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Perspective: Improving the accuracy of plant phenology observations and land-cover and land-use detection by optical satellite remote-sensing in the Asian tropics

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Recent advances in satellite-borne optical sensors led to important developments in the monitoring of tropical ecosystems in Asia, which have been strongly affected by recent anthropogenic activities and climate change. Based on our feasibility analyses conducted in Indonesia in Sumatra and Sarawak, Malaysia in Borneo, we discuss the current situation, problems, recent improvements, and future tasks regarding plant phenology observations and land-cover and land-use detection. We found that the Multispectral Instrument (MSI) on board the Sentinel-2A/2B satellites with a 10-m spatial resolution and 5-day observational intervals could be used to monitor phenology among tree species. For the Advanced Himawari Imager (AHI) on board the Himawari-8 geostationary satellite with a 1,000-m spatial resolution and 10-min observational intervals, we found that the time-series in vegetation indices without gaps due to cloud contamination may be used to accurately detect the timing and patterns of phenology among tree species, although the spatial resolution of the sensor requires further improvement. We also found and validated that text and pictures with geolocation information published on the Internet, and historical field notes could be used for ground-truthing land cover and land use in the past and present time. The future development of both high frequency (≤ 10 min) and high spatial resolution (≤ 10 m) optical sensors aboard satellites is expected to dramatically improve our understanding of ecosystems in the tropical Asia.

KEYWORDS

deforestation, general flowering event, geostationary satellite (GEO), optical sensor, cloud contamination, Sarawak (Malaysia), Sumatra

1. Introduction

In the tropics, where biodiversity is the highest (FAO, and UNEP, 2020; Secretariat of the Convention on Biological Diversity, 2020), there is an urgent need to accurately evaluate the spatiotemporal variation of ecosystem functions, ecosystem services which have recently been called "nature's contributions to people" (Díaz et al., 2018), [1]and biodiversity under the rapid anthropogenic impacts and climate change occurring there (Estoque et al., 2019). Toward this aim, we require accurate and continuous observations of plant phenology (e.g., flowering, leaf flush, leaf coloring, and leaf fall), which serve as proxies of the responses of organisms and ecosystems to the environment (Tang et al., 2016; Piao et al., 2019), and of land-cover and land-use change. Data on plant phenology, and land-cover and land-use change help to explain the spatiotemporal variability of ecosystem properties (e.g., photosynthesis and evapotranspiration, carbon stocks and flows, the land surface's albedo, and energy balances; Penþuelas et al., 2009; Kumagai et al., 2013; Richardson et al., 2013; Wu et al., 2016), emission of biogenic volatile organic compounds (BVOCs; Penþuelas et al., 2009; Richardson et al., 2013; IPCC, 2021), cultural ecosystem services (e.g., festivals and recreation opportunities; Sakurai et al., 2011; Sparks, 2014; Nagai et al., 2019), regulating ecosystem services (e.g., pollinator abundances and pollination; Lautenbach et al., 2012; Rohde and Pilliod, 2021), environmental changes in various habitats (Muraoka et al., 2012; Gray and Ewers, 2021), and biodiversity conservation (Morisette et al., 2009; Secades et al., 2014; Morellato et al., 2016). Phenological mismatch between plants and their animal pollinators and consumers caused by the changes of the timing of each phenology due to climate change, reduces the biodiversity (Visser and Gienapp, 2019; Secretariat of the Convention on Biological Diversity, 2020). The evaluation of spatial-temporal variability of the interaction between landscape, which is mainly explained by land cover and land use, and anthropogenic activities, also provides fundamental knowledge to deeply understand the spatial-temporal variability of ecosystem functions, ecosystem services and biodiversity under climate and societal changes.

Satellite remote-sensing by optical sensors is useful for evaluating the spatiotemporal variation of plant phenology, land cover, and land use over a broad scale (Muraoka et al., 2012; Nagai et al., 2020a; Shin et al., 2023). Since 1972 when Landsat-1 was launched, [2]satellite optical sensors that observe visible and near-infrared regions of the electro-magnetic spectrum have continuously monitored the state of the ground surface from plot to global scales (**Table 1** shows a summary of the specification of optical sensors on board satellites shown in this perspective paper). However, these optical sensors are affected by atmospheric noise and cloud contamination, which is the biggest disadvantage of optical sensors. The opportunity for observation under clear sky conditions in the tropics is much rarer than in other regions (Nagai et al., 2011, 2014a).

In contrast, synthetic aperture radar (SAR) on board satellites is not affected by atmospheric noise and cloud contamination and allows for nighttime observation (e.g., Phased-Array type L-band Synthetic Aperture Radar 2 on board the Advanced Land Observing Satellite [ALOS]-2) and measurement of the spatiotemporal variation of ecosystem structures. SAR transmits microwaves and then actively receives the returned microwave off the ground surface, allowing the detection of forest/non-forest domains, land use and land cover, and aboveground biomass of forests (Miettinen and Liew, 2011; Avtar et al., 2014; Shimada et al., 2014; Kou et al., 2015; Li L. et al., 2015; Stelmaszczuk-Górska et al., 2018). However, SAR cannot observe plant phenology, which is mainly shown as a characteristic of color change of canopy surface on satellite remote-sensing in optical signals. Thus, advancement in SAR technology and/or the integration of SAR and optical sensors will be needed for the accurate detection of land cover and land use (Najib et al., 2020).

To improve the accuracy of phenology observations (e.g., detection of accurate timing of flowering, leaf-flush, and leaf-fall in each ecosystem and/or tree species) and land-cover and land-use detection (e.g., categorization of various land use type and immediate detection of land cover change with a high spatial resolution), we ideally require an optical sensor with high spatial (e.g., 10 m), temporal (e.g., daily interval), and wavelength (many narrow spectral bands) resolutions. However, these three properties have not yet been attained simultaneously with a single sensor due to trade-offs especially between spatial and temporal resolutions (Nagai et al., 2020a). This limitation has made it difficult to accurately monitor the ground surface in the tropics, where the plant phenology and its synchrony among tree species are much less clear than in temperate and boreal vegetation (Harrison, 2001; Nakaji et al., 2014; Nagai et al., 2016a; Osada, 2018; Nakagawa et al.,

1 https://ipbes.net/news/natures-contributions-people-ncp-article-ipbes-experts-science

2 https://landsat.gsfc.nasa.gov/

2019). Higher diversity and heterogeneity of tree species in the Asian tropics (Lee et al., 2002) make satellite-based phenological observations difficult. Marked land-cover and land-use changes have accelerated in the tropics due to anthropogenic activities (e.g., deforestation) and climate change (e.g., forest fires triggered by the El Niño–Southern Oscillation; Ichikawa, 2007; Segah et al., 2010; Wooster et al., 2012; Hansen et al., 2013; Nagai et al., 2014a; Marlier et al., 2015; Spessa et al., 2015).

For phenology observations and detection of the interannual variation of land cover and land use, researchers have frequently used data observed by optical sensors on board public satellites with high frequency but a coarse spatial resolution, such as the Advanced Very High Resolution Radiometer (AVHRR) on board the National Oceanic and Atmospheric Administration satellite (NOAA; 1100-m spatial resolution at a daily interval; e.g., Erasmi et al., 2014; Garonna et al., 2014; Buitenwerf et al., 2015; Gao et al., 2019), the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra and Aqua satellites (250- to 500-m spatial resolution at a daily interval; e.g., Zhang et al., 2003; Miettinen et al., 2011; Pennec et al., 2011; Jin et al., 2019), and the VEGETATION optical sensor on board the Satellite Pour l'Observation de la Terre (SPOT; 1000-m spatial resolution at a daily interval, [3]e.g., Delbart et al., 2006, 2015; Segah et al., 2010; Kobayashi et al., 2016). Also for this purpose, researchers have frequently used data observed by optical sensors on board public satellites with low frequency (16-day intervals) but a moderately high spatial resolution (30 m) such as the Landsat series of satellites (Segah et al., 2010; Kou et al., 2015; Li P. et al., 2015; Ishihara and Tadano, 2017; Morozumi et al., 2019). In contrast, for the detection of land cover and land use with a fine-scale, they have frequently used data observed by optical sensors on board commercial satellites (e.g., the RapidEye: Imukova et al., 2015; Pfeifer et al., 2016; the WorldView series satellites: [4] Nomura and Mitchard, 2018; Rahmandhana et al., 2022) with a high spatial resolution (e.g., 50 cm) but quite low frequency (e.g., 46-day intervals).

