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Decision support systems for agriculture 4.0: Survey and challenges

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ABSTRACT

Undoubtedly, high demands for food from the world-wide growing population are impacting the environment and putting many pressures on agricultural productivity. Agriculture 4.0, as the fourth evolution in the farming technology, puts forward four essential requirements: increasing productivity, allocating resources reasonably, adapting to climate change, and avoiding food waste. As advanced information systems and Internet technologies are adopted in Agriculture 4.0, enormous farming data, such as meteorological information, soil conditions, marketing demands, and land uses, can be collected, analyzed, and processed for assisting farmers in making appropriate decisions and obtaining higher profits. Therefore, agricultural decision support systems for Agriculture 4.0 has become a very attractive topic for the research community. The objective of this paper aims at exploring the upcoming challenges of employing agricultural decision support systems in Agriculture 4.0. Future researchers may improve the decision support systems by overcoming these detected challenges. In this paper, the systematic literature review technique is used to survey thirteen representative decision support systems, including their applications for agricultural mission planning, water resources management, climate change adaptation, and food waste control. Each decision support system is analyzed under a systematic manner. A comprehensive evaluation is conducted from the aspects of interoperability, scalability, accessibility, usability, etc. Based on the evaluation result, upcoming challenges are detected and summarized, suggesting the development trends and demonstrating potential improvements for future research.

1. Introduction

Human beings have cultivated lands and breed animals to obtain food for their survival since ancient times. This practice, known as agriculture, has evolved following a long-term and progressive process (Tekinerdogan, 2018), going from Agriculture 1.0 to 4.0, as shown in Fig. 1.

In Fig. 1, Agriculture 1.0 refers to the traditional agricultural era, mainly replying on the manpower and animal forces. In this stage, though simple tools like sickles and shovels were used in agricultural activities, humans still cannot get rid of heavy manual labor, so productivity remained at a low level. Until the 19th century, steam engines were improved and widely used to provide new powers in all walks of life and industries, including agriculture. It came to the era of Agriculture 2.0 when various agricultural machineries were operated by farmers manually and plenty of chemicals were used. Obviously, Agriculture 2.0 significantly increased the efficiency and productivity of farm works. Nevertheless, this substantial improvement brought too harmful consequences: field chemical contaminations, destruction of the ecological environment, excessive consumption of powers, and waste of natural resources. In the 20th century, Agriculture 3.0 emerged from the rapid development of computing and electronics. Computer programs and robotic techniques allowed agricultural machineries to perform operations efficiently and intelligently. Before the problems left in Agriculture 2.0 went too far, strategies were adjusted in Agriculture 3.0. The reasonable work distribution to agricultural machineries reduced the use of chemicals, improved the precision of irrigation and so on. Nowadays, the evolution of agriculture steps into Agriculture 4.0, thanks to the employment of current technologies like Internet of Things, Big Data, Artificial Intelligence, Cloud Computing, Remote Sensing, etc. The applications of these technologies can improve the efficiency of agricultural activities significantly. For instance, Ferrandez-Pastor et al. (2016) took advantages of Internet of Things and developed a low-cost sensor and actuator network platform. This platform aims at optimizing the production efficiency, increasing quality, minimizing environmental impacts, and reducing the use of resources like energy and water. Wolfert et al. (2017) conducted a survey on applying Big Data to smart farming. They have pointed out that Big Data is now used to provide farmers with predictive insights in farming operations and real-time operational decisions. Liakos et al.

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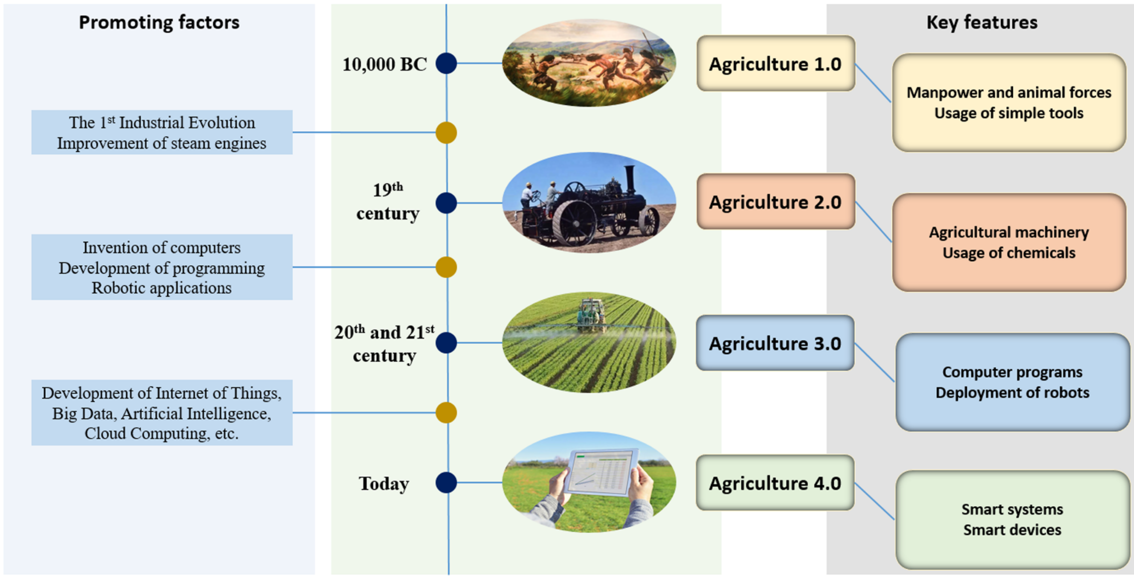


Fig. 1. A general framework of an ADSS for pest management.

(2018) explored the current state of machine learning techniques in agriculture. They have drawn a conclusion that real-time artificial intelligence enables computer programs to generate rich recommendations and insights for supporting farmers to make proper decisions. Lopez-Riquelme et al. (2017) developed a precision agriculture application on the basis of FIWARE cloud. This application is able to reduce the amount of water for irrigation tasks. Thus, their work demonstrates that using FIWARE cloud services in the agronomic context is highly beneficial. Bonfante et al. (2019) proposed LCIS DSS, an irrigation support system for improving the efficiency of water use in precision agriculture based on three different methodologies: IRRISAT® (remote sensing), W-Mod (simulation modelling), and W-Tens (situ soil sensor). Through their case study in maize, they determined that the first two approaches might represent the best solution in regards to irrigation water use efficiency. In the stage of Agriculture 4.0, it is worth mentioning that data from all fields are gathered and processed, providing a clear view for farmers.

Stakeholders and farmers may encounter difficulties in making proper decisions about agricultural management with the explosive amount of information (e.g. environmental, crop-related, and economic data) (Taechatanasat and Armstrong, 2014). Because it is challenging for them to transfer these data into practical knowledge. Thus, platforms like decision support systems (DSSs) are needed in order to assist them in making evidence-based and precise decisions.

Regarding the definition of a DSS, researchers have described this term from various viewpoints. In 1980, Jones (1980) described this term “decision support system” as “a computer-based support system for decision makers who deal with semi-structured problems to improve the quality of decisions”. Sheng and Zhang (2009) defined it as “a human-computer system which is able to collect, process, and provide information based on computers”. Yazdani et al. (2017) considered it as “a specific class of computerized information system, enabling to manage decision-making activities”. Terribile et al. (2015) explained it as a smart system that provides operational answers and supports decision-making to specific demands and problems based on collected data. Thus, considering the above definitions, an agricultural decision support system (ADSS) can be defined as a human-computer system which utilizes data from various sources, aiming at providing farmers with a list of advice for supporting their decision-making under different circumstances. One of the most representative characteristics of an ADSS is that it does not give direct instructions or commands to farmers. Because farmers are in the position of taking the final decisions.

An ADSS is not only able to provide a list of options for on-going activities, but also may help decision makers to achieve better performances in future tasks (Alenljung, 2008). Some successful examples have illustrated how Agriculture 4.0 can benefit from ADSSs. For instance, the Watson Decision Platform for Agriculture was released by IBM Watson and The Weather Company, combining agriculture with IBM’s advanced capabilities in Artificial Intelligence, Internet of Things, and Cloud Computing (Watson Decision Platform for Agriculture, https://www.ibm.com/downloads/cas/ONVXEB2A). On the one hand, this platform provides a suite of solutions that spans the farm-to-fork ecosystem and it is able to analyze any factors which have potential effects on crops. Farmers can obtain crop pictures by deploying Unmanned Aerial Vehicles (UAVs). Then, these pictures are uploaded to IBM Cloud for further analyses based on computer vision algorithms. The analytic results keep farmers updated with health conditions of crops. Thus, the working efficiency and accuracy of detecting crop diseases are greatly improved. On the other hand, owners of large-scale farms can use Watson Decision Platform to estimate the price trending in trading markets. Under this circumstance, the time for irrigation, pollination, phenology, fertilization, harvesting, and selling can be precisely controlled in order to achieve the maximum profits. It is worth noting that the inputs to Watson Decision Platform concerns various sources, such as weather data (provided by the Weather Company), soil data (moisture at multiple depths, nutrient content, fertility, and type), equipment data (gathered from sensors in devices), workflow data (planting and harvesting dates, fertilizer and pesticide application rates, and harvest outputs), and high definition visual imagery (collected by satellites, drones, and fixed-wing aircraft). IBM is not the only company who contributes to Agriculture 4.0, another company named Prospera (Digital Farming System, http://prospera.ag/) takes advantages of Computer Vision, Artificial Intelligence, and Cloud Computing for developing a digital farming system that helps farmers to analyze data collected from their fields. This system is capable of suggesting the best time for irrigation, fertilization, pollination, and harvesting by monitoring the growth rates of crops. Farmers can also be notified when crops are infected by any diseases. According to the statistics from Prospera, the yield production is estimated with 95% accuracy and productivity is increased as much as 30%. The limitation of this digital farming system is that it only concerns the scenarios of greenhouses and large-scale row crops. As a consequence, it is more interesting that Prospera can enrich the functionality of the system for providing farmers with adequate suites of solutions. Moreover, Bazzani (2005) developed DSIRR, a decision support system for irrigation. DSIRR is more than a normative platform to generate the optimal irrigation plan, but an ADSS for exploring the trade-off among conflict objectives and offering farmers compromising solutions. It considers four categories of data sources, including economic (farm income, profit, and gross domestic product), social (public support subsidy and farm employment), water (seasonality, consumption, marginal value, and irrigation technology), and environmental indicators (soil cover, nitrogen, pesticide, and energy). Based on these indicators, a linear model is used to assess the trade-off among economic-social-environmental objectives. With a user-friendly graphical interface, farmers can directly control and monitor irrigation processes. Though the water usage is significantly reduced and farmers can irrigate farming fields more efficiently, DSIRR requires further developments such as employing modular approaches, permitting to integrate new modules focusing on specific aspects of interest. Judging from above successful examples, it is concluded that ADSSs are accelerating the development paces of Agriculture 4.0 from various perspectives.

