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# Spatially explicit perceptions of ecosystem services and land cover change in forested regions of Borneo

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ABSTRACT

Spatially explicit information on local perceptions of ecosystem services is needed to inform land use planning within rapidly changing landscapes. In this paper we spatially modelled local people's use and perceptions of benefits from forest ecosystem services in Borneo, from interviews of 1837 people in 185 villages. Questions related to provisioning, cultural/spiritual, regulating and supporting ecosystem services derived from forest, and attitudes towards forest conversion. We used boosted regression trees (BRTs) to combine interview data with social and environmental predictors to understand spatial variation of perceptions across Borneo. Our results show that people use a variety of products from intact and highly degraded forests. Perceptions of benefits from forests were strongest: in human-altered forest landscapes for cultural and spiritual benefits; in human-altered and intact forests landscapes for health benefits; intact forest for direct health benefits, such as medicinal plants; and in regions with little forest and extensive plantations, for environmental benefits, such as climatic impacts from deforestation. Forest clearing for small scale agriculture was predicted to be widely supported yet less so for large-scale agriculture. Understanding perceptions of rural communities in dynamic, multi-use landscapes is important where people are often directly affected by the decline in ecosystem services.



## 1. Introduction

Current human-driven changes of natural ecosystems are resulting in widespread loss of biodiversity and natural habitats, weakening the services they provide (Balvanera et al., 2006; Brown et al., 2011; Díaz et al., 2006). It is undeniable that changes to ecosystems have resulted in considerable net gains for human well-being and economic development, but have also incurred substantial costs not only to biodiversity and natural habitats but also to those people who depend on the services they provide (Cardinale et al., 2012). If ecosystems continue to deteriorate, the benefits to current and future generations will be further diminished, possibly exacerbating poverty for the rural poor (Millennium Ecosystem Assessment, 2005). Understanding peoples' perceptions of the services provided by natural systems can provide insights into the interplay of the innate linkages between humans and their environment. This in turn can contribute towards identifying ways to reduce future impacts on society from environmental change. Such understanding is imperative within mega diverse tropical forest countries, such as those found on the island of Borneo.

Borneo's forests and peat lands are amongst the most species-rich environments in the world (Whitten et al., 2004). They provide vital ecosystem benefits at local, regional and global scales. Such benefits include: timber and non-timber forest products and other provisioning services such as fresh water (Meijaard et al., 2013); intangible cultural and spiritual benefits, important in safeguarding cultural identities (Hernández-Morcillo et al., 2013; Plieninger et al., 2013); regulating services such as prevention of certain diseases (e.g. flooding-related malaria) and natural hazards (e.g. landslides); storage of vast carbon stocks essential for mitigating regional and global

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climate change (Leh et al., 2013; Paoli et al., 2010); and underpinning supporting services that maintain the functioning of forest ecosystems (Brown et al., 2013). Yet, within Borneo rapid deforestation for agricultural and silvicultural developments has resulted in island-wide land use transitions (Dewi et al., 2005). For example, Borneo's forests were reduced by 17 million ha (30% of 1973 original forest cover) between 1973 and 2010; they currently cover 55% of the island's mass (Gaveau et al., in review). In Kalimantan, the Indonesian part of Borneo, during 2000–2010, industrial oil palm plantations increased from an estimated 8360 km$^2$ to 31,640 km$^2$, often at the expense of forests. By 2020, full lease development could convert 93,844 km$^2$ into oil palm plantations (Carlson et al., 2013). At the same time, overexploitation of forest for timber and other extractive industries is severely degrading terrestrial and fresh water ecosystems (Koh et al., 2011; Miettinen et al., 2011) and undermining the livelihoods and well-being of rural people (Cleary and Eaton, 1992; Dewi et al., 2005).

In such dynamic and multi-use landscapes it is imperative to incorporate local social perspectives and values into land use planning and land optimisation (Bagstad et al., in press; Nelson et al., 2009; Raymond et al., 2009; Sherrouse et al., 2011). Spatially explicit information on local perceptions of ecosystem services, provides a rich basis for the development of sustainable land management strategies, and could align better biodiversity conservation and social value agendas (Maes et al., 2012). Yet, despite the necessity for incorporating social values into land use planning, scientific understanding of ecosystem services is still embryonic and estimating the values of such intangible forest service's remains methodologically challenging (Plieninger et al., 2013). Few studies have tried to quantify and map non-material benefits such as cultural and spiritual services people derive from natural systems (Hernández-Morcillo et al., 2013) or people's perceptions of the services they derive.

In this paper we demonstrate a novel approach that combines primary data on rural local people's values and perceptions of ecosystem services with socio-economic and environmental spatial predictors (using Boosted Regression Tree (BRT) modelling) to understand spatial variation. BRT modelling has increasingly been used in ecological niche modelling (Eskildsen et al., 2013; Gallien et al., 2012; Pittman and Brown, 2011). Few studies have utilised this approach for wider ecological applications, such as for understanding determinants of cropland abandonment (Müller et al., 2013); sustainable management of marine ecosystem services (Palumbi et al., 2008); and assessing carbon stocks (Razakamanarivo et al., 2011). Concurrent studies to this one also have used BRT for understanding human-orangutan (*Pongo pygmaeus*) interactions (Davis et al., 2013); as well as the non-spatial components of ecosystem services derived from forests (Meijaard et al., 2013).

We use BRT modelling over other methods as it enables sophisticated regression analyses of complex responses (Elith et al., 2006, 2008). Making perceptions spatially explicit would allow them to be incorporated into broader ecosystem service analyses, for example, in an InVEST environment (Tallis et al., 2011) which could use the perception patterns to generate land use scenarios and inform outcomes through combination with biophysical and economic models. Here, we use questionnaire data of local, rural people's perceptions on the island of Borneo on: (1) the provisioning uses of forests for specific products; (2) the cultural and spiritual benefits ascertained from forest ecosystems; (3) the regulatory and supporting benefits associated with their health and environment; and (4) their perceptions of advantages and disadvantages of forest clearance. We integrate these perceptions of forest services with a set of 39 socio-economic and environmental spatial predictor variables, using BRT models. We use this approach to identify social and environmental factors that contribute substantially to perceptions of ecosystem services and land cover change, to generate spatially explicit predictions for these perceptions, and to understand spatial variations throughout the forested and non-forested regions of Borneo.

## 2. Materials and methods

### 2.1. Ethics statement

Interview surveys were led by The Nature Conservancy (TNC). Twenty non-governmental organizations (NGOs) conducted the questionnaires. The Nature Conservancy has no ethics committee, however the survey approach and design was reviewed and approved by TNC's social science specialists. The ethical board of the affiliated universities were not approached as these collaborations came after majority of the surveys were already conducted. Before conducting the interviews, permission was granted by the Indonesian Directorate General of Forest Protection and Nature Conservation, and the Director of the Sabah Wildlife Department. Importantly, prior and informed consent was obtained from all participants once project goals were described and confidentiality assured; this was done through a statement read by the interviewer and interviews were conducted after verbal consent was given from participant (see, Meijaard et al., 2011a, 2013).

