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# Cross-border forest disturbance and the role of natural rubber in mainland Southeast Asia using annual Landsat time series

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ABSTRACT

The recent rise in global demand for natural rubber (*Hevea brasiliensis*) has led to expansive areas of natural forest being transformed into monoculture plantations. This paper explores the utility of annual Landsat time series for monitoring forest disturbance and the role of natural rubber in mainland Southeast Asia from 2000 to 2012. A region on the Cambodian–Vietnamese border was chosen for this study considering four primary questions: 1) how accurately can annual Landsat time series map the location and timing of forest disturbances in evergreen and seasonal tropical forests, 2) are there cross-border differences in frontier and non-frontier forest disturbance rates between Cambodia and Vietnam, 3) what proportion of disturbances in frontier and non-frontier forests can be accounted for by the impact of rubber plantations, and 4) is there a relationship between global market prices for natural rubber and the annual rate of frontier forest clearing for rubber plantations on both sides of the border. We used LandTrendr (Landsat-based detection of trends in disturbance and recovery) for temporal segmentation of the Landsat time series and disturbance mapping. Our results show that this approach can provide accurate forest disturbance maps but that accuracy is affected by forest type. Highest accuracies were found in evergreen forest (91%), with lower accuracies in mixed (82%) and dry-deciduous forest types (86%). Our final map considering all forest types yielded an overall accuracy of 86%. Forest disturbance rates were generally higher on the Cambodian side of the border. Frontier forest disturbance rates averaged 3.8%/year in Cambodia compared to 2.5%/year in Vietnam. Conversion to rubber was the dominant form of frontier forest change in both countries (42% in Cambodia and 84% in Vietnam). Non-frontier forest disturbances averaged 4.0% and 2.5% in Cambodia and Vietnam, respectively, with most disturbances likewise linked with rubber plantations. Although rates of frontier forest disturbance differed in both countries, they each displayed similar correlations between disturbance rates related to rubber plantation expansion and price fluctuations of natural rubber. This suggests links between localized land cover/use change and international market forces, irrespective of differing political and socioeconomic backgrounds. Our study underlines the value of using dense Landsat time series when exploring the dynamics of human-induced land cover change.



## 1. Introduction

Tropical forests around the globe are undergoing a major transformation, largely attributed to anthropogenic disturbances (Wright & Muller-landau, 2006). Remote sensing analysis has identified Southeast Asia as one of the world's deforestation hotspots (Achard et al., 2002; Hansen et al., 2008a, 2013; Stibig et al., 2014), comparable to conversion rates found in Latin America. Historically, the causes of tropical deforestation have been broadly attributed to a number of factors including among others, population pressure, weak institutions and policy, and trade liberalization (Geist & Lambin, 2002; Laurance, 1999). Although each of these driving forces still heavily influences the fate of tropical forest, it is arguably the latter that currently poses the greatest threat in the Southeast Asian context (FAO, 2009; Rudel et al., 2009).

Regarding deforestation rates, distinction is often made between Insular and mainland Southeast Asia. A recent study by Stibig et al. (2014) showed annual deforestation rates (relative change percent) in Insular Southeast Asia to be much higher throughout the 1990s. From 2000 onwards, however, it was mainland Southeast Asia that experienced a greater relative change. Part of this reversal may be caused by the rising global demand for natural rubber (*Hevea brasiliensis*), fuelling increasing (but unstable) market prices from 2000–2012 (Fig. 1), and leading to unprecedented expansion of both smallholder and large

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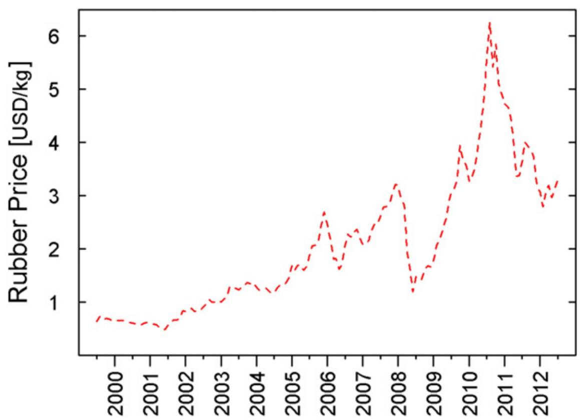


**Fig. 1.** Monthly price (USD/kg) for natural rubber on the Singapore/Malaysian stock exchange.
Source: World Bank (World Bank, 2014).

scale plantations across the region (Fox & Castella, 2013; ODC, 2014; Vrieze & Naren, 2012; Ziegler et al., 2009).

Two countries that play pivotal, albeit differing, roles in this forest transformation process in mainland Southeast Asia are Vietnam and Cambodia. In Vietnam, rapid forest loss from c. 1970 to c. 1990 (Bernard & Koninck, 1996) has been followed by a period of net reforestation during the 1990s (Meyfroidt & Lambin, 2008). In contrast, Cambodian forests had escaped earlier destruction, but are now expected to undergo major transformation (Southworth et al., 2012). Progressive market liberalization stemming from the turn of the millennium has sparked rapid expansion of rubber plantations among smallholders (Dararath et al., 2011; Hing & Thun, 2009), and more recently in the form of industrial Economic Land Concessions (ELCs). Meanwhile the natural rubber industry in Vietnam, which is already well established (FAO, 2010), is expanding rapidly again, especially since the early 2000s (Luan, 2013).

Border regions between countries provide an ideal case for studying the relative importance of political and economic impacts on land cover change (Kuemmerle et al., 2006). Although the Cambodian–Vietnamese border region shares similar natural forest composition (Wikramanayake et al., 2000), differing land governance regimes inevitably lead to alternate land cover/use change pathways. Aside from historical differences, recent regional inter-governmental cooperation led to the formation of the *Cambodian–Laos–Vietnam Triangle* in 2004, aiming to develop the border region, including investment in natural rubber plantations (Gironde, 2012; Ishida et al., 2013). Studying this border region from a remote sensing perspective will contribute to understanding how these political backgrounds have shaped historical forest cover, but also whether global market forces influence land use decisions, irrespective of political and socio-economic contexts.

When analyzing forest cover change dynamics it can be useful to consider the forest frontier, defined by Chomitz et al. (2007) as beyond the boundary where forest and agricultural (or agroforest) interact. Non-frontier forest (e.g. plantations, fallow regrowth) often do not provide the same benefits of mature frontier forest vegetation in terms of ecosystem services such as climate and water regulation, carbon storage, and biodiversity richness (e.g. Numata et al., 2011). Distinguishing between frontier and non-frontier forests in change analysis helps evaluate the quality (in broad terms) of forest undergoing change (Tropek et al., 2014).

From a monitoring perspective, the Landsat mission in particular maintains attributes that are highly suitable for mapping forest cover and associated change over time at varying spatial scales (Hansen & Loveland, 2012; Tucker et al., 2004). A number of regional scale analyses have focused on specific themes, for example, mapping selective logging (Asner et al., 2005), burned area (Matricardi et al., 2010), or shifting cultivation dynamics (Inoue et al., 2010). In Southeast Asia Landsat data has been used to map regional rubber plantation extent (Dong et al., 2013; Li & Fox, 2011) and change dynamics (Li et al., 2006; Liu et al., 2013). National scale Landsat studies have focused on general land cover change (Fry et al., 2011), or specifically on forest cover loss (Broich et al., 2011; Hansen et al., 2008b, 2009) often coupled with forest degradation (Asner et al., 2009; Margono et al., 2012). At pan-tropical to global scales Landsat analysis have largely focused on forest cover loss, taking a sampling approach (Achard et al., 2014; Hansen et al., 2008a), and more recently wall-to-wall coverage (Hansen et al., 2013). Studies with the aim of broader scale mapping of rubber plantations in Southeast Asia have generally favored the use of MODIS sensors (Dong et al., 2012; Li & Fox, 2012; Senf et al., 2013), likely due to reduced preprocessing time, coupled with the advantage of phenological time series. Advancements in automated Landsat pre-processing however (Ju et al., 2012; Zhu & Woodcock, 2012), have given rise to a new era in Landsat change detection methods, moving away from traditional bi-temporal change detection (Coppin et al., 2004), and towards more dense time-series approaches (Broich et al., 2011; Huang et al., 2010; Kennedy et al., 2010; Zhu et al., 2012). The utility of such optical time series remains to be fully explored in a tropical environment where persistent cloud and aerosol contamination presents an ongoing challenge (Grogan & Fensholt, 2013; Leinenkugel et al., 2013).

Southeast Asia hosts a wide variety of tropical forest types ranging from moist evergreen to dry-deciduous. Despite a number of studies focusing on dry forest systems (Clark et al., 2010; Helmer et al., 2010), in comparison to tropical evergreen forest, they remain largely understudied. Part of the reason for this stems from the fact that they are more difficult to monitor using satellite imagery, with dry season senescence often causing confusion in vegetation change analysis (Asner, 2001; Sánchez-Azofeifa et al., 2009), frequently leading to higher mapping error (Couturier, 2010; Barreda-Bautista et al., 2011, Chap. 11; Stibig et al., 2014). Time series trajectory approaches are considered more robust against inherent noise in the data (e.g. inter annual variation) (Hostert et al., in press) and therefore may be more suited to change detection within dry forest types. To our knowledge, no study has tested the applicability of trajectory-based forest change approaches in deciduous tropical dry forest systems.

The main objective of this study was to explore the utility of annual Landsat data for mapping land cover change associated with forest disturbance along the border region of Cambodia and Vietnam from 2000–2012, with distinct attention to the role of natural rubber plantations both in frontier and non-frontier forest systems. Using a selected study area we specifically ask the following research questions:

- How accurately can annual Landsat time series map the location and timing of forest disturbance in tropical evergreen and seasonal forest landscapes?
- Are there cross border differences in frontier and non-frontier forest disturbance rates between Cambodia and Vietnam?
- What proportion of disturbances in frontier and non-frontier forests can be accounted for by the impact of natural rubber plantations?
- Is there a relationship between global market prices for natural rubber and the annual rate of frontier forest disturbance caused by rubber plantation expansion on both sides of the border?

