Tree plantations displacing native forests: the nature and drivers of apparent forest recovery on former croplands in Southwestern China from 2000-2015

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Abstract: China is credited with undertaking some of the world's most ambitious policies to protect and restore forests, which could serve as a role model for other countries. However, the actual environmental consequences of these policies are poorly known. Here, we combine remote-sensing analysis with household interviews to assess the nature and drivers of land-cover change in southwestern China between 2000-2015, after China's major forest protection and reforestation policies came into effect. We found that while the region's gross tree cover grew by 32%, this increase was entirely due to the conversion of croplands to tree plantations, particularly monocultures. Native forests, in turn, suffered a net loss of 6.6%. Thus, instead of truly recovering forested landscapes and generating concomitant environmental benefits, the region's apparent forest recovery has effectively displaced native forests, including those that could have naturally regenerated on land freed up from agriculture. The pursuit of profit from agricultural or forestry production along with governmental encouragement and mobilization for certain land uses – including tree planting – were the dominant drivers of the observed land-cover change. An additional driver was the desire of many households to conform with the land-use decisions of their neighbors. We also found that households' lack of labor or financial resources, rather than any policy safeguards, was the primary constraint on further conversion of native forests. We conclude that to achieve genuine forest recovery along with the resulting environmental benefits, China's policies must more strongly protect existing native forests and facilitate native forest restoration. Natural regeneration, which thus far has been grossly neglected in China's forest policies, should be recognized as a legitimate means of forest restoration. In addition, social factors operating at the household level, notably the pursuit of profit and conformation to social norms, should be harnessed to promote better land-cover, biodiversity, and environmental outcomes. More generally, for China and other countries to succeed in recovering forests, policies must clearly distinguish between native forests and tree plantations.

Introduction

The recovery of forest landscapes ("forest recovery" hereafter) carries considerable promise for halting and reversing the negative biodiversity impacts of forest loss, mitigating greenhouse-gas emissions, and generating other ecosystem services (Chazdon et al., 2017). For this reason, forest recovery is attracting increasing amounts of political attention and financial investment globally (Aronson and Alexander, 2013; Suding et al., 2015). At a landscape scale, forest recovery happens when forest restoration – realized via natural regeneration, artificial reforestation, and/or the spectrum of approaches in between (Suding, 2011) – exceeds forest loss. The gain or loss of forest cover necessarily involves changes in land use and land cover, with concomitant environmental and socioeconomic implications (Foley et al., 2005). Given increasing international attention directed toward forest recovery, understanding the land-cover dynamics involved in forest recovery and their underlying drivers is of great policy relevance (Rudel et al., 2016; Uriarte and Chazdon, 2016; Wilson et al., 2017).

The question of what constitutes a forest is at the core of understanding forest recovery (Chazdon et al., 2016; Sexton et al., 2016). The definition of forest used by the United Nations Food and Agricultural Organization (FAO)--"land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ; it does not include land that is predominantly under agricultural or urban land use" (FAO, 2012)--is widely used in policy discourses worldwide and in the vast majority of national forest statistics. It is also used or implied in a number of prominent international agreements related to forest protection and recovery such as the Bonn Challenge (Bonn Challenge, 2011; see also www.infoflr.org) and the New York Declaration on Forests (United Nations, 2014). However, because this definition includes tree plantations and thus disregards their marked differences from native forests (typically consisting of diverse stands of native species) in terms of environmental, and particularly biodiversity, attributes (for reviews on this topic, see Brockerhoff et al., 2008; Liao et al., 2010; Paquette and

Messier, 2010), this definition risks misrepresenting the environmental implications of alleged forest recovery (Putz and Romero, 2015; Wilson et al., 2017; Hua et al., in press). To avoid confusion, in this article we use “tree cover” to represent what FAO defines as forest (i.e. the combination of native forests and tree plantations that meet the defined areal, tree-height, and canopy-cover requirements), and we limit the use of “forest” to the native-forest subset of land cover within the FAO definition, thereby separating it from “tree plantations”, which consist of monocultures or simple polycultures of planted trees (Lindenmayer et al., 2012a). Thus, in this article, an increase in tree cover does not necessarily correspond to forest recovery unless it involves an increase in the extent of native forests.

China is said to have undergone a remarkable increase in tree cover over the past three decades: According to the state forest inventory, China’s tree cover – reported in the inventory as “forest cover” – has increased from 12% of the country’s terrestrial area in 1981 to 21.4% in 2013 (SFA 1999-2014; see Hua et al., in press for a visualized time series of the inventory data). Such an increase is without precedent in such a short period of time in any large nation. At least for the period after year 2000, as remotely sensed land-cover data became more accessible, reports of increases in China’s tree cover have generally been corroborated by remote-sensing studies (Ren et al., 2015; Ahrends et al., 2017; Li et al., 2017). These increases are considered to be particularly attributable to a system of state programs begun in the late 1990s to promote forest protection and reforestation for ecological benefits (Robbins and Harrell, 2014; Yin and Yin, 2010), and they have been widely credited with generating enormous environmental benefits (Liu et al., 2008; Deng et al., 2014; Ouyang et al., 2016). However, multiple local studies suggest that China’s recent increase in tree cover has been dominated by tree plantations, usually monocultures (Hua et al., 2016), while native forests continue to be lost (Greenpeace East Asia, 2013-2015; Li et al., 2007; Zhai et al., 2014). Such reports highlight the fact that without differentiating between tree plantations and native forests, it is impossible to know what the increase in tree cover means for China's *forest* recovery, and indeed, for the ecological benefits that are the primary goal of the country's forest policies.

Currently, assessments of China's tree-cover dynamics that distinguish between native forests and tree plantations since the late 1990s are non-existent at the national scale and scarce at the regional scale (e.g. Hu et al., 2014; Li et al., 2007; Zhai et al., 2014). Moreover, little is known about the factors driving land-cover change related to trees, particularly why, according to some sources, native forests continue to be lost despite major government policies intended to protect them, such as the Natural Forest Protection Program (NFPP; Ren et al., 2015). While there are suggestions that NFPP and other forest policies contain loopholes that inadvertently and perversely favor tree plantation expansion over the retention of native forest (Greenpeace East Asia, 2013-2015; Zhai et al., 2014), evidence of this has been anecdotal. Thus, understanding the nature and underlying drivers of land-cover dynamics related to China's tree-cover increase, and, in particular, differentiating between tree plantations and native forests, are key to understanding the environmental implications of China's increase in tree cover and to designing effective policies to maximize its ecological benefits.

In this study, we aim to understand the nature and drivers of land-cover dynamics involved in the increase in tree cover in southwestern China between 2000-2015, a region that, according to China's state forest inventory and numerous remote-sensing studies, has undergone significant tree-cover increase during this period (Xu et al., 2006). We combine remote-sensing analysis and household interviews to ask two key questions. First, what is the nature of land-cover dynamics involved in the region's increase in tree cover, i.e., what vegetation type(s) provided the land for the increase in tree cover, and what proportion of the increase is due to tree plantations versus native forests? Second, what social and economic factors drove the land-use choice pertaining to tree cover in the region? Our goal is to provide recommendations to ensure that China's forest policies maximize the ecological benefits that can be obtained through forest recovery, including biodiversity conservation. This need is particularly salient considering China's heavy expenditures on forest protection and reforestation (Liu et al., 2008; Robbins and Harrell, 2014). Additionally, China's experience could also be informative to other developing countries, as they grapple with the challenges of recovering their forest landscapes (Hosonuma et al., 2012; Wilson et al., 2017).

Study region

We focused on a region of ~15,800 km^2 in south-central Sichuan Province in the transition zone from the western Sichuan Basin to the Hengduan mountain range (Fig. 1). The study region spans an east-to-west elevation gradient of 300-5,000 m with an accompanying gentle-to-steep topographical gradient. The area below treeline was historically forested but suffered deforestation throughout the region's long human settlement history, which continued well into the late 1990s (Elvin, 2004; Liu and Tian 2010). According to China's state forest inventory and numerous remote-sensing studies, it has more recently witnessed substantial tree-cover increase since the late 1990s (SFA, 1999-2014; Liu et al., 2014; Li et al., 2017).

Importantly, the region has been part of China's two largest forest programs: the NFPP, aimed at protecting and regenerating native forests (Ren et al., 2015), and the Grain-for-Green Program (GFGP), aimed at curbing soil erosion via compensated retirement of sloped croplands followed by reforestation (Delang and Yuan, 2015). The NFPP was introduced in 1998 and has been responsible for ~$19 billion in expenditures nationwide through 2010 (Ren et al., 2015). The GFGP was introduced in 1999 and has expended ~$47 billion nationwide through 2013 (Hua et al., 2016); it has been the single largest reforestation scheme in the study region over the past two decades. Both programs are ongoing and are expected to last until at least 2020 (NDRC, 2014; SFA, 2011). Official statistics for the region claim that the two programs have substantially curbed tree-cover loss and contributed to tree-cover regrowth from 2000-2015 (SFA, 1999-2014; Ren et al., 2015). On the other hand, considerable loss of native forests in the region has also been anecdotally reported for the same period (Greenpeace East Asia, 2013-2015).

Our previous fieldwork in the region identified four dominant types of tree cover re-established under the GFGP, all of which qualify as tree plantations but are not necessarily of native species: monocultures of (1) Eucalyptus, (2) bamboo, (3) Japanese cedar, and compositionally simple (4) mixed plantations consisting of two to five tree species (Hua et al., 2016). Monoculture plantations are created when multiple households plant the same tree species in small, neighboring parcels, while mixed plantations are typically created by households planting different tree species in neighboring parcels (although around a quarter of mixed plantation stands are *bona fide*, individual-level mixtures). GFGP incentives do not differ between monoculture and mixed plantations (Delang and Wang, 2015), thus should not influence households' land-use decisions pertaining to plantation type under GFGP. Importantly, and consistent with what is known about biodiversity in plantations in other parts of the world (Brockerhoff et al., 2008; Paquette and Messier, 2010), our previous study found that both plantation types (monoculture and mixed) fall short of the biodiversity levels associated with native forests, although mixed plantations are associated with greater biodiversity than monoculture plantations (Hua et al., 2016).

