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A Farm-To-Fork Framework to Assess the Scope and Limitations of Agricultural Data Structures

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ABSTRACT

Farming methods efficiency, agrifood systems sustainability, food traceability, and supply chain transparency depend on robust data management systems. However, current agricultural data structures (schemas, models, frameworks, file systems, etc.) and infrastructures remain disjointed across pre- and post-harvest processes, often focussing on certain supply chain stages. This paper contributes an assessment of the scope and limitations of current agricultural data structures through a new proposed framework named AgrIMAF (Agricultural Information Model Assessment Framework). AgrIMAF is a three-layered framework composed of (a) supply chain stages, (b) stakeholders, and (c) data flows produced and required by stakeholders across the chain, each serving as a criterion to assess agricultural data structures identified through a systematic literature review. We assessed 30 data structures with AgrIMAF, revealing a predominant emphasis on preharvest stages, while postharvest stages are markedly underrepresented. Stakeholders such as customers, insurers, dietitians, and waste managers were predominantly neglected in the investigated data structures. The analysis indicates extensive coverage of crop, weather, and soil data, however post-harvest categories such as traceability, marketing, consumption, and waste are frequently absent. Sustainability initiatives and biodiversity metrics are infrequently acknowledged. AgrIMAF provides a diagnostic instrument to evaluate information systems and enhance sustainable, transparent supply chains.

1 | Introduction

With growing worldwide socio-environmental concerns, the agricultural sector is increasingly being challenged to deal with complex issues related to food security, environmental and social justice, as well as consumer expectations [1, 2]. Given this context, data becomes the lifeblood of the industry as it is instrumental to meet several objectives related to efficiency, sustainability, agility, resilience, as well as stakeholders relationships along the entire supply chain [3–5]. Indeed, data represent the unique ingredient that enables the concept of precision agriculture, which is rooted in the premise of reducing agricultural inputs, minimising environmental impact, and enhancing sustainability of agricultural practices [6, 7]. Due to this paradigm, it becomes possible to perform targeted applications of agricultural inputs [8]. Despite the numerous benefits of agricultural data, the real challenge lies in their adequate management due to their heterogeneous nature, which hinders seamless integration and use in integrated analyses [9].

Access to timely and seamlessly interpretable data is rarely on par with grower decision-making processes, which depend on multidimensional heterogeneous data sources [10]. Indeed, data management and curation along the entire data value chain

Summary

- A framework named AgrIMAF is proposed and used as a three-tier assessment structure to evaluate the scope and limitations of 30 existing agricultural data structures taken from the literature.
- The results reveal a disproportionate emphasis on pre-harvest stages data management compared to post-harvest stages along with a notable schism across the farm-to-fork data value chain.
- AgrIMAF is designed to guide the development of more comprehensive agricultural data models aimed to meet the requirements of sustainability, traceability, and interoperability across the agricultural supply chain.

remains the main bottleneck to achieve this goal [11–14]. Forney and Dwiartama [15] describe the agricultural data management process as a 'very messy and complex process'. This complexity may have arisen from the proliferation of short-sighted idiosyncratic solutions focussing on specific components or steps of the supply chain [16, 17]. Consequently, these fractured solutions make it arduous to set up a streamlined and consistent data system that integrates the relevant supply chain information in a findable, accessible, interoperable and reusable (FAIR) manner [11, 18].

Current agricultural information models designs do not fully embrace the plurality of data (a) produced by various agricultural technologies and (b) needed by every actor along the supply chain. For instance, recent analyses [19] have criticised the parochial view of existing agricultural data models and highlighted that farm-to-fork transparency challenges are only addressed from the moment of harvest. Thus, the pre-harvest processes, while holding the potential to catalyse new sustainability-oriented consumer markets and ecolabel-based revenue models, are currently neglected in information models that aim to support farm-to-fork data management. With the emergence of environmentally conscious consumer markets [20] and corporate environmentalism as market strategy [21], it becomes imperative to bridge the gap between pre-harvest and post-harvest processes to truly enable a comprehensive farm-to-fork information pipeline.

A standard and comprehensive data model facilitating discovery and interoperability between different acquisition platforms and devices is widely regarded as an sinae qua non condition to bridge the pre-to post-harvest gap while delivering numerous benefits to the agricultural sector [19, 22, 23]. To develop a comprehensive information model, a thorough analysis of existing agricultural information models to identify their scope and limitations is a prime requirement. However, currently, there is a lack of a clear understanding of the capabilities of existing information models and the components of the supply chain they cover. One way to address this gap is to conduct a systematic literature review. But, even a systematic literature review would only provide a partial understanding of this gap. Prior work in this area focused on features and barriers to adoption of Farm Management Information Systems [24] and on the mapping of current applications, benefits, and challenges of the internet of Things (IoT) in the agricultural sector [25]. These achievements overlooked the data dynamics (data supply and demand) among stakeholders across the supply chain, which represents a more transparent way to address the data flow challenge across the entire supply chain. Hence, we argue that a holistic framework integrating all stages of the supply chain, actors, and data requirements and production of every actor would be a complementary but a more potent tool to further assess the scope and limitations of existing information models while providing the basis for guiding the development of more streamlined and more holistic information models.

The objective of this paper is to introduce a more holistic and integrated perspective on current agricultural information models which suffer, for example, from the following fragmentation issues: (a) a parochial view (field trials, farm machineries, field operations, or food traceability) of the supply chain [13, 26, 27], (b) poor interoperability due to lack of standards data schemas and controlled vocabularies adoption [11, 12, 18, 28]. We begin by retrieving and assessing relevant existing information models focussing on crop production, highlighting their unique features to, finally, illustrate the stages along the supply chain these models cover. To round this assessment, we propose a new Agricultural Information Models Assessment Framework (AgrIMAF) as an objective framework to assess the scope and limitations of agricultural data structures found in the literature.

2 | Methods

Our study adopts a fully streamlined approach to realize a systematic literature review to minimise references selection bias and enhance the reproducibility of the results. In a first step, we use the PRISMA framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses [29] and its flow diagram composed of 4 steps (identification, selection, eligibility and inclusion) designed to select relevant studies based on predefined inclusion and exclusion criteria and research questions. While the framework introduces the critical elements for a systematic review report and ensures adequate transparency in literature review procedure, it does not support the references searching process. This is an important aspect to avoid selection bias and to enhance the reliability of results [30, 31]. To compensate for this shortcoming, we used an emerging and promising framework named STAR [32], which is a transposition of the PICO (Population, Intervention, Comparison, and Outcomes [30]) framework for application in environmental sciences. We illustrate this approach in Table 1.

The first step of the PICO framework application, thus of the STAR framework, is to establish research questions governing this literature review.

- *How effective are existing agricultural data structures in addressing farming operations to meet the needs and challenges of stakeholders across the supply chain?*

Based on the STAR framework, we developed our search strategy using similar terms and keywords organised as Boolean equations to retrieve references related to data structures corresponding to each of the STAR elements Table 2. Thus, bibliographic references were collected independently for each one.

Using the sample Boolean equations defined in Table 2, 1565 references were identified from different databases including Web of Science, Scopus, Engineering Village, and Google Scholar. The software tool named Rayyan [33] was used to filter the references to determine the truly relevant ones. 376 of the references were deemed duplicates and, hence, omitted. After this first stage, the remaining 1189 records were analysed based on their title and abstract, resulting in the exclusion of 1125 based on the eligibility criteria defined below. The full text of the remaining 65 references were all retrieved and further assessed for relevance; 35 of them were excluded as they did not meet our criteria. Finally, 30 studies were deemed eligible for inclusion in this review. This process is summarised in Figure 1. Our inclusion criteria for the references found in the literature were as follows:

- Thematic relevance: articles must focus specifically on crop information systems and not on a sub-system information such as soil, climate, etc.
- Period of publication: articles published from 1990 through 2024 because more comprehensive agricultural information systems started with precision farming technologies development around the 1990s.
- Type of publication: only research articles, systematic reviews, and case studies.
- Articles themes: articles that discuss agrifood databases, datasets, file systems and information models.

To thoroughly assess the effectiveness, thus scope and limitations, of agricultural information systems introduced in the selected papers, we have designed the Agricultural Information Model Assessment Framework (AgrIMAF; Figure 2) based on four fundamental guiding principles:

a. Systems thinking, that is, AgrIMAF is designed from the supply chain (from farm to fork) perspective, in response to the aforementioned shortcomings of existing models, which are often limited to certain stages (e.g. cultivation, harvesting). We have therefore structured the framework around 12 key stages of the agri-food system, from preplanting to post-consumer waste management, in order to foster a systemic and comprehensive view of the supply chain when designing agricultural data structures. Hence, this principle is a cornerstone for the framework to address current challenges such as poor representativeness, and incompleteness in agri-food system data [34, 35].

b. Modularity and extensibility, that is, AgrIMAF is thought as a referential for case-specific agricultural information models design. Therewith, it considers the inclusiveness of

TABLE 1 | Summary of the translation of the PICO framework to the STAR framework.

PICO components	STAR components	Definition
P (population)	S (system)	Agricultural systems or sub-systems; soils; cropping systems; agricultural supply chain stakeholders.
I (intervention)	T (trouble/treatment)	Farming operations; agronomic inputs (e.g., pest management, irrigation, fertilization); prescriptive information; precision agriculture; agronomic amendments.
C (comparison)	A (alternative)	—
O (outcome)	R (response)	Biophysical properties (e.g., growth stages, yield, vegetation indices); agricultural data modelling; farm management information systems.

TABLE 2 | Summary table of the research strategy adopted.

STAR components	Terms	Sample keywords and Boolean equations
S (system)	Agricultural systems and sub-systems	Cropping systems database OR soil data management OR agri-food supply chain traceability information OR farm machinery management information.
T (treatment)	Agronomic treatments	Agricultural operations management OR precision nutrient sensing OR precision pest management data OR precision agricultural inputs OR crop pest and disease management OR irrigation management OR fertilization prescription maps OR smart agriculture systems OR soil amendment management OR farm management information system OR agricultural information system OR agricultural decision support system.
A (alternative)	—	—
R (response)	Physical and digital responses	Biophysical data in agriculture OR crop productivity information OR crop status information OR agricultural yield data OR vegetation indices.

