A Review: Progression of Remote Sensing (RS) and Geographical Information System (GIS) Applications in Oil Palm Management and Sustainability

Mohd Sharul Aikal Baharim¹, Nor Aizam Adnan¹, Fazly Amri Mohd², Idris Abu Seman³, Mohamad Anuar Izzuddin³ and Nordiana Abd Aziz³

¹Centre of Studies Surveying Science and Geomatics, Faculty of Architecture, Planning & Surveying Universiti Teknologi MARA, 40450, Shah Alam Selangor, Malaysia
²Centre of Studies Surveying Science and Geomatics, Faculty of Architecture, Planning & Surveying Universiti Teknologi MARA Perlis, UiTM Arau, 02600 Arau, Perlis, Malaysia
³Malaysian Palm Oil Board (MPOB), 6, Persiaran Institusi, Bandar Baru Bangi, 43000, Kajang, Selangor, Malaysia

nor_aizam@uitm.edu.my

Abstract. In agriculture management and cultivation, many researchers tend to introduce and implement new methods or techniques to improve the sectors in order to sustain a good production from the sectors. The oil palm plantation is one of the sectors that have received an improvement in development in many aspects. Thus, this paper reviews in detail the recent expansion of oil palm management and sustainability through the latest application technologies specifically in Remote Sensing (RS) and Geographical Information System (GIS) knowledge which covered land classification and crop changes, disease detection and pest control, age estimation for oil palm, above-ground biomass (AGB) and carbon estimation, tree counting for oil palm assessment and land suitability with soil nutrients. In the end, it concluded the most significant GIS and RS tools for oil palm management come from the implementation of Machine Learning (ML) and Deep Learning (DL) knowledge in it which can be improved over time through recent technologies and variation analysis to enhance the results.

1. Introduction
Since the establishment of oil palm plantation in Malaysia in 1917s as the first commercial oil palm to be formed up till 2021, the Malaysian government has been consistent in giving its full commitment toward the sector by improving and developing oil palm management as one of the main commodities in Malaysia through proper and comprehensive strategies. According to Kaniapan et al. (2021), this positive phenomenon occurs due to the need for bioenergy and oleochemicals in industry, as well as population growth and increased consumption that resulted in high crude palm oil prices. However, despite the positive results obtained from this scenario, the sustainability of oil palm is highly influenced by various factors in order to sustain the productivities which include human factors (assessment and inspection on the ground with data record) and natural factors (soil condition, pest and disease issues, ecosystem, and trees condition). In fact, these factors consider significant for oil palm cultivation which
required specific care and assessment by the farmers and researcher. As any of these factors are neglected, it will be affecting the productivity of the oil palm crude in the long term period. Through recent technologies from GIS and remote sensing tools, these factors can be monitored and assessed effectively in oil palm and are predicted to be a great approach in future for oil palm management.

2. Land Classification and Crop Changes in Oil Palm Plantation

Determination of land classification and crop changes is very important in oil palm planning and management. In general, the land classification can be described as the biophysical structure of Earth which represent its composition of it (Jansen & Gregorio, 2002). In remote sensing applications, the classification of land and its features can be done smooth and accurate in a huge area. Typical classification can be detected by remote sensing sensors example airborne (radar) or space sensor (satellite) includes of land, water bodies, forests, bare land, building and other agricultural areas (Chong et al., 2017). In oil palm plantation, a comprehensive image of a plantation through a combination of radar to produce a classification image. In Myanmar, the classification of the map provides the accuracy in their image close to the best overall classification accuracies (92.96% to 93.83%) through a combination of Landsat and L-band Synthetic Aperture Radar (SAR) data which includes oil palm plantation, landscape changes, gross forest, rubber plantation (De Alban et al., 2018). Other than that, Malaysian researchers manage to utilize the cloud-based computer infrastructure data that holds stacked Landsat images that are open-source which allows machine learning (Random Forest Method) to be applied resulting in two different periods (period 1: 1997-2003) and (period 2: 2017-2017) in 80.34% and 79.53% respectively (Shaharum et al., 2019). Moreover, the application of synthetic aperture radar ALOS PALSAR 2 data with visible (red) data from satellite Landsat Thematic Mapper for oil palm tree classification can give high accuracy up to 98.36% with bare land, water bodies and built-up area (Najib et al., 2020). Apart from that, a combination of Deep Learning (DL) knowledge in classification for oil palm area also provides high accuracy for map produced. According to Jie et al. (2020), regardless of the tree's age, it will be tuned for robust detection by using a deep convolutional neural network (CNN) and yields a detection accuracy of 98.96%.