We combined remote-sensing analysis with household interviews to understand tree-cover dynamics in this region, separating tree plantations from native forests. To understand the nature of land-cover change during the study period, we conducted satellite imagery analysis to classify land cover, including multiple tree-cover and non-tree-cover types. To understand the drivers of the observed land-cover change, we conducted spatially explicit analyses to assess the role of biophysical factors in explaining land-cover change at the level of remote-sensing image pixels, and we used semi-structured household interviews to quantify household decisions regarding land use and their underlying reasons. Importantly, for this latter part of the study, we restricted our analysis to three separate aspects of tree-cover change: native forest loss, native forest regrowth via natural regeneration on land that had previously been cleared of tree cover (hereafter "natural regeneration"), and tree-plantation establishment under GFGP reforestation. We additionally focused on household decision-making in analyzing drivers of tree-cover change, thus treating households as direct agents of land-use change, although their decision-making may also reflect underlying government policies.

Methods

Remote-sensing analysis of land-cover change

To quantify land-cover change, we classified land cover on four, 30-m-resolution Landsat images, two from 2000 and two from 2015 (https://earthexplorer.usgs.gov/). We used a ground-truth dataset to classify land cover into five classes that differ considerably in their biodiversity profiles according to our previous study (Hua et al., 2016): native forest, monoculture plantation (Eucalyptus, bamboo, or Japanese cedar; they were first classified separately and subsequently pooled), mixed plantation, cropland, and other land cover (Table 1). Our ground-truth dataset included a sub-dataset from field surveys in 2015 and another sub-dataset created from visual interpretation of randomly sampled, high-resolution Google Earth images from 2016 (https://www.google.com/earth/); altogether, our dataset covered >2000 pixels for each land-cover class in each image (Fig. 1; Supplementary Information). We set aside a random collection of 100 pixels for each land-cover class to form a validation dataset, and used the remaining pixels as the training dataset. Two assumptions underlay our remote-sensing analysis. First, the ground-truth dataset can be applied to images from both 2000 and 2015. Second, native forest, monoculture, and mixed plantations together covered the spectrum of the region's tree-cover types during the study period. These assumptions were based on our field knowledge that the region's non-forest tree cover during the study period was dominated by the plantation types used under GFGP; any potential violation of these assumptions was addressed by classification accuracy assessments and discussion of their caveats.

We conducted supervised image classification using the *randomForest* 4.6.10 package (Breiman, 2001; Liaw and Wiener, 2002) in *R* 3.4.0 (R Core Team, 2017)). After classification, we merged groups of contiguous pixels into patches using an eight-neighbor rule and merged isolated, small patches (<6 pixels or 0.5 ha) into the largest of their neighboring patches of different land-cover classes. We thus created a single thematic land-cover map for 2000 and again for 2015, which we overlaid to classify, for each pixel, the conversion of land-cover class between 2000-2015. Using an area-weighted error matrix generated by the validation dataset (Olofsson et al., 2014), we assessed the accuracy of our land-cover classification (Table 2), based on which we further assessed the classification accuracy of land-cover conversion using a sampling-based simulation approach (Table 3). Full details of our remote-sensing analysis and accuracy assessments are provided in the Supplementary Information.

Biophysical attributes as explanatory variables of land-cover change

We assessed the role of profitability (i.e. economic returns) for agricultural or forestry production, represented by a suite of biophysical attributes scored at the level of each pixel in our remote-sensing images, in explaining the three focal aspects of tree-cover change in the region. Profitability largely drives household decisions about land use for agricultural or forestry production (Busch and Ferretti-Gallon, 2017; Geist and Lambin, 2002; Lambin et al., 2001). As such, it determines not only whether a particular parcel of land is used for cropland or tree cover, but also whether it is left alone and allowed to undergo natural regeneration (Garcia-Barrios et al., 2009; Chazdon and Guariguata, 2016). Indeed, natural regeneration has been found to mostly occur on marginal land not deemed profitable for agricultural or forestry production (Asner et al. 2009; Uriarte and Chazdon 2016). And, of course, government policies also play a major role in determining what happens on a given pixel of land in China's top-down forest governance structure (Xu et al., 2006; Hua et al., in press). We tried to obtain government documentation on where NFPP and GFGP had been implemented in the region but were refused access. We were thus unable to include this information in our analysis.

The biophysical attributes we considered as indicative of profitability for agricultural or forestry production included (1) the slope of each pixel (in degrees) as a proxy for the difficulty, and thus cost, of agricultural/forestry production, (2) the proximity of each pixel to the nearest paved road (in km) as a proxy for the difficulty, and thus cost, of transportation, and (3) the proximity of each pixel to the nearest township (the smallest urban administrative unit in China; in km) as a proxy for market access (de Rezende et al., 2015). For natural regeneration, we also considered the proximity of pixels to the nearest pixel that was classified as native forest in 2000 ("distance to the nearest native forest"; in km) as a proxy for the distance to, and thus availability of, propagule sources of native trees, a key determinant of the speed and trajectory of natural regeneration (Arroyo-Rodriguez et al., 2015; Sloan et al., 2016). We did not include elevation because of its strong collinearity with one or more of the above attributes (Pearson's correlation coefficient ≥0.65; Table S1 in Supplementary Information). Slope data were obtained from the Global Digital Elevation Model 2 (gdem.ersdac.jspacesystems.or.jp/DEM), and the shapefiles of paved roads and townships were obtained from the 1:250,000 digitized map of China published by the National Geomatics Center of China that covers the period between 1980-1997 (NGCC, 2006; Wang, 2011).

Household interviews for household choices and attitudes

We conducted household interviews to assess households' choices, attitudes, and underlying reasons pertaining to tree-cover change, again treating households as key agents of land-cover dynamics. Our interviews focused on households that participated in the GFGP. Because we had previously determined in a pilot study that households commonly cleared native forests during the study period (FH unpublished data), we anticipated that GFGP households would also be able to provide information on drivers of native forest loss.

In July 2015, we interviewed 166 households (≥35 households for each GFGP plantation type). Interviews were conducted with household heads, lasted 30-40 minutes each, and used a combination of multiple-choice and open-ended questions. In villages around large expanses of the four major GFGP plantation types, we randomly selected households with the constraints that (1) the household head was available for an interview and able to provide clear answers to interview questions, (2) no more than three households were from the same village, and (3) households from a given village covered a spectrum of landholding size and socioeconomic status. We asked each household why they chose a particular plantation type, their attitudes toward a hypothetical alternative tree-cover type known to deliver better environmental benefits, and whether they had cleared native forests during the study period and their motivations for doing or not doing so (see Table S2 in Supplementary Information for details). For all multiple-choice questions pertaining to reasons, perceptions, and attitudes, we allowed respondents to give multiple answers. All required permits for household interviews were obtained from the IRB (Institutional Review Board) of Princeton University, and all respondents gave informed consent before the interviews.

Statistical analysis for drivers of tree-cover change

We analyzed the drivers of native forest loss between 2000-2015 by testing the statistical relationship between native forest loss and biophysical attributes at the pixel level, using a multinomial logistic regression. We considered a pixel to have undergone native forest loss if its classification status changed from native forest in 2000 to any of the other land-cover classes in 2015. Therefore, for this analysis, we focused on pixels that were classified as native forest in 2000, and we differentiated among four outcomes of classification status in 2015 for these pixels: (1) non-tree land cover (including cropland and other land cover), (2) monoculture plantation, (3) mixed plantation, and (4) the maintenance of pixel status as native forest in both 2000 and 2015. We further supplemented the statistical analysis with information on households' reasons for clearing or retaining native forests obtained from household interviews (Table S2 in Supplementary Information).

We analyzed the drivers of natural regeneration between 2000-2015 by testing the statistical relationship between natural regeneration and biophysical attributes at the pixel level, using a binomial logistic regression. We considered a pixel to have undergone natural regeneration if its classification status changed from non-tree cover in 2000 to native forest in 2015. Therefore, for this analysis, we focused on pixels that were classified as non-tree cover (i.e. cropland or other land cover) in 2000, and we differentiated between the Yes or No outcome with regard to natural regeneration based on pixels' classification status in 2015: (1) Yes, i.e. the pixel having undergone natural regeneration, represented by the change of pixel classification status from non-tree cover in 2000 to native forest in 2015, and (2) No, i.e. the pixel not having undergone natural regeneration, represented by the pixel maintaining the non-tree-cover status in both 2000 and 2015, or changing from the non-tree-cover status into any plantation type in 2015.

The biophysical attributes included in the statistical analyses were not strongly collinear (Pearson's correlation coefficient <0.65; Table S1 in Supplementary Information). Prior to analyses, we conducted subsampling to generate 1,000 sub-datasets for the multinomial logistic regression and binomial logistic regression, respectively, to minimize data skewness toward non-change in the response variable and spatial autocorrelation. Specifically, each sub-dataset comprised 500 pixels for each outcome of response variable, and all pixels were spaced ≥1 km apart. Thus, each sub-dataset consisted of 2,000 pixels for the multinomial logistic regression, and 1,000 pixels for the binomial logistic regression. We conducted regression analyses on each sub-dataset, based on which we calculated the mean and 95% confidence interval for the effects of each predictor variable. All regression analyses were carried out in *R* 3.3.3 (R Development Core Team 2017) with packages *rgdal* 1.2-7 (Bivand et al., 2017) and *nnet* 7.3-12 (Ripley and Venables, 2011).

For tree plantation establishment under GFGP reforestation, we focused on understanding the drivers of households' choices of specific plantation types, which should predominantly be the outcome of household decisions (Delang and Yuan, 2015); our analysis relied exclusively on household responses. By contrast, whether or not a household's landholding was reforested under GFGP should be determined by government policy based in part on land biophysical attributes such as slope (Delang and Yuan, 2015); our study did not concern this aspect. For all interview questions, we tallied the percentage of responses for each answer out of the total pool of valid questionnaires as a measure of the importance of the choices/attitudes/reasons represented by the answers. We did not apply statistical analysis because of the large numbers of possible answers relative to the limited sample sizes for most questions.