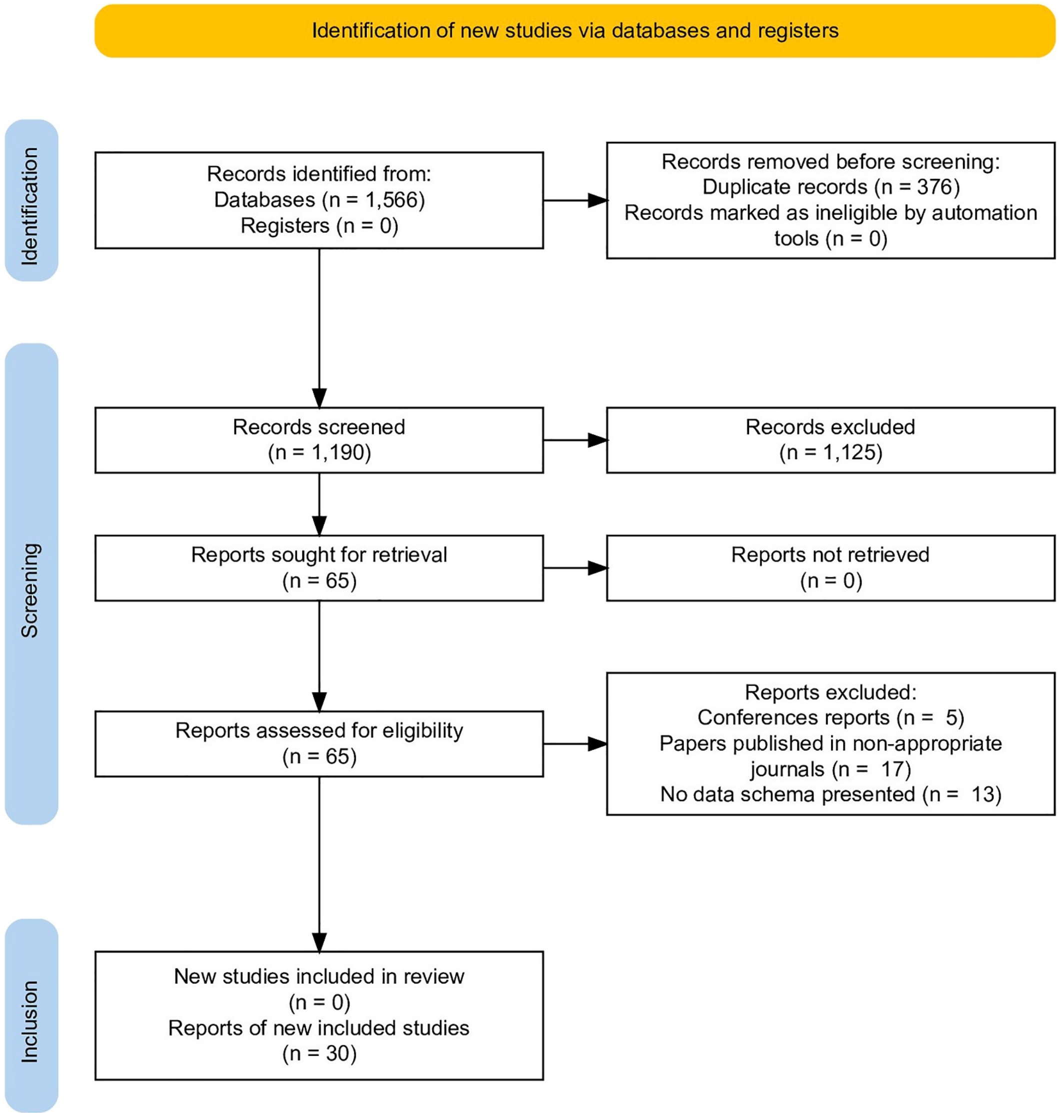

FIGURE 1 | PRISMA flow diagram illustrating the research selection process.

concerned actors and their information along with their roles as data suppliers or data requisitioners. Accordingly, AgrIMAF incorporates a cross-actor/phase typology to assess whether existing or under-development data models effectively meet the information requirements of a present case study or can be extended to support a future case study.

c. Scalability, that is, the framework is conceived to cater to the spatially-distributed nature of supply chain actors, especially when considering the 'distributed farmer' concept in the context of precision agriculture where farming decisions are perceived as the result of an assemblage of human and non-human actors beyond the farmer [36, 37].

d. Interoperability: AgrIMAF is also intended to be used as a diagnostic tool to gauge the capability and relevance of generic and community-led data models from other disciplines, such as the Observations Data Model (ODM2) [22] or the Open Geospatial Consortium's Observations and Measurements (O and M [38]) developed for observations data, to be repurposed or adapted to agri-food systems data. These 'exogenous' data models with adequate metadata could become a standard agricultural data model that enacts the farm-to-fork data management goal of the paper. Hence, beyond the design-for-interoperability principle, these data models could support the preceding three design principles.

These four principles are operationalised in a structured and reproducible analysis grid, which can be used to evaluate any existing information model according to its coverage of the supply chain stages, actors and data. As an original contribution of the paper, AgriMAF is presented in the Results section rather than as part of the Methods section.

3 | Results

3.1 | AgrIMAF: The Agricultural Information Models Assessment Framework

Agricultural data are the most important ingredients in enabling targeted application of input resources [6]. However, it has been

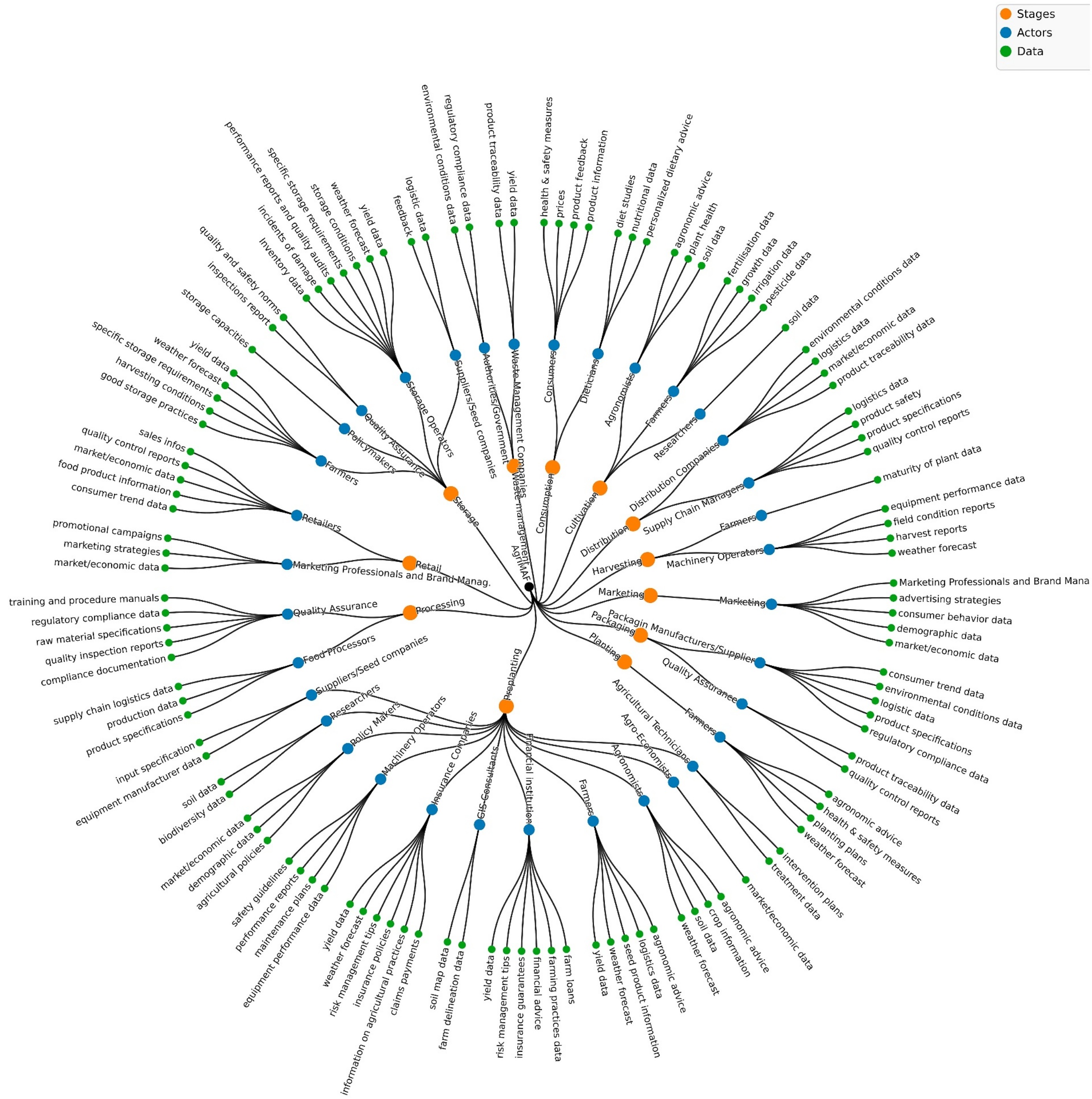

FIGURE 2 | AgrIMAF: the Agricultural Information Model Assessment Framework. The orange dots represent the 12 stages of the supply chain, while the blue dots identify the actors at each stage of the supply and the green dots the data produced or required by the actors.

noted that most of the data structures used to handle them are limited in scope, often focussing on specific steps of the supply chain [19], while neglecting those steps that are relevant to the farm-to-fork context [3, 18]. AgrIMAF (Figure 3) is developed as a structured mechanism to objectively assess the scope and limitations of existing agricultural data structures. This is ground zero for the development of a more integrated agricultural information model that meets this complex web of information supply and demand along the supply chain. Accordingly, it forms the basis for a wider effort to develop information models and data systems that bridge the data chasm of the agricultural supply chain by taking into consideration the interdependency among actors involved and, more importantly the information they exchange.

AgrIMAF is designed to embody, in a layered layout, three pillars of the agri-food systems, that is, the supply chain, the actors and the data, which occupies each one a layer of the framework. Each of these layers serves as an evaluation criterion for agricultural data structures, an approach that highlights gaps in current agricultural data systems and at the same time develop grounds for comprehensive, agricultural data structures that adheres to the farm-to-fork concept. AgriMAF is also designed to support the characterisation of information exchange among actors, that is, data supply and demand schemes across the supply chain [39]. These features are certainly pivotal to a comprehensive assessment of the scope and limitations of agricultural data structures presented in the selected papers.

