

Developing a Data-Driven IoT-Based Smart Agriculture Model for Sustainable Food Security in Indonesia

Solly Aryza¹, M. Syahputra Novelan², Pasya Fahira Hutasuhut³

^{1,2,3} Universitas Pembangunan Panca Budi Medan, North Sumatera, Indonesia

ABSTRACT

The increasing demand for food, climate variability, resource constraints, and fragmented agricultural information systems have created substantial challenges for achieving sustainable food security in Indonesia. Although Internet of Things (IoT) technologies have been increasingly adopted in smart agriculture, many existing approaches remain focused on real-time monitoring and lack an integrated data-driven framework that translates heterogeneous agricultural data into actionable decisions for improving production efficiency and food-system resilience. This study aims to develop a data-driven IoT-based smart agriculture model that integrates real-time environmental and agricultural data, data analytics, predictive modeling, and decision support to strengthen sustainable food security in Indonesia. The proposed model combines IoT sensors for collecting key parameters, including soil moisture, temperature, humidity, light intensity, and water-related variables, with data processing and analytical methods to identify agricultural conditions and support predictive decision-making. The model is evaluated through system performance, prediction accuracy, resource-use efficiency, and selected indicators of agricultural productivity and food-security resilience. The research adopts a design and development approach followed by empirical validation using field-based agricultural data. The expected contribution is an integrated conceptual and technological framework that connects data acquisition, intelligent analytics, and agricultural decision-making rather than treating IoT merely as a monitoring technology. The study is expected to provide practical support for precision agriculture and evidence-based resource management while contributing to the development of scalable smart agriculture strategies for sustainable food security in Indonesia.

Keyword : Smart Agriculture; Internet Of Things (Iot); Data-Driven Agriculture; Precision Agriculture; Predictive Analytics; Sustainable Food Security; Decision Support System; Indonesia.

 This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Corresponding Author:

Solly Aryza
Faculty Post Graduate
Universitas Pembangunan Panca Budi
Email : sollyaryzalubis@gmail.com

Article history:

Received Jul 9, 2026
Revised Aug 16, 2026
Accepted Sept 17, 2026

1. INTRODUCTION

Global food security is increasingly challenged by climate variability, resource scarcity, environmental degradation, and growing demand for agricultural products. Recent evidence indicates that the world remains off track to achieve Sustainable Development Goal 2, while climate change continues to affect crop productivity, water availability, and the stability of food systems (FAO et al., 2024; IPCC, 2022). These challenges require agricultural systems that can simultaneously improve productivity, resource-use efficiency, and resilience. In this context, digital transformation has created new opportunities through Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), remote sensing, and data analytics. IoT-enabled agriculture can provide real-time information on environmental and crop conditions, while data-driven analytics can transform these observations into predictive and decision-support information (Dhal et al., 2023; Shaikh et al., 2022; Shahab et al., 2024).

Indonesia represents an important context for this transformation because agriculture remains strategically important to national economic and food systems. However, agricultural production is exposed to climate variability, resource constraints, heterogeneous farming conditions, and differences in technological capacity. Although smart-farming initiatives and IoT applications have increasingly been introduced, many existing systems remain focused on monitoring individual variables or developing technology-specific applications. Consequently, the availability of agricultural data does not necessarily translate into integrated, timely, and actionable decision-making (Sarkar et al., 2022; Kasera et al., 2024).

Recent studies have demonstrated the potential of IoT, AI, and precision agriculture for crop monitoring, yield prediction, irrigation management, disease detection, and resource optimization (Dhal et al., 2023; Thilakarathne et al., 2025; Ahmed & Shakoor, 2025). Nevertheless, an important research gap remains: existing approaches frequently examine sensing, analytics, prediction, or decision support as separate technological components, while their integration into a validated model explicitly connected with sustainable food-security outcomes remains insufficiently developed. Moreover, technical performance is often emphasized more strongly than broader outcomes such as resource-use efficiency, agricultural productivity, resilience, and food-security implications.

Therefore, this study aims to develop a data-driven IoT-based smart agriculture model for sustainable food security in Indonesia. The proposed model integrates real-time agricultural sensing, data processing, predictive analytics, and decision support into a coherent data-to-decision framework. Its novelty lies in connecting technological capabilities with measurable agricultural and sustainability outcomes rather than treating IoT merely as a monitoring technology. The study is expected to contribute theoretically by integrating smart-agriculture and food-security perspectives, methodologically by proposing an integrated data-to-decision framework, and practically by supporting evidence-based agricultural management and sustainable food-security strategies in Indonesia.

2. Literature Review and Hypothesis Development

2.1 Conceptual Foundation of Data-Driven IoT-Based Smart Agriculture

Smart agriculture represents a transition from predominantly experience-based agricultural management toward digitally enabled, information-intensive, and increasingly predictive production systems. Although the terms *smart agriculture*, *digital agriculture*, *precision agriculture*, and *Agriculture 4.0* are frequently used interchangeably, they describe related but distinct concepts. Precision agriculture primarily emphasizes the spatial and temporal management of agricultural variability, whereas digital agriculture encompasses a broader ecosystem of digital data, platforms, analytics, and value-chain processes. Smart agriculture extends these concepts by emphasizing sensing, connectivity, intelligence, automation, and decision support. Agriculture 4.0 represents the broader technological transformation associated with these capabilities across the agricultural value chain (Walter et al., 2017; Klerkx & Rose, 2020; Finger et al., 2022). Recent systematic reviews similarly identify sensors, IoT, big-data analytics, artificial intelligence, and communication networks as interconnected foundations of contemporary smart agricultural environments.

