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Development of a Smart Agriculture Framework for Monitoring Food Production to Support Food Security

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ABSTRACT

Sustainable food security requires accurate, integrated, and relevant production information to support regional planning and decision-making. However, food production data are often presented in fragmented statistical tables, limiting the monitoring of production performance and the identification of interregional disparities. This study aims to develop a five-layer Smart Agriculture Framework for food production monitoring and evaluation and to implement it as a dashboard prototype, using Bireuen Regency, Aceh, as a case study. The study adopts a Design Science Research (DSR) approach using secondary food production data for 2025 from the Bireuen Regency Agriculture and Plantation Office and Statistics Indonesia (BPS), covering 17 subdistricts. The framework comprises five layers: field data, Internet of Things (IoT) connectivity, data platform, analytics, and evaluation and decision support. Rice production reached 158,432 tons of dry milled paddy (GKG) from a harvested area of 25,563 ha, with an average productivity of 6.20 tons/ha, equivalent to 101,301.57 tons of rice. Maize production reached 54,474.70 tons from 8,510.50 ha, while cassava production was 3,816.70 tons. Spatial analysis shows that the five leading subdistricts accounted for 46.2% of rice production, while three subdistricts contributed 94.4% of maize production. Six subdistricts had rice productivity below the regency average, indicating opportunities for targeted interventions. The dashboard prototype integrates production information, inter-subdistrict distribution, and evaluation indicators to support situational analysis and the prioritization of agricultural development. The framework can support data-driven decision-making in regional food production planning. However, operational IoT integration and field validation of its effectiveness require further development and testing.

INTRODUCTION

Food is a basic human necessity. The fulfillment of food needs is a human right guaranteed by the 1945 Constitution of the Republic of Indonesia and constitutes a foundation for developing high-quality and competitive human resources (Law of the Republic of Indonesia No. 18 of 2012 on Food, 2012). However, Indonesia's global food security performance has remained unstable. According to the Global Food Security Index (GFSI), Indonesia achieved its highest ranking during the 2018–2022 period in 2018, placing 58th out of 113 countries with a score of 63.6. In 2022, Indonesia's ranking declined by five positions to 63rd, with a score of 60.2. This decline was accompanied by a deterioration in several food security indicators, particularly food quality and safety, which fell seven positions to 78th, with a score of 56.2. The food availability indicator also changed from a score of 57.0 in 2020 to [insert the 2022 score] (Economist Impact, [year of the GFSI report used]). These developments highlight the need to strengthen food production monitoring systems that support data-driven planning and the systematic identification of food production challenges.

This situation underscores the importance of food production monitoring systems that do more than report statistical figures. Such systems should enable local governments to identify production concentrations, recognize underperforming regions, and assess the reliability of the data used for planning. At the regency level, food production data are generally available in annual statistical tables organized by commodity and administrative area. Although this format facilitates reporting, it can make interregional comparisons, the identification of productivity disparities, and the verification of consistency across tables more challenging. Bireuen Regency, Aceh Province, Indonesia, comprises 17 subdistricts and was selected as the case study because production data for rice, maize, cassava, and legumes are available at the subdistrict level. This data availability provides an opportunity to develop an analytical approach that transforms statistical records into more actionable information for food production monitoring and evaluation.

From a technological perspective, smart agriculture integrates information and communication technologies, the Internet of Things (IoT), and data analytics to improve agricultural productivity and resource-use efficiency. Quy et al. (2022) describe the smart agriculture ecosystem as an integration of IoT devices, communication technologies, data

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storage, and processing capabilities, whereas Sherazi et al. (2023) discuss the application of IoT to agricultural automation and management. Similarly, Garg and Alam (2023) examine developments in smart agriculture research, while Assimakopoulos et al. (2024) review the implementation of smart technologies in the agricultural sector. Kasera et al. (2024) further discuss IoT- and artificial intelligence-based applications across pre-harvest, harvest, and post-harvest activities. Collectively, these studies demonstrate the potential of digital technology integration to support more efficient and information-driven agricultural management.

