(Online) ISSN 2712-0554
Original Research

Heritage and Sustainable Development
Vol. 4, No. 1, 2025, pp.975-994
https://doi.org/10.37868/hsd.v4i1.1140

From evaluation to innovation: Strengthening geospatial agricultural monitoring information system in Indonesia

Rizatus Shofiyati[1], Agnes Sondita Payani[2*], Kustiyo Kustiyo[3], Muhammad Rokhis Khomarudin[4], Dede Dirgahayu[5], Fadhlullah Ramadhani[6], Muhammad Sulaiman Nur Ubay[7], Laju Gandharum[8], Heri Sadmono[9]
[1,2,3,4,5,6,7,8,9] Research Center for Geoinformatics, National Research and Innovation Agency, Indonesia

*Corresponding author E-mail: agne004@brin.go.id

Received Mar. 17, 2025
Revised Jul. 25, 2025
Accepted Aug. 19, 2025
Online Aug. 25, 2025

Abstract

The adoption of geospatial technologies is vital for improving the efficiency and accuracy of agricultural crop monitoring. This study examines the implementation of geospatial agricultural monitoring systems through interviews with four units from three institutions in Indonesia that develop these systems. The interviews focused on system maturity management and technical processing techniques, including data input, methods, preprocessing, validation, and output. Results show that three systems, SISCrop, Simotandi, and Mixed Method, exhibit Level 3 maturity in system management (Standardized), while IDMAI SIMURP is still at Level 2 (Managed), indicating in the development phase. All institutions follow standard preprocessing protocols, though variations exist in data input, applied methods, and output designs, reflecting tailored approaches. Geospatial systems demonstrate significant potential to optimize resource use. The analysis of the technical processing technique reveals significant differences in satellite sources, spatial and temporal resolutions, classification schemes, and statistical granularity. To advance their implementation, this study recommends a unified data and policy framework to align classification standards, align temporal outputs, and establish a centralized platform that integrates agricultural data for real-time sharing and use. Also recommended are policy moves designed to clear up ownership and governance issues.

Keywords: Geoinformatics technologies, Policies and standards, System maturity management, Technical processing techniques

1. Introduction

Monitoring agricultural crops is an essential tool for guaranteeing food security, ensuring that productivity can be maximized, and that agricultural practices are sustainable. The crop monitoring methods that rely on observation made in the field and sampling are slow, labor-intensive, and costly. They also tend to generate results that can be inaccurate and easily misleading. The recent rapid development of geospatial technologies, however, enables new solutions that overcome the existing crop monitoring challenges. Geospatial systems that are combined with satellite imagery and are capable of remote sensing make it possible to efficiently monitor the landscape of an agricultural field on scale. They also support decisions concerning that field, which can be described as data-driven and as having the characteristics of sustainable progress [1], [2].

Using geospatial systems in agriculture doesn't lessen existing hurdles for successful implementation. Four units at three different institutions in Indonesia developed geospatial agricultural monitoring systems. But their different technical approaches—both to the preprocessing of the data that they use as inputs and to the outputs of their systems—create the kinds of difficulties that you might expect when trying to choose a reference output. These difficulties make it tough to create standardized data integration protocols. In Indonesia, the "One Data" policy faces significant challenges because of this issue [3].

The four main crop monitoring systems have different approaches and different strengths. The Agricultural Land Resources Instrument Standard Testing Center under the Ministry of Agriculture (BBPSI SDLP Kementan) does regional-level monitoring and provides a reliable way to understand crop conditions at a regional scale (as opposed to just obtaining satellite data and trying to understand it for the same region). This is done by way of something they call *Sistem Informasi* Standing Crop (SISCrop)[1], which uses Synthetic Aperture Radar (SAR) data, particularly from Sentinel-1, to obtain this reliable information. Agricultural Data and Information Systems Center of the Ministry of Agriculture (Pusdatin Kementan) enhances this capability with Rice Planting Monitoring Information System (*Sistem Informasi Monitoring Pertanaman Padi*/Simotandi)[2], incorporating multi-resolution monitoring that combines SAR and optical data sources such as Landsat-8, enabling more detailed and multi-level analyses.

The Ministry of National Development Planning of the Republic of Indonesia (Bappenas) uses its Integrated Digital Monitoring for Agriculture and Irrigation for Strategic Irrigation Modernization and Urgent Rehabilitation Project (IDMAI SIMURP) system to support planning and policy development through a strategic-level approach that integrates optical and SAR data. Finally, Statistics Indonesia (BPS) employs its Mixed Method system for statistical monitoring at a national scale, offering essential reporting on crop conditions and trends for governmental and public use.

Data collection, classification, and analysis remain fragmented because each system operates independently. The systems lack interoperability because they use different temporal outputs, spatial resolutions, and classification systems. This study identifies that Indonesia needs an integrated system to improve its crop monitoring operations and data exchange and enhance its overall system effectiveness. The country needs to solve this fragmentation problem to boost its agricultural resilience and food security approaches. Lack of agreed standards for interoperability is one of the challenges of geospatial systems that support agriculture. The data grows more accessible, although most data remain prone to errors in various spatial formats with different metadata at diverse times and spaces. This can make the data unusable, prevent data integration, and hinder broader and more integrated analysis [4], [5].

Due to the differences in data inputs and methodologies, crop monitoring systems in Indonesia face challenges in meeting the coherence and integration requirements. The systems operate from different satellite sources that include Sentinel-1, Sentinel-2, and Landsat-8 with different spatial resolutions and revisit times. The systems also produce data at different frequencies, including 12-day and monthly intervals, and they have different validation scales at the regional and national levels. Different data aggregation and system analysis efficiency create barriers that decrease crop monitoring effectiveness.

Data outputs and statistical methodologies show no interoperability between them. The systems employ different classification schemes for rice growth phases and non-rice categories with varying granularities and definitions, which hinder integration and comparison. Statistical analysis occurs at different administrative

[1] http://scs1.bsip.pertanian.go.id/
[2] https://simotandi.pertanian.go.id/

levels, starting from villages up to provinces, which makes output alignment complex. The lack of standardization makes stakeholders unable to unite system strengths for obtaining an integrated view of Indonesian agricultural conditions.

Amplifying technical problems are gaps in policy that prevent organizations from working together effectively. We do not currently have policies that provide enough detail on how to share data or who should govern it, which leads to poorly managed and duplicated resources. Policies that provide a common set of guidelines would also help us develop a more unified data platform for agriculture, one that extends across a much larger share of the innovation space, thus yielding much greater efficiency improvement. To do all this requires a plan.

This research analyzes geospatial agricultural monitoring systems in Indonesia by assessing system maturity and technical processing methods across four different systems with an emphasis on detailed investigation. It identifies factors responsible for the variability of system outputs and delivers specific remedies to improve data standardization and enhance system integration that will achieve better consistency, interoperability, and scalability of geospatial technologies used for agricultural monitoring across the archipelago. This study fills a critical gap by integrating two normally separate lenses, organizational maturity (GMA OS) and end-to-end technical workflows (qualitative TKT matrix), and visualizing them together in a two-dimensional positioning map. A review of the geospatial-agriculture literature shows no earlier study that integrates these frameworks into one evaluation model; therefore, the dual-framework design represents a methodological innovation with clear policy significance. The investigation also makes a key contribution to the development of a unified data and policy framework that will standardize data processing, improve system integration, and achieve better accuracy in the "One Data" framework supporting sustainable agriculture in Indonesia.

2. Background

This section presents a summary of geoinformatics agricultural information systems in Indonesia and other countries that form the context of this research.

2.1. Geoinformatics agricultural monitoring information systems in Indonesia

Geoinformatics Agricultural Monitoring Information Systems (GAMIS) in Indonesia has been found to be very useful in improving agricultural productivity and encouraging sustainable agriculture. These systems have greatly improved the farmers' capabilities and increased rice yields, with better internet connectivity, user-friendly, and accurate tools [6]. Furthermore, the Integrated Cropping Calendar Information System has provided farmers with climate-adaptive strategies through the provision of specific information on planting time and crop management [7].

