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Data sovereignty and valuation model for sustainable agriculture innovation and equity

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This paper examines farmer data sovereignty and valuation approaches as critical elements for advancing sustainable agriculture. It analyses technological, educational, legal, economic, and methodological barriers to implementation, proposing a holistic approach to overcome these challenges. The study introduces an innovative data valuation model incorporating investment costs, potential commercial usage, and ecosystem services value, along with a framework for integrating this value into agricultural accounting practices. By exploring successful case studies, emerging technologies, and gender equity considerations, the paper offers insights for policymakers and stakeholders. It emphasises the need for collaborative efforts between farmers, researchers, policymakers, and technology providers to create a more sustainable, resilient, and equitable agricultural system. The study concludes by outlining future research directions to further develop and refine these approaches in the context of evolving agricultural practices and technologies.

The transformation of agriculture is a critical transition requirement to ensure planetary sustainability[1]. The sector is both a key driver of climate change and one of the most vulnerable to its adverse impacts. With the increase in global population, food production is pressuring water and land systems both in terms of usage and pollution[2]. To quantify and reduce the impacts of agricultural practices on the environment, a market and policy push towards digital agriculture and smart farming is under way[3]. This digital transition is demanding farmers create, monitor, track and release their data to government entities and private operators. This often creates an environment of unfair competition where small and non-digitally native entities are quickly losing control over their data and the value that they represent[4].

This trend is particularly evident in developed economies such as the United States, European Union member states, and Australia, where farmers are increasingly expected to create, monitor, track and release their data to government entities and private operators for compliance and optimisation purposes[5–7]. In emerging economies such as India, Brazil, and across Africa, digital agriculture initiatives (and therefore the need for farmer's data) primarily focus on financial inclusion, market access, and productivity enhancement rather than environmental compliance. For instance, India's Rs 2817 crore Digital Agriculture Mission emphasises farmer identity systems and market integration[8], while Brazil's initiatives target traceability for export competitiveness[9]. In sub-Saharan Africa, where 65% of the labour force works in agriculture but receives less than 1% of commercial bank loans, digital technologies primarily address information asymmetries and credit access rather than environmental monitoring[10,11].

Farmer data represents a critical yet undervalued asset in modern agriculture. Agricultural operations generate vast amounts of valuable information, including yield data, soil health metrics, weather patterns, input usage, and biodiversity indicators. This data drives precision agriculture technologies, informs climate adaptation strategies, and provides essential insights for sustainable farming practices.

The economic value of this data extends beyond individual farms, contributing to agricultural research, supply chain optimisation, and environmental monitoring. However, farmers often lack recognition for their role as data producers and receive limited compensation for the value their information generates. Establishing appropriate valuation frameworks and sovereignty protections is therefore essential for ensuring equitable participation in data-driven agricultural systems while advancing sustainability goals.

Addressing data sovereignty and valuation (DSV) in agriculture is of critical importance as we move towards more digitised and data-driven farming practices. Many recent studies have estimated DSV potential to support transitions to sustainable agriculture practices. For instance, Newton et al. [12] analysed the economic implications of data sovereignty measures in Australia, estimating a potential 5–10% increase in farm profitability due to improved decision-making. Similarly, Hackfort et al. [13] examined the effects of data valuation approaches in Canada, suggesting

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that farmers could capture an additional 15–20% of the value chain by monetising their agricultural data.

This paper reviews the state of the art of farmer data sovereignty and valuation approaches and analyses the barriers to implementation. It proposes a novel data valuation model that incorporates investment costs, potential commercial usage and ecosystem services value. The model offers innovative ways to quantify and recognise the value of agricultural data as an asset. This could potentially transform how we think about and manage agricultural data, leading to more equitable outcomes for farmers and contributing to the broader goals of environmental sustainability and climate resilience in agriculture. What is at play is an immature and inadequate set of approaches to protect farmers' data sovereignty while supporting innovation towards sustainable agriculture practices[14].

Current approaches to implementing data sovereignty and valuation in agriculture face multiple challenges, including technological, educational, legal, economic and methodological barriers. There is a need for a holistic, multi-faceted approach to overcome these challenges involving technological solutions, educational initiatives, legal reforms, economic incentives and policy interventions.

Furthermore, the policy implications of the comprehensive analysis of barriers and potential solutions provide valuable insights for policymakers and stakeholders working to implement data sovereignty and valuation approaches in agriculture. Finally, the authors propose future research directions and practical applications; therefore, contributing to a comprehensive framework for understanding and addressing the critical issues of data sovereignty and valuation approaches in agriculture with potential far-reaching implications for sustainable farming, farmer livelihoods and food security in the digital age.

