



How accurately may we project tropical forest-cover change? A validation of a forward-looking baseline for REDD

Sean Sloan^{a,b,c,*}, Johanne Pelletier^{d,1}

^a Department of Resource Management and Geography, The University of Melbourne, Carlton, VIC 3010, Australia

^b Climate Adaptation Flagship, The CSIRO, ATSIIP Building, James Cook University Townsville, Queensland 4811, Australia

^c Centre for Tropical Environmental Science and Sustainability, School of Marine and Tropical Biology, James Cook University, Cairns, Queensland 4870, Australia

^d Department of Biology and Global Environmental and Climate Change Center, McGill University, 1205 Dr Penfield, Montreal, Quebec H3A 1B1, Canada

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ABSTRACT

The Reduced Emissions from Deforestation and forest Degradation (REDD+) mechanism of a future post-2012 global climate-change treaty would aim to give incentive to tropical countries to reduce deforestation and thus forest-carbon emissions. It would do so by crediting tropical countries for reducing deforestation relative to a baseline scenario describing carbon emissions and removals from forest-cover change expected in the absence of REDD+. Defining a credible and accurate baseline is both critical and challenging. One approach considered promising is spatial modelling to project forest-cover change on the basis of historical trends; yet few such projections have been validated at a national scale. We develop and validate a novel GEOMOD projection of forest-cover change in Panama over 2000–2008, based on trends over 1990–2000 and 25 drivers of forest-cover change. Compared with the actual landscape of 2008, our projection is 85.2% accurate at a 100-m pixel resolution. More error is attributable to the location of projected forest (8.6%) than to its area (6.2%). Accuracy was least where forest regeneration predominated (80%), and greatest where deforestation predominated (90%). Despite the sophistication of our projection, it is slightly less accurate than if we had assumed no forest-cover change over 2000–2008. We identify factors limiting projection accuracy, including the complexity of forest-cover change, the spatial variability of forest-carbon density, and the relatively small area of change at the national scale. We conclude that, with the exception of contexts where forest-cover change is significant and straightforward and where forest-carbon density relatively uniform (e.g., agricultural frontiers), spatially projected baselines are of limited value for REDD+ – their accuracy is too limited given their relative lack of transparency. Simpler, relatively coarse scale, retrospective baselines are recommended instead.

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1. Introduction

Tropical deforestation contributes significantly to global greenhouse-gas emissions (Achard et al., 2004; DeFries et al., 2002; Houghton, 2003; IPCC, 2007). Recently, parties to The United Nations Framework Convention on Climate Change (UNFCCC) agreed on a policy framework for the creation of the REDD+ mechanism to motivate developing countries to Reduce Emissions from Deforestation and forest Degradation (REDD+) (UNFCCC,

2010). To proceed, parties are requested to determine forest 'baselines', i.e., national forest emissions and/or deforestation expected in the absence of REDD+ (UNFCCC, 2010: Para. 71b), the benchmark against which REDD+ would reward actual reductions in emissions and/or deforestation (Angelsen, 2008). Determining a credible baseline is a significant challenge. Hence, the UNFCCC recently mandated its Subsidiary Body for Scientific and Technological Advice (SBSTA) to identify procedures for establishing baselines (UNFCCC, 2010: Annex II). To complement the SBSTA and inform REDD+ negotiations, this article defines and validates a national, spatially explicit, forward-looking baseline, thus evaluating the utility of such baselines.

The term 'baseline' has various interpretations. Here, it refers to a national empirical business-as-usual scenario of forest-cover change. This baseline is the foundation of the 'reference level' whereby anticipated forest-cover change is expressed in terms of

* Corresponding author. Present address: School of Marine and Tropical Biology, James Cook University, Cairns, Queensland 4870, Australia. Tel.: +61 07 4042 1835; fax: +61 07 4042 1319.

E-mail addresses: sean.sloan@jcu.edu.au, seanpatrickloan@mac.com (S. Sloan), johannepelletier@gmail.com (J. Pelletier).

¹ Tel.: +1 514 398 6726.

carbon emissions and removals (Angelsen et al., 2011: 2). The reference level in turn provides the basis for a 'compensation baseline', essentially a negotiated national forest-emissions quota adjusted upward or downward according to national circumstances (Angelsen, 2008: 471; Angelsen et al., 2009). Clearly, if the business-as-usual baseline is not credible, then evaluating countries' performance in reducing emissions or increasing removals will prove difficult and possibly deleterious to REDD+'s efficacy.

Three main types of business-as-usual baselines have been proposed. The first, a simple-historical baseline, would extrapolate an average national historical deforestation rate over a REDD+ commitment period, e.g., The Brazilian Proposal (UNFCCC, 2007). In effect, the national average deforestation rate becomes the baseline. The second, a historical-adjusted baseline, would extrapolate an average national historical deforestation rate modified by one or more adjustment factors, such as national forest-carbon stocks, often relative to a global average, e.g., The Joint Research Centre approach (Achard et al., 2005), Combined Incentives (Strassburg et al., 2009), Compensated Reduction (Santilli et al., 2005), The Carbon Stock approach (Prior et al., 2007). Such baselines attempt to accommodate countries of varying deforestation rates and importance to the global carbon pool, and may reward performance relative to both national and international trends (see Griscom et al., 2009 for descriptions). The third, a projected baseline, would project the area and location of national forest-cover change and carbon flux on the basis of historical as well as expected forest-cover change dynamics, e.g., the Terrestrial Carbon Group proposal (2008: 11), SBSTA (2009). Such baselines are distinguished in that they are typically complex, forward-looking, spatially explicit, prospective, relatively robust, based on numerous factors, amenable to non-linear trends, and amenable to integration with forest-carbon maps.

The attraction of projected baselines is the promise of greater accuracy, utility, and thus REDD+ efficacy (cf. Brown et al., 2007). An assessment of the views of REDD+ negotiators and reference-level experts scored spatially projected reference levels as significantly higher than others reference levels with respect to accuracy, precision, and reliability of the business-as-usual scenario (Huettnner et al., 2009). Similarly, in proposing a global centre to assist countries develop accurate reference levels, Obersteiner et al. (2009: 4) advocate that "emission reference scenarios should, as far as possible, be based on geographically-explicit data and analysis and allow for down-scaling of national scenarios to assist regional and project level activities", this in order to "allow for tailored and targeted... REDD actions, since the quantity and location of deforestation drivers would be better understood". Projective approaches to reference levels have also been discussed at the UNFCCC (SBSTA, 2009, 2011), albeit with some inconclusiveness given the paucity of empirical validations of such approaches.

Indeed, the complexity of forest-cover change renders the reliability of even the 'best' spatially projected baseline indefinite. The sheer number of forest-cover change drivers as well their inconstant relevance and interactions over space and time challenge the explanatory power of many models of deforestation, let alone their predictive power (Angelsen and Kaimowitz, 1999; Persson and Azar, 2007; Pirard and Karsenty, 2009: 444; Sloan, 2011). Poor time-series data for most developing countries compounds the issue by limiting opportunities to base national projections in reality, let alone validate their accuracy over later periods, an important point considering the variability of forest-cover change over time (Combes Motel et al., 2009). Hence, though important drivers may be identified, assessing quantitatively or even qualitatively how they will affect forest-cover change over time and space is difficult. Many commentators therefore view

forest transitions – i.e., transitions from deforestation to regeneration alongside socio-economic development – as a likely source of baseline inaccuracy (Angelsen, 2008; Angelsen et al., 2009; Griscom et al., 2009; Karsenty, 2008; Pirard and Karsenty, 2009).

Insofar as such complications reduce baseline accuracy, they cloud the extent to which reported reductions in forest emissions are real or illusory, threatening the effectiveness of REDD+. A dubious baseline would disassociate the value and quantity of forest-emission reduction credits from the actual reduction in forest emissions. Consequently, countries may be under- or over-compensated for their reductions in forest emissions, and reductions in forest emissions as well as fossil emissions may be less than they might have been (Angelsen, 2008). It is therefore critical that a business-as-usual baseline be *credible*.

This article develops and validates a spatially projected business-as-usual baseline for Panama, though it is relevant to tropical countries generally. We project forest-cover change over a hypothetical 2000–2008 REDD+ commitment period using 1990–2000 as a reference period, and validate the projection against an actual 2008 forest-cover map. We also assess the role of changing forest-cover change dynamics in projection inaccuracy and utility. Unlike many projections of tropical forest cover, ours is national scale and has a fine spatial resolution, in keeping with the expectation that countries will manage forests regionally but report emissions nationally. Our projection also draws on an ample dataset on socio-economic and biophysical drivers. Relationships between drivers and forest-cover change are optimally determined using a recently developed algorithm resolving uncertainty over the relative importance of drivers.