Though ADSSs are quite helpful in farm management, the unwelcome fact is that the use of ADSSs has been limited due to some critical issues in Fig. 2 (Tyrychtr and Vostrovsky, 2017).

In Fig. 2, following issues have been pointed out.

- Farmers seldom have experiences or knowledge of using ADSSs. The typical graphical interface of ADSSs is sometimes not user-friendly and it may be confusing for farmers to perform desired operations.
- ADSS developers may ignore the requirement analyses from the end users, leading to the fact that inputs and outputs of ADSSs may not fit farmers' needs and decision-making styles.
- The functionalities of current ADSSs are limited and task-specific. An ADSS may only focus on a single perspective. As a consequence, farmers have to use several ADSSs to manage agricultural activities.
- When generating the advice, current ADSSs may miss some fundamental factors, such as climate change, soil spatial variability, crop disease, etc. The lack of these considerations may result in imprecise outputs from ADSSs.

However, the above detected issues are not complete enough. To the best of our knowledge, most of current surveys mainly focus on comparing framework differences of ADSSs and analyzing their performances on specific agricultural tasks or they just explored the current state of ADSSs within a small range (e.g. a country) (Tyrychtr and Vostrovsky, 2017; Hayman, 2004; Nguyen et al., 2007). The critical issues and upcoming challenges of employing ADSSs in Agriculture 4.0 have not been fully investigated. For understanding how ADSSs could

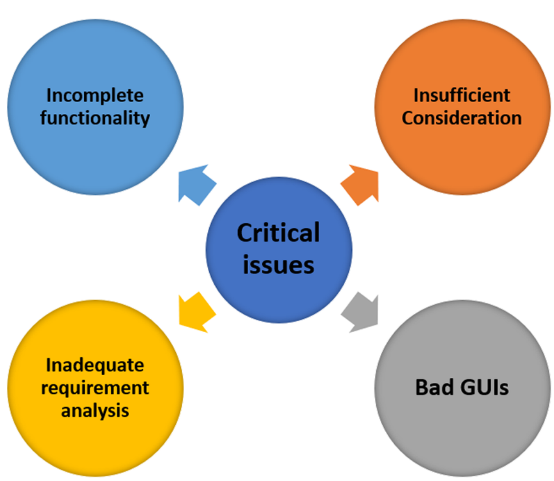


Fig. 2. Some critical issues of employing ADSSs.

be better applied to the domain of agriculture, the requirements of Agriculture 4.0 have to be analyzed beforehand.

In 2013, the German government firstly proposed Industry 4.0, known as the fourth industrial evolution (Anderl, 2015). Two years later, Agriculture 4.0 was defined and quickly attracted wide attentions from worldwide researchers (Agriculture 4.0: The future of farming technology, https://www.worldgovernmentsummit.org/api/publications). Four main requirements are put forward and listed as follows.

- 1. *Increasing productivity:* The population growth and shortage of food will consequently boost the demand for agricultural productions. Meanwhile, people's diet has been changing as well, mainly reflected in demanding for high-value animal protein. Furthermore, with the development of urbanization, infrastructures and buildings would take place of farmlands (Yuan et al., 2018).
- 2. *Allocating resources reasonably:* Natural resources are incredibly stressed nowadays. Firstly, unused lands for cultivation are rare and 25% of farmlands are marked as highly degraded due to deforestation, overcutting vegetation, inadequate fallow periods, etc. (Udias et al., 2018). Secondly, water resources are overused in an unreasonable way (Dong et al., 2018). Frequent water transfers from rivers and lakes are causing serious environmental problems. Thirdly, agricultural machineries are not efficiently deployed due to improper work distributions. A large amount of energy resources is consequently wasted. (Fountas et al., 2015).
- 3. *Adapting to climate change:* Climate change has been greatly affecting the environment. One of the main factors which leads to climate change is manmade emissions of Greenhouse Gases (GHGs). The side effects of climate change result in frequent occurrences of droughts, floods, and extreme weather conditions (Czimber and Galos, 2016). Additionally, agricultural productions are especially vulnerable and sensitive to the impacts of climate change (Kmoch et al., 2018). Lack of efforts in adapting to climate change will cause an increase in uncertainty about food quality, accessibility, and utilization.
- 4. *Avoiding food waste:* Food waste comes from each stage of the agricultural life cycle, including producing, delivering, marketing, etc. Firstly, due to the overuse of chemicals, lack of pest management, and ignorance of climate change adaptations, agricultural products may become contaminated and unqualified (van Evert et al., 2017), leading to food waste and damage to farmlands. Secondly, the world shares a globalized supply and marketing system (Borodin et al., 2016). However, the food delivery is a time-sensitive process. Inappropriate decision-making of deliveries may cause food waste. Thirdly, wasted food is harmful to the environment. Recycling and processing wasted food will consume more resources than producing new ones (Pourmoayed et al., 2016).

Based on the above four requirements, thirteen ADSSs are selected from current literatures. The objective of this paper is to review these ADSSs for Agriculture 4.0 and detect upcoming challenges by means of a systematic literature review technique, consisting of the following five steps.

- 1. *Defining a question:* What does Agriculture 4.0 require from ADSSs employments? (presented in Section 1)
- 2. *Search for literature:* Thirteen representative ADSSs are chosen from current literatures and projects according to the requirement of Agriculture 4.0. (presented in Section 2)
- 3. *Extracting information from selected works:* Each ADSS is introduced and analyzed respectively under a systematic manner. (presented in Section 2)
- 4. *Assessing the quality of selected works:* An evaluation between selected thirteen ADSSs is conducted from the aspects of interoperability, scalability, accessibility, usability, etc. (presented in Section 3)

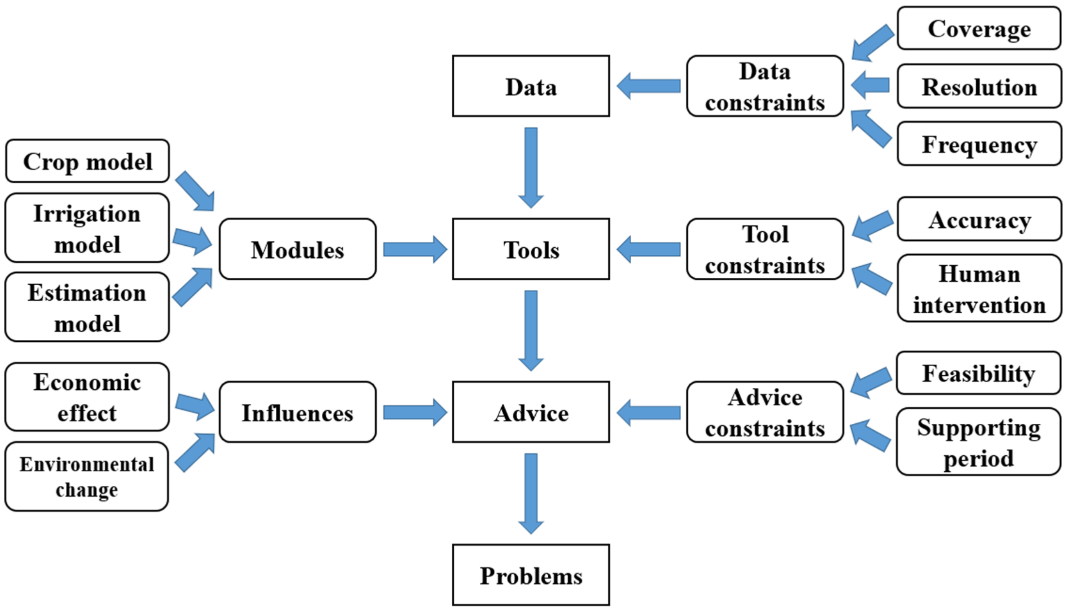


Fig. 3. A general framework of agricultural decision support systems.

- 5. *Drawing a conclusion:* Seven upcoming challenges are detected according to evaluation results. (presented in Section 4)

2. Literature review on selected ADSSs

The selected ADSSs have covered the agricultural applications in: (i) mission planning; (ii) water resources management; (iii) climate change adaptation; and (iv) food waste control. Each ADSS is explored from the systematic view by following the general framework (Fig. 3).

In Fig. 3, agricultural data should be collected in the first place and treated as inputs to the decision-making tools (modules). Advice about managing agricultural activities is generated according to the computational results. Farmers can then choose the most appropriate option and adopt it to solve the problems. It is worth mentioning that constraints should be taken into account for guaranteeing the quality of provided advice.