Results

Nature of tree-cover increase in south-central Sichuan in 2000-2015

Between 2000-2015, the region's total tree cover – including native forests and tree plantations – increased by 32% (1,935 km^2), equivalent to 12.2% of the region's land area (Figs. 2a, 2b; Table 2). However, the region's native forests decreased by 6.6% (138 km^2) during this same period, equivalent to 0.9% of the region's land area (Figs 2a, 2b; Table 2). Thus, the net tree-cover increase of the region was entirely accounted for by tree plantations. Correspondingly, the dominant form of land-cover change in the study region during this period was conversion of croplands to monoculture plantations (Fig. 2c). In all, the region's cropland area decreased by 23.5% (2,014 km^2), equivalent to 12.7% of the region's area (Figs. 2a, 2b; Table 2). Of the cropland area lost, 56.3% was converted to monoculture plantations, 36.1% to mixed plantations, and only 1.8% was allowed to regenerate as native forests (Fig. 2c). Accuracy assessments for the classification of land cover and land-cover conversion between 2000-2015 suggested reasonable performances (Tables 2, 3).

Household interview data supported the above patterns of tree-cover dynamics. Thirty-seven out of 82 respondent households (45.1%) indicated that they had converted native forests on their landholdings since GFGP started in the region in 1999. An additional 13 households indicated that they had converted "scrubland" – likely a highly degraded form of native forests (Harkness, 1998) – on their landholdings since 1999 (scrubland was most likely classified as "Other land cover" in our remote-sensing analysis; Table 1). All households that reported clearing native forests or scrublands indicated that they replaced them with monoculture or mixed plantations.

Drivers of native forest loss

Multinomial logistic regression suggested that the biophysical attributes we included in our analyses played a significant role in explaining the patterns of native forest loss in the region between 2000-2015 (Fig. 3a). Native forests on steeper slopes were less likely to be converted to non-tree cover. Native forests closer to paved roads and townships were more likely to be converted to tree plantations. These two relationships suggest that profitability for agricultural or forestry production was likely an important driver of native forest loss.

Household interview data corroborated the above findings (Figs 3b-3c). The pursuit of greater profits and government encouragement/mobilization (as perceived by the household. Anecdotes from our interactions with respondent households suggest that "government encouragement/mobilization" in our study context entailed a range of formats, from government laying out regulations for households to follow, to government providing monetary or logistical incentives, such as organizing communities to conduct land cover conversion, or providing free seeds/seedlings for tree planting; this clarification applies to "government encouragement/mobilization" used below in the article) were the two most commonly cited factors for households to convert native forests: they were cited by 49.0% and 25.5% of the 51 responding households that reported converting native forests, respectively (Fig. 3b; percentages do not sum up to 100% because respondents could select more than one factor). Community influence (i.e. conforming to the land-use decisions of other households in the community; 7.8%) and biophysical suitability (i.e. land parcels' biophysical conditions perceived to be suitable for a given replacement land cover; 5.9%) were also cited as relevant factors (Fig. 3b). Of the 30 respondent households that did not convert native forests, a lack of labor and/or finance (30%), a lack of government encouragement/mobilization (26.7%), and a lack of interest in initiating the management of the forest land involved (26.7%) were the three most commonly cited reasons (Fig. 3c). Community influence (10%) was also cited as a relevant but less important factor (Fig. 3c).

Drivers of natural regeneration

Binomial logistic regression suggested significant roles for the biophysical attributes we included in our analyses in explaining natural regeneration in the study region between 2000-2015 (Fig. 4).

Treeless land on steeper slopes, farther from townships and closer to native forests was more likely to undergo natural regeneration (Fig. 4). These results suggest that two important drivers of natural regeneration in the region were the lack of profitability for agricultural or forestry production, and proximity to native forest (hence, proximity to plant propagule sources).

Drivers of plantation choice under GFGP reforestation

Household interviews revealed that the pursuit of higher profits as well as government encouragement/mobilization were the two most important factors underlying households' choice of plantation type under GFGP reforestation (Figs. 5a-5b). Of the households planting monocultures, 43.2% and 41.9% pointed to profit incentives and government encouragement/mobilization as drivers of their choice of plantation type, respectively (Fig. 5a). Similarly, 37.6% and 35.3% of households planting mixed plantations indicated that profit incentives and government encouragement/mobilization drove their choice, respectively (Fig. 5b). Other factors cited as driving household choice of plantation type included biophysical suitability (20.3% and 23.5%, respectively for monoculture and mixed plantation households), community influence (9.5% and 15.3%), and the cost of maintenance (5.4% and 9.4%; Figs. 5a-5b).

Regarding the conditions under which households would be willing to switch to a hypothetical alternative tree-cover type known to deliver greater environmental benefits, respondent households most often cited two conditions: (1) forestry production profits must not be lower, and (2) any cost associated with switching to the alternative tree-cover type must not be paid by themselves (Fig. 5c). These two conditions were cited by 56.3% and 26.8% of the 142 households, respectively. Maintenance cost was cited as the next most important condition, with 12.7% of households indicating they would be willing to switch if maintenance costs were no higher than before. Notably, among the additional factors also cited as relevant (Fig. 5c), 6.3% of households indicated that they would be willing to switch if other households in their communities did the same, again pointing to a small but non-negligible role of community influence on land-use decisions. Finally, 3.5% of households indicated they would be willing to switch unconditionally, whereas 7.7% of households indicated they would not be willing to switch under any circumstances (Fig. 5c).

Discussion

Our remote-sensing analysis highlighted two dominant features of land-cover change related to tree cover in southwestern China between 2000-2015. First, the gross tree cover – native forests and all types of tree plantations combined – experienced a substantial net increase in both percentage and absolute area (Fig. 2a, 2b). Second, this increase was entirely accounted for by cropland conversion to tree plantations, particularly monocultures. In contrast, native forests suffered a net loss (Fig. 2c). Spatially explicit analyses of biophysical attributes representing land production profitability, along with household interviews, revealed that the two dominant drivers of land-cover change were (1) the pursuit of profits from agricultural/forestry production (including the aversion of management costs), and (2) government encouragement/mobilization for particular land uses (Figs. 3-5). Household interviews also suggested that, to some degree, households tended to conform to the land-use decisions of other households in the community (Figs. 3b, 3c, and 5), and that the lack of labor and/or financial resources was a primary constraint on households converting native forests to other land-use types (Fig. 3c).

The growth of plantations in conjunction with the loss of native forests means that, far from setting the region's forest landscape on a trajectory of recovery with concomitant benefits for biodiversity and other ecosystem services, the region's tree-cover increase has, in effect, displaced native forests. Native forests were not only directly lost via conversion to tree plantations and other uses, but were also indirectly lost when land freed up from agriculture was converted to tree plantations instead of being allowed to naturally regenerate into native forests. Tree plantations differ vastly from native forests in their capacity to support biodiversity and other ecological functions/services (Brockerhoff et al., 2008; Felton et al., 2010; Gamfeldt et al., 2013; Hulvey et al., 2013; Liao et al., 2010; in this region: Hua et al., 2016). The cryptic displacement of native forests amid increasing tree cover in our study region and other regions (Zhai et al., 2014; Heilmayr et al., 2016) thus highlights the risk of misguided environmental assessment and policy-making, when these efforts fail to discriminate between native forests and plantations, and in general, (mis)use a loosely defined "forest cover" – i.e. tree cover – as the simple metric of environmental benefits (Ahrends et al., 2017; Chazdon et al., 2016; Wilson et al., 2017). This risk is particularly salient given the magnitude of environmental dividends that could be achieved in China and globally under a bona fide commitment to the recovery of native forests (Suding et al., 2015; Chazdon et al., 2017). Notwithstanding the legitimacy and, indeed, necessity of establishing and maintaining tree plantations and integrating them into land-use planning (Paquette and Messier, 2009; Pirard et al., 2016), policies aimed at reaping the environmental benefits of forest recovery must avoid jeopardizing native forests with the use of muddled concepts and criteria.

An issue highly relevant to the benefits and costs of forest recovery that has been grossly neglected in China's policies thus far is the potential utility of natural regeneration as a means to achieve forest recovery. This issue is illustrated by our finding that the vast majority of former cropland lost from our study region between 2000-2015 was taken up by tree plantations, particularly monocultures, with < 2% undergoing natural regeneration (Fig. 2cs). China's recent policies on reforestation have placed disproportionate emphasis on active tree planting and have almost completely disregarded natural regeneration, except for in the limited context concerning degraded, but still standing, forests (SFA 1999-2014). Because of this policy bias, even regions for which natural regeneration might have been a highly effective, economical means to achieve forest recovery (Lamb 2014; Chazdon and Uriarte, 2016) have undertaken active tree planting programs (often resulting in biologically depauperate plantations) at considerable expense. The extensively studied region around the Wolong Nature Reserve provides a case in point: Despite its ideal biophysical (i.e. it borders large expanses of native forests), political (i.e. political will exists to reforest the region), and socioeconomic (i.e. rural households have access to financial compensation for reforestation, and the region is undergoing rural depopulation and shifting to non-farm incomes) conditions for natural regeneration (Chazdon and Guariguata, 2016), government-sponsored reforestation has exclusively entailed planting, at great expense, simple stands of mostly conifer trees, in contrast to the broadleaf mixed forests actually native to the region (Chen et al., 2009; FH and BF, personal observations). The rejection of natural regeneration effectively results in a lose-lose situation in terms of environmental benefits and logistical/monetary costs. We recommend that forest policies in China and other countries follow available scientific guidance (Chazdon and Guariguata, 2016; Meli et al., 2017) and successful examples (e.g. de Rezende et al., 2015) to incorporate natural regeneration more formally as a legitimate means of forest recovery where feasible and appropriate.

