Sustainability in the Digital Farming Era: A Cyber-Physical Analysis Approach for Drone Applications in Agriculture 4.0

Naoum Tsolakis, Dimitrios Bechtsis, Giorgos Vasileiadis, Ioannis Menexes, and Dionysis D. Bochtis

1 Introduction

The food sector provides pioneering grounds for utilizing intelligent automations and robotic systems with a notable example being Ocado's Customer Fulfilment Centre in Andover, England, utilizing 1,300 bots that result in delivery punctuality by 95% and order accuracy by 99% [1]. The scope of utilizing intelligent systems in food supply chains depends upon the particular strategic objectives articulated by the involved stakeholders. On the one end, in operations-focused cases similar to Ocado, robotic automation enables operational efficiency downstream the supply chain to ensure high service-levels and increased responsiveness to market demand [2, 3]. On the other end, at a strategic level, the Food and Agriculture Organization of the United Nations reported the use of unmanned aerial vehicles (UAVs), commonly known as drones, in agricultural production to increase efficiency in upstream operations to further ensure food security and sustainability [4], particularly in emerging economies. At this latter policy-making level, foresight programmes at both national and regional levels envision the sustainable future of agricultural production and further define strategies to deliver this vision [5–8]. Indicatively, the Danish Green Technological Foresight on Environmental Agriculture provided a technology foresight study to support the adoption of technology solutions that could promote environmentally friendly agriculture [5].

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Unmanned aerial systems posit a promising technological application for enabling precision farming operations and ensuring increased crop productivity in a sustainable manner [9, 10], considering also the nutritional needs of the predicted 9.8 billion global population by 2050 [11]. The global market for drone-based solutions in agriculture is projected to amount US$6.52 billion in 2026 demonstrating a compound annual growth rate of 22.6% [12]. Indicative agricultural activities where drones are utilized include: tracking livestock [13], spraying pesticides [14], remote sensing of crop health [15], evaluating field maturity and harvest readiness [16], and facilitating crop insurance claims [17]). Most importantly, drones enable precision farming operations, like: detecting weed patches [18], exploring the effect of nitrogen treatments on crops [19], monitoring crop biomass [20], identifying water stress in crops [21], and mapping vineyard vigor [22].

Considering the vital role of freshwater resources in agriculture, along with the pressing issue of water scarcity in major food producing countries like India, UAV-enabled remote sensing capabilities could be valuable for farmers to ensure water stewardship and promote environmental sustainability in the sector [23]. Indicatively, results from the "Unmanned Aerial Vehicles—Wireless Sensor Network" scheme applied on over 12,000 ha of farmland in the Republic of China demonstrated that drones can ensure irrigation efficiency with significant water savings by up to 67% [4].

Notwithstanding the documented applicability and benefits of UAVs in agriculture, especially in the light of sustainability, financial viability concerns exist due to the acquisition cost of the required sensors and the supporting infrastructure [24, 25]. To that end, proactive assessment of UAV applications is needed to inform stakeholders' decision-making process and foster the adoption of digital technologies by farmers [6, 7, 26, 27]. Nevertheless, the assessment of digital technology applications in agriculture is challenging due to a range of factors involved at an operational level, while the majority of existing approaches only enables qualitative analysis thus not allowing the quantification of prospective risks and benefits [28].

Farmers need to become aware of the functionality and the tangible gains associated with the adoption of digital technologies, like UAVs, in agricultural field operations prior to investing substantially. To this end, researchers and businesses either develop simulation models or directly implement pilot technologies to engage farmers at a cyber or at a physical space, respectively. However, unreliable results, poor communication and ineffective dissemination of information hinder farmers from developing a genuinely positive attitude towards the adoption of digital technologies [29]. Therefore, the effective transition towards an Agriculture 4.0 era, similarly to Industry 4.0 in the manufacturing sector, could be supported by the development and application of "digital twins" to understand and clearly communicate to involved stakeholders the implications of digital technologies in agriculture [30].

This research explores the utilization of UAVs in agriculture towards ensuring environmental sustainability in farming operations. Specifically, motivated by the evident need to tackle the challenge of water scarcity and ensure farmers' livelihood [31], the objective of this research is to provide a methodological approach for facilitating the anticipated use of drones for sustainable farming operations, particularly in terms of monitoring crops' water stress status and informing precision irrigation activities. In this regard, this research addresses the following Research Questions (RQs):

- RQ#1—What are the benefits and challenges associated with the application of UAVs in farming operations?
- RQ#2—Is the development of "digital twins" valid for UAVs to foresee their applicability in precision farming operations for ensuring water stewardship?

In order to address the enunciated RQs, this study applies a multiple methods approach. Firstly, a critical literature taxonomy was performed to identify and summarize advantages and disadvantages related to the applicability of UAVs in agriculture to tackle RQ#1. In an attempt to answer RQ#2, an integrated methodology to analyze "digital twins" in agriculture was proposed. Especially, the proposed methodology explores the underlining dichotomy between the cyber space analysis and the physical space testing of digital technology systems, particularly focusing on UAVs. To this end, an emulation modelling tool was developed which captures a rotary wing UAV that navigates across a conceptual orchard and monitors the water stress level of individual trees. Thereafter, based on the emulation model, two real-world pilot use cases of actual UAV systems were tested on an agricultural field. The UAVs were equipped with sensors for identifying the water status of each plant in the field to inform the planning of precision irrigation activities. This research contributes to the foresight field by adopting an operationalization view over digital technologies for sustainable agriculture and through proposing an integrated cyber-physical analysis approach for drone applications in agriculture, comprising of both an emulation-based research tool and physical assets.

2 Materials and Methods

The basic terminology, theoretical lens and research approach pertinent to this study are specified in the subsections that follow. The materials and methods were developed with a focus on UAVs, as a digital technology application, for the effective water management in agricultural fields.

2.1 Basic Terminology

The extant body of literature documents the use of "digital twins" for integrating information regarding the management of resources to then inform equivalent real-world implementations [32]. Therefore, as the focus of this research is "digital twins" for environmentally sustainable agriculture, it is necessary to define the terms in this context.

"Digital Twins"

"Digital twins" is a relatively nascent concept and the ambiguity characterizing the term is evident as most scientific articles and business reports adopt either an asset-based [33] or a supply chain-centric [34] view over the term. This research adopts a hybrid view over the term "digital twins". In particular, we claim that a "digital twin" should capture virtual emulation models of the working environment and the actual hardware system(s) performing operations in order to: (i) enable the ex-ante evaluation of functionality and operations efficiency at the cyber space; and (ii) inform the design and calibration of the actual operational units to support efficiency at the physical space. At the same time the transmission of sensed data from the physical space could be used to update the cyber space constructs, while the information should be shared across end-to-end network echelons to dynamically adjust operations according to the entire supply chain optimal performance requirements (Fig. 1). This research focuses on the first part of our definition that infers engagement at a cyber-physical interface.