2.1. ADSSs for mission planning

Current researches on ADSSs for mission planning mainly focus on two aspects: task allocation and path planning. On the one hand, agricultural tasks should be allocated to the most appropriate machineries for execution, and on the other hand, proper path planning can quickly and precisely guide agricultural machineries to the nearest destinations and then execute tasks. Generally, effective planning approaches can greatly increase the productivity because agricultural tasks are completed within the minimum time.

Four ADSSs for mission planning are reviewed in this manuscript. The first two (AgriSupport II system and Multi-robot sense-act system) are related to task allocation and the latter two (ADSS for route planning in soil-sensitive fields and On-board decision-making approach) are in regards to path planning.

2.1.1. AgriSupport II system

The AgriSupport II system aims at adopting the latest advances in decision support systems to fulfil the needs of agricultural production processes (Recio et al., 2003). The overall objective of this system is to provide farmers with sufficient agricultural decision-making suggestions like farm operation scheduling, detailed operation cost, resources usage, and profitability analysis. Two main issues are mentioned in their requirement analyses. The first issue is in regards to the complexity of agricultural problems. When planning an agricultural mission, several factors has to been taken into account: number of involved agricultural machineries, capability of these machineries, number of tasks, etc. The second issue addresses the time window of agricultural activities. Normally, an agricultural year lasts from 8 to 12 months. Certain activities should be performed at a specific time, such as when to seed, fertilize, and harvest. A delay of one or more days for mission executions may lead to unexpected economic losses.

The decision-making process in AgriSupport II system is computed by a farm planning model algorithm. This algorithm is designed to identify which work units are suitable for performing what tasks. For providing this plan, following attributes are considered as inputs to the planning model.

- *Mode:* It is defined as a possible plan for performing agricultural tasks.
- *Technical path:* It is defined as a sequence of operations to be performed. A mode is composed of several technical paths and their relationships of precedence.
- *Resource:* A technical path requires certain resources like machineries and human labors. For using resources, the technical path has to pay costs, which will be included in the estimated cost of performing operations.
- *Precedence:* It is defined as the priority of each operation in the technical paths. Those operations with a higher precedence will be executed in the first place.
- *Time window:* It is defined as the starting and completion time of modes.

After obtaining above inputs, the farm planning model algorithm computes the cost of all feasible modes and compares them with each other in order to find out the one with the lowest cost, as the optimal plan for distributing agricultural tasks to work units. This algorithm adopts the CPLEX optimizer as the decision-making tool.

The AgriSupport II system was tested in a farm in Spain where different combinations of crops were proposed and experimented with. Twenty-five case studies were considered in the experiments. Experimental results suggest that AgriSupport II system is able to provide farmers with sufficient advice about distributing agricultural works. By adopting those provided advice, farmers can perform agricultural operations with the minimum investments and achieve the greatest working efficiency. Consequently, agricultural productivity will increase, which fulfils the requirement of Agriculture 4.0.

2.1.2. Multi-robot sense-act system

Conesa-Munoz et al. (2016) proposed a multi-robot sense-act system, aiming at performing tasks automatically by using aerial and ground vehicles. The main objective of this system is to improve crop performances and maintain environmental quality by using vehicles to perform agricultural tasks in large outdoor areas autonomously. In their proposal, aerial units are responsible for gathering environmental data while ground units are considered as mission executors in farmlands. All the vehicles are controlled by a Mission Manager, connected to a Base Station computer. Within the Mission Manager, two planners are designed for commanding aerial and ground units respectively.

In regards to the aerial planner, its inputs require command signals from the Mission Manager, locations of obstacles in farmlands, and survey areas. Then, the aerial planner splits fields into small grids according to orientation, overlapping requirements, and image resolution. A Harmony Search Algorithm (Nabaei et al., 2018) is used to generate the optimal plan for aerial units to cover the whole area. In terms of the ground planner, it distributes task sequences to ground vehicles by a *meta*-heuristic optimization method. Its required inputs are operation areas and commands received from the Mission Manager. It is worth noting that turning radius and battery capacity are both considered in this planner. The output of the ground planner is the best trajectory for each ground vehicle to cover operation areas.

The multi-robot sense-act system was tested over 20 times in a farm in Spain. The experimental result shows that this system is able to generate the optimal work distribution for a site-specific herbicide treatment mission. Both aerial and ground units can work cooperatively. Notifications were sent to farmers when vehicles had unexpected failures.

Overall, this system contributes to assigning agricultural tasks to the most appropriate work units. Farmers can obtain decision supports on agricultural work distributions. Meanwhile, farmers can supervise the entire process and manage the workflow through the multi-robot sense-act system. Unexpected failures like internal errors of vehicles, valves delay, and work collisions are informed to the farmers. As a consequence, immediate requests on mission re-planning can be proposed. Lastly, thanks to images taken by aerial units and data collected by ground units, farmers can know exactly how many herbicides are needed from crops. Thus, a precise spraying can be performed by reducing the amount of herbicide usages. In general, the multi-robot sense-act system is a good fit for Agriculture 4.0.

2.1.3. ADSS for route planning in soil-sensitive fields

Bochtis et al. (2012) presented an ADSS to help farmers to deploy agricultural vehicles in soil-sensitive fields properly. The objective of their work is to optimize travel paths for minimizing damages to soil-sensitive fields from large-scale vehicles. On the one hand, route optimizations can reduce energy consumptions of vehicles and improve the working efficiency. On the other hand, it is essential to consider mechanical impacts of vehicles on the soil structure, especially the risk of soil stresses and compactions (Keller et al., 2007). The shorter path a heavy vehicle travels in the field, the less damage will this vehicle cause.

In their proposal, the system treats the soil boundary, driving direction, and potential risk indicator measurements as input data. The B-patterns optimization algorithm is employed as the decision supporting tool in the system. It takes four steps to generate the optimal plan. Initially, all tracks are sequentially sorted based on the derived relative risk map. A threshold is assigned to each track, as an indicator of distinctions between low and high risks. After the sequential permutation of tracks is generated, the number of routes is estimated. A single route is composed of sequential work operations, including filling resources, forwarding to target locations, performing operations, and returning to the facility unit. Afterwards, tracks are assigned with a route according to the sequential permutation. The last step is to measure the risk factor of each route by comparing values of normalized risk indicators and vehicles loads. Finally, the output from this ADSS is the optimal route plan.

For verifying the effectiveness of this ADSS, a case study is conducted in a field in Denmark. It used Electromagnetic Induction (EMI) as the risk indicator measurements and GreenStar 3 as the navigation component for tractors. The experimental result demonstrates that those tractors with heavy loads are dispatched to the areas with low risk indicator values. As a consequence, damaging impacts on soil stresses and compactions are significantly reduced. Conclusively, the proposed ADSS for route planning can provide farmers with the optimal plan of work distributions. Meanwhile, soil-sensitive fields can be protected from damages caused by tractors with heavy loads. More crops can be grown and agricultural productivity will increase. Thus, this proposal fulfils the requirement of Agriculture 4.0 closely.

2.1.4. On-board decision-making approach

With the development of advanced robotics, Unmanned Aerial Vehicles (UAVs) have been widely used in a board range of applications, especially in the aspect of agriculture. Alsalam et al. (2017) proposed an on-board decision-making approach for UAVs to perform agricultural operations autonomously. The objective of this work is to detect exact locations of diseased crops and then perform corresponding operations like spraying herbicides precisely. With the precise use of herbicides, toxic damages to the fields can be greatly reduced. Meanwhile, deploying UAVs to perform spraying missions can improve the working efficiency, which obviously helps farmers to increase agricultural productivity. The proposed approach is on the basis of the Observation, Orientation, Decision, and Action (OODA) loop shown in Fig. 4.

In Fig. 4, for collecting data, this approach takes measurements from ultrasonic sensors, images taken by cameras, and received commands as inputs during the observation step. After obtaining these inputs, UAVs start the mission and march to the target locations. During the step of mission execution, the on-board computer determines whether UAVs are following the correct path or not. If a UAV is flying higher than the appointed height, the decision-making component will command this vehicle to adjust its altitude. Meanwhile, the decision-making component is responsible for checking past waypoints in order to monitor the mission status. The action step includes operations like taking images, approaching to waypoints, and spraying herbicides. After the assigned mission is completed, UAVs are required to return back to the home station and convert to the observation mode.

The on-board decision-making approach was verified through several flight missions. The experimental result shows that UAVs can hover over target locations upon arrivals. The proposed approach can correctly guide UAVs to reach each waypoint. Target locations are obtained based on obtained images by running an Object-Based Image Analysis (OBIA) algorithm (Peña et al., 2013). Thus, UAVs are able to

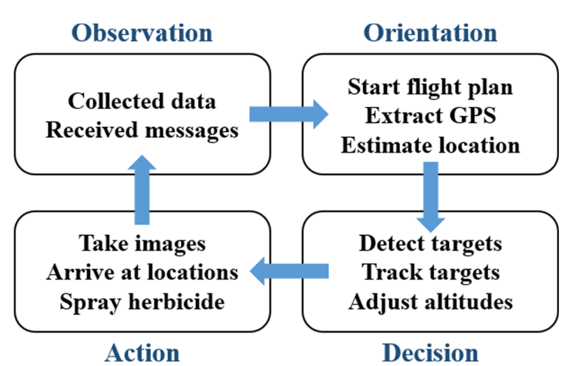


Fig. 4. The OODA loop in the proposed on-board decision-making approach.

Table 1
Summary of ADSSs for mission planning.

