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Analysis of deforestation and protected area effectiveness in Indonesia: A comparison of Bayesian spatial models

Cyrille Brun[a,b], Alex R. Cook[c,d,**], Janice Ser Huay Lee[e], Serge A. Wich[f], Lian Pin Koh[g], Luis R. Carrasco[h,*]

[a] Department of Statistics and Applied Probability, National University of Singapore, Singapore, Singapore
[b] Department of Applied Mathematics, Ecole Polytechnique in Palaiseau, France
[c] Saw Swee Hock School of Public Health, National University of Singapore, Singapore, Singapore
[d] Yale-NUS College, National University of Singapore, Singapore, Singapore
[e] Woodrow Wilson School of Public and International Affairs and Department of Ecology and Evolutionary Biology, Princeton University, Princeton, NJ, USA
[f] Research Centre for Evolutionary Psychology and Palaeoecology, School of Natural Sciences and Psychology, Liverpool John Moores University, United Kingdom
[g] Environmental Institute, School of Earth and Environmental Sciences, The University of Adelaide, Adelaide, Australia
[h] Department of Biological Sciences, National University of Singapore, Singapore, Singapore

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ABSTRACT

Tropical deforestation in Southeast Asia is one of the leading causes of carbon emissions and reductions of biodiversity. Spatially explicit analyses of the dynamics of deforestation in Indonesia are needed to support sustainable land use planning but the value of such analyses has so far been limited by data availability and geographical scope. We use remote sensing maps of land use change from 2000 to 2010 to compare Bayesian computational models: autologistic and von Thünen spatial-autoregressive models. We use the models to analyze deforestation patterns in Indonesia and the effectiveness of protected areas. Cross-validation indicated that models had an accuracy of 70–85%. We find that the spatial pattern of deforestation is explained by transport cost, agricultural rent and history of nearby illegal logging. The effectiveness of protected areas presented mixed results. After controlling for multiple confounders, protected areas of category *Ia*, exclusively managed for biodiversity conservation, were shown to be ineffective at slowing down deforestation. Our results suggest that monitoring and prevention of road construction within protected areas, using logging concessions as buffers of protected areas and geographical prioritization of control measures in illegal logging hotspots would be more effective for conservation than reliance on protected areas alone, especially under food price increasing scenarios.

1. Introduction

Over the last two decades, global rates of tropical deforestation increased from 5.6 Mha y^{-1} to 9.1 Mha y^{-1} (FAO and JRC, 2012). Southeast Asia in particular is a global hotspot for tropical deforestation (Achard et al., 2002; Hansen et al., 2008), losing ~32 Mha of forests from 1990 to 2010 (Stibig et al., 2013). During this period, Indonesia accounted for ~61% of forest loss in Southeast Asia (Stibig et al., 2013). In addition, from 2000 to 2012, 6 Mha of primary forest were lost in Indonesia—a rate higher than that of Brazil (Margono et al., 2014). Extensive deforestation in Indonesia is a cause for global concern as it contributes substantially to land-based global carbon emissions (Harris et al., 2012), and potentially high rates of biodiversity loss (Sodhi et al., 2004; Wilcove et al., 2013). Therefore, an understanding of the dynamics and spatial distribution of deforestation in Indonesia is crucial to facilitate attempts to mitigate these environmental problems.

Historically, the drivers of deforestation in Indonesia varied according to Indonesia's agricultural, geographic and economic contexts. After Indonesia's independence and prior to the mid-1980s, deforestation in Indonesia, especially in the Outer Islands (Sumatra, Indonesian Borneo, Sulawesi, and Papua), was largely associated with small-scale agricultural expansion as a result of state-led re-settlement schemes as well as a boom in industrial

* Corresponding author. Tel.: +65 91377291.
** Corresponding author at: Saw Swee Hock School of Public Health, National University of Singapore, Singapore, Singapore.
E-mail addresses: alex.richard.cook@gmail.com (A.R. Cook), dbsctlr@nus.edu.sg (L.R. Carrasco).

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logging activities (Jepson et al., 2001; Rudel et al., 2009). Roads constructed for rural development as well as logging activities reduced the travel costs for people to access forest resources and to market them (Jepson et al., 2001; Miyamoto, 2006). By the 1990s, a strong global demand for agricultural commodities, rising crop prices, and increased privatization of land resources led to widespread expansion of oil palm and fiber plantations over forests, especially on lands without clear land ownership such as peat swamps (Koh et al., 2011; Miettinen et al., 2012), as well as small to medium scale deforestation for coffee and cacao production (Clough et al., 2009; Gaveau et al., 2009c). Illegal logging, which causes significant environmental and economic damage to Indonesia's forest capital (ITTO, 2001), has also been a driver of deforestation since colonial times, but its activity intensified after the Suharto era and the subsequent government decentralization (Casson and Obidzinski, 2002).

While it has been shown that deforestation rates are lower in protected areas than in certain non-protected area regions in Indonesia (Gaveau et al., 2009a, 2012), mounting demands for timber and agricultural products along with weak enforcement have resulted in illegal logging and agricultural encroachment within Indonesia's protected areas (Jepson et al., 2001; Levang et al., 2012).

Protected areas are classified in different categories (*I–VI*) depending of their level of protection and objectives according to the International Union for Conservation of Nature (IUCN): *category Ia* that are strictly set aside to protect biodiversity and human visitation is strictly controlled (equivalent to the category of Nature Reserve in the Indonesian protected area system), *category Ib* that are large unmodified areas retaining their natural character and without permanent human habitation, *category II* that are large natural areas set aside to protect ecological processes and compatible with some uses such as educational or recreational (equivalent to National Park in the Indonesian system), *category III* set aside to protect a specific natural monument, *category IV* to protect specific species or habitats (equivalent to Wildlife Reserve in the Indonesian system), *category V* to protect areas where the interaction of people and nature has created an area of distinct character (equivalent to Nature Recreation Park, Forest Park and Hunting Park in the Indonesian system) and *category VI* that protect ecosystems and habitats together with natural resource management systems (equivalent to Marine Protected Areas in the Indonesian classification).