Sustainable Agriculture

"Sustainable agriculture" embraces the triple-helix model of sustainability (i.e., environmental, economic and social pillars) applied to the agro-food system domain. Considering that water management has strategic significance for ensuring food security and sustainability in agriculture, particularly in water scarce regions [6–8, 35], this research adopts the environmental sustainability pillar with a specific focus on freshwater appropriation in orchards investigated from the perspective of plantations' precision irrigation needs.

2.2 *Theoretical Lens*

In principal, this research adopts the lens of Foresight Theory as it aims to provide a research methodology and respective analysis toolset to "*create actionable and domain/context specific information or knowledge about the future*" [36]. In particular, this research is positioned at the level of foresight process and impact, in alignment to Piirainen and Gonzalez [36], considering that we propose a research process that allows stakeholders to proactively evaluate a technology intervention in the context of agriculture.

At a greater extent, considering the multifaceted character of foresight and our focus on the impact of an intervention to tackle environmental sustainability challenges, this research responds to the technologies' roadmap proposed by Borch [5]. Specifically, we introduce emulation and testbeds' application as a "*descriptive and systematic evaluation of the (perceived) consequences of applying a technology*" [5],

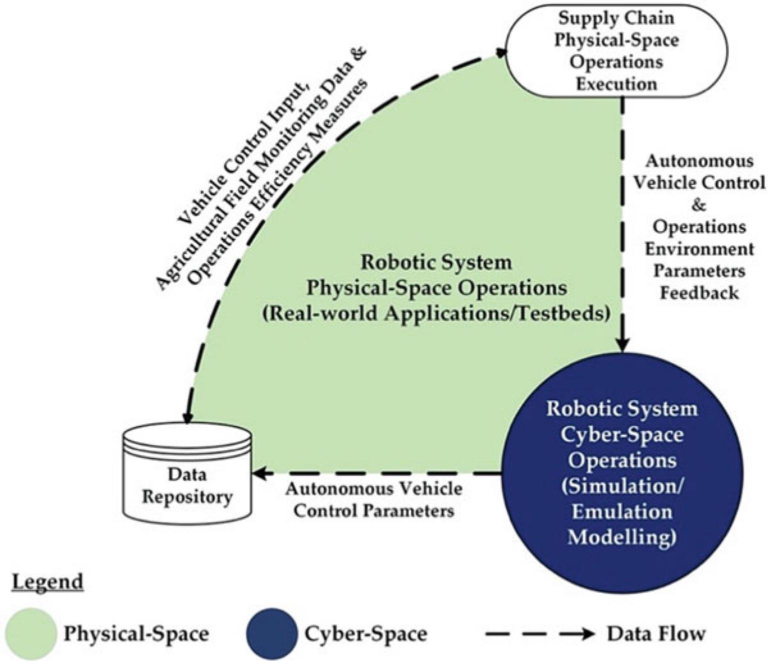

Fig. 1 "Digital Twins" in technology-driver operations

in order to inform farmers with regard to the operationalization of sustainability in agriculture via introducing automated technologies in farming activities. The proposed cyber-physical analysis approach comprising of emulation modelling and real-world technology applications can provide verification of cognitive-wise assertions about a future state of automated agricultural practices [37], hence contributing to the foresight activity.

2.3 Research Approach

This research was conducted by deploying a multistage methodological research, as depicted in Fig. 2. Initially, a literature review along with text mining and a critical taxonomy of the retrieved scientific articles were conducted to identify the benefits and challenges associated with drones in agriculture (1st Research Stage), in a robust and systematic manner. Thereafter, following the digital technologies' assessment framework proposed by Tsolakis et al. [38], the stages of emulation modelling (2nd Research Stage) and the real-world implementation of physical UAVs (3rd Research Stage) were investigated. The critical taxonomy along with the emulation model and the real-world pilot implementation of drones are specified in the subsections that follow.

Critical Taxonomy

In order to identify main benefits and challenges regarding the use of drones in agriculture, existing knowledge from peer-reviewed literature was synthesized. In this respect, to identify relevant published articles, we performed structured searches using the terms “unmanned aerial vehicles”, “drones” and “intelligent aerial vehicles”, in the ‘Article Title’ field, in combination with the terms “precision agriculture” and “precision farming”, in the ‘Article Title, Abstract, Keywords’, in the Scopus database. The timespan was set from ‘All years’ to ‘Present’. The additional use of the terms “emulation” and/or “Agriculture 4.0” did not generate any results. The reviewed articles were written in the English language. Our review was limited to scientific articles and reviews whereas conference papers were excluded from our analysis. Grey literature and online secondary sources were also retrieved to identify policy and commercial developments in the field. The literature search was not exhaustive as our aim was to identify the main advantages and disadvantages stemming from the use of drones in agriculture.

By November 2nd, 2019, a total of 22 articles studying the use of drones in agriculture was identified for review. The annual allocation of the retrieved articles is presented in Fig. 3. The recent research interest about UAVs in agriculture is evident