DSS name	Data source	Tool	Decision support	Supporting period
AgriSupport II system	Environmental, crop-related, and economic data	CPLEX optimizer	Guidance for farm operation scheduling	Short-term
Multi-robot sense-act system	Environmental and crop-related data	Meta-heuristic algorithm	Plans for herbicide treatment missions	Short-term
ADSS for route planning in soil-sensitive fields	Environmental and crop-related data	B-patterns optimization algorithm	Travel paths for agricultural vehicles	Short-term
On-board decision-making approach	Environmental and crop-related data	OODA loop	Flying paths for UAVs	Short-term

hover over targets and perform precise spraying operations. Conclusively, the proposed approach can provide farmers with decision supports on route guidance of UAVs. Also, it enables UAVs to perform precise spraying operations autonomously, which greatly improves the working efficiency of agricultural operations and reduces toxic damages from excessive chemical usages. From this perspective, the proposed decision-making approach is closely related to the requirement of Agriculture 4.0.

2.1.5. Summary of ADSSs for mission planning

Through the review result from Section 2.1.1–2.1.4, the differences between ADSSs are concluded in Table 1.

In Table 1, these four ADSSs are designed to serve the aspect of mission planning in Agriculture 4.0, providing farmers with guidance about agricultural operations like chemical treatment and scheduling of agricultural machineries. It is noted that all ADSSs collect environmental and crop-related data as inputs to their decision supporting tools (models). However, only AgriSupport II system concerns the economic data. The optimization algorithm is a favourable approach for generating the solutions. Unfortunately, all ADSSs under this category lack consideration of mid-term and long-term planning.

2.2. ADSSs for water resources management

Current researches of ADSSs for water resources management are generally concerning the irrigation systems. An irrigation system should provide farmers with effective decision supports on controlling the amount of water applied to crops and maintaining landscapes (Alarcon et al., 2016; de Wit and Crookes, 2013). It aims at ensuring wettability of soil fields and basic water needs from crop growths with the minimum water usages.

Three ADSSs from literatures are reviewed in the next sub-sections to summarize contributions from current works.

2.2.1. Smart irrigation decision support system (SIDSS)

The smart irrigation decision support system (SIDSS) was proposed by Navarro-Hellin et al. (2016). Traditionally, irrigation activities are planned by an agronomist according to resources like collected meteorological data, crop characteristics, and soil measurements. The objective of the proposed SIDSS is to generate irrigation plans in a more efficient and accurate way with the same resources. With the help of SIDSS, irrigation activities can achieve better performances with the minimum water usages.

In their proposal, SIDSS is composed of three components: a collection device, a weather station, and a decision-making component. The framework of SIDSS is presented in Fig. 5. In regards to the inputs to SIDSS, the first two components collect sensing data (volumetric water content depth, soil water potential, and soil temperature) and meteorological information (rainfall, wind speed, temperature, relative humidity, global radiation, dew point, and vapor-pressure deficit). The decision-making component is in charge of generating decision supports based on reasoning results. The reasoning process adopts two machine learning techniques: Partial Least Squares Regression (PLSR) (Mehmood et al., 2012) and Adaptive Neuro Fuzzy Inference Systems (ANFIS) (Svalina et al., 2013). PLSR is used to deduct unnecessary variables when soil measurements and meteorological data appear redundant. ANFIS is employed to minimizing estimated errors under a given threshold. The output of SIDSS presents the optimal irrigation plan, indicating the amount of water usages and the time for irrigation activities.

The smart irrigation decision support system was testified and evaluated in lemon tree plantations in south-east Spain, where water resources are very limited. The experimental result demonstrates that SIDSS is able to provide farmers with an irrigation report, which is better than the decisions made by an agronomist. The irrigation report indicates the precise amount of water usages and the time for irrigation

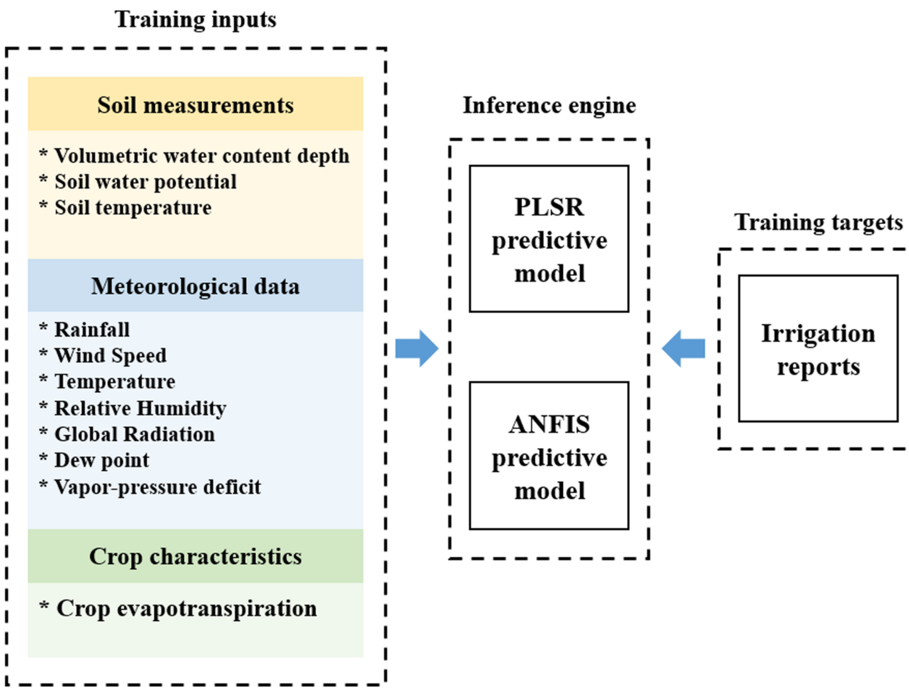


Fig. 5. The framework of SIDSS.

activities. Conclusively, SIDSS meets the requirement of Agriculture 4.0 by allocating natural resources reasonably.

2.2.2. Fuzzy decision support system (FDSS)

Giusti and Marsili-Libelli (2015) proposed a fuzzy decision support system (FDSS) and it is an improvement over an existing irrigation web service based on IRRINET model (Giannerinii and Genovesi, 2011). As a fundamental platform in agriculture planning, FDSS is developed to assist farmers in scheduling daily irrigation activities by combining a predictive model of soil moisture and an inference system. The objective of FDSS is to improve irrigation performances and reduce unnecessary water usages.

In their proposal, FDSS consists of two parts: a predictive model and an irrigation decision maker. The former component takes meteorological information, water resources availability, and crop characteristics as inputs. It is worth noting that water balances are considered as well. The predictive model generates the variable of soil moisture, which is compared with a pre-defined threshold later. If soil moisture is lower than the threshold, the irrigation decision maker is trigged to plan the next irrigation activity. The decision maker component considers three inputs: daily variation of Growing Degree Days (GDD), cumulative rain forecast, and crop evapotranspiration. The inference method used in this component is the Fuzzy C-Means algorithm. According to the decision rule set, the generated inference result suggests the amount of water to irrigate.

The proposed FDSS was tested on three crops: corn, kiwi, and potato. Comparing with the previous research work (IRRINET), the experimental result demonstrates that the performance of FDSS is much better, saving up to 13.55, 18.3, and 72.95 water units for irrigating three crops respectively. Therefore, FDSS is able to provide farmers with effective irrigation advice and help them to allocate water resources more reasonably. From this point of view, FDSS definitely fulfils the requirement of Agriculture 4.0.

2.2.3. MRGCD DSS

Due to a decrease of annual rainfall and misuse of water resources, western United States is suffering from serious drought years and has difficulties on irrigating crops. In order to reduce water consumptions in irrigated agriculture and improve the irrigation performance, a decision support system for Middle Rio Grande Conservancy District (MRGCD DSS) is presented by Oad et al. (2009). The objective of MRGCD DSS is to analyse water demands in service areas and schedule available water resources to fulfil these demands precisely and efficiently.

There are three components in MRGCD DSS: a water demand module, a scheduling module, and a water supply module. Firstly, the water demand module calculates the water shortage capacity by the ET Toolbox, according to input variables like irrigated areas, crop types, soil types etc. The Integrated Decision Support Consumptive Use (IDSCU) model is adopted to calculate the amount of water which equals to the water shortage capacity. Secondly, the water supply module presents the layout of conveyance network, including connections between canals, laterals, and service areas. The flow capacity and conveyance losses are computed in this module. Thirdly, the scheduling module generates water delivery plans for fulfilling demands from crops. As the output from MRGCD DSS, the delivery plan includes the number of laterals, irrigation time, irrigation frequency, and the amount of water.

MRGCD DSS was verified in a farmland with 28 lateral canals. The irrigation duration, irrigation interval, and flow rates were considered as evaluation criteria. Though certain discrepancies do exist between experiments and real practices, MRGCD DSS achieves better performances in most laterals. Conclusively, MRGCD DSS is able to provide sufficient decision supports for farmers on planning irrigation activities. Besides helping farmers to save water resources, it also reduces river diversions. Therefore, MRGCD DSS fulfils the requirement of Agriculture 4.0.

2.2.4. Summary of ADSSs for water resources management

Table 2 presents the differences between the selected ADSSs for water resources management.

In Table 2, SIDSS, FDSS, and MRGCD DSS provides scheduling plans of irrigation. It is concluded that environmental and crop-related data are essential. Predictive models (PLSR, ANFIS, and IDSCU model) and decision rules (Fuzzy C-Means algorithm) are used to generate the options. The supporting period is limited within a short term.

Table 2
Summary of ADSSs for water resources management.

