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A Framework to Measure Maturity of Industrial IoT Technology for Agricultural Regulatory Compliance Activities and Decentralization

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Abstract

Compliance checks are a critical aspect of any agricultural production and supply chain. These comprise a chain of activities and responsibilities shared by producers and regulators. Currently, the responsibility for collecting and processing data primarily lies with the regulators. Regulators are the primary users of regulatory technologies, while producers, such as farmers, have limited capabilities. This has been due to a lack of reliable hardware and software technology that can be deployed at the producer's sites. However, recent advancements in Artificial Intelligence (AI), the Industrial Internet of Things (IIoT), and cloud computing have significantly increased reliability and reduced deployment costs. This paper reviews the regulatory landscape of agriculture, regulatory technologies, IIoT, and their feasibility for producers, using a new Technology Readiness Framework for Compliance, specifically designed for Regulatory Technologies (RegTech) and regulation compliance. It classifies technologies into three categories: Early Stage, Emerging, and Established. It concludes that most essential agricultural issues already have mature technological solutions within the scope of IIoT that producers can use directly without supervision, while still maintaining the integrity and validity of the data. The paper discusses and measures the maturity of IIoT and other electronic and digital technologies for integration into RegTech. This categorization offers a new perspective on technology readiness and lays the foundation for future RegTech platform design, e.g., by decentralizing and empowering producers with reliable technologies.

Keywords: regulatory technologies (RegTech); e-work; AgTech; compliance check; decentralization; IIoT; sensors; supply chain

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1. Introduction

Agricultural stakeholders, including farmers, face a significant burden of regulatory reporting across areas such as farm assurance, animal records, biosecurity, environmental compliance, financial disclosures, and health and safety protocols, in addition to their routine production activities [1]. Consequently, farmers must accurately and promptly document and report their operations or provide traceability to both regulators and the wholesale market [2]. Compliance with regulations is essential not only for maintaining an entity's reputation, business sustainability, and market access [2–4] but also for ensuring food safety [2], biosecurity, environmental protection [5,6], and for preventing food

fraud [3]. While regulated entities are responsible for compliance, acquiring the necessary comprehensive knowledge can be challenging without adequate training or external support. For instance, in a study [4], farmers reported that some language used in environmental policies was difficult to understand. They also consider the financial and time costs of regulatory compliance substantial and excessively burdensome [4]. In Australia, small-scale farming is typically defined by an annual output of less than A$500,000 and is measured by either total agricultural output or land area. Most Australian farms are small and medium-sized businesses that are vulnerable to regulatory burdens that can significantly impact their operations [5]. Reducing such regulatory burdens and improving compliance efficiency, as well as the relevant regulatory environment, are crucial for the sustainability of the agricultural sector.

IIoT-enhanced Regulatory Technologies (RegTech) can help with this by automating data acquisition in a timely manner and recording information reliably [6]. By adding AI, compliance monitoring and decision-making can also be automated. Regulatory data management typically involves collecting, securely storing (locally or in the cloud), processing, and reporting compliance-relevant data. However, the digital divide across agricultural sectors leads to inconsistent practices. While some entities use advanced IIoT and digital technologies and systems, others continue to operate at a basic level, relying on manual data handling processes [7]. Currently, many producers manage compliance through manual methods, such as emails and spreadsheets, with limited use of Enterprise Resource Planning [8].

The increasing integration of IIoT and digitalization across the agricultural sector offers significant advantages for various stakeholders regarding compliance monitoring [9]. Numerous researchers have explored agricultural digitalization, but the majority of current studies concentrate on production enhancement (e.g., precision agriculture) [10] or supply chain management, such as blockchain applications in traceability [11,12]. Compared to other areas, relatively little attention has been paid to regulatory compliance. RegTech emerged as a critical solution to address the complex and often burdensome landscape of regulatory compliance [8]. The feasibility of its application within agriculture remains uncertain.

Deeper integration of IIoT and digital technologies into agriculture presents significant challenges, including the digital divide, limited rural infrastructure such as internet connectivity, financial constraints, and concerns over data privacy [6]. By examining in depth, the IIoT and other technologies used to address agricultural processes and their inherent characteristics, this paper aims to identify potential solutions to alleviate the compliance burden faced by both regulatory bodies and the entities they oversee. The key contributions of this paper are to:

- Identify the regulatory burden and process prevalent in agriculture, along with the technologies that can reduce such burden and help with regulatory compliance.
- Develop a Technology Readiness framework for agriculture, specifically for RegTech purposes. This framework, although similar to the Technology Readiness Level (TRL) framework [13], proposes 6 specific attributes and 3 maturity levels. The framework is applied to key IIoT and related digital technologies in agriculture. to establish their maturity and suitability in RegTech. We classify technologies into *Early-stage*, *Emerging*, and *Established*. The categorization sheds light on possible future integration into RegTech.

In this paper, RegTech is defined as a system between two entities: *producers*, who perform activities to create a product, such as farm outputs, and *regulators*, who are responsible for compliance checks. The RegTech system can be steered by various technologies, e.g., computational, electromechanical, and biochemical tools. In the context of agriculture,

producers include farmers, shippers, and retailers, while regulators are biosecurity officials who enforce defined laws.

A total of 121 research articles, industry papers, guidelines, and policy documents contributed to the development of the technology readiness framework for RegTech in this paper. Most documents focus on technology maturity, outlining all technology capabilities, while others focus on regulatory burden, identifying regulatory issues and the need for RegTech. Of the 121 articles, 104 were research articles, 4 were books, and 11 were reports and guidelines documents. The high number of non-research documents indicates the dependence on policymaking in compliance checks.

Approximately 47% of the articles focused on IIoT-based monitoring and smart farms, while 28% focused primarily on RegTech and compliance (including 15% of the total that also mentions IIoT). In comparison, 25% focused on technologies used in farming-related activities (11% also mentioned IIoT). Figure 1 presents trends and sources in RegTech research, along with the thematic composition.

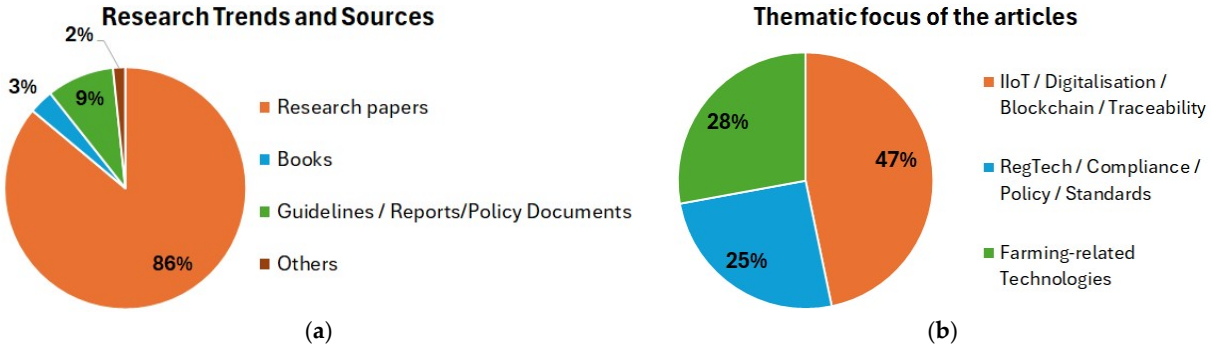


Figure 1. (**a**) RegTech Sources of research and development in recent years; (**b**) Different themes of this RegTech research.