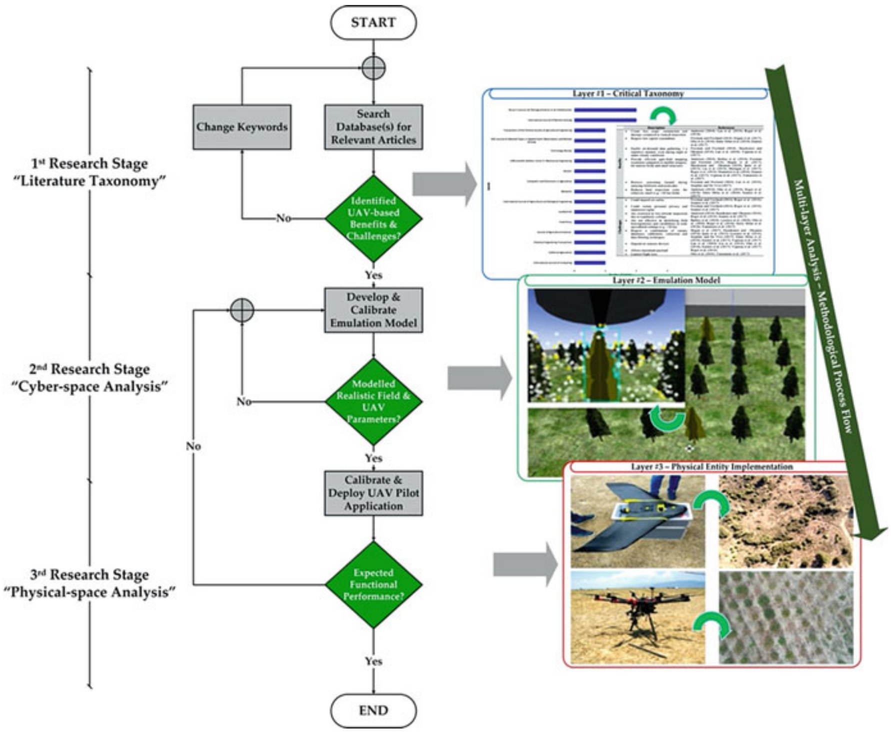

Fig. 2 Multistage methodological analysis flowchart

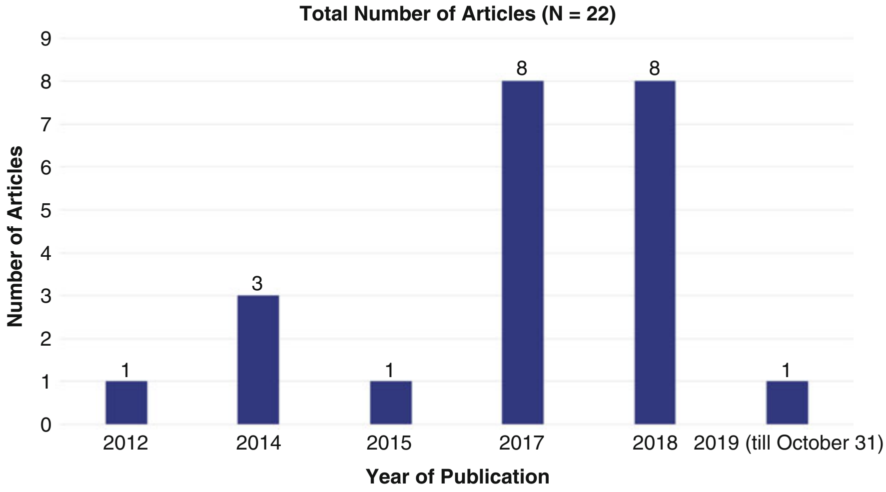

Fig. 3 Published articles by year

as the first related article was published in 2012. The rapid increase in the number of published articles demonstrates the increasing awareness about the application of UAVs in precision agriculture. Likewise, the distribution of the reviewed articles by journal is depicted in Fig. 4. Notably, the distribution of the studies among the scientific journals is quite even, thus indicating the multifaceted research opportunities stemming from the application of drones in farming operations.

In addition, we performed a text mining analysis in the abstracts of the reviewed articles through developing a bespoke programming code in R, an open-source language and environment for statistical computing. Text mining is a technique applied for natural language processing in order to unveil interesting information [39]. Figure 5a illustrates a cloud diagram that depicts the significance of the terms "drone" and "agriculture". Furthermore, Fig. 5b illustrates a circular dendrogram confirming the relevance of intelligent aerial vehicles (marked as "UAV"—unmanned aerial vehicle), including drones, for precision agriculture operations. More specifically, the 'complete-linkage' hierarchical clustering method was applied by calculating the Euclidean distance between term vectors.

Cyber-Space Analysis: Emulation Modelling

In this research, a conceptual orchard was recreated in a three-dimensional environment where an emulated model of an actual quadrotor drone could operate to monitor the water status of individual trees (Fig. 6). This model was created at the Gazebo emulation environment for representing the geomorphological characteristics of the field, thus allowing the spatial modelling across the X-, Y- and Z-axes [40]. At a next step, the emulated UAV could hover, rotate and capture canopy

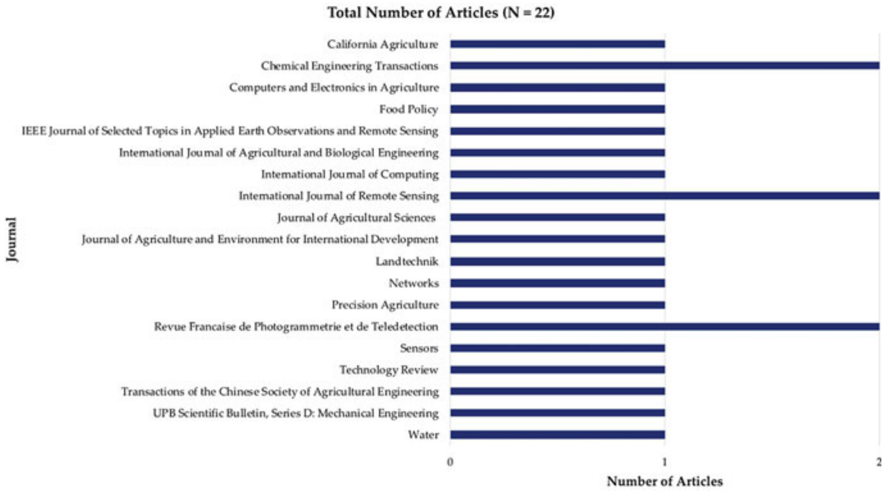

Fig. 4 Published articles by journal

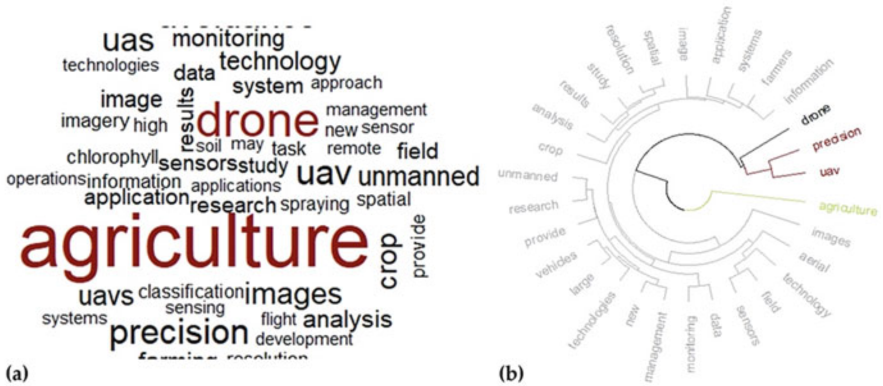

Fig. 5 Relevance of UAVs in precision agriculture demonstrated through: (**a**) a word cloud diagram comprising of 50 words; and (**b**) a circular dendrogram highlighting four clusters of the most associated terms

images of the crops at nearly any optical angle using the Robot Operating System (ROS). For the path tracking of the UAV, ROS used the Simultaneous Localization and Mapping (SLAM) procedure. Furthermore, the emulated Light Detection and Ranging (LiDAR) sensor enabled the UAV to adjust its flying altitude depending on the varying geomorphology and topography of the agricultural field, thus avoiding possible collisions. In particular, the emulated drone is the commercially available rotary wing UAV model DJI S1000.

