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REVIEW

The transparency, reliability and utility of tropical rainforest land-use and land-cover change models

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Abstract

Land-use and land-cover (LULC) change is one of the largest drivers of biodiversity loss and carbon emissions globally. We use the tropical rainforests of the Amazon, the Congo basin and South-East Asia as a case study to investigate spatial predictive models of LULC change. Current predictions differ in their modelling approaches, are highly variable and often poorly validated. We carried out a quantitative review of 48 modelling methodologies, considering model spatio-temporal scales, inputs, calibration and validation methods. In addition, we requested model outputs from each of the models reviewed and carried out a quantitative assessment of model performance for tropical LULC predictions in the Brazilian Amazon. We highlight existing shortfalls in the discipline and uncover three key points that need addressing to improve the transparency, reliability and utility of tropical LULC change models: (1) a lack of openness with regard to describing and making available the model inputs and model code; (2) the difficulties of conducting appropriate model validations; and (3) the difficulty that users of tropical LULC models face in obtaining the model predictions to help inform their own analyses and policy decisions. We further draw comparisons between tropical LULC change models in the tropics and the modelling approaches and paradigms in other disciplines, and suggest that recent changes in the climate change and species distribution modelling communities may provide a pathway that tropical LULC change modellers may emulate to further improve the discipline. Climate change models have exerted considerable influence over public perceptions of climate change and now impact policy decisions at all political levels. We suggest that tropical LULC change models have an equally high potential to influence public opinion and impact the development of land-use policies based on plausible future scenarios, but, to do that reliably may require further improvements in the discipline.

Keywords: Amazon, input data, tropical LULC change, model comparison, modelling framework, spatio-temporal scales, validation methods

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Introduction

Land-use and land-cover (LULC) change is a process that is present in all environments across the globe (Lambin *et al*., 2001; Geist & Lambin, 2002). It is driven by many natural and anthropogenic factors, and it is the largest driver of biodiversity loss at global scales (Pereira *et al*., 2010). Tropical deforestation is probably the most paradigmatic example of LULC change, because of the huge detrimental impacts forest loss can have on the future of the planet and human wellbeing (Foley *et al*., 2005). During the last two decades, 80% of new agricultural land across the world has across the world has come from conversion of tropical forest (Gibbs *et al*., 2010). Furthermore, emissions from global land-use change are the second largest anthropogenic source of carbon dioxide (CO_2), just behind fossil fuel emissions, with Southeast (SE) Asia and South America being the two main contributors (Le Quere *et al*., 2009). Losing biodiversity-rich ecosystems at such a fast rate is a major threat to the world's biodiversity (Myers, 1988; Brook *et al*., 2003; Ahrends *et al*., 2010; Sangermano *et al*., 2012). In addition, the rapid destruction of tropical forests is compromising the future of many indigenous people (Alcorn, 1993) as well as the future of local populations (Laurance, 1999).

Numerous models of tropical LULC conversion have been developed to understand the complex interactions among human and biophysical factors that drive change (Ludeke *et al*., 1990; Mertens & Lambin, 1997; Verburg *et al*., 2002; Soares-Filho *et al*., 2006). Several reviews have been written dealing with LULC models (Verburg *et al*., 2004; Matthews *et al*., 2007); nearly a decade ago Verburg *et al*. (2004) highlighted several shortfalls in LULC modelling but even today there are

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still many issues within the discipline and improvements still need to be made (Brown *et al*., 2013).

Tropical LULC models are employed to address questions concerning why changes happened in the past, to help understand the main drivers of change in the present, to predict how much and where change will occur in the future and to examine plausible scenarios of landscape modification. Predicting not only the amount of forest that will be lost in the future, but also the location of this loss, is vital for successfully implementing conservation strategies (Mertens & Lambin, 1997). Current predictions of tropical LULC change differ in their modelling approaches, and predictions of future change vary among models and, given the self-obvious difficulties of validating models that predict a future that has not yet happened, the reliability of tropical LULC models remains uncertain. Thus, modelling the processes of tropical LULC change remains a great challenge. This challenge arises partly because the physical environment can vary greatly from one region to another, and can also be in constant change. In addition, the underlying processes that drive tropical LULC change are usually very complex, combining many socio-economic, cultural, political and environmental factors (Geist & Lambin, 2002).

In the literature, there are a variety of predictive tropical LULC change models, which vary greatly in terms of methodology (e.g. agent-based, cellular automata, statistical), time frame, and the region where, and scale at which, they were calibrated. This review provides a quantitative summary of spatially-explicit predictive models of tropical LULC change, using the tropical rainforests located in the Amazon basin, SE Asia and the Congo basin as a case study. We aim to highlight the different methodologies that exist specifically with regards to differences in prediction goals, model inputs and outputs, and model calibration and validation techniques. Furthermore, we aim to evaluate the transparency, reliability and utility of tropical LULC models working in tropical regions. On the basis of the findings of this analysis, we highlight several shortcomings in the approaches taken in tropical LULC change modelling, and draw on the experience of other modelling communities to make specific recommendations with a view to strengthening the tropical LULC change modelling discipline.

Material and methods

Bibliographical search

We focussed our review on the three tropical rainforest zones in the Amazon, the Congo and SE Asia. Together, these three regions encompass more than 10 million km^2 of rainforest across 15 countries (Supporting Information – Study regions). Using ISI Web of Knowledge, we searched for papers using the keywords 'land-use change model' in combination with the additional keywords 'Congo', 'Amazon', 'Indonesia', 'Philippines', 'Malaysia' or 'Brunei' (insular SE Asia), on the 27th of June 2013, which returned a total of 1100 papers. From this, we selected a set of papers (45 in total) that specifically model tropical LULC change in these tropical regions (Supporting Information – Appendix 1). Three of these papers presented two independent models, which we treated as separate entities in our quantitative review, giving a total of 48 models. We excluded book chapters, reviews, any papers published pre-1990, papers presenting models that made no spatial predictions and papers that focussed on land uses other than forest (e.g. 'cerrado' and urban).

Quantitative summaries of the literature

To test for the transparency of this set of tropical LULC change models, we extracted the methodological information from the published papers, referring to the associated supplementary material of those papers where necessary (Table S1). Models that lack transparency are those for which we were unable to extract the information needed to replicate the model in its entirety. We covered aspects such as: (1) the spatial (cell size and extent of study area) and temporal (time period for which the model was calibrated and simulation years) scale of models. We assessed the correlation between the model extent and the cell size used, and calculated basic statistics to identify trends in the time period of models; (2) model type (e.g. cellular automata, agent-based); and (3) data inputs used. We assessed the reliability of models by (4) examining the methods used to calibrate and validate the models and (5) by running our own independent validations of model predictions. Finally, the utility was determined by (6) our ability to obtain the modelled predictions in a form that could be used by other researchers and decision makers.

We classified models into one of five categories: (1) models that were based on the decisions of agents were considered 'Agent-based' (Parker *et al*., 2008); (2) models that accounted for the neighbourhood when determining change were defined as 'Cellular automata' (White & Engelen, 2000); (3) models purely based on the extrapolation of past trends were defined as 'Statistical' (Millington *et al*., 2007); (4) models developed with the goal of optimizing income or minimizing losses were considered 'Optimization' (Chuvieco, 1993); and (5) models that used any other algorithms were defined as 'Other' (Table S1). We used a Chi-squared test to identify any significant bias in the type of models used, and further categorized them as being deterministic or stochastic. Deterministic models use inputs and create outputs that are fixed, meaning the same model run multiple times will always give the same result. By contrast, stochastic models use inputs that are described by a probability distribution of some description and so contain a degree of statistical uncertainty that can be propagated to estimate the level of uncertainty around model predictions (Rosa *et al*., 2013; Verburg *et al*., 2013).

