forests

Review

A Review of Forest Fire Combating Efforts, Challenges and Future Directions in Peninsular Malaysia, Sabah, and Sarawak

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Abstract: The land surface of Malaysia mostly constitutes forest cover. For decades, forest fires have been one of the nation's most concerning environmental issues. With the advent of machine learning, many studies have been conducted to resolve forest fire issues. However, the findings and results have been very case-specific. Most experiments have focused on particular regions with independent methodology settings, which has hindered the ability of others to reproduce works. Another major challenge is lack of benchmark datasets in this domain, which has made benchmark comparisons almost impossible to conduct. To our best knowledge, no comprehensive review and analysis have been performed to streamline the research direction for forest fires in Malaysia. Hence, this paper was aimed to review all works aimed to combat forest fire issues in Malaysia from 1989 to 2021. With the proliferation of publicly accessible satellite data in recent years, a new direction of utilising big data platforms has been postulated. The merit of this approach is that the methodology and experiments can be reproduced. Thus, it is strongly believed that the findings and analysis shown in this paper will be useful as a baseline to propagate research in this domain.

Keywords: forest fire; Malaysia; review; survey; fire map; wildfire

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1. Introduction

Fire is considered an environmental factor in the Mediterranean climate, having played an obvious evolutionary role in the structure and function of Mediterranean climate ecosystems. In the aftermath of wildfires, accelerated erosion occurs [1,2], thus threatening the natural regeneration process. Additionally, it is well-acknowledged that water erosion, biodiversity, and biotic natural capital affect recovery [3,4]. To that end, emergency post-wildfire erosion-mitigation treatments are required to enhance ecosystem sustainability as in highly fire-prone ecosystems featuring losses of biodiversity, ecosystem function, or services following wildfire events occurring with unnaturally high frequencies, the magnitude of extent or intensity can result in land degradation or even the complete transformation of the ecosystem. In addition to their impacts on the carbon cycle, such events, usually called as megafires because of their size, reduce the amount of living biomass, affect species composition, affect water and nutrient cycles, increase flood risk and soil erosion, and threaten local livelihoods by burning agricultural lands and homes. In addition, these fires have devastating impacts on local wildlife, as animals either are unable to escape from the fires or become threatened by the loss of their habitat, food and shelter.

Climate change [5] and the wildland–urban interfaces (WUIs) [6] have increased the frequency and devastating impacts of wildfires. The effects of global climate change have led to a rise in temperature and a fall in precipitation, shaping a prolonged dry and warm period that favours the ignition and spread of wildfires [5]. Radeloff et al. [6] stated that the upsurge of new housing development in WUI areas, specifically near forest regions, generally increases the likelihood of wildfire occurrence. The combination of the aforementioned conditions converts wildfires into megafires. A megafire is an extraordinary fire that devastates a large area. Megafires are notable for their physical characteristics including intensity, size, duration, and uncontrollable dimension, as well as their social characteristics, including suppression cost, damage, and fatalities [7].

Forest fires recur periodically in Malaysia due to many factors, such as human negligence [8,9], topography [10], and meteorology [11]. In the last two years [12–14], haze and forest fires caused serious environmental problems in Malaysia and its neighbouring countries. Forests play a critical role in sustaining the human environment. Most forest fires not only destroy the natural environment and ecological balance but also seriously threaten the security of life and property. Thus, the early discovery and forecasting of forest fires are both urgent and necessary for forest fire control, and they have become one of the nation's interests.

Forest fires and the resultant smoke-haze are not relatively new experiences in Malaysia. Despite improved management, wildfires have not been completely eradicated and seem to be increasing in intensity and periodically recurring due to many factors, e.g., climatic factors, improper peatland management, traditional slash and burn activities, and poor water management. In 2019, haze and forest fires caused a serious environmental problem for Malaysia and its neighbouring countries, including Indonesia, Singapore and Brunei. The forests and peatlands in Pahang caught fire in early February 2019 [15]. In August 2019, the forest fires in Riau shrouded the entire Klang valley with dense haze. Additionally, some major cities and towns in the state of Sarawak, including Kuching, were also affected by the haze resulting from the Kalimantan wildfire. Subsequently, the air quality in Kuala Baram and Miri reached hazardous levels that led to Malaysia activating its National Action Plan for Open Burning and its existing National Haze Action Plan on 14 August 2019. Many states were shrouded, including Pahang, Kuala Lumpur, Negeri Sembilan, Penang, Putrajaya, Selangor, Sabah and Sarawak, by the haze [16–18]. Subsequently, 2.4 hectares (ha) of forest were also burned in Johor in August 2019 [19]. Historical data have shown that the incidence of forest fires are more severe in Sabah [20] and Sarawak [9] than in Peninsular Malaysia. The worst fire in Sabah happened from 1983 to 1985 [21] due to the severe drought caused by the El Nino phenomenon [22]. About one million ha in mostly over-logged forests disappeared [20]. An uncontrolled forest fire can alter forest ecosystems and lead to social, economic, and environmental losses. Moreover, pollution from fires leads to respiratory problems in people living hundreds of kilometres away.

From the global perspective, the explosion of machine learning and artificial intelligence had undoubtedly inspired researchers to adopt machine learning and deep learning algorithms to combat the issues of forest fires [23,24]. However, most studies have utilised independent sets of methodology focussing on particular regions, thus preventing the replication of experiments. Since each fire incident may be triggered or promoted by different topologies, climates, weather, forest structures, or landcover conditions [25,26], solutions should be fine-tuned based on the study location to effectively tackle fires.

To the best of our knowledge, a comprehensive review and analysis has yet to be conducted in Malaysia. For this reason, all relevant forest fire efforts from 1989 to 2021 for Malaysia are described in Section 2 of this manuscript. The predominant aim of this review is to provide future researchers with a foundation to streamline, progress, and advance research on forest fires in Malaysia. Subsequently, all data that were exploited by the works performed in Malaysia are compiled and reviewed in Section 3. Following the rapid increase in the availability of public satellite data motivated by open data policies [27], traditional computing platforms may not be able to process and analyse the newfound petabytes of data. Additionally, the adoption of big data platforms such as Open Data Cube [28], Google Earth Engine [29], and Planetary Computer [30] to conduct geospatial analysis also promotes and encourages experimental reproducibility through script sharing [27]. Hence, Section 3.1 features a short discussion on the presently available big data platforms. Through the review deliberated in Section 2, we show that no previously published works exploited the advantage of machine learning for forest fire management in Malaysia.

Consequently, Section 4 presents a discussion of some of the notable machine learning and deep learning approaches used to resolve the issue of forest fires from a global perspective. Based on all the presented discussions, some challenges, future directions, and open research questions are described in Section 5 for future researchers that wish to venture into the journey of combating forest fires in Malaysia. A general methodology utilising remote sensing data to perform forest fire research is also described in Section 6. Additionally, a discussion of the need for a forest fire benchmark dataset and general techniques of forest fire detection are elaborated in Sections 7 and 8. Towards the end of the manuscript, some commonly employed fire spread models that have yet to be adopted in Malaysia are presented in Section 9. Finally, Section 10 provides the concluding remarks for this entire review.

2. Related Forest Fire Studies in Malaysia

Though several reviews have previous been conducted [23,24,31–33], none of them were dedicated to forest fires in Malaysia. Hence, a detailed description for each of the published works is provided three subsections based on their primary objectives followed by an in-depth review of each of the efforts. The first subsection discusses the initial research directions, which is intended to reveal the root causes and impacts of forest fires. The main objective of the second subsection is to generate a fire susceptibility map for predicting or locating fire incidents by utilising remote sensing information. In the third subsection, some of the efforts closely associated with forest fires such as estimating burnt areas, assessing the amount of pollutants discharged from forest fires, and analysing the relationship between haze events and mortality rate are discussed. To reiterate, the reviews provided in this section only encompass the efforts that have been performed in Malaysia.

2.1. Root Causes and Impacts of Forest Fire

The 1983 El Nino Southern Oscillation phenomenon caused a severe drought condition that ignited horrendous wildfires in the tropical forests of Borneo [22]. Despite the dry scenario precipitated by El Nino, Woods [21] mentioned that a large-scale forest fire was not triggered when severe droughts were previously encountered. He speculated this disastrous fire might have been caused by forest logging, which resulted in the forest becoming more fire prone. Approximately one million ha of forest were burnt in Sabah, Malaysia, according to Beaman et al. [20]. The incident sparked interest in researchers and communities around the world to measure the severity of the disaster. Additionally, several studies have also been conducted to theoretically investigate the root causes of forest fires.

Woods [21] studied the effect and impact of forest fires on primary tropical forests and over-logged forests in Sabah. He reported that the tree mortality rate in a logged forest is higher than in a primary forest. Regarding the recovery of forest structure, a primary forest can recover from fires but a logged forest's structure recovery greatly depends on the secondary tree species grown across the burnt areas.

Following the devastating forest fire that occurred in 1997 and 1998, the International Tropical Timber Organisation Mission visited in September 1998 to review the causes and implications of the forest fires in Kalimantan, Indonesia, and Sarawak, Malaysia [9]. They reported that primary forests (i.e., undisturbed natural forests) were considerably less likely to ignite than logged forests and industrial plantations in the possession and control of humans. They reported an estimated 6~7 million ha of land and 800 thousand ha of forests were burnt in the incident. A total financial damage of approximate 5~6 billion US dollars was assessed. Apart from the economic damage, the health of the communities in Malaysia, Indonesia, and neighbouring countries was also severely affected due to the air pollution caused by the smoke discharged from the forest fires. Haze events occurred in neighbouring countries during that period, and the atmospheric pollution index was higher than 850 for certain locations in Malaysia and Indonesia. It should be noted that an air pollutant index value exceeding 300 is considered hazardous to humans based on the standard air pollutant index in Malaysia [34]. The importance of utilising remote sensing technology to detect and predict forest fire activity was also highlighted and stressed.

Abdullah et al. [8] investigated plausible factors instigating forest fires that occurred from 1991 to 2001 in Peninsular Malaysia. The researchers identified that most of the incidents were caused by human activity such as smoking, hunting, and land preparation by farmers involving open burning. Intensified by the elongated draught condition, a fire broke out at each of the specified locations. In their study, they discovered there was no correlation between natural events and each of the forest fire incidents. The authors also emphasised that peat swamp forests were more susceptible to fire due to their unique characteristics. One possible reason deduced by them was the formation of thick humus layers in the ground that materialised over several years, becoming a potentially suitable fire fuel. From 1991 to 2001, the Selangor State of Malaysia was reported have the highest frequency of forest fire incidents.

Musa and Parlan [35] further studied the rationalisation suggested by Abdullah et al. [8] regarding the primary factor accountable for forest fires, i.e., human activity. Some of the activities mentioned include land operations to prepare for agricultural plantations and recreational activities such as hunting, picnicking, and camping. Musa and Parlan [35] also considered other natural phenomenon factors such as lightning and combustion. Akin to the observation disclosed by Woods [21], Musa and Parlan [35] wrote that primary forests were rarely affected by fires and that rates of fire spread were low even when they were affected. The authors backed their observations with the following three reasons: (i) the lower presence of fuel due to efficient ecological recycling, (ii) the availability of diversified plants, and (iii) the higher level of humidity in primary forests. Additionally, they also described three categories of fire: underground fires, surface fires and crown fires. Of these, underground and surface fires commonly occurred in Malaysian forests. They expressed that underground fires usually occur in peat swamp areas and that the detection of such fire activity is very challenging since such fires will burn and spread out very slowly through the underground. By the time a fire can be observed by a nearby community, the fire might have spread across the entire region and require huge resources to extinguish.

Diemont et al. [36] aimed to learn the root causes of forest fires for peat forests (i.e., peat swamp areas) in Southeast Asia, and they proposed some solutions to resolve the issue. Although their study location was not fixated on Malaysia, it was interesting that the authors explored the problem from a different perspective. Undeniably, several of the studies mentioned in this subsection showed that most forest fire incidents originate from human negligence. Diemont et al. [36] further investigating human activity related to land clearing associated with agriculture, and they discovered that most peat fires transpired near poor communities in Southeast Asia. Hence, international funding was suggested by the authors to replace the income of the communities from peat forests to curb forest fire incidents.

Table 1 summarises the initial related works that primarily focus on examining the effect and root causes of forest fires in Malaysia. According to the literature discussed in this subsection, it is obvious that human activity is the principal factor leading to forest fires. However, it is uncertain whether environmental conditions could advance the likelihood of forest fire occurrence in Malaysia. Thus, the next subsection on literature will be supplemented with information on related work that utilised remote sensing to understand forest fire incidents in Malaysia.

Table 1. Summary of the research efforts into the causes and effects of forest fire.

Year of Publication	References	Year of Studies	Location	Objective
1989	[21]	1983–1985	Sabah	Study the tree mortality rate and canopy loss of forest fires in over-logged forest and primary tropical forests in Sabah.
1998	[9]	1997–1998	Sarawak Indonesia	International Tropical Timber Organisation (ITTO) aimed to investigate the effects of forest fires in Indonesia and Sarawak. Human activity was found to be primary cause.
2002	[8]	1991–2001	Peninsular Malaysia	Explore the root causes of forest fire incidents, particularly for peat swamps in Malaysia. Human negligence was the predominant factor. It was reported that Selangor, Malaysia had the highest number of forest fire incidents from 1991 to 2001.
2002	[35]	1992–1998	Peninsular Malaysia	Discuss the causes of the forest fires from 1992 to 1998. Human activity was the biggest element constituting forest fire incidents. It was emphasised that peatland fires (underground fires) are difficult to detect.
2002	[36]	-	Southeast Asia	Show that peatland forest fires are a major issue in Southeast Asia, as well as reveal that most of the forest fires were ignited in the vicinity of poor communities. Authors recommended international funding as a solution to prevent forest fire incidents.

2.2. Fire Susceptibility Mapping Utilising Remote Sensing

Remote sensing is defined as the procurement of information about an object without requiring any kind of physical contact [37]. In the geoscience domain, it is commonly referred to as the acquisition of data from satellites (i.e., remote sensing imagery). A Geographic Information System (GIS) is a software tool that exploits a computer's capability of storing and processing a large amount of data to capture, store, retrieve, analyse, and display spatial information [38,39]. Some frequently used GIS software include proprietary Esri Products (e.g., ArcMap, ArcGIS Pro, and ArcView) [40] and the opensource QGIS software [41].

GIS, in conjunction with remote sensing data and machine modelling, has been commonly adopted for the task of forest fire detection [10,38]. Remote sensing imagery (i.e., satellite data) provides additional information such as vegetation, land-cover types, topography (e.g., elevation, aspect, and slope), historical hotspot data, and meteorological information to cost-effectively analyse forest fire incidents [38]. By utilising GIS technology and remote sensing data, a fire susceptibility map can be generated to suggest whether a region falls in a highly fire-prone zone or a lowly fire-prone zone. When combined with meteorological information (i.e., weather information), such a model may be able to deliver superior forecast accuracy. Early warning prediction modelling allows an authority to allocate resources for battling fires depending on the location and severity of the forecasted fire incident [11]. In this subsection, all efforts to analyse or detect forest fire through fire susceptibility mapping in Malaysia are reviewed.

Setiawan et al. [10] proposed a spatially weighted fire susceptibility model by combining or aggregating the risk score of several factors affecting forest fires in Pekan, Pahang. They considered the five following elements: land use, distance to road, slope, aspect, and elevation. For each of the factors, the authors categorised them into four different risk levels, whereby a higher level of risk score indicates a greater risk of fire hazard. For instance, the risk score was set to four if the distance from the forest to the road fell between 0 and 500 m, a risk score justified by the fact that convenient accessibility may indicate a higher rate of human activity. Once the fire risk map was generated, the authors validated it according to the hotspot occurrences in 1997 in the study location. Setiawan et al. [10] learned that most of the locations that were classified as very high or high-risk regions by the model were also recognised as actual fire hotspots in 1997. Thus, they concluded that the model was able to effectively generate a fire risk map, and they recommended it to be adopted in other areas by considering other factors in the model at the same time.

The first work of Dymond et al. [42] involved mapping and classifying fuel into eight types and two soil modifiers for Malaysia and western Indonesia by utilising land-cover [43] and tree-cover [44] information. The reclassified eight fuel types were grassland, seasonal agriculture, shrublands, slash from land clearing, slash from agroforestry, secondary forest, forest plantation, and primary forest, and the two soil modifiers were mineral and peat.

Following their previous work, Dymond et al. [45] attempted to calibrate the Fine Fuel Moisture Code and fire weather index parameters from the Canadian Forest Fire Weather Index System (CFFWIS) components in the Canadian Forest Fire Danger Rating System (CFFDRS) [46] to generate a fire danger rating system in Malaysia and Western Indonesia. Fine-tuning the original index was necessary because most of the fire models were developed based on a particular region that is affected by distinct physiographic or environmental factors that contribute to the tragedy of forest fires [25]. The study of Dymond et al. [45] was probably the first effort to incorporate meteorological data to generate a fire rating system for proactively detecting fires in Malaysia and Indonesia. They validated their models by verifying the occurrence of hotspots detected from the Along Track Scanning Radiometer (ATSR) World Fire Atlas [47] in 2001. It is worth pointing out that the index proposed in this work does not consider human activities such as distance from road.

Peng et al. [48] aimed to resolve the issue of the imprecise meteorological data required to calculate the relative humidity parameters in the fire weather index from the CFFDRS [46]. The authors mentioned that if one meteorological station was located more than 20 km away from an adjacent station, standard interpolation techniques may be ineffective for delivering precise meteorological information for the regions between each of the stations [49]. To tackle this problem, they proposed the utilisation of remote sensing information from MODIS levels 1 and 2 to estimate the relative humidity parameter. Because they validated the estimated results with relative humidity data obtained from 10 meteorological stations in Peninsular Malaysia for 30 days in August 2004, with a mean absolute error of only 5%, it is safe to assume that the employed technique is suitable for performing such estimations. Hence, in the absence of meteorological stations, particularly in remote areas, the proposed method can be used as an alternative to evaluate relative humidity.

Patah et al. [11] developed a forest fire risk index model that considered the topographic danger index, weather danger index, and fuel danger index. The topographic danger index can be calculated by using the slope, aspect, and elevation parameters, while the fuel type risk index was adopted from the Indonesia "Forest Fires Prevention and Control Project" [50]. For instance, grassland with scrub was assigned an extreme fire index, while the natural and manmade forest was assigned a lower fire index. Apart from the topographic and fuel index, the authors also accounted for vegetation density to compute the fuel hazard index since a greater density of vegetation implies a larger availability of fuel. Due to the absence of complete weather information, the weather danger index only considers the temperature and relative humidity. It was calculated by taking the mean temperature of the month, dividing it by the relative humidity of the month, and multiplying it by 100. The calculated weather danger index was further categorised into five groups, in which lower values denote lower risks and higher values indicate higher risks of fire occurrence. By adding the value of the fuel hazard index (static elements) and the weather danger index (dynamic element), the forest risk index was evaluated and can be subsequently used to construct a fire susceptibility map. The model was applied in Kuala Selangor, Selangor, for data obtained in June 1999. The authors highlighted the flexibility of the model, in which dynamic information (e.g., weather data) can be accordingly altered to manipulate the model output depending on the supplied meteorological information.

Pradhan et al. [51] built a forest fire risk index model based on a frequency ratio (i.e., likelihood ratio) statistical approach in Sungai Karang and Raja Muda Musa Forest Reserve in the Selangor State. A higher frequency ratio between the hotspot location and each of the forest fire factors implies a larger correlation between the hotspot and each factor, while a lower ratio signifies a lower correlation. The risk index was computed by accumulating each of the factors' frequency ratios, whereby a higher risk index denotes that a forest is more susceptible to fire incidents. Advanced Very-High Resolution Radiometer (AVHRR) National Oceanic and Atmospheric Administration (NOAA) remote sensing images were employed to identify the historical forest fire occurrence in the two-study locations in Selangor State from 2000 to 2005. The factors scrutinised in the authors' work included (i) land cover (extracted from Landsat-7), (ii) NDVI (processed from Landsat-7), (iii) slope (processed from Digital Elevation Map (DEM)), (iv) aspect (processed from DEM), and (v) soil map (extracted from agroclimate dataset obtained from MACRES). They reported that the model was able to achieve 73.18% accuracy, a preeminent result for fire risk mapping. However, it should be noted that the validation procedure to attain the prediction accuracy was not made available by the authors in the manuscript.

Due to the limitations of the CFFWIS, Peng et al. [52] devised a fire risk index that considers forest-cover types by exploiting the concept of pre-ignition heat energy [53] and can be calculated using the woody fuel moisture content (FMC) and fuel temperature parameters. In their work, they measured the ignition probabilities by estimating the amount of heat energy essential to flare up a fuel from its current temperature. With the five-thermal spectrum in Advanced Spaceborne Thermal Emission Reflectance Radiometer (ASTER), the authors were able to estimate the live land surface temperature (LST) parameter needed to compute the FMC. The model was tested over nine days before the fire incidents arose with the hotspots detected from ASTER in 2004 and 2005 in Peninsular Malaysia. According to the results, the proposed fire risk index significantly increased four days before the fire, demonstrating that the model was able to provide an early warning (i.e., four days) before the fire broke out.

De Groot et al. [54] were the first team of researchers to deploy a fully functional fire danger rating system (FDRS) in Malaysia and Southeast Asia in 1999, and the system is still in operation today; the system can be directly accessed from the Malaysia Meteorological Department website [55,56]. Akin to the work in Dymond et al. [45], De Groot et al. [54] calibrated the CFFWIS specifically for grass and peat fuel types, as both of them can be abundantly found across the Southeast Asia region [57]. The modified FDRS preserved a similar structure to that of the original CFFWIS. The FDRS fire weather index provides a numerical value to assess fire ignition risk, and it can be computed with the Initial Spread Index and Buildup Index. The Initial Spread Index takes the Fine Fuel Moisture Code (comprising temperature, relative humidity, wind speed, and rain) as the input parameters to anticipate the rate of fire spread, while the Duff Moisture Code and Drought Code are provided for the Buildup Index to evaluate the available combustible fuel. Because the system relies on weather information, present meteorological data will affect the generated fire risk maps. Depending on the availability of forecasted weather data, the FDRS can be used as a fire forecasting system by employing the forecasted data as the input data to the model. The accuracy of this forecasting model to provide an early warning heavily relies on the reliability of the forecasted weather information. The authors pointed out that the FDRS can be adopted as a decision-making tool to assist fire managers in planning resources before a fire is instigated.

Ainuddin and Ampun [58] adopted the Keetch-Byram Drought Index (KDBI) proposed by Keetch and Byram [59] as an alternative index to the CFFWIS. While the CFFWIS combines the weather, fuel, and topography to predict the occurrence of forest fires, the KDBI measures the soil moisture deficit (i.e., the volume of water required to maximise the soil moisture capacity) to achieve the same goal. A larger KDBI value implies a higher deficit of soil moisture, i.e., it denotes that the amount of water present in the soil for evaporation or plant transpiration is lesser [60]. On the other hand, a high KDBI value implies that the soil is very dry and may increase the probability of wildfires. In this study, the authors utilised the daily maximum temperature and total rainfall (i.e., precipitation) data obtained from the Malaysia Meteorological Department as the input parameters to compute the KDBI value. They employed the model and tested it in four weather stations located in different states in Malaysia, namely, (i) Kota Bahru, Kelantan; (ii) Kuching, Sarawak; (iii) Sandakan, Sabah; and (iv) Subang, Selangor. The four regions were selected as they represent the distinct climate and weather variations in Malaysia. Furthermore, forest fire incidents have also been reported in the vicinities of the selected areas. They presented the results of model for five years from 1 January 1990 to 31 December 1995. Based on the results, they stated that the highest mean KBDI value was recorded in the month of January in Kota Bahru, Kelantan (i.e., the region is more susceptible to forest fire in January). The authors highlighted that this was the first work to adopt the KDBI in Malaysia for the task of forest fire detection.

Similar to the work in Peng et al. [52], Pradhan [61] adopted the fire susceptibility index based on the concept of pre-ignition heat energy designed by Dasgupta, Qu and Hao [53]. In addition to the LST and FMC parameters necessary for computing the original index, Pradhan [61] further enhanced the model by incorporating other remote sensing data (e.g., fuel maps) and weather information (e.g., temperature and relative humidity) to evaluate the risk index. As opposed to the work of Peng et al. [52], Pradhan [61] estimated the LST parameter by utilising MODIS instead of ASTER. Additionally, Pradhan [61] also considered live FMC and dry/dead FMC, while Peng et al. [52] only accounted for dry woody FMC. Furthermore, an enhanced vegetation index and fuel map extracted from MODIS were further integrated to fine-tune the fire risk index to reflect the true phenomenon in accordance with the local parameters. Then, the fire susceptibility map could finally be generated based on the computed risk index. The author validated the fire risk map with the hotspots collected from ASEAN Specialised Meteorological Center (ASMC), and they discovered that most of the hotspots were identified in high risk (i.e., a risk index of greater than 20) regions of the fire risk map while no/low risk regions were recognised as urban areas and dense forests. Pradhan [61] speculated that the model had effectively assimilated the multiple parameters, and the model was deemed to have a significant spatial sensitivity and accuracy.

Mahmud et al. [62] used the analytic hierarchy process (AHP) [63] in GIS software to weigh and rank the factors influencing forest fires in Pekan, Pahang. The primary goal of this study was to generate a simple interface in ArcView software to enable inexperienced GIS users to seamlessly use and navigate the tools. Hence, the authors designed an additional menu bar inclusive of several buttons for the users to straightforwardly add and modify the parameters. To apply the AHP, users were required to supply the weight of each class/class range in each of the factors (attributes) by using the reclassify geoprocessing tools (i.e., the reclassifying factors menu bar added by the authors). Once all of them were weighted, the users could use the overlaying geoprocessing tools (i.e., overlaying factors menu bar) that utilise the AHP to produce a fire susceptibility map. It is worth pointing out that no validation or testing results were presented by the authors as the main intention of the work was to provide a user-friendly interface for users with limited knowledge of GIS software to use the tool for producing fire risk maps.

Razali et al. [64] proposed a fire susceptibility index considering fuel maps, road buffers, and canal buffers for a peat swamp forest in Batu Enam, Pahang. Instead of employing the NDVI vegetation index, the authors adopted Tasseled Cap (TC) transformation on a Landsat TM image retrieved on 3 April 1999 before performing supervised classification to categorise the land cover into nine distinct classes because the authors believed that TC was more effective at detecting peat swamp regions. Additionally, Ramsey III et al. [65] substantiated that TC was an effective algorithm to detect forest transformation resulting from fires. The authors found that the overall classification accuracy of detecting land cover was 94.63%. To incorporate human activity into the proposed index, Razali et al. [64] included the road buffer (i.e., distance to road) and canal buffer parameters. They subsequently assigned a risk index to each of the class/class ranges for the fuel map, distance to road, and canal buffers. For instance, a road buffer value between 0 and 50 m was assigned a risk index of 5, implying an extreme fire risk. This was reasonable because a nearer distance of a road to a forest would denote a higher rate of human activity since such forest is more easily accessible. The fire risk index was then calculated by summing up the risk of each pixel for all three of the factors. By utilising the index, a fire susceptibility map could then be generated. To validate the effectiveness of the model, the authors validated their results with the hotspot datasets retrieved from NOAA AVHRR in 1998, and the results suggested that the model was able to accurately detect most of the lower risk fire region. It should be noted that an acute degraded peat swamp forest fire was sparked in the study location on 12 March 1998.

Ismail et al. [66] utilised a fire risk index based on the peat depth, stand density, bulk density, moisture content, dryness index, water table, and species composition to produce a fire map. Northern Selangor, Kuala Langar, and the Southeastern Pahang peatland region were selected because they are very susceptible to forest fires, with several fire incidents reported in each region. Although it is interesting that the authors considered so many factors contributing to forest fires, it should be noted that the process of integrating various factors to compute the risk index was not delineated by the authors.

Hyer et al. [67] analysed the fire distribution patterns obtained from the product of Wildfire Automated Biomass Burning (WFABBA) from Multifunction Transport Satellite (MTSAT) and the results from MODIS MOD14 in Malaysia and Indonesia by comparing 34 months of historical data in both satellites from September 2008 to July 2011. They observed broadly similar fire pattern activity across both products. While MTSAT WFABBA's overall detection was lower than that of MODIS MOD14, it was able to pick up some of the "missing fire" in Sarawak, Malaysia, that was not recognised in MODIS MOD14. As the MTSAT was a geostationary satellite, it can provide near-real-time imagery covering Southeast Asia and Australia. Encouraged by their results, the authors concluded that the MTSAT WFABBA was a promising product for describing a real-time fire activity pattern in Southeast Asia. Hyer et al. [67] highlighted that further enhancements of the MTSAT WFABBA were obstructed by the pre-processed MTSAT data.

Analogous to the work of Mahmud et al. [62], Suliman et al. [68] also adopted the AHP mathematical model to weigh the factors influencing forest fires. While Mahmud et al. [62] aimed to build a user-friendly system, Suliman et al. [68] were devoted to weighting the potential factors (i.e., criteria) and classes (i.e., sub-criteria) through a questionnaire survey completed by three domain specialists from the Fire and Rescue Department Malaysia. Topography (e.g., slope and aspect), fuel map (e.g., eight land-cover and two soil types), and human activity (e.g., distance to road) parameters were the factors weighted by the experts. Details of the weighting and ranking can be found in the authors' initial work written in Bahasa Malaysia by Mohd and Mastura [69]. Once the weighting was evaluated by the specialist, the authors employed the AHP to produce a fire susceptibility map and subsequently disseminated the map through a WebGIS application. Suliman et al. [68] tested the model in Selangor, Malaysia, since a number of forest fire incidents had been identified over the last two decades in the study location. Based on the model, a total area of 32.83 km^2 in Selangor was recognised as region with an extreme fire risk, e.g., Raja Muda Musa Forest Reserve and Kuala Langat Forest Reserve were identified as potential fire locations. The authors also pointed out most of the high-risk areas were in regions with peat soils.

Ash'aari and Badrunsham [70] employed the ATSR World Atlas Fire data to explore the spatial and temporal distribution of fire incidents in Malaysia. Aggregated monthly hotspots generated from Algorithm 2 for ATSR World Fire Atlas from 1997 to 2008 were collected by the authors. To understand the temporal distribution, the monthly aggregated hotspots (i.e., number of fires) for 12 years were input onto a map of Malaysia. According to the results, a total of three minor (June–December, July–November, and September–October), and one major (January–April) El Nino events were observed. The authors also reported the month of April to have the highest number of fires. To realise the spatial pattern of fire occurrence in Malaysia, the states were distributed into six groups by adopting clustering analysis. Some of the notable clusters included (i) a Sabah cluster containing the highest number of fire incidents and (ii) a Selangor cluster with the lowest number of fire incidents. The authors justified the vast number of fires in Sabah as being due to biomass burning sighted in the vicinity of Indonesia. According to the literature described previously in this section, we recognise that a lot of research has exploited Selangor State as the study location since many fire incidents have been sparked there in the past. Therefore, it is speculated that the cluster analysis performed by Ash'aari and Badrunsham [70] might have been impacted by the total area of each state, as Selangor was distinguished in the cluster with the lowest number of fire incidents.

While Ash'aari and Badrunsham [70] devoted themselves to understanding the temporal and spatial distribution of fire incidents in the entirety of Malaysia, Leewe et al. [71] employed a similar technique (i.e., frequency analysis) to analyse the temporal and spatial trends of fire activity for the state of Sabah from 2006 to 2010. Instead of ASTR, Leewe et al. [71] retrieved the MODIS hotspot data from the Fire Information for Resource Management System [72]. The authors studied the monthly and annual areas of fire distribution by using the hotspot data. The highest number of hotspots were reported at 1082 in 2010, 518 in March (five-year average), and 1159 for the interior region (five-year average). Leewe et al. [71] stated that the fire distribution differed by year, month and region. By understanding the patterns of hotspots, resources can be accordingly allocated by authorities to confront fires in advance.

Jamaruppin et al. [73] utilised the raw data in thermal band 10 from Landsat 8 to estimate the temperature (i.e., Celsius) before (28 January), during (1 March), and after (17 March) the 2014 fire incidence for Pekan, Pahang. The temperature was then categorised into five distinct temperature classes depending on the temperature range. For instance, a temperature higher than 34 degrees Celsius was assigned as very high risk, while a temperature below 16 degrees Celsius was appointed as very low risk. A fire risk map was then produced by utilising the categorised temperature risk. When comparing the fire susceptibility map before and during the fire incident, it could be observed that most of the very low-risk regions had progressed to an advanced risk, as 0 km^2 was reported for the very low-risk region during the fire. The authors also evaluated the temperature changes between pre-fire and during-fire stages, as well as between during-fire and after-fire stages. They observed that most of the pixels in the studied region had a significant temperature increase during the transition from pre-fire to during-fire stages, while most of the pixels recorded a 100% decrease in temperature for the shift from during- to post-fire stages.

Miettinen et al. [74] studied the temporal and spatial distribution of peatland fire in Malaysia and Indonesia (Sumatra and Borneo Island) by utilising the MODIS hotspot detection count retrieved from the Fire Information for Resource Management System in 2015. They selected the study locations because a severe fire was ignited there in 2015 [75–77], and the fire was further aggravated by the drought conditions caused by El Nino. Based on the authors' previous work [78], they discovered that the land cover of the study locations was vastly affected by deforestation activities from 1999 to 2015 (i.e., peat swamp forests covered up 75% of the peatlands in 1999, while only 29% of peat swamp forests covered the study location in 2015). To analyse the relationship of peatland (i.e., peat soil type) with the distinct land cover (i.e., managed peatland areas, undeveloped degraded peatlands, and degraded peat swamp forest), Miettinen et al. [74] employed a peatland land-cover map created before the fire began in 2015 [78] to evaluate the fire severity in each peatland land-cover type. Two metrics, (i) the number of hotspots and (ii) fire density (i.e., fire counts relative to the area, as measured by the number of hotspots identified per 1000 km^2), were utilised by the authors to compare the fire counts between peatland and mineral soil, as well as to pinpoint the locations with high fire concentration activities. They revealed that more of the fires occurred in deforested, undeveloped peatlands (~831 hotspots per 1000 km^2) compared with pristine (i.e., undisturbed) peat swamp forests (30 hotspots per 1000 km^2). Additionally, fire density was reported to be from approximately four to ten times higher in peatland areas in contrast to mineral soils for all the studied locations. To shrink the risk of forest fire disaster in degraded undeveloped peatland, Miettinen, Shi and

Liew [74] recommended rewetting and rehabilitation (e.g., canal drainage blocking [79]) as the solutions to preserve a consistent water level for maintaining the soil moisture. The authors stated that these options were more desired than the solution involving the conversion of area to a managed agricultural. It should be noted that the authors excluded Singapore and Brunei from their work since both countries were relatively small and rarely confronted by acute fire incidents.

All the studies in this subsection are summarised and chronologically sorted based on the publication year in Table 2. Discussions in this subsection advocate the idea that the application of remote sensing to detect forest fire in Malaysia is not new since many researchers have attempted to utilise these technologies to provide unique solutions. However, the solutions presented in this section can be further enhanced and improved by adopting more advanced techniques that will be elaborated on in Section 4.

Table 2. Summary of the efforts for forest fire susceptibility map generation.

