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Navigating ethics in wireless sensor networks for sustainable agriculture

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1 Introduction

With the global population projected to reach nearly 10 billion by 2050, food systems must become dramatically more efficient and sustainable to meet the growing demand while conserving scarce resources (FAO, 2017). Digital transformation, particularly through the agricultural Internet of Things (IoT), is often seen as the solution. In fact, the agricultural IoT market is growing rapidly and is projected to reach $40 billion by 2034, mainly driven by the deployments of wireless sensor networks (WSN) (Precedence Research, 2024).

WSN deployments comprise spatially distributed nodes equipped with sensors and wireless communication modules powered by batteries or energy harvesting devices. By providing continuous high-resolution monitoring of soil moisture, microclimate, nutrient status, and crop health, these networks transmit data via protocols such as ZigBee, LoRa, or NB-IoT[1] to edge gateways or cloud platforms for real-time analysis. Farmers and agronomists can then take advantage of these insights to schedule irrigation based on real-time soil moisture measurements (Meriç, 2025), optimize fertilizer applications to match field nutrient levels (Adamo et al., 2025), and implement targeted pest management informed by sensor-enabled trap networks (Parsons et al., 2020).

Although WSNs improve agricultural efficiency and sustainability, they also raise ethical concerns, including data protection, high costs, and limited evidence on long-term environmental and economic outcomes (Elijah et al., 2018). This opinion article proposes a conceptual framework and research agenda for embedding ethical foresight in WSN deployments. We highlight the importance of ethics in ensuring reliable data for accurate decisions, protecting privacy to prevent misuse, promoting equity to reduce inequalities, safeguarding labor against displacement, and mitigating environmental risks such as wildlife disruption. Through case examples, including from the Global South, we illustrate these issues and propose solutions via technical safeguards, policy mechanisms, and community engagement, supported by a step-by-step lifecycle checklist.

1 Zigbee, LoRa, and NB-IoT are low-power wireless protocols commonly used in WSNs to enable reliable and secure data transmission. Zigbee supports short-range mesh networking, LoRa offers long-range connectivity, and NB-IoT extends cellular coverage to underserved areas.

2 Challenges and risks of WSN adoption

2.1 Data reliability: balancing precision and risk

WSNs rely on accurate sensor data to inform critical agricultural decisions, such as optimizing irrigation, fertilization, and pest control. However, data quality can be compromised by sensor calibration errors, environmental interference, power limitations, and maintenance challenges (Mahmood et al., 2015). Extreme weather, such as heavy rainfall or high winds, can disrupt sensor functionality and wireless connectivity, causing data loss or corruption. Limited power sources, like batteries, may fail or be mismanaged, leading to interrupted data collection or inaccurate transmissions. Such errors can result in flawed recommendations, risking crop losses, livestock health issues, and economic harm to farmers.

These challenges are particularly acute in low-resource settings, such as smallholder farms in Sub-Saharan Africa and South Asia, where electricity and technical expertise are scarce. Sensors in these regions face harsh conditions with limited maintenance, while most IoT devices are imported and require specialized skills that may not be locally available (Bayih et al., 2022). Dust, humidity, and temperature fluctuations accelerate sensor degradation, causing frequent faults and unreliable data. For example, a soil moisture probe in a remote field may quickly deteriorate under heat and require recalibration, a task beyond the training of many local users. Small errors such as sensor drift or battery depletion often go unnoticed, increasing the risk of misleading recommendations (Lin et al., 2019).

To ensure reliable data, technical strategies, such as sensor fault detection and isolation algorithms (Jihani et al., 2023), redundant sensing, real-time data validation, and robust calibration protocols, are essential. In the Global South, deployments should incorporate durable hardware, local training programs, and support tailored to available skills. These technical safeguards must integrate with institutional strategies to prevent data errors from causing ecological or economic harm.

2.2 Privacy and security: safeguarding farmer autonomy

WSNs generate vast amounts of sensitive data on farming practices, yields, land use, and ecological conditions, raising significant privacy concerns. In many regions, the lack of robust data protection laws worsens these issues (Ferris, 2017). For example, several African countries do not have tailored legislation for agricultural data, and farmer awareness of data protection remains low (Chichaibelu et al., 2023). This regulatory gap increases farmers' fears of data misuse, such as land speculation, sharing with competitors, or regulatory actions against them (Sykuta, 2016). These worries contribute to the reluctance to adopt WSN technologies, despite their productivity benefits.

The risks of poor data governance are clear in a 2019 Australian incident, where an animal rights group published a map of farm locations, exposing data from digital tools (Wiseman and Sanderson, 2019). This breach led the Australian government to apply the Privacy Act to aggregated farming data, illustrating how farm data can be misused in harmful ways. Such events expose farmers to manipulation by activists, insurers, or competitors, eroding trust in digital systems.

