Smart Farms: Can They Grow? A Review of the Factors Influencing the Adoption of Smart Farming

Student Number: 10615728

Abstract—Smart Farming describes advancing technologies and innovations in the agriculture sector, aiming to develop more efficient methods to feed the world. Big Data, Cloud Computing and Swarm Robotics are set to increase crop production, vields and farming efficiency. Such innovative methods play a key role in the survival of an increasing global population by discovering new ways to sustainably produce crops and high-quality, safe food. An increase in climate uncertainty and the impacts of global warming have highlighted the importance of deploying improved approaches to farming, and the solution depends on increasing soil fertility. The use of real-time data and machine vision have already improved agricultural productivity and reduced the tonnage of fertilizers and pesticides required. However, current applications within precision agriculture are industrialising the automated production of monocultural crops. Existing literature identifies the requirement of adopting agroecological practises that are sustainable. This review paper aims to conduct a methodical study of existing field robot technologies used in Smart Farming and the applications of Unmanned Ground Vehicles (UGVS) in restoring agroecosystems. Through analysis of the role UGVs have played in capturing agricultural data, the extent to which they can assist with restoring and optimising microbiome function in relation to agroecological farming has been reviewed. Furthermore, the key components required to facilitate the growth of Smart Farming and the adoption of UGVs with regards to holistic management have been discussed throughout. The management processes detail the economic, environmental and societal impacts that affect the adoption of Smart Farming, and the conclusion details the developmental path required.

Index Terms—Smart Farming, Unmanned Ground Vehicles, Precision Agriculture and Agroecosystems

I. Introduction

The United Nations Department of Economic and Social Affairs predicts a worldwide population growth of 34%, reaching 9.1 billion in 2050 [1]. Annual cereal production must rise to 3 billion tonnes, and meat production to 470 million tonnes [2]. The motivation behind investing in Smart Farming involves increasing the sustainability of the farming sector to recover and preserve key environmental resources. The World Food Studies (WOFOST) simulation model of crop production [3], used to calculate the potential agricultural crop yields, analysed the growth and realistic production rate of crops considering the expected weather and soil conditions the world will face. The depletion of nutrient rich soils, water, forests, and skilful labourers has raised concerns about crop yield potential [2]. Sustainable approaches are becoming more of a requirement to a solution and has been recognised as a prerequisite for next evolution of agriculture. Egroecosystems and their production of the key nutrients relies on upon the actions humans make when farming. The frequent use

of chemicals and heavy machinery has altered the natural ecosystem, and soil management systems are focusing on optimising microbiome function within agroecosystems [4].

Industrial farming results in soil compaction and excessive fertilization which creates a nutrient surplus in soil [5], even though their efficiency is low [6]. These actions have an adverse effect on soil properties such as moisture level, temperature, and pH levels. This greatly reduces soil fertility and therefor has decreases crop yield. Smart Farming and the Internet of Things (IoT) allows for the management of cultivation tasks while obtaining real-time data to assess performance and influential factors [7]. Innovations within agriculture relate to learning from a process to create new and improved iterations, now focusing on Green Revolution Agriculture 5.0 that focuses on the future of the planet [8], [9]. Recent trends involve the redefinition of collaboration between farmers and robots, where machines work alongside and interact with humans using artificial techniques [10]. The development of embedded systems, sensor equipment and machine vision have further improved the automation capabilities of farms.

Robots have been present in the industrial sector for decades, carrying out tasks such as transportation, inspection and the processing of materials [11], [12]. Their roles were related to relieving humans of moving heavy loads, carrying out dangerous tasks and monotonous work [12]. Now machines consist of grippers, manipulators, perception devices and are no longer fixed to single points on a production line. Autonomous developments include the adaptation of Unmanned Ground Vehicles to the agricultural sector. Motivations to integrate UGVs into the agricultural sector include reduced labour, time, and the amount of chemicals used. UGVs are free to roam agricultural land while collecting real-time data, with the ability to overcome obstacles and make their own decisions [13]. The ability to increase the consistency and variation of data has been enhanced by the introduction of robots to farmland. Precision Agriculture (PA) refers to the farming management strategy that observes, measures and processes agricultural data [14]. The information gathered enables farmers to make informed decisions that can improve the efficiency and productivity of the agricultural sector [15]. Further innovations within agriculture relate to learning from a process to create new and improved iterations, adopted from previous robotic develops within other industries [12]. The development of embedded systems, sensor equipment and machine vision have further improved the automation capabilities of farms. This has resulted in the drive to deploy UGVs on as much farmland as possible to continue obtaining

crucial data while increasing the profitability of farms [16].