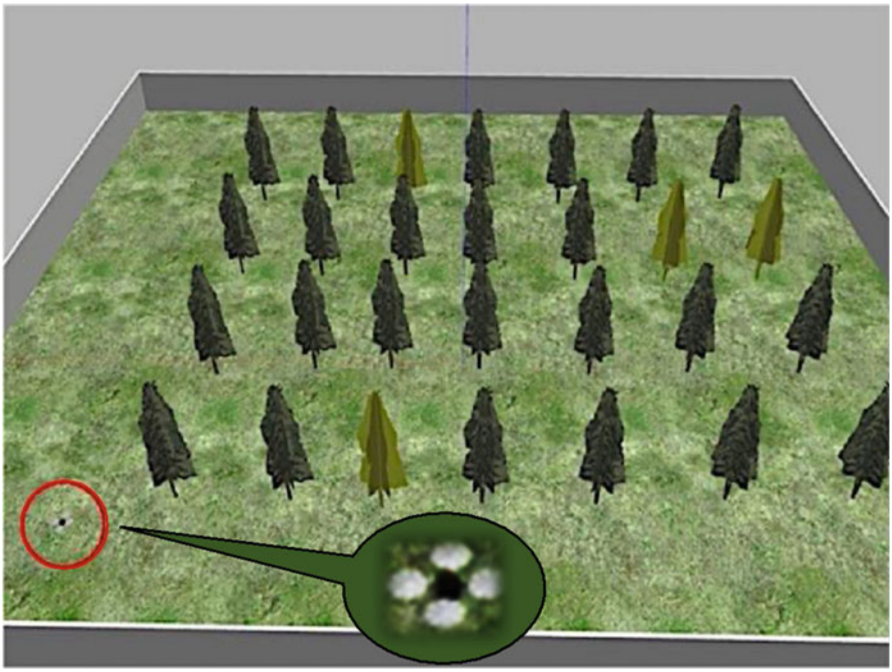

Fig. 6 Emulation model of an agricultural field environment and a quadrotor drone

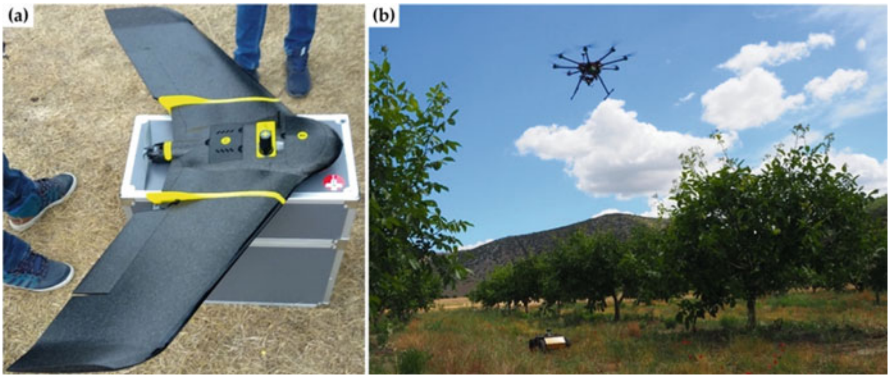

Fig. 7 Pilot implementations of: (**a**) an actual bespoke fixed wing drone in an agricultural field (model eBee); and (**b**) an actual commercial rotary wing drone (model DJI S100) along with a Husky vehicle in collaborative field operations

Physical Space Analysis: Pilot System Implementation

A real-world pilot testing for monitoring agricultural fields was performed by using an actual fixed wing drone, the model eBee provided by senseFly (Fig. 7a), along with the commercial rotary wing drone model DJI S1000 equipped with the Ardupilot Pixhawk 2 autopilot hardware (Fig. 7b). The drones are available at the Institute for Bio-Economy and Agri-Technology (iBO), an Institute of the Centre for Research and Technology—Hellas (CERTH).

3 UAVs in Agriculture: Benefits and Challenges

UAVs are one of the major platforms utilized for remote sensing in agriculture, along with satellites and balloons. Owing to their technological development, decreasing cost, increased level of modularity and enhanced flexibility, UAVs are a preferred solution for precision farming applications in both developed and developing countries. Nevertheless, the adoption of UAVs in precision farming applications requires consideration of the associated technical benefits and challenges, depending on the scope of the intended farming application.

Otto et al. [41] reviewed over 200 scientific articles on UAVs and identified agriculture as one of the most promising areas for commercial applications of such technological systems. The authors further identified promising areas for modelling research regarding UAVs. Zhang and Kovacs [42] provided a review of unmanned aerial systems used for environmental monitoring and precision agriculture activities. The authors discussed both the benefits and challenges of UAVs and stressed the necessity for additional research on the field in order to ultimately provide reliable systems which are appreciated and embraced by farmers. Furthermore, Bansod et al. [43] provided a review comparing the benefits and challenges between satellite- and drone-based solutions applied in precision farming operations. The study specifically stressed the challenges associated with the use of UAVs in agriculture across the technical, reliability, privacy rights and safety domains. Shamshiri et al. [9, 10] reviewed automated systems applied in agricultural operations and emphasized the potential of collaborating automated systems, combining multiple field robots and UAVs, in order to collect data, reveal concealed information, and optimize the use of farming inputs.

In a generic agricultural field context, the work presented by Vigneau et al. [44] discussed the capability of UAVs to monitor vegetation indices and, through data analytics and image processing, obtain biochemical and biophysical variables about crops. The authors suggested that the ability to repeat drone flights and collect data over crops' cycle stimulates research and practice interest. Simic Milas et al. [45] reported the use of UAVs for retrieving crops' structural and biochemical parameters to determine their chlorophyll content. More specifically, the authors used an unmanned aerial system to monitor and determine the chlorophyll content of corn agricultural field segments in Michigan, United States of America. Huuskonen and Oksanen [46] introduced a precision farming application for soil sampling to better inform fertilization activities in Southern Finland. The technological solution comprised of a UAV able to scan the selected agricultural field and a set of augmented reality glasses to guide users towards generated soil sampling points.

From a water management perspective, Cancela et al. [47] published a Special Issue on the use of UAVs and satellite systems for water management in agriculture. The Special Issue particularly focused on identifying methodologies for efficiently leveraging such remote sensing technology systems for water management in agriculture. Hogan et al. [48] summarized research applications of small unmanned aerial systems, along with their parameters and limitations. The authors specifically reported the ability to use UAVs for detecting water stress in plants/crops by capturing and analyzing the canopy spectral signature. Anderson [49] discussed the catalytic role of drones in introducing the big data narrative to the precision agriculture domain through examining the case of a vineyard in San Francisco, United States of America. The author of the study supported that the use of UAVs to collect accurate data can reduce water use and lower the chemical load on the environment.

