Modeling of oil palm phenology based on remote sensing data: opportunities and challenges

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Abstract. Oil palm phenology has many advantages in managing the sustainability of oil palm plantations. The phenology of oil palms is a key issue in harvest estimation, fruit bunch production, estimating oil palm taxes, replanting, fertilization, and detecting oil palm disease. One of the recently developed methods of oil palm phenology involves the use of remote sensing technology. We evaluated and reviewed the current state of oil palm phenology based on remote sensing and conducted an optimized systematic review of recent scientific publications, specifically focusing on scientific peer-reviewed papers published between 1990 and 2021, comprising over 100 existing journal papers on remote sensing for oil palm phenology. The review includes a description of the state of the art and the mapping of oil palm phenology based on sensors, biophysical tree parameters, and classification techniques and also describes the state of the art in the development of regression models of oil palm phenology based on wavelength, biophysical tree parameters, and the type of regression model. Finally, the review provided an opportunity to develop suitable techniques for the identification, classification, and the construction of regression models of oil palm phenology. There is a lot of potential in combining multisensor approaches, suitable classification methods, and regression models for oil palm phenology. For future studies on oil palm phenology, we recommend integrating machine learning with oil palm biophysical parameters based on multisensor remote sensing technologies. [DOI: 10.1117/1.JRS.16.021501]

Keywords: oil palm; phenology; remote sensing; biophysical; classification; regression model; machine learning.

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1 Introduction

The oil palm (*Elaeis guineensis* Jacq.) is a species of palm planted extensively in Southeast Asia, especially in Indonesia, Malaysia, and Thailand.[1] It is an industrial plant, used as a basic material for producing cooking oil, industrial oil, and fuel.[2] Of the four main vegetable oils that account for more than 85% of world consumption, the most consumed is palm kernel oil. Palm kernel oil is extracted from the seeds or kernels of a hard mesocarp shell and contains about 80% saturated fatty acids (oleic). It is mostly utilized in the oleochemical sector to make soaps, detergents, and other products.[3,4] Figure 1(a) shows the statistics of the oil palm consumption worldwide from 2015/2016 to 2020/2021. In 2019/2020, the palm oil usage amounted to over 73 million metric tons worldwide. That increased to ~75.45 million metric tons in the following year. Figure 1(b) shows Indonesia and Malaysia produce the most palm oil in the world.

Oil palm cultivation is rapidly expanding in tropical countries, based on the fact that oil palm production is a major economic factor.[6] Oil palm is regarded as a major element of the economies of palm oil-producing nations, with the potential to accelerate regional economic growth in these countries.[7]

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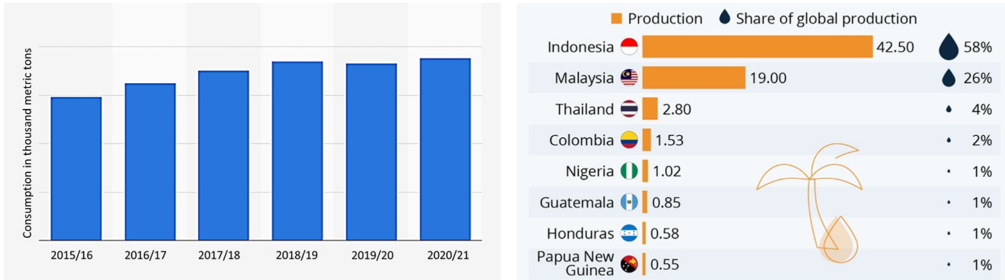

(a) (b)

Fig. 1 (a) Production volume of palm oil worldwide and (b) countries that produce the most oil palm.[5]

Currently, two methods are being used to improve the productivity of national oil palm plantations. The first step is to improve the productivity of existing oil palm plantations, specifically young and mature plants, and the second strategy involves replanting with the latest high-yielding varieties for existing oil palm plantations that are classified as old, because every year, there are fields that have reached the old phase and must be replaced.[8] According to the Indonesian Oil Palm Research Institute (IOPRI), the quality of productivity obtained from an oil palm plantation is the result of a synergy between the genetic potential of the plant variety, the environment in which it grows, and the management of its cultivation.[9] The main parameter derived from oil palm productivity data is the sustainability of oil palm development, in this case, the age or phenology parameters of oil palms.[10]

The phenology of an oil palm plantation has an impact on the physical and environmental conditions of the plantation.[11] One of the key parameters influencing the growth of fruit bunches is the phenology of the oil palm, which is a crucial component in yield estimation,[2,12] because the growth of oil palms occurs in a certain way, and their morphological characteristics may be utilized to determine their phenology.[11] The oil palm can be economically cultivated up to the age of 20 to 25 years.[13] The plant is tall and difficult to harvest at more than 25 years of age, and the quantity of fruit bunches is very limited, so it is no longer affordable to cultivate them beyond that age.[14]

According to Fig. 2, plantation age affects oil palm yield (in FFB), with black lines indicating average yield potential and red lines representing irrigation yield potential over a 25-year cycle.[15] The first harvest occurs 5 years after planting, and peak production is attained at the age of 5 to 10 years after planting. With the number of trees around 128 to 148 trees per hectare, depending on plant material, soil, and climate, with a triangular spacing of 9 m $\times$ 9 m, there are 143 trees

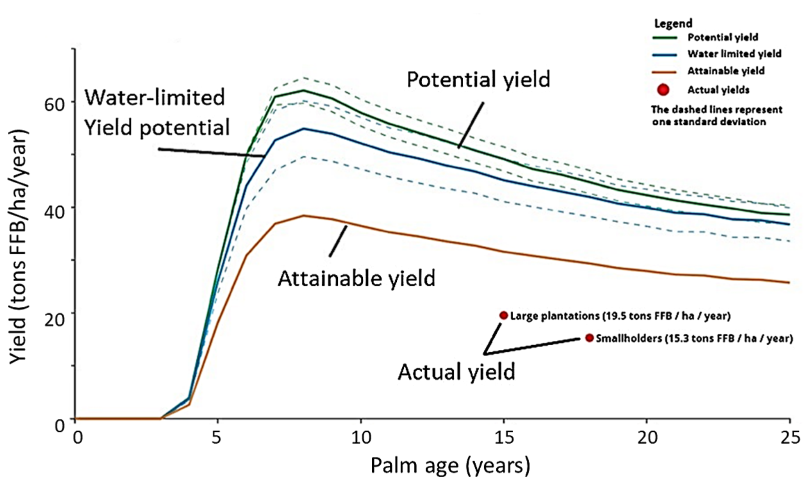

Fig. 2 The relationship of palm age and yield.[15]

