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The Business Intelligence Dashboard for Paddy Production Monitoring in Indonesia: An Upstream Perspective for Free Nutritious Meals *(MBG)* Supply Planning

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Abstract

The application of few and not enough uniform indicator has restricted the ability to monitor the rice sector through data analysis and interpretation, so that the performance of the rice sector is fragmented. The study proposes a Business Intelligence (BI) framework for analysing the national level paddy production data over 2020 to 2024. The methodology involves the preparation of data, the normalisation of the productivity indicator (kg/ha) and the development of the dashboard with Tableau Public. Based on empirical results, the national production of paddy is estimated to shrink in 2024 to 53.14 million tons, while the distribution of the paddy production remains more concentrated in Java. The harvested area or the total production fluctuated, but the average productivity was relatively stable at 8,079 kg/ha, indicating the relative stability of the structure of yield performance. The approach that is proposed aims at making it easier to interpret agriculture trends by integrating a single analytical interface for the production, land use and productivity. The results demonstrate the need for monitoring through indicators to increase analytical rigor and provide necessary evidence to make decisions in national agricultural systems.

Keywords: *Business Intelligence; Data Visualization; Food Supply Chain;* Paddy Production *Monitoring; Tableau Public.*

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1. Introduction

Rice is the main commodity for strategic food supply in Indonesia and has been an important safeguard for food availability, food market stability and nutrition policy making in Indonesia [1]. Recent (2025) studies indicate that climate shocks, rainfall anomalies and warming are still impacting agricultural production in Indonesia, and these impacts on agricultural production can be quantified, in this case on paddy production and the food-security risks of provinces. Besides, a study on Indonesian rice supply in 2025 also suggests that it is not enough to understand the supply side, but the interaction of supply, consumption and trade is needed to ensure food security [2]. These are the results of studies that show that the monitoring of paddy production is not just an agricultural problem but also a problem of information relevant to policies that needs to be responded to in time and in a geographically comparable way [3]. While doing all of this, business intelligence (BI) has become increasingly known as a data-driven decision-support capability and not merely reporting capability. According to a study from 2025 in turkey, BI capabilities can enhance performance by making decisions in the environment of supply chains informed and integrated [4]. Building on this analysis, a Scoping review on agri-food digitalisation conducted in 2025 highlights that digital tools enhance traceability, transparency, efficiency and sustainability, and suggest some practical implementation challenges, including interoperability, scalability and implementation costs [5]. Another review by 2025, of the risks in agri-food supply chains, confirms that food systems are still vulnerable to climate-related and operational risks, and that digital solutions like blockchain and satellite monitoring are becoming more relevant to strengthen climate resilience [6]. Taken together, these studies indicate that digital dashboards which integrate data from various sources can be a valuable and effective means of creating meaningful agricultural data-to-information-to-knowledge transformation [7].

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This need is especially crucial in Indonesia due to paddy production fluctuations among provinces and the non-uniform spatial distribution of the impact of climate pressure [8]. From the point of view of policy makers and stakeholders engaged in food supply coordination the heterogeneity poses a dilemma: national level data can be difficult to use to discern regional strengths, vulnerabilities, and intervention priorities. Therefore, an integrated dashboard consisting of trend analysis, spatial comparison, harvested-area pattern and productivity indicators can help provide an operational perspective on the performance of paddy production. This is in line with the recent research that focuses on digital visibility, traceability and supply-chain intelligence in agri-food systems [9].

In the light of the above, this study aims to create a Business Intelligence dashboard using Tableau Public to track the performance of paddy production in Indonesia for the period 2020-2024. The dashboard consists of a line chart that displays production trends over the years, a map that illustrates the distribution of the production by province, a bar chart that shows harvested area by province and a donut chart that shows production by province over the years. The contribution is not just about the created visual presentation, but also the development of evidence at the province level that can assist food supply planning and national nutrition-program decision making. Thus, the objectives of this research are to create and present the business intelligence dashboard for paddy production performance monitoring in Indonesia using Tableau Public, and to obtain information and data that can be used as knowledge input in the planning of the food supply chain system and national nutrition programs.

