

The Expansion of tree-based boom crops in Mainland Southeast Asia: 2001 to 2014

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Abstract: Over the past half century, countries of Mainland Southeast Asia (MSEA) – Cambodia, Laos, Myanmar, Thailand, and Vietnam – have witnessed increases in commercialized agriculture with rapid expansions of boom-crop plantations. We used MODIS EVI and SWIR time-series from 2001-2014 to classify tree-cover changes across MSEA and performed a supervised change detection using an upscaling approach by deriving samples from existing Landsat classifications. We used the random forest classifier and distinguished 24 classes (16 representing boom-crops) with an accuracy of 82.2%. Boom-crops occupy about 18% of the landscape (8% of which is rubber). Since 2003 74,960 km² of rubber have been planted; 70% of rubber is planted on former forest land, and 30% on low vegetation area (mainly former croplands). Timing, patterns of change, and deforestation rates, however, differ among the MSEA countries and the high spatial and temporal detail of our classification allowed us to quantify dynamics and discuss political and socio-economic drivers of change.

Keywords: MODIS, random forest classifier, Mainland Southeast Asia, land-cover change, boom-crops, remote sensing

1. Introduction

Since the early 1980s the five countries of Mainland Southeast Asia (MSEA), Cambodia, Laos, Myanmar, Thailand, and Vietnam, have experienced dramatic changes in rural land-use and social relations (Baird, 2011; Hall, Hirsch, & Li, 2011; Lestrelin, Castella, & Fox, 2013). Some of the main processes behind these changes (economic growth, industrialization, and urbanization) have driven the conversion of a great deal of agricultural land to commercial, industrial, residential, tourist and infrastructural uses. Processes working against agriculture, however, coexist with forces that speak to the continuing importance of farming. National policies have led to agricultural intensification and the linking of smallholder production systems to land, labor and commodities markets. In a recent survey of agrarian change in Southeast Asia, Hall et al. (2011) identified major land-cover transitions associated with ongoing socio-economic and political changes. These included loss and gain of forests, agricultural intensification and extensification including boom crops, and urbanization.

Between 1990 and 2010 forest cover in MSEA fell from 50.7 to 45.7%, particularly as a result of losses in Cambodia, Laos and Myanmar, although certain tree crop types (e.g. rubber, coconut, oil-palms) may be included in the forest definition (FAO, 2011). In Thailand, some forests are beginning to regrow on former cropland (Leblond, 2008). In Vietnam, large government-supported afforestation and reforestation programs are resulting in forest expansion, although, as in almost all countries in the region, primary forests are still being lost at high rates (Meyfroidt & Lambin, 2009). Boom crops are crops that witness rapid and extensive expansion usually triggered by increased market incentives and favorable policies, e.g., promoting agricultural transformation in the form of smallholder market integration and large scale plantations (Hall et al., 2011). Among the many types of commercial boom crops promoted in MSEA are numerous

tree-based products such as rubber, coffee, tree species for pulp and paper (particularly eucalyptus and acacia), cashews, and fruits (e.g. oranges, lychees, and longans), but also non-tree-based boom crops, such as sugarcane.

The investment of political and financial capital these developments represent, and the concomitant shifts in livelihood strategies and land-use patterns that accompany them have important social and ecological implications. Boom crops are marked by both agricultural intensification (i.e. subsistence agriculture or agro-forests are converted to new boom crops (rubber, cashews, coffee)) as well as agricultural expansion (i.e. forested lands are converted to new tree crops). We began this study with the hypothesis that most (but not all) tree-based boom crops in MSEA were marked by intensification of previously used agricultural land that was not necessarily accompanied by deforestation, but the intensification may push subsistence land-uses elsewhere.

Monitoring change in tree-dominated landscapes in MSEA is challenging because the processes of change affect the diversity of replacement crops. For example, the secondary forests associated with shifting cultivation can either be deforested or afforested depending on whether they are replaced by a variety of tree crops (rubber, oil palm, coffee) or the expansions of permanent agriculture (sugar cane, cassava) (Suepa, Qi, Lawawirojwong, & Messina, 2016; Tottrup, Rasmussen, Eklundh, & Jönsson, 2007). This study sought to document changes in tree cover at the regional scale and we used time-series of MODIS 16-day image composites to map changes in forests and tree-boom crops from 2001-2014 in parts of four MSEA countries: Thailand, Laos, Cambodia, and Vietnam, as well as in Shan State Myanmar, and Xishuangbanna Prefecture in southern Yunnan, China (Z. Li & Fox, 2011). The MODIS classification builds on our previous work at the local scale using Landsat imagery to map land-cover dynamics from

2000-2014 for selected Landsat footprints in Laos, Cambodia, Thailand, and Myanmar (cf Hurni, Schneider, Heinemann, Nong, & Fox, 2017).

This paper seeks to report the extent of tree-based boom crops in the study region in 2014; and the expansion of rubber between 2003 and 2014. We produced an up-to-date map that depicts the precise from-to (i.e., from evergreen forests, deciduous forests, or permanent agriculture to tree crop) trajectory, location, extent (useful for separating smallholders from large-scale concessions), and timing of recent changes. The paper does not present an extensive discussion of the political and economic conditions under which crop booms occur (see for instance De Koninck, 2006; De Koninck, Bernard, & Bissonnette, 2011; Gérard & Ruf, 2001; Hall, 2003; Hall et al., 2011; Ziegler, Fox, & Xu, 2009). This paper builds on previous work done by Hurni et al. (2017) on selected Landsat footprints and expands the classification to the MSEA region using MODIS time-series data to provide insights into the political and economic conditions under which these changes occurred.

2. Background

Hall et al. (2011) argue that the Southeast Asian literature permits a broad distinction between booms that have taken place under ‘secure’ conditions and those that have not. ‘Insecure’ booms take place in areas that are often conceptualized as ‘frontiers’, areas imagined by national leaders and others to be ‘resource frontiers’, with low population densities, available land, and underutilized resources (see Barney, 2008). In reality, these places are almost always occupied by small-scale farmers, especially upland minorities who have often lived there for generations (Baird, 2010, 2011), and practiced subsistence agriculture (Fox & Vogler, 2005; Schmidt-Vogt et al., 2009). In ‘secure’ booms, Hall et al. (2011: 839) write ‘the basic tenure relations that

existed before the boom survive it. In such cases, the most obvious power shaping land control during the boom is thus market power, as newly-valuable land changes hands through mutually-agreed sales and leases.’

Hall et al. (2011:841) differentiate four main actors that take part in crop booms. These include: 1) state actors; 2) private companies; 3) in situ smallholders; and 4) migrant would-be smallholders. While the various boom crops have been grown under many organizational frameworks, and while smallholders have successfully grown all of them, there is a fairly clear distinction between crops dominated by relatively independent smallholders (cocoa and coffee) and those where larger-scale production has been the rule (fast-growing trees and oil palm), with shrimp and rubber as intermediate cases (Hall et al. 2011).

3. Materials and Methods

We mapped land-cover dynamics in MSEA using the MODIS MOD13Q1 product. This product provides MODIS bands and vegetation indices (e.g. Enhanced Vegetation Index (EVI)) with circa 231m resolution as 16-day image composites by performing a pixel-based selection of the best observation acquired in the preceding 16 days of the sensors daily image acquisitions (USGS, 2017). This composition approach improves the data substantially by minimizing noise related to cloud cover, haze, etc. in the time-series. Previous studies focusing on land-cover dynamics in MSEA used EVI time-series to identify specific land-use processes or crops (e.g. shifting cultivation, rubber) and more recent studies, focusing on a broader range of dynamics and processes to determine vegetation and land-use phenology, have emphasized the importance of including band 7 (Shortwave Infrared (SWIR)) to improve the mapping accuracy of forest

dynamics (Grogan, Pflugmacher, Hostert, Verbesselt, & Fensholt, 2016; Hurni, Hett, Heinimann, Messerli, & Wiesmann, 2013; Z. Li & Fox, 2012; Suepa et al., 2016). In this study we consequently used the EVI and the SWIR band (band 7) of the MOD13Q1 product and included the full time-series of 16-day image composites from 2001 through 2014. Despite the image composition strategy our data still showed spikes, especially during the period May to September due to the persistent cloud cover that exists during the rainy season; even in a 16 day period it is not always possible to obtain a clear and noise-free observation. To improve the quality and consistency of the time-series, we thus processed the data with a smoothing algorithm using Timesat software (Eklundh & Jönsson, 2010; Jönsson & Eklundh, 2004). Timesat applies a smoothing function to the data and returns files that contain even renditions of the original data. We applied the double logistic function to smoothen the data as it showed the best performance and was recommended by other authors dealing with noisy data (Beck, Atzberger, Høgda, Johansen, & Skidmore, 2006; Eklundh & Jönsson, 2010; Hird & McDermid, 2009). We applied this fitting function to the EVI and SWIR bands covering the area of MSEA from 2001 through 2014. Finally, we rescaled the SWIR and EVI time series to improve classification accuracies by cutting off the top and bottom one percentile, linearly redistributing the remaining values between zero and one, and assigning the bottom and top one percentile a value of zero and one, respectively (van der Linden et al., 2015).

