Land Cover Change Analysis and Spatial Variations in Southeast Asian Nations: Insights on Spatial Scale Dynamics

Kristofer Lasko* and Krishna Vadrevu+

*US Army Engineer Research and Development Center (ERDC), Virginia, USA

+NASA Marshall Space Flight Center, Huntsville, AL

Abstract

Land cover type is a fundamental aspect of studies using remote sensing for environmental analysis such as monitoring deforestation, quantifying wildland fire emissions, and more. There are many land cover products available for varying time periods and spatial resolutions, each with different land cover class definitions and number of land cover classes. These differences yield inherent variation in land cover estimates. In this study, we explore the spatial and areal variation between two major datasets for their commonly available time of 2018 to 2022 (MODIS 500m Land Cover and Esri Sentinel-2 10m land cover) in the continental Southeast Asia countries of Cambodia, Laos, Myanmar, Thailand, and Vietnam. To enable comparison, we resampled the datasets and reclassified the land cover classes to a common scheme. Major disagreement was detected between Esri and MODIS, especially for the wetlands/flooded vegetation class in which only 3.6% of pixels were in agreement. In addition to quantifying variation between the datasets, we quantify land cover change at the decadal scale of 2001, 2011, and 2021 for each country and identified province-level hotspots of land cover change. Cambodia experienced the highest rate of land cover change with 67.8% of total land area changed, followed by Vietnam (58.6%), Laos (50.2%), Myanmar (46.9%), and Thailand (46.3%). The highest rate of land cover change was detected in Odtar Mean Chey, Cambodia, which had large swaths of forest area cleared for agricultural production, river damming, and more. Ultimately, many areas in the region experienced forest clearing for crop production (i.e. rice) which appeared to be classified as wetland in the MODIS product, and crop in the Esri product. Myanmar was the only country which did not experience net decline in forest area over the 2001 to 2021 time period.

Introduction

The satellite-based mapping and monitoring of land cover around the world is key for understanding changes to the Earth's surface over time and how those changes affect the environment. Land cover and associated changes play a major role in many different phenomena such as fires and associated emissions (Nunes et al. 2005; San Miguel Ayanz et al. 2012; Lasko et al. 2018), floods (Brody et al. 2014), run-off (Sriwongsitanon et al. 2011), desertification (Bestelmeyer et al. 2015; Nwilo et al. 2020), and landslides (Promper et al. 2014; Pisano et al. 2017), and more broadly as a major driver of climate change (Mahmood et al. 2010). Land cover plays a major role in early warning systems for events such as crop failures, food security risk, various disasters, government regime change, land degradation, and more (de Groot et al. 2006; Zurlini et al. 2014; Guzzetti et al. 2020; Vang Hoang et al. 2020; Becker-Reshef et al. 2023). Accordingly, land cover is often a critical foundational data layer in many different research and development applications.

There are many satellite-derived land cover and land use products available globally. The MODIS collection 6 land cover product is available annually from 2001 to 2023 offering between 67% - 87% overall accuracy with several different land cover classification schemes (e.g. IGBP, UMD, FAO) at a nominal 500m pixel resolution (Sulla-Menashe et al. 2019). While this resolution is fairly coarse to detect minute changes, high accuracy can still be had for select land cover types such as croplands, which tend to occupy broad areas (Song et al. 2021). The coarse resolution land cover products are unable to accurately detect small changes to the earth surface such as land degradation. Moderate resolution land cover products are also available which can overcome some of these issues. These include: Copernicus global land cover at 100m (Buckhorn et al. 2020), Global Land Use Extent (Hansen et al. 2022), and several more. At a slightly higher scale, the Impact Observatory produced the Sentinel-2 10m land cover product with 9 different land cover classes for the years 2018-2022 with an accuracy around 85% overall (Karra et al. 2021). Similarly, the Dynamic World land cover dataset is also available at 10m resolution from Sentinel-2. The product is primarily based on single data classification and does not contain seasonally-variable classes such as ephemeral water, evergreen and deciduous trees differentiation, etc. which can be problematic for applications requiring class precision.

It is important to consider that each of the mentioned land cover products have entirely different land cover classification schemes, production dates, resolutions, and accuracies. Selection and use of a land cover dataset is foundational to understanding the earth's surface changes and for use in any derivative application such as quantifying the types of areas burned, for example. Not only do the different products have varying numbers and types of land cover classes, but each often has a different definition (or lack of a definition) of what it considers to be each type. For example, 'trees' are often defined based on varying height thresholds which can lead to discrepancies between datasets. Some datasets may consider a cropped wetland such as paddy rice as 'wetland', while some may consider it as 'crops'. When dealing with coarser resolution land cover products such as MODIS or Copernicus, there is a percentage threshold for what constitutes a forest. What percentage of the pixel must be occupied by trees to be considered a forest? It is variable among the datasets, however, when datasets employ standardized classes such as the UMD or IGBP schemes, this can reduce these discrepancies.

Accurate land cover products are important for effective implementation of policy, such as efforts to monitor forest gain or loss for carbon cost accounting and more. The spatial resolution can play a major role in the land cover type detected. Some land cover types occur in small patches, such as built-up areas, which require moderate to fine resolution imagery for accurate detection of small areas, like roads, which are relevant to the local and regional scales.

In Southeast Asia, studies have examined land cover and land use change dynamics over time. Broadly, much of the region's land cover change is driven by phenomena such as population growth and economic development, and these drivers generally manifest as cropland loss, deforestation, reforestation, urban expansion, etc. (Vadrevu et al. 2020). Sustainable forestry practices have led to afforestation in countries like Bhutan and Nepal, whereas deforestation associated with oil palm plantation expansion or slash and burn activities has been prominent in Malaysia and Indonesia (Vadrevu et al. 2019). In Vietnam between 1990 and 2020, one study found net forest area loss (with some gain in the 90s), as well as conversion of productive croplands to built-up areas, as well as wetland loss which was primarily attributed to aquaculture increase (Phan et al. 2021). In Thailand, one study between 2000 and 2020 found decreased areas of rainfed cropland, irrigated cropland, and forest while impervious surfaces, shrubland, and wetlands increased (Wang et al. 2022). Studies in Cambodia have found decreasing trends of forest cover with expansion of croplands such as paddy rice (mostly between 2003 and 2008), which has affected the water supply in some regions (Chim et al. 2019; Sourn et al. 2021). Some of this forest cover loss has led to soil erosion hot spots (Nut et al. 2021). In Laos, studies have found areas near Vientiane to experience agricultural land conversion to urban areas, with urban areas increasing by three times between 2016 and 2020 (Phompila et al. 2022). Across Laos generally, one study found evergreen broadleaved forest had the most decrease in cover type, while cropland, deciduous trees, shrubland, wetland, and water continued to increase (Zhang et al. 2022). Another recent study noted shifting cultivation affected nearly 33% of land in Laos from 1991 to 2020, and with slash-and-burn agricultural activities increased in the past five years (Chen et al. 2023). In Myanmar, various types of land cover change were prominent including: net national mangrove cover decline of 52% between 1996 and 2016 with conversion to water (aquaculture) and built-up areas (De Alban et al. 2020). While studies have shown high rates of natural vegetation loss and forest loss in Myanmar (Yang et al. 2019), the use of the permanent forest estate and protected areas designations have resulted in preservation of forest in some areas (Lwin et al. 2020).

Study Datasets and Analysis

This study examines land cover change in continental Southeast Asia (Cambodia, Myanmar, Laos, Thailand, and Vietnam) across two time periods (2001 to 2022, and 2018 to 2022) at two different spatial resolutions (10m and 500m) based on the MODIS land cover dataset and Impact Observatory/Esri Land Cover Dataset. Each dataset contains vastly different land cover schemes. We examine how spatial resolution and classification scheme play a role in land cover proportions for each country. Further, we evaluate differences between these two datasets, identify and quantify provincial hotspots of land cover change based on a ratio of annual frequency of change to total province area, and more. Lastly, the study also locates and discusses major areas of erroneous land cover change present in the datasets and the implications of not integrating local knowledge of a province's land cover change.

Datasets

The MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid (MCD12Q1) product was acquired at collection 6 from the NASA Earth Data website (Friedl et al. 2015). It contains five different land cover schemes from which we selected the 'University of Maryland (UMD) scheme' which contains 17 land cover classes (Table 1). Within this study, we merged classes for comparison and evaluation purposes as many of the classes are very similar (table 1). The dataset is produced at a nominal 500m resolution, with an actual resolution of about 463m in our study area. The dataset is created using a decision tree classifier with various post-processing steps including a hidden Markov model to reduce false interannual variability caused by noise or missing data (Friedl et al. 2010). We note that the dataset, as acquired, erroneously labeled permanent wetlands as value '10', and the grassland class was missing. We acquired the dataset over the study area for the years 2001, 2011, 2018, 2019, 2020, 2021, and 2022. The 2018-2022 period corresponds with comparison against the Esri land cover layer. The dataset is reported to have an overall accuracy between 67% and 87% depending on the classification scheme and year of the dataset.