Results

Literature synthesis and current approaches

The relationship between data sovereignty and valuation approaches and agricultural sustainability operates through three primary mechanisms: enhanced decision-making capabilities, improved resource allocation, and incentivised adoption of sustainable practices. Enhanced decision-making capabilities emerge when farmers retain control over their data and can access comprehensive information about their operations, enabling more informed choices about sustainable farming methods. Improved resource allocation occurs when accurate data valuation allows farmers to capture fair compensation for their information contributions, providing financial resources to invest in sustainable technologies and practices. Incentivised adoption of sustainable practices results when data valuation models explicitly recognise and reward environmental stewardship, creating economic drivers for sustainability transitions. These mechanisms work synergistically to transform data from a passive byproduct of farming into an active catalyst for agricultural sustainability.

Several recent studies have demonstrated the potential for data sovereignty and valuation approaches to support agricultural sustainability transitions through these interconnected mechanisms. Enhanced decision-making capabilities have been particularly evident in research examining economic implications of data sovereignty measures.

The mechanism of improved resource allocation becomes apparent when examining how data sovereignty enables farmers to reinvest financial gains from data monetisation into sustainable practices. Implementation of DSV approaches is generally assumed to have mixed effects, potentially reducing short-term productivity but improving long-term sustainability. For example, Hatanaka et al. [3] conducted a study focusing on the potential long-term benefits of data-driven sustainable practices. Their research indicated that while there might be an initial 3–5% decrease in yields during the transition period, long-term yields could increase by 8–12% due to improved soil health and biodiversity, offering a promising outlook for sustainable agriculture.

The third mechanism, incentivised adoption of sustainable practices, manifests when data valuation models explicitly incorporate environmental benefits, creating financial rewards for sustainability improvements. A study by van den Berg et al. [15] in the Netherlands estimated an initial 3–5% decrease in yields for the first two years, followed by a 7–10% increase in yields and a 15–20% improvement in environmental indicators over ten years. Estimated impacts ranged from modest yield reductions to significant changes in production patterns and trade flows. Country-specific expert elicitations suggested varied effects across crops and regions.

While these estimates guide policy design and provide important insights under plausible assumptions, they are not sufficient and rarely account for positive ecological feedback. Furthermore, all these studies have assumed full adoption across all farms and regions. Due to a lack of field data, these analyses relied on expert estimates or assumptions of impacts to inform economic simulations. For instance, Lefore et al. [16] used a Delphi method with 50 agricultural experts selected based on their extensive field experience in sub-Saharan Africa, with an average of 15 years working directly in the region. While their regional expertise strengthens the validity of assumptions, the limited sample size and potential selection bias warrant careful interpretation of results. Bayram et al. [17] employed agent-based modelling to simulate adoption patterns and impacts in Luxembourg. A flat-rate implementation across all farms and regions seems unlikely. The intensity of data generation and use varies considerably across farm types, which allows targeting of high-impact areas or where alternatives are readily available. As countries prioritise differently, impacts would likely be more dispersed than captured in existing studies.

The interconnected nature of these three mechanisms suggests that effective data sovereignty and valuation approaches must address multiple dimensions simultaneously. There is a need for more comprehensive analyses to measure the potential impacts of implementing DSV approaches on agricultural productivity and sustainability. Improved scientific approaches can better inform decision-making. Current limitations in scope and methodology hinder evidence-based policy. Multifaceted targets require rethinking modelling approaches to capture economic, environmental and social dimensions. In impact studies, feedback between biodiversity and crop yields must be improved[18].

Addressing the complexity

Data sovereignty and valuation targets are more multifaceted than often assumed. Implementation can be achieved across agricultural and non-agricultural sectors. The EU's Code of Conduct on Agricultural Data Sharing[19] and Australia's Farm Data Code[20] offer examples of frameworks balancing farmer rights with innovation needs. Countries could prioritise different sectors in reduction plans, limiting potential negative impacts on food production[21].

Heterogeneity between farmers implies a potential for efficiency gains. Data use intensity depends on many factors, from biological to socio-economic. Studies have found sizable variability in data practices across farms facing similar conditions[22]. Farm-level data collection proposed in some policies will enable a crucial analysis of this heterogeneity to inform targeted interventions, highlighting the adaptability and potential for efficiency gains in the agricultural sector.

