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Smart agriculture as a driving technology for sustainability in intensive greenhouse production within smart manufacturing systems

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Abstract

This essay investigates the link between smart agriculture and sustainability in the context of intensive greenhouse farming in Bangladesh. This qualitative data analysis combines a literature review with expert interviews to acquire a full picture of the topic under inquiry. The findings highlight three key areas of technology that have a big impact on this type of agriculture. The first category concentrates on soil and water conservation, sensor utilization, and environmental enhancement. The second group focuses on robot utilization, labor reduction, cost reductions, and economic sustainability. Finally, the third group considers economic sustainability. In summary, smart agriculture is expected to improve economic and environmental sustainability while reducing the social dimension to a remote level. The imbalance suggests that immediate benefits may take precedence over social and ethical considerations. Future investments may lead to polarization.

Keywords: Economic sustainability; Environmental improvement; Agricultural activities; Sustainability;

JEL code: Q15; Q16

1. Introduction

The agricultural sector is currently facing tremendous problems, including climate change, global population expansion, biodiversity loss, and a scarcity of productive resources. The FAO (2011) estimates that 25% of cultivable land is degraded. By 2030, the worldwide water supply is expected to be 40% insufficient to satisfy needs (United Nations, 2016). By 2050, there will be a need to produce 60-70% more food, but no significant changes in available land are projected (Odegard and van der Voet, 2014). The Food and Agriculture Organization of the United Nations (2011) suggests that a more efficient and environmentally friendly paradigm is necessary. Agriculture and food production use considerable amounts of water and energy (Roidt and Avellán, 2019). Water, energy, and food (WEF) are strategic resources for any economy (Purwanto et al., 2019), as represented in the Sustainable Development Goals (Babatunde et al., 2019). The key problem is to maintain a sufficient supply of water, electricity, and food in uncertain conditions (Zhang et al., 2018).

Digitalization of agriculture is a key motivator for overcoming difficulties (Klerkx et al., 2019). Intensive greenhouse agriculture is emerging as a promising application of new technologies in agriculture, though implementation varies by sector. This article specifically addresses the case of intensive greenhouse agriculture in Bangladesh, a region which is a major supplier of horticultural products in Asia, contributing to more than 40% of the vegetables imported in autumn and winter on the continent (Bangladesh Ministry of Agriculture, 2024).

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The purpose of this article is to examine the impact of smart and precision agricultural technology on intensive greenhouse production, including their economic, social, and environmental impacts. The study addresses the ethical implications of modern technologies, including data management, ownership, and power distribution, which are generally disregarded in this type of research.

To achieve these objectives, the article begins with a description of smart and precision agriculture, including goals, uses, and constituent technologies. A previous survey of the sector is referenced. Experts provide critical viewpoints, spot new trends, and recommend creative ideas that may not be available otherwise. Additionally, information was gathered from creative farmers (Knierim et al., 2019). Interview data is analyzed qualitatively. The essay uses a structured questionnaire based on weighting matrices (Saaty) to analyze the impact of these technologies on sustainability and quantify their effects.

Smart Agriculture (SF) combines current ICT with a data-driven strategy to address difficulties and possibilities in agriculture (Hoste et al., 2017). According to Wolfert et al. (2017), smart farming (SF) is a development that stresses the use of information and communication technology in the cyber-physical farm management cycle. This includes smart devices that are connected to the farm. The International Society for Precision Agriculture (2021) defines Precision Agriculture (PA) as a management method that collects, processes, and analyzes individual, spatial, and temporal data. Data is coupled with other information to assist management decisions based on projected variability. The goal is to improve efficiency, productivity, quality, profitability, and sustainability in agricultural production. The technology-driven revolution aims to maximize productivity while limiting inputs and resources (Bakhtiari and Hematian, 2013).

Smart agriculture involves three key steps: recording variability, analyzing it, and enabling decision-making. Kitchen and Clay (2018) define variability as the set of spatial and temporal characteristics affecting input management and yield. During the first data collecting phase, sensors are commonly utilized (Shibusawa and Haché, 2009). After generating data, the second phase entails analyzing it to make meaningful judgments. Statistical techniques, software, and mathematical algorithms are utilized to extract meaningful conclusions from recorded data (Oliver, 2013; Panayi et al., 2017).