GIS and Remote Sensing technologies are being used more in agriculture for the estimation of crop yields, assessment of soil fertility, and pest management, thus enabling more informed and data-driven decision making [5]. The effectiveness of information and communication technologies, such as Tani Hub Android-based platforms and short message service (SMS) based monitoring systems in the distribution of agricultural information, also points to the role of technology [8].

While GAMIS has many benefits, its full potential is usually restricted by factors like poor access to technology and the demanding nature of constantly needing to update practices in the field [6], [7]. A way to overcome these challenges would be to significantly ramp up training for the system's users and, further, to improve how well these systems can be integrated with local conditions. Together, these would likely push adoption and efficiency gains much further than currently seems possible [7].

In the discussion of One Data Indonesia, particularly concerning rice data, the need for modernizing statistical production has been emphasized, incorporating big data, small area estimation, and geospatial statistics. Meanwhile, statistical development currently faces several challenges, including the increasing demand for fast and diverse data, changes in societal structures, technological advancements, and the broader utilization of statistical data. BPS periodically releases national rice production data using the Area Sampling Frame

(*Kerangka Sampel Area*, KSA) method. KSA is a sample survey (random sampling) where the population consists of rice fields and all potential rice-growing areas across Indonesia. It utilizes a sampling frame and sampling units in the form of area segments—each measuring 300 m × 300 m with nine observation points. Currently, 25,577 active segments are used, covering 230,193 observation points spread across 38 provinces, with 6,544 field officers conducting data collection. Field observations are carried out simultaneously during the last seven days of each month, with a cost of IDR 120,000 or USD 7.18 per segment. However, KSA does not provide spatially explicit information; instead, it presents data in a point-based (sampling point) or tabular format without detailed geospatial representation. This limitation makes it challenging to directly integrate KSA data with geospatial analysis for mapping or visualization purposes.

2.2. Geoinformatics agricultural monitoring information systems in other countries

Geoinformation-based crop monitoring systems have been adopted by multiple regions and countries, as in Indonesia. Notable examples include: The United States, through the United States Department of Agriculture (USDA) National Agricultural Statistics Service, implemented CropScape[3] [9]. CropScape, officially deployed since 2012, provides interactive maps for agricultural land cover data across the United States. It is designed to interactively and intuitively visualize, query, disseminate, and analyze historical and current Crop Data Layer (CDL) data via a web browser. The European Union (EU), through its Joint Research Centre (JRC), has been implementing the Monitoring Agricultural Resources (MARS) system since 1988 [10]. While initially limited to EU territories, the system expanded globally in 2016. Currently, MARS has integrated the AGRI4CAST project, which focuses on crop yield monitoring and forecasting. Through MARS, detailed farmland maps can be generated and utilized for crop vegetation monitoring. The system also provides seasonal yield forecasts for major European crops and predicts the short-term impacts of meteorological events on crop productivity. China implements CropWatch, a comprehensive system that generates various crop monitoring indicators, including crop production estimates, crop condition assessments, drought monitoring, crop planting proportions, and planting intensity indices [11], [12]. While initially focused on China, CropWatch has evolved to provide crop condition and production information at a global scale. Similarly, India utilizes the Forecasting Agricultural output using Space, Agrometeorology and Land-based observations (FASAL) system to predict crop production before harvest through remote sensing data [13]. This initiative aims to provide national-level production forecasts for major crops, including rice, wheat, cotton, sugarcane, rapeseed/mustard, rabi sorghum, winter potatoes, and jute. The program integrates satellite data, weather observations, crop information, and ancillary data to model and predict seasonal crop growth.

2.3. Related study

A literature review was conducted to identify suitable frameworks for this study. A comparative analysis was performed on five frameworks using four evaluation criteria, with a scoring system adapted from a previous study [14]. The scoring was determined through consensus among the research team before assessing the selected agricultural information systems. In this scheme, the scoring is divided into four levels: "N" (0-25% suitability), "P" (26-50% suitability), "L" (51-75% suitability), and "F" (76-100% suitability) indicate the degree of alignment between each framework and the research requirements.

Table 1. Comparative analysis of frameworks adapted from previous research

Model ID	Fitness for Purpose	Completeness	Objectivity and Assessment Method	Complexity
M1 [15]	L	P	L	P
M2 [16]	L	P	L	P
M3 [17], [18]	L	L	L	F
M4 [19]	L	L	L	L
M5 [20]	P	P	P	L

[3] https://nassgeodata.gmu.edu/CropScape/

M1 is the Capability Maturity Model Integration (CMMI) framework [15], which focuses on process improvement and capability maturity and organizations. While it provides a structured approach to evaluation system management, it lacks comprehensive coverage of essential geospatial assessment components. M2 is the *Sistem Pemerintahan Berbasis Elektronik* (SPBE) framework [16], designed to evaluate e-Government systems in Indonesia. Although it includes elements of digital governance, it is not specifically designed for geospatial monitoring systems. M3 is the Geospatial Management Assessment by Ordnance Survey (GMA OS) [17], [18], which is most relevant for evaluating agricultural information systems. Despite its relative suitability, the complexity of GMA OS is considered an alternative framework with lower resource demands that may achieve similar outputs. M4 is the GIS Capability Maturity Model by Urban and Regional Information Systems Association (URISA) [19], which focuses on evaluating GIS, but making it less technical in processing, and it's more complex than M3. M5 is the Data Management Body of Knowledge (DMBOK) framework emphasizes data governance and management best practices. While it provides structured guidelines, the objective is less suitable for approaching geospatial systems evaluations.

However, none of the evaluated frameworks fully covered the technical processing aspects of agricultural monitoring systems. To fill this gap, our study proposes a novel dual-framework configuration that, to our knowledge, has not been applied in earlier geospatial-agriculture literature: we pair GMA OS for organizational maturity with a qualitative TKT-based matrix for end-to-end technical workflows, allowing both dimensions to be visualized in a single positioning map. This combined approach ensures a comprehensive evaluation that covers both system management and technical processing aspects, providing a more holistic framework for agricultural monitoring system assessment.

Technology Readiness Level (TRL), known locally as *Tingkat Kesiapterapan Teknologi* (TKT), is a 1–9 scale used to assess the maturity of a technology—from early-stage research to full deployment [21], [22]. Originally developed by NASA to map the technology maturation process and guide development stages [21], TKT was formally adopted in Indonesia through Regulation No. 42/2016 to support the systematic evaluation of technologies for adoption by government, industry, or the public. The scale is often grouped into 4 clusters: Fundamental Research (levels 1-2), Research and Development (levels 3-5), Pilot and Demonstration (levels 6-8), and Early Adoption (level 9) [23]. TRL is widely applied to assess technology maturity across various domains, including cross-sector co-creation [24], biosecurity and plant pest detection [25], sustainable agricultural intensification [26], and geoscience and mineral resources, where it can be applied to long-term, continuous research projects [27]. These studies demonstrate that, despite differing contexts, TRL remains a relevant expert-driven framework to guide technology adoption and development. This study applies the TKT framework to help visualize the relative maturity of different crop-monitoring systems using a positioning map. By combining TKT levels with management readiness scores, each platform can be placed in a two-dimensional space, offering an intuitive comparison of technical and organizational progress and helping pinpoint areas for targeted improvement.

3. Research method

This study follows a qualitative, embedded case study design to evaluate the implementation outcomes of geospatial agricultural monitoring systems. Data were gathered from semi-structured interviews (July – August 2024) with at least two key informants who were system developers, project managers, and data analysts-selected using purposive sampling. This was supported by document review and limited field observations in Subang, Karawang, and Garut. Figure 1 illustrates the research design, which consists of three stages.

Interview guides covered two lenses:

1. Management maturity - 16 domains adapted from the GMA OS framework [17]: data capture and maintenance, data management, data sharing, geospatial technology, corporate governance structure, corporate strategy, project management, national contribution, stakeholder engagement, data standard,

product and service portfolio, product and service creation, quality management, resource situation, supply chain management, operational management.

2. Technical processing, including:
    - Data Input: Types of data sources used (e.g., satellite imagery, ground sensors) and the frequency of data updates.
    - Methods: Analytical and computational techniques applied, including models or algorithms for data processing.
    - Preprocessing: Data cleaning, normalization, and integration protocols to ensure data quality and compatibility.
    - Output Generation: Formats and usability of the final outputs, such as maps, dashboards, or reports for stakeholders.