We define model inputs as the factors or parameters that a model takes into account to make predictions. Landscape change modelling often uses many inputs because models are attempting to replicate the inherently complicated phenomena of future tropical LULC change, which is heavily influenced by human behaviour. As such, we divided model inputs into four broad categories; (1) geographic, (2) economic, (3) social and (4) biological inputs (Table S1). Geographic inputs play a vital role in tropical LULC change modelling, providing the environmental setting that describes the real world on top of which the model can make predictions. Economic inputs cover factors relating to monetary gains and losses, for example the amount of capital available or land prices. Social inputs consider what people value, how people live, and include factors such as family size and family demography. Biological inputs are used to predict the utility of converting land from forest to another land use, using soil fertility for instance (Carpentier *et al.*, 2000). Model inputs were also divided into categories according to whether they were static or dynamic. Static inputs differ from dynamic inputs in that they do not change through time in the model. For example, the location of key cities or topographical patterns can be considered static over the time periods modelled. By contrast, dynamic inputs are continuously updated within the model itself (Supporting Information – Drivers of deforestation in the tropics).

To assess the reliability of the 48 models, we recorded how the model calibration was carried out, as well as how model outputs were validated against observed data. We define reliability as how well the model reflects reality, i.e. a model with high predictive ability is more reliable than a model with low predictive ability. Calibration is formally defined as 'the estimation and adjustment of model parameters and constants to improve the agreement between model output and a data set' (Rykiel, 1996). The process of validating and assessing a model's predictive power involves comparing the model predictions against observed data (Table S1). We also conducted a series of standardized validation tests on published tropical LULC change models from the Brazilian Amazon, so we requested via e-mail digital maps of model predictions from the authors of each model we considered in this review. We e-mailed the corresponding author of each paper up to three times, and if we received no response, we e-mailed the co-authors for which we were able to find e-mail addresses.

Models for which we were unable to obtain the predictions represent models that have only limited utility for decision makers and other researchers, who will typically require access to detailed spatial information about projected tropical LULC changes [e.g. Wearn *et al.* (2012) used the tropical deforestation models of Soares-Filho *et al.* (2006) to map and predict the spatial and temporal patterns of extinction in the Brazilian Amazon]. It could be assumed that it is more difficult to obtain data from older papers, thus we conducted a binomial regression to test for the effect of paper age on our success/failure to obtain model outputs.

For the models that we were able to obtain model predictions in a format that could be compared with reliable observed data, we made quantitative comparisons of the model outputs and accuracy. Due to data availability, we focussed our quantitative comparisons on the Brazilian Amazon, for which good quality annual deforestation data over a period of more than a decade is readily available.

Using annual deforestation maps for the Brazilian Amazon (INPE, 2012), we created binary raster files representing annual (deforestation in that year) and cumulative (accumulated deforestation that occurred between 2002 and that year) observed deforestation from 2002 through 2010. For each model that we validated, we converted the vector data into raster format, matching exactly the spatial extent and resolution of the observed data to that used in model predictions. Then, using the raster maps of deforestation predictions collected from the authors, we compared on a pixel-by-pixel basis where deforestation was perfectly predicted (=match), omitted or committed. Errors of omission (false negatives; model predicted no deforestation in a location where deforestation occurred) and commission (false positives; deforestation was predicted but did not occur) differ from the sources of prediction error identified by Pontius *et al.* (2008), who compared the LULC categories between observed and predicted maps. We preferred metrics of omission and commission because it focuses the validation onto the predictions of the LULC change itself, which is almost always a very small fraction of a modelled region, rather than allowing very high, but spurious, levels of apparent model accuracy arising from the accurate prediction of locations of no change, which can be 'accurately' predicted by a null model in which no land use has changed (Wu *et al.*, 2009). Thus, the metrics we compute and present represent a more stringent test of model reliability than other metrics. We assigned all pixels in the landscape to one of the match, omission or commission categories, and summed all the pixels that matched and divided the sum by the amount of change observed to get the percentage match. There is further reluctance to use pixel-by-pixel comparison methods for tropical LULC model validation, because there is no differentiation between 'near miss' and 'far miss' errors (Pontius, 2002; Pontius *et al.*, 2004; Carlson *et al.*, 2012).

We agree that these simple metrics of match, omission and commission represent extremely stringent tests of model reliability, but we also argue that they represent exactly the ability of tropical LULC models to predict the spatial patterns of tropical LULC change, and ably represent the two cases in which those predictions can be wrong. However, to allow for near and far misses, we also calculated a distance-based measure of model match, annually and cumulatively, by defining a set of buffer zones (1, 5, 10, 50 pixels in radius) around each pixel of predicted deforestation and calculated the proportion of observed deforestation that was found within those buffers. We used pixels rather than distance, as pixel size was correlated with model extent and therefore represents a standardized metric of scale that accounts for the differences in the extent and resolution of the models we compared. This distance-based validation metric quantifies the degree of spatial error in model predictions.

Results

Spatial and temporal scales

Of the 48 models, one was pan-tropical (i.e. covered all three tropical areas), two were based in the Congo basin, 13 in SE Asia and 32 in the Amazon. The difference in number of papers found in each region may reflect differences in data availability, interest or differences in tropical LULC change pressures, with the Amazon having better data, a higher public profile and undergoing higher amounts of absolute forest loss. SE Asia and the Congo basin are more commonly studied as part of global deforestation models or as part of historical change studies (Delire *et al.*, 2001). Both Congo basin papers covered the whole Congo basin (Fig. 1b). Of the 13 SE Asia papers, seven were in the Philippines, four in Indonesia and two were in Malaysia (Fig. 1c). Only three of the Amazon forest papers covered the whole Amazon basin; 17 were applied only in the Brazilian Amazon (Fig. S1), six were in Ecuador and the remaining models were distributed among Colombia (2), Peru (1) and Bolivia (3) (Fig. 1a).

The spatial extent of tropical LULC change models was generally biased towards regional-scale models, with a median of 16 019 km^2, ranging from about 58 km^2 to more than 15 million km^2, but the extent did not significantly differ among the three regions (ANOVA: $F = 2.76$, $P = 0.07$; Amazon papers; median = 23 500 km^2, range = 290 to >10 million km^2, SE Asia papers; median = 456 km^2, range = 15–131 600 km^2; Congo basin papers = 4 million km^2). The spatial extent of models was closely correlated with the resolution, or cell size (Pearson's correlation on log extent (km^2) with log cell size (km^2); $r = 0.79$, df = 41, $P < 0.001$) (Fig. 2, for regional breakdown see Supporting Information – Spatial and temporal scales). Most tropical LULC change models selected one particular scale at which to work, and we identified just one paper that operated at multiple scales, integrating small-scale and regional-scale modelling approaches through a combination of linked models (Moreira *et al.*, 2009).