In this way we indicate the credibility of projected baselines for REDD+. We find that a national projected baseline may not achieve the required accuracy. We conclude by discussing the implications of our projection accuracy for REDD+, suggesting ways to increase accuracy, and advocating simpler approaches to baselines generally.

2. Model selection

An extensive pool of land-cover change models exists from which we might have selected one to test (Lambin, 1997; Pontius et al., 2008). For our purposes, it was prudent to select a model that, in addition to having many of the expected features, is also relatively simple, familiar, objective, accessible, and controllable by the user, to thus invite its consideration by developing countries lacking data and expertise as well as by REDD+ negotiators sceptical of 'black box' baselines (Huettnner et al., 2009; Huettnner pers. comm., 2010). On this basis, we select the GEOMOD model, the details of which we defer to the next section. It suffices here to mention here a few of its recommending features.

GEOMOD has a well-documented history of establishing forest-cover change baselines for reforestation projects of the Clean Development Mechanism (Brown et al., 2007; Dushku and Brown, 2003; Dushku et al., 2002; Hall and Dushku, 2005) and, more recently, REDD+ projects (Pedroni, 2010). Indeed, the model has been in general use and development for fifteen years (e.g., Hall et al., 1995; Pontius et al., 2001), and is now accessible within many Geographical Information Systems, such as Idrisi (Eastman, 2006) and ArcGIS (Hong et al., 2012). It therefore enjoys a high degree of institutional and academic familiarity.

The data demands of GEOMOD are relatively moderate, and its approach relatively straightforward. GEOMOD has also benefited from recent developments allowing the drivers of forest-cover change to be optimally weighted (Hong et al., 2012). The ability to weight drivers permits a safe 'try-and-see' approach to including drivers for which little a priori relevance to forest-cover change is established, as ultimately drivers are weighted according to their

actual relevance. These features suit the context in which knowledge and data are limited.

GEOMOD projections are based on straightforward empirical relationships – essentially, the historical spatial coincidence between forest-cover change and its drivers. This straightforwardness precludes the need to ‘programme’ future trends that are simply not knowable. However, GEOMOD does allow users to specify important parameters, such as expected rates of forest-cover change. These features minimize the introduction of uncertainty while preserving control over the model. They also limit the extent to which a country may manipulate model assumptions for advantage.

3. Methods

3.1. Panama as a case study

We chose Panama as the study context principally because it has sufficient historical data to project forest-cover change and then validate projection accuracy. Here, ‘sufficient historical data’ entails observations of forest-cover change and its drivers that have national coverage, are consistently defined, span almost three decades, have a fine spatial resolution, comprise numerous factors, and are temporally coincident. Other tropical countries have comparable data or, more commonly, the raw data with which to create them, such that the methods discussed below need not be particular to this study.

Panama is also an ideal context because of its great diversity of contexts, effectively a microcosm of the wider tropics, including deforesting frontiers, indigenous-controlled forests, populous regions, and areas undergoing forest transitions. The forest transitions particularly recommend Panama, given the controversy surrounding their effects on baseline accuracy.

3.2. GEOMOD

Using GEOMOD, we project forest area and location over 2000–2008 at 100-m pixel resolution on the basis of observed causes and rates of forest-cover change over 1990–2000. We then validate this projection against a map of actual forest cover in 2008 to determine the nature and extent of error. Hereafter we refer to 2000–2008 as the commitment period, and 1990–2000 as the reference period.

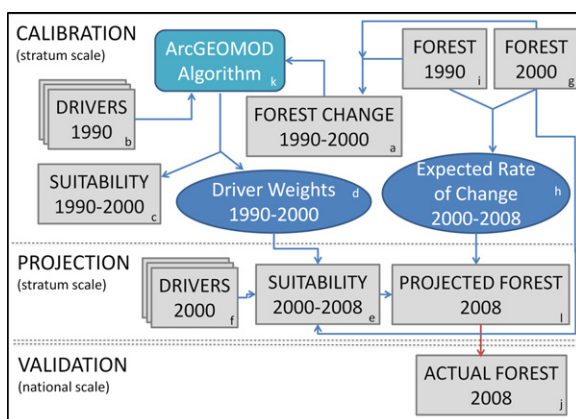


Fig. 1. The elements and operation of the GEOMOD spatial-projection model. *Notes:* Grey squares represent maps. Blue ovals represent a-spatial data. Teal square is an algorithm. All calibration and projection processes were realized once for each stratum, while the validation was realized once at the national scale. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

GEOMOD is a dynamic, spatially explicit, pixel-based model that simulates the ‘one-way’ annual transition from one land cover (e.g., forest) to another (e.g., non-forest). Fig. 1 illustrates our GEOMOD approach. One first specifies an ‘initial’ map of forest-cover change for the reference period, 1990–2000 (Fig. 1 element a), and contemporary maps for each ‘driver’ of forest-cover change, e.g., agricultural suitability (Fig. 1 element b). These maps then render a forest-cover change suitability map for the reference period (Fig. 1 element c) in two steps: (1) the value of each class of a driver is reclassified as the percentage of class area overlapping forest-cover change in the initial map, and (2) the reclassified driver maps are combined according to the formula

$$S(i) = \frac{\sum_{a=1}^A \{W_a \times P_a(i)\}}{\sum_{a=1}^A W_a} \quad (1)$$

where $S(i)$ is the suitability of pixel i , a is a given driver map, A is the number of driver maps, W_a is the weight of driver a , and $P_a(i)$ is the percent of the area of class k of driver map a where pixel i is a member of class k . In the suitability map, pixel values reflect the relative likelihood of forest-cover change. For our model, this first suitability map served only to determine driver weights (Fig. 1 element d); we created a second suitability map (Fig. 1 element e) updated for the commitment period using maps of drivers (element f) and forest cover (element g) in 2000. This latter suitability map determines the location of projected forest-cover change, as forest-cover change is projected firstly where suitability is highest, then next highest, and so on. Finally, one specifies the expected rate of forest-cover change over the commitment period, 2000–2008 (Fig. 1 element h). The parameter may be derived from the reference period, as we have done, or according to otherwise probable or prescribed trends. This parameter determines the projected area of change.

Two further parameters guide our projection. The first, regional stratification, segments Panama into regional ‘strata’ in order to account for regional rates, directions and causes of forest-cover change. We stratify by province, as detailed below. The second, the proximity principle, restricts projected forest-cover change to areas near extant forest cover, which are updated ‘annually’ as the projection progresses. On the basis of a visual analysis of forest-cover change maps, we restrict projected forest-cover change to within 100 m of extant forest in provinces deforesting over the reference period, and to within 300 m in provinces regenerating over the reference period. Brown et al. (2007), Pontius et al. (2001, 2008), Pontius and Chen (2006), and Pontius and Malanson (2005) provide detailed descriptions of GEOMOD. The remainder of this section elaborates the elements of Fig. 1.

3.3. Expected forest area

The expected rates of forest-cover change over 2000–2008 are 80% of those observed over 1990–2000, per province (Fig. 1 element h), reflecting the fact that the former period is 80% as long as the latter. Though we could have specified different rates anticipating non-linear trends, we opted not to for reasons of reliability, transparency, and convention. As our reference period spans one decade and is defined by two observations (1990 and 2000), there are too few data to predict a non-linear forest-cover change curve, and little justification for doing so. While a select few spatial models attempt probabilistic predictions of future forest area, their complexity is contrary to the transparency valued so highly by REDD+ negotiators (Huettnner et al., 2009). Thus our projection assumes constant rates of forest-cover change, in keeping with the relative agreement over this assumption. Our projection should not be confused with simple-historic approaches, however. In addition to the points of difference

detailed previously, our projection extrapolates deforestation and regeneration simultaneously for various strata within Panama, for which the distribution of forest-cover change is then predicted.

Forest-cover change is observed over 1990–2000 using Landsat-derived maps produced by Panama's National Environmental Authority (ANAM hereafter; Fig. 1 elements g and i) (ANAM, 2003). Satellite-image analysis also provides a complementary 2008 forest-cover map produced by CATHALAC (2009) for ANAM (Fig. 1 element j), with which we validate our projection. The 1990 and 2000 ANAM maps have 'very high' but unquantified accuracies (ANAM, 2003: 27). No official map accuracies are available for the 2008 map.

Forest-cover change is defined as the change from forest to non-forest (i.e., deforestation) or from non-forest to forest (i.e., regeneration), depending on the predominant direction of forest-cover change in a stratum over the reference period. Forest, in turn, is defined as the composite of all forest-cover classes of the ANAM maps save for young fallow, most of which have >80% canopy closure (Supplementary Information). Generalizing forest cover thus drastically reduces any inaccuracies in the ANAM maps.