### 2.2. Questionnaire data

Questionnaire surveys were conducted between 2008 and 2012. Most surveys were conducted in villages within known orangutan distribution areas, close to forest or within forest. The selection of villages and respondents is described by Meijaard et al. (2011b). The initial or ‘primary’ survey campaign was undertaken from April 2008 to September 2009 by 19 local NGOs in Kalimantan (who interviewed 6983 respondents in 687 villages), and one NGO in Sabah (56 respondents from 6 villages). A second survey campaign was undertaken in 2012 within new and previously sampled areas of West and East Kalimantan Provinces (236 respondents in 23 villages) as well as new areas of Sabah (145 respondents in 15 villages). A target of 10 questionnaires per village was sought to allow for both adequate estimation of village-level responses and extensive geographical coverage, within the resources of the study. The number of questionnaires obtained per village ranged from 7 to 11. See Appendix S1 in the Supporting information for the questionnaire.

Not all interview teams conducted the questionnaires with the same level of diligence and consistency. Consequently, we ascertained response reliability by measuring response patterns from each village and corresponding NGO's based on text lengths, content and variation of 'open' question responses. In some cases, interview teams had given the same answer for all respondents in a village, either indicating that the question was asked in a group rather than individual context, or that data were not appropriately recorded for each respondent. On the basis of these assessments, author EM assigned a reliability score of ‘1’ to each village if no responses had been recorded, responses were of poor quality, or responses were apparently duplicated within one village; ‘2’ if good quality, i.e., answers had been genuinely reported but not much detailed information was provided; and ‘3’ if excellent quality, i.e., detailed responses were reported for each individual respondent. We used data deemed as good and excellent in quality, reducing the dataset to 1837 respondents from 185 villages (see Fig. 1 for the locations of these 185 villages). For further details regarding the primary and secondary surveys, the quality assessment procedures and a comparison of higher and lower quality responses (see, Meijaard et al., 2013).

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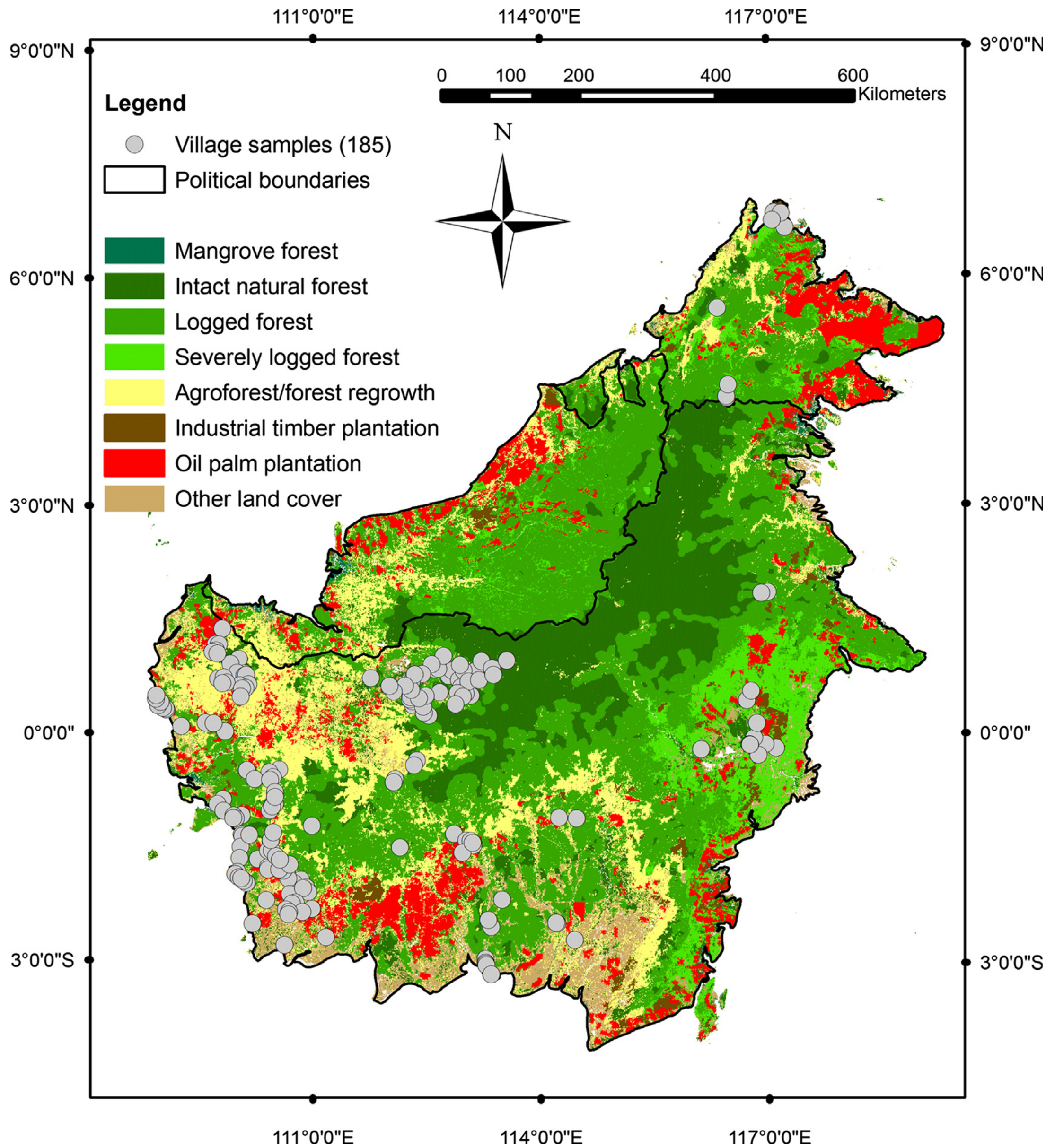


**Fig. 1.** Location and geographic context of villages ($n=185$) sampled in Indonesian and Malaysian Borneo. Villages locations are underpinned by the 2010 land cover classes used in the boosted regression tree analysis.

People's use and perceptions of ecosystem service benefits derived from forest were obtained from a number of questions relating to the provisioning, cultural/spiritual, regulating and supporting ecosystem services; as well as attitudes towards land cover change. Indices relating to each of these issues were constructed for each respondent. The indices were then aggregated to a village level; see the section on the Modelling Approach. The respondent level indices were formed as follows.

### 2.2.1. *Provisioning services*

Data for provisioning services came from respondents' answers to the closed question: "what economic benefits do you obtain from the forest?" Seven specific forest products were stated and the respondent was asked to give a 'yes' or 'no' answer for his/her use of each product. Answers were (with number of respondents in parentheses): timber (1234); rattan (950); hunting (831); traditional medicine (624); mining (245); honey (342); and aloes wood (303). The binary responses from respondents were combined in a weighted index where the weights reflected the relative economic importance of the product within local economies, based on knowledge and literature (e.g., Dewi et al., 2005; Mulyoutami et al., 2009; Pierce Colfer and Salim, 1998). The weights were as follows: timber (3); artisanal mining (3); hunting (3); rattan (2); eaglewood (2); honey (1); and traditional medicine (1). The values were summed into an index.