Some advantages of optical sensors on board public satellites are the uniformity of observed data coverage, stable long-term continuous observations from the long-term missions (e.g., the Landsat series of satellites: See text footnote 2), and free usage on the Internet. In contrast, the data observed by optical sensors on board commercial satellites tend to be low-frequency data distributed in urban areas, meaning that we cannot easily access satellite data in remote regions. Although researchers could request satellite image acquisitions of remote regions to these companies, it is an impractical idea to request periodic broad-scale satellite observations in remote regions over a long period due to the cost of obtaining such commercial data.

In the latter half of the 2010s, the spatiotemporal resolution of optical sensors on board public satellites remarkably progressed with the launch of the Multispectral Instrument (MSI) on board the Sentinel-2A/2B satellites, with a 10-m spatial resolution at 5-day intervals (; e.g., Nomura and Mitchard, 2018; Persson et al., 2018; Vrieling et al., 2018; Chang et al., 2021), [5]and the Advanced Himawari Imager (AHI) on board the Himawari-8 geostationary satellite, with a 1,000-m spatial resolution at 10-min intervals (at 2.5-min intervals around Japan; Miura et al., 2019; Yan et al., 2019; Miura and Nagai, 2020). [6]Although these optical sensors do not satisfy the need for simultaneous high spatial, temporal, and wavelength resolutions, these optical sensors will be expected to provide much more accurate and precise satellite observations, along with a reduction of uncertainties and systematic noise in land-cover and land-use detection and phenology observations (Shin et al., 2023). Continuous and extensive satellite observations by these optical sensors will be also expected to develop spatiotemporally interpolating and extrapolating *in situ* observed data on ecosystem functions and biodiversity in each tropical observation field.

In this perspective paper, based on this recent progress in the optical sensors on board satellites and the development of observation systems in the latter half of the 2010s, we focus on satellite optical sensors and discuss the current situation, problems, and recent improvements, as well as future tasks regarding phenology observations and land-cover and land-use detection in the Asian tropics. Here, we focus on island or maritime Southeast Asia. In order to discuss concretely, we review our feasibility analyses in Sarawak, Malaysia in Borneo, where our research group has conducted field studies to validate satellite remote-sensing since the 2010s, and Indonesia in Sumatra by using data from the Sentinel-2A/2B–MSI and the Himawari-8–AHI satellites. In Section 2, we describe how the accuracy of satellite phenology observations can be improved from the viewpoints of advanced resolution sensors and frequency of satellite observations. Next, in Section 3, we describe how to improve the accuracy of land-cover and land-use detection from the viewpoints of detection of year-to-year variability and collection of past and present ground-truth information. Then, in Section 4, we discuss the future tasks to help improve our understanding of Asian tropical ecosystems. Finally, in Section 5, we conclude our discussions in this perspective paper.

2. Improvements in the accuracy of satellite phenology observations

2.1. Monitoring of plant phenology by using advanced resolution sensors

Figure 1 shows the time-series of vegetation indices of Lambir Hills National Park (primary tropical rain forest; 4°12'04"N, 114°02'21"E; Nakagawa et al., 2019) and the Lambir oil palm plantation (4°09'07"N, 113°57'58"E) in Sarawak, Malaysia in Borneo observed by the Sentinel-2A/2B–MSI (atmosphere corrected data) and Himawari-8–AHI satellites. Primary tropical rain forests, oil palm plantation forests, and secondary forests are typical landscape features in this area (Ichikawa, 2007). In addition, typical canopy surface images of Lambir Hills National Park are shown in **Figure 2**. We show only NDVI values for the Himawari-8–AHI satellite because we used the reflectance data at the top of the atmosphere (i.e., atmosphere uncorrected data). For the Sentinel-2A/2B–MSI satellites, we selected observation scenes

3 https://spot-vegetation.com/en

4 https://earth.esa.int/eogateway/missions/worldview

5 https://sentinel.esa.int/web/sentinel/missions/sentinel-2

6 https://www.data.jma.go.jp/mscweb/en/index.html

TABLE 1 Summary of the optical sensors on board public satellite.

Sensor	Satellite	Spatial resolution	Temporal resolution	Spectral bands	Swath	Period	URL of specification
Multispectral Scannar (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM +), Operational Land Imager (OLI), and OLI-2	Landsat series	68 × 83 m (MSS); 30, 120 m (TM); 15, 30, 60 m (ETM +, OLI); 15, 30, 100 m (OLI-2)	18-days (MSS); 16-days	0.5-1.1μm (4 or 5 bands; MSS), 0.45-12.5μm (7 bands, TM); 0.45-12.5μm (8 bands, ETM +); 0.435-12.51 μm (11 bands, ETM +); 0.433-12.5 μm (11 bands, OLI-2)	185 km (MSS, TM, OLI, OLI-2); 183 km (ETM +)	Since 1972	https://landsat.gsfc.nasa.gov/
Advanced Very High Resolution Radiometer (AVHRR)	NOAA Polar Orbiting Environmental Satellites (POES), Meteorological Operational Satellite (MetOp)	1,100 m	daily	0.58-12.5 μm (4 or 5 bands)	2399 km	Since 1981	https://www.avl.class.noaa.gov/release/data_available/avhrr/index.htm; https://www.eumetsat.int/oursatellites/metop-series
Moderate Resolution Imaging Spectroradiometer (MODIS)	Terra and Aqua	250, 500, 1,000 m	daily	0.405-14.385 μm (36 bands)	2330 km	Since 1999 and 2002, respectively	https://modis.gsfc.nasa.gov/
Vegetation-1/2	Satellite Pour l'Observation de la Terre (SPOT)-4/5	1,000 m	daily	0.43-1.75 μm (4 bands)	2200 km	Since 1998	https://earth.esa.int/eogateway/missions/spot
Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2)	Advanced Land Observing Satellite (ALOS)	10 m	46-days	0.42-0.89 μm (4 bands)	70 km	2006-2011	https://www.eorc.jaxa.jp/ALOS/en/index_e.htm
MultiSpectral Instrument (MSI)	Sentinel-2A/2B	10, 20, 60 m	5-days	0.4924-21.857 μm (13 bands)	290 km	Since 2015 and 2017, respectively	https://sentinel.esa.int/web/sentinel/missions/sentinel-2
Advanced Himawari Imager (AHI)	Himawari-8	1000 m	10 min. (2.5 min. around Japan)	0.47-13.3μm (16 bands)	Geostationary position: 140.7°E	Since 2015	https://www.data.jma.go.jp/mscweb/en/index.html

Revised in this table in Shin et al. (2023).