We performed the classification of the full MODIS EVI and SWIR time-series from 2001-2014 using the random forest (RF) classifier implemented in EnMap-Box (Jakimow et al., 2015; van der Linden et al., 2015). Random forests are a machine learning algorithm, which provides substantially higher classification accuracies in contexts with complex ecological issues (Cutler et al., 2007; Schneider, 2012). In contrast to traditional classifiers, e.g. maximum likelihood, it

manages noise, handles non-linear relationships occurring in the remote sensing data, and makes no assumptions on data distribution (Clark, Aide, Grau, & Riner, 2010). Furthermore, it requires few user-defined parameters and its computational efficiency makes it suitable for a classification of large datasets (Jakimow et al., 2015; Pal, 2005). Random forests consist of an ensemble of decision-tree classifiers and each tree provides a vote on the most popular class assigned to the input vector (Breiman, 2001). The training dataset for each tree consist of a random subset of the overall data (sampled with replacement). The decision at each node of the tree uses a randomly selected subset of candidate classification features (i.e. the MODIS bands), whereby the number of features is constant and user defined. We set it to the square root of all features, which has been shown to provide a good compromise between predictive accuracy and overfitting (Breiman, 2001). At each node, an optimization is carried out that results in the most homogeneous split of the data (Rodriguez-Galiano & Chica-Rivas, 2014). To assess the impurity of a split we used the Gini index, and each tree is fully grown until a further subdivision does not reduce the Gini index (Cutler et al., 2007; Jakimow et al., 2015). The out-of-bag observations (i.e. the samples not included in the bootstrap sample) are then used to vote for the most frequent class within each tree and a simple majority vote over all trees provides the final classification (Breiman, 2001; Cutler et al., 2007). We used a maximum of 100 ensemble decision trees to classify the data after testing the influence of the number of decision trees on the overall accuracy by using 90% of the points for training and 10% of the points for testing. The inclusion of a larger number of trees (we used 100, 500, 1,000, and 10,000 decision trees) did not improve classification accuracies (we obtained overall accuracies of 83.33%, 82.46%, 82.16%, and 82.6% respectively) (Jakimow et al., 2015; Pal, 2005).

We classified the MODIS time-series following an ‘upscaling’ approach and extracted training

and verification points from seven Landsat-based land-cover change classifications in the region (Hurni et al. 2017). Due to the differences in pixel sizes, this operation is usually performed by defining a threshold of a majority cover of the 30m resolution land-cover classes within a MODIS pixel (circa 231m resolution), extracting the MODIS pixels that meet the threshold criteria, and classifying the MODIS data with these samples (Clark et al., 2010; DeFries, Townshend, & Hansen, 1999; Hurni et al., 2013). We adapted this approach and determined the classification scheme and the number of classification samples for an accurate classification of land-cover dynamics in iterations. As shown in Figure 1 (A), we started this process with the extraction of classification samples from the Landsat classifications of land-cover change for seven selected footprints in MSEA.

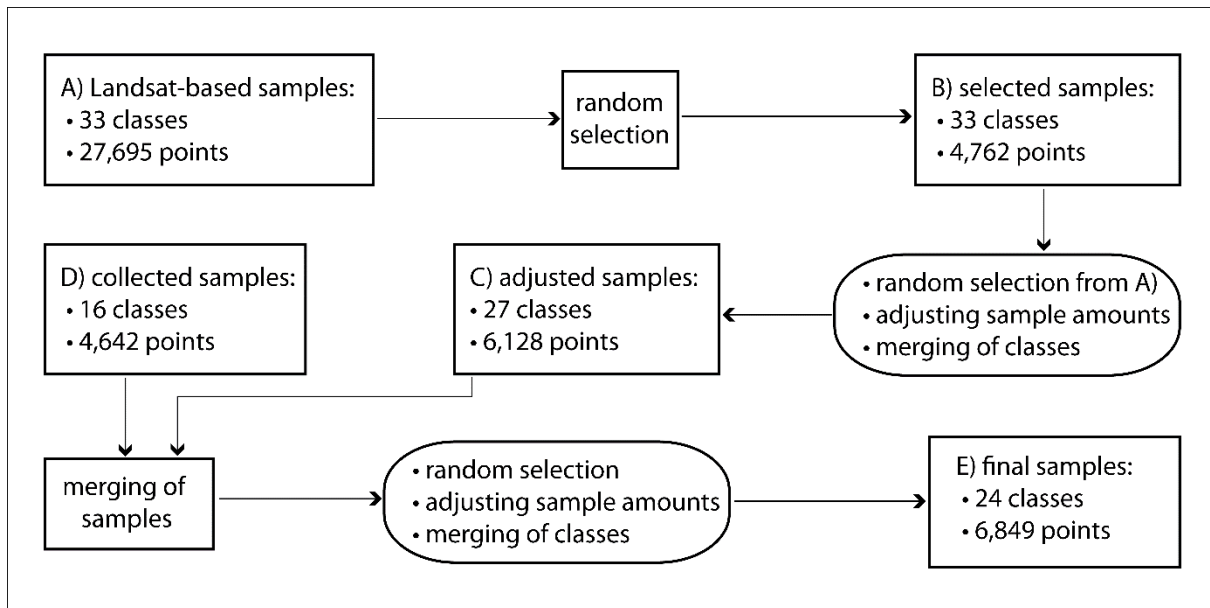


Figure 1: Overview of the classification samples collection approach. Rounded boxes represent classification iterations where we increased accuracies by adjusting sample amounts and merging classes

Working within these 7 scenes we selected only ‘pure’ pixels (i.e. the MODIS pixel is fully covered by one Landsat-based land-cover change class) because initial tests that included mixed samples resulted in lower accuracies. This provided samples on three types of land-cover and land-cover change classes: group 1) no-change classes (i.e. evergreen and deciduous forests, low vegetation areas (LVA), water, and tree plantations established before 2003); group 2) boom crop change classes (i.e. rubber, cashews, eucalyptus, coffee, sugarcane) that are subdivided into from-to change (i.e. from evergreen forests, deciduous forests, or LVA to the boom crop) and the period the change occurred (2003-2005, 2006-2008, 2009-2011, 2012-2014); and group 3) land-cover change classes without a focus on the date of the change due to the heterogeneity of the timing of change (i.e. rotational agriculture, expansion of LVA, and new water bodies). Next, we validated these samples using Google Earth high-resolution data to avoid the inclusion of classification errors of the Landsat data in the MODIS classification. We obtained 27,695 samples for a total of 33 classes, but their distribution among the classes varied significantly. Due to the difference between the MODIS and Landsat pixel size, we extracted relatively fewer sample points for the more fragmented classes in relation to their area. We obtained an abundance of sample points for the no-change classes (group 1 above); while few samples were obtained for groups 2 and 3. We needed to adjust for this imbalance of sample points across the classes. Various scholars have shown that the appropriate amount of sample points for an accurate supervised classification of land-cover change does not only depend on the class area (spatial heterogeneity), but also on the temporal heterogeneity and the classification scheme (spectral-temporal similarity of classes) (Foody & Arora, 1997; Heydari & Mountrakis, 2018; Hurni et al., 2017). To represent temporal heterogeneity, change classes consequently need relatively more sample points despite the small areas they cover. We performed these

adjustments to the sample points in iterations and started with an adjusted random selection of points based on class area shares (Figure 1 (B)). Due to the large amounts of samples and the imbalanced distribution across classes, we limited the maximum number of points for the largest class to 1,000 points and the minimum number of points to 100 and randomly selected samples for each class within this range based on the class area. In this way we obtained sufficient points for the small change classes to represent the temporal heterogeneity while the larger, usually spatially more heterogeneous classes, also obtained more points. Classes with fewer than 100 samples in total were still included in the classification. In the following classification iterations we focused on class-wise accuracies by using 75% of the samples for classification and 25% for verification. We then adjusted sample amounts for the classes with low accuracies in three ways: 1) by increasing the number of samples if more points were available; 2) by merging classes when we had already used all sample points and accuracies were still insufficient. This grouping only affected change classes and was done by crop type, e.g. conversions to cashews in different periods needed to be merged into one cashew class to obtain acceptable accuracies; and 3) by reducing the number of points for classes with large sample sizes (usually the no-change classes); most of the confusions occurred within the classes with few samples (usually the change classes). We selected samples randomly from our pool of all samples for each classification and we continued reiterations until further adjustments to the number of sample points and the classification scheme did not result in higher accuracies in terms of trade-offs among classes and the overall accuracy (Figure 1 (C)). Next, we focused on the upscaling, i.e. the performance of the classification outside the seven Landsat footprints. We used multi-temporal Google Earth high resolution images to identify locations and classes with upscaling difficulties and added sample points for those locations (Figure 1 (D)). This was also guided by

the authors' knowledge of the study area. We focused on locations where the land-cover and land-use as well as environmental conditions differed from the area covered by the Landsat classifications (e.g. Vietnam, southeastern Thailand and the Tonle Sap area in Cambodia). The different boom crops can be distinguished in the high resolution images based on the crop spacing in the x and y direction, canopy size and structure, and to a certain degree based on the RGB color representation. Figure 2 shows examples of such transformations for the boom crops. In case there were not sufficient historic high resolution images available, we identified the crop type in the recent high resolution image and the timing of the change and the land-cover before the change using Landsat time-series.

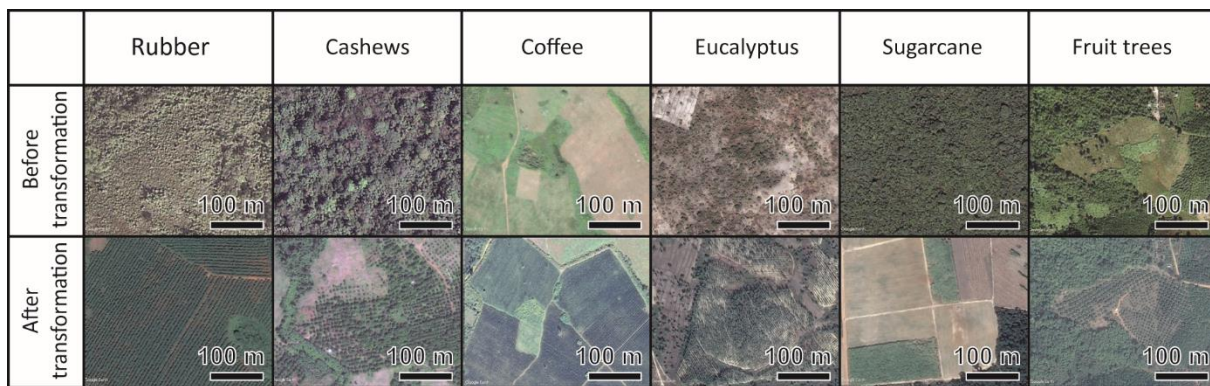


Figure 2: Examples of transformations to boom crops using Google Earth high resolution images.