Focusing on technological and technical aspects per se, Barbey et al. [50] compared Pléiades (i.e., a satellite platform) and UAV images retrieved during precision viticulture applications in France. The authors realized that for narrow vine distance rows and small structures, UAVs posit an effective imagery technology for the accurate characterization of vineyards. The work of Ipate et al. [51] presented a guideline for designing a quadrotor drone. Thereafter, the authors deployed the drone to inspect the exterior polyethylene film structure of a greenhouse and examine crops' health. Sarghini and De Vivo [52] also presented a Computational Fluid Dynamics analysis of two different heavy lift multirotor configurations to investigate the resulting aerodynamic effects in the case of spraying pesticides or fertilizers. The authors reported that multirotor UAVs can spray large areas of farmland, around 4,000–6,000 m^2, in about 10 min by achieving savings of about 20–40% in the chemicals' volume and without exposing the operator to health risks. Additionally, Sarghini and De Vivo [53] discussed the merits of intelligent aerial vehicles in agriculture and investigated the technical requirements of multirotor drones for performing agricultural tasks. The authors focused on the mechanical elements of the drone, particularly on the propulsion system, and the resulting payload and flight length capabilities of the system for performing tasks like the application of fertilizers and pesticides. In the work of Lan et al. [54] the challenging issue of obstacles' avoidance in farmlands by UAVs was investigated. The authors compared obstacle avoidance technologies and suggested the use of multisensor fusion on a UAV system to recognize distorting obstacles and enable intelligent autonomous navigation. Liu et al. [55] developed and tested a small-sized and low-cost attitude measurement unit that could be applied to agriculture-focused drones.

From a mainly methodological viewpoint, Lysenko et al. [56] proposed a Robot Plane Vegetation Index, adapted to technological capabilities of UAVs, to monitor the nitrogen nutrition of wheat plants in Ukraine. Additionally, Murugan et al. [57] developed an algorithmic approach to segregate sparse and dense areas in an Indian sugarcane field by leveraging images captured from both a satellite and a drone. The aim of the authors was to ensure precision agriculture monitoring while minimizing the cost of utilizing UAVs in India. Szantoi et al. [58] used images captured through a UAV to map orangutan habitat and agricultural areas in Indonesia. The study concluded that, in contrast to the exclusive use of satellite imagery, UAV-gathered data combined with existing satellite imagery and image classification algorithms provide a cost-effective and high-resolution imagery solution in a variety of land mapping applications. Yamamoto et al. [59] applied a super-resolution image scaling method to process low-resolution images of tomatoes in order to automatically detect and identify plant diseases. The utilized method was intended to be used to low-resolution images captured by UAVs to accelerate phenotyping and vigor diagnosis in agricultural fields.

Finally, Reger et al. [60] discussed and summarized the legislative schemes and regulations regarding the use of UAVs in Germany, the European Union, the United States of America and Japan. The authors suggested that restrictions and gaps in international regulations should be revised and addressed to avoid negative social response to UAV missions in agriculture. In the same context, Freeman and Freeland [61] discussed the regulatory landscape regarding the use of UAVs in agriculture in the United States of America. The authors highlighted the role of regulations in fostering the integration of UAVs in the American airspace to propel their commercial use in agriculture.

Table 1 summarizes the main benefits and challenges associated with the use of UAVs in agriculture and taxonomizes accordingly the retrieved scientific studies. A description for the referenced advantages and disadvantages is also provided to better comprehend the associated views on UAVs in agriculture.

4 "Digital Twins" and UAVs: Monitoring Water Stress in Orchards

In case a crop is in a water stress condition, changes in its leaves occur that generate unique electromagnetic "signatures" [48]. These changes are typically detectable in the visible light spectrum. In addition, changes in the texture of a crops' waxy coating (i.e., cuticle) might be detectable in the invisible infrared light. Therefore, the capability of UAVs to monitor water stress in orchards, inform farmers and support water stewardship depends on both the technical specifications of the system and the quality/calibration of the installed sensory equipment.

Following our proposed methodological approach on the evaluation of UAVs in agriculture via "digital twins", particularly for monitoring the water status of crops, in the subsections that follow we present the emulation model (i.e., cyber space analysis) that was developed as part of this research along with the pilot implementation (i.e., physical space analysis) of actual drone systems in an orchard. Therefore, the proposed methodology allows the creation of cyber-physical interfaces to enable more robust decision-making over the evaluation and adoption of digital technologies in agriculture.

Table 1 UAVs in agriculture: Benefits and challenges

	Description	References
Benefits	• Create less crops' compaction and damage compared to manual inspection	Anderson [49]; Lan et al. [54]; Reger et al. [60]
	• Require relatively low capital expenditure	Bansod et al. [43]; Freeman and Freeland [61]; Hogan et al. [48]; Otto et al. [41]; Sarghini and De Vivo [53]; Simic Milas et al. [45]; Szantoi et al. [58]; Zhang and Kovacs [42]
	• Enable on-demand data gathering, in a repetitive manner, even during night or under cloudy conditions	Freeman and Freeland [61]; Huuskonen and Oksanen [46]; Lan et al. [54]; Vigneau et al. [44]
	• Provide efficient agricultural field mapping resolution, specifically compared to satellite imagery, for narrow fields and small structures	Anderson [49]; Bansod et al. [43]; Barbey et al. [50]; Freeman and Freeland [61]; Hogan et al. [48]; Huuskonen and Oksanen [46]; Cancela et al. [47]; Ipate et al. [51]; Liu et al. [55]; Murugan et al. [57]; Reger et al. [60]; Shamshiri et al. [10]; Szantoi et al. [58]; Vigneau et al. [44]; Yamamoto et al. [59]; Zhang and Kovacs [42]
	• Remove poisoning hazard during spraying fertilizers and pesticides	Freeman and Freeland [61]; Lan et al. [54]; Sarghini and De Vivo [52]
	• Reduce land inspection costs for relatively small fields (e.g., <20 ha)	Anderson [49]; Otto et al. [41]; Reger et al. [60]; Sarghini and De Vivo [53]; Simic Milas et al. [45]; Szantoi et al. [58]; Zhang and Kovacs [42]
Challenges	• Could imperil air-safety	Bansod et al. [43]; Freeman and Freeland [61]; Reger et al. [60]; Sarghini and De Vivo [53]; Szantoi et al. [58]; Zhang and Kovacs [42]
	• Could violate personal privacy and landowner rights	Bansod et al. [43]; Freeman and Freeland [61]; Reger et al. [60]; Szantoi et al. [58]; Zhang and Kovacs [42]
	• Are restricted to low-altitude inspection due to regulatory ceilings	Anderson [49]; Huuskonen and Oksanen [46]; Sarghini and De Vivo [53]; Szantoi et al. [58]; Reger et al. [60]; Zhang and Kovacs [42]
	• Are not effective in identifying field heterogeneities and variabilities in wide agricultural settings (e.g., >20 ha)	Barbey et al. [50]; Otto et al. [41]; Reger et al. [60]; Simic Milas et al. [45]; Yamamoto et al. [59]
	• Require a combination of canopy databases, calibration, correction and data filtering techniques	Hogan et al. [48]; Huuskonen and Oksanen [46]; Ipate et al. [51]; Sarghini and De Vivo [53]; Simic Milas et al. [45]; Szantoi et al. [58]; Vigneau et al. [44]
	• Depend on sensory devices	Bansod et al. [43]; Lan et al. [54]; Liu et al. [55]; Otto et al. [41]; Szantoi et al. [58]; Vigneau et al. [44]

