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Review

A Review of Climate-Smart Agriculture Applications in Cyprus

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Abstract: Climate-smart agriculture is an approach for developing agricultural strategies to modernize agricultural systems using digital techniques, aiming for sustainable agriculture and ensuring food security under climate change. This article provides a systematic literature review of smart agriculture technologies towards climate-smart agriculture in Cyprus, including robotics, Internet of Things, and remote sensing. The paper starts with a review of climate-smart agriculture, presenting its importance in terms of optimizing agricultural production processes in order to address the interlinked challenges of food security and climate change. An extensive literature review of works published in the areas of robotics, Internet of Things, and remote sensing is undertaken, with particular attention paid to works carried out in relation to agriculture in Cyprus. The paper analyzes aspects of the climate-smart agriculture research situation in Cypriot agriculture, identifies gaps, and concludes with new directions.

Keywords: climate-smart agriculture; climate change; smart agriculture; Internet of Things; robotics; remote sensing; Cyprus

1. Introduction

Climatological studies have shown that from 1850 to 2015, the mean land surface air temperature has increased by 1.53 °C, while in the same period the mean surface temperature has increased by 0.87 °C [1]. Due to global population growth (estimated at 1.1% per year), as well as changes in per capita consumption of food, feed, fiber, and energy, land and freshwater use have increased. Currently, agriculture accounts for 70% of global freshwater use [1]. Since 1961, land area expansion and rapid land use intensification have contributed to the increase of the total food production by 240% by 2017 due to increases in yields [1] and land use area [2]. According to forecasted figures from the Department of Economic and Social Affairs of the United Nations, by 2050 the world population is expected to reach 9.7 billion [3]. In order to feed this population, food production should double by 2050 [4].

Climate-smart agriculture (CSA) is an approach that aims to transform, reorient, and develop agricultural systems based on digital technologies, aiming to contribute to an increase in global food security as part of climate change adaptation and mitigation efforts [5,6]. CSA comprises practices that contribute to better management of resources (e.g., land and freshwater use), development and management of ecosystems and landscapes, and provides adequate digital services for farmers to ensure the implementation of the necessary changes (e.g., smart farming technologies) [7]. The use of climate and soil data for agricultural task planning can reduce the uncertainties caused by climate change, for example by developing early warning systems for extreme weather (e.g., drought, flood, hail), as well as for pest and disease occurrence, thus increasing the ability of farmers to take early action, allocate resources effectively, and reduce associated risks. Smart farming [8,9] technologies such as robotics [10], Internet of Things (IoT) in agriculture [11], and precision agriculture [12]

(e.g., remote sensing) utilize advances in information and communication technology (ICT) to optimize farm productivity and increase the quality, yield, and profitability, while reducing the environmental footprint. The global market size of smart agriculture is expected to grow from approximately 9.5 billion U.S. dollars in 2017 to 23 billion U.S. dollars by 2022 [13].

In addition to climate change affecting agriculture and food supply, currently humanity is experiencing the effects of a pandemic, the novel coronavirus (SARS-CoV-2), which generates the COVID-19 disease. This pandemic has also had effects on agricultural activities [14]. The enforced movement restrictions have caused labor shortages (e.g., affecting agricultural activities such as harvesting), as well as starting to disrupt the agro-food supply chain (e.g., difficulties for farmers to bring their products to markets and consumers.) [15]. Nevertheless, it is also an opportunity to accelerate transformations in the agriculture sector. Mitaritonna and Ragot [16] suggested that the Covid-19 pandemic "may well accelerate the adoption of robots for picking fruits and vegetables in the European Union (EU) fields".

In the past decade, advancements in robot technology have led to an increase of domains where robots can be useful to humans. Agriculture is an suitable application area for robotics given the harsh working conditions and difficulty of the work [17,18]. Robotic technology can augment a farmer's capabilities (i.e., thinking, perception, decision-making, multitasking) to carry out repetitive, tedious, and in some cases dangerous agricultural tasks (i.e., weeding [19], spraying [20], harvesting [21]) in dynamic and unstructured environments under harsh weather conditions. In addition, the introduction of robots can help in the development of sustainable agriculture to tackle the high costs of production that derive from increased labor costs [22], the aging of rural populations [23], and the observed shortages of laborers [24,25].

Dorsemaine, et al. [26] defines IoT as "a group of infrastructures interconnecting connected objects and allowing their management, data mining, and the access to the data they generate". IoT in agriculture aims to empower farmers by providing access to data, decision support tools, automation technologies, and actuators that integrate products, knowledge, and services for increased productivity, quality improvement, and profit [27]. IoT and smart agriculture enhance the use of spatial data and real-time events (e.g., deployment of agroclimatic sensors in the field), and are currently the driving forces towards the agricultural sector's sustainability [9,28].

Remote sensing is the acquisition of information about an object (e.g., agricultural field) or phenomenon from a distance using instruments (e.g., thermal camera) or sensors mounted on a distant platform such as a satellite, unmanned aerial vehicle, or drone [29]. A number of remote sensing applications are devoted to the agricultural sector, such as crop yield estimation [30], cropland mapping [31], crop stress monitoring [32], and crop phenological development [33]. A comprehensive review of the advances in remote sensing of agriculture is provided by Atzberger [34].

The agricultural sector in Cyprus contributes around 2% to gross domestic product (down from 6.9% in 1990) and 2.1% to the labor force (down from 5.4% in 2000) [35]. The main crop products are potatoes, citrus, vegetables, and grapes, whereas meat (pork, beef, poultry, sheep, and goat) and milk (cow, sheep, goat) are the most significant livestock products consumed [36]. As for processed agricultural products, halloumi cheese is a key (export) product for Cyprus, followed by beverages such as "Zivania" and local wines [37]. In 2019, the total value of accounted agricultural products exported for 13.5% of the total domestic exports [38]. The main challenges Cypriot agriculture is facing are the prevalence of small and fragmented farm holdings, land degradation and water scarcity, the ageing of the rural population, the low education level of farmers, the lack of a skilled workforce, the high input costs (e.g., pesticides, fertilizers, irrigation), and various marketing and unfair trading practices [39]. It is also projected that agriculture in Cyprus will be highly affected by climate change impacts, such as increased temperature and decreased precipitation [40]. Furthermore, the Cypriot agricultural sector still lags behind in terms of the adoption of new smart farming technologies [41], as well as agriculture digitalization in general (e.g., using ICT for information-sharing [23]), which is a strategic goal of the next programming period (2021–2027). However, it should be noted that during

the last two years, Cyprus has introduced initiatives to boost the sector in areas such as modernization of farms [42]; water and waste management [43]; smart, resource-efficient farming; and environmental protection [41].

The objective of this article is to present a narrative review [44] based on existing research results of the applications of smart farming technologies towards climate-smart agriculture in Cyprus, including robotics, Internet of Things, and remote sensing, in order to identify any gaps, provide suggestion for new research directions, and identify challenges. The narrative review method is used to identify, evaluate, summarize, compare, and interpret the existing findings. To the best of our knowledge, no attempt has been made so far for a systematic review of climate-smart agriculture technologies applied in Cypriot agricultural sector, which is the main contribution of this study to the international literature. The following research question (RQ) is considered:

RQ-1: Which climate-smart agriculture tools and applications were applied in Cyprus during 2010–2020?