In addition to identifying the pursuit of profit (and thus economic opportunities) as a key driver of tree-cover change, as has been widely reported by other studies across the world (Busch and Ferretti-Gallon, 2017; Geist and Lambin, 2002; Lambin et al., 2001; Munteanu et al., 2014; Qasim et al., 2013; Silva et al., 2016; Waiswa et al., 2015), our study also highlights a number of less well known drivers. First, government encouragement/mobilization was consistently noted to be highly and directly influential on household decisions regarding native forest clearance and reforestation (Figs. 3b, 3c, 5a, 5b). Given the reputation of China's top-down forest governance for effective policy implementation (Xu et al., 2006), this strong governmental influence is perhaps expected. Nonetheless, the fact that China's contemporary forest policies – ostensibly guided by the goal of safeguarding and improving forests' ecological conditions, functions, and benefits (Xu et al., 2006; Yin and Yin, 2010) – fostered land-use behaviors that compromised native forests or failed to realize the ecological gains achievable under reforestation (Hua et al., 2016), highlights major pitfalls in their design and implementation. Policy makers should follow scientific advice to rectify these pitfalls (Hua et al., in press).

Second, when it comes to decisions regarding reforestation or tree planting, landholders are influenced by what their neighbors do, thereby demonstrating the importance of community norms in driving larger-scale patterns of land-use change. This finding echoes the results of a suite of studies of social norms and environmental decision-making under different contexts (Byerly et al., in press). Invoking and in some cases changing social norms have led to significant changes in behavior, including, for example, reductions in urban household water use in the United States (Ferraro and Price, 2013) and increased willingness of farmers to engage in conservation practices, also in the United States (Messer et al., 2016). Within China, social norms have been linked to increased likelihood of households re-enrolling in GFGP in a study site adjacent to our study region (Chen et al., 2009). Given the importance of household-level decisions on wider biodiversity values in our study region (Hua et al., 2016), utilizing social norms as a mechanism to guide decisions at the regional scale could deliver appreciable environmental benefits.

Third, the most important reason given by households in our study region for *not* clearing more native forests was the lack of labor and/or financial resources, suggesting that at least up until the time of our household interviews, households had both the desire and legal right to clear native forests but were hindered from doing so by economic obstacles. The absence of more durable safeguards to further deforestation underscores the vulnerability of the region's remaining native forests (Hua et al., in press). In recent years, the Chinese government has been actively encouraging the production-oriented leasing of rural land to outside enterprises (referred to as "land circulation (土地流转)" in China; Bosi Data, 2014; Zhai et al., 2014), making way for large-scale agro-/forestry businesses. Operating on completely different scales than smallholders, these enterprises have the resources and motivation to prepare large areas of land for crop or timber production. Moreover, as urbanization and rural economic transformation continue to enrich rural households, more households will have the resources they need to clear forests. China, therefore, faces the prospect of escalating losses of native forests unless it enacts policies targeted at their protection.

Three caveats associated with our remote sensing-based analysis should be noted. First, our land-cover classification assumed that the tree-cover types included in our classification scheme represented the range of tree-cover types in the study region during the study period, an assumption that may be incorrect for parts of the region not covered by field visits. Second, the relatively small proportion of the region for which we have field-based, ground-truth data likely reduced the quality of land-cover classification for those parts of the region not covered by field visits. Considering that accuracy assessments of remote-sensing analysis showed reasonable performances (Tables 2-3), these caveats would be problematic only if there were major expanses of tree-cover types not included in our classification scheme. This concern is lessened at least to some extent by the fact that the mixed plantations in our classification scheme covered a wide range of compositional characteristics (Table 1), which may enable other simple mixed tree plantations to be classified correctly. Together with the expected, correct classification of native forests, this should allow the remaining tree-cover types – the only possibility being monoculture plantations – to also be correctly classified. Finally, our statistical analysis of biophysical attributes directly used pixels' conversion status obtained from remote-sensing analysis as the response variable, in effect ignoring the uncertainty of land-cover classification. Given the differential errors of different conversion classes, this may have biased the conclusions of our statistical analyses in unknown ways. This bias is unlikely to be substantial considering the relatively small percentage of pixels incorrectly classified (Table 3); still, the relationship we found between land pixels' biophysical attributes and land conversion status should be taken with this caveat in mind.

Our findings provide several insights on how policies could be steered to achieve better biodiversity gains for the region from its tree-cover dynamics. First, the Chinese government needs to devise more robust mechanisms to facilitate native forest recovery. While China's most recent forest policies have begun to emphasize the protection of existing native forests, they still lack concrete measures to achieve this goal (Hua et al., in press). More critically, China must develop mechanisms to facilitate the restoration of native forests, which to date have been largely neglected in the country's forest policies (Hua et al., in press), and encourage natural regeneration as a means of restoring forests (Chazdon and Guariguata, 2016). Second, social factors operating at the household level should be harnessed to promote better land-cover, biodiversity, and other environmental outcomes. These include, most notably, households' strong emphasis on profitability in their land-use decision-making, and their desire to conform to community norms with respect to land use. The importance that households give to profitability when making land-use decisions highlights the need for adequate compensation to these households for any foregone opportunity costs associated with protecting and restoring native forests (Jayachandran et al., 2017; Mohebalian and Aguilar, 2018). Unfortunately, compensation standards in many of China's current forest protection/restoration programs are too low to compete against the foregone opportunity costs of alternative land uses, such as plantations or farming (Hua et al., in press). The tendency of households to do what their neighbors do points to the potential of social marketing to encourage land-use decisions that will result in more biodiversity and other ecological benefits (Nyborg et al., 2016). Finally, within the remit of production-oriented tree plantations, in light of the accumulating evidence of the economic competitiveness and greater biodiversity benefits of mixed plantations compared with monocultures (Paquette and Messier 2010; Wilson et al., 2017; in the study region: Hua et al., 2016), the above-noted policy and social mechanisms should be mobilized to also encourage a shift away from monocultures toward mixed plantations, in places where the restoration of native forest is not feasible.

Worldwide, rural emigration is creating historic opportunities for large-scale forest recovery on former agricultural lands (Chazdon and Guariguata, 2016; Meyfroidt and Lambin, 2011). This process is further encouraged by a growing list of global and regional initiatives aimed at cashing in on the environmental promises of forest recovery (Suding et al., 2015). In some circumstances, the desire to increase tree cover without differentiating between tree plantations and native forests has caused perverse consequences for biodiversity and other environmental functions/services (Brancalion and Chazdon, 2017; Lindenmayer et al., 2012b). With forest recovery gaining momentum globally, care must be taken to design policies and strategies that can achieve a fuller range of desired benefits, with particular emphasis on the recovery of native ecosystems (Chazdon et al., 2017; Mansourian et al., 2017; Suding et al., 2015).

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Tables

Table 1. Classification scheme for remote-sensing analysis of land cover in the study region.

Land-cover class		Description
Native forest		• Broadleaf subtropical evergreen forest
Mixed plantation		• Simple mixed stands comprising up to five, mostly two to three tree species • Stands can be mixed at the level of individual trees or patches (i.e. comprising small patches of monocultures) • Stands at different locations tend to vary in tree species composition
Monoculture plantation	Eucalyptus	• Mostly of lowland (≤ 650 m) distribution
	Bamboo	• May involve multiple bamboo species; considered as monoculture because of the similar and consistently simple forest structure of the bamboo species involved • Mostly of mid-elevation (500-1,000 m) distribution
	Japanese cedar	• Mostly of high-elevation (≥ 1,000 m) distribution
Cropland		• Seasonally rotational rice, corn, and vegetables
Other land cover		• All other land-cover types not included in the cover classes above

	• Typically grassland, scrubland, open areas, waterbody, rocky/bare surfaces, urban areas, paved roads, etc.

Table 2. Land-cover mapping area and classification accuracies for 2000 and 2015. PA: producer's accuracy; UA: user's accuracy; OA: overall accuracy.

Land-cover class	2000				2015			
	Map area (km^2)	PA	UA	OA	Map area (km^2)	PA	UA	OA
Native forest	2,100.91	0.82	0.78	--	1,962.93	0.83	0.85	--
Mixed plantation	2,732.90	0.67	0.70	--	3,626.46	0.82	0.80	--
Monoculture plantation	1,221.28	0.63	0.80	--	2,400.48	0.79	0.85	--
Cropland	8,588.08	0.93	0.88	--	6,573.72	0.92	0.88	--
Others	1,170.93	0.74	0.80	--	1,250.50	0.77	0.87	--
Total	15,814.09	--	--	0.82	15,814.09	--	--	0.85

Table 3. Accuracy of classification for land-cover conversion between 2000-2015. Accuracy was assessed as 95% confidence intervals (CI) of (1) the % of pixels classified as the conversion in question that were classified correctly (% correctly classified), and (2) the % of all pixels of the study region that were of the conversion in question but failed to be identified as such (% of study region omitted).