3.4. Drivers, weights, and regional stratification

We consider 25 drivers of forest-cover change (Fig. 1 elements c and f). Drivers are defined as factors influencing the likelihood of forest-cover change without necessarily 'causing' it, e.g., distance to a road. The literature reveals two important characteristics of drivers: (i) they are conjointly interactive, that is, they tend to effect forest-cover change collectively but not necessarily individually (Geist and Lambin, 2002; Rudel, 2005); and (ii) they are hierarchically interactive, that is, the effect of 'proximate' drivers (e.g., land tenure) may be amplified by 'underlying' drivers (e.g., interest rates) (Geist and Lambin, 2002). Our approach focuses on proximate drivers exclusively because underlying trends are not amenable to spatial representation. However, as described below, our approach does vary the effect of a driver according to: (i) the effects of other drivers, which accounts for both conjoint and hierarchical effects, and (ii) provincial strata, which implicitly accounts for variation in the effect of underlying factors between regions.

Table 1 defines our drivers and their source data, and distinguishes socio-economic from biophysical drivers by their grey shading. These drivers are the most comprehensive considered by comparable projection models (e.g., Brown et al., 2007; de Jong et al., 2005), which have overlooked socio-economic drivers. Our socio-economic drivers and Protected Area driver are defined for 1990 and again for 2000 so that, in concert with drivers that are static over time, those for 1990 immediately precede the reference period and thus calibrate the projection, while those for 2000 immediately precede the commitment period and thus define the projection *ex ante*. In this way, our projection utilizes the fullness of available data on historic and contemporary trends observed prior to the commitment period, in keeping with the expectation that tropical countries will establish reference levels for a future period based on past trends. Our road drivers are defined for a single, imprecisely known year. Yet as their source data was last updated in 2003, and as these drivers concern primarily long-standing principal roads, we confidently assume that all roads were established early in the reference period.

Our socio-economic drivers are defined at the county (*corregimiento*) scale ($n = 426$), as delimited in 1990, and derived from respondent-level census data provided by Panama's Department of Statistics and Census (Table 1 notes). The socio-economic drivers are those for which inter-censal change proved central to Sloan's (2011) analysis of socio-economic and forest-cover change in Panama. We emphasize that despite this ample data, our intention is to validate the credibility of a national projected business-as-usual baseline, not describe the causes of forest-cover change.

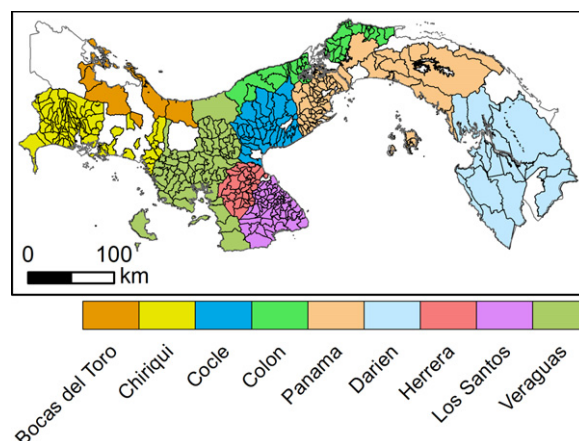


Fig. 2. The geographic extent of projections, by strata, with county limits visible. *Note:* We incorporate the indigenous Comarca Embera into its parent province of Darién given that the Comarca had too few counties to ensure the necessary diversity of driver values. We also incorporate the indigenous San Blas province into Panama province for the same reason.

Both biophysical and socio-economic drivers are necessarily categorical. Whereas biophysical-driver categories reflect natural or standardized classifications, socio-economic-driver categories are defined by the averages of national quartile values of a given socio-economic attribute in 1990 and 2000. This categorization scheme was preferred because (i) it 'standardizes' temporally variable socio-economic attributes, (ii) it is not arbitrary, (iii) it is irrespective of the probability distribution of an attribute, and (iv) it ensures that each category covers an appreciable area.

We stratify our projection by province to account for regional variation in the rate, direction and causes of forest-cover change (Fig. 2). Our stratification method is unlike that of standard GEOMOD applications that do not account for variation in the causes of forest-cover change between strata. Rather, we exploit Hong et al.'s (2012) recently developed ArcGEOMOD algorithm to optimally weight drivers (Fig. 1 element k), and stratify by developing separate projections for each stratum, with drivers weighted uniquely for each according to local reference-period dynamics. Only subsequently do we merge the per-stratum projections to form our national projection.

The ArcGEOMOD algorithm iteratively adjusts driver weights relative to each other until the forest-cover change suitability map (Fig. 1 element c; Eq. (1)) achieves maximal 'fit' with the location of forest-cover change observed over the reference period (Fig. 1 element a) (Hong et al., 2012: Sec. 2.1.2). Fit is defined by the relative operator characteristic (ROC) statistic, a measure of how well the forest-cover change suitability map agrees with the location of observed forest-cover change, where a ROC value of 1.0 signifies a perfect correspondence between forest-cover change and the highest-ranked pixels in the forest-cover change suitability map (Pontius and Schneider, 2001). Driver weights account for both interactive conjoint and hierarchical effects amongst drivers, to the extent that these improve the ROC statistic. The average ROC value for our nine strata is relatively high, at 0.82 (Table 1).

Fig. 2 presents the extent of our projection, which incorporates 82% of the national area and virtually all of its rural population. The extent is that of our strata less counties having >95% urban population or no farms enumerated by the agricultural censuses of 1990 or 2000. Some indigenous 'Special Areas' in Western Panama and the Eastern Caribbean coast were also excluded because their farms were not fully enumerated by the main agricultural census. Their exclusion should not significantly effect our assessment of projection accuracy because most of their forest is persistent over time.

Table 1

Drivers of forest-cover change, with reference-period weights used in projection, by stratum.

Driver	No. classes	Weights by stratum									Average
		Bocas del Toro ^a	Chiriqui ^a	Cocle	Colon	Darien ^a	Herrera	Los Santos	Panamá ^a	Veraguas	
Agricultural capacity – capacity for cultivation, ranching, forestry	4 ^b	0.31	2.09	2.46	1.24	1.92	0.08	1.17	0.13	2.35	1.30
Elevation – metres above sea level, originally 30-m pixel resolution	10 ^c	1.46	2.70	3.99	2.12	2.16	3.45	3.21	2.75	2.39	2.69
Life zone – forest biomes defined by climate, elevation and soils	5 ^b	0.67	0.18	0.42	4.54	0.15	0.58	0.12	2.04	0.21	0.99
Soil pH – critical values for crop response to fertilization	7	0.20	1.52	0.08	2.64	1.34	3.88	0.06	0.35	1.30	1.26
Soil texture – critical values for crop response to fertilization	6 ^b	1.55	1.25	2.93	2.28	0.29	2.08	4.92	1.80	2.15	2.14
Distance to asphalt roads – in 2-km bands up to 10 km	6	0.24	2.70	3.86	0.11	0.88	0.24	0.05	0.43	0.11	0.96
Distance to Earth roads – in 2-km bands up to 10 km	6	0.19	2.08	0.81	0.17	0.68	1.84	0.24	2.08	2.74	1.20
Distance to highway – in 2-km bands up to 10 km	6	–	0.07	1.76	0.48	–	0.11	0.03	3.67	1.28	1.06
Distance to all roads – in 2-km bands up to 10 km, w/unique values for each combo of road type and distance	16	0.19	1.30	0.09	0.34	0.97	2.36	4.29	2.79	0.97	1.48
Slope – degrees terrain slope, originally 30-m pixel resolution	9 ^c	0.22	0.75	2.57	1.48	1.30	5.01	3.74	0.76	3.16	2.11
Protected area – presence/absence of national parks and conservation areas	2	2.19	2.30	4.12	3.06	2.06	2.46	0.40	0.47	–	2.13
Cattle density – no. cattle per area agri. land	4	1.31	0.13	0.08	1.27	–	0.03	0.03	0.16	0.11	0.39
Settlement density – no. settlements <1000 residents per area county	4	0.42	1.84	0.07	1.12	–	0.03	5.65	5.24	1.50	1.98
Rural male unemployment – % rural males 18–55 years old unemployed	4	0.51	1.44	0.31	0.10	2.49	0.03	0.56	1.31	0.11	0.76
Farm forest – % agri. land in forest	4	3.50	0.07	0.15	0.18	–	0.66	2.10	2.74	0.11	1.19
Farm title – % agri. land untitled	4	2.61	0.46	0.07	3.27	9.15	0.57	0.03	0.11	0.11	1.82
Pasture predominance – % agri. land in pasture	4	0.82	1.25	0.24	0.09	–	0.75	0.41	0.34	2.91	0.85
Agri. employment – % working population in forestry or agri. activities	4	0.61	0.32	0.07	0.24	0.29	0.04	0.03	0.11	0.11	0.20
Agri. sales – % total household income from agricultural sales, for rural population employed in agri. activities	4	1.58	0.09	0.10	0.08	0.12	0.04	0.03	0.50	3.50	0.67
Female employment – % females 18–55 years old employed	4	0.56	0.26	0.07	0.14	0.90	0.15	0.03	0.15	0.42	0.30
Farm machines – no. farm machines per farm	4	3.23	0.61	2.11	1.18	0.10	0.07	0.33	0.11	0.11	0.87
Off-farm income – % agri. households obtaining most income 'off farm'	4	3.31	1.06	0.49	0.86	–	0.40	0.03	0.58	0.11	0.85
Rural income per agri. area – median personal income of rural residents w/income per area agri. land	4	1.26	1.02	6.52	1.01	1.61	0.03	0.63	0.20	4.12	1.82
Rural population per agri. area – rural population per area agri. land	4	0.45	0.47	0.67	0.35	–	2.05	0.03	0.52	0.47	0.63
Rural income – median personal income of rural residents w/income	4	0.25	0.14	0.52	0.11	0.70	0.04	1.14	0.12	0.65	0.41
ROC statistic		0.832	0.827	0.817	0.739	0.922	0.839	0.820	0.815	0.752	0.818

