Journal of King Saud University – Computer and Information Sciences 34 (2022) 1569–1594

Contents lists available at ScienceDirect

Journal of King Saud University – Computer and Information Sciences

journal homepage: www.sciencedirect.com

Expert systems in oil palm precision agriculture: A decade systematic review

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ARTICLE INFO

Article history:
Received 12 November 2021
Revised 23 January 2022
Accepted 8 February 2022
Available online 24 February 2022

Keywords:
Oil palm
Elaeis guineensis Jacq.
Expert system

ABSTRACT

Oil palm (*Elaeis guineensis* Jacq.) is of the most profitable and widespread commercial high tree crops in the tropical world, typically in Southeastern Asia. The present study aims to provide a brief but broad overview of different applications of expert systems (ESs) in oil palm precision agriculture (PA), focusing on the three main generic categories: crop, water, and soil management. This study is meant to review research articles from the past decade: 2011–2020. Based on the search strategy alongside the inclusion criteria, 108 articles were included for synthesis activity. The findings of the study reveal patterns, networks, relationships, and trends in the application of ESs in oil palm PA in the past decade. The broad insight obtained from the synthesis activity was used to identify the possible roads ahead in oil palm PA. The findings of this study could be useful and beneficial to the research community and stakeholders

Abbreviations: ABW, Average weight of fruit bunches; Acc, Accuracy; AdaBoost, Adaptive Boosting; AI, Artificial intelligence; AISA, Airborne Imaging Spectrometer for Applications; ALOS, Advanced Land-Observing Satellite; ANN, Artificial neural network; AP, available phosphorus; ASD, Analytical Spectral Device; ASW, Average silhouette width; BMP, Best management practice; BSR, Basal stem rot; BUNCH_HA, Average bunch number per hectare; CA, Cellular automata; CART, Classification and regression tree; CBS, Central Bureau of Statistics; CCVd, Coconut cadang–cadang viroid; CDA-ME, Coordinate descent algorithm-mismodelling effects; CLM-Palm, Community Land Model Palm; CNN, Convolution neural network; DA, Discriminant analysis; DECR, Department of Estate Crops in Riau; DRIS, Diagnosis and Recommendation Integrated System; DT, Decision tree; EA, Heavily logged forests; EM, Error matrix-based model-assisted; ES, Expert system; ET, Evapotranspiration; ET_O, Reference evapotranspiration; ETM+, Enhanced Thematic Mapper Plus; EVI, Enhanced vegetation index; FELDA, Federal Land Development Agency; FDM, Fuzzy Delphi method; FFB, Fresh fruit bunches; FOTO, Fourier transform textural ordination; GANN, Genetic Algorithm Neural Network; GEE, Google Earth Engine; GHG, Greenhouse gas; GIS, Geographic information system; GLCM, Grey-level co-occurrence matrix; GME, geometric mean of microbial enzyme activity; GPS, Global Positioning System; GUI, Graphic user interface; HOG, Histogram of oriented gradient; I4, Industrial 4.0; JNB, Jenks Natural Breaks; K_C, Crop coefficient; KNN, K-nearest neighbor; LCI, Life Cycle Inventory; LF, Twice logged forests; LMT, Logistic Model Tree; LDA, Linear discriminant analysis; MADAN, Multi-level Attention Domain Adaptation Network; MARE, Mean absolute relative error; MC, Markov chain; MCE, Multi-criteria evaluation; MD, Mahalanobis distance; ML, Machine learning; MLC, Maximum likelihood classifier; MMD, Malaysian Meteorological Department; MoC, moisture content; MODIS, Moderate-Resolution Imaging Spectroradiometer; MOPPD, Malaysian Oil Palm Plantation Dataset; MPOB, Malaysian Palm Oil Board; NB, Naïve Bayes; ND, Normalized different; NIR, Near infrared bands; OB, Object-base; OIF, Optimum index factor; OLI, Operational Land Imager; PA, Precision agriculture; PALSAR, Phased Array Type L-band Synthetic Aperture Radar; PC, Pixel counting; PCA, Principal Component Analysis; PCR, Principal component regression; QDA, Quadratic discriminant analysis; R^2, Coefficient of determination; RCANet, Residual Channel Attention Network; RCBD, Randomized complete block design; REMAP, Remote Ecosystem Monitoring Assessment Pipeline; RF, Random Forest; RGB, Red, Green, and Blue; RiF, Riparian forests; RMSE, Root mean square error; IfSAR, Interferometric aperture radar; IoT, Internet of things; SAR, Synthetic Aperture Radar; SfM, Structure-from-motion; SMOTE, Synthetic Minority Over-Sampling Technique; SPI, Standardized Precipitation Index; SPAD, Soil-Plant Analysis Development; SPOT, Satellite Pour l'Observation de la Terre; PB, Pixel-based; SR, Simple ratio; SVM, Support vector machine; SVM-FS, Support vector machine-feature selection; SVR, Support Vector Regression; SWAT, Soil Water Assessment Tool; TM, Thematic Mapper; UAV, Unmanned Aerial Vehicles; UGV, Unmanned Ground Vehicles; UNIANOVA, Univariate analysis of variance; USV, Unmanned Surface Vehicles; UK-DMC 2, Disaster Monitoring Constellation 2 from the UK; VHR, Very-high-resolution; WEF, Water-Energy-Food; WFEN, Water-Food-Energy Nexus.

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Peer review under responsibility of King Saud University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.jksuci.2022.02.006

Precision agriculture
Systematic review
Systematic bibliographic survey

in identifying the progress and trends of ESs in oil palm PA in the past decade, help to gain a holistic view on research gaps, potential markets, relevant advantages, the roads ahead, and contributing to further systematic research (deepen or broaden) in this topic.

Contents

1. Introduction

Oil palm (*Elaeis guineensis* Jacq.) is of the most profitable and widespread commercial high tree crops in the tropical world. In the past decade, the oil palm sector shows remarkable expansion typically in Southeastern Asia such as Indonesia and Malaysia (Luke et al., 2020; Said et al., 2021). Over time, the oil palm value chain in Indonesia and Malaysia increased significantly and complexity fulfilling the great market demand across the globe. As the primary producer, Indonesia and Malaysia respectively recorded 245.63 and 99.07 million tons in 2019, exceeding the next highest commodities production (i.e., rice and paddy) in the corresponding country by a ratio of 4.50 and 34.02 times, respectively (FAO, 2021). Comparing with 2015, the commodities production of oil palm in Indonesia and Malaysia found increased by 7.44 and 4.83 times (Pacheco et al., 2017) in 2019, respectively, and has been the largest commodities production amongst these countries for a decade (i.e., 2010 to 2019) (FAO, 2021).

Oil palm originates in West Africa fulfilling the European market demand at the beginning of the 20th century. Nevertheless, the oil palm sector in West Africa has not undergone vigorous expansion as observed in Southeastern Asia such as Indonesia and Malaysia (Pacheco et al., 2017). The oil palm development in West Africa remains stable until 1930s and the development underwent ceiling effect and stagnated in the postwar period. Malaysia, however, shows a stable development in the postwar period (i.e., 1950s) as the involvement of the state government collaborating with private companies has greatly fostered the development and expansion of oil palm. The change in Malaysian government policy to convert the rubber plantations to oil palm plantations under the Federal Land Development Agency (FELDA) has further contributed to the expansion of oil palm. The policy and oil palm plantation project were successful and profitable. In 1966, Southeastern Asia has overtaken West Africa in oil palm commodities production, dominating the global market, and remain as the primary producer until today.

Although the oil palm development began in Malaysia and underwent vigorous expansion due to the joint collaboration between government and private companies, in 1970s, the oil palm began to develop in Indonesia under the government-owned companies. In 1980s, the oil palm sector became the main priority of the Indonesian government. Various attractive policies (e.g., cheap land for oil palm plantation purposes) introduced by the government successfully attracted the attention of private companies initiating a new and profitable oil palm plantation era. Over the years, the oil palm sector in Indonesia underwent vigorous expansion and overtook Malaysia in commodities production. To date, the oil palm sector remains as the leading commodities production in Indonesia with profitable agriculture revenue.

With the increase in population associated with large-scale urbanization, land use, soil, and water are no longer inexhaustible resources. This leads to a reduction in arable land and pressure on agriculture increase over time. In early 1990s, the concept of PA has been introduced to uplift the pressing issue of limited resources. The pressure is especially significant in perennial crops such as oil palm where the crop rotation is more than 25 years (Luke et al., 2020). The main purposes of PA lie within the capability to reduce waste and losses while optimizing the utilization of available resources and profitability (Thorp, 2014; Luke et al., 2020; Yost et al., 2017). To accomplish these, ESs are adopted and are used in various categories to detect, monitor, analyze, and predict the crops and thus improve the efficiency and reliability of the PA.

1.1. Definition of precision agriculture

The concept of PA is first emerged and introduced by the United States House of Representatives in 1997. PA is defined as an integrated information and production-oriented farm system which designated and aims to improve long-term, site-specific, and whole farming production, typically in productivity, efficiency, and profitability while at the same time minimizing unwanted impacts on the environment and wildlife. Over the years, experts are allowed to further interpret the definition of PA where concepts such as environment sustainability and economic are then incorporated. Table 1 documented some of the main definitions of PA emerged over the years in chronological order.

Based on Table 1, several distinctive elements can be identified from the main definitions of PA: technology, application, and sustainability. To summarize, PA focuses in: (1) adoption of technologies to recognize (e.g., detect, monitor, analyze, and predict) spatial and temporal site-specific information, (2) incorporation of application-oriented technologies, (3) maximizing available resources and minimizing waste and negative impact to the environment.

It is undeniable that PA greatly improves crop profitability, optimizes the available resources, and minimizes wastes and losses. However, to date, the implementation of PA is at a low rate and below expectation (Mcconnell, 2019; Pathak et al., 2019). Implementation of PA technologies and systems is a long-term investment and usually involve substantial cost and could incur financial pressure on the plantation company. Moreover, the novel PA technologies and systems required a specific technical skillset to operate and maintain the corresponding technology or system for an optimized benefit. Due to the great variety in technical skillset amongst the individuals, full adoption of PA technologies and systems is very challenging (Pathak et al., 2019). To date, there are a plethora of technology-oriented modules and solutions which could help in various fields in agriculture. However, a high degree of engineering knowledge is required to integrate such modules and solutions into an ES (Higgins et al., 2017). It is recommended to implement PA technologies and systems in an incremental approach. This could avoid expensive changes in agriculture workflows and competent individuals can be employed or trained to operate and manage the PA technologies and systems over time.

1.2. Definition of expert system

ES is defined as an interactive computer-oriented system, based on the knowledge that emulates the decision-making and/ or problem-solving process performed by human experts (Oyedeji et al., 2019; Saibene et al., 2021). Back to late 1950s, ES has captured the attention of medical experts where experts proposed that computers would play an indispensable role someday in assisting medical decisions especially in diagnosis and patient management processes (Durkin, 1990). The ESs were first developed in mid of 1960s (Liao, 2005) and the definition of ES has evolved over time as new technology solutions and knowledge are emergences (Singla et al., 2014; Abu Naser and Shaath, 2016; Tavana and Hajipour, 2020). Nonetheless, the core of the ES remains unchanged over time: (1) ES is a knowledge-oriented system such that the system constantly collects and contains the essential information (Oyedeji et al., 2019). This information serves as the fundamental building blocks for a peculiar problem-solving process, (2) ES imitates the decision-making and/ or problem-solving process performed by human experts (Mirmozaffari, 2019). The decision-making process is performed via the inference engine based on a set of rules formalized from the collected information, (3) ES is an Artificial Intelligence (AI)-oriented application. ES tends to perform data collection, system modelling, and provides technical/ engineering solutions.

Since ESs are meant to resolve real-world engineering problems and emulate the decision-making/ problem-solving processes performed by human experts, thus, it is important to ensure the reliability and applicability of the corresponding ESs. In a general context, all ES shall demonstrate these characteristics: (1) consistency, such that the ES is capable to provide the same output provided the same input is given, (2) comprehensive, such that the

Table 1
Definition of PA over the years.

References	Years	Definitions of PA
(Pierce & Nowak, 1999)	1999	PA is the use of technologies and techniques to control the spatial and temporal variability in all elements of agricultural production to improve crop performance and environmental quality. PA is made possible by technological advancements.
(Kirchmann & Thorvaldsson, 2000)	2000	PA is a discipline designated to improve the efficiency of agriculture management. PA involves the development of new technologies, the modification of old technologies, and the integration of monitoring and computing at the farm level for a specific purpose.
(Zhang et al., 2002)	2002	PA is based on a system approach to reorganizing the entire agriculture system toward low-input, high-efficiency, and long-term sustainability.
(Bongiovanni & Lowenberg-Deboer, 2004)	2004	PA can assist in the ecologically responsible management of agriculture production inputs.
(McBratney et al., 2005)	2005	That type of agriculture that increases the number of (right) judgments per unit area of land per unit time with related net benefits
(Tey & Brindal, 2012)	2012	PA is a crop management method that takes into account field variability as well as site-specific variables. PA technologies are any technology that can be used alone or in combination to achieve PA.
(Pierpaoli et al., 2013)	2013	PA's applicability is based on the utilization of technology to identify and determine what is "correct."
(STOA, 2016)	2016	PA is a contemporary farming management concept that uses digital tools to track and optimize agricultural production processes.

ES is capable to collect/ derive essential information from various human experts and incorporate such information in the decision-making process. ES shall capable to provide pertinent technical solutions for a peculiar problem, and (3) availability, such that the ES shall be made available and ready to be used with essential built-in information without the need of extensive expert training period.