In Indonesia country, their researcher was also able to categorize the oil palm area in Sumatra by using a random forest classifier with integrated optical radar (Landsat), radar datasets (synthetic aperture radar (SAR) and Google Earth Engine. For oil palm classification, combining Landsat and SAR data yielded the greatest overall classification accuracy (84%) as well as the highest producer and user accuracy with 84% and 90%, respectively (Sarzynski et al., 2020). In fact, from the same region in different research, the researchers fuse the Landsat-8 and Sentinel-1 images to create alternative feature combinations through extract multitemporal spectral characteristics, SAR backscattering values, vegetation indices, and texture features for their classification and enhancing the accuracy of oil palm recognition and produced the highest model performance (OA = 96.08 % and kappa = 0.9462) (Xu et al., 2021). Next, other research also applied the GIS approach together with CA-Markov prediction to estimate the land changes between oil palm plantation and forestry which bring out the accuracy of 88% from the Kappa Test (Maulidya et al., 2021). In comparison progress of Malaysia and Indonesia countries in oil palm plantation development, Sentinel-2 satellite photos and an active deep learning algorithm able to estimate the oil palm density at a wide scale and develop comprehensive maps for Malaysia and Indonesia in different years (2017-2019). The density differences between different states within a nation to government estimated Indonesia has > 1.2 billion oil palms spanning >15 million hectares, while Malaysia has > 0.5 billion oil palms covering > 6 million hectares from the maps that have a mean absolute error of 7.3 trees/ha. (Rodríguez et al., 2021).

3. Disease Detection and Pest Control in Oil Palm Plantation

In oil palm plantation and management, plant disease and pest issues are very common dangers that occur in many countries. Many alternatives have been introduced by the government and farmers themselves to prevent the issue from getting worse however none of them is capable provides a significant result, especially in terms of assessment and detection in a large area with optimal time.
Despite that, the remote sensing and GIS technologies started to take the place by getting them on the right track to reducing the issues effectively. In-plant disease issues in oil palm, Ganoderma Basal Stem Rot (BSR) disease consider the main killer of oil palm cultivation since its effects from the root of the tree in which difficult to be detected in the early and moderate phase while blockage all the water uptake and nutrition to the tree and make them die eventually (Baharim et al. 2021). Detecting the BSR illness and its pattern is much easier with QuickBird satellite images as utilized their visible (RGB) and near-infrared bands (NIR) with six vegetation indices. It recorded the accuracy of mapping reached up to 84% in segregated oil palm plantations with affected disease trees (Santoso et al., 2010). In different research by Santos et al. (2017), they also have applied different classifiers (Support Vector Machine (SVM), Random Forest (RF) and Classification and Regression Tree (CART)) models for disease classification for the trees and managed to produce a high-quality result and it's being dominated by RF classifier model given 91% overall accuracy. As part of remote sensing application, Unmanned Aerial Vehicles (UAV) technology have been aided in the development of several valuable studies that are now considered important tools for determining the severity of plant sickness.