As the research question is very general, it is divided to three sub-questions to examine specific technologies.

RQ-1_1: What are the existing applications of agricultural robotics in Cyprus?

RQ-1_2: What are the existing IoT applications in Cypriot agriculture?

RQ-1_3: What are the existing remote sensing applications used for agricultural purposes in Cyprus?

2. Methodology

2.1. Study Area

Cyprus (latitude 35° north, longitude 33° east) is the third largest island in the Mediterranean Sea, with a total area of 9251 km^2. Cyprus has an intense Mediterranean climate, characterized by hot dry summers from mid-May to mid-September and wet changeable winters from November to mid-March, separated by short autumn (October) and spring seasons (April and May). The average annual total precipitation ranges between 300 and 550 mm in the central plain and the flat southeastern parts of the island, while ranging from 450 to nearly 1100 mm at the top of Troodos in the central mountain range. The seasonal differences between mid-summer and mid-winter temperatures are quite large, at 18 °C inland and about 14 °C on the coasts. In July and August, the mean daily temperature ranges between 29 °C on the central plain and 22 °C in the Troodos mountains, while the average maximum temperature for these months ranges between 36 °C and 27 °C, respectively. In January, the mean daily temperatures are 10 °C on the central plain and 3 °C on the higher parts of Troodos mountain range, with average minimum temperatures of 5 °C and 0 °C, respectively. The seasonal change in mean soil temperatures ranges from about 10 °C in January to 33 °C in July at 10 cm depth. On the mountains at 1000 m above sea level, these mean seasonal values are lower by about 5 °C.

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In 2019, the number of households in Cyprus with access to a personal computer (desktop, laptop, tablet) was 74.8% [45], while at the same time the percentage of enterprises (with 10 or more employees) using a personal computer was 98% [46]. Regarding broadband connections in households and enterprises, Cyprus ranks above the EU-28 average at 90% and 93%, respectively [47]. Likewise, 85% of Cypriots regularly use the Internet, 50% interact with e-government services, and 72% make use of social media.

About 52% of the active population of Cyprus is employed in science and technology professions. A small percentage (0.6%) are R&D researchers. The EU goal for research and development, as defined in the Europe 2020 Strategy [48], is to achieve a R&D intensity of at least 3% by 2020 (i.e., 3% of the GDP is to be invested in the R&D sector). Cyprus is far-off from achieving that goal as expenditure on R&D is at 0.55% (%GDP) [47].

2.2. Review Selection Method

The review selection method used was the selection literature review procedure [49–51]. According to Kitchenham and Charters [49], the review process consists of three phases: review planning, review execution, and review reporting. The review planning and execution are described in this section. The review reporting phase follows in the Results section.

The following query was developed with keywords to search articles: ("Smart Agriculture" or "Smart Farming" or "Precision Agriculture" or "Automatic Irrigation" or "Smart Irrigation" or "Disease Detection" or "Pest Management" or "Plant Monitoring" or "Crop Monitoring") and ("Climate Change") and ("Internet of Things" or "Robot" or "Remote Sensing").

The following online bibliographic databases were utilized to search for the aforementioned keywords: Scopus, IEEE Xplore, MDPI, Springer, Elsevier, SAGE, John Wiley, Taylor and Francis, and Google Scholar. The results from the searches were limited (i.e., query criteria) by year (i.e., articles published between 2010 and 2020), document type (peer reviewed articles), language (English), and subject (agriculture—specifically on Cyprus agriculture, with emphases on irrigation, soil, plant monitoring, and pest management).

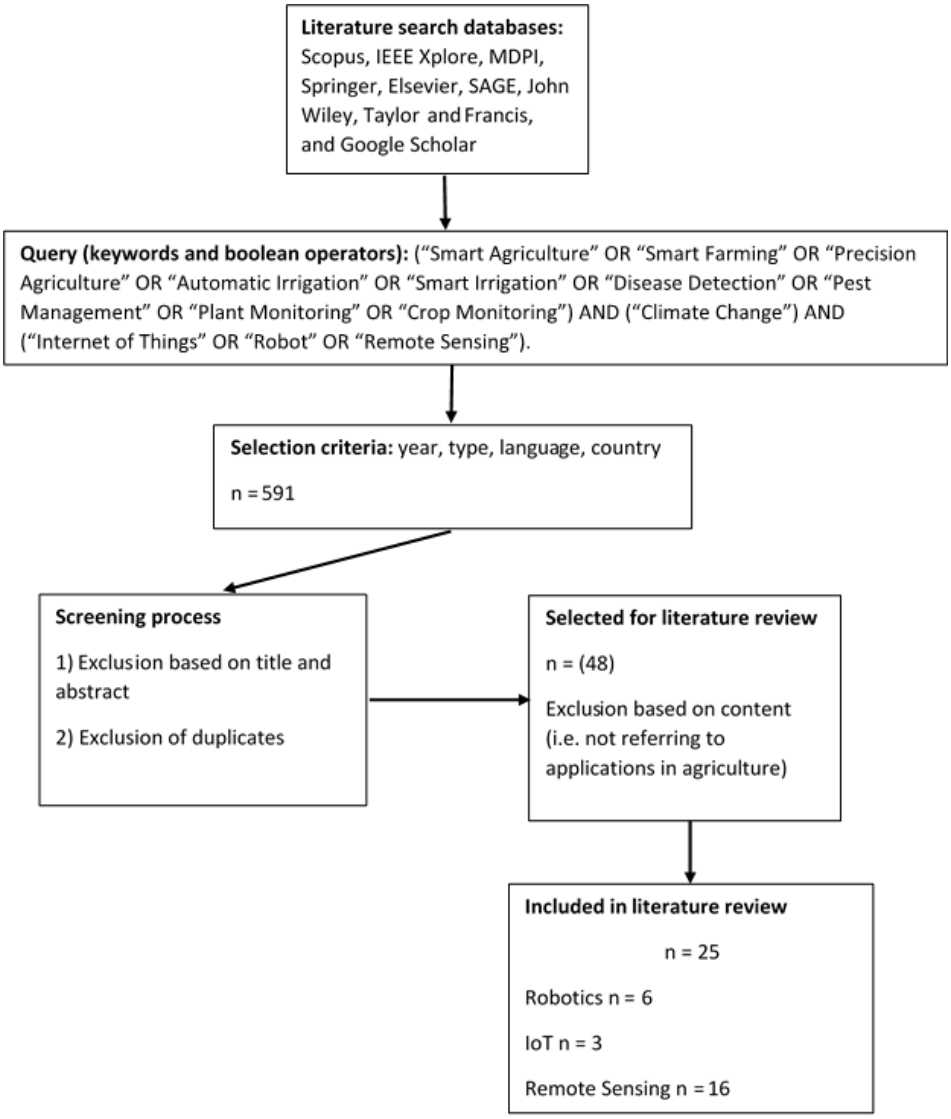

Figure 1. Flowchart of the literature search.

After applying the various selection criteria (see Figure 1), 48 out of 591 articles were selected for review per category, namely robotics (10 articles), IoT (16 articles), and remote sensing (22 articles). Of these articles, only 25 reported results from actual applications in Cypriot agriculture. These articles were included, analyzed, discussed, and classified by their respective farming application, i.e., robotics (6 articles), IoT (3 articles), and remote sensing (16 articles). The structuring of the topics within each category was in chronological order.