Different boom crop types can be distinguished based on crop spacing and canopy size and structure

We limited the sample collection to areas where multi-temporal high resolution images were available and we identified pure pixels by overlaying those areas with polygons representing the MODIS pixel size. In this second round of iterations, we used all these samples (4,642 collected Google Earth samples) and the ones from the previous iteration (6,128 selected Landsat samples). Starting from the number of samples defined in the previous iterations we randomly selected the number of classification samples from our new pool of points. We then performed

the classification in iterations with adjustments to the sample size as described above until trade-offs between class-wise and overall accuracies could not be increased. During this process we merged, for example, the eucalyptus classes into the class ‘pulp trees’, as the fast cycle of planting and harvesting related to pulp wood production did not allow us to distinguish tree types (e.g. eucalyptus from acacia). With this last step of optimizing the number of samples and their spatial distribution, we obtained a total number of 6,849 samples, ranging from 19-918 points per class; we collected 5,126 samples from our Landsat analyses and 1,723 samples from Google Earth (Figure 1 (E)). Table 1 shows the classification scheme with a total of 24 classes, six represent permanent land-cover types (group 1) and 18 land-cover change classes. Eleven of the change classes focus on rubber and sugarcane and specify from-to changes and the period of change (group 2), while the seven other change classes (group 3) do not provide information on the ‘from’ land-cover or the timing of change. This classification scheme does not include all the land-cover changes that occurred in the study area. For example it is possible that during our study period forests were converted to one boom crop and then later replaced by another boom crop (multiple transformations). However, our work at the Landsat scale as well as the revision of the MODIS samples showed that such transformations represent only a small share of the study area compared with single transformations, e.g. forests to boom crops (Hurni et al., 2017). As a result it was not possible to obtain sufficient sample points for areas with multiple transformations. The classification scheme we applied thus brings a certain generalization and only focuses on the prevailing land-cover transformations in the study area.

Table 1: The classification scheme applied to MODIS time-series for unchanged and changed land-cover types. We only included classes highlighted in the shaded cells due to absence of some classes during certain periods.

	2003-2005	2006-2008	2009-2011	2012-2014
Land-cover classes (group 1)	Water			
	Evergreen forests (F)			
	Deciduous forests (DF)			
	Low vegetation areas (LVA)			
	Rubber			
	Pineapple			
Detailed land-cover change (group 2)	Rubber from F	Rubber from F	Rubber from F	Rubber from F
	Rubber from DF	Rubber from DF	Rubber from DF	Rubber from DF
	Rubber from LVA	Rubber from LVA	Rubber from LVA	Rubber from LVA
	Sugarcane from F	Sugarcane from F	Sugarcane from F	Sugarcane from F
	Sugarcane from DF	Sugarcane from DF	Sugarcane from DF	Sugarcane from DF
Land-cover change (group 3)	Rotational agriculture			
	Expansion of low vegetation areas / Intensification			
	New hydropower dams			
	Pulp trees			
	Cashews			
	Fruit trees			
	Coffee			

F = evergreen forests; DF = deciduous forests, LVA = low vegetation area (annual crops, grass, shrubs),

We performed a ten-fold cross-validation using the 6,849 sample points to validate the classification (Kohavi, 1995). This approach split the sample points into ten equally-sized parts and used nine parts to train the classifier and the remaining part to assess the accuracy of the classification. We repeated this ten times so that each part is used once for the evaluation of the classification accuracy and the final accuracy of the map is derived by calculating the arithmetic mean of all ten accuracy assessments. The ten-fold cross-validation is considered to be more reliable than traditional approaches that split the sample points into a single training and validation set, because both, the final accuracy assessment and classification, are based on all sample points, but are still independent. This approach improves classification accuracies as potential biases between the training and validation points are avoided. Furthermore we evaluated the accuracy of mixed pixels as at the MODIS scale, land-cover dynamics often occur at the sub-pixel level (Lunetta, Knight, Ediriwickrema, Lyon, & Worthy, 2006; Setiawan &

Yoshino, 2014). We selected mixed pixels from areas covered by the Landsat classifications (7 footprints across MSEA) and extracted all pixels that showed a majority land-cover of 70-80% and of 50-60% within the MODIS pixels to evaluate how different shares of majority cover affected the classification accuracy. From these two sets of mixed pixels we then randomly selected the same number of samples as we used for the classification with the pure pixels so that we conducted three accuracy assessments (pure pixels, mixed pixels with 70-80% majority cover, and mixed pixels with 50-60% majority cover) based on the same number of validation points. For pulp trees, coffee, and sugarcane we were not able to extract the targeted amount of mixed pixels from the Landsat classifications. In the sugarcane classes the number of mixed validation pixels was very low so that accuracy estimates may have been affected. Given this limitation error adjusted area estimates were calculated according to the approach suggested by Olofsson et al. (2014) using the accuracy assessment of pure pixels only. For each class we then calculated the ratio between the area defined by the pixels and the error adjusted area estimate. These ratios for each class were then used to obtain error adjusted area estimates for each country / region.

4. Results

Figure 3 outlines the study area. It includes all of Laos and Cambodia, most of Vietnam (except north of Hanoi), northeastern Thailand and the rubber growing area southeast of Bangkok, Shan State in Myanmar, and Xishuangbanna Prefecture in southern Yunnan, China. The classification consists of 24 classes and 16 classes represent boom crops. Pulp trees, coffee, cashews, fruit trees, and pineapple are each represented by one class; while for rubber we mapped ten classes and sugarcane two classes showing from-to changes and the period of change. For visualization purposes we combined the different rubber and sugarcane classes into one rubber and one

sugarcane class (Fig. 3); Figure 4 shows an extent of the map with the full classification scheme and Figure A (supplementary material) shows the expansion of rubber around Stung Treng, Cambodia.

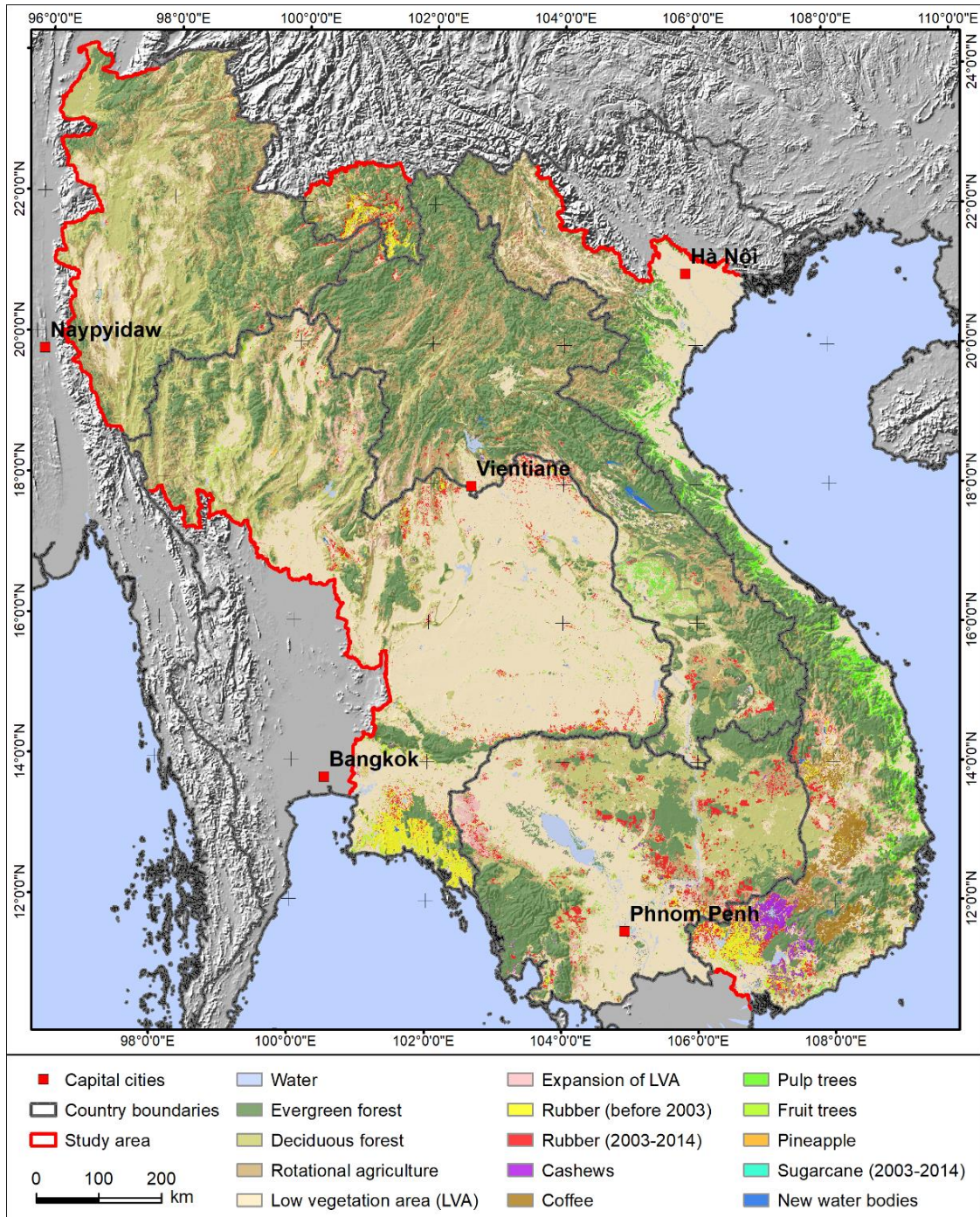


Figure 3: Land-cover change classification of Mainland Southeast Asia (MSEA). Change trajectories to rubber and sugarcane were grouped into one class.