2. Methods

The subject of this study is a business intelligence-based dashboard by data-driven that could be used for monitoring of paddy production in Indonesia. Here, our outline the methodological framework that is developed to map from raw agricultural data to meaningful insights through systematic processes, such as data collection, data processing, aggregation into analyses and visualization [10]. The purpose of the integration of these stages is to offer a framework analytical channel for reliable interpretation and decision making for the study [11]. In the current study, there is a focus on the application of secondary data sources, analytical modeling and interactive visualization techniques. Moreover, the method follows the principles of business intelligence, it involves role of data integration and business visual analytics to extract knowledge from the information. Next, more specifically, the data sources, transformation, analysis, and tooling (DPT) conducted in the creation of the proposed dashboard are explained [12].

The research method used in this study was descriptive analytical design to make a business intelligence dashboard in monitoring the performance of paddy production in Indonesia. It was a study in terms of data, pattern, and decision-support visualization; not predictive modeling [13]. The methodological structure followed is based on the latest published literature on dashboard development which stresses the following three phases of a dashboard: planning, development and deployment, while also stressing the importance of designing the dashboard to fit the intended user and use context [14]. At the same time, recent visualization research has emphasized the need to balance usability, interactivity, accessibility, and cognitive load management in dashboards, to ensure that the information on the visualization is meaningful for decision makers [15].

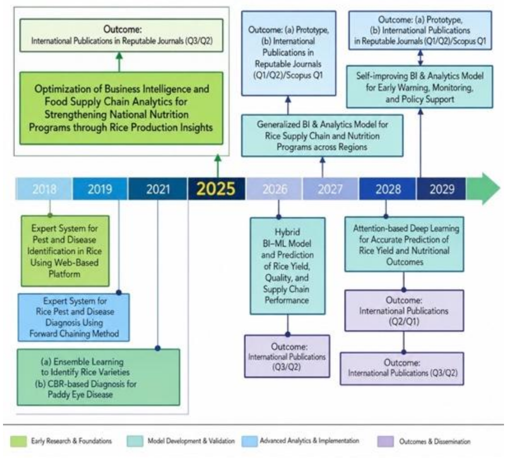

Figure 1. Research Roadmap

The research roadmap for the development of integrated Business Intelligence (BI) and Food Supply Chain Analytics for supporting national nutrition programs is shown in Figure 1, which is based on paddy production data in Indonesia. The roadmap is based on previous research on agricultural decision-support systems, machine learning and predictive analytics undertaken during the period 2018–2021. The current research phase (2025) aims at optimizing BI and food supply chain analytics and carry out analytics for actionable insights from paddy production data. Later, a hybrid BI-machine learning model is proposed to enhance rice yield, performance of supply chains, and nutrition-related indicators' prediction accuracy (2026-2027). This research will then be extended to a generalised analytics framework for use in various regions (2027-2028), before creating a self-improving BI model for early warning, monitoring and policy support (2028-2029). The expected outcomes are analytical prototypes, publications in high impact international journals (Scopus Q1-Q3), which will support evidence-based food security and national nutrition programmes.

2.1. Data Scope and Unit of Analysis

This study uses the unit of rice production performance measured across 38 provinces in Indonesia for the annual period from 2020 to 2024 in figure 2. The dataset was explicitly sourced from Statistics Indonesia *(Badan Pusat Statistik / BPS)* through their official statistical portal and agricultural publication series (e.g., Harvested Area and Paddy Production in Indonesia).