This expanding data set will join those referred to as 'Big Data', among other industries such as healthcare, banking, and manufacturing. The benefits of large data set analysis involve increased efficiency, productivity, and trend prediction [7], [10]. In the agrarian setting, the utilisation of such information has been used to enhance the knowledge of farmers while obtaining high resolution data that scientists can use to further understand agroecosystems. Agroecosystems and their production of the key nutrients rely on the actions humans make when farming. The frequent use of chemicals has altered the natural ecosystem to an extent that is often referred to as irreparable [2]. With a finite amount of arable land, water and nutrients required to ensure global food security, sustainable approaches must be at the forefront of developing work agriculture [17]. The adoption of Smart Farming globally can increase the understanding of how to overcome challenges relating to sustainable practices [18]. Farming as a practise now focuses on benefiting animals and humankind, and 'Big Data' can facilitate this.

The key features of field robots and their design have made them uniquely diverse in application. Their modular design enables them to be multifunctional, yet there is little inspiration towards diversifying their role in increasing crop variations. This review explores the current state of play within automated monocultural farming and identifies the areas for development needed to increase the growth of the Smart Farming industry. This literature review describes the existing applications of UGVs and PA from a sustainability point of view. The sources have been analysed based on their ability to adopt agroecological farming, including community dynamics that influence current trends in the hesitance to adopt Smart Farming applications. The discussion focuses on the concerns regarding 'Big Data' and its present impacts on both farmers and society. The conclusion includes an overview of the trends identified and socioeconomic challenges faced by farmers during this evolution, and what the future of polycultural Smart Farming may look like.

II. REVIEW OF FIELD ROBOTS

As the number of agricultural labourers decreases, the use of field robots has increased in intensity around the world [10]. Global Navigation Satellite Systems (GNSS) systems employed autonomous capabilities to robots in the 1970s [19], removing the requirement for constant input from drivers. Combining advancing GNSS capabilities with UGVs provides farmers with the ability deploy autonomous robots to conduct various tasks to increase crop yield. Automated conventional vehicles, in the form of tractor attachments, have been created by companies specialising in the agriculture sector. John Deere bought Blue River Technology in 2017 to develop tractor attachments in the form of robots that can analyse crops, as well collaborating with NASA to create self-driving tractors [20]. These attachments can perform automated agricultural tasks such as planting, spraying, fertilizing, and harvesting. Despite the reviews detailing their high performance and reliability, there are concerns about adaptability as the attachments are of a fixed width and cannot operate in smaller crop rows. In addition to this, tractors and their attachments are large and heavy, leading to soil compaction [21]. Soil compaction occurs as a direct result of driving large machinery over farmland, with vehicle mass and operational intensity increasing throughout the years [5].

A research paper published in 2020 presents the adoption of low-mass autonomous vehicles as the solution to reduce the degree of soil compaction [22]. The findings, reciprocated by peer reviewed literature, includes evidence that smaller machines result in less soil compaction but are unable to operate in the same capacity as larger machinery as they are still in the experimental stage [23]–[25]. The developmental pathway features the use of Controlled Traffic Farming (CTF) systems as an immediate method to restore soil fertility considering its urgent importance [22]. However, the conclusion of the research recommended using medium-scale robots due to the non-existence of harvesters capable of CTF [22]. When cultivating more diverse, agroecological farmland, small and medium-scale robots exhibit the potential to adopt sustainable approaches that have positive long-term effects on soil health [26], [27].