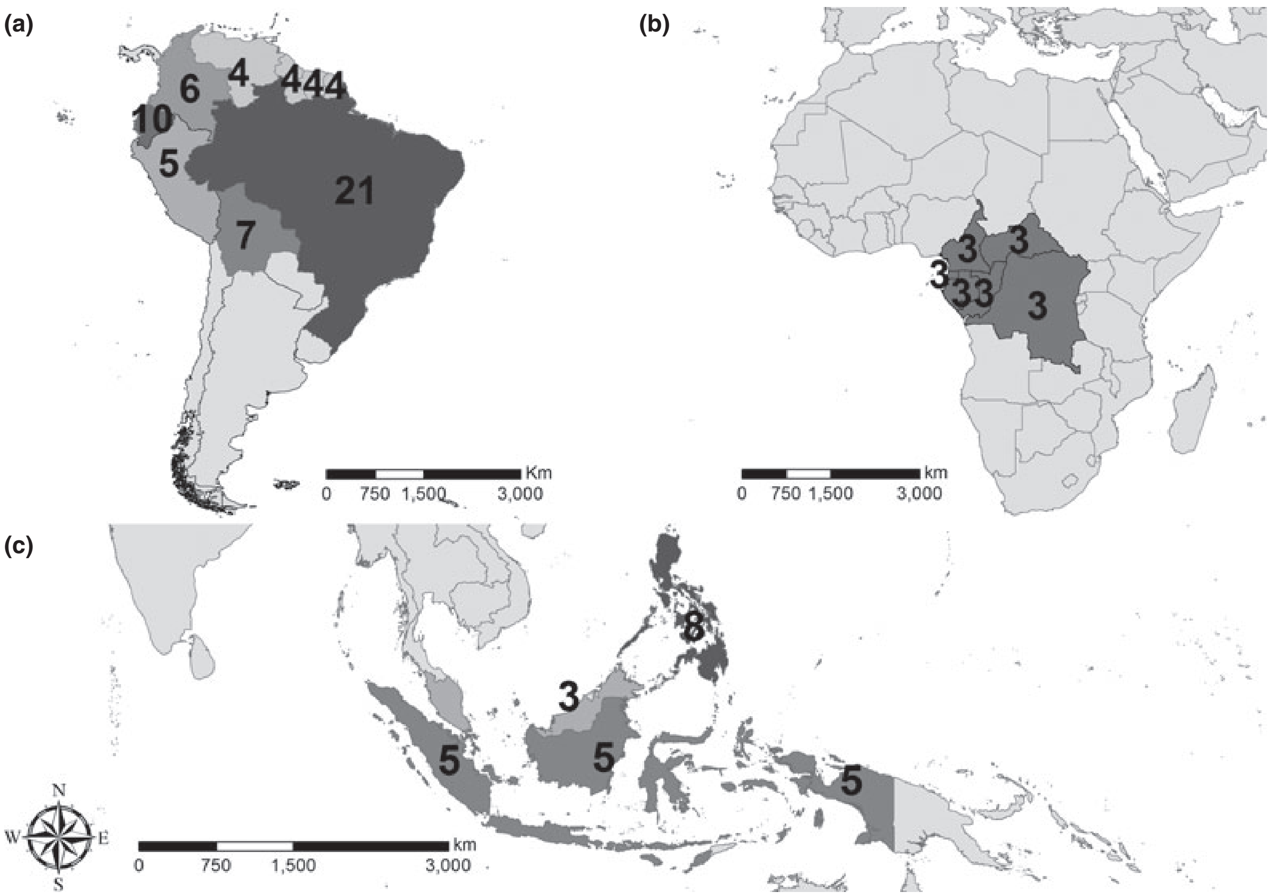

Fig. 1 Number of papers included in our review based in (a) South America, (b) the Congo basin and (c) South-East Asia. Number of papers within the Brazilian Amazon can be found in Figure S1.

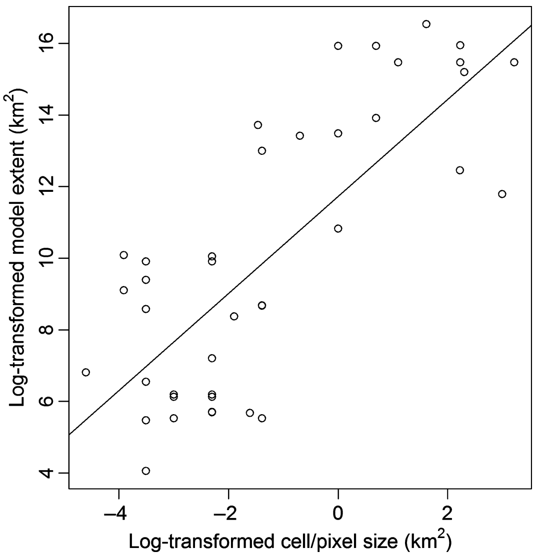

Fig. 2 Correlation between the spatial scale of all models (model extent in km^2) and their model resolution (given by the cell/pixel area in km^2).

We detected large amounts of variation in the temporal scale over which models were used to predict future tropical LULC changes. Of the 48 models, three did not provide any future predictions apart from the initial year (Etter *et al*., 2006b; Lopez & Sierra, 2010; Mann *et al*., 2010). The other 45 models that made predictions extended a median of 20 (SD = 20) years into the future, ranging from just 6 years (Verburg *et al*., 1999; Etter *et al*., 2006a; Mello & Hildebrand, 2012) to a maximum of 120 years (Zelazowski *et al*., 2011). This did not vary significantly between regions (ANOVA on log-transformed data: $F = 1.69$, $P = 0.20$; median model time in the Amazon was 25 (SD = 13), SE Asia median = 18 (SD = 5), Congo basin median = 55 (SD = 7) years). The distribution of number of years predicted was left-skewed, meaning that most papers tend to focus on short and medium temporal extents. This is likely due to a perceived tendency of model predictions to become increasingly uncertain into the future due to the very large number of dynamically adjusting variables that cannot be accurately accounted for in models (Deadman *et al*., 2004).

Model type

Across the set of 48 papers, we identified five broad categories of model types: statistical ($n = 16$), cellular automata ($n = 13$), agent-based ($n = 9$), optimization ($n = 1$) and other types of models ($n = 9$). Overall, there is a significant bias towards the use of cellular automata and statistical models (Chi-squared test, $\chi^2 = 13.25$, df = 4, $P = 0.01$). Some models fell into more than one category, such as agent-based models that were combined with cellular automata (Walsh *et al*., 2008; Sarkar *et al*., 2009). Our search criteria only found agent-based models for the Amazon. Across all models, agent-based approaches were most commonly used when modelling tropical LULC change at local and regional scales (mean extent = 9000 km^2 ± 8500, 95% CI), whereas cellular automata were used in the Amazon and SE Asia and were more commonly used for larger scale models (mean extent = 2 217 000 km^2 ± 220 000, 95% CI). There was, however, no significant effect of model type on model extent (ANOVA: $F = 0.42$, $P = 0.79$). Of the nine models classified as 'Other', the methods implemented included rule based models, the use of Markov chains and neural networks (Lambin, 1997; Pijanowski *et al*., 2002). Finally, we found a balance between deterministic ($n = 27$) and stochastic ($n = 21$) models, with a significant relationship between model type and stochasticity ($\chi^2 = 25.16$, df = 4, $P < 0.001$). Nearly all cellular automata models (90%) were stochastic, whereas 75% of statistical models were deterministic. Fifty-six per cent of models in the Amazon were stochastic, while only 15% of SE Asian models were stochastic.