3. Results

3.1. Robotics

Field application robotics (e.g., robots in agriculture) are subject to unpredictable environmental conditions and unstructured terrain effects that may impair the platform and perceptual capabilities (e.g., sunlight, full or partial shade, tree leaves). Other difficulties and complexities [52] involved in the development of autonomous agricultural robots, such as uncertainties in the fruit location, size, shape, and maturity (i.e., different colors even within the same plant), necessitate the sue of robots with sophisticated sensory systems. Despite these challenges, robots in agriculture could play an important role in optimizing field operations, tackling harsh working conditions [53] and difficult work [10], as well as in undertaking dangerous tasks, such as pesticide application. Human–robot interactions and cooperation combine the superior perceptual, thinking, and multitasking capabilities of humans with the well-defined, repetitive, stable, and precise handling operations of robots. In this case, the robots are primarily extensions of humans (e.g., farmers) that interact with their physically distant operator, who for safety reasons may not be collocated with the robot. Aspects of human–robot interactions for agricultural robots were examined extensively for an agricultural robot sprayer, the "AgriRobot" [54–56].

Adamides, et al. [57] introduced semiautomatic teleoperation of an agricultural robotic system. They specified design guidelines principles of a user interface for a human–robot cooperative robot for vineyard spraying. The proposed principles are visibility (e.g., system status), safety (e.g., emergency button), simplicity (e.g., navigation buttons), feedback (e.g., target and navigation), extensibility (e.g., algorithm for automatic cluster detection), and cognitive load reduction (e.g., fused information). Later, Adamides, et al. [54] presented a taxonomy of design guidelines for robot teleoperation, which was developed following a focused literature review using open card sorting and focus group methods. The resulting taxonomy of eight categories was as follows: (1) platform architecture and scalability, (2) error prevention and recovery, (3) visual design, (4) information presentation, (5) robot state awareness, (6) interaction effectiveness and efficiency, (7) robot environment or surroundings awareness, and (8) cognitive factors.

Adamides [58] developed a prototype for the spraying interface and tested the usability of three devices for target selection, namely a mouse on a desktop computer, a Wiimote (Wii game console remote control) on a projector, and a smart interactive whiteboard using a digital pen. The results of the study revealed that participants were most efficient and effective when using the digital pen as compared to the mouse and the Wiimote, as determined by the mean percentage of the grape clusters that were successfully sprayed compared to the total number of grapes.

Adamides, et al. [59] assessed the perceived usability of two different user interfaces for teleoperation of a vineyard spraying robot in a field study. In the first condition, participants were provided with a single view (i.e., one camera) for teleoperation of the robot, whereas in the second condition they had additional views (e.g., three cameras) supporting peripheral vision (e.g., during navigation) and targeted spraying (e.g., identifying grape clusters). The analysis of the collected data showed that users with access to the additional views condition sprayed significantly more grapes and teleoperated the robot with significantly less collisions with obstacles compared to users who did not have these aids. However, it was also found that the participants in the single-camera condition completed the task significantly faster than the multiple-camera condition.

Adamides, et al. [56] presented the design aspects and development process used to transform a general purpose mobile robotics platform (Summit XL—https://robotnik.eu/) into a semiautonomous agricultural robot sprayer. The authors described the modules that were adapted and integrated into the mobile robot platform, including an electric sprayer, a robotic arm, and various robot actuators and sensors. Two laboratory and two field studies were carried out to evaluate the usability of the user interface. Specifically, Adamides, et al. [55] examined the overall influences of two types of output devices (PC screen and head-mounted display), two types of peripheral vision support mechanisms (single view and multiple views), and two types of control input devices viz. PC keyboard and Play Station 3 gamepad (PS3), on the observed and perceived usability of a teleoperated agricultural sprayer. The evaluation included eight interaction modes involving different combinations of the 3 factors. Objective metrics of the effectiveness and efficiency of the human–robot collaboration were collected. The results from this study showed that the most important factor for human–robot interface usability was the number and placement of cameras. The type of robot control input device was also a significant factor in certain dependents, whereas the effect of the screen output type was only significant on the participants' perceived workload index. In summary, participants were significantly more effective (i.e., had less collisions and sprayed more grape clusters) in both spraying and in robot path guidance when they had access to multiple views than when they had access to only a single view. With the single-view option, participants required significantly less time to complete the task than when they had multiple views. Furthermore, when using the PC keyboard, participants required significantly less time to complete the task as compared to those using the PS3 gamepad. Participants using the PC keyboard reported a significantly lower perceived workload index compared to those using the PS3 gamepad controller. With multiple views and the PC keyboard condition, participants' perceived sense of presence was significantly higher than when they had a single view and operated with the PS3 gamepad. Finally, the PC screen contributed significantly less to the workload index compared to the head-mounted display.

This section presents the situation of robotic applications in Cypriot agriculture during 2010–2020. The literature review outcome showed that there are basically only two applications (Table 1), in accordance with the findings of Turjaand Oksanen [60]. Given that pesticides and fertilizers are widely used in agriculture to enhance crop protection and production [61], the use of robotics for targeted spraying in terms of climate-smart agriculture can lead to reduced pesticide application, thus improving sustainability and overcoming environmental concerns, as well as reducing material costs, human labor, and medical hazards [62]. However, based on the above literature review, it is also evident that other robotic applications such as harversting, which also involves a substantial labor cost, have not been examined in Cyprus as has been done in neighboring Mediterranean countries (e.g., Israel) [63]. This may be atrritbuted to the fact that Cyprus was among the countries with the most negative views with respect to robot acceptance at work (RAW). Additionally, Cyprus was among the countries that reject RAW the most [60]. The reasons behind these negative views could be a subject for future research (i.e., investigating the factors that influence Cypriot farmers' attitudes towards robotic technology adoption). Another interesting finding of this literature review is that no scientific works on robotic applications in animal production are reported, despite the fact that empirical knowledge and statistical data from the Department of Agriculture (DoA) of Cyprus show that such robotic systems (e.g., dairy robotic milking systems) do exist and are in operation in dairy cow farms in Cyprus. Specifically, in 2011 there were 8 dairy cow farms equipped with a robotic dairy milking system [64], while in 2019 this number increased to 20 robotic systems [65].

Table 1. Robotics applications in Cyprus (2010–2020).

Application Type	Technology	Crop	Reference
Spraying	Summit XL robot	Vineyard	[55,59,66,67]
Spraying	Desktop research and simulation	Not Applicable	[57,58]
Targeted spraying	Summit XL robot	Vineyard	[56,68,69]

3.2. Internet of Things

Lambrinos [70] developed a decision support system for precision agriculture that exploits data from a number of sensors obtained via a low power, wide area network (LoRaWAN), along with weather data and crop information. These data are fed into a decision support system and are made available to farmers via two methods—a web-based portal and an Android mobile phone application. At the current stage, the system focuses on the use of water (irrigation) and crop protection.