The first layer includes the 12 key stages of the agricultural supply chain, from pre-planting (P0) to waste management (P11), a consideration that allows the tracking of the entire life cycle of agricultural products. In Table 3, we define all stages of the supply chain to evaluate how well existing models support them. The number of stages covered by a data structure is an indication of the level of visibility required to track the flow of data and information across the supply chain [40]. Thus, the

FIGURE 3 | Chronological evolution of the coverage of supply chain stages by existing data structures. Each row corresponds to a data structures identified in the literature, sorted by publication year (descending). Green cells indicate that the corresponding supply chain phase is covered by the data structures, while white cells indicate non-coverage. A red dashed vertical line separates pre-harvest stages (on the left) from post-harvest stages (on the right).

TABLE 3 | A listing of the 12 stages of the agricultural supply chain actors considered as part of the AgrIMAF implementation.

Phase	ID	Description
Pre-plantation	P0	Encompasses all soil preparation and planning work before crops planting.
Plantation	P1	Seeds planting in prepared soil after careful planning and safety guidelines of farmers.
Cultivation	P2	Ongoing management of the planted crops to harvest stage.
Harvesting	P3	Activities such as cutting or picking, gathering, threshing, and so on.
Storage	P4	Storage of products according to standards and preservation rules.
Processing	P5	Transformation of raw products into consumables.
Packaging	P6	Protecting processed products and putting them into a presentable format.
Distribution	P7	Delivering products to retail and consumption sites.
Retail	P8	Selling agricultural products to end consumers or businesses.
Marketing	P9	Product promotion and distribution using demographic analysis and market data.
Consumption	P10	Consumer feedback phase.
Waste management	P11	Treatment of waste generated throughout the supply chain.

larger the number of stages covered, the more suitable the data structure might be at enhancing the efficiency of agricultural resource allocation and at mitigating waste generation throughout the supply chain [41]. The second layer encompasses the different stakeholders and their association with the supply chain stages of the first layer, a strategy that illustrates roles and interactions across the supply chain. In Table 4, we provide the list of the different actors defined in AgrIMAF and their main roles. Finally, the third layer describes the data flows between the stakeholders.

TABLE 4 | A listing of the actors of the agricultural supply chain considered as part of the AgrIMAF implementation.

Actors	Main roles
Researchers	Provide data on biodiversity, soil, and crop adaptation, supporting scientific research and agricultural practices.
Agronomists	Central actors linking scientific research to agricultural practices, offering advice and yield data based on meteorological and soil information.
Policy makers	Produce agricultural policy data and rely on market, economic, and demographic data for relevant policymaking.
Suppliers/seed companies	Generate information on seeds, logistics, and cultivars; require market data to guide their production.
Farmers	Key producers of yield data, reliant on weather forecasts, logistics, and agronomic advice for optimised production.
Agricultural technicians	Offer data on treatments, intervention plans, and equipment; require safety guidelines for their activities.
Machinery operators	Produce reports on machinery performance and maintenance; need safety guidelines to execute tasks effectively.
GIS consultants	Provide geospatial and soil mapping data; require accurate farm delimitation for resource optimization.
Agro-economists	Analyse market and economic trends, producing insights to guide agricultural decision-making.
Insurance companies	Offer risk management services for agricultural stakeholders.
Financial institutions	Provide funding and financial solutions for agriculture-related operations.
Storage operators	Manage storage conditions and preservation standards; produce inventory and performance reports while requiring yield and weather data.
Quality assurance	Define norms for storage and production; provide inspection reports and ensure adherence to safety standards.
Food processors	Transform raw products into consumables, producing detailed reports on processing rates and logistics requirements.
Packaging manufacturers/suppliers	Provide product specifications and logistics data; require consumer trend data to adapt to ecological and market needs.
Distribution companies	Offer transport and environmental condition data; rely on market and product traceability information for logistics optimization.
Supply chain managers	Ensure timely delivery of products, offering product specifications and quality reports while needing supply chain data.
Retailers	Produce marketing data to understand sales trends and require consumer and product-specific information for strategy refinement.
Marketing professionals And brand managers	Develop marketing campaigns and produce market analysis to attract consumers and improve product performance.
Consumers	Provide feedback on products, enabling companies to refine quality; require information on health and safety standards.
Dieticians	Offer personalised dietary advice based on nutritional studies, helping consumers make informed dietary choices.
Authorities/government	Produce and enforce regulations to ensure compliance across agricultural practices.
Waste management companies	Manage waste effectively to ensure sustainability within the agricultural supply chain.

The third layer is founded on the primary categories of data identified from the various agricultural data structures examined in the literature research. The data kinds were derived inductively by analysing the recurrent areas of information transferred across stakeholders. To guarantee terminological consistency and wider applicability, this first categorisation was later consolidated and confirmed using AGROVOC [42], the multilingual agricultural lexicon created by the Food and Agriculture Organization (FAO).

3.2 | Analysis of the Features of Existing Agricultural Data Structures

In Table 5 below, we describe each of the identified data structures from the selected references by specifying: (a) the citation, (b) the name of the solution, (c) the type of data structures (frameworks, conceptual models, structured files, etc.), (d) their purpose, and (e) their main features. We noticed that current structures take into account the sustainability aspects of agricultural practices, thus, precision agriculture, such as reducing inputs, optimising resources and minimising post-harvest losses [6, 7].

We noticed some chronological patterns in the development of the data structures described in Table 5. For instance, before 2010, data models focused mainly on supporting basic farm management needs including stock, cost monitoring and basic decision support. A particular observation is that some data structures comprise structured and non-structured file systems rather than database management systems [50, 54] For example, the DSSAT model [54] was created to estimate crop growth, development, and yield using biological, economic, and environmental variables. By allowing modular software architecture and integrating with GIS settings, it made basic crop rotation analysis and decision-making possible. Its limited integration capabilities and dependence on stand-alone modules, however, were indicative of the early emphasis on basic tools as well as InfoCrop [50] designed for assessing crop yields, pest-related losses, and environmental impacts in tropical agroecosystems. While it provided valuable insights into crop performance under varying conditions, it lacked real-time data processing or interoperability with other systems, typical of pre-2010 tools.

The fundamental criteria for data were advanced between 2010 and 2015 to include more intricate data models that enable more comprehensive decision-support tools and flexible software systems. Research highlights a Record-keeping and Decision-support System, which is based on PDAs (Personal Digital Assistant) [48]. To help in the production of cucumbers, it makes use of real-time record-keeping, decision support, and traceability thanks to its integration of GIS, fertilization recommendations, and early warning models for pesticide application, it illustrated the growing emphasis on real-time data synchronization and regulatory compliance. Additionally, the ABC [45] model complements the farm management approaches of Activity-Based Costing and Direct Costing. It made it possible to allocate costs accurately according to activities, which made detailed managerial decision-making easier. This model highlighted the transition from basic cost monitoring to comprehensive cost control systems. Even the Farm Management Information System (FMIS) for fruit orchards [49] is designed to manage field operations, optimise resource usage, and improve yield and product quality thanks to its geospatial data, real-time sensor inputs, and mobile/web interfaces for manual and automated data entry, demonstrating the increasing adoption of precision agriculture technologies.

From 2016 to 2019, the internet of Things (IoT), intelligent sensors and predictive analysis systems appeared to have a transformative influence on information systems to support the monitoring of agricultural operations in real-time and automated recommendations. It is the case for the AgDataBox API [55] that integrates both spatial and non-spatial agricultural data to enhance agricultural input resources. The ifarma/ifarma-ffa model [43] is another notable example integrating financial analysis (non-spatial data) and tractor communication (spatial data) to optimise resources and streamline agricultural operations.

From 2020 onwards, we have observed a shift towards a focus on interoperability and collaborative data management between agricultural actors across the supply chain. An example of the implementation of these features is the QUHOMA application that implements the EPCIS model [19] to enable, in a standard-oriented manner, the tracking of the movement and status of products across the supply chain, ensuring transparency and compliance. A second example is the iStar-based data model [44] that focuses on data exchange and the interdependency between farmers, distributors, decision-makers and other stakeholders, reinforcing coordination and efficiency in the supply chain. A third example is the ifarma/Prefer module [58] that implements a geodatabase to overcome data engineering issues as a foundation for decision-making processes in precision agriculture.

We have also observed, there was also a particular emphasis on data sovereignty, traceability and sustainability. For example, the Ploutos model [46] perfectly illustrates this evolution with its semantics-oriented approach that enables stakeholders to control their data while ensuring interoperability with existing systems, thus facilitating more sustainable food supply chains. Similarly, the proposed Farmers' Digital Information System (FDIS) [47] aims to provide small-scale farmers with integrated access to essential services such as agricultural advice, markets and financial services, creating a one-stop shop to improve their resilience and productivity. Finally, the Voluntary Food Traceability Framework [65] considers supply chain processes mapping, identification of tasks and processes that produce data along with their associated format, as well as the acquisition and analysis of traceability data, and the communication of comprehensible and useful food information to the end consumers. All these examples demonstrate that agricultural data systems have evolved from simple tasks recording to integrate resource optimization, processes sustainability, food traceability and collaborative data management throughout the supply chain.

TABLE 5 | Characteristics of agricultural data structures selected for our analysis according to the literature search strategy defined.

Reference	System name	Type	Purpose	Key features
Paraforos et al., 2017 [43]	ifarma/ifarma-ffa	Computational tool	A modular farm management information system designed to plan, monitor and keep records of all farming activities.	Support for financial analysis and tractor communication; cloud-based tool with multi-level automation capability.
Braun et al., 2020 [44]	iStar-based agricultural data platform	Conceptual model	A data and service exchange platform designed for smart farming, enabling inter-organizational collaboration.	Support for data sovereignty and stakeholders communication; provision for data-driven services.
Moysiadis et al., 2023 [19]	QUHOMA	Application (web and mobile)	A web and mobile application for tracking the movement and status of goods throughout any supply chain.	Integration of data on 'what, where, when, and why' of product movements; global interoperability based on the EPCIS standard; integration of controlled vocabularies; IoT sensor data for real-time monitoring.
Carli and Canavari, 2013 [45]	ABC	Conceptual model	A conceptual data model designed to support direct costing and activity-based costing methodologies in farm management.	Accurate cost allocation based on activities; detailed managerial decision-making; farm management systems for enhanced cost control.
Brewster et al., 2024 [46]	Ploutos	Data sharing framework	A semantic-based architecture designed to facilitate sustainable food systems by enabling data sharing in agricultural supply chains.	Data control and sharing by stakeholders; interoperability with legacy systems; integration of semantic technologies; implementation of food traceability and sustainability monitoring.
Mushi et al., 2023 [47]	Farmers' digital information system (FDIS)	Computational tool	A data management system designed to provide smallholder farmers with access to essential agricultural services for sustainable farming.	Integration of farmers, agro-dealers, advisory services, market, and financial services data; improvement in agricultural services sustainability; agricultural practices monitoring; one-stop shop for services essential to farmers.
Li et al., 2010 [48]	PRDS	Application (mobile)	A mobile PDA-based record-keeping and decision-support system designed to assist in cucumber production through real-time record-keeping, decision support, and traceability, in addition to compliance with regulations.	Implementation of a GIS environment; support for real-time data synchronization; implementation of fertilization recommendations and an early warning model for pesticide use.
Tsiropoulos and Fountas, 2015 [49]	Farm management information system (FMIS) for fruit orchards	Computational tool	A system designed for fruit orchards to manage field operations, optimise resource usage, and improve yield and product quality through precision agriculture.	Geospatial data and real-time sensor data; mobile and web-based interfaces for manual and automated data entry; decision support for irrigation and harvesting.