Beyond monitoring technologies, data analytics plays an important role in agricultural decision-making. Mughele et al. (2024) discuss the roles of IoT, big data, and machine learning in precision agriculture, while Shahab et al. (2024) review IoT-based agricultural management approaches for sustainable farming. Ahmad (2024) also examines the relationship between smart agriculture techniques and food security. Meanwhile, Naseer et al. (2024) investigate IoT adoption in agriculture, including associated security and privacy challenges. These studies indicate that developing smart agriculture systems requires more than deploying devices and collecting data; it also requires the ability to process data, maintain data reliability, and generate information relevant to users' needs.

From an information governance perspective, dashboards have become important instruments for monitoring food and nutrition systems. Zhou et al. (2022) systematically reviewed food system dashboards, while Béné et al. (2024) emphasized the importance of selecting concise, transparent, and contextually relevant indicators. Dashboards containing excessive numbers of indicators may make it difficult for non-expert users to interpret food system conditions and determine appropriate priorities. Therefore, food production monitoring dashboards should present understandable indicators that facilitate comparisons across regions and support local government planning needs.

In Indonesia, analytical methods have also been applied to classify agricultural commodities and regions based on production characteristics and food security indicators. Pangestu et al. (2024) applied the K-Means method to classify horticultural and livestock commodities according to their production characteristics. Zhafira et al. (2026) developed a K-Medoids-based classification of village-level food security in North Aceh Regency using multidimensional indicators, with the results presented through a web-based system. These studies demonstrate the potential of analytical methods and digital visualization to identify commodity characteristics and regional disparities. However, commodity and regional classification should be complemented by data validation mechanisms and evaluation indicators to ensure that analytical results can be interpreted consistently and used effectively in food production planning.

The reviewed literature indicates that smart agriculture technologies, food system dashboards, and agricultural production analytics have developed through diverse approaches. Nevertheless, an opportunity remains to develop an integrated framework that connects official statistical data, data validation and consistency assessment, production analytics, dashboard visualization, and production performance evaluation within a unified workflow. This integration can also establish a foundation for future field-sensor deployment without requiring physical IoT implementation as a prerequisite during the initial development stage. Such an approach can bridge current needs for statistical food production analysis with the longer-term development of smart agriculture systems.

To address this research gap, this study has three objectives. First, to design a five-layer smart agriculture framework for food production monitoring and evaluation. Second, to implement the framework through a dashboard prototype and analyze food production data from Bireuen Regency for 2025. Third, to evaluate the framework using performance indicators, potential productivity simulations, and data consistency validation. The main contribution of this study is a potentially replicable framework that demonstrates how data validation, analytics, and derived indicators can enhance the usefulness of official agricultural statistics for food production planning. The proposed framework is expected to provide a foundation for more systematic, transparent, and locally relevant food production monitoring and evaluation systems.

LITERATURE REVIEW

Smart agriculture integrates digital technologies to improve agricultural production, resource efficiency, and data-driven decision-making. Quy et al. (2022) and Sherazi et al. (2023) discuss the role of IoT in agricultural monitoring and automation. Further developments include smart technology implementation (Assimakopoulos et al., 2024), agricultural analytics (Garg & Alam, 2023; Mughele et al., 2024), and the integration of IoT and artificial intelligence across agricultural activities (Kasera et al., 2024; Shahab et al., 2024). Ahmad (2024) discusses smart agriculture in relation to food security, while Naseer et al. (2024) examine IoT adoption and its implementation challenges. These studies demonstrate the potential of digital technologies to support agricultural management, although regional monitoring can also begin with existing official statistics before integrating physical sensors. Data quality and visualization are essential for transforming agricultural statistics into useful information. Zhou et al. (2022) reviewed food system dashboards, while Béné et al. (2024) emphasized the importance of relevant, understandable, and context-specific indicators. In regional agricultural analysis, Pangestu et al. (2024) applied K-Means clustering to agricultural commodities, whereas Zhafira et al. (2026) used K-Medoids to classify village-level food security. These studies demonstrate the value of analytical methods and digital visualization but address different aspects of agricultural monitoring. The reviewed literature covers smart agriculture technologies, agricultural analytics, dashboard

