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Visualizing Spatial Disparities in Indonesia's Rice Productivity Using Interactive Dashboard

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Abstract: The rice sector in Indonesia is crucial to food security, livelihoods, and socio-economic stability, as rice is the main staple food. Rice productivity (yield) in Indonesia shows significant variation across districts and cities, underscoring the need to optimize yields. However, visual analytics at this level and topic, using BPS data, is still limited. This research shows that descriptive visualization of spatial disparities in yield and structural characteristics can be approached analytically using a dashboard. The analysis relies entirely on aggregate data at the Province and District/city levels from Sensus Pertanian BPS 2023 and the Disaster Risk Index (Inarisk) BNPB, which include 514 districts/cities and cover farm structure, farm practices, access to services, and demographics. This interactive dashboard is designed to facilitate exploration of visual distributions of productivity. The result shows various patterns of spatial and structural. This finding is actually an initial exploration. The dashboard serves as a practice for stakeholders to identify special provinces or districts/cities for further analysis, compare among districts, or formulate priorities for further analysis. This research is part of support for planning and decision-making based on data-driven approaches in the agricultural sector.

Keyword: Rice Productivity, Descriptive Analytics, Dashboard Visualization, District-Level Analysis, ST2023.

INTRODUCTION

Rice is the main strategic food commodity in Indonesia and has become an element of national food resilience. That is why since 2013, the Government of Indonesia has implemented multiple strategic programs to improve food production, especially rice and other essential crops, under the banner of food sovereignty. Careful management is a must, and analytics implementation should be involved in every step and aspect of the program. On the other hand, The difference in yield is documented across regions, since each region has unique agroecology, farm structure, and organizational structure (Ghani, 2019; Liu et al., 2020; Raya & Wicaksono, 2023).

Agriculture census in 2023 (ST2023, Sensus Pertanian 2023) by BPS provides district-level data on agricultural holdings, land use, and farming structures. This census dataset supports baseline monitoring and evidence-based planning (FAO, 2015).

At the same time, descriptive analytics and dashboard visualization are increasingly used to make sense of large datasets. Unlike inferential studies, descriptive analytics focuses on revealing patterns and generating follow-up questions rather than estimating formal causal models (Boehm & Finger, 2019; Fukatsu & Hirafuji, 2016; Sahni, 2023).

However, fewer publications use district/city-level census data to visualise rice productivity patterns and related structural indicators in an exploratory way. Most studies emphasise econometric modelling or case-based analysis (Gamayanti et al., 2023; Minot & Sawyer, 2016), which may be less accessible for early screening by stakeholders.

This research aims to fill the gap by developing an interactive Tableau dashboard that visualizes district-level rice yield from ST2023 together with four indicator domains and the BNPB Disaster Risk Index. The dashboard is intended to help stakeholders scan heterogeneity, benchmark districts, and prioritise areas for planning and further analysis.

Based on that information, this research suggests two questions:

1. How can district-level data from ST2023 and the BNPB Disaster Risk Index be structured into an interactive dashboard to visualise rice productivity and related structural indicators across Indonesia's districts?
2. How can stakeholders use these patterns to scan, benchmark, and prioritise districts for further analysis or intervention?

Unlike previous studies focusing on econometric modelling, case-based analysis, or province-level summaries, this study operationalises ST2023 indicators at the district/city level into an exploratory visual analytics dashboard. The dashboard structures indicators into maps, histograms, rankings, filters, and hover summaries to support rapid screening, outlier detection, and prioritisation for follow-up quantitative analysis or policy design.

METHOD

This research is limited to descriptive analytics. The purpose is to design and document a dashboard that summarizes indicators for districts/cities in ST2023 using maps, histograms, and rankings. The analysis is exploratory and focuses more on describing what is observed in aggregate census data. All indicators in this study are aggregates at the province and district/city levels and are calculated as simple percentages or averages from the raw ST2023 tables. There is no complex weighting or normalization, and the dashboard is not intended for causal inference.