An additional open-ended question was then asked "What other economic benefits do you obtain from the forest?" From this question a total of 29 responses were given, which included (with number of respondents in parentheses): fish (368); fire wood/small wood (351); forest gardens (264); rubber (157); fruit and vegetables (234); tree sap (*damar*/*jelutung*) (95); illipe nuts (*Shorea* spp.) (65); passing through and survey (47); bark of *Nothaphoebe coriacea* and *N. umbelliflora* (45); oil palm (37); employment (25); fruits from *Litsea* spp. (25); spiritual values and enjoyment (23); *Mitragyna speciosa*, leaves for medicine (16); non-timber (general) (15); edible swift nests (13); food (9); source of water (9); nipa (*Nypa fructicans*) and other roofing material (7); back up resource (6); binding materials (5); orchids and ornamental plants (5); bamboo (4); tourism (1); place for rare fauna, conservation, and research (6); prawns (3); and sugar palm (1). For the index derived from this open-ended question, the number of reported benefits was used as a summed value for each respondent.

#### 2.2.2. Cultural and spiritual services

Cultural and spiritual importance were ascertained from a multiple-choice question, “Does the forest play a significant cultural and spiritual role for you and your family?”, with answers expressing three levels of importance (with number of respondents in parentheses): very significant (871); quite significant (484); insignificant (404); and do not know (76). These responses were numerically coded as 1, 0.5, 0 and 0 respectively (i.e. ‘don't know’ answers and ‘insignificant’ answers were coded as zero values for the purpose of this study).

#### 2.2.3. Regulating services and supporting services for health

To understand aspects of how regulating services relate to health, we initially used the closed, multiple-choice question “How important are forests for you and your family's health”, with answers restricted to (with number of respondents in parentheses): very important (1236); quite important (461); not important (40); and don't know (98), coded as 1, 0.5, 0 and 0 respectively (with ‘don't know’ answers given the same value as ‘insignificant’).

An open ended question was then asked: “what is the reason for this importance of the forest for health?” Responses were divided into two categories: ‘Direct health benefits’ and ‘Environmental health benefits’. For those responses that were categorised under direct health benefits the responses included (with number of respondents in parentheses): medicine (282); general welfare, life giver, and for daily needs (252); spiritual value, people-nature association (85); forest prevents disease (e.g., malaria in open flooded areas) (77); place to live and forest protects the village from disasters (25); good for planting (12); for future generations (11); economic use and gardens (11); good soil (7); tourism and relaxation (3); and source of electricity (hydropower) (1). An index was constructed as an un-weighted sum of the number of benefits reported.

For those responses that were categorised under environmental health benefits the responses included (with number of respondents in parentheses): cool and shade from sunshine (605); source of water (342); clean air and oxygen (275); flood prevention (219); pollution prevention (98); environmental protection and species habitat (81); storm reduction and climate control (39); erosion prevention (36); landslide prevention (29); global warming (15); carbon sequestration (4); fire prevention (3); ozone protection (2); and longer or more severe dry season and droughts (2). Similarly, an index was constructed as an un-weighted sum of the number of benefits reported.

#### 2.2.4. Land cover change from forest conversion

Attitudes towards forest clearing were ascertained from the closed question: “Does forest clearance provide benefits to you and your family?” with three possible responses, ‘yes’, ‘no’, or ‘don't know’. Answer to an open-ended follow-up question regarding the respondent's opinion on forest clearing was asked, and responses recorded into three categories, two of which we analyse here.

Firstly, we analysed responses classified under ‘disadvantages of large-scale clearing for agriculture’, with answers including (with number of respondents in parentheses): deforestation doesn't benefit communities enough, they do not provide enough work, and communities suffer (259); negative environmental impacts from logging (floods, temperature increase, erosion) (199); companies don't provide enough work or other community benefits and companies benefit more than people (147); fewer forest products, including timber (122); oil palm and other plantations provide insufficient benefits (121); protection of forest needed and deforestation destroys nature (86); there is not enough forest left and deforestation will destroy remaining forest (71); affects our future needs (44); clearing reduces available land for communities and clearing destroys gardens (28); forest better for hunting and fishing, and deforestation reduces wildlife (21); once the forest is gone there is no more work (19); newcomers or outsiders benefit more than local communities (14); only temporary benefits from deforestation but long term losses; forest should be sustainably managed (10); not everyone benefits from forest clearing (8); companies manage the forest badly and companies lie (8); it is our forest, why would anyone else clear it (8); not everyone benefits from forest clearing (8); it doesn't directly make land suitable for agriculture (4); customary law prohibits it, and its illegal (4); it increases pests (2); we do not get enough compensation (2); it is better if communities manage the forest (1); and no money to invest and therefore we cannot benefit (1). The index was calculated from the number of responses (i.e. advantages or disadvantages given), at the respondent level.

Secondly, we analysed responses classified under ‘advantages of small-scale clearing for agriculture’, with answers including (with number of respondents in parentheses): for forest gardens and agricultural fields (368); for agricultural crops (198); for rubber (to plant it) (184); for rice cultivation (71); for local community, company clearing not good (51); for oil palm (to plant it) (49); for timber and fire wood (33); for fruit and vegetables (18); for building or a place to live (13); and for other forest products (5). Similarly, the index was calculated from the number of responses (i.e. advantages or disadvantages given), at the respondent level.

### 2.3. Environmental and human spatial predictors

To model perceptions of ecosystem services and attitudes towards land cover change we developed 39 spatial layers as potentially important environmental or human predictor variables. These fell within the categories of: (1) Land-use and land cover; (2) Climate and topographical variables; (3) Accessibility; (4) Socio-economic factors; and (5) Orangutan habitat (see Table 1 for descriptions and codes).