Global studies in the tropics report varying findings on the effectiveness of protected areas on reducing deforestation (Naughton-Treves et al., 2005; Nelson and Chomitz, 2011; Paul et al., 2013; Porter-Bolland et al., 2012), with some studies reporting less deforestation in strictly protected areas (IUCN Categories I–IV) (Naughton-Treves et al., 2005; Nolte et al., 2013; Paul et al., 2013), and others reporting more effective protection under multiple use protected areas (IUCN Categories V–VI) (Nelson and Chomitz, 2011; Porter-Bolland et al., 2012).

Drivers of deforestation have also been studied and spatial regression models have shown a strong relation between deforestation and the proximity to roads or rivers that facilitate transport of timber and agricultural products to markets (Angelsen, 2010; Nelson and Hellerstein, 1997). These results have been verified by analytical microeconomic and regional models that indicate a positive relationship between roads and agricultural output prices with deforestation (Angelsen and Kaimowitz, 1999).

In the case of Indonesia, the analysis of deforestation and protected area effectiveness has been limited by data availability and geographical scope. A nation-wide analysis of contemporary deforestation and protected area effectiveness would thus be useful to support land-use planning for conservation purposes.

Here we analyze the spatial distribution of deforestation in Indonesia and protected area effectiveness from 2000 to 2010 derived from 250 m spatial resolution land cover maps (Miettinen et al., 2011a). To this end, we fit and compare (a) an autologistic model and (b) a von Thünen model with spatial autoregressive components to: (i) evaluate the influence of potential factors on deforestation while controlling for multiple confounders and the spatial autocorrelation between observations; and (ii) to project future deforestation under three macroeconomic forecast scenarios derived from the Organization for Economic Co-Operation and Development (OECD), and Food and Agricultural Organization (FAO) (OECD-FAO, 2011).

2. Methods

2.1. Data collection

Drawing upon the historical context of deforestation in Indonesia, we evaluated the following factors: agricultural rent with and without deducting transport costs (autologistic and von Thünen models respectively), transport costs (in the autologistic model), elevation, illegal logging hotspots, presence of logging and timber concessions and protected area status.

Some limitations to the analysis of deforestation in Southeast Asia occur because reliable spatial deforestation data for the whole of Indonesia is notoriously difficult to obtain due to the persistence of cloud cover in the region (Miettinen et al., 2011b). Therefore the use of 250 m resolution spatial data that overcomes the cloud cover problem (Miettinen et al., 2011b) opens a window of opportunity to construct detailed statistical and mechanistic models to understand the contemporary dynamics of deforestation in Indonesia. These maps were preferred over recent global deforestation maps (Hansen et al., 2013) as they were built using independent peat swamp maps in the region and provided different land uses of the region (Miettinen et al., 2011a), which were adequate for our modeling purposes.

The scope of the analysis is the five main islands of Indonesia: Sumatra, Java, Kalimantan, Sulawesi and Papua. In order to find a reasonable compromise between data accuracy and computing time, we divided this territory in 33,989 cells of size 6.9 km $\times$ 6.9 km. Using Geographic Informatics Systems (ESRI, 2006), the following spatial maps were computed:

2.1.1. Deforestation

We employed remote sensing satellite-generated maps of land cover classification for the whole of insular Southeast Asia in 2000 and 2010 (Miettinen et al., 2011a). These maps were based on Moderate Resolution Imaging Spectroradiometer (MODIS) images and Daichi-Advanced Land Observing Satellite data. The overall classification accuracy of the maps is 85.3%. We extracted land cover data for the whole of Indonesia at two time periods: 2000 and 2010. This dataset consists of 12 land cover classes for 2000 and an additional 'large-scale palm plantation' land cover class for 2010 (Miettinen et al., 2011b). We focused our analysis on deforestation events which we define here as the conversion of forest into non-forest land cover classes between 2000 and 2010. The forest land cover classes are represented by mangrove, peat swamp forest, lowland forest, lower montane forest, and upper montane forests. The non-forest land cover classes are represented by plantation/regrowth, lowland mosaic, montane mosaic, lowland open, montane open, urban, and large-scale palm plantation. From these two maps we deduced the map of the deforested cells between 2000 and 2010. We excluded from our analysis forest degradation and did not model the possibility of forest regrowth or restoration.

2.1.2. Transport cost

We developed a map with the cost to transport timber or agricultural outputs to the nearest city of more than 150,000 habitants. To develop the map we took into account the presence or not of roads, the type of land to cross (roads, rivers, agricultural land and forest) and the slope of the terrain. We first built a weighted map estimating the cost of transport through each cell. The weights were associated to land use types and the cost of transport in each land type (see Table S1 in the *Supporting Information SI* and Fig. 1 (ESRI, 2006; Phelps et al., 2013)). The means of transport for land and across rivers or seas were trucks and boats respectively. Slope of the terrain was taken into account factored in through the volume of increase in fuel consumption by the trucks and lower effective speed. We then calculated the least expensive path to reach a city according to the weighted map and stored the transport cost associated to each cell.

2.1.3. Gross rents

The seven top crops in terms of national production value (farm gate price of the crops multiplied by the gross national production in physical terms) were considered: oil palm, rubber, rice, maize, cocoa, coffee and coconut. The percentages of area of each of these crops on each province and their yields were obtained using global crop distribution maps (Table S6 in SI, Monfreda et al., 2008; Ramankutty et al., 2008). A weighted average of the gross rent for each province was calculated.

2.1.4. Protected areas

We extracted maps of designated protected areas distributions with their associated IUCN categories from the World Database on Protected Areas (Fig. 1, WDPA Consortium, 2004).

2.1.5. Historical illegal logging hotspots

We used a map representing the hotspots of illegal logging in the years 1997–1998 according to Forest Watch Indonesia, Global Forest Watch and the World Resources Institute that corresponds to a compilation of illegal logging cases reported by local newspapers and by Forest Watch Indonesia (Matthews, 2002, pp. 99).