Fig. 1 shows the fundamental structure of an ES. ES consists of a knowledge base, working memory, and an inference engine (Liao, 2005). The knowledge base is the core of an ES such that all the essential information pertaining to the peculiar problem is well defined and stored. The essential information is the specialized knowledge or expert domain knowledge which makes an individual a human expert in the real world. In most cases, the essential information is formalized and represented using a technique known as rules. The rules are a set of "IF/ THEN" structures which closely related to known specialized knowledge. The rules are meant to emulate how human experts formulate their specialized knowledge to resolve a peculiar problem. Working memory consists of the input information (i.e., case facts) provided by the user and system information (i.e., inferred facts) deduced by the ES. The working memory can acquire additional information from sensors, spreadsheets, and databases. The inference engine is the reasoning block in an ES. The main function of the inference engine is to derive new information on the peculiar problem with the aid of specialized knowledge (obtained from knowledge base), case facts, inferred facts (both obtained from the working memory), and additional information (obtained from sensors, spreadsheets, and databases) to perform reasoning and arrive at a conclusion (i.e., technical solution).

1.3. Aims and outline of the study

Fig. 2 shows the three main generic categories in oil palm PA: crop, water, and soil management. These generic categories were identified and benchmarked in accordance with two recent literatures, specialized in agriculture (Liakos et al., 2018; Benos et al., 2021). Over the years, the synergy of ES and individuals (either expert or non-expert users) has proven to improve the workflow and management processes in PA in terms of efficiency and reliability (Liaghat et al., 2014; Habib et al., 2020; Septiarini et al., 2020). Considering the extensive domain of ESs that can be implemented on, this study intended to focus on ESs specifically in the three main generic categories aforementioned. Notice that the crop management category can be further characterized into four domains: detection, monitorization, analysis, and prediction. These domains are formulated based on the main definitions of PA as in Table 1.

Motivated by the vigorous expansion of the world of oil palm with increasing global value chain, associated with the tremendous growth in world interest using ESs to assist and support in a huge variety of peculiar problems, as well as the pressing need of PA implementation, a systematic bibliographic survey is presented in the three generic categories as in Fig. 2. In particular, this study focuses on reviewing relevant works done in the past decade: 2011 to 2020. The main purposes of this study are to identify: (1) the generic category which is most explored in ESs in oil palm PA, (2) geographical distribution analysis of the contributing organizations, (3) the most contributing journals and publishers, and (4) the temporal distribution and bibliometric analysis of the included articles. This study is posited to provide a beneficial and useful guide to all stakeholders specifically in progress and trends of ESs in oil palm PA in the past decade and helps to identify research gaps, potential markets, relevant advantages, the roads ahead, and contributing to further systematic research (deepen or broaden) in this topic.

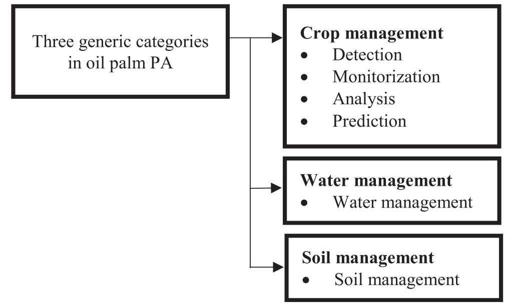

Fig. 2. Three main generic categories in oil palm PA.

This study is organized as follows: Section 2 provides a brief description of the three main genetic categories: crop, water, and soil management. In Section 3, the methods used to perform the systematic review are given in detail. Study planning and definition of performance metrics used in the literature are presented in Section 3. In Section 4, synthetic findings obtained from the study are recorded alongside corresponding figures, tables, and graphical charts. Section 5 discusses some critical aspects based on the broad insight obtained from this study. Limitations and recommendations are provided in Sections 5.2 and 5.3, respectively. Lastly, the conclusion of the study is given in Section 6.

2. Brief description of three generic categories

2.1. Crop management

The concept of crop management has been proposed in 1997 as a diverse, multifaceted, and interconnected farming practice (Marshall et al., 1997). Crop management embraces the idea of

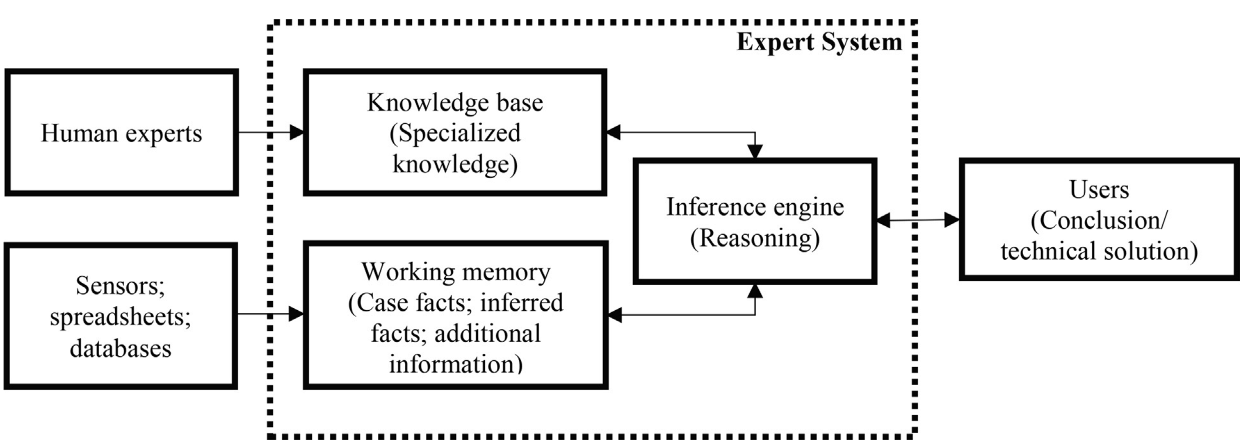

Fig. 1. Fundamental structure of an ES (adaptation from Liao (2005)).

optimizing resources utilization and yield production while minimizing wastes and losses, which is abreast with the goal of PA. Over the years, crop management is well recognized as the key component in PA (Liakos et al., 2018; Benos et al., 2021). Crop management refers to a logical combination of farming techniques in managing the physical, biological, and chemical environment of the crop with the purpose of reaching both qualitative and quantitative goals (Yvoz et al., 2020). In this study, crop management is characterized into four domains: detection, monitorization, analysis, and prediction, which cover the dominant branches in this generic category.

Detection involves versatile aspects and is meant to highlight, mark, identify, and/ or in any other manner with direct attention to the output data (e.g., image) to reveal the presence of the object of interest dependent on the applications. Over the years, ESs focusing on detection have evolved progressively covering most of the essential aspects in oil palm crop management. Nowadays, ESs are available in pest, fruits, trunk, pollination, leaf scale, disease (e.g., basal stem rot (BSR) and orange spotting diseases), and ripeness detections. Conventionally, the detections aforementioned are performed by human experts via in-field scouting. Considering the large-scale oil palm cultivation versus the low number of highly trained human experts, the detection process in various applications is tedious, cumbersome, time-consuming, and labor-intensive (Liakos et al., 2018; Benos et al., 2021). Integration of technology solutions promotes high precision with fast throughput which helps to reduce losses and maximize yield production. ESs are expected to ease all site-specific detection processes with reliable efficiency.

Monitorization involves long-term observation, usually at a regular interval, gather essential information, and record the activities of interest over time. Nutrient and landscape monitorization as well as remote sensing are some typical examples in this domain. Thanks to the advent of technology in Unmanned Aerial Vehicles (UAV), Unmanned Ground Vehicles (UGV), and Unmanned Surface Vehicles (USV), the role of monitorization using remotely sensed data is now ubiquitous and becoming the mainstream of research in this domain (Yang, 2020; Zakeri and Mariethoz, 2021). Remote sensing is typically important and prevalent in large-scale cultivation such as oil palm plantations. Over the years, many ESs have been developed to extract, process, and interpolate information based on the remotely sensed data (Chemura et al., 2015; Dong et al., 2020; Amirruddin et al., 2020b). As new technology solutions are emergence over time, the progression of ESs in monitorization, especially in remote sensing is envisaged to undergo persistent growth in the near future (Ma et al., 2019; Rizaludin Mahmud et al., 2020).

Analysis is a thorough study involving a comprehensive examination of complex, multivariate, and interconnected elements aiming to identify the essential features and discover a relationship within. Analysis has a prominent role in PA in terms of reflection specifically on the implementation of PA after a period of time. Over the years, a plethora of technology solution has been integrated as ESs and widely implemented in oil palm PA. Considering the growing body of literature in ESs for oil palm PA, the applicability and feasibility of ESs have been well-recognized (Chong et al., 2017; Khan et al., 2021). It is important for every oil palm site to evaluate, identify, and close the gaps in respective site-specific PA to foster sustainability, sound environmental management, comply with relevant standards and codes of practice, promote continual improvement, and improve profitability. Such analysis-oriented ESs can be found in applications such as Industrial 4.0 (I4), sustainability, and oil palm expansion.

Prediction refers to forecasting and estimation of specific activities based upon knowledge, database, experience, and/ or any other methods of data collection (Chlingaryan et al., 2018). Harvest, tillage, disease, biomass, and yield predictions are some typical examples in this domain. Prediction has a prominent role in oil palm PA. Early detection of problems and bottlenecks contributing towards a specific restriction has a substantial role in resource and subsequent profit optimization while minimizing wastes and losses. Prediction is not a trivia activity. In most cases, prediction requires an extensive dataset collected from multivariate and interconnected inputs alongside high-performance modules/ algorithms to attain an accurate prediction (Mancipe-Castro and Gutiérrez-Carvajal, 2021).

2.2. Water management

Oil palm plantation is rather water-intensive cultivation with a crop rotation of more than 25 years (Luke et al., 2020; Jaroenkietkajorn and Gheewala, 2020). Therefore, water management is crucial in oil palm PA in the view of water and crop production sustainability. As oil palm growth is highly dependent on water availability, effective water management could improve the production, typically in fresh fruit bunches (FFB) from the oil palm. Water quality, irrigation system, evapotranspiration (ET), soil water content, water flux, water footprint, and water-use efficiency are some popular research applications in water management. As mentioned earlier, ESs have wide applications and can be implemented at different levels covering all dominant aspects in water management. For instance, ES can be used to collect data and precisely identify water footprint. This information can be then used as input for the subsequent ES (e.g., adaptive irrigation) as the knowledge base to aid the irrigation programming aiming to monitor, forecast, and vary the water supply in accordance with site-specific weather conditions. Ultimately, the incorporation of different ESs in water management could lead to yield optimization and water-saving (Ortega-Reig et al., 2014; Nikkels et al., 2019).

2.3. Soil management

Soils are heterogeneous natural resources and host diverse communities which regulate and sustain ecosystem functions. Soil management has been found to have direct effects on oil palm yield, crop health, and resource use efficiency (El Mujtar et al., 2019; Amadu et al., 2021). Over the years, applications in soil property and soil quality are found commonly explored by researchers (Liakos et al., 2018; Benos et al., 2021). Soil property entails information such as soil temperature, texture, density, porosity, etc. (Likulunga et al., 2021). Precise information in soil property is vital in the selection of arable land and oil palm site expansion. Soil quality mainly focuses on the nutrient level of soil which contributes toward tillage, seeds growth, and crop health aiming to attain high yield with promising grades. Conventionally, soil assessment methods such as soil sampling are expensive and time-consuming involving human experts and tedious in-filed samples extraction. With the advent of technology solutions, the integration of various ESs could aid the assessment procedures and alleviate this issue with reliable outputs.

3. Systematic literature search methodology

3.1. Study planning

3.1.1. Research question

The primary research question of this study is: What are the ESs involved in oil palm PA for the past decade (i.e., 2011–2020)? The research question is intentionally formulated in a broad manner to assure inclusion of all aspects of ESs available within the three generic categories.

3.1.2. Search strategy

This study focuses on ESs in oil palm PA in the past decade (i.e., 2011–2020), thus, only research articles published within this period were included for the subsequence screening process. The study was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). In order to identify the relevant articles pertaining to ESs in oil palm PA, search engines such as Web of Science, ScienceDirect, Google Scholar, Scopus, PubMed, and Multidisciplinary Digital Publishing Institute (MDPI) were utilized. The search query was formalized by the union of keywords in two dimensions (i.e., ES and oil palm (Table 2)) in conjunction with three generic categories using the following keywords: "crop management", "water management", and "soil management". The three main generic categories covered multifaceted in oil palm PA and were selected based on two recent literatures, specialized in agriculture (Liakos et al., 2018; Benos et al., 2021). The "AND" and "OR" operators were used to formalize the search query in this study.

3.1.3. Inclusion criterion

Once a relevant article was retrieved, the references of the corresponding article were screened to search for new relevant studies that had not been identified throughout the initial search. This process was iterated until no new relevant studies were found. In stage 1, only journal articles were considered eligible. Therefore, master and doctoral thesis and/ or dissertation, books, book chapters, review papers, proceeding papers, short communications, application notes, tutorials, non-English materials, and duplicated materials were excluded. The last search of this study was performed on 9 October 2021. In stage 2, the abstract of each article was first assessed. Next, full-text screening was performed on the remaining articles to further evaluate the eligibility. Comprehensive discussions were conducted between the co-authors in the screening process, specifically in full-text screening. Articles that do not comply with the inclusion criteria would be excluded from this study. The inclusion criteria are: (1) the articles were classified under one of the three generic categories as in Fig. 2, (2) the articles were focused on ESs in oil palm PA, such that, if and only if an article focuses in ES pertaining to oil palm but unrelated to PA or an article focuses on oil palm PA but unrelated to ES would be classified as irrelevant. Fig. 3 summarizes the flowchart of the search process based on the PRISMA guidelines (Page et al., 2021). Overall, 1326 articles were first identified. After implementation of exclusion criterion (Phase 1), 1222 articles were subjected to abstract screening/ assessment (i.e., exclusion criterion (Phase 2)). 209 articles were found eligible for full-text screening. Subsequently, 109 articles were included for this study, where 109 and 108 articles were included in qualitative synthesis and quantitative synthesis (meta-analysis), respectively.

3.1.4. Data extraction

In order to answer the research question, all the included articles were studied and the data such as applications, input data, main function, modules/ algorithm, main characteristic, outputs/ key findings, and bibliometric data were extracted. A thorough analysis was performed on the extracted data. The data were then organized and tabulated using charts, graphics, and tables.