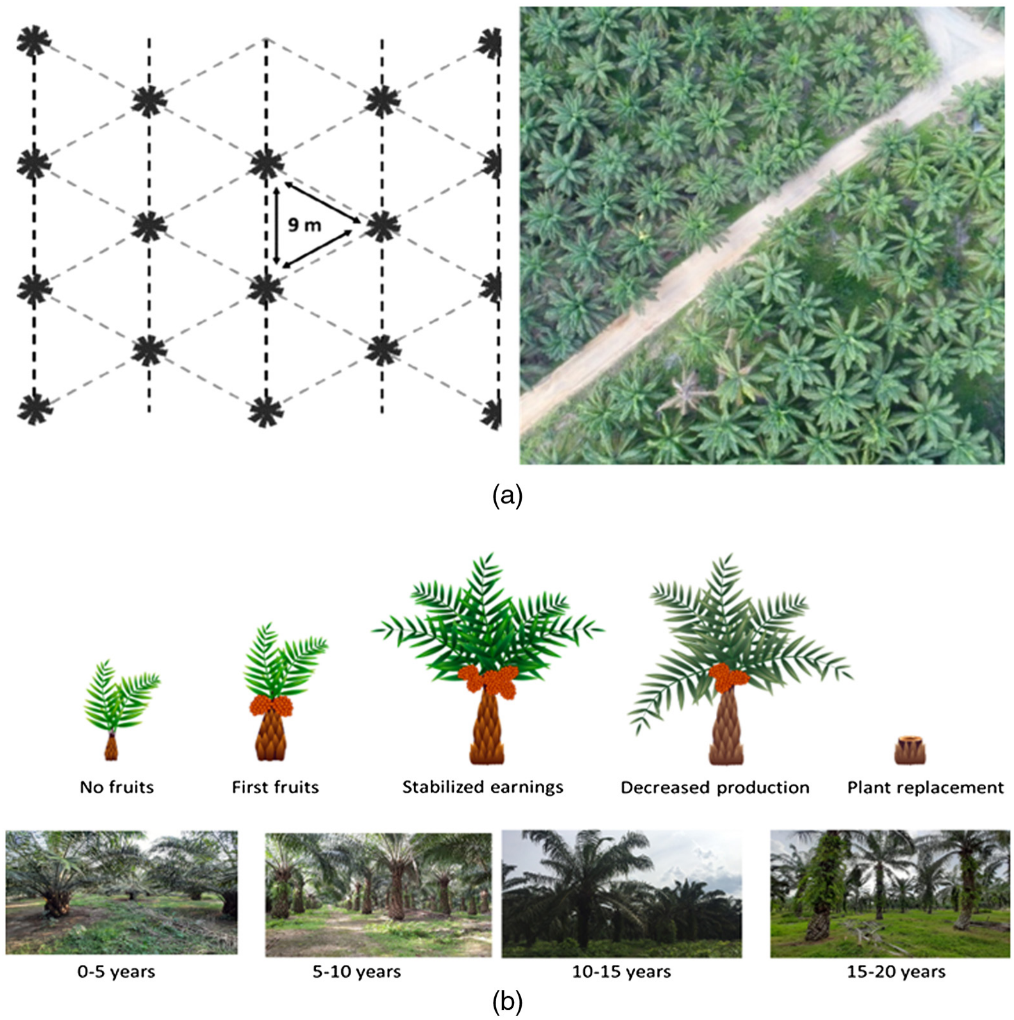

Fig. 3 (a) The oil palm planting pattern[13] and (b) oil palm growth.

per hectare[13] [Fig. 3(a)]. An indication of the results' variability due to weather variability can be seen in the band associated with it. Indicators of productivity are based on what can be achieved (blue line). It is possible to increase productivity on existing plantation lands by adopting good agronomic practices, which is defined as the difference between the actual yield and the achievable yield.[15] According to Corley,[16] the production of oil palm fruit bunches rises quickly and reaches a maximum at the age of 8 to 12 years, then gradually decreases as the plant ages up to the economic age limit of 25 years.[17] Three stages can be used to characterize the age of oil palm plantations: the young immature phase (0 to 3 years), the young mature phase (4 to 8 years), and the mature phase (over 8 years).[4] Oil palm plantations begin to produce fruit bunches in the young phase, 3 years after planting, and have a productive life in the mature phase up to 15 years after planting, then yields begin to decrease until the oil palm is replanted in the phase of old age, 25 to 30 years after planting [Fig. 3(b)].[7,18] Understanding plant growth in oil palm plantations requires an understanding of the stages of flowering and fruit maturation. The purpose of phenological observations on oil palm trees is to identify the sex ratios of flowers, phases of flowering and fruit ripening, the age of each phase of flowering and fruit ripening, and to estimate yields.[14] The phenology of an oil palm has a significant impact on yield estimations and is one of the key parameters affecting fruit bunch production.[18] Furthermore, information on oil palm phenology is important for precision agriculture to identify variations within a typical phenology group within an oil palm plantation and to optimize planning and management solutions.[19] In other cases, according to Darmawan et al.,[7] phenology information is required for estimating oil palm taxes, replanting, and detecting oil palm diseases.[7,20,21]

The physical and environmental conditions of oil palm plantations are affected by the age and productivity of the oil palms.[10] According to Chong et al.,[11] morphological characteristics can be used to predict the phenology of oil palms, since they are cultivated in specific ways. Previously, the phenology of oil palms was traditionally documented when the oil palms were first planted by labeling the land after the year of planting in standard management.[11] This information, however, is not widely accessible and is generally too difficult to collect and verify, especially from smallholders. Remote sensing has been used to monitor oil palms since the 1990s.[6] Researchers have widely utilized remote sensing technology, mostly for land cover classification in oil palm plantations. Oil palm plantations have a standard planting pattern, which includes grouping plants in blocks on a regular schedule based on plants with the same planting year. Remote sensing can be utilized to analyze the phenology of oil palm plantations.[19]

The aim of this study was to evaluate the current state of oil palm phenology based on remote sensing and conducted an optimized systematic review of recent scientific publications, specifically focusing on scientific peer-reviewed papers published between 1990 and 2021. This review is based on more than 100 existing journal papers on remote sensing for oil palm plantation phenology. The structure of this review is as follows:

1. Introduction
2. Methods for Reviewing the Literature on Oil Palm Phenology Based on Remote Sensing Data
3. State of the Art of Identification and Mapping Methods for Oil Palm Phenology
   - 3.1. Based on sensors
   - 3.2. Based on biophysical tree parameters
   - 3.3. Based on classification techniques
4. State of The Art of Developing Regression Models for Oil Palm Phenology
   - 4.1. Based on wavelength
   - 4.2. Based on biophysical tree parameters
   - 4.3. Based on the type of regression model
5. Results
   - 5.1. Identification and Mapping of Oil Palm Phenology Based on Remote Sensing
   - 5.2. Developing Regression Models of Oil Palm Phenology Based on Remote Sensing
6. Challenges and Future Directions
   - 6.1. Combining Multisensor Remote Sensing Data
   - 6.2. The Most Suitable Classification Method and Regression Model
   - 6.3. Future Direction in Oil Palm Phenology Based on Remote Sensing
7. Conclusions

2 Methods for Reviewing the Literature on Oil Palm Phenology Based on Remote Sensing Data

In this study, we evaluate the current state of oil palm phenology based on remote sensing. Oil palm phenology information is needed for harvesting, replanting, and determining the health of oil palm plantation that can be identified through remote sensing.[7] We adopted an optimized systematic review approach of recent scientific publications.[22] This technique closely follows a set of scientific procedures that expressly strive to reduce bias, primarily by attempting to discover, assess, and synthesize all relevant research to answer a specific question.[23] Scopus and Google Scholar were used to perform literature searches. These two databases are the most comprehensive in the scientific discipline and are frequently utilized to conduct literature

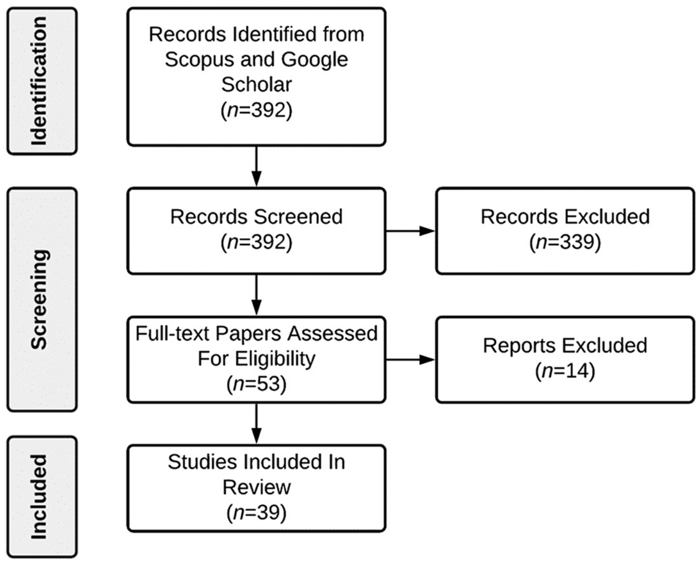

Fig. 4 The process of database searching and screening.

searches.[22] The phrases used in Scopus were "TITLE-ABS-KEY (oil palm) AND (remote sensing) AND ("age" OR "phenology" OR "health") AND PUBYEAR > 1990" and in Google Scholar, the terms "oil palm," "remote sensing," "age," "phenology," and "health" were used to search the databases. The sources were then chosen based on publications published in journals between 1990 and 2021.

The databases produced 392 papers, which were then whittled down by removing duplicates. Then, by reading the abstracts, this collection of articles was selected to select only papers that investigated oil palm phenology or age using classification approaches and identified oil palm phenology or age using a regression model. This produced 53 articles that were relevant to the issue. As a result, during the secondary filtering process, we removed several studies that did not directly related to oil palm phenology. Following that, we manually removed irrelevant articles by reviewing their whole text based on remote sensing systems, the data were then categorized as either issues or studies related to oil palm phenology, and a total of 39 papers were chosen. The database search and screening selection operations are shown in Fig. 4.