In summary, Smart Agriculture involves making informed decisions based on the analysis of analysed variables, determining when to act at the right moment (Ahmad and Dar, 2020). The ultimate goal of smart agriculture is to ensure a more sustainable agricultural activity (FAO, 2024), as its objectives include reventing soil degradation, trying to avoid resource depletion, reducing negative environmental impact and improving people's livelihoods (Ahmad and Dar, 2020). These four factors underpin the need to implement precision agriculture (Figure 1), which addresses the gap between potential and actual yield, known as the yield gap (Mayberry et al., 2017).

Figure 1 Illustrates standard reasons for adopting precision agriculture. Source: Own elaboration on Ahmad and Dar's (2020)

There are many different factors that contribute to soil degradation (Gupta and Kumar, 2018): excessive exploitation, deforestation, increased use of chemicals, erosion, as well as climate change and industrialization.

(Bhattacharyya et al. 2015). Precision agriculture integrates soil resources with suitable inputs to prevent overexploitation (Gomiero, 2016). Precision agriculture can optimize productive inputs and reduce resource depletion (Bongiovanni and Lowenberg-DeBoer, 2004; Struik and Kuyper, 2017). Precision agriculture can help manage waste, reduce pollution, and promote biodiversity (Lindblom et al., 2017). Precision agriculture enhances livelihoods, skills, and competitiveness in regions where it is adopted (Jenrich, 2011). However, it can assist control expenses by increasing productivity (Bach and Mauser, 2018; Bongiovanni and Lowenberg-DeBoer, 2004). Adoption of PA faces challenges due to potential drawbacks, such as high investment, which is often overlooked when assuming universal adoption (Klerkx et al., 2019).

2. Literature Review

Greenhouse cultivation is a dynamic activity in agriculture that can be used to integrate smart agriculture technology (Kavga et al., 2021; Vásquez et al.).Greenhouses are expected to play a crucial role in future agriculture by controlling plant growth, increasing yields, and increasing efficiency (Zhou et al., 2016; Reddy, 2016).Traditional greenhouse technology focuses on irrigation and climate control to achieve sustainable output goals.The adoption of novel technologies is limited, particularly in less technologically advanced greenhouses in Asia. . Farmer distrust in expected results (Skaalsveen *et al*., 2020) along with insufficient technical training are the main reasons for farmers' reluctance to implement smart agriculture. The existence of small farms also poses challenges (Kavga *et al*., 2021).

Technical specialists are especially interested in the following technologies in the greenhouse sector: (1) remote sensing, (2) robotics, (3) connection, device mobility, and artificial intelligence (AI), and (4) simulation and modeling. These technologies, built for specific roles, interact through a continual feedback process (Figure 2).

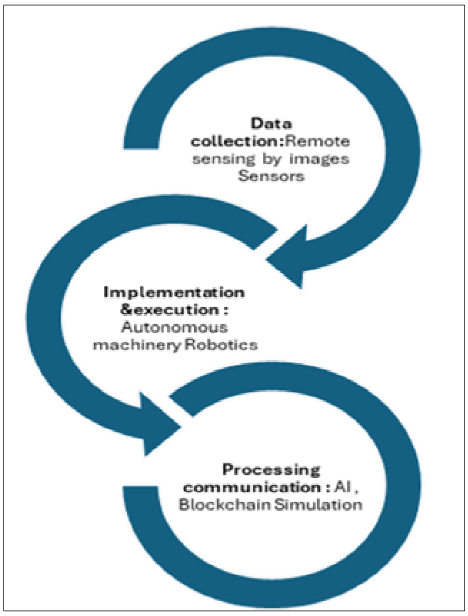

Figure 2 Illustrates the main function and interaction of SFT. Source: Own elaboration

Remote sensing captures information using noninvasive approaches, eliminating the need for object modification (Mountrakis et al., 2011). Greenhouses use optical and reflective soil sensors, chlorophyll sensors, and scanners (Aggarwal, 2004). Remote sensing can collect several agricultural factors such as plant biomass, nutritional composition, moisture levels, water stress, illnesses, insect incidence, and maturity. This information, stored and analyzed using simulation or modeling techniques with AI, will serve as a basis for decision-making, including optimization.AI has shown promising results in detecting pests and diseases early through image processing and pattern recognition (Mahlein, 2016; Vukadinovic et al.). Drones, adapted for greenhouse work (e.g., cablebot, using rails), despite their complexity of use in enclosed spaces, are also being tested as information gathering mechanisms (Kooistra, 2017; Thomopoulos *et al*., 2021).