Esri/IO LC Classes	MODIS LC Classes	ESRI-MODIS Merged Classes	MODIS Condensed LC Classes
Water	Water	Water	Water
Trees	Evergreen Needleleaf Forest	Trees + Woody Savanna	Evergreen Trees
Crops	Evergreen Broadleaf Forest	Crops	Deciduous Trees
Rangeland	Deciduous Needleleaf Forest	Rangeland / Shrubland / savanna	Mixed Trees
Bare Ground	Deciduous Broadleaf Forest	Bare Ground / Snow	Shrublands
Built Area	Mixed Forest	Built Area	Savanna
Clouds	Closed Shrublands	Wetlands	Wetlands
Snow/Ice	Open Shrublands	Cloud / Unclassified	Crops
Flooded Vegetation	Woody Savannas		Built-area
	Savannas		Bare Ground / Snow
	Grasslands		
	Permanent Wetlands		
	Croplands		
	Built-up Lands		
	Cropland/Natural Vegetation Mosaic		
	Non-vegetated Lands		
	Unclassified		

Table 1: The land cover classes from the two different products (Esri and MODIS), and the merged classes which combine similar classes from each dataset to enable comparison, and the condensed LC classes for the MODIS product which were used for land cover change analysis in this study.

The Impact Observatory produced a 10m land cover dataset using annual Sentinel-2 imagery composites (Karra et al. 2021). This dataset was created using a convolutional neural network with millions of manually labeled training data points across the globe. The study reported an overall accuracy of 85% at a global scale. The dataset is available for 2018 – 2022 and we acquired it directly from the Esri Living Atlas.

GIS Files of administrative boundaries were acquired from GADM.org at the country level and the provincial level for Cambodia, Myanmar, Laos, Thailand, and Vietnam. Google Earth Engine was used for annual cloud free compositing of Sentinel-2 Harmonized Surface Reflectance Imagery and Landsat 7 Collection 2, Tier 1, Level 2 for several figures for comparison purposes.

Methods

The objectives of this study are 1) to examine how spatial resolution (463m MODIS vs 10m Sentinel-2 ESRI), and classification scheme (e.g. MODIS vs esri in table 1) result in variation in land cover type, 2) quantify land cover change at MODIS scale at a decadal time step (2001, 2011, and 2021) using condensed land cover classes to reduce noise from changes between similar land cover types (e.g. savanna and woody savanna). 3) quantify and evaluate land cover change from 2018 – 2022 and the differences between Esri and MODIS land cover datasets at their native resolutions across all countries and provinces in the study area, 4) identify provincial hotspots of change based on frequency of land cover change relative to total area in each province. Ultimately, the study seeks to quantify major patterns of land cover change in the region, highlight the importance of considering multiple different spatial scales and land cover datasets, and that land cover datasets contain inherent error that should be accounted for in various studies such as those related to biomass burning emissions quantification, land cover change analysis, urban expansion, and much more.

For comparison purposes, the Esri and MODIS land cover classes are aggregated into the same classes as shown in table 1 under the "ESRI-MODIS Merged Classes" which contain classes that are common to both datasets and thereby enabling comparison because otherwise the classes would be different. After the classes are combined, the Esri dataset is resampled to 463M pixel size (with pixel borders aligned) using a majority filter to correspond directly with the MODIS dataset. Both datasets are reprojected to the same Albers Equal Area projection for analysis and visualization purposes.

Pixel-level frequency of land cover change is calculated for the overlapping period between the two datasets (2018 – 2022), as well as separately at the decadal scale for the MODIS data (2001, 2011, 2021) to locate hotspot areas of land cover change.

For analysis of the type of land cover lost between 2001 and 2021, we devised logical functions using python for the four most prominent types of land cover classes: croplands, shrubland/savanna, trees, and wetlands. These changes were then analyzed at the province scale and pixel scale.

We use heatmap tables to visualize the land cover extent and change over time at the country scale for both MODIS and Esri datasets. We identified the top 3 provinces overall and top province from each country that had the highest rate of land cover change based on the land cover change ratio (area of land cover change over time, to total area of the province). We emphasize how the Esri and MODIS datasets here have very different findings and the implications of this. Lastly, we used the pixel frequency of land cover change maps to identify major areas of land cover change. We visualized the changes with moderate resolution Landsat 7 (year 2001 annual cloud free composite), and Sentinel-2 (year 2021 annual cloud free composite) for 3 locations. The MODIS Pixel frequency map corresponding to these years is overlaid to highlight areas that the product performed well.

Land Cover Change at the Country Scale

The continental Southeast Asia region experienced major land cover changes between the period of 2001 and 2021, as well as between 2018 and 2022. The MODIS and Esri land cover layers for the region and their pixel frequency of change (2001 and 2021 for MODIS, 2018 and 2022 for Esri) are visualized in Figure 1 with the original land cover class for Esri, and the condensed land cover class for MODIS.

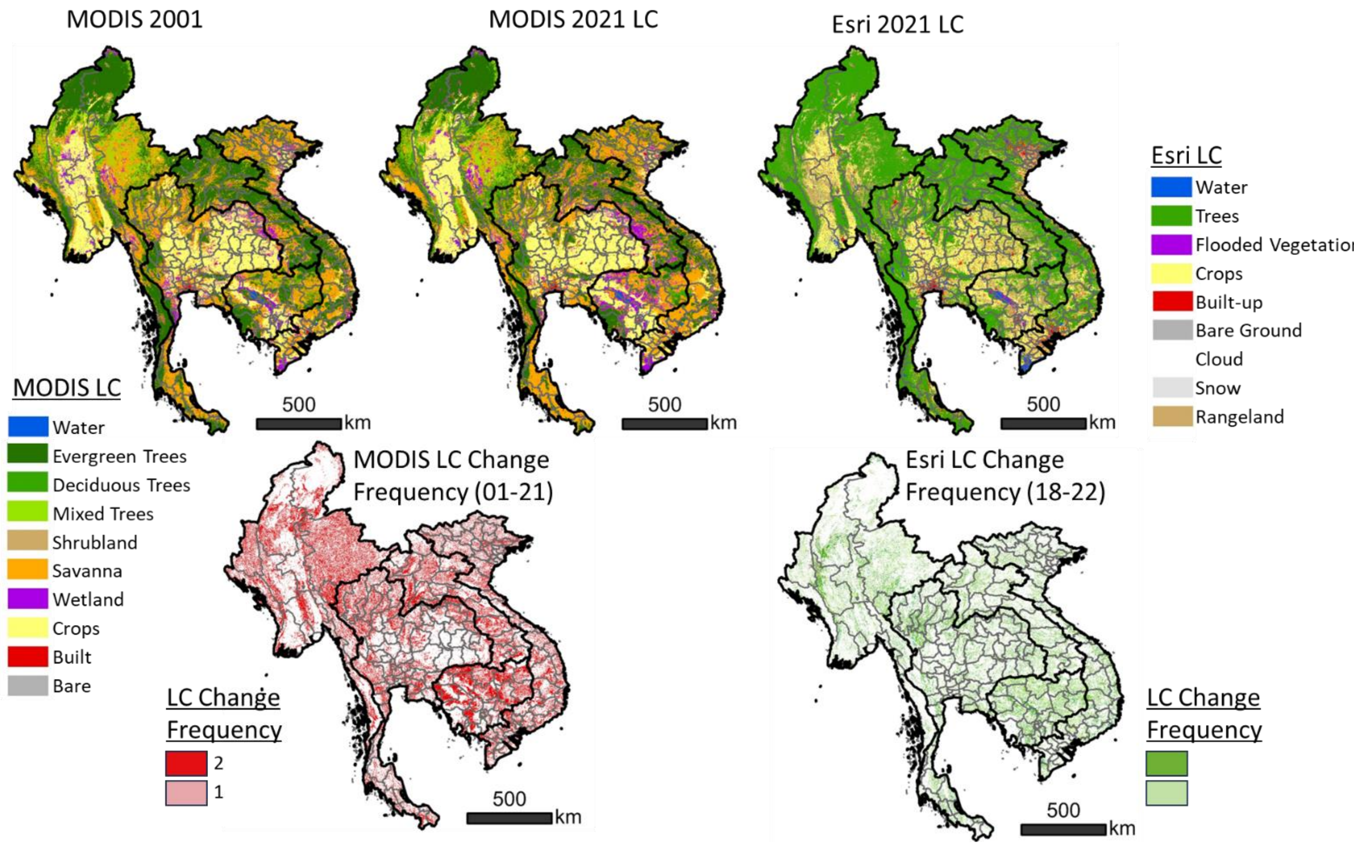

Figure 1: Visualization of the MODIS Land Cover product with the merged class scheme and associated land cover change frequency, as well as the Esri product with its original land cover scheme.