Driver weights were calculated according to forest-cover change observed over the reference period, as described in the text. All measures of income were expressed in year-2000 dollars. A driver without a weight for a given stratum was excluded from that stratum's projection because it lacked sufficient variation in its attribute. (a) Strata experienced net deforestation over reference period. All other strata experienced net regeneration over reference period. (b) Some original classes collapsed into fewer, generalized classes. (c) Finer gradation of classes at lesser elevations/slopes.

Sources by driver: Agricultural capacity after ANAM (1985a) from GIS data of IDIAP (2006); elevation and slope from 30-m digital elevation model from SRTM (2008); Life Zone digitized from ANAM (1985b); soil pH and texture from GIS data of IDIAP (2006); distance to roads/highway from GIS data of IGNTG (2003); protected area from unpublished GIS data of ANAM, with protected area year-of-establishment from ANAM (2006: Anexo I); socio-economic drivers derived from respondent-level census records of 1990 population/housing census and 1991 agricultural census, as provided by The Dept. of Statistics and Census of La Contraloría General de la República de Panamá, later aggregated to 1990 county boundaries according to county map of La Contraloría (n.d.).

3.5. Projection validation

We validate our national projection of forest cover in 2008 by comparing it to our map of actual forest cover in 2008 (Fig. 1 elements j and l). Our validation concerns *all* areas of the map, not just those eligible for change, being forested areas in deforesting strata or non-forested areas in regenerating strata. The total disagreement between the maps is defined as the proportion of pixels in the projected map whose class (forest/non-forest) differs from corresponding pixel in the actual map. This measure in turn is partitioned into two mutually exclusive elements of disagreement: disagreement in the quantity of forest, and disagreement in the allocation (i.e., distribution) of forest given its quantity. Quantity disagreement is defined as the difference between the proportions of each map area in forest cover. Allocation disagreement is defined as the extent to which a re-distribution of forest pixels in the projected map would improve its agreement with the reference map, and is also expressed in terms of the proportion of the total map area. Pontius (2000, 2011) discusses these concepts in detail, and Pontius (2002: 1041) presents simplified illustrations. Throughout, we present these elements of disagreement at the original 100-m map resolution as well as increasingly coarse resolutions, as per Pontius (2002). This accounts for the fact that: (i) our original map resolution is not necessarily the most relevant to the question of baseline accuracy, (ii) forest-cover change drivers may have varying relevance at different scales, and; (iii) our measure of allocation disagreement is insensitive to whether misallocated forest is far or near to actual forest, such that we coarsen the map resolution to assess the distances over which allocation disagreement occurs.

4. Findings

4.1. Accuracy of 2000–2008 projection

A comparison of our projected and actual 2008 forest maps registers a total disagreement over 14.8% of the landscape. This

disagreement is partitioned into 6.2% ($\sim 3700 \text{ km}^2$) quantity disagreement and 8.6% ($\sim 5200 \text{ km}^2$) allocation disagreement. In Fig. 3, which maps predicted vs. observed forest-cover change over 2000–2008, the relatively large distance separating the two classes ‘observed forest incorrectly projected as deforestation’ and ‘observed deforestation incorrectly projected as forest’ suggests that much allocation disagreement owes to shifts in the pattern/location of deforestation between the reference and commitment periods. Most quantity disagreement appears attributable to the over-estimation of regeneration during 2000–2008. Note the relatively large area of the class ‘persistent non-forest projected as regeneration’ in Fig. 3. Similarly, compare the two right-most elements of Fig. 4, which graphically presents those map classes concerning change in Fig. 3.

Although projection accuracy appears high, it is actually $\sim 4\%$ less accurate than the ‘null model’ that predicts no change over the commitment period, that is, that anticipates the 2008 landscape solely on the basis of the 2000 landscape. The null model has a disagreement of quantity and allocation of 4.3% and 7%, respectively. The inferiority of our projection relative to the null model is actually typical of spatial projections at their original-pixel resolution (e.g., Pontius et al., 2008). However, it is surprising that our projection remains inferior to the null model at increasingly coarse resolutions (Fig. 5). It would therefore appear that the forest-cover change is more complex than the rules and information by which our model projects forest-cover change. The following explores factors of this inaccuracy.

4.2. Factors of projection inaccuracy

4.2.1. Small change in large context

Our projection must predict an area of forest-cover change that is small relative to the area within which forest-cover change might occur. In such a scenario, there are far more opportunities (i.e., spaces and contexts) for forest-cover change than information with which to calibrate a projection, such that low accuracies are expected. We summarize how well our projection anticipates

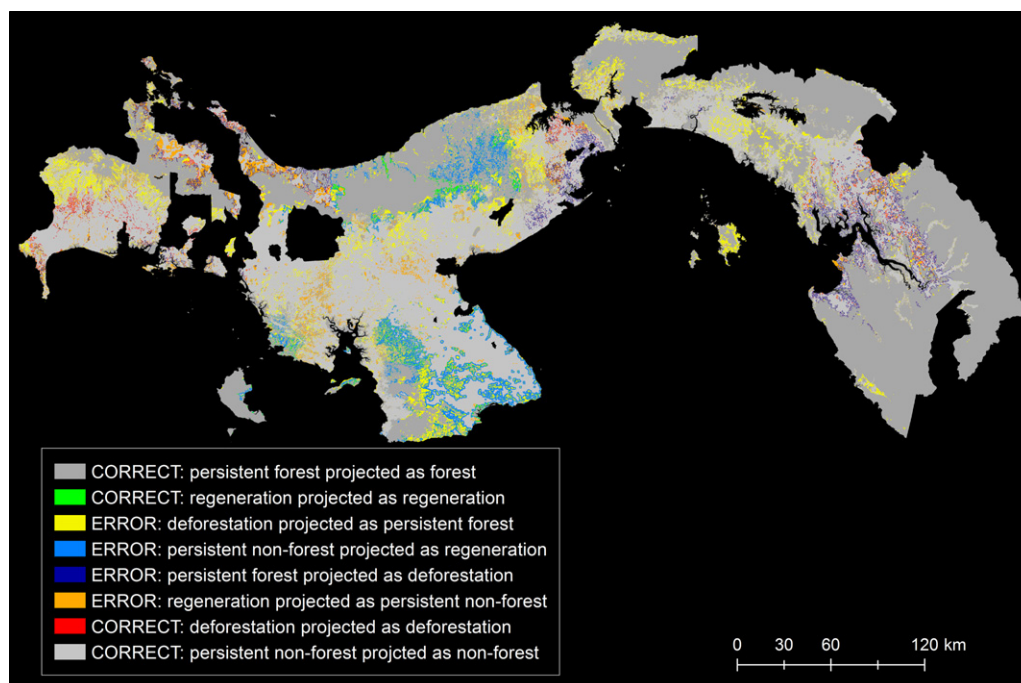


Fig. 3. Distribution of agreement and disagreement of the projection relative to observed forest cover, 2000–2008. *Note:* Colours of elements correspond to Fig. 4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

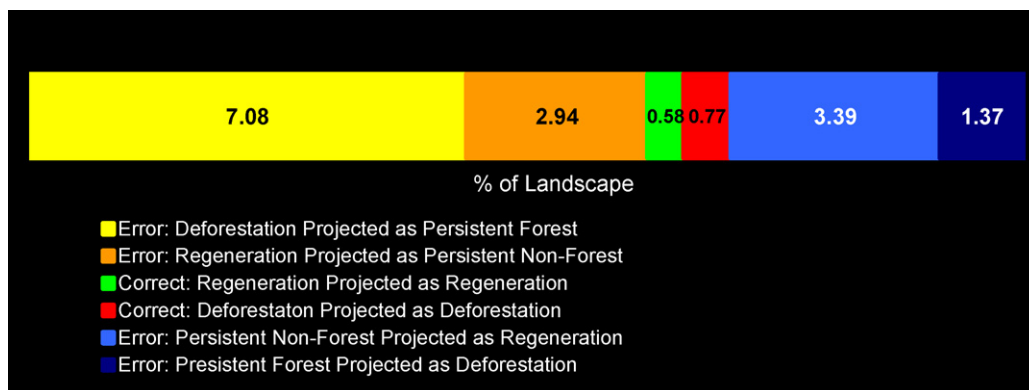


Fig. 4. Elements of agreement and disagreement of the projection relative to observed change, 2000–2008. *Note:* Colours of elements correspond to Fig. 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