We analyzed all papers and created a literature visualization based on the number of times each paper's most important words were used from 1990 until 2021 (Fig. 5), with the highest numbers in 2019. Furthermore, based on Fig. 6, we used VOS Viewer to find the terms from

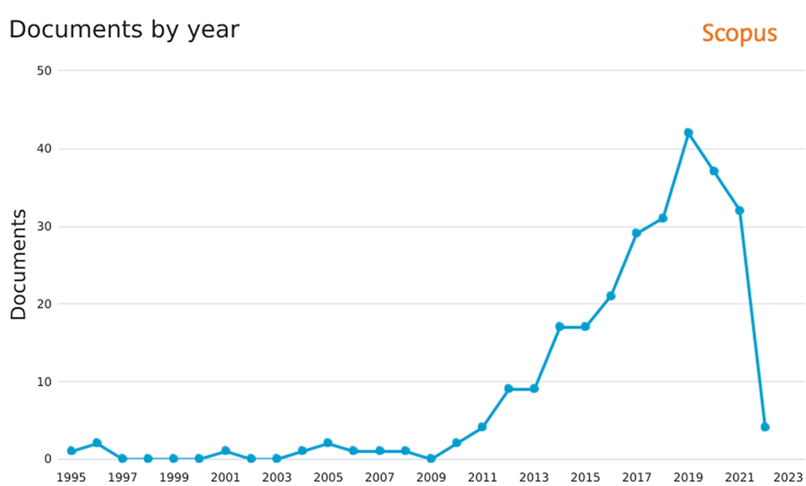

Fig. 5 Sources of articles in this study.

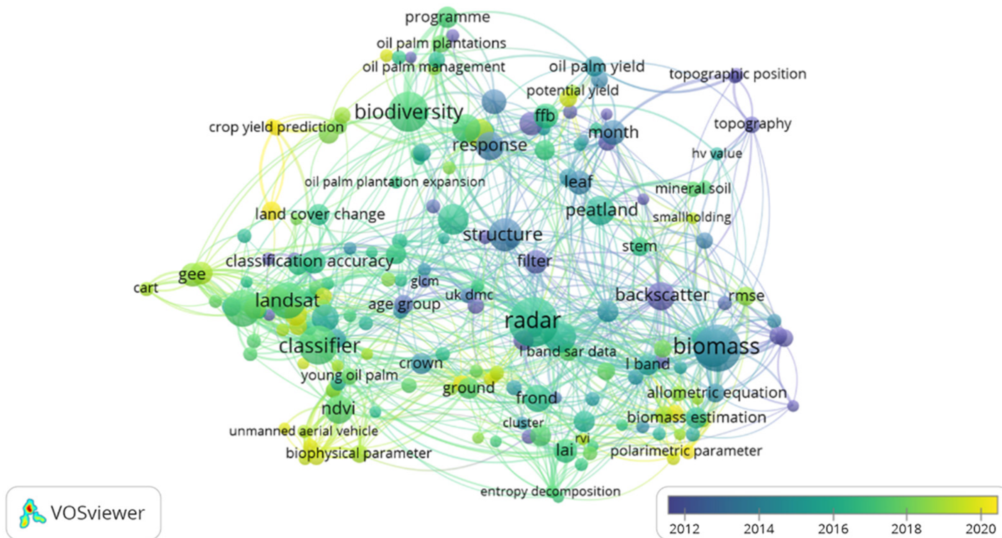

Fig. 6 Literature review based on keywords and time.

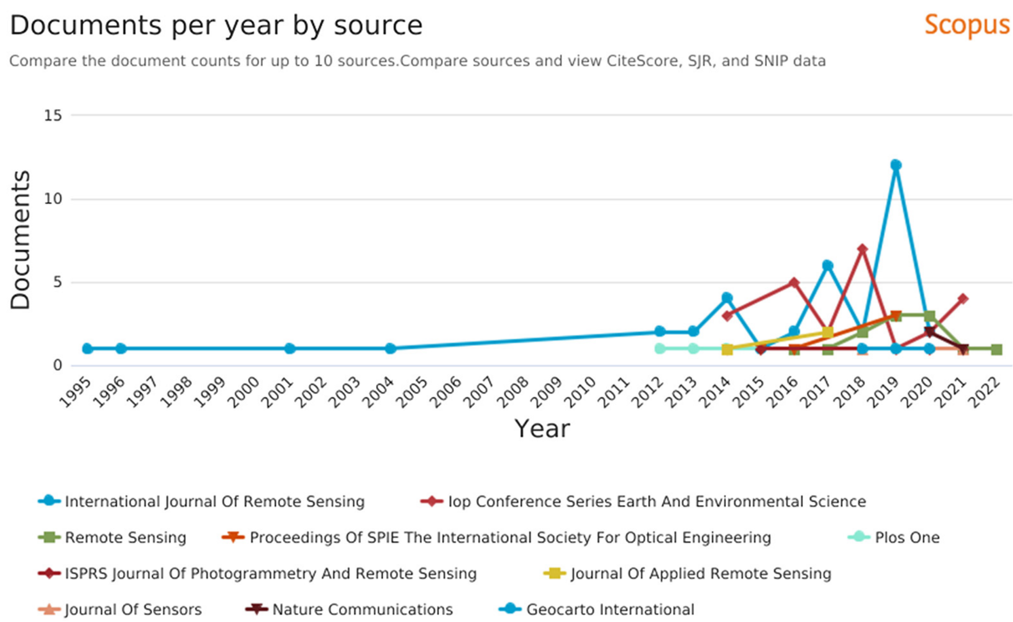

Fig. 7 Documents per year by source.

the title and abstract of all papers that highlighted the present problem of oil palm phenology utilizing remote sensing from 1990 to 2021.

Most of the papers on oil palm were found in journal articles with 392 documents with the large frequently article from *International Journal of Remote Sensing, Remote Sensing*, *Applied of Remote Sensing*, and the *Proceedings of IOP Earth and Environmental* (Fig. 7). However, oil palm publications, particularly in remote sensing-based phenology, is still limited, and this will become a challenge in the future.

3 State of the Art of the Identification and Mapping Methods for Oil Palm Phenology

Information about oil palm phenology is important for oil palm plantation management. For accurate information on trees, phenology is very important for scientific and practical reasons because it determines trees' productivity.[11] Based on passive and active sensors, biophysical tree parameters, and classification techniques, we reviewed the latest methods for identifying and mapping the spatial distribution of oil palm phenology.

3.1 *Based on Sensors*

Remote sensing has the potential to provide significant support in oil palm monitoring and potential oil palm plantation predictions.[7] Several studies in agriculture and plantations, particularly in oil palm plantations, have shown that remote sensing technology is capable of providing accurate performance estimates of the derivation of the relationship between spectral characteristics and vegetation indices in the form of canopy cover using the reflection of visual waves in red, green, blue, and infrared wavelengths.[24] The interaction between sensors and the Earth's surface can be categorized into two modes: passive sensors and active sensors.[25]

Passive sensors use solar radiation to reflect the Earth's surface and detect surface reflections. They normally absorb electromagnetic waves in the visible (430 to 720 nm) and near-infrared (750 to 950 nm) ranges.[26] Passive satellite sensors include those onboard Landsat, SPOT, Pléiades, EROS, GeoEye, WorldView, and other satellites.[11] Active sensors depend on internal energy sources, whereas passive sensors rely on external energy source mainly sunlight.[27] These utilize electromagnetic waves in the visible and near-infrared ranges (a laser rangefinder or a laser altimeter), as well as radar waves [synthetic aperture radar (SAR)].[28] Because of their potential to penetrate clouds and collect data under all-weather day/night environments, active sensors have emerged as a promising technology in the field of remote sensing.[29] TerraSAR-X, Sentinel-1A, ALOS PALSAR, RADARSAT, LiDAR, and other active sensors are examples. Passive and active sensors may be used to map oil palms based on the phenology or image characteristics of oil palm plantations[30] by measuring and classifying reflected energy using spectral signatures.[31]

Several techniques have been established to map oil palm land cover throughout the tropics utilizing satellite remote sensing data.[32] Oil palm mapping and change detection methods have been developed, with data sources derived from optical satellite Earth observations[33,34] to microwave datasets,[35,36] spatiotemporal resolutions from the regional to the national scale[37] and from single to multidecadal mapping,[6] interpretation methods ranging from manual to semiautomatic and fully automatic identification,[6,38–40] and products ranging from oil palm land cover maps to more detailed datasets on plantation structure. These include methods based on phenology for the classification of oil palm plantations,[41–44] tree counting,[34,36,38,40,45] age estimation,[10,21,46,47] yield estimation,[47–49] and a few studies have also focused on the detection of continuous oil palm changes,[50–52] allometric calculations of oil palm trees,[53–57] above-ground biomass estimation (AGB),[54,58–62] carbon estimation,[55,63–65] pest and disease detection.[66–68]

Gutiérrez-Vélez and DeFries[69] used Landsat to investigate the usage of spatial changes in vegetation greenness to detect deforestation caused by large-scale oil palm expansion in the Peruvian Amazon. McMorrow[10] estimated oil palm age using Landsat by measuring the reflectance value and showing the relationship between oil palm age. Sitoms et al. [70] also used Landsat as well as Santos and Messina,[71] Morel et al.,[62] Vadivelu et al.,[72] Lee et al.,[33] Fitrianto et al.,[73] Carolita et al.,[21] Danylo et al.,[74] Shaharum et al.,[75] and Sarzynski et al.[30]