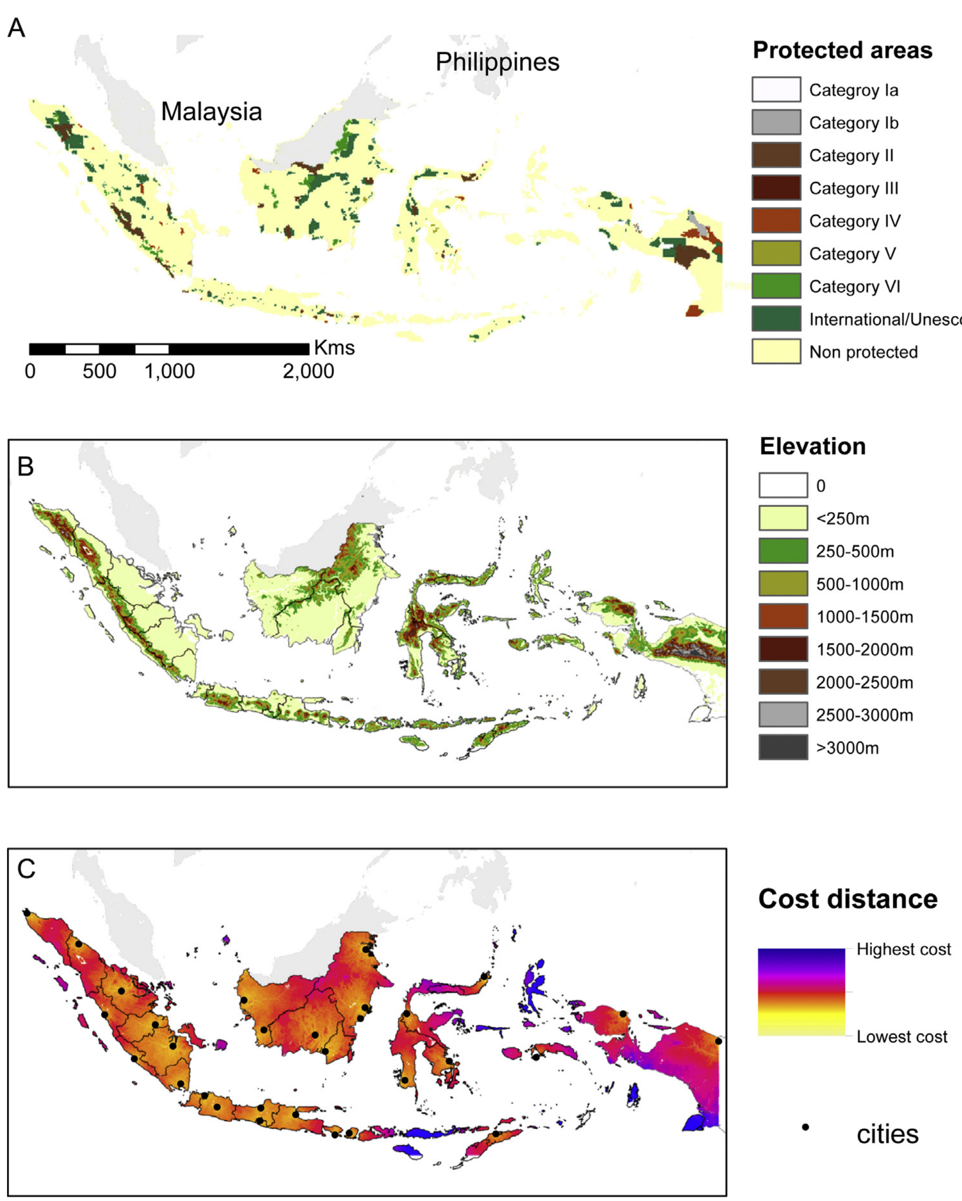

Fig. 1. Spatial input variables. (A) Protected areas per IUCN category; (B) elevation; (C) transport cost to cities with more than 150,000 habitants.

2.1.6. Logging and timber industrial plantation concessions

We employed maps describing logging concessions and industrial wood plantations (World Resources Institute, 2014).

2.2. Statistical analyses

2.2.1. Rationale for Bayesian computational methods

While regression models are useful, the use of ordinary least squares to analyze spatial data has been found to produce residuals that vary systematically over space, a phenomenon known as spatial autocorrelation (LeSage, 2000). Spatial autocorrelation needs to be accounted for because the effect of factors that are spatially correlated tend to be over-estimated (Gumpertz et al., 1997; Lichstein et al., 2002). Models that can deal with spatial autocorrelation in the analysis of spatial data are thus necessary (Dormann et al., 2007).

The use of Bayesian computational methods coupled with spatial economic land use models might allow complex spatial correlation patterns to be accounted for while providing a framework for a mechanistic interpretation of the factors driving deforestation. In particular, we use the von Thünen model that determines deforestation patterns by comparing the rent of the forest versus the rent of agricultural activities while accounting explicitly for transport costs (Angelsen, 2010). The models we used are inspired by spatial autoregressive models (autologistic regression) and the estimation of the parameters is done under the Bayesian framework using Markov Chain Monte Carlo (MCMC) computational methods. The Bayesian framework allows for more flexibility than the usual expectation-maximization (EM) algorithms because it enables inference on the mean and dispersion of all the model coefficients. In addition, the estimation of dispersion of the posterior distribution of the parameters overcomes the tendency for EM algorithms to overestimate the precision of the estimates (LeSage, 2000). In general, Bayesian methods enable as well the introduction of knowledge from external data sources through prior distributions of the parameters (Gelman et al., 2003), can deal efficiently with complications such as missing data or non-standard error distributions (Dormann et al., 2007), and is convenient for fitting mechanistic models directly to observational data (Marion et al., 2012).

2.2.2. Models

A phenomenological (autologistic model) and a mechanistic (von Thünen) model with spatial autoregressive components were fit to the data: the latter based on a theoretical understanding of the behavior of the system. To allow the model to capture the land use dynamics, the von Thünen model was fit to the entire land-use satellite maps of 2000 cross-sectionally. Hence forested cells were represented by 1 and non-forested cells by 0 and the prediction of deforestation was assessed on the entire map of 2010. However for the autologistic model, the change in deforestation between 2000 and 2010 was directly modeled. Only the forest cells in 2000 were used to fit the autologistic model and the dependent variable was equal to 0 when the cell had been deforested between the two dates and 1 if the cell was still forested in 2010. Ten-fold cross-validation was run for each of the models to estimate their predictive power represented by their error ratio.

