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The 'Geographic Emission Benchmark' model: a baseline approach to measuring emissions associated with deforestation and degradation

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This paper proposes a new land-change model, the Geographic Emission Benchmark (GEB), as an approach to quantify land-cover changes associated with deforestation and forest degradation. The GEB is designed to determine 'baseline' activity data for reference levels. Unlike other models that forecast business-as-usual future deforestation, the GEB internally (1) characterizes 'forest' and 'deforestation' with minimal processing and ground-truthing and (2) identifies 'deforestation hotspots' using open-source spatial methods to estimate regional rates of deforestation. The GEB also characterizes forest degradation and identifies leakage belts. This paper compares the accuracy of GEB with GEOMOD, a popular land-change model used in the UN-REDD (Reducing Emissions from Deforestation and Forest Degradation) Program. Using a case study of the Chinese tropics for comparison, GEB's projection is more accurate than GEOMOD's, as measured by Figure of Merit. Thus, the GEB produces baseline activity data that are moderately accurate for the setting of reference levels.

Keywords: deforestation; reference level; land-change modeling; accuracy assessment; REDD; China

1. Introduction

In 2008, the United Nations launched REDD (United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries) to provide a mechanism to mitigate climate change by sequestering forest carbon. REDD also promotes the secondary ecosystem service benefits associated with this forest conservation, including protection of biodiversity and water quality (Gibson et al., 2011; Johnson & Lewis, 2007; Robbins, 2004; Zhang, Bennett, Kannan, & Jin, 2010). The primary objective of REDD is to establish a forest carbon market system that results in the transfer of financing from industrialized countries to industrializing countries that have extensive intact forests, especially in the tropics (Food and Agriculture Organization of the United Nations [FAO], United Nations Development Programme [UNDP], & United Nations Environment Programme [UNEP], 2008). REDD is essentially a global-market-based payment-for-services system that seeks to maximize environmental and financial benefits at the local, regional, and global scales (Busch, Godoy, Turner, & Harvey, 2011; Busch et al., 2009; *Economist*, 2010; Phelps, Webb, & Adams, 2012).

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One of the many challenges facing REDD is the development of an accurate forest carbon accounting methodology for the setting of baselines for monitoring at a full range of spatial scales. For REDD implementation, setting an accurate baseline in the form of a 'reference level' or 'reference emission level' is crucial because carbon credits are based on this estimate (Lowering Emissions in Asia's Forests [LEAF], 2011; Verified Carbon Standard [VCS], 2012). They are, therefore, intertwined with the financial incentives associated with REDD (Busch et al., 2012; Herold, Verchot, Angelsen, Maniatis, & Bauch, 2012; Sathaye, Andrasko, & Chan, 2011).

Setting these baselines requires predictive land-change modeling whereby, for example, expected losses in forest carbon are estimated using business-as-usual scenarios of forest-land loss (VCS, 2012). These predictive estimates are based on observed historic trends in forest carbon loss/change. Under a business-as-usual scenario, the assumption is that deforestation and forest degradation would continue indefinitely. This assumption can be displayed graphically (Figure 1). In the figure, the solid line consists of two segments: observed historic carbon emissions and predicted future carbon emissions under a business-as-usual scenario; the latter is referred to as a reference level (i.e., RL). The dashed line represents the target emission level at the point of REDD implementation, and the shaded area between the two lines illustrates the carbon sequestration benefits (i.e., additionality).

In an ideal world, the necessary financial resources and technologies would be available to develop highly accurate RLs for forests at all spatial scales, while taking the varying land-use histories and ecosystem types into account. In many cases, however, developing highly accurate RLs is just not feasible or realistic given the need to move swiftly to develop deployable methodologies for forest carbon accounting. As such, there is a need to develop an RL baseline accounting method that can relatively quickly generate results with at least moderate accuracy. Moreover, if possible, this method

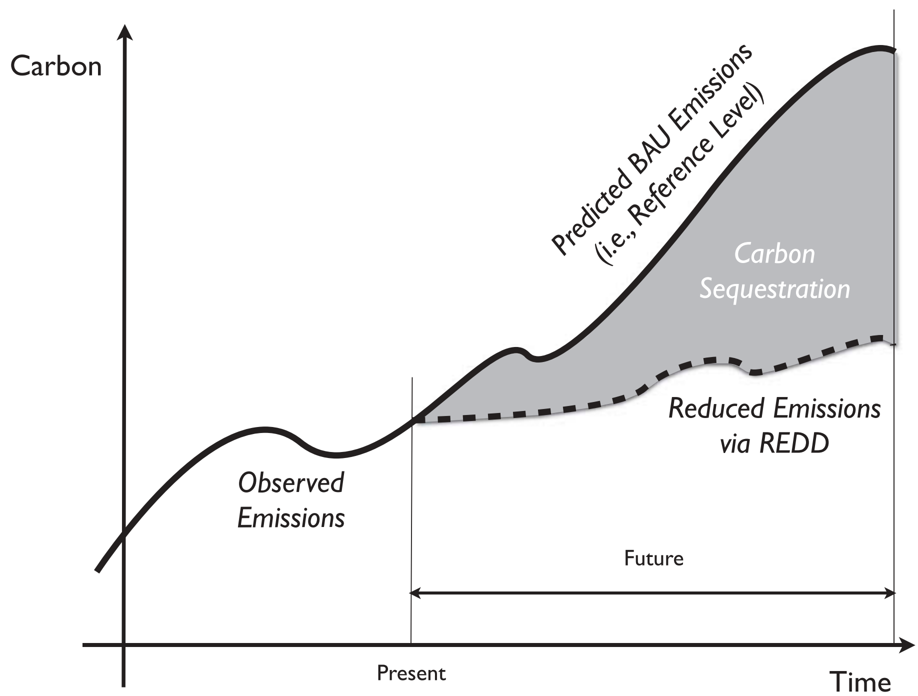

Figure 1. Concept of reference level (RL).

would use freely available, peer-reviewed data and open-source spatial approaches to enable accuracy and transparency.

In this paper, therefore, we propose a new land-change model for REDD. Entitled Geographic Emission Benchmark (GEB), this model was developed with two objectives in mind: (1) To provide the benchmark information of areal data that can be fed into RL construction; and (2) to help address definitional and scale issues in land-change modeling. Essentially, the model improves estimation practices for RLs by providing a prospective outcome that can be used as a baseline when one is to set an RL for a particular REDD project. To understand the relative predictive accuracy of GEB, we compare it with the accuracy of a popular land-change model GEOMOD using Figure of Merit by using a case study of forest in China – Xishuangbanna Dai Autonomous Prefecture (hereafter, Banna), southwest Yunnan.

1.1. REDD and the Verified Carbon Standard

All REDD projects need to be designed and implemented in accordance with internationally accepted guidelines. Guidelines provided by Verified Carbon Standard (VCS) are the most popular ones for REDD projects worldwide (Diaz, Hamilton, & Johnson, 2011). VCS also validates REDD project designs; if a project is considered qualified, then the project will be registered in the VCS Project Database, and the registration will ensure credit generation. That is, land-change modeling for REDD implementation must adhere to the VCS's criteria. To guarantee the transparency of modeling outcomes, the VCS methodology (2012) clearly mandates the need to specify 'forest' and 'deforestation' and spatial scale when calculating the rate of deforestation.