Analysis of the MODIS land cover dataset with condensed classes (table 1) between the years 2001 and 2022 found generally that evergreen trees and mixed trees both experienced major declines between 2001 and 2022 (Figure 2). Cambodia stood out the most with a reduction from 31.9% of land area in 2001 to 17.8% of land area in 2022 with most of the forest loss occurring between 2001 and 2018. Cambodia also experienced major increase in wetlands, likely partially attributed to paddy rice, with 8.3% in 2001, and 19.8% in 2022. Myanmar, Thailand and Vietnam maintained relatively constant levels of evergreen trees over the time period, while the others experienced large declines. Notable increase in deciduous tree was observed for Myanmar (3% to 6.9%) and Thailand (1.4% to 4.2%) likely attributed to the increase of agroforestry in the region which often includes species of Acacia, Acrocarpus, etc. that can be detected as deciduous trees. Natural wetland area loss has been reported by the IUCN as a major issue in the Lower Mekong Delta region. Accordingly, we found wetlands declined in Thailand, and Vietnam which likely includes some natural wetland area loss. Conversely, wetland area increased in the remaining countries. While some areas have experienced major loss of coastal wetlands and mangroves, much of this natural wetland loss was offset by expansion of aquaculture and paddy rice in Laos, Cambodia, and Myanmar. Cropland area remained relatively consistent over time for most of the countries, except for Laos (1.2% in 2001 to 2.4% in 2022) and Cambodia (20.0% in 2001 to 26.6% in 2022). Vietnam (1.4% in 2001 o 1.7% in 2022) and Cambodia (0.2% in 2001 to 0.3% in 2022) exhibited noticeable increase in built-up area compared to the other countries.

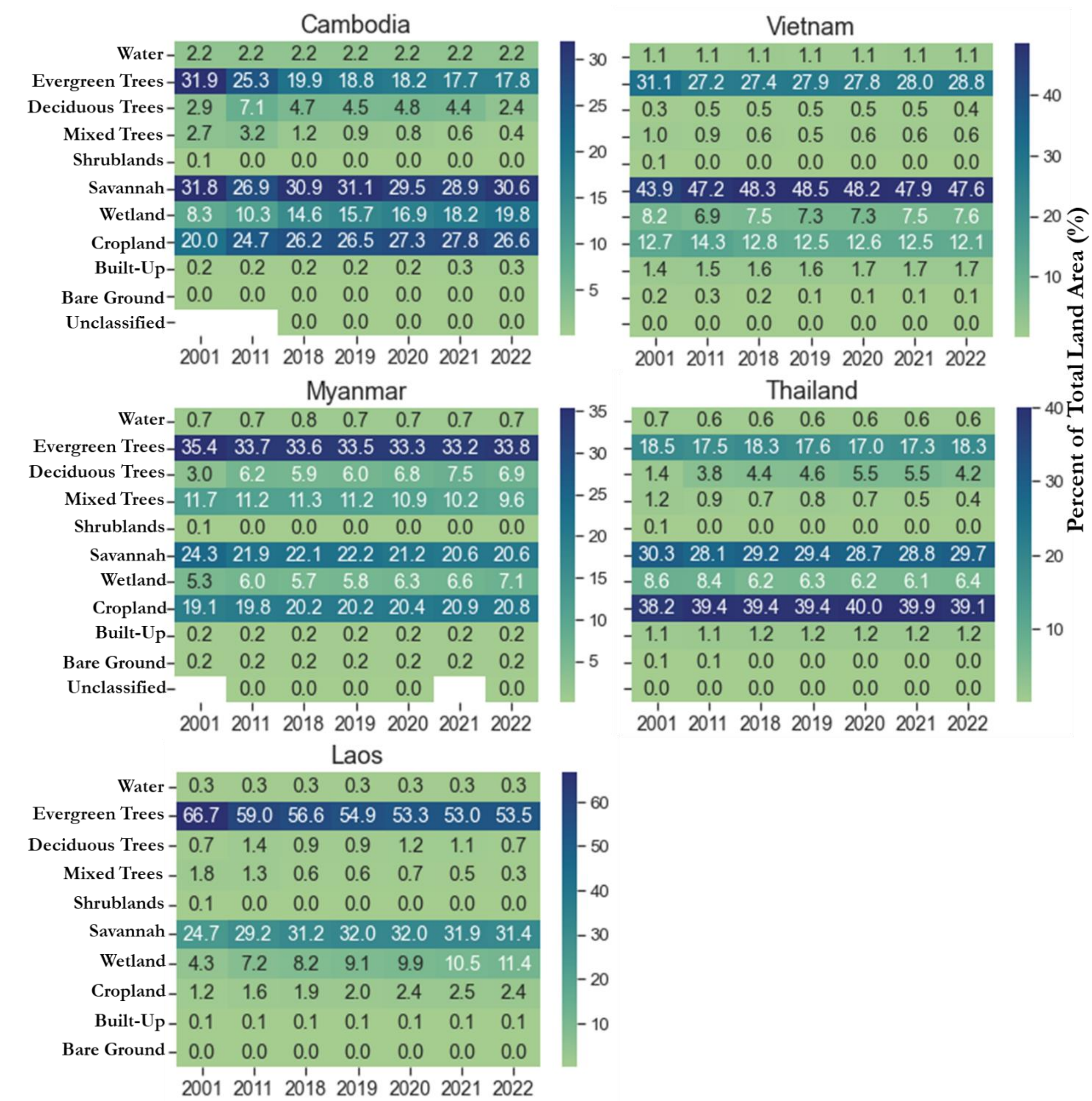

Figure 2: Land cover percentages for each class between 2001 and 2022 for the MODIS land cover product with merged classes.

The land cover change ratios were varied between MODIS and Esri land cover for the 2018 and 2022 period using the merged land cover class scheme. The difference between MODIS and Esri area of land cover change to total area was highest for Cambodia (59.5% Esri vs 34.5% MODIS), and lower for the other countries: Laos (31.0% vs 27.1%), Myanmar (31.4% vs 25.6%), Thailand (37.6% vs 24.9%), and Vietnam (37.3% vs 28.3%). These ratios indicate that across all four countries at least 24.9% (I.e. Thailand) of the land surface exhibited change in a very short period (2018 to 2022). In Vietnam, much of the actual change is attributed to the Esri dataset falsely detected change in Ca Mau province due to it falsely identifying areas of change between croplands and water.

Between 2001 and 2021 at the MODIS scale, we can see patterns of change from Shrubland, Cropland, Trees, and Wetlands in figure 3. Within the provinces of most countries, the majority change in shrubland cover between 2001 and 2021 was conversion to trees. This was likely regrowth of forests, agroforestry, etc. For most provinces in Laos, Thailand and Cambodia cropland change mostly resulted in wetlands (likely paddy rice). In the other countries, much was converted to shrubland, which likely still remained as an agricultural land use. For most provinces in Vietnam and Thailand, trees were converted into shrubland, likely attributed to slash and burn activities or forestry. The majority change of wetland class most often resulted in cropland, shrubland, or trees throughout the provinces of each country as shown in the figure. The pixel-scale map within this figure shows large swaths of forest cover lost in Cambodia, and parts of Laos, and Southern-Central Vietnam. Whereas, in Thailand and Myanmar, areas of wetland loss and shrubland loss are more concentrated.