### 2.4. Land-use and land cover

Eight land cover types were used within the analysis as the degree of forest ‘intactness’ or land cover type may impact local perceptions of the benefits people derive from forests. These included: mangrove; intact natural forest; logged forest; forest severely degraded by drought, fire and logging, and agro-forests/forest re-growth areas. Other variables included: industrial timber plantations; oil palm plantations; and, ‘other’ land cover types (see Table 1 in S1 for brief descriptions of classes). The eight land cover layers were derived from the integration of three datasets as explained in Meijaard et al. (2013). We also included a layer delineating protected area networks compiled from various government data sources (for details see, Wich et al., 2012). For each layer, we calculated the Euclidian distance to the nearest type of this land cover. We also incorporated above ground carbon stock data derived from LiDAR (Light Detection and Ranging) by Baccini et al. (2012) and converted these data into units of Mg of $CO_2$ per hectare at 30″ resolution. For carbon stock, protected areas, and the eight land cover variables, we calculated the summed values of neighbouring cells within a 10 km radius using the focal statistics tool in ArcGIS 10.0. This radius was selected as

**Table 1**
Summary table of the 39 spatial predictors used within the Boosted Regression Tree models.

| Category | Spatial predictor layers | Abbreviations |
|---|---|---|
| **Land cover/ Land use** | Distance to Mangrove | mangrove_m |
| | Statistic of neighbourhood values of Mangrove | mangrove_s |
| | Distance to Intact natural forest | intact_m |
| | Statistic of neighbourhood values of Intact natural forest | intact_s |
| | Distance to Logged forest | logged_m |
| | Statistic of neighbourhood values of Logged forest | logged_s |
| | Distance to Severely degraded logged forest | svlogged_m |
| | Statistic of neighbourhood values of Severely degraded logged forest | svlogged_s |
| | Distance to Agro-forests/forest re-growth | agroregr_m |
| | Statistic of neighbourhood values of Agro-forests/forest re-growth | agroregr_s |
| | Distance to Industrial timber plantation | indtim_m |
| | Statistic of neighbourhood values of Industrial timber plantation | indtim_s |
| | Distance to Oil palm plantations | oilpalm_m |
| | Statistic of neighbourhood values of Oil palm plantations | oilpalm_s |
| | Distance to Other land cover | otherlc_m |
| | Statistic of neighbourhood values of Other land cover | otherlc_s |
| | Distance to Protected Area | pa_m |
| | Statistic of neighbourhood values of Protected Area | pa_s |
| **Carbon** | Statistic of neighbourhood values of Carbon | carbon_s |
| **Orangutan range** | Distance to orangutan range | ou_m |
| | orangutan range | ou_s |
| **Topography** | Elevation | elevation |
| | Ruggedness | ruggedness |
| | Distance to Rivers | rivers_m |
| | River density | river_d |
| **Climate** | Temperature seasonality | temp_seaso |
| | Temperature annual range | temp_annra |
| | Precipitation seasonality | prec_seaso |
| | Precipitation annual range | prec_annra |
| **Infrastructure** | Impermeable surface | impervious |
| | Road density | road_d |
| | Settlement density | settlemt_d |
| **Accessibility** | Accessibility sum (road, river, foot) | access_sum |
| | Accessibility 10 (road, river, foot) | access_10 |
| **Population** | Population (Landscan) | pop_2007 |
| **Wealth** | Poverty Index | poverty |
| **Culture** | District percentage of Islam | islam |
| | District percentage of Christian | christian |
| | Ethnic groups | ethnic_gp |

we assumed it to be a reasonable distance for a person to travel on foot and an assumed distance characterising the localised environment of the village's nearby surroundings.

### 2.5. *Climate and topographical variables*

We used four least-correlated climatic predictor variables: temperature seasonality; temperature annual range; annual precipitation; and precipitation seasonality. These variables, along with elevation grid data originated from the WorldClim, ver. 1.4 dataset (http://www.worldclim.org/) at 30″ resolution. Additionally, we used a rugosity layer (ruggedness) generated from the elevation data using DEM surface tools (Jenness, 2012). We generated two river files: firstly, we used a kernel density tool in ArcGIS 10 to generate a river density index using spatial data sourced from HydroSHEDS (http://hydrosheds.cr.usgs.gov/index.php) (Lehner et al., 2006). Secondly, we used a major river vector file that had been digitised from landsat images, and calculated the Euclidian distance of each grid cell from the nearest major river.

### 2.6. *Accessibility*

We calculated two 'accessibility' layers using the 'path distance' tool in ArcGIS 10.0. We firstly generated a '*time distance*' layer by merging roads and river vector data and calculating estimated time to cross a 1 km cell by road or river, calculated at 2 min per kilometre. The remaining extent (i.e. cells with no rivers or no roads) was assumed by default to be only walk-able and crossing times were estimated at 10 min per 1 km on flat terrain. Elevation was incorporated within the calculation to give greater times for crossing steeper terrain. Two least-cost layers were calculated using the path distance tool in ArcGIS 10.0; one had a single threshold for population density (i.e., 10 or more people per cell); the other had a weighted sum threshold. To do this we firstly extracted grids with 10 or more people and calculated the least-cost path. Secondly we generated a 'weighted' accessibility layer by calculating and summing the path distance for cells with 1 or more persons, 2 or more people, 3 or more people and so on up to 6000, meaning cells that were accessible more easily by more people get a higher score.

### 2.7. *Socio-economic factors*

Data on socio-economic status and infrastructure were obtained from a number of sources, including: a 2010 constructed impervious surface layer (i.e. impermeable surface) (Sutton et al., 2010); a poverty index layer (Elvidge et al., 2009); and a human population density layer (estimated number of people per 1 km$^2$) from LandScan 2007™ (Bright et al., 2008). From LandScan 2007, we calculated settlement density using a kernel density function for cells with 10 or more people per 1 km grid. We generated a road density index, using a line density function from digisited 1999 to 2002 road data (Wich et al., 2012). To capture aspects of cultural variation, we digitised a broad ethnic group map for Borneo (Sellato, 1989) including: central-northern groups; Dusun and north-eastern groups; Iban and Ibanic groups; Kayan and Kenyah groups; land Dayak and western groups; Malay groups; Ngaju and Barito groups; nomadic groups and an unknown category. Finally, we incorporated religion, as religion was one of the dominant variables influencing forest use and perceptions in a concurrent study (Meijaard et al., 2013). We obtained provincial- or district-level proportions of the population that were registered as Christian and Muslim, from the Government Statistical departments from online sources (e.g., http://kalteng.bps.go.id/GIS.html) and hard documents (BPS-KalBar, 2011; BPS-KalSel, 2009; BPS-KalTim, 2011) which were then imported into the GIS.

### 2.8. *Orangutan habitat*

We included two spatial variables generated from the known geographic distribution of orangutan breeding populations (Wich et al., 2012). We included orangutan habitat because this animal is the best known conservation icon in Borneo and tends to generate significant perceptions (not necessarily positive) about forest and wildlife conservation (Meijaard and Sheil, 2008). All spatial data were developed at 30″ resolution (approximately 1 km$^2$). These were: (1) Euclidian distance from known orangutan breeding populations; and (2) summed values of neighbouring cells within a 10 km radius (using the focal statistics tool in ArcGIS 10.0).

### 2.9. *Modelling approach and mapping outputs*

#### 2.9.1. *Modelling approach*

Response variables for spatial modelling included: two for provisioning services from forests; perceptions of cultural and spiritual benefits from forest; three for varying aspects of perceptions of regulating and supporting services from forests, and two for attitudes toward land cover and land use change from forest to agriculture. Before statistical modelling, each response variable was collapsed from respondent level (considered as continuous) to average village-level values (also regarded as continuous) for the sample of 185 villages. This was necessary in order to match the spatial scale of the village-level data and the 39 predictor variables. The use of average response values provided robust estimates of central tendency and avoided mathematical and computational problems involved in fitting a repeated measures (multiple sets of perceptions) mixed model analysis.