Agricultural technology maturity is evolving. Over time, more technology is expected to mature, and more policies are expected to be set for agricultural products.

The remainder of the paper is organized as follows: Section 2 describes the agricultural process as a cycle of data collection and the role of IIoT within this cycle. Section 3 examines the current state of regulatory technologies, including their dimensions of technological maturity, economic feasibility, and social acceptability. Section 4 mentions future directions about a new decentralized compliance framework.

2. Agriculture Process and Regulatory Burden

The agricultural sector is highly heterogeneous, comprising numerous small-scale industries with diverse requirements. Plant-based agriculture varies significantly depending on crop-specific requirements, applicable laws, and industrial needs. However, there is a recurring pattern of activities across industries that repeats annually. We primarily focus on plant-based agriculture in this paper. Still, the regulatory landscape is similar for the livestock-based agriculture industry, and such industries are also included in our analysis.

2.1. Agriculture as a Cycle of Activities

Agriculture has a pattern of activities that are repeated over time. The basic operational cycle is similar across all crops, including growth, harvest, and shipping. All farming operations are dependent on parts of the crop cycle and have some of the following features that are critical for RegTech:

The farming operations process is well-defined, and growers typically follow the expected steps to grow their crops. There is little scope for farmers to deviate from this

seasonal process. From a compliance perspective, this facilitates the use of a standardized set of checks against well-established rules to assess compliance.

The farming operations process takes a long time, typically over several months, and is rigid and irreversible. It is inflexible because it is difficult to take additional steps when external factors, such as an emergency pest-control situation, require deviations from standard procedures.

The extended timeframe of agricultural production, which often lasts several months, further contributes to the inherent rigidity of these processes. From a compliance perspective, it may be more appropriate to continuously record and verify compliance rather than check only once, after all data has been accumulated. The frequency of compliance activities depends on the crop itself. This means that data collection must be accurate (manually or sensor-based) at the required time, as any incorrect data could trigger a cascading sequence of unintended consequences that would be irreversible.

Unlike more adaptable manufacturing processes, retroactively introducing additional steps or significantly altering the established sequence of activities is usually tricky, if not impossible. This inflexibility poses challenges when deviations from standard procedures are required, for example, in unexpected pest infestations that necessitate emergency interventions.

2.2. Regulatory Activities and Burden

Regulatory burden refers to the administrative and compliance requirements imposed by regulations and laws. For farming entities in Australian agriculture, legislative regulations encompass all stages of agricultural production (Stages 1–3) prior to sales and consumption (Stage 4), as illustrated in Figure 2. In this paper, we focus only on Stages 1–3, which are from a farmer or grower perspective.

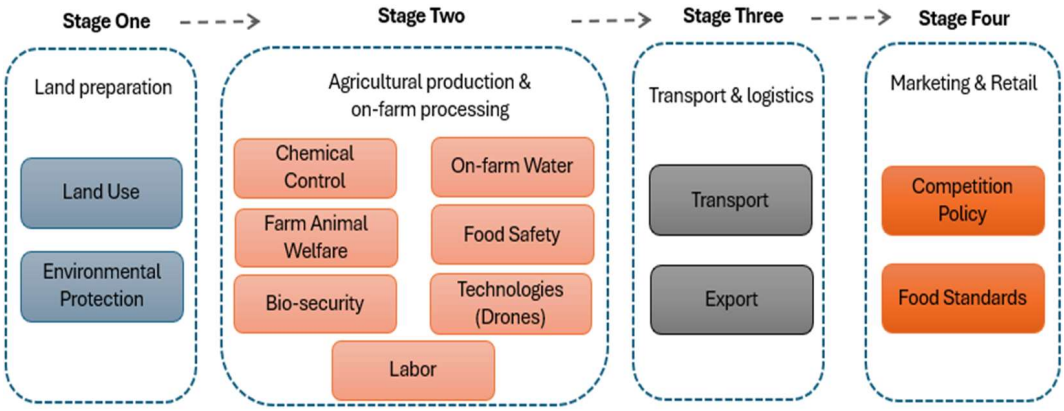


Figure 2. Regulatory requirements across all stages of the Agri-product Supply Chain.

In the general process of agri-production, farming stakeholders are required to comply with laws and rules from land use to product sales including regulations relevant to environmental protection, food safety, on-farm water, chemical residues control, labor management, packaging (i.e., labels), transport rules (such as the heavy truck license) and sales/export (such as the export certificate or permit) [14]. Compliance and administrative costs are incurred in terms of paperwork, time, and energy spent on permit applications, completing forms, and reporting [15]. For example, if a producer needs to move their oversized agricultural machine between farms, with a distance of 25 km, they may need to prepare two transport permits, one railway crossing permit, pay for two police drivers, and a license from three institutions [14]. These application processes are considered

time-consuming and burdensome in administration, and conflict with weather-dependent farming activities [14].

It has been suggested by Tasmanian Department of Economic Development and Tourism in a survey done in 2013 with the objective of reducing the time spent on compliance by businesses that the priority areas of compliance cost in the industry of "agriculture, forestry, and fishing" are "import/export regulations, licenses and permits to conduct business or commercial activities", "employment, workplace health and safety standards", and "employment licenses, permits, and controls" [16]. This survey estimated the time required weekly for regulatory compliance-related tasks at 19.9 h for business entities with staff and 3.2 h for those without staff [16], indicating a considerable overhead.

The Australian agricultural sector operates within a complex regulatory landscape that imposes significant compliance burdens on farming entities. For perishable produce, such as cherries and honey, the impact of regulatory burden can be substantial due to their limited shelf life and sensitivity to handling and storage conditions. The regulatory burden can affect perishable produce by increasing compliance costs, operational delays, and logistical challenges [17–19], market access restrictions [20], legal risks of non-compliance [21], and quality control [22]. Efforts to comply with these requirements can be costly in terms of the resources required.

Regulatory administration for agricultural products seeks to ensure product safety, environmental protection, and the well-being of the social community. However, excessive burdens can hinder the industry's growth and prosperity [23]. Therefore, minimizing these burdens is crucial to fostering the sector's healthy, robust development. This can be achieved by adopting more IIoT-enhanced RegTech applications to cost-effectively and reliably improve agricultural process efficiency.

3. RegTech in Agriculture

In this section, the role of RegTech in agriculture-related compliance checks is explained, and a detailed analysis of the current technology and economic landscape for RegTech deployment across all producers is provided.

3.1. Defining RegTech

RegTech is defined as technological solutions that "mainly use information technology for compliance and regulation" to improve regulatory processes [24]. RegTech, as a subcategory of IT, encompasses a broad set of applications designed to ensure regulatory compliance and continuously monitor products or processes, while balancing the need to protect information privacy and cybersecurity and to ensure data availability and transparency. RegTech monitors a process where

i. Individual products are produced (Stages 1–2 in Figure 2);
ii. Undergoes various changes, including ownership and packaging (Stage 3);
iii. Finally, it is consumed and has an impact on society, for example, on public health (Stage 4 in Figure 2).

