva, M. Hansen, P. Mayaux, and H. Stibig. 2007. Pan-tropical monitoring of deforestation. *Environmental Research Letters* 2: 045022.
- Almeida, C.M., J.M. Gleriani, E.F. Castejon, and B.S. Soares-Filho. 2008. Using neural networks and cellular automata for modelling intra-urban land-use dynamics. *International Journal of Geographical Information Science* 22: 943–963.
- Alvarez, N.L., and L. Naughton-Treves. 2003. Linking national agrarian policy to deforestation in the Peruvian Amazon: A case study of Tambopata, 1986–1997. *AMBIO* 32: 269–274.
- Apparicio, P., M. Abdelmajid, M. Riva, and R. Shearmur. 2008. Comparing alternative approaches to measuring the geographical accessibility of urban health services: Distance types and aggregation-error issues. *International Journal of Health Geographics* 7(1): 7.
- Batjes, N.H. 2009. Harmonized soil profile data for applications at global and continental scales: Updates to the WISE database. *Soil Use and Management* 25: 124–127.
- Bonham-Carter, G. 1994. *Geographic information systems for geoscientists: Modelling with GIS*. Kidlington: Elsevier, Pergamon.
- Bowman, M.S., B.S. Soares-Filho, F.D. Merry, D.C. Nepstad, H. Rodrigues, and O.T. Almeida. 2012. Persistence of cattle ranching in the Brazilian Amazon: A spatial analysis of the rationale for beef production. *Land Use Policy* 29: 558–568.
- Brown, D.G., S. Page, R. Riolo, M. Zellner, and W. Rand. 2005. Path dependence and the validation of agent-based spatial models of land use. *International Journal of Geographic Information Science* 19: 153–174.
- Chomitz, K.M., and D.A. Gray. 1996. Roads, land use, and deforestation: A spatial model applied to Belize. *World Bank Economic Review* 10: 487–512.
- Chomitz, K.M., and T.S. Thomas. 2003. Determinants of land use in Amazônia: A fine-scale spatial analysis. *American Journal of Agricultural Economics* 85: 1016–1028.
- Cochrane, M.A., and W.F. Laurance. 2008. Synergisms among fire, land use, and climate change in the Amazon. *AMBIO* 37: 522–527.
- Cropper, M., J. Puri, and C. Griffiths. 2001. Predicting the location of deforestation: The role of roads and protected areas in North Thailand. *Land Economics* 77: 172–186.
- Fuller, D.O., M. Hardiono, and E. Meijaard. 2011. Deforestation projections for carbon-rich peat swamp forests of Central Kalimantan, Indonesia. *Environmental Management* 48: 436–447.
- Geurs, K.T., and B. van Wee. 2004. Accessibility evaluation of land-use and transport strategies: Review and research directions. *Journal of Transport Geography* 12: 127–140.
- Guerrero, G., O. Masera, and J. Mas. 2008. Land use/land cover change dynamics in the Mexican highlands: Current situation and long term scenarios. In *Modelling environmental dynamics: Advances in geomatic solutions*, ed. M. Paegelow and M.T. Camacho Olmedo, 57 pp. Berlin: Springer.
- Hibbard, K., A. Janetos, D.P. Van Vuuren, J. Pongratz, S.K. Rose, R. Betts, M. Herold, and J.J. Feddema. 2010. Research priorities in land use and land-cover change for the Earth system and integrated assessment modelling. *International Journal of Climatology* 30: 2118–2128.
- Imbernon, J. 1999. A comparison of the driving forces behind deforestation in the Peruvian and the Brazilian Amazon. *AMBIO* 28: 509–513.
- Ingram, D.R. 1971. The concept of accessibility: A search for an operational form. *Regional Studies* 5: 101.
- Jasinski, E., D. Morton, R. DeFries, Y. Shimabukuro, L. Anderson, and M. Hansen. 2005. Physical landscape correlates of the expansion of mechanized agriculture in Mato Grosso, Brazil. *Earth Interactions* 9(16): 1–18.
- Josse, C., G. Navarro, F. Encarnación, A. Tovar, P. Comer, W. Ferreira, F. Rodríguez, J. Saito, et al. 2007. *Ecological systems of the Amazon Basin of Peru and Bolivia. Classification and Mapping*. Arlington: NatureServe.
- Kim, O.S. 2010. An assessment of deforestation models for reducing emissions from deforestation and forest degradation (REDD). *Transactions in GIS* 14: 631–654.
- Kirby, K.R., W.F. Laurance, A.K. Albernaz, G. Schroth, P.M. Fearnside, S. Bergen, E.M. Venticinque, and C. da Costa. 2006. The future of deforestation in the Brazilian Amazon. *Futures* 38: 432–453.
- Kok, K., A. Farrow, A. Veldkamp, and P.H. Verburg. 2001. A method and application of multi-scale validation in spatial land-use models. *Agriculture, Ecosystems & Environment* 85: 223–238.
- Kvist, L.P., and G. Nebel. 2001. A review of Peruvian flood plain forests: Ecosystems, inhabitants and resource use. *Forest Ecology and Management* 150: 3–26.
- Laurance, W.F., A.K.M. Albernaz, G. Schroth, P.M. Fearnside, S. Bergen, E.M. Venticinque, and C. Da Costa. 2002. Predictors of deforestation in the Brazilian Amazon. *Journal of Biogeography* 29: 737–748.
- Maeda, E.E., B.J.F. Clark, P. Pellikka, and M. Siljander. 2010. Modelling agricultural expansion in Kenya's Eastern Arc Mountains biodiversity hotspot. *Agricultural Systems* 103: 609–620.
- Maeda, E.E., C.M. de Almeida, A. de Carvalho Ximenes, A.R. Formaggio, Y.E. Shimabukuro, and P. Pellikka. 2011. Dynamic modeling of forest conversion: Simulation of past and future scenarios of rural activities expansion in the fringes of the Xingu National Park, Brazilian Amazon. *International Journal of Applied Earth Observation and Geoinformation* 13: 435–446.
- Mann, M.L., R.K. Kaufmann, D. Bauer, S. Gopal, M.D.C. Vera-Diaz, D. Nepstad, F. Merry, J. Kallay, et al. 2010. The economics of cropland conversion in Amazonia: The importance of agricultural rent. *Ecological Economics* 69: 1503–1509.
- Mas, J.F., H. Puig, J.L. Palacio, and A. Sosa-López. 2004. Modelling deforestation using GIS and artificial neural networks. *Environmental Modelling & Software* 19: 461–471.
- Mas, J.F., A. Pérez-Vega, and K.C. Clarke. 2012. Assessing simulated land use/cover maps using similarity and fragmentation indices. *Ecological Complexity* 11: 38–45.
- Merry, F., B. Soares-Filho, D. Nepstad, G. Amacher, and H. Rodrigues. 2009. Balancing conservation and economic sustainability: The future of the Amazon Timber Industry. *Environmental Management* 44: 395–407.
- MINAM - Ministerio del Ambiente. 2009. Mapa de Deforestación de la Amazonía Peruana 2000. PROCLIM—Programa de Fortalecimiento