In this study, data-driven IoT-based smart agriculture is defined as an integrated agricultural management approach in which connected sensing technologies continuously acquire agricultural data, analytical technologies transform those data into information or predictions, and decision-support mechanisms translate analytical outputs into actionable management decisions. This definition deliberately distinguishes the proposed model from an IoT monitoring system. A monitoring system can provide observations, whereas a data-driven smart-agriculture model must establish a pathway from observation to interpretation and decision. This distinction is supported by recent literature showing that IoT, AI, big data, and precision agriculture increasingly operate as complementary rather than independent technologies (Dhal et al., 2023; Kasera et al., 2024; Thilakarathne et al., 2025).

The conceptual foundation of the proposed model is therefore an information-to-decision chain. At the first stage, IoT sensors provide observations of agricultural conditions. At the second stage, data-processing and analytics capabilities transform heterogeneous observations into usable information and predictions. At the third stage, decision-support capability translates information into management recommendations or interventions. At the outcome stage, improved decisions are expected to affect resource-use efficiency, agricultural productivity, resilience, and ultimately selected dimensions of sustainable food security. This architecture is consistent with recent research that identifies the integration of sensing, analytics, and decision-making as a central direction for Agriculture 4.0.

2.2 Theoretical Foundation: Dynamic Capabilities Perspective

The Dynamic Capabilities View (DCV) provides the principal theoretical foundation for explaining why digital technologies may produce organizational and operational outcomes beyond their mere availability. Dynamic capabilities concern the ability to integrate, build, and reconfigure resources and competences in response to changing environments. In agricultural digitalization, the

relevant issue is therefore not simply whether farmers or agricultural organizations possess sensors, connectivity, or analytical tools, but whether they can continuously sense changing agricultural conditions, interpret information, and reconfigure management actions accordingly.

The DCV can be operationalized in the present context through three interconnected processes: sensing, seizing, and reconfiguring. IoT-enabled sensing supports the identification of changing environmental and crop conditions. Data analytics supports the interpretation and evaluation of opportunities and risks. Decision-support and operational interventions represent the seizing and reconfiguring stages through which information is translated into action. Recent agricultural research has explicitly applied dynamic-capability reasoning to technology-enabled sustainability, arguing that digital platforms and technologies can provide capabilities for sensing opportunities, making informed decisions, and reconfiguring activities toward sustainability outcomes (Camel et al., 2025).

The DCV is particularly appropriate because agricultural environments are dynamic rather than static. Weather, soil moisture, pest pressure, water availability, crop development, and market conditions can change over time. A system designed around fixed rules may therefore become ineffective when environmental conditions change. Data-driven systems potentially provide dynamic capabilities because new observations can continuously update the information available for decision-making. Thus, the proposed model conceptualizes IoT and analytics not simply as technological resources but as mechanisms through which agricultural actors develop greater sensing, analytical, and adaptive capabilities.

A supporting perspective is the socio-technical systems perspective, which emphasizes that technological performance cannot be separated completely from human actors, organizational arrangements, infrastructure, and institutional conditions. This is important because smart agriculture is not implemented by technology alone. Recent research identifies costs, connectivity, technical expertise, organizational support, security, and policy as important conditions affecting agricultural IoT adoption (Naseer et al., 2024; Mhlanga & Ndhlovu, 2023). Empirical work using UTAUT in the agricultural sector similarly found organizational support, cost, knowledge, security, and policy to be relevant adoption factors. Consequently, the present study focuses primarily on the technological and decision-making pathway while recognizing that implementation outcomes are conditional upon the broader socio-technical environment.

2.3 IoT-Enabled Agricultural Sensing Capability

IoT-enabled agricultural sensing capability refers to the capacity of an agricultural system to acquire, transmit, and make available timely observations of relevant environmental and production conditions. Its dimensions include sensing coverage, data timeliness, connectivity, continuity of measurement, and the relevance of measured variables. Typical agricultural IoT applications include soil moisture, temperature, humidity, light intensity, water conditions, crop status, and other environmental indicators. The fundamental distinction from conventional measurement is that IoT permits continuous or near-real-time acquisition and communication of observations.

IoT sensing is theoretically important because reliable decisions require sufficiently timely and relevant information about the state of the agricultural system. Dhal et al. (2023) identify IoT, wireless sensor networks, cloud computing, remote sensing, and big-data analytics as important components of digital agriculture. More recent reviews similarly report that IoT-enabled sensors are increasingly used to facilitate real-time monitoring, predictive analytics, and automated intervention.