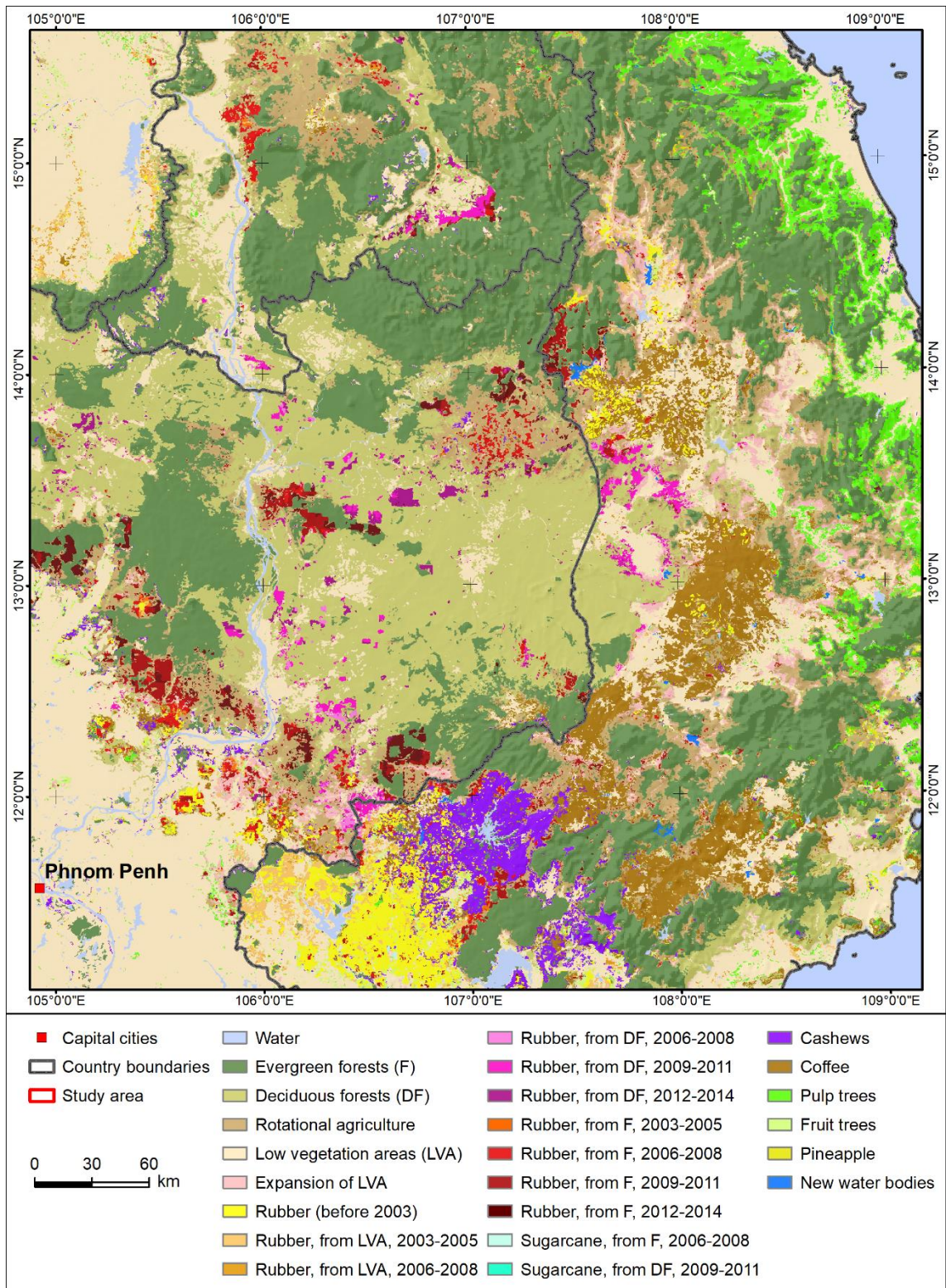


Figure 4: A selected extent of the land-cover change classification showing southern Laos, northeastern Cambodia, and the Central Highlands of Vietnam. Cambodia and Laos show mainly new rubber while in Vietnam old and new rubber as well as cashew, coffee, and pulp tree plantations occur.

The ten-fold cross validation resulted in an overall accuracy of the classification of 82.2% and only four of the classes (highlighted in table 2) show either user's or producer's accuracies (UA and PA) below 70%. High accuracies were obtained across all three groups of classes; classes with lower UA and PA only occurred in the change classes (groups 2 and 3) and prevailed in group 3, where we did not consider the timing of the change. The no-change classes (group 1) performed well and confusion was limited to the rotational agriculture class, but also some of the boom crops (e.g. pulp and fruit trees). Classes of group 2, which specify from-to changes and the period of change, performed well with only a few misclassifications occurring within rotational agriculture (mainly classes 'rubber from forests (F)'), low vegetation areas 'rubber from LVA'), and deciduous forests 'rubber from DF'). Only the class 'rubber from LVA, 2006-2008' showed a UA or PA <70% due to confusions with the class 'LVA' and to a certain degree with 'rubber from F, 2006-2008'. The class 'rubber from LVA, 2006-2008' mainly occurred in Thailand where rubber was planted by smallholders. Due to the fragmentation of this class, we were able to obtain relatively few samples when compared to the size of the class area. Most likely, the temporal heterogeneity could not be represented sufficiently with these samples, which led to misclassifications either with 'LVA' (similar dynamics up to 2010 due to the weak signal of young rubber) or 'rubber from F, 2006-2008' (the same signal for rubber regrowth from 2006-2014). Interestingly this did not occur for the class 'rubber from LVA, 2003-2005', which also occurs mainly in Thailand on fragmented plots. We used the same number of sample points for the corresponding class 'rubber from F, 2003-2005', which probably reduced misclassifications between the two classes. Similar effects have been observed by Hurni et al. (2017) where errors between classes that represented similar dynamics tended to increase when there was an imbalance among the number of sample points. Confusions with the class 'LVA' most likely

occurred because of the early conversion to rubber. With developed canopies, the signal was clear and no misclassifications with 'LVA' occurred. Most of the change classes in group 2 show high accuracies and usually the UA was bigger than the PA. Our area estimates on the expansion of boom crops can thus be considered as reliable, but we tend to slightly underestimate their expansion.

Temporally heterogeneous classes of group 3 (e.g. rotational agriculture, expansion of LVA, fruit trees, cashews, pulp trees) performed well, but tended to show lower accuracies.

Misclassifications mainly occurred within the classes of group 3 and with forests. The area of rotational agriculture is slightly overestimated and includes forested areas, 'expansion of LVA', and few pixels of boom crop classes. Conversions to low vegetation areas ('expansion of LVA') were underestimated due to confusions with rotational agriculture, LVA, and pulp trees.

Similarly fruit trees were labelled as rotational agriculture, LVA, or forests, which led to an underestimation of the area of this class. Many of these changes occurred in forested areas; a forest clear-cut is a stronger signal compared to crop or fallow regrowth, which looks similar for most crops/fallow in the first couple of years due to small canopies, intercropping, and weeds (Chen et al., 2012; Z. Li & Fox, 2011, 2012). Confusions can thus easily occur because all of these classes show some form of forest clear-cutting followed by regrowth throughout the study period. We assume that accuracies could be improved by dividing these classes into multiple classes based on periods of change, but in the study at hand this was not possible. Change dynamics of certain classes are too heterogeneous for a subdivision, which concerns e.g. rotational agriculture with a myriad of crop-fallow rotation lengths across the region, or pulp trees where planting and harvesting occurs within a couple of years. On the other hand, some fragmented classes cover rather small areas and sufficient samples for a reliable classification

could only be obtained by grouping the periods of change, as was the case for e.g. cashews and coffee. For less fragmented classes like ‘sugarcane from DF, 2009-2011’, we achieved high accuracies with as few as 19 samples. However, sugarcane shows a cropping cycle of 12-18 months, different from all the other crops. We assume that this clear signal, which differs from the signal of all the other classes, also allowed for a more accurate classification with only few points.

The accuracy assessment using mixed pixels showed that misclassifications tend to increase for MODIS pixels that represent more than one land-cover or land-cover change class. For pure pixels we obtained an overall accuracy of 82.2%; for pixels with a majority cover of one land-cover or land-cover change class of 70-80% we obtained an accuracy of 61.5%; and for pixels with a majority cover of 50-60% we obtain an accuracy of 43.4% (see Table A, supplementary material). In mixed pixels we also observe misclassification patterns, but which specific classes were confused was less clear than the evaluation using pure pixels. There are not only more misclassifications, but confusions also involve more classes. Nevertheless, certain characteristics can be observed as we move from the evaluation of pure pixels towards the evaluation of increasingly mixed pixels. In group 1, the classes ‘water’, ‘rubber (before 2003)’, and ‘pineapple’ show a high accuracy for pure pixels and UA’s are higher than PA’s. For the mixed pixels UA’s remain high but PA’s decrease rapidly and the area of these classes is thus underestimated. Among mixed pixels water is often classified as LVA, probably due to the large amounts of paddy fields that are seasonally covered by water and are included in the class LVA. ‘Rubber (before 2003)’ is confused with LVA, rotational agriculture, orchards, coffee, and earlier conversions to rubber while ‘pineapple’ is confused with LVA and fruit trees. These classes often occur next to each other, which resulted in a large number of misclassifications in

mixed pixels. Evergreen forests (mainly mixing with rotational agriculture), LVA (mainly mixing with deciduous forests), and deciduous forests (mainly mixing with LVA and rotational agriculture) show a decrease in both, UA and PA. In mixed pixels we underestimate the area of evergreen forests ($UA > PA$) while we overestimate the area of LVA and deciduous forests. Classes from group 2 (conversions to rubber and sugarcane) show similar patterns of misclassifications for mixed pixels as for the pure pixels. UA's tend to be higher than PA's, but with increasingly mixed pixels both are lower and the difference between UA and PA increases. Among both pure and mixed pixels we thus tend to underestimate the area of these classes. Confusions mainly occur in the class 'rotational agriculture' (conversions from forests to boom crops), the class LVA (conversions from LVA to boom crops), and to a certain degree among classes that show the same transformation type (e.g. forests to boom crops), but a different timing of change. For the sugarcane classes only a few mixed pixel were available for validation and a comparison with the evaluation using pure pixels was not possible. Classes in group 3 tend to show lower accuracies for the mixed pixels and only the class 'new water' retained a high UA for increasingly mixed pixels, but similar to the class 'water' the PA is substantially lower. For the other classes the relationship between UA and PA remains mostly the same, but accuracies decline with increasingly mixed pixels and misclassifications mainly occur with forests, rotational agriculture, and LVA. In mixed pixels we thus tend to underestimate the area covered by land-cover conversions (groups 2 and 3) while we overestimate the area covered by the classes deciduous forests, LVA, and rotational agriculture.