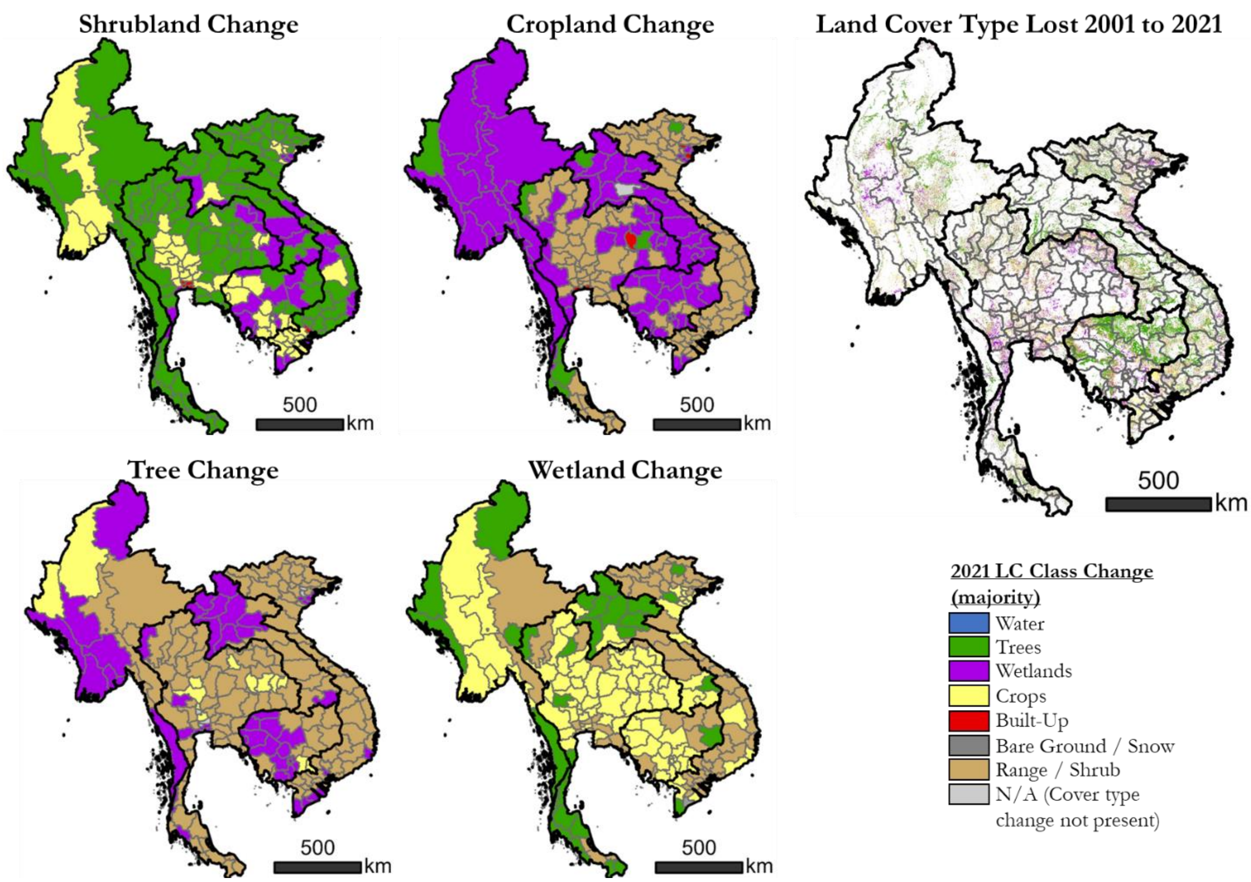

Figure 3: Change in MODIS Land cover with the combined class scheme between 2001 and 2021. The color of the province represents the majority land cover change class. The right side map visualizes the land cover class type lost between 2001 and 2021.

Land Cover Change at the Provincial Scale

At the province level, high rates of land cover change are evident across much of the continental southeast Asia as shown in figure 4. This figure illustrates the land cover change ratio (Area of change / total area) per province for the years 2018 – 2022. For MODIS, relatively high rates of land cover change were observed in Northern/Eastern Cambodia, Northern Thailand, and several other locations such as Xaignabouri, Laos (0.40), Quảng Ninh, Vietnam (0.46), or Bắc Giang, Vietnam (0.43). The top 3 provinces of MODIS land cover change between 2018 and 2022 were all in Cambodia: Otdar Mean Chey (0.60), Preah Vihéar (0.56), and Stœng Trêng (0.51). The top province of land cover change for the remaining countries was: Kayah, Myanmar (0.49), Lampang, Thailand (0.47), Quảng Ninh, Vietnam (0.46), Vientiane, Laos (0.43).

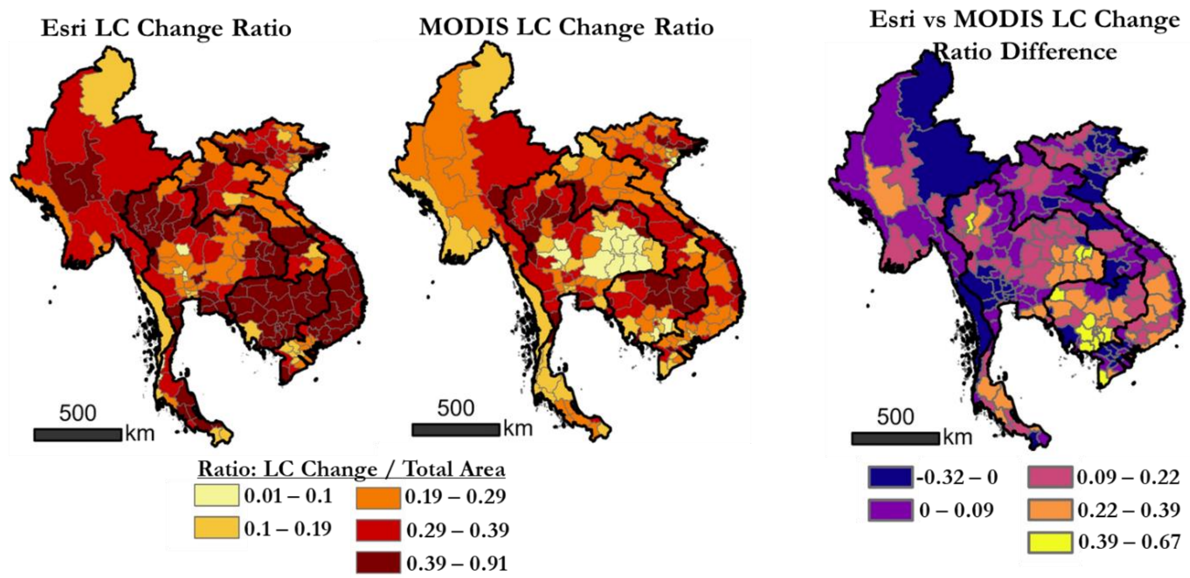

Figure 4: Ratio of land cover change to total area (Change Ratio) for each province for the Esri product and the MODIS product with the merged land cover class scheme between 2018 and 2022. The right-side map depicts the differences.

The rates of land cover change at Sentinel-2 10m scale from ESRI land cover (with the same land cover class as above) were different. For the ESRI dataset the ratio of land cover change was much different. The change rates for the top 3 provinces were: 0.91 (Lamphun, Thailand), 0.82 (Kep, Cambodia), and 0.76 (Kâmpóng Spœ, Cambodia). The top province for the remaining countries were: Cà Mau, Vietnam (0.66), Kayah, Myanmar (0.62), and Vientiane, Laos (0.49). Note that Cà Mau, Vietnam likely did not undergo such a drastic rate of land cover change, as this was confirmed by reviewing the annual composite of Sentinel-2 and Landsat 7 imagery for 2001 and 2021. The maps from figure 4 shows that large swaths of Cambodia, southeast Vietnam, Central Myanmar, Northwest Vietnam, and more experienced high rates of land cover change.

The difference in ratio between the MODIS maps and Esri map was highest in all of Cambodia's southern provinces (e.g. Kep, Kândal), Cà Mau, Vietnam, Yasothon and Lamphun Thailand, Magway, Myanmar, among others. These discrepancies in rates of land cover change were huge, with differences between 0.31 and 0.66 for the aforementioned provinces. It is very likely that some of these discrepancies between MODIS and Esri dataset were due to the spatial resolution. At a 10m scale, much more smaller change can be detected, especially change related to roadway increase, or small-scale deforestation.

Agreement between Esri and MODIS Land Cover at 463M resolution

After resampling the Esri layer to the 463M resolution to correspond with MODIS, and reclassifiying both datasets to the same merged classification scheme (table 1), agreement between pixels on land cover type was variable. 70.7% of cropland pixels between the two datasets were in agreement, with the most confused class for Esri being range/shrub, followed by built-up (table x). Trees had the highest level of agreement between the two datasets at 90.8%, followed by water at 82.6%. Wetlands had the lowest agreement rate at 3.6% where Esri was more likely to classify a MODIS Wetland pixel as Crops (33.8%) or range/shrubland (25.9%). This crop-wetland difference could be attributed to paddy rice which is both a wetland and a crop. It's very possible that Esri considers this as a crop, while MODIS considers this as a wetland. Neither classification is inherently more correct than the other.

At the province level, figure 5 illustrates the confusion between MODIS and Esri land cover at the 463m scle for the merged land cover class scheme. Each sub-figure represents the MODIS land cover and what it is most confused with in the Esri product for the majority of pixels in each province. One interesting trend is that across most of the provinces, MODIS tree class was classified as Shrub/rangelands in the Esri class. This could very well be due to the fact that at the Esri scale, a forest may be patchy (i.e. a rangeland class in esri) which could result in the discrepancy. An overwhelming majority of MODIS built-up pixels were classified as croplands. This is likely due to the fact that MODIS scale cannot accurately represent small-scale expansion of urban areas into croplands which is common in the region. MODIS Water pixels were often confused for wetland in Cambodia provinces, and Northeastern Thailand provinces. Whereas, the MODIS water pixels were reported as built-up in the provinces near Bangkok, as well as near Hanoi, and in Southern Vietnam. Additional trends can be observed in the figure.