The amount of infection caused by BSR disease was identified using index transformation approaches such as the Simple Ratio (SR), Normalized Difference Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI), and Atmospheric Resistance Vegetation Index (ARVI) from UAV image. Transforming the SR yielded the highest percentage of accuracy meanwhile accuracy of four vegetation indicators, all of which were around 85% accurate (Wiratmoko et al., 2018). Moreover, with the Object-Based Image Analysis (OBIA) technique, four separate individual bands (Green - G, Red - R, Red Edge - RE, and Near Infrared - NIR) and 11 combinations of multiple bands can be used to classify Ganoderma disease in oil palms with an accuracy of 65.5% to 76.2% for the individual bands and up to 70% to 90% when combined with different bands (Anuar et al., 2020). Recent technologies from Terrestrial Laser Scanning (TLS) techniques also played a big part in BSR disease as TLS consider a remote sensing approach. According to Azuan et al. (2019), The findings demonstrate that the crown pixel, frond angle, and frond number parameters are all connected with $R^2=0.76\ p<0.0001$, $R^2=0.96\ p<0.0001$ and $R^2=0.97\ p<0.0001$, respectively to the BSR disease severity level in a substantial way. Healthy trees (T0) were distinguished from unhealthy trees (those with mild infection [T2] and severe infection [T3]) using the crown pixel parameter, albeit there was considerable overlap with T1.

In different diseases for oil palm cultivation, GIS and remote sensing technologies are also capable in assist for assessment and detection of diseases including in the early stage. In the Republic of Ecuador, an oil palm plantation estimated at 125,000 hectares of the area was lost due to the attack of Red Ring Disease (RRD) and Bud Rot (BR). According to Torres et al. (2020), utilizing a Remotely Piloted Aircraft System (RPAS) equipped with RGB and multispectral sensor helps them to analyze spatial behaviour of the disease (symptoms and progress), baseline between affected and non-affected palms and introduced the best detection BR disease using Vegetation Index (Visible Atmospherically Resistant Index (VARI)) of the disease effectively. In another case of Fatal Yellowing (FT) disease in Brazil, the researchers performed the Local Moran Index’s analysis from GIS to analyze the spatial autocorrelation of the disease incidents in oil palm plantations (Anhê et al., 2021). It’s have been reported the research analysis managed to run even in 139 plots with different genetic material and ages. Other than that, Metisa plana (Walker) which are leaves defoliating insects in oil palms also capable cause a huge loss of USD 2.32 billion to Malaysia's oil palm sector in only two years (Ruslan et al., 2019). Thus, to investigate the environmental factors that trigger the outbreak of Metisa plana, the researchers used land surface temperature (LST), rainfall (RF), relative humidity (RH), and the Normalized Difference Vegetation Index (NDVI) analysis to it and with an accuracy of 72.64%, the model produced by combining factors able to predict the presence of Metisa plana.

High damage loss from the pest includes rats in oil palm plantations that required intensive care by the farmers to prevent continuous attacking of the tree, especially in young tree levels. The combination of GIS data and remote sensing shows a significant contribution to further analysis of this problem. According to Phua et al. (2018), GIS rat occurrence data obtained on the ground together with satellite image Geo-Eye analysis provides a possible location for the rat population in oil palm plantation. They
identified in their research how the combination of bare and open regions shrubs combined with partial shades of young palms is vital for the survival of the rat population. In overall, this part concluded the significant capabilities of RS and GIS in assist for assessment disease and pest in oil palm.