Figure 2. Indonesian Map

The dashboard seeks to deliver aggregated indicators released at both provincial and national levels to provide comprehensive comparisons over time and space [16]. Production volume (tons), harvested area (hectares), and productivity (tons/hectare) were identified as the primary variables to monitor agricultural performance and were selected for analysis. To ensure data integrity, any missing or incomplete provincial reporting across the five-year time series was handled using linear interpolation. This structural design mirrors an established approach to dashboard-centric research, which transforms static institutional datasets into interactive, user-friendly analytical products [17].

2.2. Data Preparation

Prior to visualization, the raw dataset underwent a rigorous data cleaning and harmonization process to ensure data integrity and interoperability. The dataset was cleaned and harmonized before being visualized to maintain data integrity and consistency. Completeness checks, geographic standardization, temporal formatting and unit alignment were performed as part of the preprocessing. All non-provincial records and duplicate records were removed and the provincial names were standardized based on BPS administrative rules. Every 170 validations of observations (38 provinces for 5 years; one specification per province) were checked for missing or anomalous data. The area harvested was expressed in hectares (ha); the production in metric tons (tons); and the productivity in tons/ha (or quintals/ha if applicable). Several anomalies found and harmonized outputs are given as examples in Table 1.

Table 1. Representative Examples of Raw Data Anomalies and Harmonization Pipeline Rules

Data Dimension	Raw Input Example	Preprocessing Rule	Harmonized Output
Entity Naming	DI YOGYAKARTA, D.I. Yogyakarta	Standardized to official BPS administrative casing & naming	D.I. Yogyakarta
Unit Alignment	52.4 ku/ha (Productivity)	Converted from quintals (ku) to metric tons (tons)	5.24 tons/ha
Redundancy	Rows containing INDONESIA (TOTAL)	Filtered out national sub-totals to prevent double-counting in maps.	Removed from provincial subset
Data Type / Format	Year: 2020.0 or 2020 (P)	Stripped non-numeric flags (e.g., preliminary status indicators)	2020 (Integer format)

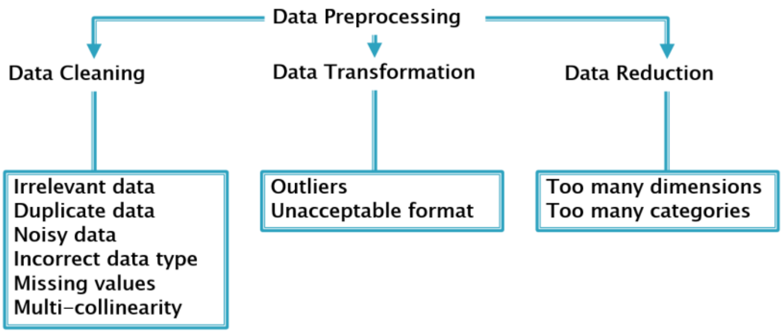

Figure 3. Data Preparation

As illustrated in Figure 3, the data preparation workflow maps out the sequential transformation pipeline from raw BPS statistical tables into the structured dataset ready for dashboard ingestion. This preparation phase is critical, as recent studies on data visualization systems demonstrate that dashboards risk delivering misleading insights if the underlying data lacks standardization [18]. Furthermore, literature on digital transformation and dashboard-style analytics emphasizes structured data preparation as a fundamental prerequisite for building reliable, decision-grade analytical products [19]. In addition to the primary variables, a derived indicator of agricultural performance was calculated to enable standardized comparison across regions and time [20]. Productivity was defined as the ratio between total paddy production and harvested area, expressed in kilograms per hectare (kg/ha), as formulated below:

$$\text{Productivity}\left(\frac{\text{kg}}{\text{ha}}\right) = \frac{\text{Total Paddy Production (kg)}}{\text{Harvested Area (ha)}}$$

2.3. Dashboard Development in Tableau Public

Tableau Public was used to create the dashboard. Tableau Public was chosen for its interactive visual analytics and for being able to publish Tableau Dashboard outputs as web accessible artifacts. Recent Tableau-based studies reveal that Tableau Public can be used as an appropriate data communication tool for analytical products in a world in which visual clarity, public interactivity and accessibility are desired [17]. The development process emphasized creating a clean, readable interface with content organized to aid in rapid comparisons, identifying trends, and geographic interpretation.