Table 2: Accuracy assessment based on a ten-fold cross-validation of the land-cover change classification (overall accuracy: 82.2%). Highlighted rows show a user or producer accuracy below 70%. Area estimates are error adjusted.

Land-cover (change) class	UA	PA	Area (km²)	Area (%)	Samples
Water	96.0	95.0	18,627.6	1.62	300
Evergreen forests (F)	83.0	89.4	289,189.9	25.08	918
Deciduous forests (DF)	82.2	87.5	158,128.0	13.71	569
Low vegetation areas (LVA)	77.9	90.2	281,789.8	24.44	735
Rubber (before 2003)	86.9	83.5	19,321.6	1.68	256
Pineapple	97.9	93.9	2,530.5	0.22	100
Rubber, from F, 2003-2005	95.2	79.0	2,294.0	0.20	100
Rubber, from LVA, 2003-2005	79.2	77.6	7,256.3	0.63	100
Rubber, from F, 2006-2008	85.6	88.3	11,534.2	1.00	350
Rubber, from DF, 2006-2008	92.2	71.0	2,687.4	0.23	100
Rubber, from LVA, 2006-2008	85.1	65.5	15,313.3	1.33	150
Rubber, from F, 2009-2011	87.1	79.1	14,099.3	1.22	360
Rubber, from DF, 2009-2011	89.9	83.7	7,477.4	0.65	202
Rubber, from F, 2012-2014	89.2	71.8	9,750.1	0.85	150
Rubber, from DF, 2012-2014	81.8	81.0	4,550.9	0.39	100
Sugarcane, from F, 2006-2008	100.0	97.9	527.0	0.05	100
Sugarcane, from DF, 2009-2011	100.0	89.5	484.1	0.04	19
Rotational Agriculture	62.5	70.4	155,287.2	13.47	706
Expansion of LVA / intensification	80.7	67.2	42,306.8	3.67	356
New Water	100.0	91.9	2,379.6	0.21	100
Pulp trees	78.2	74.7	44,829.3	3.89	400
Cashews	92.7	74.5	14,715.7	1.3	156
Fruit trees	84.5	68.0	28,487.9	2.47	202
Coffee	87.5	88.9	19,532.9	1.69	320

As shown in table 3 we found that in 2014, 25% of the landscape was covered by evergreen forest, 14% by deciduous forest, 13% by rotational agriculture, and 24% by low vegetation areas (mainly cereal crops but also scrub and bushes). In terms of tree crops we found that 8% of the landscape had been converted to rubber; while cashews covered 1% of the landscape, coffee and fruit trees each covered about 2%, and pulp trees covered 4%. Considered as a single category, tree crops accounted for 18% of the landscape. Looking only at rubber, the largest boom crop in the region, approximately 74,960 km² of land were converted to rubber between 2003 and 2014; 50% of this was planted on former evergreen forest land and 20% on deciduous forest land

(Table 4). Hence 70% of the expansion of rubber plantations caused deforestation. Thirty percent of the rubber expansion occurred on areas previously covered by low vegetation (mainly annual crops). Our hypothesis that boom crops were marked by intensification of previously used agricultural land and was not necessarily accompanied by deforestation was wrong. The expansion of rubber between 2003 and 2014 caused deforestation primarily in Cambodia and Laos, but also in Vietnam, Xishuangbanna, and Shan State as well.

Table 3: Land-cover in the selected regions of 6 countries in 2014.

Land-cover in 2014 (area in km², and % total by country)							
Land Cover	Thailand	Cambodia	Vietnam	Xishuang- banna, China	Laos	Shan State, Myanmar	Total
Evergreen Forests	37,967 12	35,437 18	59,649 24	7,443 35	108,790 50	39,837 26	289,124 25
Deciduous Forests	39,786 13	39,522 20	9,645 4	1,578 7	15,459 7	52,087 33	158,077 14
Rotational Agriculture	24,807 8	10,877 6	29,264 12	3,533 17	51,383 24	35,397 23	155,261 13
Low Veg Area	146,627 46	49,691 26	47,888 19	855 4	17,050 8	19,602 13	281,712 24
Rubber	28,614 9	29,743 15	19,166 8	6,182 29	7,656 4	2,921 2	94,282 8
Cashews	1,475 0	2,530 1	8,879 4	62 0	1,640 1	127 0	14,713 1
Coffee	1,379 0	1,088 1	15,654 6	305 1	468 0	636 0	19,530 2
Pulp Trees	4,387 1	3,059 2	31,589 13	83 0	5,483 3	227 0	44,828 4
Fruit Trees	15,634 5	3,018 2	5,678 2	724 3	2,776 1	652 0	28,481 2
All Tree Crops	51,489 16	39,439 20	80,966 33	7,355 35	18,022 8	4,562 3	201,834 18

Land-cover changes related to boom crops vary heavily between, but also within the countries of MSEA. This concerns the type of boom crops, the timing of the conversion, the land-cover type before the conversion, and plantation patterns / types (e.g. small scale vs. concessions). We

considered two external factors affecting rubber expansion, national land policies and the market price of rubber. Table 4 shows the type of land-cover that rubber replaced; Table 5 summarizes rubber expansion in 4 time periods between 2003 and 2014. Figure 5 shows rubber prices through time. Prices were relatively stable between 1978 and 2003; after that they rose steadily until the economic crisis of 2008 when they fell steeply; after 2008 rubber prices rose again through 2011 when the European economic debt crises led to a downturn in commodity prices. In 2017 rubber prices are roughly equivalent to what they were in 2005. We will explore these changes on a country by country basis.

Table 4: Land converted to rubber by country (area in km², and % total)

Land Cover	Thailand	Cambodia	Vietnam	Xishuang- banna, China	Laos	Shan State, Myanmar	Total
Rubber from evergreen forests	1,646 9	17,624 61	7,240 55	3,238 84	6,012 82	1,918 67	37,677 50
Rubber from deciduous forests	313 2	10,456 36	2,253 17	29 1	1,075 15	588 21	14,715 20
Rubber from low vegetation area	16,956 90	659 2	3,788 29	602 16	204 3	360 13	22,568 30
Rubber from evergreen and deciduous forests	1,959 4	28,080 54	9,493 18	3,266 6	7,087 14	2,506 5	52,392 100

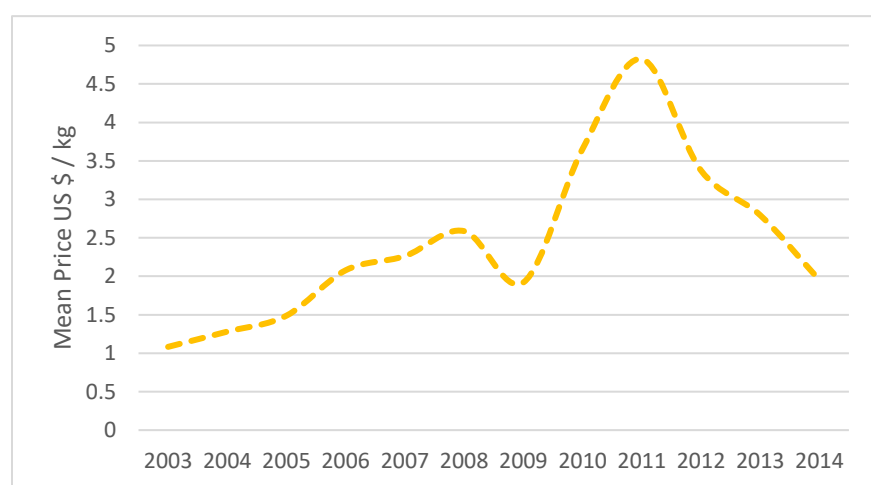


Figure 5: Mean rubber price US Dollar/kg per year (“IndexMundi,” 2017).

Thailand

Thailand shows old rubber (pre 2003, mainly occurring southeast of Bangkok on large scale plantations); this accounted for 34% of the rubber we mapped in Thailand. New rubber was planted in northeast Thailand between 2003 and 2008 by small farmers converting permanent agriculture to rubber; 90% of the rubber planted after 2003 was on areas mapped as low vegetation (crops); only 4% of deforestation caused by rubber in the region occurred in Thailand (Fig 3, Tables 2 and 3). After the 2008 economic crises, farmers in the Northeast stopped planting rubber. In northern Thailand smallholder planted fruit trees (Fig 3 and Table 1). It should be noted that while the expansion of rubber in northeast Thailand did not cause deforestation, this is because the Northeast was heavily deforested in the 1950 and 60s as the Thai government encouraged the cultivation of cash crops (Vityakon et al., 2004). It was the land used to grow these crops (rice, cassava, others) that was later converted to rubber.

In the 1970s the Thai government began to introduce rubber in the Northeast as a viable commercial tree crop. The Thai national government supported the development of infrastructure and services such as the Buriram Rubber Research Station and the numerous Offices of Rubber Replanting Aid Fund (ORRAF) found throughout the Northeast. Beginning in 1989 ORRA provided smallholders in the Northeast, those with less than 2.4 ha of land, with technical advice, free seedlings and fertilizer, low-cost credit for labor costs (including family labor), material inputs (especially herbicides), and other income generating activities. After 2004, ORRAF limited its technical advice on cultivation and free seedlings to households with up to 1 to 1.25 ha of land. We assume that these policy changes followed by the economic crisis reduced smallholder incentives to plant rubber and basically stopped rubber expansion. Figure 6 shows the area of rubber expansion in Thailand and the other countries / regions and Figure 5 the

changes in rubber prices during this period.