3.1.5. Data reporting

The findings obtained from data analysis were reported using a descriptive approach. The information of different ESs in the three main generic categories was synthesized narratively, supported with charts, graphics, and tables to facilitate comprehension while highlighting the key findings/ features. Statistical calculation and compilation were performed using Microsoft Excel 2019, whereas bibliometric analysis was performed using VOSViewer 1.6.17 software for windows (Perianes-Rodriguez et al., 2016). Statistical findings such as classification of the included articles based on the three main generic categories were illustrated using a doughnut chart, whereas, the most contributing journals and publishers,

Table 2
Search string.

Operator	Dimensions	Keywords, synonyms, and alternative terms
AND	ES	Artificial intelligence OR AI OR machine learning OR deep learning OR expert system
	Oil palm	Oil palm OR *Elaeis guineensis*

Table 3
List of tables in Appendix A.

Tables	Contents
A1	Crop management: Detection
A2	Crop management: Monitorization
A3	Crop management: Analysis
A4	Crop management: Prediction
A5	Water management
A6	Soil management

Table 4
Brief information of the main author in each cluster.

Clusters	Authors	Research areas	Organizations	Geographical areas
1	Helmi Zulhaidi bin Mohd Shafri	Geomatics; Remote sensing	Universiti Putra Malaysia	Malaysia
2	Shattri Mansor	Remote sensing; Geographic Information System (GIS); Geospatial	Universiti Putra Malaysia	Malaysia
3	Kasturi Devi Kanniah	Carbon cycle; Terrestrial vegetation; Atmospheric aerosols	Universiti Teknologi Malaysia	Malaysia
4	Siva K Balasundram	PA; Digital agriculture	Universiti Putra Malaysia	Malaysia
5	Wan Azlina Binti Wan Ab Karim Ghani	Fuel technology; Waste management and conversion technology; Chemical engineering	Universiti Putra Malaysia	Malaysia
6	Farrah Melissa Muharam	PA; Remote sensing	Universiti Putra Malaysia	Malaysia
7	Bahareh Kalantar	Machine learning; Remote Sensing and GIS; Image processing; Environmental modelling; Object detection.	Riken	Japan
8	Biswajeet Pradhan	Stochastic analysis and modelling; Natural hazards; Environmental engineering modelling; GIS; Photogrammetry and remote sensing	University of Technology Sydney	Australia

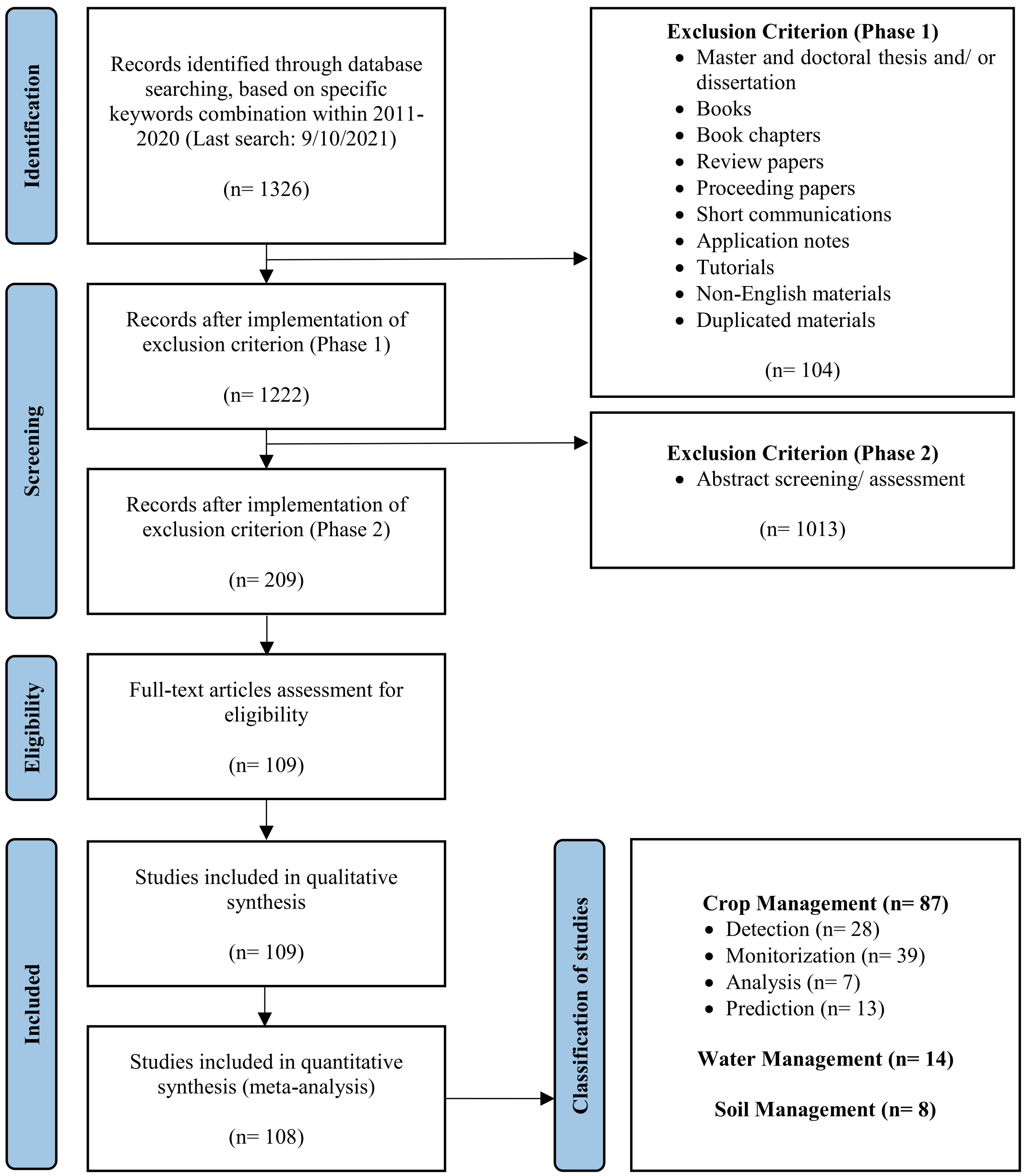

Fig. 3. Flowchart of the selection process based on the PRISMA guidelines (Page et al., 2021).

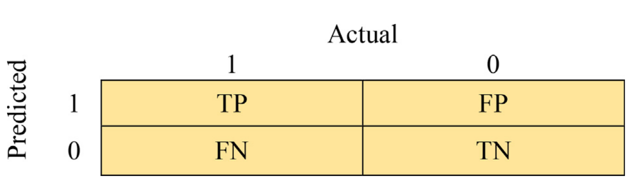

Fig. 4. A simplified confusion matrix (Benos et al., 2021).

as well as the temporal distribution analysis, were illustrated using stacked bar charts. Bibliometric analysis was visualized using the bibliometric network, world map chart, and treemap chart. All the essential information pertaining to different ESs in the three main generic categories was tabulated using tables.

3.2. Definition of performance metrics used in the literature

Unlike most of the machine learning (ML) approaches, ESs may or may be validated using conventional performance metrics such as the confusion matrix (Benos et al., 2021). The main reason is that ESs are formalized based on the knowledge that emulates the decision-making process performed by human experts where some ESs are very specific to address a peculiar problem. Assessment of such ES can be done if and only if one has access to the knowledge base with known rules and expected outcomes. This method is known as verification and validation which was introduced in the early 1980s, has roughly synonymous with the phrase "evaluation" (Boehm, 1981; Suen et al., 1990; O'Keefe and Lee, 1990). In terms of quantitative performance metrics, confusion matrix (Benos et al., 2021), typically accuracy (Acc) and F1-measure, square of the correlation coefficient (R^2) (Benos et al., 2021), and Root Mean Square Error (RMSE) (Sinambela et al., 2020) were used.

The confusion matrix is of the most common quantitative metrics used in performance evaluation, typically for classification problems, where the outputs of classification shall be at least a binary class. The confusion matrix is the summary of prediction results using count values broken down into different classes. Fig. 4 shows a simplified confusion matrix with a dimension of

2x2, namely "Actual" and "Predicted". The count values broken down are labelled as true positive (TP), true negative (TN), false positive (FP), and false negative (FN), such that TP denotes the correctly predicted event values, TN denotes the correctly predicted no-event values, FP denotes the incorrectly predicted event values, and FN denotes the incorrectly predicted no-event values.

Based on the obtained TP, TN, FP, and FN, performance metrics such as Acc, recall, precision, and F1-measure can be calculated. High values/ percentages obtained from these performance metrics demonstrate better model performance and are preferable in this study. The equations for Acc, recall, precision, and F1-measure are as follows:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$F1 - measure = \frac{2 * Recall * Precision}{Recall + Precision} \tag{4}$$

R^2 is a useful metric in linear regression, where R^2 can be used to reflect the fraction of the variation in one variable which could be explained by the other variable. RMSE is simply the square root of Mean Square Error. RMSE denotes the average distance of a particular data point from the fitted line, measured along a vertical line. The RMSE is a promising indicator of goodness of fit than a correlation coefficient as RMSE is directly interpretable in terms of measurement units. Eqs. (5) and (6) show the calculation of R^2 and RMSE, respectively.

$$R^2 = \left(\frac{T \cdot \sum_{t=1}^{T} Z(t) \cdot X(t) - \left(\sum_{t=1}^{T} Z(t)\right) \cdot \left(\sum_{t=1}^{T} X(t)\right)}{\sqrt{T \cdot \sum_{t=1}^{T} (Z(t))^2 - \left(\sum_{t=1}^{T} Z(t)\right)^2} \cdot \sqrt{T \cdot \sum_{t=1}^{T} (X(t))^2 - \left(\sum_{t=1}^{T} X(t)\right)^2}} \right)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{T} \cdot \sum_{t=1}^{T} (Z(t) - X(t))^2} \tag{6}$$

where *Z(t)* and *X(t)* denote the real and predicted values, respectively, whereas, *T* and *t* denote the testing records number and iteration at each point, respectively. Values approaching 1 are desirable in R^2. This denotes a better model performance where the regression curve fits the data efficiently. In terms of RMSE, a small value implies a better fit which reflects high accuracy in model prediction and is preferable in this study.

4. Results

4.1. Classification of the articles in terms of generic categories

Based on Fig. 3, the formalized search query (Table 2) in conjunction with other keywords has resulted in 108 articles for meta-analysis. Subsequently, these articles were grouped into three main generic categories: crop management, water management, and soil management. Notice that the crop management category can be further characterized into four domains: detection, monitorization, analysis, and prediction. Fig. 5 shows the classification of the reviewed articles in terms of generic categories and respective domains. According to Fig. 5, the crop management category dominated the research stream in ESs for oil palm PA, accounting for 79.9% of the total. This is followed by water management and soil management, which occupied 12.8% and 7.3%, respectively. Considering solely the crop management category, the monitorization domain received the highest attention from researchers which results in 35.8% in total. This is followed by detection (25.8%), prediction (11.9%), and analysis (6.4%). Overall, articles focusing on analysis (under crop management) and soil management are relatively scarce corresponding to the entire body of literature. This could be due to a high degree of heterogeneity and complexity in the field, where analyzing and modeling multivariate and interconnected parameters are often involved.

It is important to remark that all the reviewed articles are detailed in Appendix A and are summarized in Tables A1–A6, corresponding to different generic categories and respective domains. For each of the tables, from left to right, the columns show the ref-

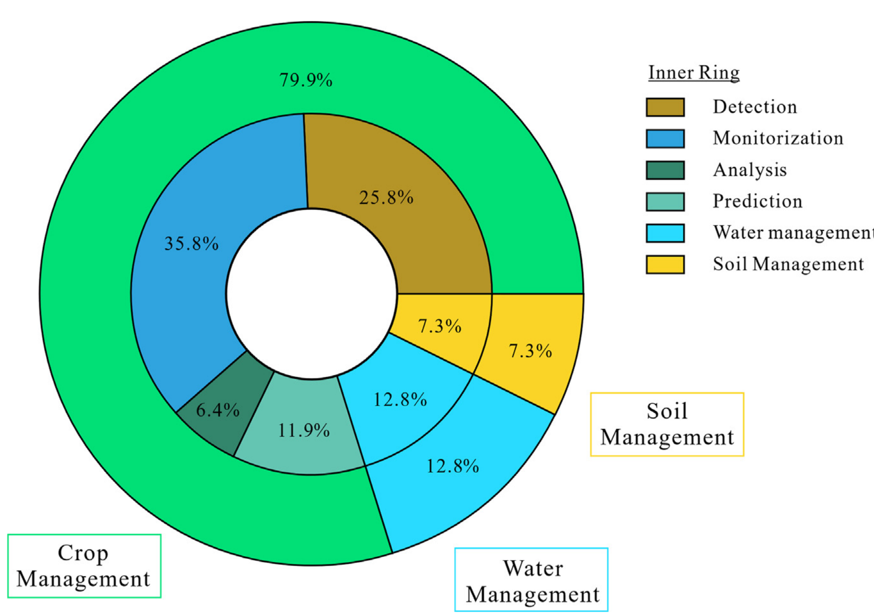

Fig. 5. Classification of the reviewed articles according to the three main generic categories and respective domains.

erences, applications, input data, functions, modules/ algorithms, main characteristics, and outputs/ key findings. As a plethora of ESs are included in this study, a list of abbreviations is given in the Abbreviation section for brevity purposes. Table 3 summarizes the aforementioned tables as in Appendix A alongside the corresponding content.