(Continues)

TABLE 5 | (Continued)

Reference	System name	Type	Purpose	Key features
Aggarwal et al., 2006 [50]	InfoCrop	Computational tool	A dynamic simulation model integrated in a graphical user interface (GUI) for assessing crop yields, losses due to pests, and environmental impacts in tropical agro-ecosystems.	Crop growth simulation; soil nitrogen balance; greenhouse gas emissions; pest impacts; and climate change scenarios; MS-Access as database management system.
Nash et al., 2009 [51]	Data-flow model for precision agriculture	Conceptual model	A comprehensive data-flows model designed to optimise and automate information management in precision agriculture in support of better decision-making, data utilization, and precision technologies adoption.	Cross-domain datasets integration (e.g., yield data, soil data); sustainability indicators and management zones generation; UML state diagram.
Papadopoulos et al., 2011 [52]	Decision support system for nitrogen fertilization	Computational tool	A fuzzy logic-based decision support system designed to optimise nitrogen fertilization in site-specific crop management and improve both environmental and economic outcomes.	Expert knowledge and fuzzy systems; nitrogen balance simulation; site-specific nitrogen recommendations.
Ngo et al., 2023 [53]	Electronic agricultural records	Computational tool	A cloud-based data wharehouse leveraging big data analytics and standardized data management to recommend optimal fertiliser quantities for crops, based on historical data and environmental factors.	Data standardisation; cloud-based hosting (Hive and Elasticsearch for data processing); big data; statistical methods for fertiliser recommendations; nutrient optimization for major crops.
Jones et al., 2003 [54]	DSSAT model	Computational tool	A modular decision support system for simulating crop growth, development, and yield.	Consideration of environmental, economic and biological datasets; link to GIS environments; crop rotation analysis; modular software design.
Bazzi et al., 2019 [55]	AgDataBox API	Computational tool	A web-based API designed to store, integrate, and manage agricultural data for precision agriculture applications to enable real-time data access and software interoperability.	Integration of spatial and non-spatial data; modular architecture; HTTP-based communication; scalable for multiple applications; data standardisation.
Ozcelik and Nisanci, 2015 [56]	LADM-TAM	Conceptual model	A geospatial data model designed to integrate tea agricultural land management with land administration systems, ensuring sustainable tea cropping and compliance with regional policies.	Consideration of the land Parcel identification system (LPIS) core model and the crop Speciality agricultural model; registration of land use rights and restrictions; implementation of geospatial data management; compliance with INSPIRE and national (Turkish) GIS standards.

(Continues)

TABLE 5 | (Continued)

Reference	System name	Type	Purpose	Key features
Khan et al., 2018 [57]	Building integrated agriculture information modelling (BIAIM)	Plug-in tool	An integrated framework combining Building information modelling (BIM) and Building integrated agriculture (BIA) supported by a custom-made database and data schema to optimise the design and management of urban agriculture facilities.	Support for real-time environmental conditions monitoring; BIM for spatial data.
Karydas et al., 2023 [58]	ifarma/PreFer module	Computational tool	A precision fertilization service (PreFer) integrated into an FMIS (ifarma) and designed to provide site-specific prescription maps for fertilization operations using multiple data sources (soil surveys, satellite imagery, yeild monitors) and machine learning.	Support for crop, inventory and financial management; implementation of a GIS environment; machine learning-based fertilization maps creation; integration of Google earth engine data.
Tummers et al., 2021 [59]	Reference architecture for FMIS	Conceptual model	A reference architecture designed to guide the development of Farm management information systems (FMIS) based on a structured approach to integrate diverse data sources and optimise farm management processes.	Support stakeholders communication; consideration of all possible modules (activities) supported by FMIS; application in livestock and crop farming.
Köksal and Tekinerdogan, 2019 [60]	IoT-based FMIS architecture	Conceptual model	An architecture design approach to develop IoT-based farm management information systems (FMIS) that meet specific smart farming requirements, ensuring effective data collection and processing for farming systems management.	Modular architecture for IoT-based FMIS; integration of various IoT protocols (MQTT, AMQP, DDS,..); support for data processing and visualisation from multiple sources; real-time monitoring and management of farm assets.
Pesonen et al., 2014 [61]	Cropinfra	Computational tool	A multi-layered service platform designed to support crop production in future farms through an internet-based service infrastructure that integrates precision agriculture and farm management systems.	Sensors in machines and equipment; stationary sensor network; machine control; integration of external services (e.g., weather and disease forecasts); SOA-based architecture; real-time data processing.
White et al., 2013 [26]	ICASA	Conceptual model	A comprehensive set of data standards developed to support agricultural research and modelling by providing a unified framework for documenting and exchanging data from field experiments, greenhouses, and growth chambers.	Standardized variables and units for agricultural data management; field experiments documentation; data and metadata for multiple processes (e.g., soil, weather, management practices); data interoperability.

(Continues)

TABLE 5 | (Continued)

Reference	System name	Type	Purpose	Key features
Giagnocavo et al., 2017 [62]	Intelligent traceability system	Information system	A traceability system designed for agricultural cooperatives that utilises IoT and big data to provide comprehensive monitoring and traceability throughout the food supply chain.	Provision for IoT-based real-time monitoring and big data for advanced analytics; adoption of the net-chain concept in the model design; enablement of multi-agent cooperation as well as compliance with food safety standards; support for automated reporting capabilities.
Sørensen et al., 2010 [39]	User-Centric FMIS for arable farming	Conceptual model	A reference design for farm management information system based on a user-centric approach to optimise information flow and decision-making for arable farming.	Implementation of core tasks analyses for planning, execution, and evaluation of farm operations; support for external services provided by agricultural services companies as well as ISOBUS for machinery communication, and real-time control; consideration of data supply and demand among actors; variants for different planning timing (operational, tactical, and strategic).
Fountas et al., 2009 [63]	University Farm information management system (UF-IMS)	Conceptual model	An information management system designed to handle both precision agriculture data and research trial data for a university experimental farm.	Support for data access via web or mobile devices (PDA); implementation of a GIS environments and data sharing among multiple users.
Sørensen et al., 2011 [64]	Future Farm management information system (FMIS)	Conceptual model	A data-flow framework for farm management information system designed to support precision agriculture and optimise farm operations through advanced data management and decision support capabilities.	Support for various farm operations (tillage, seeding, fertilizing, etc.) as well as agricultural services as features.
Latino et al., 2022 [65]	Voluntary food traceability framework	Framework	A framework designed to support the adoption of voluntary food traceability systems in agriculture 4.0 with the aim to enhance transparency, sustainability, and consumer trust.	Designed according to the food lifecycle approch; IoT technologies and data management standards integration; software application (data visualisation) for end-users; consideration of food sustainability challenges.
Fountas et al., 2015 [34]	Farm machinery management information system (FMMIS)	Conceptual model	A specialised FMIS concept designed to record, integrate and manage data from farm machinery (tractor/implements) through the ISOBUS protocol.	Support for real-time monitoring of tractor-implement system; implementation of financial and environmental impact analyses; consideration for stakeholders communication; support for on-farm experimentation and potential integration with autonomous vehicles and robotic systems.

(Continues)

TABLE 5 | (Continued)

Reference	System name	Type	Purpose	Key features
Singh et al., 2020 [66]	Agri-Info	Application (mobile and web)	A cloud-based autonomic information system designed to deliver agriculture-as-a-service using IoT and cloud computing for effective management of agricultural data.	Support for quality of service (QoS)-aware resource scheduling; provision for data acquisition from various IoT sources and stakeholders communication; utilization of fuzzy logic for automatic agricultural status diagnosis.
Devare et al., 2021 [35]	AgroFIMS	Information system	A web-based open-source tool designed to facilitate the collection, management and delivery of agronomic data according to the FAIR principles.	Support for digital fieldbook creation with standard metadata; integration of agronomic ontologies for data standardisation; support for mobile-based data collection; enablement of data sharing with external data repositories.
Craker et al., 2018 [27]	ADAPT	Framework	A software toolkit composed of a data schema, an API, and data conversion plug-ins designed to enable seamless data exchange among agricultural hardware and software systems.	Plug-ins for data formats conversion; compatibility with ISO 11783-10; lossless FMIS-to-FMIS communication via a common object data model plug-in; integration with industry standards (e.g., PAIL, SPADE).

3.3 | Comparative Analyses of Retrieved Data Structures

Here, we present a three-step assessment of all retrieved agricultural data structures based on each of the three AgrIMAF layers to expose: (a) the components of the supply chain they cover (first layer), (b) the supply chain actors considered in the data structures design (second layer), and (c) the agricultural sub-systems data they account for (third layer).

3.3.1 | Analysis of Supply Chain Stages Considered in Agricultural Data Structures

The results of this analysis are presented in Figure 3. From here we can see that the pre-harvest stages that is from pre-planting to harvest (P0–P3), coverage by current data structures, which is not the case for post-harvest stages. This result is corroborated with research indicating that technological innovations focus mainly on production phases [67].

We must highlight that among the pre-harvest segment stages, the planting stage suffers from a scant coverage despite the low complexity of the corresponding data [68]. The cultivation and harvesting stages have garnered significant attention due to their direct impact on automation and production optimization [6, 69].

The results also highlight their paucity in the post-harvest phase (P4–P11). This may be explained by the fact that post-harvest value chains are often complex and involve multiple actors and geographical locations, which complicates the data collection and integration process [67]. In the same figure, it is noticeable that around 5 data structures or models have provision for a more consistent coverage of the post-harvest stages. These often enable agricultural products to be tracked from storage to the retailer thanks to the integration of technologies such as blockchain and the IoT [70, 71]. Waste management (P11) is especially underrepresented in the reviewed data structures, even though it plays a crucial role in ensuring a sustainable circular economy and minimising the environmental impact of agricultural activities [2, 72]. The consumption phase (P10), despite of its role in a true farm-to-fork transparency, has received very little attention [2].

