Review

Application of Optical Remote Sensing in Rubber Plantations: A Systematic Review

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Abstract: Rubber (*Hevea brasiliensis*) is a tropical tree crop cultivated for the industrial production of latex. The trees are tall, perennial and long-lived, and are typically grown in plantations. In most rubber-producing countries, smallholders account for more than 85% of plantation area. Traditional practices mean that it can be difficult to monitor rubber plantations for management purposes. To overcome issues associated with monitoring traditional practices, remote sensing approaches have been successfully applied in this field. However, information on this is lacking. Therefore, this study aims to document the current status, history, development and prospects for remote sensing applications in rubber plantations by using the PRISMA framework. The review focuses on the application of optical remote sensing data in rubber. In this paper, we discuss the current role of remote sensing on specific subject areas, namely mapping, change detection, stand age estimation, carbon and biomass assessment, leaf area index (LAI) prediction and disease detection. In addition, we elaborate on the benefits gained and challenges faced while adapting this technology. These include the availability and free access to satellite imagery as the greatest benefit and the presence of clouds as one of the toughest challenges. Finally, we highlighted four potential areas where future work can be done: (1) Advancements in remote sensing data, (2) algorithm enhancements, (3) emerging processing platforms, and (4) application to less studied subject areas. This paper gives insight into strengthening the potential of remote sensing for delivering efficient and long-term services for rubber plantations.

Keywords: smallholders; natural rubber production; agroforestry; optical; remote sensing

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1. Introduction

The rubber tree, or *Hevea brasiliensis* sp. is a major tree crop cultivated for natural rubber production. It is mainly grown in tropical areas and has an economic lifespan of 30 to 35 years [1]. It occupies more than 11 million ha of agricultural land globally. An approximately 9.2 million ha (78%) of total rubber are planted in Southeast Asia, with about 3.67 million ha (31%) in Indonesia and 3.23 million ha (27%) in Thailand [2]. Natural rubber is important to the global economy, being used as a raw material for more than 40,000 industrial and non-industrial products [3]. More than 60% of global rubber production is consumed by the tire manufacturing industry [4]. The production of natural rubber in 2018 was recorded at 14.33 million tonnes [2]. The major producing countries are Thailand, Indonesia, Vietnam, India, China and Malaysia.

Rubber trees were cultivated in large estates over the last century, but rubber cultivation has gradually shifted to the smallholder sector [5]. While there are still large-scale economic concessions in countries like Brazil and Vietnam [6,7], it only accounts for a small fraction of the world's natural rubber production. Most Southeast Asian countries have shifted into smallholdings. In 2018, Southeast Asia contributes more than three-quarters of the world's natural rubber production [2].

Natural rubber production is vital for smallholder livelihoods because this sector dominates more than 75% of the world's natural rubber production [6,7]. There are a total of 13 million rubber smallholders around the world. The definition of rubber smallholders differs between countries based on the rubber land size: Malaysia (< 40.5 ha); Thailand (< 40 ha); Indonesia (< 25 ha); Laos (< 25 ha); India (< 20 ha); Sri Lanka (< 20 ha) and Myanmar (< 8 ha) [7]. However, it is reported that a majority of the rubber smallholders have less than 4 ha [8,9]. The share of smallholding in rubber production is high in Malaysia, Thailand, Myanmar, India and Indonesia, ranging between 85% and 93% [7,10]. Besides generally owning small plots, rubber smallholders implement poor agricultural practices and have limited access to financial resources [11,12]. Therefore, ensuring the sustainability of natural rubber production is crucial to world economic development.

In addition to the problems already faced by smallholders, rubber plantations are also exposed to other production challenges. These include pests and diseases [13–17]; poor agricultural management practices [18]; competition for land [16,19] and more recently, worldwide rapid expansion into unsuitable agricultural sites [20–24]. Effective plantation management and monitoring is therefore vital to ensure sustainable rubber production.

Monitoring plays an essential role in agricultural management and production [25–27]. Through effective and intensive monitoring, producers are able to identify corrective and preventive steps to optimise input while maximising production. Traditionally, rubber tree monitoring is time-consuming and labour-intensive. The collection of ground data relies heavily on conventional monitoring methods [28]. Current methods are incapable of offering accurate spatial and temporal information [29].

Remote sensing technology provides spatial and temporal information over large extents of an observed area [30–35]. It has played a vital role in mapping rubber trees at local and regional scales [18,36–38] and has facilitated understanding of changes in spatial patterns of rubber plantations over time [39].

The focus on the application of remote sensing in rubber has never been more important, due to a recent global outbreak of rubber leaf disease [40]. This outbreak has resulted in significant production declines, severely impacting the livelihood of rubber smallholders. The present work aims to provide a comprehensive review of the application of optical remote sensing to rubber plantation monitoring.

2. Methods

The paper is divided into four sections. The first section explains the methodology used for conducting a systematic literature review. The second section provides an analysis of the selected documents. The third section discusses the approaches and methods used in the identified subject areas. The paper concludes by addressing the benefits, challenges and future potential of remote sensing monitoring of rubber plantations. The paper's findings will assist researchers, rubber organisations and policymakers in decision-making processes.

In this study, we adopt the standard systematic review guidelines as outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework statement [41]. This is a well-known framework and it is widely used to generate systematic literature reviews [42]. It uses a clear and systematic method to identify, select and analyse relevant research documents from a set of formulated questions [43]. Unlike the narrative style of literature review, all available resources were used to search for related documents, thus minimising the potential for selection bias [44]. Data from the literature, that met the set criteria, was then extracted and synthesised.

2.1. Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were outlined before the search was conducted. These criteria were used to eliminate papers during the eligibility screening process [42,45,46]. These criteria reflect the objective of the review. The use of these pre-specified criteria

reduces errors, bias and inconsistency during decision-making while selecting related documents [47]. The set criteria are presented in Table 1.

Table 1. Inclusion and exclusion criteria set for the selection of documents.

Inclusion Criteria	Exclusion Criteria
<ul style="list-style-type: none"> Document discuss and focus on the application of remote sensing in the management and monitoring of rubber plantations 	<ul style="list-style-type: none"> Discuss on other factors and aspects other than the management and monitoring of rubber plantation
<ul style="list-style-type: none"> Document used and analyse optical remote sensing imagery (either solely optical remote sensing data or in combination with non-optical remote sensing data) 	<ul style="list-style-type: none"> General discussion which includes other plantation or land cover
<ul style="list-style-type: none"> Full-text available 	<ul style="list-style-type: none"> Reviews, commentaries and projection studies
<ul style="list-style-type: none"> Written in English language 	<ul style="list-style-type: none"> Published date beyond 2020

2.2. Search Methodology

Articles were searched and identified from six bibliographic databases: Science Direct, Web of Science Core Collection, Scopus, ProQuest and Google Scholar. The primary keyword (“remote sensing”) was paired with secondary keywords, such as “rubber plantation”, using Boolean operators. This keyword set was used in all databases. The searches were conducted and updated up until December 2020. Table 2 shows details the database search terms and results.

Table 2. List of database with exact search term and results.

Database	Terms	Results
ScienceDirect	“rubber plantation” AND “remote sensing”	209
Web of Science Core Collection	TOPIC: (rubber plantation*) AND TOPIC: (remote sens*)	82
Scopus	TITLE-ABS-KEY (rubber AND plantation AND remote AND sens*)	117
ProQuest	noft ¹ (rubber plantation*) AND noft (remote sens*)	47
Google Scholar	with all of the words: “rubber plantation*” with the exact phrase: “remote sens*”	474

¹ noft in ProQuest refer to “anywhere except full text”, * wildcard symbol that broadens a search in database.

All the identified articles from the search were filtered to remove duplicates, non-peer-reviewed articles, and articles from unidentifiable sources. Next, the articles were screened by title and abstract to eliminate articles that did not meet the set criteria. The full text of the remaining articles were carefully reviewed to decide whether they met the inclusion criteria. In addition, we conducted cross-referencing to ensure no related articles were missed. Finally, details from the selected articles were extracted and compiled (see Appendix A). The details extracted included authors name, year, country of study area, sensor used, sensor resolution category, spatial extent, temporal scale, classification type, approach, reference data and accuracy method used.

2.3. Additional Search

To ensure that all of the relevant literature was included in this review, we conducted a manual search by adopting the snowballing method. It is a process of identifying literature

from known references [47]. We adopted the backward snowballing technique by reviewing the selected articles' references to identify other relevant contributions in the area and including them in the review whenever the inclusion and exclusion criteria were met. This method was selected because it was considered best practice for systematic reviews [48].

3. Descriptive Analysis

Using the PRISMA framework (Figure 1), we identified 929 documents that were potentially relevant to this review. We removed 198 duplicated documents from this total. A further 631 documents were omitted due to irrelevant titles and abstracts. The search yielded a total of 100 documents for a full-text review. Of these, we excluded 45 documents, as they did not meet the inclusion criteria. We cross-referenced the remaining 55 documents and identified an additional 20 related documents. The final total of 74 documents met the set criteria for further synthesis in this review.

Figure 1. The literature selection process using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework.

3.1. Document Details

Out of 74 documents reviewed, 58 (78.4%) were peer-reviewed journal articles, 15 (20.3%) were conference papers, and one (1.3%) was a thesis. The earliest publication was in 2002 [49]. Figure 2 shows the distribution of the reviewed documents based on publication year. There were 13 documents published from 2002 to 2010. However, from 2011 onwards,

61 documents were published. This represents a total of 82.4% of the documents identified in this literature review. This is most likely due to the availability of data from recently launched satellites and the Landsat open access policy [50]. The launching of Landsat 8 in 2014 and Sentinel-2 in 2015 may also have played a critical role in the high number of publications recorded in the following years. Overall, the published documents from 2002 to 2020 display an increasing trend.

Figure 2. Distribution of the reviewed documents based on publication year (The arrows show important satellite launch years and the year Landsat implemented open access data).