Village co-ordinates (taken with a Global Positioning System (GPS) at the centre of the sampled villages) were imported into a Global Information System (GIS) along with the 39 spatial predictor variables; and values for each layer were extracted for the 185 villages. As the spatial predictor variables were at 1 km$^2$ these values therefore represent the 1 km$^2$ area surrounding the village centre. Due to methodological considerations, we retained the resolution at 1 km$^2$ and did not increase the resolution (up to 5 km$^2$ for example) as: (1) much data were developed at 1 km$^2$ and retaining original resolution and values were important in minimising errors within the datasets: and (2) in general, sampled villages were small (i.e., 104 villages had $<2000$ inhabitants; 40 villages had 2000–4000 inhabitants; only 7 villages had between 4,000 up to a maximum of 6849 inhabitants; and 34 villages had no population data) and may likely be orientated within, or close to, such a geographical extent.

We used Boosted Regression Trees (BRT), a fairly recently developed technique for model fitting, that enables sophisticated regression analyses of complex responses optimised for high predictive performance (Elith et al., 2006, 2008). We used BRTs as they fit multiple regression tree models, and this enables the selection of important variables based on their contributions over the full ensemble of models. Additionally, BRTs can handle continuous variables; can fit complex interactions between variables; can deal with inherent issues of correlated variables; and through boosting, are able to overcome issues of model instability and lack of accuracy (Friedman and Meulman, 2003).

The BRT models were fitted using the function 'gbm' in the 'dismo' package (Hijmans et al., 2013) within the R environment for statistical computing version. 2.15.0 (R Core Team, 2013). The following specifications were used: a continuous response variable with a Laplace (absolute deviation); 5000 trees with an interaction depth of 3 (i.e. including multi-way interactions), bagging fraction of 0.5 (i.e., 50% random samples used for fitting the trees), and training fraction of 0.8 (i.e., 20% data reserved for independent model testing). The performance of the model was also assessed using five-fold cross-validation and the adequacy of the choice of the number of trees was confirmed.

### 2.9.2. Mapping outputs

The BRT output prediction scores were imported into ArcGIS 10.0 and using a 1 km$^2$ grid mask, mapped and then continuous values were classified into tertiles (equal number of observations in each class). We refined the model output to areas with forest and human population. Firstly, we used the 2010 forest cover layer that included all natural forest types (including the agro-forest/regrowth class) (Gaveau et al., in review) and extracted grids that fell under this 'forest cover'. Secondly, we used the population 2007 grid data, extracted cells with 5 persons or more per 1 km$^2$, created a 10 km buffer around these 'settlements' and again extracted the tertiled grids. The final maps therefore had three tertiled classifications of ecosystem services and land cover change perceptions; and excluded areas of no forest or no people.

## 3. Results

### 3.1. Performance and variable contribution

The boosted regression tree models performed well with prediction accuracies ranging from 0.84 to 0.99 (Table 2). Table 2 shows the top 10 variables for each of the 8 BRT models, along with each variable's percentage contribution. Of the 39 spatial variables used within the models: 28 occurred within the top 10 most important variables; 18 of these occurred in two models; 13 occurred three times; 7 occurred five times; 6 occurred in six models; and 1 variable occurred in 7 models (Table 3). The six variables that occurred in six or seven of the eight models were distance to mangrove (occurring in seven models); settlement density; distance to severely logged forest; annual precipitation; distance to industrial timber plantations; and road density; and all had consistently moderately-high average percentage contribution across models (Table 3).

### 3.2. Provisioning services from forests

The model for the seven forest uses had good predictive performance with the top 10 variables explaining 70.5% of the variance of the models (Table 2). Elevation was most important,

**Table 2**
Summary of the eight models showing classification accuracy (in parentheses), top 10 variable codes the most influential on models with % contribution (%) and the summed total percentage of these top 10 variables.

| Provisioning | | | | Cultural | | | | Regulating/supporting | | | | Land cover change | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Uses 7 (0.99) | % | Uses 29 (0.98) | % | Cultural (0.94) | % | Health (0.89) | % | Direct (0.88) | % | Environmental (0.87) | % | Large scale clearing bad (0.84) | % | Small scale clearing good (0.90) | % |
| elevation | 13.5 | access_10 | 13.1 | river_d | 24.4 | prec_seaso | 12.4 | otherlc_s | 9.4 | settlemt_d | 9.5 | settlemt_d | 17.7 | svlogged_m | 12.8 |
| svlogged_m | 9.9 | indtim_m | 9.5 | settlemt_d | 8.9 | prec_annra | 9.9 | prec_annra | 7.8 | prec_annra | 9.3 | mangrove_m | 15.1 | ou_m | 9.2 |
| access_sum | 9.5 | road_d | 7.3 | svlogged_m | 7.6 | svlogged_m | 9.7 | settlemt_d | 6.9 | indtim_m | 7.4 | islam | 7.5 | carbon_s | 8.7 |
| otherlc_s | 6.4 | svlogged_m | 6.5 | road_d | 6.4 | elevation | 9.4 | prec_seaso | 6.8 | intact_m | 6.8 | road_d | 7.1 | christian | 7.9 |
| prec_annra | 5.7 | access_sum | 5.3 | carbon_s | 5.6 | road_d | 5.8 | indtim_m | 6.4 | poverty | 6.7 | svlogged_m | 4.7 | settlemt_d | 6.7 |
| indtim_m | 5.4 | mangrove_m | 4.6 | prec_seaso | 4.8 | settlemt_d | 5.0 | logged_m | 6.1 | islam | 4.5 | prec_seaso | 4.0 | pa_m | 5.3 |
| temp_seaso | 5.3 | logged_s | 4.5 | prec_annra | 4.4 | indtim_m | 4.8 | mangrove_m | 5.2 | logged_m | 4.1 | otherlc_s | 3.7 | mangrove_m | 4.3 |
| mangrove_m | 5.3 | islam | 4.4 | mangrove_m | 4.0 | access_sum | 4.3 | ou_m | 5.0 | pop_2007 | 3.7 | temp_annra | 3.7 | road_d | 3.8 |
| otherlc_m | 5.2 | otherlc_m | 4.2 | temp_annra | 3.1 | poverty | 4.2 | road_d | 4.6 | ou_s | 3.7 | indtim_m | 3.4 | prec_seaso | 3.6 |
| carbon_s | 4.4 | agroregr_m | 3.5 | poverty | 2.5 | access_10 | 4.0 | oilpalm_m | 4.6 | mangrove_m | 3.6 | access_10 | 3.4 | prec_annra | 3.2 |
| Total | 70.4 | Total | 62.8 | Total | 71.7 | Total | 69.4 | Total | 62.6 | Total | 59.2 | Total | 70.4 | Total | 65.3 |

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**Table 3**
Rank order of the spatial variables that fell within the top 10 variables in one or more of the eight BRT models. Table shows number of models variable significantly contributed in (No. models) along with the average percentage that model contributed (Ave % contribution).