From a chronological point of view, the data reveal limited coverage of the stages before 2015, reflecting a still nascent interest in data systems designed to manage data from all stages of the chain. The published data structures mainly focused on the pre-harvest segment, again with the planting stage being overlooked. The first data systems to incorporate coverage of the post-harvest segment, although it is a single phase, were introduced in 2015 [56]. Ultimately, a data structure that systematically focuses on the post-harvest segment was published [62]. Among the selected references, the data structure proposed by Latino et al. [65] is the most comprehensive structure that consistently considers both segments of the supply chain. Despite the continuing interest in more complete data systems arisen from the precision farming techniques, environmental sustainability and food traceability requirements, some critical phases of the supply chain, especially from product processing (P5) to final consumption (P10), are still often overlooked.

3.3.2 | Analysis of Supply Chain Actors Considered in Agricultural Data Structures

As we can see in Figure 4, farmers, policymakers, suppliers/seed companies and researchers interact with data that are essential for optimising productivity and guaranteeing post-harvest product quality [34]. Given the role they play, they benefit from a more important and consistent consideration in current information systems. On one hand, other players, such as agronomists, financial institutions, quality assurance, consumers and authorities/government are only partially covered, despite the fact that they also play an essential role in the supply chain. On the other hand, players such as waste management companies, insurance companies, dieticians, supply chain managers, packaging manufacturers/suppliers and GIS consultants are under-represented, although their contributions are essential to ensuring the sustainability and balance of the chain. All these gaps contribute to the data fragmentation challenges at the core of the paper and undermine the effectiveness and comprehensiveness of data structures. Adopting an integrated approach with consideration of all stakeholders, their role, their data, their interaction and promoting collaboration, is essential to avoid informational silos and improve the efficiency and transparency of agricultural systems [73].

Our study exposes obvious patterns in the way actors in the agricultural supply chain are covered. Data structures concentrated mostly on core production actors including farmers and researchers using tools such DSSAT [54] and InfoCrop [50] focussing on crop and cost management, but disregarding post-harvest players [13]. Prior to 2010, although their coverage is still limited, the development of precision agriculture gave rise to data systems such as PDA-based Record-keeping and Decision-support System (PRDS) [48] and FMIS for orchards [34, 49] which partially integrated data for agricultural technicians and insurers.

Driven by traceability and environmental concerns, data structures start to feature more cross-functional actors from 2020 onward. Researchers underline the lack of data structures encompassing the consumption and waste management phases as crucial stakeholders, including waste managers and dieticians, remain sidelined [72, 74]. This evolution shows a slow but inadequate recognition of the significance of interactions among all actors in the chain [67, 75].

3.3.3 | Analysis of the Data Categories Considered in Agricultural Data Structures

The results of this analysis are illustrated in Figure 5, where a colour gradient comprising green, light green, and grey is used to represent the status of data fluxes covered by the selected data structures, as well as the number of data structures associated with each specific data flux. The colours respectively mean: a 'complete coverage', a 'partial coverage', and a 'no coverage'. These categories are dictated by an important

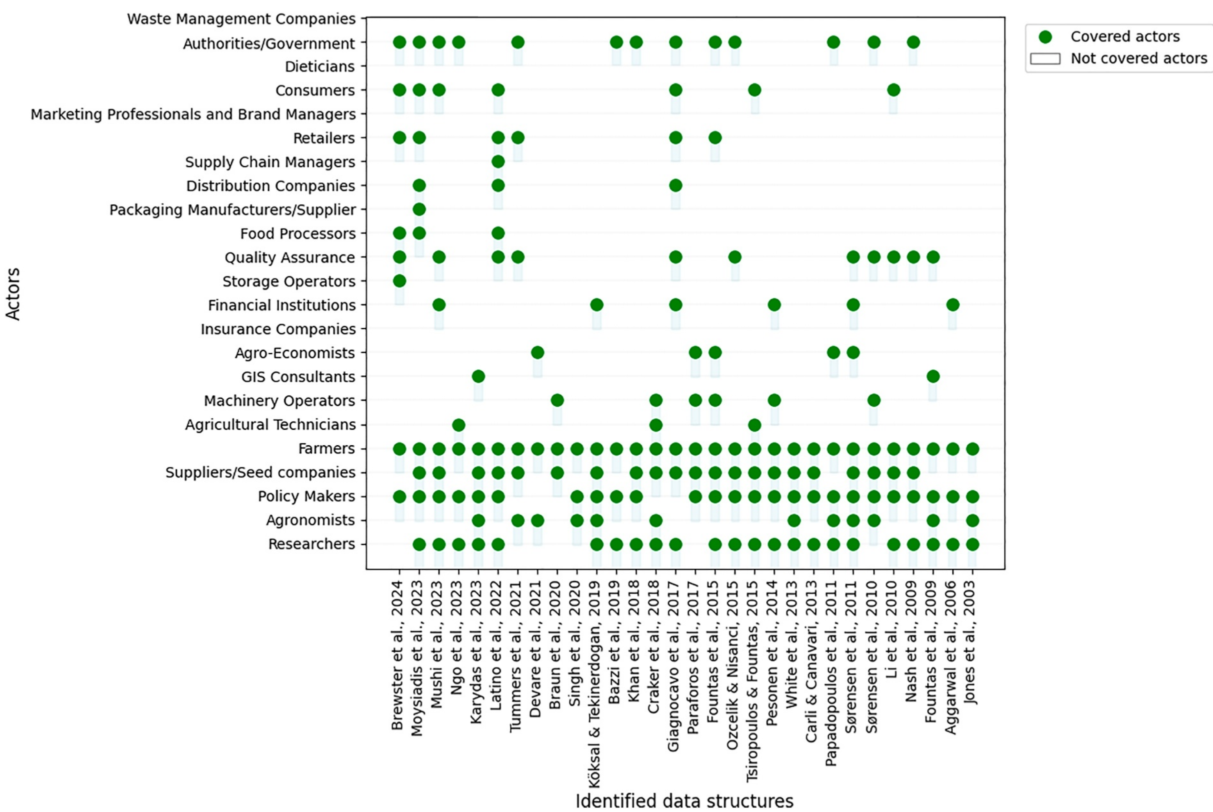

FIGURE 4 | Representation of supply chain actors in existing data structures. Each row represents a supply chain actor and each column corresponds to an identified data structure (sorted by year of publication). A green dot indicates that the actor is explicitly covered by the model. White cells represent actors not addressed by the corresponding data structure.

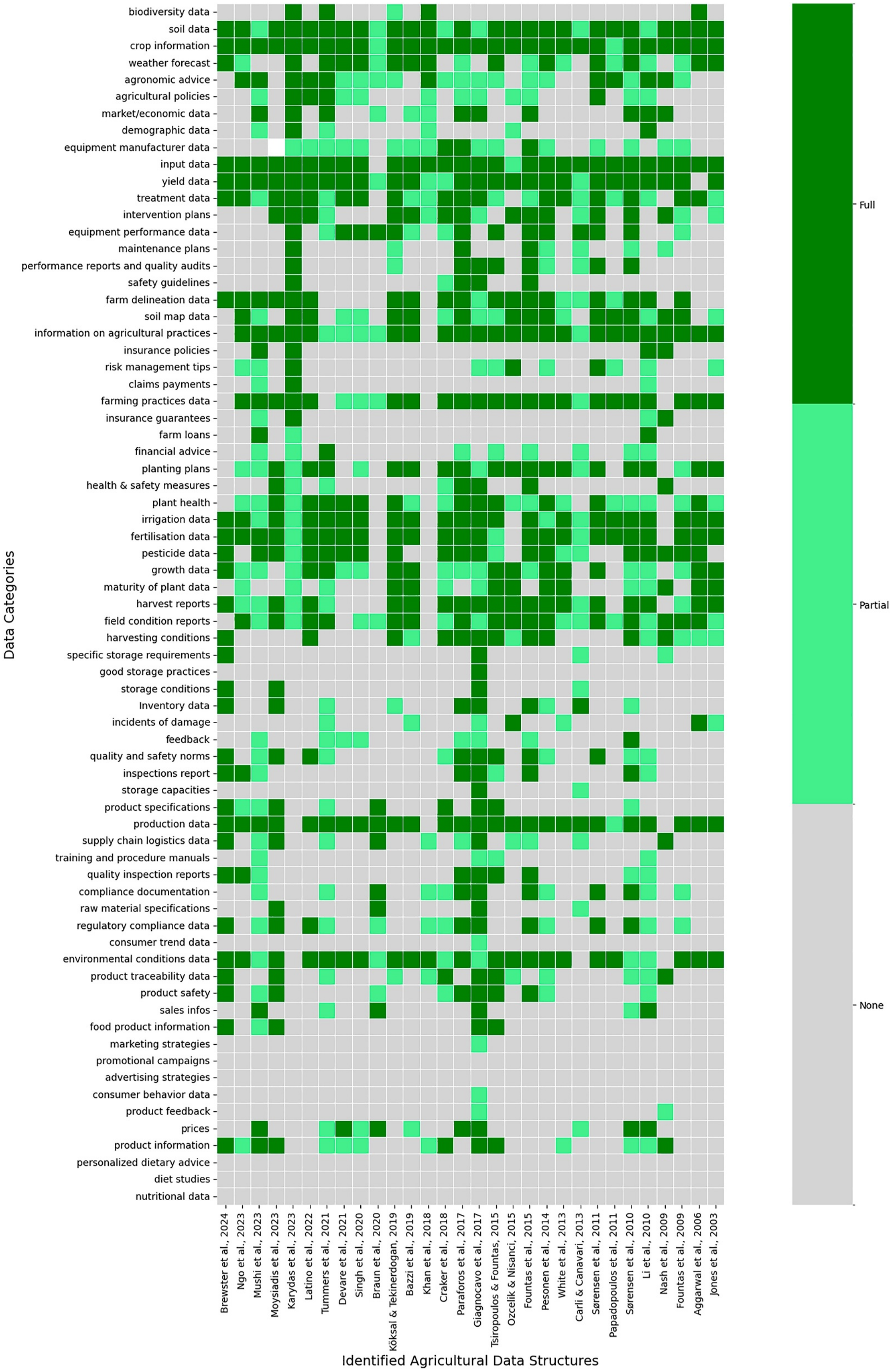

FIGURE 5 | Detailed mapping of data categories covered by agricultural data structures found in the literature. Each row represents a specific data category, and each column corresponds to an identified data structure, sorted by publication year (descending). The colour intensity indicates the level of coverage: light grey for no coverage, light green for partial coverage, and green for full coverage.

observation we have made in the literature on agricultural data structures, i.e. that of a design anomaly that the majority of data structures suffer from. We noticed that the data structures significantly adopt the process-oriented information modelling [76] design approach, which hardcodes the agricultural processes (e.g., weather, soil, crop) supported. Accordingly, when it comes to a conceptual framework, which is a generic data structure, we assume the coverage as Full. This is because such a structure theoretically offers flexibility in the type of data form a data category that the actual implementation could support. Whereas, for a conceptual data model, a computational tool or decision-support system, we consider the coverage as Partial when a data category is mentioned either in the model itself or in the paper and None otherwise. For example, the EPCIS model [19] only covers data on soil temperature and moisture, as well as electrical conductivity and salinity. Thus, we consider a Partial coverage of the category of 'soil data', which encompasses data such as texture, porosity/permeability, density, structure, pH, nutrient levels, cation exchange capacity (CEC), soil biodiversity, microbial biomass, erosion risk, enzymatic activity, leaching potential among others.