Moysiadis, et al. [71] present a use case (Digital Ecosystem Utilization—Cyprus Slovenian Pilots (CYSLOP)) of the Internet of Food and Farm 2020 (IoF2020—http://iof2020.eu) project that aims to demonstrate IoT solutions in vegetable farms in Cyprus and Slovenia. The use case objectives are: (i) to drive IoT uptake in countries where IoF2020 was not initially present; (ii) prove the sustainability of those IoT interventions, both cost- and environment-wise; and (iii) unveil their potential for post-farm or consumer-oriented applications. The selected pilot areas are located in the mountainous Limassol district, where the crops under study are aronia, goji berries, cherry trees, and raspberries (four plots); and in the coastal Ammochostos district, with two plots of open-field strawberries and cherry tomatoes (under hydroponic cultivation). The expected environmental, economic, and social impacts involve efficiency improvements in terms of pesticide and water use reductions of between 5 and 10%, a respective cost reduction of 10%, reduction of farm visits by 20%, and more than twenty newly deployed IoT devices.

Adamides, et al. [41] investigated the possible advantages of applying smart farming technology (e.g., smart soil and air sensors), aiming to support small-scale farmers by taking over the initial installation costs and offering smart farming advice through the combined utilization of heterogeneous information sources. The work offers opportunities for innovation targeting and climate change adaptation options, and could help farmers to reduce their ecological footprint. The technological approach that was deployed and utilized for the realization of "Data-Driven Potato Production" (IoT4potato), a use case of the Internet of Food and Farm 2020 (IoF2020—http://iof2020.eu), was the gaiasense smart farming (SF) solution [72]. The results of the pilot application demonstrated a potential reduction of up to 22% of total irrigation needs and important optimization opportunities for pesticide use efficiency. In detail, the farmers performed two applications of pesticides. According to the calculated infestation risk, the first pesticide application could have been applied earlier, hence increasing the efficiency of the *Phytophthora* prevention. The second pesticide application could have been avoided once the overall temperature was below 20 °C, hence the overall infestation risk was also limited.

Table 2 summarizes IoT applications in Cyprus. Obviously, smart farming and IoT technologies are new in Cypriot agriculture. The two pilot studies (CYSLOP and IoT4Potato) engage farmers, which will support the extraction of additional results, facilitating the identification of the best practices towards the large-scale realization of smart farming in Cyprus. These works offer opportunities for innovation in agriculture and climate change adaptation options, and could help farmers to achieve sustainable optimization of agricultural production and reduce their ecological footprint. No scientific works were found in relation to IoT applications in animal production farms. This is despite the fact that 96 dairy cow farms use an automated electronic system for the detection of oestrus, as reported in DoA [65], compared to 65 that were reported in 2011 [64].

Table 2. Internet of Things (IoT) applications in Cyprus (2010–2020).

Application Type	Technology	Crop	Results	Reference
Irrigation and Pest Management	GaiaSense	Potato	A 22% reduction in irrigation—if one pesticide application had been applied earlier, the second could have been avoided	[41]
Irrigation and Pest Management	Future-intelligence	Strawberries, raspberries, aronia, goji berries, cherry trees, tomatoes	Ongoing project: expected results include 20% reduction in irrigation, 10% reduction in pesticide application	[71]
Decision support system	Web-based portal and Android app	Data not provided	Ongoing project	[70]

3.3. Remote Sensing

Papadavid, et al. [73–75] integrated field spectroscopy and empirical modeling to develop models to relate the leaf area index and crop height for spring potatoes with spectral vegetation indices. The strongest regression was chosen to create LAI and crop height maps, which can be used in algorithms to estimate the evapotranspiration (ETc) or crop coefficient factor (Kc) for irrigation water management in Cyprus. Later, Papadavid, et al. [76] showed that a sophisticated irrigation schedule could be performed using meteorological and satellite image data to estimate ETc, as well as in a combination with irrigation software (e.g., WaterWare model [77]), thus contributing to the reduction of water losses in irrigation, and ultimately to the increase of the water reservoirs. Papadavid, et al. [78] used similar methods to estimate the spectral vegetation index for black-eyed beans.

During 2012–2013, Alexakis, et al. [79,80] developed a methodology and estimated the erosion rate in a catchment area in Cyprus via the integrated use of satellite remote sensing (RS), geographical information systems (GIS), and precipitation data. Their research resulted in an effective and accurate assessment of soil erosion in a considerably short time period and at low cost for large watersheds.

Papadavid, et al. [81] used meteorological data from a wireless sensor network, along with satellite images, spectroradiometer, and sun photometer measurements, in order to provide a novel tool for monitoring and determination of the irrigation demands in Cyprus. Their research results showed how RS data could be used to calculate Evapotranspiration (ETp). Later, Papadavid, et al. [82–84] used similar methods in combination with the surface energy balance algorithm for land (SEBAL) to estimate crop water requirements for chickpeas.

Papadavid and Hadjimitsis [85,86] applied statistical and remote sensing techniques to derive and map a model that could predict the yield of durum wheat in the Paphos area (southwestern region of Cyprus). They examined the use of field spectroscopy along with Landsat satellite imagery to test the accuracy of raw satellite data and the impacts of atmospheric effects on determining crop yield using remotely sensed data. Another more simple and affordable remote sensing technology, namely unmanned aerial vehicles (UAVs), was used by Themistocleous, et al. [87] to monitor agricultural areas. Table 3 summarizes the remote sensing applications in Cyprus.

Similarly to robotics and IoT, no remote sensing applications were found in the literature for animal production, whereas in other Mediterranean islands, namely Samothraki [88] and Corsica [89], remote sensing approaches have been applied to study the effects of overgrazing on land degradation and climate change, respectively. This may be due to the limited grazing applied in sheep and goat farms in Cyprus.

Table 3. Remote sensing applications in Cyprus (2010–2020).

Application Type	Technology	Crop	Results	Reference
Estimation of crop evapotranspiration	GER-1500 field spectroradiometer	Potatoes	Strong statistical relationship between leaf area index/crop height and spectral vegetation indices.	[73–75]
Estimation of crop evapotranspiration	Meteorological and low-resolution satellite data (MODIS–TERRA)	Not specified	A sophisticated irrigation schedule can be performed using meteorological and satellite image data to estimate evapotranspiration, hence contributing to the reduction of water losses in irrigation.	[76]
Monitoring of irrigation demand	Remote sensing data combined with the WaterWare model	Not specified	Results have shown that both methods could be used to estimate ETc.	[77]
Assessment of soil erosion	Remote Sensing, Geographical Information System, and precipitation data	Not Applicable	Reliable quantitative and spatial information concerning soil loss and erosion risk.	[79,80]
Estimation of crop evapotranspiration	Meteorological data from a wireless sensor network, along with satellite images, spectroradiometer, and sun photometer measurements	Not specified	Provided a novel structural tool to agricultural extension services for the monitoring and determination of irrigation demands in Cyprus.	[81]
Estimation of spectral vegetation index (NDVI)	Remote sensing, field spectroscopy, and modeling	Black-eyed beans	There are strong statistical relationships between the leaf area index and NDVI.	[78]
Estimation of crop water requirements	Landsat TM/ ETM+ and SEBAL	Chickpeas	SEBAL adopted to Cypriot conditions.	[82–84]
Estimate and map crop production (yield)	Handheld field spectroradiometer (GER 1500)	Durum wheat	Crop yield can be predicted with acceptable accuracy	[85,86]
Monitoring of agricultural areas	Unmanned aerial vehicle (UAV) quadcopter fitted with a high-resolution 12 MP GoPro Hero camera	Not specified	Documented the existing overgrazed areas and the seasonal changes in vegetation and soil	[87]

3.4. Summary of Results

Figure 2 graphically illustrates the number of publications per application category for robotics, Internet of Things, and remote sensing. The total number of research articles was 25, representing a relatively small number of works specific to climate-smart agriculture technologies applied in Cyprus. It is evident from Tables 1–3 that CSA technologies were applied to only certain crops. It is worth investigating why no applications in animal production have been reported. One of the main findings of this review is the identification of a gap (or lack) of research on CSA technologies in animal farms in Cyprus. There seems to be limited or no research works on ICT and digital farming, leading animal production farmers to find and apply such technologies on their own, thus creating a gap between scientific knowledge and practice.