Future studies should consider possible market changes. Kone et al. [23] attempted to address this gap by incorporating market dynamics into their East African agricultural systems analysis. They estimated that data sovereignty measures could lead to a 5–8% shift in market share towards smaller, more agile farming operations. Input substitution enables progress towards targets. As indices are often risk-based, substituting data sources and technologies may deliver benefits without impacting farm management[24]. Progress has already been made in some regions through such substitutions. Alternative data sources and technologies like remote sensing offer opportunities for further advances.

Barriers analysis and solutions framework

The implementation of farmer data sovereignty and valuation approaches faces numerous interconnected barriers, creating compound challenges for implementation[25]. Technological barriers interact with economic constraints, as inadequate infrastructure increases implementation costs, disproportionately affecting small-scale farmers. Educational barriers amplify legal challenges, as farmers with limited digital literacy struggle to understand data rights and protection mechanisms. This interconnected nature means that addressing individual barriers in isolation often proves insufficient, requiring comprehensive, multi-faceted intervention strategies.

Technological challenges are particularly prominent, with inadequate rural infrastructure hampering progress. Mishra et al. [26] highlight the critical need for improved internet connectivity and electricity in rural areas. Additionally, the need for interoperability between data systems and formats, as noted by Stendal et al. [27], creates significant obstacles to data sharing and integration. Limited access to user-friendly data management platforms further compounds these issues, making it difficult for farmers to manage and utilise their data effectively. In high-income agricultural contexts, these technological barriers primarily concern upgrading existing infrastructure to support advanced digital agriculture systems, while in low-income contexts, the challenge involves establishing basic digital infrastructure where none previously existed[28]. The cost differential between upgrading and building new infrastructure creates vastly different implementation timelines and resource requirements.

Barriers to education and awareness also play a crucial role. Dalberg Data Insights[29] emphasises farmers' limited understanding of data rights and ownership, which can lead to exploitation and loss of control over valuable information. This issue is exacerbated by a general need for digital literacy and skills, particularly in developing countries. Stendal et al. [27] also point out the prevalent mistrust in digital agriculture initiatives stemming from farmers' perceived loss of control over their operations and data. Educational barriers manifest differently across economic contexts. In developed agricultural systems, farmers typically possess basic literacy and may require specialised training in digital tools and data rights. Conversely, in developing regions, educational interventions must address fundamental literacy alongside digital skills[30], requiring more comprehensive and longer-term capacity building programmes.

Legal and regulatory frameworks present another set of challenges. Sullivan et al. [25] highlight the need for more evident legal structures for agricultural data ownership and sharing, creating uncertainty and potential conflicts. Kumar et al. [31]. further note the inadequacy of data protection and privacy regulations specific to the agricultural sector. These gaps in the legal landscape make it difficult to enforce farmers' data rights effectively, potentially leaving them vulnerable to exploitation. Legal framework challenges vary significantly between jurisdictions. High-income countries often possess sophisticated legal systems but lack agriculture-specific data regulations, requiring targeted amendments to existing frameworks. Low-income countries frequently face more fundamental challenges[32]. With weak rule of law, limited regulatory capacity, and inadequate enforcement mechanisms, necessitating comprehensive legal system strengthening alongside sector-specific regulations.

Economic and financial barriers pose significant hurdles, particularly for small-scale farmers. Silveira et al. [33] discuss the high costs of implementing data management systems, which can be prohibitive for many farmers. Gabriel & Gandorfer[34] emphasise the limited access to funding for small-scale farmers, further widening the digital divide between large and small agricultural operations. This disparity threatens to exacerbate existing inequalities in the agricultural sector. Economic barriers demonstrate stark contrasts between agricultural contexts[35]. In developed economies, farmers may have access to credit and government subsidies but face high technology costs and competitive pressures for rapid adoption. In developing economies, farmers often lack access to basic financial services, making even modest technology investments prohibitive without substantial external support and innovative financing mechanisms.

Methodological barriers complicate the implementation of valuation approaches for sustainable agriculture. Quantifying and monetising environmental, social, and economic benefits remains challenging. Alaoui et al. [36] point out the lack of context-specific frameworks for sustainable agriculture valuation, while Soulé et al. [37] highlight inconsistencies in existing valuation methodologies. These issues make it difficult to assess and reward sustainable farming practices accurately. Methodological challenges reflect different research and institutional capacities[38]. Developed agricultural systems benefit from robust research institutions and data collection capabilities, but struggle with complex valuation methodologies for diverse farming systems. Developing regions often lack basic data collection infrastructure and research capacity, requiring fundamental methodological development alongside technical capacity building.