4. Age Estimation in Oil Palm Plantation

As remote sensing and GIS technologies have been widely known in research plants studies, the age estimation of plants specifically oil palm trees considered important to be measured effectively to manage the sustainability and the cultivation of oil palm plantations in the long-term period. According to Rizeei et al. (2018), they managed to accurately determine the age of trees from the crown of the tree combined with a height model and multi regression algorithms. The image from the Worldview-3 satellites and airborne light detection and range (LiDAR) imagery were fully utilized in their research which resulted in high accuracy of 84.91% especially when applied classifier (SVM) and Object-Based Image Analysis (OBIA). In a different research, Landsat OLI images have been used in performing principal component analysis with connections study between canopy density (FCD) and age of oil palm tree together with advance vegetation index (AVI), bare soil index (BSI), shadow index (SI), and thermal index (TI). This method successfully classified the age of oil palm trees into four classes (seed, young, teen, and mature) (Fitrianto et al., 2018). Other than that, it’s also recorded through NDVI (Normalized Difference Vegetation Index) analysis and oil palm age variation can be estimated in the distribution of oil palm age using logarithmic regression from the same satellite. They concluded from their research that the greater the NDVI value the higher the age of oil palm (Tridawati et al., 2018). Moreover, the Enhanced Vegetation Index (EVI) time series from MODIS Vegetation Index has been used for mapping new oil palm plantations and eventually estimating the age of oil palm plantations consecutively. The total accuracy in detecting new palm oil plantations was over 94% according to the accuracy evaluation and the age of the trees estimate at the beginning proved to be correct enough at 66% (De Petris et al., 2019). Moreover, deploying the deep learning approach can provide a good result in differentiating between the young and mature levels of an oil palm tree. During the data processing, two distinct convolution neural networks (CNNs) are used, as well as a geographic information system (GIS) which produces for young and mature oil palm trees with total accuracy up to 95.11% and 92.96% respectively. Overall, the classifier outperforms previously unknown datasets effectively distinguishing oil palm from the background, plant shadows and other plants (Mubin et al., 2019).

The replanting process in oil palm plantation is a very crucial step that needs to be done for oil palm cultivation as the unproductive tree needs to be removed from the plantation, especially at the age of 25 years old and above. The satellite image from SPOT 6, base map image and other supporting data have been used successfully with spatial analysis that produced high-quality mapping which segregates between low and high of the ages 25 years old palm tree and their areas (Erwinda et al., 2021), Thus, these concluded how the contribution of remote sensing and GIS in assist for oil palm tree age estimation in a great way.

5. Above Ground Biomass (AGB) and Carbon Estimation in Oil Palm Plantation

Despite the higher demand for oil products from the whole world, sustaining a good ecosystem is a very important phase. As the natural forest functioned as the main absorber for carbon in the air, most of the natural forests have been replaced with oil palm plantations because of the needs. Thus, the assessment of oil palm plantation's role as a new carbon sinker considers major research in ecological studies through AGB (Kho and Jepsen, 2015). In remote sensing and GIS technologies, this issue can be evaluated with optimal results. By using Landsat Thematic Mapper (TM), selected Vegetation Indices and field survey data, AGB estimation together with the mapping process can be performed. Through statistical analysis conducted, it recorded that the model developed with an RMSE of 3.68 tonnes (t) h, shown to give reasonably excellent prediction in 62% of the variability of the AGB (Asari et al., 2017). Through the UAV platform in structure-from-motion photogrammetry point clouds, a few parts of oil palm (parameters) can be collected (maximum canopy height and stem height) which can be used to
quantify AGB (Fawcett et al., 2019). Other than that, different research was conducted to evaluate AGB using the textural ordination (FOTO) technique based on Fourier transforms applied to PlanetScope and FORMOSAT-2 satellite photos. According to Migloet and Goïta (2020), regardless of whether the data were generated from PlanetScope or FORMOSAT-2 photos, the result is satisfying enough as the coefficients of determination (R2) ranged from 0.80 to 0.92 (p ≤0.0005), and the relative root mean square errors (RMSE) were all fewer than 10.12%. Therefore, its proven how the technologies from GIS and RS can be added value in AGB evaluation although not too much has been explored for oil palm AGB using both knowledges.