## 2. Study area

The study area encompasses most of a single Landsat footprint (path 125, row 052) on the Cambodian–Vietnamese border (Fig. 2) and includes evergreen, mixed-deciduous, and dry-deciduous forest types (Walston et al., 2001), as well as extensive areas of plantations, predominantly natural rubber. The total study area covers 22,420 km$^2$, with 54% located in Vietnam and 46% in Cambodia. We estimated that 57% of the total land area was forest in 2000, with 59% of this classified as frontier forest (see Section 3.1). The study region is relatively flat with peaks of

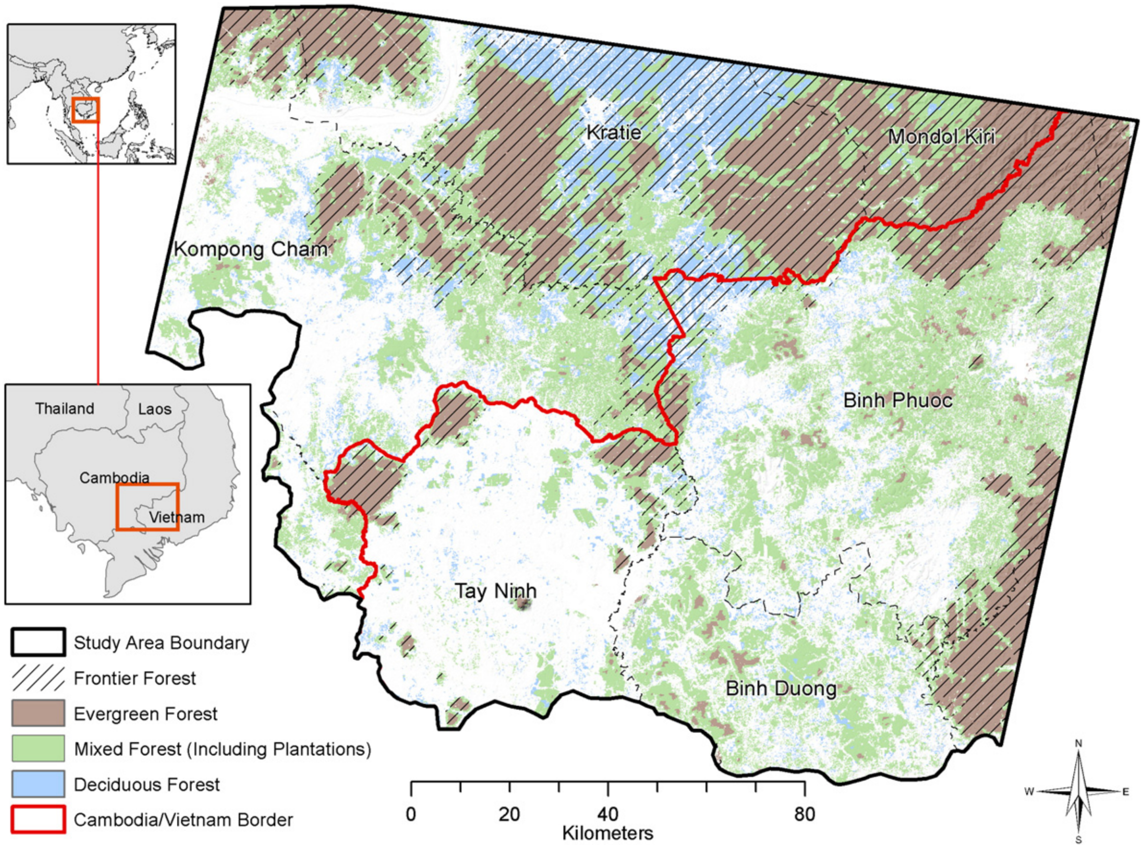


**Fig. 2.** Study area along the Cambodian/Vietnamese border. The Cambodian side is located to the north of the border (red line), the Vietnamese side to the south. Forest type, and frontier forest extent are also shown — see Methods section 3.1 for details on how these data were generated.

up to 900 m found mainly to the northeast. The area is characterized by pronounced seasons with a rainy season usually lasting from May–October, a cool/dry season from November–March, and a hot/dry season from March to May. As we were interested in forest-related land cover changes, intensive rice paddy and dense urban areas to the south and south-west were masked out prior to the analysis.

## 3. Methods

We mapped forest disturbance at annual time steps using the LandTrendr algorithm and annual, cloud-free Landsat time series composites. Assembling annual image composites requires seasonal effects to be reduced as far as possible, so that spectral variations associated with phenology are minimized. Our methodological approach begins with a stratification of the forest area into evergreen and seasonal forest types (Fig. 3). This process aids in the selection of suitable imagery based on the phenological characteristics of the forest vegetation. We then applied LandTrendr for temporal segmentation and annual disturbance mapping of Landsat time series. LandTrendr works on a single band or vegetation index. To find the optimal index, we tested different vegetation indices during the calibration step. Finally, we estimated overall accuracy and area changes using a stratified random validation sample.

### 3.1. Forest mask and stratification

Similar to Hansen et al. (2013), the 30 m vegetation continuous field (VCF) product for year 2000 (Sexton et al., 2013) was used to define the forest area based on a threshold of > 15% tree cover (Di Gregorio, 2005) and a minimum mapping unit of 11 pixels (≈ 1 ha). To stratify the forest area into evergreen, dry-deciduous, and mixed forest, we used the Land Surface Water Index (LSWI) derived from MODIS 250 m 16-day data (MOD13Q1). A number of studies have used LSWI time series to separate different land cover types including forest classes (Boles et al., 2004; Dong et al., 2013; Xiao et al., 2009). The LSWI is sensitive to equivalent water thickness (g $H_2O/m^2$) and is therefore suited for discrimination of evergreen forest, which undergoes limited seasonal water stress and retains foliage compared to mixed and dry-deciduous forest types (Fig. 4).

Although previous studies (Dong et al., 2012; Xiao et al., 2009) have used MODIS SWIR band 6 for calculating LSWI, we used the resampled SWIR band 7 from the MOD13Q1 product. LSWI was calculated for a single full season from Feb. 2000 to Feb. 2001 using Eq. (1) and an annual minimum for each pixel was determined.

$$\frac{NIR_{b2} - SWIR_{b7}}{NIR_{b2} + SWIR_{b7}}. \quad (1)$$

We selected a random sample of MODIS pixels representing evergreen, mixed and dry-deciduous forest types (100 samples each). In this study mixed forest represented seasonal forest types including mixed-deciduous forest, forest regrowth/fallow, and plantations. Sample labeling was done using visual interpretation of Landsat and high resolution imagery (see Section 3.3.3 and Fig. 7 further details). A histogram of seasonal minimum LSWI values was generated (Fig. 5) and thresholds were chosen to separate each forest class; evergreen > 0.55, mixed < 0.55 & > 0.28, and dry-deciduous < 0.28.

When estimating disturbed forest area, we distinguished between 1) country — Cambodia or Vietnam and 2) frontier or non-frontier forest. For this, we manually digitized frontier forest using Landsat imagery and Google Earth ©. Our frontier forest definition is based on forest located beyond the agriculture (or agroforest) frontier described by

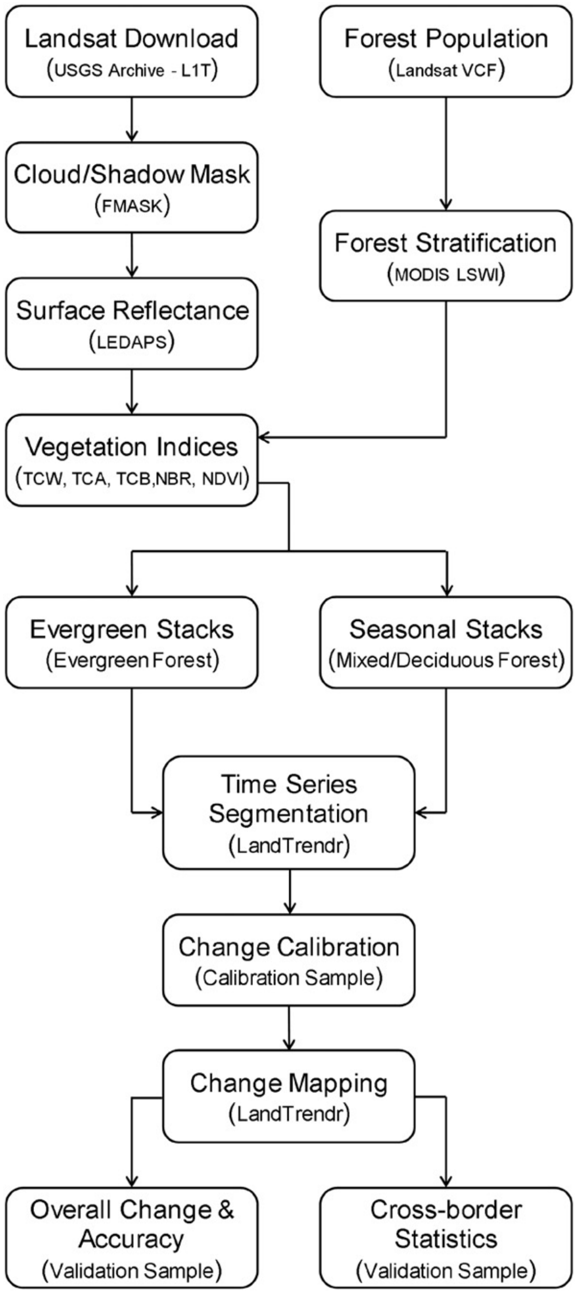


**Fig. 3.** Flowchart describing methodological steps.

Chomitz et al. (2007). We identified frontier forest as patches of continuous forest (>2 ha) that showed no signs of clearing prior to year 2000. The remaining forest was labeled as non-frontier forest, and included plantations and previously cleared forest areas (Fig. 2).

### *3.2. Landsat data and processing*

#### *3.2.1. Landsat data*

All level 1 T Landsat data acquired between 1st January 1984 to 28th February 2013 with cloud cover < 90% were downloaded from the USGS archive for path 125 and row 052. The earliest scene available that met these specifications was from 8th January 1989. Each image was first screened for cloud and cloud shadow using Fmask (Zhu & Woodcock, 2012) and converted to surface reflectance using LEDAPS (Masek et al., 2006).

Seasonal vegetation in this region can dry out very quickly as the dry season progresses making early and late dry season observations spectrally incomparable. In contrast, the spectral properties of evergreen forest were found to be comparably invariant throughout the year. For this reason, separate annual composite stacks were made for 1) evergreen forest and 2) seasonal forest (mixed and dry-deciduous). Annual composites for each stack were made using the single clear-sky observation that was closest to a selected anniversary date. Day of year (DOY) 300 was chosen as the optimal anniversary date for both composite stacks as it is the time of year where the season shifts from wet to dry (Fig. 4), meaning vegetation still has a strong and consistent signal coupled with a higher probability of getting cloud free observations. For the seasonal forest composites we restricted the selection of images to within a time window of $\pm$60 days from the anniversary date to minimize spectral changes related to vegetation phenology. For the evergreen forest composites we used all available imagery between beginning of May and end of April of the following year. A full list detailing all Landsat imagery used in each stack and for each annual composite can be found in the Supplemental material (Table S1).