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development, and regional classification. However, an opportunity remains to integrate official production statistics, data validation, analytical indicators, dashboard visualization, and performance evaluation within a single framework for regional food production monitoring. This study addresses the gap by developing a five-layer smart agriculture framework and dashboard prototype using 2025 food production data from 17 subdistricts in Bireuen Regency. The framework is evaluated through data consistency checks, performance indicators, and productivity potential simulations, while providing a pathway for future IoT sensor integration. Its contribution is a replicable approach for transforming official agricultural statistics into more useful information for regional planning.

METHOD

This study employed a Design Science Research (DSR) approach comprising problem identification, definition of solution objectives, artifact design and development, demonstration, evaluation, and communication. The resulting artifacts were a five-layer Smart Agriculture Framework and a dashboard prototype. The study was conducted in Bireuen Regency, Aceh Province, which consists of 17 subdistricts. The data comprised secondary food production statistics for 2025 obtained from the Bireuen Regency Agriculture and Plantation Office and Statistics Indonesia (BPS) of Bireuen Regency. The commodities covered were rice, maize, cassava, and legumes. The main variables included production (tons), harvested area (ha), productivity (tons/ha), and rice-equivalent output (tons). and soybeans), production rankings by subdistrict, rice production distribution, and key findings. Stage 5, evaluation: KPIs and recommendations provide decision-support information for the Agriculture and Plantation Office.

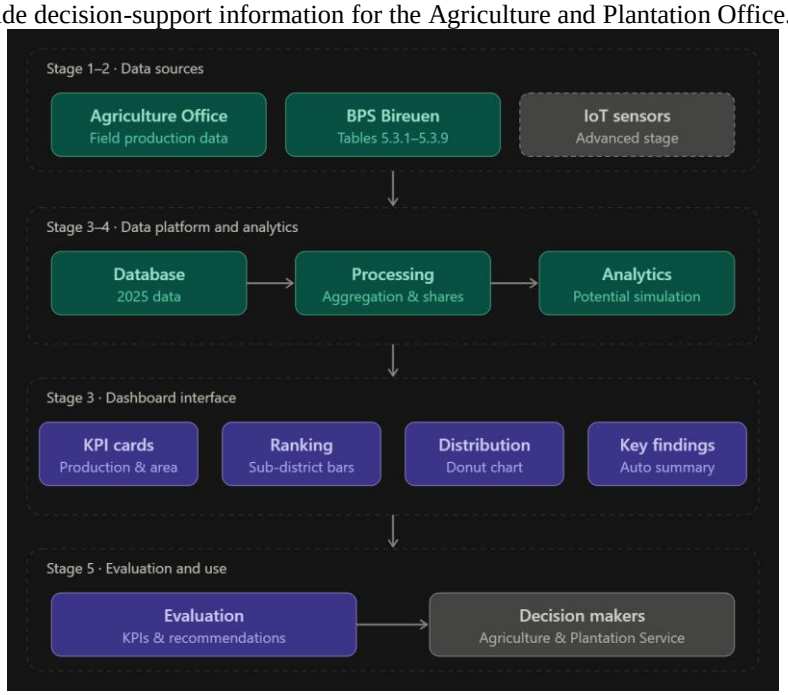


Figure1. Workflow of the proposed Smart Agriculture Framework for food production monitoring and evaluation

Figure 1. Flowchart of the framework. The block diagram follows the five stages represented in the dashboard. Stages 1–2, data sources: production data from the Bireuen Regency Agriculture and Plantation Office and BPS Bireuen (Tables 5.3.1–5.3.9). IoT sensors are shown with dashed lines because their implementation in the dashboard remains a future development stage. Stages 3–4, data platform and analytics: the 2025 database (17 subdistricts and four commodities) is processed into aggregated values and percentages. The results are then passed to the potential-simulation analytics module. Stage 3, dashboard interface: KPI cards (rice production, rice-equivalent output, harvested area, maize, cassava, and soybeans), production rankings by subdistrict, rice production distribution, and key findings. Stage 5, evaluation: KPIs and recommendations provide decision-support information for the Agriculture and Plantation Office.

