Part I. Further details on remote-sensing analysis of land-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.

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](#_ENREF_7); [Tucker et al., 1991](#_ENREF_8)) and the Global Digital Elevation Model 2 (<http://gdem.ersdac.jspacesystems.or.jp/DEM>) as predictor variables ([Ren et al., 2009](#_ENREF_6)).

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 “Other land cover” 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 “Other 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 ni->j be the number of pixels classified as conversion from land-cover class i in 2000 to j in 2015, and UAi, 2000 and UAj, 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 ni->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 ni->j, Y can be simulated by binomial draws based on ni->j (the total number of trials), UAi, 2000 (the probability of correctly classifying land cover i in year 2000), and UAj, 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 ni->j, Y, and divided them by ni->j to obtain the % of correctly classified pixels. We repeated such binomial draw for 1,000 times to obtain 1,000 estimates of ni->j, Y/ni->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 ni->j - ni->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 ni->j - ni->j, Y that should be “returned” to each of the 24 other conversion classes, for every i->j combination. Let ni->j, m->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 nomitted, m->n, should be the sum of ni->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 ni->j - ni->j, Y is to be divided among 24 other conversion classes that are not i->j, ni->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 ni->j, m->n, 2015. This pool thus consists 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 ni->j, m->n, 2000. This pool thus consists 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 ni->j, m->n, 2000\_2015. This pool thus consists 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 ni->j, m->n, 2015, ni->j, m->n, 2000 , and ni->j, m->n, 2000\_2015 can each be estimated 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 (they sum up to equal ni->j - ni->j, Y).

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 (ni->j, m->n, 2015, ni->j, m->n, 2000 , and ni->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 ni->j, m->n. For every combination of m->n, we then summed up all ni->j, m->n across all i-j combinations to obtain nomitted, m->n, i.e. the total number of “omitted” pixels for the conversion class m->n. We divided nomitted, m->n by the total number of pixels in the study region ntotal, 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 nomitted, m->n/ntotal, based on which we calculated their 95% confidence interval.

Reference

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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 land-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 land-cover type post-conversion? | Open-ended |
|  | 3 | [If 1 > 0] Why did you convert the forest? | Multiple-choice |
|  |  | Options:  a) for better profit; b) government encouragement/mobilization†; c) community influence; d) other reasons (please clarify) |  |
|  | 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? | Multiple-choice |
|  | Options:  a): profit incentives; b) low maintenance; c) government encouragement/mobilization†; d) community influence; e) other reasons (please clarify) |  |
| 6 | If switching to a different tree-cover type can generate more environmental benefits, under what conditions would you be willing to switch? (Note: we did not specify which tree-cover type this may be.) | Multiple-choice |
|  |  | 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) |  |

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.