3.2. Study Setting

The reviewed documents represented research conducted in two classes of spatial extent: Local and regional scale. Here we define local scale research as studies conducted in a single locality or country. On the other hand, regional-scale research implies a combination of cross-border studies [51]. All except six documents were conducted at a local scale. Of the six, five were small-scale cross-border research, while one was conducted at a larger scale in five countries in Southeast Asia. The lack of regional studies could be attributed to limited reference or ground data.

The local scale research was conducted in seven countries. The locations of these studies are presented in Figure 3. Out of 68 studies done at a local scale, more than one-third took place in China, making it the most dominant local scale study location. This may be due to the fact that China is a major rubber producer and the largest consumer of natural rubber [32,52]. This also reflects China's rapid planting area expansion [53]. It is also noted that most of the other study areas were located in Southeast Asia. Thailand and Malaysia had the highest number of studies at 14 and 13, respectively. Southeast Asia has the largest area planted to rubber and contributes up to 97% of total global natural rubber production [36]. Furthermore, it can be seen that the study areas lie between latitude 30°N to 30°S, which has suitable agro-climatic conditions for rubber cultivation.

Figure 3. Map of the number of studies per country for local study setting.

3.3. Remote Sensing Data

Optical remote sensing data refers to imagery data from sensors that use solar illumination. It is also known as passive remote sensing. In this review, we evaluated the remote sensing sensors referred to in each of the selected documents. Figure 4 shows the distribution of documents that use single or multiple data sources, and the temporal scale analysed. A majority of the documents (40 out of 74) used a single data source to accomplish their study objective. However, documents published in later years were more likely to have used multiple optical data sources or a combination of data from active sensors like ALOS PALSAR. The combination of multiple optical satellite sensors can enhance the analysis and interpretation of remote sensing data.

Figure 4. Distribution of documents based (a) types of sensors and (b) temporal scale analysed.

In assessing remote sensing resolutions, we discussed four types of resolutions: (1) Spatial; (2) spectral; (3) temporal; and (4) radiometric. These four resolutions reveal significant variability in details and quality. The spatial resolution of imagery used in all selected documents was found to range between 0.05 m [54] and 250 m [36]. Figure 5 lists the sensors used, along with their frequencies and respective spatial resolution classes. All except PALSAR and Sentinel-1 are optical sensors. When these data were tabulated into four classes of spatial resolution (low, medium, high and very high), the medium spatial resolution sensors were recorded as the most frequently used. Landsat TM (Landsat 4 and

5) were the most broadly used sensors in this review, followed by Landsat 7, and Landsat 8. This is because these data are freely available, in comparison to the large costs associated with high spatial resolution imagery.

Figure 5. Distribution of used sensor types with its used frequency of use of data and respective spatial resolution classes from specific satellite missions.

Generally, the higher the spatial resolution of remote sensing data, the more detailed the information. However, the requirement for high spatial resolution in a rubber plantation setting may not be necessary, due to the size of the planting areas—although this does depend on the study objective. It should be noted that high spatial resolution data normally comes with lower spatial extent, therefore requiring more tiles to be combined together to encompass a large study area. This can be a costly image processing exercise.

Of the selected documents, only two reported the use of hyperspectral images from EO-1 Hyperion, which provided 10 nm bandwidth with spectral channels ranging from 0.357 to 2.576 μm [55,56]. The remaining research used multispectral images. The used of multispectral data were prevalent because all the relevant sensors provided a range of visible (RGB) and near-infrared (NIR) wavelengths. The NIR wavelengths were especially important because surface vegetation with higher chlorophyll levels reflects more near-infrared energy. Furthermore, multispectral data are mostly free and data size is more manageable. In contrast, hyperspectral data are much larger and complex.

From the perspective of the radiometric resolution, the data ranges from as low as 6 bits, from Landsat MSS [57], to as high as 12 bits, from Landsat 8 [58]. The radiometric resolution for the satellites used in the majority of studies are Landsat MSS (6 bits), IRS-LISS III (7 bits), Landsat TM (8 bits), and Landsat ETM+ (9 bits). Interestingly, this also shows how newly-launched sensors with freely available data have improved resolution over time. The greater the bit depth, the better the measurement of small differences in reflected or emitted radiation captured.

Temporal resolution is an important criterion for multi-temporal studies. In general, a satellite with high revisit time provides the advantage of acquiring cloud-free images for multi-temporal analysis. The highest and lowest temporal resolution used in all 74 documents ranged from 1 day with MODIS [36] to 16 days with Landsat [59]. As shown in Figure 4, 59.5% (44 documents) of the selected documents used multi-temporal scale in their studies. Out of 44 documents, a majority (35 documents) used Landsat. More than 40% (20 out of 44 documents) of these studies were focused on rubber area expansion. These coincide with the rubber boom in the mid-2000s [60,61].

3.4. Accuracy Assessment

Accuracy assessments, or validation, of remote sensing data, is essential to determine the quality of information derived from it or the reliability of the outputs [62]. It is performed by comparing the outputs from remote sensing analysis to a predetermined set of reference data. The accuracy assessment result demonstrates the closeness of the information extracted from the remote sensing data to the reference data. Table 3 summarises the distribution of the reference data type and validation methods used for assessment purposes for all except six of the selected documents. These six documents did not disclose the reference data or validation method adopted in their research [54,57,63–65]. Out of 68 documents, 55 documents (more than 80%) used ground data with/without other data for reference purposes. Of these, 15 documents used ground data with high-resolution images for accuracy assessment using the error matrix with Kappa coefficient. Ground data are widely accepted for accuracy assessment of remote sensing image classification [66]. These data are normally collected through field visits. Among the ground data collected were global positioning system (GPS) points, geo-referenced photos, and physical parameters of trees, such as diameter. Aside from that, researchers also used high-resolution imagery primarily obtained from Google Earth while others used related data produced by government authorities (e.g., topographic maps, land-use map, statistical data). The high-resolution imagery from Google Earth is accessible and easy to retrieve, which may explain the reason behind its widespread use in accuracy assessment.

Table 3. Distribution of reference data type and validation methods used with the respective number of documents.

Reference Data	Validation Methods	Error Matrix			Kappa Coefficients	R ² / RMSE	Total Number of Documents
		with Kappa Coefficients	without Kappa Coefficients	with R ² / RMS Error			
Ground data Example: Sampling point, field survey, GPS point and geotagged photo		5	7	3	1	8	24
Images Example: Google Earth imagery, aerial orthophoto, Ikonos image		3	3	0	0	0	6
Other data Example: Maps (land-use, topographic, statistical data, etc.)		2	0	0	0	2	4
Combination of:							
Ground data + images		15	2	0	0	0	17
Ground data + other data		2	4	1	0	2	9
Ground data + images + other data		3	2	0	0	0	5
Images + other data		2	1	0	0	0	3
Total number of documents		32	19	4	1	12	68

A total of 55 documents used the error matrix method. From these, 32 documents provided Kappa coefficients together with the error matrix results. This method was widely used because most of the selected studies focused on the land use/land cover (LULC) method of rubber mapping, making the error matrix the most appropriate measure for thematic classification accuracy. Only one document reported the Kappa coefficient without the error matrix result, while 12 documents presented the coefficient of determination (R-squared or R²) with/or root mean square error (RMSE) value to evaluate the accuracy of

their results. These values were reported only when the study involved statistical analyses or the development of a model.

3.5. Application Categories

The current application of remote sensing in rubber plantations can be categorised into six subject areas: (1) Mapping; (2) change detection; (3) stand age; (4) biomass and carbon estimation; (5) leaf area index estimation and (6) disease detection. The selected documents were grouped into these subject areas based on the study's primary objective. When the documents incorporated more than one subject area, it was classified based on the most dominant subject area.

Figure 6 shows the distribution of documents that fall into each subject area. There were 24 documents that focused on rubber plantation mapping. This was followed by plantation area change detection, and stand age, with 20 and 15 studies, respectively. These three subject areas were most likely dominant in the selected studies because they were dependent on basic classifications and methods. The other subject areas were more complex and required additional understanding of the subject matter.

Figure 6. Distribution of the selected documents in each subject area.

It is important to point out that the disease detection subject area had least number of documents. A possible explanation could be that such studies are limited by the occurrence of the disease, which can be infrequent, and the scale of the incident, which needs to be large enough to be detected by satellite images. One document [15] had used satellite images to monitor *Phytophthora* leaf disease, which is caused by fungus. Interestingly, the study demonstrated that remote sensing techniques can facilitate the detection of leaf disease.

4. Remote Sensing Application in the Study of Rubber Plantations

In this section, we discuss the subject areas identified in the previous subsection in further detail, with a focus on the approaches and methods adopted in the selected studies. Figure 7 shows an overview of the documents in each subject area and study area conducted.

Figure 7. Distribution of the documents in each subject area based on the study area.

4.1. Plantation Mapping

Plantation mapping is an elementary process in developing a good database for plantation management. It serves as a foundation for all management processes. It is crucial to have a reliable and up-to-date rubber plantation inventory, along with other associated data, for management purposes. Two-thirds of the documents in this subject area conducted a land use/land cover (LULC) study aimed at mapping the greater extent of plantations. The analysis was employed to classify the study areas into several LULC types such as rubber, forest, oil palm, built-up area and others (e.g., [18]). Other studies in this subject area have only classified study areas into two classes: Rubber and non-rubber area [39,58,67].

Different image classification methods were applied in order to detect rubber through LULC classification. These include pixel-based (supervised) and object-based classification. Table 4 compares the classification method used in mapping rubber plantation with its respective sensor and overall accuracy results from the error matrix assessment. The most common approach in mapping rubber plantations using remote sensing was conventional supervised classifiers. Among the supervised classifiers used were Maximum Likelihood algorithm [18,65,67]; Mahalanobis typicalities [36]; Mahalanobis with multi-layer perceptron neural network [68]; Mahalanobis and Maximum Likelihood [69] and Decision Tree [58,70]. Random Forest classification has been employed in a recent study to investigate the textural feature's effect on the classification of rubber plantations [71]. There were no studies that adopted the unsupervised classification method.