2.4. Visualization Structure

The dashboard had four key visual elements. The trend of paddy production over the last five years has been analyzed using the line graph. Secondly, a spatial distribution of paddy production by province was presented by map visualization. Third, a bar chart was used to make comparisons for the harvested area between the provinces. Finally, a donut chart was utilized to summarize the annual productivity proportions. This perspective on visualization and decision-making is similar to recent findings in visualisation studies that have suggested charts, maps, dashboards, and interactive platforms as widely-used presentation methods for analysing information [21]. These visual forms were chosen to help with both temporal and spatial analysis but also for keeping the dashboard simple to be used by policy people [22].

2.5. Analytical Procedure

There were three steps to the analytical procedure. The first step included descriptive trend analysis, where the production performance of rice is looked at for the years 2020-2024. Spatial comparison, the second step, revealed provinces where the production was relative higher or lower. The third step was integrated interpretation, where there was a consideration of production, harvested area, and productivity together and to yield policy-relevant ideas for food supply monitoring [23]. It is a process similar to dashboard workflows, where the ultimate purpose goes beyond visualization to establishing a body of evidence that can be interrogated interactively by people involved in the process [24]. In recent publications interactive dashboards used for evidence synthesis and communication are also recommended since they will make information more accessible and give audiences the freedom to explore the content in line with their information need [25].

2.6. Methodological Contribution

From a methodological perspective, this study's contribution is the incorporation of paddy production indicators in a business intelligence dashboard that becomes a tool for monitoring in contexts of food supply and nutrition programs. The research Does not suggest a predictive model, but has focused on an operation based BI approach suitable for monitoring, comparison and communication of policy. This is in line with recent literature that indicated that data visualization is a tool which is most effective to support decision making, improve understanding and provide data interaction and access [26].

3. Result and Discussion

The Dashboard that has been developed depicts the production performance of rice in Indonesia for 2020-2024 using four integrated visualizations. The line chart also offers an annual overview of the trend in paddy production, which allows to detect the interannual variations in production instead of using static aggregate figures. The map visualization is used to display paddy production distribution at the provincial level, which reveals the level of spatial concentration in the Indonesian archipelago. The bar chart shows the harvested area by province, and the donut chart gives a quick summary of the patterns of productivity over the year.

The dashboard combines the learnt provincial and annual information in an interactive analytical perspective. The visualization does not show raw production data, but rather shows how production, harvested area and productivity are distributed across time and geography in one interface. This seems to be in line with the existing visualization research that identifies charts, dashboards, and interactive platforms as effective formats for gaining insight and supporting decision making.

3.1. Paddy Production Trend Analysis

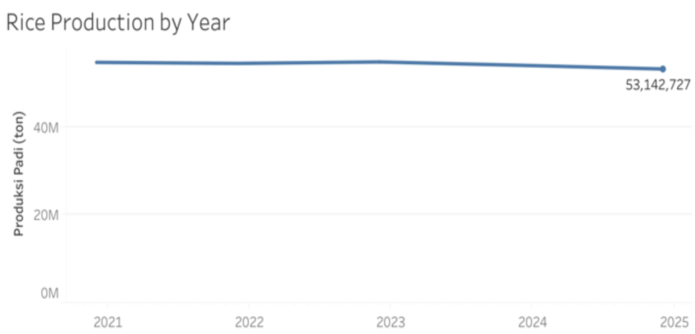

Figure 4. Paddy Production by Years

The growth trend of paddy production for the period obtained during 2020-2024 is presented in Fig. 4. From the visual analysis, it could be seen that the production of the domestic rice during the observed years has relatively smooth results, so that there were only a few fluctuations. During the earlier years, the production was around 54-55 million tons, falling to 53,142,727 tons in 2024. The relatively steady base level of paddy production in Indonesia is evidenced by this pattern, but in the latest period, there is a general downward trend.