DSS name	Data source	Tool	Decision support	Supporting period
SIDSS	Environmental and crop-related data	PLSR and ANFIS	Irrigation reports	Short-term and mid-term
FDSS	Environmental and crop-related data	Fuzzy C-Means algorithm	Advice on scheduling irrigation	Short-term
MRGCD DSS	Environmental and crop-related data	IDSCU model	Advice on scheduling irrigation	Short-term

2.3. ADSSs for climate change adaptation

Recently, researchers have been aware of the significance of climate change adaptation in agricultural decision support systems (Rickards and Howden, 2012; El-Sharkawy, 2014; Weller et al., 2016). To summarize current contributions, three research works are reviewed in the following sub-sections.

2.3.1. OCCASION

In order to maintain agricultural sustainability under climate change, Schutze and Schmitz (2010) proposed a planning system, named OCCASION, for optimizing climate change adaptation strategies in irrigated agriculture. The objective of this system is to provide farmers with estimated water demands for irrigation according to assessments of climatic variability.

In their proposal, a methodology, named Stochastic Crop-Water Production Function (SCWPF), is presented, enabling to quantify impacts of climate change on irrigation activities. The first step of SCWPF is to create climatic data by using LARS-WG stochastic weather generators (Semenov et al., 1998). After synthesizing climate scenarios, SCWPF adopts the One-Dimensional Soil-Vegetation-Atmosphere Transfer (SVAT) model (Mo et al., 2005) to simulate crop productions, crop yields, water and nitrogen conditions. The second step of SCWPF is to construct a complete Crop-Water Production Function (CWPF) by the Global Evolutional Technique for Optimal Irrigation Scheduling (GET-OPTIS). Variables from the weather generators and the SVAT model are treated as inputs to GET-OPTIS. The output of GET-OPTIS is the potential CWPFs which represent the potential optimal plan for irrigating the maximum crop yield with the minimum water volumes. In the third step, statistical characteristics of all potential CWPFs is computed in a non-parametrical way for the purpose of identifying the global optimal irrigation scheduling plan.

The proposed planning tool was tested and evaluated in a field in France. A basic scenario without rainfall and a complex scenario with variability of rainfall are considered. According to evaluation results, OCCASION has achieved the following contributions: (1) farmers can obtain adequate information about weather and soil fields. (2) this planning system allows farmers to assess the potential impacts of climatic variability on farmlands. (3) OCCASION assists farmers in adjusting irrigation scheduling plans, taking climate change into account. Conclusively, OCCASION fulfils the requirement of Agriculture 4.0.

2.3.2. LandCaRe DSS

LandCaRe DSS, as an interactive decision support system, was presented by Wenkel et al. (2013). The objective of this research is to support farmers and stakeholders on adapting farm management to climate change as follows:

- Providing both historical and predictive climate data for end users under a clear visualization.
- Providing multi-scenario and multi-model simulations for analyzing uncertainty.
- Providing potential strategies for climate change adaptation.
- Providing end users with assessments of climate change over agricultural activities.

In the proposed LandCaRe DSS, three components are closely linked: climate, ecology, and socio-economy. The climate component is used to analyze long-term and seasonal climate data (Franke and Kostner, 2007), estimating temperature trends, rainfall, precipitation, Ellenberg index, Huglin index, Schwarzel index, etc. The effects of climate change are then considered as inputs to the ecology component. Within this ecology component, various models are designed, including VEGPER (calculating the length of vegetation periods), ONTO (calculating crop developments in different stages), SVAT-CN (calculating nitrogen and Soil-Vegetation-Atmosphere-Transfer), EROSION (calculating regional water balance), GLPROD (calculating grassland productivity and forage quality), etc. In regards to the socio-economy component, it has two models: PECG and RAUMIS. The former model is used to evaluate costs and benefits by applying different climate change adaptation strategies, while the latter one assesses the impacts of climate change over future agricultural activities.

LandCaRe DSS takes the following steps to provide end users with decision supports. Firstly, agricultural problems and scenario simulations are extracted from users' definitions, including climate, soil, land use, and so on. Based on the input data, a model is selected to assess the impacts of climate change over agricultural activities. The output from the employed model is presented by maps, diagrams, tables, and statistics.

The proposed LandCaRe DSS was tested in two contrasting regions in Germany. The experimental result shows that this system is able to predict future meteorological information and the length of vegetation periods. Meanwhile, LandCaRe DSS is also capable of analyzing water demands for irrigation activities. Conclusively, successful demonstrations imply that LandCaRe DSS can provide stakeholders and farmers with sufficient decision supports on agricultural activities under climate change. Thus, the proposed ADSS fulfils the requirement of Agriculture 4.0 by adapting to climate change.

2.3.3. GIS-based DSS

For quantifying potential impacts of climate change in Semi-Arid Tropical (SAT) regions, Kadiyala et al. (2015) presented an agricultural decision support system by integrating a Decision Support System for Agrotechnology Transfer (DSSAT) crop simulation model and a Geographical Information System (GIS) component. The objective of GIS-based DSS is to assist farmers in making proper agronomic decisions under climate change to increase the productivity of ground nuts.

The proposed system consists of four major components: a GIS component, a DSSAT crop simulation model, a query system, and a spatial output generating system. Firstly, the GIS component receives spatial information about position, soil, and weather. Then, these data are considered as inputs to the crop simulation model (DSSAT). Crop growths and yield can be simulated through the DSSAT model (Jones et al., 2003). Based on the spatial information and crop data, the proposed ADSS can provide the following functionalities.

- *Prediction on future climate characteristics:* This functionality mainly concerns the predicting future rainfall and temperature.
- *Observation on base yields:* This functionality performs productivity analyses for the selected yields.
- *Assessment of climate change over crop yields:* This functionality considers how climate change may influence the crop yields.

Four adaptation strategies were tested by the proposed ADSS.

Table 3
Summary of ADSSs for climate change adaptation.

DSS name	Data source	Tool	Decision support	Supporting period
OCCASION	Environmental and crop-related data	CWPF and GET-OPTIS	Assessments of climate change	Short-term
LandCaRe DSS	Environmental, crop-related, and economic data	VEGPER, ONTO, SVAT-CN, etc.	Advice on farm management under climate change	Short-term, mid-term, and long-term
GIS-based DSS	Environmental and crop-related data	DSSAT model	Advice on increasing productivity under climate change	Short-term

Firstly, 10% longer life cycle cultivar was simulated. By applying climate change adaptation, groundnut productivity increased by 6.8% and 2.1% in southern regions and highland regions respectively. Secondly, the proposed ADSS took drought tolerance into account. The simulation result showed significant improvements in all test fields. Thirdly, heat tolerance was considered in simulations and the result demonstrated positive responses. Fourthly, adaptation strategy supplemental irrigation was tested. All regions can benefit from precision irrigation advice and base yields increased by 23.6%, 21.9%, 19.3% and 16.1% respectively. Conclusively, the proposed ADSS is able to predict future climate characteristics and monitor conditions of groundnut fields. Famers can obtain proper decision supports on performing agricultural activities under climate change. Therefore, it fulfils the requirement of Agriculture 4.0 by considering climate change adaptation.

2.3.4. Summary of ADSSs for climate change adaptation

Table 3 summarizes the research work of ADSSs for climate change adaptation.

In Table 3, LandCaRe DSS concerns the widest range of data sources when adapting to climate change, while economic data are not involved in OCCASION and GIS-based DSS. It seems that these three ADSSs favour model-based approaches and various models are adopted for assessing the impacts of climate change.

2.4. ADSSs for food waste control

Optimizing the supply chain is widely acknowledged as one of the most effective approaches for avoiding food waste. On the one hand, the optimized supply chain enables to deliver agricultural products to the nearest destinations within the minimum time (Hamprecht et al., 2005). On the other hand, consumers, as the end of supply chains, can reflect needs of markets. Responses from consumers are essential because they can provide adequate information, assisting farmers in adjusting plans of agricultural activities (Muller et al., 2009). In this section, three proposals are reviewed for analyzing current ADSSs for food waste control.

2.4.1. MOLP-based beef supply chain

The globalization of supply chains enables cross-border deliveries for agricultural products. Due to increased distances between partners, ADSSs can be used to determine suppliers, distribution channels, transportation modes, inventories at each warehouse, and so on (Cordeau et al., 2006; Harris et al., 2011). Soysal et al. (2014) applied a Multi-Objective Linear Programming model to a beef supply chain in order to demonstrate how farmers can benefit from a well-organized logistics network. The economic and environmental objective functions are considered in the proposed beef supply chain. The objective of this ADSS is to minimize the total transportation costs and the total amount of released greenhouse gas emissions.

In the proposed supply chain, following advice have to be offered during the transportation processes:

- Inventory amounts of beef in each warehouse.
- Number of tracks used during transportation.
- Type of tracks used during transportation.
- Routes for each track.

In order to provide these decision supports and achieve both economic and environmental objectives, the supply chain is mathematically formulated as a multi-objective linear programming model (Ji et al., 2018). The required inputs to the economic objective function are warehouse costs for storing beef and transportation costs for export departures and import arrivals. The input to the environmental objective function is the total amount of CO_2 emissions released during the transportation. Meanwhile, several constraints are defined, such as a balanced beef inventory in all warehouses, the capability of meeting market demands, the minimum travel paths, etc. The MOLP model is computed by the ILOG-OPL development studio and CPLEX 12.2 optimization solver. The computed Pareto frontier represents the optimal distribution strategy, as the output of the MOLP model. The optimization solver employs the Ɛ-constraint method (Dehghan et al., 2014), meaning that the economic objective function is selected for optimization, while the environmental objective function is treated as an additional constraint.