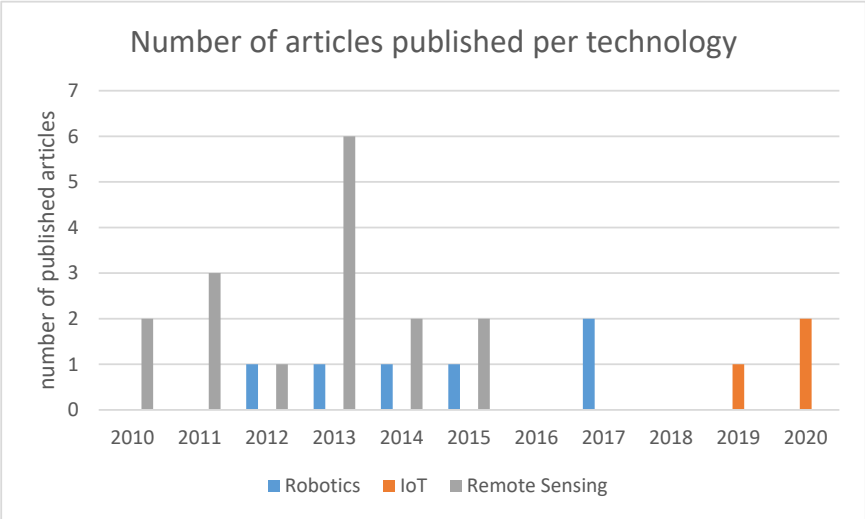

Figure 2. Numbers of publications on robotics, IoT, and remote sensing during 2010–2020 (results referring to Cyprus Climate-smart agriculture applications).

As noted by Turja and Oksanen [60], Cyprus was among the countries with the most negative views with respect to robot acceptance at work, and among the countries that reject RAW the most. These views seem to embody a conservative culture with persistent traditions, ideals, beliefs, and practices that were passed on from one generation to the next. This is also in accordance with Archontakis and Anastasiadis [60], who found that in the Southern European (e.g., Cyprus) regional agricultural sector, sustainability performance metrics are at very low levels (especially regarding the social sustainability pillar) and the adaptation of technology and innovation is rather insufficient.

Figure 3 presents a percentage pie chart of all climate-smart agriculture applications found in the literature in Cyprus, showing the percentages of each technology (robotics, IoT, remote sensing). It is clear that remote sensing technology has been investigated much more than robotics and IoT. However, taking Figure 2 into consideration, it seems that remote sensing and robotics have reached a plateau since 2017 and that IoT now shows an increasing trend.

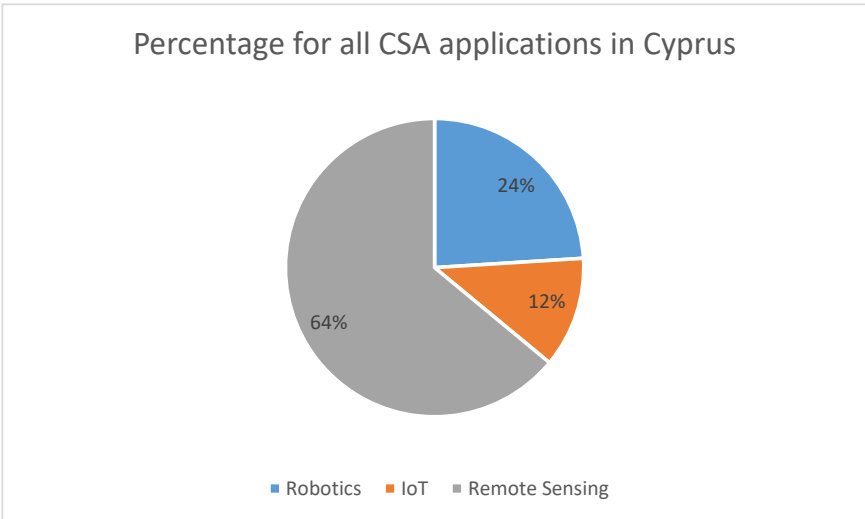

Figure 3. Percentages of publications on robotics, IoT, and remote sensing during 2010–2020 (results referring to Cyprus Climate-smart agriculture applications).

4. Conclusions

Climate-smart agriculture technologies could be key to optimizing the sustainability of agricultural processes, resulting in improved productivity, while at the same time reducing the environmental footprint. Factors such as climate change, the global population increase, the need for food security, and the reduction of human labor in agriculture, to name a few, are driving researchers and policy makers to start applying various new techniques in agriculture. Advances in technology, such as smart sensors, Internet of Things, sensor networks, cloud technology, big data, global positioning systems, remote sensing, and robotics, are used in agriculture to automate farming techniques. Smart farming techniques are applied in Cypriot agriculture as well. Cypriot farmers are learning to change their currently used farming techniques (e.g., water management, pest management) to respond suitably to the challenges of sustainability and climate change. This paper reviewed and documented research findings on applications of climate-smart agriculture, including robotics, IoT, and remote sensing, which were published between 2010 and 2020. It is evident that much more is needed to support the adoption of climate-smart agricultural approaches by farmers, not only at the R&D level, but also by policy makers (e.g., smart farming measures in rural development programs).

As noted in the Introduction, it is projected that Cyprus is going to be highly affected by climate change. As such, following the findings of this review, three big questions emerge: (a) Are the policymakers and the extension services aware of these research results? (b) To what extend have the Cypriot farmers adopted or used such technologies? (c) What measures can be taken to close the scientific gap between CSA technologies and animal production farms? These questions are directions for future research.