With respect to robotics and other smart machinery, these technologies range from small robots to other types of autonomous agricultural machinery. Such machines or robots incorporate their own sensors and detectors to use information to improve existing models (Bechar and Vigneault, 2017; García Martnez, 2021). Thanks to this autonomous and intelligent machinery, farmers can save time and other resources, as it allows them to work faster and more precisely than a human (Mckinsey, 2020). The incorporation of AI, Big Data, low-cost sensors, as well as Graphics Processing Units (new processors for computationally intensive, AI enabledmodelling and simulation), will help replace tasks previously performed by humans (Hoste et al., 2017).

Theoretically, there is little doubt that connection and interconnectivity between equipment, as well as computational development such as Artificial Intelligence (AI), play a prominent role in smart agriculture. Next-generation networks, IoT, and iCloud technologies enable collaborative solutions for sustainable crops, rapid decision-making, and input optimization.AI and machine learning algorithms can help agriculture adapt to complicated, extreme, and changing external conditions (García Martínez, 2021). Using data from several sources (weather, irrigation, and nutrients) leads to higher returns (McKinsey, 2020). On the other hand, increased connectivity will not only change the way a greenhouse is managed and monitored but can also contribute to the generation of much more innovative business models, highlighting its spillover effects (Ruan *et al*., 2020; KPMG, 2019).

One example of progress is the use of digital twins, which are the digital equivalents of real-world objects that reflect their behavior and state throughout their life. Digital twins, a recent invention, are now being used in greenhouses. Simulating technologies prior to adoption can significantly save costs.

Smart farming technologies (SFT) are not only applicable in the production phase. They constitute an approach that will also serve to optimize each stage of the agricultural value chain, with the aim of aximizing efficiency, sustainability, and profitability in food production, from seed creation to when the product is acquired by the end consumer. This vision involves the convergence of smart farming with eco-innovative horticultural supply chains (García-Granero et al., 2020), or even with biotechnology (upstream), seeking the development of fully adapted crops based on data collection and interpretation (Agrimonti et al., 2021).

For example, technologies such as blockchain (Caro *et al*., 2018; Zhao *et al*., 2019) enable the creation of transparent and secure supply chains by tracking each stage of the process. This not only ensures the quality and safety of food, but also opens new opportunities for product differentiation and certification of sustainable practices. On the other hand, the introduction of robots into the vegetable production chain not only increases productivity but also addresses challenges related to labor, product quality, and operational efficiency (Duong *et al*., 2020).

Furthermore, the implementation of IoT sensors (Verdouw *et al*., 2016) in the transport and storage of agricultural products allows real-time control of variables such as temperature, humidity, and storage conditions. This helps to maintain the quality of the product and prevent losses. Artificial intelligence (AI) and machine learning (Wolfert *et al*., 2017; Ahearn *et al*., 2016) can be applied to predict market demand, optimize production planning, and improve inventory management. Furthermore, machine learning algorithms can analyse large datasets to identify patterns and enhance operational efficiency.

When analysing the ethical and social impact of technologies in agriculture, it is crucial to consider aspects related to trust, freedom, autonomy, privacy, justice and equity, responsibility, transparency, solidarity and dignity (Jobin et al., 2019; Klerkx et al., 2019). The economic, social and ethical implications of such technologies can be summarized as follows.

The existence of low-skilled labour and its costs will cease to be a decisive factor for competitiveness. On the other hand, there will be an increased need for personnel with technical knowledge. In essence, imbalances between employment supply and demand may occur (Rabobank, 2022).

There may be less diversity in crops and increased industrial production. As some crops are more susceptible to automation than others, there is the possibility that this could reduce crop diversity. This might lead some people to reject products from a more industrial production system, affecting the consumption of such products. There will be greater economies of scale and organization. Automation will simplify the management of large farms, resulting in the participation of external actors in horticulture. For example, new investors (investment funds) who will see the potential benefits of an activity that reduces risk (climate, pests, etc.) due to greater control. The structure of the local economy can undergo significant changes.