The proposed supply chain was implemented and tested in Brazil. The idea is to export beef from Brazil to Europe. The experimental result shows that the MOLP model is able to generate the optimal distribution strategy within a reasonable time. The distribution strategy indicates the number of tracks, type of tracks, and route for each track. By following this strategy, the minimum total transportation cost and the minimum amount of released CO_2 emissions are achieved at the same time. Furthermore, the optimized logistics network not only enables a quick delivery with the minimum cost, but also ensures the food quality and safety for consumers, avoiding food waste during the transportation. Therefore, the proposed supply chain fulfils the requirement of Agriculture 4.0.

2.4.2. Quality sustainability decision support system (QSDSS)

Increased demands for food quality and safety have been challenging the global supply chain seriously. Logistics managers prefer to use decision support systems to optimize delivery strategy for ensuring the food quality and safety. Ting et al. (2013) presented a quality sustainability decision support system (QSDSS) based on the association rule mining and the Dempster's rule of combination. The main objective of QSDSS is to discover the association measures between logistics flows and provide logistics managers with decision supports for red wine deliveries, including transportation modes, types of delivered goods, delivery routes, etc.

The workflow of the proposed QSDSS is presented in Fig. 6. Firstly, the knowledge base contains pre-processed logistics flow data. These data are then extracted by the association rule mining component in order to detect interesting association rules based on support and confidence measures (Le and Lo, 2015). The Apriori algorithm (Li et al., 2016) is used in the association rule mining component for identifying the potential associations and assigning a weight to each association. Logistics managers are allowed to input a new delivery request with information about product types, quantities, and transportation modes. After receiving the new case, the Dempster's rule of combination component can aggregate related associations between cases and generate the most appropriate logistics route on the basis of assigned weights. The output of QSDSS is the route with the highest weight, as the optimal delivery strategy.

The proposed QSDSS was verified and tested through a red wine

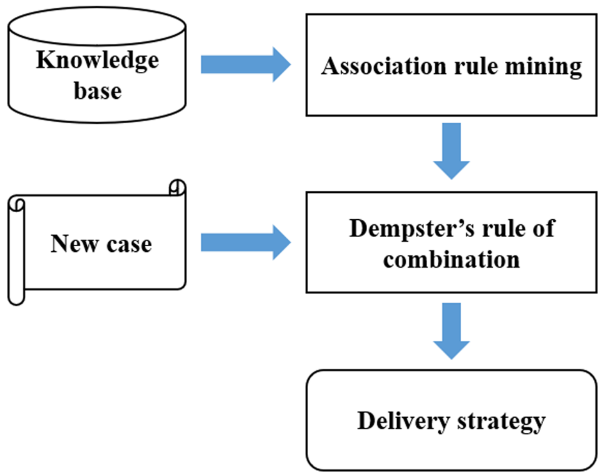


Fig. 6. The workflow of QSDSS.

industry in Collazoni. A set of potential associations was successfully extracted from the knowledge base, 145 rules in total. Meanwhile, a complete logistics route is aggregated based on the most interesting rules. Four members are selected to evaluate QSDSS, including senior managers, project consultants, and logistics coordinators. The experimental result shows that QSDSS is able to improve the delivery performance in the following aspects.

- *Securing quality level.* After adopting QSDSS, the product return rate from consumers shows a decrease by 60%.
- *Reducing logistics costs.* QSDSS enables to reduce costs of re-shipping and continual shipping by 45%.
- *Improving satisfaction of consumers.* Due to quality assurance, the number of damaged red wine decreases from 2134 to 530, avoiding returns from consumers.
- *Enhancing logistics visibility.* Hidden information (interesting associations) is mined by QSDSS and displayed to the logistics managers through a user-friendly interface, providing them with real-time decision supports.

Conclusively, by employing QSDSS, food quality and safety can be greatly assured. Therefore, QSDSS fulfils the requirement of Agriculture 4.0 in the aspect of avoiding food waste.

2.4.3. Decision support system for e-grocery deliveries

Unnecessary costs and food waste are usually resulted from inappropriate delivery options and unreasonable inventory distributions. For avoiding food losses in e-grocery deliveries, Fikar (2018) proposed a decision support system on the basis of agent-based simulations and dynamic routing procedures. The overall objective of this system is to optimize the inventory distributions and generate the optimal delivery strategy for logistics managers.

It is assumed that e-grocery providers are fully aware of the inventory distributions and quality of products at all times, while consumers prefer to receive those products with longer shelf lives. The proposed DSS for e-grocery deliveries are expected to provide logistics managers with following decision supports.

- Selections of supply points.
- Products from selected supply points.
- Selections of delivery vehicles.
- Scheduling of routes for delivery vehicles.
- Scheduling of delivery time.

In their proposal, each component of e-grocery deliveries is treated as an agent with specific behaviors. For example, supply points are treated as location agents, while delivered items are regarded as product agents. With all the agents, an agent-based simulation is formed and used to randomly generate demands from consumers and uncertainty in food decay. The required inputs to the proposed DSS are the number of supply points, number of delivery vehicles, quantities and the quality of delivered items, etc. An optimization component is used to schedule pick-up and delivery options. The scheduling plan is computed by a heuristic optimization algorithm (Tarantilis and Kiranoudis, 2001), aiming at minimizing delivery distances and maximizing food quality. After responding to all the requests from consumers, a relocate operator is used to evaluate current pick-up options and delivery strategies. The output of the proposed DSS is a complete delivery plan, displayed through a graphical interface. This delivery plan demonstrates delivery routes, delivery time, inventory distributions, etc. Additionally, the quality of delivered products and remaining items, as well as the amount of wasted food are all presented through the interface.

The proposed DSS was tested in Austria with 255 local stores, 24 vehicles, and one depot. The experimental result shows that more than one thousand items are successfully delivered or picked up by consumers. By employing the optimal delivery plan, food waste is significantly reduced and food quality is assured during the whole process. From this perspective, the proposed DSS for e-grocery deliveries fulfils the requirement of Agriculture 4.0.

2.4.4. Summary of ADSSs for food waste control

Table 4 demonstrates the analytic result from Section 2.4.1–2.4.3.

In Table 4, the selected ADSSs are in regards to controlling food waste from the point of view of optimizing the supply chain. As a consequence, the category of economic data is the main factor considered in the research work. Similar to ADSSs for mission planning, ADSSs for food waste control generate the delivery plans by employing the optimization algorithms. Unfortunately, none of these works pay attention to the long-term planning.

3. Evaluation and upcoming challenges

After presenting the thirteen ADSSs, we evaluate each one of them from eight aspects, including their accessibility, scalability, interoperability, etc. According to the evaluation result, future trends and upcoming challenges are summarized when developing new ADSSs. It is promising that future ADSSs can better serve Agriculture 4.0 by overcoming detected challenges.

3.1. Evaluation of selected ADSSs

Table 5 and 6 presents the evaluation criteria and scores: (i) if the aspect is fully considered and described with technical details, it achieves three stars (best); (ii) if the aspect is partially mentioned, but

Table 4
Summary of ADSSs for food waste control.

DSS name	Data source	Tool	Decision support	Supporting period
MOLP-based beef supply chain	Economic data	MOLP and Ɛ-constraint method	Delivery plans of transporting beef	Short-term
QSDSS	Economic data	Apriori algorithm and Dempster's rule of combination	Delivery plans of transporting wine	Short-term
DSS for e-grocery deliveries	Economic data	Heuristic optimization algorithm	Delivery plans of e-grocery	Short-term and mid-term

Table 5
Evaluation results of selected ADSSs (I).

ADSS name	Accessibility	Scalability	Interoperability	Uncertainty and dynamic factors
AgriSupport II system	★★★	★★★	★★★	★★
Multi-robot sense-act system	★★★	★★★	★★★	★★
ADSS for route planning in soil-sensitive fields	★★★	★★★	★★★	★
On-board decision-making approach	★★	★★★	★★★	★★
SIDSS	★	★★★	★★★	★★★
FDSS	★	★★★	★★★	★★
MRGCD DSS	★★★	★★★	★★★	★★
OCCASION	★	★★★	★★★	★★★
LandCaRe DSS	★★★	★★★	★★★	★★★
GIS-based DSS	★	★★★	★★★	★★
MOLP-based beef supply chain	★	★★★	★★★	★
QSDSS	★	★★★	★★★	★
DSS for e-grocery deliveries	★★★	★★★	★★★	★★★
Total Stars of evaluation criteria	**26/39**	**39/39**	**39/39**	**27/39**

without further explanations, it achieves two stars (medium); and (iii) if the aspect is not addressed at all, it achieves one star (worst). The aspects with more stars indicate that they had been thoughtfully considered in the selected ADSSs, while, those with fewer stars drew less attention and are possible to raise potential challenges in the future. Lastly, Table 7 displays the overall remarks achieved by each ADSS. The remark is measured through achieved stars divided by total 24 stars.

The evaluation criteria are selected from the Software Quality Requirements and Evaluation (SQuaRE) standard, including accessibility, interoperability, scalability, and functionality completeness (ISO/IEC 25010:2011, BSI Standards Publication, https://www.iso.org/standard/35733.html).

In Table 7, it is concluded that the average remark of all thirteen ADSSs achieves 16.31 stars (67.95%), which means current ADSSs cannot serve Agriculture 4.0 perfectly and they still have room for improvement. The best one among selected ADSSs is OCCASION, which achieves 20 stars out of 24, because this ADSS covers most of the evaluation criteria. While the MOLP-based beef supply chain achieves 12 stars out of 24 and it takes the last position due to its inadequate consideration on accessibility, uncertainty, re-planning, etc. For further explanation, evaluation details are given in the following sub-sections.