Interestingly, this outcome from the monitoring is significant as it implies that the national rice system is neither suddenly volatile nor undergoing a solid shift but a modest % reduction at the end of the phase may indicate the onset of stresses from the environment, agronomic factors or other structural factors. In practice, this is a characteristic not only for policy makers that it is a signal that production stability should likewise be maintained under an integrated analytical system.

Figure 5. Paddy Spatial Distribution

3.2. Spatial Distribution Analysis

The distribution of rice produce is shown in each province of Indonesia in figure 5. Production is clearly bound to the western region of the country, and is also quite dense on the island of Java. The darker-shade areas on the map are representative of Jawa Timur, Jawa Tengah and Jawa Barat, which emerge as the top production areas. States in eastern Indonesia, such as Papua and Maluku, have much lower production intensities, in contrast to states in the east of Java.Compared with the eastern parts of Java, production intensity is lower in eastern Indonesia, particularly in Papua and Maluku.

This spatial distribution reveals the fact that in Indonesia, paddy production is still very uneven in terms of regions. High dependency on certain provinces in the concentration of output is a result of the uneven infrastructure development, irrigation facilities, land quality and production capabilities of the provinces. This creates geographic variation on this extent as well as structural dependence on a restricted number of top performing production areas. In the context of food supply, this dependency is important as there may be a disproportionate effect on national food supply if there was disruption in the major production provinces.

3.3. Harvested Area by Province

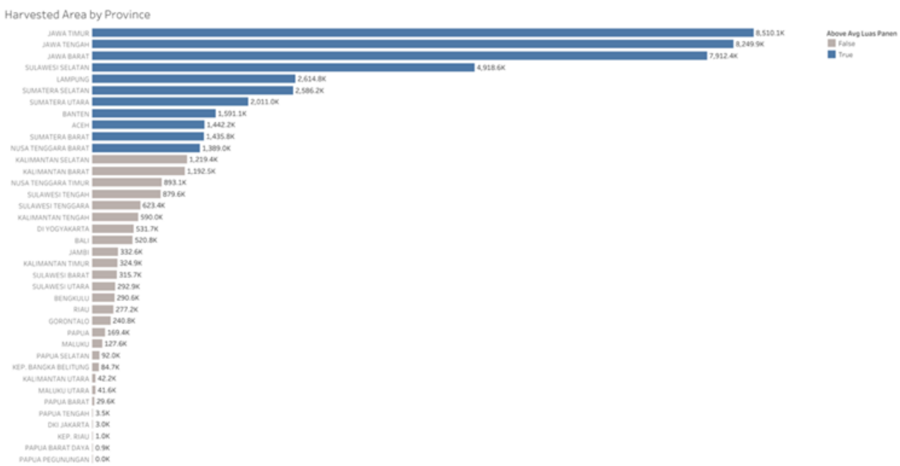

Figure 6. Harvested by Province

Figure 6 presents the area harvested by province, which gives a better understanding of the territorial basis of paddy production. The highest harvested areas are found in Jawa Timur (8.51 million hectares), Jawa Tengah (8.25 million hectares) and Jawa Barat (7.91 million hectares). The other provinces are Sulawesi Selatan (4,92 million hectares), Lampung (2.61 million hectares) and Sumatera Selatan (2.59 million hectares). The harvested area is very small in provinces at the bottom of the distribution (harvested area near 0), such as Papua Barat Daya, Papua Pegunungan, Kepulauan Riau, DKI Jakarta.

The pattern of harvested areas suggests that the capacity to grow rice is increasingly endorsed within a number of significant agricultural provinces. The results at the same time show that the performance gap cannot only be accounted for by the size of an area, because production and harvested area relationships using an index may differ between the provinces due to differences in productivity, cropping intensity and farming in the country. Hence this figure is crucial to the understanding of the production configuration in national level rice supply.