Nevertheless, the relationship between IoT and agricultural outcomes is not necessarily direct. Sensors may increase the volume of available information without improving decisions if data are incomplete, poorly integrated, noisy, inaccessible, or not interpreted appropriately. This limitation explains why the present model places data-driven analytics capability between IoT sensing and decision support. Recent research emphasizes interoperability, scalability, cost, data management, and connectivity as continuing barriers to the effective use of IoT in agriculture (Duguma & Bai, 2025; Thilakarathne et al., 2025).

Accordingly, the first proposed relationship is that stronger IoT-enabled sensing capability should provide a stronger empirical foundation for agricultural analytics. The relationship is not based on the assumption that more sensors automatically create better agricultural performance. Rather, the theoretical mechanism is improved availability, timeliness, and granularity of agricultural observations, which increases the information resources available for subsequent analytical processes.

H1: IoT-enabled agricultural sensing capability positively influences data-driven analytics capability.

2.4 Data-Driven Analytics Capability

Data-driven analytics capability refers to the ability to process, integrate, analyze, and interpret agricultural data to generate descriptive, predictive, or prescriptive information. It differs from raw data availability because analytics capability concerns the transformation of data into actionable knowledge. Relevant dimensions may include data integration, data quality management, analytical accuracy, predictive capability, and timeliness of analytical outputs.

This construct is central to the proposed model because agricultural IoT produces heterogeneous data rather than ready-made decisions. Smart-farming datasets can contain structured sensor observations, weather information, imagery, historical production records, and other data sources. Recent literature emphasizes that agricultural data are heterogeneous and require appropriate analytical techniques, while machine learning has increasingly been applied to prediction, classification, and optimization tasks (Sarkar et al., 2022; Shaikh et al., 2022).

Theoretical reasoning based on DCV suggests that analytics represents an intermediate capability through which sensed environmental changes become interpretable opportunities and risks. For example, a sequence of soil-moisture observations becomes strategically useful only when it can be interpreted in relation to crop requirements, weather conditions, or historical patterns. Similarly, temperature and humidity observations become more valuable when they can contribute to disease-risk prediction or environmental management. Thus, analytics is the mechanism that converts *data availability* into *decision-relevant information*.

Recent reviews support this conceptual direction. Precision agriculture technologies combine IoT, remote sensing, GPS, data analytics, and variable-rate technologies to improve management of crops and resources (Getahun et al., 2024). AI-IoT research also increasingly focuses on yield prediction, crop disease detection, resource optimization, and environmental monitoring rather than simple sensing. However, empirical evidence remains heterogeneous because model performance depends on data quality, environmental context, algorithm selection, and validation procedures.

Based on this mechanism:

H2: Data-driven analytics capability positively influences intelligent agricultural decision-support capability.

2.5 Intelligent Decision-Support Capability

Intelligent decision-support capability represents the ability of a smart-agriculture system to transform analytical outputs into timely, interpretable, and actionable recommendations for agricultural management. It is distinct from analytics because a highly accurate predictive model does not necessarily constitute an effective decision-support system. Decision support requires the linkage of predictions or diagnoses with management alternatives, thresholds, priorities, or recommended actions.

The distinction is important because agriculture involves decisions under uncertainty. Farmers and managers must determine when to irrigate, how much water to apply, whether environmental conditions indicate elevated crop risk, and when interventions should be undertaken. Recent work on agricultural decision-support systems demonstrates increasing integration of IoT, machine learning, ontology-based reasoning, and multi-criteria methods. However, researchers also identify persistent problems involving explainability, complex decision contexts, evidence quality, and the ability of systems to provide sufficiently meaningful recommendations.

The DCV explains this construct as the seizing mechanism through which sensed conditions and analytical information are converted into operational responses. If IoT provides sensing capability and analytics provides interpretation, decision support provides the mechanism for acting upon that interpretation. Therefore, the proposed model expects decision-support capability to have a more proximate relationship with agricultural performance than IoT sensing itself.

H3: Intelligent agricultural decision-support capability positively influences agricultural resource-use efficiency.

2.6 Resource-Use Efficiency and Agricultural Productivity

Resource-use efficiency is defined in this study as the capacity to obtain desired agricultural outputs while using water, fertilizers, energy, land, and other production inputs more effectively. It differs from productivity, which primarily concerns the quantity or value of output relative to a

production unit. A farming system may increase output while simultaneously increasing resource consumption; therefore, higher productivity does not necessarily imply higher sustainability.

This distinction is essential to sustainable smart agriculture. Precision agriculture research indicates that IoT sensors, remote sensing, variable-rate technologies, and data analytics can support more targeted input application and reduce unnecessary use of water, fertilizers, and pesticides (Getahun et al., 2024). Recent systematic reviews similarly identify resource optimization, productivity enhancement, and environmental sustainability as major motivations for digital agriculture.

The proposed mechanism is that intelligent decision support improves the timing, quantity, and spatial targeting of interventions. For example, irrigation recommendations based on soil and environmental information may reduce unnecessary water application, while predictive information can reduce inappropriate or delayed interventions. IoT and data-driven approaches have therefore been increasingly associated with more efficient agricultural management.