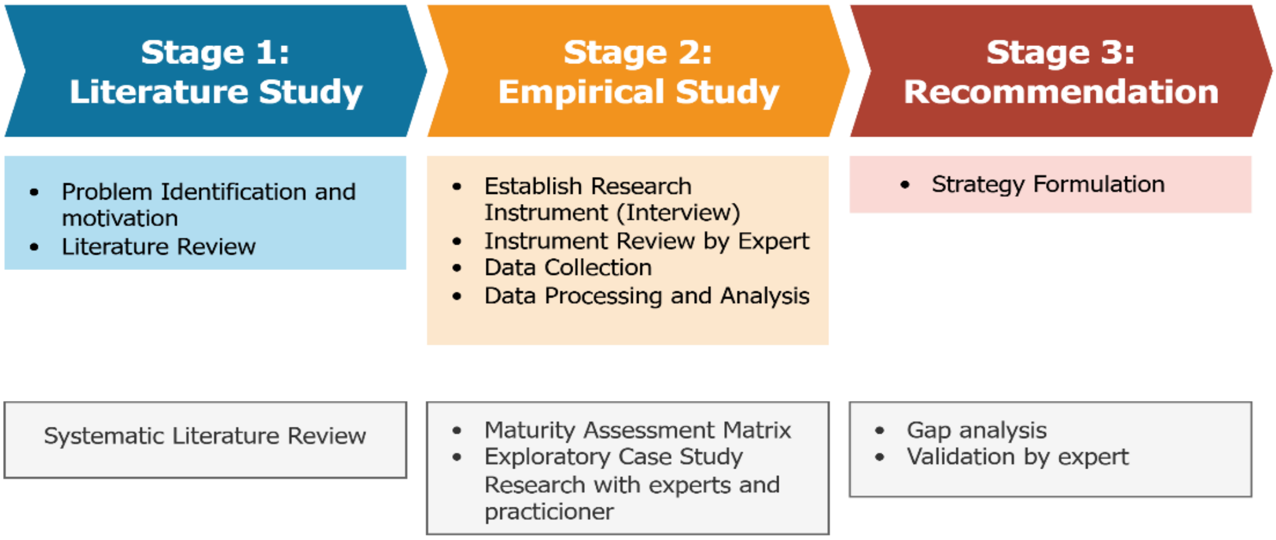


Figure 1. Research design

3.1.1. Data analysis

Data collected from participants was analyzed using approaches:

- Management maturity was qualitatively rated by mapping each participant's structured interview responses onto the four categorical levels of the GMA OS framework.
- Technical readiness was classified qualitatively with the nine-level TKT scale and used to plot the Integrated Comparative Positioning Map. An embedded-expert consensus—grounded in the technical-processing recapitulation (inputs, preprocessing, modelling, validation, outputs) and supporting artefacts—reviewed each system and agreed on a single narrative TKT label per platform; these labels function solely as inputs for the map.
- Field validation survey, using comparative analysis conducted on two closely spaced dates, comparing the rice growth phases from the crop monitoring system product information with the actual phases observed in the field, calculating the percentage of rice growth phases that matched between the system's analysis and actual field conditions.

3.2. Stage 3: Recommendation

The theoretical framework presented in Figure 2 serves as the foundation for developing recommendations for the implementation of agricultural crop monitoring systems. It integrates several key components, including regulatory frameworks, which establish the legal and institutional context for data governance and remote sensing activities. Related works and benchmarking provide insights from previous studies and best practices, while crop monitoring system management assesses the geospatial maturity of existing systems.

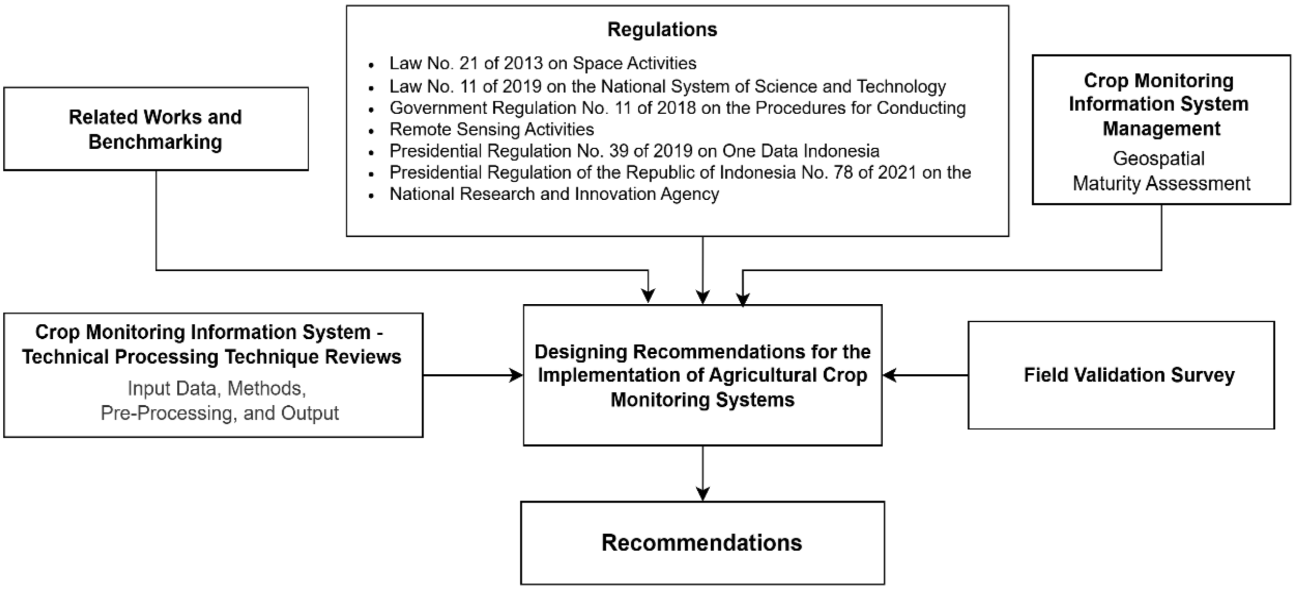


Figure 2. Theoretical framework

Subject matter experts (SMEs) validate the analysis results. They do this through focus group discussions (FGDs) and technical meetings with Kementan, BPS, and Bappenas's technical teams. The FGD is a method of collective knowledge and opinion gathering from a group of experts on the relevant subject. The initial FGD works to determine the main problem(s) along with possible answers before the second FGD concentrates on developing and clarifying the concepts generated in the first FGD. The expected outcome of these two FGD validation stages, coupled with input from various parties, is a set of comprehensive recommendations ready for implementation.

4. Results and discussion

The results and discussion of the study are presented in this section. The discussion begins with the result of the management systems' maturity assessment, which indicates the level of maturity attained in the management and operational oversight of the systems. A summary of the technical processing methods employed by each system follows. Finally, the field validation results are presented, which verify the accuracy and relevance of the findings and provide a better picture of how the systems function in actual field conditions.

4.1. System management maturity

The GMA OS framework consists of 16 assessment components, each represented by a single question, resulting in a total of 16 questions in the questionnaire. Each question provides four answer choices, corresponding to the four maturity levels of each component. The definitions for these levels are presented in Table 2. This study adopts the level nomenclature from the Capability Maturity Model Integration (CMMI) framework [15], [28] with slight modifications, merging Levels 3 and 4 of CMMI into a single level to align with the four-level structure of GMA OS.

Table 2. Maturity level

Score	Level	Definition
1	Initial	Processes are irregular, reactive, dependent on individuals, and minimally documented.
2	Managed	Processes are organized at a basic level, repeatable, and minimally documented.
3	Standardized	Processes are well-documented and controlled at each stage of implementation.
4	Optimized	Processes are optimized with continuous improvement and innovation-driven approaches.