Year of Publication	References	Year of Studies	Location	Objective
2004	[10]	1997	Pekan District, Pahang	Categorise the factors (e.g., land use, slope risk, aspect risk, elevation risk, and distance to road) into risk scores from 1 to 4. The sum of the risk score for all the factors was used to generate the fire susceptibility map.
2004	[42]	2000	Malaysia/Western Indonesia	Classify the fuel types and soil types for Malaysia and Western Indonesia based on global vegetation data.
2005	[45]	1995–2001	Malaysia/Indonesia	Calibrate the parameters of Fine Fuel Moisture Code (FFMC) and fire weather index (FWI) of the Canadian Forest Fire Weather Index System (CFFWIS) to provide early warnings of forest fires.
2006	[48]	2002–2003	Peninsular Malaysia (10 Meteorological Station)	Utilise MODIS level-1 and level-2 data to estimate the relative humidity parameters necessary to calculate the fire weather index from the CFFDRS.
2006	[11]	June 1999	Kuala Selangor	To compute a fire risk index model by considering the topography, weather (atmospheric conditions), and fuel types as the input for mapping fire risk.
2007	[51]	2000–2005	Sungai Karang, Selangor/Raja Muda Forest Reserve, Selangor	Estimate the probability of forest fires by measuring the likelihood ratio (i.e., frequency ratio) between fire hotspots and forest fire factors. To compute the forest risk index, the summation of each frequency ratio for each pixel was calculated.
2007	[52]	2004–2005	Peninsular Malaysia	Devise a fire risk index by exploiting the concept of pre-ignition heat energy that assesses the ignition probabilities by estimating the amount of heat energy necessary to burn the fuel from its current temperature.
2007	[54]	Implemented in 1999	Southeast Asia (ASEAN)	The first fire danger rating system (FDRS) was successfully implemented to provide forecasts and early warnings for fire occurrences. The FDRS is still in operation to date, and it is publicly accessible from the Malaysia Meteorological Department [55] and Indonesia Meteorological Climatological and Geophysical Agency [80].
2008	[58]	1990–1995	Kelantan, Sarawak, Sabah, and Selangor	Predict the probability of fire occurrence by measuring soil moisture (i.e., the volume of water) by adopting the Keetch–Byram Drought Index (KDBI).

Table 2. *Cont.*

Year of Publication	References	Year of Studies	Location	Objective
2009	[61]	1995–1999	Peninsular Malaysia	Enhance the original pre-ignition heat energy risk index model by incorporating temperature, relative humidity, vegetation index, and fuel map to generate the fire susceptibility map.
2009	[62]	1995–1999	Pekan, Pahang	Develop a system (interface) in ArcView to simplify the user–system interaction for generating a fire map. The authors employed the analytical hierarchy process (AHP) tools (i.e., overlaying geoprocessing tools) in GIS software.
2010	[64]	1998	Batu Enam, Jalan Pekan, Kuantan, Pahang	Design a fire hazard rating model integrating nine classes of fuel type and human activity parameters (e.g., distance to road and canal buffers) to classify the region into five degrees of fire severity risk. Instead of the NDVI, the Tasseled Cap (TC) transformation vegetation index was used as it was a more effective scheme for detecting peat swamps and burnt land.
2011	[66]	-	Selangor, Kuala Langat, and Pahang	Propose an index that considers multiple factors affecting forest fires in peat swamps (e.g., peat depth, bulk density, and moisture content) to generate a fire map.
2013	[67]	September 2008–July 2011	Malaysia and Indonesia	Investigate the suitability and reliability of the application of the Wildfire Biomass Burning Algorithm (WFFABBA) from the Multifunction Transport Satellite (MTSAT) by comparing the pattern of fire activity with the results from MODIS MOD14 in Malaysia and Indonesia.
2014 2013	[68,69]	-	Selangor	Weigh the forest fire factors essential in the analytical hierarchy process (AHP) mathematical model by conducting a survey with three domain experts from the Fire and Rescue Department Malaysia. The model was deployed in WebGIS to generate a fire risk map for Selangor, Malaysia.
2014	[70]	1997–2008	Malaysia	Utilise the number of fires collected from the ASTR World Fire Atlas product for 12 years to understand the spatial and temporal pattern of fire activity in the entirety of Malaysia by adopting monthly frequency analysis and clustering analysis.
2016	[71]	2006–2010	Sabah	Perform annual, month, and area frequency analyses using five years of fire hotspot data from the Fire Information for Resource Management System (i.e., a product of MODIS).
2016	[73]	2014	Pekan, Pahang	Utilise the thermal band from Landsat 8 to estimate and classify the temperature into five distinct severities. Analyse the temperature before, during, and after a fire incident by using the five categorised temperatures and change detection mapping.
2017	[74]	2015	Peninsular Malaysia, Sumatra, and Borneo	Investigate the relationship of fire incidents in (i) peat soil vs. mineral soil and (ii) peat soil with different land covers in Malaysia and Indonesia by using the MODIS hotspot counts obtainable from the Fire Information and Resource Management System.

2.3. Other Efforts Associated with Forest Fire

Though most researchers were motivated to locate or predict fire-prone regions, some of the works discussed in this section used a distinct approach to conduct research associated with forest fires in Malaysia.

Mahmud [81] estimated the pollutants discharged from vegetation burning (i.e., agriculture waste burning) by using the emission equation and emission factors devised by Joyner [82]. To obtain the necessary input parameters for the formula, the author utilised the number of hotspots retrieved from NOAA AVHRR to perform spatial analysis while employing the Moran Index, nearest neighbour index, and nearest neighbour hierarchical spatial clustering from February 2002 to March 2002 in Peninsular Malaysia. Selangor, Perak, and Pahang states were observed to have higher rates of fire activities in contrast to other states in the spatial analysis. Based on the information acquired from the analysis, Mahmud [81] estimated the air pollutant emissions (e.g., particulates, carbon monoxide, non-methane hydrocarbons, nitrogen oxides, sulphur dioxides, and particulate matter) and greenhouse gases (e.g., carbon dioxide, methane, nitrous dioxide, and carbon). The author discovered that the estimated carbon dioxide emission was much higher than nitrous oxides or methane. Additional validation was recommended by the author to corroborate the estimation evaluated in their work.

To evaluate the area of peat swamp burned in 1998 for Klias Peninsula located in the State of Sabah, Phua et al. [83] applied the image differencing technique to Landsat imagery before the fire (2 October 1997) and after the fire (7 December 1999) by utilising three vegetation indexes, specifically the (i) normalised burn ratio, (ii) normalised difference water index, and (iii) normalised difference vegetation index. Among the three indices, image differencing in conjunction with a normalised burn ratio enabled the most accurate estimation of the burned area. Understanding the changes that happened in the peat swamp forests (i.e., reduction in peat swamp forest area) allowed the authors to conclude that better approaches can be devised to more effectively confront fires.

Ainuddin and Goh [84] investigated the impacts of forest fires on the forest structures in Raja Musa Forest Reserve, Selangor from September 2001 to June 2002. The study location was selected by the authors because it had encountered fires since 1996. They revealed that the composition of flora species and forest structure were greatly affected by the forest fire incidents. For instance, the tree diameters in the unburnt areas were larger (10.1–20.0 cm) than the trees from burnt areas (5.1–10.0 cm). On the contrary, a total of 22 plant species were found in the unburnt region, while only 10 plant species were identified in the burnt region.

Bin Suliman et al. [85] adopted the random spread model of Serra [86] to understand the propagation of forest fires in Selangor State from 2001 to 2004. To formulate the model, they utilised fuel and spread rate maps (i.e., Southeast Asia FDRS that built upon the Initial Spread Index and Buildup Index [54]) as the primary input parameters to the model. They tested the model, and it correctly predicted most of the burnt scars in the study location. In this model, the authors assumed that there were no human interactions involved to put out fires.

Sahani et al. [87] investigated the relationship between mortality rate and forest fire haze events in the Klang Valley region by utilising the daily concentration of particulate matter (PM_{10}) and daily mortality rate from 1 January 2000 to 31 December 2007 retrieved from the Department of Statistics, Malaysia. A total of 88 days were identified as haze days (i.e., PM_{10} concentration greater than 100 $\mu g/m^3$) in the seven studied years, and the root cause of 8.56% of natural mortality was recorded to be associated with respiratory mortality. They found that there was a significant relationship between haze and respiratory mortality, and a higher mortality rate was recorded due to exposure to haze. For instance, respiratory mortality was reported to be increasing for all males, elderly males, and adult females.

Fisal et al. [88] used a social science approach to study the forest fire awareness of the community in Klias Forest Reserves, Sabah. They highlighted that the community living near the vicinity of the forest were not fully equipped with the essential knowledge to prevent fires in the peat swamp forests. Such a lack of awareness may subsequently lead to forest fire incidents. However, positive feedback was acquired from the community to work together with authorities to prevent and extinguish forest fires.

Instead of estimating the emission of pollutants by using remote sensing information, as conducted by Mahmud [81], Smith et al. [89] performed an on-site study utilising open-path transform infrared spectroscopy to assess the pollutants discharged by peat swamp forest fires in Pekan Pahang in 2005 and North Selangor in 2006. The plumes (i.e., smoke) collected from the aforementioned technique were further analysed to measure the emission factors (i.e., concentration) for 12 gas types: carbon dioxide, carbon monoxide, methane, ammonia, acetic acid, hydrogen cyanide, methanol, ethylene, ethane, formaldehyde, formic acid, and acetylene. The authors presented the first study to explain the large variability of gases in each of the plumes. They recommended the emission factors discovered from this work to be used for future peat fire emission models as a reliable alternative to the results from earlier laboratory studies.

Musri et al. [90] presented the results of post-fire restoration and rehabilitation through a case study in Raja Musa Forest Reserve, Selangor. The studied location had been repeatedly affected by fire incidence in the past decades. In the post-fire restoration process, the authors found that the Selangor State Forestry Department rewetted the soil and raised the water level of the degraded peat swamp forest by installing a check dam, canal block, clay dyke, and high-density polyethylene pipe. Subsequently, over 250,000 saplings of pioneer tree species were planted from 2009 to 2014 in the rehabilitation site of Raja Musa Forest Reserve. With the raised in water level and the regeneration of new plants, the number of forest fire occurrences has been significantly lowered [90]. The authors also introduced four basic principles to manage peat swamp forests: (i) prevention (e.g., awareness campaign), (ii) preparedness (e.g., maintenance and installation of equipment), (iii) response (e.g., immediate action to suppress small fires), and (iv) recovery (e.g., restoration and rehabilitation efforts). Furthermore, the national strategies for fire management and rehabilitation of degraded peat swamps in Malaysia were also discussed by Parish, Lew and Mohd Hassan [91].

Instead of relying on human observations, Sali et al. [92] adopted an Internet of Things (IoT) approach to monitor the condition of the Raja Musa Forest Reserve, Selangor. By deploying an IoT monitoring system, real-time data including soil temperature, soil humidity, water level, wind speed, rain precipitation, ambient humidity, and ambient temperature information could be collected. In their studies, they collected and analysed data obtained from 2020 January to March 2020.

Table 3 summarises the research works associated with forest fires, excluding studies related to fire susceptibility mapping. In this subsection, several works that were closely associated with forest fire incidents are reviewed. While fire susceptibility mapping is one of the predominant research directions, we would like to highlight some of the distinct directions such as locating regions burnt by forest fires, analysing the pollutant emissions, and post-fire management.

Table 3. Summary of the efforts (excluding studies related to fire susceptibility mapping) associated with forest fires.

Year of Publication	References	Year of Studies	Location	Objective
2005	[81]	February to March of 2002	Peninsular Malaysia	Estimate the pollutant emissions from agricultural burning by employing emission equations. Utilise remote sensing data (i.e., number of hotspots) from NOAA AVHRR to provide necessary input parameters to the formula.
2007	[83]	1997 and 1999	Klias Peninsula, Sabah	Estimate the burned peat swamp region by comparing the pre-fire (1997) and post-fire (1999) Landsat satellite imagery by employing an image differencing technique utilising three vegetation indexes.
2010	[84]	2001–2002	Raja Musa Forest Reserve, Selangor	Study the impact of forest fire on the composition of species and forest structure for the peat swamp forest.
2010	[85]	2001–2004	Selangor	Adopt the random spread model of Serra [86] to predict the area burned by forest fire by understanding the propagation of forest fires by utilising spread rates and fuel maps as the input parameters to the model.
2014	[87]	2000–2007	Klang, Selangor	Investigate the relationship between mortality rate and haze events in Klang Valley by analysing the daily mortality rate in conjunction with the daily particulate matter (PM_{10}) concentration.
2017	[88]	-	Klias Forest Reserves, Sabah	Assess the awareness of the neighbourhood around Klias Forest Reserves for forest fire prevention. Authors discovered that the community lacks awareness but is willing to cooperate to prevent and extinguish forest fires.
2018	[89]	August 2015 and July 2016	Pekan, Pahang North Selangor	Measure the emission factors (i.e., the concentration of gaseous) from the plumes collected from the peatland fires through open-path transform infrared spectroscopy.
2020	[90]	-	Raja Musa Forest Reserve, Selangor	Focus on the discussion of post-fire management through a case study in Raja Musa Forest Reserve, Selangor. Describe the restoration and rehabilitation process of degraded peat swamp forests.
2021	[92]	January 2020–March 2020	Raja Musa Forest Reserve, Selangor	Adopt an IoT approach to collect real-time environmental variables for evaluating the condition of the peat forest.

2.4. Hotspot Locations in Malaysia Based on Previous Studies

A summary of the works in Malaysia from 1989 to 2021 categorised by each of the states is shown in Table 4. From the table, it can be seen that most of the studies were performed in three main states, which were Sabah (5 out of 26), Selangor (12 out of 26) and Pahang (6 out of 26). It should be noted that the tabulated information excludes all the works that focused on Peninsular Malaysia or the entirety of Malaysia. The hotspot locations based on historical fire incidents in Malaysia are described in Figure 1.

To further substantiate the severity of forest fires in the three states, we also searched through the local news reports in Malaysia. According to several reports, several fire incidents had also been recently reported in the selected three locations, i.e., Pekan, Pahang [16,93–96]; Selangor [12,13,97,98]; and Klias, Sabah [14,99,100]. Thus, the selected locations are postulated to be suitable for conducting experimental studies related to forest fires in the future.

Table 4. Previous studies conducted in Malaysia grouped by state.

State	Specific Location	Year of Studies	References	Total No. of Studies
Sabah	-	1983–1985	[21]	5
	-	1990–1995	[58]	
	-	2006–2010	[71]	
	Klias Peninsula	1997 and 1999	[83]	
	Klias Forest Reserves	-	[88]	
Sarawak	-	1997–1998	[9]	2
	-	1990–1995	[58]	
Pahang	Pekan	1997	[10]	6
	Pekan	1995–1999	[62]	
	Pekan	1998	[64]	
	-	-	[66]	
	Pekan	2014	[73]	
	Pekan	2015 August and 2016 July	[89]	
Selangor	Kuala Selangor	1999	[11]	12
	Sungai Karang and Raja Musa Forest Reserve	2000–2005	[51]	
	Raja Musa Forest Reserve	2001–2002	[84]	
	Raja Musa Forest Reserve	-	[90]	
	Raja Musa Forest Reserve	2020	[92]	
	Kuala Langat	-	[66]	
	Klang	2000–2007	[87]	
	Kuala Langat, North Selangor	August 2015 and July 2016	[89]	
	-	2001–2004	[85]	
	-	-	[68] [69]	
	-	1990–1995	[58]	
Kelantan	-	1990–1995	[58]	1

Figure 1. Hotspot locations based on historical fire information from previous studies.

2.5. Factors Affecting Forest Fire in Malaysia

Most of the forest fire incidents in Malaysia were speculated to be principally associated with human factors [9]. However, it was unclear whether the environmental variables (i.e., land cover, topography, and meteorology) could intensify fire tragedies. A comprehensive review of the general factors constituting forest fires was presented in [101]. A few of the factors that have been utilised in the past to generate a fire susceptibility model in Malaysia are as follows: land cover, meteorological variables (i.e., temperature and humidity), topology variables (i.e., digital elevation model, aspect, and slope), and human factors (i.e., distance to road and population).

Though there are various factors contributing to forest fires in Malaysia, a rigorous and thorough analysis has yet to be completed to date in the literature. To broaden the understanding of fire incidents, subsequent analyses utilising various sources of data are necessary. Hence, all the data that were exploited by the previous studies will be described in the next section. By combining or integrating results from the previous studies with presently available data and technologies, more works can be anticipated to expand the results presented in the current literature.

3. Type of Data Utilised for Forest Fire Risk Modelling in Malaysia

In this section, the types of data are categorised into two distinct groups: public data (i.e., satellite data) and Malaysia government-centric data. The primary purpose of this section is to provide an overview of the data that have been explored in Malaysia. To ease future researchers, the accessibility for each of the satellite data and government data are also described in Tables 5 and 6.

All the derived products and the satellite versions employed by the previous studies discussed earlier in this manuscript are summarised and tabulated in Table 5. According to the table, it is obvious that the derived products from the Landsat, MODIS, and AVHRR NOAA satellites have been widely exploited.

In addition to the satellite data, some of the Malaysian government data including topography, meteorological, and population information that have been adopted in the past are also shown in Table 6. However, it should be noted that most of the mentioned data are not publicly accessible. Users that desire to obtain and use the data may need to directly request them from each of the relevant departments, and most of the applications will be subject to the approval of the department directors.

From the presented summaries, it can be seen that only limited satellite data have been applied to the task of forest fire detection in Malaysia. Following the work of previous researchers, future researchers that plan to perform similar studies in Malaysia can consider adopting Sentinel-1 Synthetic Aperture Radar [102] and Sentinel-2 imagery [103] to develop advanced fire models.

Table 5. Summary of remote sensing data utilised by previous studies in Malaysia and their accessibility.

Derived Product	Satellite Version/ Data Source	Previous Application	Accessibility
Land Cover or Fuel Type Normalized Burn Ratio (NBR) Normalized Difference Water Index (NDWI) Normalized Vegetation Index (NDVI)	Landsat Thematic Mapper (TM)—version not mentioned	[10,64,85]	Public [104] access from USGS Earth Explorer)
	Landsat-5 TM	[11,83]	
	Landsat-7 ETM	[51,68,69,83,105]	
	Landsat 8	[73]	
Land Cover (classified) for Malaysia and Indonesia	Landsat 7 Enhanced Thematic Mapper (ETM) and Landsat 8 Operational Land Imager (OLI) [78,106]	[67]	Private (The classified land cover is not available publicly)
Precipitable Water Vapor for Relative Humidity	MODIS Level-1 (MACRES)	[48]	Public [107–109]
Land Surface Temperature Surface Air Temperature for Relative Humidity Precipitable Water for Relative Humidity	MODIS Level-2	[61]	Public [110,111]
MODIS MCD14ML Collection 5 Active Fire (hotspots)	NASA's Fire Information for Resource Management System	[67,71,74]	Public [112]
Land Surface Temperature	-	[52]	Public [113]
World Fire Atlas (hotspots)	-	[45,70]	Public [114]
Historical Forest Fire Data (hotspots)	AVHRR NOAA (not specified)	[64,81,85]	Public [115]
	AVHRR NOAA 12	[51,61,105]	
	AVHRR NOAA 16	[51,61,105]	
Application of Wildfire Biomass Burning Algorithm (Hotspots)	-	[67]	Public [116]

Table 6. Summary of Malaysia government data utilised by previous studies in Malaysia and their accessibility.

Type of Data	Derived Product	Data Source	Previous Application	Accessibility
Topography	Contour Administrative Boundaries Water Resources Settlement Transportation Infrastructure	Department of National Mapping and Survey (JUPEM)	[51,61,105]	Private (apply and pay) [117] Price List [118]
	Digital Contours Digital Elevation Model Slope Gradient Slope Aspect		[11]	
	Aspect Elevation Slope	Not Mentioned	[10]	-
-	Hotspots Prone Area Fire Occurrence Map Peat Swamp Map Soil Map	Malaysia Centre of Remote Sensing (MACRES) Known as Malaysia Space Agency (since 2019)	[51,61,105]	Private (apply and pay) [119] Price list [120] Local students/universities may request some data for free for research and educational purposes [119] Raw format of the relevant data (MODIS, NOAA, LANDSAT TM, and SPOT 1–5) can be obtained from Public MYSA archive data [121]

Table 6. *Cont.*

Type of Data	Derived Product	Data Source	Previous Application	Accessibility
Population Data	Population Data Socio-economic Data	Department of Statistics Malaysia	[51,105]	Public/Available Data [122,123] Additional data requests can be sent to the Director of the Department of Statistics Malaysia
Meteorological Data	Temperature Relative Humidity Fire Danger Rating System (FDRS)	Malaysian Meteorological Services Department	[11,51,54,61,105]	Only the future 7-day forecasted weather data were made available in the official portal [124].
	Daily Air Temperature Total Daily Rainfall	Malaysian Meteorological Services Department	[58]	Archive data not available; contact Malaysia Meteorological department to request [125]
Daily Weather Data	Temperature Relative Humidity Wind Speed	National Climatic Data Center	[45]	Public [126]
-	Land-use/cover maps	Department of Forestry and Department of Agriculture	[11]	Private (apply and pay) [127]
-	Record of Past Fire Occurrences/Forest Fire Reports	Forestry Department of Peninsular Malaysia (JPSM)	[11,51,61,105]	Not Available
An initiative by National Geospatial Centre Malaysia (G2G) [128]	Malaysia Government Unit/Local Public University in Malaysia can apply for free	National Geospatial Centre Malaysia	-	Private (requests can be sent to Malaysia Government Body and Malaysia Public University only) [128]

3.1. *Discussion on the Application of Data for Forest Fire Detection*

Though some satellite data, such as those of Landsat and Sentinel-2, have been made freely available to the public [27], some of them (e.g., Sentinel-2) have yet to be adopted for the task of detecting forest fires in Malaysia. With the use of vast computing resources and data, machine learning classification techniques such as logistic regression, decision trees, support vector machines, and deep learning can be incorporated to improve the performance of forest fire detection in Malaysia [23,24].

Big Data Platform for Satellite Data

Gomes et al. [27] defined big data platforms as "computational solutions that provide functionalities for big Earth Observation (EO) data management, storage and access, which allow the processing on the server side without having to download big amounts of EO data sets". Motivated by the advancement of technologies and the adoption of open data policies supported by government and space agencies, an extensive amount of geospatial data (i.e., Earth observation data) produced from Earth observation satellites have been increasingly made freely available to researchers and societies in the past decades. For instance, approximately 5 petabytes (~equivalent to 5000 terabytes) of open data were generated from Landsat-7, Landsat-8, MODIS, Sentinel-1, Sentinel-2, and Sentinel-3 in 2019 [129]. The datasets' tremendous volume makes it challenging to store, distribute, process, and analyse them using traditional approaches. Thus, several big data platforms for EO data have been developed, e.g., Google Earth Engine [29], Open Data Cube [28], JEODPP [129], OpenEO [130], pipsCloud [131], System for Earth Observation Data Access, Processing and Analysing for Land Monitoring (SEPAL) [132], and Sentihub Hub [133]. A comprehensive review for each of the platforms was performed in [27]. It should be noted that most of the acquisition methods performed by the researchers in Section 2 focused on the individual file of geospatial data distribution through web services and portals (i.e., http or ftp).

Apart from the mentioned platforms, Microsoft also recently released its variation of a big data platform for satellite data called Planetary Computer [30]. It is worth noting that at the point of writing this manuscript, Planetary Computer also provides a hub that supplies computational resources with several options for the development environment; the five distinct options are: (i) Python environment with 4-core CPU and 32 GB of RAM; (ii) R environment with 8-core CPU and 64 GB of RAM; (iii) PyTorch environment with 4-core CPU, 28 GB of RAM and T4 GPU; (iv) TensorFlow environment with 4-core CPU, 28 GB of RAM, and T4 GPU; and (v) QGIS environment with 4-core CPU and 32 GB of RAM. To gain access to the platforms, users are required to fill in the application form provided on the Planetary Computer home page.

Considering that big EO data platforms permit some of the computational processing to be performed on the server side, future researchers should consider employing big data platforms to alleviate some processing resources from the client side. In addition, the complicated data access procedure described in our previous work [134] can be eased by utilising the big data platforms. This is made possible by the ability of most big data platforms to access publicly available datasets through their data catalogues and APIs.

4. Global View of Machine Learning and Forest Fire

From the literature reviewed in Section 2, it can be clearly recognised that the application of machine learning has not been extended to the domain of forest fires in Malaysia. However, utilising machine learning techniques in aiding forest fire detection, analysis, and prediction is not new [23,24,135–138], and these techniques have been successfully adopted in many other countries as they have been gaining more attention in recent years. Hence, this is probably a potential research direction to be delved into in the near future.

Although traditional fire detection systems such as the CFFDRS [45], FDRS [54], and Slovenia Environment Agency fire detection system [139] have been proven to be very feasible for the task of fire detection, it is plausible to improve their detection and prediction abilities by building machine learning models with a fire database containing the historical fire occurrences and all contributing factors of forest fires.

Bui et al. [140] examined forest fire susceptibility through a hybrid artificial intelligent approach that combined the usage of a neural fuzzy inference system (NF) and particle swarm optimization (PSO) in Vietnam. This hybrid approach was named Particle Swarm Optimized Neural Fuzzy (PSO-NF). The spatial information of tropical forest fire susceptibility was extracted and modelled with the adoption of PSO-NF. The forest fire model was retrieved from NF, and the best parameter values were selected through the PSO. The authors created a GIS forest fire database based on 10 factors associated with forest fires, i.e., slope, aspect, elevation, land use, NDVI, distance to road, distance to residence area, temperature, wind speed, and rainfall. Most of the factors were derived from the Landsat-8 remote sensing data, and the climatic data (i.e., temperature, wind speed and rainfall) were extracted from the National Climatic Data Center (NDCC) [126]. They also compared their proposed algorithm (PSO-NF) with random forest and support vector machine algorithms, and the classification accuracy attained by the PSO-NF (85.8%) surpassed the other two notable classifiers (85.2% and 84.9%, respectively). Later, Bui et al. [141] proposed a new hybrid methodology by amalgamating Multivariate Adaptive Regression Splines (MARS) and Differential Flower Pollination (DFP) into a new methodology named MARS-DFP. DFP was appended to the MARS as a feature extractor to retrieve the spatial patterns of forest fire severity. The proposed algorithm attained a classification accuracy of 86.57%.

Fire kernel density was utilised to detect forest fires by Monjarás-Vega et al. [142], who extracted the spatial patterns of fire occurrence at the regional and national levels in Mexico by utilising geographically weighted regression (GWR) to predict fire density. The fire kernel density was calculated by using two different approaches, which are regular grid density and kernel density, over spatial resolutions ranging from 5 to 50 km on both the dependent and the independent variables captured from human and environmental candidates.

The element of forest fire susceptibility was also exploited by Moayedi et al. [143] in a high fire-prone region in Iran. An ensemble fuzzy method was proposed by aggregating the results retrieved from an adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), PSO, and differential evolution (DE) evolutionary algorithms. The GIS forest fire database was built based on 15 ignition factors, i.e., elevation, slope aspect, wind speed, plan curvature, soil type, temperature, distance to river, distance from road, distance from village, land use, slope degree, rainfall, topographic wetness index, evaporation, and NDVI. It should be noted that the authors did not specify the source for each of the mentioned factors. The best performance results were attained by ANFIS-GA, with which the area under receiver operating characteristics (AUROC) was calculated as 0.8503 and the mean squared error (MSE) was calculated as 0.1638.

Instead of predicting forest fire incidents akin to many other works, Sevinc et al. [144] sought to predict the probability of an event that triggered a forest fire by utilising a Bayesian network model. The primary motivation of the authors was to investigate the reason behind each forest fire incident, as the probable causes for almost 54% of forest fires were disclosed to be unknown in the location of study. The empirical testing was conducted in the Mugla Regional Directorate of Forestry area located southwest of Turkey. To assemble the Bayesian network model for each of the causes of fire occurrence, the authors incorporated wind speed, month, distance from settlement, amount of burnt area, relative humidity, temperature, distance from agricultural land, distance from road, and tree species. Sevinc et al. [144] reported an AUC score of 0.91 for hunting, indicating that hunting is the most plausible ignition factor for forest fires that happened between 2008 and 2018.

Table 7 summarises the related works discussed in this section. A thorough review associated with machine learning techniques in the task of forest fire detection or prediction as presented in [23,24].

Table 7. Summary of general machine learning classification techniques used for forest fire detection tasks.

Year of Publication	Reference	Year of Studies	Dataset	Objective
2017	[140]	Lam Dong, Vietnam	GIS database built based on the 10 factors associated with forest fires	To investigate forest fire susceptibility through the combined usage of neural fuzzy inference system (NF) and particle swarm optimization (PSO).
2019	[141]	Lam Dong, Vietnam	GIS database built based on the 10 factors associated with forest fire	To produce a forest fire susceptibility map through a hybrid methodology by combining Multivariate Adaptive Regression Splines (MARS) and Differential Flower Pollination (DFP).
2020	[142]	Mexico	GIS database built based on the 16 factors associated with forest fires	To adopt geographically weighted regression (GWR) to predict fire density.
2020	[143]	Iran	GIS point database utilising 15 forest fire factors	To segregate the location into different fire-prone risks by combining adaptive neuro-fuzzy inference system (ANFIS) with the genetic algorithm (GA), particle swarm optimisation (PSO), or differential evolution (DE).
2020	[144]	Turkey	Table data including fire causes and 9 ignition factors	To investigate the probable causes for the fires by building Bayesian networks for each fire cause along with the ignition factors.

Deep Learning and Forest Fire

Deep learning techniques, which are gaining popularity in recent years, have also been adopted to improve the models in the forest fire domain. Due to their success in the field of image processing and handling spatial information [145], researchers from the fire domain have also exploited similar techniques by utilising satellite remote sensing data, satellite imageries, unmanned aerial vehicle (UAV) images (e.g., drone), and surveillance camera footage.

Zhang et al. [146] proposed a deep convolutional neural network (CNN) to automatically annotate the fire regions in an image by using bounding boxes. To improve the fire patch localisation annotation, the authors designed a two-level (cascaded) CNN where the first CNN model was trained with the full image to identify whether the image contained at least one fire patch and the second CNN model was trained with the fire patches to accurately locate the fire regions in the image. A total of 25 videos from a fire detection dataset [147] were utilised to build their dataset. The authors then extracted one image from every five frames and resized them to 240×320, followed by the manual annotations of fire boundaries with 32×32 bounding boxes. A subset of the data comprising 178 training images (12,460 patches) and 59 testing images (4130 patches) was used to evaluate the CNN models. A comparison of the performance of the proposed CNN against the support vector machine linear classifier showed that the CNN achieved a detection accuracy of 90.1% and the support vector machine only achieved a detection accuracy of 89% on the testing dataset.

A fine-tuned CNN trained with a CCTV surveillance camera containing 68,457 images was devised by Muhammad, Ahmad and Baik [148]. The proposed algorithm was able to detect fire in images with distinct indoor and outdoor environments. The authors emphasised that the model could process 17 frames/s, and the performance of the model in terms of precision, recall, and f-measure were recorded at 0.82, 0.98, and 0.89, respectively.

Hodges and Lattimer [149] presented a Deep Convolutional Inverse Graphic Network (DCIGN) that combined both CNN and transpose convolutional layers to estimate the spread of wildfires after ignition from 6 h to 24 h. The authors exploited 13 fire attributes, such as aspect, fuel model, slope, moisture, and canopy height, to train the model. A precision of 0.97, sensitivity of 0.92, and f-measure of 0.93 were found when using the proposed technique.

An AlexNet CNN model with modified adaptive pooling combined with traditional image processing was proposed by Wang et al. [150] to automatically locate fire pixels from images obtained from the Corsica Fire Database. The authors stated that the present studies only applied CNN directly to the fire images without considering colour features. Thus, they segregated the fire regions in the images by utilising the colour features before training the CNN model. Subsequently, the best classification accuracy of 90.7% was reported by the authors when they trained and evaluated the model using only the segmented images instead of the full original images.

Zhang et al. [151] adopted 14 influencing fire factors—elevation, slope, aspect, average temperature, average precipitation, surface roughness, average wind speed, maximum temperature, specific humidity, precipitation rate, forest coverage ratio, NDVI, distance to roads, and distance to rivers—to train a CNN algorithm to forecast a spatial prediction map. Data from 2002 to 2010 collected from the Yunnan Province of China were used in the study. The authors also applied feature selection techniques such as multicollinearity analysis and information gain ratio to evaluate the importance of each fire attribute. Additionally, an oversampling technique was employed to resolve the issue of the imbalance class while proportional stratified sampling was also utilised to fairly compare the performance of the CNN with other benchmark classifiers such as random forest, support vector machine, multi-layer perceptron (MLP), and kernel logistic regression. The authors reported that a high AUC of 0.86 was attained by the proposed CNN.

To benefit from the real-time aerial images captured from UAVs, a low-power CNN deep learning algorithm based on YOLOv3 was devised by Jiao et al. [152] to improve the accuracy and speed of detection. The authors utilised the UAVs' internal computing resources to determine whether any fire pixels were detected from studied footage. They justified that the transmission of a large amount of data from the UAVs to the cloud services was not feasible. At the same time, contents in the videos or images may be susceptible to privacy issues. To resolve these concerns, only the results (i.e., fire or no fire detected) were sent from the UAVs to the cloud services. It should be highlighted that the YOLOv3 model was trained on a desktop computer before embedding it onto the UAVs for evaluation and testing purposes. A precision of 0.82, recall of 0.79, and f1-score of 0.81 were achieved by the proposed model.

Ban et al. [102] proposed a deep learning framework based on a CNN to automatically identify burnt regions by training the model with the Sentinel-1 Synthetic Aperture Radar (SAR) images. The experiments were conducted based on two fire incidents in Canada and one fire incident in America. The authors emphasised the feasibility of SAR images in wildfire monitoring as SAR is an active sensor that can produce microwave signals and receive the returned signals (i.e., backscattered). In other words, SAR does not need to rely on the availability of sunlight, so it can capture all images during the day and night-time. By training the CNN model with SAR images containing the VV and VH polarisation, the model was able to detect the progression of wildfires in all three of the study locations. When comparing the proposed CNN against the traditional log-ratio method, Ban et al. [102] reported a considerable improvement in terms of the Kappa metrics, which were improved by 0.11, 0.27, and 0.30 for the three respective incidents.

Similar to the work of Jiao et al. [152], Wang et al. [153] developed a lightweight YOLO and MobileNetv3 integrated with a pruned network and knowledge distillation process to improve the speed and accuracy of real-time detection on a UAV. They pretrained their models with the MSCOCO dataset before training the models utilising a fire dataset. A total of 1069 fire and 775 non-fire images were supplied to allow the model to learn the characteristics of fire regions. The proposed model was able to achieve a recall of 98.41%, precision of 88.57%, and accuracy of 96.11%. While the performance of the proposed model was on par with other baseline models, the authors emphasised that the proposed technique was able to reduce the inference (i.e., testing) time required from 153.8 ms (YOLOv4 model) to 37.4 ms (proposed model). This was enabled by tremendous reductions in model parameters resulting in an approximate 95.87% inference time reduction compared with the YOLOv4 model.

Table 8 summarises all the deep learning algorithms adopted in the forest fire domain. Among the eight pieces of literature reviewed in this section, five studies utilised images from UAV or CCTV to perform image recognition and three studies exploited the availability of remote sensing information to perform relevant fire detection tasks.