with cloud cover $\leq$ 10%, but we plotted all values observed by the Himawari-8–AHI satellites. For the Himawari-8–AHI satellite, we plotted values observed at 3 h around the culmination time because there was no property in the data regarding the cloud contamination. Despite the occurrence of general flowering in Lambir Hills National Park in May 2019, which occurs every 1–4 years, and the color of the canopy surface changing from dark green to whitish green (Sakai et al., 2006; Azmy et al., 2016; Chechina and Hamann, 2019; Ushio et al., 2020), every vegetation index showed no clear seasonal change (low values may be affected by cloud contamination). During the general flowering period, no data were observed by the Sentinel-2A/2B–MSI satellites under clear sky conditions (**Figure 1**). MSI Green-Red Vegetation Index (GRVI; Motohka et al., 2010) values observed at Lambir Hills National Park were about 0.05 smaller than those at the Lambir oil palm plantation, reflecting the difference in color of the canopy surface between tropical rain forest (dark green) and the oil palm plantation (light green). Nagai et al. (2016a) reported that NDVI and GRVI values observed by the photodiode sensors installed at the top of a crane tower in Lambir Hills National Park were almost constant throughout the year. In contrast, the time-series of the ratio of R, G, and B digital numbers to the total RGB digital numbers extracted from daily canopy surface images taken at Lambir Hills National Park showed characteristics of leaf flush and flowering among individual trees (Nagai et al., 2016a). These results indicate the possibility that long-term continuous observations by future advanced optical sensors on board satellites with a high spatial resolution and high temporal resolution (high frequent) may detect characteristics of phenology for each tree species in a tropical rain forest. In fact, the RGB composite images observed by the PlanetScope constellation of satellites, which consist of approximately 180 microsatellites (as of 16 November 2022; a commercial endeavor),[7,8] with an approximately 3-m spatial resolution at a daily interval could detect the characteristics of flowering phenology among tree species in Lambir Hills National Park during the general flowering event in May 2019 (Miura et al., 2023). The swath range that can be observed at one time by each PlanetScope microsatellite is narrow (25 km), but the entire observation system of approximately 180 microsatellites resolved the trade-off between spatial and temporal resolutions. Some previous studies indicated this advantage of PlanetScope constellation of satellites observations in alpine, temperate, and

7 https://earth.esa.int/eogateway/missions/planetscope
8 https://www.planet.com/products/planet-imagery/

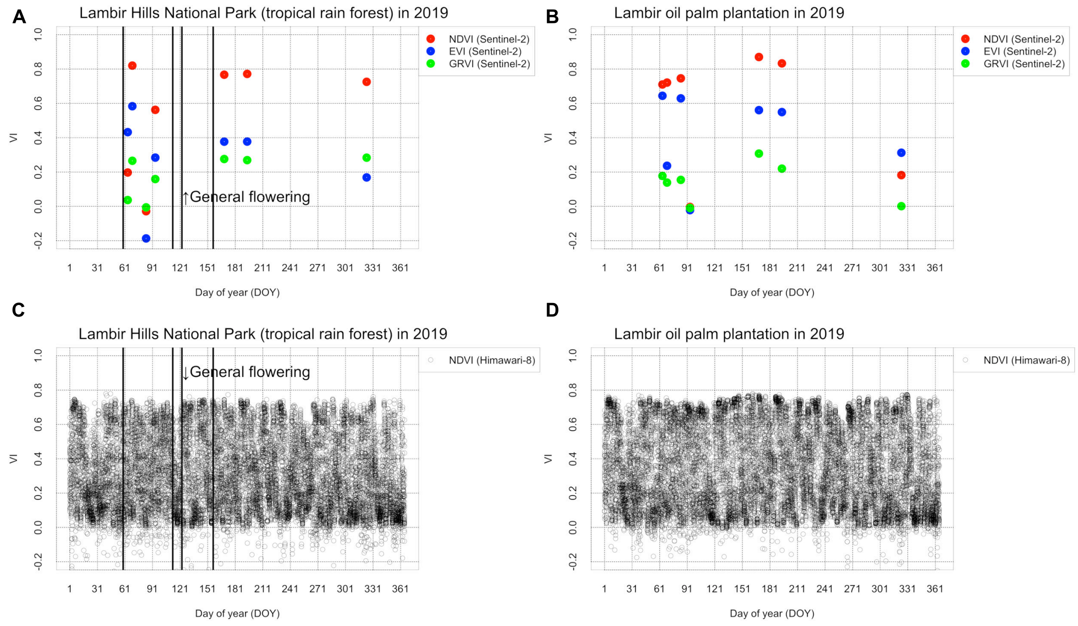

FIGURE 1
Time-series of vegetation indices observed by **(A,B)** the Sentinel-2A/2B–MSI and **(C,D)** the Himawari-8–AHI satellites in Lambir Hills National Park (primitive tropical rain forests; 4°12′04″N, 114°02′21″E) and the Lambir oil palm plantation (4°09′07″N, 113°57′58″E) in northwestern Borneo. The thick vertical solid lines in **(A,C)** indicate the dates of canopy surface images in **Figure 2**. Cloud contamination appeared in Lambir Hills National Park and the Lambir oil palm plantation images on 5 March, 10 March (only in the Lambir oil palm plantation), 25 March, 4 April, and 20 November (only in the Lambir oil palm plantation). A cloud shadow appeared in Lambir Hills National Park image on 20 November.

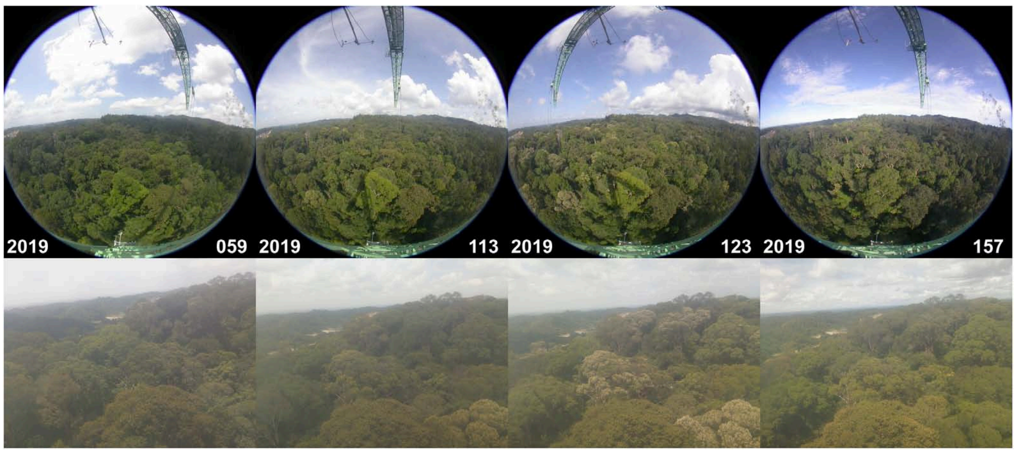

FIGURE 2
Typical canopy surface images taken at the top of a crane tower in Lambir Hills National Park (http://www.pheno-eye.org/). The day of year (DOY) is shown in the bottom-right corners of each image. General flowering was shown on DOY 123.

tropical regions (Leach et al., 2019; John et al., 2020; Wang et al., 2020, 2023; Moon et al., 2021; Wu et al., 2021).