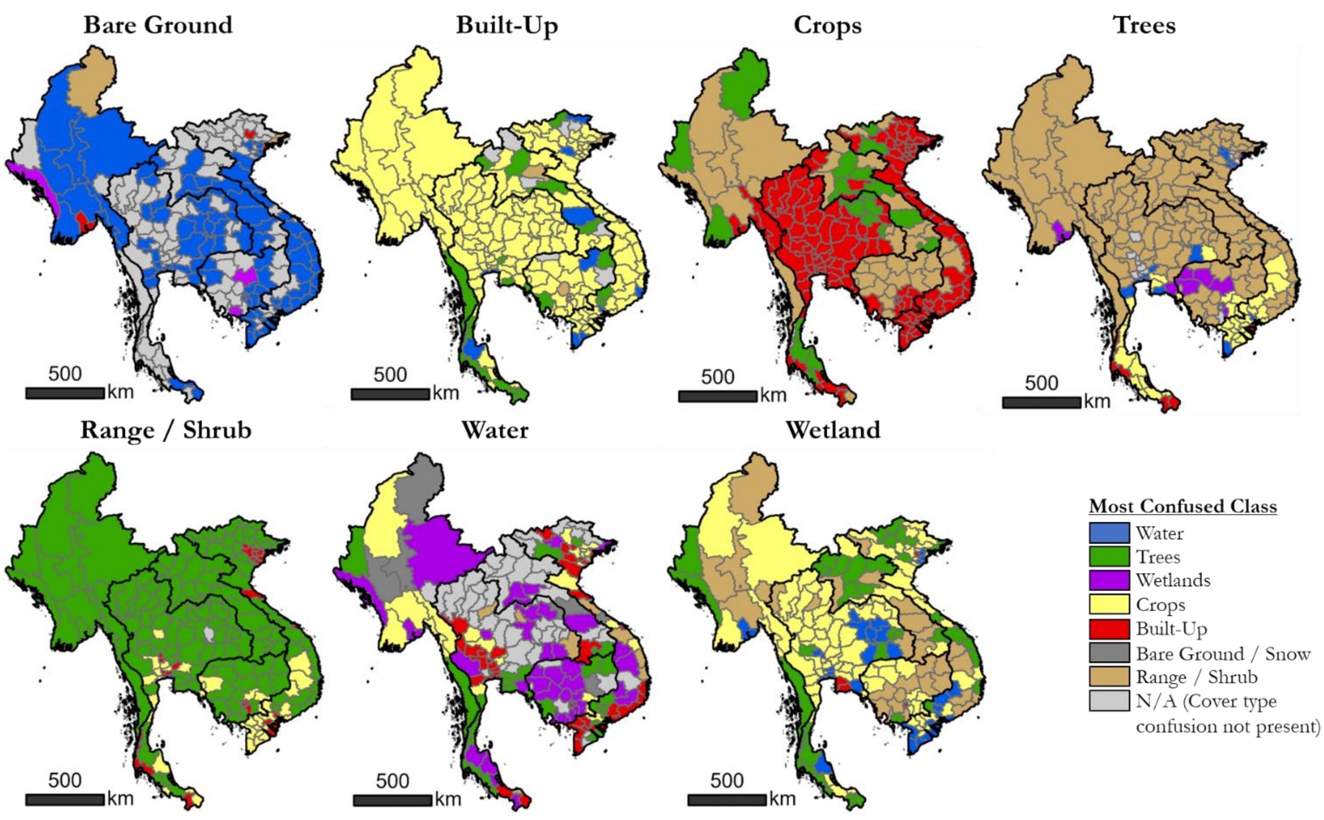

Figure 5: Confusion between the MODIS and Esri land cover products at 463M MODIS pixel scale with the merged land cover class scheme from table 1. Each sub-figure represents MODIS land cover type for 2022, and the legend/colors represent the most confused Esri land cover class per province.

These differences in land cover are visualized with 1m imagery in figure 6. This image is located in Buôn Ma Thuột and surrounding regions of Dak Lak Province within the Central Highlands of Vietnam. It's evident that the spatial scale of MODIS and Esri really play a role here. Much of the sub-urban and ex-urban expansion found in the imagery is not detected in the MODIS product, because it is relatively small and likely not detectable in a 463m MODIS pixel. Whereas, the Esri product appears to exaggerate the extent of the urban growth via some kind of region growing algorithm, as also noted in prior studies (Lasko et al. 2023; Lasko et al. 2024). It is evident that a lot of woody savanna and savanna are detected in MODIS. These classes are reported by the MODIS product as a percentage of trees (30-60%, and 10-30% respectively). So while, the Esri product maps trees in small locations, the MODIS product classifies many of the pixels as savanna or woody savanna as much of these areas are a mix of forest and cropland which cannot be individually separated at the MODIS scale. While the maps appear to be very different, both accurately represent the land cover in most cases. However, one issue is that the Esri product more accurately delineates cropped area in this image, whereas the MODIS product appears to count much of the cropped area or mosaic crop landscape as savanna.

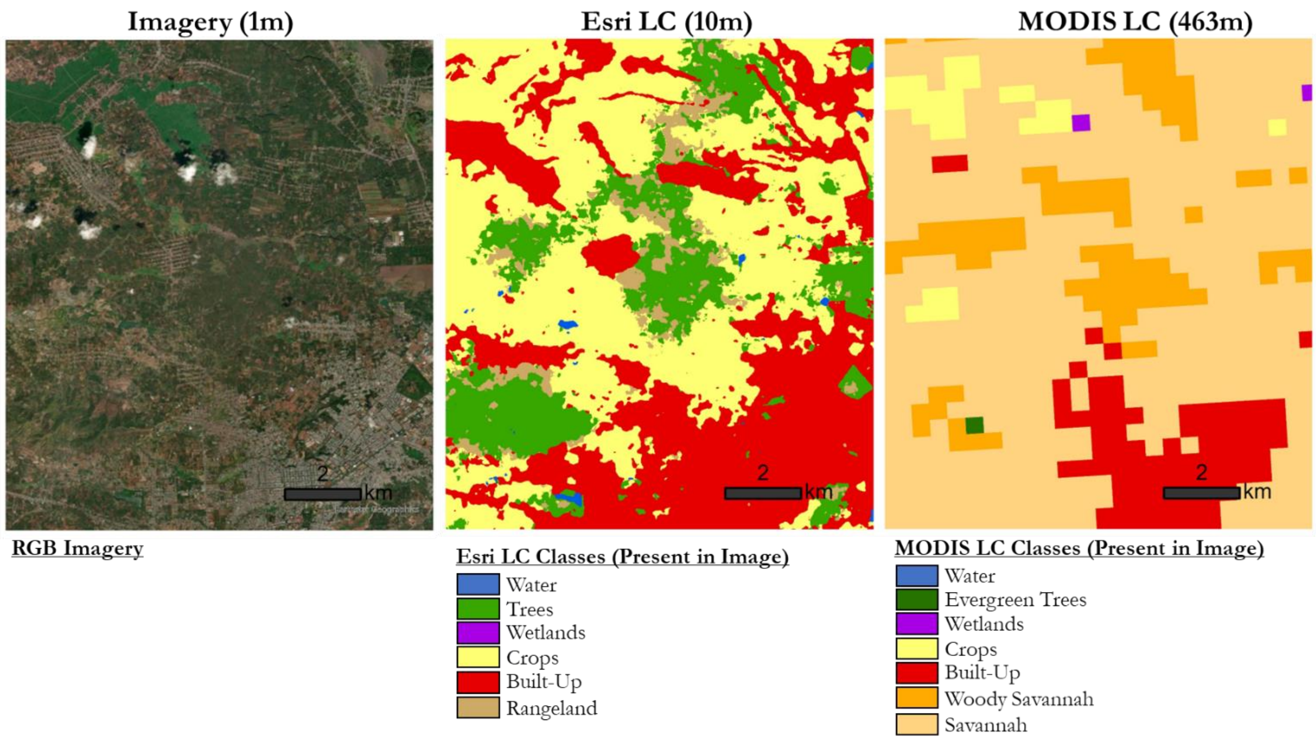

Figure 6: High resolution 1m imagery shown with the Esri and MODIS land cover datasets at their original spatial resolutions over Buôn Ma Thuột, Vietnam located within Dak Lak province in the Central Highlands. The original classes for Esri are shown, while MODIS classes are the condensed scheme (table 1).

Hotspot Areas of Land Cover Change 2001 , 2011, 2021 at Decadal Scale

We identified the provinces that underwent the highest ratio of land cover change for the years 2001, 2011, and 2021 at a decadal scale using the MODIS land cover data with the merged class scheme (table 1). The top 3 provinces were Otdar Mean Chey (Cambodia) with a land cover change ratio of 1.17, Preah Vihéar, Cambodia with a change ratio of 1.05, and Bueng Kan with a ratio of 1.03. All three of these provinces had more than 100% of their land area change over the 20 year period. This means that multiple pixels underwent more than 1 change over the time period. Further, the highest land cover change rate for provinces in other countries were: Kayah, Myanmar (0.87), Bình Phước, Vietnam (0.87), and Vientiane prefecture, Laos (0.83). Otdar Mean Chey, Cambodia, Preah Vihéar, Cambodia, and Vientiane, Laos all had high rates of land cover change for the 2018 to 2022 period as well as mentioned in a prior section of the text. Figure 7 illustrates the land cover percentages for each year for the top 3 provinces overall with the highest rates of change, the province with the highest rate of change for each country, and the province with the highest absolute area of change for each country (Chiang Mai, Savannakhét, Shan, Sơn La).