Table 8. Summary of deep learning techniques in forest fire detection tasks.

Year of Publication	Reference	Dataset	Objective	Algorithm
2016	[146]	Image: unmanned aerial vehicle (UAV)	Establish computer vision/image recognition	Full image and fine-grained patch fire classifier with deep convolutional neural networks (CNNs)
2018	[148]	Image: CCTV surveillance camera	Establish computer vision/image recognition	Fine-tuned CNN
2019	[149]	Remote sensing data consists of 13 fire-influencing attributes	Estimate the spread of wildfires	Deep Convolutional Inverse Graphic Network (DGIGN)—Deep CNN and transport CNN
2019	[150]	Image: Corsica Fire Database	Establish computer vision/image recognition	Conventional image processing, AlexNet CNN, and modified adaptive pooling
2019	[151]	Remote sensing data containing 14 fire-influencing factors	Classify fire pixels	Feature selection: multicollinearity analysis/information gain ratio and CNN
2019	[152]	Image: UAV	Establish computer vision/image recognition (real-time)	Low-power YOLOv3 CNN
2020	[102]	Satellite Image: SAR Image (Sentinel-1 Synthetic Aperture Radar)	Establish automatic burnt region detection	CNN
2021	[153]	Image: UAV	Establish computer vision/image recognition	Lightweight YOLO and MobileNetV3 with pruned network and knowledge distillation

5. Challenges and Future Direction of Forest Fire Efforts in Malaysia

To exploit the potential of machine learning for the task of forest fire detection in Malaysia, the first necessary step is to collect remote sensing data and any other ground data. However, there are various challenges involved in the data acquisition process. Though there are a tremendous amount of remote sensing data available, it remains challenging to collect and utilise them effectively to produce significant research results. Additionally, data from the Malaysian government may be restricted to their department's internal usage. An additional manual application is mandatory to obtain access to some data (e.g., historical forest fire data). In a situation when the historical forest fire data cannot be obtained from the government department, researchers need to perform data validation of the fire location and fire occurrence time through other approaches (e.g., satellite imagery validation and newspaper validation). Data validation is vital because the performance of a model greatly relies on the precision of annotated data labels.

As the works related to understanding the factors of fire occurrence in Malaysia remain limited, it is crucial to study the attributes of forest fires by correlating the fire incidents with various remote sensing data and ground data. Subsequently, machine learning or deep learning algorithms can be adopted by utilising all remote sensing data and ground data collected to either predict fire pixels on spatial maps or to forecast future spatial fire maps. Alternatively, researchers can also consider tackling the issue of forest fires from the perspective of optical sensors (e.g., digital camera and UAV) [32,33], wireless sensor networks [154–156], or satellite imagery fire pixel classification [102].

It is also worth pointing out that several researchers have identified that most intense forest fires have arisen in peat swamp forests [8,35,85]. They have highlighted that fires in peat swamp forests cannot be easily detected as they unnoticeably spread through the underground. Thus, investigating the factors of forest fires in peat swamp forests is definitely a worthy future research direction.

Open Research Questions

Based on the reviewed literature, we formulated four research questions for future studies to address, which will be further discussed in the following paragraphs.

Research Question #1: What are the influencing factors of forest fires in Malaysia? To understand the elements constituting forest fires in Malaysia, it is necessary to perform a thorough investigation of the historical forest fire incidents by utilising remote sensing data. Though several similar studies have been performed in Central Kalimantan, the Mediterranean region of Europe, and the North America continent [157–159], it is still extremely vital to perform this type of analysis to examine the local influencing factors of each fire occurrence because the factors contributing to fires may vary depending on location since each region is influenced by distinct climates, temperatures, weather, local fuels, topography, etc. [25].

Research Question #2: How can remote sensing data (i.e., satellite data) be used to build a machine learning model in Malaysia for the task of forest fire detection? Unlike any other field of study, a general machine modelling technique cannot be deployed in the task of forest fire detection because of the variation in training data collected from different regions [26,138]. In other words, it is not feasible to build a fire model by using the data attained from a region in Australia and subsequently implement it in the country of Malaysia since fires might be affected by different factors. Thus, the analysis results following Research Question #1 can be further exploited to build a forest fire dataset specifically for the country of Malaysia. Once the dataset has been established, a few machine classifiers can then be employed to evaluate its usability (i.e., utility).

Research Question #3: Can forest fire incidents be identified earlier to prevent disastrous fire tragedies? Once the model from Research Question #2 has been devised, it is feasible to forecast the risk or the occurrence of fires at certain locations by utilising the forecasted data (e.g., wind speed and land surface temperature) from satellites or meteorology stations to the machine model. For a forecasted fire region, analysts or domain experts can further analyse the fire factors and undertake appropriate measures to prevent fire incident. For example, peat swamp fires tend to be triggered in prolonged drought scenarios [8]. Ideally, if the detected land surface temperature and drought level are relatively high, authorities can then increase the water table level of the peat swamp region to prevent fire incidents [160]. To aid the task of factor analysis, we recommend exploring the use of fuzzy cognitive maps [161] or Bayesian networks for discovering the causal relationships between each factor and fire occurrence. Based on the relationship presented by the model, analysts and domain experts can certainly gain a more in-depth understanding of fire occurrence.

Research Question #4: Can the models and experiments be made reproducible and scalable to a global level? In past works related to forest fires in Malaysia, researchers have been required to access and pre-process satellite data before importing them into GIS software to perform further analysis. The inconsistency of the pre-processing and analysis steps may hinder the experiments' potential to be reproduced and scaled. With the availability of a big data platform for EO data, researchers can seamlessly access satellite data to perform their analysis. Since the same datasets are exploited by researchers, experiments can be easily reproduced through code sharing. To accommodate the model on a global scale, some platforms would just require simple tweaks to their code. For instance, Open Data Cube [28], which is an open-source software, can be used if the local computing resources can accommodate the analysis task. However, in a scenario with a lack of computing resources, the Google Earth Engine [29] and Planetary Computer [30] platforms can be exploited to alleviate the local computing resources as some of the heavy processing can be performed on their servers.

6. Proposed General Methodology to Utilise Remote Sensing Data for Forest Fire Efforts in Malaysia

The proposed methodology to utilise remote sensing data for forest fire efforts is succinctly deliberated in this section as a solution proposed to address the arising research questions described in Section 5. Figure 2 presents the general flow of the overall works that can be undertaken in the future. Each of the steps numbered in the figure will be elaborated to offer a better insight into the proposed research methodology. It is postulated that the proposed methodology can also be applied to other locations or countries, as well as other research problems in the geoscience domain.

Step 1: Data Discovery. Firstly, the study locations must be selected in this phase. The preferred locations are forests that have dealt with fire incidents in the past. Based on the historical fire incidence data provided in Table 4, (i) Pekan, Pahang; (ii) Raja Musa Forest Reserve, Selangor; and (iii) Klias, Sabah are the most suitable locations to be studied and investigated. To obtain the necessary information (i.e., statistics, area burnt, and location of forest fire) related to the selected locations, a request can be sent to the Forestry Department of Peninsular Malaysia (JPSM) for Peninsular Malaysia or Sabah Forestry Department for the state of Sabah. In the absence of historical fire incident information from government departments, MODIS active fire product hotspots [112] can be substituted as historical fire spots. It should be noted that the hotspots from MODIS have been exploited in several works related to a forest fire in the literature [159,162,163].

Step 2: Remote Sensing Data Extraction. Once the locations and historical fire incidents or hotspots have been identified, a big data platform for satellite data or direct access from a data provider (e.g., NASA) can be utilised to access and extract all the relevant remote sensing data from various satellite sensors. For instance, slope, aspect, elevation, land cover, land surface temperature, and sea surface temperature can be obtained or derived from extracted data. It should be remarked that some of the information might be required to undergo further processing procedures before it can be utilised to build the forest fire dataset. The utilisation of big data platforms such as Open Data Cube [28], Google Earth Engine [29], and Planetary Computer [30] will undoubtedly facilitate and improve the process of satellite data acquisition.

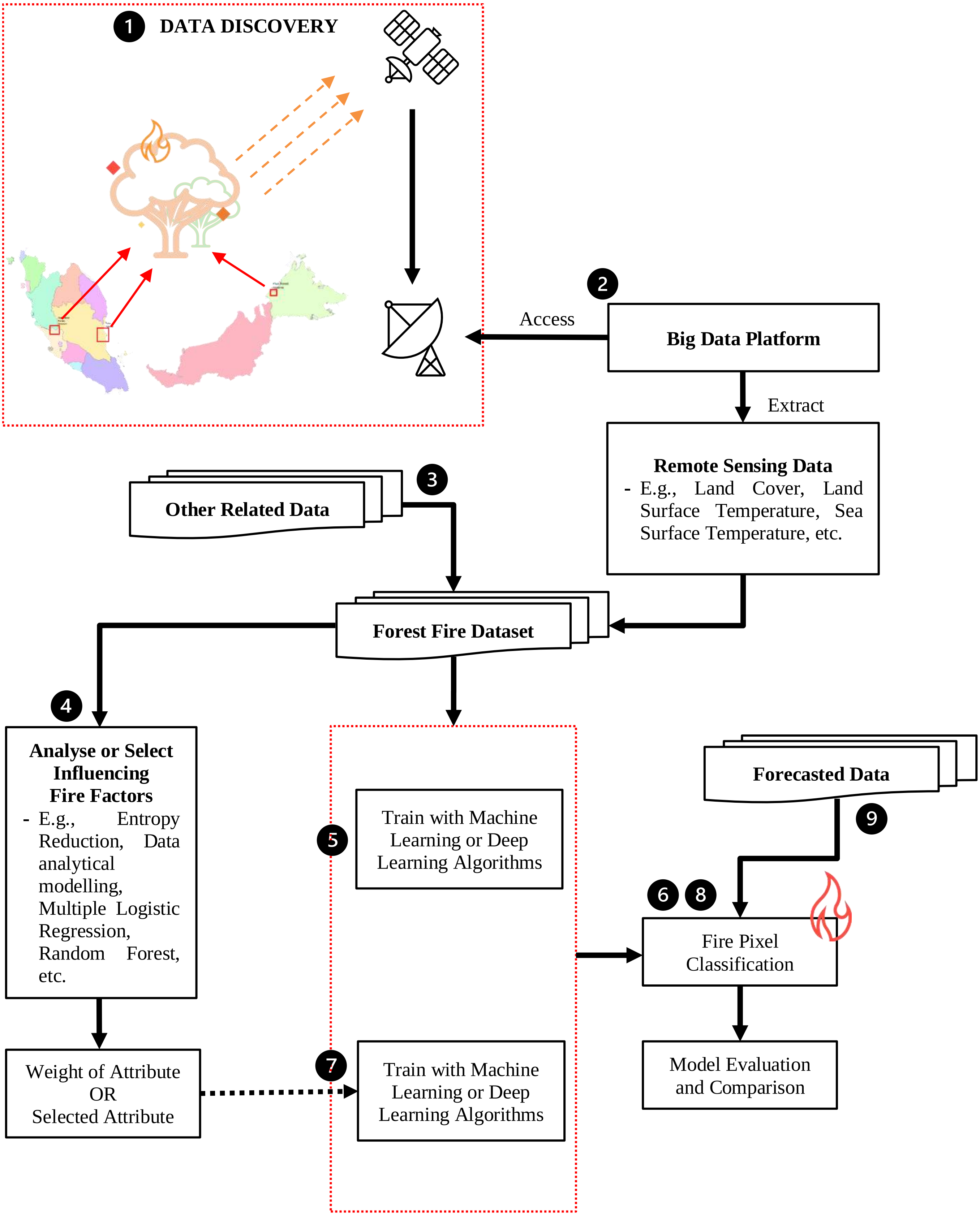

Figure 2. Proposed general methodology.

Step 3: Forest Fire Datasets Establishment. In addition to the remote sensing data mentioned in Step 2, other related data such as distance to road, distance to residential area, distance to river, population density, and socioeconomic information can also be assimilated as the influencing factors to create the forest fire dataset. Some of these data can be obtained or accessed from the Malaysia government portal, as described in Table 6.

Step 4: Feature Analysis and Selection. After building the forest fire datasets, statistical analysis can then be exploited to assess the relationship between each attribute and forest fire incident. Some of the works in the literature adopted entropy reduction [144] and data analytical modelling in GIS [159] to discover the most significant influencing forest fire factors. Once the importance of each attribute has been evaluated, the metrics can be fine-tuned as the weight of each attribute and subsequently supplied to the machine classifiers. On the other hand, feature selection techniques through machine classifiers such as multiple logistic regression [157] and random forest [157] have also been carried out by researchers to select the primary affecting attributes to build their models.

Steps 5 and 6: Machine Learning Training and Evaluation without Attribute Weighting and Feature Selection. Machine learning classification models (e.g., random forest, support vector machine, and decision tree) or other deep learning models can then be adopted to build the model using the forest fire datasets. Once the models have been trained, they can then be used as predictors to measure the likelihood of a certain pixel being a fire pixel or a normal pixel.

Steps 7 and 8: Machine Learning Training and Evaluation with Attribute Weighting and Feature Selection. To assess the impacts of attribute weighting or feature selection obtained in Step 4, a similar experimental procedure as described in Steps 5 and 6 can be repeated by incorporating the weighted attributes or only the selected features to build the model. Some evaluation metrics (e.g., classification accuracy) can then be used to evaluate the improvement or degradation effects resulting from the application of attribute weighting or feature selection.

Step 9: Forecasting Future Fire Incidence. Generally, three methods can be used to predict future fire incidents; the first strategy requires the forecasted data from satellite or weather station to be extracted and supplied as the testing data. For example, the next seven days of meteorological data (e.g., rainfall, temperature, and wind speed) can be provided to the trained models in Step 5 or 7 to foresee whether the location will be identified as a fire-prone pixel. On the other hand, advanced analysis techniques such as trend analysis or hotspot analysis schemes can be employed to visualise and forecast the future trends of fires. Alternatively, fuzzy cognitive mapping models can be exploited to uncover the causal relationships between the factors and fire incidents.

7. Forest Fire Benchmark Datasets

In the machine learning community, a benchmark dataset representing a real-world data science problem is commonly utilised to discover the best solution for a specific problem by measuring the performance of different machine learning models [164]. Generally, a classifier trained by tabular data (e.g., breast cancer [165]) or images (e.g., ImageNet [166]) can be used to perform prediction tasks. Unlike the typical machine learning field, the general geoscience domain must deal with a tremendous volume of remote sensing data to create a benchmark dataset. Before building such a dataset, it is also necessary to study the relevant factors contributing to the problem to extract the relevant attributes. For instance, land-cover types, temperature, humidity, and digital elevation models are some of the critical factors in forest fire occurrence based on previous studies, e.g., by Ganteaume et al. [101]. Additionally, the use of validation data from previous field studies (i.e., verifying forest fire locations from a field study) is also essential to enhance the credibility of a dataset. Furthermore, a prediction task in the geoscience domain can span from the present to several minutes, months, or even years.

Though it is not an easy task to create a benchmark dataset, particularly in the geoscience domain, several weather and climate benchmark datasets have been created and are directly accessible from http://mldata.pangeo.io/ (accessed on 10 August 2022). For example, the WeatherBench [167] benchmark dataset can be exploited with a machine learning algorithm to forecast 3–5 days of global weather patterns. Presently, there are only two publicly accessible forest fire datasets [135,168]. Cortez and Morais [135] focused on the regression problem to predict the burnt area regions in Portugal by exploiting 13 attributes and 517 instances, while Sayad et al. [168] attempted to classify fire and non-fire pixels in Canada by utilising three influencing attributes and a total of 1713 instances. Both of the datasets only utilised a small number of attributes and instances. Referring to the geoscience benchmark dataset criteria set forth by Dueben et al. [164], it can be concluded that no standard benchmark dataset for a forest fire is publicly available to date. Hence, we recommend utilising a big data platform in conjunction with the benchmark dataset guidelines as described by Dueben et al. [164] to create a forest fire benchmark dataset, starting from the country of Malaysia.

Forest Fire Validation Data

As mentioned earlier in Section 5, historical forest fire data can be requested from local government agencies. In a scenario in which such data cannot be obtained, the validation of the fire scene can be rendered with satellite imagery or newspaper articles. Alternatively, post-fire burned area products from the Copernicus Emergency Management Service (EMS) [169] and European Forest Fire Information System (EFFIS) [170] can also be exploited to validate fire activity data. However, these products do not contain any record of fire activity in the country of Malaysia. Therefore, satellite-based, post-fire burned products such as FireCGI51 [171] or MCD64A1 [172,173] can be substituted to recognise burnt areas and to perform the validation of fire incident data.

8. Overview of Forest Fire Detection and Monitoring

Traditionally, human-based observation, either from the public or patrol staff, was utilised to discover the occurrence of forest fires. However, such an approach is not feasible in the sense that the fire incidents will only be reported once they are visible. Additionally, the surveillance time is limited to a certain period of the day. Thus, optical sensors such as digital camera surveillance systems are designed to replace human observation. Though digital cameras can effectively detect fires with a low number of false alarms, the deployment of such systems is very expensive as it requires communication infrastructure and a camera tower to establish them. Recently, UAV vision-based system detection has also been developed by several authors [33]. It should be noted that most optical sensor approaches require image processing techniques, along with machine learning or deep learning algorithms, to determine whether a fire occurs in an image.

Alternatively, several works based on wireless sensor networks have also been developed to detect the occurrence of a fire before it is triggered [154–156]. Generally, a sensor will collect and analyse parameters such as pressure, humidity, temperature, carbon dioxide, and nitrogen dioxide to determine the presence of a fire. A detailed survey of the variation of fire detection techniques was presented in [32,174].

On the other hand, satellite-based systems such as AVHRR or VIIRS [115] and MODIS Active Fire Products [112] have been employed to determine the potential fire hotspots. The primary disadvantage of this mechanism is its inability to detect a fire in real time because the detection of a location is based on the cycle time of a satellite to return to the same location. With the advancement of technology, one recent research study was focused on uncovering the burnt area from a forest fire by performing deep learning image classification from SAR images [102]. To draw out the strength of the satellite remote sensing data, researchers have also exploited remote sensing data to forecast fire maps [151]. The availability of the public and an enormous amount of remote sensing data [27] have undoubtedly motivated researchers to utilise them in various applications. We refer to [23,24] for reviews of the application of machine learning to build forest fire prediction and detection systems. Figure 3 provides a general overview of forest fire detection and monitoring technology.

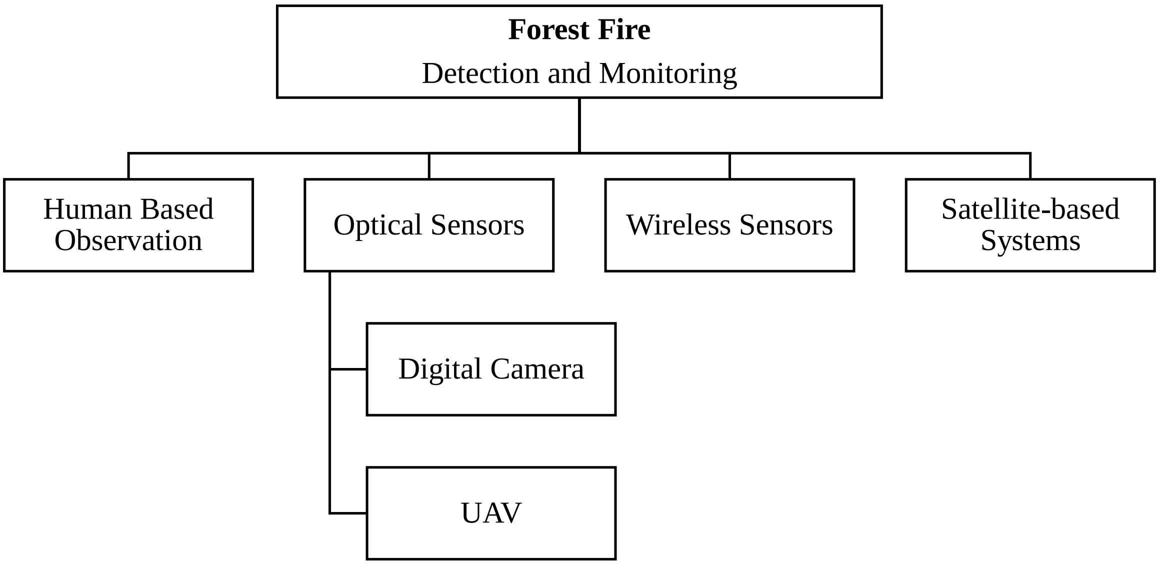

Figure 3. Overview of forest fire detection and monitoring technology.

9. Other Relevant Studies Commonly Employed in Forest Fire Domain

In contrast to all the works presented in this manuscript, several research fields related to fire spread models commonly employed around the world have also yet to be adopted in Malaysia. Some of these include physical-based models [175,176], computational fluid dynamics (CFD) models [177–179], geometrical models [180,181], and cellular automata models [182–184]. The fundamentals of a physical model involve the chemistry and/or physics of combustion to simulate fire spread [175]. For example, Koo et al. [176] simulated fire spread activity by utilising the concepts of energy conversation and heat transfer. From their experiments, they discovered that wind and slope attributes were some influencing factors. The advancement of computational power has encouraged the usage of physical models exploiting the computational model to predict the spread of fire [178]. For instance, William et al. [179] utilised CFD to solve a three-dimensional time-dependant equation considering fluid motion, combustion, and heat transfer in order to develop the Wildland Fire Dynamic Simulator. Geometrical modelling is focussed on the application of physical, mathematical and/or computational methods to study the geometry (i.e., shape) of a flame in different scenarios. To illustrate, Lin et al. [180] studied flame geometry in terms of horizontal flame length, vertical flame height, flame base drag, and flame tilt angle in an experiment utilising propane as fuel for four distinct dimensions of gaseous burners with varying air speed (i.e., wind speed) conditions. A cellular automata model is a local grid-based stochastic modelling technique [183]. For example, such a model will split an entire forest into multiple smaller cells, and each cell changes state (e.g., no fuel, contain fuel but not burning, burning, and burnt) depending on the state of the neighbouring cells and time-steps [183]. Hence, researchers may also consider developing the aforementioned models from the physics, chemistry, or mathematics perspectives to build fire spread models.

10. Conclusions

This manuscript predominantly summarises background information for forest fire research in Malaysia. It begins with an exploration of forest-fire-associated research works performed in Malaysia. Then, some of the influencing forest fire factors are briefly discussed. The procurement of data, especially public remote sensing (i.e., satellite date) data that have been utilised in Malaysia, is provided in Section 3. It should be highlighted that only a small amount of satellite data has been adopted in Malaysia. In addition, a small discussion related to big data platforms for accessing remote sensing information is also provided. It is necessary to understand the different acquisition procedures to access the data because these remote sensing data are vital for the establishment of a machine learning-based forest fire dataset in Malaysia.

Section 4 is mainly devoted to exploring the utilisation of machine learning to detect forest fires from a global perspective. From the presented literature, it can be recognised that the application of machine learning for fire detection tasks is definitely not new. However, a finding from the review presented in Section 2 shows that no one has exploited the potential of a machine learning algorithm for forest-fire-related tasks in Malaysia. Subsequently, some of the challenges to utilising machine classifiers for the task of forest fire detection in Malaysia are also discussed in Section 5. Additionally, some future directions and research questions are also contemplated in the same section to provide future researchers in Malaysia avenues for the extension of the literature in the forest fire domain. A general methodology to apply machine learning by making use of remote sensing data and ground data for the task of forest fire detection in Malaysia is proposed in Section 6. In view of technology advancement, it is postulated that the application of machine learning or deep learning algorithms will undoubtedly improve fire monitoring and detection in Malaysia. It can be certain that the ability to accurately detect or forecast fires will assist authorities to efficiently allocate fire-fighting resources to reduce the severity of forest fire incidents. Next, Section 7 highlights that there are no presently available forest fire benchmark datasets, and some general recommendations to create a standard benchmark dataset are also provided in this section. An overview of forest fire detection and monitoring solutions such as human observation, optical sensors, and wireless sensors are briefly discussed in Section 8. Towards the end of the manuscript, some of the methods and techniques associated with fire spread models from the perspectives of mathematics, chemistry, and/or physics are presented in Section 9. It is important to emphasise that these models have been commonly exploited across other countries, but the adoption of these models is still very rare in Malaysia.

In conclusion, research in the forest fire domain in Malaysia comprises discovering the causes of fires, revealing the impacts of fires, and generating fire risk maps by utilising remote sensing data. From this review, it can be speculated that human activity and negligence are the predominant factors in instigating forest fires in Malaysia. To fathom whether environmental variables were some of the influencing fire factors, researchers have also exploited various remote sensing data in conjunction with fire activity information to reveal the relationship between them. Specifically, temperature and precipitation have been shown to exhibit a high correlation with most fire activity. While machine learning has not been utilised in Malaysia, our review suggests that the adoption of machine learning or deep learning techniques will definitely aid in the task of fire prediction or detection in Malaysia. In summation, this review paper aspires to serve as an avenue to facilitate future researchers in their initial stage of exploration for the battle against forest fires in Malaysia.

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Early Monitoring of Health Status of Plantation-Grown *Eucalyptus pellita* at Large Spatial Scale via Visible Spectrum Imaging of Canopy Foliage Using Unmanned Aerial Vehicles

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Abstract: *Eucalyptus* is a diverse genus from which several species are often deployed for commercial industrial tree plantation due to their desirable wood properties for utilization in both solid wood and fiber products, as well as their growth and productivity in many environments. In this study, a method for monitoring the health status of a 22.78 ha *Eucalyptus pellita* plantation stand was developed using the red-green-blue channels captured using an unmanned aerial vehicle. The ortho-image was generated, and visual atmospheric resistance index (VARI) indices were developed. Herein, four classification levels of pest and disease were generated using the VARI-green algorithm. The range of normalized VARI-green indices was between −2.0 and 2.0. The results identified seven dead trees (VARI-green index −2 to 0), five trees that were severely infected (VARI-green index 0 to 0.05), 967 trees that were mildly infected (VARI-green index 0.06 to 0.16), and 10,090 trees that were considered healthy (VARI-green index 0.17 to 2.00). The VARI-green indices were verified by manual ground-truthing and by comparison with normalized difference vegetation index which showed a mean correlation of 0.73. This study has shown practical application of aerial survey of a large-scale operational area of industrial tree plantation via low-cost UAV and RGB camera, to analyze VARI-green images in the detection of pest and disease.

Keywords: *Eucalyptus*; health status; VARI-green; aerial survey; pest; disease

1. Introduction

Plantations of genus *Eucalyptus* L'Hér now amount to more than 20 million hectares globally [1] and are the second largest global forest plantation species behind *Pinus* L. [2]. Their capability for fast growth, ability to grow in a range of site conditions, ease of propagation, and their desirable wood qualities have led to widespread establishment of large *Eucalyptus* plantations in many countries of Southeast Asia which has over 2.5 million planted ha [3]. The wood of *Eucalyptus* is suitable for use in a variety of products, such as sawn timber, pulp, paper, civil construction, furniture and energy production purposes, and veneer or plywood production. In the Malaysian state of Sabah on Borneo Island, *Eucalyptus* species and hybrids have been shown to have high productivity and have a variety of end use potentials [4–7]. As countries increasingly restrict the access to natural forests for log supply, there are estimates that 50% of the world's hardwood harvest could come from *Eucalyptus* plantations by 2030 [8]. In the Malaysian states of Sarawak and Sabah, industrial tree plantations are predominantly planted with *Eucalyptus pellita* F. Muell. or eucalypt hybrids. The prevalence of eucalypts in recent years is the result of a major outbreak of *Ceratocystis* among the previously dominant species, *Acacia mangium* Willd., resulting in a high rate of mortality [9–12]. The risk of pest and disease remains constant and it is therefore essential to monitor plantations to detect any potential incidence of disease. Any pest and disease outbreak in Eucalypt plantations has the potential to endanger the Malaysian forest industry, which aims to produce 75 million m^3 of timber per annum to meet the raw material requirement of the Malaysian timber industry, which in the past 10 years has exported more than RM100 billion (USD24.4 billion) of wood products or 17% of Malaysia's total export [13].

To monitor for potential outbreak of pest and disease in *E. pellita* plantations, field surveys are important for pest and disease detection, however they are labor-intensive, time-consuming, and are not practical in areas with particularly steep terrain. Instead, precision agriculture techniques using high resolution remote sensing from unmanned aerial vehicles (UAV) with a variety of different sensors, or even conventional red-green-blue (RGB) cameras, would lead to cheaper and more practical monitoring of forest health [14–17]. Furthermore, rapid development of hardware and software, and improvement in the miniaturization of the sensors have led to the widespread use of UAV for obtaining higher temporal and spatial resolution [18–20]. It is now possible for UAVs to fly in excess of 20 h [21] and to cover more than 200 ha per flight [18]. This is sufficient to address the needs of most forest plantation operations which require collecting data in a shorter time, with fewer personnel and with minimal impact on the field. The use of UAV together with big data analytics and artificial intelligence provides new approaches for plant phenotyping [20,22–25] determination of plant height (growth) [26,27] to evaluate plant varieties [28] and detection of pest [29]) and disease [30,31].

Several vegetation indices (VI) have been developed for remotely sensed images. They mostly cover the visible region of the spectrum (red, green, blue, the so-called RGB channels) or shortwave near-infrared (SWNIR), although the SWNIR region is ill-defined, but is commonly accepted to range from approximately 800 nm (red-edge) to 2500 nm. Given the high cost of true NIR spectral cameras that are capable of operating above ~1300 nm, most vegetation indices are actually confined to the visible and red-edge (up to around 1200 nm). One important consideration for remote sensing with UAVs is the payload weight, and this, combined with cost, further reduces the potential camera systems to simple RGB cameras. For RGB images, the visual atmospheric resistance index (VARI) green index [32] can benefit from normalized difference vegetation index (NDVI) using the ERTS-1 satellite (later Landsat-1) multispectral scanner [33,34].

Remotely sensed data have been used for plant phenotyping, including indices to assess plant health status [16–18,30,35–38]. The authors of [30] claimed that the use of UAV RGB imagery is more effective for estimation of disease resistance of potato light blight compared to visual assessments. Most recently, VARI-green provided reliable information to monitor tree health in *Eucalyptus pellita* in Indonesia [39]. Despite the potential advantages of UAV to collect high-resolution imagery, its application to detect biotic damage in forest plantation are currently rare in the literature. In this study, pest and disease symptoms in a stand of *E. pellita* were demonstrated using a similarly low-cost consumer UAV equipped with a similarly low-cost consumer RGB camera. This was an intentional decision to explore the capability of a readily available and affordable system without the need for expensive or sophisticated equipment such as hyperspectral/multispectral cameras. The aim of the study were to (1) investigate the health status of 1–2-year-old *Eucalyptus pellita* in a commercial plantation using VARI-green, (2) ground-truth the VARI-green result with proximally sensed NDVI data visual inspection, and (3) develop a range of indices of VARI-green as benchmark for detection and monitoring of health status.

2. Methods

2.1. Study Area and Tree Health Data

This study was undertaken in the industrial tree plantation of Brumas estate at Sabah Softwoods Berhad (Tawau, Sabah, located at latitude 4°35′36″ N and longitude 117°45′31″ E between 200 and 600 m elevation above sea level in the southern regionof the Malaysian state of Sabah on the island of Borneo (Figure 1). The total planted area at SSB is approximately 18,000 hectares, which is predominantly *E. pellita* (60%) and *Falcataria moluccana* Barneby & Grimes (formerly *Albizia falcataria* L. Fosberg) as a secondary species (25%), along with *Eucalyptus* hybrids (5%) and conservation plantings (10%). The soil is dominated by Tanjung Lipat soil type with clay texture between 25% to 35% and Kumansi type with >40% clay content [40]. Block 42H, a commercial planting of *E. pellita* and selected for this study, was planted in May 2018, with an area of 22.78 ha at a spacing of 3 m × 3 m (1111 stems per hectare, sph). A younger commercial planting (six-month-old *E.pellita*) was also assessed in Block 42G. In this block, a total of 4399 trees were planted in an area of 7.56 ha.

Figure 1. Location of the Sabah Softwoods Berhad, Brumas Estate, and location of Sabah within Borneo.

2.2. Early Inventory Measurement

The early inventory measurement (EIM) was completed five months after planting, while the ground-truth verification was completed after completion of the flight used for the VARI-green analysis.

In the EIM, visual inspection of *E. pellita* health was conducted at all study sites to establish ground reference dataset. Tree health inspection was undertaken by an experienced assessor who was trained and actively engaged in pest and disease survey in Sabah Softwood plantations.

The block 42H was chosen because of the young age when assessed using an unmanned aerial vehicle in November 2019 (1 year 7 months [19 months]), and the early inventory measurement (EIM) on the block which showed a variety of tree health status from virulent to dead.

2.3. Unmanned Aerial Vehicle Image Acquisition

High-resolution aerial images were acquired using an unmanned aerial vehicle (UAV) namely a Phantom 4 Pro, (Shenzen DJI Sciences and Technologies (DJI), Shenzhen, China, Figure 2) equipped with a readily available consumer market RGB camera (Go-Pro 5, San Mateo, CA, USA) with a payload weight of 500 g. This configuration of UAV was used to obtain high spatial resolution imagery in the visible spectrum. The aerial survey work was undertaken on 27 November 2019, with an altitude above canopy of 129 m and overlapping image swathes of 60% (forward) and 30% (side). Map Pilot for DJI software (Drones Made Easy, San Diego, CA, USA) was used to set the parameters (Table 1) for flightpath planning and control the movement and speed of the UAV. The constant ground sample distance (GSD) mode was set during the flight. A total of 178 images were obtained. The ground truth (GT) covered 24 plots (radius of 11.5 m) randomly scattered in the block which represents 4.22% of the total area (22.87 ha).

Figure 2. (**a**). Phantom 4 Pro UAV. (**b**) Researcher controlling the UAV. (**c**) Flight path.

Table 1. Flying path for control movement.

Pre-Processing Parameter	Values
Flying Height	129 m
Ground Sample distance	3.5 cm
Flight Line	Parallel
Camera snapping	Auto
Image Ratio	3:02
ISO	100
F-stop	4.5
Shutter	1/200 s
Capture Rates	3.02
Speed	Auto
Flight Duration	30 min

Ground truth assessments were conducted to classify infestation levels on *E. pellita* caused by pests and diseases. Tree health status was based on the following conditions: healthy (no sign of infestation on foliage and stem), moderate (distortion in foliage and shoots dieback), severe (splitting of stem with distortion and/or discoloration in foliage), and dead (trees no longer functional with discoloration of vascular tissues and wilting of foliage). These severity levels were used to demonstrate the potential of RGB remote images to distinguish health status of individual trees.

2.4. Image Processing

Images were processing using Agisoft Metashape software (Agisoft, St Petersburg, Russia) to generate ortho-images using parameters shown in Table 2, which is this similar to the parameters used by Del-Campo-Sanchez et al. [18]. Three key steps were used to process the UAV images: initial processing, point cloud densification, and ortho-image generation. For initial processing, an automatic aerial triangulation (AAT) algorithm was used to refine the exterior orientation for all images (N = 178) in order to compute direct georeferencing for each image. Then, bundle block adjustment (BBA) was automatically performed to utilize the measured distance between points in order to generate an adjusted relative three-dimensional (3D) coordinate system. For point cloud densification (Figure 3), the X, Y, Z position and the color information were computed based on the automatic tie points (ATP) in the initial processing stage. In ortho-image generation, digital surface models (DSM) with resolution 0.135 m were generated and used as reference for ortho-mosaic image creation. Agisoft software was used to import a third-party surface model for ortho-image generation, light detection and ranging (LIDAR), or interferometry synthetic aperture radar (IFSAR).