Table 5: Expansion of rubber in MSEA by country/region and year (area in km², and % total)

Class Names	Thailand	Cambodia	Vietnam	Xishuang- banna, China	Laos	Shan State, Myanmar	Total
Rubber, before 2003	9,699 34	1,005 3	5,885 31	2,313 37	365 5	55 2	19,322 20
Rubber, 2003-2005	5,104 18	667 2	2,521 13	963 16	234 3	61 2	9,550 10
Rubber, 2006-2008	13,463 47	4,456 15	3,763 20	2,793 45	3,256 43	1,802 62	29,533 31
Rubber, 2009-2011	271 1	12,502 42	5,713 30	87 1	2,695 35	310 11	21,576 23
Rubber, 2012-2014	77 0	11,114 37	1,284 7	26 0	1,106 14	693 24	14,301 15
Total	28,614	29,743	19,166	6,182	7,656	2,921	94,282
% of total rubber	30	32	20	7	8	3	100

Cambodia

In Cambodia, 79% of the conversion to rubber occurred between 2009 and 2014 (Table 5): and 97% of this conversion replaced forest lands; 54% of all deforestation caused by the conversion to rubber in the mapped region occurred in Cambodia (Table 2). Fruit trees, cashews, pulp trees, and coffee also occur, but on fewer and smaller plantations compared to rubber (Fig 4). The 2001 Land Law established a relatively comprehensive legal framework for land tenure and administration and extended ‘ownership’ rights to residential and agricultural land. The law also formalized a system for granting land concessions for economic purposes such as an agribusiness enterprise (Economic Land Concessions, or ELCs); the law stipulated that ELCs have a maximum duration of 99 years, are limited to 10,000 hectares per concessionaire, and concession land must be put to use within twelve months of being granted (Scurrah & Hirsch, 2015). All but one of the rubber concessions were granted after 2005 (Open Development Cambodia (ODC),

2017). In 2012 the government placed a moratorium on the issuing of new ELCs and instructed a review of existing concessions. Figure 6 shows the area of rubber expansion in Cambodia. A small amount of rubber (1,005 km²) had been planted before 2003, while only 667 km² was planted between 2003 and 2005. After 2005 both rubber expansion and rubber prices (Figure 5) rose rapidly until 2011. After 2012, further rubber expansion was prohibited by the moratorium, however, companies that had already received their concession continued to plant new rubber in order to meet the requirement that all concession land be utilized. Interviews with officials from three different rubber concessions in the Northeast indicated that given the low rubber prices they were trying to diversify their new plantings with cashews and black pepper. Most of the rubber we mapped in Cambodia was grown on large concessions although some smallholder rubber was also noted.

Vietnam

In northern and central Vietnam pulp tree plantations prevail while southern Vietnam shows large scale plantations of old and new rubber (72% of the new rubber was planted on forest land; and 18% of the deforestation caused by rubber in the region was in Vietnam), cashews, and coffee (Fig 3 and Tables 1 and 2). Thirty-one percent of the rubber we mapped in Vietnam was planted before 2003; and 33% was planted between 2003 and 2008 (Table 5). In 2009 the Prime Minister's Office issued Decision 750/QD-TTg aiming to increase Vietnam's rubber plantation area to 8,000 km² by 2020 (Akram-Lodhi, 2010) and 37% of the rubber we mapped was planted after 2009. Today, Gia Lai Province (Central Highlands) has become the key location for rubber plantation expansion with total area accounting for 12% of the total rubber plantation area of the country; Dak Lak Province (Central Highlands, south of Gia Lai Province) accounts for 4% of the total rubber plantation area of the country in 2012. Figure 6 shows the area of rubber

expansion in Vietnam and of the other countries / regions and Figure 5 the changes in rubber prices during this period.

Xishuangbanna Prefecture, Yunnan, China

Thirty-seven percent of the rubber in Xishuangbanna was planted before 2003 (Table 5); new smallholder plots were established between 2006 and 2008 (85% were converted from forests; approximately 6% of the deforestation caused by rubber in the region was in Xishuangbanna) (Fig 3, Tables 2 and 3). In early 1950's China introduced rubber into Xishuangbanna to be grown on large-scale state collective farms. In 1982 China dismantled farming communes and returned land to farmers for growing crops—which included rubber in Xishuangbanna. China strengthened incentives for planting rubber in 2002 with the 'Grain for Green' campaign to promote economic development and stop shifting cultivation. Rubber is considered a 'forest' tree and farmers were subsidized for replacing their shifting cultivation fields with rubber trees (Fox & Castella, 2013). Figure 6 shows the area of rubber expansion in Xishuangbanna. After the 2008 economic crisis only 113 Km² of rubber were planted.

Laos

As of 2014 Laos still had 57% forest cover; most rubber plantations were established after 2006; and 97% were planted on previously forested land. Laos accounted for 14% of the deforestation in the region caused by rubber expansion (Tables 1, 2 and 3). In northern Laos rubber is the main boom crop (smallholders and concessions) while in the South large scale plantations of rubber, pulp trees, and sugarcane occur (Figs 3 and 4). The Lao government introduced new land laws in the 1990s to demarcate forests and protected areas. The 1996 National Land Forest Allocation Policy delineated village boundaries and recognized villages' rights to manage and use

agricultural land and limited forest resources. A land titling program funded by World Bank and Australian Agency for International Development (1998 to 2007) led to the granting of large concessions to companies from neighboring countries. In southern Laos, the largest recipients of land concessions are Vietnamese investors in rubber plantations (Manivong, Cramb, & Newby, 2014). In 2004 China established the Opium Replacement Program (ORP) to curb opium production. The ORP provided Chinese companies financial and bureaucratic support to invest in large-scale commercial agriculture in northern Laos and Myanmar. Rubber was the main crop established through ORP support. In 2007 Laos placed a moratorium on land concessions and a second moratorium was announced in 2012 (Lu, 2017). A ceiling of 3,000 km² (nationwide) was placed on rubber; as of 2014 we mapped 7,656 km² of rubber. Figure 6 shows the area of rubber expansion in Laos and of the other countries / regions and Figure 5 the changes in rubber prices during this period. Rubber planting in Laos basically stopped after the 2011 economic crises.

Shan State, Myanmar

Shan State shows 59% forest cover and rubber is the main tree crop (Table 1). Most rubber planting occurred after 2006 on forest lands (88%); only 5% of the deforestation in the region caused by rubber was in Shan State (Table 2); Figure 3 shows conversion of forests to large scale plantations. As in Laos, China established the Opium Replacement Program in 2004 to curb opium production and provided Chinese companies financial and bureaucratic support for investing in large-scale commercial agriculture in Myanmar (Lu, 2017). Rubber was the main crop established through ORP support. In 2012 Myanmar passed the Farmland Law, the Vacant, Fallow, and Virgin lands Management Law, and the Forest Investment Law. These laws have enabled the granting of large scale concessions for tree crops. To date, most land concessions are being granted in upland areas particularly along the Thai and Chinese borders. This is partially

because tenure in the uplands has historically been regulated by customary land, yet customary land-use rights are not formally recognized by the government (Scurrah, Hirsch, & Woods, 2015). Figure 6 shows the area of rubber expansion in Shan State, Myanmar, Figure 5 the changes in rubber prices. As in Xishuangbanna, and to a lesser extent Laos, rubber planting basically stopped after the 2008 economic crises. There was a slight uptick in rubber planting after 2012.

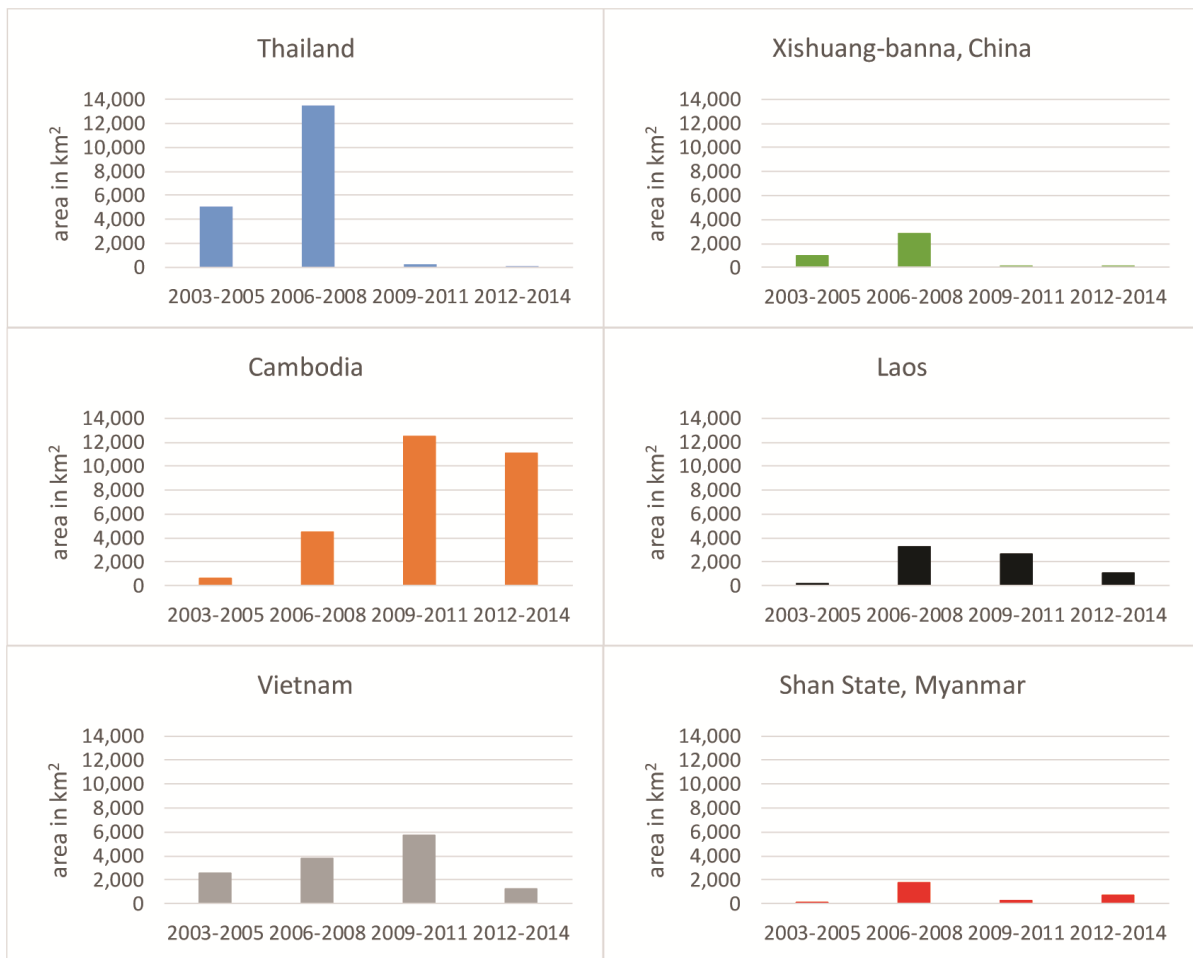


Figure 6: Error adjusted area of rubber expansion in Thailand, Cambodia, Vietnam, Laos, Shan State (Myanmar), and Xishuangbanna (China) as derived from land-cover change classification.