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References

1. IPCC. *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*; IPCC: Geneva, Switzerland, 2019.
2. Martin, A.; Coolsaet, B.; Corbera, E.; Dawson, N.; Fisher, J.; Franks, P.; Mertz, O.; Pascual, U.; Rasmussen, L.; Ryan, C. Land use intensification: The promise of sustainability and the reality of trade-offs. In *Ecosystem Services and Poverty Alleviation*; Routledge: London, UK, 2018.
3. UN. World Population Is Expected to Reach 9.7 Billion in 2050. Available online: https://www.un.org/development/desa/en/news/population/world-population-prospects-2019.html (accessed on 10 July 2020).
4. FAO. *How to Feed the World in 2050*; FAO: Roma, Italy, 2009; pp. 837–839.
5. FAO. *"Climate-smart" Agriculture: Policies, Practices and Financing for Food Security, Adaptation and Mitigation*; Food and Agriculture Organization of the United Nations: Roma, Italy, 2010.
6. Hellin, J.; Fisher, E. Climate-smart agriculture and non-agricultural livelihood transformation. *Climate* **2019**, *7*, 48. [CrossRef]
7. Zecca, F. The Use of Internet of Things for the Sustainability of the Agricultural Sector: The Case of Climate Smart Agriculture. *Int. J. Civil Eng. Technol.* **2019**, *10*, 494–501.
8. Walter, A.; Finger, R.; Huber, R.; Buchmann, N. Opinion: Smart farming is key to developing sustainable agriculture. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 6148–6150. [CrossRef]
9. Balafoutis, A.T.; Evert, F.K.V.; Fountas, S. Smart Farming Technology Trends: Economic and Environmental Effects, Labor Impact, and Adoption Readiness. *Agronomy* **2020**, *10*, 743. [CrossRef]
10. Edan, Y. Food and Agriculture Robotics. In *Handbook of Industrial Robotics*, 2nd ed.; Nof, S.Y., Ed.; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 1999.
11. Brewster, C.; Roussaki, I.; Kalatzis, N.; Doolin, K.; Ellis, K. IoT in agriculture: Designing a Europe-wide large-scale pilot. *IEEE Commun. Mag.* **2017**, *55*, 26–33. [CrossRef]

12. Gebbers, R.; Adamchuk, V.I. Precision agriculture and food security. *Science* **2010**, *327*, 828–831. [CrossRef]
13. Shahbandeh, M. Global Market Size of Smart Farming 2017–2022. Available online: https://www.statista.com/statistics/720062/market-value-smart-agriculture-worldwide/ (accessed on 6 July 2020).
14. Siche, R. What is the impact of COVID-19 disease on agriculture? *Sci. Agropecu.* **2020**, *11*, 3–6. [CrossRef]
15. Richards, T.J.; Rickard, B. COVID-19 impact on fruit and vegetable markets. *Can. J. Agric. Econ. Rev. Can. D'Agroecon.* **2020**, *68*, 189–194. [CrossRef]
16. Mitaritonna, C.; Ragot, L. *After Covid-19, Will Seasonal Migrant Agricultural Workers in Europe Be Replaced by Robots?* CEPII Research Center: Paris, France, 2020.
17. Edan, Y.; Shufeng, H.; Naoshi, K. Automation in agriculture. In *Springer Handbook of Automation*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 1095–1128.
18. Hollingum, J. Robots in agriculture. *Ind. Robot Int. J. Ind. Serv. Robot.* **1999**, *26*, 438–446. [CrossRef]
19. Igawa, H.; Tanaka, T.; Kaneko, S.; Tada, T.; Suzuki, S. Visual and tactual recognition of trunk of grape for weeding robot in vineyards. In Proceedings of the 2009 35th Annual Conference of IEEE Industrial Electronics, Porto, Portugal, 3–5 November 2009; pp. 4274–4279.
20. Berenstein, R.; Edan, Y. Human-robot collaborative site-specific sprayer. *J. Field Robot.* **2017**, *34*, 1519–1530. [CrossRef]
21. Bac, C.W.; Henten, E.J.; Hemming, J.; Edan, Y. Harvesting Robots for High-value Crops: State of the art Review and Challenges Ahead. *J. Field Robot.* **2014**, *31*, 888–911. [CrossRef]
22. Bechar, A.; Eben-Chaime, M. Hand-held computers to increase accuracy and productivity in agricultural work study. *Int. J. Prod. Perform. Manag.* **2014**, *63*, 194–208. [CrossRef]
23. Adamides, G.; Stylianou, A.; Kosmas, P.C.; Apostolopoulos, C.D. Factors affecting PC and Internet usage by the rural population of Cyprus. *Agric. Econ. Rev.* **2013**, *14*, 16–36.
24. Murakami, N.; Ito, A.; Will, J.D.; Steffen, M.; Inoue, K.; Kita, K.; Miyaura, S. Development of a teleoperation system for agricultural vehicles. *Comput. Electron. Agric.* **2008**, *63*, 81–88. [CrossRef]
25. Pedersen, M.; Fountas, S.; Blackmore, S. Agricultural robots-applications and economic perspectives. In *Service Robot Applications*; I-Tech Education and Publishing KG: Rijeka, Croatia, 2008.
26. Dorsemaine, B.; Gaulier, J.-P.; Wary, J.-P.; Kheir, N.; Urien, P. Internet of things: A definition & taxonomy. In Proceedings of the 2015 9th International Conference on Next Generation Mobile Applications, Services and Technologies, Cambridge, UK, 9–11 September 2015; pp. 72–77.
27. Elijah, O.; Rahman, T.A.; Orikumhi, I.; Leow, C.Y.; Hindia, M.N. An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges. *IEEE Internet Things J.* **2018**, *5*, 3758–3773. [CrossRef]
28. Villa-Henriksen, A.; Edwards, G.T.; Pesonen, L.A.; Green, O.; Sørensen, C.A.G. Internet of Things in arable farming: Implementation, applications, challenges and potential. *Biosyst. Eng.* **2020**, *191*, 60–84. [CrossRef]
29. Weiss, M.; Jacob, F.; Duveiller, G. Remote sensing for agricultural applications: A meta-review. *Remote Sens. Environ.* **2020**, *236*, 111402. [CrossRef]
30. Awad, M.M. Toward precision in crop yield estimation using remote sensing and optimization techniques. *Agriculture* **2019**, *9*, 54. [CrossRef]
31. Xie, Y.; Lark, T.J.; Brown, J.F.; Gibbs, H.K. Mapping irrigated cropland extent across the conterminous United States at 30 m resolution using a semi-automatic training approach on Google Earth Engine. *ISPRS J. Photogramm. Remote Sens.* **2019**, *155*, 136–149. [CrossRef]
32. Zhou, J.; Khot, L.R.; Boydston, R.A.; Miklas, P.N.; Porter, L. Low altitude remote sensing technologies for crop stress monitoring: A case study on spatial and temporal monitoring of irrigated pinto bean. *Precis. Agric.* **2018**, *19*, 555–569. [CrossRef]
33. Hussain, S.; Gao, K.; Din, M.; Gao, Y.; Shi, Z.; Wang, S. Assessment of UAV-Onboard Multispectral Sensor for non-destructive site-specific rapeseed crop phenotype variable at different phenological stages and resolutions. *Remote Sens.* **2020**, *12*, 397. [CrossRef]
34. Atzberger, C. Advances in remote sensing of agriculture: Context description, existing operational monitoring systems and major information needs. *Remote Sens.* **2013**, *5*, 949–981. [CrossRef]
35. Bank, W. World Bank Open Data. Available online: https://data.worldbank.org (accessed on 3 July 2020).
36. Commision, E. Analytical factsheet for Cyprus: Nine Objectives for a Future Common Agricultural Policy. Available online: https://ec.europa.eu/info/sites/info/files/food-farming-fisheries/by_country/documents/analytical_factsheet_cy.pdf (accessed on 3 July 2020).