Table 2. Agisoft processing parameters.

Processing Parameters	Values
Alignment	
Accuracy	High
Generic Preselection	Yes
Reference Preselection	No
key point limit	40,000
Tie point limit	4000
Adaptive camera model fitting	Yes
Matching time	11 min 52 s
Alignment time	3 min 11 s
Optimization	
Parameters	F, b1, b2, cx, cy, k1-k4, p1, p2
Adaptive camera model fitting	No
Optimization time	8 s
Dense point cloud	
Points	16,653,614
Point colors	3 band (RGB), unit 8
Red	625–700 nm
Green	500–565 nm
Blue	450–485 nm
Reconstructions	
Quality	High
Depth filtering	Mild
Depth maps generation time	2 h 34 min
Dense cloud generation time	3 h 51 min
Total Raw Images	178 Pcs

The geomatic information obtained by GSD photogrammetric techniques is in this study a minimum of 3.5 cm pixel^{-1}. The tie points for the cloud characteristics are summarized in Table 3. The setting during the flight plan met the geomatic proposed desirable quality of final ortho-mosaic product. The ortho-images covered 27.22 hectares and provided information at a resolution of 3.5 cm GSD. The volume of data obtained from this setting were summarized in Table 4.

Table 3. Detected tie point and generated dense point cloud.

Tie Point Cloud	
Point	102,671 of 108,813
Root Mean Square reprojection error	0.162116 (1.16695 pix)
Max reprojection error	0.487534 (44.9617 pix)
Mean key point size	5.71308 pix
Effective overlap	3.46308
Dense Point Cloud	
Point	21,985,408

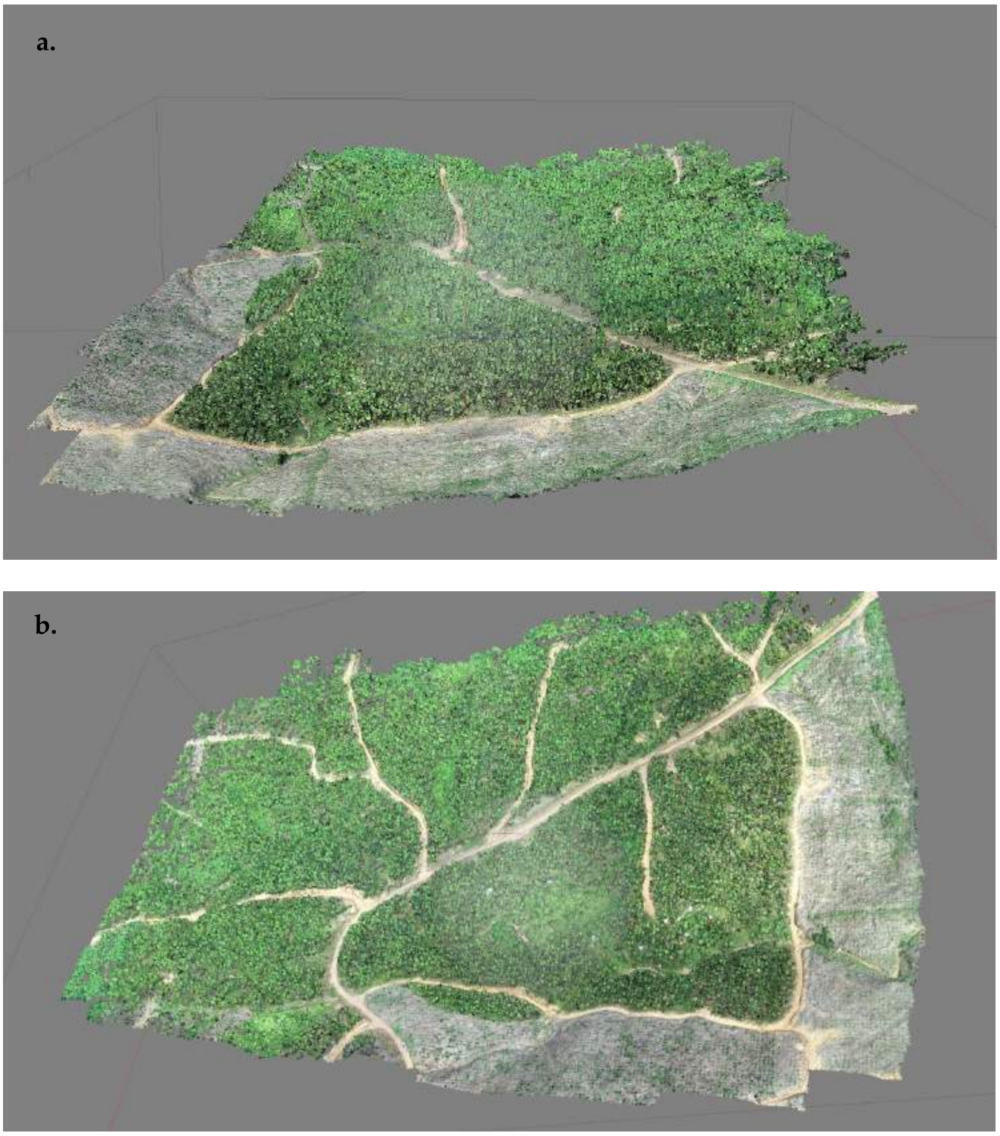

Figure 3. Point cloud densification of Block 42H. (**a**) Oblique view. (**b**) Vertical view.

Table 4. Volume of the biggest generated Geomatic products.

Geomatic Product	Size
Collected Image	178 files (1.43 gb)
Agisoft PhotoScan Project	6.11 gb
Full Orthoimage	606 mb
Nonground Orthoimage	393.40 mb
Full Orthoimage Affection Binary	-
Validation Mask	-
Red band	639.21 mb
Green band	639.21 mb
Blue band	639.21 mb

2.5. Image Analysis

Image analysis was performed using ArcGIS version 10.1 (Esri, Redlands, CA, USA). The UAV images were converted into vector shapefiles (.shp), after which, point location of the trees was plotted and buffered at a 1.0 m radius using the editor and multiple ring buffer tools. Forest blocks, roads, and stream features in the study area were digitized to represent the complete land cover map of Block 42H. The digitized tree was buffered to

1.0 m radius as an estimation of the *Eucalyptus* trees crown diameter affected by disease or mortality. The estimation is based on the maximum healthy tree crown diameter in Block 42H. The buffering layer were then overlaid and clipped on the VARI-green image using Extract tools. The VARI-green index is a vegetation index produced entirely in the visible region of the spectrum using the three visible channels of red (R, 564–580 nm), green (G, 534–545 nm), and blue (B, 420–440 nm) using the algorithm of [32] ($(G - R)/(G + R - B)$). The index generates a greenness level, from which tree health can be determined. The higher the index level, the healthy the trees.

The processed image bands were separated into single bands of R, G, and B using "make a raster layer" in management tools. Then, the single band inserted in raster calculator using syntax dialog. The VARI-green index was computed using Spatial Analyst of Raster calculator tool then, the value was normalized with an absolute value 10 (ABX) and log was set to Log_{10}. After the soil threshold was determined, the VARI-green image was clipped using Data Analysis tools to isolate the individual trees from soil feature. Total digital value in the VARI-green image was normalized using ABX and LOG formula. Log 10 was used to raise the digital number. The range between -2 and 2 represents the damage severity levels for infected trees (light green) to healthy trees (deep green).

2.6. Zonal Statistics

Once separation between trees and soil on the VARI-green raster image is completed, the calculations of digital number were made to identify the healthy and unhealthy trees. The Zonal Statistic tools in ArcGIS 10.1 were used to calculate the digital number on the VARI-green image. With zonal statistic tools, all digital numbers on the VARI-green were calculated based on each zone dataset. A single output value is computed for every zone in the input dataset. The statistic input was recorded using Excel files for every tree on the VARI-green raster image. The digital values from the VARI-green raster ranged from -101 to 96.

2.7. Normalized Difference Vegetation Index (NDVI)

A GreenSeeker handheld crop sensor (Trimble Inc., Sunnyvale, CA, USA) was used to measure the Normalized Difference Vegetation Index (NDVI) for each tree located in the three selected plots 1, 17, and 24. These plots were chosen because of the highest number of dead trees were recorded during the EIM.

2.8. Confusion Matrix and Kappa Coefficient

In this study, classification of tree health class was developed based on unsupervised classification available in ArcGIS software. After that, confusion matrix and kappa coefficient were derived for classification. Kappa used to calculate proposed classification method performance, which higher kappa value approaching +1.0 showed strong correlation between classification and validation or reference class data. Furthermore, note that Kappa is not a measure of accuracy but of agreement beyond chance, and thus chance correction is not needed [41].

The confusion matrix was created based on the individual class accuracy that was calculated by dividing the element for each class (row and column). Next, the Producers Accuracy can be generated by dividing each of the major diagonal class with total number of elements on the column of category. The User Accuracy was computed by dividing each of the major diagonal with total number of rows of the element that was classified. Then, the value of kappa coefficient can be generated by using equations below, were the nearest the kappa value to 1, represent the perfect agreement [42].

3. Results

3.1. Tree Health Data and VARI-Green Indices

In Block 42H (aged 1 year 7 months [19 months] old), a total of 11,069 *E. pellita* trees were recorded and assigned to one of the four classifications of tree health Table 5 based on infestation levels. Seven trees were classified as dead (VARI-green index −2 to 0), five trees were severely infected (VARI-green index 0 to 0.05), 967 trees were mildly infected (VARI-green index 0.06 to 0.16), and 10,090 trees were considered healthy (VARI-green index 0.17 to 2.00). The individual overall tree health status shown in the map of Block 42H in (Figure 4).

The VARI-green analysis undertaken in the 6-month-old stand (Block 42G) was, however, unsuccessful due to the size of the tree crowns being too small for detection.

Results of 24 plots assessed in Block 42H during early inventory monitoring, ground-truthing, and after VARI-green analysis are given in Figure 5. In total, 1065 trees were recorded as living during the EIM, and 754 trees were recorded as living after VARI-green analysis. In total, 25 trees were recorded dead during the EIM and one was recorded dead after VARI-green analysis. In total, 23 trees were recorded as missing during the EIM, while 255 trees were recorded missing after VARI-green analysis. The summary ground-truth results Table 6, verified one tree as dead (Class 1) and one tree as severely infected (Class 2), respectively, while 58 trees were recorded as being mildly infected (Class 3) and 686 trees were recorded as healthy (Class 4).

The NDVI data (Supplementary Tables S1–S3) were collected to further validate the VARI-green indices data. The resulting correlation between NDVI and VARI-green showed slight differences by plot with a mean correlation value for the three trial plots of ~0.73. The highest correlation value was observed in Plot 17 followed by Plot 24 and Plot 1 with values of 0.78, 0.72, and 0.69 respectively.

To assess the accuracy classification of tree health, we adopted a confusion matrix of the classification and kappa coefficient. The confusion matrix in Table 7 shows model prediction for each class are approximately between 60% to 100%, however class II of severe class showed very low accuracy with 0.02%. For this matrix, producer's accuracy was between 71% and 100%, meanwhile user's accuracies were between 0.0% and 98%. The overall accuracy of 0.91 succeeded in identifying almost all tree health categories with more than 90% accuracy.

Table 5. Classification of health status base on the percentage of indices value of VARI-green.

Class	Health Status	VARI-Green Value	Number of Trees	Symptoms	Causal Agent
1	Dead	−2–0	7	Trees no longer functional due to vascular and leaves discoloration	Pathogenic microorganism (*Ralstonia solanacearum*)
2	Severe infection	0–0.05	5	Splitting of trunk at stem with stippling leaves and discoloration	Stem borer (*Zeuzera coffeae*, *Endoclita* sp.) and phytophagous insects (*Helopeltis* sp.)
3	Mild infection	0.06–0.16	967	Distortion of foliage and shoots dieback	Sap-sucking insect (*Helopeltis* sp.)
4	Healthy	0.17–2.00	10,090	No sign of infestation on leaves and trunk	

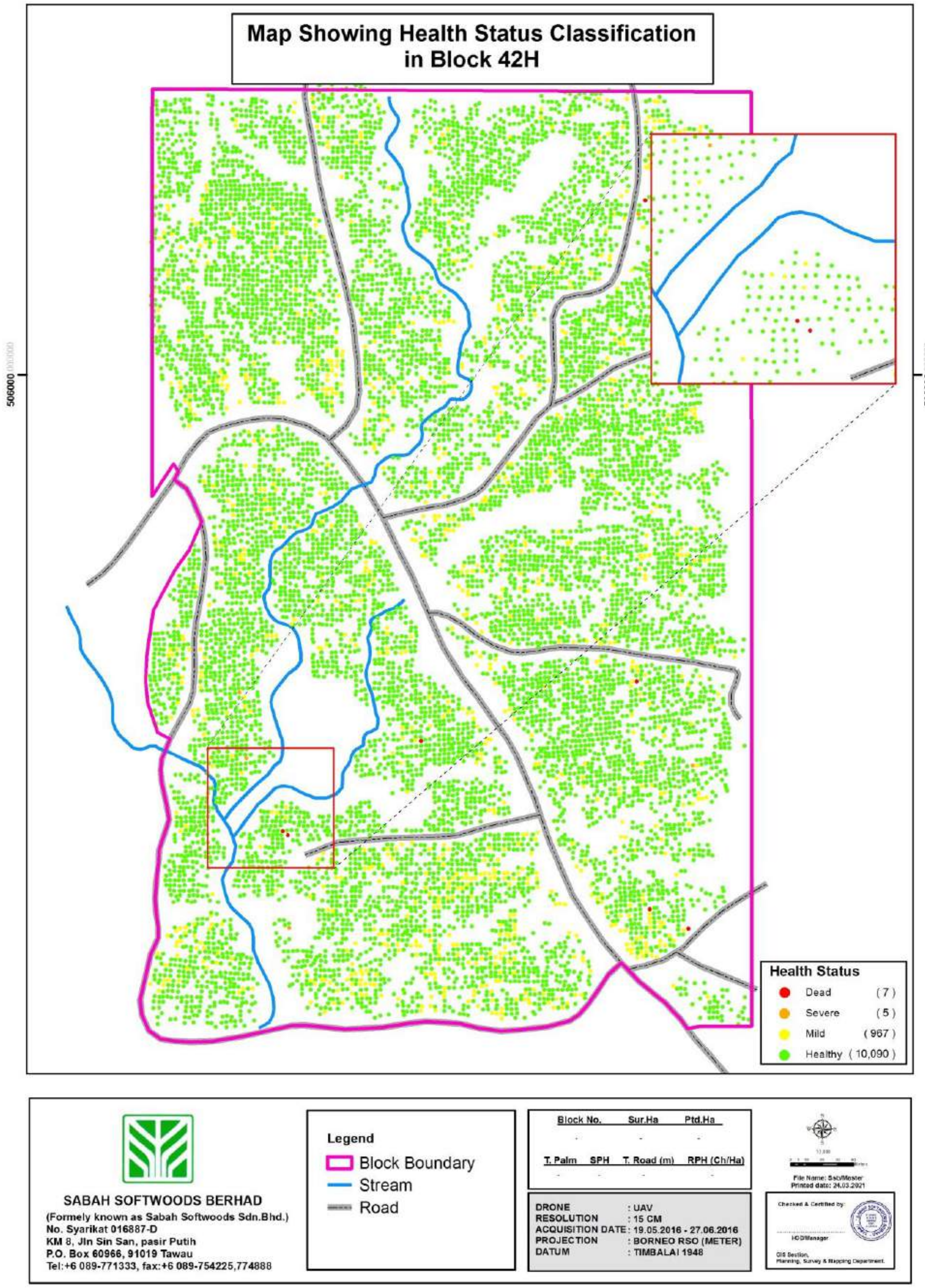

Figure 4. VARI-green result for Block 42H showing individual tree health status.

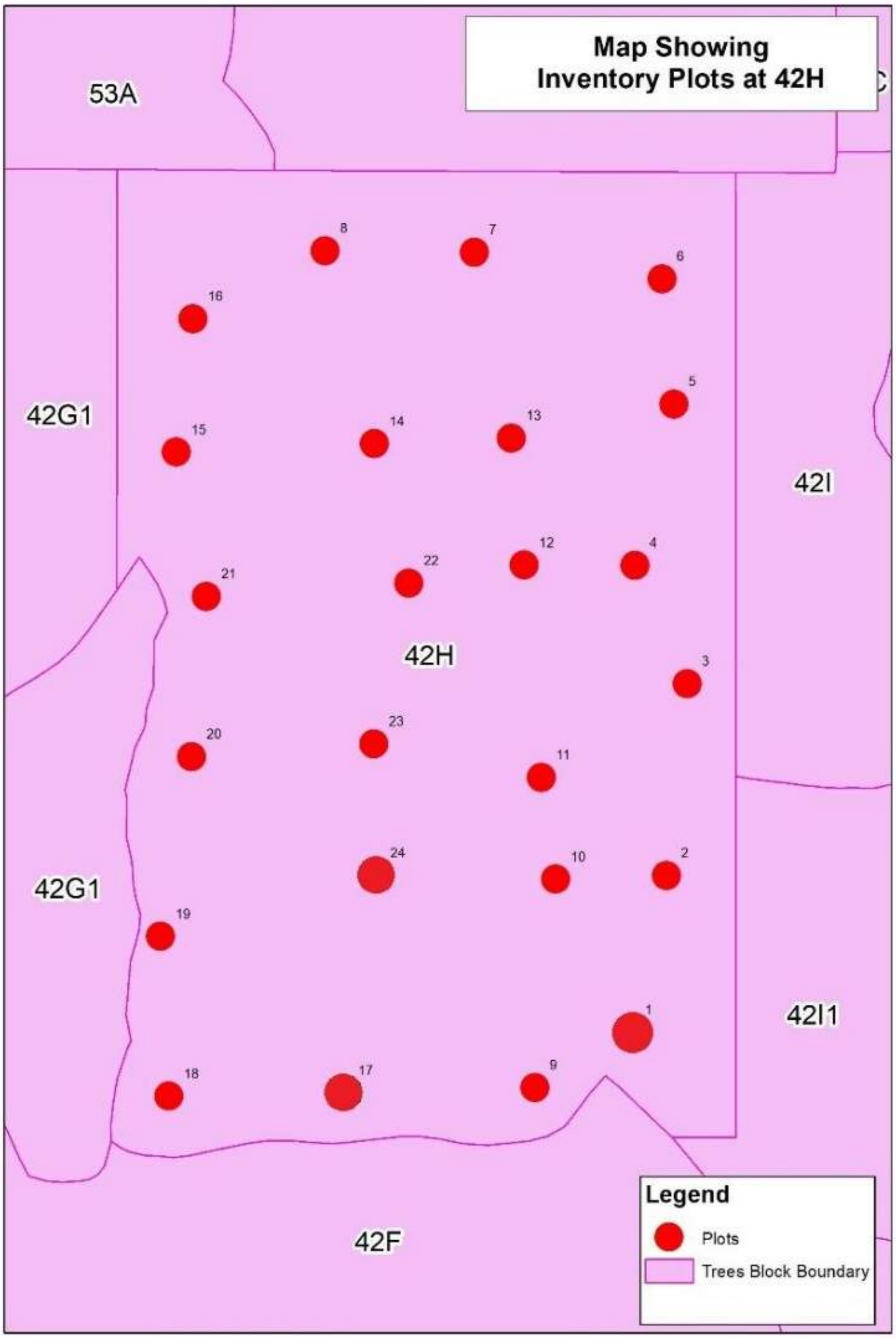

Figure 5. Schematic of the 24 inventory plots within Block 42H.

Table 6. Early monitoring measurement and results of VARI-green analysis.

Early Monitoring Measurement (EIM)							VARI-Green Analysis					
Plot No.	**Up Slope (°)**	**Down Slope (°)**	**Plot Radius (M)**	**Live Trees**	**Dead Trees**	**Missing Tree (Qty)**	**Live Trees**	**Dead (Class 1)**	**Severe (Class 2)**	**Mild (Class 3)**	**Health (Class 4)**	**Missing Trees (Qty)**
1	5	6	11.29	37	4	4	36	1	-	8	27	10
2	23	22	11.41	41	-	2	33	-	1	1	31	9
3	33	21	11.48	41	3	1	30	-	-	-	30	15
4	38	38	11.68	46	1	1	34	-	-	-	34	11
5	22	25	11.44	46	1	-	13	-	-	-	13	14
6	5	15	11.31	46	-	-	23	-	-	3	20	16
7	28	22	11.44	47	1	2	37	-	-	-	37	8
8	15	22	11.38	43	-	-	31	-	-	1	30	12
9	21	25	11.44	49	1	-	29	-	-	-	29	11
10	40	28	11.57	46	2	1	34	-	-	4	34	11
11	25	25	11.48	46	1	-	36	-	-		36	7
12	25	20	11.44	48	-	-	35	-	-	5	30	6
13	30	33	11.57	48	-	-	24	-	-	1	23	14
14	26	24	11.48	47	-	1	32	-	-	-	32	9
15	25	21	11.44	46	1	2	35	-	-	1	34	11
16	38	30	11.62	45	2	-	31	-	-	4	27	12
17	27	25	11.48	35	3	4	34	-	-	13	21	5
18	30	20	11.48	43	1	1	26	-	-	-	26	14
19	23	35	11.53	51	-	-	36	-	-	2	34	10
20	30	30	11.57	48	-	-	35	-	-	-	35	6
21	17	15	11.35	43	-	-	36	-	-	3	33	6
22	12	17	11.33	45	-	-	26	-	-	6	20	11
23	17	13	11.35	39	1	2	28	-	-	5	23	12
24	17	13	11.35	39	3	2	28	-	-	1	27	15
				1065	25	23	742	1	1	58	686	255

Table 7. Confusion matrix of tree health status based on unsupervised classification for the study area.

Predict	Class 1	Class 2	Class 3	Class 4	Total	User Accuracy
Dead	7.00	1.00	0.00	0.00	8.00	0.86
Severe	0.00	5.00	67.00	154.00	226.00	0.02
Mild	0.00	1.00	939.00	627.00	1567.00	0.60
Health	0.00	0.00	156.00	9112.00	9268.00	0.98
Total	7.00	7.00	1162.00	9893.00	11,069.00	
Producer Accuracy	1.00	0.71	0.81	0.92		

3.2. Range of Index Map of VARI-Green as Benchmark for Detection of Health Status Using UAV

In this study, four classifications of health status were developed as a benchmark for detection of individual tree health (Figure 6). Classification was based on the percentage of red within the VARI-green result for each individual tree. The resulting VARI-green index values were assigned to one of the four health classes.

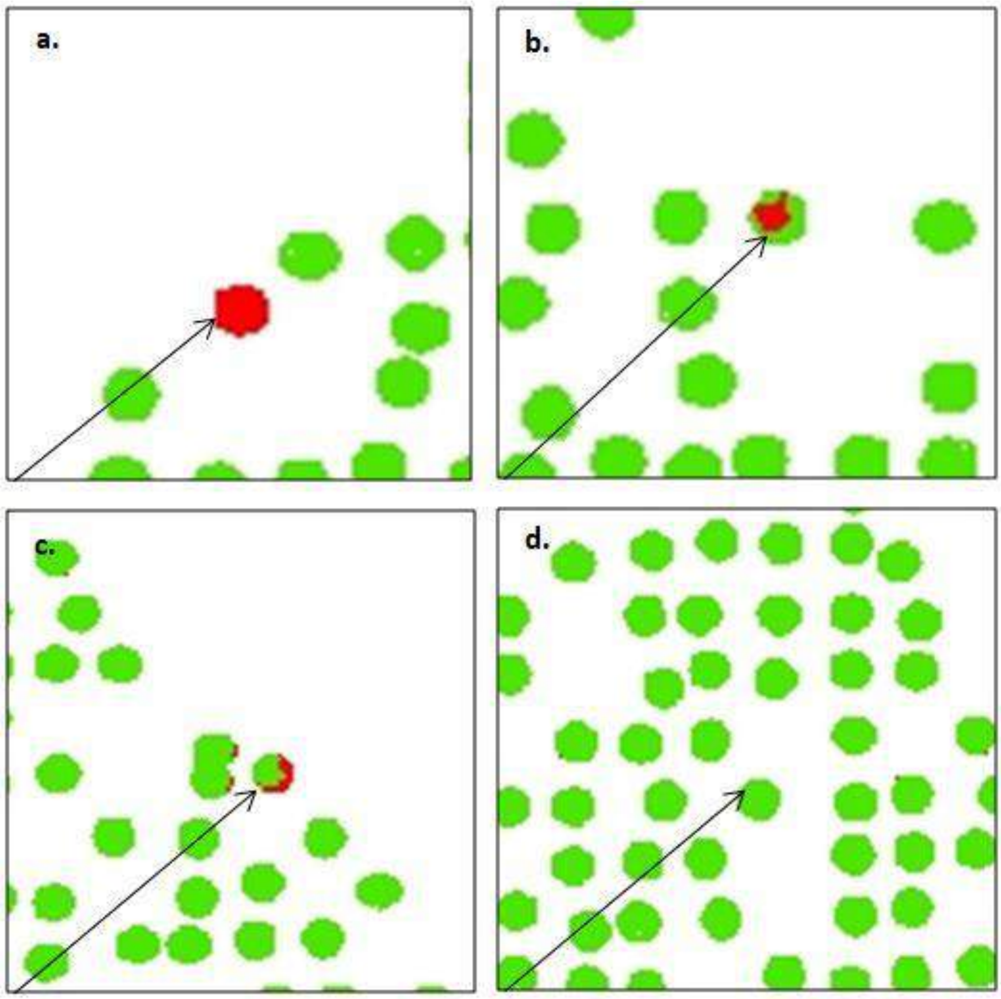

Figure 6. VARI-green classification of four health status indices: (**a**) Dead. (**b**) Severe infection. (**c**) Mild infection. (**d**) Healthy.

Figure 7 shows the procedure to generate VARI-green plots from the raw data. Orthomosaic rasters (Figure 7a) from RGB processed data clearly show the normal visualization of selected plot, from which the VARI-green raster is calculated (Section 2.5). The VARI-green raster (Figure 7b) is a result that shows the selected plot via hyperspectral visualization. To ease analysis, the tree data were isolated from soil to produce the tree-based VARI-green (Figure 7c). Due to the crowded indices data, normalized VARI-green output (Figure 7d) is produced to normalize the data between two classifications of indices, namely, 2 to 0 and 0 to −2. From these data, the classification of tree health status was created, based on the percentage of red in the VARI-green tree crown (Figure 8).

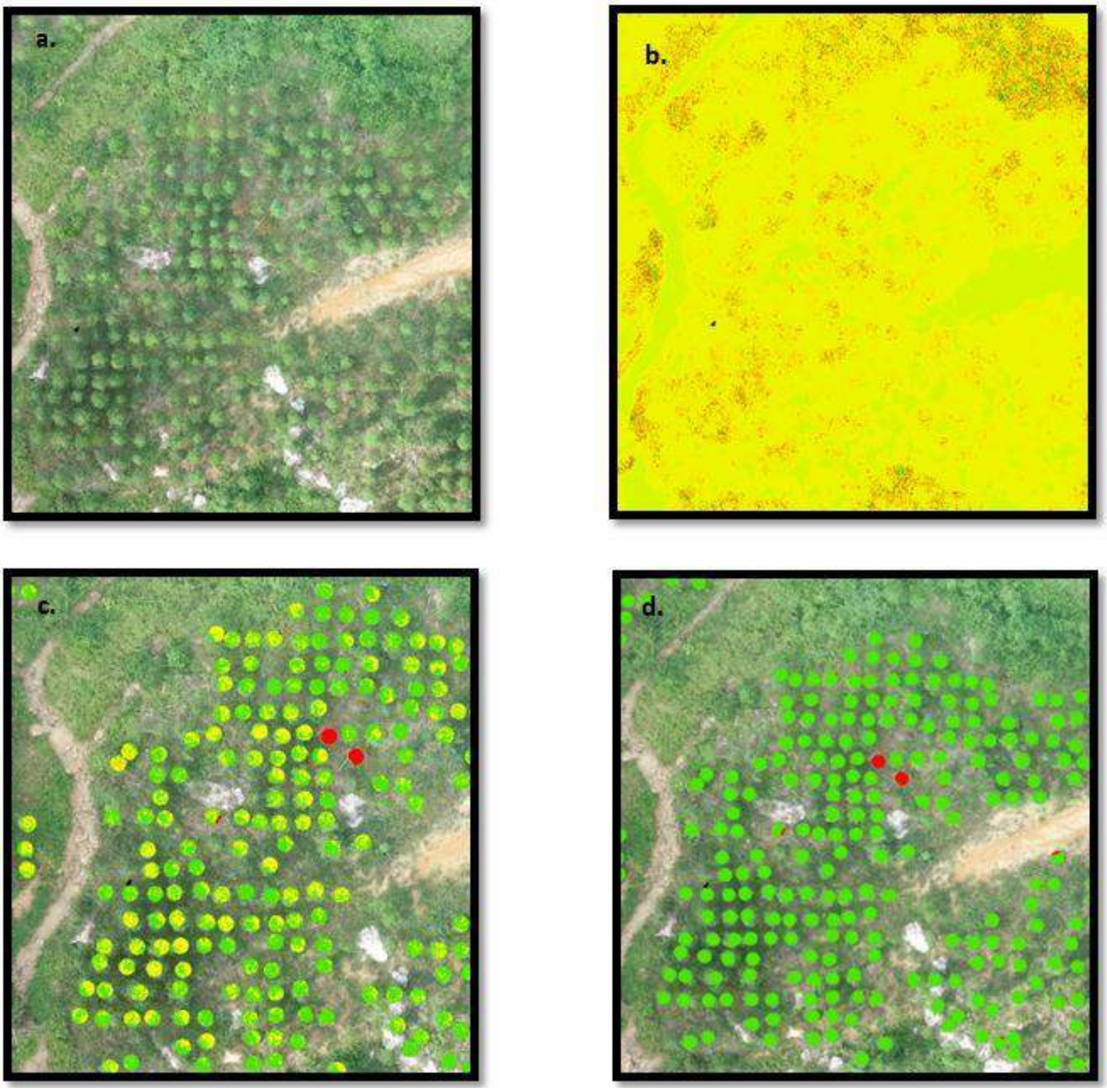

Figure 7. VARI-green image overlay with ortho-mosaic images showing the result of VARI-green from the raw data result to the normalized data result. (**a**) Ortho-mosaic Image Raster. (**b**) VARI-green raster. (**c**) Clipped Normalised VARI-green raster. (**d**) Normalised VARI-green raster.

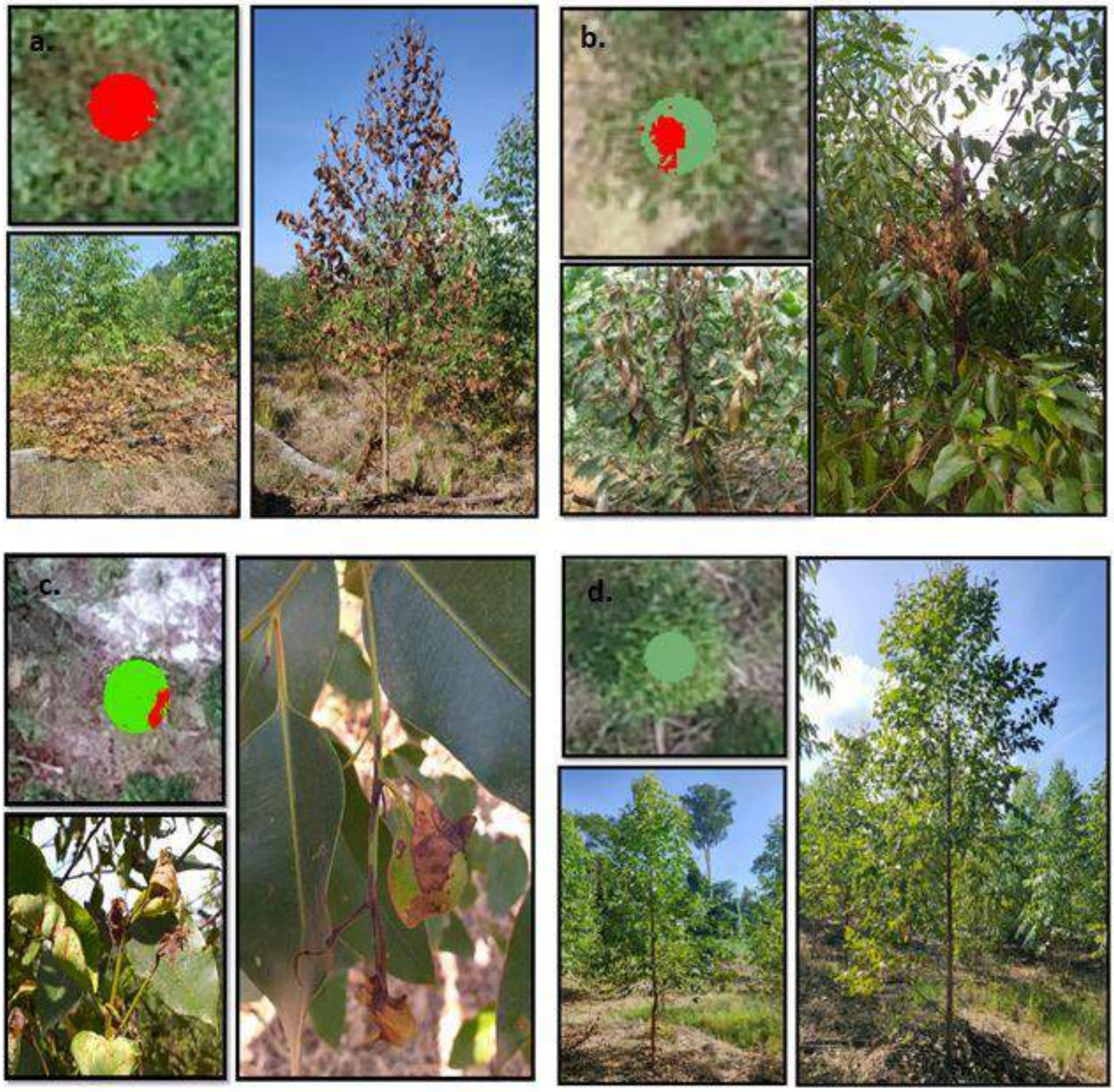

Figure 8. VARI-green and ground-truth images of (**a**) Class-1, dead; (**b**) Class-2, severe infection; (**c**) Class-3, mild infection; and (**d**) Class-4, healthy trees.

3.3. VARI-Green Pattern and Tree Health Status

The VARI-green classification map quantifies the amount of greenness in an image and differentiates between infestation levels of individual trees based on the relative amount of red in the green image. Dead trees (Class 1) appeared in the VARI-green raster pattern as totally red (Figure 8a), while severe infection (Class 2), caused in this instance by stem borer, was represented by VARI-green raster signatures with up to 80% red at the center of trees encircled by green (Class 2: Figure 8b). For mild infection (Class 3), trees show distortion in foliage and shoot dieback with VARI-green showing scattered red on individual trees (Class 3: Figure 8c). Healthy trees (Class 4) show no sign of infection on foliage and stems. The VARI-green raster pattern for Class 4 shows complete, or nearly complete, green or individual trees (Class 4: Figure 8d). Based on this variation in VARI-green pattern, the majority of trees in Block 42H are almost in perfect condition or healthy.