In the agricultural sector, compliance with agri-products regulations is not limited to farming entities; it must be maintained throughout the entire supply chain. Product traceability data is critical evidence to demonstrate compliance by producers or other stakeholders, especially in the case of an incident [21]. In this paper, we focus exclusively on the role of producers, such as farmers, and cover only production and shipment.

RegTech is an amalgamation of technologies that primarily extend IIoT capabilities, specifically for compliance monitoring. RegTech comprises several steps, beginning with data collection via manual data entry on digital platforms or, in advanced versions, via IIoT sensors. In the second step, regulators define a set of rules. In the third step, the

collected data is processed. For example, an image is analyzed for objects, or a time series is analyzed for anomalies, to reach a compliance-related decision at a particular point in time by checking it against the rules. Hence, the successful integration of IIoT-enhanced RegTech in agriculture depends on the existing AgTech maturity as summarized in Table 1 and shown in Figure 3.

Table 1. Conceptual Comparison between AgTech and RegTech.

IIoT AgTech	RegTech with IIoT	How Can These Be Blended?
Optimization is the aim.	Compliance is the aim.	RegTech can piggyback on existing IIoT and digital technologies.
Heavyweight–Hi-tech AI and data analysis for prediction/optimization and management.	Lightweight–only check for compliance (if things happen within limits)	An extra layer of functionality can be created on existing software to summarize its output for compliance decisions
Private consumption of services and data	Data is meant to be shared.	The required data can be shared only with designated authorities when needed.
Data originates from the farm and remains there	Not all data/services come from the farm or remain on the farm	The required data can be shared only with designated authorities when needed.
No strong external stakeholder	Strong external stakeholder (regulator)	The required data can be shared only with designated authorities when needed.
Farmer dependent	Time-bound (data must be collected at the right time and place)	A minimum set of IIoT hardware and software needs to be deployed

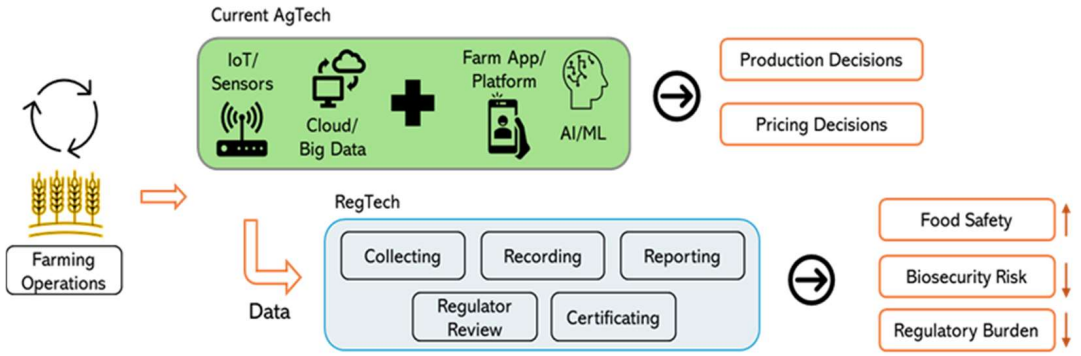


Figure 3. RegTech and IIoT for Compliance Checks.

It should be noted that the decision to embed RegTech into framing practice can be driven by a number of factors beyond mere technological capabilities. These include differences in the product's profitability and social acceptance or need for surveillance. While Australia's agricultural landscapes provide a comprehensive picture of regulatory burden, the proposed framework can be adapted to any region of the world, assuming there is consumer-driven demand from producers for such technologies.

3.2. Key RegTech and IIoT Technologies

RegTech relies heavily on modern ICT infrastructure, including cloud computing for data storage and processing, mobile devices for data collection, and secure networks for data transmission. At its core, RegTech is about leveraging data to improve regulatory compliance. This involves collecting data from various sources (e.g., manual data entry, sensors, IoT devices, local or cloud databases, and reports), analyzing it to identify patterns, trends, and anomalies, and using insights to inform decision-making and automate compliance tasks.

This technology-driven approach enhances transparency and operational efficiency for businesses and regulators. RegTech tools aim to automate rule monitoring, risk assessment, reporting, and status updates, and AI can boost these capabilities [25]. Its core purpose remains to automate and streamline regulatory compliance. The most common AgTech technologies applicable to RegTech are explained below.

- *IIoT*: This technology is applied in Agriculture for real-time monitoring of environmental conditions such as soil water, pest control, livestock health, food safety, and anti-counterfeiting traceability [6]. This existing IIoT infrastructure can be repurposed for RegTech to meet compliance requirements. For instance, data on pesticide and fertilizer applications, water use, and emissions can be automatically recorded and reported to support environmental compliance.
- *Sensors*: Their cost has fallen over the years. They simply gather precise data about the farm environment and operations, such as soil nutrient levels [26], pesticide residues [27], and product quality [28]. These existing tools can easily be used for compliance tasks. They can monitor food quality throughout the supply chain to ensure safety, detect contamination quickly, and track environmental conditions to help meet regulatory requirements.
- *AI and Machine Learning (ML)*: Both are already used in farming for tasks such as pest and disease detection and prediction [29], weed identification [30], product grading [31], and optimizing resource use. These existing analytical tools create major opportunities for RegTech. AI/ML can analyze farm data to identify compliance risks and prioritize inspections. They can detect anomalies that indicate noncompliance and automate the generation of reports for regulators. This approach yields synergistic benefits from the initial AgTech investment.
- *Computer Vision*: Computer vision capabilities in AgTech include product identification, sorting, and quality control [32], and pest and disease detection [33]. These provide a strong foundation for automated compliance verification in RegTech. This technology can help verify compliance with labeling regulations, product quality standards, and other visual inspection requirements, reducing the need for manual inspection.
- *Blockchain*: It has been employed for supply chain traceability and provenance verification [3]. This technology's inherent security and immutability create an audit trail of compliance activities, enhancing audit efficiency and transparency. Furthermore, it provides a secure and verifiable platform for storing and managing certifications [34], and enhance confidence in compliance claims for cross-border transactions.
- *Radio-Frequency Identification (RFID) and Near Field Communication (NFC)*: Both play a crucial role in AgTech for livestock tracking and product identification [28]. Their ability to provide granular tracking information makes them particularly valuable to RegTech. They enable rapid, efficient product recalls, thereby minimizing potential harm to consumers and economic losses for producers.
- *Farm Management Software (FMS)*: FMS is commonly used for crop life cycle reporting, record-keeping, and managing daily farm activities [35]. By using its existing data collection, recording, and storage capabilities, RegTech can automate the generation of compliance reports or provide auditors with direct access to the necessary data for compliance verification [36].
- *Drones and Satellites*: Both are already implemented in AgTech for pest and disease monitoring [37], pesticide application [38], air pollution identification [39], and yield prediction and field mapping. Compliance monitoring can be streamlined and made more efficient by using existing imagery. For instance, this imagery can verify compliance with land use regulations, environmental restrictions, and crop insurance requirements.