High-resolution satellite datasets can also produce optimal performance in estimating the age of oil palm trees, as Chemura et al.[1] demonstrated by integrating multispectral data with WorldView-2 and performing regression analysis to reveal the oil palm age with biophysical parameters. IKONOS was used by Thenkabail et al.[55] and Agustin et al.[41] Active sensors can also focus on the physics of scattering processes. This method has primarily been used for identification purposes and is capable of understanding backscatter value using SAR data. Nordin et al.[76] used AIRSAR data in the classification of oil palm age based on biophysical parameters. Other imagery that is commonly used is ALOS PALSAR. For example, Darmawan et al.[47] used ALOS PALSAR-2 to show a correlation between backscatter value and oil palm age. In another case study, Yayusman and Nagasawa[77] classified young oil palms and mature oil palms for a smallholder plantation. Morel et al.[61] estimated biophysical parameters to identify oil palm age, and Tan et al.[49] estimated tree height and diameter at breast height. Furthermore, recent studies have investigated or made comparisons between sensors. For example, Avtar et al.[78] investigated a model of oil palm age using ALOS PALSAR, RADARSAT, and TerraSAR-X data. Carolita et al.[21] made the comparison between active sensor (Sentinel-1A) and passive sensor (Landsat-8). Darmawan et al.[7] investigated an oil palm phenology scattering model based on TerraSAR-X, Sentinel-1A, and ALOS PALSAR-2 data.

Recent studies have combined passive and active sensors with the aim of obtaining high accuracy; for example, Lee and Bretschneider[79] discovered that combining microwave and optical data could effectively map oil palm trees in a heterogeneous environment with an overall accuracy of 94%, relative to using Landsat (84%) and PALSAR (89%) data separately. Sarzynski et al.[30] used Landsat-8 and ALOS PALSAR data for oil palm age classification. Danylo et al.[80] mapped the extent and age of productive oil palm plantations using Landsat and Sentinel-1A data.

Aside from the radar–optical combination, the integration of light detection and ranging (LiDAR) and optical data has been used in oil palm mapping. LiDAR, which is recognized for its extremely high spatial resolution, can generate three-dimensional (3D) details (measuring canopy height and terrain elevation). It offers a 3D view of current oil palm plantation conditions when combined with an optical image, which is incredibly useful for plantation management and planning.[45] For example, Avtar et al.[81] used multispectral unmanned aerial vehicle (UAV) LiDAR data for estimating biophysical parameters.

3.2 *Based on Biophysical Tree Parameters*

In traditional management practices, oil palm phenology is documented when the oil palms are first planted in the field by labeling the field according to the year of planting.[49] As oil palms grow, they demonstrate an allometric formation, in which various tree parts grow at different speeds.[53] Individually, these biophysical structures of the oil palm may be calculated. They are classified as biophysical parameters, and some of them are known to be associated with the oil palms' growth stages (young, mature, and old) and they may also be used to discriminate them into specific phenology categories. These biophysical parameters include the oil palms' leaf area index (LAI), crown projection area (CPA), and height.[53] Shadow, roughness, and spectral response are examples of how these parameters are manifested.[10]

The concept of LAI is based on the area of one-sided leaf tissue per unit of ground surface.[82] The basic concept of LAI is to identify the structure of trees by calculating the density of the surface of the leaves in a canopy, which could result in the effective interception of light, air, and water.[46,83] Phenology would increase the LAI, with more fronds and leaves around the crowns of the oil palms.[84] This relationship thus makes LAI a valuable feature in the estimation of oil palm phenology.[84] CPA is similar to the percentage of canopy cover but is expressed as the canopy area that is covered by an individual oil palm.[10] To calculate the region of the oil palm's crown, high-resolution satellite imagery is needed. Satellite data contain different responses in various spectral bands, which make it possible to distinguish, segment, and delineate an oil palm's crown core, rachis edges, and background.[1] For example, the crown core appears brighter than the edges and background. Oil palm crowns can be delineated using object-based image processing, allowing CPA to be determined. In this area, a positive linear relationship with age is observed with the projected oil palm crown area.[1]

The oil palm tree does not stop growing in height throughout its life. This feature of growth is very useful in estimating oil palm age.[19] Throughout its life cycle, the height of the oil palm grows by 30 to 60 cm each year, depending on its physical condition and genetic factors.[85] Different methods, such as interferometry synthetic aperture radar (InSAR), can be used to obtain information about height.[86] Using only field-measured information, oil palm height showed a strong linear relationship with age.[49] Tree height has proven to be a potentially useful indicator for estimating oil palm phenology.[53] Another biophysical parameter, diameter at breast height, is insignificantly related to the phenology of oil palms since oil palm trunks do not grow after 2 years of maturity.[85]

Several studies have used biomass to estimate the phenology of oil palms. Thenkabail et al.[55] used stem height to estimate the aboveground biomass of young oil palm trees (aged from 1 to 5 years). Khalid et al.[87] used total height as a descriptive variable to estimate biomass for mid-mature (23-year-old) Malaysian oil palm plantations. SAR for oil palm plantations is an important parameter, extracted from normalized backscatter, that is related to AGB. Nordin et al.[76] used a biomass index and created an empirical biomass model for oil palms. The results of SAR applications in tropical forests can be applied to oil palm plantations. Due to their standardized geometry, the use of the same plant species, and the identical ages of the trees planted in a single plantation, the resulting data are easy to interpret. Kee et al.[44] investigated oil palm tree discrimination using three parameters—LAI, biomass, and height—to assess the backscattering value of oil palms using data from the C-band and L-band. Lazecky et al.[88] also analyzed an oil palm plantation based on Sentinel 1 A (C-band) data.

3.3 *Based on Classification Techniques*

A classification image algorithm can be used to sort an image into age categories to provide information regarding oil palm plantations.[55] Oil palm identification has been used successfully in a variety of image classification approaches. Image classification involves categorizing pixels based on different features, such as spectral signatures, indices, contextual details, and many more.[89] The techniques of image classification can be divided into supervised and unsupervised techniques.[90] Supervised classification techniques include the use of support vector machine (SVM), random forest (RF), spectral angle mapper (SAM), fuzzy adaptive resonance theory supervised predictive mapping, Mahalanobis distance, radial basis function, decision tree (DT), multilayer perception, naive Bayes, maximum likelihood classifier (MLC), and fuzzy logic analyses.[51]

There are numerous classification techniques available, with MLC being the most common parametric classifier due to its good classification performance. Santos and Messina,[71] MLC for the identification of oil palm yields. Tan et al. [49] separated the ages of oil palm trees, and Vadivelu et al.[72] also performed oil palm age classifications. Yayusman and Nagasawa[77] also classified young and mature oil palms. On the other hand, unsupervised classification techniques include the affinity propagation (AP) cluster algorithm, fuzzy C-means algorithms, the K-means algorithm, iterative self-organizing data (ISODATA), etc.[91] Thenkabail et al.[56] carried out unsupervised ISOCLASS classification. Tan et al.,[50] Razali et al.,[92] and Danylo et al.[75] also used unsupervised classification (ISODATA) on a cloud computing Google Earth Engine (GEE) to reveal the age of oil palms in Southeast Asia. Other researchers have used a combination of classification methodologies to obtain the best level of accuracy. Morel et al.[63] effectively distinguished between forest and oil palm areas based on Landsat data using unsupervised k-means and maximum likelihood methods with a DT, as well as calculating aboveground biomass using ALOS PALSAR. A recent study performed by Carolita et al.[21] showed a possible method of mapping oil palm age based on a SPOT-6 normalized vegetation differential index (NDVI) pixel-based classifier.

Object-based image analysis (OBIA) is another method of classifying oil palm phenology. Instead of analyzing individual pixels, OBIA of remote sensing data requires the grouping of pixels into homogeneous segments or objects.[93] These segments provide additional information about individual pixels, such as the mean, variance, and mean ratio values per band.[93] Accumulating pixels into segments further reduces the computing costs involved with working with finer-resolution satellite imagery, which is becoming more available as sensor quality improves. This type of image segmentation algorithm is classified into four categories: point-, edge-, and region-based, and combined algorithms.[45] Oil palm mapping can be carried out by combining pixels with identical values, clustering areas, and categorizing them based on texture, context, and geometry.[45] Rizeei et al.,[46] for example, were able to estimated oil palm tree counts and perform age predictions using WorldView-3 imagery and LiDAR data, utilizing an optimized OBIA method. Chemura et al.[1] used OBIA to estimate the age of oil palm plantations (years after planting) by integrating high-resolution multispectral remote sensing data and regression techniques.