2.2.3. von Thünen model

To evaluate the dynamics between agriculture expansion and forest conservation, a von Thünen land rent versus forest rent model was developed (S1 Supporting Methods in SI, Angelsen, 2010; von Thünen and Hall, 1966). The rent represents the profit resulting from the cultivation of the land. The model compares the rent of agricultural land uses with the rent of the forest using sustainable timber harvest where a key factor of the model is the distance to the nearest city (von Thünen and Hall, 1966). The land is allocated by the model to the use with the highest rent. The model predicts deforestation between 2000 and 2010 in a cell when it is forested in 2000 and the agricultural rent is higher than the rent of the forest. The agricultural rent takes into account the benefits from selling the outputs at the market minus the labor, capital and transport costs (the mathematical description of the model is given below and expanded in the *Supporting Methods* in *SI*). We assumed that the benefit from selling the timber from forests conversion cancels out with the costs of land clearing and preparation (Grieg-Gran, 2008). To be able to account for the effectiveness of protected areas, we expand the von Thünen model with a cost component representing the intangible cost of the expected liability resulting from converting land inside protected areas. We also added a component for the increase in production costs and lower yields related to high elevation. Cost components were also added for logging concessions and illegal logging. The rationale is that concessions and existing illegal logging before 2000 in an area indicate the presence of the mechanisms and transport systems necessary to deforest (e.g. logging roads and forest tracks) and this is expected to lower costs of deforestation. The rent of the forest is the benefits from selling the maximum sustainable production of timber at the market minus the labor, capital and transport costs. We introduced a spatial component inside the von Thünen framework by expanding it into a Conditional Auto-Regressive model (*Supporting Methods* in *SI*). The closest neighbors of each cell were taken into consideration to determine the rent of the cell. The extended cost, viz. protected areas, elevation, logging concessions, illegal logging, and the autoregressive components were estimated directly from the data using MCMC methods (Gelman et al., 2003) using the 2000 data only. These data were used to fit the rent of the agricultural land r^a and the rent of the forest r^f on each cell i. These are defined as (see Table 1 for variable definitions):

$$r_i^a = O_i^a - wl^a - qk^a - d_i^a - e_i$$
$$r_i^f = p^f y^f - wl^f - qk^f - d_i^f$$

where $e_i = \sum_{j=1}^{n} \alpha_j P_i^j + \alpha_7 I_i - \alpha_8 E_i + \alpha_9 c_i$ represents the extension of the traditional von Thünen model. Each observation is modeled as:

$$y_i = sign(r_i^a - r_i^f + \epsilon_i)$$

Table 1
List of variables and their description.

Variable name	Variable description
O^a	Value of agricultural production for each cell and is calculated as the area-based weighted average of agricultural yield times price of the crops grown in each region
w	Yearly wages
l^a, l^f	Agricultural labor and timber forest labor respectively for each cell
q	Annual cost of capital
k^a, k^f	Capital needed for production in each agriculture or forest cell respectively
d^a, d^f	The transport costs of the production in each cell to the nearest city with a population greater than 150,000 habitants
p^f	Timber price
y^f	Maximum sustainable yield of timber per cell per year
$\alpha_j P^j$	Cost of cultivating crops (or deforesting) on a protected area of category j
$\alpha_7 I$	Cost or benefit of cultivating crops (or deforesting) where illegal logging happened before
$\alpha_8 E$	Cost of cultivating crops in areas with high elevation
$\alpha_9 c$	Cost or the benefit of cultivating crops (or deforesting) in logging concessions or timber industrial plantations

where ε_i is the error term that is assumed to follow a Gaussian distribution.

Hence when $r_i^a - r_i^f > 0$, agriculture is expected to be used on the land and elsewhere forest is used. The likelihood function was developed according to Gaussian Conditional Autoregressive models (*Supporting Methods* in *SI*).

2.2.4. Autologistic regression model

An autologistic regression with the same explanatory variables as those used in the von Thünen model was developed. The autologistic model is an extension of a logistic model which also takes into consideration the closest neighbors of each cell to account for spatial autocorrelation (*Supporting Methods* in *SI*). The autologistic model was used to fit deforestation data from 2000 to 2010 in those cells forested in 2000. We chose the probability threshold that maximized the Matthews correlation coefficient. The cells with probabilities to be deforested above the threshold are said to have been deforested between 2000 and 2010. The model was fitted using MCMC methods (*Supporting Methods* in *SI*).

The autologistic model is defined as follows:

$$\log\frac{(P(y_i = 1))}{(P(y_i = 0))} = \beta X_i^t + \rho \sum_{i\sim j}(y_j - \mu_j)$$

where X_i is the vector of the different predictors, β is the vector of coefficients of the regression, ρ is the spatial correlation dependence parameter and μ_j is the independence expectation of y_j where j means that j is a neighbor of i (*Supporting Methods* in *SI*). On top of the usual logistic regression equation, the autoregressive effect of the neighbors is characterized by the second term, i.e.: $\rho\sum_{i\sim j}(y_j - \mu_j)$.

2.2.5. Macroeconomic scenarios

In order to project future deforestation for the next period of 10 years, three macroeconomic scenarios derived from the Organization for Economic Co-Operation and Development (OECD), and Food and Agricultural Organization (FAO) (OECD-FAO, 2011) were used: *macroeconomic scenario 1*, food price inflation with a 20% agricultural commodity price increase between 2011 and 2020; *macroeconomic scenario 2*, market flooding with a 20% reduction in agricultural commodity prices due to the increases in supply; and *macroeconomic scenario 3*, oil price increase and a subsequent 25% increase in transport costs and 4% increase in agricultural commodity prices. These scenarios are not forecasts about the future but represent plausible scenarios that illustrate the range of deforestation implications of different market evolutions. The FAO-OECD scenarios were chosen because they are supported by a strong combination of expertise at the commodity, country and policy levels.

3. Results

3.1. Factors influencing deforestation

The effect of protected areas varied for different categories. Category *Ia* protected areas, which are exclusively managed for biodiversity conservation, present 14% of their areas deforested from 2000 to 2010. This is almost as high as the average 16% deforestation rates (Table 2). Mixed results were obtained for different categories of protected areas. The von Thünen model showed that categories *Ia* and *V* had a greater probability of being deforested than land outside these protected areas, all other factors being equal (Fig. 2, 95% posterior credible interval CI [−0.79,−0.23] and [−1.59,−0.35] respectively). The autologistic model showed that category *Ib* presented higher probability of deforestation (CI [−1.08,−0.11]) but this was in contrast to the results from the von Thünen model. The autologistic model could however not find evidence of effectiveness of the rest of protected areas (CI encompassing zero) but the von Thünen indicated that categories *Ib*, *II*, *IV*, *VI* and "*other/UNESCO*" slowed down deforestation. However deforestation still occurs within the boundaries of these categories of protected areas and ranged from 5% to 9% of their areas (Table 2).