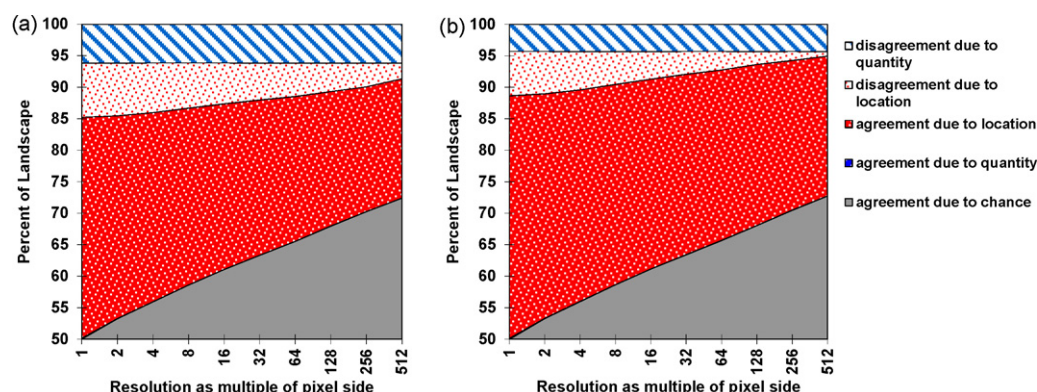


Fig. 5. Elements of agreement and disagreement at increasingly coarse resolutions for (a) projection and (b) null model. *Note:* Elements of disagreement and agreement should be interpreted differently. The former refer to the extent to which the projection is less than perfect; the latter to the extent to which the projection is better than random. The negligible quantity agreement of our projection reflects the fact that roughly 50% of Panama is forested in the projection, as it would be in a random estimation of forest/non-forest cover. For details of these elements see Prior et al. (2007).

forest-cover change via the Figure of Merit, a measure of the overlap between the projected and actual forest-cover change of Figs. 2 and 3, as defined by the formula:

$$\text{Figure of Merit} = \left[\frac{A}{A + B + C} \right] \times 100\%$$

where A = correct: area of observed change correctly projected as change, B = error: area of observed change incorrectly projected as persistence, C = error: area of observed change incorrectly projected as change, and where 100% represents a perfect projection of change. Our Figure of Merit is 8.36% for change observed over 11.3% of the landscape over the commitment period. Such a figure for such a relative area of change is low but not unlike those of other projection models. In a review of nine such models in thirteen contexts, Pontius et al. (2008: 25) find that those observing land-cover change over $\sim <10\%$ of the landscape had Figures of Merit of $<15\%$.

4.2.2. Changing relationships between drivers and forest-cover change

Our projection incorporates driver weighted to optimally simulate forest-cover change over the reference period. Changes in the relationship amongst drivers and forest-cover change between the reference and commitment periods may therefore underlie projection inaccuracy.

We examine the magnitude of shifts in relationships between drivers and change by comparing driver weights defined for the

reference period and used in our projection to weights defined for the commitment period (Fig. 6). Weights in Fig. 6 are differentiated according to whether the driver is socio-economic or biophysical, and whether they are defined for a stratum that experienced

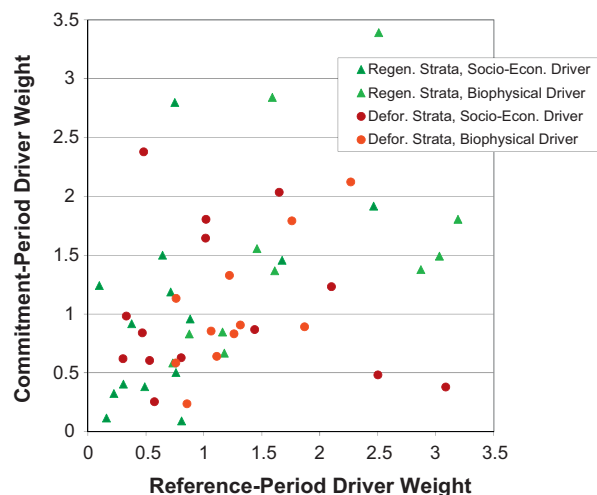


Fig. 6. Correspondence between optimal driver weights for reference and commitment periods, by direction of forest-cover change and driver type. *Notes:* Line-of-best-fit $R^2 = 0.25$ as produced by ordinary least-squares regression predicting average commitment-period driver weights using average reference-period driver weights. Regression equation: $Y = 0.605 + 0.369X$, with X significant at $p < 0.01$ for $n = 25$ weights (cases). Average weights not shown.

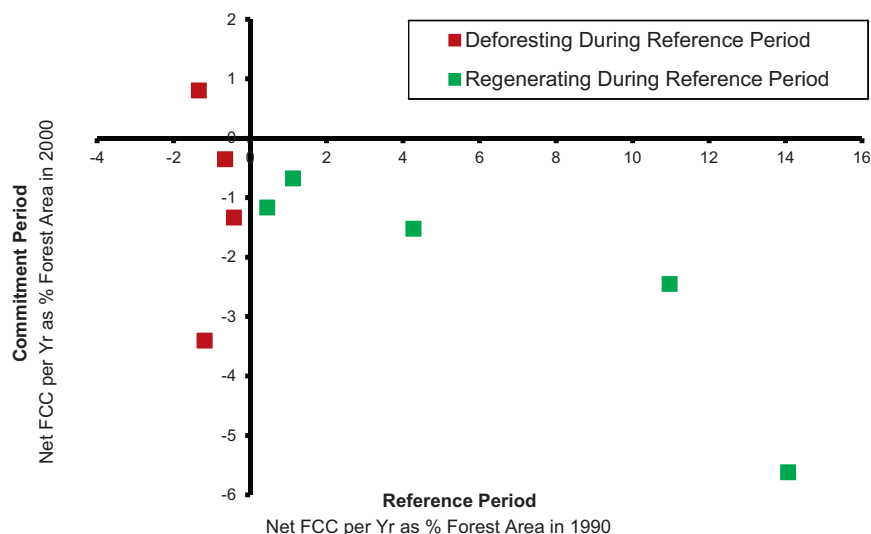


Fig. 7. Net forest-cover change over reference and commitment periods, by stratum.

regeneration or deforestation over the reference period (Table 1). Ideally, a strong linear relationship would exist between the weights of each period, indicating that the importance of a driver is consistent between periods and that reference-period weights appropriately guide our projection. We observe that the relationship is only somewhat linear. It is increasingly weak and inconsistent for drivers weighted highly ($> \sim 1.75$) in the reference period, and is variable for drivers weighted moderately ($< \sim 1.5$) in the reference period. Drivers with high reference-period weights exhibit large discrepancies with their commitment-period weights. Note the downward bend in the constellation of points beyond ~ 1.75 on the x-axis in Fig. 6. Biophysical-driver weights in deforesting strata are exceptional in that they have a relatively strong linear relationship. However, in general, drivers deemed most important in the reference period are not nearly as important in the commitment period. The use of reference-period driver weights in our projection must therefore account for some inaccuracy. Still, the overall linear shape of the constellation of points in Fig. 6 also suggests that weights are unlikely to be a principal source of inaccuracy.

The overall linear shape of the constellation of points in Fig. 6 suggests that weighting our projection as we have yielded greater accuracy than if equal weights had been assumed, or if weights had been defined theoretically or by reference to another context. Therefore, though the assumption of consistent relationships between drivers and change is not entirely valid, it is still preferable to alternative assumptions.

4.2.3. Changing trends in forest-cover change

Changes in relationships between drivers and forest-cover change may owe to shifts in socio-economic conditions relative to forest cover (e.g., increasing affluence in forest frontiers), or to shifts in the trajectory and pattern of forest-cover change relative to socio-economic and biophysical conditions (e.g., rapid lowland deforestation giving way to slower upland deforestation). Though such shifts probably coincide, it is instructive to consider shifts in the trajectory and pattern of forest-cover change in isolation, as the presumption of their consistency is a key feature of our projection and projections generally.