RESULT

This study examines food production in Bireuen Regency in 2025 across 17 subdistricts, based on data from the Bireuen Regency Agriculture and Plantation Office as published by BPS Bireuen. The data include harvested area, productivity, and rice production; rice and rice-equivalent output; maize and soybean production; secondary-crop planting area; and harvested area, productivity, and production of maize, peanuts, and cassava. The data were processed to derive indicators including each subdistrict's contribution to the regency total, productivity gaps, spatial concentration of production, and commodity composition. All totals reported below were recalculated from subdistrict-

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level data; discrepancies from the published totals are noted where applicable.

Table 1. Summary of major food commodity production in Bireuen Regency, 2025

Commodity	Harvested area (ha)	Productivity (tons/ha)	Production (tons)	Share of tonnage (%)
Rice (GKG)	25,563	6.20	158,432.00	73.1
Maize	8,510.50	6.40	54,474.70	25.1
Cassava	144.00	26.85	3,866.70*	1.8
Peanuts	28.00	—	79.60*	<0.1
Soybeans	0	—	0	0

In 2025, rice production in Bireuen Regency reached 158,432 tons of dry milled paddy (GKG) from a harvested area of 25,563 ha, with an average productivity of 6.20 tons/ha. Rice-equivalent output amounted to 101,301.57 tons. A uniform conversion factor of 0.6394 (63.94%) was applied to convert GKG to rice across all subdistricts.

Production was concentrated in several subdistricts. Peusangan was the largest contributor (18,340 tons; 11.6%), followed by Simpang Mamplam (16,948 tons; 10.7%) and Samalanga (14,815 tons; 9.4%). These three subdistricts accounted for 31.6%, while the five leading subdistricts (including Gandapura and Kuta Blang) accounted for 46.2% of regency production. The lowest production levels were recorded in Juli (4,831 tons), Peulimbang (5,024 tons), and Kota Juang (5,179 tons). The ratio of the highest to the lowest production was 3.8, and the coefficient of variation across subdistricts was 45%.

Table 2. Five largest rice-producing subdistricts, 2025

Subdistrict	Harvested area (ha)	Productivity (tons/ha)	GKG production (tons)	Contribution (%)
Peusangan	2,800	6.55	18,340	11.6
Simpang Mamplam	2,690	6.30	16,948	10.7
Samalanga	2,390	6.20	14,815	9.4
Gandapura	2,133	5.80	12,373	7.8
Kuta Blang	1,718	6.25	10,736	6.8

Rice productivity across subdistricts varied within a relatively narrow range, from 5.50 tons/ha in Peusangan Siblah Krueng to 6.70 tons/ha in Kuala and Jangka. Six subdistricts had productivity below the regency average: Peudada (5.60), Juli (5.80), Peusangan Selatan (5.80), Peusangan Siblah Krueng (5.50), Makmur (5.85), and Gandapura (5.80 tons/ha). Across the 17 subdistricts, rice production was very strongly correlated with harvested area (r = 0.99), but weakly correlated with productivity (r = 0.29).

DISCUSSION

The analysis results show that food production in Bireuen Regency in 2025 will still be dominated by rice and maize commodities, with respective contributions of 73.1% and 25.1% to the total tonnage of the four commodities analyzed. This condition indicates that the regional food production structure is highly dependent on these two commodities, particularly rice as the main staple food source. However, the distribution of rice production across sub-districts shows a spatial concentration, with the top ten sub-districts contributing 75.0% of the regency's total production. In addition, the production coefficient of variation of 43.7% indicates a considerable disparity in production achievements among sub-districts. Although harvested area has a very strong correlation with production (r = 0.99), the correlation between productivity and production is relatively weak (r = 0.29). These findings indicate that aggregate production is more closely related to harvested area than to variations in productivity per hectare. Therefore, food production improvement strategies should not merely focus on expanding harvested areas, but also consider increasing productivity, resource use efficiency, and the agricultural characteristics of each sub-district. In this context, the development of a *Framework Smart Agriculture* is necessary to integrate data on harvested area, productivity, production, spatial distribution, and other supporting indicators into a structured monitoring and evaluation system. This integration is expected to help identify priority areas, monitor changes in production performance, and support the formulation of data-driven food security policies in Bireuen Regency.