5. Discussion

We performed a supervised change detection in an upscaling approach to classify land-cover dynamics with a focus on boom crops in MSEA using 16-day image composites of MODIS EVI and SWIR data from 2001-2014. In comparison with other mapping activities that focused on the MSEA region (e.g. Z. Li & Fox, 2012; Miettinen, Shi, & Liew, 2016; Stibig, Achard, Carboni, Raši, & Miettinen, 2014) we obtained similar accuracies, but our map provides more detail on boom crop change and smallholder land-use practices (e.g. rotational agriculture). The map of Stibig et al. (2014) identified multiple forest types, plantations, and their change, but the analysis is based on a systematic sampling across MSEA, which can provide valuable information on e.g. forest loss in the region, but spatially explicit information on changes cannot be provided. The wall-to-wall map of Miettinen et al. (2016) also provides more detail on forest types in MSEA, but their map includes Insular Southeast Asia and they focused on large scale oil palm plantations while other dynamics related to tree plantations were grouped with the class 'regrowth'. Considering that land-use practices with crop-fallow rotation are widely practiced in MSEA, boom crops need to be mapped as a separate class to quantify land-use and land-cover changes. Li and Fox (2012) did this by focusing on rubber only. Their map provides valuable information on the distribution of young (< 4 years old) and old rubber in MSEA for 2010, but without information on change. Our map provides such detail, with information on plantation extents in 2014 (i.e. pulp trees, cashews, coffee, pineapple, fruit trees) and detailed information on conversions related to rubber and sugarcane. Dynamics can thus be analyzed for different periods and e.g. deforestation rates associated with the expansion of rubber quantified.

Our classification was performed in iterations and each iteration focused on improving class-wise and overall accuracies by adjusting sample size of the classes through a random selection of

points from a larger pool of samples and adapting the classification scheme. This allowed us to obtain an accurate classification of land-cover change with an overall accuracy for pure pixels of 82.2% and only four of the 24 classes show either UA or PA below 70%. We found that class-wise accuracies are affected by temporal heterogeneity of each class, area, and fragmentation; i.e. for small and fragmented classes (mostly the change classes) we usually obtained fewer points due to the MODIS pixel size. These change classes, however, would need more points to fully represent their temporal heterogeneity and obtain a reliable classification (Foody & Arora, 1997; Hurni et al., 2017; Pal, 2005). During the iterations we focused on these issues (i.e. trade-offs in accuracies in relation to class area, class heterogeneity, and sample sized) and by adjusting the number of sample points among classes we managed to obtain good accuracies for 20 classes and acceptable accuracies for the four remaining classes. We obtained our most accurate classifications when classes covered similar areas and represented similar dynamics (i.e. had similar spatio-temporal heterogeneity) and a similar number of sample points. Heydari and Mountrakis (2018) also demonstrated the importance of obtaining balanced numbers of sample points between classes when using machine learning classifiers; overall accuracies dropped significantly when using different size samples among the classes.

We evaluated the accuracy of the map using pure and mixed pixels and found that accuracies for mixed pixels were substantially lower, with an overall accuracy of 61.5% for pixels with a majority cover of 70-80% and of 43.4% for pixels with a majority cover of 50-60%. For both, pure and mixed pixels, however, misclassification patterns are similar and the transformation classes (groups 2 and 3) show more errors. On the one hand the transformation classes mix with the corresponding 'from' class, e.g. 'rubber from evergreen forests' mixes with 'evergreen forests'. On the other hand the transformation classes mix with themselves, e.g. the type of

change (from-to) is classified correctly, but the timing of the change is wrong or confusions with the class ‘rotational agriculture’ occur. The majority of the transformation classes (groups 2 and 3) show higher UA’s than PA’s and the difference between UA and PA usually increases with increasingly mixed pixels. We thus tend to underestimate the area covered by these classes and while we provide error adjusted area estimates based on the evaluation of pure pixels, we did not perform this for the mixed pixels. As a result our area estimates still show a certain bias and our calculations do not consider uncertainties related to mixed pixels. Due to the lower accuracy of mixed pixels, we can also expect that transformations that cover larger areas are classified more accurately compared to small scale dynamics.

Rubber caused deforestation in all countries in the region except Thailand, and even there it was planted on land deforested to plant annual crops. The expansion of rubber, however, has slowed as international prices have fallen (Figure 6). The Rubber Economist (2017) does not expect there to be another boom in rubber prices / demand in the short to medium term future, but they still forecast that the consumption of rubber (natural and synthetic) will increase from 27.52 million tons in 2016 to 29.41 million tons in 2017, i.e. an annual growth rate of 3.7%. They predict that the growth pattern of the rubber industry for the next few years will remain slow but steady (The Rubber Economist, 2017). Already, we have seen a boom in bananas replacing rubber in northern Laos (Friis & Nielsen, 2016), and frequent reports of cashews and black pepper being planted in northeast Cambodia as farmers diversify from planting more rubber (Thorng & Chao, 2016).

While we may see a decrease in the expansion of rubber because of market prices, another problem may also soon affect rubber plantations—a shortage of labor. In precolonial Southeast Asia, land was more plentiful than labor. As Jim Scott writes (2009:24) ‘Wars in precolonial

Southeast Asia were less about territory than about the seizure of as many captives as possible who were then resettled at the core of the winner's territory.' Today, as industrial estates and plantations continue to develop, labor is again becoming a constraint on agriculture. This can be seen in the wages rubber plantations are paying to attract and maintain tappers despite low rubber prices on the global market. Fox et al. (under review) interviewed 69 tappers in Stung Treng, Cambodia; they reported an average wage of \$157 (640,000 Riel) per month; with a minimum of \$20.00 (80,000 Riel) and a maximum of \$270 (1,100,000 Riel). In addition to their wage, workers receive free housing, and a rice allowance per worker and per child. In comparison the Radio Free Asia (2017) reported that the minimum monthly wage for garment and footwear workers is \$170 a month. Clearly, in order to keep workers, plantation owners have to pay competitive wages.

Likewise in northern Laos, Lu (2017) reported that recruiting and training labor in Laos is proving far more difficult for companies than in China where rubber is much more established. One company manager noted that 'this year we're realizing there is a labor problem' (Luang Namtha, December 2012) while another stated, 'labor is the main bottleneck for rubber development here' (Luang Namtha, November 2012). Compared to China, Laos has an extremely limited labor supply.

Pholphirul (2013: 78) reports that in northern Thailand the option of hiring non-village labor applies not just to workers from other parts of Thailand, but also from neighboring countries. Increasingly, workers from Cambodia, Laos and Myanmar are working on Thai rice farms, fruit orchards and rubber estates. Rigg (2006) suggests the main cause of labor migration in Southeast Asia is the opportunity for higher income or higher wage rates and the ability to transfer money home. Li (2017) cautions that labor migration may not be a 'pathway out of poverty' but a

temporary stop-gap for the extreme poor, who find themselves ejected when they become surplus to the requirements of their employers in the urban industrial sector (e.g., because of an economic downturn), without necessarily having the option simply to return home. Likewise, Barney (2012) in analyzing youth migration from central Laos to Thailand argues that decisions to migrate cannot be disconnected from broader issues of agrarian change. For example, the allocation of large areas of village land to powerful outsiders effectively coerces members of dispossessed households to migrate as a survival strategy.

Regardless of whether migration leads to higher incomes from non-farm employment (Manivong et al., 2014) or are a ‘temporary stop-gap’ on a downward spiral (T. M. Li, 2017), higher wages and the need for employers to compete for laborers in a tight labor market, will affect the profitability of rubber plantations. While the world will continue to consume natural rubber, the rate at which new rubber is planted may be slower for foreseeable future.

6. Conclusions

This project sought to map the extent of tree-based crops in the study region in 2014; and the expansion of rubber and sugarcane between 2003 and 2014. The map provides information on the extent of boom crops (e.g. cashews, pulp trees, coffee, and fruit trees) and detailed information on the expansion of sugarcane and rubber plantations for the MSEA region, allowing for a comparison between countries and sub-national regions. To our knowledge such detailed information has not so far been available at regional level and given the ecological and socio-economic implications of boom crop expansion it can provide valuable insights on how dynamics vary across the region, e.g. the deforestation rates in different countries or administrative units associated with the expansion of rubber. We performed a supervised multi-

date composite change detection technique using the random forest classifier in an upscaling approach. Previous research stressed the importance of obtaining sufficient sample points to represent the spatio-temporal heterogeneity of each class while balancing the number of points among classes to obtain good classification accuracies (Foody & Arora, 1997; Heydari & Mountrakis, 2018). We followed these suggestion and by iteratively adjusting class-wise sample size and the classification scheme, we managed to improve the accuracies of all classes and obtained high accuracies for most classes. It is important to note that we performed the selection of samples randomly by drawing from a larger pool of sample points. This guaranteed that accuracies, and thus the following classification iterations, were not biased by a targeted addition of sample points. Given the large number of sample points required by such a classification approach, future studies may assess how class-wise accuracies are affected by a reduction of the featurespace (i.e. using only a selection of MODIS bands that are most relevant for a specific classification problem). Grogan et al. (2016) showed that such a reduction of the featurespace affects classification accuracies only marginally but improves computational time, while other researchers obtained similar accuracies even by reducing the number of sample points (Pal, 2006).