For the object-oriented approach classification, Dai et al. [73] used the K-Nearest Neighbour classification during the period of defoliation to delineate the study area. Two other documents compared pixel- and object-based classification methods to identify the rubber plantations in the study area [29], as well as various spectral vegetation indices [79]. Supervised classification approaches offer managers and smallholders a more user-friendly method compared with other methods for mapping rubber plantations.

Table 4. Comparison of classification and overall accuracy for mapping rubber plantations.

Sensor	Classification	Overall Accuracy	Reference
IRS	False colour composite and vegetation indices	n/a	[38]
TM	Maximum Likelihood	97.2%	[18]
TM	Maximum Likelihood for logistic regression	87.0%	[67]
LISS III	Maximum Likelihood	97.0%	[65]
ASTER	Mahalanobis with neural network	99.7–98.7%	[68]
MODIS	Mahalanobis typicality	98.1–98.1%	[36]
TM, ETM+, PALSAR	Phenology-based algorithm-using VIs	92.0%	[72]
TM	Maximum Likelihood and Mahalanobis	91.2%	[69]
TM	k-Nearest Neighbour	90.0%	[73]
TM, ETM+, OLI	Phenology-based algorithm-using VIs	89.9%	[74]
OLI	Phenology-based algorithm-using VIs	92.0–96.0%	[39]
TM, ETM+, OLI	Support Vector Machine	97.1%	[59]
SPOT-5	Mahalanobis distance (MD), k-Nearest Neighbour (k-NN), Support Vector Machine (SVM) and Decision Tree (DT)	80.8–97.5%	[29]
IRS	Visual interpretation and vectorization	95.2%	[75]
TM, PALSAR	Decision Tree	87.5%	[70]
OLI	Decision Tree	92.2%	[58]
MODIS, TM, ETM+, PALSAR	Pixel- and object- based with phenology	72.7–91.0%	[76]
MODIS, TM, ETM+, OLI	Fused time series indices (NDVI, EVI, NDMI, NBR, and TCA)	89.5%	[31]
OLI	Phenology-based algorithm using renormalized modified normalized burn ratio (RMNBR) index	94.8%	[77]
OLI	Phenology-based algorithm using re-normalization of two vegetation moisture indices (NDVI and NDM)	92.3%	[78]
OLI	False Colour Method, Unsupervised Classification, Supervised Classification and Spectral Vegetation Indices (SVIs)	81.0–83.0%	[79]
Sentinel-2	Phenology-based algorithm using Red-edge Spectral Indices (RESI)	92.5%	[80]
OLI	Phenology-based algorithm using difference Normalized Burn Ratio (NBR)	93.3%	[81]
Sentinel-1, Sentinel-2, GF-1, OLI	Spectral and textural features	90.36–92.38%	[71]

Based on the Table 4, very high overall accuracies were achieved from the supervised classification of Maximum Likelihood, Mahalanobis, Support Vector Machine and K-nearest

neighbour. The overall accuracy of these algorithms was evaluated on the produced map of several land use. It can be seen that the application of the same algorithm can provide different results. For example, while adopting the Decision Tree algorithm, Dibs et al. [29], Shidiq et al. [70] and Han et al. [58] reported an accuracy of 80.8%, 87.5% and 92.2%, respectively. The results are influenced by parameters such as: (1) The remote sensing dataset used; (2) the reference data set; and (3) the physical characteristics of study location [82,83].

Studies conducted between 2003 and 2012 were primarily focused on simple rubber area recognition. More recently, researchers have adopted more complex measures such as the exploitation of rubber's unique phenological characteristics (called wintering, which involves defoliation and refoilation), in the delineation of rubber trees plantations [59,81]. Most rubber leaves fall off during the defoliation process before new leaves start to emerge in the refoilation process [4]. From a remote sensing perspective, this characteristic makes rubber plantations clearly distinct from other land cover types such as forest and oil palm, meaning that rubber detection, identification and classification is highly accurate. This characteristic also helps to identify and outline rubber plantations within fragmented tropical mountainous lands [76]. Two studies have extracted phenological time phase information to help distinguish rubber while adopting Decision Tree [72] and pixel and object-based approaches [76].

Researchers have developed multiple phenology-based algorithms using vegetation indices derived from Landsat [39,53,74,78,81] and Sentinel [80]. Studies that have applied phenology-based algorithms on images to map rubber plantations have shown three advantages: (1) It is easier to distinguish rubber from natural forest and cropland [39]; (2) it improves classification results [39,58,74]; and (3) it generates reliable and accurate maps of rubber areas.

4.2. Change Detection

In remote sensing, change detection is a process of identifying differences in land features at different times. Rubber plantation change detection studies are primarily focused on estimating the expansion or reduction of the planting area. Findings from these studies highlight two major points. First, most of the study areas were experiencing a period of expansion. The largest planting area expansion was detected in Xishuangbanna, China, which increased six times between 1987 and 2018 [77,84]. It is thought that the expansion was driven by attractive economic returns [57,85,86] derived from the increase in rubber prices between 2001 and 2011 [87]. Second, global rubber expansion has occurred at the natural forest's cost [88]. Although rubber expansion has boosted smallholders' income by almost ten times [89], the conversion of natural forest into monoculture rubber plantation has resulted in the loss of biodiversity [85,90].

Change detection in general has become more feasible due to freely available satellite images. Land use/land cover change (LULCC) detection is used to observe and evaluate land feature changes based on produced land use/land cover maps performed using multi-temporal image datasets [91–93]. Selected studies in this subject area have analysed LULCC through several classification methods. This technique has been useful in monitoring the rubber area expansion and reduction at local [85] and regional scale [88].

In the case of rubber LULCC detection, three main classification methods were adopted to map land use/land cover. The methods include: (1) Visual interpretation [19,63]; (2) pixel and object-based classifications; and (3) phenology-based algorithms. Table 5 highlights the classification method, temporal period and accuracy obtained in the studies of change detection in rubber plantations. Four documents used the popular method of supervised classification using the Maximum Likelihood algorithm to investigate rubber expansion [57,64,94,95]. Other supervised algorithms used were Decision Tree [62,96–98] and shapelet based algorithms [99]. Grogan et al. [88] used the Landtrends algorithm to study forest disturbance due to rubber area increment. Vadjunec et al. [100] adopted the hybrid classification of unsupervised and supervised approaches to develop 12 classes of

land-use maps from Landsat TM and ETM+ images. Apart from the pixel-based approach, two studies have used the object-based approach to classify land covers [85,101]. Instead of using available classification methods, two recent documents [77,84] used a self-developed phenology-based algorithm to monitor rubber expansion.

Table 5. Comparison of classification and overall accuracy for change detection studies in rubber plantations.

Sensor	Classification	Temporal Period	Previous Land Cover	Accuracy	Reference
TM, ETM+	Supervised classification	1998 to 2003	Forests, shifting agriculture	OA = >80%	[89]
TM	Supervised classification (Maximum Likelihood)	1989 to 1993 1993 to 1999	n/a	n/a	[64]
MSS, TM, ETM+	Supervised classification (Maximum Likelihood)	1976 to 2003	forest	OA = 90.1%	[94]
MSS, TM, ETM+	Supervised classification (Maximum Likelihood)	1976 to 1990 1990 to 2006	Forest and paddy	n/a	[57]
TM, ETM+	Hybrid unsupervised/supervised	1986 to 2003	Forest	OA = 85.0%	[100]
MSS, TM, ETM+	Object-based	1973 to 2005	Forest	OA = 89.3%	[102]
THEOS	Supervised classification	2002 to 2011	Forest and paddy	Kappa = 0.87	[19]
MSS, TM, ETM+, MODIS	Newly proposed vegetation indices (Planted density)	1980 to 2010 1990 to 2010 2000 to 2010	Forest	OA = 82.3–86.9%	[32]
ETM+	Principal component analysis (PCA) and spectral vegetation index (NDVI)	2003 to 2006 2006 to 2009 2009 to 2012	Forest	OA = 87.0%	[103]
TM, ETM+, MODIS	Supervised classification (LandTrendr classification)	2000 to 2012	Forest	OA = 86.0%	[88]
TM, ETM+, RapidEye	Object-based	1988 to 2002 2002 to 2010	Forest	OA = 87.5%–88.7%	[85]
TM, ETM+	Supervised classification (Decision Tree)	2000 to 2010	Paddy and woodland	OA = 86.59%	[97]
TM, ETM+, OLI	Supervised classification (Decision Tree)	1989 to 2000 2000 to 2013	Forest	OA = 83.9–86.5%	[62]
TM, ETM+, OLI	Supervised classification (shapelet-based) land clearing-establishment of rubber plantation	1995 to 2015	Forest and non-forest	OA = 89.0%	[99]
LISS III	Visual interpretation	1997 to 2013	Forest	n/a	[63]
TM, ETM+	Supervised classification (Decision Tree)	2004 to 2012	Forest	OA = 92.0%	[96]
TM, ETM+, MODIS, PALSAR	Phenology-based algorithm	2000 to 2010	Forest	OA = 95.0%	[98]
MODIS, OLI, Sentinel-2	Random Forest classifier, Breaks For Additive Season and Trend (BFAST), and non-parametric regression	2001 to 2015	Forest	OA = 86.0%	[87]
TM, ETM+, OLI	Phenology-based algorithm (change rate of the Landsat-derived normalized burn ratio)	1996 to 2000 2001 to 2005 2006 to 2010 2011 to 2015	Forest	OA = 92.0–97.0%	[53]
TM, ETM+, OLI	Phenology-based multiple normalization	1987 to 2018	Forest	OA = 94.7%	[84]

As seen in the Table 5, five studies show an overall accuracy higher than 90%. Three from these studies used phenology-based algorithm, while another used Maximum Likelihood and Decision Tree supervised method. However, it is difficult to identify the

best-suited change detection method, as several factors may affect the selection criteria [82]. The factors are remote sensing data resolutions, quality of data, physical characteristics of features of interest, atmospheric effect, image registration and study area size [83].