The re-design of small and medium scale UGVs for the agricultural sector has taken various approaches, specialised for different tasks, and facilitating adaptive features. The industry states the definition of a field crop robot as being a "mobile, autonomous, decision making, mechatronic device that accomplishes crop production tasks (e.g. soil preparation, seeding, transplanting, weeding, pest control and harvesting) under human supervision, but without direct human labour" [28]. Literature highlights that UGVs are not as limited in their payload as other alternatives, such as Unmanned Aerial Vehicles (UAVs), as they can be equipped with additional sensors and equipment capable of obtaining high resolution data from a closer proximity to the target [29], [30]. The Robotriks Traction Unit (RTU) [31] with adjustable wheel spacing and a modular design enables the user to dictate its configuration. The RTU uses recognition systems to assist with the harvesting process and has been trialled with more complicated scenarios involving fruit picking [32]. XAG's R150, a configurable UGV capable of precision crop protection, field scouting and on-farm material delivery [33]. This UGV is capable of applying small amounts of fertilizers and pesticides directly onto the target, decreasing their impact on soil health. Further advantages of lightweight crop robots such as the RTU and R150 include their weather resistant designs and increased battery capacities. The next agriculture revolution is said to involve the use of green renewable energy sources from which field robots will be powered, the transition to incorporating greener power sources has been eased by their modular designs [34].

III. UGV AUTONOMY AND SWARM CAPABILITIES

Path planning is an important part of navigating autonomous UGVs that utilises Machine Learning techniques (ML). It

involves constructing paths between the current location and the target that also includes obstacle avoidance, coping with unknown objects in real-time. Localistion, mapping and motion control are important factors to consider when navigating farmland and has been demonstrated through open-source tools such as ArduPilot's Mission Planner [35], [36]. Naio Technologie, founded in 2011, have designed robots for farms and vineyards, showcasing the knowledge they have obtained from through-life observation to assess their performance [37]. Oz, the autonomous weeding robot, requires the length, width, and number of crop rows to navigate the farm [38], [39]. Thorough testing through an increased deployment of UGVs on farms and simulations have increased their ability to navigate new environments. This involves cases where the land is both unstructured in its natural state and affected by weather. Naio's own simulator, where literature details the performance of Oz when surveying various crops with different amounts of weeds amongst them [16], [40]. Eight different ML algorithms were used to assess the performance of Oz. The results showed that two out of eight algorithms were able to accurately identify 100% of the weeds in all scenarios [40]. The subsequent experiments on farmland proved that the system remains robust when faced with non-ideal crops, and its accuracy is predicted to increase along with advancements in sensor equipment [40].

'Ant Colony Optimisation', a swarm intelligence algorithm, has been proposed as a potential approach to distributing multiple UGVs to acquire data from larger farms [41]. Simulations have been used to test the potential for real world applications in continuous environments [42]. The research paper documents the performance of the algorithm given a variety of challenges reflected in a range of real-world circumstances and applications. It can find optimal or near-optimal paths in every simulated environment, and can consider path length, smoothness, and safety. The swarm population size was found to have no significant impact on the performance of the algorithm, showing great potential for manipulating multiple UGVs within the same environment. The next advancement in swarm robotics involves dynamic obstacle avoidance, particularly with other members of the swarm [43].

IV. PRECISION AGRICULTURE AND BIG DATA

Companies such as Agribot highlight the benefits of PA, collating historical data to document reduced labour costs, improved inventory management, environmental control [44]. Soil Organic Carbon (SOC) levels are the most used indicator of soil health, and its role in soil fertility has played a key part in farming for over a century [45]. Literature suggests that the understanding of the organic carbon pool is still lacking [46]. A solution to this problem involves encouragement of farmers worldwide to deploy PA techniques and UGVs with the necessary sensors. This enables farmers to obtain the relevant data required to understand individual site's soil properties [47]. This can be directly linked to UGV literature stating that field robots can increase the variety in crops produced due to their data acquisition capabilities [26], [48], [49].