37. Profile, C. Agriculture and Food: Agile Agribusiness. Available online: https://www.cyprusprofile.com/sectors/agriculture-and-food (accessed on 3 July 2020).
38. Commission, E. Statistical Factsheet Cyprus. Available online: https://ec.europa.eu/info/sites/info/files/food-farming-fisheries/farming/documents/agri-statistical-factsheet-cy_en.pdf (accessed on 3 July 2020).
39. Markou, M.; Stylianou, A.; Giannakopoulou, M.; Adamides, G. Identifying business-to-business unfair trading practices in the food supply chain: The case of Cyprus. *New Medit* **2020**, *1*, 19–34. [CrossRef]
40. DoM. The Climate of Cyprus. Available online: http://www.moa.gov.cy/moa/ms/ms.nsf/DMLcyclimate_en/DMLcyclimate_en (accessed on 2 July 2020).
41. Adamides, G.; Kalatzis, N.; Stylianou, A.; Marianos, N.; Chatzipapadopoulos, F.; Giannakopoulou, M.; Papadavid, G.; Vassiliou, V.; Neocleous, D. Smart Farming Techniques for Climate Change Adaptation in Cyprus. *Atmosphere* **2020**, *11*, 557. [CrossRef]
42. Savvas, D.; Neocleous, D. Developments in soilless/hydroponic cultivation of vegetables. In *Achieving Sustainable Cultivation of Vegetables*; Hochmuth, G., Ed.; Burleigh Dodds Science Publishing: Cambridge, UK, 2019.
43. Nikolaou, G.; Neocleous, D.; Christou, A.; Kitta, E.; Katsoulas, N. Implementing Sustainable Irrigation in Water-Scarce Regions under the Impact of Climate Change. *Agronomy* **2020**, *10*, 1120. [CrossRef]
44. Mayer, P. *Guidelines for Writing a Review Article*; Zurich-Basel Plant Science Center: Zurich, Switzerland, 2009; Volume 82, pp. 443–446.
45. CYStat. *Survey Results—Ict Usage in Households and by Individuals 2019*; Cyprus Statistical Service: Nicosia, Cyprus, 2019.
46. CYStat. *Survey Results—Ict Usage and E-Commerce in Enterprises 2019*; Cyprus Statistical Service: Nicosia, Cyprus, 2019.
47. CYStat. Cyprus in the EU scale. In *General Statistics*; Statistical Service: Nicosia, Cyprus, 2020; Volume III, p. 35.
48. EUROSTAT. Europe 2020 Strategy. Available online: https://ec.europa.eu/eurostat/web/europe-2020-indicators (accessed on 2 July 2020).
49. Kitchenham, B.; Charters, S. *Guidelines for Performing Systematic Literature Reviews in Software Engineering*; Technical Report, Ver. 2.3 EBSE Technical Report; EBSE: Goyang-si, Korea, 2007.
50. Zhong, Q. Supporting Study Selection of Systematic Literature Reviews in Software Engineering with Text Mining. In *Information Processing Science*; University of Oulu: Oulu, Finland, 2017.
51. Kitchenham, B.; Pretorius, R.; Budgen, D.; Brereton, O.P.; Turner, M.; Niazi, M.; Linkman, S. Systematic literature reviews in software engineering—A tertiary study. *Inf. Softw. Technol.* **2010**, *52*, 792–805. [CrossRef]
52. Edan, Y. Design of an Autonomous Agricultural Robot. *Appl. Intell.* **1995**, *5*, 41–50. [CrossRef]
53. Isaacs, G.W. Robotic applications in agriculture. *Acta Hortic.* **1986**, 123–128. [CrossRef]
54. Adamides, G.; Christou, G.; Katsanos, C.; Xenos, M.; Hadzilacos, T. Usability Guidelines for the Design of Robot Teleoperation: A Taxonomy. *IEEE Trans. Hum. Mach. Syst.* **2015**, *45*, 256–262. [CrossRef]
55. Adamides, G.; Katsanos, C.; Parmet, Y.; Christou, G.; Xenos, M.; Hadzilacos, T.; Edan, Y. HRI usability evaluation of interaction modes for a teleoperated agricultural robotic sprayer. *Appl. Ergon.* **2017**, *62*, 237–246. [CrossRef]
56. Adamides, G.; Katsanos, C.; Constantinou, I.; Christou, G.; Xenos, M.; Hadzilacos, T.; Edan, Y. Design and development of a semi-autonomous agricultural vineyard sprayer: Human–robot interaction aspects. *J. Field Robot.* **2017**, *34*, 1407–1426. [CrossRef]
57. Adamides, G.; Berenstein, R.; Ben-Halevi, I.; Hadzilacos, T.; Edan, Y. User Interface Design Principles for Robotics in Agriculture: The case of telerobotic navigation and target selection for spraying. In Proceedings of the AFITA 2012 8th Asian Conference for Information Technology in Agriculture, Taipei, Taiwan, 3–6 September 2012; p. 8.
58. Adamides, G.; Katsanos, C.; Christou, G.; Xenos, M.; Kostaras, N.; Hadzilacos, T. Human-Robot Interaction in Agriculture: Usability Evaluation of three Input Devices for Spraying Grape Clusters. In Proceedings of the EFITA-WCCA-CIGR Conference "Sustainable Agriculture through ICT Innovation", Turin, Italy, 24–27 June 2013; p. 8.