All data is taken from "Sensus Pertanian 2023 Tahap II tanaman Pangan (ST2023) held by BPS (BPS, 2023) (Table 1 and Table 2). ST2023 is a national census conducted every 10 years that collects information on agricultural households and agricultural holdings across various themes, including area, commodity, farm practices, access to services, and demography.

Table 1. Summary Table of Data compilation result

No	Column	n_rows	n_unique	n_zero	n_positive
1	No.	514	514	0	514
2	Province	514	38	n/a	n/a
3	Regency/City	514	514	n/a	n/a
4	mean_age	514	514	0	514
5	percent_female	514	514	0	514
6	years_of_schooling	514	514	0	514
7	avg_area_per_farm	514	467	48	466
8	percent_Fertilizer	514	514	1	513
9	percent_Pesticide	514	514	1	513
10	percent_member	514	513	2	512
11	percent_partnership	514	508	7	507
12	percent__KUR	514	506	9	505
13	percent_technology	514	472	42	472

No	Column	n_rows	n_unique	n_zero	n_positive
14	percent_insurance	514	496	19	495
15	percent_r&c_bookkeping	514	505	9	505
16	percent_fertilizer_subsidy	514	502	13	501
17	percent_tools_subsidy	514	501	14	500
18	Inarisk	514	444	0	500
19	Yield	514	443	48	466

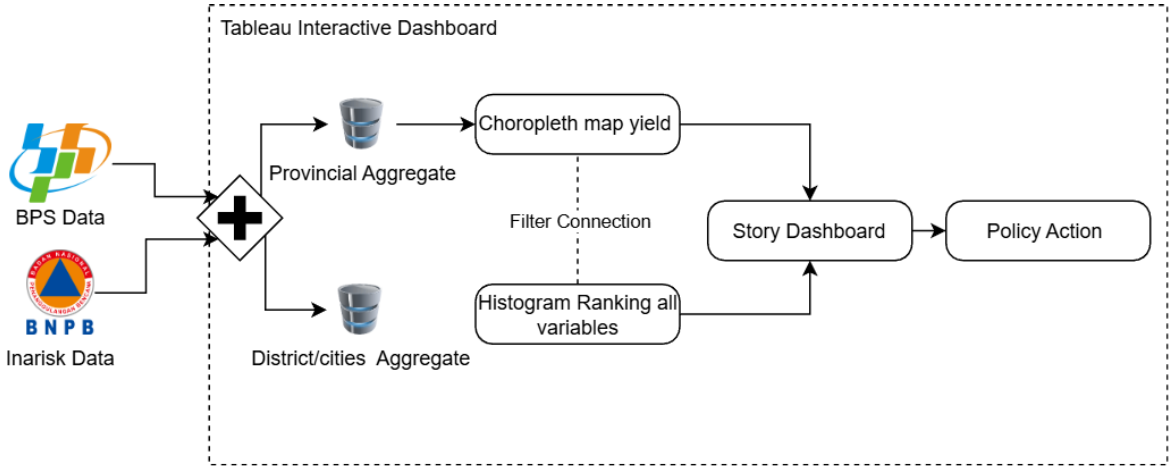
Source: Research data preprocessed from BPS

Table 2. Total data of compilation result

Metrics	Total
n_row	19
n_column	514
n_cells	9766

Source: Research data preprocessed from BPS

The dashboard is built in Tableau. Almost all variables are visualized in histogram graphs and ranked from highest to lowest, except the yield, which is also shown on a geospatial map (Figure 1). The province data in the map or histogram serves as a filter for the districts/cities, and they are not needed for unit analysis. Hover around to make selection certain for interactivity, while the vertical reference line shows the national average for each indicator to make visual comparison easier.