Table 3. Simulated potential increase in rice productivity to 6.50 tons/ha

Subdistrict	Harvested area (ha)	2025 productivity (tons/ha)	Additional potential (tons GKG)	Share of potential (%)
Gandapura	2,133	5.80	1,493	17.4
Peusangan Siblah Krueng	1,238	5.50	1,238	14.4
Makmur	1,553	5.85	1,009	11.7
Nine other subdistricts	—	<6.50	4,850	56.5
Regency total	—	—	8,590	100.0

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Table 4. Results of source-data consistency checks

Commodity	Test	Finding	Status
Rice	Harvested area × productivity = production; sum across subdistricts = total	Consistent within rounding; subdistrict harvested areas sum to 25,562 ha, while the printed total is 25,563 ha.	Consistent (rounding)
Maize	Harvested area × productivity = production; sum across subdistricts = total	Consistent; Kuta Blang is recorded as an immature crop harvest with no production figure.	Consistent
Cassava	Sum across subdistricts = total	Printed total is 3,816.70 tons, while the sum across subdistricts is 3,866.70 tons (a difference of 50.00 tons).	Requires verification
Peanuts	Sum across subdistricts = total; harvested area × productivity = production	Printed total is 8,754.10 tons, while the sum across subdistricts is 79.60 tons. Samalanga (8 ha × 1.80 ≠ 29.70 tons) and Simpang Mamplam (18 ha × 2.00 ≠ 46.30 tons) do not reconcile.	Severe inconsistency

Productivity among subdistricts is relatively narrow, ranging from 5.50 tons/ha (Peusangan Siblah Krueng) to 6.70 tons/ha (Kuala and Jangka). Six subdistricts have productivity below the regency average, namely Peudada (5.60), Juli (5.80), Peusangan Selatan (5.80), Peusangan Siblah Krueng (5.50), Makmur (5.85), and Gandapura (5.80 tons/ha). Among the 17 subdistricts, production is very strongly correlated with harvested area (r = 0.99) but weakly correlated with productivity (r = 0.29).

Maize, Cassava, Peanuts, and Soybeans

Maize production reached 54,474.70 tons from a harvested area of 8,510.50 ha, with productivity of 6.40 tons/ha. The harvested area represented 85.6% of the total planted area of 9,938.30 ha. Three subdistricts accounted for 94.4% of maize production: Jeumpa (26,364 tons; 48.4%), Juli (16,466.7 tons; 30.2%), and Peudada (8,568 tons; 15.7%). Their weighted productivity was 6.48 tons/ha, higher than the 5.30 tons/ha recorded across the other 13 subdistricts with available data. Kuta Blang was recorded as having an immature crop harvest, so production data were unavailable.

Cassava was harvested from 144 ha, with productivity of 26.85 tons/ha. Peusangan contributed approximately 40% of cassava production (57 ha; 1,539 tons). Peanuts were harvested in only four subdistricts—Samalanga, Simpang Mamplam, Kuala, and Peusangan Selatan—with a total harvested area of 28 ha, 64% of which was located in Simpang Mamplam. Other commodities were marginal: mung beans were planted on 10 ha in Kuta Blang and sweet potatoes on 18 ha in Simpang Mamplam, while soybeans were not cultivated.

The observed concentration of rice production and productivity gaps raises a further question: how much additional production could be achieved if these gaps were reduced?