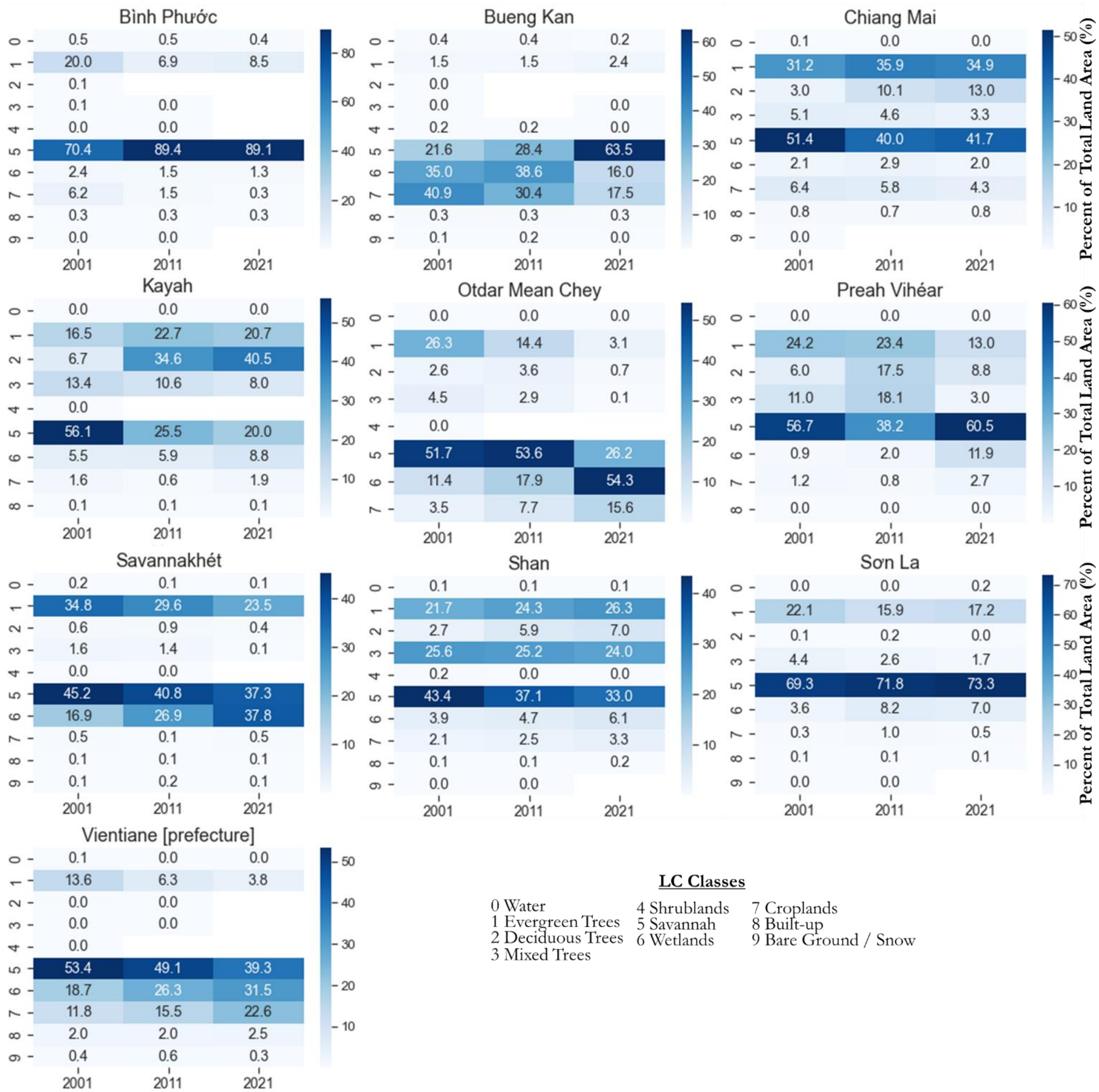

Figure 7: Land Cover areas for the MODIS product with merged land cover classes between 2001 and 2021 for the hotspot provinces including: province with highest rate of change per country, and province with highest absolute amount of change.

Bình Phước, Vietnam had 20.0% of land area occupied by Evergreen trees in 2001, which sharply declined to 6.9% in 2011, with a slight rebound to 8.5% in 2021. A major loss in cropland area was also observed. The area experienced gain in Savanna area during that time period, much of which could be attributed to agroforestry practices such as rubber plantations (Hoang et al. 2020).

Bueng Kan, Thailand had drastic increase in savanna from 21.6% in 2001 to 63.5% in 2021. It also saw notable decline in wetland and cropland area. Much of this change is attributed to an increase in para rubber plantations (Maiandang 2017), which likely manifested as increase in savanna area.

Chiang Mai, Thailand experienced a slight increase in evergreen forest, and a drastic increase in deciduous forest between 2001 and 2021 (3.0% to 13.0%). A decline in savanna area from 51.4% to 41.7% was also observed. Much of this change can be attributed to an increase of orchards, conversion of forest to agricultural lands, and urban growth (McGrath et al. 2017; Lee et al. 2022).

Kayah, Myanmar experienced a massive gain in deciduous trees with 6.7% in 2001 and 40.5% in 2021. A slight increase in evergreen trees and wetlands was also observed, while cropland area remained fairly low. Savanna area saw a drastic decline from 56.1% to 20.0%. Some of this can be attributed to logging, rather than complete forest clearing (Tun et al. 2021) and a lower number of protected areas as compared with other provinces in Myanmar (Liu et al. 2016). Increase of rubber plantations has also played a role (Aye et al. 2019).

Land cover change in Otdar Mean Chey was the highest out of all provinces. Sharp declines in forest area and savannah were observed, while wetlands and croplands experienced large gains. This is likely indicative of deforestation and conversion to various crops and rice (as detected as wetlands). In Pheah Vihear province, economic land concessions, immigration, logging and agricultural activity have played a role in the land cover change (Dara 2019).

In Laos, Savannakhet experienced forest cover decline via loss of savanna and evergreen tree cover with a major gain in wetland area attributed to paddy rice expansion. Croplands most often displaced tree cover (SOUPHIHALATH et al. 2017). Vientiane underwent a similar change with expansion of cropland, and wetlands attributed to paddy rice. Further, urban expansion also played a role with an increase from 2.0% to 2.5% from 2001 to 2021. The land cover change dynamics for the other top provinces are shown in the figure 7.

Hotspot Areas of Land Cover Change 2018 to 2022 period

The Esri land cover data was only available for the 2018 to 2022 period so we evaluated the top provinces of land cover change for that time frame and compared that with the same provinces for the MODIS data during the same time period. Both datasets were processed with their original spatial resolutions for the purpose of this evaluation. The top 3 provinces of the ratio of land cover change area to total area were: Lamphun, Thailand (0.91), Kep, Cambodia (0.82), and Kâmpóng Spœ, Cambodia (0.76). The top province of change in each of the remaining countries were: Cà Mau, Vietnam (0.65), Kayah, Myanmar (0.62), and Vientiane, Laos (0.49). The provinces identified as the highest absolute area of change for each country were: Shan, Myanmar with over 55,000km^2 of land area change, followed by Chiang Mai, Thailand with over 9,000km^2 of land cover change, Savannakhét, Laos with over 8,000km^2 of land cover change, and Đắk Lắk, Vietnam with over 7000km^2 of land cover change. Figure 8 visualizes the Esri land cover percentages for the notable provinces between 2018 and 2022.

Ca Mau, Vietnam was reported to have major gain of water (41.3% in 2018 and 55.6% in 2022) with a decline in flooded vegetation, and major decline in crops (39.4% to 22.1%). However, these changes were not observed in the MODIS land cover product. Dak Lak Vietnam was reported to have a gain in tree cover from 38.7% to 44.1% in 2022, offset primarily by loss in rangeland area. This trend may also not be accurate, as recent studies have reported forest cover loss or minimal change during the 2010 to 2020 time period (Tran et al. 2024). Ninh Thuan Vietnam had very high variation in tree cover and rangeland between each year of the period. It's highly unlikely that rangeland changed from 22.6% to 40.9% to 27.2% between 2019 and 2021. Recent news sources report major reforestation efforts in this province between 2023-2025 (VNnews.vn).