Drivers of deforestation in the tropics

Tropical LULC change models used an average of 10 (SD = 7.6) inputs, with some models using as few as five (Walker *et al*., 2004; Nepstad *et al*., 2009; Müller *et al*., 2011) and one as many as 47 (Moreira *et al*., 2009). The average number of inputs did not vary between the three tropical regions (ANOVA: $F = 0.51$, df = 44, $P = 0.60$; Amazon average = 9 (SD = 7.4), SE Asia average = 11 (SD = 6.9), Congo basin average = 6 (SD = 0.7)). Across papers, we found that model inputs fell into four broad categories; (1) geographical, (2) economic, (3) social and (4) biological inputs (Fig. 3, for regional break down see Fig. S2).

Every model considered in our review used a geographical input of some description, and typically used these inputs to aid in determining the spatial location of changes. The three geographical inputs that were used most consistently were roads (34/48 papers), landscape factors (30/48) and soil factors (25/48). Distance to roads, urban centres and past deforestation are typically negatively correlated with future deforestation, with higher deforestation occurring in close proximity to these locations (De Koning *et al*., 1999b; Verburg *et al*., 2002; Soler *et al*., 2007; Mann *et al*., 2010; Maeda *et al*., 2011). The suitability of land for agriculture influences deforestation probabilities, with nutrient rich soils more likely to be deforested than nutrient poor soils (Etter *et al*., 2006b; Soler *et al*., 2007). Further,

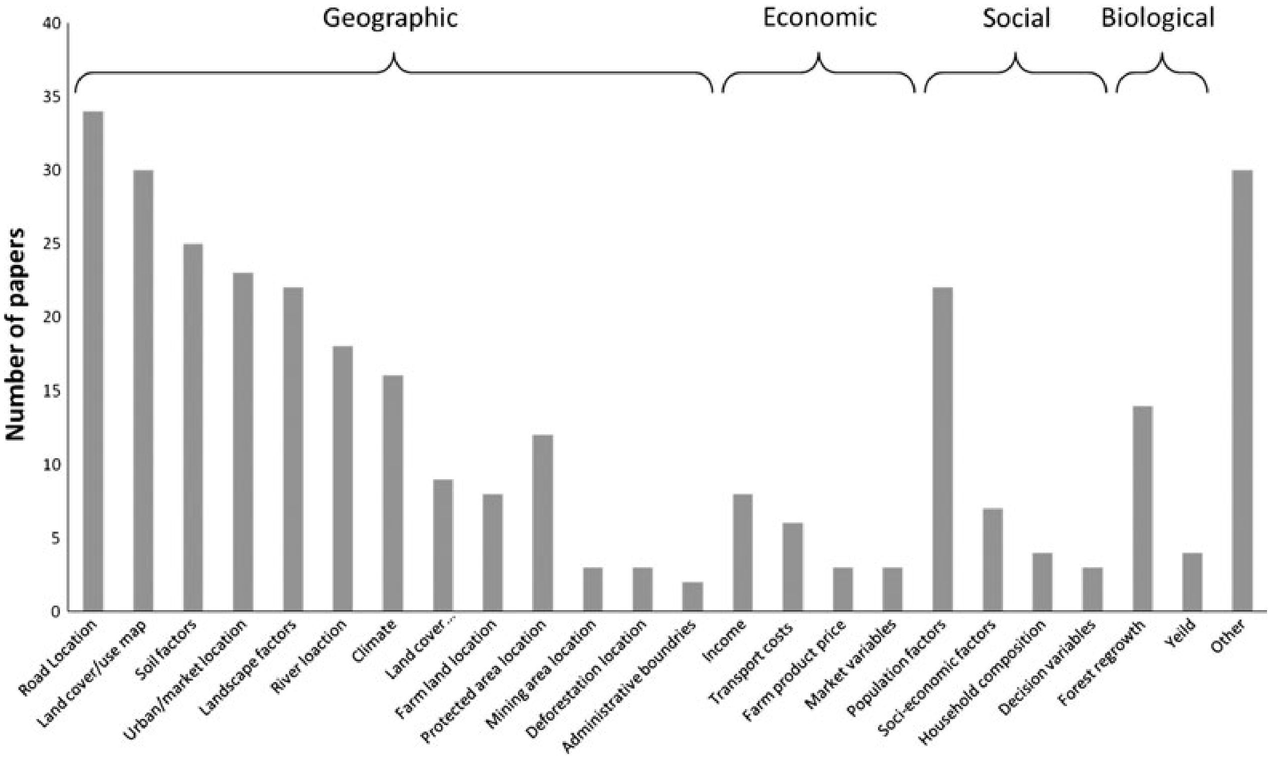

Fig. 3 Number of models using each input type. Inputs are divided according to class; geographic, economic, social or biological. Soil factors have been put into a single group that consists of factors such as soil moisture and soil texture. Landscape factors include inputs such as altitude and slope; climate includes rainfall, temperature, dry season length etc. If a paper uses multiple inputs from a group it is still counted only once e.g. if soil fertility, moisture and texture are used, it counts as one soil factor. The same information for each region is given in Figure S2.

deforestation tends to occur on flat land at low elevation and is much less likely on slopes which are harder to farm (Müller *et al.*, 2011).

Economic inputs such as the price of farm goods, the value of land and gross domestic product (GDP) were used in 15 of the 48 models and are typically used to predict the amount, rather than the spatial location, of tropical LULC changes (De Koning *et al.*, 1999b). Given that the vast majority of tropical LULC change is associated with development (e.g. agriculture and resource extraction), it is not surprising that economic indicators, such as agricultural goods prices, make good predictors of how people and/or governments are likely to alter the land cover and land use of an area. For instance, Soares-Filho *et al.* (2004) found that 71% of the variance in annual deforestation rates was explained by gross national product, although Ewers *et al.* (2008) used time-series analyses to demonstrate there is no statistical evidence that any economic variables, including per capita GDP, have systematically caused variation in deforestation rates.

More than half of the models (25/48) made use of social inputs to connect people to tropical LULC change decisions based on assumptions about their behaviour. For example, Walker *et al.* (2004) showed that household demography was the main factor affecting land allocation (conversion) decisions. They suggested that a household economy framework, which takes into account social and economic factors, may be a more appropriate approach than simple profit maximization approaches to tropical LULC modelling (Walker *et al.*, 2004). Nearly all tropical LULC change over the last century has been a direct result of individual and social responses to changes in the economic climate (Lambin *et al.*, 2003), and a key assumption of many economic-based models is that people will seek to maximize utility (Evans *et al.*, 2001), which can be in the form of financial or commodity gains. This, however, may not be appropriate for the Amazon, which represents a frontier setting, where the institutions necessary for profit maximization may not be present or fully functional (Walker *et al.*, 2004).

Research at both local and regional scales have found complex relationships, feedbacks and interactions between human (social, political, economic) and environmental systems (Deadman *et al.*, 2004). One such relationship is that between road construction and deforestation, with this causal interaction driven by economic and cultural factors (Geist & Lambin, 2002). Another common relationship is found between property rights and deforestation; Araujo *et al.* (2009) found that insecurity in property rights and social conflicts increased deforestation, because landowners needed to assert use of the land to avoid expropriation and squatters deforested in the hope that property rights will be awarded in the future. Differences in how models assume people will behave can exert large effects on model predictions, as shown by scenarios modelled by Dale *et al.* (1994), that compared alternative behaviours of farmers and their farming practices. In one scenario, it was assumed that farmers will make innovative use of their land and implement positive agro-forestry practices, leading to predictions that 40% of forested land would be cleared by farmers after 40 years. By contrast, when the model assumes that farmers will not use innovative practices and do not implement agro-forestry, the model predicted that 100% of the land would be deforested within just 10 years.