According to Food and Agriculture Organization (FAO) [2], the global area under rubber plantations expanded by 25% over the 2008–2018 decade. This equates to an annual increase of 3% over this period and 90% of this expansion occurred in Asia. Chakraborty et al. [63] also stated that rubber could expand four-fold by 2050. Accurate information on rubber expansion, particularly from a spatial and temporal perspective, is essential for policymakers to formulate, monitor and plan strategic land use policy. Studies included in this literature indicate that some regions have already implemented regulations to control rubber expansion in natural forest areas [100]. Change detection study is also vital in evaluating rubber's impact on the environment [96].

4.3. Stand Age Estimation

Rubber trees are tapped after four to eight years of planting [104] or more commonly after seven years [105,106]. Generally, under good agricultural practices, latex production peaks at 20 years before the yield starts to stagnate and decline. After the economic lifespan of 30 to 35 years, trees are often cut down for timber production. Therefore, information on rubber stand age is crucial for rubber plantation management because it indicates latex production level.

In predicting rubber plantation stand ages, three practical approaches were adopted by the identified studies [107]: (1) Statistical models; (2) image classification and (3) land use land cover change (LULCC) detection. Table 6 details the approach, age resolution and accuracy obtained in the studies of stand age estimation for rubber plantations. It is noticeable that different age resolution or groups were defined and used in these studies. Due to the different approaches and age groups, multiple accuracy assessments were used.

Table 6. Comparison of approach method, age resolution and accuracy in stand age estimation studies of rubber plantations.

Sensor	Approach	Age Resolution	Accuracy	Reference
Landsat TM	Statistical Model	-	RMSE = 6.4–8.2 years	[108]
Landsat 8	Statistical Model	5, 10, 15 and 20	$R^2 = 0.4335$ – 0.4912	[109]
Landsat TM	Statistical Model	-	RMSE = 5.96 years	[110]
EO-1 Hyperion	Statistical Model	5–25	$R^2 = 0.624$, RMSE = 2.625 years	[55]
Landsat TM, Landsat 7, Landsat 8	Statistical Model	3–15	OA = 87%	[111]
SPOT-2, SPOT-4, SPOT-5, THEOS	Image Classification	<5, 5–10 and > 10	OA = 89.8%	[112]
Landsat TM	Image Classification	≤2, 2–4, >4	-	[113]
THEOS	Image Classification	<5, 5–10 and > 10	Kappa: 0.627–0.677	[86]
Pléiades	Image Classification	≤7, 7–15, >15	OA = 94–97%	[114]
SPOT-5	Image Classification	≤7, 7–25, >25	OA = 77–91%	[115]
Landsat TM, Landsat 7, Landsat 8	Image Classification	Annual	OA = 84.4–84.7%	[116]
Landsat TM/ETM+, PALSAR	LULCC Detection	≤5, 6–10, >10	OA = 85%	[98]
Landsat TM, Landsat 7	LULCC Detection	Annual	RMSE = 2.5 years	[117]
TM/ETM+/OLI	LULCC Detection	Annual	$R^2 = 0.85/0.99$, RMSE = 2.34/0.54 years	[107]
Landsat TM, Landsat 7, Landsat 8	LULCC Detection	≤5, 6–10, 11–15, 16–20, 21–25, 26–30, and ≥31	OA = 92.8%	[118]

In the statistical models, correlation analysis was used to develop models by establishing relationships between rubber plantation stand ages and spectral reflectance [108–110], and/or vegetation indices [55,111]. For the image classification approach, different classifi-

cation techniques were used to recognise multiple rubber stand age groups. Studies applied supervised classifications such as Maximum Likelihood [86,114]; Mahalanobis [68]; and Spectral Angle Mapper [115]. In these studies, rubber plantations were divided into age groups categorised by maturity or latex production level [115], rubber growth phenology and field management trees [118], or simply based on the availability of field data [36,114]. For instance, Dib and Mansor [115] developed three age classes based on latex production level; <7 years, 7–20 years, and >25 years to represent the no latex, high latex, and low latex production period, respectively.

There were no standard age groups developed by any of the studies. The ability to develop such a standard may have been hindered by the fact that most rubber plantations are multiclonal—this is a common practice to avoid yield losses. Different rubber clones have different growth rates and maturation age, which creates in-field variability. In addition to this, environmental factors (e.g., soil and weather), and management practices (e.g., fertiliser), also influence rubber growth.

LULCC detection was used to identify the establishment year of rubber trees through ground landscape changes. New plantation establishment often involves the common practice of land clearing and transplanting rubber seedlings. These specific events are used to estimate rubber stand age. To date, four documents [107,117–119], categorised under the LULCC approach, used various vegetation indices and non-visible spectral bands to identify the establishment year of a rubber plantation. Although this approach predicts rubber age accurately, the age of older rubber plantations cannot be estimated if land clearing or transplanting cannot be detected remotely. Ground reference data of the cleared area is crucial to confirm that the area is planted with rubber trees.

The identification of rubber stand age can help government agencies predict latex production at a local, regional, and national scales. This data may be useful in forecasting timber production from the plantation. Considering the long economic life of rubber, stand age information is essential as it is also a primary indicator for monitoring biomass [108] and assessing carbon stocks [120].

4.4. Biomass and Carbon Estimation

Rubber trees are typically grown for approximately 25 to 35 years before being felled for timber production. The total carbon stock of rubber in plantations has been estimated to be higher than many tropical forestry and agroforestry systems [121]. The time-average carbon stock of lowland and highland rubber plantations is estimated to be 58 MgC/ha and 28 MgC/ha respectively [106]. The role of rubber in mitigating climate change has been recognised globally [122–124]. Therefore, the accurate estimation of biomass and carbon stock in rubber plantations has become more critical than previously.

A conventional method of calculating a tree's biomass involves cutting down sample trees and weighing their different components [125]. However, this method is undesirable because it is destructive and limited to small, accessible areas [126]. Researchers have used rubber plantation maps produced from remotely sensed data to estimate biomass and carbon. In studying rubber plantation biomass, all studies primarily focused on above-ground biomass (AGB). The study of carbon stocks in rubber plantations is derived from the AGB estimations.

Table 7 shows the comparison of method, accuracy and sensor used in the studies focused on biomass and carbon estimation. A majority (seven out of nine) documents within this subject area applied specific allometric equations to predict AGB and carbon of rubber plantations, and correlated these estimates with satellite image datasets [106,127–132]. The developed biomass and carbon estimation models were created using several methods: (1) Vegetation indices models [130,132]; (2) computational models [129,133] and (3) tree growth parameter models [127,128].

Table 7. Comparison of method and accuracy in biomass and carbon estimation related studies.

Sensor	Allometric Equation	Method	Accuracy	Reference
Landsat TM	No	Maximum-likelihood for logistic regression	RMSE = 6.4–8.2 years	[49]
THEOS	Yes	Tree growth parameter models (object-based classification)	$R^2 = 0.36$	[127]
THEOS	Yes	Tree growth parameter models (object-based classification)	$R^2 = 0.531\text{--}0.865$ RMSE = 0.39–1.93 t/ha RMSE = 0.17–11.97 tC/ha	[128]
Worldview-2	Yes	Supervised- Stepwise Linear regression and Artificial neural network models	Kappa = 0.627–0.677	[129]
IKONOS, SPOT, RapidEye, Landsat	Yes	Rapid Carbon Stock Appraisal (RaCSA) method	$R^2 = 0.968\text{--}0.982$	[106]
ASTER	No	Vegetation index (MSAVI)	$R^2 = 0.709$	[130]
ASTER	Yes	Vegetation index model (MSAVI)	$R^2 = 0.681$	[131]
Sentinel-2	Yes	Vegetation indices model (RVI, NDVI, ARVI, and SARVI)	$R^2 = 0.473$	[132]
Landsat 7, Landsat 8, Sentinel-2	Yes	Regression and Random Forest model	$R^2 = 0.82\text{--}0.96$ RMSE = 4.08–10.59 Mg/ha biomass	[133]

Two studies calculated the vegetation indices using specific bands of selected remote sensing data to correlate with biomass and carbon stock derived from the allometric equations. Anurogo et al. [130] used the Modified Soil Adjusted Vegetation Index (MSAVI) and found that MSAVI offered a moderate relationship to biomass with R^2 of 0.681. Alternatively, Pratama [132] studied four different vegetation indices to identify the most appropriate vegetation indices to accurately estimate carbon stock. The vegetation indices are: Ratio Vegetation Index (RVI), Normalised Difference Vegetation Index (NDVI), Atmospheric Resistant Vegetation Index (ARVI) and Soil and Atmospherically Resistant Vegetation Index (SARVI). The ARVI-based estimation model for the exponential regression type had an accuracy of 84.4% (supported by $R^2 = 0.522$).

Yasen and Koedsin [129] have used eight spectral bands from WorldView-2 imagery as inputs to develop stepwise multiple linear regression (SMLR) and artificial neural network (ANNs) models. The performance of the two biomass models was evaluated. The ANNs model showed higher R^2 (0.66) than the SMLR model (0.33). This finding was in line with two other studies [134,135] that reported the ANNs provided better estimation than SMLR in estimating biomass. Another study [133] used a combination of Landsat-Sentinel 2 based variables with a stand age parameter data to develop several biomass models based on a regression and Random Forest algorithm. The finding indicates that the stand age parameter has improved the prediction accuracy of rubber plantation biomass. A hybrid model integrating the optimal results from both regression and Random Forest models provide better performance in predicting biomass ($R^2 = 0.83$ and RMSE = 12.48 Mg/ha)."