In recent decades, machine learning classifiers have emerged as powerful classifiers and have been widely adopted for classification purposes due to their higher accuracy and performance compared to MLC.[94] Analyses using artificial intelligence to identify oil palm land cover, such as SVM, RF, classification and regression tree (CART), deep learning (DL), artificial neural network (ANN), and other machine learning algorithms, have been used in an attempt to obtain significant improvements.[95] Descals et al.[96] used cloud computing and the RF classification approach to discriminate between young and mature oil palms based on Sentinel 1 and Sentinel 2 data. Ordway et al.[39] also used RF models to classify imagery in 2000 and 2015 according to land cover types: forest, mature oil palms, immature monocultures, and other land cover, based on Landsat data. De Alban et al.[97] combined Landsat and L-band SAR data to improve land cover classifications using the RF classification method in Google Earth Engine. Shaharum et al.[75] also used GEE to characterize oil palm land cover for the first time across Peninsular Malaysia, using nonparametric machine learning algorithms such as SVM, CART, and RF, obtaining the best accuracy using SVM, at 93.16%.

To address automation issues, more recent works have used DL in computerized oil palm plantation analyses. For instance, the DL approach has been used in palm tree detection and counting.[40] The convolutional neural network (CNN), a widely used DL model, has achieved great performance in many studies in the computer vision field, such as image classification. Li et al.[38] proposed using DL to detect plants instead of manual detection methods. They used data from a manual count to train and improve the performance of a CNN system. Mubin et al.[41] also used a CNN to distinguish between young and mature oil palm trees.

4 State of the Art of Developing Regression Models of Oil Palm Phenology Based on Remote Sensing

Some other cases in the literature concern the identification of oil palm phenology using regression models. Regression models can be developed based on correlations between remote sensing data and the ages of oil palms derived from field surveys. We reviewed the existing studies on the use of regression models of oil palm phenology based on wavelength, biophysical tree parameters, and on the type of regression model.

4.1 *Based on Wavelength*

Depending on the wavelength, electromagnetic radiation may be available from a natural source, or it must be transmitted by an instrument. Typical passive sensor systems on space platforms include panchromatic systems, multispectral systems, and hyperspectral systems. A multispectral sensor is a multichannel detector with a few spectral bands.[25] Each channel is sensitive to radiation within a narrow wavelength band. Visible light refers to energy in the blue (0.4 to 0.5 μm), green (0.5 to 0.6 μm), and red (0.6 to 0.7 μm) bands of the electromagnetic spectrum.[98] The middle-infrared region (often referred to as the short-wavelength infrared) includes energy with a wavelength of 1.3 to 3 μm. The thermal infrared region contains light at 3 to 5 μm and 8 to 14 μm. McMorrow[10] used Landsat TM data to estimated age parameters by analyzing the spectral band and infrared index. Sitoms et al.[71] analyzed a phenology model using the spectral index. Tan et al.[50] performed comparisons using bands 1, 2, 3; NDVI; and surface reflectance data from Landsat and UK-DMC. For high spatial resolutions, Carolita et al.[99] succeeded in estimating age using NDVI based on SPOT 6 data.

Active sensors use frequencies from 1 to 90 GHz. The wavelengths of active sensors are intrinsically linked to the penetration capabilities of the transmitted microwave signal, such that longer-wavelength signals can penetrate deeper into vegetation canopies and soils.[100] An active sensor can obtain information in the electromagnetic spectrum bands K (1.1 to 1.7 cm), X (2.4 to 3.8 cm), C (3.8 to 7.5 cm), L (15 to 30 cm), and P (30 to 100 cm),[101] with the polarization of horizontal-to-horizontal (HH), vertical-to-vertical (VV), horizontal-to-vertical (HV), or vertical-to-horizontal (VH), which have varying ranges and azimuth resolutions.[101] SAR releases electromagnetic radiation in the microwave range of wavelengths and receives backscatter radiation when interacting with objects on the Earth's surface.[29] Backscattering has been used in many studies to describe vegetation dynamics, based on current microwave wavelengths in the X-, C-, and L- bands.[27] For example, Tan et al.[50] applied the gray-level co-occurrence matrix (GLCM) technique to ALOS PALSAR-2 data to determine the ages of oil palm trees. Carolita et al.[21] developed a regression model based on the correlation backscattering value from SAR Sentinel-1A data (band C) and age information collected from oil palm age-block data.

Okarda et al.[21] discovered that the relationship between age and backscattering has a strong correlation for HH and HV polarized signals, and so the value of backscattering can be useful for analyzing the height and age of oil palm trees.

4.2 *Based on Biophysical Tree Parameters*

Plant biophysical parameters can be used to determine the phenological characteristics of oil palms and are also recognized to be related to the growth stages of oil palms (young, mature, and old) and can be categorized into various age classes.[10,11] Assessing and quantifying biophysical parameters of vegetation cover are extremely important problems when monitoring land cover and associated changes, identifying vegetation stress, and assessing yield. These parameters can be used to quantify the state of crops within agriculture monitoring tasks under the global agriculture monitoring initiative, and they have already proved to be efficient for crop yield and production predictions and estimates.[102] Remote sensing data from space are the only source of information that enable the regular and consistent estimation of biophysical parameters at the regional, national, and global scales.[103] Both optical and SAR imagery can be used to extract biophysical values.

Phenology information is a good indicator for yield prediction as it influences the quality and quantity of the fresh fruit bunches.[1] To determine the phenology, many researchers have investigated biophysical parameters. These parameters are used to identify the biophysical characteristics of oil palms. Oil palm phenology begins at the age of zero; in this stage young oil palms are not much affected by competition before the leaves start to overlap and yields per palm in the first few years may be more or less constant up to quite high densities.[16] Thus, the optimum is very high when production starts, but this falls to below 150 palms/ha within 10 years.[82] At any one age, quite a wide range of optimal densities has been recorded.[16] Oil palm fruits can be harvested throughout the year. In oil palms older than about 10 years, leaf area does not change much, so the optimum might be expected to remain fairly constant after reaching a minimum ∼12 to 13 years after planting, and the optimum density increases slightly in later years.[104] This has been attributed to better light distribution through the canopy as differences in palm height become more marked, and light penetration through the canopy was found to increase in year 13 from its minimum in years 9 to 11, with the variation in palm height increasing with age.[105] Another factor may be that the LAI is maximal at about 10 years and then falls slightly.

An allometric equation is often used in forestry to relate the measurable parameters of plants (such as age, diameter at breast height, and tree height) to carbon stocks.[54] An allometric equation can be developed based on a strong statistical relationship between the carbon stocks obtained from the plot-based measurement of certain parameters. Moreover, these parameters provide an important piece of information to complete the allometric equation for the estimation of biomass.[49] This further indicates the carbon stock of oil palms and its environmental effects.[19] In oil palms, parameters such as age and trunk height are applied in an allometric equation for determining carbon stocks.[60] For example, Shashikant et al.[60] used different allometric equations to investigate the relationship between radar backscattering and AGB data on age differences. Kanniah et al.[106] estimated the LAI and fPAR values of an oil palm ecosystem in Malaysia using remote sensing. The data derived from near-infrared signals from UK-DMC 2 and LAI were computed on the basis of hemispherical photos. The model was used to increase the LAI from the plot to the region level. The results revealed a strong relationship between the LAI data and the validation data. The authors discovered that the LAI and fPAR values from UK-DMC 2 and MODIS matched well after comparing these results to MOD15A data.

4.3 *Based on the Type of Regression Model*

A wide range of studies have been conducted using different remote sensing approaches to estimate the age of oil palms, which can be grouped into two main categories: radiative transfer models and statistical regression models. The most common method for estimating phenology is regression analysis.[107] A regression analysis or other statistical technique is used to determine a correlation or relationship between two sets of information.[10] Regression models are used to understand how changes in the predictor values are associated with changes in the response mean. There are a variety of regression methodologies based on the type of response variable, the type of model that is required to provide an adequate fit to the data and the estimation method, such as whether it is linear, multiple linear, or nonlinear.[108] The most common models are simple linear and multiple linear models. Nonlinear regression analysis is commonly used for more complicated data sets in which the dependent and independent variables show a nonlinear relationship. There are three purposes for regression analysis: (1) prediction, (2) design of the model, and (3) assessment of parameters.[109] This procedure has been specifically used to analyze the relationship between extracted features and ground-measured biophysical parameters.[10]

In the case of oil palm phenology, many studies have used linear and nonlinear regression approaches, such as Nordin et al.[76] using AIRSAR; Tan et al.,[50] Avtar et al.,[79] Darmawan et al.,[48] and Darmawan et al.[7] using ALOS PALSAR, who found that the relationship between age and biophisycal parameters presented a nonlinear logarithmic equation, with R^2 ranging from 0.4 to 0.8. McMorrow[10] used Landsat data and Okarda et al.[21] used ALOS PALSAR data, showing a linear regression relationship between age and spectral index equation, with $R^2 = 0.7$. On the other hand, a nonlinear quadratic equation, with an average R^2 value of 0.8 using optical and SAR data, has been demonstrated by Tan et al.,[50] Carolita et al.,[21] and Rizeei et al.,[46] and Darmawan et al.,[7] using Sentinel-1A data.