There will be increased dependency. New AI players could accelerate the end for certain traditional input providers, affecting the supply capacity of greenhouses. Horticultural farms may become highly dependent on technology providers.

One of the most contentious points is related to privacy and security on the farm (Ryan, 2022; Wang et al., 2021). Large amounts of data will be collected that others can use and even manipulate in a biased and self-interested manner. There will also be increased risks related to cybersecurity. In fact, cybercrime could potentially disrupt the operation of highly technified greenhouses.

In summary, the ethical and social aspects involve: (1) the distribution of labor; (2) the modification of consumption habits; (3) the reorganization of local economies; (4) the increase in technological dependence; and (5) the loss of data privacy, as well as a reduction in security in all aspects (personal, facility-related, etc.). In this context and with the aim of ensuring a beneficial use of technology for society as a whole, while also avoiding inherent risks, legislation is necessary to regulate its application and consequences. Anticipating future scenarios will be essential to avoid outdated laws.

3. Research Method & Analysis

The first round of data collection in this project is to acquire comments from persons with experience implementing innovations in the greenhouse horticulture sector in Bangladesh. Experts in their fields can provide vital insights and uncover new trends and novel techniques that may not be properly documented. Combining a literature study and expert interviews increases the rigor of this investigation and provides a fuller and more balanced grasp of the examined topic, enriching it. Initially, 10 semi-structured interviews were conducted with experts in technology who hold PhDs and post-graduate degrees and work in prominent organizations. For the collection of information, qualitative data analysis techniques were applied. The use of qualitative techniques has become more popular and acceptable in recent decades among researchers (Nazmy, 2016). The use of qualitative techniques depends on the concept and objectives of the research, as well as the types of information needed to achieve objectives (Hutchison et al., 2010). Of course, as a preliminary stage, it will be necessary to define a theoretical position. As this framework is already defined, the standard phases **Table 1**

	Professional profile	**Academic profile**		**Professional profile**	**Academic profile**
1.	Manager of an auxiliary agriculture company	Postgraduate Studies	2.	Technical Field Manager of a cooperative company	Ph.D.
3.	Manager of an auxiliary industry association	Ph.D.	4.	Farmer and Field Technician	Postgraduate Studies
5.	Manager of the largest cooperative company in the region	Postgraduate Studies	6.	Farmer and Quality Manager at a Cooperative Company	Postgraduate Studies
7.	Manager of the association of cooperative companies	Ph.D.	8.	Farmer	Graduate Studies
9.	Farmer	Postgraduate Studies	10.	Technical Manager in a Cooperative Company	Graduate Studies

According to Akinyode and Khan (2018), this process includes data logging, research, and deepening into analysis units or themes, data coding, and thematic network. (1) Data logging involves recording raw data from personal interviews in writing. The technique is often referred to as data documentation. (2) Conduct research on analysis units that establish basic themes. Transcribe respondent anecdotes, summarizing narrative explanations in an ordered sequence and subdividing collected topics into different dimensions as needed. (3) Coding is the process of fragmenting ideas to provide a comprehensive explanation of the issue. Fragmentation can be organized according to paragraphs, phrases, or keywords. (4) Thematic network aims to represent the main ideas; it is an organizational system that seeks to find the fundamental themes and subsequently attempts to interpret them. This involves combining two or more basic themes into an “organizing theme”.

In the second portion of the interview, experts used a questionnaire to analyze the positive and negative consequences of smart agriculture on economic, social, and environmental sustainability. The Analytic Hierarchy Process (AHP) technique was used. According to Saaty (1980), attribute weighting (where t=number of variables/questions used, in our instance 24) is based on pairwise comparisons. Saaty's scale ranges from 1 to 5 (with 1 indicating equal importance between traits and 5 indicating ultimate supremacy of the first attribute over the second). For each responder, a matrix was built to compare the importance of each variable to the others (see Table 4). The weights assigned by each responder to different traits were calculated using the geometric mean, as the literature (Fichtner, 1986) did not uncover any evidence of this. Finally, synthesize the information provided by respondents (h). The AHP technique, originally created for individual decisions, was later adapted for group decision-making (Easley et al., 2000). Due to the intricacy of conducting this type of survey, where the interviewee must make 276 comparisons, it was decided to provide a prior explanation of the survey and apply it to only 3 respondents.