Finally, biological inputs included variables such as plant growth rates, agricultural yield and crop nutrient demands (i.e. the soil requirements of various crops). For example, crop nutrient demands in conjunction with soil fertility determines the viability of different crop types that might replace a forest, with highly fertile areas likely to become arable land (e.g. coffee or maize) and low fertility areas more likely to become pastoral land. Another biological input that was often used (17/48 models) was forest regrowth rate and/or the probability of forest regrowth (Soares-Filho *et al.*, 2002). Distance to regrowth has also been used to predict deforestation, with the observation that deforestation and distance to regrowth are negatively correlated (Soares-Filho *et al.*, 2002). However, only papers from the Amazon appeared to use regrowth as a model input.

The relative importance of inputs varied with location, not only between models, but also within models working in different regions. For example, Wassenaar *et al.* (2007) found that existing fragmentation was one of the most significant model inputs across seven Amazonian regions modelled, however there were regional differences in model structure. Altitude was an important predictor of deforestation within the Ecuadorian Amazon, along the edge of the Andes mountain range, but was not important in the other six regions that were much less topographically complex. Also, Etter *et al.* (2006b) found that distance to towns and roads were important predictors of deforestation in both Andean and Amazonian regions, while soil fertility was important in the Andean but not Amazonian regions, whereas the number of rain days was more important in the Amazon.

Regional differences in the causes of deforestation patterns make it important that papers explicitly state the inputs they are modelling, but this was not always the case. For example, Moreira *et al.* (2009) used '40 environmental, demographical, agrarian structure, technological and market connectivity indicators', but these were not listed. In other cases, the definitions associated with model inputs were not always clear. For example, Dale *et al.* (1994) and Soler *et al.* (2007) used 'soils' as an input variable, but did not specify if they were referring to soil type, soil fertility, soil texture, or some other metric associated with soil. By contrast, De Koning *et al.* (1999b) explicitly stated that they used soil texture and fertility, finding that in the Andean region, texture and soil fertility were both important modelling parameters, while in the Amazon region neither played a role at the scales modelled.

Landscape factors were typically static inputs to tropical LULC models, although the LULC map itself represents an obvious exception, changing at each time step of a model as tropical LULC change progresses (Messina & Walsh, 2001; Soares-Filho *et al.*, 2004; Verburg *et al.*, 2006; Walsh *et al.*, 2008). Dynamic economic inputs were also used, with each year's activities (conversion into farmland for instance) resulting in new stocks of finances and/or resources that become the foundation of the next year's activities (Carpentier *et al.*, 2000). Not all dynamic inputs build through time as these examples above. For example, Messina & Walsh (2001) used a cellular automata module to select locations for deforestation based on neighbourhood rules, implementing a random number generator to recreate the dispersiveness of deforestation and to allow for stochastic deforestation events, and Walker *et al.* (2004) determined the number of deforestation events through a probability model that used a uniform distribution. In both cases, the use of a probabilistic or stochastic selection of deforestation events makes the amount and location of deforestation a dynamic input. Some inputs are actually dynamic but were treated as static in models, and this is particularly true of roads. Most models we examined used roads as an input, but more than two-thirds of those (34/48) treated roads as a static input. Only papers that use the DINAMICA or IDRISI road constructor modules used roads as a dynamic and spatially explicit phenomenon (Messina & Walsh, 2001; Soares-Filho *et al.*, 2004, 2006; Lapola *et al.*, 2010; Carlson *et al.*, 2012).

Model calibration

In tropical LULC change modelling, there are three key aspects of LULC change that need to be estimated: the rate, the type and the location of change. There are several calibration methods employed by the papers modelling tropical LULC change in the tropics, but only one direct comparison of different methods on the same datasets (Etter *et al.*, 2006b), making it difficult to quantify the relative reliability of the various options. All calibration techniques applied statistical methods to empirical observations of historical data to estimate parameter values and weights (Supporting Information – Model calibration). Some model calibrations were combined with expert knowledge to capture inputs known to be important despite a statistical model simplification process removing them (Soler *et al.*, 2007) and one-off events such as changes to agricultural subsidies (Wassenaar *et al.*, 2007), while others utilized rules to determine outcomes (Justice *et al.*, 2001).

Economic approaches to modelling tropical LULC change tended to use more process-based methods for calibrating models than did other techniques that relied more heavily on extrapolating spatial patterns. Some models developed a 'demand module' that estimated the economic demand for particular agricultural product and used that to determine the amount of land needed to be converted (De Koning *et al.*, 1999b). Similarly, where a key aim is to maximize utility or minimize costs, calibration techniques such as linear programming have been used to derive model input values that give rise to optimal solutions. This approach was employed by Lusiana *et al.* (2012), who used an agent-based, farm-level modelling where the main goal was to maximize land returns.

Across all 48 models we reviewed, 19 were missing at least one important piece of information required to replicate the results. One of the most common issues was the availability of the code used to generate the model. Thirty of 48 models used available software that could be used to replicate the construction and running of the model IDRISI using Land change modeller or GEOMOD ($n = 5$), DINAMICA ($n = 8$), LandSHIFT ($n = 2$), CLUE/CLUE-S ($n = 12$), TerraME ($n = 1$), SITE ($n = 1$) and FALLOW ($n = 1$), while others did not use commercially or freely available software. These latter models cannot be replicated as none made the source code, or pseudo-code that would allow competent programmers to replicate the authors' code, available. Most SE Asia papers utilized CLUE/CLUE-S (8/13), while the most commonly used software in the Amazon was DINAMICA (7/32).

The difficulties of model validation

We found that 27 models validated a single year of predictions and in several of those models, the time period used in the validation was the same as used to calibrate the model, suggesting a degree of circularity in the validations (Verburg *et al.*, 2002; Soler *et al.*, 2007; Wassenaar *et al.*, 2007; Lopez & Sierra, 2010; Maeda *et al.*, 2011; Lusiana *et al.*, 2012), even when spatial partitioning the data for calibration and validation. It is important that a clear distinction is made between calibration and validation, preferably from different time periods, in order for model results to be trusted (Estoque & Murayama, 2012). Three of 48 models were validated at two points in time (Soares-Filho *et al.*, 2002; Michalski *et al.*, 2008; Carlson *et al.*, 2012), two models were validated at three points in time (Deadman *et al.*, 2004; Silvestrini *et al.*, 2011), and one study validated their predictions at four points (Evans *et al.*, 2001). Fifteen models did not clearly state a validation method (Justice *et al.*, 2001; Laurance *et al.*, 2001; Ferraz *et al.*, 2005; Priess *et al.*, 2007; Sarkar *et al.*, 2009; Mena *et al.*, 2011; Zelazowski *et al.*, 2011), used just visual comparison (Moreira *et al.*, 2009; Mann *et al.*, 2010), argued that the modelling approach had been validated elsewhere (Dale *et al.*, 1994; De Koning *et al.*, 1999a; Soares-Filho *et al.*, 2004, 2006; Nepstad *et al.*, 2009), or cited lack of data availability (Verburg *et al.*, 2006) (Table S1).