Using the outlined selection criteria we had almost 100% coverage for the evergreen stack from 1999 onwards, with intermittent years of coverage pre-1999 (Fig. 6A). Applying the more strict time window for the seasonal stack resulted in some years having only partial coverage post-1999 and comparably less coverage in the pre-1999 era (Fig. 6B). Overall we had acceptable coverage for mapping forest disturbance from 2000 onwards (Fig. 6C).

#### *3.2.2. Landsat time series analysis*

Time series analysis was carried out on Landsat image stacks using LandTrendr (Kennedy et al., 2010). LandTrendr is a temporal segmentation and fitting algorithm used to map forest cover change processes at annual time steps. The aim of LandTrendr is to derive spectral-temporal trajectories associated with disturbances and regrowth on a pixel-by-

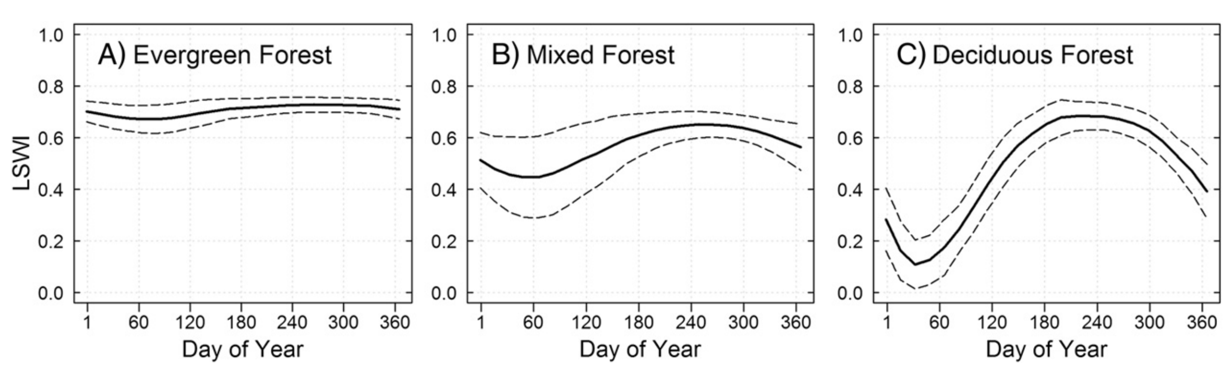


**Fig. 4.** Smoothed Land Surface Water Index (LSWI) time series of evergreen, mixed, and dry-deciduous forest derived from MODIS (MOD13Q1). Time series are based on 100 samples from each forest type. Dotted lines indicate one standard deviation.

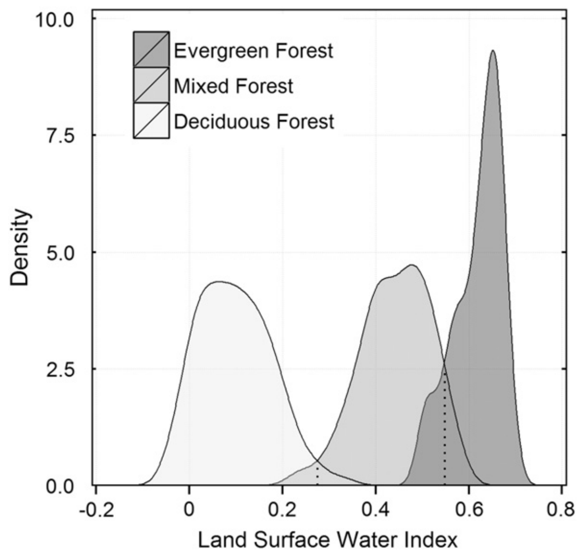


**Fig. 5.** Frequency distribution of MODIS-based minimum Land Surface Water Index (LSWI) from year 2000/2001 for three forest types: evergreen, mixed, and dry-deciduous forest.

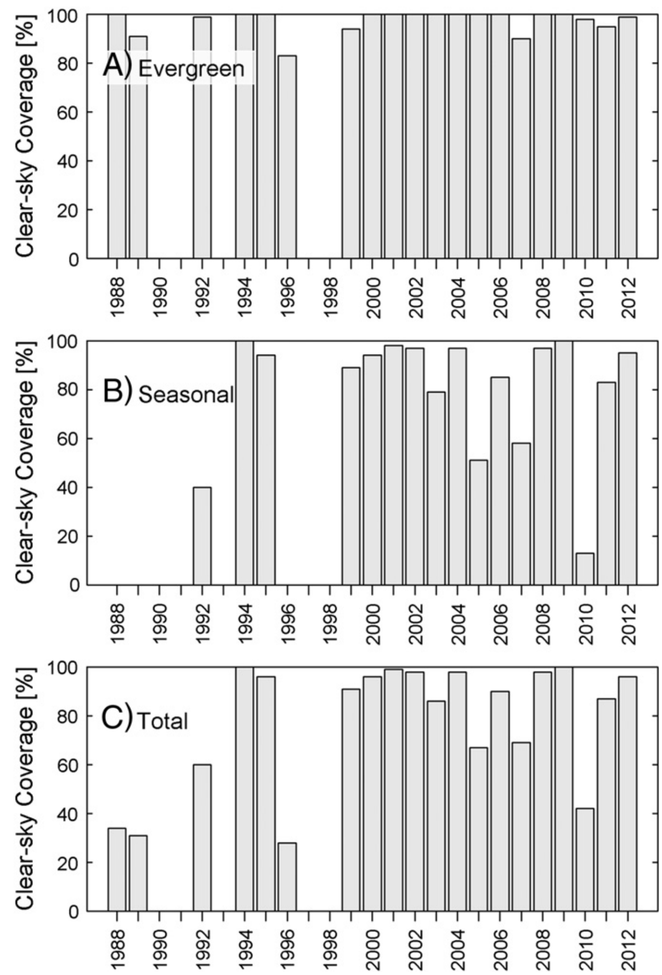


**Fig. 6.** Annual Landsat data availability for the evergreen forest stack (A), the seasonal forest stack (B) and total forest coverage (C).

pixel basis, using regression methods and point-to-point fitting. By simplifying the time series into linear segments, a range of different change processes can be captured, ranging from abrupt (e.g. fire or stand clearing) to more gradual events (e.g. forest regrowth or pest infestations). For further details and applications of LandTrendr see Kennedy et al. (2010, 2012), Griffiths et al. (2012) and Pflugmacher et al. (2014).

We chose to test the performance of five indices which are responsive to different vegetation cover/disturbance properties including vegetation greenness, moisture content, canopy structure, and exposed soil signal. We generated Landsat time series stacks using the Normalized Difference Vegetation Index (NDVI) (Tucker, 1978), Normalized Burn Ratio (NBR) (Key & Benson, 1999), Tasseled Cap Wetness ($TC_W$), Tasseled Cap Brightness ($TC_B$) (Crist, 1985), and Tasseled Cap Angle ($TC_A$) (Powell et al., 2010).

### 3.2.3. Forest disturbance mapping

Due to data availability constraints (Fig. 6) we mapped forest disturbances from 2000 onwards only. Although data before 2000 were too sparse for annual disturbance detection, we included all time steps in the LandTrendr algorithm because doing so improved the overall trajectory fitting, particularly when changes occured shortly after 2000. In this study we used LandTrendr to map annual forest clearing or ‘stand-replacing’ disturbances — hereby referred to as ‘forest disturbance’. These events are characterized by abrupt (1–3 year) segments, showing a steep magnitude decline or rise in the spectral response depending on the index used.

To identify segments associated with stand-replacing disturbances we estimated the minimum disturbance magnitude threshold for each spectral index using a calibration sample. For each forest type we collected 160 random change and no-change samples (3 × 3 Landsat pixel blocks). Each sample was labeled as either change or no-change based on manual interpretation of image chips using all available Landsat imagery together with temporal-spectral profiles and supplemental imagery (Aster & high resolution Google Earth), similar to Cohen et al. (2010). The average sample size per year in the random calibration sample was 37. All years had above 25 samples each, except for 2000, 2001, and 2002, which had 0, 3, and 13 samples, respectively. Using a sliding threshold, we estimated Producer's and User's accuracy curves for the change class using each spectral index, and for each forest type. We considered magnitude thresholds to be optimal at a point where the gain in User's accuracy was evenly balanced by the loss in Producer's accuracy described by the following equation:

$$\left|\frac{d\,\mathrm{PA}(\Delta\mathrm{Index})}{d\,\Delta\mathrm{Index}}\right| = \left|\frac{d\,\mathrm{UA}(\Delta\mathrm{Index})}{d\Delta\mathrm{Index}}\right| \tag{2}$$

where PA is the Producer's accuracy, UA is the User's accuracy, and Index is the spectral index being calibrated.

We chose the spectral index with the highest accuracy as the *primary* mapping index. We then tested if combining change mapped using other indices (hereby referred to as *secondary* indices) with the change mapped using the primary mapping index improved accuracies. Combining change indices was straightforward; pixels mapped as change using a secondary index, but as no-change using the primary index, were simply added to the primary index change map. When combining mapping results we used a more conservative change magnitude threshold for the secondary index to avoid potential inflation of the overall commission error. Here we chose a threshold where the change commission error equaled 5%. Finally, we applied a minimum mapping unit of 11 pixels (≈1 ha) to the disturbance map.

## 3.3. Accuracy assessment and land cover change statistics

### 3.3.1. Sample design

For the final forest change map our aim was to assess its accuracy and estimate annual change area with 95% confidence intervals. To achieve this we used a stratified random sample, allocating 500 samples to the change classes and 500 samples to the undisturbed map class. To ensure that each disturbance year had an adequate sample size, we first selected a minimum of 25 samples per change year and then distributed the remaining samples proportionally to the map class area.

For the cross-border comparison our aim was to estimate annual change statistics on each side of the border in both frontier and non-frontier forests. For this, the same validation sample was stratified using two additional strata — country (Cambodia or Vietnam) and forest category (frontier or non-frontier). After applying the additional stratification we added supplementary random samples to strata with low sample counts to ensure that each stratum had at least 10 samples. In all, a total of 212 supplementary samples were added for the cross-border assessment. For all samples (1212 in total) we used a 3 × 3 pixel block as the spatial assessment unit, with the sample label decided by the majority vote within each block.