3.4. Paddy Productivity Analysis

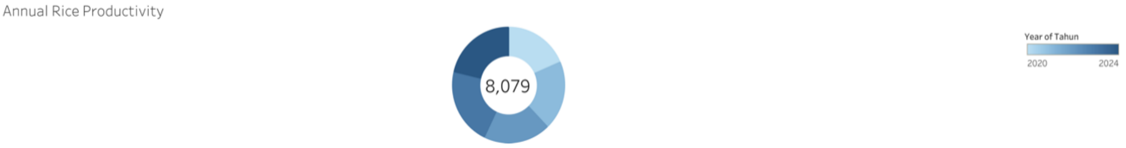

Figure 7. Annual Paddy Productivity

An overall productivity for paddy was 8,079 kg/ha, which is summarized in figure 7. This is showing a medium (moderate) and fairly steady productivity during the period observed. The productivity indicator will be significant not just because it considers the area harvested, but because it also takes into account land use efficiency in rice cultivation. That is, a province may not have a large harvested area and have adequate productivity but still not be efficient.

The productivity outcome indicates a reasonably good stability of the efficiency base to produce rice in Indonesia, nonetheless there are possibilities for optimizing paddy production in each area. These variations may be electronic, due to irrigation systems, technology adopted, quality of seeds and farming methods. Therefore, productivity should be used as a strategic set of indicators along with the production volume and harvested area.

3.5. Discussion

In this study, the developed dashboard shows that incorporating temporal, spatial and operational indicators into a single analytical environment is a promising way in which business intelligence can be utilized for agricultural monitoring. The concentration of paddy production in Java is consistent with previous studies highlighting regional disparities in Indonesian agriculture. This indicates a structural dependency on a limited number of high-output regions, which may increase systemic vulnerability to localized disruptions. From a methodological standpoint, the dashboard prioritizes interpretability and usability, enabling rapid insight generation for stakeholders.

However, this simplicity limits the inclusion of downstream variables such as logistics, distribution, and consumption. Therefore, the system should be interpreted as an upstream analytical tool rather than a complete food supply chain model. Based on the results, it can be seen that the paddy production in Indonesia is relatively stable, however, the decreased production in the future towards 2024 and the very high concentration of paddy production in the region of Java make it not possible to give any certainty of being resilient without continuous monitoring in Fig 8.

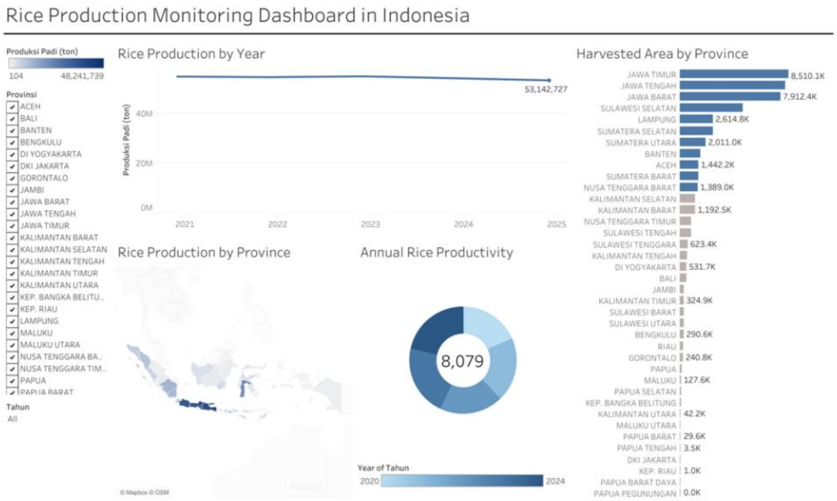

Figure 8. Paddy Production Monitoring Dashboard

It is worthy to note that in Fig. 8, our has been turned into a decision-support artefact instead of a process of reporting of agricultural data, which is one of the major contributions of this study. The national trend is presented in the line chart, the regional differences in the harvested area are shown in the map, the provincial information on production supporting provinces as shown in the bar chart and the productivity information as shown in the productivity chart gives an efficiency-based perspective. Through a judicial interpretation of both, it is easier to figure out strategic production zones, vulnerable areas and likely weak links in the rice supply chain.