Simulation of Potential Rice Productivity

Under a target scenario of 6.50 tons/ha, the regency could potentially obtain an additional 8,590 tons of GKG (+5.4%), equivalent to approximately 5,492 tons of rice (Table 3). The five subdistricts already achieving productivity of at least 6.50 tons/ha would not contribute additional potential under this scenario. Three priority subdistricts—Gandapura, Peusangan Siblah Krueng, and Makmur—accounted for 43.5% of the total additional production potential. As a sensitivity estimate, each 0.1-ton/ha increase in regency-level productivity would correspond to 2,556 additional tons of GKG.

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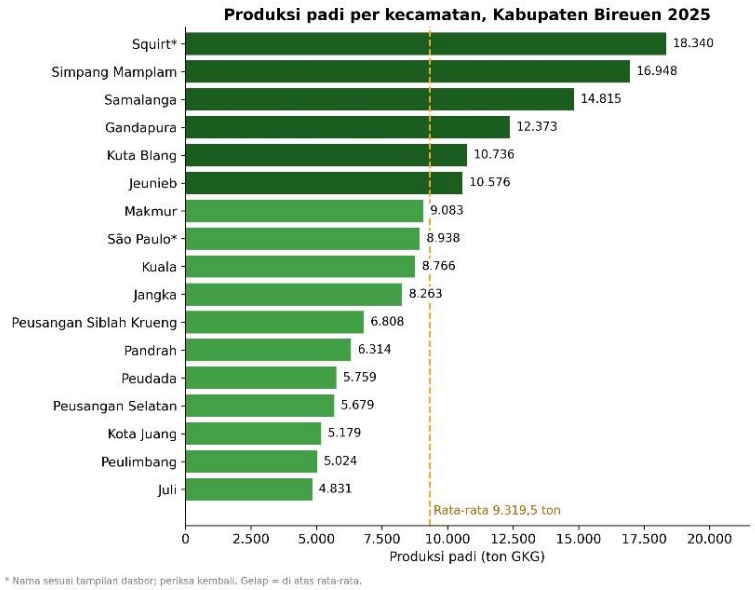


Figure 2. Rice production distribution by subdistrict in Bireuen Regency, 2025.

The figure illustrates rice production distribution across subdistricts in Bireuen Regency in 2025. The highest production was recorded in Peusangan at 18,340 tons of GKG, followed by Simpang Mamplam at 16,948 tons and Samalanga at 14,815 tons. The lowest production levels were found in Juli (4,831 tons), Peulimbang (5,024 tons), and Kota Juang (5,179 tons). The dashed line represents average production of approximately 9,319.5 tons; six subdistricts were above this average and eleven were below it. These differences indicate disparities in rice production across subdistricts and highlight the need for data-driven monitoring to identify priority areas and formulate strategies for increasing production in support of sustainable food security.

Data Consistency Validation

Automated checks classified the rice and maize data as consistent, as the product of harvested area and productivity corresponded to reported production within rounding limits. The same checks identified inconsistencies in two secondary commodities (Table 4).

Table 4. Results of source-data consistency checks

Commodity	Test	Finding	Status
Rice	Harvested area × productivity = production; sum across subdistricts = total	Consistent within rounding; subdistrict harvested areas sum to 25,562 ha, while the printed total is 25,563 ha.	Consistent (rounding)
Maize	Harvested area × productivity = production; sum across subdistricts = total	Consistent; Kuta Blang is recorded as an immature crop harvest with no production figure.	Consistent
Cassava	Sum across subdistricts = total	Printed total is 3,816.70 tons, while the sum across subdistricts is 3,866.70 tons (a difference of 50.00 tons).	Requires verification
Peanuts	Sum across subdistricts = total; harvested area × productivity = production	Printed total is 8,754.10 tons, while the sum across subdistricts is 79.60 tons. Samalanga (8 ha × 1.80 ≠ 29.70 tons) and Simpang Mamplam (18 ha × 2.00 ≠ 46.30 tons) do not reconcile.	Severe inconsistency

After validating the results of the source data examination, the framework model that has been created can then be seen in the following figure.