*3.3.2. Accuracy and change area estimates*

Using an approach similar to that of Cohen et al. (2010) (see Section 3.2.3) we recorded the year of disturbance onset (if any) as the change year for each reference sample. For consistency between our reference sample labels and our annual composite stacks (see Section 3.2.1), we assessed all samples for change using the same 12 month annual time step (May–April). To assess the map accuracy we considered the mapped change year to be correct if it matched the reference year ± 1, and calculated Producer's and User's accuracies for each forest type. Following Card (1982) and Olofsson et al. (2013), we adjusted for the disproportional sampling using the mapped area proportions to estimate area-adjusted accuracies for the change map. The area calculation should consider the error in every year to give an unbiased annual area estimate. This is especially important for years where there are data gaps as the independent reference sample corrects for any mapping bias. We calculated the annual proportional error matrix without using the 1-year relaxation to estimate disturbed forest area for each year, including the 95% confidence interval.

Our area estimates relate to the forested area in year 2000 (see Section 3.1). Thereby, we omit forest regeneration/expansion outside the forested area from 2000, which means that the overall net forest cover loss for the entire region may be lower than the reported estimates. Likewise, our rubber expansion estimates do not include the establishment of rubber plantations on areas that were not forested in 2000. When reporting annual area estimates in percent (%), we used percentages relative to the original forest area of each forest category in year 2000.

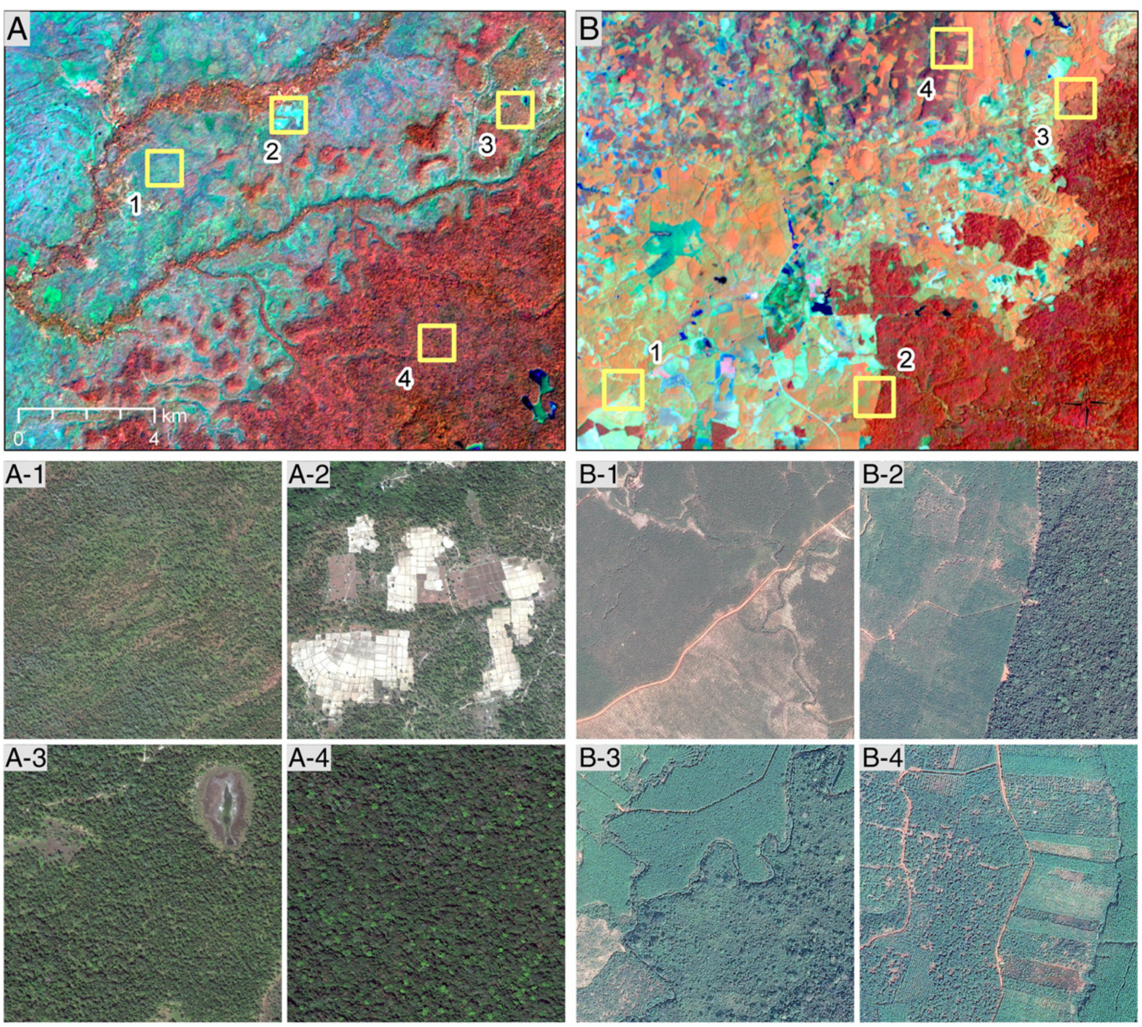


**Fig. 7.** Land cover/use identification using Landsat and high resolution imagery from Google Earth. Each of the 4 yellow squares (1 $km^2$) in each Landsat image (A) and (B) are represented by numbered high resolution image chips in panels below. Natural forest types and agriculture are illustrated in panel (A) using a Landsat 7 image from November 2001 (RGB = 4–5–2); dry-deciduous forest (A-1), agriculture surrounded by dry-deciduous forest (A-2), mixed-deciduous forest (A-3) and evergreen forest (A-4). Different forest types and plantations are illustrated in panel (B) using a Landsat 8 image from March 2014 (RGB = 5–6–3); mature and immature rubber plantation (B-1), rubber/evergreen forest frontier (B-2), rubber and forest regrowth (B-3) and other woody plantations with interspersed rubber (B-4).

#### 3.3.3. Land cover/use change assessment

To assess land cover/use change arising from forest disturbance we recorded a number of descriptive labels for every change sample, including; 1) pre-disturbance land cover/use in year 2000, 2) post-disturbance land cover/use in 2012, and 3) industrial versus smallholder land cover/use change. Land cover/use was interpreted using multi-temporal Landsat 5 (30 m), pan-sharpened Landsat 7 and 8 (15 m), and Aster (15 m). High resolution Google Earth imagery was also available for almost the entire (98%) study area. Land cover/use labels included: Forest, Forest Regrowth, Agriculture, Rubber Plantation, Woody Plantation, Other, and Unknown. We found dry season false color composites using a combination of visible, near-infrared, and shortwave-infrared bands provided optimal separation between different classes. Evergreen, mixed-deciduous and dry-deciduous forest could be separated using early dry season imagery (Fig. 7A). To distinguish rubber from other forest/woody vegetation, imagery from the late dry season/early wet season was best. At this time of year rubber is in the foliation phase and has a distinct reflectance in the near-infrared and shortwave-infrared bands (Dong et al., 2013). Using false color composites (TM/ETM RGB = 4–5–2, OLI RGB = 5–6–3) rubber appeared a distinctive orange color (Fig. 7B) and was readily distinguished from evergreen forest (bright red, Fig. 7B-2), forest regrowth (reddish-brown, Fig. 7B-3) and other woody plantations (purple, Fig. 7B-4). The “Unknown” label was assigned to samples whereby the specific land cover/use could not be determined by the available imagery due to lacking spatial detail or the sparseness of vegetation post-disturbance. The label ‘Other’ was assigned to miscellaneous land cover/use changes including disturbances caused by mining, road construction, and hydrological dam flooding.

Smallholder land cover/use change was distinguished from industrial scale by elements such as size, shape, and pattern of the land cover patch and surrounding patches. Smallholder plots were generally less than 10 ha, part of an irregular patchwork of tree cover of varying age, and often located close to residential dwellings. Industrial scale plots were much larger, forming regular patterns, and associated with surrounding homogenous areas of plantations.

### 3.4. Global rubber markets and frontier forest disturbance

To analyze potential linkages between global rubber markets and frontier forest disturbance we compared rubber price statistics and annual disturbance rates attributed to rubber plantation expansion. We obtained monthly natural rubber prices from the Singapore/Malaysian stock exchange (World Bank, 2014) (Fig. 1) and calculated both yearly means and yearly rates of change (i.e. slope of yearly market trends) over the May–April period. The rates of change in rubber price were estimated using linear regression of the twelve monthly values. Using simple linear regression, we then investigated the relationship between; 1) mean market prices and annual disturbance rates related to rubber plantation expansion, and 2) rates of change in price and year-to-year changes in disturbance rates related to rubber in frontier forests.

## 4. Results

### 4.1. Forest monitoring with Landsat

#### 4.1.1. LandTrendr calibration

The calibration of the change magnitude showed that $TC_W$ was the most accurate individual indicator of change (Table 1) and was therefore chosen as the primary mapping index. Applying Eq. (2) resulted in slightly different threshold values for each forest type; evergreen 0.031 $\Delta TC_W$, mixed 0.028 $\Delta TC_W$, and deciduous 0.033 $\Delta TC_W$ (Fig. 8). $TC_W$ showed comparable accuracies to NBR, while $TC_A$, NDVI, and $TC_B$ time series were less accurate. We found that combining $TC_W$ with NBR as a secondary index increased the Producer's accuracy while

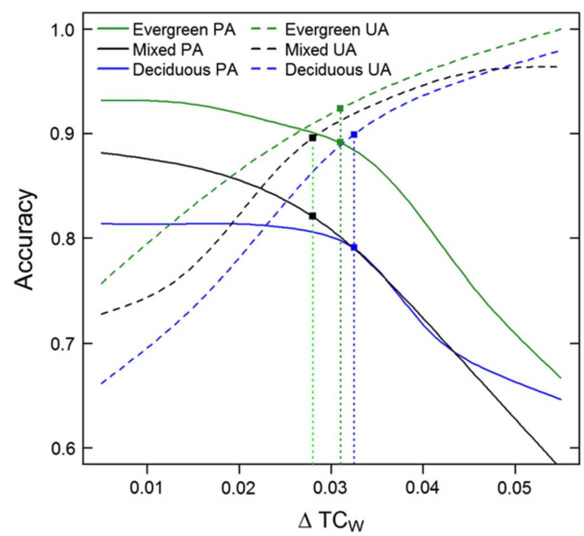


**Fig. 8.** Calibration of change/no change magnitude for evergreen (dark green), mixed (black), and dry-deciduous (blue) forest. Producer's and user's accuracies (PA and UA) for each forest type were determined using sliding threshold and a calibration sample of 320 points (160 change, and 160 no change). Threshold values (vertical dotted lines) for each forest type were determined using Eq. (1).