In addition the spatial focus of paddy production on Java also holds implications for national food planning. This concentration could lead to dependency risk as it may mirror existing infrastructure and increased levels of cultivations. Disruption to the primary production provinces could have a meaningful impact on supply in the country. Thus, a monitoring system like the one built in this study can help by not only monitoring but also help to raise awareness of risks and formulate plans for risk reduction mitigation.

The findings are particularly important for the context of national nutrition programs and SPPG-related nutrition supply planning since rice is still a staple food commodities as a major part of the food system. The dashboard can be used as a tool to identify upstream production center, surplus regions or regions with low production contribution. This data can be utilized to enhance coordination between monitoring of the farm and planning for food deliveries. Thus, the study furnishes a useful tool for how Business Intelligence technology can be used to connect with food supply chain analytics for policy informed decision making.

The findings indicate that, overall, the platform Tableau Public is a good tool for creating an interactive paddy production monitoring dashboard. Most importantly, the study demonstrated the success of applying visual analytics to turn heterogeneous agricultural data into useful, structured insights for monitoring, planning and policy support.

4. Conclusion

In this study, a business intelligence (BI) dashboard that monitors paddy production in Indonesia was developed with Tableau Public software, mainly to integrate temporal and spatial and productivity indicators into a single analytical reportable. The outcomes show the dashboard can help cultivate features from raw agricultural data into structure, meaningful insights for data-driven decision making.

Conclusion based on the result. Based on the result the information, the production of rice in Indonesia during 2020-2024 period was relatively stable, but experienced a slight decline in the last year. Furthermore, the spatial analysis indicates a significant level of spatial clustering in a relatively small amount of provinces with a high concentration of production specifically the ones that include Java Island, this suggests a structural dependency in the food production system especially in the national dimension. The area cropped analysis also verified an uneven production capacity distribution, and efficiency through production indicator found reasonable level of efficiency with potential for optimization further.

These findings are integrated to show that these are not all indicators for a complete understanding of the performance of paddy production. Rather, a multi-dimensional approach (production volume, land use, and productivity) is needed to depict comprehensively the complexity of agricultural systems. The proposed dashboard is not just an visualization tool but is also a decision-support tool to allow stakeholders to more quickly understand trends, gaps and any potential risks.

The practical implications of this study are relevant to support the national food planning as well as food supply and nutrition related programs such as SPPG. This mapping capability helps to design better distribution strategies, as well as to increase the resilience of the food system, since it includes the ability to determine key production regions and areas with low contribution. Thus, the dashboard, when properly configured, has strategic potential to connect agricultural data analysis and action.

In this context, this paper becomes valuable contribution to the previous works as it shows the use of Business Intelligence in Agriculture filed, especially on paddy production monitoring. The system proposed is more user-friendly than traditional reporting systems in a real-world decision-making context, as it puts special focus on interactive and integrative analytics.

Nevertheless, there are some drawbacks in this study. First, the analysis is based on data averaged over the region, which may not fully reflect variations within the region. Second, all the analytics on the dashboard are descriptive and do not yet include predictive or prescriptive analytics. Future work is therefore suggested to continue this research work, where machine learning-based production forecasting methods can be integrated, inclusion of climatic variables along with environmental factors in the system and real time data integration can be extended.

Finally, the study has shown that, with the use of business intelligence tools like Tableau Public, the monitoring process in agriculture can be greatly enhanced, with quality, accessible and actionable insights. The suggested dashboard structure provides a flexible framework to be expanded and enhanced to use as a tool to underpin sustainable food systems and evidence-based policy making.

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