McMorrow[19] using Landsat TM data showed a negative nonlinear correlation between the brightness of Landsat TM imagery and the age of the oil palms, meaning that a smaller reflectance value indicated a younger age oil palm. Carolita et al.[21]using SPOT showed that variations in NDVI can describe oil palm growth using the formula $y = -0.0004x^2 + 0.0107x + 0.3912$, where x is the age of the oil palm and Y is the NDVI, with $R^2 = 0.657$. Comparison of the utilization of Landsat 8 imagery with regression analysis techniques indicates that the age of oil palm plants can be analyzed using spectral index NDVI data with $R^2 = 0.85$. Chemura et al.[1] also estimated the age of oil palms in Ghana by integrating multispectral data generated from WorldView-2 high-resolution satellite imagery and regression analysis techniques. Correlations between age and CPA can be used to evaluate oil palm age models. According to the results of this study, there is a strong relationship between age and CPA in oil palms over the age of 13 years. Correlations with biomass parameters were observed by Nordin et al.[77] using AIRSAR data. Different polarizations [horizontal (H) and vertical (V)] of radar remote sensing data were utilized to investigate the ages of oil palms.[47] Both studies using the ALOS PALSAR series agreed that (1) HH was statistically related to the age of oil palms better than HV and (2) the backscattering value increased with age due to the increase in biomass.

Shashikant et al.[59] tested the relationship between radar backscattering and AGB data with certain allometric equations in relation to age variants. Tan et al.[50] used ALOS PALSAR-2 data to detect the age of oil palm trees using the GLCM technique. Pohl and Loong[110] researched the application of InSAR topography and developed high-profile oil palms; this information was useful for mapping the age profile of oil palms. They analyzed the relationship between tree height and the ages of oil palms, applying a linear regression model. This relationship resulted in a height-to-age empirical model to form an equation that can derive age values from the heights of oil palm trees in Malaysia.

The relationship between age and backscattering on mineral soils and peatlands has a strong correlation for HH and HV, as found by Okarda et al.[20] According to Okarda and colleagues, the importance of backscattering may be useful in analyzing the height and age of oil palm trees.[20] Carolita et al.[21] produced a regression model with a correlation between backscattering value from SAR Sentinel-1A data (band C) and age obtained from oil palm age-block data. In the C-band, the researchers found that tree cover pixels were considered oil palms if the VV/VH difference was greater than 7.4 dB and VH backscattering was less than −13 dB.[111] However, smaller wavelengths such as the C-band have been used successfully to predict phenology.[111] Darmawan et al.[7] aimed to explore the potential analysis of phenology characteristics using SAR data with X-, C-, and L-band measurements. The results showed that the most promising region was the C band, with VV polarization, with $R^2 = 0.85$.

5 Results

5.1 *Identification and Mapping of Oil Palm Phenology Based on Remote Sensing*

Previous researchers have investigated classification methods to distinguish between oil palm plantations and other land cover elements and have then used these classification methods to distinguish between age groups (Table 1).

Many classification techniques in machine learning, such as RF, SVM, and ANN, have improved in terms of accuracy, with error levels around 80% to 90%. Hyperspectral imagery can provide improved levels of detail on oil palms for phenology analyses using biophysical parameters. However, all techniques should be applied when adopting methods for one location and applying them to other locations as there are various factors that affect the accuracy of the classification outcomes, such as scale, phenology, and variations in topography and background signals. There is no single type of data that is suitable for all oil palm areas.[115]

Machine learning with RF, SVM, and CNN techniques showed higher accuracy than other techniques. Gutiérrez-Vélez and DeFries[69] used RF classification based on vegetation index with an accuracy of 96.3% using Landsat imagery data. Using the same technique, Lee et al.[34] identified immature oil palms based on Landsat data with a cloud computing GEE, showing an accuracy of 91.2%. Amirruddin et al.[114] made a comparison of RF and DT based on hyperspectral imagery with accuracies of 98.77% for RF and 90.48% for DT. Sarzynski et al.[31] used RF based on a fusion of Landsat 8 and ALOS PALSAR-2 techniques, with an accuracy of 84%. A CNN method was developed by Mubin et al.[41] based on WorldView-3 for the identification of young and mature oil palms, with an overall accuracy of 95.11% for young oil palms and 92.96% for mature oil palms. Furthermore, an SVM technique showed an average accuracy of 84.91% for Rizeei et al.[45] and Shaharum et al.[76] achieved 93.16% accuracy.

5.2 *Developing Regression Models of Oil Palm Phenology Based on Remote Sensing*

Aside from classification methods, one approach to determining the ages of oil palms is through modeling algorithms that use regression to show the correlation between oil palm age parameters based on wavelength and biophysical parameters (Table 2).

All remote sensing data can be applied in developing oil palm phenology models. The choice depends on the biophysical parameter used for estimating oil palm age. For passive sensors, Landsat imagery is commonly used to extract oil palm parameters using spectral indexes, such as NDVI and a quadratic nonlinear regression model. Furthermore, the use of WorldView imagery was applied by Chemura et al.,[1] using the biophysical parameter CPA, with $R^2 = 0.88$. Many studies have chosen L-band penetration in active sensors because it provides the ability to detect and measure biophysical parameters with moderate coefficient determination, using aboveground biomass, for example, and the model involves logarithmic nonlinear regression. Nordin et al.,[77] for example, demonstrated a coefficient determination of 0.8 using AIRSAR data with biophysical parameters relating to biomass. This means that biomass has a strong correlation with standing age. Tan et al.[50] analyzed the biophysical parameters of height tree and diameter at breast height of oil palms based on ALOS PALSAR data, with $R^2 = 0.9$. On the other hand, comparisons of Sentinel-1A data with VV polarization conducted by Darmawan et al.[7] showed quadratic linear regression with a higher R^2 value of 0.85. Nonlinear regression was applied for the purpose of better coefficient determination (R^2), with quadratic and logarithmic types giving R^2 values ranging from 0.5 to 0.8, from moderate to strong correlations.

6 Challenges and Future Directions

Remote sensing technology generates information for the purpose of describing oil palm conditions, as well as processing and reanalyzing the data using customized management practices.[24] The use of active and passive sensors with a variety of wavelengths, biophysical tree parameters, and classification and regression methods can involve challenges, particularly

Table 1 Oil palm phenology using classification methods.

Author	Classification technique	Sensor	Accuracy	Parameter
76	Supervised classification	AIRSAR	1 year = 73%	Biomass
			2 years = 99%	
			15 years = 96%	
			20 years = 63%	
			25 years = 82%	
55	ISOCLASS	IKONOS	74.5%	Biomass
71	MLC	RADARSAT and Landsat ETM+	83%	Oil palm crops
112	Supervised classification SAM algorithm	Airborne hyperspectral	93.33%	The characteristics of a matured oil palm plantation
62	K-means, MLC, and DT	Landsat ETM+ ALOS-PALSAR	97.0%	Aboveground biomass
49	ISODATA, MLC, and RF	UK-DMC2 and ALOS PALSAR	45.3% to 52.9%	Radiance, vegetation indices, and fraction of shadow in response to the age of oil palm trees
69	RF	Landsat TM/ETM+ and ALOS-PALSAR	Landsat = 96.3%	Vegetation indices
			ALOS-PALSAR = 94%	
113	Vegetation index (NDVI, Simple ratio, and SAVI)	UK-DMC2 and MODIS	$R^2 = 0.70$	LAI and fPAR
			$R^2 = 0.66$	
72	MLC, NN, and SVM	Landsat TM	MLC = 47.26%	Phase II involves oil palm age classification
			NN = 34.58%	
			SVM = 54.18%	

Table 1 (*Continued*).