Addressing privacy requires ethical data governance frameworks that prioritize farmer autonomy. Secure storage, end-to-end encryption[2], and clear ownership rules are vital to maintain farmer control. Farmers should provide informed consent for data use and revoke permissions as needed. The EU Code of Conduct on Agricultural Data Sharing (COPA-COGECA et al., 2020) offers a model, emphasizing transparency, equitable data-sharing agreements, and farmer participation in data ecosystems. These principles help balance the tension between farmer autonomy and the needs of third-party stakeholders, such as agribusinesses and technology firms, that rely on farm data for predictive analytics and decision-support tools.

Beyond governance, securing WSNs is challenging due to limited sensor resources and dynamic agricultural environments (Urooj et al., 2023). Weak encryption, unprotected communication links, and inadequate authentication protocols can expose WSNs to breaches, compromising farmer privacy and leading to competitive disadvantages or financial losses. To mitigate these risks, WSNs must incorporate robust security measures, including multi-level authentication, regular vulnerability assessments, and timely software updates. A "privacy-by-design"[3] approach, embedding protections early, plus clear ownership agreements, can strengthen security, build trust, and promote adoption.

2.3 Equity and transparency: building trust in agricultural decisions

AI and machine learning models in WSNs can transform agricultural management, but they must prioritize fairness and transparency to avoid biases (Ferrara, 2024). Bias often stems from data collection, where sensors are mainly deployed on large, well-funded farms, creating datasets that favor irrigated, high-input systems. This leads to unsuitable recommendations for smallholder or rainfed farms, potentially causing harm. Label errors[4] worsen skewed predictions, as yield or pest data from areas with poor digital infrastructure are often incomplete. Key contextual factors, like land tenure, credit access, and local practices, are rarely captured, ignoring real-world conditions and exacerbating inequalities.

Algorithmic bias is evident when systems favor specific crops or regions. Most agricultural datasets focus on commodity crops,

2 End-to-end encryption is a communication method in which data is encrypted on the sender's device and decrypted only on the recipient's device, ensuring that no intermediaries can access it.

3 Privacy-by-design is a system development approach that integrates privacy protections into the design and architecture from the very beginning.

4 Label errors refer to incorrect or misclassified data points, such as misidentifying crop yield or pest presence, which can cause prediction errors in machine learning models and result in inaccurate outcomes.

such as corn, soybeans, and canola, from large-scale operations (Bronson, 2022). For example, a fertilizer algorithm trained on industrial corn data might overestimate inputs for subsistence crops in the Global South, widening productivity gaps. This perpetuates a biased view of farming that prioritizes high-input production, disadvantaging smallholders (Bronson, 2022).

To promote equity, models should be audited with diverse datasets and involve underrepresented farmers in design. Transparency and explainability are key (Felzmann et al., 2020). User interfaces should show how recommendations are generated; for instance, an irrigation alert could display soil moisture values and thresholds, allowing farmers to adjust advice. In low-literacy settings, use voice prompts or icons. Ethical AI should enable opt-in/out for automated advice and integrate farmers' qualitative inputs, such as local pest observations or traditional indicators. Integrating WSN data with indigenous knowledge and local expertise ultimately yields more robust guidance.

2.4 Social impacts: navigating automation and labor displacement

The integration of WSNs and automation in agriculture boosts efficiency but poses socioeconomic challenges, including job displacement and erosion of rural livelihoods (Rotz et al., 2019). As automated systems handle tasks like monitoring and decision-making, manual labor roles diminish, threatening employment in rural areas where agriculture is the main income source and alternatives are limited. Without policies, this can widen social inequalities and rural-urban divides. For example, automated milking systems in European dairy farms reduce labor time by 20–62%, easing physical demands but displacing traditional roles, while shifting workers to herd management, data analysis, and system maintenance (Martin et al., 2022).

To mitigate job displacement from automation, deployment strategies should include comprehensive transition plans. These encompass reskilling and upskilling initiatives to prepare workers for digital agriculture competencies, including WSN data management, interpretation, and sensor maintenance. Such programs can foster emerging roles in a technology-augmented sector (Bronson and Knezevic, 2016). Additionally, inclusive policies promoting varied skill development can ease the move from manual to supervisory or strategic positions. Empirical research underscores that effective automation reallocates human efforts to knowledge-driven tasks rather than eradicating them (Acemoglu and Restrepo, 2019), potentially yielding more rewarding and less strenuous job opportunities.