Land-cover conversion		% of study region	% correctly classified		% of study region omitted	
From (2000)	To (2015)		Lower 95% CI	Upper 95% CI	Lower 95% CI	Upper 95% CI
Native forest	Native forest	9.77%	66.24%	66.36%	0.26%	0.27%
Native forest	Mixed plantation	2.01%	62.27%	62.53%	1.27%	1.28%
Native forest	Monoculture	0.53%	66.04%	66.58%	0.81%	0.82%
Native forest	Cropland	0.02%	67.46%	69.80%	1.36%	1.37%
Native forest	Others	0.95%	67.67%	68.04%	0.41%	0.42%
Mixed plantation	Native forest	1.56%	59.35%	59.66%	1.33%	1.34%
Mixed plantation	Mixed plantation	12.80%	55.94%	56.06%	0.95%	0.95%
Mixed plantation	Monoculture	0.86%	59.30%	59.71%	1.62%	1.63%
Mixed plantation	Cropland	1.52%	61.44%	61.75%	2.89%	2.90%
Mixed plantation	Others	0.53%	60.65%	61.16%	0.88%	0.88%
Monoculture	Native forest	2.43%	67.64%	68.38%	0.77%	0.78%
Monoculture	Mixed plantation	1.12%	63.82%	64.17%	1.49%	1.50%
Monoculture	Monoculture	4.87%	67.92%	68.08%	0.55%	0.56%
Monoculture	Cropland	1.14%	70.23%	70.57%	1.50%	1.51%
Monoculture	Others	0.35%	69.30%	69.92%	0.46%	0.47%
Others	Native forest	0.58%	67.74%	68.23%	0.44%	0.45%

Others	Mixed plantation	0.88%	63.80%	64.21%	0.89%	0.89%
Others	Monoculture	0.61%	67.78%	68.24%	0.51%	0.52%
Others	Cropland	1.45%	70.25%	70.55%	0.85%	0.86%
Others	Others	3.88%	69.51%	69.69%	0.18%	0.18%
Cropland	Native forest	0.25%	74.45%	75.15%	2.02%	2.03%
Cropland	Mixed plantation	6.12%	70.33%	70.48%	3.59%	3.60%
Cropland	Monoculture	8.30%	74.73%	74.86%	2.04%	2.05%
Cropland	Cropland	37.43%	77.41%	77.47%	1.26%	1.27%
Cropland	Others	2.20%	76.44%	76.67%	1.25%	1.25%

Figure legends

Figure 1. Map of the study region displaying distribution of ground-truth data points. Polygons with names are counties included in the study region.

Figure 2. Nature of tree-cover change in the study region between 2000-2015. (a) Thematic land-cover maps of the study region in 2000 and 2015. (b) The pattern of conversion among different land-cover classes between 2000-2015 based on the two thematic maps, shown by a circular plot. The plot consists of two concentric outer "wheels" and a set of inner "links". The wheels display the relative area of different land-cover classes in 2000 and 2015 with colored segments. Specifically, each segment (representing each land-cover class) on the inner wheel comprises a solid sub-segment and a blank sub-segment, whose lengths are proportional to the areas of the corresponding land-cover class in 2000 and 2015, respectively. The inner links display the conversion of land-cover class between 2000 and 2015, by connecting any pair of one "origin" land-cover class in 2000 (represented by a solid sub-segment on the inner wheel) with one "destination" land-cover class in 2015 (represented by a blank sub-segment on the inner wheel). Links are color-coded with the same color as that of the "origin" land-cover class, and their thickness at the base (i.e. where they abut the inner wheel) is proportional to the number of pixels involved in the corresponding conversion.

Figure 3. Drivers of native forest loss in the study region. (a) Role of biophysical attributes in explaining the probability – represented as its odds ratio on a log scale – of native forest conversion to three alternative land-cover classes on the pixel level. Results are based on multinomial logistic regression of 1,000 sub-sampled datasets. Error bars represent 95% confidence intervals; the absence of error bars for slope and distance to town is due to their extremely small confidence intervals. (b) The number of households that indicated different reasons for converting native forests to other land-cover types. (c) The number of households that indicated different reasons for not converting native forests. For (b) and (c), "n" on top of the figures indicates the number of households that returned valid questionnaires for the focal question; "government mobilization" is a shorthand for

“government encouragement/mobilization”; “biophysical conditions” mean that biophysical conditions were perceived to be suitable, or unsuitable, for the replacement land cover, respectively.

Figure 4. Drivers of natural regeneration in the study region, as shown by the role of biophysical attributes in explaining the probability – represented as its odds ratio on a log scale – of non-tree-cover converting to native forest on the pixel level. Results are based on binomial logistic regression of 1,000 sub-sampled datasets. Error bars represent 95% confidence intervals; the absence of error bars for slope and distance to town is due to their extremely small confidence intervals.

Figure 5. Drivers of tree plantation type choice in GFGP artificial reforestation. (a) The number of households planting monoculture plantations and (b) mixed plantations for GFGP reforestation that indicated different reasons or their choice of plantation types. (c) The number of households that indicated different conditions for their willingness to switch from the current plantation type to a hypothetical tree-cover type for environmental benefits. For all three panels, “n” on top of figures indicates the number of households that returned valid questionnaires for the focal question; “government mobilization” is a shorthand for “government encouragement/mobilization”; “biophysical conditions” mean that biophysical conditions were perceived to be suitable for the tree-cover type in question; “maintenance cost” means that the amount of maintenance cost made/would make it preferable to choose the tree-cover type in question.

Figures

Figure 1.

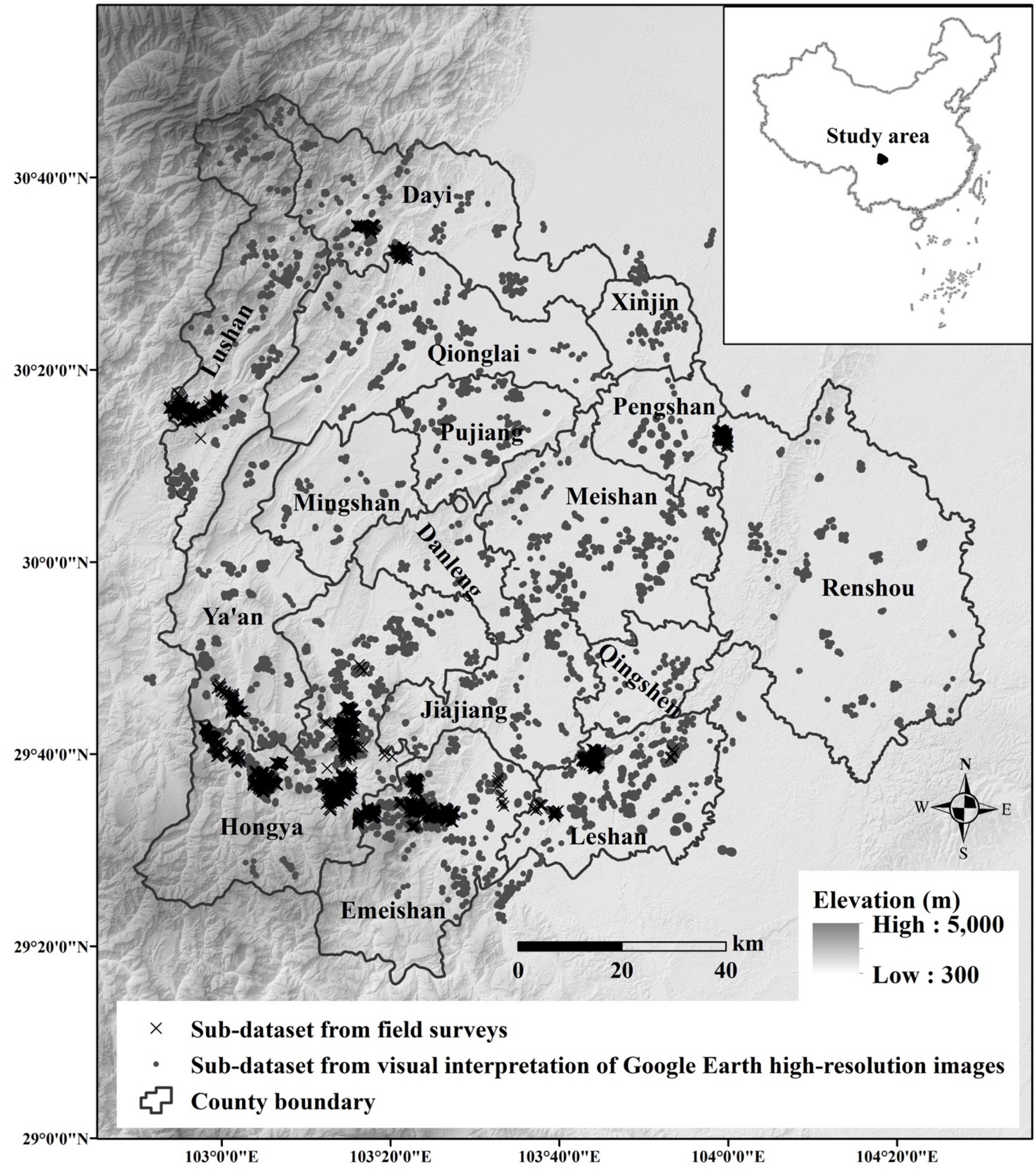
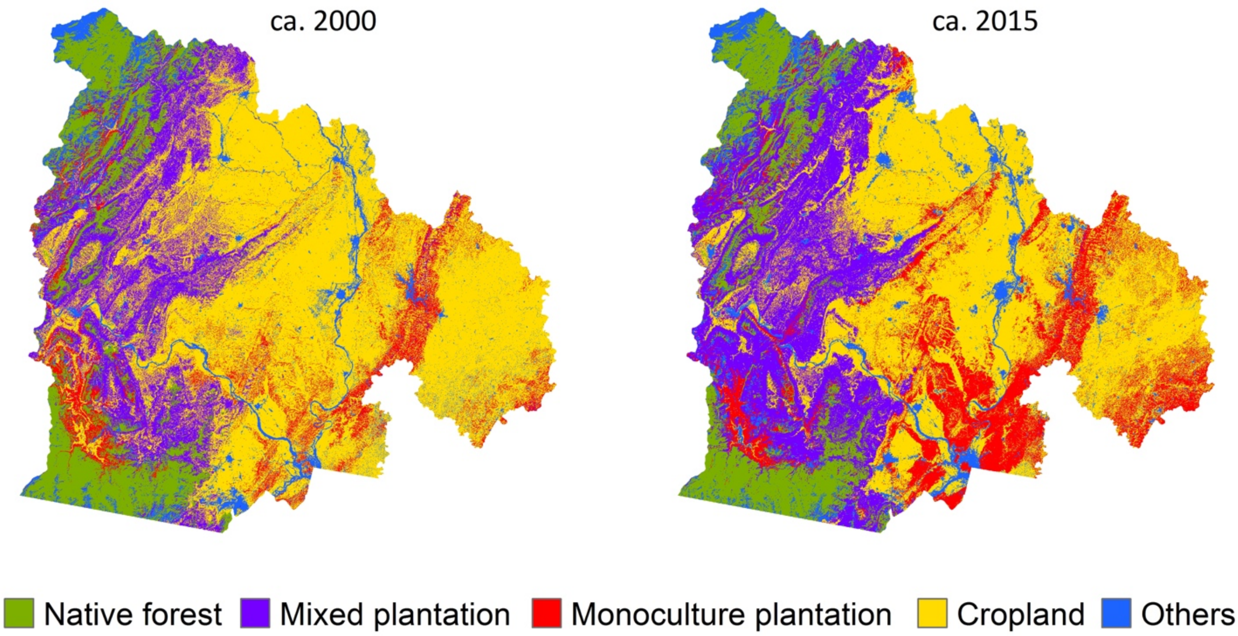