Charoenjit et al. [127,128] used spectral and textural parameters as inputs into their tree girth/age models, which were created using object-based image analysis. Both studies first classified rubber trees into three age groups, with the age range for each class (young, middle and old) being slightly different. The model accuracy reported for the 2015 study had an RMSE of 0.17 tC/ha.

Overall, remote sensing analysis for biomass and carbon stock estimation in rubber plantations shows moderate accuracy. Further studies need to be conducted to find the most suitable methods delivering higher accuracy. Studies in this subject area were only a

snapshot conducted at a specific time. Thus, future studies should consider conducting multi-temporal analysis to monitor biomass and carbon stock over time.

4.5. Leaf Area Index Estimation

Leaf area index (LAI) refers to the ratio of upper leaf surface area to ground area in broadleaf canopies [136]. LAI is a commonly used parameter in predicting biomass [137]. The LAI values are also a beneficial indicator of plant canopy structure and density [105]. Highly accurate predicted values can play an essential role in rubber plantation management [138].

However, in rubber, researchers primarily used this biophysical characteristic as an indicator for evaluating the physical conditions of rubber plantations [56] and to predict latex yield [33,139]. Three studies have estimated the LAI values through regression models [33,56,139]. These studies are listed in Table 8.

Table 8. Comparison of method and accuracy for leaf area index (LAI) studies in rubber plantations.

Sensor	Method	Accuracy	Reference
EO-1 Hyperion	Regression model based on: Simple Ratio Index	$R^2 = 0.820$, RMSE = 0.170	[56]
	Normalized Difference Vegetation Index	$R^2 = 0.794$, RMSE = 0.162	
	Modified Simple Ratio Index	$R^2 = 0.815$, RMSE = 0.166	
	Modified Soil Adjusted Vegetation Index	$R^2 = 0.775$, RMSE = 0.160	
HJ-1, ZY3	Stepwise regression model	$R^2 = 0.43\text{--}0.51$, RMSE = 0.52–0.82	[33]
	Recurrent neural network model	$R^2 = 0.54\text{--}0.58$, RMSE = 0.47–0.71	
WorldView-2	Stepwise regression model	$R^2 = 0.59$, RMSE = 0.49	[139]
	Artificial neural network model	$R^2 = 0.83$, RMSE = 0.31	

One of the studies in this subject area have created LAI prediction models using vegetation indices models or computational models. Kewplang and Vaiphasa [56] studied the capability of hyperspectral data for estimating rubber plantation LAI based on four selected vegetation indices: (1) Simple ratio index (SR_{705}); (2) Modified Simple Ratio index (MSR_{705}); (3) Normalized Difference Vegetation Index ($NDVI_{705}$) and (4) Modified Soil Adjusted Vegetation Index ($MSAVI_{705}$). The findings show that $MSAVI_{705}$ was chosen as the best-fitted model, with R^2 of 0.775 because it had the lowest RMSE values (0.160) among all the models.

For computational models, Chen et al. [33] predicted the spatial-temporal LAI of rubber plantations on Hainan Island by using a recurrent neural network of Nonlinear AutoRegressive networks with exogenous inputs (NARX) model. The model was developed using spectral bands and seven vegetation indices in order to capture the LAI dynamics. This model performed well during field validation with R^2 of 0.88 and a RMSE of 0.24, although only moderate R^2 of 0.54 to 0.58 was produced when tested on field data. Still, this model showed better results than the stepwise regression model. At the same time, Koedsin and Yasen [139] used spectral bands as input variables for Stepwise Multiple Linear Regression (SMLR) and Artificial Neural Networks (ANNs) models to estimate the LAI of rubber trees in Thailand. The results indicated that the ANNs model gives the most accurate (RMSE = 0.31) prediction compared to the SMLR model when validating with ground data. Among all models, regardless of the study locations and sensors used, the neural network model showed better performance in predicting LAI for rubber plantations.

In creating regression models, bands and vegetation indices were inserted as inputs to find the highest correlation to the observed LAI. The input with the highest correlation was then used to predict the LAI for the study area. In these studies, different sensor imagery was tested, including EO-1 Hyperion [56], HJ-1A/1B [33], and WorldView-2 [139]. The regression models produced moderate to high R^2 (between 0.5 and 0.8), indicating the viability of estimating LAI value for rubber plantations. These developed models have

also demonstrated the viability of retrieving spatial-temporal LAI of rubber plantations through remote sensing data. To date, several satellite-derived LAI products are offered by multiple satellites, for instance, MODIS, SPOT, AVHRR, and Envisat [140]. However, none of the studies has exploited these products to study LAI for rubber plantation.

4.6. Disease Detection

One of the main challenges in rubber plantation management is the outbreak of pests and diseases. Rubber diseases can be divided into three categories based on tree structure: Leaf; bark; and root. Several major pest and disease incidences in rubber have been reported over the years [141,142]. For example, abnormal leaf fall, powdery mildew, Colletotrichum leaf spot, and Corynespora leaf fall—which occurred in India in 2015 [14]. While remote sensing offers the ability to detect pest and disease incidences, there have only been three studies undertaken for pest and disease incidence in rubber.

Two platforms were observed to obtain data for the detection, mapping and investigation of disease outbreaks in rubber: Satellite and UAV as in Table 9. Two studies [15,143] used satellite imagery to detect and monitor leaf diseases at plantation level. Ranganath et al. [143] used multi-date imagery from the IRS satellite to evaluate its potential for detecting and monitoring the outbreak of Corynespora and Gloeosporium fungi in rubber plantations in the south of India. They applied the Maximum Likelihood algorithm to delineate healthy and infected rubber trees. On the other hand, Pradeep et al. [15] demonstrated the capability of using leaf area index (LAI) values extracted from the MODIS 15A2 product to monitor abnormal leaf fall caused by Phytophthora sp. in their study area. This was mapped using LISS III 2012 and 2013 data. Both studies attained an accuracy of 82% from the image classification method used.

Table 9. Comparison of selected parameters on studies conducted to detect rubber tree diseases.

Sensor	Platform	Method	Leaf Disease	Accuracy	Location	Reference
IRS	Satellite	Image classification (Supervised-Maximum likelihood)	Corynespora Leaf Fall, Gloeosporium Leaf Disease	OA = 82%	Karnataka, India	[143]
IRS, MODIS	Satellite	Image classification (Unsupervised-K-means)	Phytophthora Leaf Fall	OA = 82%	Kerala and Kanyakumari, India	[15]
Drone	UAV	Vegetation index	Oidium Leaf Disease	-	Johor, Malaysia	[54]

Mohd Ali et al. [54] conducted leaf disease detection on multiple rubber clones, using data from compact sensors mounted on a UAV. The study was based on two spectral regions: Visible and near-infrared. Eight different rubber clone leaves, at a predefined range of conditions (healthy, unhealthy and severe), were randomly selected for further analysis. All three conditions were able to be detected using the NIR region, demonstrating the capability to extract more information when using higher spatial resolution.

All these studies focus on disease detection, primarily leaf diseases. There was no study conducted on pests, or the bark and root diseases of rubber. This could be due to the fact that: (1) Insects and pests do not cause serious problems [52]; and (2) remote sensing data's inability to capture the changes caused by bark and root disease to a tree. On the other hand, leaf disease typically alters tree structure by reducing the canopy or changing the characteristic of the leaves, which makes it far more detectable with optical remote sensing. While this implicitly affects latex yield, if the tree's canopy is in severe condition, with fewer long-term leaves, the reduced canopy can change a spectral bands' reflectance and absorbance. On the other hand, rubber bark and root disease cannot be detected and examined using optical remote sensing imagery because the symptoms or affected spots

are unable to be seen. This may be the reason why all studies identified in disease detection have focused on leaf diseases. Future studies could look into the possibilities of using changes in other biophysical properties as an indicator of root and bark diseases

5. Discussion

Remote sensing technology, particularly satellite technology, remains a critical data source for continuous monitoring of vegetation dynamics at large scales. Although remote sensing offers numerous benefits, challenges remain in the application of the technology to rubber plantations. This section discusses both benefits and challenges in the application of remote sensing in a rubber plantation context. We also analyse and discuss future potential applications.

5.1. Benefits

Remote sensing techniques have widely improved the ability to map plantations, track changes in rubber acreage, detect rubber stand age, estimate carbon, biomass, and LAI, and detect rubber leaf diseases. In this section, four main benefits are emphasised and discussed. First, remote sensing imagery enables a larger area of plantation to be studied. Image mosaicking allows the combination of multiple scenes or tiles for large study areas. Plantation areas located in mountainous landscapes, and those without proper access roads, can be effectively mapped for monitoring and management purposes. Despite being a smallholder crop, rubber plantations are generally concentrated over large areas, which makes remote sensing a viable primary tool for mapping.

Another benefit is that most optical imagery data are free, comprehensive and easily accessible. We have observed that the application of remote sensing techniques in various subject areas identified in this study has expanded in line with the rise of zero-cost imagery (e.g., from Landsat and MODIS) because it reduces operational and research costs. Further, these imageries offer various spatial, spectral, and resolution specifications that can meet a diverse set of study objectives. The imagery data can be selected, filtered and downloaded at the user's convenience from an open-access website. This is particularly important for rubber smallholders, who often lack access to funding. However, to ensure that smallholders benefit from this, government agencies need to play a significant role in providing training, or in conducting research and sharing the findings with growers.

In addition, remote sensing enables the analysis of historical image data sets for up to 50 years, depending on the satellite. The long-term data archive from various sensors provides the advantage of long-term monitoring of rubber plantations. This is crucial, considering that rubber is a perennial crop that can last up to 30 years. Multi-temporal studies of specific events such as rubber disease incidents and weather anomalies can be conducted. Government agencies and relevant stakeholders can also conduct an assessment of rubber related policies over time, particularly those that relate to LULC.

The fourth benefit that should be highlighted is the ability to overcome constraints in obtaining rubber-related information. Relevant stakeholders can retrieve information such as rubber planting area and location by using the remote sensing approach. They no longer need to rely on information from smallholders in order to gather plantation data. This will improve data gathering methods and data quality [79].