Additionally, RegTech solutions can automate the generation, formatting, and submission of regulatory reports, thereby forming a robust, integrated RegTech ecosystem. This aligns with the final step of the data flow, as shown in Figure 3.

3.3. Assessing Technological Maturity

To increase the uptake of RegTech and realize its associated benefits, the technologies must be ready for such purposes. Furthermore, for any future decentralization of RegTech activities, which would reallocate RegTech activities to independent stakeholders at all levels rather than to regulators alone, technologies must be sufficiently mature to ensure reliability through automation and ease of use. It should also be cost-effective and widely deployed among all stakeholders.

3.3.1. Technological Maturity Framework for RegTech

As noted in the previous sections, the current availability and application status of digital technologies in the agricultural sector are vital to RegTech implementation. To gain a comprehensive understanding of the global development of digital technologies, research on agricultural technologies should be categorized by maturity. To assess the technological capacity of the agriculture sector, this paper proposes and evaluates a Technology Readiness Assessment Framework for Compliance (TRAFC). This framework uses three distinct maturity levels to differentiate the degree of technological maturity across six key *attributes* with regard to RegTech. The primary function of this differentiation is to assess the suitability and readiness of existing technologies for regulatory compliance management.

This framework comprises three core regulatory compliance attributes that represent distinct perspectives on technology maturity for handling data in an IIoT environment: data delivery, data resolution, and data safety.

1. Data delivery and accessibility refer to the speed, reliability, and ease of data transfer from the point of collection (e.g., a sensor or device) through the network to the user interface (i.e., screen or decision-making system). It assesses the technical mechanisms that ensure data are readily accessible and timely, supporting real-time regulatory decisions.
2. Data resolution refers to the scale, volume, and level of granularity of the collected data for compliance checks. It assesses the spatial and temporal density of data required to support precise decisions at the necessary scale.
3. Data integrity and security concern the trustworthiness, accuracy, and confidentiality of collected and transmitted data. It assesses the risk of data being inaccurate, compromised, or modified without authorization during its lifecycle. These three attributes are critical for regulatory compliance because regulators require accurate, sufficient, and timely data to enforce standards such as biosecurity traceability, cold-chain monitoring, and chemical application reporting.

Additionally, three operational attributes are introduced to represent ease of use for compliance:

4. Automation refers to the degree to which the technology minimizes human intervention and manual workloads without risk of failure. A highly automated operational process is expected to reduce labor and management costs associated with farming. This would also ensure more frequent data collection and consistent regulatory checks.
5. Interoperability indicates the seamless and secure exchange of collected data or devices to software compatibilities.
6. Availability refers to whether users can access the application with ease, without barriers or complex procurement procedures. When interoperability and availability

are high, they act as catalysts for more frequent, reliable compliance checks involving multiple stakeholders, especially when they are not well known to each other.

We propose a 3-tier maturity scale for each attribute, as shown in Table 2. The differences in levels are based on characteristics and their relevance to agriculture. The attributes above and their levels are generalizable to the assessment of all types of technology for RegTech purposes. A three-level scale adequately captures maturity as either not yet ready for RegTech or having at least functional readiness, if not full strategic readiness.

Table 2. Technology Readiness Levels for each attribute in the context of RegTech.

	Attribute	Level 1 (High Compliance Risk)	Level 2 (Functional Readiness)	Level 3 (Strategic Readiness)
1	*Data Delivery*	Disconnected and manual data transfer, poor remote coverage. Data is collected locally on a device, stored, and must be manually transferred by the user.	Remote connectivity, but not 100% reliable; Automated to the central hub. Data is automatically transferred when a network connection is available.	Real-time or on-demand, reliable high-speed delivery regardless of location or temporary connectivity issues.
2	*Data Resolution*	Low resolution, data cannot support specific, actionable compliance decisions, or when not sure what decision can be made with the data	Medium resolution, data support discrete (binary) compliance decisions,	High-resolution, very high-level decisions can be made based on the data.
3	*Data integrity and security/risk*	High risk (low accuracy, weak security); data is easily manipulated, lost, or corrupted	Moderate risk, improving accuracy, basic data security protocols. Data is generally reliable, but can be questioned by regulators	Low risk (high accuracy, strong security); Data is immutable, cryptographically secured, and fully auditable with a verified chain of custody
4	*Automation*	Mostly manual or manually triggered workflows. Requires high labor input and constant human intervention for core tasks.	Partial automation; requires manual steps to change configurations in response to unknown factors	Fully automated workflows; Requires minimal human oversight for routine compliance tasks.
5	*Interoperability*	Currently not integrated with any external system, or difficult to integrate with an external system	Can integrate with limited external systems, but must have the capability to integrate with governmental or peak bodies' systems	Easy to integrate with any external systems
6	*Availability*	A few apps or devices (limited vendor options)	Growing competition (multiple vendors) limits viable adoption to large-scale producers.	Wide and diverse market availability (multiple vendors) using standardized components

Based on these six attributes and the levels, we can classify a technology's readiness, which can ultimately be related to the Technology Readiness Level (TRL) [13] scale used by industries, into three stages:

- *Early stage* (*E.S.*, Proof of Concept): technologies at this level are still considered as under development or in the initial stages of pilot projects. Their feasibility and potential

benefits are being explored, but they are not yet widely available for commercial use. This loosely follows TRL 1–6.

For the purpose of our framework, for a technology, at least one of the three core data feature attributes must be at level 1; the three operational attributes are typically at level 1 but may exhibit isolated level 2 capabilities. Compliance with this stage technology is primarily manual, non-real-time, and highly vulnerable to data loss, human error, and audit failure.

- *Emerging* (Growth Stage): technologies at this stage have transitioned from the initial concept stage and are being adopted by early users. They are commercially available but may still have limitations in terms of functionality or scalability. This loosely follows TRL 6–7.

For the purpose of our framework, for a technology, all three core data feature attributes must be at level 2 or higher, and the three operational attributes must be at level 1 or level 2. At this stage, technology can automate and streamline compliance reporting, but the system may struggle with complex integrations, high workloads, or poor network coverage.

- *Established* (*Est*., Mature Stage): technologies at this level are widely adopted and considered standard practice within their respective industries. They are well-developed and reliable, and they offer a broad range of functionalities. This loosely follows TRL 8–9.

For the purpose of our framework, for a technology, all three data feature attributes must be at level 3; three operational attributes must be at level 2 or level 3. Technology at this stage could enable full automated, real-time compliance validation and support zero data loss while requiring minimal human intervention.

The above definition of the maturity criteria is rooted in RegTech's core purpose: generating verifiable, trusted evidence of compliance. This prioritizes the data quality as data integrity is non-negotiable. Because any deficiency in data integrity, granularity, or reliable delivery will undermine the regulator's trust. At the same time, operational attributes may be set to level 2 during the established stage. This is a necessary trade-off for real-world deployment, given practical constraints arising from legacy equipment and varying regional network coverage in the agriculture sector.

The same technology is assessed at different maturity levels across use cases. This is due to two main factors:

- The granularity in which the information can be collected, and the ability to process the information for the use case purpose.
- The ability to control the process with high precision for the specific use case purpose.

We present two specific technologies that can be classified into multiple stages depending on the target application and other classifications as well.