Market barriers further impede progress. The limited demand for sustainably produced agricultural products and insufficient price premiums fail to incentivise farmers to adopt more sustainable practices. Stock & Gardezi[39] also note the concentrated ownership of data by equipment and service providers, which can limit farmers' control over their information and decision-making processes. Market barriers exhibit distinct patterns across economic contexts. Developed markets often feature sophisticated consumer demand for sustainable products but face challenges with market fragmentation and complex certification requirements. Emerging markets typically demonstrate growing middle-class demand for quality products but lack established premium markets for sustainably produced goods, requiring market development alongside production capacity building.

As Campuzano et al. [40] identified, policy barriers include misalignment between agricultural policies and sustainability goals. Robinson et al. [41] highlight insufficient incentives for adopting sustainable practices, while Kumar et al. [42] point out the need for more support for long-term investments in sustainable farming. These policy gaps hinder the transition to more sustainable agricultural systems. Policy barriers reflect different governance capacities and priorities. High-income countries often struggle with policy coordination across sectors and balancing competing stakeholder interests within democratic systems. Low-income countries frequently face capacity constraints in policy development and implementation, requiring institutional strengthening and technical assistance to develop effective agricultural data governance frameworks.

Addressing the barriers

A multifaceted approach is necessary to overcome these challenges. Technological solutions should prioritise investments in rural broadband and electricity infrastructure, as Mishra et al. [26] suggested. Developing user-friendly, interoperable data management platforms and promoting the adoption of common data standards in agriculture, as proposed by Stendal et al. [27], are crucial steps. Abbas et al. [43] emphasise the importance of designing data systems that respect participant sovereignty and privacy constraints.

Educational and awareness initiatives are essential. Investing in training programmes to improve farmers' digital literacy and data management skills can empower them to take control of their data. *These training programmes should be delivered through established agricultural extension services, farmer cooperatives, and public-private partnerships. Implementation would involve agricultural extension agents, digital literacy specialists, and farmer peer educators working collaboratively to ensure culturally appropriate and accessible training delivery*. Pereira et al. [44] suggest conducting awareness campaigns on the benefits of data sovereignty and sustainable agriculture. Bößner & Mal[45] propose establishing multi-stakeholder learning networks and peer-to-peer knowledge platforms to facilitate sharing and collaboration.

Legal and regulatory reforms are critical for creating a supportive environment. van der Burg et al. [46] call for developing clear legal frameworks for agricultural data ownership and sharing. Kamilaris et al. [47] stress the need to strengthen data protection and privacy regulations specific to the agricultural sector. It is also crucial to ensure that regulations are regularly updated to keep pace with technological advancements.

Economic and financial incentives can significantly drive change. Lioutas & Charatsari[48] suggest providing targeted financial support for sustainable agriculture adoption. *While developing market-based mechanisms such as certification schemes, eco-labels, and payments for ecosystem services can create additional incentives, implementation in low-income countries requires simplified frameworks, reduced administrative burden,* *and phased introduction aligned with existing institutional capacity.* Ensuring fair and consistent price premiums for sustainably produced products is also essential.

Implementation responsibility varies by intervention type. Governments should lead infrastructure investment and regulatory reform, while technology providers must prioritise interoperability and user-friendly design. Farmer organisations can facilitate peer-to-peer learning, and international development agencies should support capacity building in lower-income contexts. Private sector actors should focus on developing affordable, scalable solutions, while research institutions must provide evidence-based guidance for policy development and implementation strategies.

Policy interventions should align agricultural policies with sustainability goals, as proposed by Edelenbosch et al. [49]. Redirecting subsidies towards initiatives promoting soil health, biodiversity, and climate resilience can drive systemic change. Camaréna[50] and Pedersen et al. [51] highlight the potential of using public food procurement to support sustainably produced food. Engaging in multi-stakeholder collaborations to leverage expertise and resources and implementing participatory data governance models, as suggested by Geuns et al.[14], can foster innovation and inclusivity.

Figure 1 (Farmer data sovereignty and valuation: issues, solutions and interactions) summarises the complexity of the barriers to farmer data sovereignty and the challenges to valuation approaches.