Figure 2.

a


ca. 2000
ca. 2015
Native forest
Mixed plantation
Monoculture plantation
Cropland
Others

b

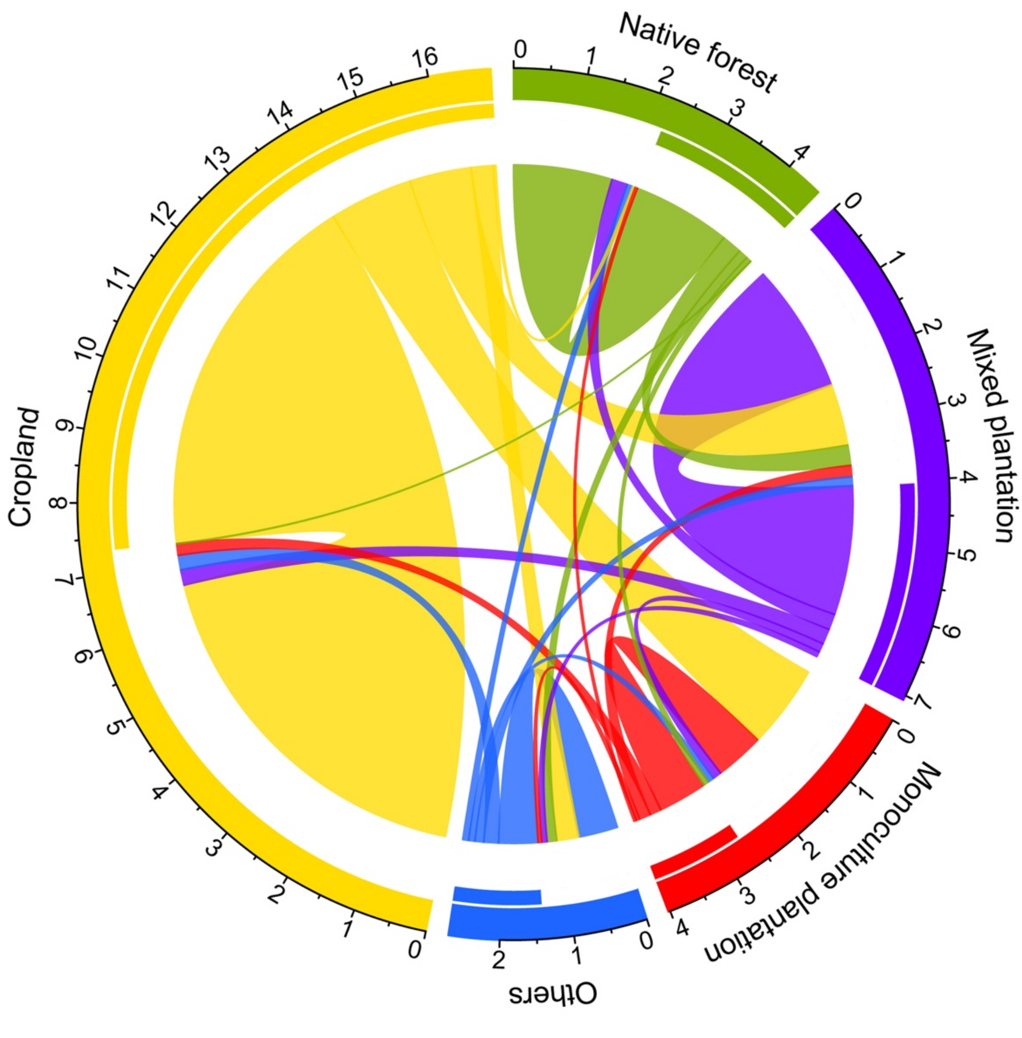

Native forest
Mixed plantation
Monoculture plantation
Others
Cropland

Figure 3.

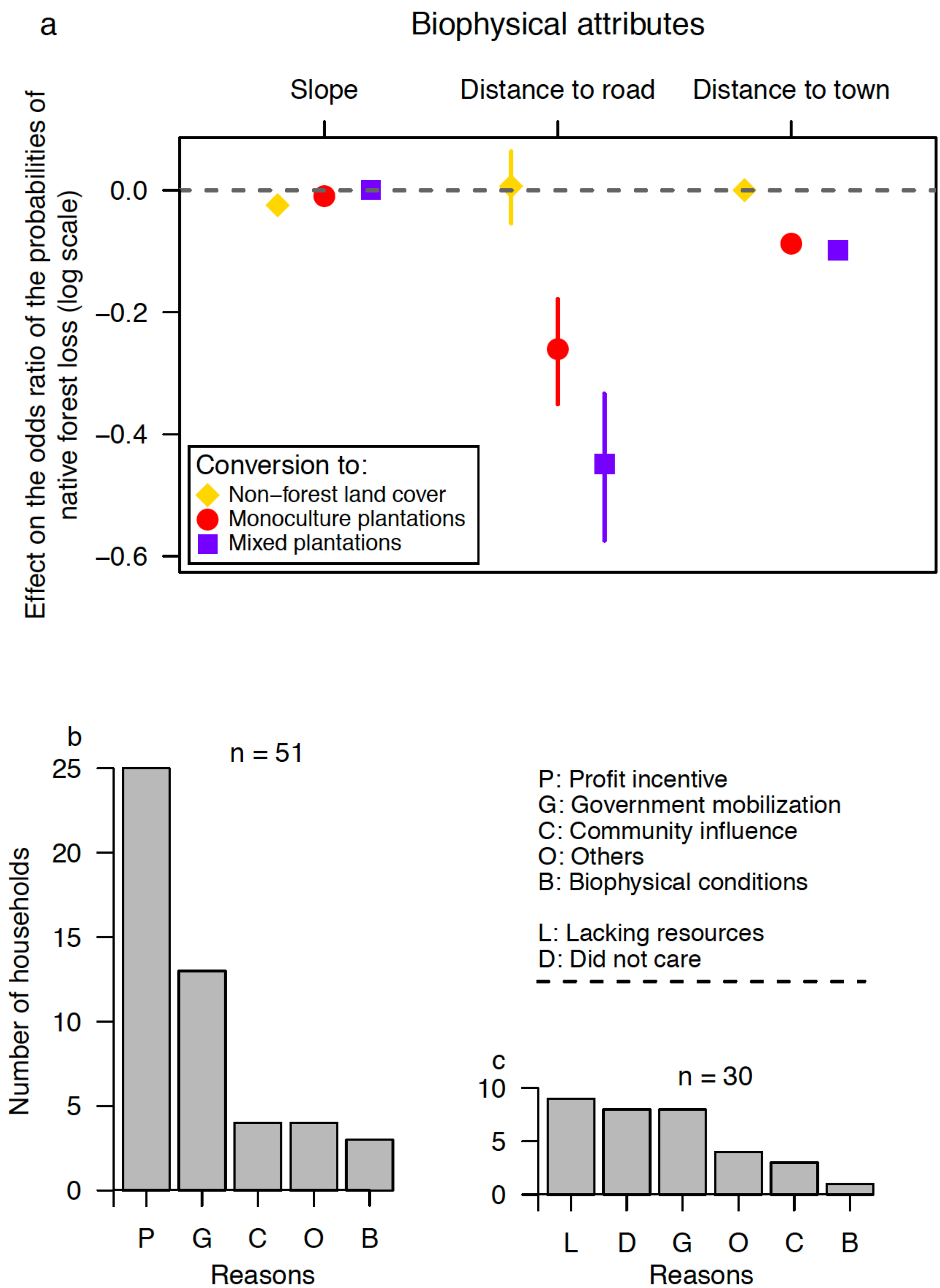

a
Biophysical attributes
Slope
Distance to road
Distance to town
Effect on the odds ratio of the probabilities of native forest loss (log scale)
0.0
−0.2
−0.4
−0.6
Conversion to:
Non−forest land cover
Monoculture plantations
Mixed plantations
b
n = 51
Number of households
25
20
15
10
5
0
P G C O B
Reasons
P: Profit incentive
G: Government mobilization
C: Community influence
O: Others
B: Biophysical conditions
L: Lacking resources
D: Did not care
c
n = 30
10
5
0
L D G O C B
Reasons

Figure 4.