3.3.2. Measuring Technology Readiness: Drones

Drone and ML applications in weed control, such as spraying and weed identification, are assessed as *emerging*; drone applications in disease monitoring, such as crop health monitoring, are categorized as *established*; but drone applications in farm environment plan audit are in an *early stage*.

The drone application for crop health monitoring is assessed as being at an *established* stage because it uses proven multispectral science and automated, cloud-based workflows to deliver high-quality data and ensure data integrity for strategic decision-making. In addition, the flight and data analysis processes are fully automated, and many companies sell such drones.

In contrast, weed control and spraying remain in the *emerging* stage due to physical bottlenecks, such as limited battery life and small pesticide tanks, as well as technical risks associated with AI (e.g., AI may misclassify crop species as weeds). Data resolution is higher than data delivery because the drone must detect tiny weeds to be effective, but processing weed maps often requires specialized computers or manual map transfers. Furthermore, the low availability stems from the relatively high cost of dedicated spraying drones. A radar chart of drone technology readiness is shown in Figure 4.

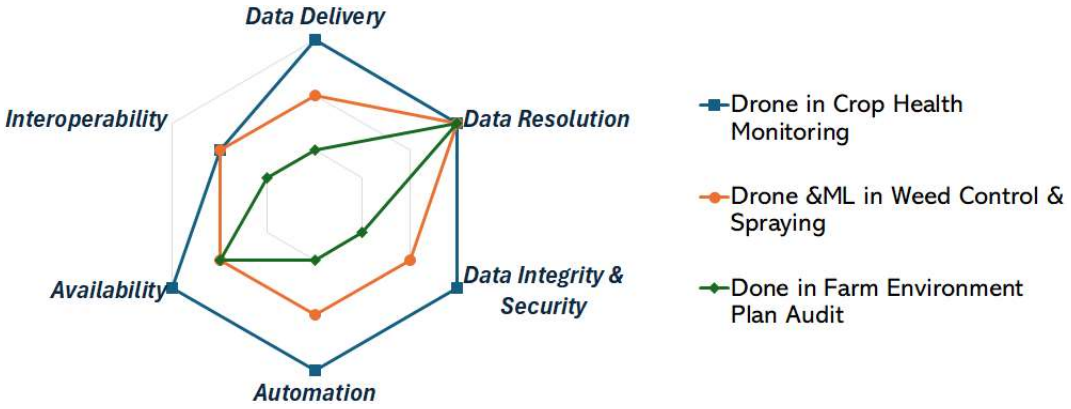


Figure 4. Readiness scores of drone applications using the proposed framework in three use cases.

The farm environment plan audit is categorized as an *early stage* because the rules for its use are not clear yet. Even though the data resolution is high, there are no established rules for storing or sharing this audit data. Data integrity and security are low because the data cannot be used safely as a legal record or proof in a standardized audit, which could pose significant risks to both users and regulators. Moreover, the process is implied as highly manual and person-dependent, as the benefits depend on positive relationships between farmers and compliance officers [40].

3.3.3. Measuring Technology Readiness: Blockchain

The application of blockchain in agri-food distribution, food safety and quality, and beef cattle product traceability is assessed as an *emerging* maturity level. However, its implementation for compliance management in cross-border transactions is assessed at an *early* stage. This assessment result is based on the scores of the six attributes listed in Table 2. A radar chart of blockchain technology readiness is shown in Figure 5.

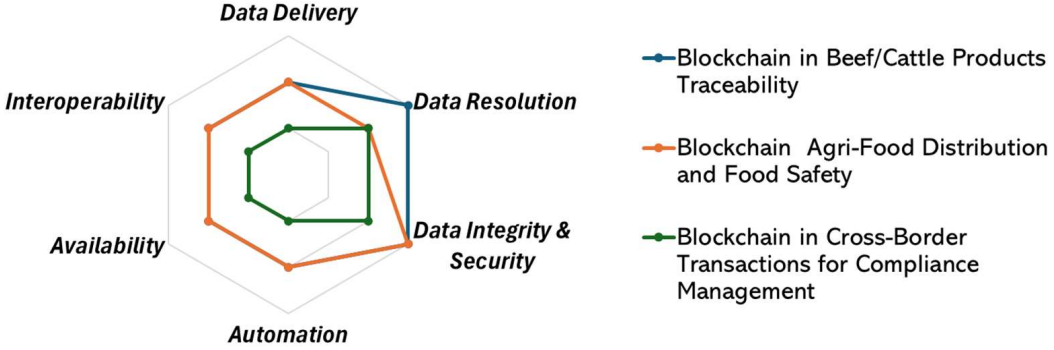


Figure 5. Readiness scores of blockchain using the proposed framework in three use cases.

While the application of blockchain in both agri-food distribution and beef cattle traceability use cases achieves high data integrity through cryptographic security, their progression to the "established" stage is constrained by the infrastructural and physical

realities of the agricultural sector. The first reason is limitations in the network infrastructure. Remote agricultural environments, including farms, pastures, and transit routes, consistently lack reliable, real-time network connectivity [41]. Consequently, data cannot be streamed continuously; instead, transmission relies on delayed batch uploads triggered only when physical nodes regain network access. The second reason is the physical–digital divide. Although blockchain ensures immutability for on-chain records, it cannot independently verify the accuracy of data prior to entry. Both use cases require physical interventions, such as manual barcode scanning or RFID ear tags, to bridge the physical–digital gap, thereby limiting full automation. The third point is the variation in data resolution. Notably, beef traceability achieves a higher data resolution by utilizing RFID technology to monitor individual animals, whereas general agri-food distribution currently operates at the batch or lot level. Despite this distinction, both applications share similar deployment costs and systemic limitations, keeping their operational attribute scores at a medium level.

Conversely, blockchain adoption for cross-border compliance management remains in its *early* stages. Its maturity has been primarily hindered by sovereign, legal, and regulatory barriers rather than technological shortcomings [42,43]. Data delivery is fragmented. The most significant bottleneck occurs at national borders. In the absence of globally unified digital customs protocols, data from an exporting country's blockchain cannot easily flow into an importing jurisdiction's systems [44,45]. Within the context of RegTech, data integrity extends beyond cryptographic security and requires explicit trust from regulators. Standardized, universal products for cross-border blockchain compliance are currently absent [46]. This results in highly complex technical integration, and substantial manual review and intervention remain necessary.

3.3.4. Measuring Technology Readiness: Sensors

Here we show the classification of three miscellaneous sensor types, which are not necessary across three categories for the same sensor.

As seen in Table 3, the application of sensors for both livestock health monitoring and real-time traceability of agricultural yields and distribution is *established*. But the maturity of the sensors used in pesticide residue detection is assessed as *emerging*. A radar chart of sensor technology readiness is shown in Figure 6.