(continued)

Table 1 (continued)

	Description	References
	• Allow maximum payload	Bansod et al. [43]; Reger et al. [60]; Sarghini and De Vivo [52]
	• Allow limited flight time	Bansod et al. [43]; Cancela et al. [47]; Otto et al. [41]; Yamamoto et al. [59]

4.1 Cyber Space: Emulation Modelling

An emulation model can be used to evaluate the performance of a UAV equipped with appropriate sensors. A drone can navigate across an agricultural field or an orchard, detect individual plants, monitor water stress level and detect freshwater requirements of crops, and inform precision irrigation activities. An emulation model can be used to first assess the functional characteristics of a UAV within the environment of operations, assess the performance of the sensors used to scan the crops, map the spatial characteristics of the orchard and autonomously navigate the aerial vehicle in the orchard at an optimal route.

In particular, the developed model consists of emulated constructs of the: (i) orchard layout; (ii) trees within the orchard; (iii) a UAV; and (iv) sensors and cameras equipping the drone. The UAV can then navigate autonomously within the orchard based on the aerial vehicle's routing algorithm embedded in the model and the signals received from the emulated sensors, as depicted in Fig. 8a. The Simultaneous Localization and Mapping procedure along with the perception of the Light Detection And Ranging sensor in the emulated orchard environment are demonstrated in Fig. 8b. The view of the on-board multispectral camera embedded on the UAV is illustrated in Fig. 8c. A camera was emulated to enable plant detection, allow water stress status identification per plant, and ensure vehicle's safety during the autonomous operations in the emulated orchard. Real-time object detection and processing in agricultural environments is exceedingly complex as opposed to typical industrial settings where autonomous robotic systems may be operating [62].

The emulation model further enables the UAV to monitor the water stress level of multiple trees through a single camera (Fig. 9a). The implementation of the flora recognition and the water stress status identification are based on color detection as well as template matching. In this regard, the monitoring per tree is based on continuous sampling of the orchard and tress (when identified), and a corresponding matching of the retrieved signals to the tree reference models stored in the images' library of the emulation model (Fig. 9a). The UAV can then identify and indicate the water status of trees both in cases of water need (e.g., light green trees) and in no water stress situations (e.g., dark green trees), as indicated in Fig. 9b.

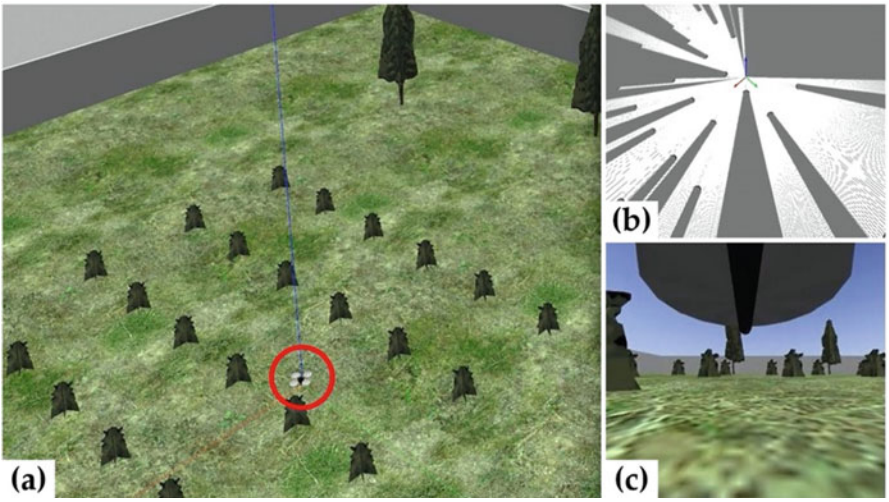

Fig. 8 Emulation model of: (**a**) an orchard environment and a UAV; (**b**) sensors used for navigating the UAV in the orchard; (**c**) an on-board multispectral camera capturing the view of the UAV over the orchard trees

4.2 Physical Space: UAV Systems Deployment

The deployed pilot UAV systems can be used to monitor the status of an agricultural field and identify the water stress level of plants using multispectral cameras. Field irrigation status and water bodies can be identified using band combinations from multispectral and hyperspectral cameras. Hyperspectral imaging has been extensively used for recognizing physiological and structural characteristics in plants and crops. Existing studies suggest the use of machine vision for 3D imaging to enable plant phenotyping (e.g., in potatoes) that could be then used to inform farmers about recommended water application [63]. To that effect, UAVs can effectively monitor the status of agricultural fields and communicate with Farming Information Systems for storing the gathered data.

At the pilot study of the fixed wing unmanned aerial system, the eBee drone with the Sequoia multispectral camera was used for measurements. This type of camera could also be applicable for determining vegetation and other ground features that are captured by the UAV. The band combinations from the multispectral camera are illustrated in Fig. 10.

Finally, the use of the compact digital camera Sony RX100 III with the rotary wing DJI S1000 drone could monitor the status of the irrigation equipment at the agricultural field and possibly control any automated valves for the execution of precision irrigation activities (Fig. 11). The precision irrigation activities could be controlled accordingly to improve freshwater management, depending on various environmental conditions.