4. Discussion

The results of VARI (Visual Atmospheric Resistance Index) image analysis using the green channel suggest that UAV equipped with RGB cameras can be used to monitor plant health status in plantation forests. In this study, the effectiveness of a UAV equipped with a RGB camera was trialed in a young (19-month-old) stand of plantation-grown *Eucalyptus pellita* in the wet tropics in Sabah, Borneo, Malaysia. Without the need for more expensive hyperspectral cameras, simple RGB images processed using the VARI-green algorithm were able to assess pest and disease early in the growth stage. The result of this study has shown that the infestation and infection of unhealthy *E. pellita* in industrial tree plantation could be detected with the VARI-green images obtained from a low-cost drone with a low-cost RGB camera across a large area (22.78 ha). This is because VARI-green has been found to be less sensitive to atmospheric effects than NDVI, allowing a good estimation of vegetation fractions as found by [32,39].

Considering the typical host specificity of pest and disease of *E. pellita*, the classification of VARI-green images can be categorized into four classes. This classification was based on the interpretation with VARI-green index of ortho-mosaic images and ground truth verification. Confusion matrix was developed to calculate misclassification or error classification according to [43]. The result showed that our proposed methods achieve satisfactory performance, with a kappa coefficient of 0.62 and overall accuracy of 91% [44]. However, this study lacks molecular identification, while ground verification of plant health status classes is based on typical symptoms shown by the pathogen and the presence of insect pests. In the case of the dead, Class 1 *E. pellita*, the main cause of mortality was the soilborne pathogen, *Ralstonia solanacearum*. During ground inspection, dead trees exhibited leaf drop for entire the crown, branch dieback, and reduced growth. *Ralstonia* has been reported as a destructive phytopathogen that infects the xylem tissue leading to tree death [2,45] and has been reported to cause mortality in young *E. pellita* in Indonesia [39].

Based on ground verification, Class 2 was mainly caused by stem borers *Zeuzera coffeae* (Cossidae) and *Endoclita* sp. (Hepialidae) with trees showing symptoms of splitting stems and stunted growth. Attack by stem borer has been reported to interrupt nutrient transportation due to swollen stems that cause breaking of the crown top resulting in poor wood quality [46]. For Class 3, trees were infected by mirid bugs, *Helopeltis* sp. (Miridae). *Helopeltis* predominantly attack young Eucalypt leaves and shoots causing lesions, curling and drying of the foliage [47]. In addition to pest infestations, tree plantations may also suffer from water stress that causes leaf shedding however most trees retained younger leaves to cope with water deficit [48].

Overall, the early inventory monitoring results show 4% of seedling death and missing trees within the sample plots (0.96 ha) at 3 months post planting. The VARI-green data obtained 19-months post planting show 34% of seedlings as dead or missing in the sample plots (0.96 ha) from VARI-green analysis of RGB images. As a newly planted block, the trees in Block 42H are vulnerable due to their small size. They face hazards such as hot, dry weather, insect infestation, browsing by larger animals [49] or competition from vigorous weed growth although site preparation requires weed-free establishment according to Sabah Softwoods' standard operating procedure [50]. Despite this, it is accepted as normal in plantation forestry that 5–10% of the seedlings may die from one or other of these causes within the first year [49]. As shown in the results (Table 6), the high number of missing trees after VARI-green analysis compared to EIM is up to 30% may influence by several factor. The VARI-green analysis was performed 19 months post planting compared to the EIM assessment at 3 months post planting. Within this period, numerous changes have occurred in terms of tree mortality, due to any one of several biotic and/or abiotic events, e.g., drought and hot weather and infestation of pest and disease. The difference in assessment of dead and missing trees between the VARI-green result and the EIM assessment may be due to errors in either or both survey methods. The RGB images acquired by UAV may suffer from parallax error that occurs due to changes in the relative position of the object or the observation point, whereas double counting or missing counting during the manual early inventory measurement may result in discrepancies. In this study, the VARI-green analysis and ground-truth verification in three plots were able to reduce the counting error with respect to the EIM. These results agree with those of [30] whereby the use of UAV RGB imagery is more effective for estimation of tree heath compared to visual assessments.

From a viewpoint of managing the plantation forest, VARI-green analysis indicates that only 0.06% of trees were dead and 0.04% of tree we severely infected, while 9% of the trees showed mild inhibition and 90% the trees were healthy in the total area of 22.78 ha. In terms of overall survey area, this study is amongst the largest undertaken for the detection of pest and disease in any crop: [31] covered 0.19 ha of potato crop, [39] assessed 3 ha of *E. pellita*, [30] 0.14 ha of potato crop, and [18] 5.03 ha of vineyard. The development of a health indices map combined with the practical survey of large areas shows the novelty of the study. The health indices map is easy to use, allowing plantation forest managers to view the health status of commercial forests block using comparatively low-cost technology in a rapid manner. Use of UAV to survey forest health would enable considerably larger areas to be assessed (23 ha in 30 min) compared to ground crews (10 ha per day). Aerial surveys of tree health would allow decision-making on operational procedures such as treatment of the infected area or replanting of missing trees.

Detection of early plant stress [51]; nutrient status [52]; and plant phenotyping including height, flower, and canopy cover [53] use NDVI for mapping vegetation condition and status [54]. However, NDVI requires a multispectral sensor operating in the red-edge near-infrared (NIR) wavelength range [16,17]. Near infrared cameras are more expensive than RGB cameras and require time-consuming calibration procedures [54] unlike VARI-green. VARI-green is based simply on RGB images [18] and can operate at very high resolution using low-cost UAV. This study developed plant health indices using a GoPro consumer RGB camera which was considerably cheaper than a UAV equipped with a hyperspectral camera. Though the reliability and simplicity of VARI-green has earned its popular use [54], other plant indices have been developed using conventional RGB camera. Ref. [32] found VARI-green to be minimally sensitive to atmospheric effects allowing estimation of vegetation fraction with an error of <10% in a wide range of atmospheric optical densities. This study has verified the remotely sensed VARI-green indices with proximal NDVI measures, which have shown acceptable agreement.

The total flight time of 30 min used in this study was shown to be sufficient to cover the survey area of around 23 hectares. Due to the short duration of the flight and the ease of development of plant health indices for *E. pellita*, it is proposed that UAVs with simple RGB cameras have the potential and cost effectiveness to operate in large-scale monitoring of plant health not only in Malaysia, but also within the tropical countries where *E. pellita* is grown. The study provides a methodology to assess infection on the ground with aid of remote sensing UAV image for minimal cost. It is an innovative technique that can be included in plantation management plans, not only for tree plantations, but it may also be suitable for other plantation crops such as oil palm. It is not intended that this method be a total replacement of conventional ground verification or conventional surveying methods. Instead, it is intended that aerial survey provide complementary data to rapidly and safely distinguish unhealthy areas of plantation with minimal labor cost. This would allow growers to quickly target affected areas which would be ground-truthed by trained field crews who could back-up the identification of the disease outbreak using molecular identification and morphology identification. The relationship between VARI-green and ground survey showed good agreement providing a reliable classification tool for plantation managers. The four classes of plant health status have been selected for the management to provide extra information regarding the tree's health enabling better decision-making to control pest and disease outbreaks.

While this study was proven to be reliable for *E. pellita* at a stand age of 19 months, younger trees failed to be detected by the VARI-green algorithm due to the small crown size. In a forest block of 6-month-old *E. pellita* (Block 42G), VARI-green analysis was unable to differentiate between trees, indicating that there must be a minimum canopy size before VARI-green can produce reliable result. These findings also suggest that forest plantation deployed with species such as *Albizia* sp. and *Tectona grandis* may encounter similar problems of confounding values in VARI-green analysis due to overlapping crown.

5. Conclusions

There are competing needs for speed and ease of monitoring large areas of planted forest and the need for accuracy and precision. In a practical operation for a forest grower managing tens of thousands of hectares of planted forest, aerial survey of forest health using VARI-green from RGB imaging, is a qualitative assessment that is provides information across a large area at the expense of lower accuracy. It is the relative area that is affected which is important. To determine whether 30% of an area is potentially affected does not require a high degree of accuracy: it is simply enough to know that between 25% and 35% is affected, or less than 10% or more than 50%, etc. The commercial leverage achieved by using UAV remote sensing systems to assess tree health is the ability to survey large areas in a short period of time, and even more powerfully the ability to survey remote and steep terrain safely, without the need for ground crews to be present. This study has shown that significant plantation areas (in this instance 22.78 ha.) can be surveyed in half a day.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/f12101393/s1, Table S1: NDVI value for each tree in Plot 1, Supplementary Table S2: NDVI value for each tree in Plot 17 and Supplementary Table S3: NDVI value for each tree in Plot 24.

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MANGROVE VEGETATION HEALTH ASSESSMENT BASED ON REMOTE SENSING INDICES FOR TANJUNG PIAI, MALAY PENINSULAR

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ABSTRACT

Mangroves critically require conservation activity due to human encroachment and environmental unsustainability. The forests must be conserving through monitoring activities with an application of remote sensing satellites. Recent high-resolution multispectral satellite was used to produce Normalized Difference Vegetation Index (NDVI) and Tasselled Cap transformation (TC) indices mapping for the area. Satellite Pour l'Observation de la Terre (SPOT) SPOT-6 was employed for ground truthing. The area was only a part of mangrove forest area of Tanjung Piai which estimated about 106 ha. Although, the relationship between the spectral indices and dendrometry parameters was weak, we found a very significant between NDVI (mean) and stem density (y=10.529x + 12.773) with R2=0.1579. The sites with NDVI calculated varied from 0.10 to 0.26 (P1 and P2), under the environmental stress due to sand deposition found was regard as unhealthy vegetation areas. Whereas, site P5 with NDVI (mean) 0.67 is due to far distance from risk wave's zone, therefore having young/growing trees with large lush green cover was regard as healthy vegetation area. High greenness indicated in TC means, the bands respond to a combination of high absorption of chlorophyll in the visible bands and the high reflectance of leaf structures in the near-infrared band, which is characteristic of healthy green vegetation. Overall, our study showed our tested WV-2 image combined with ground data provided valuable information of mangrove health assessment for Tanjung Piai, Johor, Malay Peninsula.

Keywords: mangrove; Peninsular Malaysia; Tasselled Cap; vegetation indices

INTRODUCTION

Mangroves are environmentally and economically important for Malaysia. The forests fulfil socio-economic and environmental functions (Hossain & Nuruddin, 2016), which include the provision of a large variety of wood and non-wood forest products (NWFPs), and coastal protection against the effects of wind, waves, and water currents. Mangrove forests are pristine and offer a high aqua-biodiversity of lands. Mangrove forests are also sensitive lands that are vulnerable to climate change and aggressive human activities. Such disturbances have caused mangrove tree depletion from time to time. In tropical forests, particularly in Peninsular Malaysia forests, conversion has become a threatening factor to mangrove forests. Additionally, mangroves support conservation of biological diversity; protection of coral reefs, sea grass beds, and shipping lanes against siltation; and the provision of spawning grounds and nutrients for a variety of fish and shellfish, including many commercial species (Davies *et al*., 2010). To date, mangroves are proven nursery areas for shrimp, fish, and crustaceans (Heenkenda *et al*., 2015). Mangrove forests in Peninsular Malaysia can be found, namely, in Tumpat, located in Delta Kelantan; Matang Mangrove Forest Reserve, Perak; Mangrove Forest, Tanjung Tuan in Port Dickson, Negeri Sembilan, and also Sungai Pulai Forest Reserve in the southern part of Peninsular Malaysia. Disturbances affecting mangroves include land conversion of the seaside to valuable economic assets, such as construction of aquaculture projects, which can diminish the mangrove forests. A report from the Food and Agriculture Organization of the United Nations (FAO) indicated that the mangrove areas have decreased from around 16.1 million hectares in 1990 to 15.6 million hectares in 2010. Elsewhere, Africa is facing problems with mangroves involving poor farming practices; conversion of mangroves to cash crop estates; shrimp farming; and increased clearing and tree cutting for fuel wood and charcoal (Drigo *et al*., 2009).

Inadequate research on assessing mangrove vegetation under stress has contributed to uncertainty in assessing their current role in the global carbon and water cycle and projecting their future change. Since the importance of mangroves is widely known, with the forest consisting of wide and unique varieties of vegetation that can grow despite exposure to wave impacts and water salinity in the harsh coastal environment (Motamedi *et al*., 2014), protection and conservation of mangrove areas is a critical task and a prerequisite for further research using the most efficient and recent technology available (Crist & Cicone, 1984). Studies have found the relationship between human activities and environmental impacts are difficult to assess and regulate in coastal and marine environments because the environmental resources are almost always governed by common property resource (CPR) management systems, whereas terrestrial environments are generally managed by the government or private sector (Sherbinin *et al*., 2007). Therefore, other types of monitoring systems, such as by available, highly efficient temporal and effective technology, should be adapted.

Since the advent of satellite imagery, the application of remote sensing technology for mangrove conservation is continuing. Spectral information from different satellites provides various information. Remote sensing technology has been integrated in assessing the vulnerability of wetlands and mangroves, especially the utilization of the photochemical reflectance index (PRI) for characterizing plant stress because it can exhibit a strong response to salinity exposure. Satellite technology is suitable for this kind of forest because satellite imagery can provide spectral information on chlorophyll content which, furthermore, can assess vegetation stress. To date, various mathematical combinations of spectral channels in satellite images have been used as sensitive indicators of the present condition and vigour of green vegetation. Hence, many studies demonstrated the usefulness of the indices, a matter that has been discussed comprehensively in (Smith *et al*., 2014). Mangroves have a certain phenology, such as replacing old leaves with new leaf growth, and they also loosen leaves at a high rate. This can be an indicator that remote sensing can sense the gap during replacement and new growth of leaves.

Researchers continuingly study vegetation stress with the Thematic Mapper (TM)/Enhanced Thematic Mapper (ETM) for the Landsat satellite and the Satellite Pour l'Observation de la Terre (SPOT) satellite, which are among those tested for land use change studies in China (Zhang & Zhang, 2007). Beyond land use change studies, scientists investigated forests by applying mathematical equations to the spectral bands. A recent study by Schultz et al. (2016) performed various vegetation indices from Landsat data for forest monitoring in tropical forest regions of Brazil, Ethiopia, and Vietnam. In that study, multiple indices were used with the inclusion of the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI). There was mention that even more complex mathematical routines are not suitable for mangrove monitoring because of problems with the mangrove phenology stages, which routines can be combined with other indices. Therefore, more studies are required, as suggested by (Kamal *et al.*, 2016).

NDVI is an index based on visible and near-infrared wavelength that was originally introduced by (Rouse *et al*., 1974). The vegetation index of NDVI, for example, is sensitive to chlorophyll and photosynthetic vegetation (Slik & Eichhorn, 2003) and, therefore, useful for detecting biomass reduction in tropical forests because of abiotic stress. The index has been tested in forest biomes, including deciduous and evergreen broadleaf, tropical rainforest, herbaceous savannah, and in the succession of crops (Hmimina *et al*., 2013). Additionally, studies that applied indices for mangrove include (Heenkenda *et al*., 2016; Kongwongjan *et al*., 2012; Kovacs *et al*., 2005), whereas Tasselled Cap transformation is index producing three data structure axes defining the vegetation information content: brightness—a weighted sum of all bands, as determined by the phonological variation in soil reflectance; greenness, which is orthogonal to brightness and measures the contrast between the near-infrared and visible bands; and wetness, which relates to canopy and soil moisture. In a comprehensive statement (Crist & Cicone, 1984) defined TC as an orientation data plane such that the two features which define it are directly related to physical scene characteristics. Other potential indices include the Soil-Adjusted Vegetation Index (SAVI), which has been applied by (Luo *et al*., 2010), and the Advanced Vegetation Index (AVI) (Gobron *et al*., 2000), which was applied elsewhere.

The objective of this study was to employ vegetation indices of NDVI and TC transformation by employing WV2 imagery for assessing a mangrove health area for conservation of the Peninsular Malaysia mangrove forest. This kind of study can be applied for forestry department programs as a conservation mechanism.

METHODOLOGY

Study Area

This section is offered to provide some information on the background of the study site. Tanjung Piai serves difference of 40 % in biodiversity aspects from other mangroves sites namely, Pulau Kukup which is located proximity to one and another. The forest structure of the two different types of mangrove forests indicated some similarities in terms of family and species dominance, species diversity and productivity. Both Pulau Kukup and Tanjung Piai were a Bruguiera-Rhizophora mangrove forest type. Both sites had intermediate level of tree species diversity and aboveground biomass (Juliana, 2012). Again, the Tanjung Piai are among richer with natural resources with other areas namely Sungai Pulai Forest Reserve and Pulau Kukup demonstrated in a study of (Yaakup *et al*., 2006). Tanjung Piai is also importance for natural habitats for shellfishes, residential and migratory water birds and also act as important cockle breeding grounds which also found in the mangrove areas of Kuala Gula, Kuala Merbok, Kuala Selangor, and Pontian. This is because all the area bestowed with extensive areas of mudflats as well as other areas of Malaysia's coast facing Straits of Malacca (Amir *et al*., 2015).

In terms of economic importance, Tanjung Piai was among contribution to sustainability of rural tourism for Malaysia. According to a study conducted by (Amir *et al*., 2015), they mentioned that Malaysia's tourism industry collected in a Gross National Income (GNI) of RM47.2bil in 2012 and ranked as the second largest foreign exchange earner after manufactured goods and the seventh largest contributor to the Malaysian economy, after referred to other study reported in Malaysia's trusted newspaper.

For social aspects, villagers use the mangrove forests for fishing and some of them have extracted forest resources, for example for coal, and from rivers, such as fishing crabs and shrimps. The study area map is shown in Figure 1. Mangroves surrounding the mainland area experienced land conversion. For example, historical Landsat images in 1989 to 2014 at Tanjung Piai estuarine systems showed land cover had changed dominantly by oil palms, rubber, urban areas. This study found that oil palm plantations increased in 2005 onwards, but, oppositely, rubber showed a drastic decrease of about 96 % (Kanniah *et al*., 2015).

Fig. 1: Peninsular Malaysia shown the study area with 7, 5, 3 band combination for natural colour derivation.

The pristine land is in Johor National Park's managed piece of land which was registered as The Ramsar Convention on Wetlands of International Importance, RAMSAR site (no. 1289). The area supports many threatened and vulnerable wetland-dependent species, such as the Pig-tailed Macaque and Long-tailed Macaque, birds like the Mangrove Pitta, Mangrove Blue Flycatcher, Mangrove Whistler, and the globally vulnerable Lesser Adjutant which may be observed in the vicinity of the Johor Parks site (RAMSAR, 2003).

Ground data for tree structure sampling

The fieldwork in Tanjung Piai was conducted in September 2016. The location was pre-visited for geolocation of sampling points. Sampling was conducted to estimate stem density (number of stems/0.01 ha) and basal area (m^2/0.01 ha) as parameters. In this study, a minimum distance of 10 m x 10 m was chosen to developed sampling plots according to a study by Shah, Mustafa Kamal, Rosli, Hakeem, & Hoque (2016). The measurement included diameter at breast height (DBH), seedling counting, rubbish observation and the distance (m) between the plots and the walkway and to the sea. The study consisted of six (6) sampling points, which made it a total area of the sampling plots or the study area was 6 x 100 m^2 or 600 m^2 which this procedure allows an understanding of the mean stem diameter of each mangrove species and their relative importance in structuring the mangrove at Tanjung Piai. At each plot, the central coordinates were obtained from GPS and those features were photographed. All these findings (ground inventory) were used to develop a final health vegetation assessment map for Tanjung Piai.

As found in (Lewis *et al*., 2015), important forest structures attributed to characterizing mangrove health include biomass, basal area, canopy height, frequency, density, dominance, importance value, and the resulting calculated Complexity Index (CI).

Satellite Data and analysis

Satellite images employed for the study was a WV-2 with a 2.0-m multispectral resolution bands purchased from local vendor which is Dig Dat Company, located in Ampang, Kuala Lumpur, Malaysia. The image dated 15 June 2015 was chosen because the scene showed minimal cloud cover and the location clipped for the study area showed no presence of cloud cover. A study by Kamal *et al.* (2016) utilized the image for assessment of the leaf area index for mangrove areas in Indonesia. The mangrove area that is located at the seaside makes researching mangrove areas more convenient with respect to handling remote sensing data compared with lowland areas. This is because lowland tropical forests consist of multiple layers, multiple species of forest trees, and a rich forest floor making visualizing forest images in remote sensing more difficult. The application of satellite remote sensing has been emphasized by (Heenkenda *et al*., 2016) in a study for extracting biophysical variables for the Northern Territory of Australia.

We employed SPOT-6 with 1.5 m resolution for the ground truthing procedure. In this study, a cloud detection procedure was conducted based on a comparison with Google Earth images of the study area. Mangrove habitat samples with a spectral health index were ground checked on 15 November 2016. In this activity, the ground thruthing points can be referred to Figure 1 and Table 2 for complete locality.

In this study, a cloud detection procedure was conducted based on a comparison with Google Maps imagery of the study area focusing on the area of interest (AOI). Based on the satimagingcorp.com web page, WV-2 is a new satellite after WV-1 which the image have one (1) high-resolution panchromatic band and four (4) new bands (red-edge, coastal, yellow and near infrared-2, and four (4) standard bands consisted of red, green, blue, and near-infrared-1 bands as showed in Table 1. All bands having specific spectral range, for example for the new bands: coastal bands with spectral range of 400 to 450 nm which is a shorter wave blue called coastal blue. Yellow bands have wavelengths of 585 to 625 nm is a band straddling red edge located at 630 to 690 nm. Finally, a new band of near-infrared-2 slightly overlapped near-infrared 1 and is less than 1110 nm (Yarbrough *et al.*, 2014).

Table 1: Details specification for WV-2 satellite employed for the index

Bands number	Spectral range (nm)	Bands number	Spectral range (nm)
B1-Coastal (new)	400–450	B5-Red	630–690
B2-Blue	450–510	B6-Red Edge	705–745
B3-Green	510–580	B7-Near-Infrared-1	770–895
B4-Yellow (new)	585–625	B8-Near-Infrared-2	860–1040

Table 2: Details of ground verification coordinate

Point	Coordinate (x,y) RSO
1	612600, 139950
2	610800, 141700
3	612000, 140500
4	611700, 140800
5	610500, 142300
6	612900, 140200
7	611100, 141700

Normalized Difference Vegetation Index (NDVI)

NDVI is an index based on visible and near-infrared wavelengths (Rouse *et al.*, 1974). The index has been tested in forest biomes, including deciduous and evergreen broadleaf, tropical rain forest, herbaceous savannah, and also the succession of crops (Hmimina *et al.*, 2013), whereas TC transformation has developed the index by producing three data structure axes defining the vegetation information content: brightness—a weighted sum of all bands, as determined by the phonological variation in soil reflectance; greenness, which is orthogonal to the brightness and measures the contrast between the near-infrared and visible bands; and wetness, which relates to the canopy and soil moisture (Crist & Cicone, 1984). The objective of this study was to employ NDVI for mangrove health assessing for mangrove areas. The indices have a native scaling of −1 to +1. See Table 3 for description bands utilised for the calculation.

Table 3: Spectral reflectance indices and WV-2 bands utilized the study

Index	Formulation	Source
NDVI	(B5 Red - B7 Near-IR1) / (B5 Red + B7 Near-IR1)	[12]
TC	TC Coefficient	[25]

Tasselled Cap Transformation

Remote sensing technology with advanced of spectral properties combine the reflectance measurements from different portions of the electromagnetic spectrum to provide information about vegetation coverage on the ground. Based on mathematical formulae, the spectral bands were developed for a proper analysis of land features. Vegetation has high reflectance in NIR, but lower in the blue and the red regions of the spectrum due to its absorption by chlorophyll for photosynthesis. Certain vegetation indices can be developed to distinguished stress vegetation among healthy vegetation. In tropical forests, the Tasselled Cap transformation index can be referred to (Kauth & Thomas, 1976) with the concept of a 'triangular cap-shaped region with a tassel' that can be separated into a 'plane of vegetation' and a 'plane of soil' after comparison with brightness and greenness; and brightness and wetness. In this study, mangrove samples were collected, and tested TC index based on ENVI software.

The index transformed image into Brightness, Greenness, Wetness, Fourth, Fifth and Sixth different equivalent features derived from the image. Each of the characteristics has special applications that have been proven by many studies: brightness for soil, greenness for vegetation, and wetness for the interrelationship of soil and canopy moisture. This study applied Kauth-Thomas (K-T) transform coefficients for the reflectance data of the WV-2 sensor (Yarbrough *et al*., 2014).

RESULTS

Mangroves structural attributes

The results can be referred in Table 4. The results showed that a part of tree density at Tanjung Piai varied between 10 and 24 stems/0.01 ha (sites P4 and P5), while basal area varied from 0.021 to 0.065 m^2/0.01 ha (sites P3 and P1). Other sites, which are site P1 and P2 represent their mature nature with density 15 stems/0.01 ha); basal area 0.049 and 0.065 m^2/0.01 ha) which have relatively low stem densities and high basal areas. Those sites are located 0 to less than 10 m from bay-mangrove periphery, which they were surrounded with sand pack, rope and plastics, represented mature tree with high risk from sea area (Table 5). Higher density area can be found at sites P3, P5 and P6 is due to its location of more than 10 m from mangrove periphery bay and this area can represented a young and lush green mangrove forest. The distance indicated heavy outside materials namely, sand pack can't get through particularly to the P5 and P6 sites, therefore protect from sea risen and erosion risks. Site P1 and P2 at the bay-mangrove periphery the most southernmost part of Peninsular

Malaysia, and it is the most southern section in the Asian mainland, submitted to high-impact current/waves and sand deposition, causing the death and incline of several mature trees.

Table 4: Mangrove structural parameters from sampling

	Site					
	P1	P2	P3	P4	P5	P6
Total tree density (stems/0.01 ha)	15	15	20	10	24	17
Total basal area (m2/0.01 ha)	0.065	0.049	0.021	0.043	0.037	0.052
Mean NDVI	0.10	0.26	0.38	0.44	0.57	0.57

Table 5: **Mangrove of others parameters observed from sampling**

Site	Rubbish	Death	Live	Incline	Soil	Distance	
		Tree	Seedling			From walkway (meter)	From the bay-mangrove periphery(meter)
Plot 1	Sand pack, rope and rubbish plastic	0	97	2	Sandy eroded	Less than 10 m	0 m
Plot 2	Sand pack, rope and rubbish plastic and ball	3	70	0	Sandy eroded	More than 10 m	Less than 10 m
Plot 3	Plastic, wood, net, bottles, plastic containers	4	33	0	Sandy	More than 10 m	More than 10 m
Plot 4	Food plastic	4	33	0	Sandy	More than 10 m	More than 10 m
Plot 5	Glass and plastics bottle	3	More than 200	0	No soil erosion	0 m	More than 10 m
Plot 6	Glass bottles and	9	35	0	No erosion	0 m	More than 10 m

NDVI

Whereas NDVI data calculated varied from 0.10 to 0.26 (site P1 and P2), under the environmental stress due to sand deposition found by sand pack that caused poor tidal inundation indicated unhealthy vegetation. Meanwhile, Figure 2 showed destruction caused by Iskandar Regional Development Authority (IRDA) development projects.

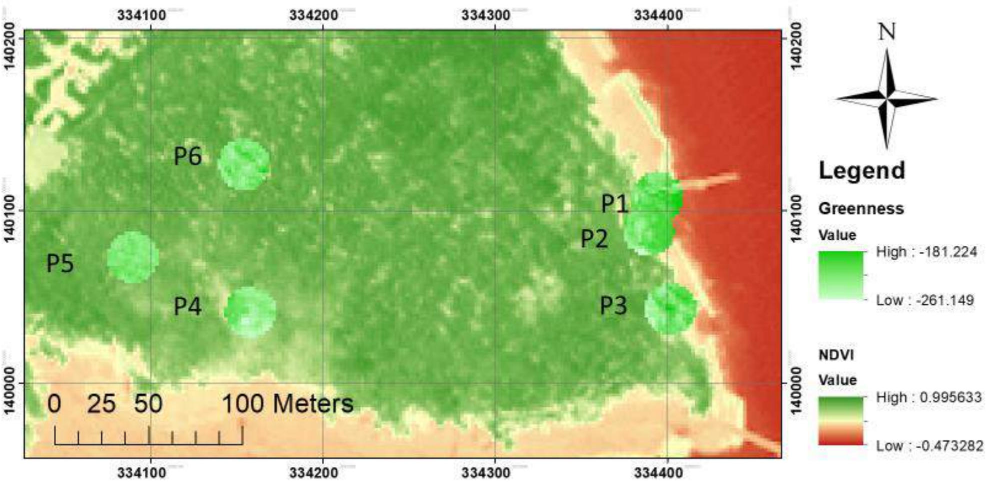
Fig. 2: (a) Fallen trees, as cited in Barau (2017) as a result of Iskandar Regional Development Authority (IRDA) project, and (b) rubbish stuck between trees also found in the study area.

TC

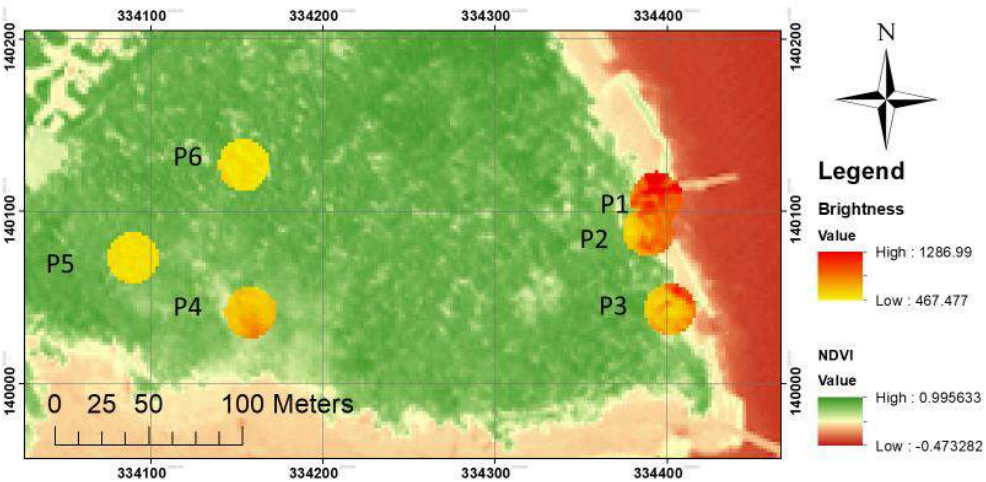
In general, TC is important variable as NDVI index to assess nature of the tree. Greenness-wetness space has the same effects on the vegetation and is slightly better than the brightness space in terms of differentiation among wet soils and the green of vegetation.

Fig. 3: TC overlaid with TC band combination (Greenness, Brightness and Wetness) on each transformed spectrum.

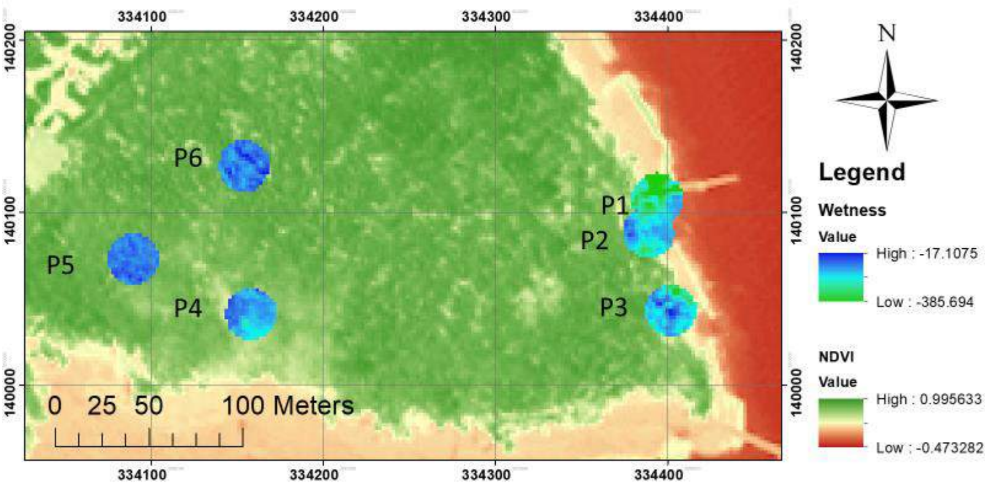
(a) Greeness



(b) Brightness



(c) Wetness



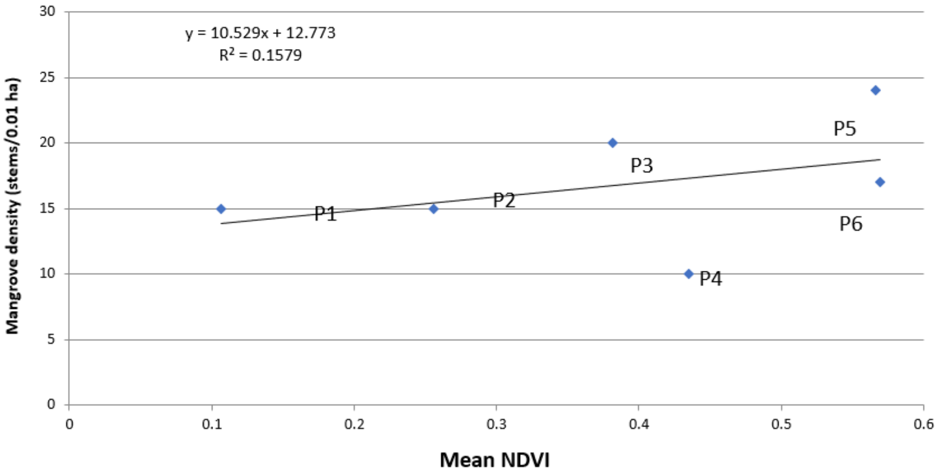
Which high greenness indicated in TC means, the bands respond to a combination of high absorption of chlorophyll in the visible bands and the high reflectance of leaf structures in the near-infrared band, which is characteristic of healthy green vegetation (Yang *et al*., 2015). Greenness-wetness space has the same effects on the vegetation and is slightly better than the brightness space in terms of differentiation among wet soils and the green of vegetation. TC brightness showed brighter at sites P1 and P2 and relatively much darker at site P5 and P6. As mentioned earlier, among others site P1, P2 and P3 showed less green therefore followed by more wetness captured in the TC image at these sites, indicating trees in this site were in the water due to continuously erosion happen in that area.