Table 2
Summary variables and proportion deforested between 2000 and 2010.

Variable	Number of cells	Forested 2000	Deforested 2000–2010	% deforested
Total	33,989	16,602	2624	16
Protected areas	7103	5100	508	10
Category Ia	205	118	17	14
Category Ib	222	213	13	6
Category II	1674	1279	121	9
Category IV	652	419	35	8
Category V	48	12	2	17
Category VI	664	534	26	5
Category Unesco/other	3644	2525	294	12
Illegal hotspot before 2000	112	28	16	57
Forest concessions	11,147	6558	1249	19

In the autologistic model, deforestation was found to be lower as the transport cost to the market increased (CI [0.01, 0.25], Fig. 2). High agricultural rent led to higher deforestation (CI [−1.06,−0.49], Fig. 2). The results of the autologistic model with regards to transport costs and agricultural rents are thus consistent with the theory underpinning the von Thünen model by which deforestation is driven by agricultural rents including transport costs.

Elevation was shown to reduce deforestation in both the autologistic and von Thünen models (CI [0.08,0.16] and CI [0.07,0.08] respectively, Fig. 2). The correlation between elevation and transport costs was however low (correlation coefficient, $r = 0.18$).

Historical illegal logging hotspots before 2000 were good predictors of deforestation between 2000 and 2010 (CI [−1.73,−0.02] and CI [−3.17,−0.99] for autologistic and von Thünen models respectively, Fig. 2). The probability of being deforested was found to be lower within forest concessions or industrial timber plantations ([0.06,0.37] and [1.32,1.42] than in other locations outside concessions all factors being equal for autologistic and von Thünen models respectively, Fig. 2).

3.2. Models predictive performance

The best predictive model for deforestation was the autologistic model with an accuracy of 85% (Table S3). The von Thünen model, despite its simplicity, was able to capture the main deforestation patterns with an accuracy of 70% (Table S3). The higher accuracy of the autologistic model was expected as the autologistic model uses deforestation information from 2000 and 2010 while the von Thünen model only uses land-use information from the year 2000.

Both models captured deforestation remarkably well in the center south, west and east of Java and the North of Kalimantan (Fig. 3). The von Thünen model, however, overpredicted deforestation—3000 predicted deforested cells versus 2688 actual deforested cells. The autologistic model, on the other hand, was also able to capture well the deforestation hotspots in Sulawesi (Fig. 3). Of the main islands of Indonesia, deforestation in Papua was the least well captured mainly because of paucity of reliable road maps, especially those of private company roads constructed by large scale agro-industrial projects.

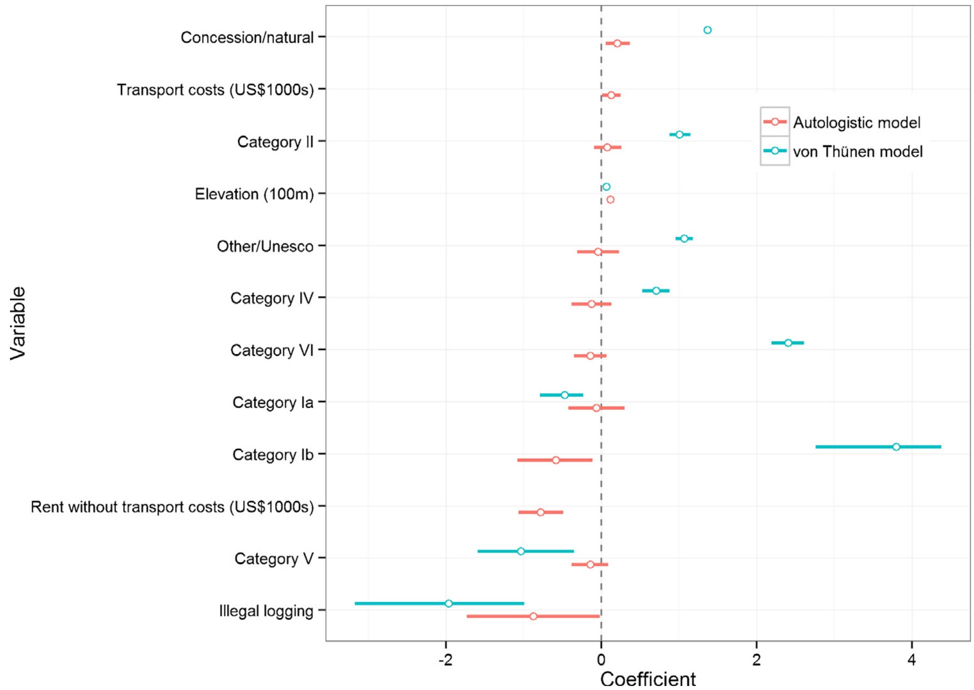

Fig. 2. Results from fitting autologistic and von Thünen models using Markov Chain Monte Carlo methods. The bars represent the posterior distribution 95% credible interval. The circles represent the coefficient estimate.

3.3. Deforestation projections under macroeconomic scenarios

According to the models, deforestation between 2010 and 2020 is likely to occur in close proximity to the areas that have been deforested before 2010, identifying the south and west part of Kalimantan, the north-west Sumatra and West Papua as areas that will be subject to the greatest rates of deforestation (Fig. 4). Specifically, under the von Thünen model and *macroeconomic scenario 1*, the top five regencies with highest area projected to be deforested are: Asmat, Teluk Bintuni (Papua), Kapuas Hulu and Ketapang (West Kalimantan) and Maluke Tenggara (Maluku islands) (Table S6 shows the rank of projected deforestation by regency). From the autologistic model, three out of the top five regencies overlap: Ketapang, Maluku Tenggara and Kapuas Hulu and the next two: Maluku Tenggara Barat (Maluku islands), and Pontianak (West Kalimantan), are located in similar provinces (Table S6). The top protected areas in terms of projected future deforestation under *macroeconomic scenario 1* are: Kepulauan Aru Tenggara (category *Ia*), Belat Besar Linau, Gunung Leuser National Park, Sebangau, Kerinci Seblat (category *II*) by the autologistic model and Kepulauan Aru Tenggara (category *Ia*), Pulau Kobroor, Jamdena, Morowali (category *Ia*) and Sungai Kayan by the von Thünen model (Table S7 shows the rank of projected deforestation by protected area).