| Top 10 variables | No. models | Ave % contribution | Top 10 variables | No. models | Ave % contribution |
|---|---|---|---|---|---|
| mangrove_m | 7 | 6.0 | ou_m | 2 | 7.1 |
| settlemt_d | 6 | 9.1 | otherlc_m | 2 | 4.7 |
| svlogged_m | 6 | 8.5 | temp_annra | 2 | 3.4 |
| prec_annra | 6 | 6.7 | logged_m | 2 | 5.1 |
| indtim_m | 6 | 6.1 | logged_s | 1 | 4.5 |
| road_d | 6 | 5.8 | agroregr_m | 1 | 3.5 |
| prec_seaso | 5 | 6.3 | river_d | 1 | 24.4 |
| access_sum | 3 | 6.4 | christian | 1 | 7.9 |
| otherlc_s | 3 | 6.5 | temp_seaso | 1 | 5.3 |
| access_10 | 3 | 6.9 | ou_s | 1 | 3.7 |
| carbon_s | 3 | 6.2 | pop_2007 | 1 | 3.7 |
| poverty | 3 | 4.5 | oilpalm_m | 1 | 4.6 |
| islam | 3 | 5.5 | pa_m | 1 | 5.3 |
| elevation | 2 | 11.4 | intact_m | 1 | 6.8 |

with distance to severely logged forest constituting the second determining factor, followed by accessibility (summed version) and summed value of ‘other’ non-forest land use classes within a 10 km radius (Table 2). High predicted use areas as depicted in Fig. 2a are located largely within the elevated central belt of the island, while lower usage was predicted in the lower, costal zones.

The model for the 29 forest uses derived from the open question on provisioning services had good classification accuracy; with the top 10 variables explaining 62.8% of the model. The most important variables were: accessibility (10); distance to industrial timber plantations; road density; distance to severely logged forest; and summed access (Table 2). High predicted uses were located within northern East Kalimantan, northern Sarawak and several other areas including southern and western Central Kalimantan (Fig. 2b).

### 3.3. Cultural and spiritual benefits from forests

The model of cultural and spiritual benefits derived from forest had good overall prediction accuracy, with 71.7% of the model explained by the top 10 variables (Table 2). The most important predictors for the model's variance were river density, settlement density; distance to severely logged forest; road density; and summed above ground carbon within a 10 km radius (Table 2). Stronger perceptions of cultural and spiritual benefits from forest (Fig. 2c) were located in either forest frontier regions (i.e., where deforestation is ongoing) or areas of relatively higher affluence such as Sabah.

### 3.4. Regulating services and supporting services for health

The model for regulating services for health had good overall prediction accuracy. The top 10 variables totalled 69.5%, with 41.4% accounted for by four variables: precipitation seasonality; precipitation annual range; distance to severely logged areas; and elevation (Table 2). The predicted areas for high importance values for these services (Fig. 2d) were located in either forest frontier areas or elevated areas in Sabah, Sarawak and East Kalimantan, and near the border between West and Central Kalimantan. Within the interior of Borneo perceived health benefits from forests were predicted to be moderate rather than high.

Models for responses to the open question on health benefits performed well (Table 2). For Direct Health Benefits, the top 10 variables accounted for 62.6% of variance (Table 2) with the sixth greatest predictors (43.4% of variance) being: summed cover of other land classes within a 10 km radius; precipitation annual range; settlement density; precipitation seasonality; distance to industrial timber plantations and distance to logged forest. High appreciation values were within the forested interior of Borneo, with low appreciation in the coastal lowlands of Kalimantan (Fig. 2e), but not in coastal Sarawak and Brunei Darussalam where values were predicted as high.

The top 10 variables for environmental health benefits accounted for only 59.3% of variance, with the six strongest variables being settlement density; annual precipitation; distance to industrial timber plantations; distance to intact forest; poverty and the percentage of population following Islam (Table 2). The modelled spatial patterns for perceived environmental benefits (Fig. 2f) from forests are distinctly different from our other models and generally suggest high perception values in the lowlands of Kalimantan and western Sabah, moderate in the interior of the island and low in the forest fringes.

### 3.5. Spatial patterns of perceptions of land clearing

The model for ‘disadvantage of large scale clearing for agriculture’ had good overall prediction accuracy with 70.5% of variance explained by the top 10 variables (Table 2). The model was strongly driven by spatial variables related to development e.g., settlement density and road density; with other important variables being distance to mangrove and the percentage of population following Islam. The spatial outputs (Fig. 2g) suggest strong perceptions that industrial scale clearing is bad for respondents' wellbeing in areas such as western and southern East Kalimantan, Central Kalimantan, and South Kalimantan.

The model for ‘advantages of small scale clearing of forest for agriculture’ had good prediction accuracy with 65.3% of variance explained by the top 10 variables. This model was highly driven by distance to severely logged areas and distance to orangutan distribution, followed by sum of carbon cover; the percentage of population who are Christian; settlement density; and distance to protected areas (Table 2). Strong positive perceptions are widespread in severely logged areas of Sarawak, Sabah, and northern East Kalimantan (Fig. 2h), whereas views of small-scale clearing as neutral or negative are largely predicted within southern Borneo.

## 4. Discussion and conclusions

This study demonstrates progressive advances towards understanding and mapping perceptions of the human-ecological environment i.e., the non-economic values of users (Brown, 2013). Such advances are necessary for incorporating aspects of social values into landscape level land use planning and management (Bryan et al., 2010; Cowling et al., 2008). This is becoming more pertinent especially in regions undergoing land use change and where rural communities are still dependent on the multiple services derived from natural ecosystems such as forests (Millennium Ecosystem Assessment, 2005). Our methodological approach provides maps of perception values on the relative importance of ecosystem services across landscapes; whilst also enhancing the understanding of the socio-economic and environmental drivers influencing people's perceptions. This is important in creating and implementing more sustainable development plans that are more environmentally centric. We used this approach to understand spatial variation across the island of Borneo, a region under rapid land cover change (Gaveau et al., in review).