VCS methodology (2012) uses definitions for 'forest' and of 'deforestation' from the Global Observation of Forest and Land Cover Dynamics' Sourcebook (GOFC-GOLD, 2010), which is largely based on definitions from the Intergovernmental Panel on Climate Change (IPCC, 2006) and Food and Agriculture Organization of the United Nations (FAO, 2006a, 2007). To qualify as a 'forest (i.e., forestland)' under GOFC-GOLD criteria, it must be >0.05–1 ha in size, >10–30% in canopy-cover, and >2–5 m in height. 'Other wooded lands' refer to the trees that do not meet this criteria. For each criterion, one value within the range has to be chosen. This provides flexibility so that terms and definitions can be used across a range of countries and ecosystems (GOFC-GOLD, 2010); according to some estimates, there are more than 90 different definitions of 'forest' around the world (ICRAF, 2012; Lepers et al., 2005; Ramankutty et al., 2007). 'Deforestation' refers to conversion from a forest land-cover category to a non-forest land-cover category. 'Forest degradation' indicates situations where forest remains in the same land-cover category, but is degraded as measured by loss in biomass, carbon, or some other indicator.

Although providing such flexibility seems reasonable and practical, it actually hinders a direct, global comparison of regional REDD projects, and given how REDD is geared towards generating regional-level carbon credits that are to be traded at the global level, it is essential to be able to readily accomplish such a comparison. Therefore, there is a need to develop a benchmark definition of 'forest' so that the definition can be applied to different regions consistently, so that the outcomes will be directly comparable. This will enable ongoing and future REDD projects to use this benchmark definition as a reference when comparing projects.

According to VCS methodology (2012), REDD projects need to account for spatial complexity by specifying (a) reference region, (b) leakage belt, and (c) project area. The reference region refers to the spatial extent of an RL and is crucial for determining the rate of historical deforestation for a given time period. The leakage belt refers to the area at risk of becoming more vulnerable as a result of a potential REDD project. The project area refers to the location and geographic scope of the actual REDD project. In terms of specifying these components, a detailed methodology is not provided. In particular, the reference region is not required to be specified objectively when estimating rates of deforestation and/or forest degradation; this reference region is generally determined in a qualitative manner. Paladino and Pontius Jr. (2004), however, point out that the size of a reference region can affect deforestation forecasting outcomes. Brown et al. (2007) demonstrated that different RL methodologies can produce substantially different outcomes and that using differing reference region sizes magnified this fluctuation. They found that for one specific study area and one time period, there could be an almost 40% variation in terms of forest-cover change estimate due to different spatial extents and levels of data aggregation. Similar research has been done by Soares-Filho (2012).

The importance of clearly delineating the reference region can be illustrated graphically (Figure 2). An area of forest has been partially deforested, but adjacent forests are intact. Delineating a reference region by including these adjacent forests, as well as the deforested areas, results in a lower rate of deforestation than if these forests were excluded. The absolute quantity of deforestation, however, remains the same – and problematically so. Thus, in an attempt to claim maximum carbon credits, one might be inclined to maximize the deforestation rate by manipulating the reference region. Determining a reference region without this in mind raises questions about the credibility of REDD carbon credits. Therefore, this issue needs to be resolved for successful REDD implementation.

An RL has two components: (a) data on areal change of forestland and (b) associated forest carbon density information (Brown et al., 2007). Both are necessary to determine carbon emissions profiles when a particular forestland is disturbed under a business-as-

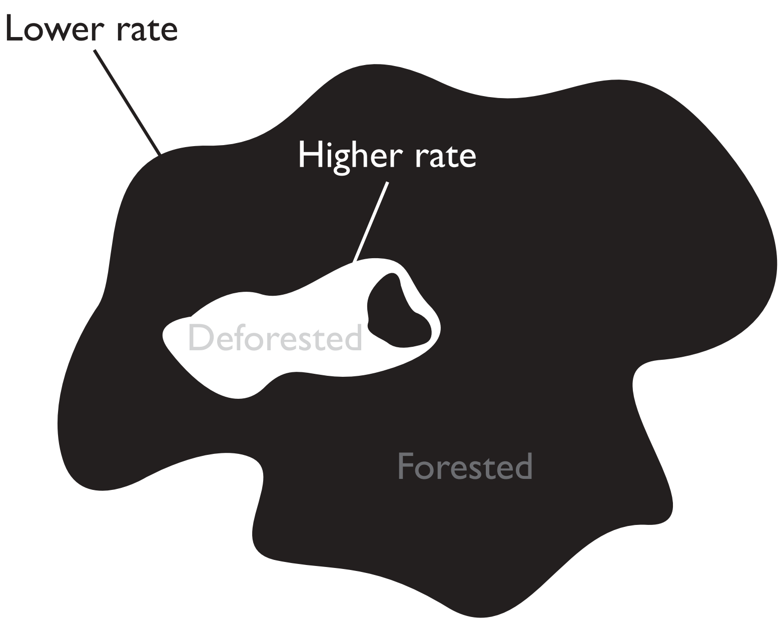

Figure 2. Spatial complexity of deforestation rate calibration.

usual scenario. Multiplying areal and density data yields information on mass, which is expressed in terms of tonnes of carbon dioxide equivalent (tCO_2e). This paper focuses exclusively on the areal change of forestland – spatially explicit and prospective areal data provided by land-change modeling.

1.2. GEOMOD and GEB

GEOMOD is the most frequently used land-change model for providing areal data for an RL (Benito & Peñas 2008; Brown, 2002, 2005; Dushku & Brown, 2003; Harris, Petrova, Stolle, & Brown, 2008; Kim, 2010; Sathaye & Andrasko, 2007a, 2007b; Sloan & Pelletier, 2012), and this is why GEB is compared to GEOMOD. That is, the comparison is geared towards assessing the utility of the new model with respect to the most popular one. GEOMOD is embedded in computer programs such as Idrisi (Eastman, 2012) and ArcGIS (Hong et al., 2012), and the details of the model are well-documented (Pontius & Chen, 2006). Nonetheless, GEOMOD introduces uncertainty because the model, by design, does not consider how the definition of 'forest' affects result outcomes, nor does it control for the varying spatial extents (i.e., reference regions). To address these shortcomings, GEB uses a mixed method approach to dictate business-as-usual future deforestation (Figure 3).

GEB is a land-change model specifically geared towards REDD. Unlike GEOMOD, GEB internally (a) characterizes basic terms such as 'forest' in a general sense based on remotely sensed global data sets and (b) identifies 'deforestation hotspots' using a spatial clustering technique to delineate reference regions in a data-driven manner. Another primary objective of GEB is to produce results with moderate accuracy quickly and with minimal processing and ground-truthing.

To characterize 'forest' and 'deforestation' and to forecast future deforestation based on that characterization, GEB uses Globcover and Vegetation Continuous Field (VCF),

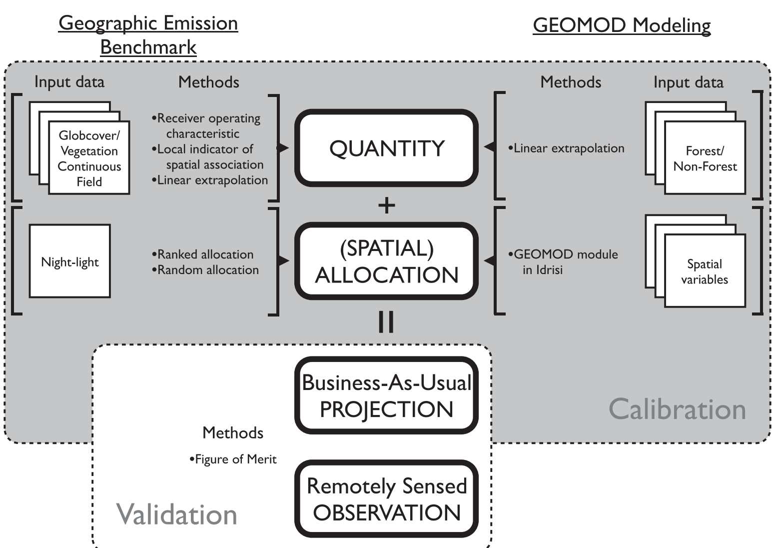

Figure 3. Structural differences between the Geographic Emission Benchmark (GEB) and GEOMOD models.

both of which have been pre-processed and ground-truthed (Bicheron et al., 2008; Bontemps et al., 2011; Hansen et al., 2002, 2003), accompanied by Receiver Operating Characteristic (ROC). In contrast, GEOMOD uses differently characterized forest/non-forest maps, most of which require extensive pre-processing of multispectral images and ground-truthing (Kim, 2010; Sloan & Pelletier, 2012). To measure the relative accuracy, GEB performance is compared to GEOMOD's, such that GEB's characterization of 'forest' is used for the GEOMOD run as well.