3.1.1. Accessibility

This aspect mainly refers to the graphical user interface (GUI) of an ADSS (Shirogane et al., 2008). A GUI is necessary because it provides operators with the possibility of establishing new missions, monitoring mission status, checking available information, etc. Meanwhile, it should visualize the generate decision supports for users.

In Table 5, we note that seven of selected ADSSs provide GUIs for operators (stakeholders and farmers), including AgriSupport II system, multi-robot sense-act system, ADSS for route planning in soil-sensitive fields, etc. Some good examples of GUIs are presented in Fig. 7.

In Fig. 7, the GUI of AgriSupport II system enables to enter data and present generated decision supports for agricultural activities. Moreover, operators can perform machinery analysis, task programming, and economic analysis. They can also obtain recommendations (a list of feasible options for operations) through this GUI. The GUI of the multi-robot sense-act system displays data generated by the Mission Manager component, such as plans, execution states, alarms, and so on, guiding operators through different workflow steps.

Generally, the graphical visualization can hide complexity of ADSSs, enabling farmers to manage agricultural activities more easily and efficiently. Thus, as an essential component, a GUI can improve the accessibility of ADSSs. However, nearly half of the selected ADSSs have not addressed this issue. Furthermore, the GUIs provided by current ADSSs sometimes display the computation processes and require complex text inputs, leading to noises and confusions for farmers.

3.1.2. Scalability

This aspect addresses the capability of ADSSs to process the growing amount of missions (Chu et al., 2016). Meanwhile, the scalability indicates the extendibility of an ADSS. For example, extra components can be added into an ADSS for enriching its functionality.

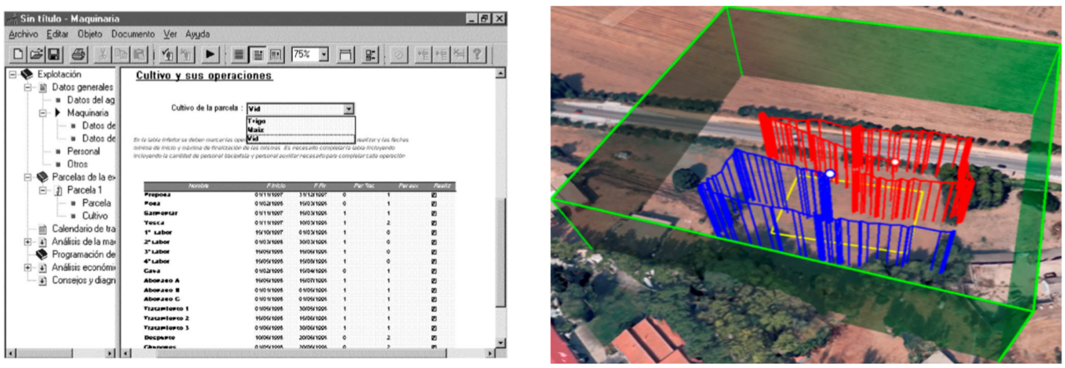
According to Table 5, it is satisfied that all thirteen ADSSs have concerned the aspect of scalability (achieving all 39 stars). For example, QSDSS is composed of several components. It is possible to add new components in its architecture. Meanwhile, operators can define new cases when the number of red wine orders increases, which means QSDSS can deal with the growing amount of missions. LandCaRe also pays attention to this aspect. It employs multiple decision support models to generate strategies for agricultural activities. It is promising to introduce more models for enriching its functionalities.

Table 6
Evaluation results of selected ADSSs (II).

ADSS name	Re-planning	Expert knowledge	Prediction and forecast	Analysis on historical information
AgriSupport II system	★	★★	★	★
Multi-robot sense-act system	★	★★	★	★
ADSS for route planning in soil-sensitive fields	★	★	★★	★★
On-board decision-making approach	★★	★	★	★
SIDSS	★	★★★	★★★	★
FDSS	★	★	★★★	★
MRGCD DSS	★	★★	★★	★★★
OCCASION	★★★	★	★★★	★★★
LandCaRe DSS	★	★★	★★★	★
GIS-based DSS	★	★	★★★	★
MOLP-based beef supply chain	★	★	★	★
QSDSS	★	★★	★	★
DSS for e-grocery deliveries	★	★	★	★★
Total stars of evaluation criteria	**16/39**	**20/39**	**25/39**	**19/39**

Table 7
Overall remarks of selected ADSSs.

ADSS name	Overall remark	ADSS name	Overall remark
AgriSupport II system	16/24 (66.67%)	OCCASION	20/24 (83.33%)
Multi-robot sense-act system	16/24 (66.67%)	LandCaRe DSS	19/24 (79.17%)
ADSS for route planning in soil-sensitive fields	16/24 (66.67%)	GIS-based DSS	16/24 (66.67%)
On-board decision-making approach	15/24 (62.50%)	MOLP-based beef supply chain	12/24 (50.00%)
SIDSS	18/24 (75.00%)	QSDSS	13/24 (54.17%)
FDSS	15/24 (62.50%)	DSS for e-grocery deliveries	17/24 (70.83%)
MRGCD DSS	19/24 (79.17%)		



(a) **(b)**

Fig. 7. Examples of presented GUIs: **(a)** AgriSupport II system; **(b)** Multi-robot sense-act system.

Conclusively, current research works have achieved great contributions to the aspect of scalability.

3.1.3. Interoperability

On the one hand, interoperability emphasizes on integrating functions and knowledge from heterogeneous components in a single ADSS, on the other hand, it represents that an ADSS can work with other external components or systems (Teixeira et al., 2018). For instance, an ADSS for climate change adaptation can link with an external weather station to obtain the meteorological information.

According to Table 5, all selected ADSSs have taken interoperability into account (achieving all 39 stars). For instance, components of QSDSS can work with each other cooperatively. After pre-processing, data formats of product types, quantity, delivery routes, and transportation modes are unified. Thus, heterogeneous components can share a common understanding for the collected information. Another example can refer to SIDSS. This proposed decision support system can work with an external weather station for collecting the meteorological information. Sensing data from collection devices can also be transmitted to the decision support component in SIDSS.

Overall, the developers of ADSSs have made great efforts on the aspect of interoperability.

3.1.4. Uncertainty and dynamic factors

Uncertainty and dynamic factors may cause unexpected results. Thus, ADSSs should consider these changes during runtime (Verbeke, 2005).

In Table 5, it is glad to see that more than half of selected ADSSs have addressed the issue of uncertainty and dynamic factors (achieving 27 stars out of 39), especially for those ADSSs for climate change adaptation (achieving 8 stars out of 9). For instance, SIDSS considers soil temperature, soil water potential, rainfall, wind speed, temperature, humidity, and global radiation when generating the decision supports. These dynamic variables absolutely have tremendous impacts on irrigation activities. Adequate rainfall will surely reduce the amount of water usages and the frequency of irrigation activities.

For those ADSSs which have not concerned uncertainty and dynamic factors, such as the MOLP-based beef supply chain, it is suggested that authors should pay attention to this issue. Because uncertainty like meteorological conditions may cause a delay during international deliveries.

Conclusively, uncertainty and dynamic factors should not be ignored in ADSSs and further improvements on this issue are expected in the future.

3.1.5. Re-planning

Unexpected failures may occur when performing agricultural activities. Therefore, integrating re-planning mechanisms (Zhou et al., 2018) into ADSSs seems to be a promising approach. The re-planning mechanism is supposed to enhance the robustness of decision supports by adjusting current strategies or generating new ones.

Unfortunately, in Table 6, the aspect of re-planning draws the least attention among all criteria (19 stars out of 39). Only two ADSSs have concerned this aspect: multi-robot sense-act system and OCCASION. In the former ADSS, authors mentioned that robot teams can re-plan the overall tasks in case of failure of one unit. Because an unexpected failure may stop the entire work until the machine is repaired. This feature of fault tolerance can greatly enhance the robustness of this ADSS. While in the latter ADSS, OCCASION focuses on scheduling irrigation activities under climate change. As the environment is dynamically changing with times, a re-planning process is a necessity to adjust current adaptation strategies.

It is disappointing that the rest of ADSSs has not covered the aspect of re-planning. Therefore, this is a serious challenge for future ADSSs.

3.1.6. Expert knowledge

Knowledge from experienced experts is highly valuable for ADSSs when generating the feasible decision supports (Poch et al., 2004). Moreover, experts can adjust inappropriate strategies.

In Table 6, we detect that six of selected ADSSs have employed the expert knowledge (achieving 20 stars out of 39). For example, QSDSS is on the basis of the Dempster's rule of combination. The decision rule set is pre-defined by experienced users or domain experts. Similarly, the supply network module of MRGCD DSS takes opinions of experienced users as additional constraints. Under this circumstance, the generated decision supports will better fit users' needs and their decision-making styles.

Due to the limitations of computation time and complexity of agricultural problems, an ADSS may provide users with inaccurate decision supports, sometimes even wrong advice. Therefore, it is worth considering to adopt knowledge from experienced users and domain experts. However, current ADSSs remain to be improved in this aspect.

3.1.7. *Prediction and forecast*

Predictions of productivity, market fluctuations, and costs (Patel et al., 2018) may enable ADSSs to generate more accurate decision supports, while forecasts of meteorological information (Pham and Kamei, 2012) are especially helpful when planning agricultural activities.

In Table 6, seven of selected ADSSs support the function of prediction and forecast, such as SIDSS, FDSS, OCCASION, and so on. For example, a predictive model of soil moisture is designed in FDSS. This model concerns input variables of growing degree days, crop evapotranspiration, and rainfall. The output is in regards to the prediction of soil moisture, which can help the irrigation decision maker component to generate more accurate advice. For OCCASION, the impacts of the predicted climate variability on the maize growth and irrigation are considered during experiments.