The NDVI and its relationship with dendrometry parameters

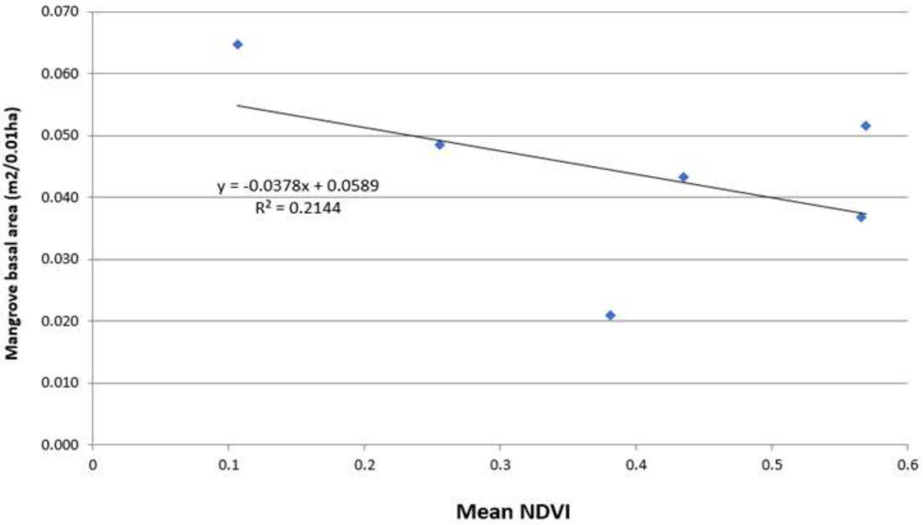
Figure 4 shows the NDVI regression results for NDVI (mean) and mangrove density (stems/0.01 ha) and NDVI (mean) and mangrove basal area. The results suggested that the relationship, although relatively weak, but was particularly significant and meaningful between NDVI and mangrove density (R2=0.1579).

Fig. 4: Illustration of simple linear regression between (a) mean NDVI and density and (b) mean NDVI and basal area

(a)



(b)



DISCUSSION

Overall, the study suggests sites can be delineated into two area which is unhealthy and healthy vegetation due to environmental stress. Vegetation can reflect greater NDVI at healthy vegetation sites, in opposite reflected weaker NDVI at unhealthy sites. Study showed healthy vegetation has a higher NDVI value than unhealthy vegetation (Zhang *et al*., 2005). This indication can also help Johor National Park maintain conservation programs which, at the same time, supports high value mangrove species protection. In fact, high value forests can apply this finding for assisting them to include mangroves as high value forests. The final map can be implemented as a health indicator area for the Forestry Department of Peninsular Malaysia (FDPM) conservation index, for mangrove areas of Tanjung Piai.

TC showed similar results with NDVI, which showed highly greenness transformation of spectral at healthy sites whereas more brightness features at unhealthy sites. Sites trees that standing apart making greenness colour shown from TC much lighter than the healthy vegetation area. This is because mangrove forests usually appear in abundance and have high similarity within one composition if no interference by other factors occurs, such as different logging cycles, disease, or different tree mortality rates that could be caused by strikes, waves, and so on. In addition, greenness was caused by higher density of the sites filling gaps (created in unhealthy vegetation sites) between tress and lowered reflectance value in the area, showed by P5 (stem density: 24; basal area: 0.037). Mangroves always appeared as other plants, which define them as a “community of trees, shrubs, palms or ground ferns, generally exceeding more than half a meter in height, and which normally grows above mean sea level in the intertidal zones of marine coastal environments, or estuarine margins” (Juliana *et al*., 2014). The spectral index of NDVI and TC has combined the results of the biomass status, the brightness of the soil, the greenness of the vegetation, and the wetness of the water (Crist & Cicone, 1984; Huang *et al.*, 2002).

The unhealthy vegetation area appeared very near to the sea or bay-mangrove periphery. Therefore, the tree is unsuccessful at overstocking because of the greater tendency for developing gaps, particularly during high sea waves. Due to this, it is susceptible to diseases, poor health, and pests. In general, P1 and P2 has showed its ability for recovering its overall forest health to its natural state with new young seedling emerged (P1:97 and P2: 70) (Table 4). Other sampling points were not able to establish because of inaccessibility to the area, since the area is prohibited for access without research permission from the Department of Irrigation and Drainage. The objectives of the band combinations in TC were to further interpret and extract information from WV-2 data for mangrove vegetation health classification. This is because visual inspection for forest cover is very important because the signature of mangrove forests is different from other types of forest.

In the future, this type of index can be applied as a mechanism of health index assessment of mangrove areas in Peninsular Malaysia before pursuing development related activities. In fact, many studies previously conducted were based on soil, climatology, impact of erosion on mangrove trees, pests and disease, fire, etc., which can be employed for integration with our index, after mutual agreement created (if necessary). The study has presented NDVI as a potential health indicator once combined with the TC index for the mangrove area of the Tanjung Piai.

CONCLUSIONS

The study showed mangrove health assessment can be delineated and presented for assisting conservation interpretation based on satellite image which can be implemented for conservation activity for Peninsula Malaysia coastal areas. The study also suggests that unhealthy and healthy delineated areas should be preserved for maintaining mangrove areas from development-related activities, particularly infrastructure development.

The study found high NDVI value is an indication of high vegetation water content to high vegetation fractional vegetation cover (FVC). This is due to NDVI being correlated to biomass, leaf area index (LAI), and among them, also to productivity (Sánchez-Azofeifa *et al*., 2003). In the beginning, of mangrove species stays in a gap and as it grows to a certain height, they are started to build a mangrove community. However, in Johor, particularly Tanjung Piai coastal erosion is also responsible for the loss of mangrove cover due to long-term projects within other unfinished projects, namely those cited in a report by (Serina, 2017): the Tanjung Piai Maritime Industrial Park by Benelac Holdings Berhad, the Tanjung Agas Oil and Gas Maritime Industrial Park within the Pulai River, the Port of Tanjung Pelepas planned expansion, Singapore's mega-port development in Tuas, the Sunway Iskandar project around the Pendas River, and the impact on the sea grass meadows and coastal mangroves in the Tebrau Straits.

The high NDVI at site P5 (0.67) is due to far distance from risk wave's zone, therefore having young and growing trees with large lush green cover. Therefore, the area reflected greater NDVI indicated healthy vegetation that was found similar with a study conducted at Kelantan Delta in 2011 (Satyanarayana *et al*., 2011). The risk zone is the area where elevation is lower than the mean high tide level (Motamedi *et al*., 2014). Oppositely, as stated higher NDVI distributed to the eastern area appears away from the sea which this pattern is characterized by the sea, influenced by the wind, waves, and pollution.

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REVIEW

A bibliometric analysis of tropical mangrove forest land use change from 2010 to 2020

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Abstract
Mangrove land use changes of varied intensities have long been a problem in tropical mangrove forests. This has resulted in various degrees of mangrove land use modification, which catch many interests in the region for research. The research provided here is a bibliometric analysis of scholarly articles published around the world in various publication document types on changes in land use of tropical mangrove forests based on remote sensing and Geographical Information System (GIS). Scientific data analysis was undertaken by using bibliometric approaches on 6,574 papers extracted from the Scopus databases between 2010 and 2020. The findings revealed that the number of publications continuously climbed from under 400 to an average of 50–60 per year till 2019. The data showed that the mangrove forest modifications study gained traction when the highest number of citations, 9,236 in 2015, were observed. We can also notice that the overall number of citations fluctuated a lot during the first five years (2010–2015) but increased from 2013 to 2015. The findings demonstrate how remote sensing satellites have aided vegetation and land study in recent years. The findings also revealed that the analysis tools of Land Use Change, Vegetation Index, Mangrove, Tropical Country, Remote Sensing, and Tropical contributed to scientific knowledge of current issues of mangrove land use change in the tropical region. The authors' keywords, Remote Sensing in particular, supplied roughly 43%, Normalized Difference Vegetation Index (13%), Vegetation Index (9%), and other keywords contributed less than 7%. The growth pattern of the keywords "MODIS" and "Landsat" implies that both will stay important over the next five years, according to an analysis of the type of satellite used in land use assessment. Meanwhile, papers pertaining to policy on land use change, food security, and forest resources were evaluated in order to highlight policy and academic research findings on the topics. The application of the Normalized Difference Vegetation Index, which is a very relevant tool that can be used in monitoring land use changes and assessing vegetation status because it is a desirable technique in measuring plant health and vigour, can help fill the research gaps presented in this study. This review can help with the development of better mangrove land use change approaches in tropical mangroves and around the world using satellite remote sensing and GIS.

Keywords Mangrove · Land use change · MODIS · Malaysia

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1 Introduction

Realizing the importance of land and oceanic region to human life has motivated continual studies and explorations of this field. One of the most powerful tools to explore the land is remote sensing techniques. Both remote sensing and GIS have become indispensable, particularly in the tropical region for forest monitoring, irrigation, land use, and others. For example, the application of remote sensing and GIS is common in monitoring mangroves in tropical region. Mangroves, as we know, provide a wide variety of ecosystem services, such as protecting the coast from erosion and home to various organisms that are beneficial for humans. Remote sensing helps to monitor recent issues on mangrove degradation. The decline of mangroves these days is alarming, and it is crucial to revise the status of the mangrove forests.

Over the last decade, there is a soaring interest in the application of remote sensing and GIS in tropical mangrove studies. The outstanding role of remote sensing in provisioning information on Earth and water surfaces has drawn the attention of researchers all over the world. There are also various new techniques in GIS and their broad application in remote sensing reported recently. For example, Mao et al., (2013) developed a new approach to estimate epsilon for atmospheric correction of satellite image data that can be applied for the coastal and oceanic region. Zabolotskikh et al., (2013), on the other hand, developed a novel algorithm for the accurate estimation of sea surface wind speed and applied it to satellite passive microwave sensing. Most recently, the application of remote sensing is reported by Cardoso-Fernandes et al., (2019) to observe and map lithium (Li) bearing pegmatites in the Fregeneda–Almendra region. A canopy height model was developed using a machine learning algorithm approach coupled with the application of Landsat satellite sensors for vegetation in the Darwin area, Northern Australia (Staben et al., 2018). Meanwhile, a recent study by Yu et al., (2019) tested a new methodology called backdating and an object-based method for accurate land cover classification and change analysis. From the viewpoint of a researcher, a comprehensive review of this subject can be a valuable reference for future scientists in mangrove land-use change that integrates remote sensing and GIS techniques.

Tropical countries are regions located along the equator of the Earth that can be divided into several continents, including North America, South America, and Southeast Asia. Most tropical countries experience a dry and wet season throughout the year. The abundance and diversity of tropical regions are well documented, as evidenced by the numerous studies that have been undertaken. These studies reflect the objectives of RAMSAR. For example, Oostdijk et al., (2018) applied remote sensing using high-resolution satellite image to determine improvements in mangrove forests under different hydrological condition. Pham et al., (2019) used remote sensing to evaluate the growth of mangrove forests in Can Gio, Vietnam. Cissel et al., (2018) monitored the changes in the mangrove forest in Campeche, Mexico using satellite data from Landsat. Earlier, Jia et al., (2018) discovered the decline and growth of mangrove forests that provided the first dataset of mangrove forests for more than 40 years in China using remote sensing analysis. There is also a study on a 15-year time series of four vegetation indices that were used to assess the phenology of mangrove forest in Southeast Mexico (Pastor-Guzman et al., 2018).

Malaysia became a party to the Convention on Biological Diversity in 1992 and the National Biodiversity Committee that was set up in 1994 to protect and manage international biological resource and to ensure the fair and equitable sharing of biological resources and technology. Tanjung Piai is one of the mangrove forests in Malaysia identified as one of the RAMSAR sites that is considered as “Wetland of International Importance”. Other countries such as Thailand, Vietnam, Laos, and Indonesia also participate in the RAMSAR party, and they have at least one mangrove identified that was adopted to this convention. Generally, policy and decision-makers base their development decisions upon simple monetary calculations, i.e. pros and cons of the proposals presented before them; however, the importance of wetlands for the environment and human societies is traditionally underrated in these calculations because of the difficulty of assigning dollar values to the wetland ecosystem’s values and benefits, goods and services (Ramsar, 2016).

Bibliometric analysis is an effective research tool widely used in various fields of scientific investigation. Recently, Duan et al., (2020) conducted a bibliometric analysis to evaluate the application of remote sensing in monitoring protected areas. Wang et al., (2019a, 2019b) provided new insights into research trends of remote sensing in crop growth monitoring in China over the past 20 years through bibliometric analysis. Elsewhere, bibliometric analysis is also applied in physical activity and ageing studies (Muller et al., 2016). Most importantly, it is a method that can provide a detailed overview of global trends for a given research area. Notably, a bibliometric analysis by Huang and Lu, (2017) on the history and trend of urban heat island research from 1991 to 2015. In summary, the bibliometric technique is able to draw out information on current topics, the most advanced and knowledge gaps in a particular field of study. In remote sensing, bibliometric analysis helps reveal and determine the trends in research publication and its application. For example, a bibliometric analysis was conducted in the field of engineering to assess the current development of Industry 4.0 (Muhuri et al., 2019). In a case study in China, bibliometric analysis was used to monitor the research trends in support vector machines, one of the classification techniques for remote sensing (Yu et al., 2019). Therefore, bibliometric analysis has been effective in identifying research trends in various scientific fields.

It is essential to identify the patterns of publication in the studies of mangrove land use change using remotes sensing/GIS. This is because there have been limited studies and updated reviews on land use change, particularly on remote sensing in the tropical region, which deserve to be highlighted. Accordingly, the database of the Academia provides the source for bibliometric analysis on drought monitoring study and prediction in Africa (Adisa et al., 2020). Meanwhile, numerous reviews are conducted on mangrove ecosystems (ResearchGate.net), recent status on mangrove in Brazil (mdpi.com) (Diniz et al., 2019), and carbon stock assessment of mangrove using remote sensing (ReseachGate.net) (Bindu et al., 2020). However, the reviews on mangrove land use change in tropical countries are limited with the most recent ones by Kuenzer et al. (2011) and Wang et al., (2019a, 2019b) on the evaluation of mangrove using remote sensing techniques.

The selection of keywords is based on the high usage of satellites, such as Landsat in land use studies, which has witnessed a rapid increase in land use change related to mangrove forests. There is also MODIS, a highly dependent land product for vegetation status, which offers a vast utilization in the tropical region. The present study found that using the uppermost research topic in mangrove land use change studies generates one of the informative articles that can be used as a reference for future studies in remote sensing application, particularly in assessing land use change in tropical mangroves. Furthermore, such research conducted in that locality can provide valuable input for human intervention in the events of natural disasters such as tsunami and flooding. It may assist policymakers and land managers in constructing new methods for managing their forest and land for food security (Rochdane et al., 2014). Moreover, research on the application of remote sensing is ongoing in search of a better classification method for forested land to assist policymaker in managing forested land (Alon et al., 2020; Panuju et al., 2020), specifically in mangrove (Amoakoh et al., 2021).

Therefore, the main objective of this study was to evaluate the scientific knowledge on changes in land use of tropical mangrove forests that are based on the use of remote sensing. Specifically, the study investigated the patterns in the occurrence of land use change through the evolution of publications. To achieve this, a bibliometric analysis of mangrove land use change that employs remote sensing/GIS techniques was performed from 2010–2020. Studies that are published throughout this period have demonstrated the extensive application of the method to monitor land use in tropical mangrove along with the discovery of other novel approaches. The missing link is the connection between the challenge of developing techniques and managing a rapid change of environment. Based on the critical review of the methodology, it is hoped that the outcomes could provide valuable insight into the policy impact on the studied issue. Most importantly, the researchers could utilize the information as an input in establishing the groundwork for presenting solutions to national crises to the government and policymakers.

2 Materials and methods

2.1 Materials

In this study, scientific documents on mangrove land use change using remote sensing were retrieved from Scopus, which is most commonly used as the core collection database for bibliographic analysis research with more than 15,000 peer-reviewed literature. In the Scopus database, users can refine search results by the types of documents. Keywords are included in the title, abstract, and keywords of the quest. The results were refined according to tropical countries retrieved from Hobo Traveler.com (https://www.hobotraveler.com/tropical/list-ofotropicalcountries.php); the searching period was limited to the year between 2010 and 2020. Various keywords were entered on the search for remote sensing-based, land use change of mangroves in tropical countries. For example, "land use change" AND “vegetation index" AND “mangrove” AND “tropical country”. Another combination was also attempted, for example, “vegetation index”, OR "remote sensing" AND “mangrove” AND “land use change”. The words “tropical”, “tropical country”, and “tropical climate” were used in every query. In total, 7,356 documents were retrieved from the search. Data were manually sorted to omit duplicates of documents. As a result, a total of 6,574 records were recovered. Table 1 summarizes the characteristics of the retrieved documents, based on document type, e.g. articles, book chapters, letter, etc.

The retrieved documents comprised of studies published as conference paper, review and book chapters that are influential materials in mangrove land use change in remote sensing topic. Other materials of little influence on the topic are documents providing commentary, editorials and opinion such as editorial materials. The selection of an enormous type of document category enables policy and relevant organization to access the information in a short time. The study found that such materials, which can be in the form of letter—rapid or short communication available in open access, are highly relevant and therefore included in document analyses for this study. The 10 top-keywords that emerged from this study were subjected to further analysis.

Table 1 Types of documents considered in mangrove land use change using remote sensing in tropical countries (2010–2020)

Document Type	Number of Documents
Articles	4,796
Conference papers	1,618
Review	76
Book chapter	69
Note	4
Short survey	4
Data paper	3
Editorial material	3
Letter	1
Total	6,574

3 Results

3.1 Trends in scientific publication of mangrove land use change using remote sensing in tropical countries

Figure 1 depicts the annual distribution of published articles in mangrove land use change using remote sensing between 2010 and 2020. The research efforts began to gain traction in 2010. From under 400 publications, the number steadily increased for an average of 50–60 publication per year until 2019. However, it fell slightly in 2020 to a total of 738 publications. Overall, a total of 64,481 citations from the Scopus database were collected for the mangrove study.

In terms of the citation, a maximum number of citations was recorded in 2015, with a total of 9,236. (Fig. 2) We can see from the figure that the total citations fluctuated significantly for the first five years (2010–2015) but showed an increment from 2013 to

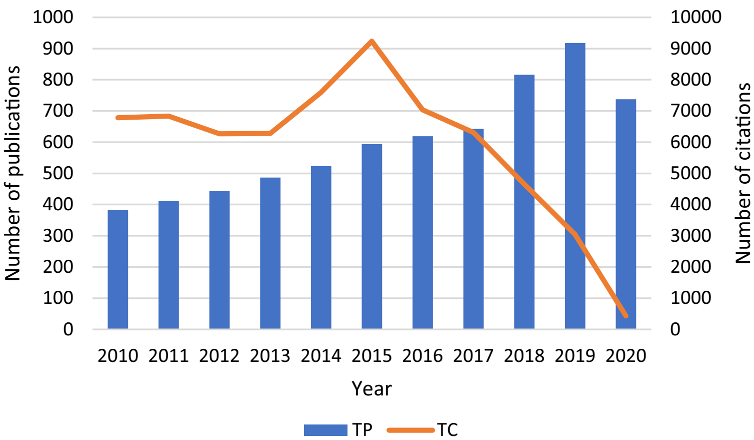
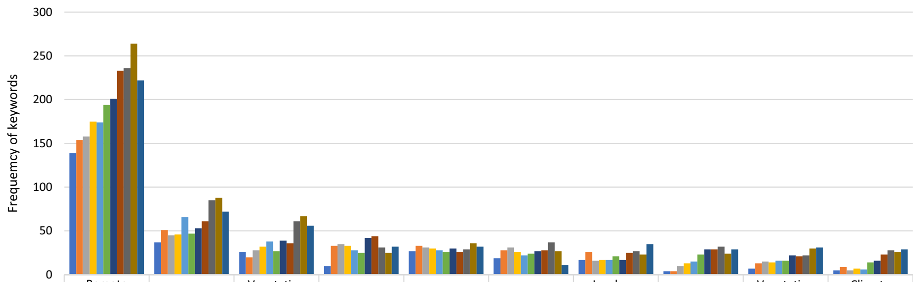


Fig. 1 Number of publications and citations for mangrove land use change using remote sensing in tropical countries (2010–2020)



	Remote sensing	NDVI	Vegetation index	MODIS	GIS	Land use	Land use change	Landsat	Vegetation indices	Climate change
2010	139	37	26	10	27	19	17	4	7	5
2011	154	51	20	33	33	28	26	4	13	9
2012	158	45	28	35	31	31	16	10	15	5
2013	175	46	32	33	30	26	17	13	14	7
2014	174	66	38	28	28	22	17	15	16	6
2015	194	47	27	25	26	24	21	23	16	14
2016	201	53	39	42	30	27	17	29	22	16
2017	233	61	36	44	26	28	25	29	21	23
2018	236	85	61	31	29	37	27	32	22	28
2019	264	88	67	25	36	27	23	24	30	26
2020	222	72	56	32	32	11	35	29	31	29

Fig. 2 Annual distribution of keywords in mangrove land use change using remote sensing studies in tropical countries (2010–2020)

2015. The study found that the number of citations fell from 9,236 to 432 in the next five years (2016–2020).

3.2 Publication citation analysis

The study by Giri et al. (2010), which has more than 1,000 citations, has the highest number of citations with 1,137. The paper deals with the monitoring of mangrove distribution using satellite data, and the results concluded that the highest distribution of mangroves is in Asia, which accounts for 42% of the world's mangrove forests. The second paper with the highest number of citations is Jiyuan et al. (2014), with total citations of 591, on the evaluation of land use changes, causes and trends in China. A moderate citation with a total count of 241 citations was reported by Rudorff et al. (2010) that was published in the journal Remote Sensing of Issue 4, page 1057–1076.

Publications on remote sensing research in tropical countries have one of the lowest citation rates. There are 823 articles with just one citation. In 2020, 112 of the 823 papers were published as articles. The lack of attention from researchers and recent publication may have contributed to the reason for these papers having only one citation. The publication by Olorunfemi et al. (2020), which deals on the vulnerability of flooding and soil erosion in Southwestern Nigeria, is one of the papers with one citation. It also explains the considerable attention on remote sensing-based research in tropical countries during the first five years of the study period relative to recent years, and the research was based on mangrove land use change monitoring.

3.3 Keyword's and publication analysis

Table 2 reveals the top 10 keywords most used by researchers in mangrove land use change using remote sensing/GIS. These keywords were extracted from the title or abstract of the 6,527 analysed data, and a total of 33,130 keywords were extracted. Specifically, 5,002 keywords emerged from the 6,574 publications.

4 Discussion

4.1 Top 10 keyword's analysis

Floods, landslides, and tsunamis are typical natural disasters that occur in tropical regions. Such disasters have had a great deal of impact on the countries involved, especially on the land cover or land use. Because more disasters have happened in the region, more research has been conducted in places where they are more likely to occur, as seen by the increase in the number of keywords for "climate change". A study in Little Andaman Island, India, was carried out to track land use changes before and after a tsunami had occurred (Shankar et al., 2013), which demonstrated the use of the "climate change" keyword. Since the occurrence of the tsunami in Japan in 2011, more studies are published such as Sharma et al., (2011) who tracked land use changes caused by heavy flooding that occurred in 2005 in Gujarat, India, affecting three districts. Later, Liou et al., (2012) also use MODIS information to evaluate the rice field and yield losses in Fukushima and Miyagi after a tsunami had occurred in 2011 that was triggered by the Great East Japan Earthquake. Thus, it can be inferred that researchers have gained considerable interests in climate change studies as demonstrated by "climate change" and "remote sensing" keywords in certain subjects as a result of the occurrence of incidents and disaster in a region.

For the past 10 years, remote sensing has been a major prospect for monitoring land use change based on the "land-use" and "land-use change" keywords. Most of the papers published in 2010–2020 focused on land use or land cover change, which are based on the title of the research since many mangrove forest areas were converted to agricultural land for food security purposes. Jiyuan et al., (2014), for example, published work on tracking land use changes in China to update its Land-Use/Cover Datasets (CLUDs), which received 591

Table 2 Analysis of the top 10 keywords of mangrove land use change using remote sensing in tropical countries (2010 – 2020)

No	Keywords	Frequency	Percentage (%)
1	Remote sensing	2,150	43
2	NDVI	649	13
3	Vegetation index	430	9
4	MODIS	337	7
5	GIS	328	6
6	Land use	280	6
7	Land use change	241	5
8	Landsat	212	4
9	Vegetation indices	207	4
10	Climate change	168	3
Total		5,002	

citations. The research has identified the conversion from forests to cities as a method to accommodate migrating workers from the villages and suburbs. A larger area for urbanization is required, as evidenced by the massive malls that have sprung up in recent years in major cities. As a result, the government is mapping the demands of departmental and private sectors for land use planning for future urbanization projects. These require updated land use maps, and hence, more studies anticipate new techniques for rapid and accurate maps. Meanwhile, the urbanization in Shanghai, China, during the transformative economy (1979–2009) occurs at a rapid rate (Yin et al., 2011), and its publication was one of the earlier contributing researches to the “land-use” and “land use change” keywords.

In contrast, the use of "land use" as a keyword has declined. Its rank has dropped from fifth in 2010 to 15th in 2020. Therefore, the present study uses the keyword "land use changes" instead of "land use" for clarity purposes. Also, since many land use changes have happened because of the urbanization across the globes, research has mostly employed the available satellite in evaluating land use change before and after the urban development. Accordingly, numerous studies have utilized remote sensing to investigate the driving causes of land use change (Qasim et al., 2013); update land use maps using different classification methods due to the rapid land use change (Deilmai et al., 2014); mapping agricultural areas to aid governmental planning on important crop area status (Razali et al., 2014), and land use change effects on coastal wetlands (Razali et al., 2014).

4.2 Normalized difference vegetation index (NDVI)

The Normalized Difference Vegetation Measure, or NDVI, is a vegetation index that can discern areas of vegetation and their state in general. Many papers on NDVI evaluation have been published in parallel in remote sensing journals. The terms "NDVI" and "vegetation indices" refer to quantitative vegetation analysis used in remote sensing studies. NDVI was, in fact, one of the hottest subjects among scholars over the 11-years. Before 2010, NDVI was used as a precursor for vegetation research, but it was shown to be very efficient for global use. Therefore, the continuous use in studies makes it the second most often used keyword. Besides, the NDVI is also used to classify diverse types of vegetation. For example, NDVI has been proven to detect senescence in a wheat crop cultivated in Mexico (Lopes & Reynolds, 2012). In India, the use of NDVI is extensive owing to the country’s high population, which necessitates the comprehensive use of remote sensing indices in order to protect its natural resources and green land for future generations. The NDVI is also employed to detect changes in vegetation such as in plantation area, high vegetation area and dry agricultural area. In the Hindu Kush Himalaya, NDVI is utilized to detect changes in vegetation area by distinguishing the vegetation pixels from non-vegetation pixels (Anderson, 2020).

After NDVI, MODIS emerged as the third most used keyword, which is as expected because MODIS has an NDVI product called MOD13Q1 v006, which is generated every 16 days at a spatial resolution of 250 m (m) and is classified as a Level 3 product (LP DAAC 2021). The product service has been servicing the global community since before 2010. Naturally, MODIS product ranking improved as the NDVI increased. However, the frequency appearance of "NDVI" fluctuated throughout 2014 to 2017 and then increased until 2019. Simultaneously, the red-edge band began to appear in vegetation health indices research in 2015 and 2016, which revealed its use in distinguishing between poor and good vegetative health (Imanishi et al., 2004; Wang et al., 2016; Zhang & Zhou, 2015). As a result, the NDVI is less used in studies where the red-edge index was first used, particularly for agricultural purposes.

Another reason to attribute the fluctuation is the use of other vegetation indices, such as the Leaf Area Index (LAI) for estimating green biomass (Heenkenda et al., 2016; Tan et al., 2014; Wu, 2014; Zhang & Zhou 2015). Meanwhile, other indices such as the Enhanced Vegetation Index (EVI) and Normalized Difference Water Index (NDWI) were associated with data on climate variables (Ladle et al., 2010). The trends from 2016 to 2020 showed that NDVI and other vegetation indices have become essential quantitative instruments in remote sensing, and the NDVI keyword will become more widely recognized as an active instrument in vegetation studies.

4.3 Landsat and moderate resolution imaging spectroradiometer (MODIS)

"Landsat" and "MODIS" refer to satellite data and sensors, respectively. As time passes, the resolution of satellite data changes and users now have the option of analysing between low- and high-resolution satellite data. Many providers even offer users high-resolution satellite data. Regardless, given the ease of accessibility and data acquisition, high-resolution satellite data are preferable for better analysis and understanding. In the most common author keywords, "Landsat" and "MODIS" appeared in the opposite order.

During the study period, MODIS was retained as the top five author keywords, while Landsat ranked eighth, indicating the capability of MODIS and its usage in remote sensing research. MODIS has three spatial resolutions of 250 m, 500 m, and 1000 m, as well as one to two days of temporal resolution, making it ideal for most worldwide application studies even after ten years. Numerous research has used MODIS as a worldwide overview of vegetation state since the application demonstrated an increase in demand from 2010 to 2020, whereas the demand for Landsat has decreased.

Landsat is one of the first satellite data and sensors during the introduction of remote sensing. Landsat data are now publicly accessible from the US Geological Survey (USGS) on the EarthExplorer website, which enables us to explore and examine with satellite data more precisely. Over the years, Landsat has demonstrated its capabilities to compete with other satellite data owing to its open-source feature. Much research has been undertaken for temporal historical land use change. However, the emergence of other satellites, such as WorldView, SPOT 8, GeoEye, and others, which provide greater resolution, has put Landsat in a disadvantage position; hence, the rapid decline observed during the study period, from 36 in 2010 to 9 in 2020. Nonetheless, Landsat data are still utilized for various research in 2020.

The growth pattern of the keywords "MODIS" and "Landsat" indicates that both remain essential over the next five years. Landsat satellite data time series, for example, were used to observe aquatic vegetation in a shallow lake in China, also known as a yellow algal bloom (Qing et al., 2020). Similarly, in Vietnam, Landsat time-series data were also employed to study the influence of urban heat islands on ground surface temperature throughout the summer (Nguyen, 2020). This highlights the satellite's capability to assist with vegetation and land research in recent years.

Since 2020, the world has been facing an unprecedented situation caused by the COVID-19 pandemic. According to the World Health Organization, the issue is expected to become the forefront of every aspect of life in the next five years (WHO, 2021). Nevertheless, the organization body remains committed to the quest for global solution in critical areas such as crop drought, forest fires, agricultural water stress, land use change, and urbanization.

However, with many countries urging the focus of investigations to be pivoted to the pandemic's impact on the nations and the studies on vaccination and public health because of the health crises, financial resources for research in forests and plants are drying up.

Recently, researchers have used "remote sensing" to derive satellite data into spatial data, along with the Geographical Information System or "GIS". Remote sensing and GIS, in its essence, must work together with remote sensing producing satellite data, while the GIS analyses the data using specific spatial software. In terms of ranking, GIS experienced a slight decline during the study period, from the third in 2010 down to the sixth in 2020. With a total of 36 posts, the largest number of documents published with "GIS" was found in 2019. In the beginning, the study reveals that researchers chose to employ remote sensing rather than GIS to characterize their analyses. However, upon observing the current trends of open-source software, various software such as QGIS and GRASS GIS are offering applications and tools that combined GIS with pre-processing features. Catalyst Professional (PCI Geomatica), Erdas Imagine, and ENVI are licenced software that integrates both applications. ArcGIS, on the other hand, offers a built-in tool for image processing, which makes the GIS keyword hidden in remote sensing.

Climate change is a global occurrence in which the weather changes. It has been a hot topic for debate over the past decade as it had a major impact on the world. The rank of climate change rose significantly from 23rd in 2010 to eighth in 2020, indicating the primary focus in much research. It also suggests its prominence as a research hotspot in the future. Between 2010 and 2011, a total of 195 papers were published with the keyword climate change. It is a typical independent variable or parameter in remote sensing study. In the Southeast Asian region, for example, Liew et al., (2011) presented a report on climate change using remotely sensed knowledge. This is because remote sensing is a valid input whose data are available online and publicly accessible at no cost from open-source websites. Massive temporal analyses are also available using open-source data, and by utilising remote sensing, the effects of climate change can be observed in many geographical locations, temporal and spatial resolution. Elsewhere, Pauca-Tanco (2012) uses Landsat time-series data to track and analyse climate change in wetland vegetation in Peru.

4.4 Policy impacts on mangrove land use change using remote sensing/GIS

In this study, documents relevant to the policy have been collected from the total publications listed above. One of them is a report on countries' developing policies, which is preceded by Hou et al., (2016). The study evaluated policy on substituting farmland for forests and its effect on land use and ecological vulnerability in Yan'an, China. In another study on remote sensing of mangrove land use, Wang et al. (2020) categorized the vulnerability of the ecology into potential, slight, medium, and heavy to assists China's Environmental Protection Law. Wongsai (2012), on the other hand, studied the changes in land use in Phuket for urban planning policy and found that the buildings were being built on land that should be used for farmland and nature reserves. The study reported the rate of transformation from forest conservation and rural and agricultural areas to residential areas by 3.19% (10.051 km^2) and 10.95% (15.598 km^2), respectively, after observation through Phuket Town Planning Policy in 2005 and 2009. Mu et al. (2012) used remote sensing to track changes in Central China's landscape patterns and concluded that agricultural preservation policies should be weighted as before since the population has continued to increase, which results in rapid urban development. Therefore, further studies on land use change policies should be carried out and derive the proposal based on the outcomes.

4.4.1 Sustainable development goal (SDG)

In terms of policy, the United Nations has rightly established the Sustainable Development Goals (SDGs) in conjunction with the declaration of "A blueprint to achieve a better and more sustainable future for all by 2030" (United Nation 2019). Unfortunately, the COVID-19 outbreak has disrupted the implementation of the SDG in 2020, causing it to fall short of the target (The Sustainable Development Goals 2020).

In 2015, 195 nations joined forces with the United Nation pledging to make the world a better place (Wang et al., 2019a, b). The SDG goals contain a list of research areas that scientists can focus on. Please visits United Nation website (https://sdgs.un.org/goals) to get more information about the goals. The SDG goals will ensure that the land will be saved, as shown by the promising outcomes from articles and conference papers produced for mangrove land use change using remote sensing, especially in tropical countries. This study topic falls on Life on Land of SDG 15, which concerns the protection, restoration, and promotion of sustainable use of terrestrial ecosystems, sustainable forests management, combat desertification, halt and reverse land degradation and halt biodiversity loss. If the outcomes continuously produce a performance over the next five years, this agenda will eventually be achieved. The study anticipates that the remote sensing keyword will continue to reign while the climate change keyword will rise in mangrove land use topics in the future.

Specifically, the keywords "land use" and "land use change" are associated very much with the SDG in many regards, i.e. SDG 6, SDG 11, SDG 13, and SDG 15. Changes in the pattern of keywords from land use to land use change showed that researchers are aware of the importance of safeguarding life on land through remote sensing tools. The study also urged more research in the future to use NDVI and other vegetation indices that deal with mangrove land use and land use change issues in tropical countries. Based on the findings, the use of NDVI, vegetation index, and vegetation indices from 2010 to 2020 show potential with increasing usage in this research topic.

Good forest management on using the land for urbanization and proper utilization of forest resources may save human's existence on earth. Forest monitoring efforts support SDG 13 (Climate Action) and SDG 14 (Life Below Water) (The Sustainable Development Goals 2020), which are related to the use of MODIS and Landsat keywords. These satellites enable the SDG to be realized within a reasonable period through a wide range of satellite products and open-source capabilities. The number of publications using satellite images for mangrove land use change is increasing. Thus, this study also anticipates more research into the use of open-source Landsat data and new products offered by MODIS for tackling and monitoring the mangrove depletion issue. These two satellites are projected to play a crucial role in assessing land use change in forested areas, with significant potential of the satellite to be used in other regions indefinitely as seen by their increased utilization.