Enhancing Data Sovereignty and Valuation Approaches - Examining specific examples of successful data sovereignty and valuation initiatives across different agricultural contexts is crucial to enhancing these approaches. For instance, the European Union's Code of Conduct on Agricultural Data Sharing provides a framework for transparent data exchange in agriculture, balancing farmers' rights with innovation needs[52]. In Australia, the Farm Data Code offers guidelines for agricultural data management, emphasising farmer control and consent[53]. These case studies demonstrate the benefits of transparent data governance and implementation challenges across diverse regulatory landscapes.

The tension between data sovereignty and open data for agricultural innovation presents a complex challenge. While data sovereignty protects farmers' interests, open data can accelerate research and innovation. Bronson[54] argues that carefully managed data-sharing platforms can balance these concerns, allowing for collaborative research while maintaining farmer control over sensitive information. Such platforms could foster innovation without compromising individual data rights.

Emerging technologies offer promising solutions for enhancing data sovereignty and valuation in agriculture. Blockchain technology, for example, can provide secure, transparent records of data transactions and ownership. Kamilaris et al. [47] demonstrate how blockchain can create immutable records of agricultural data, ensuring traceability and farmer control. Artificial intelligence and machine learning algorithms can automate complex valuation processes for ecosystem services, as shown by Liakos et al. [55] in their work on AI-driven sustainability assessments in agriculture.

Gender dimensions of data sovereignty require specific attention to ensure equitable access and benefits. Lefore et al. [16] highlight the gender gap in digital agriculture, noting that women farmers often have less access to digital technologies and lower levels of digital literacy. Addressing these disparities through targeted training programmes and gender-sensitive technology design is crucial for inclusive data sovereignty initiatives. Furthermore, ensuring women's participation in data governance decision-making can lead to more equitable outcomes[56]. Implementation strategies should incorporate gender-responsive indicators to monitor differential impacts and ensure that data sovereignty frameworks do not inadvertently reinforce existing inequalities in agricultural technology access and benefit distribution.

Anticipating and mitigating potential unintended consequences is essential when implementing these approaches. For instance, overly restrictive data sovereignty measures could inadvertently create barriers for small-scale farmers to participate in valuable data-sharing initiatives. Where large agribusinesses control vast amounts of agricultural data, Weersink et al. [57] caution against the risk of data monopolies forming, potentially disadvantageous to smaller operations. Additionally, poorly designed valuation approaches might incentivise unsustainable practices if they fail to account for long-term environmental impacts. As proposed by Dusadeerungsikul & Nof[58], regular monitoring and adaptive management strategies can help identify and address these issues as they arise.

Discussion

This paper contributes to scholarship by proposing an integrated framework linking data sovereignty principles with practical valuation methodologies, addressing a critical gap in agricultural digitalisation literature. The research demonstrates how accounting innovations can operationalise data value recognition while maintaining farmer control over digital assets.