To specify quantity, GEB employs Local Indicator of Spatial Association (LISA) in addition to the linear extrapolation of GEOMOD. In other words, the LISA application determines the reference region for the GEB run, while GEOMOD allows inputting a subjectively determined reference region. In this sense, GEOMOD and GEB consider different quantities when projecting business-as-usual forest-cover change.

GEOMOD combines spatial variables by using weighted summation to produce a ranked 'transition potential' map that spatially allocates potential for deforestation and other forest-cover changes (Eastman, Van Fossen, & Solórzano, 2005). GEB substitutes these spatial variables with night-light imagery. GEB assigns the pixels proportional to the night-light pixel values (i.e., ranked allocation) and randomly assigns pixels when there is not enough variation in these values (i.e., random allocation). This approach assumes that night-light imagery serves as a suitable proxy for the range of anthropogenic disturbances that GEOMOD's spatial variables are designed to capture. This night-light layer is considered differently compared to the spatial variables used for the GEOMOD run. In GEB, the night-light layer functions as an internal 'null method' that determines the pixel allocation; therefore, by design, if the night-light layer were to be replaced by other data sources, then the GEB is not GEB anymore. 'Null method' means that no calculation is needed to produce a rank map, whereas GEOMOD calibrates numerous spatial variables to produce a similar rank map. The concept of 'null method' justifies the validity of comparing GEB and GEOMOD because the night-light layer combines various aspects of the Earth's surface, such as road networks and population density, when collecting and storing night-light information through satellite-borne sensors. GEOMOD combines these various aspects through computation; data for this are collected individually. In the end, the night-light layer and GEOMOD's outcome both show humans' niche or transition potential of deforestation in a ranked map form. In brief, both GEB and GEOMOD aim to produce an areal outcome at a detailed scale – i.e., Tier 3, according to IPCC (2006) – in a spatially and temporally explicit manner.

1.3. Study area

Banna prefecture in Yunnan province has experienced deforestation and forest degradation since the 1970s (Li, Aide, Ma, Liu, & Cao, 2007; Li, Ma, Aide, & Liu, 2008; Qiu, 2009; van Vliet et al., 2012; Xu, 2011); thus, this site is appropriate as a case study (Figure 4). The area is about 2 million hectares in size, with elevation ranges from 0 to 1919 m (mean elevation = 655.37 m). The latitude and longitude of the lower left and upper right of Banna are 99.9432 E, 21.1410 N, and 101.8382 E, 22.5915 N, respectively. Banna is one of the few tropical areas in China, and its climatic and geographical conditions are more similar to those of Southeast Asian countries than other parts of China. At the continental level, it is part of the Indo-Burma biodiversity hotspot (Myers, Mittermeier, Mittermeier, da Fonseca, & Kent, 2000) and a member of Greater Mekong Subregion (Xi, 2009). Despite many Chinese forestry and land-use policies over the past few decades (FAO, 2001, 2006b, 2010; Information Office of the State Council of the People's Republic of

Figure 4. Map of the study areas: Banna prefecture (black) and Yunnan province (gray).

China, 2008; Li et al., 2007, 2008; Murray & Cook, 2004; Resources for the Future [RFF] & Center for International Forestry Research [CIFOR], 2003; Xu et al., 2006), Banna remains vulnerable to deforestation and/or forest degradation. The area was composed of almost largely closed-canopy tropical rainforest; by 2003, less than half of these forests were left, including just 3.6% of old-growth tropical rainforests (Li, Ma, Liu, & Liu, 2009; Li et al., 2007, 2008). This is equivalent to losing about 6 million tonnes of biomass every year since 1976 (Qiu, 2009).

2. Data sources

The data used for the study area are of 'moderate' spatial resolution (Achard et al., 2010; DeFries et al., 2007), with pixel sizes ranging from 90 to 1000 m resolution. All data were resampled to 500 × 500 m. For forest-cover raster data, GEB uses Globcover and VCF. Globcover shows forest-cover information in categorical form (Figure 5a), while the VCF shows it in continuous form (Figure 5b) by measuring the physical amount of sunlight penetrating layers of foliage (Hansen et al., 2003). Canopy-cover is often used as a proxy (albeit an incomplete one) for forest-cover (Saatchi et al., 2011).

The GEB model uses night-light data from 2005 (DMSP, 2005). These data show visible light spectra at night, and pixel values are normalized by percent length of observation (Figure 6). For example, if light is observed only half of the night, where this observation repeats on a daily basis (for one year), the pixel value would be 50%. Because night-light data are considered a good proxy for human activity at the global scale, they are increasingly popular inputs for gridded population maps – including LandScan (Dobson, Bright, Coleman, & Worley, 2000; Oak Ridge National Laboratory