How can we detect the characteristics of phenology in tropical rain forests consisting of evergreen broad-leaved trees, with seasonality much less clear than that of deciduous trees, with optical sensors on board satellites? Previous studies reported that the RGB composite images observed by the Sentinel-2A/2B–MSI satellites, with the highest spatial resolution among the optical sensors on board public satellites, detected the color change on the canopy surface of *Castanopsis sieboldii*, *Castanopsis cuspidate*, and *Lithocarpus edulis* (evergreen oak tree species) caused by leaf flush (light green) and successive flowering (cream) in Japan (Nagai et al., 2020b; Shinohara and Nasahara, 2022; Shin et al., 2023). These plants are insect-pollinated flowers of Fagaceae and their flowers bloom across the whole canopy surface. The timing of flowering is different among these tree species (*L. edulis* is approximately one month later than *C. sieboldii* and *C. cuspidate*). In a tropical rainforest in Borneo (Lambir Hills National Park), Miura et al. (2023) reported that the spectral reflectance observed by the PlanetScope constellation satellites detected the characteristic of color change on the canopy surface of *Dryobalanops aromatica*, *Shorea ochracea*, *Swintonia foxworthyi*, and *Pentace borneensis*

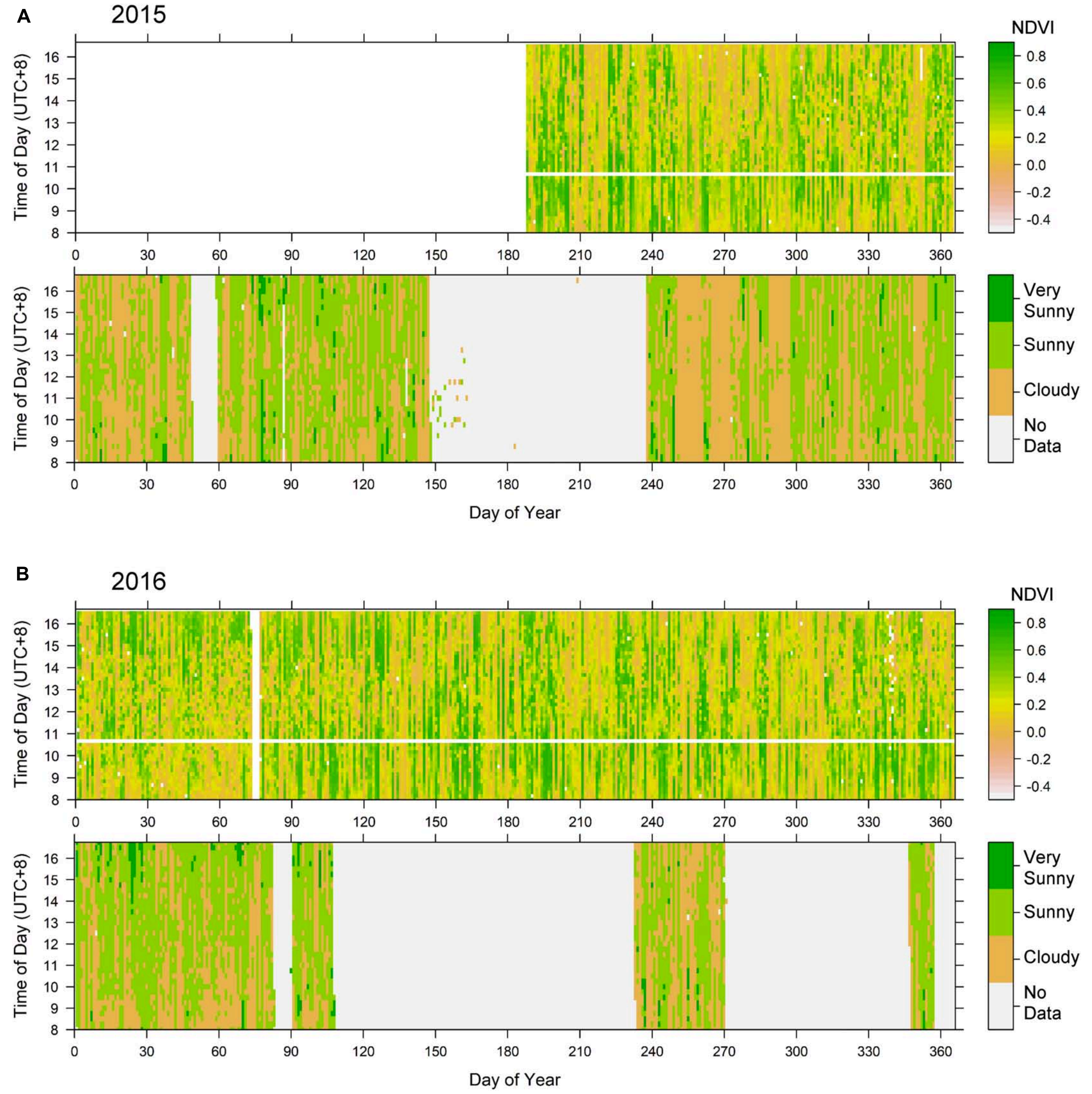

FIGURE 3
Relationship between NDVI values observed by the Himawari-8–AHI satellite and state of cloud cover based on *in situ* observed sky images in Lambir Hills National Park during 8:05 and 16:45 LST (UTC + 8) from **(A)** 2015 and **(B)** 2016 (sky images from Nagai et al., 2018).

during a general flowering in 2019. These results indicate the possibility that satellite-based observations may be used to track the phenological timing and patterns of various tree species in tropical rain forests in tandem with ground-truth information.

Remote-sensing can detect the color of the canopy surface of various tree species, which indicate the characteristics of leaf traits (leaf size, leaf biomass, leaf thickness, amount of pigments in a leaf, and angle of leaves) and structures (tree structure and height) (Sims and Gamon, 2002; Luke et al., 2013; Noda et al., 2014; Asner et al., 2015; Noda et al., 2021; Rahmandhana et al., 2022). The characteristics of leaf longevity, which is explained by leaf-flush and leaf-fall phenology, were correlated with the type of photosynthesis, leaf traits and structures, and climate (Wright et al., 2004; Kikuzawa, 2005; Onoda et al., 2011; Kikuzawa et al., 2013). These facts indicate the importance of discriminating each tree species by referring to the characteristics of phenology and canopy structures and mapping the geographic distributions for each tree species at a broad scale. In Lambir Hills National Park, however, the geographic distribution of each tree species is heterogeneous due to microtopography (Lee et al., 2002). The collection of ground-truth information for various tree species, thus, is both an important and challenging task. Integrating *in situ* and satellite-based phenological observations should also result in the tree discrimination of forests in the Asian tropics.

2.2. Improvement of the frequency of satellite observations

As mentioned above, the Sentinel-2A/2B–MSI satellites have the potential to remarkably improve phenology observations in the tropics. The MSI observations occur at 5-day intervals, however, and in 2019, we only obtained seven scenes with cloud cover ≤ 10% (**Figure 1**). In addition, we confirmed that cloud contamination appeared in Lambir Hills National Park and the Lambir oil palm plantation images on 5 March, 10 March (only in the Lambir oil