When researching economic studies, and the potential for global adoption of precision farming, the resources primarily focused on UGVs facilitating monoculture production methods [1], [26]. This process refers to repeatedly producing one single type of crop on the same plot of land. The practice allows farmers to set up a common routine involving seeding, fertilisation, and irrigation patterns. By using the same process, farmers save setup and production costs, acquiring larger profits [50]. However, the negative impacts of monocultural farming have been known since the 1970 blight epidemic highlighted the importance of crop diversity [51]. These longlasting, adverse effects are well documented and the causes of which are becoming more apparent as more global reviews are produced. Laura Ditzler, a frequent publisher of studies regarding soil health and a member of the Farm Systems Ecology Group in Europe [52], has co-produced multiple studies reviewing the effects of such practices [47]. Partial budgets have been used to estimate the economic benefits of farm robots within their existing applications in monocultural farming. However, the literature commonly documented shortterm effects and not the long term, often disregarding how monocultural farming results degrades soil health and therefore fertility [14], [53].

V. DISCUSSION OF FACTORS INFLUENCING THE ADOPTION OF SMART FARMING

A. Economic Factors

When comparing the innovative technologies used within industry against those in agriculture, it is evident that there is a lack of expertise and other factors influencing digitisation. The high deployment cost has limited the number of farms willing to invest in equipment required to manage livestock, farmland that requires a high level of maintenance, which is often difficult to carry out in rural areas [1]. A consensus among the literature that discusses the potential adoption of precision farming methods suggests that larger farms are more likely to, and have the necessary infrastructure to, invest in such opportunities [54]. From the public perspective of increasing concern regarding food security [55], to the farmers seeking improved efficiency, there is the additional business perspective with a focus on making informed decisions based on existing technology performance. This coincides with preexisting patterns regarding the gradual incorporation of new, advancing technology into agricultural where farmers take strategic delays to observe the impacts of such investments [56].

Market estimates determine that autonomous field robots' operations result in profit, it does not mean that they will continue to be developed for that specific use [1]. The size of the relevant market for such robots is often too small, meaning that the development cost cannot be covered. This results in companies performing a technology gap analysis or securing pre-payment from customers wishing to contribute to innovations regarding the production of high value crop [50]. This leads to an increase in concerns regarding the knowledge gap involving understanding how to approach the automated

farming of polyculture agriculture, one of the most beneficial techniques for conserving ecosystem health [53].

B. Environmental Factors

Research details the importance of the atmospheric composition and PA applications refer to a range of tests that farmers have been using to manage soil health [57]. A particular study on agricultural management [24] which has been greatly peer reviewed and respected as a reputable source due to the in-depth critical analysis of the impacts of monoculture, raises the importance of crop rotation within PA [47]. The publication details the effects of monoculture, fertilizers, and tillage techniques on soil fertility with data collected over 60 years from various sources. It highlights that the automation of farming predominantly focuses on enabling industrial monocultural production techniques [47]. This acknowledgement is backed up by numerous publications raising the same concern when evaluating the sustainability of Smart Farms [27], [53]. The paper then concludes by summarising the importance of soil management systems and suggests the adoption of more sustainable approaches through the capabilities of Smart Farming [47].

C. Societal Factors

The literature documenting the farmers' viewpoint often details the hesitance to trust those who have little farming experience [56]. A recurring theme discusses the direct impact that new practices and methods would have on their livelihoods. The interpersonal networks created between farmers facilitates the sharing of knowledge amongst those who have farming ties and has been demonstrated in several studies [58], [59]. It has been proven that social learning can accelerate theoretical understanding and cooperation [60], [61] and has played an important role in the transition towards developing new approaches based on experimental knowledge [59]. With family run farms accounting for around 75% of the world's agricultural land [62], the social networks in the various regions approach Smart Farming with shared concerns. Although the learning alliances are created through farmers working alongside their relatives and other families, the decision regarding adopting new practices often involves multiple stakeholders who must agree [63].

The existence of 'Big Data' applications raises both data privacy and power-dynamic concerns amongst farmers and external players within the agri-food chain [64]. Carbonell highlights a concern that farmers have regarding agribusinesses having an increased degree of power. The publication discusses the corporate players within agriculture that, while leading innovation within the bioengineering sector, resort to power exploitation. For example, Monsanto [65], and American agrochecmical and biologically engineered agriculture company founded in 1901 has appeared in ethics reviews [66]. Their large influence on the economy within agriculture has been discussed in relation to removing farmers' autonomy with "Technology Use Agreement" for genetically modified seeds [67]. This company, among others using coercive legal

tactics, is investing in 'Big Data' with information brokers [68]. Carbonell reiterates the fact that farmers fear their data will be used to put them at a disadvantage, concluding that the data become open-sourced with a degree of anonymity [64].