6. Optimization of Oil Palm Tree Counting Assessment

In the assessment for oil palm sustainability, the large and wide area estimation sometimes can be a disadvantage in determining the right oil palm tree that is affected by disease or pest. According to Mansour and Chockalingam (2020), manual assessment through eye observation (field-based survey) can be labour intensive, costly, and high time consumed. However, this problem can be countered through the great support of GIS and RS methods efficiently. According to Takeuchi and Khiabani (2017), UAV imageries that performed Local Maximum Filtering (LMF) techniques can be used in tree counting for young tree analysis compared to Template Machine (TM) with Precision, Recall, and F-measure in quantify detection tree in 0.7, 0.84, and 0.74, respectively. Other than that, oil palm tree counting can also be performed using Template Matching Algorithm (TMA), ISO Cluster Unsupervised Classification (ICUC), and Tree Canopy Segmentation (TCS) however it is reported that the TCS is the best method (Norzaki and Tahar, 2018). The number of trees discovered by the TCS approach is 77,963 trees, with a 96% success rate together with TMA and ICUC are 89% and 82%, respectively. Other than that, utilizing an automatic algorithm based on deep learning through combination outputs of two separate convolutional neural networks that are trained on partially different subsets of data and various spatial scales provides a promising result in inventories of the individual tree from UAV image. According to Zortea et al. (2018), total detection accuracies vary from 91.2% to 98.8% with orthomosaics with decimeter spatial resolution. In fact, machine learning classifiers especially Support Vector Machine (SVM) from UAV images with feature descriptors based on the histogram of oriented gradient (HOG) designed for oil palm trees work well together in tree counting analysis. According to Wang et al. (2018), overall accuracy at the training site for oil palm tree detection is 99.21%, while at the four validation sites, it is revealed 99.39%, 99.06%, 99.90%, and 94.63%.

In different research in Malaysia, high-resolution satellite imagery (Quickbird) with a two-stage convolutional neural network (TS-CNN)-based oil palm recognition approach in a large-scale area has been applied for tree detection with 20,000 sample trees from manual human interpretation. Comparison of the result obtained with their methods with single-stage methods (CNN, Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN)) was significantly high in which 87.95%, 81.80%, 80.61%, and 78.35% for, respectively (Li et al., 2019). In fact, the other researcher also started to show their interest in tree counting analysis by developing their model from high-resolution satellite images such as the cross-regional oil palm tree detection (CROPTD) method. When compared to the baseline technique (Faster R-CNN), CROPTD improves detection accuracy by 8.69% and outperforms the other two state-of-the-art domain adaptive object recognition algorithms by 4.99-2.21% (Wu et al., 2020). This positive initiative has been followed by other research in developing the classifier model to improve the tree counting assessment such as the Multi-level Attention Domain Adaptation Network (MADAN). According to Zheng et al. (2020), MADAN enhances detection accuracy by 14.98% in terms of average F1-score when compared to the Baseline technique (without DA), and it outperforms previous domain adaptation methods by 3.55% – 14.49%. Moreover, the application of a variation deep learning framework can also be an added value for oil palm tree counting assessment. In the latest research by Ammar et al. (2021), several contemporary convolutional neural network models such as Faster R-CNN, YOLOv3, YOLOv4, and EfficientDet have been tested for oil palm tree counting yet the optimal trade-off between accuracy and speed was found only in YOLOv4 and EfficientDet-D5 that close up 99 % means average precision and 7.4 FPS. This result has proven
sufficient to conduct further analysis by applying the deep learning framework. In the end, the assessment of oil palm tree counting gets much easier with all these analyses.

7. Land Suitability and Soil Nutrients for Oil Palm Plantation

High demand for oil palm product (biodiesel and eatery product) have forced the expansion of new oil palm plantation to be developed especially in the Asian country. However, the process of oil palm development is very difficult and complex as many factors need to be considered before the area is chosen includes of land suitability, climate, soil texture, and possible nutrients needed for the plants (Jaroenkietkajorn and Gheewala, 2021). In GIS application, various analyses can be conducted to assist in that phase, especially on assessment and decision making. Through research conducted in Nigeria, geospatial distribution of soil chemical properties can be determined effectively using a global positioning system (GPS) and GIS mapping and being concluded how the soil variation significantly impacted by slope position and soil depth condition in oil palm (Olubanjo and Maidoh, 2017). In Indonesia, their researchers have performed a good quality mapping in identifying the best potential area for oil palm development (Harahap et al., 2019). Various environmental factors (temperature, rainfall, oxygen availability, place height, humidity, etc.) have been collected on the ground before being spatialized to be mapped using GIS software. Thus, the output of the research is shown remarkably with further analysis can be performed using those data. The results are supported by Rendana et al. (2021) while analysing the current and potential areas for oil palm development. It has been reported by them how GIS revealed gently sloping side and the low gradient slope edge are both acceptable places for oil palm planting.