We performed the accuracy assessment for pure pixels and for mixed pixels with a majority cover of 70-80% and for mixed pixels with a majority cover of 50-60%. Similar to previous research working at MODIS resolution we found that sub-pixel changes occur and that such mixed pixels tend to show more misclassifications (Lunetta et al., 2006; Setiawan & Yoshino, 2014). With increasingly mixed pixels classification accuracies decline and differences between UA and PA increase, which has implications for the calculation of error adjusted area estimates (Olofsson et al. 2014). In this study we based the error adjusted area estimates on the accuracy

assessment of pure pixels. We, however, showed that with increasingly mixed pixels, accuracies also decline. Future research should address how to best include variations in mixed-pixel accuracies in error adjusted area estimates.

We found that in 2014, 25% of the landscape was covered by evergreen forest, 14% by deciduous forest, 13% by rotational agriculture, and 24% by low vegetation (mainly cereal crops but also scrub and bushes). In 2014 eight percent of the landscape was classified as rubber (94,282 km²); while cashews covered 1% of the landscape, coffee and fruit trees each covered 2%, and pulp trees covered 4%. Tree crops accounted for 18% of the landscape. Approximately 74,960 km² of land were converted to rubber between 2003 and 2014; 70% percent of the expansion of rubber plantations caused deforestation; while 30 % occurred on areas previously covered by low vegetation (mainly crops). Our results nullified our hypothesis that boom crops were marked by intensification of previously used agricultural land and were not necessarily accompanied by deforestation. The expansion of rubber between 2003 and 2014 caused deforestation primarily in Cambodia and Laos, but also in Vietnam, Xishaungbanna, and Shan State.

We began this paper with the distinction between booms that have taken place under ‘secure’ conditions and those that have not (Hall et al. 2011). The maps we produced showing large scale land concessions for rubber in southern Laos and northeast Cambodia represent the ‘insecure’ booms’ Hall argues that take place in areas imagined as ‘frontiers’ (Hall et al. 2011: 839). In northeast Thailand, northern Laos, Xishuangbanna, and Vietnam for the most part we find smallholder rubber plantations or what Hall et al. (2011:83) describe as ‘secure’ booms because ‘the basic tenure relations that existed before the boom survive it.’ The Rubber Economist (2017) estimates that most major rubber producing countries have a relatively high percentage share of

smallholdings and the world share of natural rubber smallholding is around 73% of the total rubber area. As Hall et al. (2011:842) suggest various boom crops have been grown under many organizational frameworks, and while smallholders have successfully grown all of them, there is a fairly clear distinction between crops dominated by relatively independent smallholders (cocoa and coffee) and those where larger-scale production has been the rule (fast-growing trees and oil palm), with shrimp and rubber as intermediate cases. Clearly rubber can be grown as a successful smallholder crop.

As Fox and Castella (2013) suggest, in order to promote the establishment of a vibrant smallholder rubber sector the state needs to establish and effectively implement national policies and institutional structures to support smallholder rubber cultivators. National legislation needs to be developed that recognizes customary claims to land and grants farmers and farming communities legal access to the land they have traditionally used through either secure tenure on long-term use rights. In addition to access rights, national agencies need to support smallholders through integrate efforts to provide extension, credit, transport and marketing facilities such as that provided by the Offices of Rubber Replanting Aid Fund (ORRAF) in Thailand. It may also be useful to establish a governing and coordinating body to work closely with all sectors related to the rubber industry. At the local level, smallholder farmer groups need to be organized and/or supported in order to strengthen rubber cultivation, tapping, processing and marketing. These institutional arrangements need to be considered by policymakers as an imperative to support the sustainability and economic viability of smallholders' rubber production. Rubber smallholders may also benefit from advice on how to diversify their crop selection

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Supplementary Material

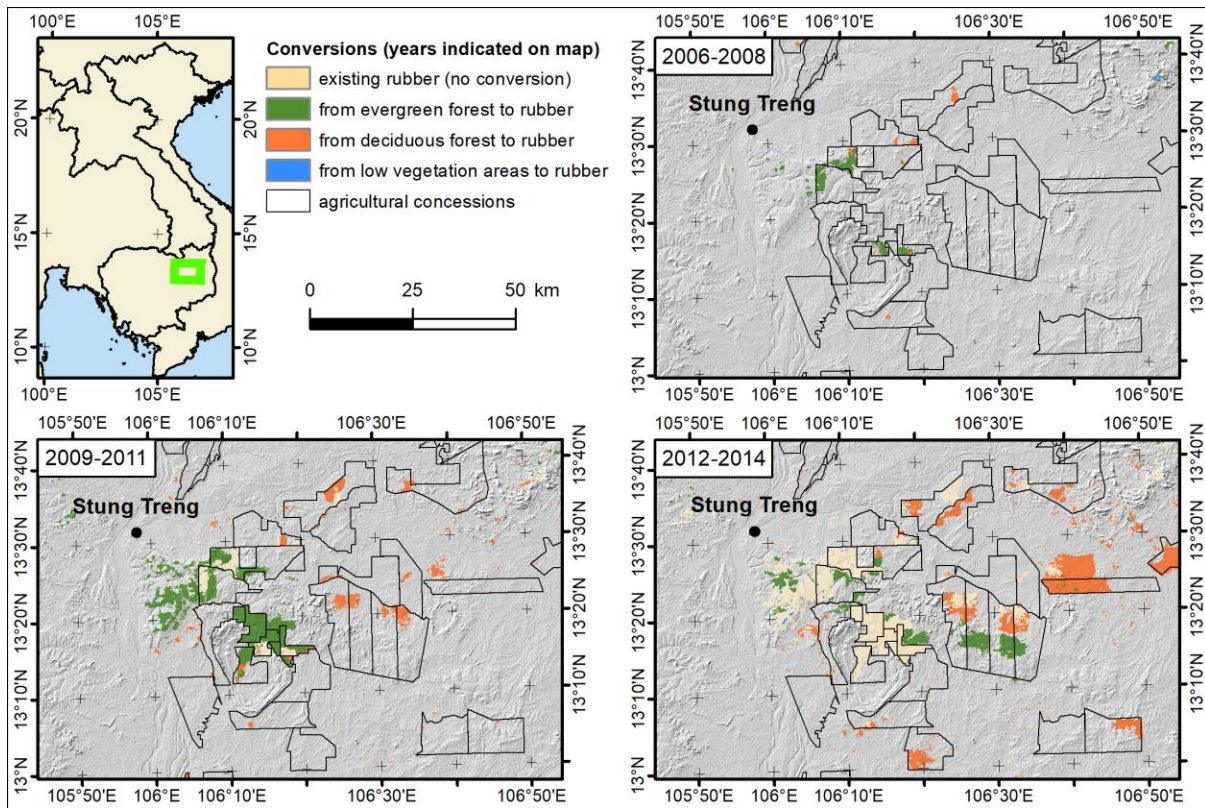


Figure A: Conversions to rubber by year and conversion type around Stung Treng, Cambodia. Black outlined areas represent economic land concessions granted by the government of Cambodia for plantation crops.

Table A: Accuracy assessment of the classification for pure pixels and mixed pixels. For the evaluation of the mixed pixels, we selected areas where the main land-cover (change) class covers 70-80% and 50-60% of the MODIS pixel. Overall accuracies range from 82.2% (pure pixels) to 61.5% (70-80% pure pixels) and 43.4% (50-60% pure pixels).

Land-cover (change) class	Pure pixels			70-80% pure pixels			50-60% pure pixels		
	UA	PA	Samples	UA	PA	Samples	UA	PA	Samples
Water	96	95	300	95.8	46.0	300	84.1	24.7	300
Evergreen forests (F)	83	89.4	918	70.0	62.2	918	53.2	41.6	918
Deciduous forests (DF)	82.2	87.5	569	54.2	72.6	569	31.8	52.0	569
Low vegetation areas (LVA)	77.9	90.2	735	58.5	80.8	735	37.9	62.3	735
Rubber (before 2003)	86.9	83.5	256	89.5	66.4	256	83.5	45.3	256
Pineapple	97.9	93.9	100	95.0	76.0	100	94.3	33.0	100
Rubber, from F, 2003-2005	95.2	79	100	75.8	47.0	100	63.6	21.0	100
Rubber, from LVA, 2003-2005	79.2	77.6	100	52.3	69.0	100	36.3	53.0	100
Rubber, from F, 2006-2008	85.6	88.3	350	80.9	66.6	350	70.9	45.1	350
Rubber, from DF, 2006-2008	92.2	71	100	78.1	50.0	100	78.4	29.0	100
Rubber, from LVA, 2006-2008	85.1	65.5	150	60.2	53.3	150	44.3	38.7	150
Rubber, from F, 2009-2011	87.1	79.1	360	81.1	53.6	360	67.5	37.5	360
Rubber, from DF, 2009-2011	89.9	83.7	202	74.3	54.5	202	56.9	36.6	202
Rubber, from F, 2012-2014	89.2	71.8	150	78.0	56.7	150	65.9	36.0	150
Rubber, from DF, 2012-2014	81.8	81	100	53.3	49.0	100	44.2	34.0	100
Sugarcane, from F, 2006-2008	100	97.9	100	100.0	100.0	6	66.7	50.0	4
Sugarcane, from DF, 2009-2011	100	89.5	19	0.0	0.0	1	0.0	0.0	2
Rotational Agriculture	62.5	70.4	706	37.0	61.8	706	25.5	49.2	706
Expansion of LVA / intensification	80.7	67.2	356	74.7	59.8	356	55.8	42.1	356
New Water	100	91.9	100	97.5	39.0	100	95.8	23.0	100
Pulp trees	78.2	74.7	400	66.1	65.0	123	64.2	54.6	273
Cashews	92.7	74.5	156	68.4	25.0	156	45.5	12.8	156
Fruit trees	84.5	68	202	57.0	44.6	202	36.9	36.1	202
Coffee	87.5	88.9	320	41.0	54.8	62	42.4	34.0	106