VI. CONCLUSION

This systematic review of the current ability of UGVs within agriculture conducted in this paper identifies the advantages and limitations of their application within Smart Farming. The number of UGVs on the market is limited and has a focus on monocultural farming. However, their presence on farms has a direct positive correlation with crop yield and production efficiency. These achievements relate to their decreased mass, configurable designs for various applications and fertilizer application efficiency, all of which have a reduced negative impact on soil fertility. In summary, sustainable agricultural practises will increase soil fertility and aid in meeting global food demands by introducing more UGVs onto various sites, collating data from a diverse range of crops and utilising precision farming.

The adoption of Smart Farming and UGVs leads back to farmers' concerns regarding Big Data as a result of past experiences within the agriculture sector. To mitigate the potential risk of power dynamics, funding future innovations through government grants and public organisations would remove the aspect of co-corporate ownership. Additionally, future developments must be made more affordable to present themselves as a viable purchase for farmers. Further developments in swarm robotics paired with the current design path of UGVs involves the production of field robot fleets with various specialisations. Such solutions have the potential to further reduce investment fees for farmers by operating on a rental basis. This utilises the strength of social networks within the farming industry by encouraging farmers to trial and rotate different UGV fleets with different functionalities. This rental approach enables an expansive range of data to be retrieved from various crops on a range of soil sites.

In conclusion, a holistic approach to the future of agriculture would not only benefit farmers, but also the general public by addressing the climate crisis and preserving soil fertility. To further reduce the negative ecological effects farming has on the environment; the next agricultural revolution must benefit agroecological systems. The next agricultural revolution must be green in order to grow.

REFERENCES

- J. Lowenberg-DeBoer, I. Y. Huang, V. Grigoriadis, and S. Blackmore, "Economics of robots and automation in field crop production," *Precision Agriculture*, vol. 21, no. 2, pp. 278–299, 2020.
- [2] X. Tian, B. A. Engel, H. Qian, E. Hua, S. Sun, and Y. Wang, "Will reaching the maximum achievable yield potential meet future global food demand?" *Journal of Cleaner Production*, vol. 294, p. 126285, 2021.
- [3] C. v. Van Diepen, J. v. Wolf, H. Van Keulen, and C. Rappoldt, "Wofost: a simulation model of crop production," *Soil use and management*, vol. 5, no. 1, pp. 16–24, 1989.
- [4] N. Rust, S. Iversen, S. Vella, R. Hansda, M. Reed, and F. Areal, "Social factors influencing adoption," 2021.