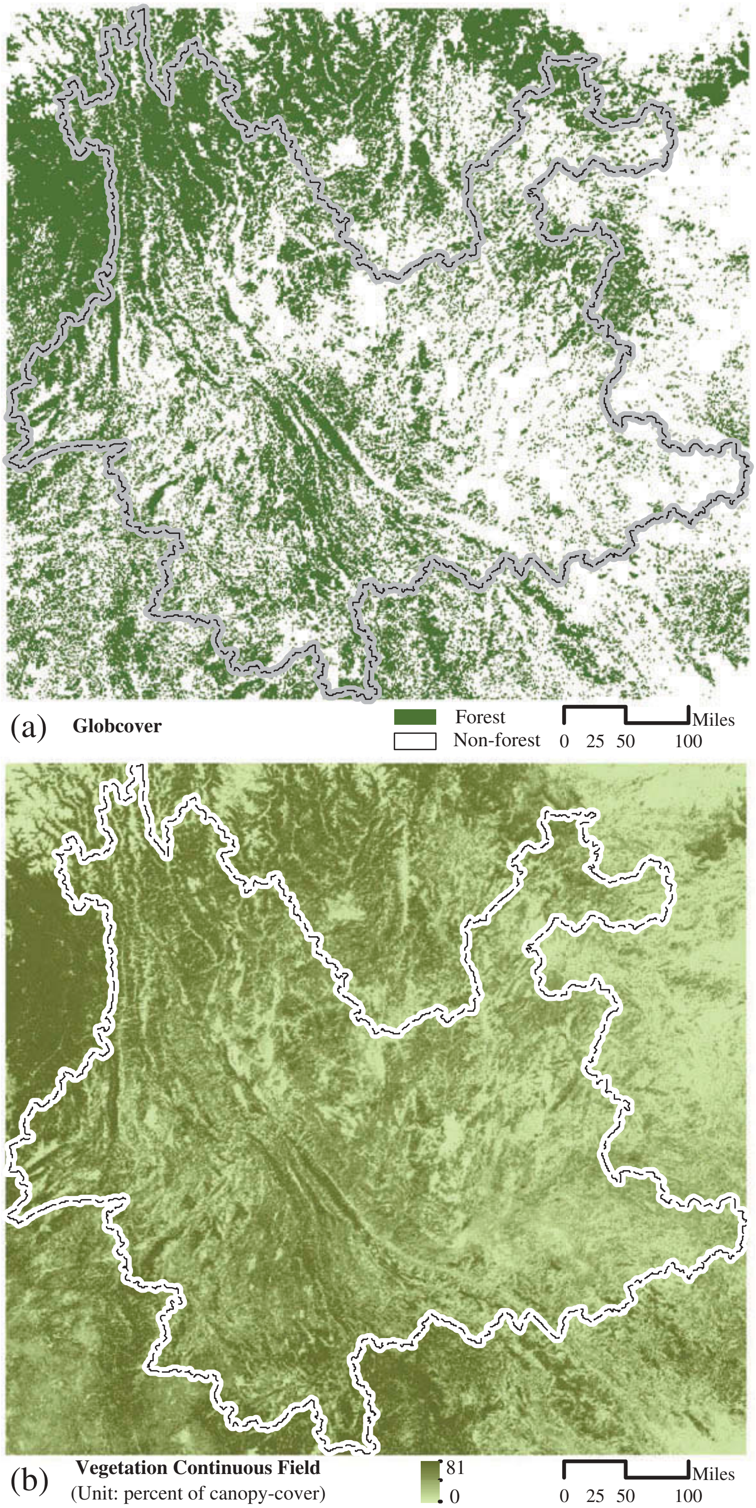

Figure 5. (a) Globcover-based binary map of forest and non-forest and (b) Vegetation Continuous Field (VCF) of Yunnan province as a part of the Geographic Emission Benchmark (GEB).

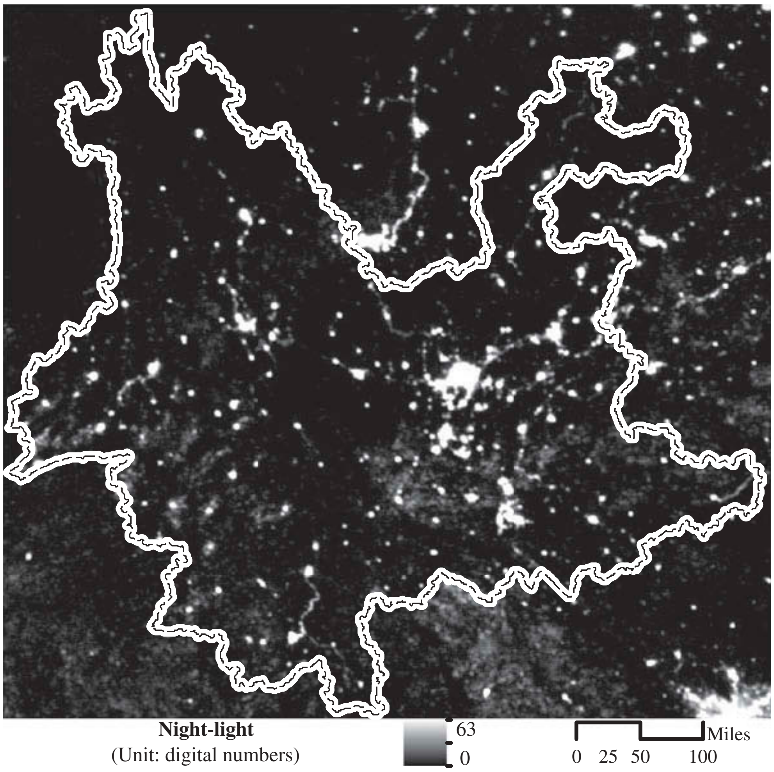

Figure 6. Night-light imagery of Yunnan province for the Geographic Emission Benchmark's (GEB's) spatial allocation.

[ORNL], 2008), Global Rural–Urban Mapping Project ([GRUMP]; Center for International Earth Science Information Network [CIESIN], International Food Policy Research Institute [IPFRI], World Bank, & Centro Internacional de Agricultura Tropical [CIAT], 2004), and History Database of the Global Environment ([HYDE]; Goldewijk, Beusen, & Janssen, 2010; Goldewijk, Beusen, Van Drecht, & De Vos, 2011). The data sources for GEB are summarized in Table 1.

For the GEOMOD run, data include road, railroad, stream layers (China Historical GIS at Harvard University [CHGIS], 2007); population maps (CIESIN et al., 2004); and digital elevation models (USGS, 2006). Distance maps are generated based on the road, railroad, and stream layers while slopes and aspects are produced based on the elevation data (Figure 7). As the purpose of this paper is to forecast future deforestation under a business-as-usual scenario using past data, post-2005 data are excluded, such as LandScan (ORNL, 2008) or Global Digital Elevation Map ([GDEM], Ministry of Economy, Trade,

Table 1. Data sources for the Geographic Emission Benchmark (GEB).

Type	Spatial resolution (in meters)	Temporal/spatial coverage
Globcover	300 × 300	2005–2006, 2009/Global
Vegetation Continuous Field	500 × 500	2000–2010 (annually)/Global
Night-light	1000 × 1000	1992–2010 (annually)/Global

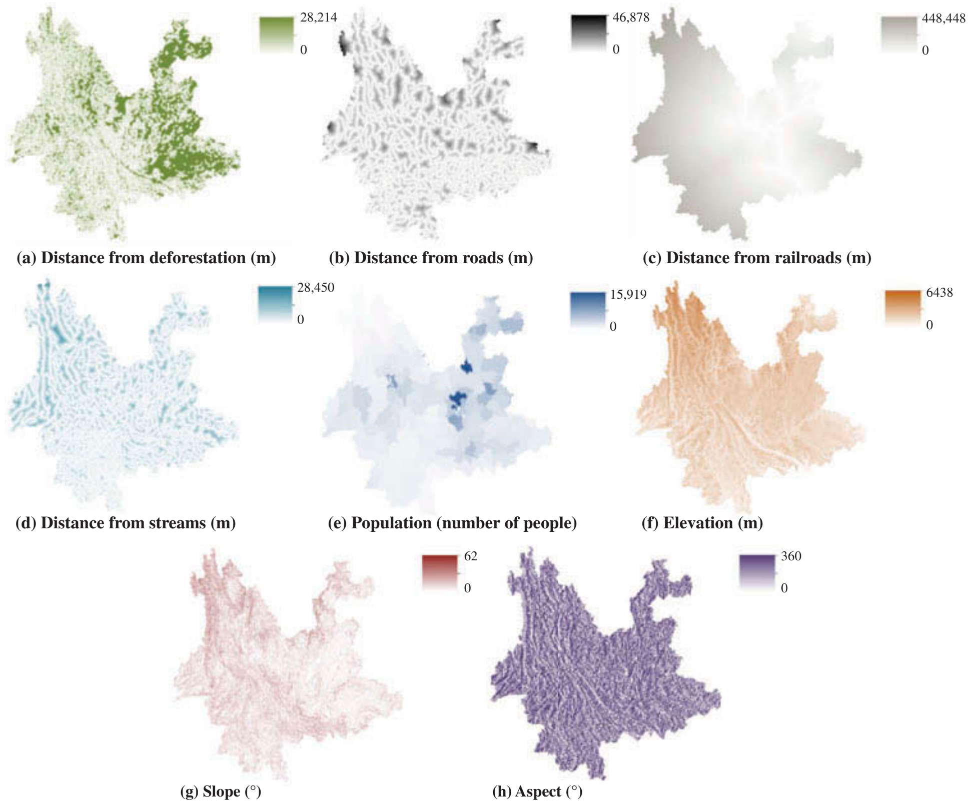

Figure 7. Spatial variables of Yunnan province for the GEOMOD modeling's spatial allocation. To view this figure in colour, please see the online version of the journal.