In different studies by Mfondoum et al. (2019), GIS-based multi-criteria decision making through Weighted Linear Combination (WLC) and Fuzzy Analytic Hierarchy Process (FAHP) analysis can help them in determine the best potential area to develop new oil palm plantation while considering most of the environmental factors (rainfall, temperature, sunlight, slope, elevation, soil fertility, soil moisture, and forest cover area). Moreover, research conducted by Wongsai et al. (2020) in Thailand, revealed how the landscape variable affects the expansion of oil palm plantations, especially from slope and drainage factors. The research was performed by using THEOS satellite image with the support of a vector machine classifier and logistic regression model for their relationship analysis. Moreover, In Indonesia country, their researchers have produced a good quality map for smallholder farmers' oil palm plantations. According to Safriyana et al. (2020), the plantation suitability map revealed that 13.88% of Independent Smallholder Farmers (ISF) owned plantations are potential with 71.21% in the developing category, and 14.91% in the non-potential category through GIS and Analytical Hierarchy Process (AHP) technique.

In soil nutrients of oil palm plantation, variabilities of soil contents can help in production for oil palm plantation while reducing the soil degradation issue. In GIS and remote sensing performances, the assessment for soil in oil palm can be analyzed to improve the quality of crops and further analysis in oil palm. According to Behera et al. (2018), spatial variability and zone delineation management for oil palm crops in India have been successfully revealed using GIS with semi-variogram and Kriging analysis with strong spatial dependence among soil properties (PH value, electrical conductivity (EC), soil organic carbon (SOC), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sulphur (S), and boron (B)). In different studies, soil variabilities also influence the disease outbreak specifically in Basal Stem Rot (BSR) disease for oil palm plantations. According to Tajuddin et al. (2020), assessment and identification of soil variation in oil palm using GIS generated map revealed a highly significant correlation between imbalance nutrients (Nitrogen (N), Potassium (P), Phosphorus (K)) in soil with disease outbreak in oil palm where being it has been justifying that it could be one of the factors the disease outbreak. Next, the interpolation method in GIS is well known for its application in estimating soil variation. This is proven through the implementation of Ordinary Kriging (OK) and Empirical Bayesian Kriging (EBK) as acceptable interpolation algorithms which results in the lowest prediction error for soil properties in oil palm (Tan et al., 2020). Other than that, the geostatistical method from semi-variogram and Ordinary Kriging (OK) method are also being applied in land degradation
analysis as it poses a great threat to oil palm cultivation. According to Kindohoundé et al. (2021), most of the soils under the oil palm crops are deficient in nitrogen, phosphate, and potassium when being analyzed together with the map produced. In recent research, Artificial Intelligent (AI) has been developed together with GIS technologies as an expert dynamic system in providing advice and fertilization in a fast way. Surprisingly, the system works well by offering nutritional requirements based on oil palm age, population, productivity, land size, and location (Firmansyah et al., 2021). The researchers also added in their conclusion view how the application can produce a recommendation for the type of fertilizer, frequency, amount, and application timing.