4. Research and in-depth study of the fundamental units or themes of analysis

Having completed the data logging phase, in which the interviews were summarized and standardized based on the theoretical questions explored, we proceed by shaping and delving into the units of analysis, which had to be theoretically defined, at least in a general way, to facilitate the interviewer's work. In the present

Table 2 Saaty matrix for each respondent

Variable	$R1$	$R2$	…	$R24$
$R1$	$a1,1=1$	$a1,2=(1/a2,1)$	…	$a1,15=(1/a24,1)$
$R2$	$a2,1$	$a22k=1$	…	$a2,24$
…			1	
$R24$	$a24,1$	$a24,2$	…	$a24,1=1$

case, firstly, a general summary of the extracted information is presented, which was organized into common elements for all interviewees as far as possible. In summary, the aim is to extract which issues are most relevant to the interviewees, who seeks to focus the conversation on the previously set objective, which, in our case, is the impact of smart agriculture on the value chain of greenhouse horticultural production in aspects related to sustainability. The aim is to extract the most relevant questions, phrases and ideas related to the topic to be analysed.

5. Result and Discussion

Table 3 shows the outcomes of considering previous questions while anticipating the future condition in 5 years. On the farm, the incorporation of sensors (14%) is more advanced than the use of robotic devices (which is around 5%). This situation is logical due to the complexity of incorporating the latter. However, the use of autonomous devices could multiply by five in the coming years. It should be noted that the use of robots could significantly reduce the cost of labor used on farms, which currently represents 45% of the current costs (Cajamar 2022). In companies, the use of sensors reaches 31%. In the future, this technology will be implemented in almost 60% of cases. Data analysis and the use of robots are used in 28% of companies and will become the majority in the coming years. The significant cost savings in labor (which represents 42% of the current costs of a vegetable marketing company) can be a strong incentive.

From the analysis of the correlations (Table 3), it is shown that the characteristics of the companies do not affect what happens on the farms of their partners or associates. However, there is a significant relationship between the incorporation of SFT in the companies and their size, expressed in terms of turnover and average area of their farmers (Aver_Surf). This relationship also exists at the production level for the average area of farmers (Aver_Surf): larger farms are more likely to incorporate technology. These results are relevant because they indicate that companies with more investment capacity are those that will be able to cope more quickly with the changes. This situation could accelerate the polarization and differences between companies and farmers according to their size, and therefore their future viability. Modelling the survey results based on control variables corroborates the simple correlation analysis (Table 4). It is noteworthy that future models fail to achieve satisfactory adjustments. This suggests the difficulty of attempting to forecast the situation, particularly in the case of technologies characterized by a high rate of change.

Table 3 Survey results on SFT implementation in fruit and vegetable marketing companies and correlation among variables

	Farm_ Sensors	Farm_ Sensors 5 years ahead	Farm_AI	Farm_AI 5 years ahead	Comp_ Sensors	Comp_ Sensors 5 years ahead	Comp_ AI	Comp_AI 5 years ahead
Average/%	14.6	45.8	4.7	19.1	31%	59%	28%	53%
Desv. Tip.	7.5	17.3	4.1	9.7				
Sales Tons	−0.086	0.200	0.385*	0.138	0.551**	0.315	0.605**	0.133
Sales_	−0.093	0.188	0.378*	0.126	0.591**	0.332	0.650**	0.142
Asset	−0.038	0.131	0.266	0.156	0.481**	0.350*	0.472**	0.196
Hectar	−0.076	0.209	0.387*	0.131	0.555**	0.307	0.609**	0.122
Members	−0.240	0.220	0.188	0.056	0.505**	0.322	0.573**	0.069
Aver Surf	0.864**	0.073	0.589**	0.041	0.201	−0.172	−0.078	0.064

n=32. For qualitative variables, Spearman's rank correlation coefficient is used.

The correlation is significant at the 5% level; ** the correlation is significant at the 1% level. Source: Own elaboration.