The goals of the SDGs allow greater emphasis on research funding at the international and local levels. Likewise, between reach and focal issues, universities and academic organizations should operate within the SDG objectives. Therefore, the SDG should aim to provide feedback on scientific information published in journal articles, conference papers, and reports on the application of remote sensing technology. Coordination for better information transmission to policymakers is also essential for successful resource management policy.

4.4.2 Policy impact on food security

Food security is a complex issue that is being discussed across sectors in academia. It is affected primarily by agricultural activities, especially when there is a shortage and drought occurrence, which in turn, pose threats to climate change. Research on land use change in mangrove areas provides precautionary measures against the perils to food safety. The increased use of technology has sped up conservation efforts of high-risk mangroves from future degradation. For example, despite the maintenance, preservation, and harvest management efforts in the Matang Mangrove Forest Reserve in the Malaysian Peninsula (Goessens et al., 2014), the mangrove system remains vulnerable to potential degradation if remote sensing technology is not used soon enough. Generally, food security involves ensuring an adequate supply of food and its access by the population, mostly through generating sufficient demand via income growth or transfers. That is, encouraging the farmers and industrial player into adopting technology that can efficiently monitor plant growth in agricultural fields.

Because vegetation indices, particularly NDVI, can measure plant status, it has become a desirable technique in measuring plant health and vigour. The NDVI from leaf level can be measured using Green Seeker instruments, which is then digitally converted for spatial interpolation and further analysis. The NDVI from canopy level is a normalized ratio of near-infrared to visible red that can be retrieved from satellite images (Rouse et al., 1974). Throughout the assessment period from 2010 to 2020, NDVI has become an essential tool in measuring the mangrove, which utilized MODIS or Landsat satellite image. Both NDVI and MODIS showed significant progress, indicating their availability for use in other important forest landscape change studies. Thus, food production can be increased and stabilized through remote sensing and GIS techniques. Also, the study recommends government intervention to strengthen a country's food security policy.

In a study, the ability of NDVI and other vegetation indices to discriminate between healthy and infected palms was evaluated. Chong et al., (2017) have found the sign of low vital that indicates a symptom of Ganoderma disease. Malaysia, Indonesia, Thailand, and Papua New Guinea together produced nearly 90% of the world's palm oil output in 2000 (Ng, 2000). Since then, palm oil has made a massive contribution to the national income, benefitting 570,000 people in Malaysia alone, with another 290,000 people employed downstream. Therefore, the study showed that, in addition to NDVI, other indices also serve a similar role in strengthening food security in the context of mangrove land use change. Regardless, the frequency of keyword appearance for NDVI remains higher than any other indices, based on the 10 top-keywords finding. It also indicates that NDVI is highly used in mangrove land use change analysis since 2010 with increased frequency of usage. Other than the NDVI, a highly responsive index to land use change should be tested in tropical countries since it was generated more than 30 years ago (Rouse et al., 1974). Other indexes such as red-edge that utilized red-edge wavelength as discussed in the previous section can be a supporting tool for speedy detection of changes in mangrove that are due to degradation and assists food security policy development. This is because the index can detect disease in the agricultural area as tested in oil palm plantation and recently in a forested area.

Food security in developing countries tends to be influenced by both micro- and macro-factors such as the adoption of new technologies, support for farmer-accessible institutions, food price policy, as well as monetary, fiscal, and exchange rate policies that affect the overall economic growth and income distribution. Such issues are elaborately discussed in a book entitled "Food Security Policy in Developing Countries" by Abdulai and Kuhlgatz, (2012). The food security agenda is categorized under SDG No. 2, based on ending hunger, achieve food security and improved nutrition, and promote sustainable agriculture.

In 2018, a food security report has recommended innovative technology in precision farming systems that could be game-changers to the future of food security systems (Stordalen & Fan, 2018). The top keywords most used by researchers in mangrove land use change studies indicate the extensive use of remote sensing tools between 2010 and 2020, as shown by the predominant appearance of "remote sensing" keyword in articles and conference research. Hence, the study can help future research to respond readily to the various needs in the future in developing effective policy for food security.

The COVID-19 pandemic, which has brought the globe to a standstill, has caused multiple meltdowns with devastating impacts on food systems, social, and economic development (Swinnen & McDermott, 2020). However, agricultural sectors are emerging stronger as a result of increased awareness of technology-wise management such as precision farming that uses automated fertilizer and irrigation management. The application of remote sensing of indices, which are currently published in various documents category, creates a possibility for a larger company to explore. Also, it facilitates pest and disease assessment, monitoring of drought conditions, regulate the use of fertilisers and estimation of crop growth productivity. Presumably, relevant organizations and policymakers may have overlooked scientific information that is documented in different format, i.e. journal articles, short communication, and reports, in favour of simple publications designed for the layman.

4.4.3 Policy impact on forest resources

The publication mentioned and discussed above further illustrated the present situation on the ground in which some of the research is conducted based on current trends of issues. This was emphasized by Kanniah et al. (2015), where mangroves were converted to land use activities from 1989 to 2014, including residential areas, oil palm plantations, wetlands, barren land and industrial land as the government undertook economic ventures. The research focused on this subject gives a huge impact to policymaker in governing forest resources, which the finding identified the significance of remote sensing in monitoring palm oil, particularly that concerns industrial, environmental, and economic aspects.

This is because natural regeneration ensures long-lasting flora and fauna and the presence of forest species of similar quality in the future. It can also be an important source of recovery of ecosystem services (ES), which is critical for humanity, especially for climate change mitigation and adaptation goals (Naime et al. 2020). Among the various types of documents collected for this study, the report on countries' developing policies preceded by Hou et al., (2015) is noteworthy. It pertains to policy evaluation of substituting farmland from forests and its effect on land use and ecological vulnerability in Yan'an, China. In another study, Boupun and Wongsai (2012) examined the changes in land use in Phuket for urban planning policy and found that the buildings were built on land that should be used for farmland and nature reserves. Mu et al. (2012) used remote sensing to track changes in Central China's landscape patterns and concluded that agricultural preservation policies should be weighted as before, since the population continues to increase which results in rapid urban development. Therefore, further studies on policy-related land use change are necessary to derive a recommendation.

Malaysia has taken a step forward to become a party to the Convention on Biological Diversity in 1992 and the National Biodiversity Committee that was set up in 1994, along with neighbouring countries such as Thailand, Vietnam, Laos and Indonesia; they have at least one mangrove identified that was adopted to this convention. The statement that links to mangrove land use change using remote sensing tools is where many publications analysed in this study support the RAMSAR agenda, specifically with the usage of MODIS and Landsat for the protection of mangrove area. The objective of the RAMSAR agenda is to protect and manage international biological resources and ensure the fair and equitable sharing of biological resources and technology. Since RAMSAR requires additional studies in assessing the status of mangrove in tropical countries, the present study aptly supports the agenda of RAMSAR.

5 Conclusion

The studies on mangrove land use change in tropical countries using remote sensing/GIS have been investigated from two different perspectives, notably the forestry and agricultural as well as policy impact on food security and forest resources. The study's goal was to assess the scientific information on changes in land use of tropical mangrove forests based on remote sensing. The study specifically explored patterns in the incidence of land use change via the evolution of publications.

This study concludes that mangrove land use change studies have evolved from using NDVI from Landsat data to using updated products of MODIS to detect changes in vegetation for better understanding and classification of the land use change of the area. This study found, the use of spatial tools, such as remote sensing and GIS in drought studies, can be identified as one of fundamental research methodologies that has yet to be fully explored, especially in the use of vegetation indices. Therefore, there is a need to focus on the use of these tools for future research endeavours given the advantage offered by the technologies. The present study also determines that the use of NDVI and other vegetation indices that can be used for example Enhanced Vegetation Index (EVI) is an emerging subject for mangrove land use change. Therefore, the study proposed the use of these technologies is coupled with machine learning as a means to provide rapid and adequate tools needed for the development of integrated mangrove land use techniques. Specifically, for the purpose of updating status on tropical mangrove detection in which the tools could facilitate scaling to regional and local scales. Most importantly, the usability of vegetation indices using a different scale and resolution are identified as the major future research gap that has to be addressed.

Continuous research revealed that nagging issues occurring in tropical countries could affect policy implementation in terms of safeguarding food and forest resources. The agenda established in the SDG is comprehensive, which includes addressing the issues on forest resources, food security, humanity and most importantly, climate change. With solid support from countries across the globe, the research gaps can be resolved through research undertakings financed by multiple organizations with strong interests in the subject such as universities, institutions, and companies.

The study also discovered that some of the techniques of mangrove detection on assessing land use change are already implemented but are kept confidential, or its publication may not be intended for scholarly use. Therefore, it could present a valuable research gap that has to be addressed in the future. Regardless, other forms of communication such as seminar, webinars, and short talks by industries and companies can be one of the methods to assemble the information and techniques that are known only to the industries. This article demonstrated that there are many mangrove forests that need to be saved as soon as feasible. Similar challenges occur around the world, such as forest depletion.

There are several limits to the study, such as the fact that it can only be conducted using a database subscribed to by your university. This entailed a higher subscription fee, which should be maintained. However, there are additional solutions, such as using freeware to acquire literature databases that are not covered in this work. Currently available tools for research application are costly such as the land use change system integrated with various satellite images and product inclusion of land uses. As a result, more donors should donate to this type of study to protect more mangrove forests for future generations. Simultaneously, research in collaboration with global organizations should be prioritized to ensure that the study objective can be implemented in other parts of the world. Therefore, future research could benefit from the fruitful cooperation of various organization such as the Food and Agricultural Organization (FAO) and local agencies of the agricultural aspect.

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Bibliometric Analysis of Global Trends on Soil Moisture Assessment Using the Remote Sensing Research Study from 2000 to 2020

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Abstract Soil moisture assessment on production land is gaining more attention as one of the critical factors and had a remarkable impact on agriculture production, life as well as global warming. Bibliometric analysis is performed by extracting datasets from SCOPUS from 2000 to 2020 to analyse soil moisture using remote sensing study and progress in the last two decades. The outcome indicates that study on the development of soil moisture monitoring tools using remote sensing has been increasing especially for international cooperation articles. International Geoscience and Remote Sensing Symposium (IGARSS) recorded the most productive journal published articles in this field. Among the top active countries that produce most articles were the USA followed by China. The current keywords search on soil mechanism and satellite technology frequently searched in this field. Global issues that focus on the relationship between soil moisture and environmental forecast such as drought, climate change and global warming by using remote sensing technology needed more high impact research outputs in the future.

Keywords Soil moisture · Remote sensing · Bibliometric · Trend

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1 Introduction

Soil moisture is an important factor in the natural ecology that provides physiological state to the plant and microorganism growth and development as well as for plant rooting (Noguchi et al. 2016). Variation in soil moisture content impacted the hydrological mechanism such as evapotranspiration, transport of water and soil solutes (Yamashita et al. 2003). Not only does soil moisture play an important role in watering plants (Sawatsky and Li, 1997), to water (Rawls et al., 2003) plant (Li et al., 2011) but it also plays an important part in agriculture (Jensen, 1982). The availability of detailed data on soil moisture is also critical for classifying habitat in relation to water gradient because plants have different relationships with water that are also associated with topographical variation in water availability (Marryanna et al., 2012). Soil moisture studies are important for irrigation management practices in parched and semi-parched land (Subbaiah, 2013; Bell et al., 2020) as well as to improve crop productivity

(Bodner, Nakhforoosh, and Kaul, 2015; Medrano et al., 2015).

Remote sensing performed spatial scale (Cheema, 2011), which was used to collect surface hydrology and vegetation information (Chen et al., 2005). Soil moisture spatio-temporal volatility can be studied by retrieving spatio-temporal continuous soil moisture and other various data from remote sensing images (Zhang et al., 2020). Medium-resolution spectrometers and microwave radiometer satellites for soil water and seawater salinity were part of the remote sensing data image products that are widely used in soil moisture research (Petropoulos, Ireland, and Barrett, 2015; Karthikeyan et al., 2017; Reichle, 2008).

Bibliometrics or systematic analysis is a tool that provides network mapping and trends in the state of the art for a given specified fields related to scientific knowledge (Wang, 2015). This analysis can identify, interpret and classify the performance of the publications by author, keyword, country, year and others that quantitatively highlight research niche and trends (Zhang et al., 2020). Various articles with different scopes for soil moisture using remote sensing research (Cui et al., 2019; McColl et al., 2017) but only few bibliometric review that can reflect the trend has been conducted.

To understand the direction and gaps in soil moisture assessment using remote sensing as a tool in research, bibliometric analysis is conducted to find the pattern and trend from 2000 until 2020 with various perspectives to expose the variance and contemporary research method in the global trend. This study is conducted by clarifying the correlation between annual publications, keywords, source country, institutions and journals. Innovative approach was implemented, such as collaborative network analysis and keyword mapping to reveal the trend and pattern from multiple perspectives. Further studies should be conducted in the future to reduce the knowledge gap in this subject by using remote sensing in research methods that are available in global research networks and trends.

2 Material and Methods

2.1 Data Collection

Data exploitation of this research is searched and compiled from SCOPUS database over 10 years recent from 2000 to 2020. The search data keywords used are “soil moisture” AND “remote sensing” with extended search to document titles, abstracts and keywords of the entire SCOPUS database. The search queries the keywords in 2000 until 2020. The publications that matched the search keywords were 6417 articles, which were then collected for further study and analysis.

2.2 Data Analysis

Bibliometric analysis was performed to expose trends, network mapping and patterns in the soil moisture using remote sensing study research by multiple features such as annual publications, keywords, source country, institutions and journals. From the SCOPUS dataset provided from the search query, the individual data and details were downloaded in Microsoft Excel for data processing. Data network mapping was visualised using software VOSviewer (Wolfe et al., 2002). The software creates co-occurrence and frequency network from the data downloaded and presents the network mapping of each feature. The node represents the degree of centrality, while the thickness of the line represents the intensity of collaboration. The larger the nodes, the more crucial it is, while the thicker the line of the network, the stronger the relation.

3 Results and Discussion

3.1 Development of Research Activity by Quantitative Method by Article Outputs

Figure 1 shows the distribution lines of the annual number of articles and citation per article from 2000 to 2020. MODIS or shorted form of the Moderate Resolution Imaging Spectroradiometer was launched on December 1999 (Wolfe et al., 2002). MODIS is a remote sensing algorithm that derives time series globally on multiple geophysical parameters (Vermote et al., 2002). This research focusing on articles that published after MODIS was launched starting from the year 2000. The numbers of citations per article are increasing and reach its peak value (47.71) in the year 2002 and then went down and keep dropping until year 2020. This is because citation rates are highly influenced by the

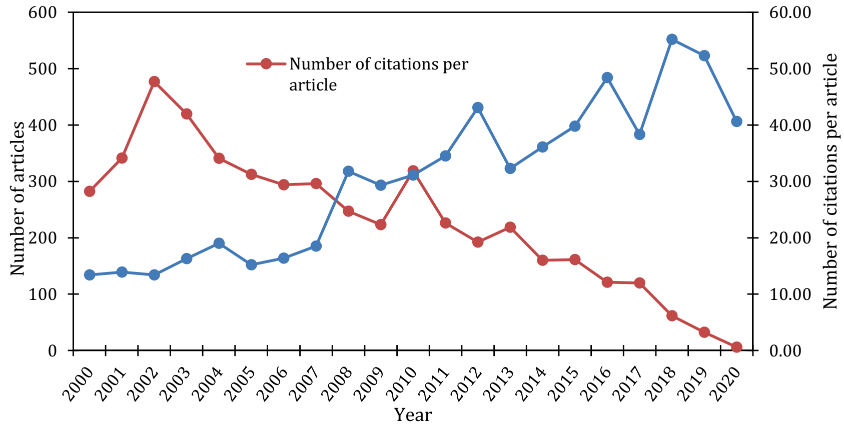

Fig. 1 The annual number of articles and citations per article from 2000 to 2020

discipline and the number of people employed in that field. For the numbers of articles, the published article keeps increasing gradually until recent year. After rapid evolution, internet became easier to access online publication that increases the number of articles. Meanwhile, it can lead to lower citations per article where researchers have large number of publications but shorter publication time.

From the total acquired 6417 articles related to soil moisture and remote sensing research, the data were sorted by annual total publications from the years 2000 until 2020. Table 1 shows the total number of articles published by year, total citations and number of citations per article. The number of articles shows a significant increase from 134 in 2000 to 185 in 2007 which represent the launching of MODIS specifically in soil moisture research. MODIS remote sensing images are generally used to evaluate ecology system and have been engaged as susceptibility model of environment (Leuven & Poudevigne, 2002; Maina et al., 2008) and build resilience indices and work structure (Ares & Bertiller, 2001; Forbes et al., 2009). In the matter of disaster readiness, remote sensing has the capability to equip essential reinforcement and monitoring during disaster and post-disaster rebuilding (Forbes et al., 2009). As a result of the fast growth of the internet, where publications and articles are simpler to access internationally, the total number of articles increased to 318 in 2008, more than double from 2007. As summary, the table illustrates the pattern of rising, except for total citations illustrating the expanding inflation of scientific knowledge in soil moisture using remote sensing research study in the past two decades.

Table 1 Article output in soil moisture using remote sensing research from 2000 to 2020

Year	TA	TC	TC/TA
2000	134	3783	28.23
2001	139	4746	34.14
2002	134	6393	47.71
2003	163	6839	41.96
2004	190	6474	34.07
2005	152	4750	31.25
2006	164	4819	29.38
2007	185	5481	29.63
2008	318	7862	24.72
2009	293	6535	22.30
2010	311	9913	31.87
2011	345	7810	22.64
2012	431	8290	19.23
2013	323	7064	21.87
2014	361	5784	16.02
2015	398	6426	16.15
2016	484	5869	12.13
2017	383	4587	11.98
2018	552	3411	6.18
2019	523	1682	3.22
2020	406	237	0.58

Abbreviations: *TA* total number of articles, *TC* total number of citations, *TC/TA* number of citations per article

3.2 Analysis of Journals and Institutions

The root of the journal with high acknowledgement can be identified based on the statistical study of the distribution of journals that publish articles in the soil moisture using remote sensing research field (Hengl et al., 2009). Table 2 shows the top 20 productive journals that publish articles in this research field along with the total number of citations and number of citations per article. *International Geoscience and Remote Sensing Symposium (IGARSS)* published the most articles (895) in the last two decades reckoning 25.8% of the total. *Remote Sensing of Environment* ranked first in terms of total citations with 19,227 accounting 25.01% compared to other journals. This figure indicates that remote sensing topic attracted a wide discussion especially in environment element on the monitoring approach with a modest amount of outputs. *The International Society for Optical Engineering* also ranked high as they published 289 articles (8.32%) and ranked third in terms of articles publications and second for total citations is IEEE Transactions on Geoscience and Remote Sensing journal which accounting for 309 articles published (8.89%) and 15,063 citations (19.60%) respectively.

Table 3 shows the top 20 productive institutions in the soil moisture study using remote sensing tools for research for the last two decades. The top institutions scattered across the USA and China and added with institutions from Austria, Belgium, Australia, France, the UK and Italy. In terms of the number of publications, US Department of Agriculture in the USA and the Chinese Academy of Sciences were relatively higher than other institutions with 297 articles (17.61%) and 213 articles (12.63%) respectively. Meanwhile, NASA Goddard Space Flight Centre recorded high number of citations (7031) followed by US Department of Agriculture (6600) and California Institute of Technology (6080). However, in terms of citation number per article, these three institutions drop to rank number

Table 2 The top 20 productive journals in remote sensing soil moisture research from 2000 to 2020

Journals	TA	TA%	TC	TC%	TC/TA
International Geoscience and Remote Sensing Symposium (IGARSS)	895	25.76	2798	3.64	3.13
The International Society for Optical Engineering	356	10.24	645	0.84	1.81
IEEE Transactions on Geoscience and Remote Sensing	309	8.89	15,063	19.60	48.75
Remote Sensing of Environment	289	8.32	19,227	25.01	66.53
Remote Sensing	261	7.51	3054	3.97	11.70
International Journal of Remote Sensing	162	4.66	3339	4.34	20.61
Journal of Hydrology	139	4.00	6082	7.91	43.76
International Archives of The Photogrammetry, Remote Sensing and Spatial Information Sciences	122	3.51	338	0.44	2.77
Water Resources Research	120	3.45	6021	7.83	50.18
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	116	3.34	2232	2.90	19.24
Hydrology and Earth System Sciences	108	3.11	4086	5.32	37.83
Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering	102	2.94	475	0.62	4.66
Journal of Hydrometeorology	90	2.59	3947	5.14	43.86
Iahs-Aish Publication	82	2.36	146	0.19	1.78
Agricultural Water Management	58	1.67	1392	1.81	24.00
Hydrological Processes	57	1.64	1657	2.16	29.07
Agricultural and Forest Meteorology	55	1.58	2100	2.73	38.18
European Space Agency	53	1.53	19	0.02	0.36
IEEE Geoscience and Remote Sensing Letters	53	1.53	1117	1.45	21.08
Geophysical Research Letters	48	1.38	3125	4.07	65.10

Abbreviations: *TA* total number of articles, *TC* total number of citations, *TC/TA* number of citations per article

Table 3 The top 20 productive institutions in remote sensing soil moisture research from 2000 to 2020

Institution	Country	TA	TC	TC/TA
US Department of Agriculture	USA	297	6600	22.22
Chinese Academy of Sciences	China	213	5307	24.92
California Institute of Technology	USA	160	6080	38.00
Beijing Normal University	China	154	563	3.66
NASA Goddard Space Flight Centre	USA	139	7031	50.58
University of Chinese Academy of Sciences	China	119	1168	9.82
Vienna University of Technology	Austria	73	4854	66.49
Ghent University	Belgium	66	1209	18.32
Monash University	Australia	63	1094	17.37
Massachusetts Institute of Technology	USA	53	2893	54.58
Centre D'etudes Spatiales de la Biosphère	France	48	1857	38.69
University of Maryland	USA	48	2588	53.92
Wuhan University	China	44	161	3.66
Hohai University	China	44	132	3.00
IEEE	USA	41	2645	64.51
Princeton University	USA	34	1754	51.59
Peking University	China	27	200	7.41
European Centre for Medium-Range Weather Forecasts	UK	25	2032	81.28
Research Institute for Geo-hydrological Protection	Italy	24	1269	52.88
Joint Centre for Global Change Studies	China	15	87	5.80

Abbreviations: *TA* total number of articles, *TC* total number of citations, *TC/TA* number of citations per article, *US* United States, *NASA* National Aeronautics and Space Administration, *IEEE* Institute of Electrical and Electronics Engineers

8th, 12th and 10th, respectively. This is due to high low number of published articles in those countries. The leading institutions for number of citations per article are European Centre for Medium-Range Weather Forecasts in the UK which is accounting for 81.28. Next to them is Vienna University of Technology in Austria (66.49) and IEEE in the USA (64.51).

3.3 Analysis of Productive Countries

Table 4 summarises the top 20 productive countries that contributed to soil moisture using remote sensing research with total number of articles and citations for independent and collaborative published articles. The USA and China lead the development of the study by publishing generous number of articles which are 3391 and 2786, respectively. Nonetheless, China still ranked one of the lowest number citations per article (8.60) as the total citations only 23,968 compared to the USA due to short publication time. One explanation for the low impact factor is that Chinese scientists prefer to publish papers with few references. Another explanation is that, like scientists in other countries, Chinese scientists tend to publish their best work in big or top English-language journals. Austria contributed a high number of citations per article (40.35) and ranked first because of the lower number of publications but high number of citations. Meanwhile, Spain, Germany, Australia, the Netherlands, Canada, Belgium and Brazil where the average of citations per article is above 20 had performed the fundamental roles in soil moisture using remote sensing research study. The USA and China also had contributed significantly in collaborating research with other countries. In addition, the ratio of international collaboration is higher than independent articles for all 20 countries. This indicates that the international cooperation gave the influence of research outputs in the soil moisture using remote sensing. It is remarkable that the publications of the articles were notably correlated with country economy development. All the G7 countries, the USA, France, Italy, Germany, Canada, the UK and Japan, were in the top 20 countries accounting a total of 51.63% articles in the last two decades.

Figure 2 shows the cooperation network of the top 20 productive countries in soil moisture using remote sensing research fields. The bigger node had the most collaborative network with more countries, and the degree of centrality is also an outstanding. The USA is the centre of the global network followed

Table 4 The top 20 productive countries in remote sensing soil moisture research from 2000 to 2020

Country	TA	TC	TC/TA	IA	IC	IC/IA	CA	CC	CC/CA
USA	3391	95,993	28.31	1237	33,552	27.12	2154	62,441	28.99
China	2786	23,968	8.60	1157	6966	6.02	1629	17,002	10.44
France	733	21,744	29.66	178	3927	22.06	555	17,817	32.10
Italy	648	14,169	21.87	196	2357	12.03	452	11,812	26.13
Spain	520	10,122	19.47	148	1650	11.15	372	8472	22.77
India	503	3455	6.87	219	1250	5.71	284	2205	7.76
Germany	486	10,693	22.00	124	1489	12.01	362	9204	25.43
Australia	484	11,733	24.24	120	1510	12.58	364	10,223	28.09
Netherlands	452	15,708	34.75	58	952	16.41	394	14,756	37.45
Canada	395	7825	19.81	131	2190	16.72	264	5635	21.34
UK	320	10,906	34.08	54	878	16.26	266	10,028	37.70
Japan	254	2961	11.66	82	561	6.84	172	2400	13.95
Austria	226	9119	40.35	34	366	10.76	192	8753	45.59
Belgium	188	4170	22.18	40	799	19.98	148	3371	22.78
South Korea	156	2543	16.30	60	858	14.30	96	1685	17.55
Russian Federation	155	1522	9.82	60	166	2.77	95	1356	14.27
Iran	121	561	4.64	44	160	3.64	77	401	5.21
Brazil	99	2343	23.67	29	278	9.59	70	2065	29.50
Taiwan	82	782	9.54	28	106	3.79	54	676	12.52
Israel	62	1144	18.45	22	240	10.91	40	904	22.60

Abbreviations: *TA* total number of articles, *TC* total number of citations, *TC/TA* number of citations per article, *IA* number of independent articles, *IC* number of citations for independent articles, *IC/IA* number of citations per independent articles, *CA* number of internationally collaborative articles, *CC* number of citations for internationally collaborative articles, *CC/CA* number of citations per internationally collaborative articles

by China and France. The USA had associated mostly with China, France, Spain and the Netherlands based on the thickness of the network line of the countries. Thick line network signified the large number of collaborative articles globally. South Korea and the Russian Federation showed thin lines of collaborative network as they published more independent articles that collaborate with other countries. Among the top 20 countries, Israel and Taiwan not have published any internationally cooperation with other top 20 countries. Major countries such as the USA, France and others were also expanded their collaboration network outwards. From the visualisation network and analysis, it can be proved that countries with advanced technology of science manage the direction of soil moisture using remote sensing research fields. In addition, global collaboration also can contribute to advancement of the study.

3.4 Analysis of Keywords

Researchers used lists of keywords to obtain expressive terms of particular genres (Tang et al., 2020). For a specific scientific field study, keyword plays a large role as it can reflect the root contents of articles and compilation of keywords can reveal the pattern and trends of specific academic research (Wang et al., 2012). In the study of soil moisture using remote sensing, noticeably there was a gap of keywords that are missing in the early MODIS launched between the years 2000 and 2005. Keywords that are related to plant growth mechanism such as "evapotranspiration" and agricultural production such as "agriculture" and "drought" as shown in Table 5 are missing in the early stages. After MODIS was launched in December 1999, the frequencies of keywords were the combination of soil moisture and remote sensing research. With the rapid development of remote sensing and computer technology in recent years, the research of soil moisture and other soil properties has become significantly matured and shown noteworthy increase frequency of keywords since 2006.

Alongside the search terms, "climate change" is one of the greatest global concerns that captivated worldwide attention which was ranked 9th in 2011 and recent indicated that soil moisture is a vital role in forecasting climate change. Research had been done and it is proved that soil moisture can be a limiting factor for land carbon uptake where, through the water stress, it could decrease the gross primary

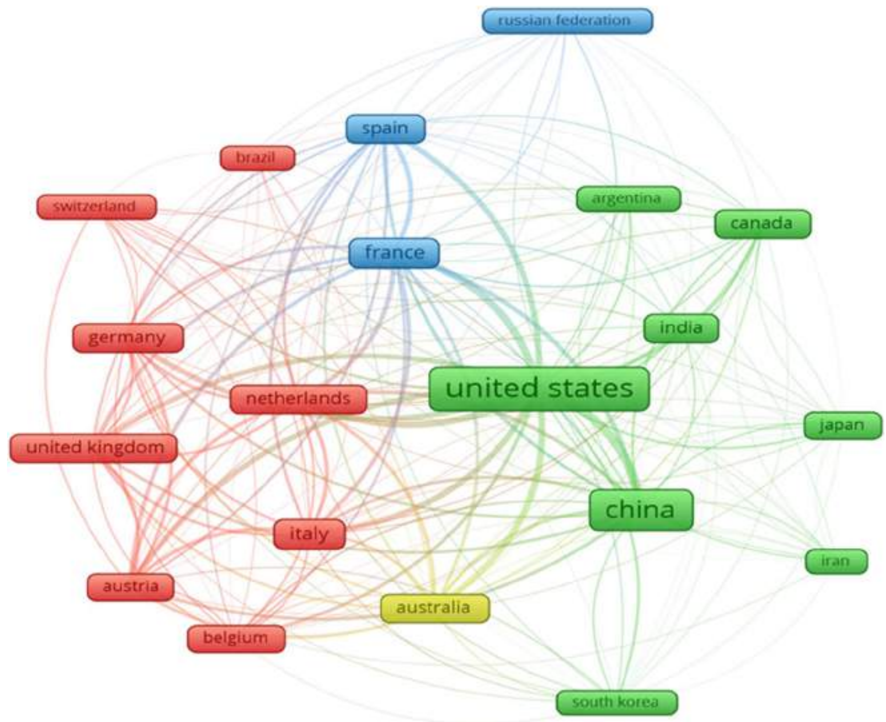

Fig. 2 Core international collaboration network map of the top 20 productive countries

Table 5 The top 20 high-frequency keywords from 2000 to 2020

Publication year	2000–2005		2006–2010		2011–2015		2011–2020	
Keywords	F	R	F	R	F	R	F	R
Soil moisture	494	2	1113	2	1679	1	2052	1
Remote sensing	811	1	1182	1	1629	2	2033	2
Soil surveys	-	-	259	6	400	3	528	3
Soils	471	3	143	12	241	7	383	4
Moisture	465	4	146	11	249	5	366	5
Evapotranspiration	-	-	101	21	202	9	259	6
Satellite data	-	-	87	31	203	8	258	7
Radiometers	161	6	197	8	242	6	257	8
Drought	-	-	114	15	166	14	249	9
Climate change	-	-	-	-	92	54	230	10
Satellites	79	16	96	22	111	37	221	11
The mean square error	-	-	-	-	75	69	218	12
Crops	56	24	84	33	115	32	214	13
Modis	-	-	75	43	161	16	211	14
Agriculture	-	-	67	48	157	17	210	15
Satellite imagery	-	-	108	18	202	10	196	16
Ndvi	-	-	68	46	103	45	191	17
China	-	-	58	59	119	27	178	18
Moisture control	-	-	107	19	86	58	174	19
Rain	-	-	89	28	128	24	166	20

Abbreviations: *F* frequency of keywords, *R* the rank of the keywords

production and worsen climate extremes (Green et al., 2019). Mainly, the study of soil moisture in climate change topic consists of the effect of climate change on soil moisture and soil moisture erosion (Guo et al., 2019; Haile, Tang, Li, Liu, & Zhang, 2020) applying the soil moisture as one of the essential variables that plays a major role in predicting the climate change models (Berg & Sheffield, 2018).

Figure 3 is a visualised network of keywords that had a frequency more than 50 and more using VOSviewer software from the recent years of 2011 until 2020. The network is divided into four clusters and illustrated by different colours. For the biggest cluster which is displayed in red colour, keywords “water content”, “drought”, “evapotranspiration” and other keywords that were related to “soil moisture” were included. This searched cluster indicated the relationship between soil moisture and agricultural production and growth mechanisms. It is essential to focus on the soil moisture in monitoring drought predicting, early warning and others as soil moisture drought can give huge influences the irrigation agriculture and long period of draught can be a threat to food security (Haile et al., 2020). In the smallest cluster in yellow colour, keywords related to soil–vegetation–atmosphere system such as “vegetation” and “atmospheric temperature” were included. This cluster is highly related to climate change as there are differences in responses of soil moisture to climate change in various parts worldwide, and the projection of soil moisture remained uncertainties (Berg & Sheffield, 2018). Therefore, further research needs to be done to enhance the prediction and forecast models of climate change and drought by understanding and investigating among the element of soil–vegetation–atmosphere mechanism.

“Satellite data,” “radiometer” and “calibration” alongside with other keywords were included in green cluster as it was related to the MODIS remote sensing tools. Almost related to blue cluster, both of these cluster describing the research approach of soil moisture based on remote sensing technology. This method used to improve and upgrade the accuracy of soil moisture measurement and monitoring as remote sensing technology is establishing multi-index or multivariate soil moisture inversion models by using multiple satellite datasets (Zhang et al., 2020). Soil moisture data in deep soil layers can be obtained by developing method by using satellite data thus can be a great approach on drought monitoring in large spatial scale (Haile et al., 2020).

4 Conclusions

In this study, bibliometric review was portrayed to analyse and reveal the trends and patterns in soil moisture using remote sensing research fields. MODIS is one of the remote sensing satellites launched that benefitted soil moisture study. This study collected reliable SCOPUS database from 2000 until 2020 with data interpreted software VOSviewer.

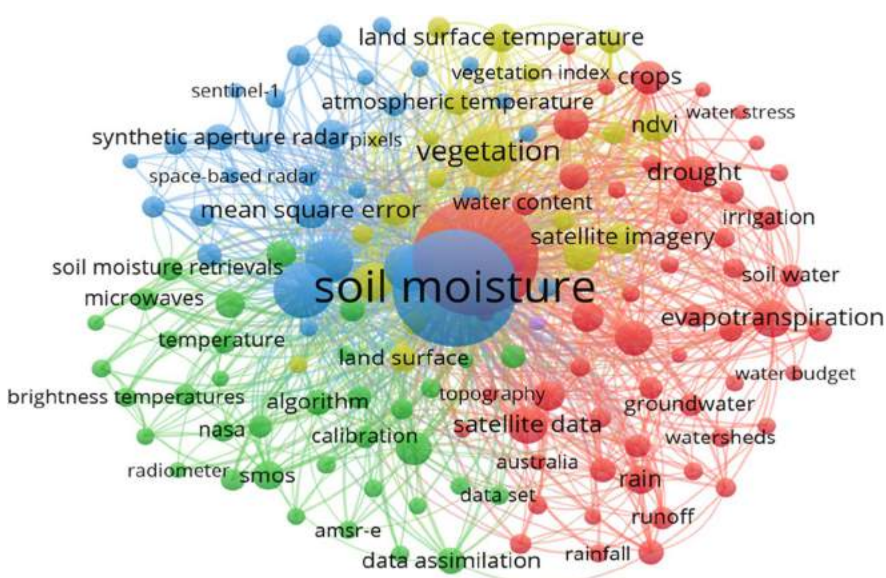

Fig. 3 The co-occurrence network map of keywords from 2011 to 2020

The exported and analysed data shows that annually, the number of articles gradually increases steadily proving that soil moisture using remote sensing had wide study prospects. Global cooperation specifically between developed countries such as the USA, France and other countries is noticeably an essential incentive to the further study in soil moisture using remote sensing. This can be seen from the published articles, and citations per article of international cooperation had higher frequency than independent published articles. As for developing countries, more high impact articles and outputs are needed to be produced in the future. Many developed countries' universities lack the framework of ethical oversight boards. Colleagues from both developing and developed countries could work together on requests for support from agencies. Researchers from developing countries will be able to access the existing ethical review processes at universities in developed countries as a result of this collaboration. In terms of soil moisture, the study is mostly related to agriculture production and life such as environmental, agriculture and ecology. The soil moisture data are also important as it can be applied for drought and climate change prediction models. With the aid of remote sensing technology, the ease of access of internet, advanced satellite data and high-quality references from the previous studies by other researchers, the accuracy of the models can be improved remarkably. Hence, global warming issue that concerned worldwide could be reducing with high precision models.