8. Suggestions and Recommendations in Oil Palm Cultivation

In these final sections, it can be concluded how GIS and remote sensing work very well in supporting oil palm management in various aspects in the efficient, accurate and consistent results. There is almost no doubt the capabilities of both technologies as future tools in agriculture development specifically in oil palm plantations as significant platforms ahead. As reported in this paper, most of the success came from the implementation of machine learning and deep learning analysis in GIS and remote sensing knowledge. Thus, this process itself revealed how the researchers and farmers are aware of how the world evolved in technologies and possibly make everything getting better in oil palm management. However, there are still a few things that can be improved including the instruments used and analysis conducted. Recently, the application of LiDAR technology has been implemented widely in other agriculture yet there are very limited studies involved with LiDAR application in oil palm cultivation. Other than that, Ground Penetrating Radar (GPR) instruments are also less used in agriculture although it's functioned as reported in different research manages to analyze such as pipe conditions on the ground. In this phase, other researchers can also focus on water flow on pipes (leakages) for oil palm sustainability. In the analysis aspect, most of the studies provide analysis or systems developed for oil palm management in stand-alone analysis. Thus, the accuracies of some of them can be moderate or high categories. This analysis can be enhanced with more details with added different methods or techniques together with the existing method. Therefore, all the researchers should look up for any possible weaknesses that can be identified in the analysis phases as we are hoping for a new approach in the analysis together with improvement for oil palm cultivation.

References

[1] Ammar A, Koubaa A, and Benjdira B 2021 Agronomy 11 8 p 1458
[2] Asari N, Suratman M N, and Jaafer J 2017 International Journal of Remote Sensing 38 16 pp 4741-4764
[3] Anhê B B, Santos A V F, Neto A A L M, Farias P R S and De Carvalho L L B 2021 Canadian Journal of Plant Pathology 44 1 pp 82-93
[4] Azuan H N, Khairunniza-Bejo S, Abdullah A F, Kassim M S M and Ahmad D 2019 Plant Disease 103 12 pp 3218-3225
[5] Baharim M S A, Adnan N A, Mohd F A, Othman N A, Abdul Rahim H, Azis M H, Seman I A, Izzuddin M A, Shahabuddin N A and Nordiana A A 2021 Geocarto International pp 1–27
[6] Behera S K, Mathur R K, Shukla A K, Suresh K and Prakash C 2018 CATENA 165 pp 251–259.
[7] Chong K L, Kanniah K D, Pohl C and Tan K P 2017 Geo-Spatial Information Science 20 2 pp 184-200
[8] De Alban J, Connette G, Oswald P and Webb E 2018 Remote Sensing 10 2 p 306
[9] De Petris S, Boccardo P and Borgogno-Mondino E 2019 International Journal of Remote Sensing 40 19 pp 7297-7311
[10] Erwinda, Hati D P, Mulyani A and Nugroho E S 2021 IOP Conference Series: Earth and Environmental Science 757 1 p 012034
[11] Fawcett D, Azlan B, Hill T C, Kho L K, Bennie J and Anderson K 2019 International Journal of Remote Sensing 40 19 pp 7538–7560
[12] Firmansyah E, Pardamean B, Ginting C, Mawandha H G, Pratama Putra D and Suparyanto T
International Conference on Information Management and Technology (ICIMTech) pp 6-11

[13] Fitrianto A C, Darmawan A, Tokimatsu K and Sufwandika M 2018 IOP Conference Series: Earth and Environmental Science 148 p 012020.

[14] Harahap F S, Sitompul R, Rauf A, Rahmatawaty, Harahap D E and Walida H 2019 IOP Conference Series: Earth and Environmental Science 260 1 pp 1–8.

[15] Jansen L J M, and Gregorio A D 2002 Agriculture, Ecosystems & Environment 91 pp 89-100

[16] Jaroenkietkajorn U and Gheewala S H 2021 Sustainable Production and Consumption 28 pp 1104-1113

[17] Jie B X, Zulkifley M A and Mohamed N A 2020 11th IEEE Control and System Graduate Research Colloquium (ICSGRC) pp 38-42

[18] Kaniapan S, Hassan S, Ya H, Patma Nesan K and Azcem M 2021 Sustainability 13 6 p 3110

[19] Kho L K and Jepsen M R 2015 Singapore Journal of Tropical Geography 36 2 pp 249–266.