Given the predictions of future deforestation under *macroeconomic scenario 1*, some mitigating actions that could be implemented such as expansion of existing and establishment of new protected areas could be: expansion of Sebangau and Gunung Palung National Parks to the north, Sungai Kayan to the north-west (west, south and north of Kalimantan respectively, Fig. 4), establish protected areas in the regencies of Kabupaten and Asmat in Papua, expand Dabas Liegums Nature Reserve toward the west and northwest (Southeast Sulawesi, Fig. 4), strengthen the protection in Belat Besar Linau, Berbak, Gunung Leuser National Park and Seberida protected areas and expand The Leuser Ecosystem conservation area to the north (Sumatra, Fig. 4).

Both models were highly sensitive to changes in agricultural prices. From the von Thünen model, compared to a baseline scenario where the prices and all other parameters do not change, an increase of 20% in agricultural prices, as expected from the OECD–FAO *macroeconomic scenario 1*, would lead to 54% increase in deforestation (Table S4). The *macroeconomic scenario 2* with price reductions due to market flooding leads to a decrease of 46% in deforestation. The *macroeconomic scenario 3* with increased agricultural prices and transport costs leads to a decrease of 6% of deforestation (Table S4). Larger variations are predicted with the autologistic model: *macroeconomic scenario 1* leads to a 70% increase in deforestation, *macroeconomic scenario 2* to a decrease of 36% and *macroeconomic scenario 3* to a 30% increase (Table S4).

4. Discussion

Our analysis could not find evidence that protected areas in categories *Ia* and *V* were effective with regards to slowing down deforestation and, according to the von Thünen model, they were more likely to present higher deforestation rates from 2000 to 2010. This is in contrast with analyses based on satellite data for specific islands like Sumatra from the previous time period of 1990 to 2000 (Gaveau et al., 2009a) and for analyses that showed that stricter protected area categories tended to be more effective (Naughton-Treves et al., 2005), but confirms predictions that protected areas were expected to suffer mounting pressure after 2000, chiefly due to the exhaustion of logging concessions and because much of the remaining most valuable timber is within protected areas (Curran et al., 2004). This turn of events is alarming because it shows that protected areas of category *Ia*—the main strongholds of biodiversity conservation—could be poorly enforced. When in the 1990s it was relatively easy to harvest timber in logging concessions without resorting to harvest within protected areas, protected areas seemed effective. Under the current context in which the scarcity of logging concessions forces loggers to overcome the fear of incurring liabilities, protected areas

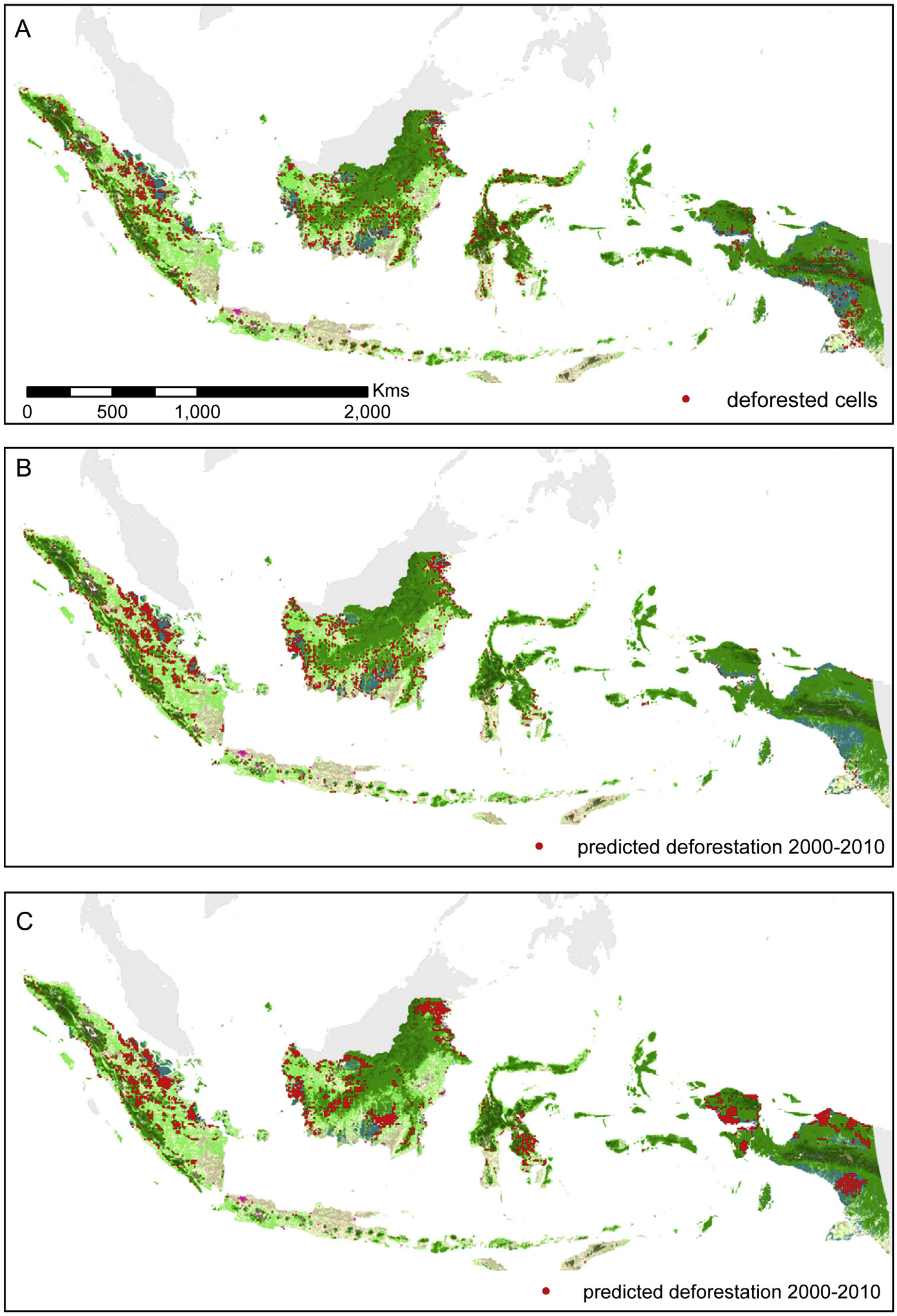

Fig. 3. Maps of actual deforestation versus models' predictions from 2000 to 2010. (A) Actual deforestation. (B) auto-logistic model predictions. (C) von Thünen model predictions.

appear weak. The reason why category *Ia* behaves differently to other less strict categories might respond to the fact that, due to their stricter management in the past, they contain some of the main remnants of high value timber. The results for category *V* and the identification of the actual on the ground processes in category *Ia* call for further research on the ground. If the exhaustion of forest concessions is responsible for the leakage of logging activities in protected areas, then the creation of new logging concessions or the further implementation of forest plantations could be a way to reduce the pressure on protected areas through meeting the demand for timber. Other logging pressures may also respond to small-scale agricultural expansion such as cacao in Sulawesi, coffee in South Sumatra and oil palm in Riau (Abood et al., 2014). Stronger enforcement of the protected areas and alternative livelihoods to small-scale farmers could help reduce these pressures.