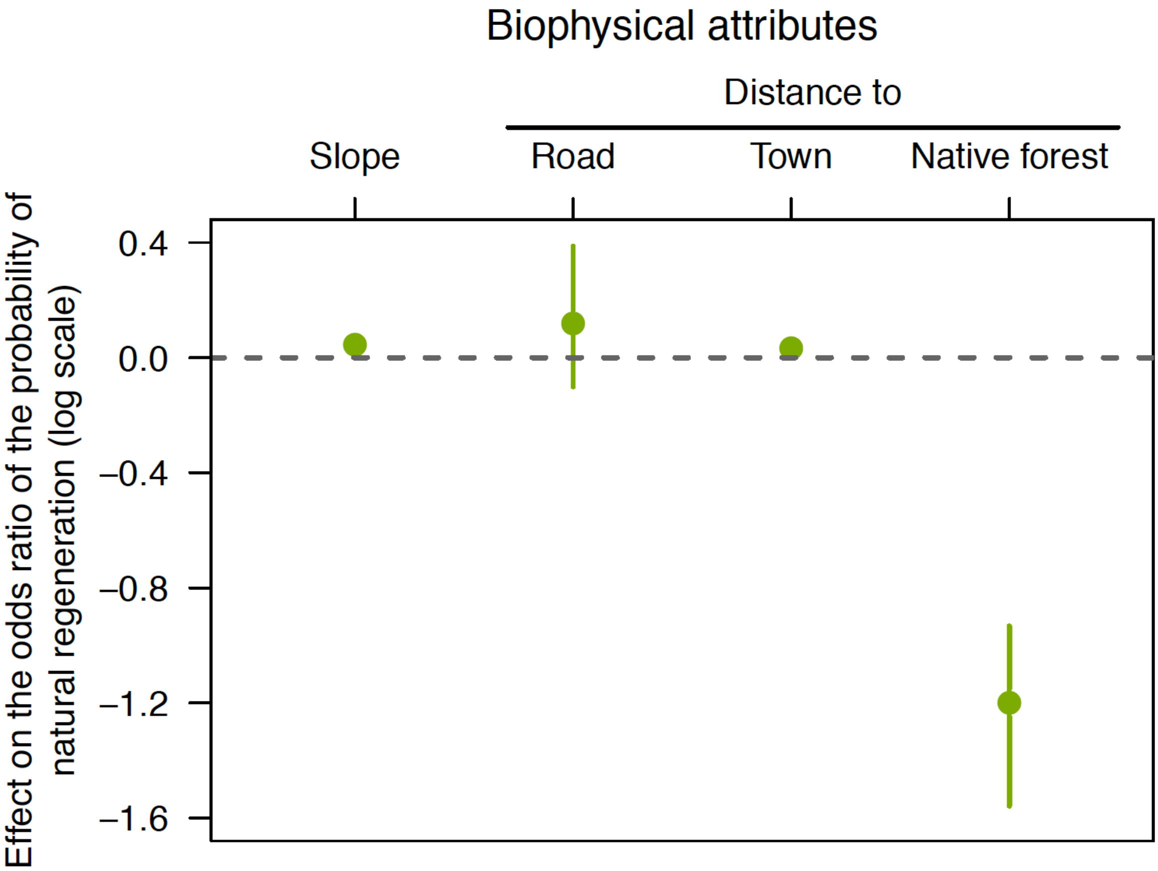
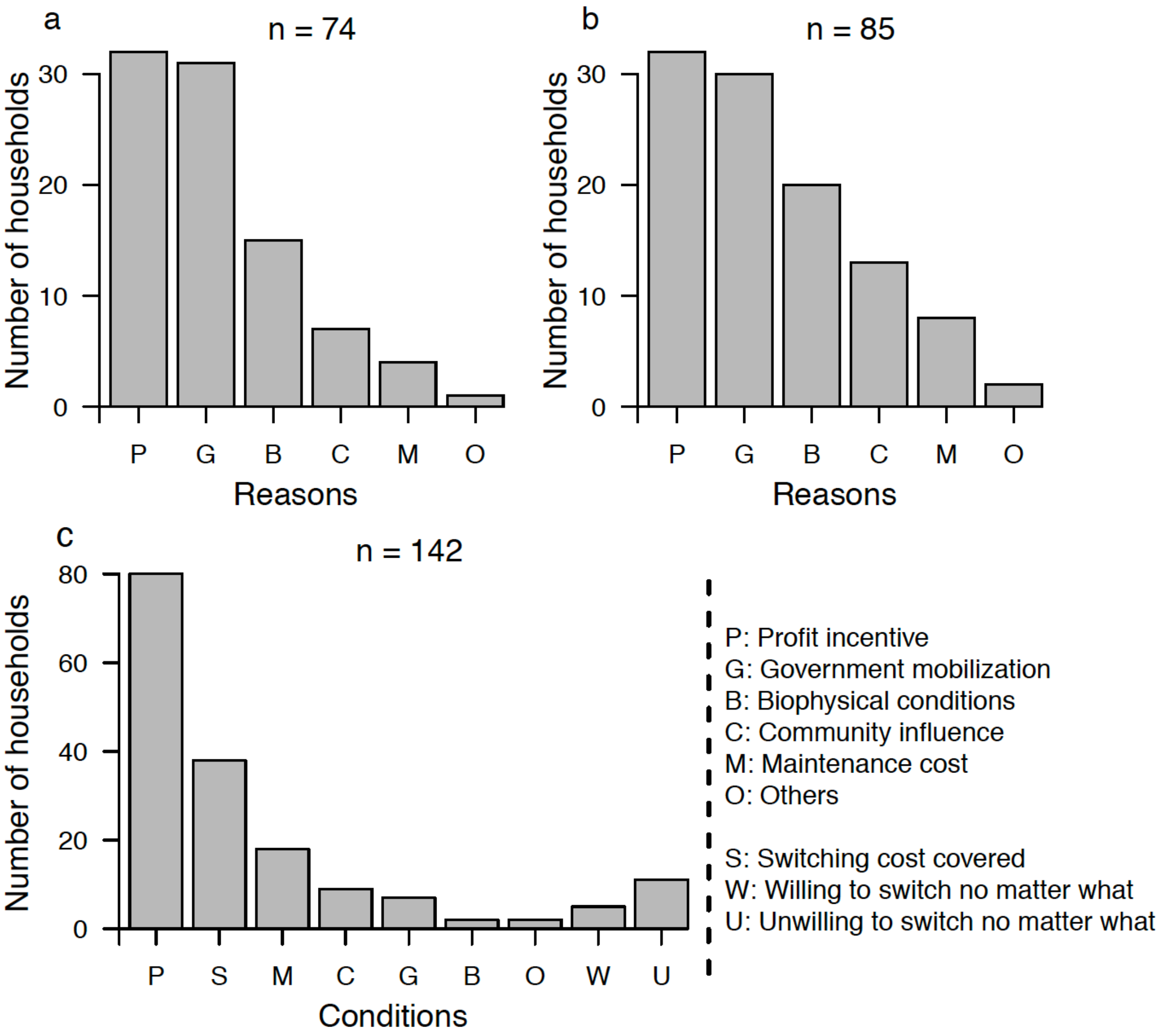

Biophysical attributes
Distance to
Slope
Road
Town
Native forest
Effect on the odds ratio of the probability of natural regeneration (log scale)
0.4
0.0
−0.4
−0.8
−1.2
−1.6

Figure 5.


a
n = 74
Number of households
0
10
20
30
P
G
B
C
M
O
Reasons
b
n = 85
Number of households
0
10
20
30
P
G
B
C
M
O
Reasons
c
n = 142
Number of households
0
20
40
60
80
P
S
M
C
G
B
O
W
U
Conditions
P: Profit incentive
G: Government mobilization
B: Biophysical conditions
C: Community influence
M: Maintenance cost
O: Others
S: Switching cost covered
W: Willing to switch no matter what
U: Unwilling to switch no matter what

Part I. Further details on remote-sensing analysis of forest-cover change

Satellite images

The four images we used for remote sensing analysis were all Standard Terrain Correction products (L1T) obtained from the U.S. Geological Survey Landsat Archives (https://landsat.usgs.gov/). They included two Landsat Enhanced Thematic Mapper Plus ("ETM+" hereafter) images obtained from 2000 (one with path-row 130-039 taken on December 9th 1999, and the other with path-row 129-039 taken on November 2nd 2000), and two Landsat 8 Operational Land Imager ("OLI" hereafter) images from 2015 (one with path-row 129-039 taken on December 19th 2014, and the other with path-row 130-039 taken on February 12th 2015). We used only images from the winter season of the northern hemisphere to minimize the influence of cloud cover.

We geo-referenced all images to UTM/WGS 84 coordinates, and conducted image-to-image registration to geometrically correct the ETM+ images using the OLI images such that the root mean square error was <0.5 pixel (15 m). For supervised classification, we used Landsat original bands (bands 1~5 and 7 for ETM+ and bands 1~7 for Landsat 8 OLI) in combination with the Normalized Difference Vegetation Index (NDVI; Tucker, 1979; Tucker et al., 1991) and the Global Digital Elevation Model 2 (http://gdem.ersdac.jspacesystems.or.jp/DEM) as predictor variables (Ren et al., 2009).

Ground-truth dataset

We collected our field-based sub-dataset of ground-truth information during biodiversity field surveys in 2015, the details of which are provided in Hua et al. 2016. In brief, we visited large expanses of all land-cover classes except for the "others" class to survey for their associated bird and bee communities. We recorded the GPS coordinates of the biodiversity sampling points (for birds) and plots (for bees), along with their corresponding land-cover information. Field points for the three types of monoculture plantation (namely, Eucalyptus, bamboo, and Japanese cedar) were registered separately, in accordance with our later procedure where these three plantation types were classified separately before being combined into the land-cover class of monoculture plantation. In all, we collected 245 field points for native forest, 327 for mixed plantation, 108 for Eucalyptus plantation, 105 for bamboo plantation, 107 for Japanese cedar plantation, and 130 for cropland.

To generate additional ground-truth information, we randomly placed sampling points within the study region on Google Earth high-resolution image, and identified their corresponding land-cover information by visual interpretation. This step was particularly useful to (1) extend the spatial coverage of our ground-truth dataset to areas not covered by field surveys, and (2) generate ground-truth data for the "others" land-cover class for which we did not have field-based ground-truth data. We aimed to generate enough Google Earth-based sampling points such that the total number of ground-truth sampling point for each land-cover class was at least 2,000 (the number of ground-truth sampling points for each of the three monoculture plantation types was at least 500).