Besides being a non-destructive method to gather information on rubber plantations, remote sensing data can also be analysed and interpreted for multiple purposes. There is a wide extent of information that can be gathered from either a single or set of remotely sensed image. In rubber plantations, this information may be used in research activities that involves plantation mapping, stand age estimation, biomass and carbon estimation.

5.2. Challenges

There were several key challenges identified in the application of remote sensing to rubber plantings. First, the difficulty of obtaining cloud-free images is a major constraint because rubber plantations are primarily located in tropical areas. Tropical areas experience

hot, humid weather and have a climate characterised by abundant rainfall, high humidity, and heavy cloud-cover conditions [119].

Second, rubber planting pixels are often misclassified as other land cover types [101], particularly because they are mainly located close to natural forests and other plantations. This has led to several inaccurate estimations of rubber planting areas. For instance, rubber was misclassified as forest in a study conducted in Northeastern Thailand [71]. This is because mature rubber trees possess similar spectral reflectance to forest and certain plantations [29,113]. Rubber was also mistakenly categorised as cropland, [59], oil palm in particular. Both share similar spectral characteristics and are cultivated in the same geographical areas [144]. However, characterising oil palm canopy using an object-based approach could minimise this problem.

It is also difficult to delineate rubber at different growth stages. The difficulties of separating rubber into several classes of stand ages are due to high intra-class variability [36]. This issue is further complicated by the presence of multiple clones in the plantations. Furthermore, younger rubber trees exhibit mixed spectral reflectance that emanates from a mixture of soil and other vegetation undergrowth [29]. Young or immature rubber plantations are also typically intercropped with rapidly growing cash crops such as maize, cocoa, cassava, and pineapple [62,145]. The young rubber trees have the spectral characteristics of open-canopy [111] where it only covers a small fraction of the planted area during the first five years of planting [36]. Thus, misclassification can arise due to a heterogeneous and complex mixture of land cover among these land features. Apart from the more general challenges inherent in the application of remote sensing, there is a critical question to be addressed—how can this technology be useful and practical for all relevant stakeholders, particularly rubber smallholders? While remote sensing may be affordable and feasible for researchers, managers, and rubber organisations, a lot more thought should go into how the technology can benefit smallholder farmers, who account for more than 85% of total global production [7]. In general, smallholders have limited financial access, possess low education levels, implement poor agricultural practices and have low adoption of new agricultural technology [11,12,146,147]. Therefore, relevant rubber organisations, private or government, will need to play an effective role to ensure that the technology is accessible. For example, these organisations can extract and analyse remote sensing data and disseminate their findings to smallholders through extension agents. A working framework would need to be developed so that smallholders can integrate the newly acquired information into their daily decision-making processes. As smallholders are the primary producers, this would benefit the industry as a whole.

5.3. Future Potentials

This section highlights and discusses four prospects for improving remote sensing rubber monitoring, based on the above-mentioned challenges. The identified prospects are the use of higher resolution data, algorithm enhancements, emerging processing platforms, and the application of remote sensing to less studied subject areas.

5.3.1. Use of Higher Resolution Data

The increasing trend of remote sensing data availability and accessibility has provided opportunities to improve its application to rubber studies. Landsat has proven to be the most widely used satellite data source in rubber tree studies, with almost 50 years of publicly accessible data.

The development of optical remote sensing is ongoing. The recent introduction of new sensors with improved spectral, spatial and temporal resolutions is providing richer datasets [148]. In 2015, several sensors were launched, including Sentinel-2A/B, and PlanetScope. These sensors have yet to be explored extensively in rubber tree monitoring. From selected documents in the review, only five reported the use of Sentinel-2 data for analysis [71,81,87,132,133]. At the time of this review, no studies have used image datasets from PlanetScope.

Sentinel-2A/B data offer 13 spectral bands, which come with narrower bandwidths compared to other satellites. It is also the first satellite to provide three bands in the red edge spectrum range. The presence of these narrow spectral bandwidths could also improve the bio-physical estimation of rubber trees. For example, Band 5 of the Sentinel-2 satellite offers bandwidth between 697 and 711 nm. It provides the capability to accurately capture leaf chlorophyll-a content, which peaks at 705 nm. The chlorophyll-a is necessary for photosynthesis and is a measure of plant health [149]. In rubber, this information can be useful in monitoring rubber leaf disease outbreaks and facilitating the understanding of rubber phenology.

The higher spatial resolution provided by Sentinel-2 (10 m) and PlanetScope (3 m) may improve the accuracy and estimation of remote sensing outputs in monitoring rubber trees. The use of these sensors will reduce spatial variability, thus allowing precise information to be extracted from remote sensing derived indices and products. The adoption of these sensors in rubber studies can potentially address the misclassification and occurrence of high intra-class variability in rubber monitoring.

Furthermore, Sentinel-2 and PlanetScope offer high revisit frequency, at 5-day and daily frequencies, respectively. This high revisit frequency increases the opportunity to obtain more images. This is important for rubber studies as most rubber plantations are located in cloud-prone areas and high revisit frequency will improve the chances of obtaining clear images. Near real-time research on rubber tree monitoring could also be conducted.

Data from these satellites are also freely available, which could enable broader adoption by an industry that is often underfunded. The operationalisation of remote sensing in rubber, in this case, could be focused on the dissemination of information to smallholder farmers. Future research should look towards adopting freely available higher resolution images in order to overcome current challenges faced in the application of rubber studies.

Apart from satellites, unmanned aerial vehicles (UAV) have potential. Drones can provide detailed imagery, with pixel sizes in centimetres, due to operating at lower altitude. UAV can collect imagery under cloud cover and offer good flexibility in timing and frequency. Unfortunately, in rubber plantations, the application is bounded by several limitations. Tall rubber trees and large rubber plantations make the operation of drones challenging, particularly at the mature, closed canopy stage. More importantly, the affordability of this technology is a problem, as the rubber industry has suffered prolonged low rubber prices for almost a decade.

Future studies should also consider data fusion from multiple sensors (e.g., a combination of MODIS and Landsat). In this review, only ten documents, or 13.3% of the selected documents, used multiple sensors of different resolutions to achieve their set research objectives. Multisensor data fusion has received huge attention from researchers [150], and this has been boosted by the accessibility and availability of big remote sensing data. Data fusion involves a trade-off between the spatial and temporal resolution of satellite sensors. There are two categories of data fusion: Spatial-spectral fusion and spatial-temporal fusion. These result in finer spectral or temporal resolution data for analysis. Combining both datasets brings added value and knowledge to the remote sensing user [151]. It also improves the interpretation of data sources and is able to produce high-quality data representation [152]. This fusion technique could be useful for rubber planting land detection, recognition, identification and classification, and even for change detection at a plantation and leaf-level scale. The technology, in general, is considered to be a feasible and cost-effective way to obtain high-resolution data where it overcomes technology limitations and budget constraints [153–155].

In addition to this, the combination of imagery from passive and active sensors can provide different perspectives in order to better understand and evaluate rubber plantations, including the capability to overcome cloud cover issues in a study area. This kind of approach may elevate studies to the next level where stand age, biomass, carbon and disease detection can take place. Free-to-use active sensor data include RADARSAT.

However, in this review, less than 10% (seven documents) of selected documents were found to integrate passive and active sensor data in their study.

5.3.2. Algorithm Enhancements

Another opportunity identified in this review is the adoption of machine learning in the algorithm and methods used for image classification. We observed a transition in the algorithm used in the selected studies. There was a clear move away from the classic classifiers used in the earlier studies to more advanced classifiers. Studies published earlier performed visual interpretations and pixel-based classifications, with a high number of studies applying the maximum likelihood classifier. More recent studies adopted advanced classifiers such as the Support Vector Machine, Random Forest and Decision Tree. These produced results with much higher accuracy than the classic classifiers. However, these advanced classifiers have yet to be thoroughly explored in the classification of rubber trees. Advanced classifiers deliver a sophisticated approach to feature extraction and multi-temporal classification [148]. They have the capability to handle a large amount of data, which is important in the era of big data. The adoption of these classifiers would be useful when hundreds to thousands of images need to be analysed for a study, particularly for global-scale rubber studies.

In addition to adopting the advanced classifiers, several studies have developed their own rubber phenology-based algorithms. These algorithms were designed to exploit rubber's unique foliation and refoliation characteristics. An improvement in classification results was achieved when these algorithms were adopted because they were able to overcome the difficulties in delineating rubber from other land use/cover types. The rubber phenology-based algorithms have demonstrated promise in accurately mapping and updating the spatial distribution of rubber plantations. We expect to see an increase in the use of self-developed and advanced algorithms in future rubber studies.

5.3.3. Use of Emerging Processing Platforms

With the advent of self-developed and more advanced algorithms, future studies will need access to high-performance computing resources for data processing. Several institutions (e.g., National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS)) and company-based infrastructures (e.g., Google Earth Engine (GEE), the Amazon Web Services (AWS), the Copernicus Data and Information Access Services (DIAS)) have made significant efforts to meet this need, some of which are currently underway [156].

For example, GEE provides open-access satellite data and enables researchers to conduct analysis and to visualise geospatial datasets. Due to its capacity for handling large image datasets, and the availability of ready-to-run Javascript interfaces and active developer forums, this platform has seen an exponential increase in the number of users [157]. These processing platforms have diminished technological barriers, and eased data handling for large-scale studies, through cloud-based storage. At the time of this review, none of the included studies had taken advantage of the available processing platforms. Thus, future studies should consider using processing platforms when conducting rubber studies at a regional or global scale.

5.3.4. Application in Less Studied Subject Areas

Despite the promising progress in the application of remote sensing to monitoring rubber trees, several key areas were not comprehensively covered by the selected literature. This includes biomass and carbon estimation (9 out of 74 documents), leaf area index estimation (3 out of 74 documents), and disease detection (3 out of 74 documents). It is vital to have a comprehensive understanding of these topics because they reflect and influence the decisions of management, actors, and policymakers.