4.2. Geographical distribution and network analysis of the contributing organizations

The main purpose of this section is to analyze the geographical distribution and network of the contributing organizations for all the included articles. In terms of geographical distribution, a world map chart is used to visualize the outstretch of the included articles across the globe. Fig. 6 shows the geographical distribution of the contributing organizations. For each article, only the geographical area of the corresponding author is taken into account. For an article with more than one corresponding author, each geographical area is allowed to contribute once in the final world map chart. Based on Fig. 6, research and investigation in ESs for oil palm PA are found dominantly contributed by Southeastern Asia countries, where the leading ones are Malaysia and Indonesia, respectively contributed 48.1% (52 articles) and 10.2% (11 articles) from 2011 to 2020. This is followed by China (7.4%, 8 articles), Thailand (5.6%, 6 articles), and the United Kingdom (4.6%, 5 articles). The remarkable contribution from Malaysia and Indonesia could be attributed to the availability of large-scale oil palm plantation sites across these countries which facilitate efforts typically in in-field data collection and act as a testbed for various ESs verification and validation purposes. It is worthwhile to remark that West Africa, the origin of oil palm, shows minimal contribution toward ESs in oil palm PA, where only 1.9% (2 articles) were found from Nigeria from 2011 to 2020.

In terms of geographical network analysis, the synergy between countries is depicted. Fig. 7 shows the geographical network of the contributing organizations. Based on Fig. 7, it is evident that Malaysia has the strongest and largest network amongst all 22 countries, which is reflected via the largest node. This is followed by the United Kingdom and Indonesia. Based on Fig. 6, although the United Kingdom contributes only 4.6% (5 articles) as the corresponding author, nevertheless, organizations from the United Kingdom demonstrates a strong collaboration network as co-author with countries such as Malaysia, Nigeria, Denmark, Kenya, China, United States, and Netherlands. Whereas, for Indonesia, the collaboration network is found amongst countries such as Australia, Japan, Philippines, and Singapore. It is interesting to remark that a weak collaboration network is found between Malaysia and Indonesia, although both the countries are located closely in Southeastern Asia with oil palm as the primary commodities. From Fig. 7, the synergy between developing and developed countries is found. For instance, developing countries such as Malaysia worked in close liaison with developed countries such as the United Kingdom. A similar network is found between Indonesia (developing country) and Japan, as well as Australia (developed countries). This could be attributed to active knowledge adoption from the developed countries, fostering the integration of emerging techniques, producing complementation results which lead to better reliability and applicability in various ESs.

4.3. Distribution of the most contributing journals

Fig. 8 shows the most contributing international journals in ESs for oil palm PA. Overall, 55 journals were found from all the included articles. Considering the widespread of contributing journals, only journals with at least 3 articles publication are included in this analysis. Based on Fig. 8, the journal, namely the *International Journal of Remote Sensing* shows a remarkable contribution, occupying 21.3% (23 articles) amongst the included articles. This is followed by *Computers and Electronics in Agriculture* (8.3%, 9 articles), *Remote Sensing Applications: Society and Environment* (3.7%, 4 articles), *Remote Sensing* (3.7%, 4 articles), *Scientia Horticulturae* (2.8%, 3 articles), and *Agricultural Water Management* (2.8%, 3 articles). In a general remark, monitorization (crop management) typically remote sensing-oriented research is predominant in these journals. This is reflected by a high number of publications from journals such as the *International Journal of Remote Sensing*, *Remote Sensing Applications: Society and Environment*, and *Remote Sensing*. These journals share similar aims and scopes whereby the main focus lies within the theory, science, and technology of remote sensing and novel applications of remotely sensed data. *Computers and Electron-*

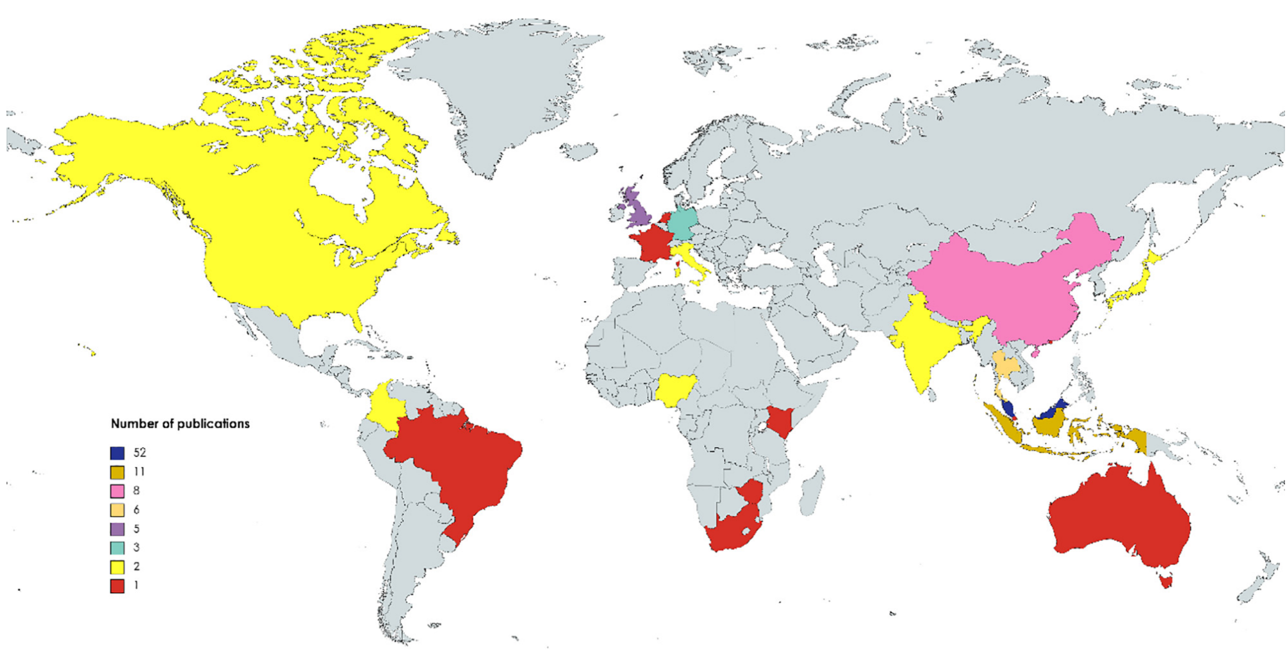

Fig. 6. Geographical distribution of the contributing organizations.

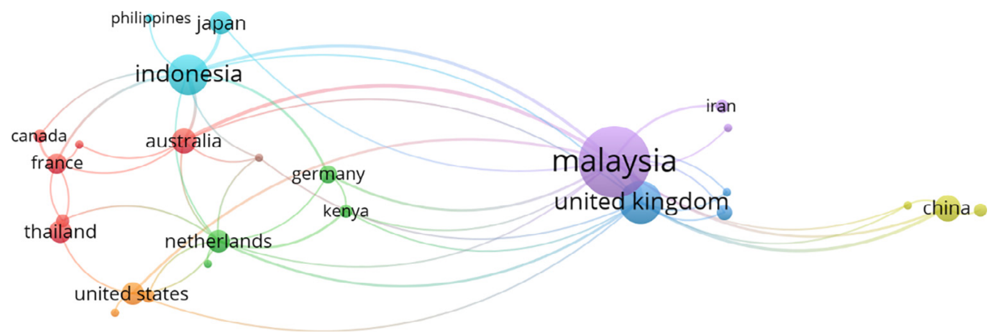

Fig. 7. Geographical network of the contributing organizations.

ics in Agriculture is a well-established international journal focusing on computer or electronic methods in diverse agriculture areas, which include crop management, water management, and soil management. Articles with technology-oriented, typically advent ESs specifically in PA and/ or smart agriculture would be the primary interest of this journal. *Scientia Horticulturae* is an international journal publishing articles relevant to horticultural crops. Engineering articles focusing on technical aspects would be considered in this journal if and only if the articles demonstrate direct effects toward the corresponding living crop. Thus, only articles in crop management (i.e., detection and prediction) are observed in this journal whereby these articles demonstrate a direct relation toward oil palm cultivation. As the name suggested, *Agricultural Water Management* is an international journal catering for water management relevant research. Thus, articles such as adaptive irrigation systems, site-specific water management, water footprint, and water use efficiency can be found in this journal.

4.4. Distribution of the most contributing publishers

As aforementioned, search engines such as Web of Science, ScienceDirect, Google Scholar, Scopus, PubMed, and MDPI were utilized to perform the search query in conjunction with other keywords. From all the included articles, 6 main contributing publishers have been identified: Elsevier, Taylor & Francis, others, MDPI, Springer, and IEEE. Fig. 9 shows the most contributing publishers characterized based on the three main generic categories with the respective domains. Based on the figure, Elsevier appeared to be the most contributing publisher, contributing 42.6% (46 articles) in total. This is followed by Taylor & Francis (28.7, 31 articles), others (13.0%, 14 articles), MDPI (7.4%, 8 articles), Springer (5.6%, 6 articles), and IEEE (2.8%, 3 articles). In a general remark, the publishers maintain an oligopoly relationship in publications and the identified trend is aligned with a previous finding involved analysis of 4 decades (i.e., 1973–2013) of publishing trend where Elsevier, Taylor & Francis, and Springer are amongst the top publishers in various topics (Larivière et al., 2015). It is worthwhile to remark that open access scientific journal publisher such as MDPI has gained interest amongst researches across the globe, who have concern in ownership of articles and type of access (Rodrigues et al., 2020). Nevertheless, it is important to note that the contributing publishers are subjective to topics. The main purpose of this analysis is meant to remark the top publishers specifically in ESs for oil palm PA. Based on Fig. 9, it is evident that all the publishers are actively publishing articles focusing on crop management (e.g., detection, monitorization, analysis, and prediction), where the topic of analysis received the least attention. Also, ESs in water and soil management are less likely to be found in publishers such as IEEE and Springer. A high number of articles focusing on monitorization (crop management) can be found in Taylor & Francis. This could be attributed to some of the popular journals such as the International Journal of Remote Sensing and Geocarto International. A high number of articles concerning water management can be found in Elsevier. This is mainly due to the availability of well-established international journals specifically addressing this topic. Some of these journals are Agricul-

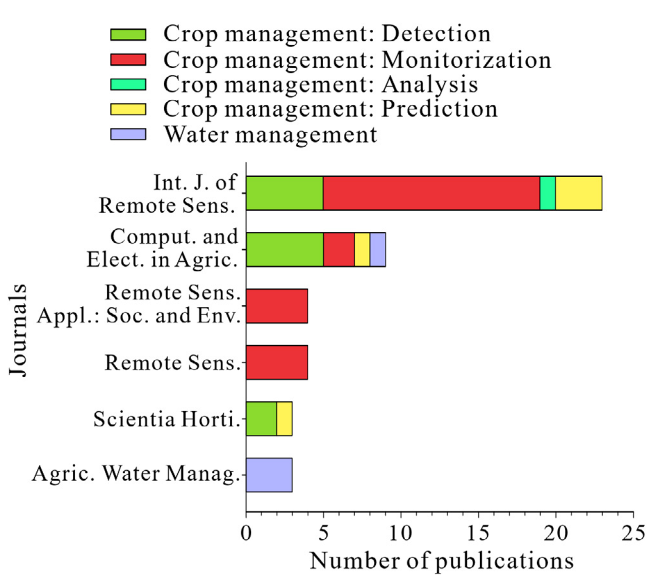

Fig. 8. The most contributing international journals with at least 3 articles publication.

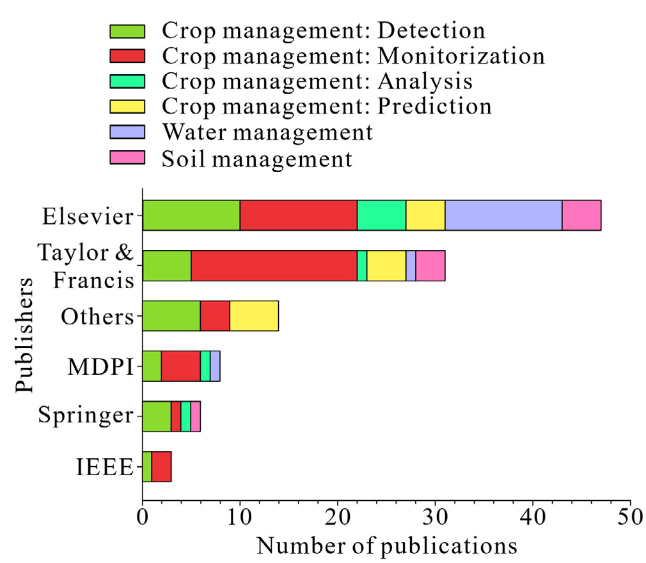

Fig. 9. The most contributing publishers.

tural Water Management, Computers and Electronics in Agriculture, and Sustainable Production and Consumption.

4.5. Temporal distribution analysis

Fig. 10 shows the temporal distribution of the included articles from 2011 to 2020. Based on the figure, the temporal distribution shows a continual increment in interest on the topic specifically in ESs for oil palm PA. As compared with 2011, the number of articles has been increased by 266.7% in 2020. The number of articles in 2019 has recorded the highest publication in the past decade with a total of 23 articles, which is comparative to the number of articles in 2020 (i.e., 22 articles). Over the years, the research interest surrounding the topic has been broadened and meant to focus on the implementation of ESs in multifaceted applications for oil palm PA. In 2011, a small number of articles are found in crop management (i.e., detection (2 articles), analysis (1 article), and prediction (2 articles)) and soil management (1 article). Comparing to 2020, the number of articles has been greatly increased covering the three main generic categories, such that 17, 4, and 1 articles found in crop, water, and soil management, respectively. The accelerating rate of articles in ESs covering multi-dimension in oil palm PA could be attributed to the continuous advancement in technology solutions, typically in AI-oriented engineering solutions in agriculture. Also, it is undeniable that the pressing need for PA implementation by various authorities to uplift the environmental burden as well as increasing demand in site-specific efficiency by the stakeholders have a prominent role in the observed trend.