**Table 1**
Producers accuracy (PA), users accuracy (UA), overall accuracy (OA), and optimal threshold (TH) for spectral indices in evergreen, mixed and dry-deciduous forest. Only one combined group ($TC_W$ + NBR) is shown for brevity. Results are based on a calibration sample of 320 points (160 change, and 160 no change) for each forest type.

| | | Evergreen forest | | | | Mixed forest | | | | Deciduous forest | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PA | UA | OA | ΔTH | PA | UA | OA | ΔTH | PA | UA | OA | ΔTH |
| $TC_W$ | Change | 0.89 | 0.92 | 0.91 | 0.031 | 0.82 | 0.90 | 0.86 | 0.028 | 0.79 | 0.90 | 0.85 | 0.033 |
| | No change | 0.93 | 0.90 | | | 0.91 | 0.84 | | | 0.91 | 0.82 | | |
| NBR | Change | 0.87 | 0.92 | 0.90 | 0.10 | 0.73 | 0.89 | 0.82 | 0.14 | 0.81 | 0.86 | 0.84 | 0.11 |
| | No change | 0.92 | 0.88 | | | 0.91 | 0.77 | | | 0.87 | 0.83 | | |
| $TC_A$ | Change | 0.79 | 0.88 | 0.84 | 70 | 0.75 | 0.79 | 0.78 | 50 | 0.72 | 0.89 | 0.82 | 75 |
| | No change | 0.90 | 0.81 | | | 0.80 | 0.76 | | | 0.91 | 0.77 | | |
| NDVI | Change | 0.81 | 0.87 | 0.85 | 0.12 | 0.75 | 0.76 | 0.76 | 0.09 | 0.72 | 0.87 | 0.81 | 0.14 |
| | No change | 0.88 | 0.82 | | | 0.76 | 0.76 | | | 0.90 | 0.77 | | |
| $TC_B$ | Change | 0.75 | 0.85 | 0.81 | 0.058 | 0.58 | 0.76 | 0.70 | 0.055 | 0.56 | 0.81 | 0.72 | 0.068 |
| | No change | 0.87 | 0.78 | | | 0.82 | 0.67 | | | 0.87 | 0.67 | | |
| $TC_W$ + NBR[a] | Change | 0.95 | 0.90 | 0.92 | 0.031 | 0.90 | 0.88 | 0.89 | 0.028 | 0.86 | 0.88 | 0.87 | 0.033 |
| | No change | 0.90 | 0.95 | | 0.14[a] | 0.88 | 0.90 | | 0.22[a] | 0.89 | 0.86 | | 0.20[a] |

[a] A conservative threshold was used which targeted a change commission error of 5%.

preserving the User's accuracy at acceptable levels (Table 1). We proceeded with this combination for mapping forest disturbance.

### 4.1.2. Disturbance mapping in different forest types

In year 2000, 12,684 km$^2$ of the study area was forested (57% of study area), from which 51% was mixed forest (including plantations), 34% evergreen forest, and 15% dry-deciduous forest (Fig. 2). The LandTrendr change detection performed well in each of the three forest types, effectively capturing trajectories and abrupt change (Fig. 9). Nonetheless there were notable differences in the mapping accuracies between forest types (Table 2). Accuracies in evergreen forest (0.91) were notably higher than in mixed (0.82) and dry-deciduous (0.86) forest.

**Table 2**
Area-adjusted Producer's Accuracy (PA), User's Accuracy (UA), and Overall Accuracy (OA) of the mapping results produced by LandTrendr for the three forest types. The matching criterion used was mapped year = reference year ± 1.

| Class | Evergreen forest | | | Mixed forest | | | Deciduous forest | | |
|---|---|---|---|---|---|---|---|---|---|
| | PA | UA | OA | PA | UA | OA | PA | UA | OA |
| Change | 0.82 | 0.85 | 0.91 | 0.70 | 0.78 | 0.82 | 0.77 | 0.78 | 0.86 |
| No change | 0.98 | 0.96 | | 0.92 | 0.85 | | 0.92 | 0.91 | |

### 4.1.3. Overall map accuracy

Using the ±1 year matching rule (mapped year = reference year ± 1), our results yielded an overall area-adjusted map accuracy of 86%. Omission and commission errors for the no-change class were low, at 5% and 11% respectively. Omission and commission errors for the individual change classes were larger, averaging, 22% and 25% respectively. If the matching criterion was relaxed so that the timing of disturbance was disregarded (mapped year = any reference year) the overall accuracy of the resulting binary map increased to 90%. However, if a more strict matching criterion is applied (mapped year = reference year), the accuracy of the annual disturbance map was 81% (Table 3).

### 4.1.4. Overall disturbance rates and patterns

A wide variety of disturbance patterns were visible throughout the study. Large swaths of frontier clearings are prevalent, primarily making way for expansive smallholder and industrial scale agriculture and rubber plantations (Fig. 10A and B). A significant portion of the mixed forest class was composed of mature rubber plantations. Rubber plantations operate on a cyclical basis and are cleared and replanted every 15–20 years due to diminishing rubber production over time. These patterns were also captured quite well in the annual Landsat time series in the form of a more structured and regular patchwork (Fig. 10C).

Based on the map area-adjusted reference proportions (Table 3), we estimated that 570,620 ha ± 15% of total forest cover (frontier and non-

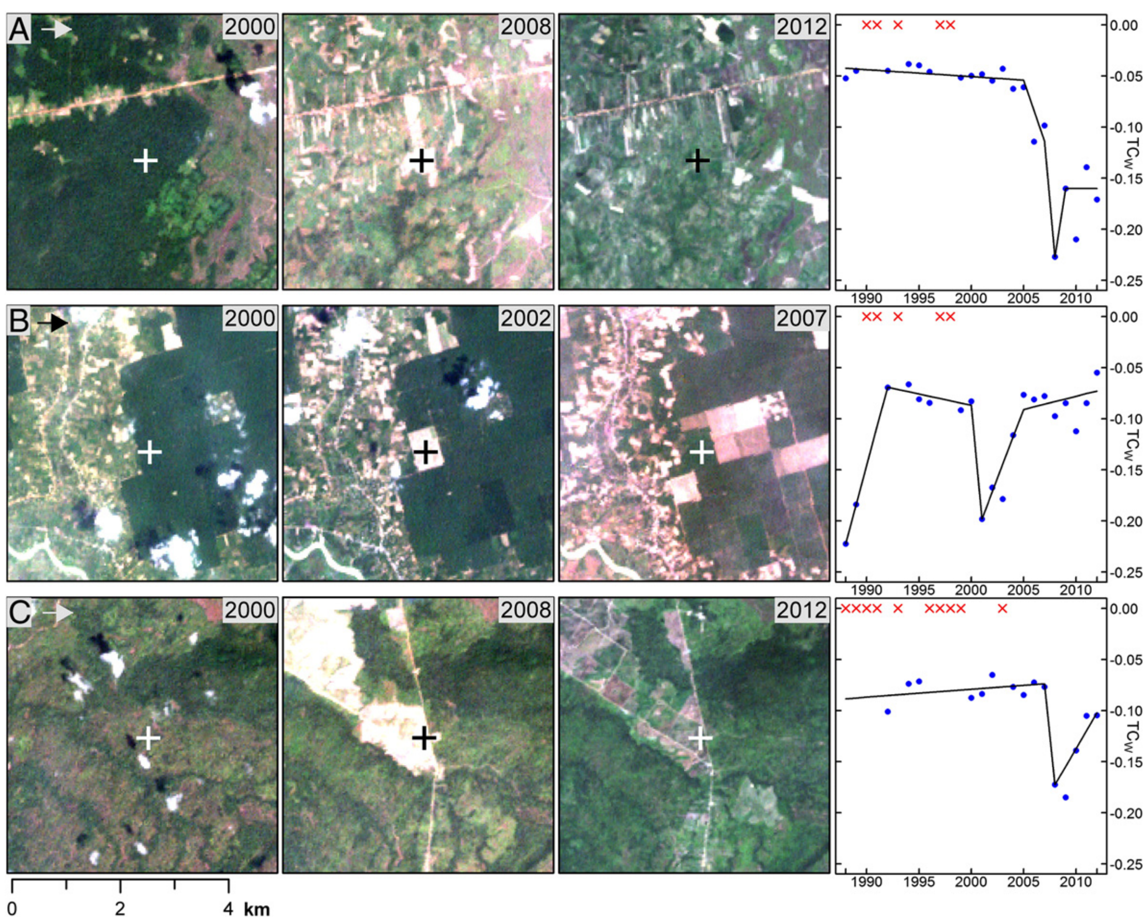


**Fig. 9.** Examples of trajectories with related Landsat imagery (RGB = 3–2–1) for (A) smallholder agricultural expansion in evergreen forest, (B) cyclical clearing in industrial rubber plantation, and (C) clearing for industrial rubber plantation in dry-deciduous forest. Blue dots in the plots indicate Landsat tasseled-cap wetness values, fitted segments are shown by the black line. Data gaps (clouds or no imagery available) are indicated by a red cross.