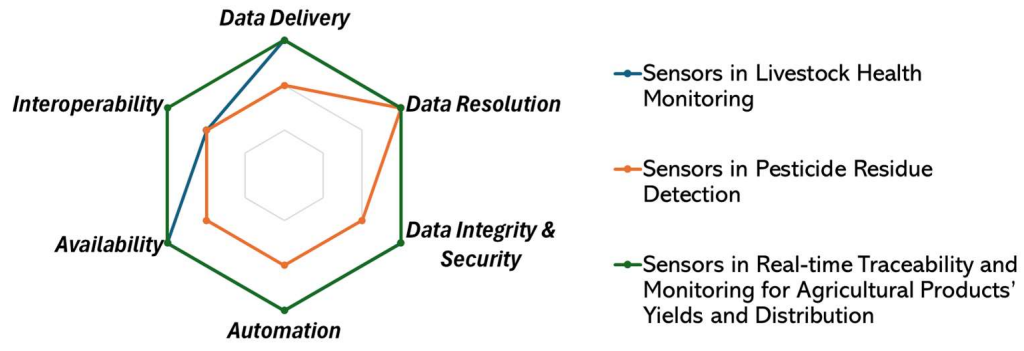


Figure 6. Readiness scores of sensor applications using the proposed framework in three use cases.

The key driver behind the maturation of application scenarios in livestock health monitoring and real-time traceability for agricultural yields and distribution lies in the successful elimination of manual intervention. Wearable livestock sensors and yield monitors embedded in heavy machinery enable reliable, real-time data transmission via local gateways or active cellular networks, thereby avoiding network coverage limitations in vast rural areas [47,48]. Additionally, there is a tamper-proof chain of

evidence. Telemetry technology permanently binds data to specific physical assets, such as individual animal identification codes, through hardware devices like electronic ear tags or sealed cold chain transport containers [49,50]. This hardware-level binding mechanism operates independently of user actions, virtually eliminating the risk of human tampering and ensuring that records are highly traceable. The third point is operational standardization and high-resolution data. Both applications capture highly precise data (level 3), ranging from individual biometric parameters to sub-meter yield mapping. Furthermore, they use standardized global communication protocols, enabling full operational independence and seamless integration across diverse regulatory and supply-chain monitoring systems.

The use of sensors for pesticide residue detection remains at an *emerging* stage. Its maturation is primarily limited by physical bottlenecks and manual dependencies, rather than by a lack of analytical precision. Firstly, data delivery and automation are constrained by a sampling bottleneck. Unlike passive asset monitoring, pesticide detection requires operators to personally select, extract, and prepare specific soil or crop samples. This manual dependency means data cannot be transmitted continuously; instead, it relies on batch uploads performed only after manual field testing is complete. This limits both data delivery and automation to a medium maturity level. Furthermore, vulnerabilities exist in data integrity. The physical sampling process prior to analysis may be subject to critical flaws, as manual intervention introduces risks of selective sampling bias or localized contamination, thereby preventing the system from meeting the consistent trust standards required for high maturity levels. The third issue concerns market and system barriers. High-precision, field-deployable biosensors carry significant capital costs, limiting their widespread adoption primarily to large-scale operations [51].

3.3.5. Technology Maturity Status

Table 3 reviews the readiness of current digital technologies used in agriculture within this framework. Based on the attributes listed in Table 2, the estimated maturity of each technology for regulatory management is analyzed. The table shows that the same technology is assessed at different maturity levels across use cases.

Table 3. Technology Readiness for RegTech using TRAFC.

Functions/ Applications	Sub Theme (Use Case)	Primary Technologies	Readiness for RegTech	Ref.
Land	Land Cover Classification	AI/ML	Emerging	[52]
Soil Management	Soil Moisture Estimation	AI/ML	Emerging	[53]
Seed	Seed Classification	Computer Vision/ML	Emerging	[54]
Crop Production	Crop Classification	Deep Learning (DL)	Emerging	[55]
	Vegetable or Fruit Grading	AI/ML	Emerging	[31]
Weed Control	Weed Identification	DL	Emerging	[30,56,57]
	Weed Detection	DL	Emerging	[58]
	Spraying and Weed Identification	Drone & ML	Emerging	[59]

Table 3. *Cont.*

Functions/ Applications	Sub Theme (Use Case)	Primary Technologies	Readiness for RegTech	Ref.
Diseases Monitoring	Plant Disease Classification	ML/DL/Computer Vision	Emerging	[29,33,60–62]
	Disease Detection	AI/ML	Emerging	[63,64]
	Disease Localization	DL	Emerging	[65]
	Crop Health Monitoring	Drone	Est.	[66–68]
	Livestock Health Monitoring and Record	Sensor/Wireless Sensor Network (WSN)/Biosensor	Est.	[47,69–71]
		RFID	Est.	[72]
Pest & Disease Control	Pest Identification and Control	IIoT	E.S.	[73,74]
	Spraying	Drone	Est.	[75]
	Plant Pest and Disease Monitoring	Drones and Satellites	Est.	[37,76]
	Plant Pest and Disease Detection/Identification/Classification	AI and ML	Emerging	[77–80]
	Insect Classification and Detection	ML	Emerging	[81]
	Pesticide Application	Drones	Emerging	[38,75]
	Pesticide Residue Detection	Sensors	Emerging	[27,82]
Food Traceability	Transparency in agri-food distribution, food origin and sourcing, food safety, and quality.	Blockchain	Emerging	[11,12]
	Real-time traceability and monitoring for agricultural products' yields and distribution	Sensors	Est.	[49,83,84]
	Fresh Fruits and Vegetables Traceability	IIoT networks	E.S.	[85]
Anti-counterfeiting	Food Anti-counterfeiting	Blockchain & IIoT	Emerging	[3]
	Beef Cattle Products Traceability	Blockchain	Emerging	[86]
	Wine Anti-counterfeiting	RFID	Est.	[28,87]
	Agricultural Products Provenance	NFC	Est.	[88,89]
	Food Safety and Commercial Fraud	DNA Barcoding	E.S.	[90,91]
	Food Authentication and Traceability/Animal Identification, and Meat Products Traceability	Chemical Fingerprinting	E.S.	[92,93]
Quality Control and Inspection	Product Identification and Sorting (inspection and quality control of fruits and vegetables/food products)	Computer Vision	Emerging	[32,94]
Real-time Data Collection	Precision Agriculture/Environmental Factors Control for Crops	IIoT	Est.	[10,48,95]

Table 3. *Cont.*

Functions/ Applications	Sub Theme (Use Case)	Primary Technologies	Readiness for RegTech	Ref.
Livestock Management	Precision Livestock Farming	Agricultural Robots	Emerging	[96,97]
	Moving Indoor Livestock	Drone	E.S.	[98]
	Behavior Recognition	ML/DL	Emerging	[99,100]
Product Management	Product Monitoring/Food Security	Blockchain	Emerging	[101]
	Food Safety Monitoring	Blockchain & IIoT	Emerging	[102–104]
Crop Life Cycle Reporting	Crop Production; Crop Data Management	Farm Management Software	Est.	[105,106]
Environment Monitoring	Crop Farming	AI/ML	Emerging	[107]
	Remote real-time unattended agriculture environment monitoring (habitat, greenhouse, climate, forest)	WSN	Est.	[108–110]
	Soil Water Content (Irrigation scheduling); controlled environment monitoring, and controlling	IIoT sensors	Est.	[26]
	Soil source pollution identification in forestry/air pollution	Drone, ML	Emerging	[39,111]
Technology Compatibility	Farm Digitalization	Integration System	E.S.	[1]
Agricultural Regulation Translation	Automatic Rule Classification (Pesticide Regulations)	ML & Natural Language Processing (NLP)	E.S.	[25]
Compliance Management	Halal Certification	AI/Blockchain	E.S.	[34,112]
	Cross-Border Transactions	Blockchain	E.S.	[113]
	Cross-compliance with Environmental Requirements	FMS	Emerging	[36,114]
	Smart Sustainability Compliance Reporting	Integrate Farm Management Information System (FMIS) & Farm Financial Accounting (FFA)	E.S.	[115]
	Automatic Compliance Control	Standards/legislation encoding & Computer Inference System	E.S.	[116]
	Farm events record keeping/GAP (good agricultural practices) compliance	Decision support system ("GAP-a-Farm")	E.S.	[117,118]
	Law Compliance Check	AI	E.S.	[119]