The assessment findings for 16 GMA OS framework components appear in Table 3 for the four crop monitoring systems: SISCrop, Simotandi, IDMAI SIMURP, and Mixed Method. The assessment divides each component into four distinct maturity levels, which include Initial (Level 1), Managed (Level 2), Standardized (Level 3), and Optimized (Level 4). The systems SISCrop, Simotandi, and Mixed Method reached Standardized (Level 3) operational maturity. Their processes are standardized, well-documented, and consistently implemented, reflecting readiness to support institutional objectives effectively. On the other hand, IDMAI SIMURP was assessed at Managed (Level 2), which suggests that while some processes are organized and repeatable, they are not yet fully standardized or stable. This indicates that IDMAI SIMURP is still in the development phase and requires further improvements to achieve operational maturity. Overall, the results show that most of the systems evaluated are functioning well, with only one system needing significant enhancements to reach a comparable level of maturity.

Table 3. Summary of GMA OS Assessment

No	Domain	Level			
		SISCrop	Simotandi	IDMAI SIMURP	Mixed Method
1	Data capture and maintenance process	Standardized	Managed	Initial	Optimized
2	Data management	Standardized	Managed	Managed	Optimized
3	Data sharing	Standardized	Managed	Initial	Managed
4	Geospatial technology	Managed	Standardized	Initial	Optimized
5	Corporate governance structure	Standardized	Managed	Managed	Optimized
6	Corporate strategy	Standardized	Standardized	Standardized	Standardized
7	Project management	Standardized	Managed	Standardized	Optimized
8	National contribution	Standardized	Managed	Managed	Optimized
9	Stakeholder engagement	Standardized	Standardized	Optimized	Managed
10	Data standard	Standardized	Standardized	Managed	Optimized
11	Product and service portfolio	Standardized	Standardized	Managed	Managed
12	Product and service creation	Standardized	Standardized	Managed	Standardized
13	Quality management	Standardized	Managed	Managed	Optimized
14	Resource situation	Standardized	Standardized	Managed	Optimized
15	Supply chain management	Standardized	Standardized	Standardized	Optimized
16	Operational management	Standardized	Managed	Standardized	Standardized
	Summary Level	Standardized	Standardized	Managed	Standardized

4.2. Technical processing technique

The technical processing analysis reviews the methodologies and workflows employed by each crop monitoring system, focusing on data input, preprocessing protocols, analysis protocols, output, and validation techniques. This analysis highlights the extent to which systems share standardized practices and leverage available geospatial technologies to support operational objectives. The following section presents the results of the technical processing review, emphasizing commonalities and differences across the systems.

Table 4. Input data

Input Data	SISCrop		Simotandi	IDMAI SIMURP		Mixed Method
Remote sensing data	SAR	optic	SAR	optic	SAR	SAR
Satellite	Sentinel 1	Landsat 8	Sentinel 1	Sentinel 2	Sentinel 1	Sentinel 1

Input Data	SISCrop		Simotandi	IDMAI SIMURP		Mixed Method
Spatial resolution	10 m	25 m	10 m	20 m	10 m	20 m
Spectral channel	VV, VH	NIR, SWIR1	VH	11 bands	VV, VH	VV, VH
Data periodic	15 days	16 days	12 days	15 days	15 days	12 days
Validation	Regional			3 districts	National	
Secondary data	paddy field map			paddy field map, rainfall rate data, DEM	paddy field map	

Source: The data displayed was obtained based on the results of interviews with key informants from each system development institution.

Table 4 highlights the input data sources and characteristics used by crop monitoring systems across various institutions. SISCrop and Simotandi rely on Sentinel-1 SAR data, with PUSDATIN further enhancing its monitoring capabilities by integrating Landsat-8 optical imagery. IDMAI SIMURP also incorporates both SAR and optical data (e.g., Sentinel-2), while Mixed Method relies solely on Sentinel-1 for its statistical outputs. Spatial resolutions vary, with SAR-based systems achieving 10 m resolution, while Landsat-8 data used by Simotandi operates at 25 m resolution, and Sentinel-2 data at 20 m. Validation approaches also differ, with Kementan systems conducting regional-level validation to ensure localized accuracy, whereas BPS applies nationwide validation protocols, prioritizing national-scale reliability over regional detail.

Table 5. Recapitulation of pre-processing, method, analysis, output, and validation

Component	SISCrop	Simotandi	IDMAI SIMURP	Mixed Method
Pre-processing Optic Data				
Geometric correction	Not using optic data	Ortho	Ortho	Not using optic data
Radiometric correction		ToA, BRDF	Surface Reff.	
Spatial Filtering		-	Median	
Temporal Filtering		Median, Avg	Median	
Spectral Indices		NIR, SWR1	NDVI, EVI, NDWI	
Temporal Indices		30 series	-	
Missing Data Filling		Linear interpolation, quadratic	Interpolation, Extrapolation	
Pre-processing SAR Data				
Geometric correction	Ortho	Ortho	Ortho	Ortho
Radiometric correction		Gamma Naught	Gamma Naught	Sigma Naught
Spatial Filtering		Lee 3x3	Refined Lee	
Spectral Indices	VH, RVI	VH	RVI, VV, VH	
Temporal Indices		Temporal 10 series	Mean, STDev	
Missing Data Filling	Previous period	Previous period	Interpolation	Whittaker Imputation

Component	SISCrop	Simotandi	IDMAI SIMURP	Mixed Method
		Analysis Method		
Classification approach	Machine Learning	Analytic	Machine Learning	Machine Learning
Machine Learning Method		-	RF, SVM, Xboost	Gboost, Catboost, LGBM. RF
		Output Data		
Periodic output	15 days	12/16 days	15 days	Monthly
Class output	2 non-Paddy classes, 4 classes of Rice phase	3 non-Paddy classes, 6 classes of Rice phase	0 non-Paddy classes 4 classes of the Rice phase	4 non-Paddy classes 3 classes of the Rice phase
Statistical analysis	Disctrict	Village, District, Province	Village, District, Province, irrigation area	District, Province
		Validation		
Field verification	3000 samples	1111 samples	not done	36 point x 26 districts in 10 provinces
Accuracy	± 80-87 %	80.3 % (for Landsat-8)	-	85% (For Indramayu)

Source: The data displayed was obtained based on the results of interviews with key informants from each system development institution. Accuracy figures were obtained directly from the developer institutions through confusion-matrix evaluation, but Overall Accuracy is used as the common benchmark.

Table 5 outlines the preprocessing protocols for optical and SAR data across four crop monitoring systems. All systems execute fundamental geometric and radiometric corrections to standardize imagery. Cluster analysis (uses basic statistical operations). Most systems (SISCrop, IDMAI SIMURP, and Mixed Method) perform machine learning on output from the previous task to classify rice growth phase and non-paddy areas. They differ in the type of machine learning they use and in the enormous variety of output that is produced. This variety is manifested in differences in periodicity, spatial scale, and other properties of the output. The temporal frequency output illustrates a notable distinction between the systems. BPS creates month-to-month reports that fulfill statistical requirements but are inadequate for true real-time decision support. Kementan and Bappenas produce results on a far timelier basis, issuing their outputs at 12- to 15-day intervals—enough of a difference for time-sensitive monitoring. While SISCrop does split up non-rice classes in its own unique way, IDMAI, SISCrop SIMURP, and Mixed Method are far more alike than any of them are with BPS in terms of the statistical analysis levels they provide. While BPS focuses more on district and provincial levels, Kementan and Bappenas extend studies from the sub-district level all the way up to the provincial level.

Every system has its unique strengths and weaknesses. SISCrop provides consistently weather-resistant monitoring, using SAR data, but it has a limited classification system. Simotandi has a very detailed classification system and performs in-depth, multi-level analysis. However, Simotandi's output is irregular, making system integration a challenge. IDMAI produces strategically multi-analytical outputs at a scale that makes them useful for agricultural policy decisions. However, the output frequency is a problem; IDMAI is simply not a dynamic monitoring system. The Mixed Method system produces output at the national level. Its governance is strong enough that the outputs are consistent. However, compared to some other systems, the

Mixed Method system outputs appear quite infrequently. In the next chapter, we will discuss how these systems can be integrated.

4.2.1. Commonalities: Adherence to standard preprocessing protocols across all institutions

A main observation from the technical processing evaluation demonstrates that all systems follow identical preprocessing procedures. The established protocols, which include geometric correction, radiometric correction, filtering, and the use of spectral and temporal indices, ensure that analysis data maintains consistent quality and comparability. The uniform data processing standards between institutions produce dependable results that enable better cross-system evaluations for improved decision-making in crop monitoring and management.