We observe the trajectory of forest-cover change to be inconsistent and thus a tenuous basis by which to define a business-as-usual baseline. Inconsistency is greatest where regeneration is concerned. If forest-cover change were consis-

tent, the points representing strata in Fig. 7 would define a positive linear relationship in the lower-left and upper-right quadrants. We observe no such relationship. Strata experiencing net deforestation over the reference-period do cluster in the lower-left quadrant, as they should, but have no linear relationship. More importantly, strata experiencing net regeneration over the reference period exhibit a *negative* linear relationship, that is, a reversal of the direction of forest-cover change in proportion to the rate of regeneration over the reference period. This reflects the fact that much of the forest regenerated over the reference period was cleared over the commitment period. Nationally, such inconsistencies yield errant estimations of the quantity of forest in 2008 and, therefore, underlie projection inaccuracy.

The greater inconsistency of forest-cover change amongst strata regenerating over the reference period suggests that projection accuracy is reduced to the extent that regeneration occurs over a reference period. We corroborate this possibility in Fig. 8, which graphs the quantity disagreement and allocation disagreement of our projection separately for strata experiencing deforestation and regeneration over the reference period. As can be seen, our projection for deforesting strata has half the total error (11%) than for regenerating strata (20%) at the raw map resolution, though neither projection is superior to its null model. Most of the superior accuracy of the deforesting-strata projection owes to its negligible quantity disagreement. More surprising is that allocation disagreement of the deforesting-strata projection is high, at 10.7% (raw resolution), roughly 5% more than for the regenerating strata. Hence, there is a trade-off between quantity disagreement and allocation disagreement in regenerating and deforesting contexts. Just as it is untrue that regeneration rates persist between periods, it is untrue that the pattern and location of deforestation persists, as illustrated in Fig. 9.

4.2.4. Relative importance of historical forest-cover change and drivers

To assess sensitivity to the accuracy of information defining our main projection parameters – namely forest-cover change rates and driver weights for the commitment period – we compare in Fig. 10 four projections for 2000–2008 having increasingly accurate parameter information. In doing so, we also assess the relative importance of each parameter with respect to accuracy. The information defining our four projections is below:

Projection	Parameter	
	Forest-cover change rate	Driver weight
A	Estimated: rate extrapolated from the reference period	Estimated: driver weights based on reference-period dynamics
B	Perfect: rate observed over the commitment period	Estimated: driver weights based on reference-period dynamics
C	Estimated: rate extrapolated from the reference period	Perfect: driver weights based on commitment-period dynamics
D	Perfect: rate observed over the commitment period	Perfect: driver weights based on commitment-period dynamics

Projection A is our original projection using information from 2000 and the reference period only. Projections B and C are those using commitment-period and reference-period information. Projection D is one using 'perfect' commitment-period information. Only projection A is a true projection, since the others incorporate information from the commitment period. Projections A–D correspond to panels a–d in Fig. 10.

The forest-cover change rate over the commitment period is by far the most critical parameter for projection accuracy, accounting for essentially all the variation between the four projections. Note in Fig. 10 the similarity between projections B and D, which use forest-cover change rates observed over the commitment period,

and projections A and C, which use forest-cover change rates from the reference period. Note also that projections B and D are 3.6% more accurate than projections A and C, and indeed are marginally more accurate than the null model.

The observation that the parameter for rate of forest-cover change is most critical to accuracy is corroborated by two others. First, the inconstancy of forest-cover change rates between periods in Fig. 7 is greater than the inconstancy of driver weights in Fig. 6. Second, as Pontius et al. (2007) conclude after simulating deforestation using a similar projection model, the quantity of projected forest-cover change ultimately constrains the maximum potential accuracy regardless of how accurately forest is allocated. Finally, it is worth noting that, just like our projection for strata experiencing deforestation over the reference period (Fig. 8a), projections B and D trade lower quantity disagreement for higher allocation disagreement.

As projection D illustrates, even with 'perfect' information our projection only achieves 89% accuracy (raw resolution). In our opinion, beyond issues of data quality and the complexity of forest-cover change, at least two unexplored factors contribute to this outcome:

1. Two-way forest-cover change – For a given stratum, deforestation and regeneration occur simultaneously (Fig. 11). The landscape resultant of simultaneous forest-cover change trends

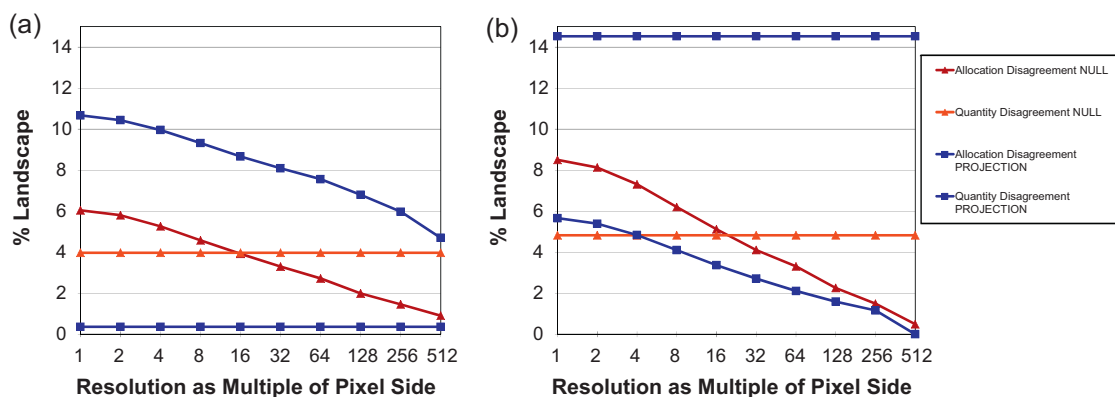


Fig. 8. Elements of disagreement of projection and null model at increasingly coarse resolutions, for strata experiencing (a) net deforestation and (b) net regeneration over the reference period.

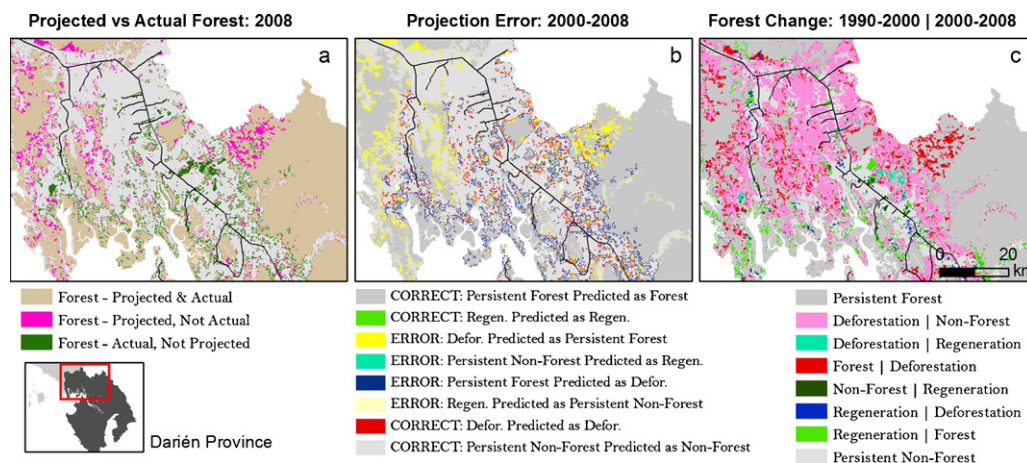


Fig. 9. Shifts in the location/pattern of deforestation between reference and commitment periods, resultant projection error, and long-term patterns of forest-cover change for a province experiencing net deforestation over the reference and commitment periods. *Interpretative note:* A shift in the location/pattern of deforestation between reference and commitment periods contributes to projection inaccuracy because our projection is calibrated according to the locations/patterns of reference-period deforestation. Observe in Panel c that reference-period deforestation in Darién concentrated along the highway, whereas commitment-period deforestation diffused away from the highway into more marginal areas. This shift reflects changing drivers but also a 'natural' spatial evolution of a deforesting landscape. The shift is reflected as discrepancies in the pattern of projected vs. actual forest (Panel a) and an increase in error with distance from the highway (Panel b).