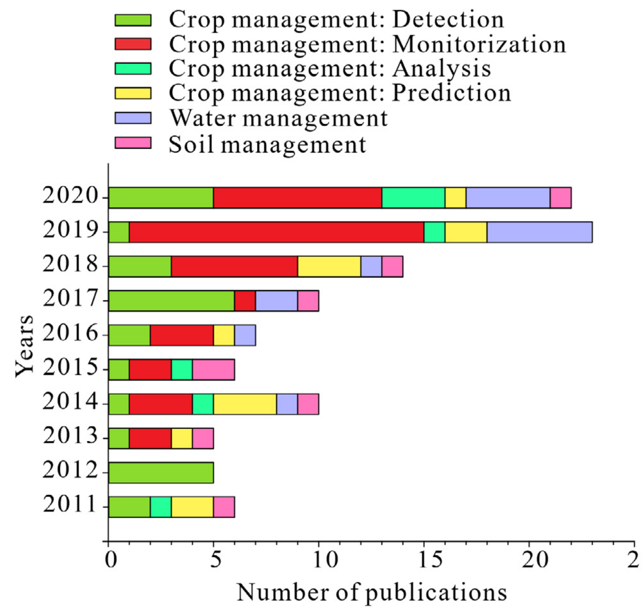

Fig. 10. Temporal distribution of the included articles from 2011 to 2020.

4.6. Subject areas profiling

Fig. 11 shows a treemap chart where the subject areas profile is illustrated using the "subject areas" indexed in Scopus. These subject areas are extracted from 55 journals based on the included articles in this study. Based on Fig. 11, the majority of journals publishing the included articles fall within the subject areas of Agricultural and Biological Sciences: Agronomy and Crop Science, occupying10.0% (12 journals) in total. This is followed by Agricultural and Biological Sciences: Soil Science (6.7%, 8 journals) and Social Sciences: Geography, Planning and Development (5.0%, 6 journals). Journals with subject areas of Environmental Science: Water Science and Technology as well as Engineering: Electrical and Electronic Engineering, both received the same percentage of 4.2% (5 journals). A relatively small number of articles are found in AI-oriented subject areas such as Computer Science: Artificial Intelligence (0.8%, 1 journal). This could be due to application basis (i.e., oil palm) engineering problem-solving, typically suitable for the subject area under Agricultural and Biological Sciences.

4.7. Keywords co-occurrence mapping

Fig. 12 shows the keywords co-occurrence mapping extracted from the included articles which are indexed in the Scopus. Based on the figure, five broad thematic clusters are identified. These clusters can be characterized into subjects (two clusters) and methods used (three clusters). In terms of subjects, the keyword, namely "oil palm" is naturally located at the center of the keywords map as the oil palm is the center of research for all the included articles. This is followed by "yield" and "water deficit", predominant the second cluster in the keywords map. In terms of methods used, the three main predominant keywords in each cluster are: "machine learning", "remote sensing", and "principal component analysis". The ML approach has been well-recognized as a prominent tool with high reliability and efficiency covering all the engineering problems in the three main generic categories. Remote sensing is specifically important and shows persistent growth in literature (e.g., crop management: monitorization) due to the emergence of UAV, UGV, and USV alongside advent technology solutions. The Principal Component Analysis (PCA) is especially important in crop management: prediction and is commonly used as a dimensionality reduction method for various applications. It is worthwhile to remark that deep learning approaches such as artificial neural networks (ANN) and convolutional neural networks (CNN) demonstrate prominent roles in conjunction with methods such as ML and PCA. This highlights the popularity and applicability of deep learning approaches as ESs to resolve complex engineering problems in oil palm PA.

4.8. Co-authorship network analysis

Co-authorship network analysis reflects the scientific collaboration and/ or interaction that takes place between two or more experts, aims to facilitate sharing of knowledge, meaning, and fulfillment of works with a mutually shared objective (Fonseca et al., 2016). Experts commonly collaborate to enhance the opportunity to discover new knowledge, increase specialization within the subject areas, and the need for diverse engineering knowledge and skills for integration of highly complex infrastructures. Fig. 13 shows the co-authorship network analysis for this study, where eight thematic clusters are identified from the analysis. The authors brief information (i.e., cluster, author, research areas, organization, and geographical area) pertaining to the most remarkable node in each cluster is summarized in Table 4.

5. Discussion, limitations, and recommendations

5.1. Discussion

Implementation of oil palm PA is an issue complicated by multiple factors, where this issue contemplates the acquisition and interpretation of diverse information obtained from the site-specific crop, water, and soil. Interpretation of multifaceted and interconnected elements are always a delicate task. In most cases, the interpretation process is dependent on the expertise and perception of the human experts. This process is qualitative and subjective, whereby susceptible to inter- and intra-observers variability. This is where ESs, integrated with sensors, as well as new communication technology solutions (e.g., the internet of things (IoT)), can provide useful support to farmers and stakeholders.

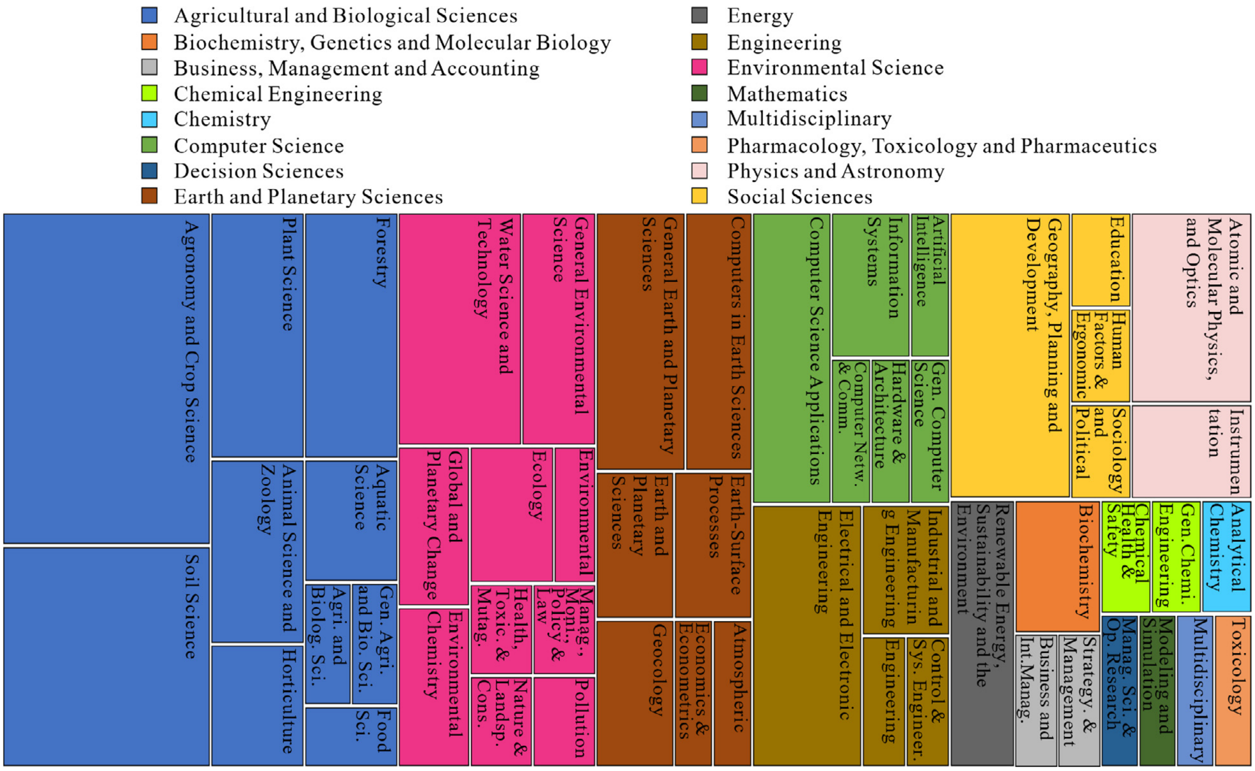

Fig. 11. Treemap chart of the subject areas.

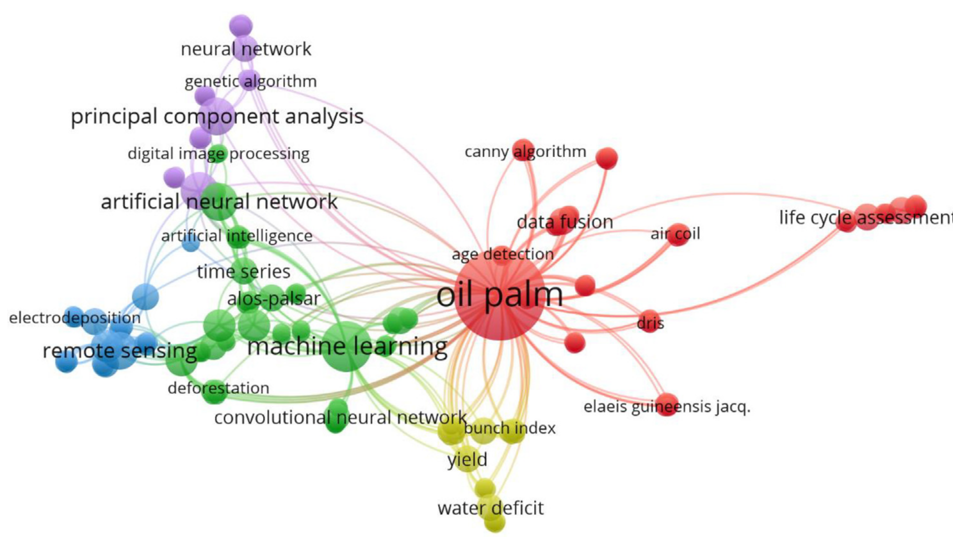

Fig. 12. Keywords co-occurrence mapping.

Over the years, the application of ESs has proven its capability of handling imprecise and ambiguous data, providing recommendation and/ or engineering solutions for individuals (e.g., operators) with a limited background in a specific area (e.g., BSR detection (Liaghat et al., 2014; Ahmadi et al., 2017; Khaled et al., 2020) and FFB ripeness detection (Ibrahim et al., 2018; Herman et al., 2020; Sinambela et al., 2020) [60–62]).

A careful review of the included articles found that most of the ESs in crop management, typically in domains such as detection, monitorization, and prediction, implemented knowledge-based design alongside with ML approach (Liaghat et al., 2014; Khaled et al., 2018; Yousefi et al., 2020) or deep learning approach (Silalahi et al., 2016; Ahmadi et al., 2017; Freudenberg et al., 2019; Diana et al., 2019). Some ESs integrated with sensors (Juman et al., 2016; Sinambela et al., 2020; Rahmat et al., 2020) and graphic user interface (GUI) (Hazir et al., 2012a; Lee et al., 2016; Shaharum et al., 2018) to enrich the input information, which complements the data in the working memory (refer to Fig. 1), aiming for better accuracy and reliability. Some ESs are designed to provide recommendations, especially when dealing with multifaceted and interconnected elements. Such ESs can be found in crop management, specifically in the monitorization domain (Owolarafe and Oni, 2011; Abdul-Hamid et al., 2020; Hashemvand Khiabani and Takeuchi, 2020). In water management, ESs focusing on measurement systems can be found (Meijide et al., 2017; Safitri et al., 2018; Subramaniam et al., 2020), where some are equipped with sensors (Olafisoye et al., 2014) and involve multielement analysis (Jaroenkietkajorn and Gheewala, 2020). In soil

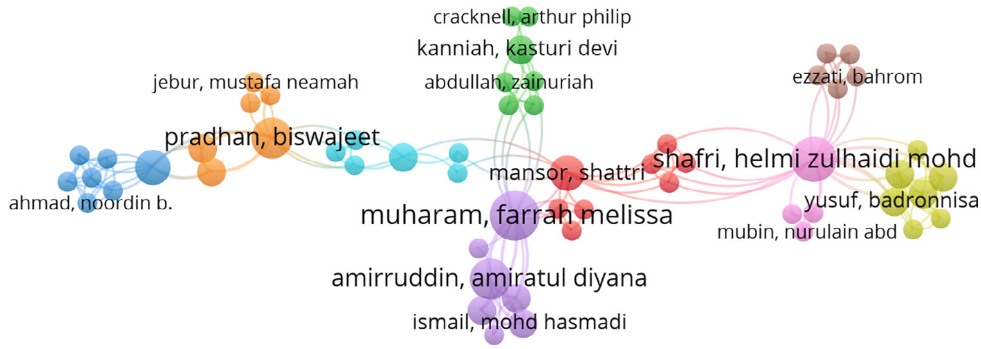

Fig. 13. Co-authorship network analysis.

management, the ESs are biased toward analysis purposes, where ESs in conflict analysis (Cristancho et al., 2011; Oviasogie et al., 2011) and multivariate analysis (Behera et al., 2018; Boafo et al., 2020) using AI approach can be commonly found.

Based on the study, data collection aiming to populate the knowledge base of an ES are commonly performed by searching the relevant literature (Hoffmann et al., 2014; Abdul-Hamid et al., 2020) and/ or identifying the prominent features (Fadilah et al., 2012; Kalantar et al., 2017; Sabri et al., 2018; Hamsa et al., 2019) in which best represent the peculiar problem. In some cases, surveys or interviews (Owolarafe and Oni, 2011; Abdul-Hamid et al., 2020; Choong and McKay, 2014; Nourqolipour et al., 2015) are performed to complement the data collection process. Notice that very limited articles are found with an in-depth discussion on the structure of the knowledge base in an ES, typically in the knowledge acquisition and representation processes. The most common description found (if there is any) would be by searching or benchmarking the state-of-the-art, questionnaire approach, and/ or via a survey approach.

In terms of input data, images-based data, typically RGB images constituted the most common choice amongst the included articles, typically in crop management: detection and monitorization domains. This observation justifies the broad application of ML and deep learning approaches, such as the support vector machine (SVM) and CNN, respectively, in handling image-type input data efficiently. Notice that in crop management: monitorization domain, imagery data collected via remote sensing using UAV, UGV, and USV, as well as imaging from satellites are commonly used. It is observed that data collection via a UAV is commonly used than that of satellite imaging because the UAV imaging approach has higher tolerance toward weather change alongside promising resolution. Concerning water and soil management, input data is likely to be in-field collected agrometeorological data such as air humidity, rain amount, soil humidity, soil moisture, and soil temperature.