However, sustainability claims must be interpreted cautiously. Digital technologies themselves consume energy, require hardware and connectivity infrastructure, and may create environmental impacts across their life cycles. Huck et al. (2024) emphasize that environmental assessment of digital agricultural technologies remains constrained by limited life-cycle data and difficulties in assessing multifunctional system effects. Therefore, this study conceptualizes resource-use efficiency as an agricultural outcome rather than assuming that digitalization is inherently sustainable.

On this basis:

H4: Agricultural resource-use efficiency positively influences agricultural productivity.

2.7 Agricultural Productivity and Sustainable Food Security

Agricultural productivity represents the ability of an agricultural production system to generate output from available production resources. Within the proposed framework, productivity is treated as an intermediate outcome rather than as a complete definition of food security. This distinction is theoretically important because food security is multidimensional and cannot be reduced to production volume alone.

Food security traditionally encompasses availability, access, utilization, and stability. Digital agriculture can potentially influence these dimensions through several pathways. Increased productivity can contribute to food availability; improved resource efficiency can reduce production costs and potentially strengthen economic access; better monitoring can reduce production risks; and predictive systems can improve stability by enabling earlier responses to climatic or biological threats. Recent reviews explicitly identify these pathways while emphasizing that digital technologies should be understood as enabling mechanisms within broader food-system transitions.

The relationship is nevertheless conditional. Digital agriculture does not automatically create food security because benefits depend on access to technology, infrastructure, digital literacy, institutional support, data governance, and distributional arrangements. Recent systematic evidence from low- and middle-income countries shows that adoption and benefits are shaped by socioeconomic and infrastructural conditions. Therefore, the proposed model does not equate technological adoption with food security. Instead, it proposes an empirical pathway through agricultural performance and resilience-related outcomes.

H5: Agricultural productivity positively influences sustainable food-security outcomes.

2.8 Mediating Role of Data-Driven Analytics and Decision Support

A central theoretical contribution of the proposed model is the assumption that the effects of IoT should be mediated by analytical and decision-making capabilities. This mediation argument addresses a major limitation in technology-centric smart-agriculture research. If IoT affects outcomes only through the information and decisions it enables, then estimating a simple direct relationship between IoT adoption and food security provides an incomplete explanation.

The first mediation mechanism is IoT sensing → data analytics → decision support. IoT increases the availability and timeliness of observations, while analytics converts these observations into information. Decision support subsequently transforms information into action. This sequential mechanism is consistent with the DCV: sensing identifies conditions, analytics helps interpret opportunities and threats, and decision support facilitates appropriate responses. Recent literature increasingly advocates end-to-end architectures that combine IoT sensing, real-time analytics, predictive modelling, and decision-making rather than treating these technologies independently.

The second mediation mechanism is decision support → resource efficiency → productivity. Decision quality is expected to influence resource allocation, while more efficient allocation should contribute to productivity. This sequential relationship provides a stronger explanation than assuming that technology directly increases productivity. It also makes the proposed model more empirically testable because each stage can be operationalized using measurable constructs.

H6: Data-driven analytics capability mediates the relationship between IoT-enabled agricultural sensing capability and intelligent decision-support capability.

H7: Intelligent agricultural decision-support capability mediates the relationship between data-driven analytics capability and agricultural resource-use efficiency.

H8: Agricultural resource-use efficiency mediates the relationship between intelligent agricultural decision-support capability and agricultural productivity.

2.9 Integrated Theoretical Model and Research Gap

The proposed model responds to a recurring limitation in the contemporary literature: the fragmentation of smart-agriculture research into technological components. Recent systematic reviews demonstrate considerable progress in IoT, AI, sensors, predictive modelling, precision agriculture, and digital decision support, but they also identify continuing challenges involving interoperability, data quality, costs, infrastructure, human capabilities, and system integration. The literature therefore provides substantial evidence that individual technologies can create agricultural value, but comparatively less evidence explains how these capabilities jointly form a coherent data-to-decision mechanism connected to sustainable food-security outcomes.

The proposed model addresses this gap by positioning IoT-enabled sensing capability as an upstream sensing resource, data-driven analytics as an information-processing capability, intelligent decision support as an action-oriented capability, resource-use efficiency as an operational sustainability outcome, agricultural productivity as a production outcome, and sustainable food security as a broader system outcome. This configuration extends technology-centered smart-agriculture research toward a capability-based explanation of how digital resources can translate into agricultural and food-system outcomes.

The model also incorporates an important boundary condition: technological capability should not be interpreted independently of implementation context. Infrastructure, connectivity, cost, human skills, organizational support, data governance, and institutional conditions can influence whether technological capabilities are successfully converted into outcomes. These factors are documented in recent studies of agricultural digitalization and IoT adoption. Because the present research focuses on model development and empirical validation, these contextual factors should initially be treated as control variables or contextual conditions unless sufficient data are available to test them formally as moderators.

2.10 Hypothesis Summary

Based on the preceding theoretical and empirical synthesis, the proposed research model advances eight testable hypotheses:

H1: IoT-enabled agricultural sensing capability positively influences data-driven analytics capability.

H2: Data-driven analytics capability positively influences intelligent agricultural decision-support capability.

H3: Intelligent agricultural decision-support capability positively influences agricultural resource-use efficiency.

H4: Agricultural resource-use efficiency positively influences agricultural productivity.