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Data Availability Not applicable.

Code Availability Not applicable.

Declarations

Conflict of Interest The authors declare no competing interests.

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Chapter

Coastal Landscapes of Peninsular Malaysia: The Changes and Implications for Their Resilience and Ecosystem Services

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Abstract

Coastal landscapes are not only supporting the most productive and ecologically valuable ecosystem but are also fast changing, caused by both anthropogenic and natural processes. Changes in the form of diminishing vegetation cover, water body and increasing urbanization in Terengganu, East Coast of Peninsular Malaysia, for the years of 2000 and 2017 were assessed using Moderate Resolution Imaging Spectroradiometer satellite (MODIS) product. Images were processed based on Erdas Imagine software and then projected to World Geodetic System (WGS 84) coordinates based on ArcGIS 10.0. Significant reduction is detected in vegetation cover, from 46.5% in the year 2000 to 26.6% in 2017, coinciding with an increase in urban areas (from 3.3 to 33.6%). Changes due to urbanization raise concern over the loss of coastal landscape and may impact its resilience, so it may no longer be able to provide key ecosystem services. This understudied ecosystem deserves to be conserved for its ecosystem services. The paper argues that looking at the data presented, the resilience or the capacity of the Terengganu coastal landscape in maintaining its ecosystem services in the near future might have been compromised. Recommendations on how these valuable landscapes could be best conserved for social and ecological sustainability are put forward.

Keywords: coastal ecosystem, coastal wetland, dune landscape, ecosystem service, land use change, resilience, socioecological landscape

1. Introduction

Sustainable development is a key agenda for present and future development and perhaps global concerted effort to reduce.

The concept of resilience in relation to ecology and ecosystem is defined as the ability of the ecosystem to absorb the disturbance without shifting to an alternative state and losing function and services [1]. It is often used to describe the characteristic features of a system that are related to sustainability, and the concept of resilience is used in various interdisciplinary works, particularly in addressing the interactions between people and nature. Resilience is also associated with the capacity of the ecosystem to undergo disturbance and maintain its functions and controls [2]. For example, changes in grass species in the rangeland reduce its capacity to continue functioning ecologically (such as in water use and nutrient cycle) under heavy grazing by animals [3]. Ecosystem resilience can play a prime role in maintaining conditions that will sustain the provision of ecosystem services that contribute to the human well-being, in this case the well-being of coastal communities. The resilience of the ecosystem could directly affect the socioecological system. The objective of this chapter is to discuss the resilience of the coastal ecosystem of Terengganu, East Coast of Peninsular Malaysia, based on land use cover changes in Terengganu between years 2000 and 2017. Threats faced by the coastal ecosystem of Terengganu that may affect system resilience and ecosystem services are also discussed.

The ecosystem services concept was coined to address various benefits and values provided to humankind by ecosystems, which arise from ecological functions and biodiversity [4, 5]. The benefits and values could be direct or indirect, covering a wide range of vital goods and services that are classified into various ecological functions, for example, the provisioning service (such as providing goods or raw materials), regulatory services (such as air and water purification, water and nutrient cycling and regulation, soil formation and retention, atmospheric carbon sequestration) and supporting services. The last is the prerequisite for three other sets of ecosystem services (provisioning, regulating and cultural). However, the classification and typology of ecosystem services are varied and sometimes debatable in terms of application and relevance [6]. Nevertheless, ecosystem services as a concept are acknowledged to be an important tool to raise awareness on ecosystem's importance, particularly through identification of the goods and services made available by the ecosystem. The quantification of ecosystem services provide a monetary dimension, creating a potential link between biodiversity conservation and market value. In this chapter, we identify and discuss key ecosystem services of the coastal ecosystem of Terengganu and how it might have been interrupted by the changes.

Worldwide, coastal landscapes change tremendously due to urbanization and various other pressures both from anthropogenic-based and natural processes. Coastal landscapes are among the most densely populated zone as this zone provides enormous values and services to human population. Coastal ecosystem is commonly addressed together as 'estuarine and coastal ecosystems' (ECEs) due to their close connectivity and complexity in providing ecological services [7]. It not only holds high key economic values and vital ecosystem services but also supports integrated systems of social and ecological landscapes (SEL) [8]. At the global scale, coastal vegetation varies across geographical regions. In Malaysia and other tropical countries, there are three common vegetation types easily found in coastal zones, namely, mangroves, peat swamp forest and freshwater swamp. Coastal vegetation plays a significant role in stabilizing coastal ecosystems, for example, by modifying and stabilizing the physical environment [9]. The loss of coastal vegetation or changes in land use cover of terrestrial ecosystem could change the biomass and productivity leading to the changes in carbon cycling processes [10]. Coastal wetland reclamation causes loss in ecosystem services, for example, in Lianyungang Province in China [11]. Coastal wetland ecosystem varies in subtypes which comprises of estuaries, marshes, salt ponds, lagoons, mangroves, intertidal habitats and other coastal system subtypes. All wetland ecosystems vary in terms of unit value and ecosystem services rendered and even within the same eco-subtype; the unit value may vary with different space and time [4]. Thus, for the unit value of ecosystem services, different coastal wetland should be conserved and managed differently.

The East Coast of Peninsular Malaysia coastal plain is originated from marine-based deposit arranged in a series of ridge and depression parallel to the shoreline [12]. This soil formation is classified as "beach ridges interspersed with swales"

(**BRIS**) or locally known as *tanah beris* or *tanah bris*, where *tanah* is soil in Malay. BRIS soil formation is an oligotrophic type of soil, infertile and unsuitable for agriculture [13]. BRIS soil composes of more than 90% of sand (**Figure 1**). Despite that, it supports adapted and distinct vegetation formation which differs from common lowland tropical rainforest [14]. BRIS soil system occurs more abundant in the state of Terengganu relative to other states in the East Coast of Peninsular Malaysia, namely, Pahang, Kelantan and Johor. Coincidently, Terengganu also poses the longest coast compared to the other east coast states. Being one of the main oil-producing states in Malaysia, the coastal plain of Terengganu is already well developed with coastal road, settlement and infrastructures. However, it is a worrying fact that about 30% of Malaysia's coastlines are exposed to erosion [15]. More worrying is the fact that coastline erosion or accretion is not only caused by large monsoon waves but also by a more complicated interaction of offshore bottom bathymetry and island shelters, whereby these two components become a site-specific factor that helps to focus or disperse the energy of the monsoon waves to localize erosion or accretion [16]. Coastal erosion further became more frequent, subsequent to major sea reclamation for an airport runway upgrading in 2008 [17].

In the past decades, Terengganu has rapidly developed its overall economy through the federal government's East Coast Economic Region (ECER) Master Plan that was launched in 2008 headed by the East Coast Economic Region Development Council (ECERDC) [18]. The development programs and projects, among others, aim to raise the income levels and reduce poverty of the Terengganu population by expanding employment prospects in the east coast regions. Many of the projects take place along the coast itself, for example, development of a new central business district (CBD) at the north and south estuary of the Kuala Terengganu town centre and the planned development of the 600-km east coast rail line (ECRL) planned for linking key industrial hubs in Terengganu with Kuantan Port in Pahang and Port Klang in Selangor, both to its south. Some developments in Terengganu are located on the shoreline itself, for example, hipster concept restaurants along the coast of Tok Jembal, in Kuala Nerus district. Looking at this trend, the future outlook for Terengganu coastal ecosystem is rather challenging based on the worrying fact that about 30% of Malaysia coastlines are exposed to erosion [15]. Terengganu coastline erosion or accretion is not only caused by large monsoon wave but also by a more complicated interaction of offshore bottom bathymetry and island shelters [19]. Coastal erosion then becomes more frequent as a result of major sea reclamation for an airport runway upgrading in 2008 [17]. Further development in the coastal

Figure 1.
Examples of typical soil series (Rudua and Rhu Tapai soil series) under beach ridges interspersed with swales (BRIS) system in the East Coast of Peninsular Malaysia compose more than 90% of sand.

zone of Terengganu needs in-depth analysis on the current physical setting to reduce impact on coastal environment and community. This paper discusses coastal changes in Terengganu by looking at land use changes in terms of vegetation cover, urbanization and water body from the years 2000 to 2017 and the impact of these changes to Terengganu coastal ecosystem resilience and ecosystem services.

2. Changes in coastal landscapes and implications for ecosystem services

2.1 Ecosystem services of coastal landscapes

Among the most significant ecosystem services of coastal landscapes is perhaps coastal protection. The coastlines of eastern Peninsular Malaysia are directly exposed to the South China Sea's strong winds and dynamic coastal processes. Coastal vegetation acts as a first line of defence from physical elements of wind and wave due to exposure to the annually occurring northeast monsoon. At the same time, coastal vegetation holds together structurally loose coastal sandy soil. The Terengganu coast is also blessed with a prominent stretch of pure stand of *Melaleuca cajuputi* trees which barricade strong wind, protecting its coast and inland [20]. Having soil attributes of beach ridge system or BRIS, many parts of the coast of Terengganu also support a seasonal freshwater swamp or often addressed locally as *paya gelam* (in Malay) or gelam swamp as this swamp is dominated by gelam or *M. cajuputi*. This swamp is a seasonal wetland where its volume of water is contributed mainly by rain and to some extent by the overflow of small river tributaries during the monsoon season. Gelam swamp could support up to a 2–4 metre depth of water which is closely related to its function of mitigating flood in coastal areas and inland, particularly in the rainy season during monsoon months. Swale element in beach ridge soil of the East Coast of Peninsular Malaysia coastal plain acts as a sponge to keep subterranean water source, thus regulating local hydrological cycle [21]. Supporting one of the rarest type of wetland, a freshwater seasonal wetland (e.g. in Tasik Berombak of Setiu Coast and Jambu Bongkok, Dungun) [22]. The BRIS soil formation system plays a critical role in the local hydrological cycle, since it stores underground water and a deep layer of sand (~15 m below ground as recorded in Tasik Berombak, Setiu, Terengganu) which then act as a natural water filter and storage for clean freshwater—an important source for nearby areas becoming a part of a complex hydrological system of the coastal plain [21]. Although this kind of regulatory services carried out by BRIS soil ecosystem is hardly visible, the effect on social resilience on the local community is profound. It plays a critical role in providing adequate amount of good quality freshwater to support local economic activities of the coastal community, for example, in the district of Setiu, where the brackish lagoon is heavily used for aquaculture activities.

Other than the hydrological aspect, some part of BRIS soil ecosystem is comprised of newly developed peat, which is an important form of carbon storage [23]. Soil carbon together with above and below ground biomass of plants is a very important carbon sink. Even though above ground carbon in the biomass of *M. cajuputi* on dune landscape of Terengganu is much lower than other common Malaysian tropical lowland forests [24], *M. cajuputi* tree stand still serves as an important local carbon stock that could help in mitigating climate change effect. Carbon fixed in the above and below ground biomass of *M. cajuputi* could help reduce carbon being released to the atmosphere, thus reducing the effect of global warming. The benefit of conserving forest for carbon stock is well discussed as part of many ecosystem services of forest [4]. Sparse natural vegetation growing on the coastal plain of Terengganu plays a vital role in stabilizing the loose structure of coastal soil, growing on both ridge (dry area) and depression (swales or water-logged areas) of sand dunes. On the ridge, vegetation is growing in the clump to optimize soil resources needed for growth and development. Removal of natural vegetation either by natural (e.g. wild fire) or anthropogenic activities (e.g. legal and illegal sand mining) may cause coastal erosion, leaving the soil prone to be invaded by exotic invasive species of *Acacia mangium* (Fabaceae) or indigenous species *Catunaregam tomentosa* (Rubiaceae) [25]. *Acacia mangium* is not yet declared as invasive species in Malaysia, but its ability to negatively affect and alter nearby plant composition in its presence, particularly through its allelopathic effect, is well known [26]. *Acacia mangium* can easily invade BRIS ecosystem due to open canopy and low stature of its vegetation that grows in clumping pattern. The abundance of *A. mangium* mother trees in and around the coastal ecosystem of Terengganu facilitates the dispersion of this species. The seed of *A. mangium* is dispersed by birds and wind and easily germinates underneath vegetation clump. Many degraded BRIS soil ecosystems along the coast of Terengganu are already invaded and totally taken over by this species [4, 20, 25]. It is well acknowledged that invasive plant species can decrease resilience by reducing the biodiversity in the ecosystem that is being invaded and eventually will interrupt key ecosystem services provided by one ecosystem [27]. However, for the coastal landscape of Terengganu, the lack of interest and awareness from local authorities may have contributed to the lack of research funding to address this issue.

Provisioning services of the coastal landscape of the East Coast of Peninsular Malaysia are closely related to support livelihoods of its fishery communities, for example, the utilization of the most abundant plant resources, *M. cajuputi* (Gelam) wood and other parts. Woods of *M. cajuputi* are processed for charcoal and poles which are used as construction material and in scaffolding for small-scale construction such as for fishing jetty and port. The bark of gelam is traditionally used to seal boat walls (caulking) [28], assisted by waterproof properties of the bark. Gelam tree is also widely planted as ornamental tree in urban areas and public parks throughout the country. The potential value of gelam in provisioning service includes the use of gelam in greening effort [29]. The tiny and abundant seed can germinate and grow well into seedlings, or vegetatively it can propagate easily using its root suckers [30]. Fire resistance of this tree provides an advantage for using this species in restoration effort. In the wild and on BRIS ecosystem disturbed habitat, postfire recovery of gelam is quickly taking place by regenerating coppice shoots, which originated from its apical buds underneath the bark [31]. Gelam provides a renewable resource of woods and poles and potentially can be used to produce *cajuput* oil, a secondary compound from its leaves which may be useful for pharmaceutical industry. The 'cajuput' oil industry is surviving well in Indonesia [32] and Thailand [33]. However, similar industry is still untapped in Malaysia or Terengganu, possibly due to low essential oil content in its leaves, about <1% of it dry weight [34]. Although *M. cajuputi* has low yield of essential oil, it is still a promising natural plant extract and is a far more environmentally friendly consumer product to replace chemical-based products [35].

Indirect use of pure Gelam stand supports healthy populations of bees and stingless bees, giving a source of sought after honey, collected by the local fishermen as their side income [36]. In swampy part of coastal plain, gelam trees act as a key species in the swampy part of coastal plain, supporting a healthy population of freshwater fishes that are commonly caught by the locals for their ornamental (e.g. tigerbarb) and also for nutritional values (e.g. catfish, snake head and climbing perch). The fishes are abundant during the monsoon season in Terengganu. There are more than 60 species of ornamental freshwater fishes recorded in the riverine system and swamps of Terengganu [37, 38]. Other than supporting freshwater fishes, gelam swamp provides habitat for hydrophytes (submerged, emergent, floating rooted) and woody and nonwoody associated plants. Carnivorous plants of *Nepenthes*, *Drosera* and *Utricularia* are also common at the fringe of the swamp offering a view of a montane or heath kind of flora on the lowland that is easily accessible for ecotourism or showcase [39]. A far more puzzling flora in the gelam swamp of Terengganu is the occurrence of an endemic sedge species of Peninsular Malaysia, *Websteria confervoides* (Cyperaceae), which is so far only recorded in Lake Bera (Pahang) dan Jambu Bongkok, Dungun (Terengganu). This plant depends greatly on the existence of the coastal wetland of gelam swamp and only abundant during high water level (0.5–2 m) [24]. The mechanism of how this plant could maintain its population in the dry swamp after a long drought in the dry season or non-monsoon months is still understudied and worth exploring. In Malaysia in general, intensive research on forest and vegetation are primarily focused on the dipterocarp forest for the inland forest and mangroves in the coast. It is worrying that lack of research in this similar kind of vegetation on the coastal plain of Malaysia will contribute to the poor understanding on how this ecosystem function provides key ecosystem services. Consequently, lack of knowledge about the ecosystem function may prevent us from building the resilience of this disappearing coastal ecosystem.

The ridge areas on the dune which are dryer due to its loose sandy structure surprisingly support quite a number of adapted coastal vegetation [25], including more than 30 species of wild orchids [40] (**Figure 2**). Thus, the Terengganu coastal plain could be an important gene bank for wild orchids that could support commercial orchid industry, one of the option values under the total economic valuation (TEV) [5]. The aesthetic value of this coastal ecosystem together with its natural flora, fauna and landscapes could potentially be conserved and highlighted as one of the many ecotourism products for Terengganu to add to the economic benefit to the coastal communities. This value could be a monetary trade-off for conserving Terengganu BRIS ecosystem. With all the outlined ecological values, services and potentials, gelam forest is no doubt a valuable premise for Terengganu's coastal ecosystem resilience. Maintaining healthy Gelam forests will help maintain their ecological services for the benefit of the coastal environment that supports the livelihoods of coastal communities. Rather than being seen as unproductive and unimportant, gelam forest should be conserved for their values and services. Awareness on the importance of gelam forests to the sustainability of coastal ecosystem and people should be intensified. Factors contributing to the risk faced by the Gelam forest are outlined in the next section.

Figure 2.
Natural vegetation on dry part (ridge) of BRIS soil ecosystem on Terengganu coast with a clumping pattern of vegetation (left image) and wild orchid species, Phalaenopsis pulcherrima*, thriving well underneath vegetation clump (right image).*

2.2 Threats to gelam forest and coastal landscape of Terengganu

The coastal ecosystem of Terengganu is at risk of disappearing if there is no effort in conserving or managing this ecosystem in a sustainable way. Fragmentations of Terengganu coastal ecosystem are mainly due to reclamation for housing or settlement on a private land, or a development of new township and infrastructure on the state owned land. This is primarily due to its strategic location along the main coastal road, as well as on the lower terrain. Failure in seeing the values of natural ecosystem, shadowed by the lack of value for agriculture, and BRIS soil ecosystem is considered as a barren land and wasteland that deserve to be converted to other land uses. This ecosystem is also threatened by illegal chemical and solid waste dumping, as observed in many areas along the coast of Setiu (north of Kuala Terengganu) and Marang (south of Kuala Terengganu) (**Figure 3**). The lack of public knowledge about the values of BRIS soil coastal ecosystem and low civic mindedness are identified as primary causes to this problem. Lack of human presence and visible activities in the ecosystem itself also encourage the act of illegal dumping. Frequent monitoring by local authority could help reduce the incidence of illegal waste dumping [20, 25].

BRIS soil vegetation can easily catch fire, particularly in non-monsoon months or drought season (**Figure 3**) which can be of natural process and human induced. High incidence of sunray and high temperature of sandy soil surface may initiate fire naturally. Fire can also occur simply from human reckless behaviour, for example, by throwing cigarette butts into the dry and sparse vegetation on BRIS soil ecosystem. There was an extensive fire occurrence recorded along Terengganu coast [41] and several places along coastal road in Setiu experiencing fire in 2016, coinciding with low rainfall and drought in 2014–2016 [30]. Fire is one of driven factors for ecological succession [42] and sometimes needed for vegetation regeneration [43]. However, with the presence of fire-adapted species, ecosystem resilience is negatively affected [44]. This brings us to the next threat faced by Terengganu

Figure 3.
Threats to coastal ecosystem of Terengganu, frequent fire occurrence particularly during drought or non-monsoon months (top row images), illegal sand mining (bottom row, left image) and illegal dumping (bottom row, right image).

coastal ecosystem, which is colonization of *A. mangium*. It is well noted that a slight modification to BRIS soil ecosystem on Terengganu coast leads to colonization of invasive *A. mangium* [20]. Many sites of BRIS soil vegetation has been replaced totally by *A. mangium* with no sign of natural vegetation underneath. On the other hand, the natural vegetation could be replaced totally by the ferocious spiny shrub of *Randia tomentosa* (Rubiaceae). Changes in plant composition reduce the resilience of the ecosystem, whereby it is shifted towards less diverse in species [1]. This eventually affects many ecosystem services related to plant's roles, for example, in regulating soil nutrient cycle and supporting animal diversity.

The other major threat to BRIS soil ecosystem of Terengganu is sand mining, which commenced a few years back when there was a high demand for sand from the Terengganu coast as it contains high-quality silica. Sand is mined illegally and possibly being transported to the other states or countries to meet the demand. The illegal and small-scale sand mines operated by removing small patches of sand, usually not that far from the coast itself. However, there is one site being mined with the size as big as football field near Lembah Bidong in Setiu district (**Figure 3**). Experimental study at this degraded site indicates that regeneration of natural vegetation is low and occurs at a very slow rate. Thus, illegal small-scale sand mining could be interfering with key ecosystem services of the coastal ecosystem due to removal of sand and vegetation. In the case of legal and large-scale sand mining, currently Terengganu has two sites of sand mining, privately operated and declared as not detrimental to the coastal environment. However, it is doubtful that the impact of sand mining to the coastal ecosystem is low; rather, the extent of the impact is still uncertain and unknown, as the sand mining is a newly emerging economic activity in Terengganu. The hope is that this industry will be well regulated and monitored by the authority to minimize its impact on the coastal environment.

2.3 Changes in the coastal landscapes of Terengganu (Years 2000–2017)

Based on images of Terengganu vegetation cover for years 2000 and 2017, it is clear that the coastal area of Terengganu is changing due to urbanization (**Figure 4**). Urban area has increased from about 3.3% in the year of 2000 to 33.6% in 2017 (**Table 1**). Even though the outline data does not specifically indicate differences contributed by the reduction of coastal area, it is clear that there is an increase in urbanization areas along the coast of Terengganu in 2017. Major changes to the Terengganu coastline begin in 2008 when parts of the sea off Terengganu were reclaimed for an airport runway upgrading [17]. Such major reclamation not only caused erosion but also halted the natural accretion process by disturbing sediment transport along the coastline [45]. Consequently, episodic erosion occurred in the northern part of the Terengganu coastline, and the most recent erosion occurs in Kampung Mengabang Telipot, north of Kuala Terengganu state capital [46].

Erosion and accretion are natural processes and part of ecological coastal dynamic. However, severe erosion fundamentally indicates failure of managing coastal zone when longshore sediment transport is interrupted by engineering works such as construction of groynes and breakwaters along the northern Terengganu coast [47]; most possibly it is happening in recent breakwater establishment along the coast of Terengganu (**Figure 5**). Other possible causes of erosion are removal of natural vegetation that can dissipate the wave energy, reduction of sediment supply from engineering works in rivers such as dams and barrages, sand mining from river bed and unregulated or uncontrolled dredging and sand mining activities in near shore areas. All of these factors seem to be part of the contributing agents to Terengganu coastal erosion. It is a prime challenge for the authority of the state of Terengganu to find a creative engineering technique to solve this

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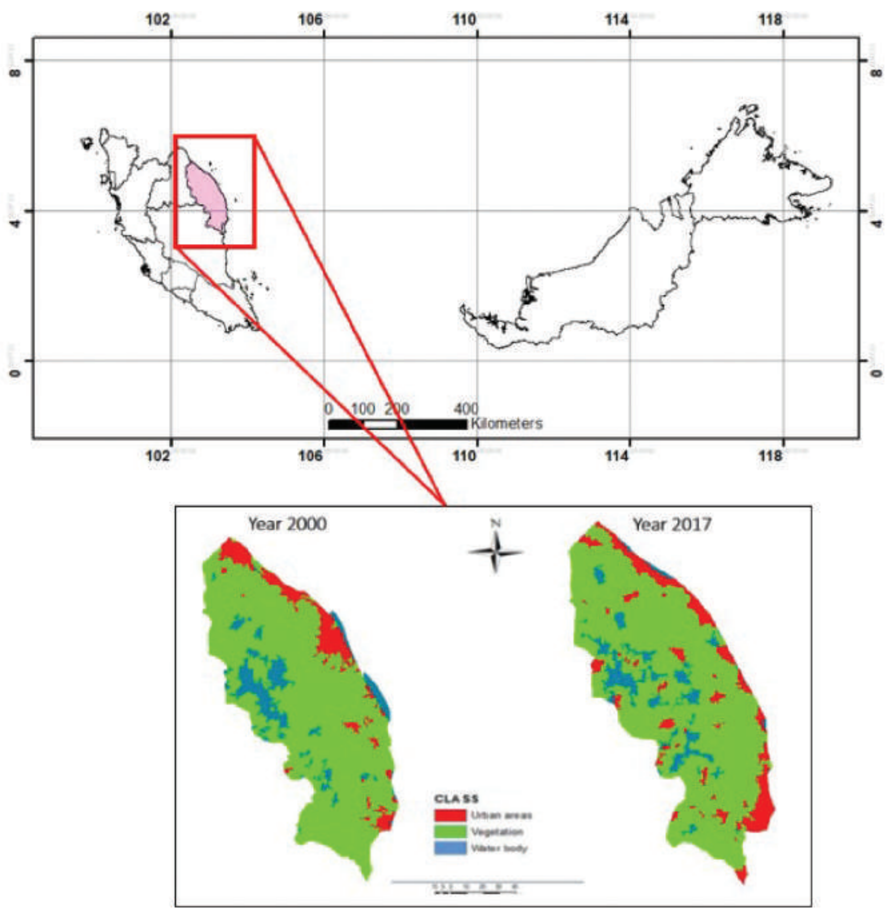

Figure 4.
Map of Peninsular Malaysia (top row) and vegetation cover in the state of Terengganu, East Coast of Peninsular Malaysia, for the years 2000 and 2017 (bottom row). Image source: Land Process Distributed Active Archive Centre (LPDAAC).

Land Use Classification	Year 2000		Year 2006		Year 2017	
	Hectare	Percentage	Hectare	Percentage	Hectare	Percentage
Water bodies	15674.43	50.1	15477.64	53.2	13092.78	39.7
Vegetation	14547.42	46.5	15300.67	31.5	8787.50	26.6
Urban area	1038.49	3.3	4458.33	15.3	11094.25	33.6
Total	31260.34	100	29097.90	100	32974.53	100

Note: Data in hectare are extracted from satellite images obtained from the Land Process Distributed Active Archive Centre (LPDAAC).

Table 1.
Vegetation cover for the state of Terengganu, Peninsular Malaysia, for years 2000, 2006 and 2017

Figure 5.
Coastal erosion along the Universiti Malaysia Terengganu (UMT) campus in Kuala Nerus district, north of Kuala Terengganu (left image), and breakwaters constructed to solve erosion along north of Terengganu (right images). White arrows mark extension of airport runway in 2008. Source: Media Kreatif UMT (left image) and Mr. Mokhtar Ishak (right image).

complicated 'man versus nature' situation. To ensure the sustainability of the coast, significant efforts should be made to maintain ecological infrastructures or multi-functional network of ecosystem provided by coastal wetlands [11]. Considering the dynamics of the Terengganu coast, it is recommended that the coastal sustainable land use planning (SLUP) strategy be adopted. SLUP is evident to enhance coastal resilience, so that coastal ecosystem could continue to provide key ecosystem services, particularly for the benefit of the coastal community [8, 48, 49].

The reduction of vegetation cover in some parts of the coastal areas of Terengganu is possibly due to vegetation removal for aquaculture activities and settlement construction. In the coastal areas of Terengganu, apart from mangrove trees and associated plants, *M. cajuputi* (gelam) tree clearance is common. For example, in Kemaman and Setiu districts, pure stand gelam trees are cleared to make ways for township development and aquaculture complex, respectively. Vegetation clearance using heavy machineries is a common practice during land preparation for the construction of residential or commercial buildings. Should the sites happen to be on swampy or wet areas, sand or top soil is used to reclaim them before construction commence. In most of the state in Malaysia, regreening or revegetation of the developed areas is voluntary and not regulated. This could contribute to the loss of vegetation in newly developed urban areas. However, the reverse may happen whereby land is cleared for oil palm plantation, which then contributes to the increase in vegetation cover; albeit, oil palm plantations are a monocrop and not biodiverse. Therefore, oil palm plantations and natural stands of gelam may not be similar in quality and quantity of providing ecosystem services.

2.4 Impact of coastal landscape changes on ecosystem resilience and social environment

An interesting shift that has taken place in resilience thinking that is of relevance to this paper. The premise in resilient thinking that ecological resilience is key to the management of changes occurring in complex and dynamic systems of people and nature cannot be understood if there is little understanding of the social drivers of change that contributes to that ecological resilience [50]. 'People do change the resilience of ecological systems' ([50]:p.428).

Complexity and diversity as well as fragility are deemed to be the characteristics of both social and natural systems so that responses to interventions or encroachments are unpredictable. Ecological resilience taken to mean the capacity for renewal in a dynamic environment is required in order for the system to respond to the social drivers of change, albeit in an unpredictable manner. The major social drivers of change that are most mentioned in the literature, because of their generalized presence in landscapes and regions around the world, are acknowledged to be unsustainable land use, abandonment and urbanization [51]. These some drivers are also occurring in the coastal landscapes of Terengganu, as mentioned in earlier sections of this paper.

The tendency to focus on man-made degradation of ecosystems in studies of resilience has been criticized. Instead, it is recommended that solutions should be focused on creative processes of accumulating natural capital developed and should include their intangible values. This is also due to the assessment practices that commonly focus on visible or tangible change (biodiversity loss, brittle stability, of 'an accident waiting to happen') [50]. Examples of intangible values are those associated with biodiversity conservation (for ecotourism, or for ecosystems services it renders to human populations).

Since human well-being is also linked to non-tangible (non-market values), there has been an increasing interest in cultural landscapes (heritage places, regions that have iconic value for identity formation—nationalism—such as Mount Kinabalu for Sabahans of Malaysia, the pastoral landscapes of England and many more). These non-market values are broadly captured by the literature on 'cultural values' [52, 53]. We will focus on one element of cultural values, namely, identity strengthening, which is linked to a sense of place. According to [52] the concept of a sense of place 'embeds all dimensions of peoples' perceptions and interpretations of the environment, such as attachment, identity or symbolic meaning, and has the potential to link social and ecological issues'. An example of a sense of place, in this instance the link between the Terengganu coastal system and the identity of fishers, can be taken as an example as below.

Livelihood security of artisanal fishers of Terengganu depends on the sea—near shore and further in the open South China Sea. However, the sea provides more than livelihoods to fishers. Anecdotal evidence from newspaper clippings indicate that despite risks from coastal erosion, many local residents find it difficult to leave because they claim that they have nowhere to go [54]. As well, among artisanal fishers of the Setiu wetlands in Terengganu, despite risks from weather disturbances and being employed in more stable occupations such as in aquaculture, many fishers maintain their fishing trips out to at least three to four times a week except during severe monsoons [55]. This maintenance of their connection with the sea is what distinguishes those who consider themselves as 'real' fishers versus those who are not (including those who have boats and equipment but do not pursue fishing seriously). The sea then carries the intangible value of providing some fishers with a mechanism for strengthening their cultural identity. Similar findings on the effects of place (whether marine or terrestrial) and identity are evident in many studies around the world [56]. For example, in Sabah, Bajau fishers identify themselves with the inland sea surrounding the Banggi Island chain and their identity found strength in seaweed cultivation, despite the fact that fishing as an activity provided them with a higher return for hours worked than labour intensive seaweed cultivation [57].

The bio-security of Gelam forests depends on the degree of its resilience as well as the social resilience of the local communities that have lived alongside them or who are benefitted from the health of these forests. The ecosystem services provided by the wetlands and the dry swamp of Gelam forests are including uses in the construction of sea-going fishing boats. Freshwater fishes found in flooded lakes and riverine systems during the annual monsoon season provide extra source of nutrition to local communities as outlined in earlier sections of this paper. But the reverse provision of services by local communities, through their local knowledge in the sustainable management (through use) of natural resources from inland forests and seas, has not been well researched.

Consequently, a lot more research needs to be done on how local communities form knowledge about their landscapes. Secondly, given the understanding that throughout history there are very few landscapes in the world that have not been shaped by local communities [54], to what extent has local knowledge shaped the characteristics of the gelam landscape? These are valid questions to ask because despite the transformation of landscapes by drivers of development as the Terengganu coast has been, certain cultural values are not totally lost as viewed in fishers' identity and place. As to why local knowledge research is important, there is a consensus that environmental degradation is not amenable for its solution to one body of knowledge alone but from a variety of knowledge types and disciplines.

3. Conclusion

There is a reduction in vegetation cover in Terengganu from the years 2000 and 2017, and it coincides with the increase in coverage of urban areas. Even though our data do not particularly reflect specific changes to coastal areas, this reduction in vegetation cover deserves to be addressed. It is time that the complexity of coastal ecosystem be valued as a social ecological landscape. Sustainable land use planning (SLUP) may be a good model to be adopted in managing coastal ecosystem of Terengganu. Sustainable solutions should be applied to aim for social, economic and environmental benefits. In-depth research on each component of social and ecological system and their connectivity should be enhanced to further understand coastal ecosystem resilience and assist the authority in the planning and managing of coastal ecosystem [58]. Better valuation of the landscape could be conducted to include general public perception analysis in the development planning [59]. Local knowledge of the ecosystem ought to be encouraged for their value to planning.

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Conflict of interest

There is no conflict of interest in this publication.

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Characterizing and Assessing Forest Density and Productivity of Ulu Muda Forest Reserve Based on Satellite Imageries

4

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Abstract

The NPP was calculated for 2-m resolution image of Ulu Muda Forest Reserve (UMFR), in Sik, North of Peninsular Malaysia. The GeoEye-1 image was first preprocessed, and land use was classified based on object-based image analysis (OBIA) based on PCI Geomatics Catalyst Professional image processing software. Attributes were segmented by employing three segmentation methods, namely, finer, 50 scale; moderate, 200; and coarse, 350. Based on accuracy assessment, a moderate scale of 200 showed the best kappa with 0.67, whereas for finer and coarse were 0.44 and 0.27, respectively. The moderate segmentation method showed a moderate number of attributes that sufficiently assist in collecting accuracy sampling that resulted in a higher kappa coefficient in the study. Biophysical indices, such as Absorbed Photosynthetically Active Radiation (APAR), Normalized Difference Vegetation Index (NDVI) and the fraction of Photosynthetically Active Radiation (fAPAR), were calculated for the study based on the satellite images. The study showed that the coarse method of NDVI had the highest mean value of 0.709, followed by 0.698 for moderate and 0.966 for finer method. A high NDVI value indicated that the area in UMFR is covered by high-density vegetation dominated by lowland forest. Meanwhile, the

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