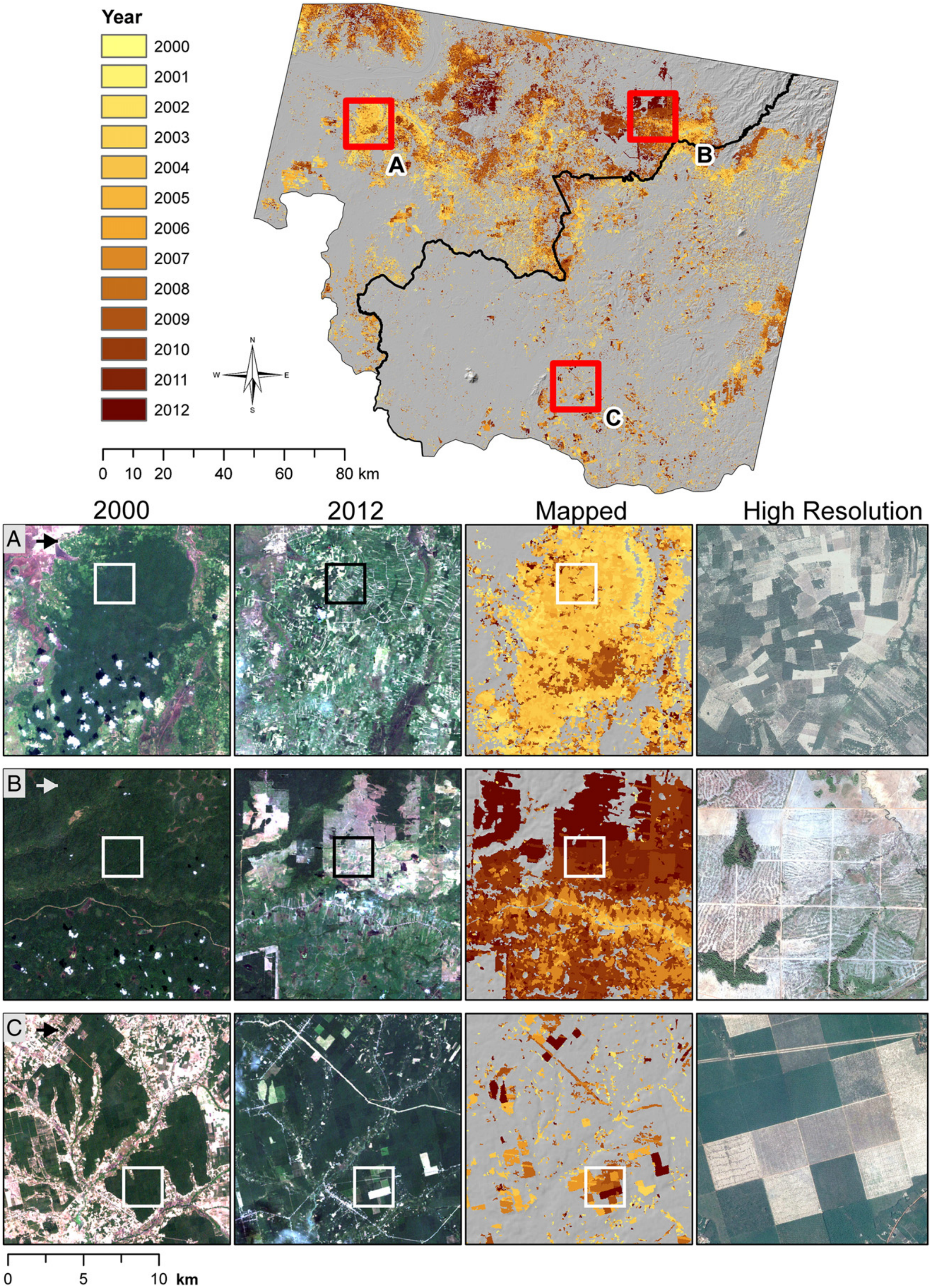


**Fig. 10.** Landsat imagery and mapping of different disturbance processes within the study area; frontier forest clearing for smallholder rubber plantations and agriculture (A), industrial rubber plantations (B), and clearing within established rubber plantations (C) (RGB = 3–2–1). The extents of the high resolution imagery (right panels) are indicated by the square boxes within the other panels. High resolution data was from Google Earth©.

**Table 3**
Proportional error matrix for the change map. Cells with 0.000 means the error was less than 0.0005. For interpretation, the entire forest area has a proportion of 1 (bottom right corner). The mapped area proportions of each class are presented in the row totals (far right column), while the estimated reference area proportions are presented in the column totals (bottom row). Diagonal sum = 0.81. Total map accuracy = 0.81 / 1 × 100 = 81%. (SF = stable forest).

| | | Reference sample | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | SF | Total |
| Disturbance map | 2000 | 0.002 | 0.001 | 0.000 | 0.001 | 0.000 | – | – | – | – | – | – | – | – | 0.006 | 0.010 |
| | 2001 | – | 0.005 | 0.000 | – | 0.001 | – | 0.000 | – | – | – | – | – | – | 0.001 | 0.007 |
| | 2002 | – | – | 0.012 | 0.002 | 0.001 | – | – | – | – | – | – | – | – | 0.002 | 0.017 |
| | 2003 | – | – | 0.004 | 0.033 | 0.002 | 0.001 | – | – | – | – | – | – | – | 0.002 | 0.041 |
| | 2004 | – | – | 0.001 | 0.001 | 0.032 | 0.003 | – | – | – | 0.001 | 0.001 | – | – | 0.001 | 0.039 |
| | 2005 | – | – | 0.003 | – | 0.001 | 0.022 | 0.007 | 0.001 | – | – | – | – | – | 0.001 | 0.035 |
| | 2006 | – | – | – | – | – | 0.001 | 0.019 | 0.005 | 0.001 | 0.001 | 0.001 | – | – | 0.001 | 0.028 |
| | 2007 | – | – | 0.001 | 0.001 | 0.002 | 0.002 | – | 0.031 | 0.003 | 0.001 | – | – | 0.001 | 0.003 | 0.044 |
| | 2008 | – | – | – | – | – | 0.001 | – | 0.002 | 0.017 | – | 0.003 | – | 0.001 | 0.001 | 0.024 |
| | 2009 | – | – | 0.001 | – | – | 0.004 | 0.001 | 0.002 | 0.001 | 0.017 | 0.007 | 0.002 | – | 0.005 | 0.040 |
| | 2010 | – | – | – | – | 0.001 | 0.002 | 0.001 | 0.004 | 0.001 | – | 0.050 | 0.011 | 0.001 | 0.004 | 0.074 |
| | 2011 | – | – | – | – | – | – | – | 0.001 | – | – | – | 0.018 | – | 0.004 | 0.022 |
| | 2012 | – | – | – | – | 0.001 | – | 0.001 | 0.001 | 0.002 | – | 0.001 | 0.001 | 0.028 | 0.002 | 0.036 |
| | SF | 0.001 | 0.001 | 0.006 | 0.006 | 0.007 | 0.006 | 0.005 | 0.006 | 0.001 | 0.005 | 0.010 | 0.006 | 0.003 | 0.519 | 0.582 |
| | Total | 0.003 | 0.007 | 0.027 | 0.044 | 0.048 | 0.042 | 0.033 | 0.052 | 0.025 | 0.025 | 0.073 | 0.037 | 0.034 | 0.550 | 1 |

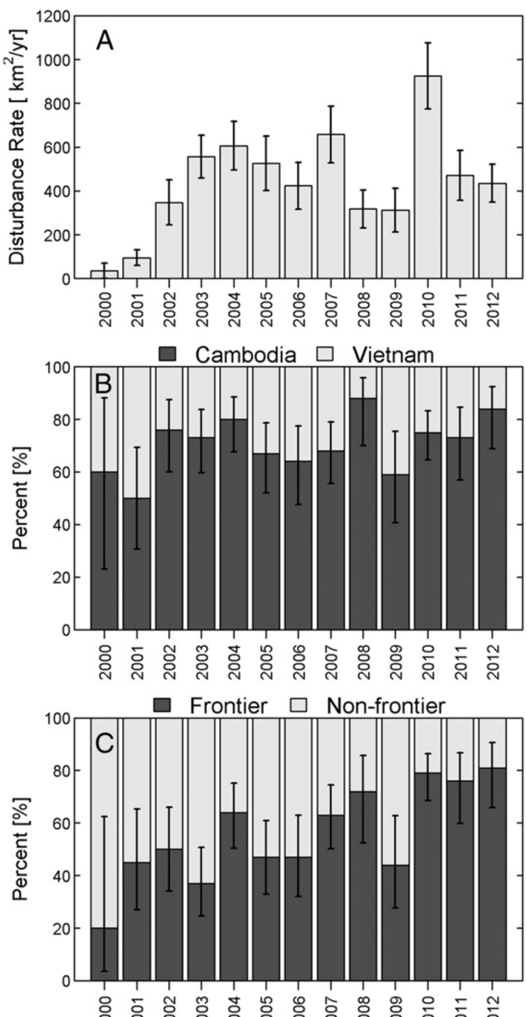


**Fig. 11.** Area change estimates with 95% confidence intervals for total forest area from 2000 to 2012 (A), proportion of disturbed forest area in Cambodia/Vietnam (B), and proportion of disturbed forest area within frontier and non-frontier forests (C).

frontier) was disturbed from 2000–2012, representing 45% gross forest disturbance relative to the original forest cover area in year 2000. Disturbance rates were lowest in 2000 and 2001, but rapidly increased thereafter, reaching a peak in 2010 (Fig. 11A). With the exception of 2000 and 2001, the majority of disturbed forest area was located on the Cambodian side of the border, averaging 70% annually from 2002 to 2012 (Fig. 11B). In general, the proportion of annually disturbed area occurring within frontier forest increased over the 13 year time period (Fig. 11C).

### *4.2. Cross-border comparison of disturbance rates, patterns, and drivers*

#### *4.2.1. Disturbances within frontier forest*

Frontier forest disturbance rates were found to be consistently higher in Cambodia compared to Vietnam, with the exception of the years 2003 and 2009 (Fig. 12A and B). The highest frontier forest disturbance rates for both countries occurred in 2010, with 11.2% in Cambodia compared to 5.9% in Vietnam. Frontier disturbance rates fluctuated below 5% for both countries from 2000 to 2009, with the exception of 2007. From 2010 onwards however, disturbance rates were much higher on the Cambodian side of the border. An estimated total of 49.1% (2607 $km^2$) of frontier forest was disturbed in Cambodia over the study period, compared to 31.8% (682 $km^2$) in Vietnam.

Land cover/use change patterns in Cambodian frontier forest can be divided into two general phases (Fig. 12C and E). Before 2007, land cover change was almost exclusively attributed to smallholders, with most frontier forest being cleared for either agriculture or the establishment of plantations. From 2007 onwards however, there has been an abrupt increase in industrial scale disturbances. The amount of frontier forest change in Cambodia accounted for by conversions to rubber was estimated to be 42%. In Vietnam, the vast majority of all frontier forest change has resulted in conversion to rubber (84% annual average). Change is attributed to both smallholders and industrial scale expansion throughout the study period, with the latter becoming more dominant from 2008 onwards (Fig. 12D and F).