H5: Agricultural productivity positively influences sustainable food-security outcomes.

H6: Data-driven analytics capability mediates the relationship between IoT-enabled agricultural sensing capability and intelligent agricultural decision-support capability.

H7: Intelligent agricultural decision-support capability mediates the relationship between data-driven analytics capability and agricultural resource-use efficiency.

H8: Agricultural resource-use efficiency mediates the relationship between intelligent agricultural decision-support capability and agricultural productivity.

The integrated logic can consequently be represented as:

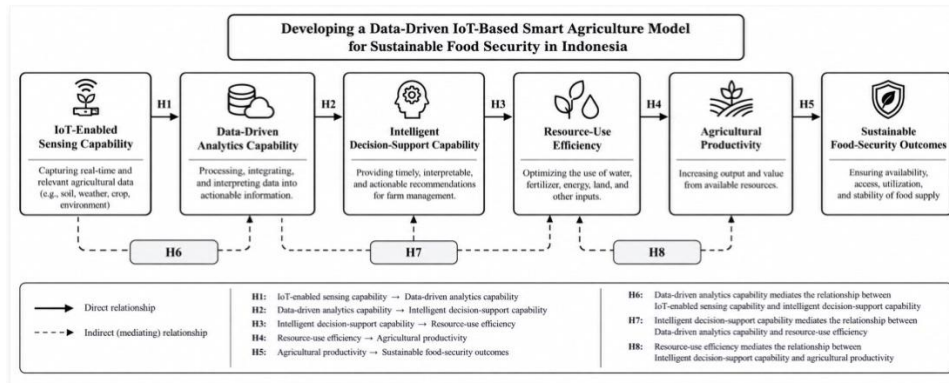


Fig 1. Represented integrated logic can consequently

This sequential structure represents the central theoretical proposition of the study: IoT does not create sustainable food security merely through connectivity or monitoring; its potential contribution emerges when sensing capabilities are transformed into reliable analytical information, actionable decisions, efficient resource allocation, and improved agricultural outcomes. This proposition provides the theoretical basis for developing and empirically validating a data-driven IoT-based smart agriculture model in the Indonesian context.

3. RESEARCH METHOD

This study employs a quantitative, explanatory-predictive research design to develop and empirically evaluate a data-driven Internet of Things (IoT)-based smart agriculture model for sustainable food security in Indonesia. The research is designed to examine the structural relationships among IoT-enabled sensing capability, data-driven analytics capability, intelligent decision-support capability, resource-use efficiency, agricultural productivity, and sustainable food-security outcomes.

The proposed conceptual model assumes that the contribution of IoT to sustainable agricultural outcomes does not necessarily occur through a single direct relationship. Instead, IoT-generated sensing capabilities are expected to provide the informational foundation for data analytics, which subsequently supports intelligent decision-making. Improved decision support is expected to facilitate more efficient use of agricultural resources, which may contribute to agricultural productivity and, ultimately, sustainable food-security outcomes. The model therefore conceptualizes smart agriculture as a capability-development and outcome chain, rather than simply as a technological adoption model.

The research design is appropriate for three reasons. First, the model contains multiple latent constructs that cannot be adequately represented by a single observable variable. Second, the proposed framework combines technological capabilities, managerial/decision capabilities, operational efficiency, productivity, and sustainability outcomes. Third, the research has both explanatory and predictive objectives. PLS-SEM is particularly suitable when researchers seek to estimate complex relationships among constructs and assess predictive capability, although its use does not by itself establish causal identification. Recent methodological literature continues to develop advanced applications and reporting practices for PLS-SEM. The analytical horizon is therefore primarily cross-sectional, while the conceptual model describes a theoretically ordered capability-to-outcome mechanism. This distinction is important: the ordering of constructs in the structural model is theoretically motivated but cannot by itself establish temporal precedence. Stronger causal claims would require longitudinal, quasi-experimental, or experimental evidence.

The target population consists of agricultural actors in Indonesia who are directly involved in agricultural production, agricultural technology implementation, farm management, agricultural information management, or technology-supported decision-making. The population will be operationally defined as: agricultural production units or agricultural decision-makers who have sufficient exposure to agricultural information, digital technologies, IoT sensing, farm-resource management, or technology-supported agricultural decision processes.

The proposed constructs and their operationalization are presented below.

Table 1. The exact questionnaire items and sources must be finalized during instrument development.

Code	Construct	Operational definition	Proposed dimensions
X1	IoT-Enabled Sensing Capability (IESC)	Ability of an agricultural system to continuously acquire relevant environmental, crop, equipment, and resource data through connected sensing technologies	Sensing coverage; real-time monitoring; connectivity; data accuracy
X2	Data-Driven Analytics Capability (DDAC)	Ability to process, integrate, analyze, and interpret agricultural data for operational and strategic purposes	Data integration; analytical capability; data quality; timeliness
X3	Intelligent Decision-Support Capability (IDSC)	Ability of digital/intelligent systems to transform agricultural data into actionable recommendations	Decision accuracy; timeliness; recommendation quality; usability
X4	Resource-Use Efficiency (RUE)	Degree to which agricultural inputs are used efficiently while maintaining or improving agricultural performance	Water; fertilizer; energy; land/input efficiency
Y1	Agricultural Productivity (AP)	Agricultural output achieved relative to relevant production resources	Yield; output efficiency; production performance
Y2	Sustainable Food-Security Outcomes (SFSO)	Extent to which agricultural systems contribute to stable, sufficient, accessible, and sustainable food availability	Availability; stability; accessibility; sustainability