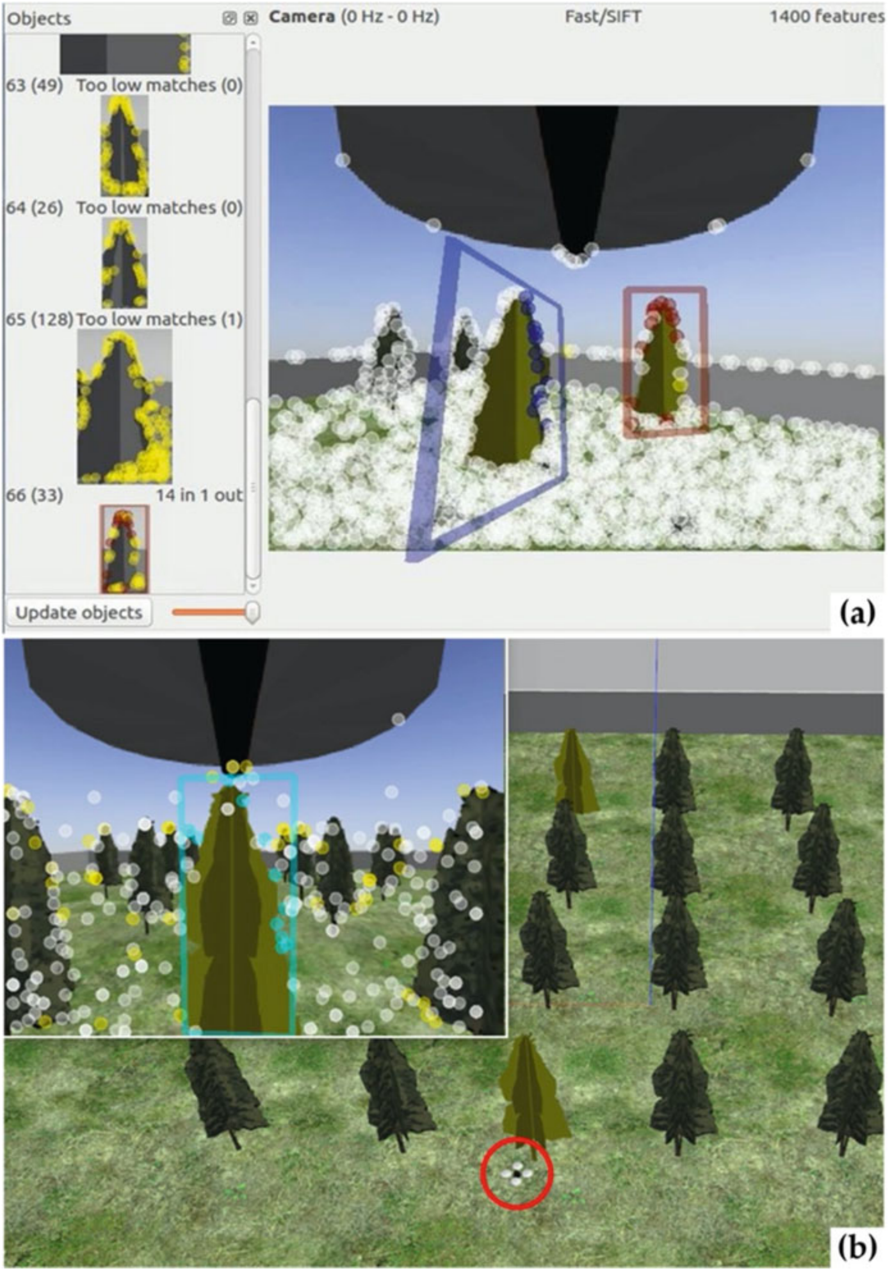

Fig. 9 Functionality of the emulation model includes: (**a**) monitoring of multiple trees through matching input signals to the data library; (**b**) identifying and indicating the water status of trees both in cases of water need (e.g., light green trees) and in no water stress situations (e.g., dark green trees)

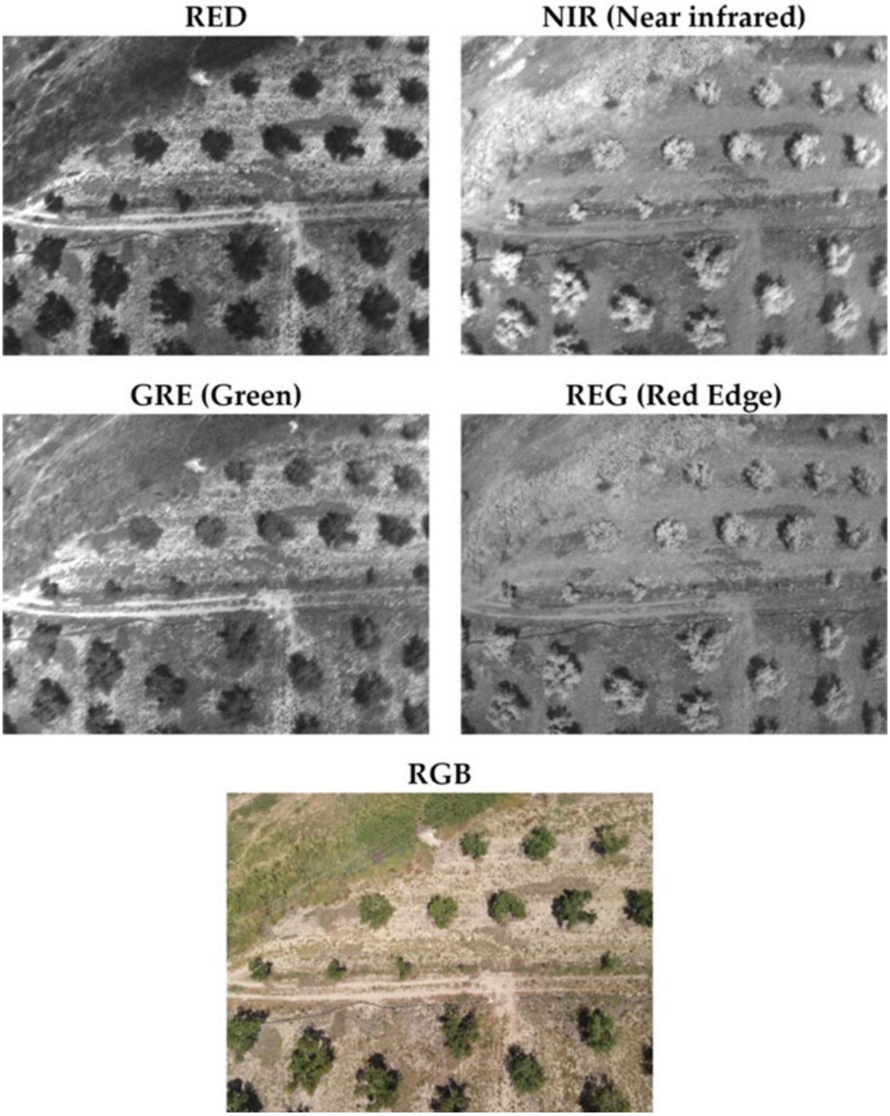

Fig. 10 Band combinations from the multispectral camera

5 Conclusions

Our multistage cyber-physical analysis approach is used to address the articulated research queries. In particular, out critical taxonomy helped respond to RQ#1 with the main advantage of UAVs in agriculture being the efficient mapping of agricultural fields. Furthermore, the greatest identified challenge refers to the need for