#### *4.2.2. Disturbances within non-frontier forest*

For non-frontier forest, higher disturbance rates occurred earlier in the time series reaching a maximum in 2003 of 11.9% and 4.9%

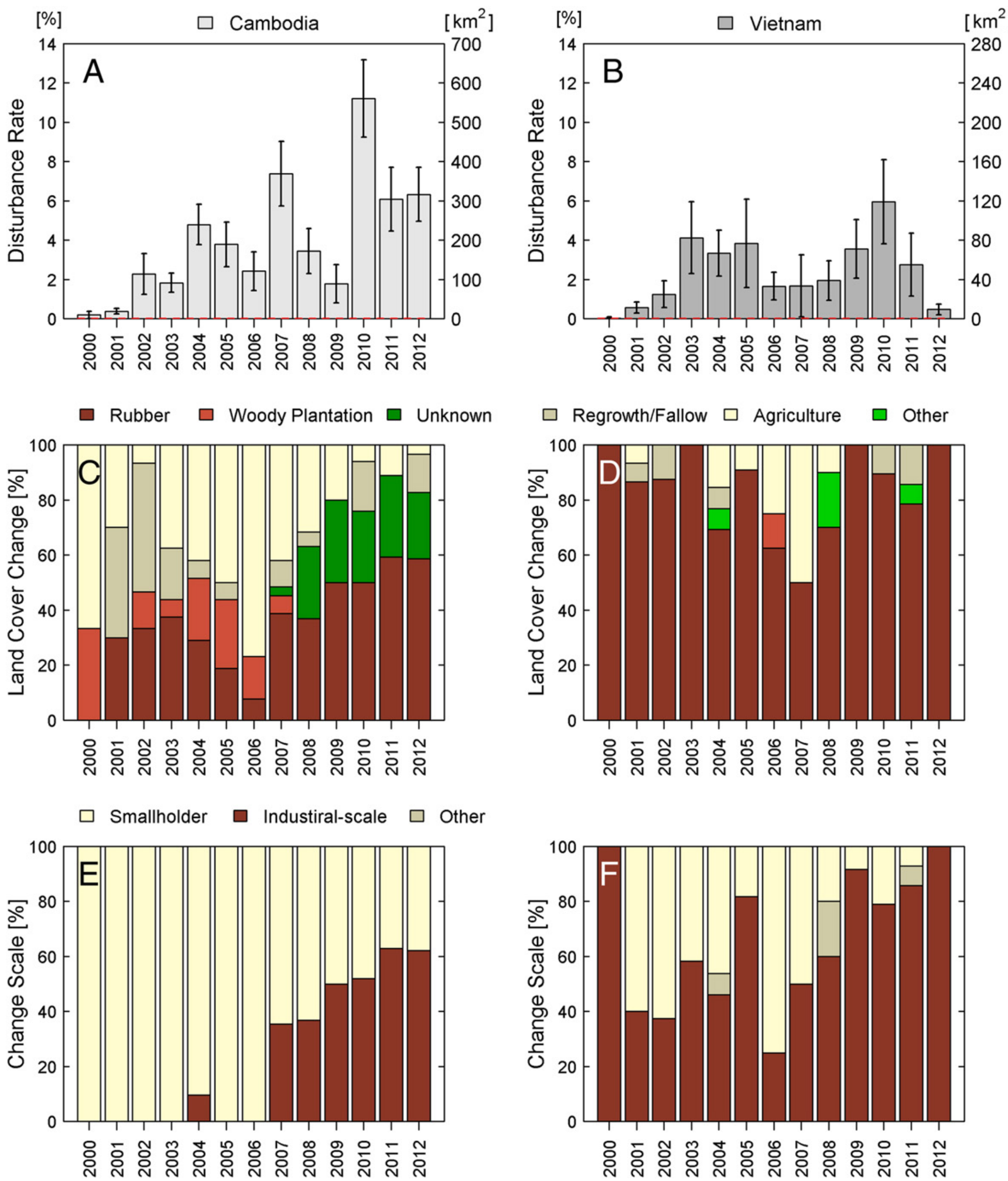


Fig. 12. Cross border change statistics for frontier forest. Area change estimates with 95% confidence intervals from 2000 to 2012 — (A) Cambodia and (B) Vietnam, annual estimated proportion of land cover change type — (C) Cambodia and (D) Vietnam, and annual estimated proportions of scale of disturbance — (E) Cambodia and (F) Vietnam.

in Cambodia and Vietnam, respectively (Fig. 13). After this peak, disturbance rates tended to reduce up to 2012, more dramatically so in Cambodia. In total, 52.1% (1160 $km^2$) of non-frontier forest was disturbed in Cambodia, compared to 32.1% (1290 $km^2$) in Vietnam, giving averages of 4.0%/year and 2.5%/year, respectively.

Almost all (95%) disturbed area within non-frontier forest in Vietnam was associated with natural rubber plantations — 86% located within existing rubber plantations and 9% conversions from forest regrowth/fallow to rubber. Although smallholders were responsible for a significant portion of this, industrial scale plantations were accountable for a considerably larger share, especially so from 2008 onwards. In Cambodia the picture was more mixed. Although a significant portion of the disturbed area was cleared and replanted rubber (33%), a major share of change was forest regrowth/fallow converted to either rubber plantation or agriculture (27% each). Prior to 2007 the majority of change was attributed to smallholders, with industrial scale change increasing thereafter.

### 4.3. Market demand for rubber and frontier forest disturbances

Annual disturbance rates in frontier forest attributed to rubber plantation expansion were found to be positively correlated with fluctuations in global rubber prices, on both sides of the border (Fig. 14). In Cambodia, annual mean rubber price and annual rates of change in price were both highly correlated ($p < 0.01$) with annual disturbance rates and year-to-year changes in disturbance rates related to rubber plantations, respectively (Fig. 14A & C). This indicates that both market price and market outlook are related to changes in disturbance rates on the Cambodian side of the border. In Vietnam, there was a weak correlation between annual mean rubber price and annual disturbance rates ($p = 0.08$), but a

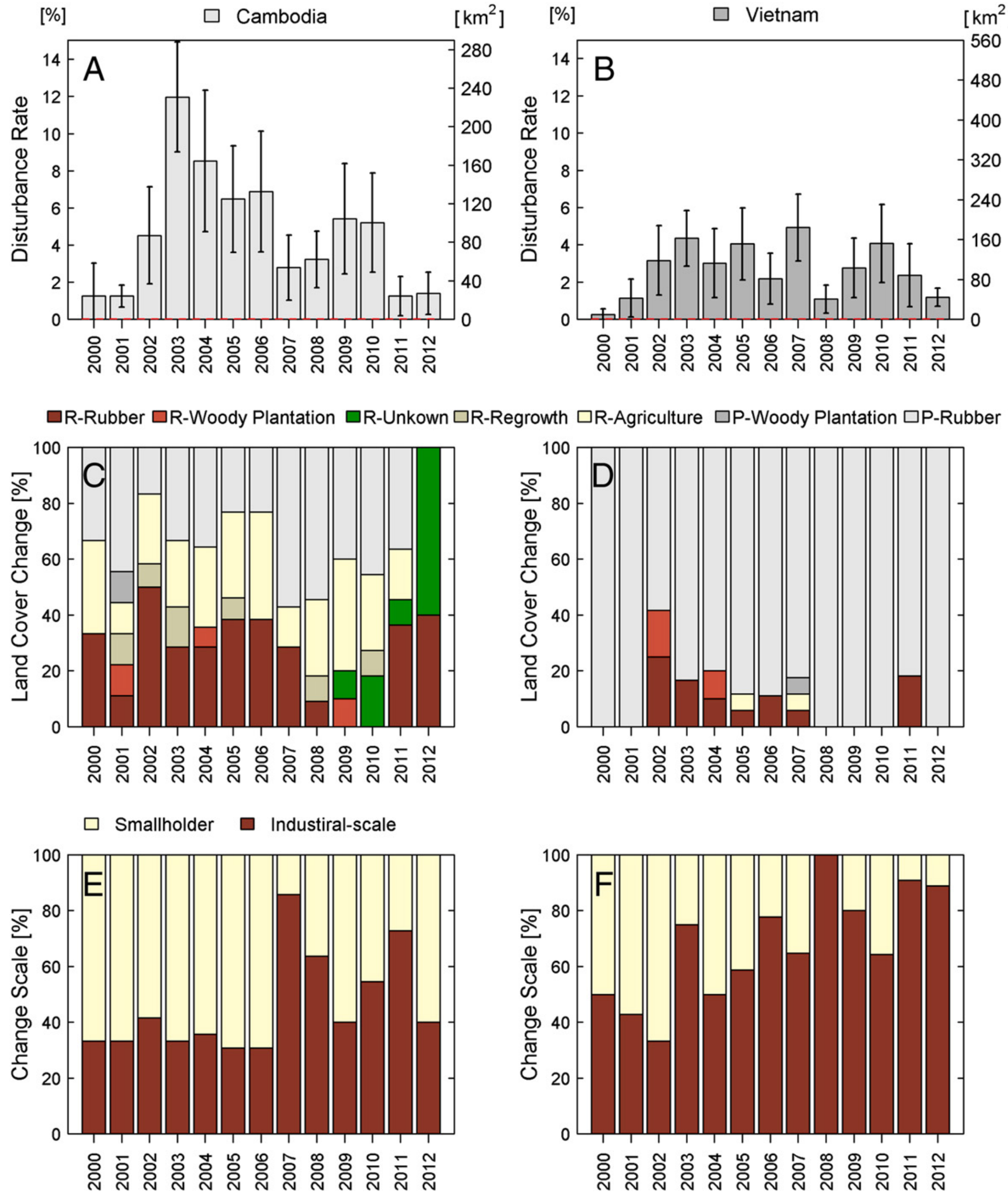


**Fig. 13.** Cross border change statistics for non-frontier forest. Area-adjusted change estimates with 95% confidence intervals from 2000 to 2012 — (A) Cambodia and (B) Vietnam, annual estimated proportion of land cover change type — (C) Cambodia and (D) Vietnam, and annual estimated proportions of scale of disturbance — (E) Cambodia and (F) Vietnam. 'R-' means forest regrowth/fallow was the original land cover, while 'P-' means the original land cover was rubber plantation. (e.g. 'R-Rubber' means a change from forest regrowth/fallow to rubber).

stronger correlation between annual rates of change in price and year-to-year change in disturbance rates ($p < 0.01$) (Fig. 14B & D respectively), indicating that the general direction of the market price (positive or negative) had more influence on disturbance rates compared to the absolute price.