Table 2. Data sources for the GEOMOD modeling.

Type	Data format	Temporal/spatial coverage
Elevation	Raster (90 × 90 meters)	2000/Global
Aspect	Raster (90 × 90 meters)	2000/Global
Slope	Raster (90 × 90 meters)	2000/Global
Population	Vector (Polygon)	1990, 1995, 2000/Global
Road	Vector (Line)	1993/China
Railroad	Vector (Line)	1993/China
Stream	Vector (Line)	1993/China

and Industry [METI] & National Aeronautics and Space Administration [NASA], 2011). The data sources for GEOMOD are summarized in Table 2.

3. Methods

The process to run the GEB model and then compare the results to GEOMOD results is as follows. First, to develop the forest-cover map, VCF and Globcover are overlaid and assessed for similarity and for local-scale data accuracy. As only six Globcover forest classes (i.e., Categories 40–100) include information of tree height, these are the only ones considered as 'forest' in the GEB modeling. These forest classes (e.g., closed/open, broad-/needle-leaved, and evergreen/deciduous) are grouped into one forest category and identified as 'forest' if taller than 5 m, larger than 9 ha, and containing more than 15% crown-cover (i.e., Globcover classes 40–100). This is a more conservative definition of 'forest' than the GOFC-GOLD definition and an approach similar to Grassi, Monn, Federici, Achard, and Mollicone (2008), who argue that if an estimate for REDD projects cannot be fully accurate, then at minimum it should be conservative. The 'non-forest' category includes the rest (Figure 5a). This reclassified Globcover can be used to quantify deforestation. However, the data cannot smoothly display forest-cover heterogeneity, which is essential for mapping forest degradation. VCF is the opposite. In VCF, the data measure the physical amount of sunlight that penetrates layers of foliage to reach the ground; therefore, when one solely uses VCF to define 'forest,' one runs a risk of including other wooded lands or excluding relevant forests. Therefore, using Globcover and VCF in tandem overcomes their individual limitations when characterizing 'forest,' 'deforestation,' and 'forest degradation.'

Overlaying the two data sets provides an estimate of the percent of canopy-cover actually equivalent to the 'forest' threshold. To do this, the pixel count of the reclassified Globcover 'forest' category is accounted, as is each VCF bin. These bins are added up until the count is identical to the pixel count of the reclassified Globcover 'forest' category. If the pixel count of this category falls between two pixel counts of VCF bins, the higher VCF value is chosen as the threshold that determines 'forest' in terms of percent canopy-cover. This classification approach is in accordance with Grassi et al. (2008).

Once 'forest' is characterized, change-detection analysis is performed to indicate 'deforestation' (i.e., forest to non-forest) at the pixel level. The deforestation pixels are later aggregated for each county; a LISA is then used to identify statistically significant deforestation 'hotspots.' In GEB, these hotspots then serve as the reference region, whereas in the GEOMOD run, Banna prefecture serves as the reference region. For the GEB-GEOMOD comparison, two rates of deforestation are calibrated with the same forest-cover maps and then converted into pixels. These are then spatially allocated using the night-light data (for GEB) and other spatial variables (for GEOMOD) in order to produce the projected outcomes of business-as-usual forest-cover change. Finally, Figure of Merit is used to validate the two projections with the observed forest-cover map. We now explain these modeling steps in more detail.

3.1. Receiver operating characteristic

Since both Globcover and VCF are ground-truthed and peer-reviewed, they are considered fairly accurate at the global level. However, their global-scale data accuracy might vary by region. The similarity and local-scale data accuracy of Globcover and VCF are assessed using ROC. The assumption is that because both data sets are presumably measuring the same object (i.e., forest) in an accurate manner, they should show high similarity. For example, if the similarity of the two data sets is low for a particular region, then their local-scale data accuracy is also considered low. ROC can assess the agreement of the two forest-cover maps, where one map must be binary and the other one has to be continuous. The binary map refers to the forest and non-forest map that is reclassified from the 2005 Globcover (Figure 5a), while the continuous map indicates the 2005 VCF (Figure 5b).

Table 3. Receiver Operating Characteristic's (ROC's) contingency table.

		Forest-cover map		
		Forest ('1')	non-forest ('0')	Total
VCF	Forest (within threshold)	A	B	A + B
	Non-forest (otherwise)	C	D	C + D
	Total	A + C	B + D	A + B + C + D

For each threshold of the ROC, two data points (x, y) were generated; x is the 'specificity,' or 'the proportion of correctly classified negative observations,' and y is the 'sensitivity,' or 'the proportion of correctly classified positive observations' (Robin et al., 2011, p. 1). These data points are plotted and connected to form an ROC curve. The sensitivity is derived from $A/(A + C)$ while the specificity is derived from $D/(B + D)$, where A, B, C, and D are aggregated pixel counts of agreements and disagreements for each threshold (Table 3). When the ROC refers to 'relative' operating characteristic, the specificity is replaced by $B/(B + D)$, that is, percent of false positive, hence resulting in the opposite direction of the x-axis (Pontius Jr. & Schneider, 2001, p. 239).

The ROC, or more specifically the Area Under the Curve (AUC), was calculated according to the following equation:

$$AUC = \sum_{i=1}^{n} (x_i - x_{i+1}) \times \left\{ y_i + \frac{(y_{i+1} - y_i)}{2} \right\}, \tag{1}$$

where x_i is the specificity for the threshold i, y_i is the sensitivity for threshold i, and $n + 1$ is the number of thresholds. AUC ranges from 50% (i.e., no agreement) to 100% (i.e., perfect agreement). The ROC analysis was performed using pROC package (Robin et al., 2011).

3.2. Change-detection analysis

To quantify the amount of change between 2000 and 2005, a pixel-level change-detection analysis was conducted on the VCF layers. VCF's pixels are constructed as continuous values, so the change-detection analysis produces continuous values too. If, after change analysis, a pixel contained a value equal to or greater than the threshold, then it was considered 'degraded' rather than 'deforested.' Pixels initially lower than the threshold in 2000 but then exceeding it by 2005 were labeled 'forest regrowth.'

3.3. Local indicator of spatial association

After deforestation and forest degradation were identified at the pixel level, the pixels were aggregated for each county. Anselin's (1995) LISA was used to delineate hotspots of deforestation and forest degradation. LISA identifies four forest hotspot types: High–High (HH), High–Low (HL), Low–High (LH), and Low–Low (LL). When a county that experiences rapid deforestation is surrounded by other bordering counties that also have high rates of deforestation, then the county is categorized HH. The other types of hotspots are specified based on the same logic. This type of spatial clustering seems to provide useful information to guide REDD implementation. For example, HH counties, or regions, might receive priority consideration. Areas with a minimum of 95% confidence were considered deforestation (and forest degradation) hotspots.