### 4.1. The importance of provisioning services

Within many forested regions the services people derived from ecosystems are in jeopardy as rapid forest conversion, and forest

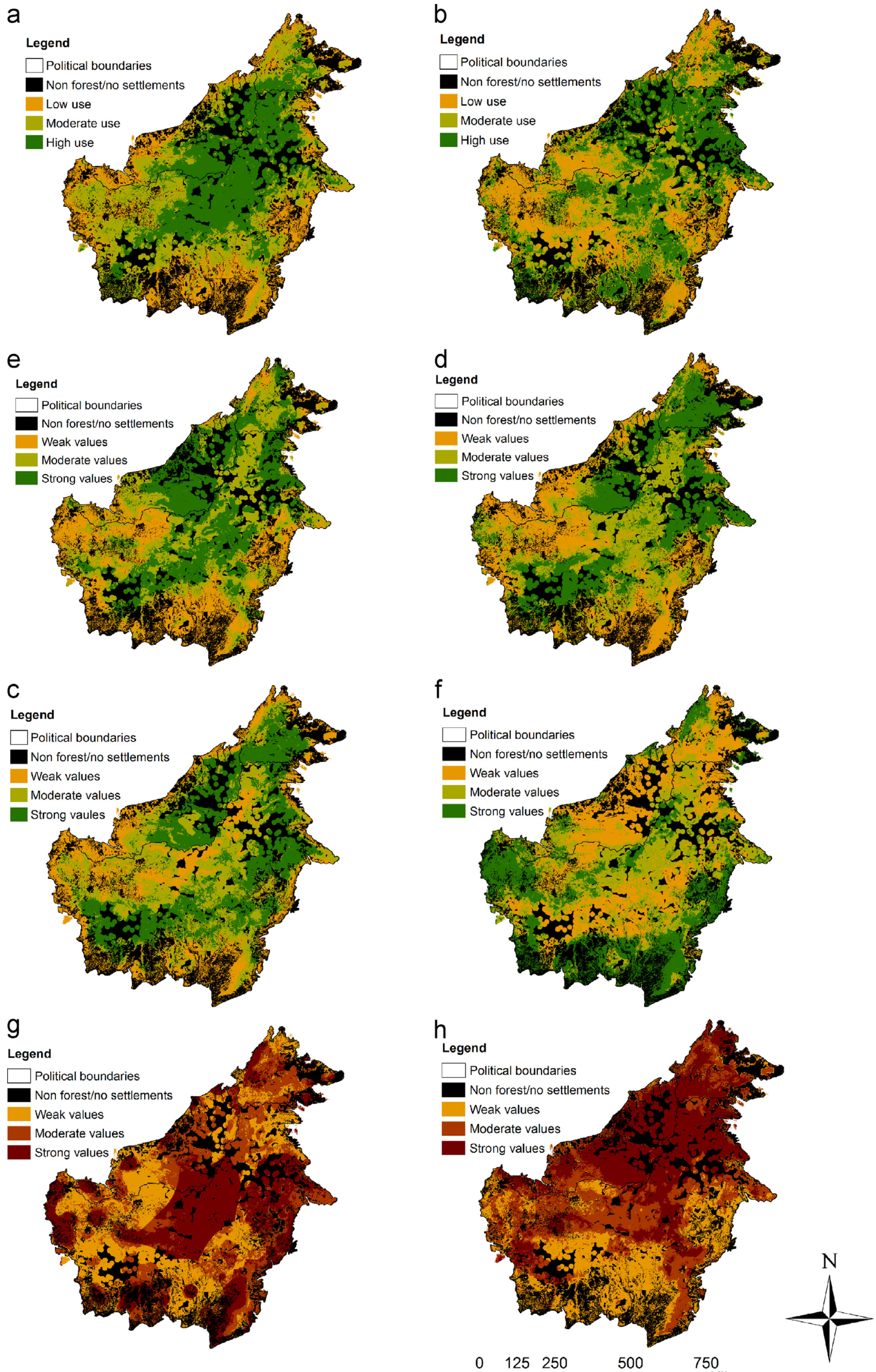


**Fig. 2.** Spatially explicit maps from the boosted regression tree anlyses, of perception values of rural villages on the ecosystem services they derive from forests including: uses of seven forest products (a); uses of 29 other forest products (b); cultural and spiritual benefits (c); health benefits (d); direct benefits (e); and environmental benefits (f); as well as, perceptions related to largescale clearing for agriculture (g); and, smallscale clearing for agriculture (h).

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degradation by logging, drought and fire for example is altering landscapes and ecosystem function (Cardinale et al., 2012). This is of particular importance for those people who live close to large forest areas as they often have greater dependency on forest-products (Sunderlin et al., 2008). This notion was supported by the model of the seven specific forest products (i.e., timber, rattan, bush-meat, traditional medicine, minerals from mining, honey and aloes wood) and the model of the wider set of products ($n=29$ products). These models predicted high usage of products within remote and intact expanses of forest, where these resources are likely more abundant and accessible and where communities may depend on a larger suit of forest resources for their livelihoods and well-being (Levang et al., 2005).

Low usage of the seven forest products however, appears to be associated with landscapes that have either undergone much forest conversion (at fine or large scales), or have been impacted by over-harvesting of resources leading to forest degradation (Asner et al., 2009). These patterns may be explained by studies by Brown et al. (2011) and Thapa and Chapman (2010) who note that forests may be functionally depleted of particular resources for local communities if over extraction has occurred. Within our Borneo context, areas of low predicted usage of the seven products include: the peat swamp forests in southern Central Kalimantan that were drained, burnt during the 1997–98 El Niño-Southern Oscillation event, and massively converted to oil palm and small-scale agriculture; and the severely degraded landscapes in south-east of East Kalimantan influenced by drought and fire during the 1982–83 and 1997–98 El Niño events (Malingreau et al., 1985; Siegert et al., 2001). Low usage of forest products also occurred in areas with higher density infrastructure (e.g., parts of the west coasts of Sabah and Sarawak) and may reflect areas with increasing use of purchased processed goods (from urban areas) and lower reliance on raw materials from the forest.

Interestingly, the model of the wider set of products ($n=29$) predicted high usage in these highly altered landscapes where agro-forestry, severely degraded forests, or industrial timber plantations are prevalent. This trend is likely explained by the products reported in this category such as fish, fire wood, forest gardens, rubber gardens, and fruits and vegetables occurring within such altered landscapes. The services that rural people depend on can vary over time and space. Moreover, the benefits of agro-forest systems can also be important for provisioning resources for rural people's livelihoods (Müller et al., 2013). Furthermore, it is important to note that there may be differences between what respondents in the local communities consider 'forest' (e.g. any area with substantial tree cover), and how forest is scientifically defined (Sasaki and Putz, 2009).

### 4.2. Cultural and spiritual ecosystem services at landscape level

Measuring and mapping cultural services contributes to understanding the full suite of potential ecosystem services and who they benefit (Beverly et al., 2008; Raymond et al., 2009). Cultural and spiritual services from landscapes are linked to perceived well-being even when dependency on regulating services or provisioning services has declined (Guo et al., 2010). Our results show strong perceptions of cultural and spiritual benefits from forest in agricultural frontier regions where perhaps forest dependency is decreasing and in areas of assumed relatively higher affluence, also noted in other studies (Plieninger et al., 2013).

Our findings however show that in areas deforested a long time ago (e.g., coastal lowlands of Borneo and several major river basins) people may have lost cultural and spiritual values associated with forests. Lower perception values also occurred in areas with extensive and remote forests. However, it is possible that this pattern reflects a modelling bias due to few samples within these predicted areas (i.e., the core of Borneo) or alternatively may simply be a response of forest-based communities being less perceptive of linkages between forest benefits and cultural values than those whom have witnessed forest loss, and in turn loss of cultural identity (Tengberg et al., 2012). This possibility warrants further study. However, it is clear that people hold stronger spiritual and cultural values ascertained from forests in areas where they are likely to lose these forests in the near future. It is therefore important that these values should be taken into consideration in land use planning, particularly as cultural services have low potential for mediation (Millennium Ecosystem Assessment, 2005). This means that substitution of ecosystem services for cultural and spiritual benefits will be close to impossible, in contrast to some aspects of provisioning or regulating services (Levang et al., 2005).