Based on this rationale, Figure 5 provides a detailed representation of the association between each agricultural data structure identified and the different data categories covered. It can be noticed that data categories such as crop information, soil data and yield data have received significant coverage in agricultural data structures. This is due particularly to the importance of farm-level operations in addition to the advent of precision farming technologies such as soil sensors, yield monitoring systems and farm management information systems.

On the other hand, a significant under-representation of data categories related to the post-harvest segment of the supply chain is noted. Data on marketing strategies, biodiversity composition, and consumer behaviour, which are crucial for sustainability and traceability, are unfortunately overlooked despite calls for their integration into agricultural information systems [43, 77]. This deficiency limits the ability of agricultural data systems to align farming practices with emerging market expectations [74] and can be attributed to the complexity of post-harvest value chains, which often involve diverse actors and fragmented data flows [67]. This is a historical shortcoming in the development of agricultural data structures that are geared more towards optimising production operations rather than towards whole chain data management.

4 | Discussion

This study aims to analyse existing agricultural data structures, be it conceptual frameworks, conceptual or logical data models, and structured or non-structured file systems that feed computational tools and decision-support systems, in terms of their consideration of: (a) the different stages of the supply chain, (b) the data produced and needed by different actors of the supply chain, and (c) the overall data flows across the supply chain. To conduct this analysis, we developed an analytical framework named AgrIMAF composed of three layers pertaining to the agricultural supply chain (the stages, the stakeholders, and the data). The results of our analyses certainly demonstrate the overall capability of AgrIMAF to be used as a diagnostic tool to assess the scope and limitations of agricultural data structures.

AgrIMAF stands out as a mechanism to identify data gaps from three different perspectives in agricultural data structures. For instance, through our analyses, we were able to highlight the stages, the stakeholders and the data fluxes that each of the data structures has considered either fully or partially or not at all. Accordingly, we anticipate a new role for AgrIMAF which is that of being used as a tool for agricultural data structures or information models design that reflects the data exhaustiveness of the sub-domain being studied. The exhaustiveness of agricultural information systems may become a strategic approach for ensuring regulatory compliance and quality standards as consumer demands for sustainable and fully traceable agricultural products increase. For instance, recent studies [19, 67] emphasise the importance of integrating accurate and comprehensive data across the entire supply chain to enhance transparency and accountability. This is even more necessary when considering the multifaceted impacts of climate change on food quality and food storage conditions [78, 79], for example. Hence, although the AgrIMAF design as well as our analyses have been focused on crop supply chain, they are equally applicable to livestock supply chain data management. Accordingly, AgrIMAF is positioned to support the design of agricultural data systems that aim at informing and empowering citizens with more democratic food system as well as establishing better relationships between farmers and food consumers [4, 5].

The design of AgrIMAF may be considered as a response to the recent call 'to treat agricultural production as a sociotechnical phenomenon and promote a sociotechnical-system approach to data and information models development [80]. Accordingly, AgrIMAF meets the definition of Agricultural Hydro-informatics: Sociotechnology, which must identify, support and promote corrective measures, and ultimately implement those (if necessary) capable of improving the performance of the technology ecosystem as a whole. It is designed to support data modelling tasks and potentially data governance for processes where an assemblage of stakeholders is engaged in data-enabling dynamics. Thus, the proposed framework can be construed as an archetype of frameworks to diagnose the exhaustiveness of information systems not only in the agricultural sector, but also in other domains, such as healthcare [81] and construction supply chain [82].

Despite the features and potential applications of the proposed framework discussed above, a limitation of the current study is that it has not considered ontologies [83] as a data structure. The rationale for this omission is mainly based on the practical focus of our work. For instance, our goal is to support comprehensive and efficient data management (storage, query, and sharing) across the supply chain to meet the data supply and demand of the stakeholders, thus, the considered data structures (data models, conceptual frameworks, file systems) offer a more scalable and practical alternative to ontologies. Furthermore, ontologies do not describe a specific computer representation for information [84], thus, they are not designed to support the purpose of our work [85]. However, the framework itself, by considering the relationships between stakeholders and their data supply and demand across the supply provides the foundation for the development of an ontology that represents the knowledge across the supply chain. A second limitation of the framework is that it is not designed to serve as a formal data model for implementation. While AgrIMAF enables a structured evaluation of the coverage and gaps of existing information systems, its purpose is analytical and conceptual rather than technical or computational. Therefore, it does not propose a standardized schema or entity-relationship structure. However, the conceptual clarity it provides could inform the later design of more integrated and holistic data models. A third limitation of the framework as well as the study is that Controlled Vocabularies used as ancillary information to describe the data were not taken into account. However, our review of the literature did not reveal considerations of Controlled Vocabularies as part of the data structures analysed. These limitations can be examined by applying the framework to a vocabulary and ontology repository, such as the AgroPortal [86], a task that is beyond the scope of the paper. Future developments could transform AgrIMAF into a fully operational assessment and design tool by integrating semantic standards, and validation through practical applications across real-world agricultural data systems.

Although the systematic approach adopted enabled a rigorous assessment, we acknowledge that the study is also limited to data structures published in academic journals. The scope of this study could be expanded through the integration of non-academic or undocumented models.

5 | Conclusion

This paper introduces a new framework named AgrIMAF designed as a diagnostic tool to assess the scope and limitations of agricultural data structures, that is, conceptual frameworks, conceptual or logical data models, and structured or non-structured file systems. The framework is composed of three pillars of the agri-food systems, that is, the supply chain, the actors and the data. Each of these components constitutes a layer of the framework and serves as an evaluation criterion for agricultural data structures.

The three criteria were applied to assess the exhaustiveness of existing agricultural data structures published either as standalone models or integrated in plug-in and computational tools. Through the analyses, we observed that current agricultural data structures focus mainly on the pre-harvest phases while largely overlooking the post-harvest phases, in particular, waste management and consumption. This suggests the need to develop more comprehensive data systems aiming at covering the entire supply chain while meeting the specific data production and demand of each stakeholder.

The originality of this work lies in the proposed AgrIMAF's holistic approach, and its ability to expose not only the data produced and required by each actor, but also the data-related dynamics between the actors of each phase of the supply chain. This consideration is crucial to overcoming the challenges of data fragmentation and optimising agricultural practices in a context of sustainability and transparency across the supply chain. However, this study focuses only on academically documented data structures and does not consider the unpublished private or commercial data structures. As future work, we plan to use the framework to evaluate the relevance of existing data models from the environmental sciences domain to gauge their applicability in tackling the data fragmentation problem in the agricultural sector.

Author Contributions

Cheikh M. M. Thiaw: writing – original draft, conceptualization, methodology. **Louis R. E. Asie:** conceptualization, methodology. **Herlest B. Lovince:** writing – review and editing. **Alain N. Rousseau:** writing –review and editing. **Paul Celicourt:** project administration, writing – original draft, funding acquisition, methodology, writing – review and editing, conceptualization, supervision.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The original contributions presented in the study are included in the article, further enquiries can be directed to the corresponding author/s.

References

1. J. Pretty, W. J. Sutherland, J. Ashby, et al., "The Top 100 Questions of Importance to the Future of Global Agriculture," *International Journal of Agricultural Sustainability* 8, no. 4 (2010): 219–236, https://doi.org/10.3763/ijas.2010.0534.

2. Y. Hu, T. Zhao, Y. Guo, et al., "100 Essential Questions for the Future of Agriculture," *Modern Agriculture* 1, no. 1 (2023): 4–12, https://doi.org/10.1002/moda.5.

3. M. Lezoche, J. E. Hernandez, MdM. E. A. Díaz, H. Panetto, and J. Kacprzyk, "Agri-Food 4.0: A Survey of the Supply Chains and Technologies for the Future Agriculture," *Computers in Industry* 117 (2020): 103187, https://doi.org/10.1016/j.compind.2020.103187.

4. M. Shepherd, J. A. Turner, B. Small, and D. Wheeler, "Priorities for Science to Overcome Hurdles Thwarting the Full Promise of the 'Digital Agriculture' Revolution," *Journal of the Science of Food and Agriculture* 100, no. 14 (2020): 5083–5092, https://doi.org/10.1002/jsfa.9346.

5. J. Ingram, D. Maye, C. Bailye, et al., "What Are the Priority Research Questions for Digital Agriculture?," *Land Use Policy* 114 (2022): 105962, https://doi.org/10.1016/j.landusepol.2021.105962.

6. R. Gebbers and V. I. Adamchuk, "Precision Agriculture and Food Security," *Science.* 327, no. 5967 (2010): 828–831, https://doi.org/10.1126/science.1183899.

7. B. Basso and J. Antle, "Digital Agriculture to Design Sustainable Agricultural Systems," *Nature Sustainability* 3, no. 4 (2020): 254–256, https://doi.org/10.1038/s41893-020-0510-0.

8. A. McBratney, B. Whelan, T. Ancev, and J. Bouma, "Future Directions of Precision Agriculture," *Precision Agriculture* 6, no. 1 (2005): 7–23, https://doi.org/10.1007/s11119-005-0681-8.

9. G. Kumar, S. Basri, A. A. Imam, S. A. Khowaja, L. F. Capretz, and A. O. Balogun, "Data Harmonization for Heterogeneous Datasets: A Systematic Literature Review," *Applied Sciences* 11, no. 17 (2021): 8275, https://doi.org/10.3390/app11178275.

10. C. Eastwood, M. Ayre, R. Nettle, and B. D. Rue, "Making Sense in the Cloud: Farm Advisory Services in a Smart Farming Future," *NJAS—Wageningen Journal of Life Sciences* 90, no. 1 (2019): 100298, https://doi.org/10.1016/j.njas.2019.04.004.