LISA was calculated based on the following equation:

$$I_Y = \frac{N\ \Sigma_i\ \Sigma_{j \neq i} w_{ij}(y_i - \bar{y})\left(y_j - \bar{y}\right)}{\left(\Sigma_i\ \Sigma_{j \neq i} w_{ij}\right)\Sigma_i(y_i - \bar{y})^2} \tag{2}$$

where I_Y represents the LISA of the variable Y that the researcher is interested in (e.g., rate of deforestation); w_{ij} denotes an element of a spatial weight matrix W, while the element shows a type of spatial association between locations i and j. y_i indicates the variable that the researcher is interested in at location i, and $\bar{y}$ shows the average value of all y_is for the study area. The spatial weight matrix, W, was created using Queen's method and only considers first order connectivity, i.e., when county i borders county j, then '1' is assigned to w_{ij}, if not '0.' Lastly, N is the total number of observations. The LISA analysis was performed using OpenGeoDa (Anselin, Syabri, & Kho, 2006).

3.4. *Business-as-usual forest-cover change*

To demonstrate how rates of forest-cover change vary when different reference regions are applied, deforestation and forest degradation were calculated at the Banna prefecture and hotspot levels using the following equation:

$$RD_{i(2000,2005)} = \frac{AD_{i(2000,2005)}}{AF_{i(2000)}} \tag{3}$$

where $RD_{i(2000,2005)}$ indicates the rate of forest disturbed between 2000 and 2005 in region i, $AD_{i(2000,2005)}$ refers to the amount of forest disturbed between 2000 and 2005 in region i (in hectares), and $AF_{i(2000)}$ dictates the amount of existing forest in 2000 in region i (in hectares). The forest disturbed simultaneously indicates both deforestation and forest degradation.

Rates were assumed to be consistent over time; therefore, the business-as-usual forest-cover change/loss between 2005 and 2010 maintains the same rate as it did between 2000 and 2005. This assumption is identical to the logic of the linear extrapolation method in GEOMOD modeling (Pontius & Chen, 2006).

The rates (between 2000 and 2005) calibrated at the hotspot level and prefecture level are used to dictate the quantity of forest-cover loss (between 2005 and 2010) for the GEB and GEOMOD, respectively. Only business-as-usual scenarios of *deforestation* are projected because there are no data to validate projections of forest degradation. In GEB, if the night-light data do not have enough variation in terms of pixel values, then many pixels may be ranked as a tie. Leftover pixels are allocated randomly after all the ranks produced by the night-light imagery are consumed. This random spatial allocation is done by the sp package (Pebesma & Bivand, 2012).

3.5. *Figure of Merit*

To compare the relative validity of the two projections under a business-as-usual scenario, we conducted a test for Figure of Merit (FoM), which ranges from 0% to 100% (perfect prediction). We overlaid the observed forest-cover map of 2005, the predicted forest-cover map of 2010, and the observed forest-cover map of 2009. We assumed the difference in forest-cover between 2009 and 2010 to be negligible. The FoM is expressed mathematically as follows:

$$\text{Figure of Merit} = B/(A + B + C) \tag{4}$$

where A is a number of pixels for 'error due to observed change predicted as persistence' (or misses), B is a number of pixels for 'correct due to observed change predicted as change' (or hits), and C is a number of pixels for 'error due to observed persistence predicted as change' (or false alarms) (Pontius et al., 2008, p. 20).

4. Results

The purpose of the range of test and model runs was to assess how well GEB works and to measure its relative accuracy with respect to GEOMOD. First and foremost, GEB allows the user to systematically characterize 'forest' and 'deforestation' based on the remotely sensed forest-cover data where their definitions are similar to (and more conservative than) VCS's criteria. The agreement between the binary (Globcover) and continuous (VCF) maps was an AUC of 81% (Figure 8), indicating fair accuracy in the forest-cover maps at the Yunnan province level; that is, the estimates generated by GEB in this case study are considered reliable. Using the GEB definition of forest, 31% of the VCF's pixels can be considered 'forests.' After the change-detection analysis, if the pixels were

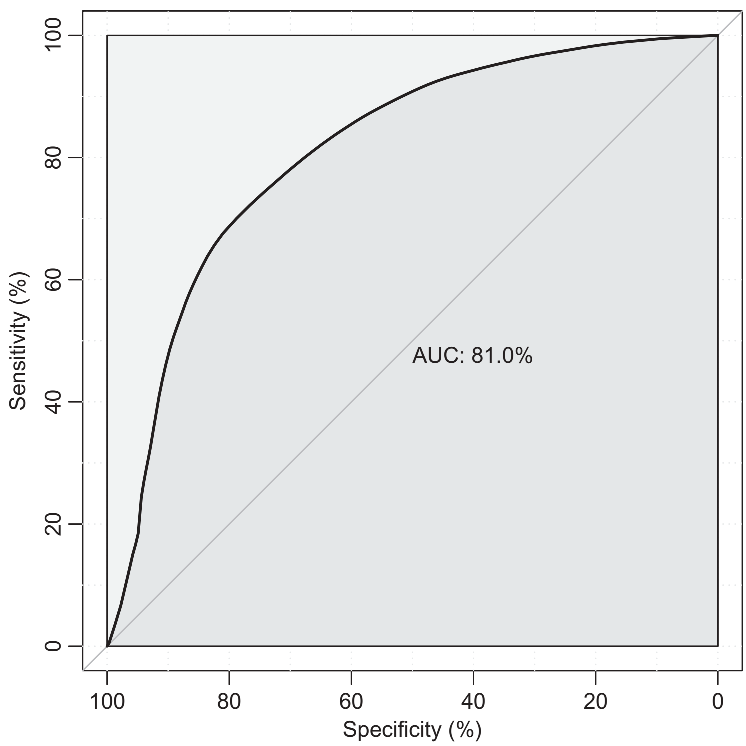

Figure 8. Area Under the Curve (AUC) of the Globcover and Vegetation Continuous Field (VCF) as part of the Geographic Emission Benchmark (GEB).

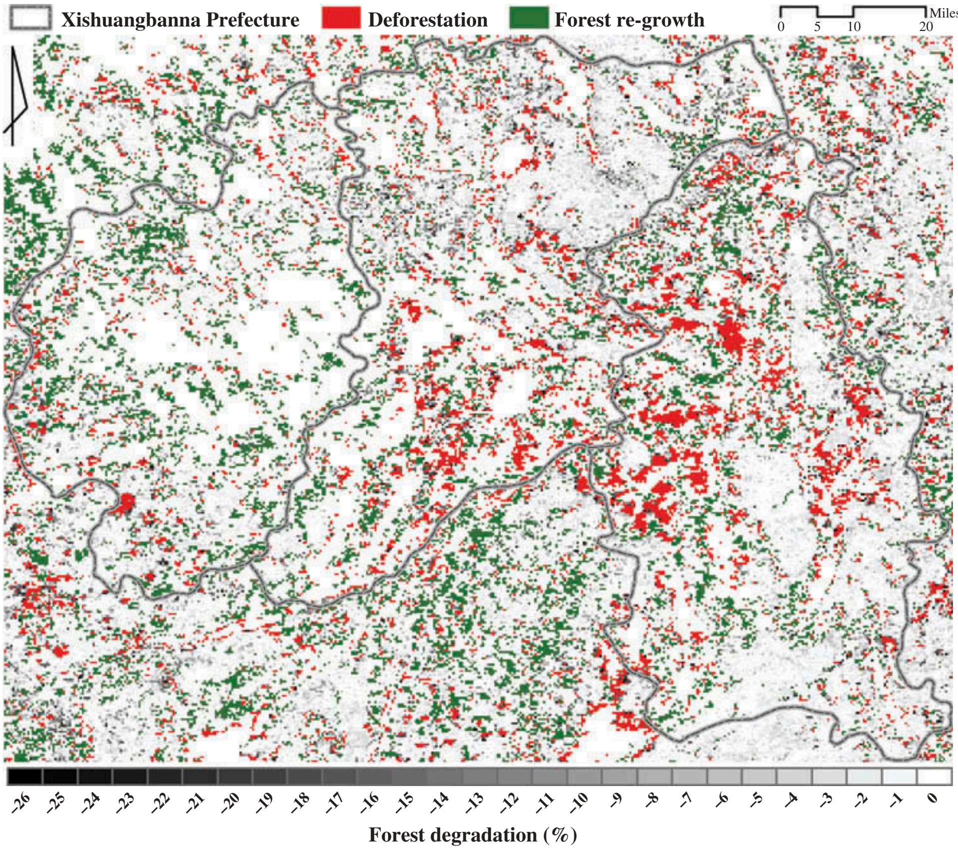

Figure 9. Observed deforestation, forest degradation, and forest re-growth between 2000 and 2005 of Banna prefecture, as characterized by the Geographic Emission Benchmark (GEB). To view this figure in colour, please see the online version of the journal.