Author	Classification technique	Sensor	Accuracy	Parameter
92	ISODATA and *K*-means	MODIS and ALOS	94%	Young oil palm
77	MLC	ALOS	Mature = 92%	Smallholders' oil palm plantation
		AVNIR-2	Young = 64.44%	
1	OBIA	WorldView-2	80.6%	CPA
41	Segmentation-based fractal texture analysis	IKONOS panchromatic	72.5%	The extraction of fractal-based texture features
33	CART and RF	Landsat in Google Earth Engine	CART = 93.6%	Immature oil palm
			RFT= 91.2%	
99	NDVI	SPOT 6	$R^2 = 0.67$	Canopy
45	SVM and OBIA	WorldView-3 and LiDAR	84.91%	Tree crown and tree height
73	Advanced vegetation index, bare soil index, shadow index, and thermal index	Landsat 5, 7, 8	85.71%	FCD
40	CNN	WorldView-3	Young = 95.11%	Mature and young oil palms
			Mature = 92.96%	
96	RF	Sentinel-1 and Sentinel-2	Sentinel-1 = 93.5%	Typology and age
			Sentinel-2 = 90.2%	
114	DT and RF	Hyperspectral	RF= 92.79% to 98.77%	Chlorophyll
			DT = 56.30% to 90.48%	

Table 1 (*Continued*).

Author	Classification technique	Sensor	Accuracy	Parameter
74	ISODATA	Sentinel-1, Sentinel-2, Landsat 5, and 7	Kalimantan = 80%	Bare soil index (BSI)
			Sumatra = 83%	
			Insular Malaysia = 82.78%	
			Peninsular Malaysia = 84.95%	
			Thailand = 80.33%	
75	SVM, CART, and RF	Landsat 8	SVM = 93.16%	—
			CART = 80.08%	
			RF = 86.50%	
30	RF	Landsat 8 and ALOS PALSAR 2	84%	
81	NDVI and NDRE	Multispectral sensors on UAV	—	Canopy height and CPA

Table 2 Oil palm phenology models.

Author	Phenology model	R^2	Parameter	Sensor
76	$y = 85.634\,\mathrm{Ln}(x) + 77.993$	0.80	Biomass	AIRSAR
	$y = 68.51\,\mathrm{Ln}(x) + 62.388$	0.80		
10	$y = 1.888 - 0.260x$	0.7	Spectral Band	Landsat TM
	$y = -0.03746 + 0.07861x$	0.8	Infrared index	
70	$y = 61.3 - 0.54x_1 + 39.39x_2 - 42.3x_3$	0.69	Spectral index	Landsat TM
49	$y = -10.80\ \ln(x) + 123.40$	0.76	Band 1	UK-DMC-2
	$y = -1.79\ \ln(x) + 24.08$	0.20	Band 2	ALOS
	$y = -3.00\ \ln(x) + 24.58$	0.40	Band 3	PALSAR
	$y = -0.001\ \ln(x) + 0.68$	0.01	NDVI	
	$y = -0.14\ \ln(x) + 5.36$	0.02	SR	
	$y = -0.01\ \ln(x) + 1.01$	0.01	SAVI	
	$y = -0.13\ \ln(x) + 0.013$	0.80	ShadowFraction	
	$y = -2.07\ \ln(x) + 15.54$	0.79	Band 1 GLCM	
	$y = -0.59\ \ln(x) + 2.23$	0.43	Band 2 GLCM	
	$y = -0.11\ \ln(x) + 20.36$	0.19	Band 3 GLCM	
	$y = 2.00\ \ln(x) - 13.48$	0.49	LAI	
	$y = 1.05\ \ln(x) - 15.65$	0.27	LAI	
	$y = -0.09\ \ln(x) + 0.88$	0.26	Tree height	
	$y = 0.000x^3 - 0.030x^2 + 0.714x - 0.892$	0.96	DBH	
	$y = 0.492x$	0.90		
	$y = -0.002x + 0.704$	0.02		
78	$y = 1.2598\ \ln(x) - 18.577$	0.49	HV	PALSAR, RADARSAT, TerraSAR-X
	$y = 1.144\ \ln(x) - 9.8119$	0.62	HH	
	$y = 1.3666\ \ln(x) - 17.496$	0.77	HV	
1	$\mathrm{Age\,(year)} = 0.59 + 0.15 \times \mathrm{CPA}(\mathrm{m}^2)$	0.88	CPA	WorldView-2
47	$y = -0.2783x + 23752$	0.23	FFB	ALOS PALSAR 2
	$y = 0.8845\ \ln(x) - 13.655$	0.63	HH	
	$y = 0.6445\ \ln(x) - 20.497$	0.42	HV	
99	$y = -0.0004x^2 + 0.0107x + 0.3912$		NDVI	SPOT 6
45	$y = 1.2803x - 0.9951$	0.88	LRF	WorldView and LiDAR
	$y = 0.0404x^2 + 0.4605x + 1.9856$	0.91	PRF	
	$y = 2.8103e^{0.1218x}$	0.90	ERF	

Table 2 (*Continued*).

Author	Phenology model	R^2	Parameter	Sensor
20	$y = 213x + 26.03$	0.55	Mineral soil	ALOS PALSAR-2
	$y = 0.63x + 16.55$	0.37	Mineral soil	
	$y = 0.46x + 9.20$	0.36	HH and peatland	
	$y = 0.57x + 14.74$	0.28	HV and peatland	
21	$y = -0.0003x^2 + 0.0068x + 0.4388$	0.85	NDVI	Landsat 8
	$y = -0.0222x^2 + 0.4579x - 17.311$	0.77	HV	Sentinel 1
	$y = -0.0219x^2 + 0.4594x - 9.8191$	0.68	HH	
116	$y = -0.0003 + 0.0068x + 0.438$	0.84	NDVI	Landsat, SPOT, Pleiades, and Sentinel 2
	$y = -0.00032 + 0.0055x + 0.8393$	0.81		
	$y = -0.0002 + 0.0071x + 0.78$	0.8		
	$y = -0.0002 + 0.0071x + 0.4388$	0.85		
	$y = -0.0002 + 0.0081x + 0.8272$	0.96		
	$y = -0.0008 + 0.0017x + 0.797$	0.61		
	$y = -0.0005 + 0.0111x + 0.817$	0.85		
	$y = -0.0002 + 0.0084x + 0.792$	0.7		
	$y = -0.0002 + 0.0084x + 0.792$	0.7		
	$y = -0.0002 + 0.0058x + 0.874$	0.88		
6	$y = -0.2153x - 9.9086$	0.66	HH	TerraSAR-X, Sentinel-1A, and ALOS PALSAR-2
	$y = -0.0072x^2 + 0.1787x - 9.0757$	0.81	VH	
	$y = -0.0046x^2 + 0.1071x - 15.858$	0.85	VV	
	$y = 1.756 \ln(x) - 22.069$	0.71	HV	
	$y = 2.0916 \ln(x) - 19.379$	0.77	HH	

in improving and developing suitable techniques for identification and classification, and developing regression models of oil palm phenology.

6.1 *Combining Multisensor Remote Sensing Data*

The use of active and passive sensors has proven to be successful in classification applications and algorithm models with high accuracy have been developed. Passive sensors are generally used to analyze oil palm phenology simultaneously at the regional scale and can also be used to identify vegetation indices and biophysical parameters such as LAI and forest canopy density (FCD). Active sensors can also be used for identifying oil palm age using biophysical parameters, such as aboveground biomass, tree height, and canopy height.

Active sensors can only obtain complex data under various transmitting and receiving polarizations and biophysical parameters can only be extracted through regression models or machine learning.[117] With the advancement of active sensors (SAR), multipolarization SAR methods are evolving, which involve adaptions to the shape and orientation of vegetation components. According to Izzawati et al.,[118] the key variables influencing the accuracy of tree height estimations are canopy shape, tree density, and slope. According to Pohl et al.[119] and Tan et al.,[50] active sensors can provide important information on tree height to complete the list of biophysical parameters used to estimate the productivity of a plantations using polarimetry and interferometric techniques (PolInSAR). These techniques can be used to estimate tree height by subtracting a digital terrain model from an InSAR height estimate or using dual PolInSAR data generated from X-band, C-band, L-band, and P-band data.[120] PolInSAR seems to be a very effective instrument for ecology and forestry because it can provide highly accurate estimations of canopy height and forest biomass,[119] but it has not yet been implemented in oil palm phenology studies.

Furthermore, the use of passive and active data to identify oil palm plantations emphasizes the usefulness of multisensory and data fusion techniques, which combine various data features to improve accuracy.[30] According to Rashid et al.,[94] for oil palm classification, the fusion of data from multisensors is highly recommended. Mohd Najib et al.[121] have also combined multisensor data using ALOS PALSAR-2 and Landsat TM to detect mature and young oil palms and their results showed an accuracy of 98.36% in Peninsular Malaysia. Sarzynski et al.[31] evaluated the use of a semiautomated approach with an RF method as a classifier and combined optical and radar datasets to classify oil palm land-cover in 2015 in Sumatra, Indonesia, using Google Earth Engine with an overall accuracy of 84%. Danylo et al.[18] used Sentinel 1 to generate an oil palm plantation map, and a Landsat time series was used to analyze an oil palm plantation, first detected using NDVI and BSI. In other plantations, the fusion of data from various remote sensing sources has already been undertaken; for example, optical and SAR analyses of paddy fields were effectively combined for rice identification and mapping,[119] with high accuracy.