### 4.3. The importance of regulatory services and supporting services for health

For rural communities especially, health of people is interwoven with access to a myriad of ecosystem services such as nutrition, medicine, water, clean air amongst others (Xu et al., 2008). Our initial model on health benefits from forests shows strong support of this with 67% of respondents who stated that forests are 'very important' to their health and the health of their family. Strong perceptions of forest benefits for health were located firstly in forest transition zones where people are experiencing impacts from environmental change; and secondly, in certain regions with extensive forest cover (e.g., in upland regions around the border between West and Central Kalimantan Provinces, and in forested parts of East Kalimantan, Sabah, and Sarawak). This suggests that benefits are still identifiable by people regardless of the integrity of the forest systems in which they are reliant on.

From the direct health benefits category, the principal responses were access to traditional medicine from forests, life-giver, protective benefits from forest (e.g., by preventing disease and disasters or tempering climatic extremes), and spiritual values that people consider beneficial to their health. Our models predicted highest appreciation in forested interior regions and low appreciation in altered landscapes (e.g. coastal lowlands) with models driven by distance to certain land cover types.

Land cover and land use change both directly and indirectly affects people's health by moderating ecosystem services (Vitousek et al., 1997). Our model on environmental benefits was dominated by the responses: forest are important to regulate temperatures, provide shade; as a source of water; to provide clean air and oxygen; and to prevent floods, pollution and erosion and driven by distance to forests and settlement size. Regions with high appreciation were in coastal lowlands that have very limited natural forest cover as a result of past land cover change (Gaveau et al., in review). The fact that people experience significant negative environmental impacts following deforestation indicates that these impacts should not be ignored and their costs (and distribution) weighed against the economic benefits derived from deforestation. These insights are of significance as the rate at which land use change is occurring may go beyond the capacity of the ecosystem to recover ,(Lambin and Giest, 2006) impacting for example long term health of those rural communities with limited access to western medicines or other provisions needed for their well-being.

### 4.4. Spatial patterns of perceptions of land clearing for agriculture

Understanding rural people's perceptions of forest conversion to agriculture is crucial within dynamic environments where deforestation rates are high (Langner et al., 2007). Perceptions on the disadvantages of large scale clearing for agriculture were strongly driven by variables related to economic development (e.g., settlement and road density). Patterns indicate that industrialised clearing may be opposed in areas impacted by past deforestation e.g., northern coastal parts of West Kalimantan, and western South Kalimantan Province, which was largely deforested in the 19th century (Knapen, 2001). Negative perceptions of clearing were also prevalent in interior forested regions as forest-dwelling people may be aware of the negative impacts commercial agriculture may have on their current way of life and livelihood options (Meijaard et al., 2013).

Such perception assessments are pertinent at the national level for the Indonesian and Malaysian Governments but should also be of significance to areas targeted for oil palm such as the Congo and Amazon basin, amongst other regions (Butler and Laurance, 2009; Rowling, 2013). For areas undergoing current oil palm establishment (e.g., southern Central Kalimantan and around Tanjung Puting National Park) our models predict weak perceptions from people in regard to potential negative impacts of forest conversion. Such views may be weaker in regions if conversion generates direct benefits for peoples through illegal logging, land sale, improved market access, and employment (Dove, 1993; Feintrenie et al., 2010). Whether or not local communities ultimately benefit from oil palm development depends highly on local-level politics (Rist et al., 2010).

Strong perceptions regarding advantages of forest clearance for small scale agriculture were widespread in areas where people were more forest-reliant, and in agricultural frontier regions undergoing environmental change; as perceived benefits could be significant (Sayer et al., 2012). Positive perceptions are expected where small scale clearing directly benefits local people largely due to high profitability of crops such as oil palm (Butler et al., 2009). However, oil palm was not the only crop and the ability to create forest gardens and other agricultural crops such as rubber and rice production were also mentioned and can be important livelihood options.

Interestingly weak perceptions of benefits from small scale agriculture however, were widespread throughout regions where extensive plantation development has occurred and is occurring (Koh et al., 2011; Wich et al., 2012). Further to this, forest conversion (even small scale) seems unsupported in regions where forest is highly valued for environmental health benefits (e.g., Central and Southern Kalimantan). This may be the case if people's current livelihoods and wellbeing are threatened. These regions may have seen significant land use change and mounting negative impacts such as flooding, variation in climate, seasonal shifts and other associated environmental issues due to forest conversion (Wells et al., 2013). For Borneo, this raises the possibility of social unrest if forest conversion continues, particularly if combined with tensions over land tenure and displacement of local communities (Rist et al., 2010). Such perceptions of local communities need to be incorporated into land use planning so that informed decisions can be made (Hauck et al., 2012).

### 4.5. Strengths and limitations

From a methodological perspective, we acknowledge a number of methodical limitations and outline how we addressed these potential issues in the data treatment and analyses within the Borneo wide dataset to allow other studies to improve on methods used within this study. Firstly, the original sampling design for villages was orientated towards orangutan distribution areas within or near forest (Meijaard et al., 2011a); hence these areas are over-represented relative to a random spatial sample of villages across the island. To attempt to neutralise this issue, the secondary surveys were chosen to improve data variation and capture regions in un-sampled areas (and incorporate missing ethnic groups and religious identities). Interviewee reliability was also a potential issue often associated with interview-based methods (Tourangeau and Yan, 2007). Interviewer reliability was an issue within a sub-set of NGOs (see, Meijaard et al., 2013). As a result we aimed to minimise the inclusion of poor data into the models by assessing 'reliability' (see Section 2.2). This approach reduced the dataset to 185 villages however this dataset was deemed robust.

Spatial autocorrelation may have been an issue due to 'clumping' of sampled villages and correlated spatial variables. However, sampling covered a very wide geographic area and diverse 'environmental space', and boosted regression tree methods are generally robust to correlations among predictors (Elith et al., 2008); therefore limiting potential issues within model outputs. Lastly, and importantly, the 39 spatial predictor layers show varying degrees of uncertainty. However, best data were used and poor quality data were emitted from the spatial framework leaving the 39 predictor variables.

We fully acknowledge methodological considerations in our modelling approach. Nevertheless, our treatment of data and use of appropriate statistical analyses has minimised these potential issues. In this study, we hope to: (1) provision information on people's perceptions of ecosystem services derived from forests within the Borneo context, with global relevance; and (2) demonstrate a robust and versatile methodological approach to modelling and mapping a range of social values thereby providing alternative methods for understanding ecosystems services. Understanding and generating spatially explicit maps on such perspectives are needed and should be incorporated into land use and development planning and future implementation strategies.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.ecoser.2013.11.004.

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