However, current contributions to the prediction and forecast in ADSSs are not enough. Thus, future improvements on this aspect remains to be achieved.

3.1.8. *Analysis on historical information*

Historical data and strategies contain valuable information which can improve the quality of future decision supports (Poczeta et al., 2018). For example, considering historical strategies as a training set, machine learning techniques can be adopted for learning successful experiences from the training set.

In Table 6, around one third of selected ADSSs have performed analysis on historical information. For example, DSS for e-grocery deliveries takes consumer's historical pick-up preferences into account when generating the optimal delivery plan. MRGCD DSS concerns historical environmental data for comparing with current situations.

However, ignorance of analyzing historical information indeed worries us. Because historical information not only includes successful experiences, but also failure cases. Current agricultural activities can be performed by referring to the solutions for past cases, which had been successfully dealt with before. Thus, it is suggested that future ADSSs can cover historical information.

3.2. *Upcoming challenges*

According to the summary of thirteen ADSSs in Table 1–4 and the evaluation result in Table 5–7, several upcoming challenges are detected. These challenges demonstrate the potential improvements and developing trends of ADSSs for researchers in the future. By overcoming the detected challenges, future ADSSs can better serve Agriculture 4.0.

- *Simplifying GUIs to enhance accessibility of ADSSs:* Though more than half of selected ADSSs have provided farmers with GUIs for visualizing gathered data, establishing agricultural missions, and monitoring the status of on-going missions, it is reported that farmers sometimes have difficulties on performing desired operations through provided GUIs. Undoubtedly, most of farmers are not familiar with computer knowledge and optimization algorithms. Meanwhile, farmers prefer not to spend too much time in learning how to use decision support systems. When designing an ADSS, it is suggested that the GUIs should be as simple as possible (Rose et al., 2016). Simplified and user-friendly GUIs enable farmers to get started with ADSSs more quickly. Data visualizations like showing results in formats of map, table, list, line chart, pie chart, and flow chart are especially welcomed. Operations like dragging, clicking, and drawing on portable devices are also acceptable for farmers. Unnecessary text inputs and displays of computation processes should be avoided in GUIs because such information may cause tremendous confusions from farmers' point of view. After all, farmers care more about obtaining decision supports on how to perform agricultural activities in the most efficient way, not how the strategies and solutions are computed.
- *Enriching decision supports for the whole life cycle of Agriculture 4.0*: In Agriculture 4.0, an ADSS is supposed to provide farmers with adequate advice during the whole life cycle. According to the duration of agricultural activities, short-term, mid-term, and long-term planning is defined (Francis et al., 2008). A short-term planning covers tactical day-to-day decision-making activities, such as assigning agricultural tasks to the most appropriate machineries, generating the optimal travel paths for each machinery, scheduling daily and weekly irrigation activities, etc. A mid-term planning should offer seasonal decision supports for farmers. For instance, fertilization is usually performed by farmers based on their own observations and experiences in the past, leading to imprecise chemical usages and causing seriously damages to soil fields and crops. However, with the help of mid-term planning, ADSSs can provide farmers with detailed advice about the perfect time to fertilize, the amount of chemical applications, and position of crops. Regarding the long-term planning, it generally refers to the yearly decision-making activities. For example, agricultural machineries surely suffer from equipment losses. After serving for several months, old and damaged components have to be replaced by new ones. By monitoring the status of each machinery, ADSSs can notify farmers about which machineries are non-operational anymore and what components should be bought for replacement. Unfortunately, current ADSSs mainly focus on short-term planning, lacking considerations on mid-term and long-term planning. Therefore, it is urgent to integrate more functionalities of ADSSs and enrich decision supports throughout the whole life cycle of Agriculture 4.0.
- *Adapting to uncertainty and dynamic factors*: Uncertainty and dynamic factors do exist in agriculture, but the fact is that few ADSSs take them into account. Generally, uncertainty and dynamic factors come from the following aspects. Firstly, meteorological conditions have great influences on crop growths. For example, rising temperature may shorten the growth circle of crops. Consequently, fertilization, weeding, and harvesting periods should change correspondingly as well (Asseng et al., 2004). ADSSs have to take uncertainty and dynamic factors of climate change into account for providing farmers with accurate decision supports. Secondly, conditions of farmlands are dynamically changing as well, especially soil moisture and remaining nutrition in the fields (Banger et al., 2017). A low value of soil moisture requires farmers to perform irrigation activities more frequently, while a high value of nutrition remaining in the fields requires farmers to fertilize less amount of manures. Monitoring on environmental changes is vital because decision supports are generated based on these dynamic data. Thirdly, farmers have to handle uncertainty and dynamic factors of economic effects from markets (Lin et al., 2013). The price of an agricultural product may be affected by several factors like total production, logistics, inventory in local warehouses, consumers' demands, etc. Little changes in a single factor may lead to a chain reaction. Thus, it is suggested that ADSSs should pay attention to uncertainty and dynamic factors.
- *Considering re-planning components*: Re-planning is a challenging topic for ADSSs. On the one hand, unexpected failures and issues may arise from time to time, such as mechanical failures of an agricultural machinery and sudden changes in weather. These failures and issues may lead to the impossibility of following original

strategies to complete assigned missions (Evers et al., 2014). Therefore, ADSSs should adjust current strategies or generating a new solution for providing further decision supports for farmers to continue agricultural missions. On the other hand, when an agricultural mission is being executed, ADSSs detect a better strategy for carrying on the rest of the mission (Zhou et al., 2018). Consequently, ADSSs should inform farmers of the latest suggestions. By adopting the newly generated strategy, farmers can complete the rest of the mission more efficiently and smoothly.

- *Adopting knowledge from experienced experts*: Some researchers intend to develop ADSSs which resolve agricultural problems autonomously without any human interventions. Unfortunately, current ADSSs have not reached such intelligent level yet. Due to the limitation of computation time and complexity of agricultural problems, ADSSs may provide farmers with inaccurate decision supports, sometimes even wrong suggestions. Therefore, agricultural knowledge from experienced experts is needed for the purpose of validating the feasibility of generated strategies and correcting the mistakes in provided decision supports (Kamali et al., 2017). An interactive interface should be designed in ADSSs, allowing experts to express their knowledge and opinions. By checking generated strategies before executing, ADSSs are able to lower the possibility of making mistakes.
- *Enabling prediction and forecast*: Though predictions and forecasts are especially helpful for farmers to get prepared in advance, few ADSSs take this issue into consideration. Generally, the following four types of predictions and forecasts are recommended. Firstly, crop growths depend on multiple factors like weather, soil, irrigation, and fertilization. An early estimation on agricultural production is helpful for farmers to detect whether certain operations should be performed to improve product quality (Chlingaryan et al., 2018). Secondly, forecasts of climate change enable farmers to adjust crop management and avoid unnecessary climatic risks (Han et al., 2017). Thirdly, by detecting potential symptoms and early signs, ADSSs are able to warn farmers about possible occurrences of pests and diseases, helping them to take certain precautions to avoid further losses (Chougule et al., 2016). Fourthly, by analyzing market fluctuations, ADSSs can predict consumers' demands and the price trend of agricultural products. As a consequence, farmers will then produce more market-oriented products in order to gain higher profits (MacFarlane, 1996).
- *Performing analysis on historical information*: Strategies of historical missions usually contain valuable information, including not only successful experiences, but also failure cases. However, current ADSSs seldom analyze historical information. A historical mission strategy is applicable under the circumstance of a corresponding historical data set. It is promising to compare the real-time data set with historical ones to generate feasible strategies for current missions within a shorter computation time by using intelligent algorithms like machine learning, deep learning, bio-inspired algorithms (Ali et al., 2018). Because similar patterns between historical and current data sets may be recognized and matched. Successful experiences in past cases can be used as references in performing current agricultural activities. Meanwhile, ADSSs can abandon useless strategies by judging from failures in past cases. Furthermore, by learning from historical data sets, regular patterns can be drawn and used to predict future circumstances (Ghorbani et al., 2019). Conclusively, the efficiency of decision-making and quality of generated decision supports can be significantly improved by performing analysis on historical information.

4. Conclusions

This paper has presented a comprehensive survey of current agricultural decision support systems for Agriculture 4.0. Due to the capability of processing a large amount of agricultural data and handling complex environment, an ADSS is very helpful for assisting farmers in performing various agricultural activities.

Based on the requirement of Agriculture 4.0, thirteen ADSSs are selected from current literatures and projects. These ADSSs are surveyed through their data sources, planning tools, generated decision supports, solved problems, and supporting periods. Eight aspects (accessibility, scalability, interoperability, etc.) are selected from the SQuaRE standard and treated as criteria for evaluating these ADSSs and detecting their shortcomings. Based on the evaluation results, it is detected that the selected thirteen ADSSs only achieved an average remark at 16.31 stars (full remark at 24 stars). Therefore, the following challenges are summarized: (i) simplifying graphical user interfaces to improve accessibility and usability; (ii) enriching functionalities to provide more adequate decision supports during the whole life cycle of Agriculture 4.0; (iii) adapting to uncertainty and dynamic factors to provide accurate decision supports; iv) considering re-planning mechanisms to strengthen the robustness of ADSSs; (v) adopting knowledge from experienced experts in case of adjusting inappropriate decision supports; (vi) enabling prediction and forecast to prepare farmers for future decision-making activities; and (vii) performing analysis on historical information to enhance the quality of decision supports.

Conclusively, these challenges demonstrate future development trends of employing ADSSs in Agriculture 4.0 and potential improvements of ADSSs for researchers. It is promising to see that future ADSSs can better serve Agriculture 4.0 by overcoming these challenges.

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.

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