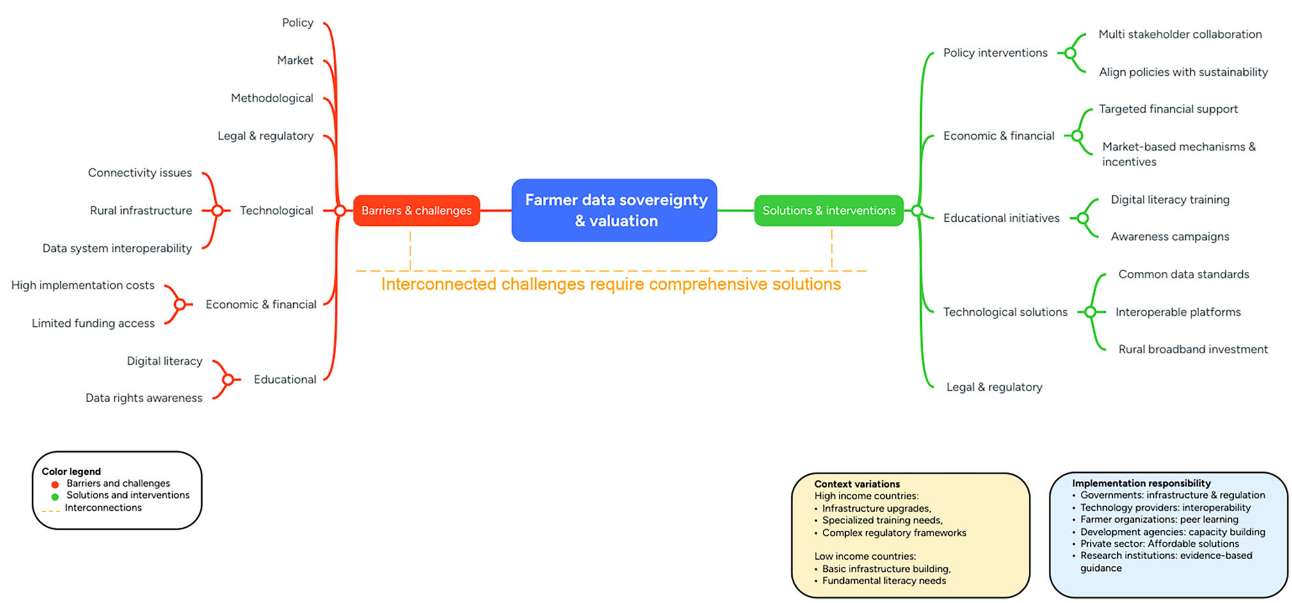

Fig. 1 | Farmer data sovereignty and valuation: issues, solutions and interactions. This conceptual framework illustrates the interconnected nature of barriers (red) and solutions (green) for implementing data sovereignty and valuation approaches in agricultural systems. The complexity of barriers and challenges to valuation approaches.

The comprehensive analysis presented establishes a theoretical foundation grounded in institutional economics, resource-based theory, and Commons governance principles, providing a robust framework for understanding agricultural data as strategic assets. The proposed data valuation model, incorporating investment costs, potential commercial usage, and ecosystem services value, offers practitioners a quantifiable methodology for recognising data value while addressing the complex interplay between economic incentives and environmental stewardship.

The research identifies and systematically addresses interconnected barriers spanning technological, educational, legal, economic, and methodological dimensions. The analysis demonstrates how these barriers manifest differently across high-income and low-income agricultural contexts, requiring tailored intervention strategies that acknowledge varying infrastructure capabilities, regulatory frameworks, and market development stages. The proposed solutions emphasise multi-stakeholder collaboration and context-specific implementation approaches that balance innovation potential with farmer sovereignty protection.

The integration of the valuation framework with natural capital accounting systems represents a significant methodological advancement, enabling comprehensive assessment of agricultural assets that encompasses both traditional economic measures and environmental contributions. The accounting treatment proposed for agricultural data as intangible assets provides a practical pathway for implementing data valuation while maintaining conservative financial reporting standards appropriate for emerging asset categories.

The mathematical consistency framework ensures robust implementation across diverse agricultural contexts through established multi-criteria decision analysis methodologies. The weighting factor ranges and normalisation procedures provide operational guidance while maintaining flexibility for different farm types and regional conditions, addressing practical implementation challenges identified in the literature.

Priority research areas include developing context-specific weighting methodologies for the valuation model across different agricultural systems, conducting longitudinal studies in pilot regions to validate model effectiveness, and investigating institutional mechanisms for scaling data governance frameworks. Additional research priorities encompass examining the relationship between data sovereignty implementation and agricultural productivity outcomes, developing standardised metrics for ecosystem services valuation in agricultural contexts, and assessing the effectiveness of different stakeholder engagement models in promoting equitable data governance.

Empirical validation represents a critical next step, requiring controlled studies across diverse agricultural systems to test model effectiveness and refine weighting methodologies. Such studies should examine both short-term adoption patterns and long-term sustainability outcomes, with particular attention to differential impacts across farm sizes, geographic regions, and crop types. Research should also investigate the institutional arrangements necessary for scaling data governance frameworks from individual farm implementations to regional and national agricultural systems.

The policy implications suggest that successful implementation requires coordinated efforts across multiple governance levels, with particular attention to regulatory frameworks that protect farmer data rights while enabling innovation. The research indicates that market-based mechanisms for data valuation require supportive institutional infrastructure, including standardised valuation methodologies, transparent pricing mechanisms, and accessible technical support for smaller agricultural operations.

Moving forward, the adaptive management approach outlined in this research emphasises the importance of regular review and adjustment based on emerging evidence and technological developments. The framework's flexibility allows for evolution as agricultural data markets mature and environmental valuation methodologies advance, ensuring continued relevance as the digital transformation of agriculture progresses.

The success of these initiatives ultimately depends on fostering collaborative relationships among farmers, researchers, policymakers, and technology providers that prioritise trust, transparency, and equitable benefit distribution. By implementing the integrated framework proposed in this research, stakeholders can advance toward a more sustainable, resilient, and equitable agricultural system that harnesses the value of digital technologies while preserving farmer autonomy and environmental stewardship principles essential for long-term food system sustainability.