It is self-obviously problematic to validate predictions for a future that has not yet happened and this certainly contributes to the issues raised above. One solution that is available is to spatially partition data, using one subset of the data to calibrate the model and the other to validate the model. Another solution that is available in some, but not all, cases is to employ backward validation, which involves running a model in 'reverse' to predict historical rather than future land-use patterns. For instance, De Koning *et al.* (1999b) modelled deforestation in Ecuador from 1991 to 2010 and validated their model by using it to backcast tropical LULC changes from 1991 to 1974. This allowed them to validate their model against an extensive land-use dataset based on an agricultural census carried out in that year. They found a strong positive correlation between their model predictions and observed tropical LULC patterns with correlation coefficients varying between 0.71 and 0.96.

Availability of model predictions

Of 48 published models, we were able to collect 25 predicted data sets either directly from the authors or via downloadable content (Supporting Information – Availability of model predictions). This is suggestive of a general lack of utility of tropical LULC models. Some of the papers we reviewed are old and it could be expected that it is more difficult to contact authors of, and obtain model predictions from, older as opposed to recent publications. This does not appear to be the case, however, as we were able to obtain just 5 model predictions from the 12 papers published post-2010. Furthermore, there was no significant effect of year of publication on our ability to obtain the model predictions (binomial regression; $z = -0.03$, df = 26, $P = 0.97$).

Quantitative assessment of model performance

We focus our quantitative assessment on models conducted in the Brazilian Amazon for which we were able to obtain independent deforestation data (INPE, 2012) against which to validate the model predictions. We recognize two important caveats that must be associated with this analysis: (1) such a tight geographical restriction applies arbitrary limits to the wider generality of our conclusions; and (2) our analysis focuses on authors and models who have made their model predictions freely available, pointing a potentially unfair spotlight on authors that we believe are making important contributions to the transparency and utility of the discipline.

There were three papers that contributed models that we were able to submit to our validation exercise (out of 21 models from the Brazilian Amazon), two of which comprised a complete time series of model predictions (Soares-Filho *et al.*, 2006; Yanai *et al.*, 2012), whereas the other comprised a single map of predicted tropical LULC at the end of the model prediction period (Wassenaar *et al.*, 2007). Different model scenarios, such as the Business as Usual and Governance scenarios of Soares-Filho *et al.* (2006), and the Baseline, with leakage and with reduced leakage scenarios of Yanai *et al.* (2012) were treated as separate models in our validations, giving a total of five models. We hasten to add that were able to obtain predicted outputs from an additional 4 of the 21 models in the Brazilian Amazon, but the predicted maps were available only for a time that has not yet occurred and so could not be included in this analysis (e.g. we cannot yet validate predictions made for the year 2020).

When assessed year-by-year (annually), model match was very low for all models (0–3%; Fig. 4a and Table S2). Cumulative match, which compares the accumulated deforestation patterns from the start of the model until a given time point in the future (2003–2010), was also low but increased as model duration extended, reaching 1–10% by 2010 (Fig. 4b). Errors of commission also tended to increase through time, both on annual and cumulative comparisons (Fig. 4a and b, respectively), whereas omission errors decreased through time for both annual cumulative comparisons (Fig. 4a and b). All models had similar proportions of match, but there were large differences in the errors of omission and commission, both in terms of error rates through time (Fig. 4b) and the spatial distribution of those errors (Fig. S3–S5). For example, the Wassenaar *et al.* (2007) model tended to have higher omission errors in the eastern Amazon and higher commission errors in the south (Fig. S3), whereas the Soares-Filho *et al.* (2006) models had highest commission errors in the north and relatively evenly distributed omission and commission errors along the Arc of Deforestation (Fig. S4 and S5).

For all models, annual predictions still had very low match rates at the smallest buffer size (1 pixel), but cumulative model predictions performed better, reaching 32%, 33% and 42% matches (Table S2). Unsurprisingly, model predictions improved with increasing buffer size, with nearly 100% of all deforestation events falling within 50 pixels of model. For the two papers that presented alternative scenarios, the scenario that predicted higher overall rates of deforestation invariably had higher levels of match, indicating that overpredicting deforestation rates, and simultaneously ignoring patterns of omission and commission errors may generate misleading estimates of model accuracy.

Discussion

Our quantitative review of the tropical deforestation modelling literature has demonstrated several shortfalls in the discipline that can be strengthened in the future, uncovering three key points that we believe need addressing to improve the transparency, reliability and utility of tropical LULC change models. First, it was sometimes difficult to understand the construction of models and the variables used in the modelling process. Second, there were few attempts to assess the accuracy of models through rigorous and multi-year validation. Third, it was difficult to obtain the outputs of many models, meaning the difficult work put in by tropical LULC modellers to predict future forest patterns is often not available as an input for researchers in other disciplines.

Appropriate scales are process-specific

There is no optimal scale (resolution/cell size, extent/study area) over which to model tropical LULC change; each scale allows different insights into the processes and outcomes of tropical LULC change (Walsh *et al.*, 1999; Rindfuss *et al.*, 2004, 2008). It has been suggested that multi-scale studies provide complementary insights required for effective environmental management (Verburg & Veldkamp, 2004; Verburg *et al.*, 2006). However, the spatial scale applied in modelling is often a limitation imposed by available data and computational power rather than research choice; this can