2.5 Environmental impacts: balancing benefits and ecological risks

WSNs in agriculture offer significant environmental benefits but also pose ecological risks that require careful management. WSNs enhance resource efficiency by optimizing water, fertilizer, and pesticide use, thereby reducing environmental degradation and promoting sustainability. For example, real-time soil moisture monitoring enables precise irrigation scheduling, minimizing water waste and preventing over-irrigation, which can lead to soil erosion and nutrient leaching (Abdollahi et al., 2021). At the same time, electronic devices can pose hazards to livestock and wildlife (Mark, 2019). In pasture-based systems, GPS collars and sensors support animal welfare by enabling early detection of disease or heat stress, yet they also carry risks such as collar injuries or stress from virtual fencing that delivers electric shocks, underscoring the need for animal-friendly designs (Herlin et al., 2021).

The presence of WSN devices in natural habitats can disrupt wildlife behavior and migration patterns. Buried soil sensors can temporarily disturb soil structure, with uncertain long-term effects on subterranean life. Automated systems, if over-relied upon, may prioritize efficiency over ecological diversity, potentially simplifying habitats and harming species (Goddard et al., 2021). Unrecovered sensor components contribute to electronic waste, threatening biodiversity through hazardous material accumulation. Environmental assessments highlight that improper disposal of WSN components can lead to environmental contamination (Bonvoisin et al., 2012). To mitigate these risks, adopting biodegradable sensors that decompose naturally or implementing robust recycling and repurposing programs is critical to minimize ecological harm and align with circular economy principles in agricultural technology.

3 Toward ethical and sustainable WSN deployments

As illustrated in Figure 1, the responsible integration of WSNs relies on three interconnected pillars: technical safeguards, policy mechanisms, and community engagement. By aligning engineering best practices with governance structures and stakeholder participation, this framework transforms abstract ethical concerns into practical, actionable strategies.

Embedding ethical safeguards at the design stage is essential for trust, transparency, and resilience. Technically, strategies like data anonymization[5] at the sensor edge, which removes personally identifiable information such as farm locations or owner details before transmission, protect farmer privacy and commercial confidentiality (Amiri-Zarandi et al., 2022). Open architectures and standardized protocols based on common standards promote device interoperability across manufacturers, reduce vendor lock-in[6], and spur innovation through seamless integration of new tools (Roccatello et al., 2025). Privacy-preserving methods such as federated learning[7] enable collaborative crop yield predictions across farms without exchanging raw data, thereby mitigating breach risks (Žalik and Žalik, 2023). Secure over-the-air firmware updates[8] and tamper-resistant hardware with physical protections

5 Data anonymization is the process of modifying data to prevent the identification of individuals or entities while preserving its utility for analysis.

6 Vendor lock-in occurs when WSN users are restricted to a single provider's hardware or software, limiting flexibility and increasing costs.

7 Federated learning is a machine learning approach in which models are trained across multiple devices or locations without transferring the underlying data, thereby preserving privacy.

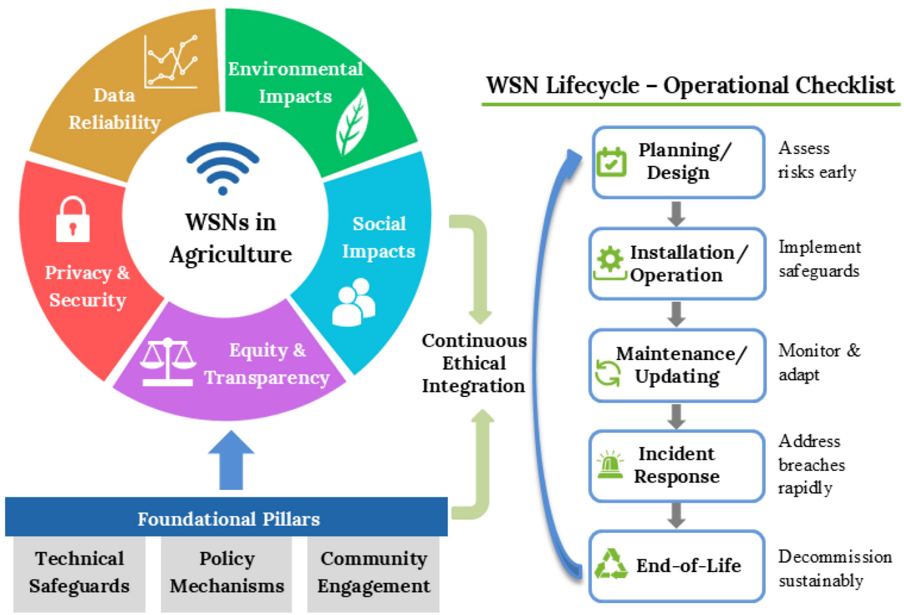

FIGURE 1
Ethical framework for WSNs: integrating data reliability, privacy, equity, social, and environmental impacts with technical safeguards, policy mechanisms, and community engagement via a lifecycle checklist.

against unauthorized alterations safeguard against cyber threats like malware (Kerliu et al., 2019). In the Global South, where infrastructure is variable, low-cost solar-powered nodes and mobile interfaces enhance accessibility by leveraging high smartphone penetration to align with local realities. These embedded measures make WSNs robust, transparent, and ethically grounded.