Table 3. *Cont.*

Functions/ Applications	Sub Theme (Use Case)	Primary Technologies	Readiness for RegTech	Ref.
Admin Issues	Farm Environment Plans Audit	Drone	E.S.	[40]
	Farm Audit Streaming, Simplified Reporting, Lab Analysis Management	Global Compliance Platform (Agri-Place)	E.S.	[120]
	Simplifying audit and inspection, document management and verification, and improving the certification process	AI	E.S.	[121]

Based on the above assessment, the technologies underpinning RegTech are sufficiently mature for widespread application in the agricultural sector. Digital technologies facilitate a streamlined flow of regulatory information in the agricultural sector. Data originating from sensors or FMS is efficiently collected and analyzed by AI algorithms, and the resulting insights are readily shared with regulators. Similarly, reports derived from FMS, which encompass vital farm data such as land use and chemical applications, can be readily distributed to stakeholders, including auditors and regulators. The existing infrastructure of food supply chain traceability platforms, built on blockchain and IoT, inherently ensures compliance with food safety and origin mandates. Complementing this, AI-driven compliance-monitoring systems continuously analyze data from AgTech systems to flag potential biosecurity or animal-welfare violations. Smart audit tools further enhance this information flow by digitizing checklists, automating verification, and providing instant access to necessary data.

The agricultural sector can make good use of these advancements to address compliance challenges across environmental regulations, food safety, animal welfare, and product traceability. This enables the development of reliable, scalable, and cost-effective RegTech solutions tailored to the sector's specific needs. It is worth noting that while a few technologies, such as NLP and online platforms, are not within the scope of IIoT, most technologies are already prevalent in IIoT. Some sensing technologies, such as DNA and chemical fingerprinting, can eventually be integrated into IIoT.

3.4. Economic Maturity

The adoption of digital technologies depends on farmers' assessment of whether the anticipated benefits outweigh the associated costs. The economic feasibility of extensive RegTech-based activities encompasses a wide range of factors, including:

i. The cost and price of the product, i.e., its profitability and value. Low-value products are less motivating for producers to adopt RegTech and are more likely to adopt centralized RegTech [122,123].
ii. The risk of the product being counterfeited, thus causing reputational harm and, in turn, economic harm. A higher risk of counterfeiting would be a motivating factor for implementing RegTech and decentralizing it, thereby enabling greater flexibility in implementing anti-counterfeit measures [124].
iii. The capital cost of installing RegTech-related infrastructure is affected by, for example, the lower the initial cost of implementing RegTech, the easier it is to decentralize it by enabling smaller stakeholders to install the infrastructure [125].

iv. The ongoing operational cost of RegTech, or specifically, any additional cost of operating RegTech, may include additional labor costs or increased risk of failing to acquire the necessary data [126,127].

Based on Table 3, drones, farm management information systems, and computer vision are high-cost and relatively risky from an economic perspective. All other established technologies are already financially viable.

The economic maturity of digital RegTech consists of a multidimensional assessment of risk. In this context, "risk" could be high capital expenditures (CAPEX), ongoing operational expenditures (OPEX), hidden data-management costs, uncertain returns on investment (ROI), and severe legal or compliance exposures resulting from technological failure. The implementation of different agricultural technologies presents different economic risks.

For instance, the economic barriers to drone adoption include physical infrastructure and maintenance, which require substantial initial CAPEX and recurring OPEX, such as multispectral sensors, battery degradation, and hiring or training certified pilots. These costs further result in uncertain ROI.

While FMIS may have lower initial CAPEX, its economic risk lies in long-term data management burdens. The integration of FMIS requires subscription fees. In addition, farmers may underestimate the hidden labor costs associated with manual data entry, data cleaning, and the technical challenges of system integration. If data management is too costly or time-consuming, the system may fail to generate reliable evidence of compliance.

Computer vision for automated weed control or disease detection introduces a risk of algorithmic misclassification. If a computer vision model misidentifies a protected native plant species as a weed during an automated chemical application, or fails to detect a regulated quarantine pest, the producer faces immediate regulatory penalties and severe legal liability [128,129]. Consequently, the high cost of algorithmic failure restricts the economic maturity of these systems in strict regulatory environments.

As shown in Table 3, this section's analysis demonstrates that RegTech can be implemented economically using existing and emerging technologies. While established technologies are fewer in number, they cover the most critical aspects of the agricultural cycle. Emerging and early-stage technologies, expected to be commercialized within a few years, also address core aspects of agricultural production and logistics.

3.5. Social Factors

While technical feasibility and economic viability are essential prerequisites for RegTech adoption, social factors significantly influence their actual uptake and success [130–132]. Farmers are considered the primary drivers of new technology adoption [133]. Even if the technology is available and affordable, its implementation can be hindered by stakeholders' unwillingness to use it [134]. This "willingness to use" encompasses several key aspects:

- *Bias* in recording and analysing regulatory data by automated processes. Biased training data, flawed algorithms, or human oversight can all contribute to bias. Bias in regulatory data analysis can lead to unfair or discriminatory outcomes, thereby reducing stakeholders' willingness to adopt or rely on such analyses. This reluctance can hinder broader IIoT and RegTech implementation.
- *Perceived Ease of Use*: The technology must be user-friendly and easy to understand, even for those with limited technical expertise. Complex or difficult-to-use systems are often rejected, even if they offer significant benefits.

- *Trust and Confidence* with increased regulatory scrutiny: Stakeholders must have trust in the technology and the data it generates. Concerns about data privacy, security, and the system's reliability can significantly hinder adoption [133].
- *Training and Support*: Adequate training and ongoing support are crucial for the successful adoption of technology [135,136]. Stakeholders need to be confident that they have the necessary skills and resources to use the technology effectively.

4. Future Decentralized Compliance Management Framework

The future of RegTech lies in decentralization. As the regulator conducts most regulatory compliance checks, there is an upper limit to what can be achieved through just visitation and reporting [137]. This is due to a shortage of manpower and time. This is more difficult in agriculture, as the process is lengthy, spans a wide area, and produces a wide variety of end products that follow different rules. As in Table 3, most regulatory technologies are already suitable for implementation in agriculture. This could be implemented via tangible devices, supported by software, that generate compliance-related data. Such systems can be updated with specific rules in each production cycle. IIoT data can already be collected in real time, and its authenticity can be reliably verified using existing IIoT infrastructure. A future decentralized system could assign shared responsibility for compliance checks to producers and regulators, thereby increasing surveillance while reducing the burden on regulators.