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Figure 3. Dashboard prototype overview: five framework layers and key food production indicators of Bireuen Regency (2025)

Figure 3 presents the main page of the dashboard prototype. The upper section displays the five layers of the Smart Agriculture Framework: field data, IoT connectivity, data platform, analytics, and evaluation and decision support. Field data are sourced from the Bireuen Regency Agriculture and Plantation Office and BPS, the data platform layer is realized through the dashboard itself, and the analytics layer provides potential simulation, while the evaluation layer presents key performance indicators and recommendations. The IoT connectivity layer is shown as a future development stage, as sensor integration has not yet been operationalized. The lower section summarizes six production indicators for 2025: rice production of 158,432 tons of GKG (equivalent to 101,301.57 tons of rice), a rice harvested area of 25,563 ha with an average productivity of 6.20 tons/ha, maize production of 54,474.70 tons from 8,510.50 ha, cassava production of 3,816.70 tons, and no recorded soybean production.

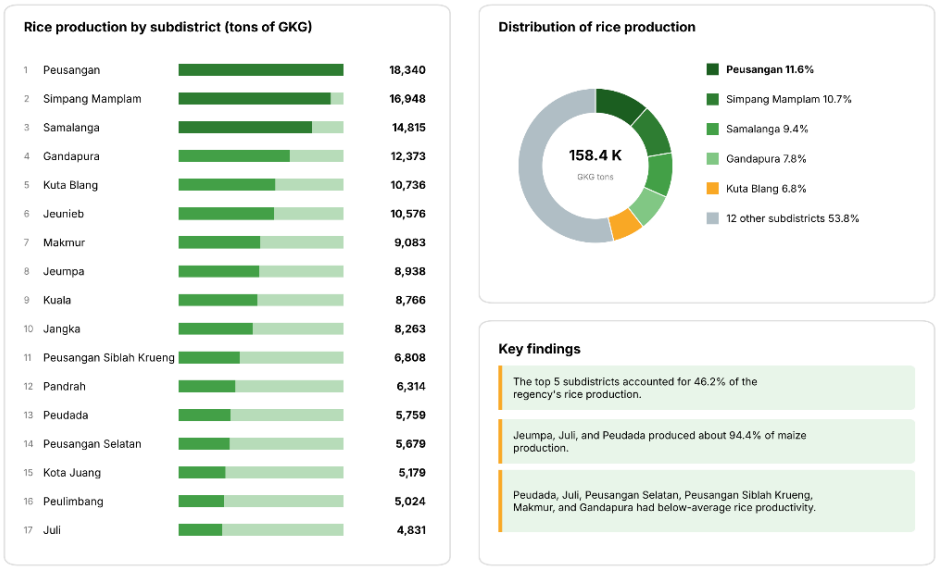


Figure 4. Dashboard prototype displaying rice production by subdistrict, its distribution, and key findings for Bireuen Regency (2025)

Figure 4 presents the dashboard prototype, which consists of three panels. The left panel ranks the 17 subdistricts by rice production (tons of GKG), allowing the highest and lowest producers to be identified at a glance. The upper-right panel shows the share of each subdistrict in the regency's total production of 158.4 thousand tons, where the five leading subdistricts account for 46.2% and the remaining 12 subdistricts for 53.8%. The lower-right panel summarizes the key findings, including the concentration of maize production in three subdistricts (94.4%) and the six subdistricts with below-average rice productivity. Together, these panels support situational analysis and the prioritization of targeted interventions.

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CONCLUSION

This study developed a Smart Agriculture Framework design to support food production monitoring and evaluation in Bireuen Regency. The 2025 analysis showed that rice accounted for 73.1% and maize for 25.1% of the total production of the four commodities analyzed. A simulation targeting rice productivity of 6.50 tons/ha indicated an additional production potential of 8,590 tons of GKG (5.4%), equivalent to approximately 5,492 tons of rice. Furthermore, the ten leading subdistricts contributed 75.0% of the regency's rice production, indicating a concentration of production across subdistricts. Integrating production data, consistency validation, potential simulation, and dashboard visualization within the proposed framework has the potential to support data-driven decision-making, improve planning efficiency, and strengthen sustainable food security.