Policy mechanisms play an equally critical role in guiding the responsible use of WSNs. Governments can legislate data protection standards, mandating encryption for data transmission, authentication protocols for user verification, and clear guidelines on ethical data handling, including rules for third-party sharing (Ferris, 2017). In partnership with industry, policymakers should craft frameworks for data exchange, covering sensor-generated data ownership, informed consent requirements for farmers, and accountability via misuse penalties. Economic tools such as subsidies to offset sensor costs for smallholders in the Global South, tax incentives for eco-friendly deployments, and sustainability certifications for low-impact systems can drive adoption while addressing environmental risks like battery disposal. Furthermore, ethical labor standards, workforce reskilling for digital tasks like sensor maintenance, and social safety nets to counter automation-induced job losses in manual monitoring ensure that innovation supports economic resilience, social equity, and environmental stewardship.

At the core of this triad lies community engagement, which grounds WSN integration in local contexts and values. Educating farmers and stakeholders on benefits like real-time crop monitoring for improved yields, alongside limitations such as battery dependency or network gaps, and rights to control or delete data, empowers informed choices. Community-led structures like cooperatives for collective data management or advisory boards for deployment reviews foster transparent, participatory oversight. Involving locals in planning sensor placements with field-specific knowledge, providing hands-on installation training, and facilitating data dashboard interpretation aligns technologies with community priorities, boosting acceptance and trust (Carolan, 2017). In the Global South, co-design incorporating indigenous knowledge such as traditional agroforestry practices for pest management into algorithms and training in local languages further enhances relevance and equity. Ongoing dialogues among farmers, researchers, policymakers, and environmental advocates can co-create region-specific ethical standards, adapting to challenges like arid climates or smallholder systems.

To operationalize this framework, we propose a lifecycle-aligned checklist (Table 1) spanning five stages: (1) Planning/Design: Assess risks early; (2) Installation/Operation: Implement safeguards; (3) Maintenance/Updating: Monitor and adapt; (4) Incident Response: Address breaches rapidly; (5) End-of-Life: Decommission sustainably. This structured approach embeds ethics continuously across the WSN lifecycle.

4 Conclusion

WSN deployments mark a new era in agriculture, creating unprecedented opportunities for efficiency and sustainability. To fully realize these benefits, a comprehensive ethical framework is

8 Over-the-air firmware updates are wireless updates that install new software on devices such as sensors without requiring physical connections, enhancing security by enabling remote patching of vulnerabilities.

TABLE 1 Lifecycle ethics checklist for WSN deployments.

Stage	Technical safeguards	Policy mechanisms	Community engagement
Planning/design	Conduct bias audits on data models; integrate federated learning for privacy-preserving collaboration (Žalik and Žalik, 2023).	Develop transparent and easy-to-read data license agreements and obtain informed consent (Kaur et al., 2022); assess equity impacts for smallholders.	Consult local farmers on needs; form advisory boards to incorporate indigenous knowledge.
Installation/operation	Deploy redundant sensors for reliability; use data anonymization to protect data in transit (Amiri-Zarandi et al., 2022).	Enforce data encryption standards (Hazrati et al., 2022); monitor for labor displacement via usage logs.	Train users on intuitive interfaces; collect feedback through community platforms.
Maintenance/updating	Perform over-the-air firmware updates with tamper detection (Kerliu et al., 2019); validate against environmental baselines.	Update policies for emerging threats (e.g., AI bias regulations); incentivize electronic waste recycling.	Involve locals in upkeep; reskill workers for sensor maintenance roles.
Incident response	Activate fault isolation algorithms (Jihani et al., 2023); isolate breaches to prevent data leaks.	Report incidents per legal frameworks; audit for equity violations.	Notify affected communities promptly; co-develop recovery plans.
End-of-life	Design for recyclability; assess full ecological footprint using environmental assessment methods (Bonvoisin et al., 2012).	Mandate decommissioning protocols; repurpose hardware for community use; restore land if damaged	Share technical knowledge; evaluate long-term social impacts.

needed that integrates technical safeguards, policy mechanisms, and community engagement. Addressing issues of data reliability, privacy, equity, labor, and environmental impact through a unified lifecycle approach transforms WSNs from neutral tools into accountable systems that adapt to real-world conditions. This framework, illustrated with case examples, highlights ethics across deployment stages from pre-deployment to end-of-life. Future research should test its applicability in diverse agroecological contexts, quantify long-term outcomes, and refine policies that both empower farmers and foster innovation. Ultimately, embedding ethics into WSNs can advance digital agriculture that is not only high performing but also equitable and environmentally responsible.

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