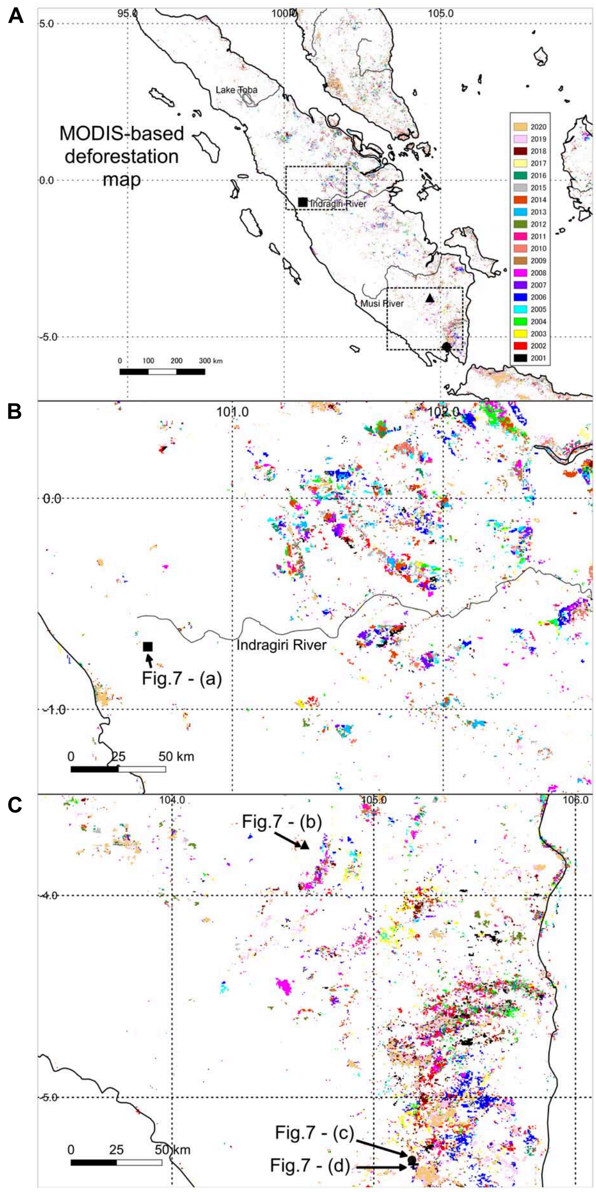

FIGURE 4
Spatiotemporal variation of deforestation in Indonesia in Sumatra from 2001 to 2020 detected by analyzing the time-series of daily GRVI observed by the Terra/Aqua–MODIS satellites (adapted from Nagai et al., 2014b). Each color indicates the latest deforested year. The dashed squares in **(A)** are enlarged in **(B)** and **(C)**. Boundary and river data come from the "1:10 m cultural vectors" published by Natural Earth (https://www.naturalearthdata.com).

palm plantation), 25 March, 4 April, and 20 November (only in the Lambir oil palm plantation) by visually checking the RGB composite images. In addition, we confirmed that a cloud shadow appeared in Lambir Hills National Park image on 20 November. Therefore, it appears that the Sentinel-2A/2B–MSI satellites cannot observe the characteristics of phenology for each tree species in the suitable period under clear sky conditions. In contrast, the observation frequency of the Himawari-8–AHI satellite under clear sky conditions is much higher than that of the Sentinel-2A/2B–MSI (**Figure 1**). In fact, even though the sky image taken at 10:30 (LST) in Lambir Hills National Park, which was the time of the Sentinel-2A/2B–MSI satellites passage, showed cloudy skies, many other images showed clear skies at other times (Nagai et al., 2018).

In previous phenology studies that analyzed time-series of satellite-observed vegetation indices, the researchers used the 8-day, 10-day, and bimonthly composite data in order to eliminate noise and missing data caused by atmospheric noise and cloud contamination and smoothed the composite time-series data by applying some fitting functions (Zhang et al., 2003; Delbart et al., 2006, 2015; Erasmi et al., 2009, 2014; Pennec et al., 2011; Wu et al., 2014; Garonna et al., 2014; Buitenwerf et al., 2015; Kobayashi et al., 2016; Park et al., 2016; Gao et al., 2019; Jin et al., 2019). These analyses were based on the hypothesis that vegetation indices observed under clear sky conditions, which might show the most accurate value, were higher than those under cloudy and rainy conditions. Therefore, the smoothed values are estimated values

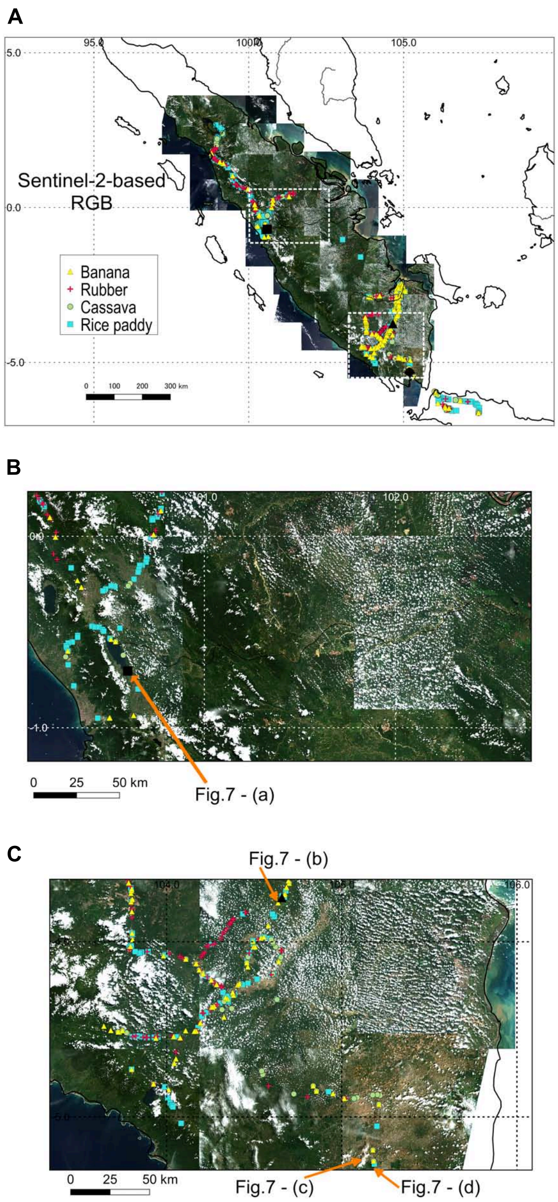

FIGURE 5
RGB composite images of Indonesia in Sumatra observed by the Sentinel-2A/2B–MSI satellites in 2020. The RGB composite images for the Sentinel-2A/2B–MSI satellites were composed of 73 days of data observed under clear sky conditions. For the Sentinels-2A/2B–MSI satellites, we estimated the atmospheric corrected ground surface reflectance data by using the SNAP application (Sentinel Toolboxes: https://step.esa.int/main/download/snap-download/). The dashed squares in **(A)** are enlarged in **(B,C)**. The colored symbols mark the locations of rice paddy, banana, cassava, and rubber recorded in field notes in 1978 (https://fieldnote.archiving.jp/). Boundary and river data come from the "1:10 m cultural vectors" published by Natural Earth (https://www.naturalearthdata.com).

but not true values. The values smoothed by applying the fitting functions may include two types of systematic errors: (1) an actual value was eventually eliminated, or (2) an actual missing value was eventually misread as a true value. For instance, in the case of an abrupt decrease of vegetation caused by a landslide, vegetation indices after the landslide may be eliminated as noise by applying some fitting functions. In addition, in the case of successive cloudy and rainy conditions in a certain period, smoothed vegetation indices may be misinterpreted as a decrease of vegetation. Thus, from a statistical viewpoint, we should avoid smoothing as much as possible.

The frequency of the observations of vegetation indices in East Asia by the Himawari-8–AHI satellite is 10-min intervals. If we only select the vegetation indices observed during the daytime that were little affected by the solar elevation angle (e.g., 3 h around noon), we can obtain many data observed under clear sky conditions (Miura et al., 2019). **Figure 3** shows the relationship between NDVI values observed by the Himawari-8–AHI satellite and state of cloud cover based on *in situ* observed sky images in Lambir Hills National Park during 8:05 and 16:45 LST (UTC + 8) from 2015 to 2016. The occurrences of higher NDVI values (> 0.8) coincided well with the timings of *in situ* "very sunny" or "sunny" sky conditions, despite including missing data of sky images. The analysis of **Figure 3** indicated that the number of days with clear sky conditions ranged from 57 to 96, which was much more than vegetation index observed by the Terra/Aqua–MODIS satellites (1–5 days per month in the southwest monsoon period [May–October] and 0–2 days per month in the northeast monsoon period [November–April] in Borneo; at a daily interval; Nagai et al., 2014a). In addition, the confidence in the change in vegetation indices, which was detected by the actual change of vegetation or not (i.e., systematic noise caused by atmospheric noise and cloud contamination), may also increase by checking high-frequency continuously observed data under clear sky conditions. So, if we can extract data observed only under clear sky conditions, we scarcely need to smooth by applying fitting functions. Despite a coarse spatial resolution (1,000 m), the vegetation indices observed by the Himawari-8–AHI satellite may indicate fairly accurate values.