Methods

Theoretical framework

The analysis draws on institutional economics theory to understand data governance challenges, resource-based view of the firm to conceptualise data as strategic assets, and commons theory to address collective action problems in data sharing. Institutional economics provides the foundation for understanding how formal and informal rules shape data governance relationships between farmers, technology providers, and government entities[59]. The resource-based view positions agricultural data as intangible assets that can provide competitive advantages when properly managed and valued, similar to other knowledge-based resources that generate sustainable competitive advantage[60] Commons theory addresses the collective action challenges inherent in agricultural data sharing, where individual farmers must balance private data control with collective benefits from data aggregation and analysis[61,62]. These theoretical perspectives collectively inform our understanding of how data sovereignty and valuation mechanisms can be designed to promote both individual farmer welfare and broader agricultural sustainability goals.

Innovative Data Valuation Model in Agriculture and Related Accounting Impacts: To address the gap in the current literature regarding data valuation in agriculture, we propose an innovative model that builds on both investment costs and potential commercial usage. The model is expressed as Eq. (1):

$$(\mathrm{DV} = (\mathrm{IC}^{*}\alpha) + (\mathrm{PCU}^{*}\beta) + (\mathrm{ESV}^{*}\gamma) \tag{1}$$

Where:

DV = Data Value
IC = Investment Cost
PCU = Potential Commercial Usage
ESV = Ecosystem Services Value
α, β, γ = Weighting factors based on data type and market conditions

Investment Cost (IC) includes data collection, storage, and management expenses. Potential Commercial Usage (PCU) is calculated based on market demand for similar datasets and potential applications in tech innovations. Ecosystem Services Value (ESV) quantifies the data's contribution to environmental sustainability, drawing on methodologies proposed by Sudardeva & Pal[63].

Weighting factors should reflect data type characteristics, with α emphasising cost recovery for basic operational data, β prioritising market value for commercially valuable datasets, and γ highlighting environmental impact for sustainability-focused data collection. The determination of appropriate weighting factors requires consideration of the data's primary purpose, market maturity for specific data types, and policy priorities[64]. regarding environmental sustainability[65].

To illustrate model application, consider a 500-hectare wheat farm investing $10,000 annually in data collection (IC), with comparable datasets valued at $15,000 in agricultural technology markets (PCU), and generating ecosystem services worth $8000 through carbon sequestration tracking (ESV). Using equal weighting ($\alpha = \beta = \gamma = 0.33$), the data value equals $10,890. This practical example demonstrates how the model integrates multiple value dimensions while providing transparent valuation methodology that can be adapted across different farming contexts and data types[66]. The model empirical demonstration and accounting explanation can be found in the Supplementary Information.

To integrate this value into balance sheets, we propose recognising agricultural data as an intangible asset, like intellectual property. The journal entry would be:

Table 1 | Example view of ledger entry for agricultural data asset recognition

Account no	Account name	Amount (USD)
1610	Dr. Agricultural Data Asset	100,000.00
3410	CR. Data Valuation Reserve	100,000.00

This accounting framework demonstrates the journal entries required to recognise agricultural data as an intangible asset on farm balance sheets.
Journal Entry
Agricultural Data Asset Recognition
Date: 2024-09-23

Dr. Agricultural Data Asset XXX
Cr. Data Valuation Reserve XXX

The debit entry creates a new "Agricultural Data Asset" account, where "Dr." stands for "Debit". In accounting, debits increase asset accounts. Here, we will create a new "Agricultural Data Asset" asset. The XXX represents the monetary value assigned to this data using the valuation model proposed earlier ($DV = (IC * \alpha) + (PCU * \beta) + (ESV * \gamma)$).

The corresponding credit entry, "Cr." stands for "Credit". This line creates a corresponding credit entry to balance the debit. The "Data Valuation Reserve" is a type of equity account similar to a revaluation reserve used for other assets.

In the example above (Table 1 : Example - View of ledger entry), the 1000–1999 range is often used for assets, which is why the Agricultural Data Asset is given a number in the 1600 s (possibly indicating other intangible assets). The 3000–3999 range is often used for liabilities and equity accounts, which is why the Data Valuation Reserve (acting as a contra-asset or valuation account) is given a number in the 3400 s. Of note, this positioning is a *parti pris*. Indeed, Contra-Asset Accounts also often use the same first three digits as the related asset, with the last digit indicating it's a contra account. Hence, the numbering could also be 1610 and 1619.

These account numbers help in organising the general ledger and make it easier to locate and track specific types of transactions.