Fig. 11 Testing of a commercial rotary wing UAV in a neophyte orchard for irrigation system monitoring

equipment calibration along with data filtering techniques to streamline with the structure of existing canopy-related databases to facilitate the field mapping operations. Regarding RQ#2, an emulation model, that could comprise a "digital twin" for the ex-ante assessment of UAVs during precision farming operations, was developed to inform orchard-related irrigation decisions for water stewardship. The detection of water stress can be performed by multispectral cameras that capture near-infrared light canopy reflections. Emulation models could be also used to comparatively assess the impact of alternative digital technology options in operations. Furthermore, the pilot implementation demonstrates that drones can be used to assess water stress across large farms at a high accuracy level to then plan precision farming (e.g., irrigation) operations. However, sensors need to be first calibrated and databases of canopy spectral signatures have to be developed to reliably detect crops under water stress.

Agriculture 4.0 can be realized by investigating the interplay and synergistic operation of automated vehicles enabled by data exchange in the cyber-physical space. Indicatively, recent advances focus on the joint implementation of drones with augmented reality (e.g., wearable technologies, smart glasses) to assist farmers in gathering data and inform precision farming operations [46, 64]. Regarding the assessment of drone systems' efficiency for water stewardship, the identification of performance indicators could inform about the appropriate sensors to install on the drones. Representative indicators are the 'Normalized Difference Vegetation Index' and the 'Land Surface Wetness Index' which are used to specify crop vigor and crop water status, respectively.

5.1 Theory Contributions

The literature on the digitalization of agriculture is inchoate as the extant research efforts myopically focus on the technical and functional aspects of innovative technologies and overlook the related Operations Management and sustainability-wise implications [65]. Additionally, foresight is in principal an instrument for both the executive and legislative branches of governmental authorities aiming at informing policy designs and implementation [66]. To this effect, technology foresight analysis exercises over intelligent aerial vehicles could be argued that are often decoupled from the quantification of subsequent environmental pressures at a granular level of operations.

This research attempts to contribute to the foresight field by adopting an operationalization view over digital technologies for sustainable agriculture via proposing a multistage methodological analysis approach comprising of: (i) academic literature review and critical taxonomy; (ii) emulation modelling; and (iii) testbed application. The adoption of this approach and the engagement in the different levels of analysis could help interrogate UAVs' operational aspects with regard to monitoring water stress levels of individual plants in orchards to then inform the planning of precision irrigation activities. In particular, emulation modelling of real-world agricultural settings and UAVs, along with the pilot implementation of the emulated vehicles, could allow the creation of cyber-physical interfaces to enable more robust performance evaluation and foster the adoption of drones in agriculture. At a greater extent, the proposed "digital twin" analysis perspective of the operational environment (i.e., orchard), in conjunction with the applied digital technologies (i.e., drone and sensors), methodologically contributes to the field of robotic science [67, 68].

5.2 Practice Implications

The real-world operational context and the tangible sustainability benefits attained via the adoption of digital technologies in agriculture are often uncertain or ill-defined thus often creating uncertainty and ambiguity to farmers [29, 69]. To this end, the adoption rate of innovative technologies in agricultural operations stagnates, hence possibly impacting the sustainability performance of the sector both regionally (e.g., exploitation of local natural resources and activities' impact on the surrounding ecosystem) and internationally (e.g., virtual flows of natural resources such as freshwater). In addition, scholars in social sciences are concerned with regard to the impact of digital agricultural technologies to rural communities via highlighting the possible exploitation and marginalization of farmers by corporations and landowners [70, 71].

In the light of the abovementioned concerns, this research promotes the adoption of UAVs for freshwater stewardship in farming operations by: (i) identifying and summarizing advantages and disadvantages related to the utilization of UAVs in agriculture; and (ii) examining "digital twins" in agriculture by developing a cyber-physical analysis approach for UAVs that can help farmers to become aware about the functionality, operational characteristics and sustainability merits of physical drone counterparts. In this regard, farmers can have access to low-cost ex-ante, yet informative, assessments of the functional capabilities and performance of alternative UAV applications they foresee for their operations. In addition, farmers can use a "digital twin" of the agricultural field to articulate alternative foresight scenarios with regard to the dipole "drone application—appropriation of freshwater resources" (i.e., groundwater or surface water reserves) and plan their crop rotations accordingly. This need is particularly prominent in water scarce regions like the State of Punjab in India or South East England in the UK. Concerning the water sustainability scope, the emulation model could also allow the operational assessment of alternative intelligent vehicles and sensory equipment which are commercially available [72].

5.3 Limitations

In conducting this research, some technical limitations exist which provide stimulating grounds for exploring future research avenues. Firstly, the literature review considered only one database (i.e., Scopus), hence it was not possible to identify particular UAV-related benefits and challenges that could be covered in other databases. Secondly, the water stress level of each individual tree in the emulation model was programmed to be binary (i.e., water stress and no water stress). The inclusion of an algorithm for simulating the water requirements of particular plants could enable the emulation model to project the long-term irrigation requirements in an agricultural holding. Furthermore, the emulation tool could incorporate weather data to account for the flight capability and functional stability of a UAV system. Thirdly, the applied multistage methodological analysis approach could be expanded to include further analysis modules to enable a more scientific evidence-based decision-making process over the adoption of digital technologies for achieving particular sustainability goals.

5.4 Future Research

Agriculture 4.0 technologies have proven benefits, predominantly to agricultural small and medium-sized enterprises, in terms of [73]: (i) increased yields; (ii) reduced costs; (iii) greater profits; (iv) informed decisions; and (v) sustainability. Nevertheless, the adoption of digital technology applications in farms is still circumscribed as the underlining opportunity of evidence-based knowledge in farming is not recognized, yet. In this regard, considering future research directions, we are planning to enrich the applied approach with further analysis stages based on an active engagement with farmers and digital technology solution providers to motivate managerial beliefs that dictate adoption decisions on smart agriculture.

Moreover, future research efforts should expand the view of "digital twins" from the unit of operations echelon (i.e., orchard) to an agro-food supply network system level in order to assess the end-to-end sustainability impact of digital technologies [74]. In this regard, we will be able to make contribution to the Operations Management field by investigating the impact of digital technologies on inventory control, responsiveness and resilience across end-to-end agri-food supply networks. The synergistic action between automated vehicles and drones, or humans and drones, unfolds further research opportunities.

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