## 5. Discussion

### 5.1. Disturbance mapping

$TC_W$ and NBR were found to be the optimal performing indices for the change detection. Similarly, other studies have found $TC_W$ to best represent vegetative parameters in diverse forest types for trend and change analysis (Cohen et al., 2002; Czerwinski et al., 2014) and considering its close relationship to NBR (Jin & Sader, 2005), it is expected that results using the latter compare well. Other indices ($TC_A$, $TC_B$, NDVI) were outperformed by $TC_W$ and NBR. Part of the reason for this was the more adverse effect of residual cloud and haze missed by the cloud masking procedure. Specifically, NDVI and $TC_B$ were affected most by cloud edges and atmospheric haze that were missed in the masking process, mimicking the signal of vegetation disturbance, and leading to false positive detections. We experienced that combining $TC_W$ and NBR improved change mapping. Combining indices with greater sensitivity to vegetation greenness and soil exposure may

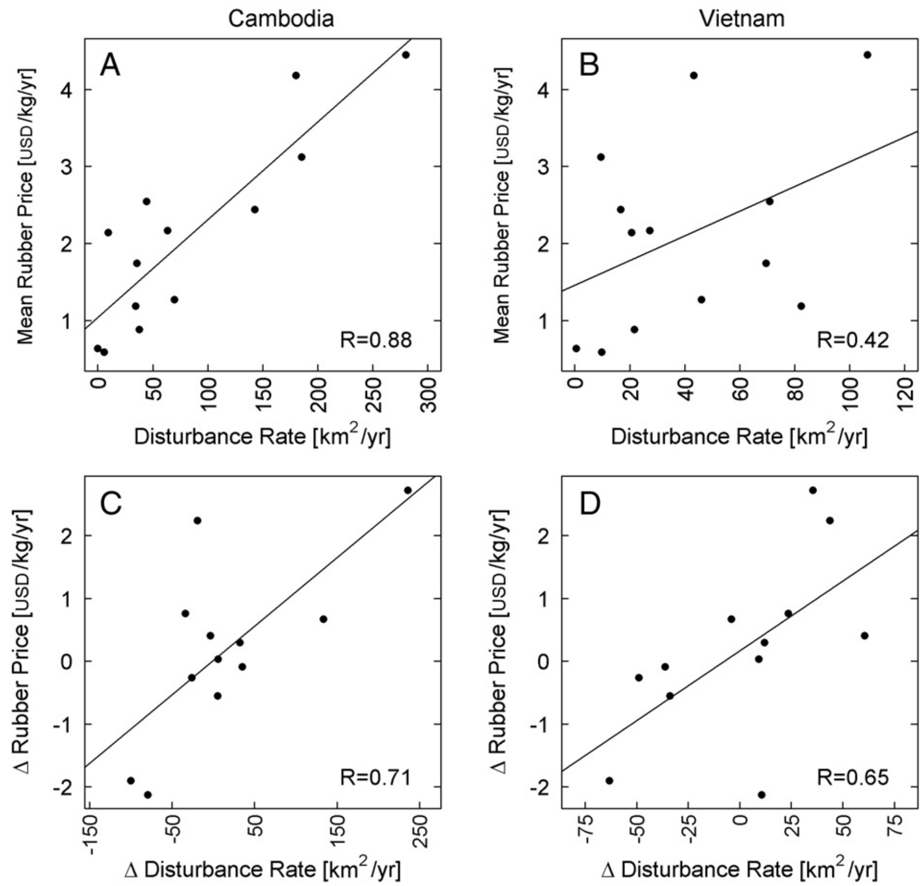


**Fig. 14.** Relationship between rubber price and rubber related frontier forest disturbance; Yearly mean rubber price vs annual disturbance rates for Cambodia (A) and Vietnam (B), and yearly rates of change in rubber price vs year-to-year change in disturbance rates in Cambodia (C) and Vietnam (D). All correlations were significant at a level of $p < 0.01$ except for (B) ($p = 0.08$).

further improve mapping accuracies, providing that false positives are minimized.

Evergreen forest had consistently higher accuracy results, with mixed and dry-deciduous forests producing relatively lower, yet satisfactory accuracies (Tables 1 and 2). These accuracies compare well with other studies using similar approaches in temperate forests (Griffiths et al., 2012; Kennedy et al., 2012). Table 3 shows that a significant portion of error comes from inaccurate mapping of timing of disturbances. The likely reason for lower accuracies stems from the influence of phenology in mixed and dry-deciduous forests (Fig. 4), contributing to a more noisy annual composite time series. For example we found signal noise in the time series to intermittently misrepresent the onset of a disturbance prior to the real change event. We used surface reflectance to derive each index time series. Image-to-image normalization would add another pre-processing step, however it may further reduce inherent noise and improve the continuity of the signal, likely improving accuracies (Schroeder et al., 2006; Vicente-Serrano et al., 2008). However, relative normalization is complicated by the landscape's diverse forest phenology.

### 5.2. Cross-border land cover/use change

Rates of forest disturbance were found to be exceptionally high in this border region, with Cambodia experiencing 49.9% of total forest disturbed, compared to 32.1% in Vietnam. This is far beyond the national averages reported by Hansen et al. (2013) for the same time period; 13.2% and 6.8% for Cambodia and Vietnam, respectively, suggesting the border region to be a hotspot for forest cover change.

Our analysis show that disturbances related to rubber plantations far outweigh any other forest cover change in both frontier and non-frontier forests along this border region. According to regional statistics and literature the trends observed here are not confined to our study area. In Vietnam rubber plantation area has surpassed the country's rubber strategy, growing by 53% from 2000–2010 (FAO, 2010), with later years seeing more pronounced increases (Luan, 2013). Our analysis captures part of a planned rubber expansion in the Southeastern region of Vietnam (Phuc & Nghi, 2014). Similar scale expansions are taking place in the North Central and South Central Coastal regions, with larger rubber developments planned for the Central Highlands. Similar to our study, Phuc and Nhgi (2014) report that the vast majority of new rubber plantations in this region are coming from the clearance of relatively mature natural forest on the forest frontier.

Of the Vietnamese rubber area in 2012 reported by Luan (2013), 12% of this is located within Laos (6.2%) and Cambodia (5.8%), on land leased by Vietnamese state rubber companies. This total is projected to reach 20% during the 2015–2020 period, accounting for 200,000 ha, and is a reflection of growing inter-governmental cooperation in the *Cambodia–Laos–Vietnam Triangle* comprised of the intersecting border regions (Gironde, 2012; Ishida et al., 2013; Laungaramsri, 2012). The role of large-scale development in Cambodia's rubber sector is evident in our study showing an increased industrial scale activity from 2007 onwards (Fig. 12E). This is driven by national policy heavily promoting the expansion of large-scale plantations in the form of Economic Land Concessions (ELCs) (ODC, 2014). In our study area over 145,600 ha has been granted as ELCs since 2006, mostly targeting the rubber industry, which is a direct reflection of what is happening throughout different parts of Cambodia with over 1.6 million ha granted as ELCs from

2000–2012, mainly located in forested areas in the east and northeast of the country (Licadho, 2014).

Besides industrial scale clearing, a considerable portion of forest disturbance on the Cambodian side of the border can be attributed to the recent influx of migrants to previous low population density/high forest cover regions (ODC, 2014). For example, in Snoul district (Kratie Province), where a significant fraction of disturbances have occurred, the population increased by over 75% between 1998 and 2008. Similar patterns are seen in the close-by districts of Kaev Seima (Mondulkiri Province) and Dambae (Kampong Cham Province) (see Fig. 2 for Province locations). This increased population pressure is captured well in our analysis as it has been smallholder land cover/use change that has dominated up to 2007. The promotion of rubber among smallholders has had a role to play in this transformation (Dararath et al., 2011; Fox & Castella, 2013). Similar forest disturbance patterns are expected to be seen in other provinces previously characterized by high forest cover and low population density but which have recently experience significant in-migration for example, Oddar Meanchey, Preah Vihear, Rattanakiri, and Stung Treng (ODC, 2014). Indeed internal migration is widely recognized by the Cambodian government as leading to added pressure to natural resources and placing them in risk of destruction (RGC, 2008).

### 5.3. Linking global markets and regional land cover change

Our annual disturbance rates in frontier forest related to rubber plantations correlated well with fluctuating market prices (Fig. 14), providing evidence of strong interactions between global markets, national policy, and forest-to-rubber land cover change. Such interactions have been seen before with regard to other global commodities. De Konnick (2006) describes the rapid expansion of coffee plantations in the Central Highlands of Vietnam in response to global coffee prices, primarily led by smallholders. In Southeast Asia the area under oil palm plantation grew from 4.2 million ha in 2000 to 7.1 million ha in 2009, with a vast amount of additional land either in transition or zoned for future development (McCarthy, 2010). This has been similarly linked to rising global market demand, but led by larger scale agrarian change. These past studies tend to descriptively link aggregated statistics of production and/or land cover change to increased market demand. In contrast, our results describe an explicit statistical relationship between price fluctuations and forest disturbance at annual time scales, offering a more detailed insight and empirical approach to analyzing these relationships. While the observed correlations should be interpreted with caution without a more detailed driver analysis, our study underlines the value of using higher temporal resolution imagery to better understand such dynamic associations.

## 6. Conclusion

The process of forest transformation across mainland Southeast Asia is gathering speed, primarily due to conversions to global commodities, such as natural rubber. Our study shows that using annual Landsat time series in combination with a trajectory-based change detection method can be an effective toolset in mapping disturbances caused by such transformations.

Firstly, we found highest forest disturbance accuracies in evergreen forest (91%), with lower accuracies found in mixed (82%) and dry-deciduous (86%) forest types. Diverse forest types often present a challenge for mapping disturbances, however our approach proved capable of providing accurate change data for the study region, with an overall map accuracy of 86%. Secondly, we found higher rates of frontier forest disturbance on the Cambodian (3.8%/year) side of the border during the study period compared to Vietnam (2.5%/year). Similarly, disturbance rates in non-frontier forests were higher in Cambodia (4.0%/year) compared to Vietnam (2.5%/year). Thirdly, we found that the majority of forest disturbance in the region was related to rubber plantations. On the Cambodian side of the border an estimated 42% of frontier forest disturbance area was accounted for by conversions to rubber, compared to 84% in Vietnam. In non-frontier forest 60% of disturbances were associated with rubber plantations in Cambodia, compared to 95% in Vietnam. Finally, we found strong positive correlations between natural rubber price and annual rates of frontier forest disturbance attributed to rubber plantation expansion.

The border region between Cambodia and Vietnam was shown to be particularly active. Rates of disturbance have increased dramatically since the turn of the millennium, with some of the later years being exceptionally high. In both countries national policies aimed at expanding rubber plantations are heavily impacting natural forest cover, with internal migration bringing an additional pressure to Cambodian forest resources. Our study demonstrates the value of dense Landsat time series for monitoring past and future forest change on an annual basis, helping to reveal dynamic responses to regional to global drivers of change.

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.rse.2015.03.001.

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