- [5] S. Gürsoy, "Soil compaction due to increased machinery intensity in agricultural production: Its main causes, effects and management," *Technology in Agriculture*, pp. 1–18, 2021.
- [6] G. Mustafa, N. Hayat, and B. A. Alotaibi, "How and why to prevent over fertilization to get sustainable crop production," in *Sustainable Plant Nutrition*. Elsevier, 2023, pp. 339–354.
- [7] J. Muangprathub, N. Boonnam, S. Kajornkasirat, N. Lekbangpong, A. Wanichsombat, and P. Nillaor, "Iot and agriculture data analysis for smart farm," *Computers and electronics in agriculture*, vol. 156, pp. 467–474, 2019.
- [8] J. Britt, R. Cushman, C. Dechow, H. Dobson, P. Humblot, M. Hutjens, G. Jones, P. Ruegg, I. Sheldon, and J. Stevenson, "Invited review: Learning from the future—a vision for dairy farms and cows in 2067," *Journal of dairy science*, vol. 101, no. 5, pp. 3722–3741, 2018.
- [9] V. Saiz-Rubio and F. Rovira-Más, "From smart farming towards agriculture 5.0: A review on crop data management," *Agronomy*, vol. 10, no. 2, p. 207, 2020.
- [10] A. Grau, M. Indri, L. L. Bello, and T. Sauter, "Industrial robotics in factory automation: From the early stage to the internet of things," in IECON 2017-43rd annual conference of the IEEE industrial electronics society. IEEE, 2017, pp. 6159–6164.
- [11] —, "Robots in industry: The past, present, and future of a growing collaboration with humans," *IEEE Industrial Electronics Magazine*, vol. 15, no. 1, pp. 50–61, 2020.
- [12] M. Edwards, "Robots in industry: An overview," Applied ergonomics, vol. 15, no. 1, pp. 45–53, 1984.
- [13] S. Wolfert, D. Goense, and C. A. G. Sørensen, "A future internet collaboration platform for safe and healthy food from farm to fork," in 2014 annual SRII global conference. IEEE, 2014, pp. 266–273.
- [14] R. Gebbers and V. I. Adamchuk, "Precision agriculture and food security," *Science*, vol. 327, no. 5967, pp. 828–831, 2010.
- [15] H. El Bilali and M. S. Allahyari, "Transition towards sustainability in agriculture and food systems: Role of information and communication technologies," *Information Processing in Agriculture*, vol. 5, no. 4, pp. 456–464, 2018.
- [16] S. Bonadies, A. Lefcourt, and S. A. Gadsden, "A survey of unmanned ground vehicles with applications to agricultural and environmental sensing," in *Autonomous air and ground sensing systems for agricultural* optimization and phenotyping, vol. 9866. SPIE, 2016, pp. 142–155.
- [17] N. Tarannum, M. K. Rhaman, S. A. Khan, and S. R. Shakil, "A brief overview and systematic approach for using agricultural robot in developing countries," *J Mod Sci Tech*, vol. 3, pp. 88–101, 2015.
- [18] B. Bartkowski, S. Bartke, K. Helming, C. Paul, A.-K. Techen, and B. Hansjürgens, "Potential of the economic valuation of soil-based ecosystem services to inform sustainable soil management and policy," *PeerJ*, vol. 8, p. e8749, 2020.
- [19] A. Julian, "Design and performance of a steering control system for agricultural tractors," *Journal of Agricultural Engineering Research*, vol. 16, no. 3, pp. 324–336, 1971.
- [20] K. Grosch, "John deere-bringing ai to agriculture," 2018.
- [21] M. R. Shaheb, R. Venkatesh, and S. A. Shearer, "A review on the effect of soil compaction and its management for sustainable crop production," *Journal of Biosystems Engineering*, pp. 1–23, 2021.
- [22] J. E. McPhee, D. L. Antille, J. N. Tullberg, R. B. Doyle, and M. Boersma, "Managing soil compaction—a choice of low-mass autonomous vehicles or controlled traffic?" *Biosystems Engineering*, vol. 195, pp. 227–241, 2020.
- [23] M. Hamza and W. K. Anderson, "Soil compaction in cropping systems: A review of the nature, causes and possible solutions," *Soil and tillage research*, vol. 82, no. 2, pp. 121–145, 2005.
- [24] X. Liu, S. Herbert, A. Hashemi, X. f. Zhang, G. Ding et al., "Effects of agricultural management on soil organic matter and carbon transformation-a review," *Plant Soil and Environment*, vol. 52, no. 12, p. 531, 2006.
- [25] T. Batey, "Soil compaction and soil management—a review," Soil use and management, vol. 25, no. 4, pp. 335–345, 2009.
- [26] S. G. Vougioukas, "Agricultural robotics," Annual Review of Control, Robotics, and Autonomous Systems, vol. 2, no. 1, pp. 365–392, 2019.
- [27] T. Daum, "Farm robots: ecological utopia or dystopia?" Trends in Ecology & Evolution, vol. 36, no. 9, pp. 774–777, 2021.
- [28] T. Martin, P. Gasselin, N. Hostiou, G. Feron, L. Laurens, and F. Purseigle, "Robots and transformations of work on farms: A systematic review," in *The 2nd International Symposium on Work in Agriculture*, 2021.