At present, however, the Himawari-8–AHI satellite is still not suitable with regard to spatial resolution for phenology observations in tropical rain forests. In fact, despite the high frequency of observations under clear sky conditions, no characteristic change in the time-series of NDVI was shown in May 2019, when the general flowering occurred in Lambir Hills National Park (**Figures 1**, **2**). The time-series in GRVI, which can detect the change of color of the canopy surface (Motohka et al., 2010; Nagai et al., 2014b), might capture some characteristic of temporal change. In Lambir Hills National Park, the time-series in the ratio of RGB digital numbers for each individual tree extracted from daily canopy surface images showed differences among tree species around the general flowering period (Nagai et al., 2016a). In contrast, those for the whole canopy showed almost constant values throughout the year (Nagai et al., 2016a), perhaps because not all individuals and tree species flowered at the same time. In this case, the target region of canopy surface images was within at most 100 m (Nagai et al., 2016a), but in the Lambir Hills National Park, which consists of over 1000 tree species (Lee et al., 2002), vegetation indices observed by the Himawari-8–AHI satellite can detect the average phenology of various tree species within a 1,000-m-by-1,000-m area. Therefore, for accurate phenology observations in tropical rain forests, we require an onboard optical sensor with a high spatial resolution to discriminate each tree individual (≤ 10 m) at high temporal frequencies (on the order of 10-min interval) to eliminate cloud contaminations in satellite data.

Despite the uncertainty caused by the heterogeneity of tree species and microtopography, previous studies indicated that the time-series of vegetation indices could be used to accurately detect the spatiotemporal variation of leaf flush and leaf fall in deciduous forests in Japan by validating the indices against long-term continuous *in situ* observed data (Miura et al., 2019; Yan et al., 2019). Despite the effect of microtopography (elevation) on phenology and the differences in timing and patterns of leaf flush and leaf fall among tree species (Inoue et al., 2014; Nagai et al., 2014b; Shin et al., 2021a), leaf flush and leaf fall within a narrow region (e.g., 1,000-m square) occur rapidly and nearly simultaneously. The Japanese government is planning to launch a geostationary satellite with an optical sensor with a 3- to 4-m spatial resolution. [9]Such future developments in optical sensors on board satellites with high observation frequency and high spatial resolution will remarkably improve the accuracy of phenology observations in tropical rain forests, where the phenological timing and patterns differ among the numerous and highly diverse tree species (Osada, 2018; Reich et al., 2004).

3. Improvements in the accuracy of land-cover and land-use detection

3.1. Detection of year-to-year variability of land-cover and land-use change

Figure 4 shows that the interannual variation of deforestation from 2001 to 2020 could be detected by analyzing the time-series of the daily GRVI observed by the Terra/Aqua–MODIS satellites [500-m spatial resolution; adapted from Nagai et al. (2014b)] in Indonesia in Sumatra, where marked land-cover and land-use change has occurred due to deforestation and expansion of oil palm plantations (Ichikawa, 2007; Fitzherbert et al., 2008; GEAS, 2011; Koh et al., 2011; Miettinen et al., 2011; Hansen et al., 2013; Carlson et al., 2014; Nagai et al., 2014a; Estoque et al., 2019; Najib et al., 2020). Here, we defined deforestation as having occurred at points where the ratio of number of days observed GRVI < 0 under clear sky conditions to total observed GRVI under clear sky conditions was above 80% (Nagai et al., 2014a). This hypothesis was based on the fact that GRVI < 0 after leaf fall or when there was no vegetation (Motohka et al., 2010; Nagai et al., 2014b). In the deforested area detected by the Terra/Aqua–MODIS satellites (**Figure 4**), we also identify that vegetation is sparse by visually inspecting the RGB composite images observed by the Sentinel-2A/2B–MSI satellites with a 10-m spatial resolution (shown in brown; **Figure 5**). In addition, we identify that GRVI observed by the Sentinel-2A/2B–MSI satellites showed under 0 (**Figure 6**). From 2001 to 2020, the deforested areas continuously expanded in Riau (central Sumatra; **Figure 4C**) and Lampung (southern Sumatra; **Figure 4B**). In Indonesia, the loss rate of primary forests has declined since 2016 according to the Secretariat of the Convention on Biological Diversity (2020); however, our analysis suggests that the deforestation is still ongoing.

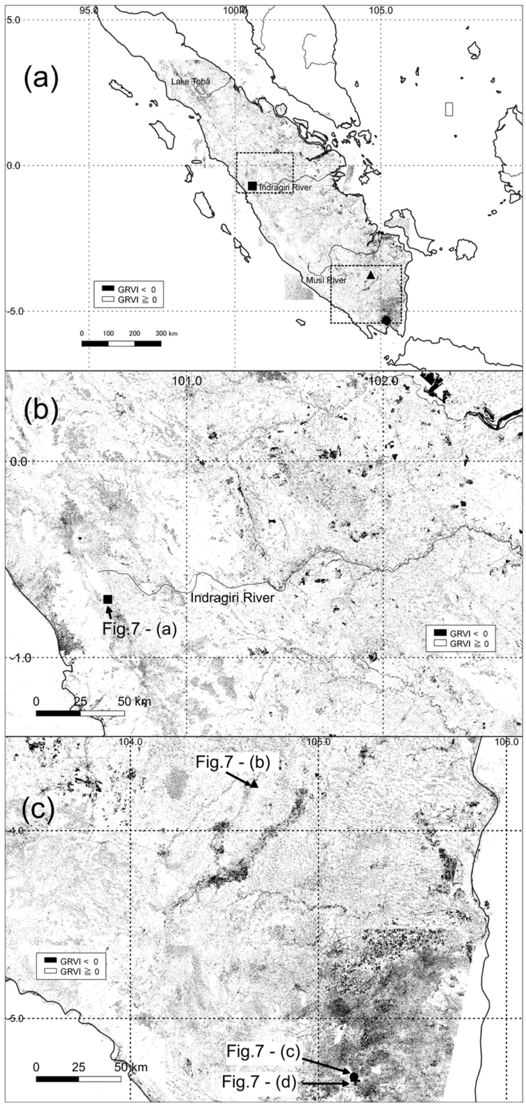

FIGURE 6
GRVI of Indonesia in Sumatra observed by the Sentinel-2A/2B–MSI satellites in 2020. No algorithm was applied to remove cloud contamination. The black symbols mark the locations of rice paddy, banana, cassava, and rubber recorded in field notes in 1978 (https://fieldnote.archiving.jp/). Boundary and river data come from the "1:10 m cultural vectors" published by Natural Earth (https://www.naturalearthdata.com). The dashed squares in **(a)** are enlarged in **(b)** and **(c)**.