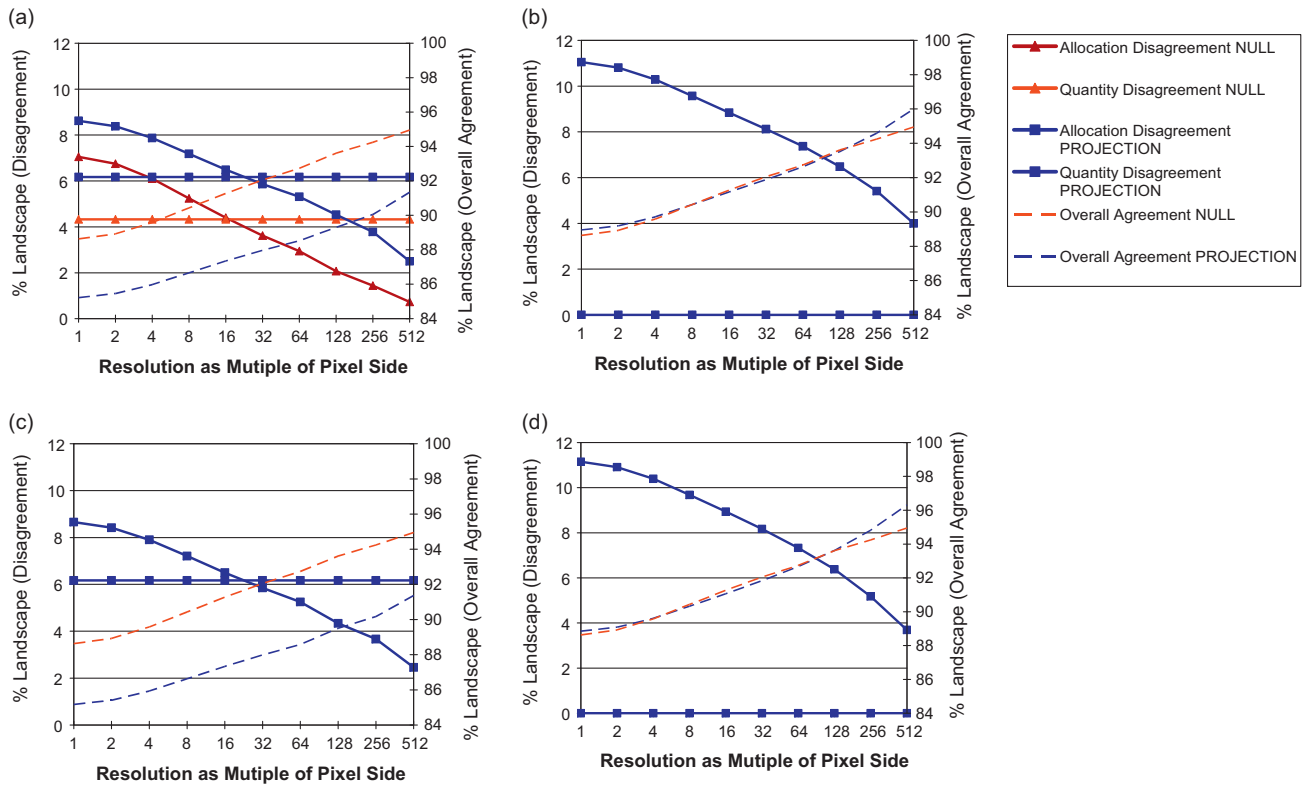


Fig. 10. Accuracy of projection with increasingly accurate parameters concerning forest cover and driver weights for commitment period. *Note:* Dashed lines should be interpreted using the rightmost y-axis.

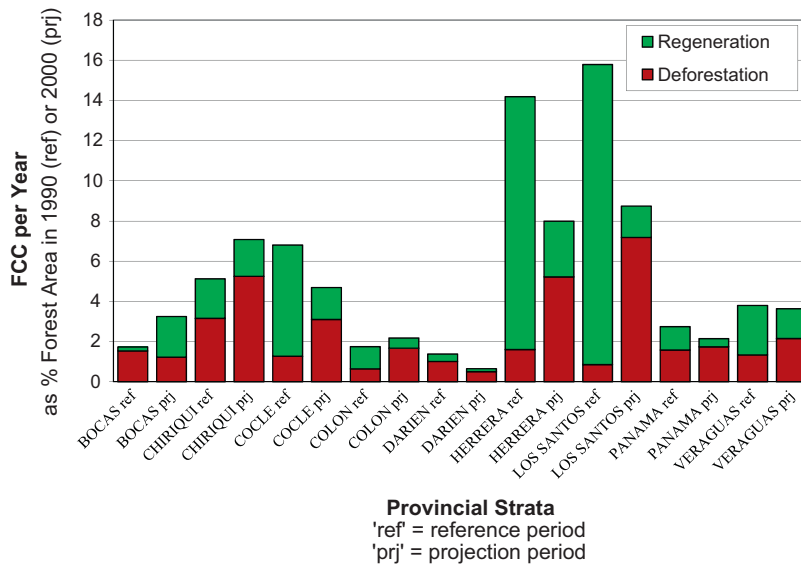


Fig. 11. Simultaneity of deforestation and regeneration, by stratum, for reference and commitment periods.

is undoubtedly different to that projected on the basis of a presumed continuity of a dominant *net* forest-cover change trend over time. Hence, a 'one-way' projection invariably overlooks secondary forest-cover change trends of potential importance.

2. National Mosaic Maps – Our projection was based on national maps officially for 1990, 2000 and 2008. We therefore assumed a reference period of ten years and a commitment period of eight years. In reality, our maps are *mosaics* of satellite images having acquisition years ranging ± 2 years relative to the official map year. Hence, for a given location, the actual length of the reference

and commitment periods will differ to that assumed. To the extent that the assumed and actual lengths of our reference and commitment periods differ across Panama, our projection may have been hampered.

5. Discussion

Sophisticated, spatially explicit, projective modelling has been considered a promising approach to establishing national business-as-usual scenario for REDD+ (Griscom et al., 2009; Huettner

et al., 2009) and for national conservation agendas generally (Soares-Filho et al., 2006). This article examined the accuracy of a projected-baseline model in order to inform developing countries on their options as they prepare for REDD+, as well as to further projected-baseline research. This baseline presented here has a limited ability to anticipate forest-cover change, particularly where regeneration is concerned, and casts doubt on the validity of such baseline models generally. Here we discuss the factors challenging projection accuracy, some ways to improve accuracy, and the implications of this study for REDD+.

5.1. Factors limiting projected-baseline accuracy

Non-linearity: Our projection assumed a linear relationship amongst rates of forest-cover change as well as driver weights (importance), between the reference and commitment periods. We find that, even at a regional scale, the linear extrapolation of forest-cover change and driver importance between periods is dubious, yet also necessary and more accurate than non-linear estimations. Were our projection carried forward for another decade, its accuracy probably would have diminished further, given the non-linearity of forest-cover change rates and the effect of drivers over time. Accuracy may also diminish over time with policy changes, as these may 're-set' the conditions for which a projection was optimized (cf. Ericsson and Irons, 1995; Lucas, 1976). Structural econometric models may attempt to simulate non-linear changes to conditions (e.g., economic returns to agriculture) as a means of predicting behaviour effecting forest-cover change (e.g., decision to convert forest to agriculture) (Kindermann et al., 2006); yet these are no better at anticipating policy changes, and their complexity and dependence on a myriad of assumptions renders them unattractive as a basis for a reference level. The tenuousness of the assumption of linearity undermines the foundation on which most REDD+ reference-level proposals rest.

Small change in large context: Where the area of forest-cover change is small relative to the area in which forest-cover change might occur, there are far more opportunities for forest-cover change than information by which to inform its projection, such that large (allocation) error is expected. This is relevant to most tropical countries – forest-cover change is almost always relatively minor – and especially to those having high levels of forest cover and low to moderate deforestation rates, the latter numbering 23 of the 53 tropical countries classified by Griscorn et al. (2009). Three implications follow. First, countries with higher deforestation rates may be more amenable to relatively accurate projected baselines. Second, countries experiencing may be less amenable to accurate projection given that regeneration often has a minor, fragmented footprint (Sloan, 2011). Third, as longer projection periods entail greater cumulative forest-cover change, they may facilitate more accurate projected baselines if projection accuracy does not rapidly decay with time (cf. Pontius and Spencer, 2005).

Complexity and diversity: Research on the causes of tropical deforestation reveals the complexity of forest-cover change drivers (Geist and Lambin, 2002; Lambin et al., 2001) as well as their susceptibility to change over time (Angelsen and Kaimowitz, 2001; Rudel et al., 2009). For instance, the integrated pathways of Panamanian social and forest-cover trends presented by Sloan (2011) depict trends begetting altered, new, or even contrary trends after only one decade. Unsurprisingly, Sloan's (2011) decades of fine-scale observation of dozens of drivers afforded only a partial explanation of forest-cover change. Complexity is compounded by the spatial heterogeneity of forest-cover change dynamics, in turn compounded by incalculable interactions between local and underlying factors. Ultimately, some forest-cover change will always remain unexplainable and thus

unpredictable. If a historical forest-cover change dynamic is the best predictor of a future dynamic, it is nevertheless a limited.