4.2.2. Differences: Variability in data input, methods, and output designs

The systems demonstrated different preprocessing protocols in their data input, processing methods, and output designs. The different classification methods that use machine learning algorithms such as Random Forest (RF) and Support Vector Machines (SVM), and analytical models result in multiple data analysis approaches. The output periodicity, along with the generated class types, shows differences that might reduce result comparability between systems. The system's interoperability requires additional standardization of methods and outputs for better system integration.

Table 6. Key technical differences

Aspect	SISCrop	Simotandi	IDMAI SIMURP	Mixed Method
Primary sensor	SAR,	Optical & SAR	Optic & SAR	SAR
Spatial resolution	10 m	25 m & 10 m	10 - 20 m	20 m
Classification approach	VV, VH	NIR, SWIR1	11 bands	VV, VH
Output frequency	15 days	16 days	15 days	12 days
Reporting scale	District	Village, District, Province	Village, District, Province	District, Province
Validation & accuracy	3 000 field samples, OA 80–87 %	1,111 samples, OA 80.3 %	Not yet reported	Indramayu, OA 85 %

Source: The data displayed was obtained based on the results of interviews with key informants from each system development institution. Accuracy figures were obtained directly from the developer institutions through confusion-matrix evaluation, but Overall Accuracy is used as the common benchmark.

4.3. Integrated comparative positioning of crop-monitoring systems

A qualitative, expert-embedded approach was adopted to assess each system's Technology Readiness Level (TRL/TKT) on a nine-point scale. The nine TKT levels reflect a set of standardized criteria that a technology must satisfy to be categorized at a given level, as adapted from the European Space Agency's (ESA) TRL handbook [29]. During structured consensus sessions, team members—each directly involved in developing or managing the systems—linked real-world artefacts and documentation to the formal descriptors in the TKT framework. This interpretive approach aligns with how TKT assessments are commonly applied in agro-technology studies [26], [30].

Ratings were produced through an embedded-expert consensus: team members who design or operate the platforms jointly reviewed documentation, field artefacts, and validation results, then agreed on categorical placements. Using this framework, SISCrop and SIMOTANDI reached TKT 7, reflecting their advanced development status: both systems deliver validated outputs and have begun institutional scaling. IDMAI SIMURP scored TKT 6, indicating strong applied research maturity and policy-facing, hence one tier below full development. Mixed Method was scored TKT 5, although it shows strong management practices, its technical components are still undergoing model validation and have not yet been formally adopted nationwide.

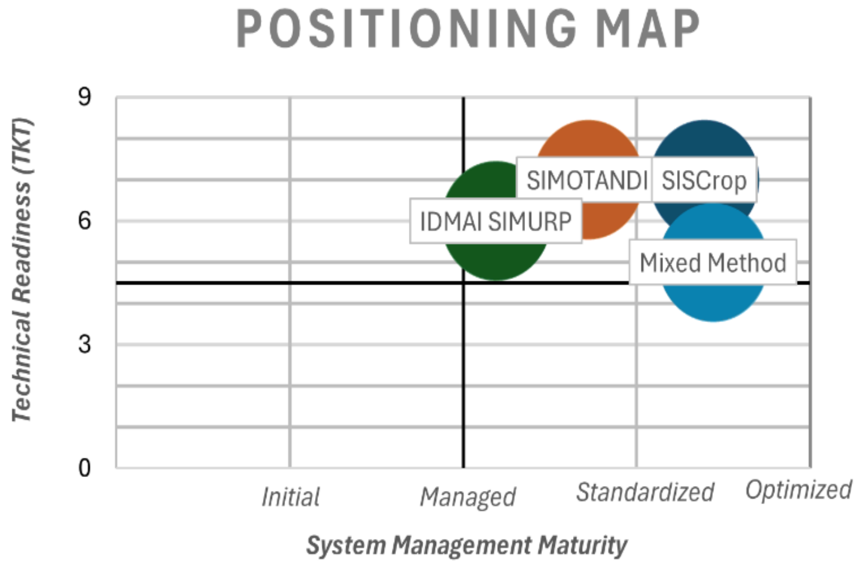
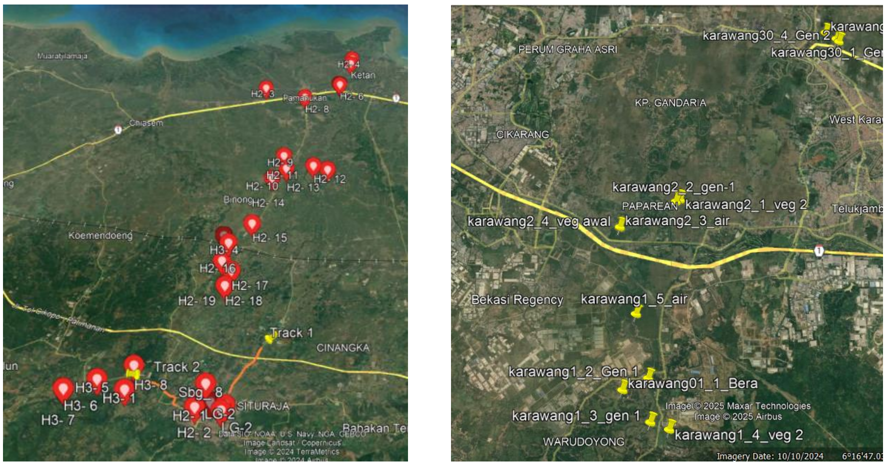


Figure 3. Positioning map of Indonesian crop-monitoring systems plotted by management maturity (GMA-OS average) and technical readiness (TKT)

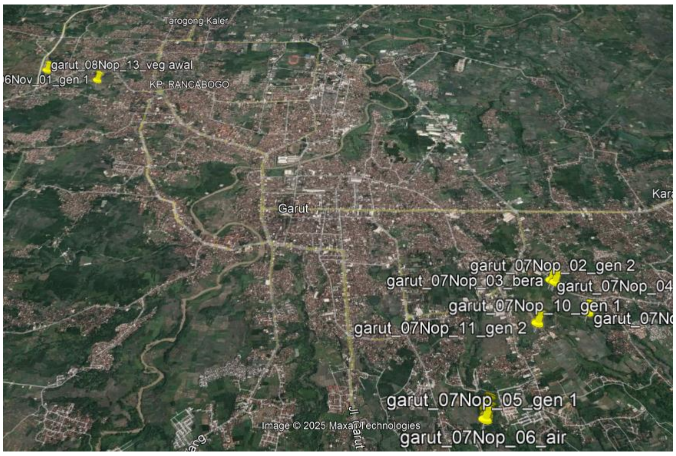
All four systems occupy the top-right quadrant of our positioning map in Figure 3—classified as “Managed” for organizational readiness and at least “Intermediate” in technical maturity—demonstrating a common foundation for improving interoperability and scaling capacity. The map also points to specific priorities: strengthening Mixed Method’s technical hardening and SIMURP’s managerial consolidation. The use of TKT scales as narrative indicators in qualitative assessments is well-established in related research fields. Our approach aligns with this tradition, offering a clear, side-by-side snapshot of Indonesia’s crop-monitoring platforms while preserving the nuance of expert-led evaluation.

4.4. Field validation survey

The field-verification was conducted in three West Java districts—Subang (24–26 September 2024), Karawang (30 September–2 October 2024), and Garut (6–8 November 2024)—selected to encompass irrigated and rain-fed lowlands as well as upland rice ecosystems, ensuring that every major agro-ecological zone and phenological phase of the rice crop was represented within the sample frame. Although the 2024 field validation survey was limited to West Java because of budget constraints, the same protocol will be extended to other provinces in the next funding cycle to capture a wider range of climatic and soil conditions. The field survey points used in this research are shown in Figure 4. All ground observations were collected by a team of remote-sensing specialists who had followed a standard procedure for crop-monitoring validation. Their expertise and consistent methodology ensured reliable reference data for accurate assessment.