There were however differences in the estimation of protected area effectiveness between the von Thünen and autologistic models that reflect the different nature of the models and the data used to construct them. By contrast with the autologistic model, the von Thünen model does not estimate the coefficients for travel cost and agricultural rent, which are fixed. In the case of the

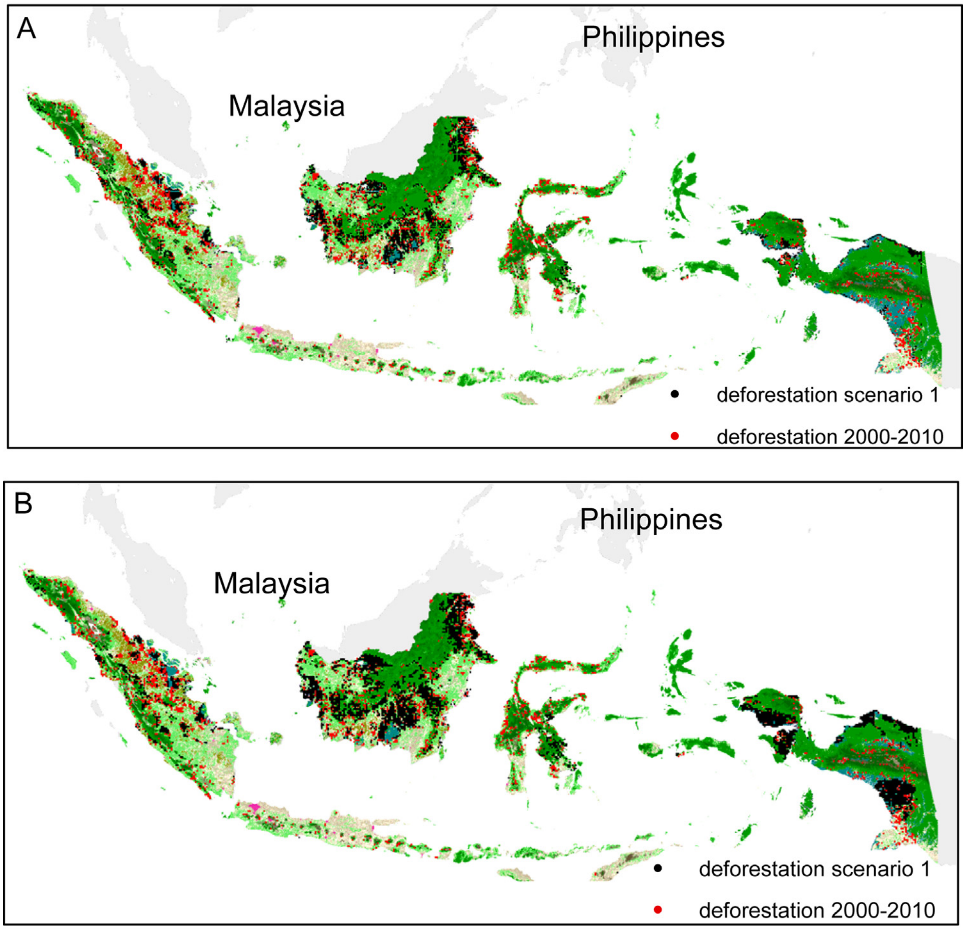

Fig. 4. Deforestation predictions from 2000–2010 ("deforestation 2000–2010") and from 2010 to 2020 ("deforestation scenario 1") under *macroeconomic scenario 1* using the autologistic model (B) and von Thünen model (C).

autologistic model, this extra flexibility to use protected areas, agricultural rent or transport costs to explain deforestation leads to more alternative parameter combinations that could represent plausible explanations of the data. This flexibility could be problematic as protected area location tends to be biased toward less productive land away from cities (Joppa and Pfaff, 2009), making it more difficult to tease out the effect of protected areas versus agricultural rents.

The second reason for these differences is that the two models deal with spatial autocorrelation differently. The spatial autoregressive component of the von Thünen model does not change directly the probability of deforestation in the model but the covariance of the distribution of the error term. This is not the case in the autologistic model where the autocorrelation structure is included directly in the model and, as a result, its effect could be stronger. Thus, in the cases where the protected areas are spatially aggregated, the autologistic model could explain deforestation largely from the dynamics of neighboring cells, reducing the role that protected areas have as a variable. To test this hypothesis, we further ran a logistic regression analysis without spatial autocorrelation. The effects regarding protected area effectiveness presented a similar direction in the effects as those of the von Thünen model, showing how accounting for spatial autocorrelation reduced the effect (categories *II*, *IV*, *VI*, *other/Unesco*) or even changed the direction of the effect (categories *Ib*) of protected areas in the autologistic model.

The comparison of the models showed other differences: the von Thünen model, which describes the potential for deforestation based on rent differentials, tends to overestimate deforestation rates, which might reflect a time lag between the realization of the rent differential and the actual deforestation. Land tenure regimes such as *hak milik* (right of ownership) or *hak pakai* (use right of land) might also prevent uncontrolled deforestation even if there is a rent differential, but due to data paucity on the distribution of tenured land, these factors could not be incorporated. Nonetheless, simulating the von Thünen model forward can be useful to pinpoint the areas at most risk of conversion under future price increases and this could help in devising sustainable land planning strategies. In contrast, higher predictive accuracy was obtained from the autologistic model. The lower accuracy of the von Thünen model is however compensated as it allows for a mechanistic understanding of the dynamics of deforestation.