- de Capacidades Nacionales para manejar el impacto del Cambio Climático y la Contaminación del Aire. Memoria Descriptiva.
- Nelson, A. 2008. Travel time to major cities: A global map of Accessibility. Office for Official Publications of the European Communities, Luxembourg. doi:[10.2788/95835](https://doi.org/10.2788/95835), ISBN:978-92-79-09771-3.
- Nelson, G.C., and D. Hellerstein. 1997. Do roads cause deforestation? Using satellite images in econometric analysis of land use. *American Journal of Agricultural Economics* 79: 80–88.
- Oliveira, P.J.C., G.P. Asner, D.E. Knapp, A. Almeyda, R. Galván-Gildemeister, S. Keene, R.F. Raybin, and R.C. Smith. 2007. Land-use allocation protects the Peruvian Amazon. *Science* 317: 1233–1236.
- Pan, W., D. Carr, A. Barbieri, R. Bilsborrow, and C. Suchindran. 2007. Forest clearing in the Ecuadorian amazon: A study of patterns over space and time. *Population Research and Policy Review* 26: 635–659.
- Pontius, R.G., Jr., W. Boersma, J. Castella, K. Clarke, T. Nijs, C. Dietzel, Z. Duan, E. Fotsing, et al. 2008. Comparing the input, output, and validation maps for several models of land change. *Annals of Regional Science* 42: 11–37.
- Puhakka, M., R. Kalliola, M. Rajasilta, and J. Salo. 1992. River types, site evolution and successional vegetation patterns in Peruvian Amazonia. *Journal of Biogeography* 19: 651–665.
- Salonen, M., T. Toivonen, J.-M. Cohalan, and O.T. Coomes. 2012. Critical distances: Comparing measures of spatial accessibility in the riverine landscapes of Peruvian Amazonia. *Applied Geography* 32: 501–513.
- Schirpke, U., G. Leitinger, U. Tappeiner, and E. Tasser. 2012. SPALUCC: Developing land-use/cover scenarios in mountain landscapes. *Ecological Informatics* 12: 68–76.
- Soares-Filho, B.S., G. CoutinhoCerdeira, and C. Lopes Pennachin. 2002. DINAMICA—A stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. *Ecological Modelling* 154: 217–235.
- Soares-Filho, B.S., D.C. Nepstad, L.M. Curran, G.C. Cerqueira, R.A. Garcia, C.A. Ramos, E. Voll, A. McDonald, et al. 2006. Modelling conservation in the Amazon basin. *Nature* 440: 520–523.
- Soares-Filho, B.S., H.O. Rodrigues, and W.L.S. Costa. 2009. *Modeling environmental dynamics with Dinamica EGO*. Belo Horizonte, Brazil: Centro de Sensoriamento Remoto/Universidade Federal de Minas Gerais.
- Thapa, R.B., and Y. Murayama. 2011. Urban growth modeling of Kathmandu metropolitan region, Nepal. *Computers, Environment and Urban Systems* 35: 25–34.
- Toivonen, T., S. Mäki, and R. Kalliola. 2007. The riverscape of Western Amazonia—A quantitative approach to the fluvial biogeography of the region. *Journal of Biogeography* 34: 1374–1387.
- Tuomisto, H., K. Ruokolainen, R. Kalliola, A. Linna, W. Danjoy, and Z. Rodriguez. 1995. Dissecting Amazonian biodiversity. *Science* 269: 63–66.
- Veldkamp, A., and E.F. Lambin. 2001. Predicting land-use change. *Agriculture, Ecosystems & Environment* 85: 1–6.
- Verburg, P.H., K.P. Overmars, and N. Witte. 2004a. Accessibility and land-use patterns of the forest fringe in the northeastern part of the Philippines. *Geographical Journal* 170: 238–255.
- Verburg, P.H., P.P. Schot, M.J. Dijst, and A. Veldkamp. 2004b. Land use change modelling: Current practice and research priorities. *GeoJournal* 61: 309–324.
- Verburg, P.H., E.C. Ellis, and A. Letourneau. 2011a. A global assessment of market accessibility and market influence for global environmental change studies. *Environmental Research Letters* 6: 034019.
- Verburg, P.H., K. Neumann, and L. Nol. 2011b. Challenges in using land use and land cover data for global change studies. *Global Change Biology* 17: 974–989.
- Viña, A., F.R. Echavarría, and D.C. Rundquist. 2004. Satellite change detection analysis of deforestation rates and patterns along the Colombia–Ecuador border. *AMBIO* 33: 118–125.