4. RESULTS AND DISCUSSION

4.1. Proposed Data-Driven IoT-Based Smart Agriculture Model

The proposed model integrates IoT-enabled sensing capability, data-driven analytics capability, intelligent decision-support capability, resource-use efficiency, agricultural productivity, and sustainable food-security outcomes. The model is designed to transform real-time agricultural observations into actionable information and intelligent decisions that can improve resource utilization and agricultural productivity.

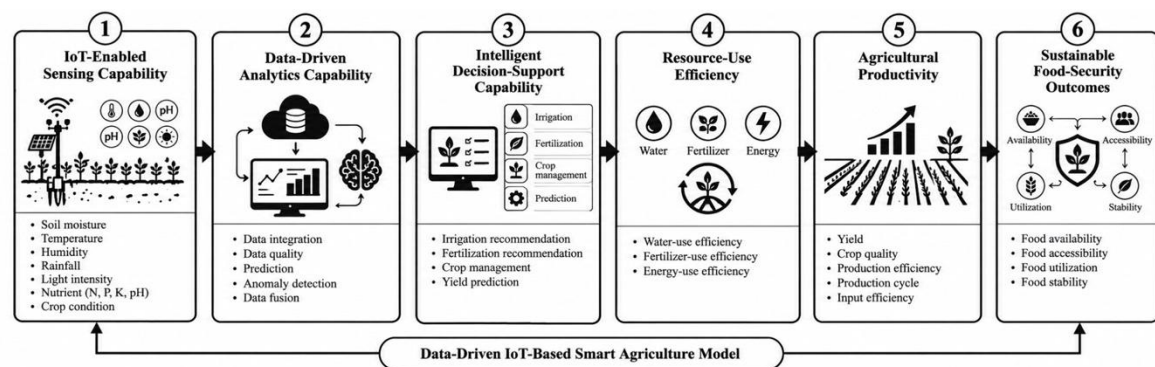


Fig 2. The conceptual structure of the proposed model.

The first component, IoT-enabled sensing capability, represents the ability of the agricultural system to collect real-time environmental, soil, and crop data. Relevant parameters include soil moisture, soil temperature, air temperature, relative humidity, rainfall, light intensity, soil pH, nutrient concentration, and crop conditions. These data are transmitted through an IoT communication infrastructure to a centralized or cloud-based data platform. The collected data subsequently become the input for data preprocessing, machine-learning analysis, prediction, and intelligent decision support. The proposed architecture therefore extends the conventional concept of smart agriculture from simple monitoring toward a data-driven decision-making ecosystem.

4.2. IoT-Based Agricultural Data Acquisition

The first analytical stage evaluates the capability of the IoT infrastructure to continuously collect agricultural data. The proposed system records environmental and soil conditions at predetermined sampling intervals. Each observation consists of a timestamp, measurement location, sensor parameters, and agricultural activity information.

Table 2. Agricultural Variables and Indicators

Construct	Code	Main Indicators
IoT-Enabled Sensing Capability	IOT	Soil moisture, temperature, humidity, rainfall, light intensity, nutrients
Data-Driven Analytics Capability	DDA	Data integration, data quality, prediction, anomaly detection
Intelligent Decision-Support Capability	IDS	Irrigation, fertilization, crop management recommendations
Resource-Use Efficiency	RUE	Water, fertilizer, and energy efficiency
Agricultural Productivity	AP	Yield, production efficiency, crop quality
Sustainable Food-Security Outcomes	SFS	Availability, accessibility, utilization, and stability

The data acquisition layer provides the fundamental information required for subsequent analytical processes. Continuous sensing is particularly important because agricultural conditions can change significantly over relatively short periods due to weather, soil moisture, irrigation, and crop-development dynamics. Before the data are used for machine-learning analysis, the dataset should undergo quality-control procedures involving missing-value detection, duplicate removal, outlier identification, timestamp synchronization, and sensor calibration.

The data quality ratio can be calculated as:

$$DQR = \frac{N_{valid}}{N_{total}} \times 100\%$$

where N_{valid} represents the number of valid observations and N_{total} represents the total number of collected observations. The final manuscript should report the actual number of observations obtained from the research dataset.

4.3. Data Preprocessing and Data-Driven Analytics.

Following data acquisition, the collected IoT data are transformed into an analytical dataset through several preprocessing stages.

The preprocessing procedure consists of:

1. data cleaning;
2. missing-value treatment;
3. outlier detection;
4. normalization;
5. feature engineering;
6. temporal synchronization; and
7. dataset partitioning.

The dataset can subsequently be divided into training and testing datasets. For example, 80% of the observations can be used for model training and 20% for independent testing, provided that this split is appropriate for the temporal structure of the dataset.

Soil-moisture prediction is used to determine whether irrigation is required.