Eventually, the choice of the model will depend on data availability and purpose. The von Thünen model can be useful if spatial data are scarce or available only at a single time point, for it can provide land-use change projections that capture the salient economic dynamics. Provided that the theoretical framework represents appropriately the system, it can also be useful at teasing out the effectiveness of protected areas by reducing the number of plausible explanations. On the other hand, the autologistic model can provide higher accuracy of forecasts in the presence of repeat high resolutions maps, when the main aim is to obtain more spatially accurate predictions than a mechanistic understanding of the drivers of deforestation.

In general, the use of Bayesian spatial autoregressive models provides flexibility in dealing with complex datasets that present spatial and temporal correlation, with explanatory variables that are correlated (e.g. in our case, slope, a component of transport costs can be correlated with altitude) and allowing to represent environmental systems with a spatial component in a natural way (Cook et al., 2007). An example of alternative and less computationally intensive methods used to evaluate the effectiveness of protected areas or payment for ecosystem services schemes are propensity score matching (e.g. Gaveau et al., 2013). These methods attempt to identify "matched pairs" of locations while controlling for a number of potential confounders that are translated in a propensity score (e.g. accessibility confounders in Gaveau et al., 2013). One limitation of these methods is that only observable potential confounding variables can be accounted for while bias due to latent unobserved variables or spatial autocorrelation between observations cannot be incorporated (Garrido et al., 2014). While propensity score matching is preferred for small number of observations per potential confounder, regression-based methods are preferred when the number of observations is large (Cepeda et al., 2003), as would be the case with high-resolution maps. Bayesian spatial autoregressive models, on the other hand, may require sophisticated computing methods and large computation time, making computationally simpler methods such as logistic regression or propensity score matching preferred if time constraints exist.

Roads have been described as proximate causes of deforestation (Gaveau et al., 2009b; Geist and Lambin, 2002) but it is sometimes difficult to establish the direction of causality (Angelsen, 2010). Our results with regards to transport costs show that deforestation is associated with roads and points toward roads causing deforestation and not the inverse, with our models predicting correctly deforestation close to roads extant in 2000. This reinforces the idea that careful road planning is fundamental for tropical forest conservation (Laurance et al., 2014), i.e. road constructions should circumvent the proximity of biodiversity hotspots and protected areas as much as possible. Relatedly, our results highlight the importance of low agricultural rents and high transport costs to curb deforestation. These results show that isolation is very effective at preventing deforestation and could counter the effect of increasing agriculture prices. Nevertheless, biodiversity richness and carbon may be higher in the more easily accessible lowlands and might not always benefit from the effects of isolation and altitude (Koh and Ghazoul, 2010; Sodhi et al., 2004; Wich et al., 2008).

Elevation was shown to protect against deforestation. This result is however not related to an association with transport cost and might be instead due to lower agricultural yields with altitude. This protection against deforestation is congruent with the bias of protected area location at higher altitude as they support less conversion pressures (Joppa and Pfaff, 2009). The observed low correlation between elevation and transport costs may however respond to the use of a cost distance function in which elevation only plays a partial role (via higher fuel consumption in slopes and longer roads) together with distance from cities. A measure that integrates slope and elevation such as topographic ruggedness could offer new insights and further research should aim at incorporating it.

We also found that deforestation between 2000 and 2010 is strongly linked to illegal logging hotspots. The geographical persistence of illegal logging hotspots opens a window of opportunity to prioritize monitoring and enforcement efforts. Using the generated deforestation predictive maps, policy makers could reduce the cost of extensive monitoring programs by concentrating efforts on areas that present high probability of illegal deforestation.

After controlling for other factors, lower rates of deforestation occurred within logging concessions and forest plantations (similar results were found in Gaveau et al., 2012). Although these results would require further investigation, some explanations could be the exhaustion of good timber within concessions with the subsequent slowdown of harvest or the improved management of the concession through a perceived improved tenure security from managers. These results have policy implications as they suggest that placing timber concessions around protected areas could help protecting them against deforestation, and indeed suggestions have been made to design logging and industrial timber concessions as protected areas of type VI (Gaveau et al., 2013).

Our analysis presents some caveats. In general, the datasets used, as far as we are aware, represent the best data available for Indonesia. These datasets are however not exempt of uncertainty. For instance, the distribution of protected areas may contain "paper parks" that are not enforced in reality. In addition, the sources of information within the World Database on Protected Areas are varied leading to inaccuracies and issues of resolution that cannot be easily assessed (Chape et al., 2005). Related to this uncertainty, our results regarding protected areas of type *Ia* and *V* should also be treated with caution. The number of cells in each category affected by deforestation is low (30 out of 300 for category *Ia* and 2 out of 12 for category *V*) and the results could be affected by the inherent error of remote sensing products (85.3% accuracy in the maps we used). These sources of uncertainty could lead to potential perimeter interior ratio effects resulting from cells overlaying the edges of the protected area that could be misclassified as deforestation inside when they are actually occurring outside. In addition, the distribution of agricultural crops and potential yields correspond to global datasets derived from national inventories, thus being associated to high uncertainty. Further analysis would thus be warranted when more accurate datasets (e.g. exclusion of "paper parks") are made available. Neither could we find maps of illegal logging for years after 1997, which would have been ideal as illegal logging can be a highly dynamic process. Nonetheless, it is remarkable that the illegal logging hotspots remained as significant predictors during the time span considered. We have not considered maps of oil palm concessions and pulp and paper concessions, which have been shown to influence deforestation (Carlson et al., 2013; Gaveau et al., 2013). These information has however been partially covered by considering the distribution of oil palm plantations and logging and timber concessions. Further research should consider the inclusion of these layers explicitly.

5. Conclusions

Through the comparison of Bayesian spatial autoregressive models, we showed that deforestation in Indonesia can be explained by economic forces such as low transport costs, induced by the presence of roads, and high agricultural rents. Future increases in agricultural commodities prices will impose strong pressures on Indonesian forests. Protected areas of category *Ia*, core for the conservation of biodiversity, do not appear as an effective way to prevent deforestation, presumably due to the mounting pressure as a result of the exhaustion of logging concessions and conversion of forests to farmland. Our results suggest that a sustainable design of road networks, using timber and logging concessions as buffers around protected areas and spatial prioritization of control measures in historical illegal logging hotspots would be more effective than reliance on protected areas alone.

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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.2015.02.004.

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