(a) (b)



(c)

Figure 4. Distribution of field survey points in (a) Subang, (b) Karawang, and (c) Garut

The verification results show that all information systems need substantial accuracy improvements for further evaluation. The results indicate possible data quality problems that need better validation procedures. The system accuracy can be enhanced by evaluating data collection methods and through regular training and calibration, and by strengthening field validation procedures. The accuracy of crop monitoring systems will increase after implementing these improvements, thus delivering better benefits to farmers and land managers.

5. Recommendation

This section distils the study's technical and organizational findings into concrete, regulation-anchored actions that enable one harmonized crop-monitoring ecosystem. The recommendation spells out what each regulation requires and who is responsible for making it happen.

5.1. National Agricultural Reference Dataset (NARD): A unified training data backbone for model improvement

For Artificial Intelligence (AI) to track crops accurately in Indonesia, the models need more than just lots of data—they need field samples that reflect the country's many agro-ecological zones. To deliver that kind of performance nationwide, we propose a National Agricultural Reference Dataset (NARD) Repository, a shared archive of multi-sensor image chips and harmonized field surveys collected by Kementan, BPS, BRIN, and provincial offices. An open, country-wide corpus would cut model bias, enable continual re-training, and make AI crop monitoring reliable across Indonesia's highly varied landscapes. Leveraging AI, remote sensing data can be utilized to generate rice growth phase maps, but this requires high-quality training data that is well-distributed across Indonesia. The KSA rice dataset, collected monthly by BPS, can serve as a training dataset for identifying rice growth phases. By integrating KSA data with remote sensing in GEOAI, a more accurate rice growth monitoring system can be developed for Indonesia.

5.2. Technical foundation and harmonized classification

The pre-processing of remote sensing data already utilizes standardized algorithms; however, improvements in geometric and radiometric accuracy are necessary to align with the latest advancements. Standardized ready-to-use data is essential for improving efficiency and consistency across crop monitoring systems [31], [32], [33]. A centralized approach, such as adopting a datacube model, could ensure that all necessary geospatial data—pre-processed, organized, and readily accessible—meets the diverse needs of various stakeholders. This would eliminate redundancies, as institutions would no longer need to individually handle raw data, saving significant time and resources while maintaining data quality and accessibility [34]. In this effort, BRIN can play a key role in conducting research to define standardized data processing methods that align with the specific requirements of crop monitoring.

The various methods of classification, the application of machine learning and analytical techniques in disparate systems, and the employment of different machine learning algorithms underline the necessity of collaboration across disciplines. Each institution can achieve much more than it can alone in this area by pooling expertise and experimental results to form universal models or algorithms for all systems to use. This would guarantee not just standard output (including land cover and crop phase classification) from the different monitoring systems for any one moment in time, but also enhanced reliability of results across the board.

5.3. Inter-agency operating model

Figure 5 presents the Proposed Unified Strategy and Policy Implications through a five-layer ArchiMate view: Motivation, Strategy, Business, Application, and Technology. ArchiMate is used because of its standard, layered syntax to trace each legal driver straight down to the cloud node that implements it, giving both policymakers and engineers a common language. These five layers are sufficient: they capture everything from regulations and capabilities to agency roles and infrastructure.

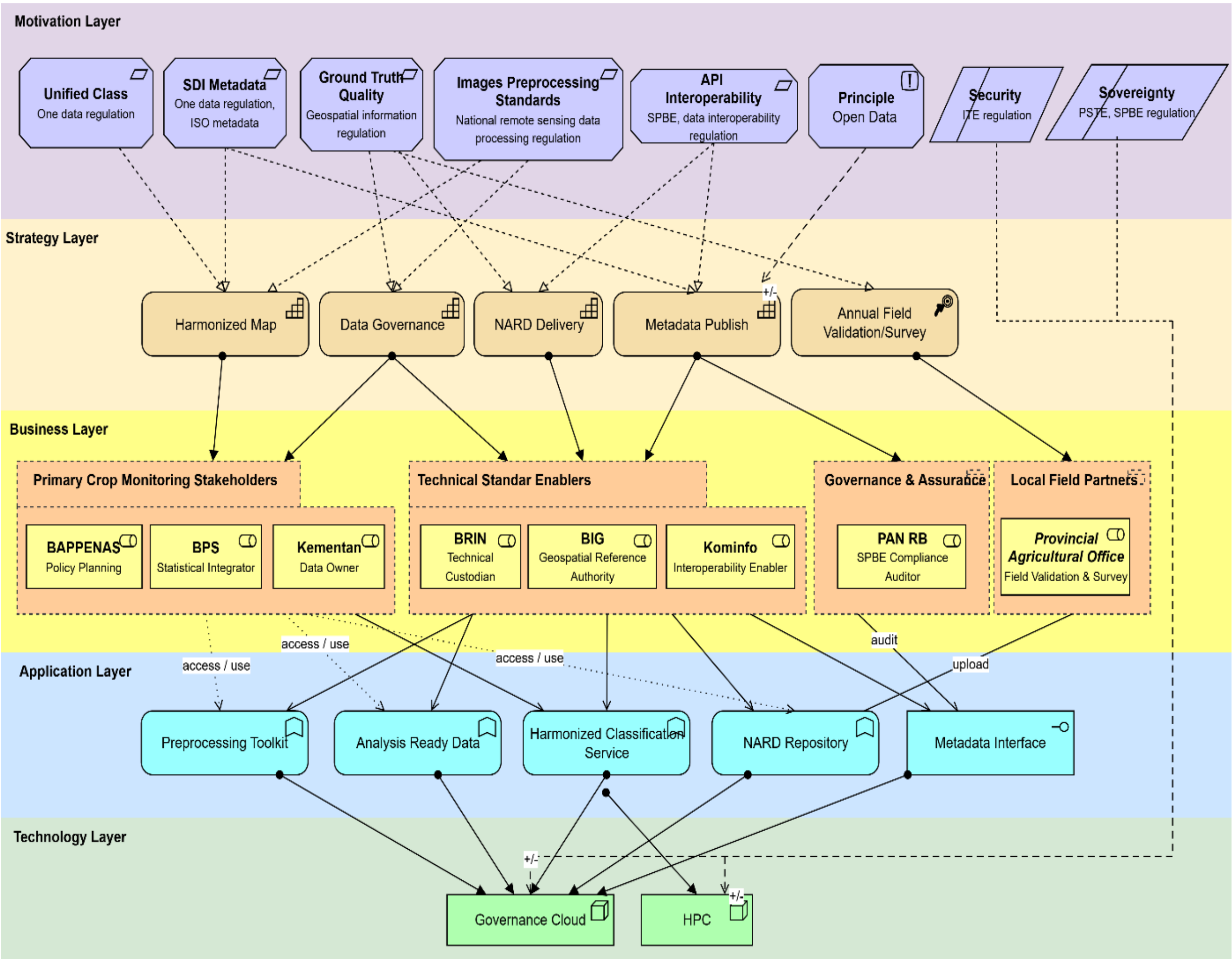


Figure 5. Proposed unified framework and policy implications

We bundle Kementan, BPS, and Bappenas into a *Primary Crop-Monitoring Stakeholders* collaboration that owns ground-truth, statistics, and regulation planning. A second collaboration is BRIN, BIG, and Kominfo, which acts as Technical & Standards Enablers, hosting the cloud pipeline and maintaining spatial reference. Oversight remains with PAN-RB (*Governance & Assurance*). Arrows in the diagram connect each legal constraint directly to the Governance Cloud and HPC nodes, guaranteeing compliance and security controls. Regulations appear as Requirements or Constraints in the Motivation layer of Figure 5, linking legal mandates to the cloud nodes that run data workloads. Each regulation is described in detail in Table 7.