Interannual variation of deforestation in the tropics has been detected by analyzing the time-series of vegetation indices observed by the Landsat series (30-m spatial resolution at 16-day intervals; Hansen et al., 2013). However, for those satellites capturing data at 16-day intervals, it is possible that no data are observed under clear sky conditions throughout an entire year especially in the Asian tropics, which is one of regions with active atmospheric water circulation. In addition, in the case of the ETM + sensor on board the Landsat-7 satellite, each observation scene always included partial missing data due to a systematic error in the sensor (malfunction of the scan line corrector; Wang et al., 2021). For the Terra/Aqua–MODIS satellite observations with a 500-m spatial resolution, we could detect large-scale land-cover and land-use

9 https://www8.cao.go.jp/space/comittee/27-anpo/anpo-dai32/siryou1-1.pdf

FIGURE 7
Example of Mapillary images (https://www.mapillary.com/) taken at four points where the typical landscapes in Indonesia in Sumatra were recorded in field notes in 1978 (https://fieldnote.archiving.jp/): **(a)** rice paddy (geolocation based on the field note: 0°41′58.9"S, 100°36′02.4"E; geolocation based on the Mapillary image: 0°42′13.0"S, 100°35′56.0"E; location gap of about 500 m), **(b)** banana (geolocation based on the field note: 3°44′18.5"S, 104°39′33.6"E; geolocation based on the Mapillary image: 3°44′52.2"S, 104°39′28.1"E; location gap of about 1,100 m), **(c)** cassava (geolocation based on the field note: 5°19′12.9"S, 105°11′59.1"E; geolocation based on the Mapillary image: 5°18′40.0"S, 105°11′21.4"E; location gap of about 1,500 m), and **(d)** rubber (geolocation based on the field note: 5°19′49.6"S, 105°12′20.5"E; geolocation based on the Mapillary image: 5°19′54.4"S, 105°11′47.2"E; location gap of about 1,100 m). The Mapillary images are provided under the Creative Commons Attribution ShareAlike license (CC-BY-SA; https://www.mapillary.com/).

change in the tropics, including the establishment of oil palm and acacia plantations after deforestation (Nagai et al., 2014a), but we could not accurately detect local-scale changes such as the loss of vegetation caused by a landslide, which typically occurs at an area smaller than a footprint of satellite data (1 pixel size of satellite data) with a coarse spatial resolution (500-m or 1,000-m; Miura and Nagai, 2020). In contrast, high-frequency observations by the Sentinel-2A/2B–MSI satellites with a 10-m spatial resolution at 5-day intervals may improve the accuracy of detecting interannual variation of land cover and land use in the tropics. Using the time-series of the vegetation index observed by the Sentinel-2A/2B–MSI satellites, whose data will be accumulated over a long period, should help us to more accurately detect the interannual variation of the geographic distribution of deforestation by applying the same analysis as was applied to the Terra/Aqua–MODIS satellites data.

3.2. Collection of past and present ground-truth information

To improve and validate the accuracy of satellite-based land-cover and land-use maps, we must collect ground-truth information at multiple points (Tsutsumida et al., 2019). One way to achieve this is by using digital camera images with the geolocation information, time, and date shot at multiple points that have been uploaded on the Mapillary website, [10]which is a crowdsourcing project. For some reported points, we can use images taken on different dates, thus allowing us to obtain evidence of land-cover and land-use change over a short period. Funada and Tsutsumida (2022) also indicated the usability of the street-level photographs published on the Mapillary to map the geographical distribution of cherry flowering in Fukushima in Japan. The text and images uploaded to the Degree Conference Project (DCP) website[11] are also useful ground-truth information regarding land cover and land use. Previous studies reported the suitability of information on the DCP for use in validating satellite-based land-cover and land-use maps (Iwao et al., 2011; Soyama et al., 2017).

Figure 7 shows Mapillary images at four locations that were typical landscapes in Indonesia in Sumatra, according to field notes recorded in 1978 (full details are mentioned later). Mapillary also contains many images taken at intervals along the route of a participant's trip by using a car-mounted camera. Such uploaded data may have a geographic bias and be concentrated in areas that are strongly affected by anthropogenic activities (e.g., on streets). Compared with Mapillary, there is less systematic bias in the geographic distribution of target points published on the DCP website, which allows users to choose the intersection of

10 https://www.mapillary.com/
11 https://confluence.org/

latitude and longitude integer values in remote regions that have been little affected by human activities. However, the data volume of Mapillary (more than 1.8 billion street-level images as of 16 November 2022; See text footnote 10) is much larger than that of the DCP (about 1.32 million photographs as of 16 November 2022; See text footnote 11), making the usability of Mapillary superior. By actively uploading captured images with geolocation information on Mapillary, especially in the points and areas where images have not yet been uploaded, field scientists can help to reduce the missing areas of *in situ* observations.

Another important issue is how to obtain ground-truth information regarding land cover and land use in the past. This solution deepens our understanding of the conversion processes of deforestation and agricultural expansion. We may estimate the historical land cover and land use by examining the present conditions. For instance, we can assume that areas now covered by oil palm and acacia plantations in Sarawak, Malaysia in Borneo were once covered by tropical rain forests (Nagai et al., 2014a). Without ground-truthing, however, those values will always remain as estimates. To solve this issue, landscape descriptions in research field notes may provide useful ground-truth information regarding past land cover and land use. A group of Japanese scientists at Kyoto University launched the "Inheriting field notes" project (Takata et al., 2014; Yamada, 2015)[12] and have published 46,281 sets of digitalized field notes on their website. [13]Those field notes include field trips in the Middle East, the Mediterranean, Africa, South Asia, East Asia, Southeast Asia, and Oceania from 1967 to 2016 (mainly the 1980s and 1990s). At the time of the field trips, researchers could not use the tools to capture geolocation information, such as a Global Positioning System (GPS) receiver or a digital camera with this function. However, by thoroughly examining the time-series of objective descriptions in the field notes, we can roughly identify the landscape at a certain point.

For instance, by applying a text mining approach to field notes recorded in Indonesia in Sumatra in 1978 (1802 items) we analyzed the frequency of the words used (Yamamoto et al., 2015). The field notes included typical words regarding landscapes, such as rice paddy (total of 283 cases), banana (164 cases), cassava (136 cases), and rubber (185 cases), which allowed us to identify the landscape at that time. These words are also useful ground-truth information regarding the land cover and land use in Indonesia in Sumatra in 1978. We plotted the locations of rice paddy, banana, cassava, and rubber extracted from the field notes in **Figure 5**. In addition, by using the Mapillary images (**Figure 7**), we compared the land cover and land use in 1978 published on field notes with those at the present time. Despite the difficulty in checking precise geolocations, we could validate that there was no land-cover and land-use change at two points, where rice paddy and banana were recorded in the field notes. However, like the Mapillary images, many points recorded on the field notes may be located in areas that were strongly affected by anthropogenic activities. The retirement and decease of owners will accelerate the loss of personal analog data such as field notes. Rescuing and archiving of these analog data and information is an urgent issue (Shin et al., 2020).

4. Future tasks to help improve our understanding of Asian tropical ecosystems

To improve our understanding of Asian tropical ecosystems, we propose five issues that need to be addressed: (1) further collecting ground-truth information from multiple locations and various periods; (2) improving the classification of plant functional types (PFTs) on land-cover and land-use maps and detecting the interannual variation of PFTs; (3) studying the interactions between terrestrial and marine ecosystems; (4) investigating the interaction between land-cover and land-use change and anthropogenic activities; and (5) developing integrative analysis and evaluation of *in situ* and satellite-observed data.

4.1. Further collection of ground-truth information from multiple locations and various periods

In conjunction with the development of optical sensors on board satellites, researchers also need to gather ground-truth information obtained at multiple locations in various periods. The quality of satellite data depends on the accuracy and precision of atmospheric and geometric corrections of those data. Previous studies used locally collected data such as daily phenology images and spectrum data observed from towers (Nagai et al., 2014a, 2020a,b; Nakaji et al., 2014; Lopes et al., 2016). Such ground-truth information provides accurate and precise data collected over a long period. However, the number of locations in the tropics where phenology images and spectrum data are being collected is still limited (Nakaji et al., 2014; Nasahara and Nagai, 2015; Lopes et al., 2016; Alberton et al., 2017; Nagai et al., 2018, 2020a).