Two-way forest-cover change: In a given region, forest-cover change may be appreciably 'two-way', that is, characterized by both deforestation and regeneration over space and time (Fig. 11). A projection of only the predominant trend (e.g., *net* deforestation) therefore entails error attributable to overlooking the secondary trend (e.g., regeneration), be it coincident to or successive of the predominant trend. Our analysis suggests that projected baselines are most accurate where forest-cover change is largely one-way, and more accurate still where that forest-cover change is deforestation. Spatial projections are probably most appropriate in contexts characterized by simple deforestation (e.g., along forest-penetration roads), less appropriate in contexts of complex deforestation (e.g., fragmentation), and less appropriate still in contexts of simultaneous regeneration and deforestation (e.g. as in forest-transition countries). Most countries will contain all of these contexts to some degree, and modellers must consider their relative areas against factors such as model complexity when deciding how to proceed. While more complex models can consider 'two-way' forest-cover change, we doubt that such would prove worthwhile. The complexity of a two-way landscape is daunting, especially considering the relative simplicity of the national-scale data and our limited understanding of the drivers of regeneration *vis-à-vis* deforestation.

Allocation error and forest carbon: Allocation disagreement was the greatest element of error in our projection. Allocation error is of interest because it bears on the accuracy of estimated emissions – the potential advantage of a spatial projection is an ability to relate local forest losses/gains with known local forest-carbon densities to thus accurately estimate emissions/removals. The greatest uncertainty of forest emissions in turn is the carbon density of mature forest cover, which is compounded significantly by its spatial variability (Chave et al., 2003; Malhi et al., 2006; Pelletier et al., 2011, in press). Hence, allocation error in a projected baseline not only hinders the consideration of local forest-carbon densities (accuracy foregone), but it also increases the uncertainty of emissions/removals ultimately estimated (accuracy reduced).

5.2. Ways to improve projection accuracy

This article presents one approach to projecting forest-cover change at a national scale in order to define a business-as-usual baseline. Taking the preceding into account, more accurate projections of national-scale forest-cover change may be possible should certain aspects of our approach be adjusted. Adjustments might include:

- Predicting the area of forest-cover change on the basis of probability, not extrapolation. The number and time span of historical observations are key. Difficult issues arise in the context of REDD+ should a lack of time-series data for a single country be resolved via using data from other countries representing a chronosequence of forest-cover change, or via econometric assumptions determining non-linear trends.
- Projecting deforestation and regeneration simultaneously over time and space (cf. Eastman et al., 2005). As with point (a), historical reference data are critical.
- Using detailed, very fine-scale driver data (e.g., dirt roads), more finely gradated categories of driver values, and finer-scale socio-economic data. Regarding the latter, though our county-scale socio-economic data were spatially fine relative to the scale of the projection (Fig. 2), their scale nonetheless may have poorly captured the distribution of forest-cover change. Excepting the simplest of socio-economic measures (e.g., population), finer-scale and more ample socio-economic data

are unlikely to be available. However, like our data, they could be derived from the respondent-level census data that most countries archive.

- (d) Using smaller, more numerous strata, as delimited empirically or according to regions relevant to forest-cover change (e.g., biomes, agricultural zones), or both. Small strata might locally 'contain' projection error attributable to forest-cover change extrapolation or allocation, and thus limit it nationally. Small strata might therefore partially resolve the problem of small change in a large context. Strata size is key. If too small, per-stratum forest-cover change extrapolations may be volatile, probabilistic estimations of forest-cover change will be based on too little information, driver weights invariable, and driver interactions moot – though the latter two outcomes are not necessarily undesirable. If too large, the ability of strata to 'contain' projection error is lost. A simple but promising adaptation of the above is to stratify a projection by the intersection of fine-scale regional boundaries and forest-carbon/biomass classes, and then to extrapolate forest-cover change per stratum without regard to the spatial allocation of forest-cover change therein.
- (e) Using more complex spatial models. For instance, Sangermano et al.'s (2012) neural-network projection of Bolivian deforestation and Castella et al.'s (2005) agent-based projection of northern Vietnamese agrarian transitions achieved relatively high Figure of Merit of 25–30% (Sangermano pers. comm., 2011; Pontius et al., 2011). However, projection complexity came at the expense of transparency. Further, as with projections generally, they missed more forest-cover change than they captured.
- (f) Coarsening the spatial resolution of the projection. This would lessen misallocation error as well as the small-change-in-large-context issue. However, resolution may have to be *significantly* coarsened to have achieve a Figure of Merit > 50%, which is counter to the rationale of a spatially projected baseline. Moreover, as Fig. 10a suggests, coarsening may still fail to yield accuracies superior to the null model.

Such adjustments must respect the confines of data availability as well as reference level transparency and clarity. These confines pose significant challenges to a projected baseline.

5.3. The worth of a projected baseline for REDD+

A survey of REDD+ negotiators reveals that the promise of accuracy and precision recommends spatially explicit projected baselines over simpler baselines that ranked higher in other aspects, such as transparency, sovereignty, and clarity (Huettnner et al., 2009). The underwhelming accuracy of our projected baseline – indicative of the limitations of spatial models generally – questions the worth of projected baselines for REDD+. With the accuracy of our baseline underwhelming, its complexity situates it unfavourably relative to simpler baselines.

We recommend 'stepping back' from such detailed, projected baselines to take a simpler, more aggregate approach to reference levels, be it spatially explicit or otherwise. Doing so may lessen or even preclude allocation error while exploiting the likelihood that forest-cover change is more consistent at greater spatial scales, all features which promote accuracy. Consider Griscom et al. (2009), who find that four simple, national-scale, historical-adjusted reference levels – described previously as extrapolating an average national deforestation rate modified by an adjustment factor – approximated the actual quantity of emission-reduction credits awarded to 53 tropical countries to within 25% over a hypothetical REDD+ commitment period. It is doubtful that emission-reduction credits based on a spatially projected business-as-usual baseline

would have similar credibility (cf. Pelletier et al., 2011). Our recommendation therefore takes the reference-level debate full circle, for whereas Griscom et al. (2009: 909) wrote that

"[m]ore sophisticated forward looking modelling methods involving analysis of deforestation drivers and spatially explicit data (e.g., Soares-Filho et al., 2006) offer the potential for yet more refined estimations of 'business as usual' baselines..."

we suggest that simpler, more aggregate approaches are preferable given their relative transparency, comprehension and apparent credibility.

Some cautions are in order in making such a recommendation, however. First, simple, aggregate, a-spatial approaches to the reference level are not *necessarily* more accurate. For example, doubt exists as to the reliability of the national FAO statistical data on which the former are typically based (Grainger, 1996, 2008, 2010).

Second, projected business-as-usual baselines cannot yet be completely dismissed as a basis of a reference level. As discussed above, numerous options to improve projection accuracy still merit exploration. Of particular interest are approaches that would aggregate and simplify a projected baseline, that it might retain desirable features of both spatial projections and simple, national-scale, historical-adjusted reference levels, e.g., spatial aggregation sufficient to 'capture' the regional inertia of forest-cover change; spatial explicitness indifferent to allocation error within a given forest-carbon class; geographic stratification by which to 'contain' erroneous extrapolations of forest-cover change; computational simplicity, including variations of historical extrapolations of forest-cover change. Further research is needed to test the merits of such a quasi-spatial approach.

Further, while the preceding implicitly implies an institutional arrangement whereby each country formulates its reference level individually – the dominant paradigm under consideration – it is also possible that more harmonized arrangements may arise. These would promote reference-level consistency, transparency and comparability, potentially mitigating the shortcomings of projected reference levels. For example, regional blocks of countries could cooperatively determine national reference levels using harmonized data and similar modelling approaches or, as Obersteiner et al. (2009) propose, an international centre could establish reference levels in a globally consistent manner. Such arrangements may facilitate better data, probabilistic predictions of forest area, and relatively complex and therefore presumably more accurate spatial models for reference levels while maintaining transparency and consistency (cf. Kindermann et al., 2006).

Regardless of the role of spatial projections in reference levels, our analysis shows that they can still play an important role in informing REDD+ implementation. For example, they may quantitatively describe the nature, importance, and spatial heterogeneity of drivers of forest-cover change across sub-national regions ahead of policy formulation (Table 1 and Fig. 6), and identify areas within which to 'target' policy (Fig. 8b). Spatial projections also remain the recommended approach to business-as-usual baseline determination for regional REDD+ projects (Brown et al., 2007).

In summary, the accuracy of a spatially projected business-as-usual scenario of forest-cover change is unlikely to be acceptable for the purposes of REDD+. Alternative projection approaches or institutional arrangements may yield more accurate or otherwise more acceptable projected business-as-usual scenarios, though we remain sceptical of the utility of projected scenarios for reference-level determination. We believe that non-Annex I countries should not pursue national projected reference levels, and should instead recur to simpler, more aggregated approaches to reference level

determination such as historical-adjusted reference levels or, possibly, the quasi-spatial projections mentioned above.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at [doi:10.1016/j.gloenvcha.2012.02.001](https://doi.org/10.1016/j.gloenvcha.2012.02.001).

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