Table 7. Regulatory drivers in the ArchiMate Motivation layer

Motivation Element	Regulation	Key obligation/constraint
Principle – Open Data	Law No. 14/2008 on Public Information Disclosure	Public-sector datasets must be released unless specifically classified.
Requirement – Pre-processing Standard	Government Regulation (GR) No. 11/2018 on the Conduct of Remote-Sensing Activities	Remote-sensing data used by government systems shall pass geometric and radiometric quality checks defined in BIG/SNI standards.
Requirement – SDI Metadata & Custodians	Presidential Regulation (PR) No. 39/2019 on Indonesia One-Data (SDI)	Agencies must publish ISO 19115 Metadata and appoint Data Custodians and Data Supervisors.
Requirement – API Interoperability	Ministry of Communication & Informatics Regulation No. 5/2020 on Data Interoperability	National Data-Exchange APIs must use REST/JSON with the prescribed schema and security headers.
Constraint – Data Sovereignty	GR No. 71/2019 on Electronic Systems and Transactions (PSTE)	All public-sector data centers and disaster-recovery sites must be in Indonesian territory or in a government-approved jurisdiction.
Constraint – Security & Integrity	Law No. 11/2008 on Electronic Information and Transactions, as amended by Law No. 19/2016	Systems shall guarantee authentication, data integrity, and non-repudiation for electronic records.
Requirement – SPBE Audit Compliance	PR No. 95/2018 on E-Government (SPBE) and Ministry of Administrative & Bureaucratic Reform Regulation No. 59/2020	PAN-RB conducts annual SPBE evaluations and issues an index measuring cross-agency data-exchange maturity.

Primary crop-monitoring stakeholders, Kementan, BPS, and Bappenas, own the core business outputs; Kementan supplies field surveys and crop-class definitions, BPS fuses the harmonised maps into official statistics, and BAPPENAS aligns results with national policy planning and budgets. The Technical & Standards Enablers cluster, BRIN, BIG, and Kominfo, keeps the engine running: BRIN operates the ARD and preprocessing toolkit, BIG safeguards spatial reference and metadata standards, and Kominfo hosts the NARD and GovCloud environment plus the interoperability gateway. Oversight sits with Governance & Assurance, where PAN-RB audits cross-agency SPBE indicators and organisational maturity. Finally, Provincial Agricultural Offices feed the system with annual ground-truth samples, closing the data-quality loop from field to cloud.

6. Conclusions

The agricultural crop monitoring system developed through geoinformatics gives immediate access to agricultural data for strategic planning. Interviews with ministries/agencies showed that the data processing standards varied between institutions, although the pre-processing stage followed established norms. The three primary institutions have well-established management, but Bappenas needs to improve its system management. Field verification across three districts showed a low alignment between analytical results and actual field conditions. It indicates the need to improve analytical methods and enhance system accuracy.

The research investigates four major crop monitoring systems in Indonesia, including SISCrop, Simotandi, IDMAI SIMURP, and Mixed Method, which show their strong capabilities and limitations. SISCrop shows effective SAR-based monitoring capabilities, yet its classification schemes show limited detail in their categorization systems. Simotandi provides detailed classifications with multi-level analysis, but its temporal output inconsistencies create problems for system interoperability. The strategic monitoring capabilities of IDMAI SIMURP stand out through its multi-scale output features, although the system updates infrequently, while Mixed Method generates strong nationwide statistical reports, but offers less to offer real-time monitoring. The analysis confirms that standardization, along with policy integration, must address data collection gaps and classification discrepancies, and governance issues to create a unified crop monitoring system.

The proposed unified data and policy framework presents a framework to unify crop monitoring systems in Indonesia, which addresses their current challenges. A centralized NARD should be established under this framework to merge system outputs from SISCrop, Simotandi, IDMAI SIMURP, and Mixed Method, enabling real-time API-based data sharing. The policy should require metadata and open data protocol enforcement and establish governance systems to enhance cross-agency collaboration. The unified approach seeks to boost data accessibility, together with operational efficiency and crop monitoring effectiveness in Indonesia.

Future work should integrate artificial intelligence (AI) and Internet of Things (IoT) technologies into the unified framework to boost predictive abilities and real-time monitoring capabilities. AI technology could automate classification tasks, while IoT sensors would offer ground-level verification, which would enhance data precision. Studies should evaluate the socio-economic effects of system harmonization on food security through decision-making enhancement and resource efficiency improvement, and sustainable agricultural practice support. These advancements would establish Indonesia's agricultural sector as a benchmark for using technology together with policy integration to combat worldwide food security problems.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

Funding information

This research was funded by the Research Organization for Aeronautics and Space (ORPA), National Research and Innovation Agency (BRIN) under funding code CFC 05.29, 2024.

Acknowledgements

The authors would like to express their gratitude to the Indonesian Center for Agricultural Land Resources Instrument Standard Testing (BBPSI SDLP) and the Center for Agricultural Data and Information Systems (Pusdatin) of the Ministry of Agriculture (Kementan), the Directorate of Methodology Development for Census and Surveys of the Statistics Indonesia (BPS), and the Directorate of Water Resources Management of the National Development Planning Agency (Bappenas) for their valuable support and insights throughout this study. This work would not have been possible without the collective efforts and contributions of these institutions, and we sincerely appreciate their partnership.

Author contribution

Rizatus Shofiyati, Muhammad Rokhis Khomarudin, Kustiyo Kustiyo: study conception and design; Kustiyo Kustiyo, Dede Dirgahayu, Fadhlullah Ramadhani, Agnes Sondita Payani, Muhammad Sulaiman Nur Ubay, Laju Gandharum: data collection; Rizatus Shofiyati, Kustiyo Kustiyo, Agnes Sondita Payani, Fadhlullah Ramadhani, Muhammad Sulaiman Nur Ubay, Heri Sadmono: analysis and interpretation of results; Rizatus Shofiyati, Agnes Sondita Payani, Laju Gandharum, Heri Sadmono: draft preparation. All authors approved the final version of the manuscript.

Ethical approval statement

Ethical approval is not applicable to this research.

Informed consent

Informed consent for the publication of personal data in this article was not obtained because the manuscript does not include identifiable personal data. The study only presents findings derived from interviews with relevant teams, without disclosing individual identities.

Declaration of use of AI in the writing process

The authors used OpenAI's ChatGPT strictly for language refinement and translation to enhance clarity and coherence. All intellectual content, analysis, and conclusions were independently developed by the authors, who thoroughly reviewed and finalized the manuscript.

References

[1] S. I. Hassan, M. M. Alam, M. Y. Zia, M. Rashid, U. Illahi, and M. M. Su'ud, "Rice Crop Counting Using Aerial Imagery and GIS for the Assessment of Soil Health to Increase Crop Yield", *Sensors*, vol. 22, no. 21, 2022, doi: https://doi.org/10.3390/s22218567

[2] J. C. Nagavi, B. K. Shukla, A. Bhati, A. Rai, and S. Verma, "Harnessing Geospatial Technology for Sustainable Development: A Multifaceted Analysis of Current Practices and Future Prospects", in *Sustainable Development and Geospatial Technology*, C. Sharma, A. K. Shukla, S. Pathak, and V. P. Singh, Eds., Cham: Springer, Cham, 2024, pp. 147–170. doi: https://doi.org/10.1007/978-3-031-65683-5_8

[3] A. R. Maulana, "Implementation of One Indonesian Data for An Integrated Official Statistical System", *Educational Studies and Research Journal*, 2024, doi: https://doi.org/10.60036/tykdbn37

[4] A. Fannouch, Y. Gahi, and J. Gharib, "Unified Data Framework for Enhanced Data Management, Consumption, Provisioning, Processing and Movement", in *Proceedings of the 7th International Conference on Networking, Intelligent Systems and Security*, in NISS '24. New York, NY, USA: Association for Computing Machinery, 2024. doi: https://doi.org/10.1145/3659677.3659836

[5] M. Mathenge, B. G. J. S. Sonneveld, and J. E. W. Broerse, "Application of GIS in Agriculture in Promoting Evidence-Informed Decision Making for Improving Agriculture Sustainability: A Systematic Review", *Sustainability (Switzerland)*, vol. 14, no. 16, 2022, doi: https://doi.org/10.3390/su14169974

[6] H. B. Santoso, A. R. C, R. Delima, and A. Wibowo, "Study and Recommendation of Agricultural Land Mapping System", *Ultima InfoSys : Jurnal Ilmu Sistem Informasi*, vol. 11, no. 1, pp. 40–50, 2020, doi: https://doi.org/10.31937/si.v9i1.1213

[7] Y. Apriyana *et al.*, "The Integrated Cropping Calendar Information System: A Coping Mechanism to Climate Variability for Sustainable Agriculture in Indonesia", *Sustainability*, vol. 13, no. 11, p. 6495, 2021, doi: https://doi.org/10.3390/su13116495