Another way to obtain detailed ground-truth information from multiple locations for a broad-scale picture of historical changes in land cover and land use is to examine "social sensing data," a type of big data. These include videos posted to YouTube and old television programs (De Frenne et al., 2018; Shin et al., 2022b), and text and photographs with geotag information posted to social networking services (e.g., Twitter, Instagram, and Flickr; Fernández-Bellon and Kane, 2020; Silva et al., 2018; Song et al., 2020; Yoshimura and Hiura, 2017). The interests and movement of people at various locations can also be tracked by analyzing the access statistics of Google (Google Trends: Takada, 2012; Proulx et al., 2013), [14]number of visitors at Wikipedia (Fernández-Bellon and Kane, 2020), and geolocation information of mobile phones (Chang et al., 2021; Pintér and Felde, 2021). For instance, the analysis of Twitter posts was useful for evaluating the spatiotemporal variation of the timing of leaf coloring in Japan (Shin et al., 2021b). Kotani et al. (2021) and Shin et al. (2022a) analyzed the time-series of Google Trends and/or Yandex statistics (a major search engine in Russia)[15] to assess the spatiotemporal characteristics of people's interest in the use of berries in Arctic and the Russian Far East regions,

12 https://newsletter.cseas.kyoto-u.ac.jp/jp/02/02_02_yanagisawa.html
13 https://fieldnote.archiving.jp/
14 https://trends.google.com/trends/
15 https://wordstat.yandex.com

which the authors used as proxy data of ripening phenology. Likewise, people's interests in oil extracted from illipe nuts (Borneo tallow nut), which are seeds of Dipterocarpaceae species (Blicher-Mathiesen, 1994), may be useful as ground-truth information for ripening phenology in Sarawak, Malaysia Borneo.

4.2. Improving classification of PFTs on land-cover and land-use maps and detecting interannual variation of PFTs

As an example of a detailed land-cover and land-use map in Asia with a high spatial resolution, the Japan Aerospace Exploration Agency has published the land-cover and land-use maps of Japan and Vietnam with 10-m or 30-m spatial resolutions by integrative analysis of data from multi-satellites such as the Sentinel-2A/2B–MSI, the ALOS–AVNIR2 (Advanced Visible and Near Infrared Radiometer type 2), the Landsat series satellites, and the ALOS2–PALSAR2 (Hirayama et al., 2022; Hoang et al., 2020). [16]However, these maps of Japan did not account for the interannual variation in land cover and land use. In addition, PFTs were classified into broad categories, such as deciduous broad-leaved forest and evergreen coniferous forest. To accurately evaluate the spatiotemporal variation of the heat, water, and carbon cycles and biodiversity in the tropics, and to understand the sensitivity of vegetation to environmental change and succession, accurate classification of PFTs and detection of their interannual variation are needed. For instance, traits of photosynthesis and evapotranspiration differ among ecosystems and tree species in the tropics (Ishida et al., 2005; Kenzo et al., 2004, 2006, 2011, 2015). The improved classification of PFTs and discrimination of tree species based on photosynthesis, leaf traits, and leaf and canopy structures are important tasks because these traits help to account for the sensitivity of the flowering, leaf-flush, and leaf-fall phenology and leaf longevity to environmental changes and succession.

4.3. Studying the interactions between terrestrial and marine ecosystems

The soil in the tropics is oligotrophic (Fujii et al., 2018), and land-cover and land-use change due to deforestation has strongly affected not only the heat, water, and carbon cycles (Carlson et al., 2014; Kumagai et al., 2013; Takahashi et al., 2017), but also coastal ecosystems due to the outflow of nutrients from the soil surface to rivers (Tanaka et al., 2021). To accurately evaluate the spatiotemporal variation of ecosystem functions, ecosystem services, and biodiversity triggered by anthropogenic activities and climate change, we need to improve our understanding of the interactions between terrestrial and marine ecosystems. The SeaWiFS (1.13-km at a daily interval) [17]and Aqua–MODIS satellites, which were launched around 2000, observe ocean color and allow for estimation of chlorophyll concentration (O'Reilly et al., 1998; Schollaert et al., 2003; Gregg and Casey, 2004; Siswanto and Tanaka, 2014; Groom et al., 2019). In addition, the Second Generation Global Imager (SGLI) on board the Global Change Observation Mission-Climate (GCOM-C) satellite (250-m at 2-day intervals)[18] improved the accuracy and precision of ocean color observations (Murakami, 2016; Matsuoka et al., 2021). Further research should examine, for instance, the relationship between the interannual variation of deforestation and the spatiotemporal variation of the chlorophyll concentrations in the coastal areas of some river basins.

4.4. Investigating the interaction between land-cover and land-use change and anthropogenic activities

To understand the spatiotemporal variation of ecosystem services and biodiversity, we must evaluate the spatiotemporal variation of the interaction between land-cover and land-use change and anthropogenic activities. For this, the nighttime light data observed by the Visible Infrared Imaging Radiometer Suite (VIIRS) on board the Suomi NPP satellite (Day/Night Band [DNB]; 750-m at a daily interval; Elvidge et al., 2017, 2021)[19] may be useful, as land-cover and land-use change has caused the spatiotemporal variation of nighttime light. In a study of 46 cities with more than 50,000 inhabitants, Ivan et al. (2020) reported the suitability of the Suomi NPP–VIIRS satellite-observed nighttime light to evaluate the geographic variation of income. Studies of tropical regions could use these satellite data to examine the relationship between the interannual variation of deforestation and spatiotemporal expansion of the nighttime light.

4.5. Developing integrative analysis and evaluation of in situ and satellite-observed data

Despite the language barrier (Amano et al., 2016), the collection of *in situ* observed data and ecophysiological information in each country and region (especially non-English data and information; Nagai et al., 2016b; Takeuchi et al., 2021) will accelerate the development of integrative analysis and evaluation of *in situ* and satellite-observed data. As noted by Farley et al. (2018), researchers should aim to conduct more big data analyses by integrating citizen science, which has superior veracity; real-time sensor networks, which have superior velocity; *in situ* observed data collected by scientists, which have superior variety; and remote-sensing, which has a superior volume. The support of international scientific networking communities such as the Asia-Pacific Biodiversity Observation Network (Takeuchi et al., 2021)[20], the Asia-Oceania GEO, [21]and the East Asia and Pacific International Long-Term Ecological Research Network (Kim et al., 2018)[22] is indispensable for the development of these integrated

16 https://www.eorc.jaxa.jp/ALOS/jp/dataset/lulc_j.htm
17 https://oceancolor.gsfc.nasa.gov/SeaWiFS/
18 https://suzaku.eorc.jaxa.jp/GCOM_C/index.html
19 https://ncc.nesdis.noaa.gov/VIIRS/
20 http://www.esabii.biodic.go.jp/ap-bon/japanese/index.html
21 https://aogeo.net/en/
22 https://www.ilter.network/

studies. Takeuchi et al. (2021) emphasized the necessity of satellite observations that provide the academic perspectives and evidence needed to implement natural ecosystem conservation policies. We further encourage the use of *in situ* observed data to improve the accuracy and precision of analyses of satellite observations and reinforcing the networking of research communities working with *in situ* and satellite observations in the Asian tropics (Dronova and Taddeo, 2022; Shin et al., 2023).

5. Conclusion

Our discussions in this perspective paper can be summarized that future advances in the optical sensors on board satellites with high frequency ($\leq$ 10 min) and high spatial resolution ($\leq$ 10 m) are expected to deepen our understanding of ecosystems in the Asian tropics, thus improving our knowledge of phenological changes as well as land-cover and land-use changes due to anthropogenic activities and climate change. Consequently, we could deeply understand the temporal change of the friction between people and ecosystems in the Asian tropics (i.e., degree of the unsustainable circumstances) under societal and climate changes. Despite unclear phenology with a high biodiversity as well as high heterogeneity of land cover and land use, the day is undoubtedly coming when we can monitor tropical ecosystems in Asia even at the individual tree scale. Now, we are in the beginning of a new era of satellite remote-sensing.

Author contributions

NS designed the study. NS, CK, TM, and KI collected and analyzed the data. NS, TM, and YT wrote the manuscript. All authors contributed to critical manuscript revision and read and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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