In this study, the main purpose is to provide a brief but broad overview of different applications of ESs in oil palm PA, specifically in the three main generic categories (i.e., crop, water, and soil management) and respective domains. All the included articles are selected based on the PRISMA guidelines with search strategy as detailed in Section 3.1.2. From the search procedure, 108 articles were retrieved and included for the subsequent analysis. Based on the observation, the ESs proposed in all the included articles have provided improvement and/ or at least an aid/ support to the conventional approach in handling various aspects in oil palm PA. For completeness, a graphical summary (Fig. 14) is used to summarize the applicability of ESs in oil palm PA across the three main generic categories. Some of the remarkable highlights are: (1) the ES is accessible to all users, such that the ES could emulate the decision-making and/ or problem-solving process performed by the human experts; (2) the capability of providing aid/ support, typically for non-experts in detection, monitorization, analysis, and prediction; (3) optimize the utilization of available resources and minimize waste, thus, increase profitability and reduce losses; (4) integration of advent communication technology solutions and allow constant monitorization as well as continuous communication using user-friendly GUI; (5) an ideal solution toward PA in oil palm cultivation. Enhance the management experience with greater efficiency and reliability alongside precise site-specific information.

5.2. Limitations

The findings of this study are subjected to the following limitations. Firstly, only full-text materials available in the English language are included in this study. Non-English language materials are beyond the scope of this study and are excluded based on exclusion criteria (Phase 1) in accordance with the PRISMA guidelines. This may introduce some bias in the analysis as described in Section 4. Secondly, there are possibilities of missing out some relevant articles specifically in ESs for oil palm PA, typically for articles that are not indexed by Scopus, and/ or using uncommon keywords which are synonymous to the search strings as tabulated in Table 2. Thirdly, the analysis of results for each included article is based on the expertise of the authors of this study, specifically in the field of engineering and computer science. Thus, the outcome of the analysis could be biased towards the technical aspect of the proposals than that of the site-specific agriculture and crop evaluation. In the future, the study shall be enriched by including perspectives from agriculture experts to assure a balanced evaluation of the ESs typically in oil palm PA. Lastly, this study only includes articles from the past decade (i.e., 2011–2020). Due to the continuous emergence of technology solutions and engineering knowledge, the research trend is expected to undergo a persistent change in the near future. However, considering the diversity and number of databases/ search engines used to retrieve the articles (as detailed in Section 3.1.2), this study has confidence that the majority of the targeted literature was included and the findings herein reflect the current state of research accordingly.

5.3. Recommendations

Based on the study, some pointers have been identified where a thorough analysis is worthwhile performed in the near future: (1) site-specific information is one of the key elements in PA as detailed in Section 1.1. With that, sensors and GUI can be widely integrated into the ES and act as the additional information module to enrich the working memory. It is important to remark that for GUI application, the input information acquired from the users shall not be knowledge dependent where expert training is required, as most of the users may not an expert in the subject area; (2) since comprehensive and availability are the key characteristics in ES, thus, big data could be used to enrich the knowledge

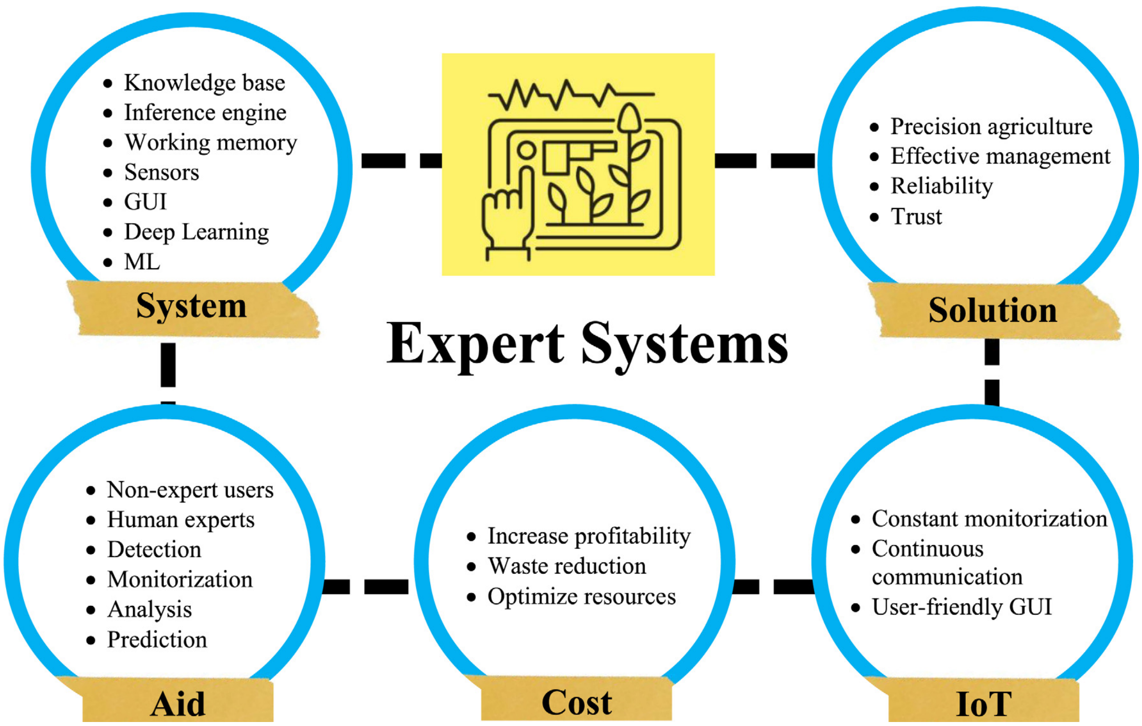

Fig. 14. A graphical summary of the ESs features in oil palm PA.

base of an ES. Knowledge acquisition and representation in an ES is a complex and heterogeneous task that is tedious and highly time-consuming. With the aid of big data, the knowledge base is expected to be sufficiently comprehensive to serve as the fundamental building block for inference engines in decision making. Site-specific information could be then acquired using sensors to further complement the working memory, aiming for better reliability and accuracy; (3) implementation of user subjectivity in ES, such that different users can be assigned with different access/control over the ES. This approach can be implemented to enhance flexibility and customization of parameters in an ES; (4) considering the versatile aspects in oil palm PA across the three main generic categories, convergence research could be a solution toward this research problem. Convergence research is introduced recently which is meant to resolve vexing research problems, typically suitable for heterogeneous research that outstretches multiple disciplines (Advisory Committee For Environmental Research and Education, 2018; Wilson, 2019; Talbot et al., 2021). The key of convergence research is to integrate experts, knowledge, and methods across different disciplines to formalize a novel framework and catalyze new scientific discovery.

6. Conclusion

In this study, a bird's eye view of the body of research reviewing articles in ESs for oil palm PA is presented. A thorough search strategy based on the PRISMA guidelines offered a clear overview of how research communities contribute, what is the core methods employed, and how research efforts and collaboration networks developed over time. Based on the thematic and meta-analysis, this study has identified: (1) the main research stream in oil palm PA fall within the crop management category (i.e., 79.9% in total), where monitorization domain occupied up to 35.8%; (2) geographical distribution analysis found that organizations from the Southeastern Asia remarks the highest contribution toward this topic, where Malaysia recorded the highest publication by 48.1% (52 articles) for the past decade; (3) considering the high number of articles in crop management: monitorization, the *International Journal of Remote Sensing* has attained the highest contribution, occupying 21.3% (23 articles); (4) the publishers maintain an oligopoly relationship in publications with Elsevier as the top publisher; (5) as compared with 2011, the number of articles has been increased by 266.7% in 2020 with highest publication record in 2019 (23 articles); (6) the subject area for this topic is mostly found within the Agricultural and Biological Sciences: Agronomy and Crop Science, occupying10.0% (12 journals) in total; (7) five broad thematic clusters found in keyword co-occurrence analysis, where two subjects clusters (i.e., "oil palm", "yield", and "water deficit") and three methods clusters (i.e., "machine learning", "remote sensing", and "principal component analysis") are identified; (8) Co-authorship network analysis found eight thematic clusters, where six of the most remarkable node corresponding to each cluster are from Malaysia, one from Japan, and one from Australia. The broad insight from this synthesis activity was used to identify the possible roads ahead in research efforts specifically in oil palm PA with the implementation of ESs. Systematic review could be a useful reference to guide the research scholars, industry players, farmers, and all relevant stakeholders in identifying the progress and trends, enabling them to gain a broad and holistic view on the body of literature in ESs for oil palm PA.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

In this section, the included articles are summarized in the corresponding tables (i.e., Tables A1–A6) as described in Table 3, based on the three main generic categories and the respective domains.

Table A1
Crop Management: Detection.

References	Applications	Input data	Functions	Modules/Algorithms	Main Characteristics	Outputs/Key findings
(Phua et al., 2018)	Pest detection	Satellite images and GIS data	Detection of rat in oil palm plantation	Logistic regression	Knowledge representation based on probabilities	Acc: approximately 80.0%
(Septiarini et al., 2020)	Fruits detection	RGB images	Automatic segmentation of oil palm fruits	Contour-basedsegmentation	Machine vision	Acc: 90.1%
(Juman et al., 2016)	Trunk detection	RGB images	Tree trunk detection in oil palm estate	KINECT sensor with Viola and Jones detector and the proposed pre-processing	Optical camera Communication; IoT devices	Acc: 100.0% (night), 100.0% (morning/evening), and 94.0% (afternoon)
(Yousefi et al., 2020)	Pollination detection	Thermal and meteorological data	Classification and detection of oil palm female inflorescences anthesis stages	RF; KNN; SVM	Knowledge base; ML	Acc (Producer): 88.7% (exogenous + exogenous features), 71.4% (endogenous features)Acc (User): 88.3% (exogenous + exogenous features), 72.4% (endogenous features)
(Amirruddin et al., 2017)	Leaf scale measurement	Leaf spectral data	Assessment of leaf spectral measurements	DA; SVM	ML	Acc: 71.0% to 88.0%
(Santoso et al., 2011)	Disease detection	QuickBird imagery data	Detection of BSR	Combination of six vegetation indices derived from visible and NIR	Knowledge base	Acc: 84.0%
(Shafri et al., 2012)	Disease detection	Field spectroradiometer data	Detection of stressed oil palm	AISA	Programable AI	Acc: 86.0% (Optimized hyperspectral indices)
(Liaghat et al., 2014)	Disease detection	Leaflet spectral data	Detection of BSR	Mid-infrared spectroscopy	Knowledge base design; ML	Acc: 92.0% (overall), 90.0% (individual classification using pre-processed raw dataset)
(Ahmadi et al., 2017)	Disease detection	Leaflet spectral data	Detection of BSR	ANN	Knowledge base design; neural network	Acc: 83.3%
(Santoso et al., 2017)	Disease detection	QuickBirdimagery data	Detection of BSR	RF	Knowledge base; RF	Acc: 91.0%
(Izzuddin et al., 2017)	Disease detection	Spectroradiometer data	Application of six spectral indices for early detection of *Ganoderma* disease in oil palm seedlings	Significant wavelength selection; OIF; ASW	Knowledge base	Spectral indices of Ratio 2 are the best output with ASW of 99.0%
(Khaled et al., 2018)	Disease detection	Leaflet spectral data	Detection of BSR	SVM; ANN	Knowledge base design; ML; neural network	Acc: 88.64% (SVM-FS model)
(Santoso et al., 2019a)	Disease detection	WorldView-3 imagery data	Detection of BSR	DT; RF; SVM	Knowledge base design; ML	Acc: 54.1% (SVM)
(Golhani et al., 2019b)	Disease detection	Leaf scale data	Detection of orange spotting disease	Analytic Spectral Device HandHeld 2 (325–1075 nm)	Measurement device, IoT	Enhanced vegetation index 2 was selected as a best spectral index
(Khaled et al., 2020)	Disease detection	Leaflet spectral data	Detection of BSR	QDA with PCA	Knowledge base; ML	Acc: 96.4%
(Rahmat et al., 2020)	Disease detection	Rubber wood samples data	Stress detection in oil palm leaves	Graphene oxide (rGO) and zinc oxide nanoparticles (ZnO-NPs) as surface modifiers	Sensor; surface modifier	Promising R^2 for G. boninense with a limit of detection of 1.75 mg/L_{14l} and 3.23 mg/L_{30l}
(May & Amaran, 2011)	Ripeness detection	RGB images	FFB ripeness detection	Fuzzy logic system	Fuzzy knowledge base	Acc: 86.7%
(Fadilah et al., 2012)	Ripeness detection	RGB images	FFB ripeness detection	ANN with reduced features based on PCA	Features extraction; neural network	Acc: 93.3%
(Kassim et al., 2012)	Ripeness detection	RGB images	FFB ripeness detection	Maturity Table	Knowledge base design	Key findings: Maturity Table (an application) has great potential for FFB maturity detection which helps in site specific harvesting
(Hazir et al., 2012a)	Ripeness detection	FFB samples data	FFB ripeness detection	STATISTICA 8.0	GUI; ML	Acc: 87.7%

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Table A1 (*continued*)

References	Applications	Input data	Functions	Modules/Algorithms	Main Characteristics	Outputs/Key findings
(Hazir et al., 2012b)	Ripeness detection	FFB samples data	FFB ripeness detection	Classification and Regression Tree	Knowledge base; regression tree	Acc: 90.0%
(Harun et al., 2013)	Ripeness detection	Moisture data	FFB ripeness detection	Inductive Concept Frequency Technique	Knowledge base design	The inductance and resonant characteristics of the air coil sensor shows significant changes toward different ripeness levels
(Taparugssanagorn et al., 2015)	Ripeness detection	RGB images	FFB ripeness detection	Kullback–Leibler distance	Machine vision; IoT design	Acc: 96.0%
(Silalahi et al., 2016)	Ripeness detection	NIR spectral data	FFB ripeness detection	GANN	Knowledge base; neural network	Acc: 84.5%
(Sabri et al., 2018)	Ripeness detection	FFB samples data	FFB ripeness detection	SVM; color features	Features extraction; ML	Acc: 96.6% (SVM with color moment)
(Ibrahim et al., 2018)	Ripeness detection	FFB samples data	FFB ripeness detection	CNN	Knowledge base; neural network	Acc: 100.0%
(Herman et al., 2020)	Ripeness detection	RGB images	FFB ripeness detection	ResAtt DenseNet architecture	Knowledge base; neural network	F1-measure: 69.3%
(Sinambela et al., 2020)	Ripeness detection	FFB samples data	FFB ripeness detection	DA	IoT design; inductive sensor	Acc: 100.0%

GIS: Geographic information system; Acc: Accuracy; RGB: Red, Green, and Blue; IoT: Internet of things; RF: Random forest; KNN: K-nearest neighbor; SVM: Support vector machine; ML: Machine learning; DA: Discriminant analysis; BSR: Basal stem rot; NIR: Near infrared bands; AISA: Airborne Imaging Spectrometer for Applications; AI: Artificial intelligence; ANN: Artificial neural network; OIF: Optimum index factor; ASW: Average silhouette width; SVM-FS: Support vector machine-feature selection; DT: Decision tree; CCVd: Coconut cadang–cadang viroid; QDA: Quadratic discriminant analysis; PCA: Principal Component Analysis; R^2: Coefficient of determination; FFB: Fresh fruit bunches; GUI: Graphic user interface; GANN: Genetic Algorithm Neural Network; CNN: Convolution neural network.