- [29] M. Kondoyanni, D. Loukatos, C. Maraveas, C. Drosos, and K. G. Arvanitis, "Bio-inspired robots and structures toward fostering the modernization of agriculture," *Biomimetics*, vol. 7, no. 2, p. 69, 2022.
- [30] S. Saeedi, M. Trentini, M. Seto, and H. Li, "Multiple-robot simultaneous localization and mapping: A review," *Journal of Field Robotics*, vol. 33, no. 1, pp. 3–46, 2016.
- [31] Robotriks, "The robotriks traction unit," 2022. [Online]. Available: https://www.robotriks.co.uk/the-rtu
- [32] F. Wu, J. Duan, S. Chen, Y. Ye, P. Ai, and Z. Yang, "Multi-target recognition of bananas and automatic positioning for the inflorescence axis cutting point," *Frontiers in plant science*, vol. 12, 2021.
- [33] XAG, "Xag's r150 unmanned ground vehicle," 2023. [Online]. Available: https://www.xa.com/en/xauv_r150
- [34] S. Gorjian, H. Ebadi, M. Trommsdorff, H. Sharon, M. Demant, and S. Schindele, "The advent of modern solar-powered electric agricultural machinery: A solution for sustainable farm operations," *Journal of cleaner production*, vol. 292, p. 126030, 2021.
- [35] C. M. Shoemaker and J. A. Bornstein, "The demo iii ugv program: A testbed for autonomous navigation research," in *Proceedings of the 1998 IEEE International Symposium on Intelligent Control (ISIC) held jointly with IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA) Intell.* IEEE, 1998, pp. 644–651.
- [36] ArduPilot Dev Team, "Mission planner," 2021. [Online]. Available: https://ardupilot.org/planner/
- [37] Naio Technologies, "Naio," 2022. [Online]. Available: https://www.naio-technologies.com/en/home/
- [38] L. F. Oliveira, A. P. Moreira, and M. F. Silva, "Advances in agriculture robotics: A state-of-the-art review and challenges ahead," *Robotics*, vol. 10, no. 2, p. 52, 2021.
- [39] G. Gil, D. Casagrande, L. P. Cortés, and R. Verschae, "Why the low adoption of robotics in the farms? challenges for the establishment of commercial agricultural robots," *Smart Agricultural Technology*, vol. 3, p. 100069, 2023.
- [40] F. B. Malavazi, R. Guyonneau, J.-B. Fasquel, S. Lagrange, and F. Mercier, "Lidar-only based navigation algorithm for an autonomous agricultural robot," *Computers and electronics in agriculture*, vol. 154, pp. 71–79, 2018.
- [41] J. Liu, S. Anavatti, M. Garratt, and H. A. Abbass, "Modified continuous ant colony optimisation for multiple unmanned ground vehicle path planning," *Expert Systems with Applications*, vol. 196, p. 116605, 2022.
- [42] M. Nazarahari, E. Khanmirza, and S. Doostie, "Multi-objective multi-robot path planning in continuous environment using an enhanced genetic algorithm," *Expert Systems with Applications*, vol. 115, pp. 106–120, 2019.
- [43] J. Van Den Berg, D. Ferguson, and J. Kuffner, "Anytime path planning and replanning in dynamic environments," in *Proceedings 2006 IEEE International Conference on Robotics and Automation*, 2006. ICRA 2006. IEEE, 2006, pp. 2366–2371.
- [44] AgriRobot, "Autonomous agricultural robots," 2022. [Online]. Available: https://agrirobot.ai/
- [45] I. Alyabina, A. Golubinsky, V. Kirillova, and D. Khitrov, "Soil resources and agriculture in the center of european russia at the end of the 18th century," *Eurasian Soil Science*, vol. 48, no. 11, pp. 1182–1192, 2015.
- [46] J. P. Scharlemann, E. V. Tanner, R. Hiederer, and V. Kapos, "Global soil carbon: understanding and managing the largest terrestrial carbon pool," *Carbon Management*, vol. 5, no. 1, pp. 81–91, 2014.
- [47] L. Ditzler and C. Driessen, "Automating agroecology: How to design a farming robot without a monocultural mindset?" *Journal of Agricultural* and Environmental Ethics, vol. 35, no. 1, pp. 1–31, 2022.
- [48] K. H. Coble, A. K. Mishra, S. Ferrell, and T. Griffin, "Big data in agriculture: A challenge for the future," *Applied Economic Perspectives* and Policy, vol. 40, no. 1, pp. 79–96, 2018.
- [49] J. J. Roldán, J. del Cerro, D. Garzón-Ramos, P. Garcia-Aunon, M. Garzón, J. De León, and A. Barrientos, "Robots in agriculture: State of art and practical experiences," *Service robots*, pp. 67–90, 2018.
- [50] C. W. Bac, E. J. Van Henten, J. Hemming, and Y. Edan, "Harvesting robots for high-value crops: State-of-the-art review and challenges ahead," *Journal of Field Robotics*, vol. 31, no. 6, pp. 888–911, 2014.
- [51] A. Ullstrup, "The impacts of the southern corn leaf blight epidemics of 1970-1971," *Annual review of phytopathology*, vol. 10, no. 1, pp. 37–50, 1972.
- [52] W. U. R. (WUR), "Farming systems ecology group," 2002. [Online]. Available: https://www.wur.nl/en/research-results/ chair-groups/plant-sciences/farming-systems-ecology-group.htm