Agricultural RegTech can leverage IIoT to streamline the collection of compliance-related data, thereby improving the efficiency and reliability of daily monitoring. This system would incorporate on-demand visualization capabilities, offering timely insights through user-friendly dashboards, interactive charts, and mobile access. Visualization checks can be triggered either by AI-detected anomalies or by human experts when deeper analysis or judgment is required.

While the decentralization of compliance checks with RegTech may still be at least a few years away, if it becomes feasible, it will need a structure that enables the assessment of both the monitoring requirements and the shared responsibilities of all stakeholders.

4.1. Monitoring Coverage-Time and Space

Monitoring coverage involves data collection strategies, specifically whether they are fully automated or semi-automated, to provide the most precise assessment of the farm situation. For these two parameters, the following must be considered:

- *frequency of data collection*: Assuming technology can accurately collect data, it is necessary to collect the data at the correct frequency or on demand for compliance purposes, to ensure the data can be used for verification and compliance. Frequency can vary and may be adjusted by regulators or farmers, ranging from real-time to event-oriented.
- *data collection location*: In addition to adhering to the correct data collection times, it is crucial to gather the most critical data from the designated locations. This "space" dimension refers to the extent to which the relevant area or objects are monitored, with higher spatial coverage offering better RegTech oversight. Coverage can range from complete (e.g., scanning every item) to partial (e.g., sampling or sensor density).

The appropriate combination of time and space coverage will vary depending on the specific regulatory requirements. For instance, real-time temperature monitoring during food transport may be crucial to ensuring food safety, whereas less frequent soil nutrient monitoring may be sufficient to meet environmental regulations.

4.2. Shared Responsibility

Similarly to shared responsibility in cloud-based applications, RegTech requires a shared, decentralized approach. Individuals authorized to initiate and record compliance check activities must also be responsible for maintaining the records. Examples of the responsibilities and activities required are as follows:

a. *shared responsibility*: RegTech would need to distribute the compliance activity to minimize the risk of missing any information or misidentifying a non-compliance. Shared responsibility should delineate clear expectations regarding the activities to be undertaken, including their frequency and location, for the respective stakeholders. Activities are to be done by everybody, i.e., every stakeholder holds a piece of the information chain, and the data is always attributed to the corresponding stakeholder.
b. *smooth exchange or handover of the product*: Every time the product changes ownership, the data previously collected about the product by RegTech needs to be passed on. The manner and quantity of this information should vary with regard to the privacy of trade information.
c. *trust in the stakeholder*: The shared responsibility is based on the trust that the owners intend to record compliance-related information and possess the technical ability to utilize advanced RegTech to collect the information and perform compliance checks.

4.3. Benefits of Decentralization

The decentralized compliance-check model offers multiple benefits from multiple perspectives. First, it enhances compliance coverage and granularity through continuous data collection and automated analysis powered by IIoT and AI, enabling local-level monitoring and handling of larger data volumes. This results in more detailed and comprehensive oversight. Second, AI can analyze data in real time, providing instant feedback and alerts to support continuous compliance checks and proactive responses, thereby eliminating delays associated with manual reviews.

Third, it enables more flexible, context-specific compliance by accounting for local conditions and exceptions that are often overlooked in centralized systems, thereby building greater trust among regulated entities. Lastly, it reduces compliance management costs, especially in sectors such as agriculture, by integrating compliance into everyday operations. This shift transforms it from a periodic burden into a seamless, ongoing process, thereby easing the workload on central authorities.

4.4. Risk Management

Along with its benefits, decentralization entails considerable risk. These risks must be categorized, and measures must be implemented to mitigate them, such as ensuring equipment reliability and redundancy.

4.4.1. Reliability of Personnel and Equipment

The most significant factor that could inhibit RegTech and the decentralization of compliance checks is the risk of forged compliance outcomes or the unintentional omission of critical data needed for compliance checks. This risk must be identified and managed in accordance with the industry and product-specific requirements. Typically, the higher the level of RegTech integration, the greater the risk.

The current state of technology does not permit completely unmanned operations, but human roles can be incrementally reduced as new technologies emerge. For agricultural compliance, this means that some simple tasks can be fully automated, while more complex ones will still require human intervention. To facilitate this transition, RegTech developers

can gradually reduce reliance on automated compliance checks, in line with the level of technology and the reliability of human skills.

4.4.2. Redundancy of Technology and Operation

Another issue is the reliability of the devices and the network they connect to. It is essential to ensure the continuous reliability of IoT device-collected data by preventing errors arising from network issues, hardware malfunctions, or unintended human error. One potential solution to this problem is equipment redundancy. For instance, deploying redundant IoT sensors in the field ensures continuous data collection even if one malfunctions. Redundancy can be both temporal and spatial. The system may require producers to repeat the same compliance activity multiple times to ensure that data is recorded at least once. RegTech may require multiple sensors and storage to monitor the same entity.

4.4.3. Social and Legal Risks

Technological solutions can both support RegTech in depth and provide mechanisms to address associated technical risks. However, there must also be a range of legal and socioeconomic conditions in place to enable decentralization. The cost of implementing RegTech is expected to decline as AI advances, but legal responsibility remains a critical issue.

Decentralization does not, as such, pose a linear increase in risk. This is because producers are already required to maintain records and be accountable for their products. Decentralization is intended to enhance this process, and the increased risk is solely due to the possibility of technology failure. The penalty for failing to maintain records would be the same under both centralized and decentralized compliance-check methods.

However, in a decentralized compliance framework, accountability for data collection should rest with producers and other stakeholders if they own and operate the devices. In this case, they should also own that data. It would be difficult for regulators to assume that responsibility, as the environment is still managed by the producers, even if the devices are installed and managed by regulators.

Further research is needed in this regard to gather perceptions from farmers, regulators, and consumers through surveys. These would provide a clear picture of the social acceptance and value of stronger regulatory technologies. With technology being mature enough or soon to be mature enough, it will largely be determined by these social factors.

5. Conclusions

Compliance checks are crucial for ensuring product integrity across the supply chain and the safety of product consumption. Currently, many compliance checks are primarily supervised, centralized activities driven by regulatory authorities on behalf of governments, in the interest of public health and financial stability. Modern technology is maturing and evolving rapidly, enabling producers, such as farmers and shippers, to monitor their goods and provide regulators with real-time, reliable data. RegTech is a viable solution in agriculture, and various sectors of the industry can benefit from a common infrastructure. It is critical to have a reliable understanding of technologies suitable for RegTech, relative to alternatives, to increase the uptake of such practices. The TRAFC can provide a basic understanding of the gradual integration of RegTech into agricultural practices. It can also inform future development strategies for a technology while maintaining a focus on regulatory complexities, thereby enabling seamless integration for optimal outcomes.

Furthermore, RegTech can facilitate the decentralization of compliance checks. While the onus for compliance checks remains with regulators, IIoT, AI, and cloud computing can enable semi-autonomous, real-time data collection, allowing regulators to monitor

agricultural processes with significantly less physical effort. Such efforts could lead to greater compliance at lower cost, with increased stakeholder participation.

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