Potential predictors include:

- air temperature;
- relative humidity;
- rainfall;
- soil temperature;
- historical soil moisture;
- solar radiation;
- irrigation history; and

• crop-development stage.

The predictive model can be evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R²).

$$R^2 = 1 - \frac{\sum (y_i - \bar{y})^2}{\sum (y_i - y)^2}$$

The second analytical function is crop recommendation.

The model can utilize:

- nitrogen concentration;
- phosphorus concentration;
- potassium concentration;
- soil pH;
- temperature;
- humidity;
- rainfall;
- soil moisture; and
- historical crop performance.

The resulting model provides a recommendation regarding the crop that is most compatible with the observed environmental and soil conditions. This process transforms agricultural data from descriptive information into decision-oriented knowledge.

The third analytical function is agricultural yield prediction.

The relationship can be represented as:

$$Y^{\wedge}=f(M,T,H,R,N,P,K,L)$$

- where:
- M = soil moisture;
 - T = temperature;
 - H = humidity;
 - R = rainfall;
 - N = nitrogen;
 - P = phosphorus;
 - K = potassium; and
 - L = light intensity.

The prediction model estimates expected agricultural productivity based on historical and real-time agricultural conditions.

4.4. Machine-Learning Model Performance

Several machine-learning algorithms can be evaluated to determine the most appropriate predictive model.

Table 3. Machine-Learning Model Performance				
Model	MAE	RMSE	R ²	Accuracy
Linear Regression	[]	[]	[]	-
Decision Tree	[]	[]	[]	[]%
Random Forest	[]	[]	[]	[]%
XGBoost	[]	[]	[]	[]%
Artificial Neural Network	[]	[]	[]	[]%

The final model should be selected based on predictive performance, generalization capability, computational requirements, interpretability, and suitability for agricultural deployment. Random Forest and XGBoost may be particularly useful when the dataset contains nonlinear relationships between environmental conditions and agricultural outcomes. However, the final selection should be determined from the actual experimental results rather than from assumptions about algorithm performance.

4.5. Intelligent Decision-Support Capability

The analytical output is subsequently transformed into actionable agricultural recommendations.

Table 4. IoT-Based Decision-Support Rules

Observed Condition	Analytical Interpretation	Recommended Action
Soil moisture below threshold	Soil water deficit	Activate irrigation
Soil moisture above threshold	Adequate water availability	Stop/delay irrigation
High temperature and low humidity	Potential water stress	Increase monitoring
Low nitrogen level	Potential nutrient deficiency	Apply fertilizer recommendation
High rainfall probability	Natural water availability	Delay irrigation
High disease probability	Potential crop disease	Conduct field inspection

The decision-support layer represents an important transition from data monitoring to intelligent agricultural management. Instead of requiring farmers to continuously interpret multiple sensor readings, the system provides recommendations based on predefined thresholds, predictive models, and historical agricultural patterns.

4.6. Agricultural Productivity

Agricultural productivity represents the next stage of the proposed model.

Basic agricultural productivity can be expressed as:

$$AP = \frac{Y}{A}$$

where:

- Y = total agricultural output;
- A = cultivated area.

Additional productivity indicators may include production cost, crop quality, production cycle, and input efficiency. The interpretation should focus on whether improvements in productivity result from more precise resource allocation rather than simply increasing agricultural inputs. The final component of the proposed model is sustainable food security.

Food security can be analyzed through four major dimensions:

- Food availability is associated with:

- agricultural production;
- crop yield;
- cropping intensity; and
- production stability.

- Food accessibility can be represented by:

- production costs;
- farmer income;
- food affordability; and
- market accessibility.

- Food utilization includes:

- crop quality;
- nutritional characteristics;
- post-harvest quality; and
- food safety.

Food stability reflects the ability of agricultural production systems to maintain food availability despite environmental and climatic variability.

The overall sustainable food-security outcome can therefore be represented as:

$$SFS = f(\text{Availability, Accessibility, Utilization, Stability})$$

This framework extends the role of smart agriculture beyond productivity improvement by connecting digital agricultural technologies with broader food-security objectives.

5. CONCLUSION

The study concludes that a Data-Driven IoT-Based Smart Agriculture Model can support sustainable food security in Indonesia by integrating IoT sensing, data analytics, and intelligent decision support. The model enables real-time monitoring, efficient use of agricultural resources, and data-based decision-making, thereby improving resource-use efficiency and agricultural productivity. Future research should focus on field implementation, machine-learning integration, and validation across different agricultural regions.