equal to or greater than a threshold of 54% of the canopy-cover, then these were considered as 'forest degradation,' and below this, 'deforestation.' Pixels initially lower than 54% in 2000 but exceeding this by 2005 were considered 'forest re-growth.'

Figure 9 shows the development of forest-cover data by GEB in a spatially explicit way at the Banna prefecture level. From this map, it is possible to conclude that Banna had experienced substantial deforestation between 2000 and 2005. When the red pixels are aggregated and quantified (Figure 9), the loss due to deforestation in Banna prefecture is estimated to be 57,258 ha (Table 4), or an average annual loss of 11,452 ha of

Table 4. Amounts and rates of observed forest-cover loss between 2000 and 2005 at different spatial levels.

	Prefecture level	Hotspot level	Province level
Deforestation (observed)	57,258 ha	228,052 ha	582,399 ha
Total forest in 2000	363,610 ha	1,169,182 ha	3,639,533 ha
Deforestation rate	15.75%	19.51%	16.00%
Degradation (observed)	199,300 ha	550,487 ha	1,828,275 ha
Total forest in 2000	363,610 ha	964,175 ha	3,639,533 ha
Degradation rate	54.81%	57.10%	50.23%

forest-cover between 2000 and 2005. This estimate of GEB is similar to that made by Li et al. (2007), who estimated 345,423 ha of forest-cover were lost between 1976 and 2003 in Banna, or 12,793 ha annually.

Using GEB, it is also possible to objectively delineate statistically significant hotspots of deforestation and forest degradation. Figure 10 indicates the four types of hotspots of deforestation and forest degradation between 2000 and 2005. The hotspots are classed based on the *p*-values, and darker colors indicate higher statistical significance. Gray shows statistically insignificant relationships, based on a 95% confidence interval. Banna prefecture has HH hotspots both in terms of deforestation and forest degradation. The larger red hotspot of deforestation situated in southern Yunnan portrays the broader context of deforestation underway in Banna, justifying use of the hotspot as a reference region for the GEB run.

Table 4 shows how rates of deforestation (and of degradation) vary when different sizes of reference regions are employed, and these varying rates of deforestation reveal the importance of developing clear rules for determining the reference region. Quite naturally, the rate at the hotspot level is higher (19.51%) than the rates at the prefecture and province levels, and this is also true for degradation. When one produces an RL without quantitatively identifying the associated hotspot of deforestation and/or degradation, but while qualitatively specifying the reference region, the resulting RL may be underestimated.

Finally, the GEB predicts a more accurate projection than the GEOMOD run, at least for this case study. Figure 11 shows the business-as-usual projections of deforestation by both GEB and GEOMOD. The extent of the two maps is identical to the HH hotspot (95%) in Figure 10. Although the GEOMOD run did not take into account this broader spatial scale when projecting future deforestation under a business-as-usual scenario, for the ease of comparison, the outcome of GEOMOD is also presented with the same spatial extent. It becomes evident how these two models differ. The GEB projects business-as-usual deforestation with the broader context in mind (including Banna, of course), whereas GEOMOD implicitly assumes that deforestation in Banna is independent of its adjacent areas. Measured by FoMs, the GEB turns out to have a higher predictive accuracy (30.16%) than the GEOMOD (26.50%) when compared at the Banna prefecture level. Thus, it does make more sense to assume the areas adjacent to Banna are experiencing similar deforestation and that it is important to take such context into account when projecting a business-as-usual scenario of future deforestation.

5. Discussion

UN-REDD (2013) employs the IPCC approach of combining activity data and emission factors to quantify GHG emissions of a particular activity such as deforestation. According to IPCC (2006), ‘activity data’ indicates ‘[quantitative] information on the extent to which a human activity takes place’ (1.6), while an ‘emission factor’ refers to ‘the corresponding GHG emissions per unit activity’ (Kim, 2013, p. 155). In short, GEB produces spatially explicit and prospective activity data that can be fed into an RL to produce an emission baseline and other useful outputs for REDD projects.

First and foremost, while there are no specific guidelines suggested by VCS to quantitatively delineate reference regions, GEB presents a scientific method to do so. Once a reference region is identified by GEB, REDD projects that fall into the reference region are assumed to have the same rate of deforestation when proving their additionality, where it is defined as ‘the extent to which project interventions lead to GHG benefits