Table A2
Crop Management: Monitorization.

References	Applications	Input data	Functions	Modules/Algorithms	Main characteristics	Outputs/Key findings
(Amirruddin et al., 2020b)	Nutrient monitorization	Leaflet spectral data	Study of hyperspectral sensing with imbalance data approaches in nutrient monitorization	LMT; NB; SMOTE; AdaBoost; SMOTE + AdaBoost	Knowledge base; ML	Acc: 76.1% to 100.0%
(Oon et al., 2019a)	Landscape monitorization	Landsat-8 level-2 imagery data	Oil palm landscape monitorization	RF	Knowledge base; RF	Acc: 95.5%
(Hayashi et al., 2020)	Landscape monitorization	Sound data	Oil palm landscape monitorization using acoustic data detection	Acoustic dissimilarity analysis	Knowledge base design; Sensor; AI	Significant differences in location and time factors between the oil palm plantation and the surroundingforests
(Mitchell et al., 2020)	Landscape monitorization	Soundscape data	Oil palm landscape monitorization using acoustic indices	Acoustic complexity index analysis	Knowledge base design; Sensor; AI	Acoustic indices have great potential in landscape-wide studies provided sufficient spatial replication is available
(Gutiérrez-Vélez & DeFries, 2013)	Remote sensing	MODIS and Landsat data	Oil palm plantation remote sensing	Coarse-scale approach	Sensor; IoT; AI	Acc: 94.0%
(Tan et al., 2013)	Remote sensing	UK-DMC 2 imagery data	Oil palm tree age assessment using remote sensing	UK-DMC 2 and ALOS PALSAR	Knowledge base design; Features extraction; IoT; User alert system	The texture measurement and fraction of shadow have great potential in age detection age for oil palm trees
(Jebur et al., 2014)	Remote sensing	SPOT 5 satellite images	Oil palm land cover mapping	SVM-PB; SVM-OB	Features extraction; ML; Inference engine	Acc: 76.7% (SVM-PB) and 81.3% (SVM-OB)
(Srestasathiern & Rakwatin, 2014)	Remote sensing	QuickBirdImagery data	Oil palm tree counting using remote sensing	Data sampling; rank transformation; feature selection; semi-variogram computation; non-maximal suppression	Features extraction; AI	Acc: 90.0%
(Nooni et al., 2014)	Remote sensing	Landsat ETM + imagery data	Oil palm land cover mapping	SVM with Bhattacharyya distance	ML; knowledge representation based on probabilities	Acc: 78.3%
(Teng et al., 2015)	Remote sensing	L-band SAR data	Assessment of medium scattering model for oil palm	Dense medium scattering model based on the iterative solutions of the radiative transfer equations	Knowledge base design; IoT	L-band SAR is applicable in oil palm remote sensing
(Chemura et al., 2015)	Remote sensing	WorldView-2 multispectral data	Detection of oil palm age using remote sensing	Hierarchical classification using object-oriented image analysis techniques	Knowledge base; rule base design	Acc: 80.6% (user accuracy) and 68.4% (producer accuracy)
(Cheng et al., 2016)	Remote sensing	Landsat and PALSAR images	Oil palm land cover mapping	SVM; MD	ML	R^2: 0.8 (Landsat + PALSAR with SVM) and 0.9 (Landsat + PALSAR with MD)
(Lee et al., 2016)	Remote sensing	Landsat images	Oil palm land cover mapping	GEE	GUI; IoT	GEE has great potential in oil palm land cover mapping
(Kalantar et al., 2017)	Remote sensing	UAV images	Oil palm tree counting using remote sensing	UAV-based palm tree inventory	Features extraction; ML; Inference engine	F1-measure: 87.0%
(Li et al., 2017)	Remote sensing	QuickBird Imagery data	Oil palm tree counting using remote sensing	CNN	Knowledge base; neural network	Acc: 96.0% (regions 1 and 2) and 99.0% (region 3)
(Rizeei et al., 2018)	Remote sensing	WorldView-3 Imagery and LiDAR data	Oil palm tree counting and age estimation	Integrated OB Image Analysis Height Model and Regression Analysis	Features extraction; ML; IoT	Acc: 98.8% (tree counting) and 84.9% (age estimation)
(Shaharum et al., 2018)	Remote sensing	Multispectral data	Oil palm land cover mapping	ENVI software; SVM	GUI; IoT; ML	Acc: 98.2%
(Freudenberg et al., 2019)	Remote sensing	WorldView-2 multispectral data	Oil palm tree counting using remote sensing	U-Net	Knowledge base; neural network	Acc: 89.0% (region 1) and 92.0% (region 2)
(Camacho et al., 2019)	Remote sensing	Hyperspectral images	Analysis of spectral variability in hyperspectral imagery for stressed oil palm	CDA-ME algorithm	Inference engine	Acc: 70.0% (with spectral variability)

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Table A2 (*continued*)

References	Applications	Input data	Functions	Modules/Algorithms	Main characteristics	Outputs/Key findings
(Cheng et al., 2019)	Remote sensing	PALSAR-1 and PALSAR-2 images	Oil palm land cover mapping	Maximum likelihood classifier-oriented supervised classification with PC and EM methods	Knowledge representation based on probabilities	RF algorithm outperformed SVM and MLC in terms of computation cost and mapping accuracy
(Shaharum et al., 2019)	Remote sensing	Landsat data	Oil palm land cover mapping	REMAP	RF; IoT; Inference engine; Cloud computing	Acc: 80.3% (Period 1) and 79.5% (Period 2)
(Perbet et al., 2019)	Remote sensing	Landsat-8, Sentinel-1, and Sentinel-2 data	Near real-time oil palm mapping (deforestation detection)	Change Vector Analysis	Inference engine; GUI; user alert system	Acc: 97.0%
(Hamsa et al., 2019)	Remote sensing	Satellite Pour l'Observation de la Terre (SPOT)-5 multispectral images	Detection of oil palm age	GLCM texture measurement	Feature extraction; ML	Acc: 84.0%
(Oon et al., 2019b)	Remote sensing	ALOS-2 PALSAR-2L-band imagery data	Oil palm plantation identification using remote sensing (an assessment of backscatter)	ALOS-2-PALSAR-2L-band and Sentinel-1C-band analysis	IoT; Feature extraction	ALOS-2-PALSAR-2L-band and Sentinel-1C-band have great potential in oil palm landscape discrimination
(Nurul Fatin et al., 2019)	Remote sensing	Meteorological data	Oil palm drought season detection	MODIS and SPI index analysis	Domain knowledge; IoT; Inference engine	Drought detection can be done using MODIS and SPI index
(Fawcett et al., 2019)	Remote sensing	UAV images	Oil palm canopy segmentation and height estimation	SfM photogrammetry workflows	IoT; Inference engine	Acc: 98.2%
(Amirruddin & Muharam, 2019)	Remote sensing	SPOT-6 satellite images	To examine the nitrogen status in mature oil palm plantation	LDA; SVM	Fuzzy knowledge base; ML	Acc: 81.8%
(Wang et al., 2019)	Remote sensing	UAV images	Automatic detection of oil palm trees using HOG and SVM	HOG; SVM	Features extraction; ML	Acc: 99.4% (test site 1), 99.1% (test site 2), 99.9% (test site 3), and 94.6% (test site 4)
(De Petris et al., 2019)	Remote sensing	EVI imagery data	Oil palm detection and characterization	MODIS-derived EVI time series	Sensor; GUI; IoT	Acc: 94.0%
(Mubin et al., 2019)	Remote sensing	RGB WorldView-3 (WV-3) images	Detection of oil palm tree	GIS; CNN	Knowledge base; neural network	Acc: 95.1% (young) and 93.0%, (mature)
(Li et al., 2019)	Remote sensing	QuickBird Imagery data	Oil palm tree counting using remote sensing	Two-stage CNN	Knowledge base; neural network	Acc: 88.0%
(Toh et al., 2019)	Remote sensing	L-band SAR data	Assessment of medium scattering model for oil palm	Dense medium scattering model based on the radiative transfer theory	Rule base design	L-band SAR is applicable in oil palm remote sensing
(Puttinaovarat & Horkaew, 2019)	Remote sensing	Google satellite images	Oil palm tree counting using remote sensing	Pre-processing: GoogLeNet CNN; Detection: Gabor + SVM	Knowledge base; ML; neural network	Acc: 92.29% (Gabor + SVM, overall result)
(Zheng et al., 2020)	Remote sensing	QuickBird and Google Earth data	Oil palm tree counting using remote sensing	MADAN	Domain knowledge design; IoT; GUI	Acc: 84.8%
(Amirruddin et al., 2020a)	Remote sensing	Leaflet spectral data	Remote sensing of chlorophyll sufficiency levels in oil palm	JNB classification	Fuzzy knowledge base	Acc: 92.8 to 98.8%
(Ferreira et al., 2020)	Remote sensing	UAV images	Oil palm tree counting using remote sensing	CNN	Knowledge base; neural network	Acc: 98.6% (Detection in *Açaí*) and 96.6% (Detection in *Paxiubão*)
(Nur Shafira Nisa Shaharum et al., 2020)	Remote sensing	Landsat 8 data	Oil palm land cover mapping	GEE; SVM; CART; RF	GUI; IoT; ML	Acc: 93.2% (SVM), 80.1% (CART), and 86.5% (RF)
(Dong et al., 2020)	Remote sensing	MOPPD	Oil palm land cover mapping	RCANet	Knowledge base; neural network	Acc: 96.8%
(Li et al., 2020)	Remote sensing	Landsat 4, 5 TM and Landsat 8 OLI Tier 1 surface reflectance data	Long-term oil palm land cover mapping	GEE	GUI; IoT	Growth rate: 83.5% (2000 to 2018)

Table A2 (*continued*)

References	Applications	Input data	Functions	Modules/Algorithms	Main characteristics	Outputs/Key findings
(Liu et al., 2020)	Remote sensing	Aerial view imagery data	Automatic detection of oil palm tree	Faster-RCNN	Knowledge base; neural network	Acc: 97.1% (Site 1), 96.6% (Site 2), and 97.8% (Site 3)

LMT: Logistic Model Tree; NB: Naïve Bayes; SMOTE: Synthetic Minority Over-Sampling Technique; AdaBoost: Adaptive Boosting; ML: Machine learning; Acc: Accuracy; RF: Random forest; AI: Artificial intelligence; MODIS: Moderate-Resolution Imaging Spectroradiometer; IoT: Internet of things; UK-DMC 2: Disaster Monitoring Constellation 2 from the UK; ALOS PALSAR: Advanced Land-Observing Satellite Phased Array L-band Synthetic Aperture Radar; SPOT: Satellite Pour l'Observation de la Terre; SVM: Support vector machine; PB: Pixel-based; OB: Object-base; ETM+: Enhanced Thematic Mapper Plus; SAR: Synthetic aperture radar; PALSAR: Phased Array Type L-band Synthetic Aperture Radar; MD: Mahalanobis distance; R^2: Coefficient of determination; GEE: Google Earth Engine; GUI: Graphic user interface; UAV: Unmanned Aerial Vehicle; CNN: Convolutional neural networks; CDA-ME: Ccoordinate descent algorithm-mismodelling effects; PC: Pixel counting; EM: Error matrix-based model-assisted; MLC: Maximum likelihood classifier; REMAP: Remote Ecosystem Monitoring Assessment Pipeline; GLCM: Grey-level co-occurrence matrix; ALOS: Advanced Land-Observing Satellite; SPI: Standardized Precipitation Index; SfM: Structure-from-motion; LDA: Linear discriminant analysis; HOG: Histogram of oriented gradient; EVI: Enhanced vegetation index; GIS: Geographic information system; MADAN: Multi-level Attention Domain Adaptation Network; JNB: Jenks Natural Breaks; CART: Classification and regression tree; MOPPD: Malaysian Oil Palm Plantation Dataset; RCANet: Residual Channel Attention Network; TM: Thematic Mapper; OLI: Operational Land Imager.

Table A3
Crop Management: Analysis.