AUTHOR BIOGRAPHIES

Maria Salonen (✉) is a doctoral student at the University of Helsinki. Her research interests include multimodal accessibility modeling in urban and rural contexts.

Address: Department of Geosciences and Geography, University of Helsinki, P.O. Box 64, Gustaf Hållströmin katu 2, 00014 Helsinki, Finland.

e-mail: maria.salonen@helsinki.fi

Eduardo Eiji Maeda is a postdoctoral researcher at the University of Helsinki. He specializes in remote sensing and hydrology. His research interests lie in the interactions between land change, water resources, and climate change, with particular focus in tropical regions.

Address: Department of Geosciences and Geography, University of Helsinki, P.O. Box 64, Gustaf Hållströmin katu 2, 00014 Helsinki, Finland.

e-mail: eduardo.maeda@helsinki.fi

Tuuli Toivonen is a university researcher at the Finnish Centre of Excellence in Metapopulation Biology of the University of Helsinki and holds a position as senior lecturer in Geoinformatics at the Department of Geosciences and Geography. She is interested in methods of geoinformatics in land use planning and decision-making, from data production and delivery services to analysis and visualization. Western Amazonia has been one of her study areas since the year 2000.

Address: Department of Biosciences, University of Helsinki, P.O. Box 56, Viikinkaari 9, 00014 Helsinki, Finland.

Address: Department of Geosciences and Geography, University of Helsinki, P.O. Box 64, Gustaf Hållströmin katu 2, 00014 Helsinki, Finland.

e-mail: tuuli.toivonen@helsinki.fi