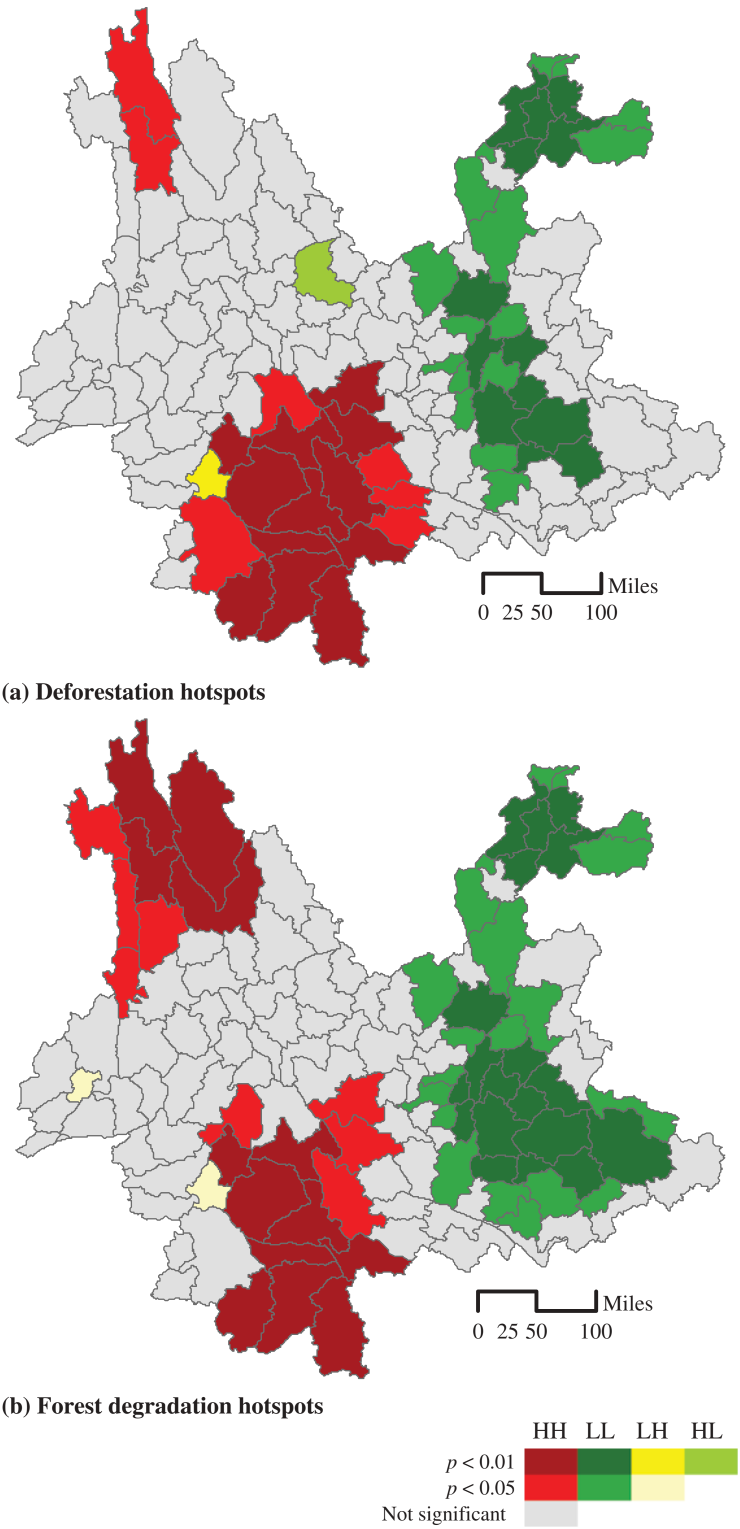

Figure 10. Hotspots of observed deforestation and forest degradation between 2000 and 2005 of Yunnan province as part of the Geographic Emission Benchmark (GEB). To view this figure in colour, please see the online version of the journal.

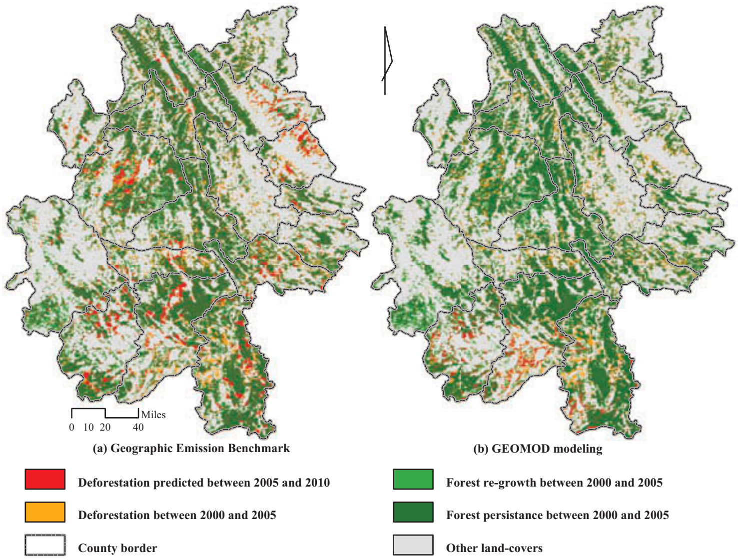

Figure 11. Business-as-usual loss of forest-cover projected by the Geographic Emission Benchmark (GEB) and GEOMOD modeling. To view this figure in colour, please see the online version of the journal.

that are additional to business-as-usual' (IPCC, 2000). The produced activity data, indicating a business-as-usual future deforestation scenario, should be always reported with the associated ROC and FoM to assure the local-scale data and modeling accuracies, and users must keep these in mind when interpreting the results. Further, if more sophisticated land-change models, such as CLUE-S (Verburg et al., 2002), Dynamica-EGO (Soares-Filho et al., 2006), and Land Change Modeler (Kim, 2010; Sangermano, Toledano, & Eastman, 2012), are to be used and accompanied with higher spatial resolution forest-cover maps, their performance should be better than the GEB.

GEB's estimation is moderately accurate. Moreover, when compared with estimates by Li et al. (2007), GEB's estimation required less processing and ground-truthing. Li et al. (2007) used Landsat, which provides higher spatial resolution satellite images (30 × 30 m) than Globcover (300 × 300 m) and VCF (500 × 500 m), to characterize forests and to perform change-detection analyses. Their forest category includes tropical seasonal rain-forests, mountainous rainforests, and subtropical evergreen broadleaf forests, while GEB considers the forest's biophysical characteristics regardless of their forest type. Although the estimate made by GEB is somewhat lower than that of Li et al. (2007), we cannot conclude that one estimate is more accurate than the other as it is not clear whether the difference is due to different satellite images or definitions used. At least, an RL associated with the GEB outcome will result in a land-cover change estimate by meeting the criteria of VCS. In addition, there are potential uncertainties of using Landsat because a pixel of Landsat imagery is equivalent to 0.09 ha, so a forest must be constituted with 6 pixels when a country's minimum forest area is set to 0.5 ha. If there are 5 or fewer pixels agglomerated, those pixels should not be considered a forest; thus, their transition to other land-cover categories would not count as 'deforestation.'

Second, it is possible to objectively identify a potential leakage belt using LISA. In other words, if a county turns out to be a member of LH hotspots, REDD stakeholders may want to pay more attention to the county because of potential leakage issues; the county is surrounded by counties with higher deforestation rates, so it is likely the county's deforestation may be affected by its neighbors. The yellow polygons in Figure 10 exemplify this. While identifying leakage belts and managing them are important for REDD to assure valid carbon sequestration activities, VCS (2010) only suggests *qualitative* approaches to identify these belts.

Third, GEB is capable of mapping forest degradation, a crucial but sometimes neglected component of REDD. It is well-known that accounting carbon loss due to forest degradation is more difficult than that of deforestation (Newell & Vos, 2011, 2012). For this reason, high-resolution data are indispensable (Asner, 2009; Asner et al., 2010), but expensive to purchase and time-consuming to process. Given the second 'D' of REDD stands for forest degradation, it appears reasonable to have, at least, a transparent estimate of degradation that has at least moderate accuracy. Since the outcome of deforestation appears moderately accurate, we expect the similar accuracy for degradation. GEB provides a series of useful estimates that can be produced quickly, making it a suitable land-change model for REDD implementation.

Although the GEB does not have a ready-made user interface, the model can be executed via a series of open-source computer programs, namely R (www.r-project.org), OpenGeoDa (geodacenter.asu.edu/ogeoda), and Quantum GIS (www.qgis.org). The use of free global data sets and open source statistical computer programs that support spatial analyses will facilitate the dissemination of the findings in this paper. In particular, REDD stakeholders who do not have sufficient resources for conducting costly pilot studies may find the GEB model and its outcome useful. Lastly, future GEB applications must consider employing a newer version of VCF (DiMiceli et al., 2011) and Landsat-based tree-cover maps (Hansen et al., 2013).

Finally, GEB proposes an alternative to address quantity, which has been found to be the most influential variable in the prediction of carbon emissions (Gutiérrez-Vélez & Pontius Jr., 2012; Sloan & Pelletier, 2012). It is not clear from this paper whether the GEB's higher accuracy is due to quantity or allocation. This limitation is also a limitation of VCS methodology (2012) since it only requires FoM to assess the accuracy of a prediction. The FoM is not designed to assess predictive accuracy of land-change models by differentiating between quantity and allocation (Kim, 2010). Therefore, REDD stakeholders must keep this limitation in mind when setting an RL. As such, producing an accurate RL or quantifying the climate change benefits of REDD is a challenging task, and without addressing the challenge systematically, successful REDD implementation is unlikely.

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