Simulation for assessing the classification accuracy of land-cover conversion status

Similar to the producer's accuracy and user's accuracy approach for land-cover classification, we assessed the classification accuracy of land-cover conversion status in two ways: commission error (or false positive) and omission error (or false negative). For commission error, we quantified the amount of pixel classified as a particular conversion status that were in fact not of the conversion status in question; we expressed this amount using the % of pixels out of the total number of pixels classified as a particular conversion status (i.e. % of "committed" pixels), and reported this information as the % of correctly classified pixels (i.e. 1 - % of "committed" pixels). For omission error, we quantified amount of pixels that were in fact of a particular conversion status but that failed to be identified as such; we expressed this amount using the % of pixels out of the total number of pixels in the study region. We used a sampling-based simulation scheme for the estimation of both errors, which simulated the unknown number of "committed" and "omitted" pixels for each of the 25 conversion status classes (Table 3) over 1,000 runs. We report the 95% confidence intervals of the commission error and omission error based on the results of these simulation runs.

For each conversion class, we simulated the number of "committed" pixels based on the commission errors of classification for the two land covers involved in 2000 and 2015, respectively, which were known from the user's accuracy ("UA" hereafter) of land-cover classification (i.e. they are 1-UA; Table 2). Let $n_{i\text{->}j}$ be the number of pixels classified as conversion from land-cover class i in 2000 to j in 2015, and $UA_{i,2000}$ and $UA_{j,2015}$ be the user's accuracy for land-cover class i in 2000 and land-cover class j in 2015, the number of correctly classified pixels, denoted as $n_{i\text{->}j,Y}$ should be those that were correctly classified in terms of land-cover class in both 2000 and 2015. Without knowing the true land-cover class of each pixel, possible values of $n_{i\text{->}j,Y}$ can be simulated by binomial draws based on $n_{i\text{->}j}$ (the total number of trials), 1-$UA_{i,2000}$ (the probability of correctly classifying land cover i in year 2000), and 1-$UA_{j,2015}$ (the probability of correctly classifying land cover j in year 2015). We identified the pixels corresponding to positive draw outcomes (i.e. correct classification of land-cover class) for both 2000 and 2015 as those that were correctly classified in terms of conversion status, tallied their number to obtain $n_{i\text{->}j,Y}$, and divided them by $n_{i\text{->}j}$ to obtain the % of correctly classified pixels. We repeated such binomial draw for 1,000 times to obtain 1,000 estimates of $n_{i\text{->}j,Y}/n_{i\text{->}j}$, based on which we calculated their 95% confidence interval.

Similarly, for each conversion class, we simulated the number of "omitted" pixels based on omission errors of classification for the two land covers involved in 2000 and 2015, respectively, which were known from the producer's accuracy ("PA" hereafter) of land-cover classification (i.e. they are 1-PA; Table 2). The "omitted" pixels for a given conversion are essentially the collection of a portion of the pixels that were "committed" with regard to other conversion classes. Viewed from a flip perspective, for the conversion class i->j, the collection of incorrectly classified pixels, numbered at $n_{i\text{->}j}$ - $n_{i\text{->}j,Y}$, should in fact have belonged to one of the other 24 conversion classes (Table 3), and have been "omitted" from them. The estimation of omission error for the classification of land-cover conversion status thus hinges on estimating the numbers of pixels out of $n_{i\text{->}j}$ - $n_{i\text{->}j,Y}$ that should be "returned" to each of the 24 other conversion classes, for every i->j combination. Let $n_{i\text{->}j,m\text{->}n}$ denote the number of pixels classified as conversion class i->j but that have in fact been converted from land cover m in 2000 to n in 2015, respectively, the number of "omitted" pixels for the conversion class m->n, denoted as $n_{omitted, m->n}$, should be the sum of $n_{i->j, m->n}$ for every i->j combination except when i is the same value as m and j is the same value as n.

Because $n_{i->j}$ - $n_{i->j,Y}$ is to be divided among 24 other conversion classes that are not i->j, $n_{i->j, m->n}$ can be simulated by multinomial draws based on the relative probabilities of pixel assignment into the "true" conversion classes. The "true" conversion classes can be viewed as comprising three pools. (1) Pool #1: where m equals i, i.e. the misclassification of conversion status was due only to misclassification of land-cover class in 2015; we denote its size as $n_{i->j, m->n, 2015}$. This pool thus comprises of the four conversion classes from i in 2000 to any of the four land-cover classes that is not j in 2015. (2) Pool #2: where n equals j, i.e. the misclassification of conversion status was due only to misclassification of land-cover class in 2000; we denote its size as $n_{i->j, m->n, 2000}$. This pool thus comprises of the four conversion classes from any of the four land-cover classes that is not i in 2000 to j in 2015. (3) Pool #3: where neither does m equal i or n equal j; i.e. the misclassification of conversion status was due to misclassification of land-cover class in both 2000 and 2015; we denote its size as $n_{i->j, m->n, 2000\_2015}$. This pool thus comprises of the 16 conversion classes from any of the four land-cover classes that is not i in 2000 to any of the four land-cover classes that is not j in 2015. The values for $n_{i->j, m->n, 2015}$, $n_{i->j, m->n, 2000}$, and $n_{i->j, m->n, 2000\_2015}$ can each be estimated from the binomial draw above (they sum up to equal $n_{i->j}$ - $n_{i->j,Y}$), to serve as the total number of trials that are to be assigned (and "returned") to each of the "true" conversion classes within each pool using multinomial draws.

With regard to the relative probabilities with which to conduct the multinomial draws, we made the assumption that they were proportional to the omission errors of the land-cover class(es) involved, weighted by the true extent of the land-cover class in question in the study region. Thus, with regard to Pools #1 and #2, for each "true" conversion class to their pixels were to be assigned, the relative probability was directly the weighted omission error for the one land-cover class concerned. With regard to Pool #3, for each "true" conversion class to which its pixels were to be assigned, the relative probability was the product of the weighted omission errors of the two land-cover classes concerned. We followed Stehman 2013 in estimating the true extent of each of the five land-cover classes in 2000 and 2015 based on UA and PA (Equation 21 in Stehman 2013), and in turn calculated the weighted omission error for each land-cover class in 2000 and 2015 (Table S3).

We thus conducted, for each i-j combination, three separate sets of multinomial draws based on their respective number of trials ($n_{i->j, m->n, 2015}$, $n_{i->j, m->n, 2000}$, and $n_{i->j, m->n, 2000\_2015}$, respectively) and relative probabilities of outcomes. For each i-j combination, we identified the pixels corresponding to positive outcomes for each "true" conversion class (i.e. those that should be assigned to each of the "true" conversion classes), and tallied these numbers within each "true" conversion class to obtain $n_{i->j, m->n}$. For every combination of m->n, we then summed up all $n_{i->j, m->n}$ across all i-j combinations to obtain $n_{omitted, m->n}$, i.e. the total number of "omitted" pixels for the conversion class m->n. We divided $n_{omitted, m->n}$ by the total number of pixels in the study region n_{total}, to obtain the % of "omitted" pixels of the conversion class m->n. We repeated such multinomial draws for 1,000 times to obtain 1,000 estimates of $n_{omitted, m->n}/n_{total}$, based on which we calculated their 95% confidence interval.

Part II. Supplementary tables

Table S1. Pearson's correlation coefficient among candidate biophysical attributes for all pixels of the study region.

	Slope	Distance to the nearest paved road	Distance to the nearest township	Distance to the nearest native forest in 2000	Elevation
Slope	1	0.32	0.42	-0.45	0.61
Distance to the nearest paved road	0.32	1	0.51	-0.14	0.57
Distance to the nearest township	0.42	0.51	1	-0.18	0.69
Distance to the nearest native forest in 2000	-0.45	-0.14	-0.18	1	-0.49
Elevation	0.61	0.57	0.69	-0.49	1

Table S2. Detailed household survey questions. All multiple-choice questions allowed for more than one choices.

Aspect of forest -cover change	No.	Question	Nature of question
Native forest conversion	1	Since 1999, how many Chinese mu (15 mu = 1 hectare) of previously existing native forest have you converted into other types?	Open-ended
	2	[If 1 > 0] What was the forest type post-conversion?	Open-ended
	3	[If 1 > 0] Why did you convert the forest? Options: a) for better profit; b) government encouragement/mobilization†; c) community influence; d) other reasons (please clarify)	Multiple-choice
	4	[If 1 = 0] Why did you not convert the forest?	Multiple-choice

		Options: a) no one did this (community influence); b) no encouragement/mobilization from government†; c) no labor and/or financial resources; d) no interest in managing land; e) other reasons (please clarify)	
GFGP artificial reforestation	5	Why did you choose the current GFGP tree species? Options: a): profit incentives; b) low maintenance; c) government encouragement/mobilization†; d) community influence; e) other reasons (please clarify)	Multiple-choice
	6	If switching to a different forest type can generate more environmental benefits, under what conditions would you be willing to switch? (Note: we did not specify which forest type this may be.) Options: a): cost of switching is covered; b) profit is no lower than now; c) maintenance intensity is no higher than now; e) other conditions (please clarify)	Multiple-choice

Note: † - "government encouragement/mobilization" refers to any perceived encouragement or mobilization for certain land use from the government, as reported by respondent households. Anecdotes from our interactions with respondent households suggest that it entailed a range of formats, from government laying out regulations for households to follow, to government providing monetary or logistical incentives, such as organizing communities to conduct land cover conversion, or providing free seeds/seedlings for tree planting.

Table S3. Weighted omission error for each land-cover class in 2000 and 2015.

Land-cover class	2000			2015		
	Omission error	True extent†	Weighted omission error	Omission error	True extent†	Weighted omission error
Native forest	0.18	1,947,772	0.020	0.17	2,110,751	0.020
Mixed plantation	0.33	3,001,408	0.056	0.18	4,240,251	0.043
Monoculture plantation	0.37	1,356,978	0.029	0.21	2,526,633	0.030
Cropland	0.07	10,245,161	0.041	0.08	7,550,130	0.034
Others	0.26	1,019,897	0.015	0.23	1,143,450	0.015

Note: † - True extent of the land-cover classes is expressed as the number of pixels.