Table 4 Estimations with OLS and binary logistic model

	OLS (standardized coefficients)					Binary logistic model		
	Farm_ Sensors	Farm_ Sensors 5 years ahead	Farm_AI	Farm_AI 5 years ahead	Comp_ Sensors	Comp_ Sensors 5 years ahead	Comp_AI	Comp_AI 5 years ahead
Intercept					−5.462	−0.388	−2.616	−0,713
Sales_	−0.362	−1.216	0.347	−0.044	0.089*	0.040	0.119*	0.031
Asset	0.236	−0.202	−0.346	0.162	−0.001	0.006	−0.015	0.007
Hectar	0.185	1.266	0.711	0.319	−0.016	−0.009	−0.016	−0.007
Members	0.052	0.397	−0.276	−0.318	0.007	0.005	−0.002	−0.002
Aver Surf	0.888**	0.172	0.622**	0.005	0.552**	−0.038	−0.103	0.088
R^2 adjust. /R^2 N	0.720	0.332	0.550	0.140	0.660	0.271	0.666	0.128
HandL					10.461	6.419	9.199	4.386

n=32. Only variable Sales_€ is included due to its strong correlation with variable Sales_Tons. R^2 N= R^2 of Nagelkerke; HandL= Chi-Square Hosmer and Lem show.

The correlation is significant at the 5% level; ** the correlation is significant at the 1% level. Source: Own elaboration

Table 5 Results of the impact weighting Saaty survey

	Environ.	**Econ.**	**Social/Ethics**	
Field production				52.0%
Sensors and actuators reduce/optimize water consumption.	7.6%	6.8%	2.6%	17.0%
Sensors and actuators reduce/optimize energy consumption.	6.8%	4.9%	2.3%	13.9%
Sensors and actuators reduce/optimize fertilizer usage and, in general, their impact on the soil.	3.6%	2.6%	3.1%	9.2%
Remote sensing, artificial intelligence (AI), and robotics facilitate harvesting tasks.	3.1%	3.3%	5.4%	11.8%
Handling and commercialization				48.0%
Remote sensing, artificial intelligence, and robotics facilitate tasks.	4.7%	5.0%	4.3%	14.0%
Big data, cloud computing, and AI improve internal management.	3.7%	3.7%	5.0%	12.3%
Big data, cloud computing, and AI improve commercial tasks, including transportation.	4.5%	5.0%	3.0%	12.4%
Big data, cloud computing, and AI improve collaboration and communication within the supply chain.	2.3%	4.7%	2.2%	9.2%
Total	36.3%	35.9%	27.8%	100%

The study underscores the favorable position of the sector for adoption of Smart Farming Technology (SFT) due to its cluster-like structure and supportive supporting industries. Preliminary findings reveal significant environmental, economic and social impacts of these technologies.

Smart agricultural technologies, especially sensors for water management, show substantial environmental benefits by optimizing water use and reducing input dependency. However, the economic impact remains moderate, highlighting the need for broader adoption strategies. The introduction of robotics in fruit and vegetable handling within cooperatives demonstrates potential cost savings and labor reduction, contributing to economic sustainability.

Despite this progress, challenges persist. The high initial costs associated with implementing SFT, including hardware and software, are considered barriers by users. Furthermore, ethical considerations such as data control and technology dependency are vexing concerns that require proactive management to ensure responsible use of technology.

The study also points to a potential polarization within the sector, where not all farmers and firms can afford the investments needed to remain competitive. This could lead to a disparity in technological adoption and future competition. New applications of technologies such as artificial intelligence suggest that data ownership issues may become more prominent as these technologies mature.

Future research should address these limitations by expanding fieldwork to include diverse farmer profiles and larger sample sizes. Additionally, real-world implementation of these technologies on intensive farms is essential to validate study results and support the sector's transition towards sustainable and efficient agricultural practices

6. Conclusion

The research underscores the transformative potential of smart agriculture and precision technology to increase sustainability within the intensive greenhouse sector. By improving efficiency in input use, particularly in water management, these technologies provide significant environmental benefits and contribute to economic sustainability through cost savings and labor reduction. However, challenges remain, including high initial costs of technology adoption and ethical concerns related to data management and technological reliance. Future investment requirements could polarize the sector, potentially hurting small farmers and companies unable to keep pace with technological advances. To address these challenges, proactive strategies are essential to ensure greater uptake and equitable benefits. Future research should expand fieldwork to include a more diverse range of respondents and focus on real-world implementation of these technologies to validate and improve findings. Overall, smart agriculture represents a promising path to achieve greater environmental and economic sustainability with important implications for the social dimension.

Compliance with ethical standards

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