The advancement of remote sensing data, algorithms, and processing platforms will allow more detailed and precise mapping in order to monitor rubber trees. Since mapping

is a fundamental step for any study, this is expected to indirectly increase the accuracy of biomass, carbon, and leaf area index estimation. There is also huge potential for rubber disease detection studies. Accurate mapping will provide data to assist in epidemiology studies and to control and manage disease outbreaks, in particular leaf diseases.

The recent outbreak of rubber leaf disease has created more opportunities for remote sensing studies in the area of rubber disease detection. As of December 2019, five countries were reported to have experienced *Pestalotiopsis* leaf disease attack, with some plantations facing major outbreaks [40]. These countries are Indonesia, Malaysia, Sri Lanka, India and Thailand. The disease causes rubber tree leaves to fall and has affected large rubber plantation areas in these countries. Subsequently, latex production drops by up to 50%. In the long run, this will impact an affected country's economy. More significantly for the rubber community, millions of smallholders will be impacted.

Remote sensing technology studies on current disease attacks can allow a comprehensive understanding of the disease outbreaks. Disease mapping, with remote sensing, can disclose disease locations on large scales of the affected areas. On the other hand, spread pattern analysis may help farmers and plantation managers to control disease spread, as well as projecting yield losses in real-time or into the future. This may lead to reduced chemical and pesticide use, reduced environmental impacts and lower production costs [158]. It may also enable better strategies for the control and prevention of disease in the future. Ultimately, there is significant potential for remote sensing to contribute to these less-studied subject areas.

6. Conclusions

This paper presents an overview of optical remote sensing applications to the study of rubber plantations. The selected studies have demonstrated the use of this technology in the management and monitoring of rubber plantations at various scales (e.g., regional, local, and canopy-leaf scale) and subject areas. The following points summarize the main finding of this review.

1. The number of studies keeps increasing partly due to the availability of remote sensing data over the years and the rubber boom in the mid-2000s. The majority of the selected studies are focused at a local scale with the most common study locations in Xishuangbanna and Hainan Island, China. Fewer studies were conducted in Southeast Asian countries, although there are a lot of major rubber producing countries in the region.
2. More studies at the regional scale using remote sensing should also be undertaken. It has now become more feasible given the enhancement of big data algorithms and emerging processing platforms.
3. Subject areas of mapping, change detection and stand age were extensively explored using several types of remote sensing data and classification algorithms. In contrast, for biomass, carbon and leaf area index estimation, most studies develop models to establish relationships between remote sensing data and these parameters. Examples of model inputs include spectral bands, vegetation indices and tree growth data.
4. Disease detection remains understudied but has the potential for growth. The use of remote sensing technology may benefit future studies on recent leaf fall disease outbreaks by examining changes in trees, understanding the spread pattern, estimating affected area, and predicting yield loss. The findings give greater control and support in monitoring and managing rubber plantations, especially for millions of smallholders.
5. The unique and outstanding rubber phenology characteristics have helped to delineate rubber from other land cover types and reduce misclassification error. Several recent documents have exploited this characteristic while performing classification, and some have developed phenology-based algorithm.
6. Expectedly, Landsat is the most frequently used optical sensor in the selected studies of this review. This is due to its long-term and free-cost availability. Future studies

are suggested to consider using freely available high-resolution remote sensing data (e.g. Sentinel-2, PlanetScope) and data fusion from multiple sensors with different resolutions in the study of monitoring rubber. Fewer studies have employed these types of data and demonstrated better accuracy than single-source remote sensing data studies.

In general, remote sensing plays a significant role in providing a deeper understanding of rubber management. The information retrieved through remote sensing images is vital for smallholders, plantation managers, and other decision-makers. Information on plantation expansion is also crucial in understanding the spatial extent and negative impacts of rubber expansion on the environment. Remote sensing data will support land management decisions and land use policies. Furthermore, the information retrieved from remotely sensed data has become a core indicator for monitoring plantation areas, observing biomass, assessing carbon stocks, and predicting yield gain or loss. Remote sensing is expected to continue play a growing and important role in managing global rubber production in the future.

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Appendix A

Table A1. A summary of the 74 studies assembled for this review. The attributes recorded include authors name, year, country of study area, sensor used, sensor resolution category, spatial extent, temporal scale, subject area, approach, reference data (ground data, high resolution image, and others) and accuracy method used (error matrix, kappa and R²/RMSE). [Note: Y = yes and N = no.].

No	Authors	Ref	Year	Country	Sensor	Sensor Resolution	Spatial Extent	Temporal Scale	Subject Area	Approach	Reference Data			Accuracy Method		
											Ground Data	High Resolution Image	Others	Error Matrix	Kappa	R ² /RMSE
1	Rao et al.	[38]	2003	India	IRS	Medium	Local	Multi-temporal	Mapping	Land cover	Y	N	N	N	N	N
2	Suratman	[18]	2003	Malaysia	Landsat TM	Medium	Local	Uni-temporal	Mapping	Land cover	N	N	Y	Y	Y	N
3	Suratman et al.	[67]	2005	Malaysia	Landsat TM	Medium	Local	Uni-temporal	Mapping	Statistical model	Y	N	Y	Y	N	N
4	Meti et al.	[65]	2008	India	LISS III	Medium	Local	Uni-temporal	Mapping	Land cover	N	N	N	Y	Y	N
5	Li & Fox	[68]	2011	Thailand, Laos, China	ASTER	Medium	Regional	Uni-temporal	Mapping	Land cover	Y	Y	N	Y	Y	Y
6	Li & Fox	[36]	2012	China, Myanmar, Laos, Thailand, Vietnam, Cambodia	MODIS	Low	Regional	Multi-temporal	Mapping	Land cover	N	Y	Y	Y	Y	N
7	Dong et al.	[72]	2013	China	Landsat TM, Landsat 7, PALSAR	Low + Medium	Local	Multi-temporal	Mapping	Phenology-based Algorithm	Y	Y	Y	Y	Y	N
8	Shidiq et al.	[69]	2014	Malaysia	Landsat TM	Medium	Local	Multi-temporal	Mapping	Land cover	N	N	Y	Y	Y	N
9	Dai et al.	[73]	2014	China	Landsat TM	Medium	Local	Uni-temporal	Mapping	Land cover	Y	Y	N	Y	Y	N
10	P. Li et al.	[74]	2015	China	Landsat TM, Landsat 7, Landsat 8	Medium	Local	Multi-temporal	Mapping	Phenology-based Algorithm	Y	Y	N	Y	Y	N
11	Fan et al.	[39]	2015	China	Landsat 8	Medium	Local	Multi-temporal	Mapping	Phenology-based Algorithm	Y	Y	N	Y	Y	N
12	Abd Razak et al.	[59]	2017	Malaysia	Landsat TM, Landsat 7, Landsat 8	Medium	Local	Multi-temporal	Mapping	Land cover	N	Y	N	Y	Y	N
13	Dibs et al.	[29]	2017	Malaysia	SPOT-5	Medium	Local	Uni-temporal	Mapping	Land cover	Y	N	N	Y	Y	N
14	Pradeep et al.	[75]	2017	India	IRS	Medium	Local	Uni-temporal	Mapping	Land cover	Y	N	Y	Y	N	N
15	Shidiq et al.	[70]	2017	Malaysia	Landsat 5, PALSAR	Medium	Local	Uni-temporal	Mapping	Land cover	Y	N	N	Y	Y	N
16	Han et al.	[58]	2018	China	Landsat 8	Medium	Local	Multi-temporal	Mapping	Land cover	Y	Y	N	Y	Y	N

Table A1. Cont.

No	Authors	Ref	Year	Country	Sensor	Sensor Resolution	Spatial Extent	Temporal Scale	Subject Area	Approach	Reference Data			Accuracy Method		
											Ground Data	High Resolution Image	Others	Error Matrix	Kappa	R ² /RMSE
17	Zhai et al.	[76]	2018	China	MODIS, Landsat 5, Landsat 7, PALSAR	Low+ Medium	Local	Multi-temporal	Mapping	Phenology-based Algorithm	Y	Y	N	Y	Y	N
18	Gao et al.	[31]	2019	China	MODIS, Landsat TM, Landsat 7, Landsat 8	Low + Medium	Local	Multi-temporal	Mapping	Land cover	Y	Y	N	Y	Y	N
19	Xiao et al.	[77]	2019	China	Landsat 8	Medium	Local	Uni-temporal	Mapping	Phenology-based Algorithm	Y	Y	N	Y	Y	N
20	Xiao et al.	[78]	2019	China	Landsat 8	Medium	Local	Multi-temporal	Mapping	Phenology-based Algorithm	Y	Y	N	Y	Y	N
21	Hazir & Muda	[79]	2020	Malaysia	Landsat 8	Medium	Local	Multi-temporal	Mapping	Land cover	Y	N	N	Y	N	N
22	Xiao et al.	[80]	2020	Laos	Sentinel-2	High	Local	Multi-temporal	Mapping	Phenology-based Algorithm	Y	Y	N	Y	Y	N
23	Xiao et al.	[81]	2020	Laos	Landsat 8	Medium	Local	Multi-temporal	Mapping	Phenology-based Algorithm	Y	Y	Y	Y	Y	N
24	Zhang et al.	[71]	2020	Thailand	Sentinel-1, Sentinel-2, GaoFen-1, Landsat 8	Medium + High	Local	Uni-temporal	Mapping	Textural and Spectral Features	Y	Y	N	Y	Y	N
25	Liu et al.	[89]	2006	China	Landsat TM, Landsat 7	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	Y	Y	Y	N	N
26	Suratman	[64]	2007	Selangor	Landsat TM	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	N	Y	N	N	N
27	H. Li et al.	[94]	2007	China	Landsat MSS, Landsat TM, Landsat 7	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	N	Y	Y	N	N
28	Pensuk & Shrestha	[57]	2008	Thailand	Landsat MSS, Landsat TM, Landsat 7	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	N	N	N	N	N
29	Vadjunec et al.	[100]	2009	Brazil	Landsat TM, Landsat 7	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	N	N	Y	N	N
30	Ekadinata & Vincent	[101]	2011	Indonesia	Landsat MSS, Landsat TM, Landsat 7	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	N	N	Y	N	N
31	Mongkolsawat & Putklang	[19]	2012	Thailand	THEOS	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	N	N	Y	Y	N

Table A1. Cont.