59. Adamides, G.; Christou, G.; Katsanos, C.; Kostaras, N.; Xenos, M.; Hadzilacos, T.; Yael, E. A reality-based interaction interface for an agricultural teleoperated robot sprayer. In Proceedings of the International Conference on Robotics and Associated High Technologies and Equipment for Agriculture and Forestry, Madrid, Spain, 22–23 May 2014.
60. Turja, T.; Oksanen, A. Robot Acceptance at Work: A Multilevel Analysis Based on 27 EU Countries. *Int. J. Soc. Robot.* **2019**, *11*, 679–689. [CrossRef]
61. Gangemi, S.; Miozzi, E.; Teodoro, M.; Briguglio, G.; De Luca, A.; Alibrando, C.; Polito, I.; Libra, M. Occupational exposure to pesticides as a possible risk factor for the development of chronic diseases in humans. *Mol. Med. Rep.* **2016**, *14*, 4475–4488. [CrossRef]
62. Berenstein, R.; Shahar, O.; Shapiro, A.; Edan, Y. Grape clusters and foliage detection algorithms for autonomous selective vineyard sprayer. *Intell. Serv. Robot.* **2010**, *3*, 233–243. [CrossRef]
63. Arad, B.; Balendonck, J.; Barth, R.; Ben-Shahar, O.; Edan, Y.; Hellström, T.; Hemming, J.; Kurtser, P.; Ringdahl, O.; Tielen, T. Development of a sweet pepper harvesting robot. *J. Field Robot.* **2020**, *37*, 1027–1039. [CrossRef]
64. DoA. *Episkopisi Ageladotrofias 2011 (Overview of Cow Breeding 2011)*; Ministry of Agriculture, Natural Resources and Environment: Nicosia, Cyprus, 2012.
65. DoA. *Episkopisi Ageladotrofias 2019 (Overview of Cow Breeding 2019)*; Ministry of Agriculure, Rural Development and Environment: Nicosia, Cyprus, 2020.
66. Adamides, G.; Katsanos, C.; Christou, G.; Xenos, M.; Papadavid, G.; Hadzilacos, T. User interface considerations for telerobotics: The case of an agricultural robot sprayer. In Proceedings of the Second International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2014), Paphos, Cyprus, 12 August 2014; pp. 92291W–92298W.
67. Adamides, G.; Katsanos, C.; Parmet, Y.; Christou, G.; Xenos, M.; Hadzilacos, T.; Edan, Y. HRI usability evaluation of input/output devices and concurrent views presented for a teleoperated agricultural robot. *Appl. Ergon.* **2016**. submitted.
68. Adamides, G. User Interfaces for Human-Robot Interaction: Application on a Semi-Autonomous Agricultural Robot Sprayer. Ph.D. Thesis, Open University of Cyprus, Nicosia, Cyprus, 2016.
69. Adamides, G.; Katsanos, C.; Constantinou, I.; Xenos, M.; Hadzilacos, T.; Edan, Y. Design and development of a semi-autonomous agricultural vineyard sprayer. *J. Field Robot.* **2016**. submitted.
70. Lambrinos, L. Internet of Things in Agriculture: A Decision Support System for Precision Farming. In Proceedings of the 2019 IEEE International Conference on Dependable, Autonomic and Secure Computing, International Conference on Pervasive Intelligence and Computing, International Conference on Cloud and Big Data Computing, International Conference on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech), Fukuoka, Japan, 5–8 August 2019; pp. 889–892.
71. Moysiadis, T.; Adamides, G.; Stylianou, A.; Zotos, N.; Giannakopoulou, M.; Alexiou, G. Use of IoT technologies for irrigation and plant protection: The case for Cypriot fruits and vegetables. In *Bio-economy and Agri-production: Concepts and Evidence*; Bochtis, D., Achillas, C., Banias, G., Lampridi, M., Eds.; Academic Press: Cambridge, MA, USA, 2020, in press.
72. Kalatzis, N.; Marianos, N.; Chatzipapadopoulos, F. IoT and data interoperability in agriculture: A case study on the gaiasense TM smart farming solution. In Proceedings of the 2019 Global IoT Summit (GIoTS), Aarhus, Denmark, 17–21 June 2019; pp. 1–6.
73. Papadavid, G.; Diofantos, H.G.; Kyriacos, T.; Leonidas, T. Spectral vegetation indices from field spectroscopy intended for evapotranspiration purposes for spring potatoes in Cyprus. In Proceedings of the Remote Sensing for Agriculture, Ecosystems, and Hydrology XII, Toulouse, France, 22 October 2010; p. 782410.
74. Papadavid, G.C.; Hadjimitsis, D.G.; Toulios, L.; Michaelides, S. Mapping potato crop height and leaf area index through vegetation indices using remote sensing in Cyprus. *J. Appl. Remote Sens.* **2011**, *5*, 053526. [CrossRef]
75. Perdikou, S.; Papadavid, G.; Hadjimitsis, M.; Hadjimitsis, D.; Neofytou, N. A simple method to estimate vegetation indices and crop canopy factors using field spectroscopy for solanum tuberosum during the whole phenological cycle. In Proceedings of the First International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2013), Paphos, Cyprus, 5 August 2013; p. 87950Y.

76. Papadavid, G.; Hadjimitsis, D.; Michaelides, S.; Nisantzi, A. Crop evapotranspiration estimation using remote sensing and the existing network of meteorological stations in Cyprus. *Adv. Geosci.* **2011**, *30*, 39–44. [CrossRef]
77. Papadavid, G.; Hadjimitsis, D.; Fedra, K.; Michaelides, S. Smart management and irrigation demand monitoring in Cyprus, using remote sensing and water resources simulation and optimization. *Adv. Geosci.* **2011**, *30*, 31–37. [CrossRef]
78. Papadavid, G.; Fasoula, D.; Hadjimitsis, M.; Perdikou, P.S.; Hadjimitsis, D.G. Image based remote sensing method for modeling black-eyed beans (Vigna unguiculata) Leaf Area Index (LAI) and Crop Height (CH) over Cyprus. *Cent. Eur. J. Geosci.* **2013**, *5*, 1–11. [CrossRef]
79. Alexakis, D.D.; Hadjimitsis, D.G.; Agapiou, A.; Themistokleous, K.; Papoutsa, C. Assessing soil erosion rate in a catchment area in Cyprus using remote sensing and GIS. *Adv. Geosci.* **2012**, 187–194. [CrossRef]
80. Alexakis, D.D.; Hadjimitsis, D.G.; Agapiou, A. Integrated use of remote sensing, GIS and precipitation data for the assessment of soil erosion rate in the catchment area of "Yialias" in Cyprus. *Atmos. Res.* **2013**, *131*, 108–124. [CrossRef]
81. Papadavid, G.; Kountios, G.; Michailidis, A. Monitoring and determination of irrigation demand in Cyprus. *Glob. Nest J.* **2013**, *15*, 93–101.
82. Papadavid, G.; Hadjimitsis, M.; Perdikou, S.; Hadjimitsis, D.; Papadavid, C.; Neophytou, N.; Kountios, G.; Michaelides, A. Application of SEBAL methodology for estimating and disseminating through third generation mobile phones crop water requirements in Cyprus. In Proceedings of the First International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2013), Paphos, Cyprus, 5 August 2013; p. 87951Q.
83. Papadavid, G.; Hadjimitsis, D.; Michaelides, S.; Toulios, L.; Agapiou, A. A comparison of a hydrological and an energy balance model for estimating evapotranspiration of chickpeas at paphos (SW Cyprus) agricultural area. In *Advances in Meteorology, Climatology and Atmospheric Physics*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 247–252.
84. Papadavid, G.; Toulios, L.; Hadjimitsis, D.; Kountios, G. Establishing a method for estimating crop water requirements using the SEBAL method in Cyprus. In Proceedings of the Second International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2014), Paphos, Cyprus, 12 August 2014; p. 92290L.
85. Papadavid, G.; Hadjimitsis, D. An image based method for crop yield prediction using remotely sensed and crop canopy data: The case of Paphos district, western Cyprus. In Proceedings of the Second International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2014), Paphos, Cyprus, 12 August 2014; p. 92290Z.
86. Papadavid, G.; Hadjimitsis, D.G. Impact of atmospheric effects on crop yield modelling in Cyprus using Landsat's satellite imagery and field spectroscopy. In Proceedings of the Third International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2015), Paphos, Cyprus, 19 June 2015; p. 95351G.
87. Themistocleous, K.; Agapiou, A.; Lysandrou, V.; Hadjimitsis, D.G. The use of UAVs for remote sensing applications: Case studies in Cyprus. In Proceedings of the Earth Resources and Environmental Remote Sensing/GIS Applications VI, Toulouse, France, 20 October 2015; p. 96440T.
88. Fetzel, T.; Petridis, P.; Noll, D.; Singh, S.J.; Fischer-Kowalski, M. Reaching a socio-ecological tipping point: Overgrazing on the Greek island of Samothraki and the role of European agricultural policies. *Land Use Policy* **2018**, *76*, 21–28. [CrossRef]
89. Vigan, A.; Lasseur, J.; Benoit, M.; Mouillot, F.; Eugène, M.; Mansard, L.; Vigne, M.; Lecomte, P.; Dutilly, C. Evaluating livestock mobility as a strategy for climate change mitigation: Combining models to address the specificities of pastoral systems. *Agric. Ecosyst. Environ.* **2017**, *242*, 89–101. [CrossRef]