6.2 *Most Suitable Classification Method and Regression Model*

Machine learning approaches have been shown to be able to utilize different kinds of remote sensing data. The recent evolution in artificial intelligence, such as development of DL, promises to bring remote sensing technology to new standards of performance, with improvements in detection and classification.[122] This information is critical for determining crop health and productivity and serves as an essential measure for agriculture planning and management.[123] In relation to oil palm management practices, recent studies have proposed the use of remote sensing technology using various data sources and advanced image processing methods based on machine learning and DL. According to Chong et al.,[11] in a general sense, for the discrimination of oil palms and other plantations, classification is carried out by classifying pixels of similar attributes/values depending on the used classifier. Machine learning methods, based on RF classifiers, are very effective in the identification and mapping of oil palms. According to Sarzynski et al.,[31] RF is a class of DTs that can increase the precision of classifying and detecting plantations, for example, in oil palms, depending on the data they collect. Furthermore, according to Shaharum et al.,[76] the RF algorithm derived oil palm information better than the other classifier used, and the RF algorithm enhanced classification when the RF trees were ensembled into a forest.[69] Moreover, according to Attarchi and Gloaguen,[124] nonparametric RF models can accommodate a large number of correlated input variables and biased data, while avoiding overfitting. As a result, RF models are highly useful for mapping heterogeneous landscapes. In addition, incipient developments in deep machine learning approaches, such as CNNs, are gaining attention due to their promising capability for automatically extracting valuable contextual information from remote sensing data, with potential usefulness in large-scale classifications.[97] Li et al.[38] proposed using DL to detect plants instead of manual detection methods. According to Toh et al.,[125] DL classification requires a large dataset for optimal classification training. In addition to being very accurate, according to Bonet et al.,[126] the DL approach, such as the use of CNNs, is very flexible as it can be used straightforwardly to identify similar plants, or those of different varieties, decreasing the number of misclassified oil palms. All these classification techniques show improvements in accuracy up to 90%.

In one study, OBIA was found to be more accurate than pixel-based analysis. Chemura et al.[1] adopted WorldView-2 data to investigate oil palm age using an OBIA classification method to identify the crown area, combined with a regression technique. Their results showed an overall accuracy of 72.8%, a segmentation goodness of fit of 0.69, and a correlation with field-measured crown area of 0.9, which indicated the successful delineation of individual tree crowns using OBIA.

The modeling of oil palm phenology based on regression models does not always display linear behavior. Oil palm phenology normally exhibits a nonlinear type of relationship.[127] Nonlinear machine learning techniques are a type of highly efficient regression approaches that have been used successfully in the analysis of biophysical parameters. According to Frost,[128] nonlinear regression also requires a continuous dependent variable, but it provides a greater flexibility in the fitting of curves than linear regression. According to Chong et al.,[11] the biophysical characteristics of the tree have also proved to be potentially reliable indicators for the estimation of oil palm age. Most nonlinear models have one continuous independent variable, but it is possible to have more than one.[129] According to Ali et al.,[130] such techniques can learn and estimate even complicated nonlinear mappings, using advanced machine learning methods and the information contained in a series of comparison samples. ANNs are among the most frequently used techniques in the field of biophysical parameter retrieval, and these have been widely investigated in many application domains.

Recent studies have involved the use of ANNs in oil palm studies. Hilal et al.[127] showed that ANN was a significant modeling instrument, showed terrific potential for the optimization of prediction models, with high precision in many related areas of study. All regression models can show improved coefficient determination (R^2) values, ranging from moderate (0.4) to strong (0.9) relationships. Furthermore, machine learning techniques do not always produce high-precision results because good results depend on the machine-learning model set-up, the training samples, and the input parameters.[127] In addition, in the case of paddy fields, the best classification methods are SVM and RF, and CNN and recurrent neural network techniques will require phenology and textural feature information to improve the accuracy of their data.[126]

6.3 *Future Direction in Oil Palm Phenology Based on Remote Sensing*

According to Refs. 106 and 131, LAI can identify phenology based on optical sensor spectral values derived from NDVI. According to Refs. 45, 95, and 125, machine learning classifiers (RF, SVM, DT) have emerged as effective classifications and have been extensively utilized for classification applications due to their better accuracy and performance. According to Refs. 95, 127, and 132, machine learning-based regression algorithms such as RF, CNN, and SVR could be very useful for predicting oil palm production including phenology. Furthermore, rather than a single algorithm, an ensemble of numerous algorithms should be considered to improve the robustness of the prediction model. Sarzynski et al.[30] demonstrated improved accuracy based on machine learning RF classification in the analysis of oil palm plantations using multisensor and data fusion techniques. Descals et al.[133] used a DL CNN for semantic segmentation with 98% overall accuracy. According to Ref. 132, the detection and classification of oil palm trees using DL need to be performed using high-resolution images and requires field survey data to study the important biophysical characteristics of oil palm trees and to evaluate the reliability of the results.

According to Refs. 81, 103, 119, 125, 131, and 134, regression models of oil palm phenology must be created to be developed based on biophysical tree parameters, researchers can make estimates about oil palm phenology by analyzing the canopy layer, fruit bunch, and tree height using allometric techniques. Regression model is used to analyze the relationship between biophysical characteristics extracted from an image with data from measurements in the field. Regression model-based algorithms using machine learning could be very effective in making predictions about oil palm phenology.

In the oil palm industry, UAV-based imaging provides low cost flexible data acquisition with less weather constraints and higher spatial/temporal resolution, as compared with high-resolution satellite data.[81] There are various applications of UAV, such as monitoring canopy structure and condition, mapping biomass, and precision agriculture.[135] Yarak et al.[132] applied high-resolution imagery from a UAV, combined with the DL approach, for the automatic detection and health classification of oil palm trees using three important biophysical characteristics: crown size, crown color, and crown density. According to Pohl,[69] classification of polarimetric and interferometric (PolInSAR) data to estimate heights (biomass) information and to provide information on oil palm frond shapes and changes as well as moisture parameters of plants and soil.

Table 3 Recommendation for further studies on oil palm phenology based on remote sensing.

Task	Parameter	Remote sensing data	Method
Identification, classification, and mapping	LAI, canopy density, NDVI	Landsat, high resolution images, UAV LiDAR	Machine learning (RF, SVM, DT), OBIA
Developing regression model	LAI, canopy height, biomass	SAR, PolInSAR, UAV LiDAR	Nonlinear regression using machine learning

In the future, remote sensing technology is expected to evolve into high-tech industries, in which systems are coupled with artificial intelligence and big data[136] to examine the relationship between environmental and socioeconomic indicators.[137] For future direction, we recommend some parameters, remote sensing data sources, and methods in Table 3. According to Table 3, we have recommendation for further studies on oil palm phenology based on remote sensing to identify, classify, and mapping can be use parameter such as LAI, canopy density, and NDVI derived from Landsat, high resolution images, and UAV LiDAR based on machine learning such as RF, SVM, DT, and OBIA method. For developing regression model can be use LAI, canopy height, biomass derived from SAR, PolInSAR, and UAV LiDAR based on nonlinear regression using machine learning method. This recommendation, we believe will be more accurate for identification, classification, and mapping, also developing regression model. However, the accuracy is influenced by testing and validation data, climate factors, precision errors, soil characteristics, spatial mixtures, and other external factors.

7 Conclusions

The results showed that the identification and mapping of oil palm phenology can be conducted based on sensors, including passive sensors, which estimate oil palm age by analyzing the spectral response, using data from MODIS, Landsat, SPOT, IKONOS, WorldView, etc. In active sensors, backscattering characteristics were analyzed, with the use of data from sources, such as TerraSAR-X, Sentinel-1A, ALOS PALSAR, LiDAR. Many studies used biophysical parameters approach such as LAI, CPA, and tree height were carried out through shadow, roughness, and spectral responses for estimating oil palm phenology. Machine learning (such as SVM, RF, and CNN) was used to identify images and predict oil palm phenology using a technique based on classification methods and regression models with the accuracy levels around 98%. Aside from that, OBIA offers an accuracy of more than 90% for a small area. However, the remaining challenge is the improvement of suitable techniques for the identification, classification, and development of regression models for oil palm phenology. This challenge can be suggested for future studies by integrating machine learning with oil palm biophysical parameters using multisensor remote sensing technologies, and CNN machine learning can be further developed for classification and regression models with a large number of parameters.

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