No	Authors	Ref	Year	Country	Sensor	Sensor Resolution	Spatial Extent	Temporal Scale	Subject Area	Approach	Reference Data		Accuracy Method			
											Ground Data	High Resolution Image	Others	Error Matrix	Kappa	R ² /RMSE
32	Xiaona Liu et al.	[32]	2013	China, Laos, Myanmar	Landsat MSS, Landsat TM, Landsat 7, MODIS	Low+ Medium	Regional	Multi-temporal	Change Detection	Land use/land cover change	Y	N	Y	Y	N	N
33	Phompila et al.	[103]	2014	Laos	Landsat 7	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	Y	N	Y	N	N
34	Grogan et al.	[88]	2015	Cambodia, Vietnam	Landsat TM, Landsat 7, MODIS	Low + Medium	Regional	Multi-temporal	Change Detection	Land use/land cover change	N	Y	N	Y	N	N
35	H. Chen et al.	[85]	2016	China	Landsat TM, Landsat 7, RapidEye	Medium + High	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	Y	N	Y	Y	N
36	X. Liu et al.	[97]	2016	Laos, China	Landsat TM, Landsat 7	Medium	Regional	Multi-temporal	Change Detection	Land use/land cover change	Y	N	N	Y	N	N
37	Sun et al.	[62]	2017	China	Landsat TM, Landsat 7, Landsat 8	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	Y	N	Y	Y	N
38	Ye et al.	[99]	2018	Cambodia	Landsat TM, Landsat 7, Landsat 8	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	N	Y	N	Y	Y	N
39	Chakraborty et al.	[63]	2018	India	LISS III	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	N	N	N	N	N
40	Özdoğan et al.	[96]	2018	Laos	Landsat TM, Landsat 7	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	N	N	Y	N	N
41	Kou et al.	[98]	2018	China	MODIS, Landsat 5, Landsat 7, PALSAR	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	Y	Y	Y	N	N
42	Grogan et al.	[87]	2019	Cambodia	MODIS, Landsat TM, Landsat 7, Landsat8, Sentinel-2	Low+ Medium + High	Local	Multi-temporal	Change Detection	Land use/land cover change	N	Y	N	Y	N	N
43	Xiao et al.	[53]	2019	China	Landsat TM, Landsat 7, Landsat 8	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	Y	N	Y	Y	N

Table A1. Cont.

No	Authors	Ref	Year	Country	Sensor	Sensor Resolution	Spatial Extent	Temporal Scale	Subject Area	Approach	Reference Data		Accuracy Method			
											Ground Data	High Resolution Image	Others	Error Matrix	Kappa	R ² /RMSE
44	Xiao et al.	[84]	2019	China	Landsat TM, Landsat 7, Landsat 8	Medium	Local	Multi-temporal	Change Detection	Land use/land cover change	Y	Y	Y	Y	Y	N
45	Suratman et al.	[108]	2004	Malaysia	Landsat TM	Medium	Local	Uni-temporal	Stand Age	Statistical Model	Y	N	Y	Y	N	Y
46	Mongkolsawat et al.	[112]	2010	Thailand	SPOT-2, SPOT-4, SPOT-5, THEOS	Medium	Local	Uni-temporal	Stand Age	Image Classification	Y	N	Y	Y	Y	N
47	Li & Fox	[113]	2011	Thailand	Landsat TM	Medium	Local	Uni-temporal	Stand Age	Image Classification	N	N	Y	N	N	Y
48	Putklang et al.	[86]	2012	Thailand	THEOS	Medium	Local	Uni-temporal	Stand Age	Image Classification	Y	N	N	N	Y	N
49	Chen et al.	[110]	2012	China	Landsat TM	Medium	Local	Uni-temporal	Stand Age	Statistical Model	N	N	N	N	N	Y
50	Koedsin & Huete	[114]	2015	Thailand	Pléiades	Very High	Local	Uni-temporal	Stand Age	Image Classification	N	Y	Y	Y	Y	N
51	Dibs & Mansor	[115]	2015	Malaysia	SPOT-5	Medium	Local	Uni-temporal	Stand Age	Image Classification	Y	N	Y	Y	Y	N
52	Kou et al.	[119]	2015	China	Landsat TM, Landsat 7, PALSAR	Medium	Local	Multi-temporal	Stand Age	Land Use Land Cover (LULC) Detection	Y	Y	N	Y	Y	N
53	Shidiq & Ismail	[109]	2016	Malaysia	Landsat 8	Medium	Local	Uni-temporal	Stand Age	Statistical Model	Y	N	N	N	N	Y
54	Beckschäfer	[117]	2017	China	Landsat TM, Landsat 7	Medium	Local	Multi-temporal	Stand Age	Land Use Land Cover (LULC) Detection	N	Y	N	Y	N	N
55	Kaewplang & Srihanu	[55]	2017	Thailand	EO-1 Hyperion	High	Local	Uni-temporal	Stand Age	Statistical Model	Y	N	N	N	N	Y
56	G. Chen et al.	[111]	2018	China, Myanmar, Laos	Landsat TM, Landsat 7, Landsat 8	Medium	Regional	Multi-temporal	Stand Age	Statistical Model	N	Y	N	Y	Y	N
57	Chen et al.	[107]	2018	China	Landsat TM, Landsat 7, Landsat 8, PALSAR	Medium	Local	Multi-temporal	Stand Age	Land Use Land Cover (LULC) Detection	Y	Y	N	Y	N	N
58	Xiao et al.	[118]	2019	China	Landsat TM, Landsat 7, Landsat 8	Medium	Local	Multi-temporal	Stand Age	Land Use Land Cover (LULC) Detection	Y	N	N	Y	Y	N

Table A1. Cont.

No	Authors	Ref	Year	Country	Sensor	Sensor Resolution	Spatial Extent	Temporal Scale	Subject Area	Approach	Reference Data		Accuracy Method			
											Ground Data	High Resolution Image	Others	Error Matrix	Kappa	R ² /RMSE
59	Somching et al.	[116]	2020	Thailand	Landsat TM, Landsat 7, Landsat 8	Medium	Local	Multi-temporal	Stand Age	Image Classification	N	Y	Y	Y	N	N
60	Suratman et al.	[49]	2002	Malaysia	Landsat TM	Medium	Local	Uni-temporal	Biomass and Carbon	Statistical model	Y	N	N	Y	N	Y
61	Charoenjit et al.	[127]	2012	Thailand	THEOS	Medium	Local	Uni-temporal	Biomass and Carbon	Tree Allometry	Y	N	N	Y	Y	N
62	Charoenjit et al.	[128]	2015	Thailand	THEOS	Medium	Local	Uni-temporal	Biomass and Carbon	Tree Allometry	Y	N	Y	N	N	Y
63	Yasen & Koedsin	[129]	2015	Thailand	Worldview-2	Very High	Local	Uni-temporal	Biomass and Carbon	Tree Allometry	Y	N	N	N	N	Y
64	Yang et al.	[106]	2016	China	IKONOS, SPOT, RapidEye, Landsat	Medium + High + Very High	Local	Multi-temporal	Biomass and Carbon	Tree Allometry	Y	N	N	N	N	Y
65	Anurogo et al.	[130]	2018	Indonesia	ASTER	Medium	Local	Uni-temporal	Biomass and Carbon	Tree Allometry	Y	N	N	N	N	Y
66	Anurogo et al.	[131]	2018	Indonesia	ASTER	Medium	Local	Uni-temporal	Biomass and Carbon	Tree Allometry	Y	N	N	Y	N	Y
67	Pratama & Danoe-doro	[132]	2020	Indonesia	Sentinel-2	High	Local	Uni-temporal	Biomass and Carbon	Tree Allometry	Y	N	Y	N	N	Y
68	Chen et al.	[133]	2020	China	Landsat 7, Landsat 8, Sentinel-2	Medium + High	Local	Uni-temporal	Biomass and Carbon	Tree Allometry	Y	N	N	N	N	Y
69	Kaewplang & Vaiphasa	[56]	2014	Thailand	EO-1 Hyperion	Medium	Local	Uni-temporal	Leaf Area Index	Regression model	Y	N	N	N	N	Y
70	Chen et al.	[33]	2015	China	HJ-1, ZY3	Medium + High	Local	Multi-temporal	Leaf Area Index	Regression model	Y	N	N	N	N	Y
71	Koedsin & Yasen	[139]	2016	Thailand	WorldView-2	Very High	Local	Uni-temporal	Leaf Area Index	Regression model	Y	N	N	Y	N	Y
72	Ranganathet al.	[143]	2004	India	IRS	Medium	Local	Multi-temporal	Disease	Satellite platform	Y	N	N	Y	N	N

Table A1. Cont.

No	Authors	Ref	Year	Country	Sensor	Sensor Resolution	Spatial Extent	Temporal Scale	Subject Area	Approach	Reference Data		Accuracy Method			
											Ground Data	High Resolution Image	Others	Error Matrix	Kappa	R ² /RMSE
73	Pradeep et al.	[15]	2014	India	IRS, MODIS	Low + Medium	Local	Multi-temporal	Disease	Satellite platform	Y	N	N	Y	N	N
74	Mohd Ali et al.	[54]	2018	Malaysia	Drone	Very High	Local	Uni-temporal	Disease	Unmanned Aerial Vehicle (UAV)	Y	N	N	N	N	N

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