- [53] A. Streed, M. Kantar, B. Tomlinson, and B. Raghavan, "How sustainable is the smart farm," in Workshop on Computing within Limits (June 2021). https://doi. org/10.21428/bf6fb269. f2d0adaf, 2021.
- [54] E. D. Fraser, "The challenge of feeding a diverse and growing population," *Physiology & behavior*, vol. 221, p. 112908, 2020.
- [55] A. Weersink, E. Fraser, D. Pannell, E. Duncan, S. Rotz et al., "Opportunities and challenges for big data in agricultural and environmental analysis," *Annual Review of Resource Economics*, vol. 10, no. 1, pp. 19–37, 2018.
- [56] K. Skaalsveen, J. Ingram, and J. Urquhart, "The role of farmers' social networks in the implementation of no-till farming practices," *Agricultural Systems*, vol. 181, p. 102824, 2020.
- [57] R. Akhter and S. A. Sofi, "Precision agriculture using iot data analytics and machine learning," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 8, pp. 5602–5618, 2022.
- [58] M. E. Isaac, B. H. Erickson, S. J. Quashie-Sam, and V. R. Timmer, "Transfer of knowledge on agroforestry management practices: the structure of farmer advice networks," *Ecology and society*, vol. 12, no. 2, 2007.
- [59] A. Dolinska and P. d'Aquino, "Farmers as agents in innovation systems. empowering farmers for innovation through communities of practice," *Agricultural systems*, vol. 142, pp. 122–130, 2016.
- [60] S. Chaudhuri, M. Roy, L. M. McDonald, and Y. Emendack, "Reflections on farmers' social networks: a means for sustainable agricultural development?" *Environment, Development and Sustainability*, vol. 23, no. 3, pp. 2973–3008, 2021.
- [61] M. Lubell, M. Niles, and M. Hoffman, "Extension 3.0: Managing agricultural knowledge systems in the network age," *Society & Natural Resources*, vol. 27, no. 10, pp. 1089–1103, 2014.
- [62] S. K. Lowder, J. Skoet, and T. Raney, "The number, size, and distribution of farms, smallholder farms, and family farms worldwide," World Development, vol. 87, pp. 16–29, 2016.
- [63] S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, "Big data in smart farming-a review," *Agricultural systems*, vol. 153, pp. 69–80, 2017.
- [64] I. Carbonell, "The ethics of big data in big agriculture," *Internet Policy Review*, vol. 5, no. 1, 2016.
- [65] Monsanto, "Virtual patent marking website," 2022. [Online]. Available: http://www.monsantotechnology.com/
- [66] T. L. Beauchamp, N. E. Bowie, and D. G. Arnold, Ethical theory and business. Pearson Education New York, 2004.
- [67] R. Birner, T. Daum, and C. Pray, "Who drives the digital revolution in agriculture? a review of supply-side trends, players and challenges," *Applied Economic Perspectives and Policy*, vol. 43, no. 4, pp. 1260– 1285, 2021.
- [68] M. Pantoja, F. J. Kurfess, and I. Humer, "Deep learning for agriculture," in 2020 ASEE Virtual Annual Conference Content Access, 2020.