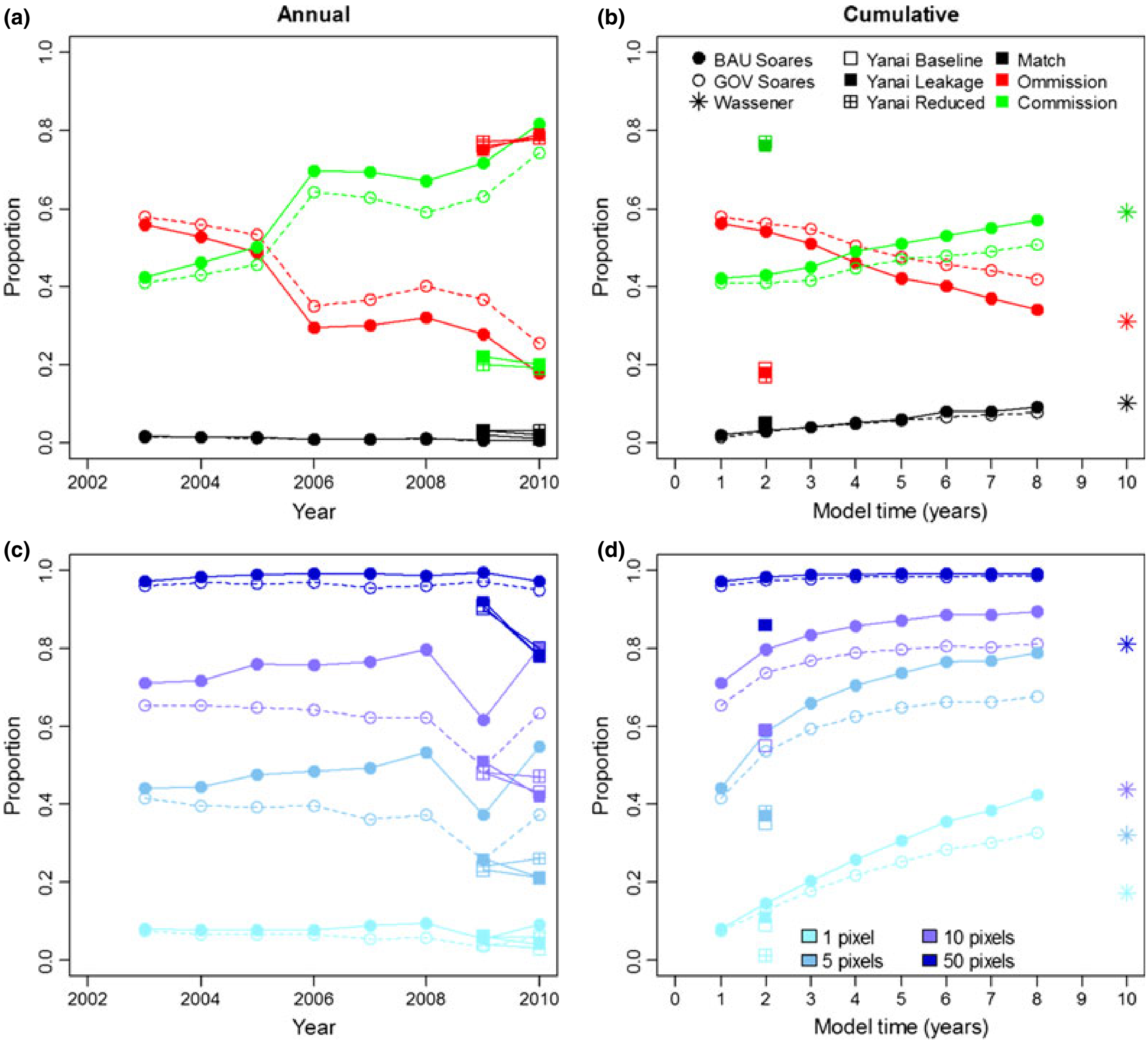

Fig. 4 Pixel-by-pixel comparisons between observed deforestation and predictions made (a) annually and (b) cumulatively by Soares-Filho *et al*. (2006) at 1 × 1 km grid cells, from both governance (GOV) and business-as-usual scenarios between 2003 and 2010, and by Yanai *et al*. (2012) for 2009 and 2010 at 250 m grid cells for the baseline, with leakage and with reduced leakage scenarios. Proportion of observed deforestation within four distance classes (1, 5, 10 and 50 pixels) of predicted deforestation, calculated (c) annually and (d) cumulatively. In addition, (b) and (d) show comparisons between observed deforestation and predictions made by Wassenaar *et al*. (2007) (5 km pixel size).

inevitably influence the applicability of the model results (Verburg & Veldkamp, 2004). Working at any particular scale has strengths and weaknesses. For example, farm-level models can simulate farmers' decisions and reactions to market variations such as changes in commodity prices. However, these models are usually site-specific, making it very difficult to generalize them to larger areas or other tropical regions. Larger scale models, on the other hand, tend to use aggregated data which often average variability across the region modelled and therefore lose detail when interpreted at fine spatial scales (Mertens & Lambin, 1997).

The biggest weakness in model formulation?

Road maps and distance to roads were the most commonly used inputs for tropical LULC change modelling. Despite knowing that road networks in the tropics are highly dynamic (Brandão & Souza, 2006; Laporte *et al*., 2007), with almost 17 000 km of new roads constructed each year in the Brazilian Amazon alone (Ahmed *et al*., 2013b), most models treated road networks as a static pattern. Roads are the key spatial determinant of deforestation patterns (Forman & Alexander, 1998; Fearnside, 2005; Finer *et al*., 2008), determining the accessibility of land and cost of transportation which in turn determines the viability of land-use change in a given area. We suggest the reason for treating roads as a static phenomenon is that modelling the expansion of road networks is itself a formidable challenge, and one that has been identified as a key weakness in our ability to predict tropical LULC change in the Amazon (Barlow *et al.* 2011, Supporting Information – Modelling road expansion).

Certainly, there are several modelling frameworks available to predict the development of road networks and that were used in the tropical LULC models included in our review (Messina & Walsh, 2001; Soares-Filho *et al*., 2004, 2006; Lapola *et al*., 2010), but we were unable to find any peer-reviewed presentation of these particular road models, nor any numerical validations of the road model predictions. While it is clearly desirable to have a dynamic road model integrated with deforestation models, it is not so clear that an untested road model represents an improvement over the use of static road networks alone. There are road modelling approaches that have been validated (Arima *et al*., 2005, 2008; Ahmed *et al*., 2013a; Walker *et al*., 2013), and we expect that the future of tropical LULC change modelling will begin to incorporate such advances.

How certain are we about tropical LULC model predictions?

Although we recognize that the choice of number of years to validate model predictions is, in almost all situations, limited by the data available, we suggest that the relatively limited amounts of rigorous model validation in the literature places bounds on the degree to which tropical LULC model predictions can be considered reliable. We found three of the most recent models developed in SE Asia utilized the most recent validation methods put forward by Pontius & Millones (2011) of any of the papers in our review (Estoque & Murayama, 2012; Lusiana *et al*., 2012; Memarian *et al*., 2012). All three of these models were published in 2012, among the most recent models we reviewed and perhaps indicating a positive trend towards more rigorous model validation. There are many methods available to validate tropical LULC models; for example, Pontius *et al*. (2008) and Pontius & Millones (2011) presented logical frameworks for validating model predictions. Choosing among the options is, however, a difficult task, partly because the basic question of ‘what is a good fit’ for tropical LULC change models is a difficult one to answer (Messina & Walsh, 2001; Messina *et al*., 2008) (Supporting Information – The difficulties of model validation).

We found remarkably low rates of prediction accuracy from the three Brazilian tropical LULC models we were able to test ourselves, and this was particularly true of year-by-year predictions. However, because our analysis was arbitrarily confined to a small number of models from just one tropical region, we have no way of determining if the rates of model success we quantified are typical of the field as a whole. When accumulated over longer time periods, model accuracy invariably improved, suggesting that over long time frames, it is possible to predict the spatial patterns of tropical LULC change with reasonable certainty.

Despite the extensive literature detailing the importance of uncertainty and sensitivity of models (Pontius & Batchu, 2003; Pontius *et al*., 2003, 2006; Ligmann-Zielinska & Sun, 2010; Pontius & Petrova, 2010), it was surprising that few of the models we reviewed presented any estimate of uncertainty around their model predictions. Uncertainty estimates can be achieved by developing and modelling alternative scenarios (Soares-Filho *et al*., 2006; Overmars *et al*., 2007; Priess *et al*., 2007; Moreira *et al*., 2009), or by using the statistical errors quantified during model calibration to estimate probabilities of tropical LULC change (Carlson *et al*., 2012; Rosa *et al*., 2013; Verburg *et al*., 2013). Across the models we reviewed, the most common approach to quantifying uncertainty was to present competing scenarios of tropical LULC change, thereby providing bounds on the likely patterns of tropical LULC under different possible futures. Scenarios are the only method available to handle uncertainty about certain types of one-off events (Soler *et al*., 2007), such as unpredictable policy decisions.

Apart from scenarios, there remain additional opportunities to quantify the uncertainty surrounding model predictions under a given set of assumptions, based primarily on methods that propagate the statistical errors quantified during model calibration. Few of the models in our review incorporated stochastic elements that allowed for the uncertainty to be directly quantified but these techniques for quantifying uncertainty have only recently been developed and applied to LULC models in the tropics or elsewhere (Van Asselen & Verburg, 2012; Rosa *et al*., 2013), explaining why they are not more widely applied.

In the absence of data against which to validate model predictions, we strongly recommend authors attempt to quantify the uncertainty associated with their model predictions, thereby providing readers and users with an indication of the reliability of model predictions. We anticipate that making the quantification of uncertainty, either in the form of scenarios or propagation of statistical uncertainty, a common practice will represent an important step for the tropical LULC modelling discipline.