[8] Z. Bunyamin, N. N. Andayani, T. Fahdiana, Suwardi, and M. Azrai, "Application of ICT Tools in Food Crops Monitoring in Indonesia", *IOP Conference Series: Earth and Environmental Science*, vol. 484, no. 1, 2020, doi: https://doi.org/10.1088/1755-1315/484/1/012060

[9] W. Han, Z. Yang, L. Di, A. L. Yagci, and S. Han, "Making Cropland Data Layer Data Accessible and Actionable in GIS Education", *Journal of Geography*, vol. 113, no. 3, pp. 129–138, May 2014, doi: https://doi.org/10.1080/00221341.2013.838286

[10] V. Berezovsky, R. Aleshko, K. Shoshina, and I. Vasendina, "Development of a Methodology for Automated Processing of Spatial Data of Agricultural Land Based on Machine Learning", *E3S Web of Conferences*, vol. 531, 2024, doi: https://doi.org/10.1051/e3sconf/202453104008

[11] B. Wu, J. Meng, Q. Li, N. Yan, X. Du, and M. Zhang, "Remote Sensing-Based Global Crop Monitoring:

Experiences With China's Cropwatch System", *International Journal of Digital Earth*, vol. 7, no. 2, pp. 113–137, Feb. 2014, doi: https://doi.org/10.1080/17538947.2013.821185

[12] P. Zhao, "Research on Application of Agricultural Remote Sensing Technology in Big Data Era", in *2022 IEEE 2nd International Conference on Electronic Technology, Communication and Information (ICETCI)*, 2022, pp. 1270–1272. doi: https://doi.org/10.1109/ICETCI55101.2022.9832113

[13] S. K. Chaudhari, A. Patra, P. Dey, S. K. Bal, S. Gorantiwar, and R. Parsad, "Sensor based Monitoring for Improving Agricultural Productivity and Sustainability-A Review", *Journal of the Indian Society of Soil Science*, vol. 70, no. 2, pp. 121–141, 2022, doi: https://doi.org/10.5958/0974-0228.2022.00013.5

[14] M. O. Gökalp, E. Gökalp, K. Kayabay, A. Koçyiğit, and P. E. Eren, "Data-Driven Manufacturing: An Assessment Model for Data Science Maturity", *Journal of Manufacturing Systems*, vol. 60, pp. 527–546, Jan. 2021, doi: https://doi.org/10.1016/j.jmsy.2021.07.011

[15] Software Engineering Institute (SEI), "CMMI for development, version 1.3, staged representation,", Software Engineering Institute (SEI). Accessed: Sep. 09, 2024. [Online]. Available: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://se.inf.ethz.ch/courses/2013b_fall/dsl/slides/reading_material/cmmi-for-development_13.pdf

[16] Government of Indonesia, *Regulation of the Minister for Administrative and Bureaucratic Reform of the Republic of Indonesia No. 59 of 2020: Monitoring and Evaluation of Electronic-Based Government Systems (Peraturan KemenPANRB No 59 Tahun 2020 Tentang Pemantauan dan Evaluasi SPBE*. 2020.

[17] A. S. Izza and D. Diyono, "Geospatial Information Infrastructure Maturity Assessment Method of Indonesian Local Government Using Capability Maturity Model Integration (CMMI) and Geospatial Maturity Assessment Ordnance Survey (GMA OS)", *JGISE: Journal of Geospatial Information Science and Engineering*, vol. 6, no. 1, p. 38, 2023, doi: https://doi.org/10.22146/jgise.82534

[18] Ordnance Survey, "Geospatial Maturity Assessment Ordnance Survey", 2024. Accessed: Jul. 12, 2024. [Online]. Available: https://www.ordnancesurvey.co.uk/customers/international/geospatial-readiness-assessment

[19] GIS Management Institute, "Gis Capability Maturity Model". Accessed: Sep. 09, 2024. [Online]. Available: http://www.urisa.org

[20] DAMA International, *DMBOK - Data Management Body of Knowledge 2nd Edition*. New Jersey: Technics Publication, 2017.

[21] J. C. Mankins, "Technology Readiness Levels-A White Paper", 1995. [Online]. Available: https://api.semanticscholar.org/CorpusID:108011329

[22] A. Olechowski, S. D. Eppinger, and N. Joglekar, "Technology readiness levels at 40: A study of state-of-the-art use, challenges, and opportunities", in *2015 Portland International Conference on Management of Engineering and Technology (PICMET)*, 2015, pp. 2084–2094. doi: https://doi.org/10.1109/PICMET.2015.7273196

[23] Government of Canada, "Technology Readiness Level (TRL) Assessment Tool", Clean Growth Hub. Accessed: Jul. 19, 2025. [Online]. Available: https://ised-isde.canada.ca/site/clean-growth-hub/en/technology-readiness-level-trl-assessment-tool

[24] S. Yfanti and N. Sakkas, "Technology Readiness Levels (TRLs) in the Era of Co-Creation", *Applied System Innovation*, vol. 7, no. 2, pp. 1–13, 2024, doi: https://doi.org/10.3390/asi7020032

[25] P. A. White, H. Frye, M. F. Christensen, A. E. Gelfand, and J. A. Silander, "Spatial Functional Data Modeling of Plant Reflectances", *Annals of Applied Statistics*, vol. 16, no. 3, pp. 1919–1936, 2022, doi: https://doi.org/10.1214/21-AOAS1576

[26] M. Maciejczak and J. Faltmann, "Assessing Readiness Levels of Production Technologies for Sustainable Intensification of Agriculture", *Applied Studies in Agribusiness and Commerce*, vol. 12, no. 1–2, pp. 47–52, 2018, doi: https://doi.org/10.19041/apstract/2018/1-2/7

[27] E.-Y. Ahn, S.-Y. Kim, and J.-W. Lee, "Technology Readiness Levels (TRLs) Indicator Development for Geoscience and Mineral Resources R&D", *Economic and Environmental Geology*, vol. 48, no. 5, pp. 421–429, 2015, doi: https://doi.org/10.9719/EEG.2015.48.5.421

[28] I. G. Sudiantara, M. Sudarma, and I. M. O. Widyantara, "Measuring Maturity Level On The Process of Developing an Online Presence System With CMMI Framework", *International Journal of Engineering and Emerging Technology*, vol. 6, no. 2, pp. 201–229, 2021.

[29] ESA, "Technology Readiness Levels Handbook for Space Applications", European Space Agency. Accessed: Jul. 16, 2025. [Online]. Available: https://connectivity.esa.int/sites/default/files/TRL_Handbook.pdf

[30] R. White *et al.*, "Technology development for the early detection of plant pests: a framework for assessing Technology Readiness Levels (TRLs) in environmental science", *Journal of Plant Diseases and Protection*, vol. 129, no. 5, pp. 1249–1261, 2022, doi: https://doi.org/10.1007/s41348-022-00599-3

[31] F. M. Ferreira *et al.*, "Bioenergy Elephant Grass Genotype Selection Leveraged by Spatial Modeling of Conventional and High-Throughput Phenotyping Data", *Journal of Cleaner Production*, vol. 363, 2022, doi: https://doi.org/10.1016/j.jclepro.2022.132286

[32] T. Drivas, V. Sitokonstantinou, I. Tsardanidis, A. Koukos, C. Kontoes, and V. Karathanassi, "A Data Cube of Big Satellite Image Time-Series for Agriculture Monitoring", in *2022 IEEE 14th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP)*, 2022, pp. 1–5. doi: https://doi.org/10.1109/IVMSP54334.2022.9816291

[33] G. Giuliani, E. Egger, J. Italiano, C. Poussin, J. P. Richard, and B. Chatenoux, "Essential variables for environmental monitoring: What are the possible contributions of earth observation data cubes?", *Data*, vol. 5, no. 4, pp. 1–25, 2020, doi: https://doi.org/10.3390/data5040100

[34] F. Muchsin, K. Ulfa, K. A. Pradono, Hendayani, Dianovita, and K. W. Veronica, "Development of Landsat-8 ARD Products for User Service in Indonesia", *IOP Conference Series: Earth and Environmental Science*, vol. 1047, no. 1, 2022, doi: https://doi.org/10.1088/1755-1315/1047/1/012004

This page intentionally left blank.