[20] Kindohoundé N S, Nodichao L, Aholoukpé N S H and Saidou A 2021 African Crop Science Journal 29 1 pp 141–156

[21] Li W, Dong R, Fu H and Yu L 2018 Remote Sensing 11 1

[22] Maulidiya A, Damayanti A, Indra T L and Dinyati M 2021 Journal of Physics: Conference Series 1811 1 p 012072

[23] Mansour S and Chockalingam J 2020 Spatial Information Research 28 5 pp 579-588

[24] Anuar M A, Hamzah A, Nisfariza and Idris A S 2020 Journal of Oil Palm Research 32 pp 497-508

[25] Migolet P and Goïta K 2020 Remote Sensing 12 18 p 2926

[26] Mubin N A, Nadarajoo E, Shafri H Z and Hamedifar A 2019 International Journal of Remote Sensing 40 19 pp 7500-7515

[27] Najib M N E, Kanniah K D, Cracknell A P and Yu L 2020 Forests 11 8 p 858

[28] Olubanjo O and Maidoh F U 2017 Nigerian Journal of Soil Science 27 pp 173-184.

[29] Phua M H, Chon C W, Ahmad A H and Hafidzi M N 2017 Precision Agriculture 19 1 pp 42-54

[30] Rendana M, Rahi S. A, Idris W M, Rahman Z A and Lihan T 2022 Journal of Sustainable Agriculture 37 1 p 100

[31] Ruslan S A, Muhamad F M, Omar D, Zhuakfi L Z D and Zambri M P 2019 IOP Conference Series: Earth and Environmental Science 230 p 012110

[32] Rizye M H, Shafri H Z, Mohamoud M A, Pradhan B and Kalantar B 2018 Journal of Sensors 2018 pp 1-13

[33] Rodríguez A C, D’Aronco S, Schindler K and Wegner J D 2021 Remote Sensing of Environment 261 p 112479

[34] Takeuchi W and Khiabani P H 2019 Unmanned Aerial Vehicle: Applications in Agriculture and Environment pp 71-84

[35] Tajudin N S, Musa M H, Seman I A and Amri C N 2020 Journal of Oil Palm Research 32 pp 427-438

[36] Tan S Q, Mat Su A S, Wayayok A and Sukor A S 2020 IOP Conference Series: Earth and Environmental Science 540 1 p 012066

[37] Safriyana S, Marimin M, Anggraeni E and Sailah I 2020 Journal of Science and Technology Policy Management 12 2 pp 283-308

[38] Tridawati A, Darmawan S and Armijon 2018 IOP Conference Series: Earth and Environmental Science 169 p 012063

[39] Torres M V, Sinde-González I, Gil-Docampo M, Bravo-Yandún V and Toukeridis T 2020 Remote Sensing 12 19 p 3229

[40] Santos H, Gunawan T, Jamiko R H, Darmosarkoro W and Minasny B 2010 Precision Agriculture 12 2 pp 233-248

[41] Sarzynski T, Giam X, Carrasco L and Lee J S 2020 Remote Sensing 12 7 p 1220

[42] Shaharum N S, Shafri H Z, Ghani W A, Samsatli S, Prince H M, Yusuf B and Hamud A M 2019
Acknowledgments
The authors would like to thank the Ministry of Higher Education (MOHE), Malaysia for the financial support under Fundamental Research Grant Scheme (FRGS) (Grant No: FRGS/1/2021/WAB04/UiTM/02/2 and 600-RMC/FRGS 5/3 (066/2021). We would like to express our immense gratitude to the Centre of Studies Surveying Science and Geomatics, Faculty of Architecture, Planning & Surveying, Universiti Teknologi MARA (UiTM), and Malaysian Palm Oil Board (MPOB) teams for the facilities and expert knowledge they contributed during research work.