The purpose of this accounting treatment serves four primary objectives:

1. Recognise the value of agricultural data as an asset on the balance sheet, which reflects the growing importance and value of data in modern agriculture.
2. Create a separate reserve account to offset this asset rather than immediately recognise it as income. This conservative approach acknowledges the unique nature and potential volatility of data valuation.
3. Provide transparency about the value of data assets to stakeholders, including investors, lenders, and partners.
4. Allow for potential future adjustments. If the data's value changes, the asset and reserve accounts can be adjusted to update it.

The proposed methodology has potential to create value in the agricultural sector, pending empirical validation and field testing, rather than representing established practice with proven outcomes. The recognition of data as intangible assets aligns with emerging accounting standards for digital assets while acknowledging the unique characteristics of agricultural information systems[67]. Implementation requires careful consideration of valuation uncertainty, periodic revaluation protocols, and regulatory approval from relevant accounting standards bodies.

This approach is novel in the agricultural sector and reflects an attempt to align accounting practices with the realities of the digital age. However, it is essential to note that this method is proposed and has yet to be widely adopted or recognised by accounting standards. Implementation requires approval from accounting bodies and regulators.

Using a reserve account (rather than directly increasing equity or recognising income) also provides a buffer against potential overvaluation, reflecting the uncertain and evolving nature of data valuation in agriculture.

This approach aligns with recent developments in accounting for digital assets[68] while reflecting the unique characteristics of agricultural data.

Another advantage of our methodology intended for assessing agricultural data as an intangible asset is that it can be incorporated into natural capital accounting, thus offering a more comprehensive perspective on a farm's aggregate assets, including its ecological resources. Natural capital accounting measures the economic worth of ecosystem services and natural resources. *Natural capital accounting* is an emerging field that aims to quantify and integrate the value of ecosystem services and natural resources into economic decision-making and national accounts. It encompasses tangible assets like minerals and timber, and intangible services such as pollination and carbon sequestration. According to a study by Bastien-Olvera et al. in Nature[69], this approach provides a more comprehensive view of a nation's wealth and well-being than traditional economic indicators alone. In Australia, the government has implemented a national environmental-economic accounting system. For example, the Australian Bureau of Statistics reported in 2024 that the Great Barrier Reef contributed an estimated AU$6.4 billion annually to the economy through tourism and ecosystem services[70], highlighting the importance of preserving this natural asset for both ecological and economic reasons. This vision aligns well with the Ecosystem Services Value (ESV) part of the proposed data valuation model. By integrating agricultural data valuation into natural capital accounting, agriculturists and policy-makers may better comprehend the interrelationship between agrarian practices, data management, and environmental sustainability[71].

In the end, such integration particularly supports data sovereignty principles by explicitly recognising and quantifying the value farmers create through sustainable practices, incentivising the collection and management of environmentally beneficial data[72].

Data sovereignty in agriculture underscores agriculturists' control over their data and potential value, which the proposed model supports by explicitly recognising and quantifying[52]. The proposed methodology represents a significant conceptual advance that requires empirical validation to demonstrate practical effectiveness in agricultural contexts. Moreover, including ESV in the valuation model incentivises collecting and managing data that buttresses sustainable farming practices. This approach could encourage agriculturists to adopt more environmentally benign methods, as the data generated from these practices would possess recognised value on their balance sheets.

However, challenges persist in standardising these valuation methods across diverse agricultural contexts and ensuring that the data used for valuation adheres to established data sovereignty principles while maintaining comparability across different farming systems[73].

Data availability

All data generated or analyzed during this study are included in this published article [and its supplementary information files].

Code availability

No custom code was developed for this study. The mathematical model uses standard arithmetic operations.

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Author contributions

All authors, Stephanie Camarena (SC) and Caroline Gans Combe (CGC), have read and approved the manuscript. Conceptualisation: SC and CGC contributed to the conceptual framework development. Data Curation: Data collection and validation were performed collaboratively between SC and CGC. Formal Analysis: Economic analysis conducted by CGC. Investigation: Case study implementation conducted by SC and CGC. Methodology: Integrated framework design by SC and CGC. Resources: Access to data and computational resources were conducted by SC and CGC. Validation: Results validated through multiple iterations and analysis were conducted by SC and CGC. Visualisation: Figures and data presentation were conducted by SC and CGC. Writing—Original Draft: Manuscript preparation and initial draft was done by SC and CGC. Writing—Review and Editing: Manuscript revision and final editing were done by SC and CGC collectively.

Competing interests

The authors declare no competing interests.

Additional information

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