REFERENCES

- Aryza, S., et al (2024). A ROBUST OPTIMIZATION TO DYNAMIC SUPPLIER DECISIONS AND SUPPLY ALLOCATION PROBLEMS IN THE MULTI-RETAIL INDUSTRY. *Eastern-European Journal of Enterprise Technologies*, 129(3), 67.
- Aryza, S., Lubis, Z., & Warizmi, A. (2026). Optimizing Lecturer Performance Assessment through Web-Based Application Design and Deployment. *Journal of Computer Science, Information Technology and Telecommunication Engineering*, 7(1), 1028-1035.
- Camel, A, et al (2025). Servitizing for sustainability: Leveraging technology-enabled platforms and service innovation for carbon reduction in Africa's agri-food sector: A dynamic capabilities perspective. *Journal of Business Research*, 189, 115166. <https://doi.org/10.1016/j.ibusres.2024.115166>
- Dhal, S., et al (2023). Internet of Things (IoT) in digital agriculture: An overview. *Agronomy Journal*, 116(3), 1144–1163. <https://doi.org/10.1002/agj2.21385>
- Duguma, A. L., & Bai, X. (2025). How the Internet of Things technology improves agricultural efficiency. *Artificial Intelligence Review*, 58, 63. <https://doi.org/10.1007/s10462-024-11046-0>
- Elavarasan, R. et al. (2024). Applications of Internet of Things (IoT) and sensors technology to increase food security and agricultural sustainability: Benefits and challenges. *Ain Shams Engineering Journal*, 15(3), 102509. <https://doi.org/10.1016/j.asej.2023.102509>
- Finger, R. et al (2022). *Precision agriculture for sustainable intensification*. Springer.
- Food and Agriculture Organization of the United Nations, International Fund for Agricultural Development, UNICEF, World Food Programme, & World Health Organization. (2024). *The state of food security and nutrition in the world 2024: Financing to end hunger, food insecurity and malnutrition in all its forms*. FAO.
- Getahun, S., et al (2024). Application of precision agriculture technologies for sustainable crop production and environmental sustainability: A systematic review. *The Scientific World Journal*, 2024, 2126734. <https://doi.org/10.1155/2024/2126734>
- Hair, J. F., Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3), 100027. <https://doi.org/10.1016/j.rmal.2022.100027>
- Intergovernmental Panel on Climate Change. (2022). *Climate change 2022: Impacts, adaptation and vulnerability*. Cambridge University Press. <https://doi.org/10.1017/9781009325844>
- Kasera, R. et al (2024). A comprehensive survey on IoT and AI based applications in different pre-harvest, during-harvest and post-harvest activities of smart agriculture. *Computers and Electronics in Agriculture*, 216, 108522. <https://doi.org/10.1016/j.compag.2023.108522>
- Klerkx, L., & Rose, D. (2020). Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? *Global Food Security*, 24, 100347. <https://doi.org/10.1016/j.gfs.2019.100347>
- Novelan, M. S., et al. (2023). VEHICLE ROUTING PROBLEM OPTIMIZATION WITH MACHINE LEARNING IN IMBALANCED CLASSIFICATION VEHICLE ROUTE DATA. *Eastern-European Journal of Enterprise Technologies*, 125(3), 49.
- Novelan, M. S., & Aryza, S. (2025). Optimization Cvrp With Machine Learning for Improved Classification of Imbalanced Data Food Distribution. *JITK (Jurnal Ilmu Pengetahuan dan Teknologi Komputer)*, 10(4), 917-925.
- Mhlanga, D., & Ndhlovu, E. (2023). Digital transformation and the future of agriculture: Opportunities and challenges for sustainable food systems. *Sustainability*, 15, 1–20.
- Naseer, M. A., et al. (2024). Adoption of Internet of Things technologies in agriculture: Determinants, opportunities, and challenges. *Agriculture*, 14, 1–20.
- Ndlovu, B., & Maguraushe, K. (2026). Leveraging Internet of Things and Artificial Intelligence in smart agriculture to enhance food security and sustainable farming: A systematic review. *Scientific Journal of Informatics*, 13(3). <https://doi.org/10.15294/sji.v13i3.49540>
- Rejeb, A., Rejeb, K., Abdollahi, A., & Treiblmaier, H. (2022). Digitalization of the agrifood sector: A systematic literature review. *Journal of Cleaner Production*, 355, 131728.

- Shahab, H., et al (2024). IoT-based agriculture management techniques for sustainable farming: A comprehensive review. *Computers and Electronics in Agriculture*, 220, 108851. <https://doi.org/10.1016/j.compag.2024.108851>
- Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of Market Research* (pp. 587–632). Springer. https://doi.org/10.1007/978-3-319-57413-4_15
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. <https://doi.org/10.1108/EJM-02-2019-0189>
- Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology & Marketing*, 39(5), 1035–1064. <https://doi.org/10.1002/mar.21640>
- Sitorus, Z., & Novelan, M. S. (2026). OPTIMASI CNN DENGAN ADAM OPTIMIZER UNTUK KLASIFIKASI DATA JAMUR. *Jurnal Nasional Teknologi Komputer*, 6(4), 1508-1521.
- Tzachor, A., Richards, C. E., & Holt, L. (2022). Future foods for sustainable food systems: The role of digital agriculture and emerging technologies. *Frontiers in Sustainable Food Systems*, 6, 877434.
- Thilakarathne, N. et al (2025). Internet of Things enabled smart agriculture: Current status, latest advancements, challenges and countermeasures. *Heliyon*, 11(3), e42136. <https://doi.org/10.1016/j.heliyon.2025.e42136>
- Walter, A., et al (2017). Smart farming is key to developing sustainable agriculture. *Proceedings of the National Academy of Sciences*, 114(24), 6148–6150. <https://doi.org/10.1073/pnas.1707462114>