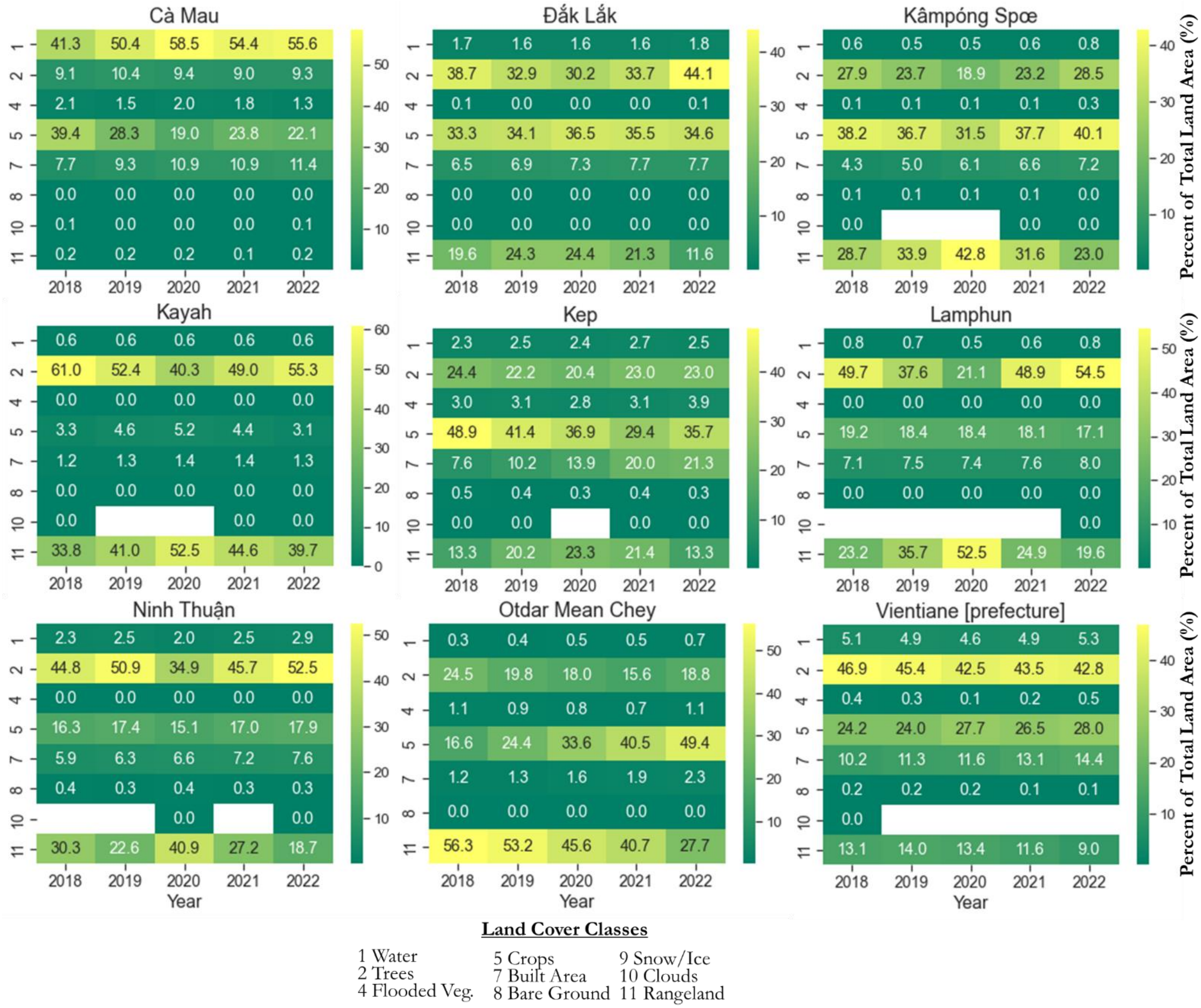

Figure 8: Provinces with the highest land cover change ratio for the Esri product between 2018 and 2022.

In Cambodia, Otdar Mean Chey province was reported to have major decline in rangeland (56.3% in 2018 to 27.7% in 2022) offset by an increase in cropland area. Tree cover also experienced a notable decline. These drastic changes in such a short time period are unlikely to be realistic and could be errors in the dataset. However, as seen in figure 10, we observed large swaths of forest clearing for agricultural activities between 2001 and 2021. It's unclear how much of this truly occurred between 2018 and 2022. Kep, Cambodia was reported to have a major decline in crops, with a tripling in built area from 7.6% in 2018 to 21.3% in 2022. Kampong Speu, Cambodia had rivers dammed over the past several decades which resulted in major increase in agricultural land (Chhinh et al. 2023). It's probable that the slight increase observed in figure 10 coincides with this (38.2% in 2018 to 40.1% in 2022). A study analyzing land cover change from 2006 to 2018 found drastic decline in forest area with conversion to agriculture, and small amounts converted to rubber plantations (Khorn et al. 2020).

The preceding paragraphs in this sections described the provinces with the highest ratio of land cover change to total area between 2018 and 2022 using the Esri 10m land cover product with its original land cover classes. Figure 9 visualizes those same provinces, but with the MODIS 500m land cover product with the condensed land cover class scheme (table 1). Immediately, it is clear that many of these provinces were not observed to undergo rapid and major land cover change in the MODIS product. For example, Ca Mau, Vietnam had a high rate of land cover change in the Esri product (0.66), whereas the MODIS product had it listed much lower at 0.19. In the MODIS product, we observed a slight increase in evergreen tree area, decrease in savanna area, while the remaining classes were fairly constant through time. After viewing imagery composites in Google Earth Engine, Cau Mau province did not appear to undergo a drastic change in land cover between 2018 and 2022. The area remains occupied by shrimp-rice crop rotation. The area experiences heavy cloud cover which reduces the amount of imagery available, which likely led to errors in the Esri land cover model.

One similarity observed between the land cover change in MODIS and Esri was they both found Odtar Mean Chey to have very high rates of land cover change. In MODIS, this province saw a decrease in savanna area from 48.5% in 2018 to 23.3% in 2022, as well as slight decline in evergreen tree area, deciduous tree area, and a drastic increase in wetland area, likely paddy rice, from 32.5% to 59.5%. Similarly, Vientiane experienced high rates of land cover change in both products. In MODIS, it was observed to have a major decline in savanna (46.5% to 38.1%) with an increase in wetlands (24.7% to 33.5%). Slight decrease in evergreen trees was observed, as was a slight increase in built-up area.

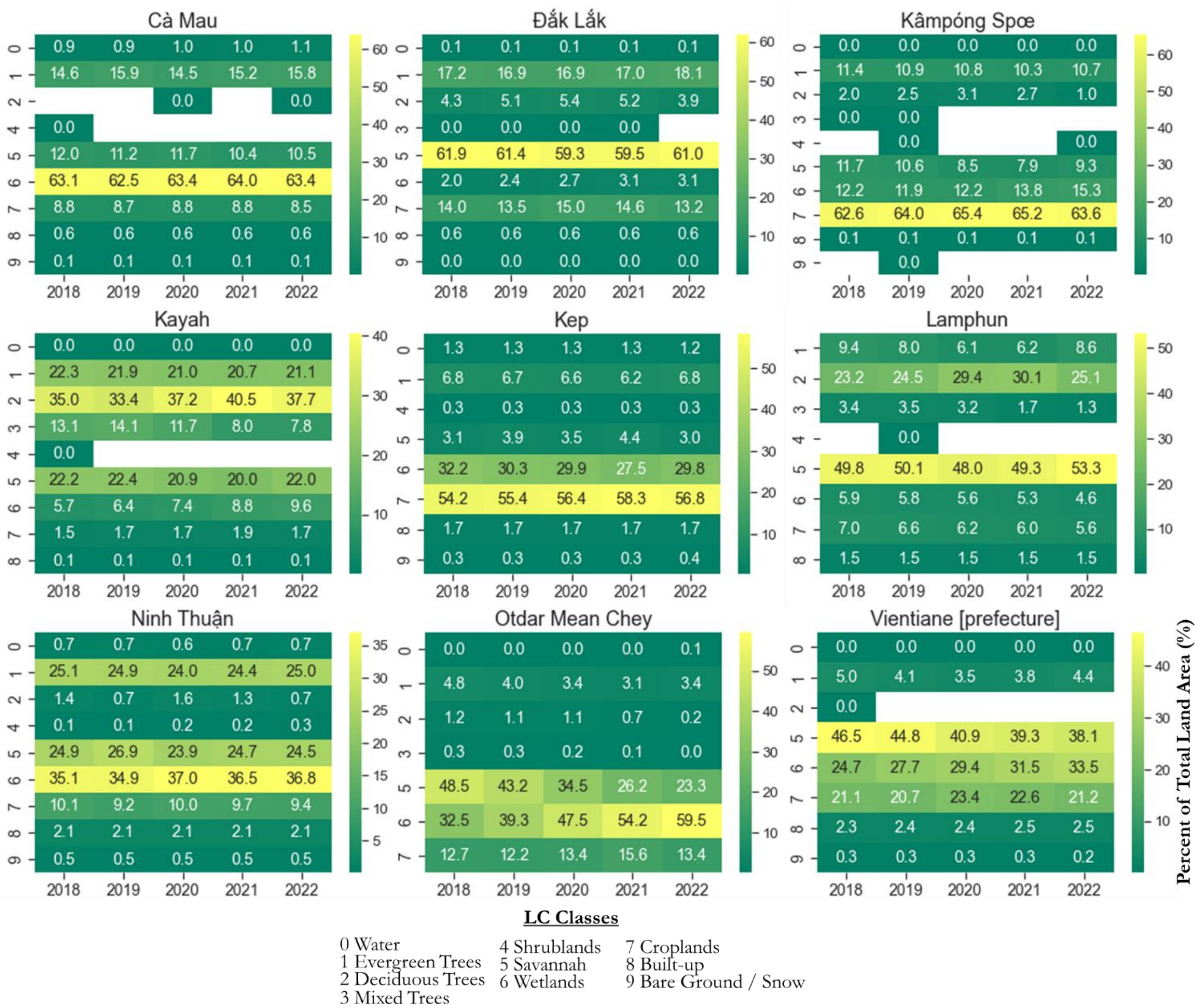

Figure 9: Visualization of the MODIS land cover percentage area for the same provinces as the Esri product from figure 8 for comparison purposes. Note major discrepancies between provinces such as Ca Mau. Gaps in the chart indicate that land cover type was not present within the province.