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REFERENCES

Ahmad, T., Ahsan, S., Farooq, M. A., Gulzar, M., Mubben, M., Hussain, A., ... Firdous, N. (2024). Role of smart agriculture techniques in food security: A systematic review. Journal of Agronomy and Crop Science, 210(5), Article e12758. https://doi.org/10.1111/jac.12758

Assimakopoulos, F., Vassilakis, C., Margaris, D., Kotis, K., & Spiliotopoulos, D. (2024). The implementation of "smart" technologies in the agricultural sector: A review. Information, 15(8), Article 466. https://doi.org/10.3390/info15080466

Béné, C., & Abdulai, A.-R. (2024). Navigating the politics and processes of food systems transformation: Guidance from a holistic framework. Frontiers in Sustainable Food Systems, 8, Article 1399024. https://doi.org/10.3389/fsufs.2024.1399024

Béné, C., Chege, C. K., Even, B., Hernandez, R. A., Lundy, M., Prager, S. D., & Wiegel, J. (2024). Why building participatory dashboards is key for sustainable food system transformation. Frontiers in Sustainable Food Systems, 8, Article 1405670. https://doi.org/10.3389/fsufs.2024.1405670

Economist Impact. (2022). Global Food Security Index 2022: Indonesia country report. https://impact.economist.com/sustainability/project/food-security-index/reports/Economist_Impact_GFSI_2022_Indonesia_country_report_Sep_2022.pdf

Garg, D., & Alam, M. (2023). Smart agriculture: A literature review. Journal of Management Analytics, 10(2), 359–415. https://doi.org/10.1080/23270012.2023.2207184

Kasera, R. K., Gour, S., & Acharjee, T. (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, Article 108522. https://doi.org/10.1016/j.compag.2023.108522

Mughele, E. S., Okuyade, O. S., Abdullahi, I. M., Maliki, D., & Duada, I. A. (2024). Roles of IoT, big data and machine learning in precision agriculture: A systematic review. Scientia Africana, 23(1), 33–44. https://doi.org/10.4314/sa.v23i1.3

Naseer, A., Shmoon, M., Shakeel, T., Rehman, S. U., Ahmad, A., & Gruhn, V. (2024). A systematic literature review of the IoT in agriculture: Global adoption, innovations, security, and privacy challenges. IEEE Access, 12, 60986–61021. https://doi.org/10.1109/ACCESS.2024.3394617

Quy, V. K., Hau, N. V., Anh, D. V., Quy, N. M., Ban, N. T., Lanza, S., ... Muzirafuti, A. (2022). IoT-enabled smart agriculture: Architecture, applications, and challenges. Applied Sciences, 12(7), Article 3396. https://doi.org/10.3390/app12073396

Republik Indonesia. (2012). Undang-Undang Republik Indonesia Nomor 18 Tahun 2012 tentang Pangan [Law of the Republic of Indonesia Number 18 of 2012 on Food].

Shahab, H., Iqbal, M., Sohaib, A., Khan, F. U., & Waqas, M. (2024). IoT-based agriculture management techniques for sustainable farming: A comprehensive review. Computers and Electronics in Agriculture, 220, Article 108851. https://doi.org/10.1016/j.compag.2024.108851

Sherazi, H. H. R., Arif, S., Munir, M. S., Ali, M., Hassan, B., & Siddiqi, Y. (2023). Utilizing Internet of Things for automating food security and savvy agriculture: A review. In Proceedings of the 28th International Conference on Automation and Computing (ICAC 2023). IEEE. https://doi.org/10.1109/ICAC57885.2023.10275173

Zhafira, T., Bustami, B., & Nunsina. (2026). Clustering of food security levels in North Aceh using K-Medoids. Journal of Applied Informatics and Computing, 10(3), 2476–2488. https://doi.org/10.30871/jaic.v10i3.12881

Zhou, B., Liang, S., Monahan, K. M., Singh, G. M., Simpson, R. B., Reedy, J., ... Naumova, E. N. (2022). Food and nutrition systems dashboards: A systematic review. Advances in Nutrition, 13(3), 748–757. https://doi.org/10.1093/advances/nmac022

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