11. J. Top, S. Janssen, H. Boogaard, R. Knapen, and G. Şimşek-Şenel, "Cultivating FAIR Principles for Agri-Food Data," *Computers and Electronics in Agriculture* 196 (2022): 106909, https://doi.org/10.1016/j.compag.2022.106909.

12. E. L. White, J. A. Thomasson, B. Auvermann, et al., "Report From the Conference, 'Identifying Obstacles to Applying Big Data in Agriculture'," *Precision Agriculture* 22, no. 1 (2021): 306–315, https://doi.org/10.1007/s11119-020-09738-y.

13. S. J. Janssen, C. H. Porter, A. D. Moore, et al., "Towards a New Generation of Agricultural System Data, Models and Knowledge Products: Information and Communication Technology," *Agricultural Systems* 155 (2017): 200–212, https://doi.org/10.1016/j.agsy.2016.09.017.

14. J. W. Jones, J. M. Antle, B. Basso, et al., "Toward a New Generation of Agricultural System Data, Models, and Knowledge Products: State of Agricultural Systems Science," *Agricultural Systems* 155 (2017): 269–288, https://doi.org/10.1016/j.agsy.2016.09.021.

15. J. Forney and A. Dwiartama, "The Project, the Everyday, and Reflexivity in Sociotechnical agri-food Assemblages: Proposing a Conceptual Model of Digitalisation," *Agriculture and Human Values* 40, no. 2 (2023): 441–454, https://doi.org/10.1007/s10460-022-10385-4.

16. D. Applegate, A. Berger, D. Berne, et al., "Toward geopolitical-context-enabled Interoperability in Precision Agriculture: Aggateway's SPADE, PAIL, WAVE, CART and ADAPT," in *Proceedings of the 13th International Conference on Precision Agriculture* 31 (2016).

17. A. D. Balmos, F. A. Castiblanco, A. J. Neustedter, J. V. Krogmeier, and D. R. Buckmaster, "Isoblue Avena: A Framework for Agricultural Edge Computing and Data Sovereignty," *IEEE Micro* 42, no. 1 (2022): 78–86, https://doi.org/10.1109/mm.2021.3134830.

18. S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big Data in Smart Farming–A Review," *Agricultural Systems* 153 (2017): 69–80, https://doi.org/10.1016/j.agsy.2017.01.023.

19. T. Moysiadis, K. Spanaki, A. Kassahun, et al., "Agrifood Supply Chain Traceability: Data Sharing in a Farm-To-Fork Case," *Benchmarking: An International Journal* 30, no. 9 (2023): 3090–3123, https://doi.org/10.1108/bij-01-2022-0006.

20. T. Lang and M. Heasman, *Food Wars: The Global Battle for Mouths, Minds and Markets* (Routledge, 2015).

21. P. Bansal and K. Roth, "Why Companies Go Green: A Model of Ecological Responsiveness," *Academy of Management Journal* 43, no. 4 (2000): 717–736, https://doi.org/10.2307/1556363.

22. J. S. Horsburgh, A. K. Aufdenkampe, E. Mayorga, et al., "Observations Data Model 2: A Community Information Model for Spatially Discrete Earth Observations," *Environmental Modelling and Software* 79 (2016): 55–74, https://doi.org/10.1016/j.envsoft.2016.01.010.

23. P. Celicourt, R. Sam, and M. Piasecki, "Rapid Prototyping of an Automated Sensor-To-Server Environmental Data Acquisition System Adopting A FAIR-Oriented Approach," *Journal of Environmental Informatics.* 41, no. 1 (2023), https://doi.org/10.3808/jei.202300483.

24. J. Tummers, A. Kassahun, and B. Tekinerdogan, "Obstacles and Features of Farm Management Information Systems: A Systematic Literature Review," *Computers and Electronics in Agriculture* 157 (2019): 189–204, https://doi.org/10.1016/j.compag.2018.12.044.

25. A. Kamilaris, A. Kartakoullis, and F. X. Prenafeta-Boldú, "A Review on the Practice of Big Data Analysis in Agriculture," *Computers and Electronics in Agriculture* 143 (2017): 23–37, https://doi.org/10.1016/j.compag.2017.09.037.

26. J. W. White, L. Hunt, K. J. Boote, et al., "Integrated Description of Agricultural Field Experiments and Production: The ICASA Version 2.0 Data Standards," *Computers and Electronics in Agriculture* 96 (2013): 1–12, https://doi.org/10.1016/j.compag.2013.04.003.

27. B. Craker, D. Danford, R. Ferreyra, et al., "Adapt: A Rosetta Stone for Agricultural Data," in *Proceeding of the 14th International Conference on Precision Agriculture* 13 (2018): 2020.

28. P. Kumar, T. Hendriks, H. Panoutsopoulos, and C. Brewster, "Investigating FAIR Data Principles Compliance in Horizon 2020 Funded Agri-Food and Rural Development Multi-Actor Projects," *Agricultural Systems* 214 (2024): 103822, https://doi.org/10.1016/j.agsy.2023.103822.

29. M. J. Page, J. E. McKenzie, P. M. Bossuyt, et al., "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews," *BMJ* 372 (2021): n71, https://doi.org/10.1136/bmj.n71.

30. A. M. Methley, S. Campbell, C. Chew-Graham, R. McNally, and S. Cheraghi-Sohi, "PICO, PICOS and SPIDER: A Comparison Study of Specificity and Sensitivity in Three Search Tools for Qualitative Systematic Reviews," *BMC Health Services Research* 14, no. 1 (2014): 1–10, https://doi.org/10.1186/s12913-014-0579-0.

31. A. Møller and P. Myles, "What Makes a Good Systematic Review and Meta-Analysis?," *British Journal of Addiction: British Journal of Anaesthesia* 117, no. 4 (2016): 428–430, https://doi.org/10.1093/bja/aew264.

32. Celicourt P., Drapeau J., Lovince H. B., et al. STAR: A Transposition of the PICO Framework to Environmental Sciences, Engineering and Beyond. (in prep.).

33. M. Ouzzani, H. Hammady, Z. Fedorowicz, and A. Elmagarmid, "Rayyan—A Web and Mobile App for Systematic Reviews," *Systematic Reviews* 5 (2016): 1–10, https://doi.org/10.1186/s13643-016-0384-4.

34. S. Fountas, C. G. Sorensen, Z. Tsiropoulos, C. Cavalaris, V. Liakos, and T. Gemtos, "Farm Machinery Management Information System," *Computers and Electronics in Agriculture* 110 (2015): 131–138, https://doi.org/10.1016/j.compag.2014.11.011.

35. M. Devare, C. Aubert, O. E. Benites Alfaro, I. O. Perez Masias, and M. A. Laporte, "Agrofims: A Tool to Enable Digital Collection of Standards-Compliant FAIR Data," *Frontiers in Sustainable Food Systems* 5 (2021): 726646, https://doi.org/10.3389/fsufs.2021.726646.

36. D. C. Rose, C. Keating, E. Vrain, and C. Morris, "Beyond Individuals: Toward a 'Distributed' Approach to Farmer Decision-Making Behavior," *Food and Energy Security* 7, no. 4 (2018): e00123, https://doi.org/10.1002/fes3.155.

37. M. Comi, "The Distributed Farmer: Rethinking US Midwestern Precision Agriculture Techniques," *Environmental Sociology* 6, no. 4 (2020): 403–415, https://doi.org/10.1080/23251042.2020.1794426.

38. S. Cox, "Observations and Measurements-Part 1-Observation Schema," *OpenGIS Implementation Standard OGC 07-022r1* (2007).

39. C. Sorensen, L. Pesonen, S. Fountas, et al., "A User-Centric Approach for Information Modelling in Arable Farming," *Computers and Electronics in Agriculture* 73, no. 1 (2010): 44–55, https://doi.org/10.1016/j.compag.2010.04.003.

40. J. M. Antle, J. W. Jones, and C. E. Rosenzweig, "Next Generation Agricultural System Data, Models and Knowledge Products: Introduction," *Agricultural Systems* 155 (2017): 186–190, https://doi.org/10.1016/j.agsy.2016.09.003.

41. C. Zhang and J. M. Kovacs, "The Application of Small Unmanned Aerial Systems for Precision Agriculture: A Review," *Precision Agriculture* 13, no. 6 (2012): 693–712, https://doi.org/10.1007/s11119-012-9274-5.

42. C. Caracciolo, A. Stellato, A. Morshed, et al., "The AGROVOC Linked Dataset," *Semantic Web* 4, no. 3 (2013): 341–348, https://doi.org/10.3233/sw-130106.

43. D. S. Paraforos, V. Vassiliadis, D. Kortenbruck, et al., "Multi-Level Automation of Farm Management Information Systems," *Computers*

and Electronics in Agriculture 142 (2017): 504–514, https://doi.org/10.1016/j.compag.2017.11.022.

44. S. Braun, I. Koren, M. Van Dyck, M. Jarke, "An Agricultural Data Platform Istar Model," in *iStar* (2020): 19–24.

45. G. Carli and M. Canavari, "Introducing Direct Costing and Activity Based Costing in a Farm Management System: A Conceptual Model," *Procedia Technology* 8 (2013): 397–405, https://doi.org/10.1016/j.protcy.2013.11.052.

46. C. Brewster, N. Kalatzis, B. Nouwt, H. Kruiger, and J. Verhoosel, "Data Sharing in Agricultural Supply Chains: Using Semantics to Enable Sustainable Food Systems," *Semantic Web* 15, no. 4 (2024): 1207–1237, https://doi.org/10.3233/sw-233287.

47. G. E. Mushi, G. D. M. Serugendo, and P. Y. Burgi, "Data Management System for Sustainable Agriculture Among Smallholder Farmers in Tanzania: Research-In-Progress," *Information Technology for Development* 29, no. 4 (2023): 558–581, https://doi.org/10.1080/02681102.2023.2215528.

48. M. Li, J. P. Qian, X. T. Yang, C. H. Sun, and Z. T. Ji, "A PDA-Based Record-Keeping and Decision-Support System for Traceability in Cucumber Production," *Computers and Electronics in Agriculture* 70, no. 1 (2010): 69–77, https://doi.org/10.1016/j.compag.2009.09.009.

49. Z. Tsiropoulos and S. Fountas, *Farm Management Information System for Fruit Orchards* (Wageningen Academic, 2015), 429–436.