Moderate resolution land cover change in hot spot areas

Landsat 7 imagery from 2001 and Sentinel-2 imagery from 2021 were composited into cloud free composites based on annual imagery for each year using Google Earth Engine within selected sites of heavy land cover change determined from the MODIS Land Cover Product. In Figure 10, we see the creation of the new capital of Myanmar, Naypyidaw. This included construction of new urban areas, roads, and creation of reservoirs via river damming. We can also see some forest clearing. Interestingly, the MODIS land cover product did not detect much of the major changes that are evident within the 2001 Landsat and 2021 Sentinel-2 imagery.

Over the Cambodia and Thailand border, we observe large swaths of forest clearing on the Cambodia side, with these lands replaced by agriculture. One river was also dammed in the area to create a reservoir to support agricultural activity. The MODIS land cover product appears to detect these changes very effectively. Within Quang Tri Province, Vietnam, multiple areas of smaller sized forest clearing are evident, and some old areas of forest clearing can be seen regrowing in the imagery. Substantial increase in urban area is also apparent. The MODIS Land Cover product appears to capture a large amount of land cover change beyond what can be seen in the two dates, this is likely due to forestry with trees like Acacia that are planted and harvested every 4-5 years.

The Vientiane, Laos scene depicts substantial urban expansion on the East and south-central portions of the image. Apparent increase in forest clearing is also evident throughout the central and western portion of the image. Several areas in the North and West portions of the image appear to have forest area regrown. The MODIS land cover product appears to effectively capture much, but not all the land cover change between these time periods.

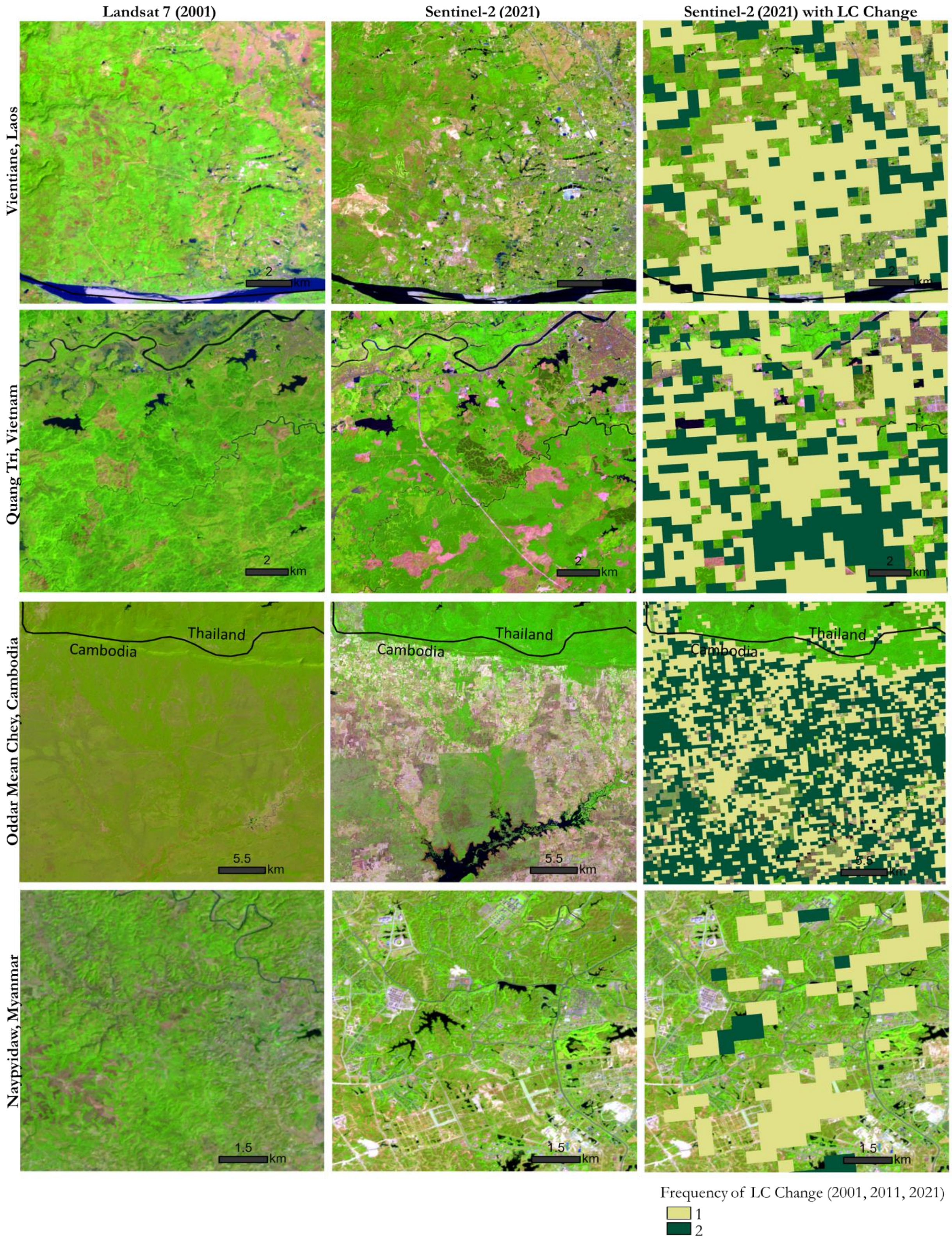

Figure 10: Hotspot areas of change visualized at moderate resolution with the MODIS land cover product frequency of change overlaid for comparison.

Conclusion

The Continental Southeast Asia region countries of Cambodia, Myanmar, Laos, Thailand, and Vietnam experienced major levels of land cover change between 2001 and 2021, as well as during the 2018 to 2022 period as monitored at the MODIS scale (500m) and the Sentinel-2 scale (10m). At a decadal scale for the time period of 2001, 2011, and 2021, 40.0% of the region's area underwent land cover change at least 1 time, as measured by MODIS. Of the different countries, Cambodia experienced the highest rate of land cover change with 67.8% of total land area change, followed by Vietnam (58.6%), Laos (50.2%), Myanmar (46.9%), and Thailand (46.3%). Cambodia experienced the highest rates of forest cover loss with evergreen forest area declining from 31.9% to 17.8% and mixed forest declining from 2.7% to 0.4%. Myanmar had no (0.2%) net change in forest area between that same period. Thailand experienced a net increase in forest area (21.0% to 22.9% for all forest types except savannas). Vietnam saw a slight decline in forest area from 32.3% (excluding savanna) to 29.8%. Laos experienced moderate rate of forest loss with 69.2% in 2001 to 54.5% in 2021 (excluding savanna classes). Cambodia, Laos, and Myanmar experienced notable gains in wetland area attributed to paddy rice and aquaculture, while Vietnam and Thailand had slight decreases.

This study also found key hotspot areas of changes within the provinces of each country. In Cambodia, Otdar Mean Chey experienced the highest rate of land cover change dominated by forest clearing and conversion to crops and wetlands (i.e. rice). In Laos, Vientiane saw large declines in forest and savanna area replaced by gains in cropland, wetland (i.e. rice), and built-up area from urban expansion. In Myanmar, Kayah state experienced tree cover gains, in contrast to most other provinces. It experienced a massive increase in deciduous tree area, slight increase in evergreen tree area, and slight decrease in mixed tree area. However, savanna area drastically decreased, likely due to forest regrowth. Bueng Kan, Thailand also experienced abnormal land cover change with an increase in savanna area, decrease in cropland and wetlands. Bueng Kan has a number of rubber plantations in the area.

We examined hotspot areas of change with composites of Landsat 7 and Sentinel-2 over selected major change sites such as Vientiane, Laos, and identified how the MODIS land cover product can detect some, but not all changes. It did apparently poor in detecting change in Napyidaw, Myanmar with the construction of the new Capitol.

Importantly, this study examined the MODIS 500m land cover product in comparison to the Esri Sentinel-2 10m land cover product. Both products, had different spatial scales and land cover class schemes (e.g. Esri 10 class vs MODIS 16+ class depending on selected scheme). After resampling and aligning to a similar classification scheme, we found the products have major disagreement on land cover type and associated change between the period of 2018 to 2022 (when both products are available). We found that the products have the strongest agreement on tree cover and water, with poor agreement on wetlands, and rangeland/shrubland. Some of this is attributed to the resolution, and the different number and definitions of land cover classes, as well as variation in algorithm and image quality. The Esri product identified a lot of false positive land cover change in provinces such as Ca Mau, Vietnam which contains a lot of cloud cover and in fact did not experience dramatic land cover change between 2018-2022. Ultimately, we found that these products have major disagreement on land cover type and that users should be aware of limitations with the products when relying on them for derivative applications such as biomass burning emissions assessment, methane quantification, and much more. For assessments conducted at a country scale or smaller, researchers should not rely on either of these products, and should instead create their own or locate a product with high accuracy at the local scale.

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