How transparent are tropical LULC models?

We were unable to obtain the information required to replicate authors' results for nearly half of the published tropical LULC models we reviewed. We believe that this is important: the requirement to describe methods in enough detail to allow them to be replicated forms a basic tenet in many sciences and there is no reason why the discipline of tropical LULC modelling should be any different. We suggest that this highlights a considerable shortcoming of the tropical LULC change field, but it is one for which there are relatively straightforward solutions available.

The fact that program codes developed to run tropical LULC change models were often not available does not mean that all models are not repeatable, as many used freely or commercially available software that could be used to reconstruct the published models. For bespoke models, it is obviously a very challenging exercise to provide source code that is documented in the detail required for others to replicate, but that argument does not apply to presenting pseudo-code, which represents a reasonable short-cut to making code available to others.

Having access to source code or the software used by authors to construct their models does not guarantee an ability to replicate analyses, because a sizeable number of papers did not provide adequate details about their model inputs, again preventing others from replicating their results. We believe that presenting a full list of the data used in a tropical LULC model should be a basic requirement that is enforced through the peer review process, but even when presented, there are important metadata required to fully interpret the data. There are frameworks available for describing detailed metadata to associate all data inputs that could accompany data generated by the authors themselves (e.g. http://www.v-c-s.org/methodologies/VM0015), and this would represent best practice. However, many authors do not themselves generate the primary data used in their models, and the responsibility for generating such metadata should most appropriately lie with those who create the data and make it available for wider use.

The future of tropical LULC change modelling

Tropical LULC change models have been prominent in the literature for many years, but our review has uncovered three key points that need attention to improve the transparency, reliability and utility of tropical LULC change models applied in the tropics. These three issues have been raised individually in the past by various authors, and by drawing them together here we hope to stimulate improvements to the discipline. First, we have identified a lack of openness with regard to presenting and making available the model inputs, model code and model outputs that prevents the community from fully understanding and rigorously comparing models (Grimm *et al*., 2006). Second, there are considerable difficulties involved in validating model outputs, and indeed a lack of consensus on the appropriate techniques (Verburg & Veldkamp, 2005; Messina *et al*., 2008). Third, there is no standardized model framework that can be used as a basis for comparing tropical LULC models and generating multi-model inference (Grimm *et al*., 2006; Messina *et al*., 2008).

We suggest that the rise of climate change models provide a pathway that tropical LULC change modellers may emulate to improve the discipline. While we recognize tropical LULC modelling approaches in the tropics differ substantially from each other (and certainly exhibit more model-to-model variation than the modelling approaches used in predicting climate change), the key aim of predicting tropical LULC change is the same regardless of the approach taken (i.e. to predict the future of the landscape), thus model outputs should be made available for people to use and to compare. We certainly do not advocate a move towards producing a unified methodology where every model uses the same code and approach, recognizing that there is strength in having a diversity of approaches. However, we do believe that to harness that strength, we need to be able to overlap the spatial predictions of all models, weight those predictions by either the validation errors or the quantified uncertainty of the models that generated them, and thereby gain informative among-model comparisons and provide a basis from which to make predictions based on model averaging.

Climate change modelling exists in what is likely to prove a simplified context relative to tropical LULC change, but has made considerable progress towards solving some of the aforementioned problems that may have instructive value for our discipline. The World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project (CMIP3) set up an archive (WCRP CMIP3 Multi-Model Dataset) to provide IPCC model outputs in a standardized format (WCRP, 2012). Similarly, the discipline standard and requirement of most journals covering the field of Genomics, Transcriptomics and Proteomics, research have to register sequence data in an online repository or as supplementary material (e.g. GenBank). This transparency of data has allowed greater progress and has been recognized as aiding 'one of the greatest scientific revolutions of the last century' (Reichman *et al.*, 2011). Furthermore, evidence suggests that papers with available data are cited more often when compared with papers that do not make data available (Reichman *et al.*, 2011). In the context of tropical LULC models, the most important data are the predictions themselves, as they can form an important base for other purposes such as predicting future patterns of extinction risk (Hubbell *et al.*, 2008; Feeley & Silman, 2009; Bird *et al.*, 2012; Wearn *et al.*, 2012) or feeding into climate models via vegetation-atmosphere feedbacks (Feddema *et al.*, 2005; Zaehle *et al.*, 2007; Moss *et al.*, 2010). With the increasing support for open data from governments (e.g. UK government, http://data.gov.uk/; and The National Science Foundation, http://www.nsf.gov/news/news_summ.jsp?cntn_id=127043), funding bodies and scientists (Reichman *et al.*, 2011; Costello *et al.*, 2013), we should expect tropical LULC model outputs to become more widely available in the future.

Since the early 1990s, atmospheric climate modellers adopted a standard protocol for GCMs (General Circulation Models) (Gates, 1992). The protocol provided a framework for model diagnosis, validation and intercomparison (Tebaldi & Knutti, 2007), and has since been used widely. The field of tropical LULC change modelling would benefit from a similar framework, and particularly so to ensure a progressive raising of the standards with respect to model validation. Agent-based modelling has made headway towards this with the Overview, Design concepts and Details (ODD) framework (Grimm *et al.*, 2006), the MR POTATOE-HEAD framework (Parker *et al.*, 2008) and work done by Polhill & Gotts (2009). Another recent attempt to standardize the presentation and documentation of tropical LULC models used in REDD projects was proposed by the Voluntary Carbon Standards (http://www.v-c-s.org/methodologies/VM0015), so there are avenues open to the discipline for increasing the transparency of tropical LULC models.

One advantage to be gained from improved model documentation and availability of model predictions is that they allow the analysis of multi-model ensembles, which are now commonly used in climate modelling and form important components of reports from the IPCC. Similar approaches have been developed for species distribution models (Diniz-Filho *et al.*, 2009, 2010) on the back of pre-emptive calls for such approaches (Araújo & New, 2007) and aided by quantitative model comparison exercises such as those conducted by Elith *et al.* (2006). Combining models in an ensemble increases the reliability and consistency of predictions (Tebaldi & Knutti, 2007), and this approach has found utility in other disciplines such as public health (Thomson *et al.*, 2006) and agriculture (Cantelaube & Terres, 2005). Disparities among tropical LULC models applied in the tropics, in terms of scale, resolution, model type and model inputs, combined with a more basic failure to make model predictions available, currently prevents such methods from being applied to questions of tropical LULC change.

Climate change models have exerted considerable influence over public perceptions of climate change and now impact policy decisions at all political levels. It is clear that LULC models have an equally high potential to influence public opinion and impact the development of land-use policies based on plausible future scenarios. This has already been demonstrated in European contexts (Verburg *et al.*, 2008), but to obtain that impact more widely, and to further improve the confidence with which tropical LULC models can be used to impact policy, requires changes to the standard practice that is currently prevalent in the discipline, as revealed by our quantitative review. We found that it was often difficult to understand how models were constructed, that there were few attempts to assess the accuracy or quantify the statistical uncertainty of models, that model accuracy was surprisingly low when independently validated, and that it was often difficult to obtain the outputs of models. We suggest that further improvements to the transparency of tropical LULC models, increasing the frequency with which uncertainty in such models is quantified and making model predictions more widely available would greatly increase the utility of tropical LULC models, and will be a necessary step towards generating scenarios that can be confidently used to influence environmental policy.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1: The transparency, reliability and utility of tropical rainforest land-use and land-cover change models.