References	Applications	Input data	Functions	Modules/Algorithms	Main characteristics	Outputs/Key findings
(Abdul-Hamid et al., 2020)	I4 analysis	List of proposed challenges	To impede challenges on I4 in oil palm plantation	FDM	Fuzzy knowledge base	Identificationof 18 essential challenges in I4 for oil palm plantation
(Owolarafe & Oni, 2011)	Sustainable analysis	Questionnaire	To analyze the technology and centralized processing system in oil palm plantation	Extraction rate based on Hartley method (Hartley, 1988)	Inference engine	Modern mill technology and centralized processing system have great potential to improve the oil palm yield and site management
(Choong & McKay, 2014)	Sustainable analysis	Plantation tier data	To analyze the areas contributing toward sustainability in oil palm plantation	NetLogo	Inference engine	(1) Align information based on supply network tiers; (2) Data aggregation within tiers; (3) Connecting and tracing the network; (4) Identify the origin of an information in the network
(Tohiran et al., 2019)	Sustainable analysis	Vector data	To analyze and evaluate the effect of cattle-grazing in oil palm plantation	Heuristic study	Domain knowledge base design	(1) cattle-grazing as a method to maintain manageable undergrowth; (2) align with sustainable palm oil certification policy; (3) promote cattle-oil palm integration
(Nourqolipour et al., 2015)	Oil palm expansion analysis	Vector data	To analyze spatial and temporal development of oil palm expansion	CA; MCE; MC	Knowledge representation based on probabilities; Inference engine	(1) Spatial patterns of oil palm plantations tend to continue; (2) other land categories would be remained fragmented
(Li et al., 2020)	Oil palm expansion analysis	Vector data	To analyze spatial and temporal development of oil palm expansion	GEE	GUI; IoT	(1) Detected oil palm growth rate at 83.5% in Malaysia; (2) Topography, crude palm oil prices, and deforestation are closely related to oil palm expansion
(Hashemvand Khiabani & Takeuchi, 2020)	Oil palm expansion analysis	SAR data	To analyze the specific objectives on oil palm expansion	GEE	GUI; IoT	Government can focus in subsidizing areas such as fertilizers, productive cultivars, and new technology solutions to increase oil palm yield

I4: Industrial 4.0; FDM: Fuzzy Delphi method; CA: Cellular automata; MCE: Multi-criteria evaluation; MC: Markov chain; GEE: Google Earth Engine; GUI: Graphic user interface; IoT: Internet of things; SAR: Synthetic Aperture Radar

Table A4
Crop Management: Prediction.

References	Applications	Input data	Functions	Modules/Algorithms	Main characteristics	Outputs/Key findings
(Sinambela et al., 2020)	Harvest prediction	FFB samples data	Harvest prediction for FFB	Polynomial regression	IoT design; inductive sensor	RMSE: 13.5
(Muhadi et al., 2019)	Tillage prediction	Faro laser scanner and GPS data	To improve DEM for oil palm replanting phase	Data fusion; IfSAR	Knowledge base design; IoT	RMSE: 2.3 (Station 1) and 2.1 (Station 2)
(Golhani et al., 2019a)	Disease prediction	Leaf reflectance data	To predict chlorophyll content at leaf scale in oil palm seedlings for orange spotting detection	Hyperspectral hand-held spectroradiometer ((ASD FieldSpec–II); portable chlorophyll meter (Minolta SPAD-502).	Knowledge representation based on probabilities	RMSE: 3.7
(Morel et al., 2011)	Biomass prediction	Forest mensuration data	To estimate and predict aboveground biomass	ALOS PALSAR	Knowledge representation based on probabilities; IoT	R^2: 0.21; $p < 0.001$
(Singh et al., 2014a)	Biomass prediction	VHR SPOT imagery data	To estimate and predict aboveground biomass	FOTO	Knowledge representation based on probabilities; Fourier transform	R^2: 0.96; $p = 0.042$
(Singh et al., 2014b)	Biomass prediction	Landsat TM and SPOT 5 imagery data	To estimate and predict aboveground biomass	Texture analysis	Features extraction; AI	R^2: 0.84 (EA), 0.92 (LF), and 0.76 (RiF)
(Ismail & Khamis, 2011)	Yield prediction	Yield production data	To predict future yield in oil palm plantation	ANN	Knowledge base; neural network	(1) The number of hidden nodes has a significant influence on the network performance; (2) No effect resulting from the number of runs or the momentum term value on the network performance
(Combres et al., 2013)	Yield prediction	Meteorological data	To estimate and predict monthly number of harvests FFB	ECOPALM	Inference engine	RMSE: 42.5
(Hoffmann et al., 2014)	Yield prediction	Light interception, photosynthesis, respiration, biomass production, and flowering data	To model, simulate, and predict the potential growth and yield of oil palm	PALMSIM.	Knowledge base design; Inference engine	Acc: 81.4% (observation from the optimal fertilizer plots)
(Mustakim et al., 2016)	Yield prediction	Production and productivity data	To predict future yield in oil palm plantation	SVR; ANN	Knowledge representation based on probabilities; Neural network	RMSE: 6.0 (SVR) and 9.0 (ANN)
(Chapman et al., 2018)	Yield prediction	Topography, site information, daily rainfall, and soil survey data	To predict future yield in oil palm plantation	Bayesian networks	ML	Acc: 78.3% (FFB), 94.9 (ABW), and 85.6 (BUNCH_HA)
(Diana et al., 2019)	Yield prediction	SPOT-6 satellite imagery data	To predict future yield in oil palm plantation	ANN	Knowledge base; neural network	Acc: 87.0%
(Santoso et al., 2019b)	Yield prediction	Leaflet spectral data	To predict the oil palm leaf nutrient content	Multivariate analysis with PCR	Knowledge base design	R^2: 0.76 to 0.90 (all variables of ND and SR)

FFB: Fresh fruit bunches; IoT: Internet of things; RMSE: Root mean square error; GPS: Global Positioning System; IfSAR: Interferometric aperture radar; ASD: Analytical Spectral Device; SPAD: Soil-Plant Analysis Development; ALOS PALSAR: Advanced Land-Observing Satellite Phased Array L-band Synthetic Aperture Radar; R^2: Coefficient of determination; VHR: Very-high-resolution; SPOT: Satellite Pour l'Observation de la Terre; FOTO: Fourier transform textural ordination; AI: Artificial intelligence; EA: Heavily logged forests; LF: Twice logged forests; RiF: Riparian forests; MPOB: Malaysian Palm Oil Board; ANN: Artificial neural network; Acc: Accuracy; CBS: Central Bureau of Statistics; DECR: Department of Estate Crops in Riau; SVR Support Vector Regression; ML: Machine learning; ABW: Average weight of fruit bunches; BUNCH_HA: Average bunch number per hectare; PCR: Principal component regression; ND: Normalized different; SR: Simple ratio.

Table A5
Water Management.

References	Domain	Input data	Functions	Modules/Algorithms	Main characteristic	Outputs/Key findings
(Olafisoye et al., 2014)	Water quality	In-situ water samples data	To trace and major elements in ground water	Inductively coupled plasma optical emission spectrometer	Multielement analysis; sensor	(1) Plants are more prone to absorb ground water than that of the flowing water; (2) Water is a pathway of elemental contamination in oil palm trees
(Foong et al., 2019)	Irrigation system	Fertilization and rainfall data	To investigate the role of irrigation system to oil palm plantation development	Input-output optimization model	Optimization; sustainable ES	Irrigation system can cater low yield issue during dry season.
(Safitri et al., 2018)	ET and soil water content	Soil moisture, rainfall, and soil samples data	To trace water footprint	Penman–Monteith; van Genuchten; Darcy's law and Richards' equation; S degree of saturation	Measurement system	(1) The total water footprint values obtained were between 0.56 and 1.14 m3/kg; (2) Oil palm water usage: 3.07–3.73 mm/day
(Chia et al., 2020)	ET	Meteorological data	To estimate the ET_O in oil palm plantation	SVM	Knowledge representation based on probabilities; ML	MARE: 0.02 (SVM-Mak model at Station 48,620 (Sitiawan))
(Meijide et al., 2017)	Water flux	Turbulent flux data	To detect the water flux in oil palm plantation	Eddy covariance technique; CLM-Palm	Modelling; Measurement system	Demonstrate data relevant for the parametrization of larger-scale models, which can contribute to understanding the climatic feedbacks of oil palm expansion
(Silalertruksa et al., 2017)	Water footprint	Life cycle inventory data (MTEC, 2014; Ecoinvent, 2012)	To trace water-use and water scarcity footprint	Life-cycle GHG; water scarcity footprint assessment	Measurement system	Promotion of oil palm expansion must consider both the land and climate sustainability. Several important recommendations have been discussed in the article.
(Subramaniam et al., 2020)	Water footprint	Life cycle inventory data	To trace water footprint for oil palm supply chain	Life cycle impact assessment; water accounting and vulnerability evaluation method	Measurement system	Oil palm plantation required extensive rain water consumption and thus suitable to be cultivate in tropic regions with high rain fall all year long.
(Cock et al., 2016)	Water-use efficiency	Topography, site information, daily rainfall, and soil survey data	To management under well-defined growing conditions.	Homologous events	Knowledge input from experts; knowledge base design; Multielement analysis;	Provide better insights on how to manage and improve the oil palm yield
(Ashraf et al., 2019)	Water-use efficiency	Vegetation structure, microclimate, and soil samples data	To determine the effect of alley-cropping system in water-use efficiency	Alley-cropping system	Sustainable system	Alley-cropping systems have great potential as a climate-smart practice in sustainable oil palm agriculture
(Culman et al., 2019)	Water-use efficiency	Agrometeorological data	To assist in irrigation management in oil palm	Wireless Sensor Network; Agricultural Production Systems Simulator	Inference engine	Results from simulation showed a 27.0% increase in the FFB yield between 2016 and 2017 in the treatment with irrigation
(Rhebergen et al., 2019)	Water-use efficiency	Crop production, leaf sampling, physiological measurements, and yield gaps data	To quantify and access the effect of water in oil palm yield	Simple linear regression model; Best Management Practices; reference yield; UNIANOVA	Knowledge representation based on probabilities; Domain knowledge	Results of the simulation shows that irrigation and fertilizer have potential to close yield gaps in mature oil palm stands
(Rulli et al., 2019)	Water-use efficiency	Palm Oil statistics (BPS, 2018), forest cover map (Hansen et al., 2013), and georeferenced data (Yan, 2017)	To quantify and investigate the effect of water scarcity on oil palm production	Blue water scarcity	Multielement analysis; Conflict analysis	To assure a sustainable agriculture, adverse environmental impacts (and the demands that drive them) must be reduced globally and not simply displaced elsewhere
(Heidari et al., 2020)	Water-use efficiency	Climatological data	To analyze the relationship between water cycling and oil palm cultivation	Calibrated SWAT hydrologic-agronomic model	Measurement system	A planting density of 150 palm/ha was the most efficient for water use and fruit production
(Jaroenkietkajorn & Gheewala, 2020)	Water-use efficiency	Water and energy consumption data	To select arable lands for oil palm.	WFEN and WEF nexus assessment method	Multielement analysis	Expansion of oil palm plantation in the future would dependent on availability of a good irrigation infrastructure

ES: Expert system; ET: Evapotranspiration; ET_O: Reference evapotranspiration; K_C: Crop coefficient; MMD: Malaysian Meteorological Department; SVM: Support vector machine; ML: Machine learning; MARE: Mean absolute relative error; CLM-Palm: Community Land Model Palm; LCI: Life Cycle Inventory; GHG: Greenhouse gas; FFB: Fresh fruit bunches; UNIANOVA: Univariate analysis of variance; SWAT: Soil Water Assessment Tool; WFEN: Water-Food-Energy Nexus; WEF: Water-Energy-Food.

Table A6
Soil Management.

References	Domain	Input data	Functions	Modules/Algorithms	Main characteristics	Outputs/Key findings
(Comte et al., 2013)	Soil quality	Composite oil samples data	To access landscape-scale assessment	Fertilizer sequences analysis	Knowledge base design; Inference engine	Significant soil response found in long-term organic fertilizer application in both loamy-sand uplands and loamy lowlands.
(S. K. Behera et al., 2016)	Soil quality	Soil samples data	To assess the soil nutrient status and leaf nutrient concentration	DRIS	Inference engine	Capable to determine the optimal ranges of nutrient which can be used to guide the diagnostic of soil quality and selection of fertilizers
(Cristancho et al., 2011)	Soil property	Soil samples data	To determine the effect of soil acidity on oil palm progenies	RCBD	Statistical analysis; Conflict analysis	Increasing rates of magnesium limestone and magnesium carbonate can improve soil pH and lower exchangeable aluminum.
(Oviasogie et al., 2011)	Soil property	Leave samples data	To assess the concentration of copper and zinc in oil palm wetland soils	Chemical fractionation analysis	Multivariate fractionation; Conflict analysis	Bioaccumulation pattern of copper and zinc shows the amount of both the nutrients are sufficient in wetland soils
(Nelson et al., 2014)	Soil property	Throughfall, root biomass, and soil respiration data	To investigate lateral tree-scale variability based on soil and plant-oriented properties	Radial pattern analysis; grid approach analysis	Knowledge base design	Deduced three methods to account spatial variation within the repeating tree unit (a hexagon)
(Tao et al., 2017)	Soil property	Weather and soil samples data	To analyze the relationship between best practice management, soil properties, and oil palm production	BMP	Domain knowledge; Knowledge base design	(1) Best management practices can increase fruits production by 12.0%; (2) Partitioning of dry matter to the fronds decreased by 8% under best management practices
(Sanjib K. Behera et al., 2018)	Soil property	Soil samples data	To analyze the spatial variability of soil properties and delineation of soil management	SAS 9.2 software pack (SAS, 2011)	Fuzzy knowledge; Multivariate analysis; AI	Methods used in delineating management zones could be useful for site-soil nutrient management in oil palm plantations
(Boafo et al., 2020)	Soil property	Soil samples data	To determine the effects of organic soil amendments on soil quality in oil palm production	Multivariate principal componentanalysis	Multivariate analysis; AI	The most sensitive soil indicators and their weighted values in descending order were: GME > AP > MoC

DRIS: Diagnosis and Recommendation Integrated System; RCBD: Randomized complete block design; BMP: Best management practice; AI: Artificial intelligence; GME: geometric mean of microbial enzyme activity; AP: available phosphorus; MoC: moisture content.

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