50. P. K. Aggarwal, N. Kalra, S. Chander, and H. Pathak, "Infocrop: A Dynamic Simulation Model for the Assessment of Crop Yields, Losses due to Pests, and Environmental Impact of AGRO-Ecosystems in Tropical Environments. I. Model Description," *Agricultural Systems* 89, no. 1 (2006): 1–25, https://doi.org/10.1016/j.agsy.2005.08.001.

51. E. Nash, F. Dreger, J. Schwarz, R. Bill, and A. Werner, "Development of a Model of Data-Flows for Precision Agriculture Based on a Collaborative Research Project," *Computers and Electronics in Agriculture* 66, no. 1 (2009): 25–37, https://doi.org/10.1016/j.compag.2008.11.005.

52. A. Papadopoulos, D. Kalivas, and T. Hatzichristos, "Decision Support System for Nitrogen Fertilization Using Fuzzy Theory," *Computers and Electronics in Agriculture* 78, no. 2 (2011): 130–139, https://doi.org/10.1016/j.compag.2011.06.007.

53. V. M. Ngo, T. V. T. Duong, T. B. T. Nguyen, C. N. Dang, and O. Conlan, "A Big Data Smart Agricultural System: Recommending Optimum Fertilisers for Crops," *International Journal of Information Technology* 15, no. 1 (2023): 249–265, https://doi.org/10.1007/s41870-022-01150-1.

54. J. W. Jones, G. Hoogenboom, C. H. Porter, et al., "The DSSAT Cropping System Model," *European Journal of Agronomy* 18, no. 3–4 (2003): 235–265, https://doi.org/10.1016/s1161-0301(02)00107-7.

55. C. L. Bazzi, E. P. Jasse, P. S. G. Magalhães, et al., "Agdatabox API–Integration of Data and Software in Precision Agriculture," *SoftwareX* 10 (2019): 100327, https://doi.org/10.1016/j.softx.2019.100327.

56. A. E. Ozcelik and R. Nisanci, "Building of Geo-Spatial Data Model for Tea Agricultural Crop-Lands Compliance With LPIS Core Model (LCM) Based Land Administration Domain Standards," *Computers and Electronics in Agriculture* 117 (2015): 8–21, https://doi.org/10.1016/j.compag.2015.07.008.

57. R. Khan, Z. Aziz, and V. Ahmed, "Building Integrated Agriculture Information Modelling (BIAIM): An Integrated Approach Towards Urban Agriculture," *Sustainable Cities and Society* 37 (2018): 594–607, https://doi.org/10.1016/j.scs.2017.10.027.

58. C. Karydas, M. Chatziantoniou, K. Stamkopoulos, M. Iatrou, V. Vassiliadis, and S. Mourelatos, "Embedding a Precision Agriculture Service Into a Farm Management Information System-Ifarma/PreFer," *Smart Agricultural Technology* 4 (2023): 100175, https://doi.org/10.1016/j.atech.2023.100175.

59. J. Tummers, A. Kassahun, and B. Tekinerdogan, "Reference Architecture Design for Farm Management Information Systems: A Multi-Case Study Approach," *Precision Agriculture* 22, no. 1 (2021): 22–50, https://doi.org/10.1007/s11119-020-09728-0.

60. Ö Köksal and B. Tekinerdogan, "Architecture Design Approach for Iot-Based Farm Management Information Systems," *Precision Agriculture* 20, no. 5 (2019): 926–958, https://doi.org/10.1007/s11119-018-09624-8.

61. L. A. Pesonen, F. K. W. Teye, A. K. Ronkainen, et al., "Cropinfra–An Internet-Based Service Infrastructure to Support Crop Production in Future Farms," *Biosystems Engineering* 120 (2014): 92–101, https://doi.org/10.1016/j.biosystemseng.2013.09.005.

62. C. Giagnocavo, F. Bienvenido, L. Ming, Z. Yurong, J. A. Sanchez-Molina, and Y. Xinting, "Agricultural Cooperatives and the Role of Organisational Models in New Intelligent Traceability Systems and Big Data Analysis," *International Journal of Agricultural and Biological Engineering* 10, no. 5 (2017): 115–125, https://doi.org/10.25165/j.ijabe.20171005.3089.

63. S. Fountas, M. Kyhn, H. L. Jakobsen, D. Wulfsohn, S. Blackmore, and H. Griepentrog, "A Systems Analysis of Information System Requirements for an Experimental Farm," *Precision Agriculture* 10, no. 3 (2009): 247–261, https://doi.org/10.1007/s11119-008-9098-5.

64. C. Sørensen, L. Pesonen, D. Bochtis, S. Vougioukas, and P. Suomi, "Functional Requirements for a Future Farm Management Information System," *Computers and Electronics in Agriculture* 76, no. 2 (2011): 266–276, https://doi.org/10.1016/j.compag.2011.02.005.

65. M. E. Latino, M. Menegoli, M. Lazoi, and A. Corallo, "Voluntary Traceability in Food Supply Chain: A Framework Leading Its Implementation in Agriculture 4.0," *Technological Forecasting and Social Change* 178 (2022): 121564, https://doi.org/10.1016/j.techfore.2022.121564.

66. S. Singh, I. Chana, and R. Buyya, "Agri-Info: Cloud Based Autonomic System for Delivering Agriculture as a Service," *Internet of Things* 9 (2020): 100131, https://doi.org/10.1016/j.iot.2019.100131.

67. T. Reardon, R. Echeverria, J. Berdegué, et al., "Rapid Transformation of Food Systems in Developing Regions: Highlighting the Role of Agricultural Research and Innovations," *Agricultural Systems* 172 (2019): 47–59.

68. Y. Ding, L. Yang, X. He, et al., "Development and Performance Evaluation of an Automatic Section Control System for Corn Precision Planters," *Computers and Electronics in Agriculture* 206 (2023): 107670, https://doi.org/10.1016/j.compag.2023.107670.

69. dB. Solan, F. Baret, dG. Sousa, J. Orensanz, and P. Boyer, "Apport Des Réseaux De Capteurs Connectés Au Suivi Des Cultures," *Innovations Agronomiques* 63 (2018): 457–473.

70. M. M. Aung and Y. S. Chang, "Traceability in a Food Supply Chain: Safety and Quality Perspectives," *Food Control* 39 (2014): 172–184, https://doi.org/10.1016/j.foodcont.2013.11.007.

71. A. Bekolli, L. A. Guardiola, and A. Meca, "Profit Allocation in Agricultural Supply Chains: Exploring the Nexus of Cooperation and Compensation," *TOP* (2024): 1–31, https://doi.org/10.1007/s11750-024-00692-w.

72. E. Papargyropoulou, R. Lozano, J. K. Steinberger, N. Wright, and bZ. Ujang, "The Food Waste Hierarchy as a Framework for the Management of Food Surplus and Food Waste," *Journal of Cleaner Production* 76 (2014): 106–115, https://doi.org/10.1016/j.jclepro.2014.04.020.

73. P. Gasselin, S. Lardon, C. Cerdan, S. Loudiyi, D. Sautier, "Gouverner La Coexistence Et La Confrontation Des Modèles Agricoles Et Alimentaires Dans Les Territoires: Paradigme, Postures, Méthodes," (2021).

74. D. C. Rose and J. Chilvers, "Agriculture 4.0: Broadening Responsible Innovation in an Era of Smart Farming," *Frontiers in Sustainable Food Systems* 2 (2018): 87, https://doi.org/10.3389/fsufs.2018.00087.

75. N. Subramanian, A. Joshi, and D. Bagga, "Transparent and Traceable Food Supply Chain Management," *arXiv preprint arXiv:2305.12188* (2023).

76. H. Zhang, B. Zhu, Y. Li, O. Yaman, and U. Roy, "Development and Utilization of a Process-Oriented Information Model for Sustainable Manufacturing," *Journal of Manufacturing Systems* 37 (2015): 459–466, https://doi.org/10.1016/j.jmsy.2015.05.003.

77. L. Lipper, P. Thornton, B. M. Campbell, et al., "Climate-Smart Agriculture for Food Security," *Nature Climate Change* 4, no. 12 (2014): 1068–1072, https://doi.org/10.1038/nclimate2437.

78. J. Moses, D. Jayas, and K. Alagusundaram, "Climate Change and Its Implications on Stored Food Grains," *Agricultural Research* 4, no. 1 (2015): 21–30, https://doi.org/10.1007/s40003-015-0152-z.

79. J. A. Winkler, L. Soldo, Y. Tang, et al., "Potential Impacts of Climate Change on Storage Conditions for Commercial Agriculture: An Example for Potato Production in Michigan," *Climatic Change* 151, no. 2 (2018): 275–287, https://doi.org/10.1007/s10584-018-2301-4.

80. P. Celicourt, A. N. Rousseau, S. J. Gumiere, and M. Camporese, "Agricultural Hydroinformatics: A Blueprint for an Emerging Framework to Foster Water management-Centric Sustainability Transitions in Farming Systems," *Frontiers in Water* 2 (2020): 586516, https://doi.org/10.3389/frwa.2020.586516.

81. B. Fabian, T. Ermakova, and P. Junghanns, "Collaborative and Secure Sharing of Healthcare Data in Multi-Clouds," *Information Systems* 48 (2015): 132–150, https://doi.org/10.1016/j.is.2014.05.004.

82. M. Das, J. C. Cheng, and K. H. Law, "An Ontology-Based Web Service Framework for Construction Supply Chain Collaboration and Management," *Engineering Construction and Architectural Management* 22, no. 5 (2015): 551–572, https://doi.org/10.1108/ecam-07-2014-0089.

83. E. Arnaud, M. A. Laporte, S. Kim, et al., "The Ontologies Community of Practice: A CGIAR Initiative for Big Data in Agrifood Systems," *Patterns* 1, no. 7 (2020): 100105, https://doi.org/10.1016/j.patter.2020.100105.

84. C. Martinez-Cruz, I. J. Blanco, and M. A. Vila, "Ontologies Versus Relational Databases: Are They so Different? A Comparison," *Artificial Intelligence Review* 38, no. 4 (2012): 271–290, https://doi.org/10.1007/s10462-011-9251-9.

85. M. Sir, Z. Bradac, and P. Fiedler, "Ontology Versus Database," *IFAC-PapersOnLine* 48, no. 4 (2015): 220–225, https://doi.org/10.1016/j.ifacol.2015.07.036.

86. C. Jonquet, A. Toulet, E. Arnaud, et al., "Agroportal: A Vocabulary and Ontology Repository for Agronomy," *Computers and Electronics in Agriculture* 144 (2018): 126–143, https://doi.org/10.1016/j.compag.2017.10.012.