Source: Research Results

Figure 1. Conceptual Flow

Four domains are being chosen, and all are defined at the district/city level (Figure 2). The first Domain shows rice yield and field structure, including rice yield in tons per hectare at the province and district levels. Also, the average farm area in hectares. The second Domain concerns household characteristics and includes percentages of women, farmer age, and year of schooling. The third Domain is showing farm practices. That includes the proportion of agricultural holdings using fertilizer and pesticides, the proportion joining a farmer group, and the proportion in a formal partnership (contract). The fourth Domain is focus more on the support and access-to-services for farmer that include e the percentage of regular and complete bookkeeping record, percentage of access to KUR (Kredit Usaha Rakyat, a lending program), percentage of agricultural insurance, percentage of getting fertilizer aid and tools/machinery subsidy, and also the percentage of technology adoption related with production reported in ST2023. All indicators are calculated as averages or simple percentages based on calculations from the raw data for ST2023.

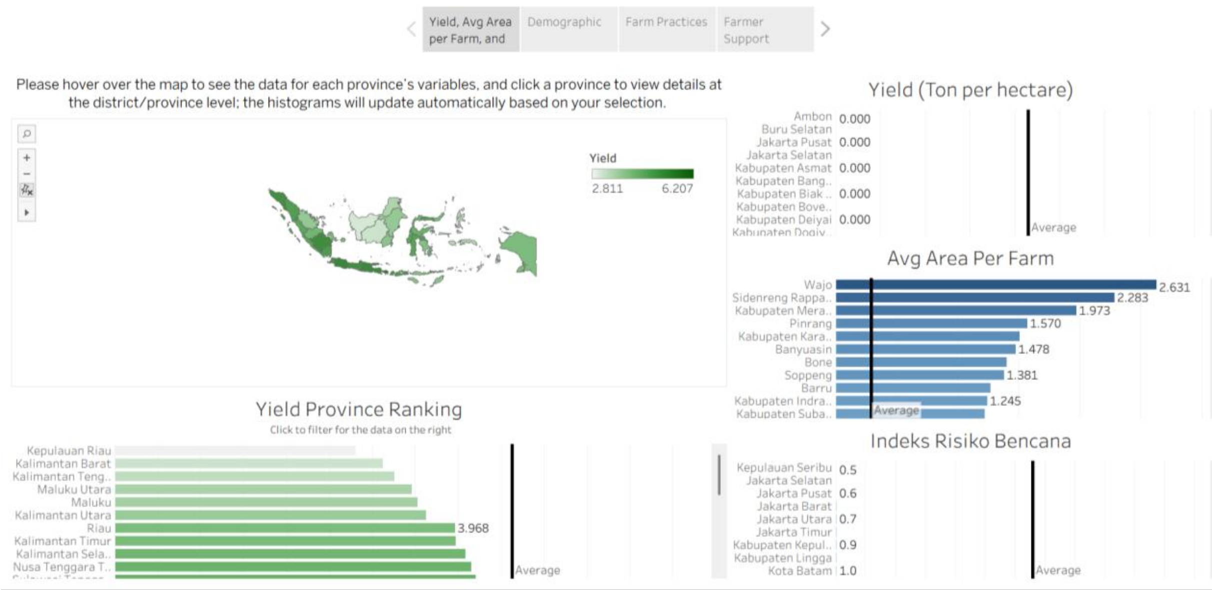
Source: Research Results
Figure 2. Dashboard Slide flow

Conceptually, the workflow in this research is: data compilation from ST2023 and Inarisk, indicator construction, dashboard visualization in Tableau, and stakeholder use of the dashboard for scanning, benchmarking, and prioritising districts for follow-up analysis or intervention design.

RESULTS AND DISCUSSION

Rice Productivity and Land Structure

Figure 1 shows the yield results and the field structure. Average area per farm is the amount of rice area per agricultural holding, providing a scope for mechanization, inputs, and economic scale that will affect efficiency in terms of technical and yield (Rahman et al., 2012). Inarisk is the level of risk the region faces. Agriculture is disrupted by floods, droughts, landslides, and other natural disasters that disrupt crop cycles and harvests, leading to decreased yields (BNPB, 2024). Rice yield is the amount of rice produced per hectare, measured in tons per hectare, and is used as the primary productivity factor and as a compass for analyzing other factors (FAO,2025).

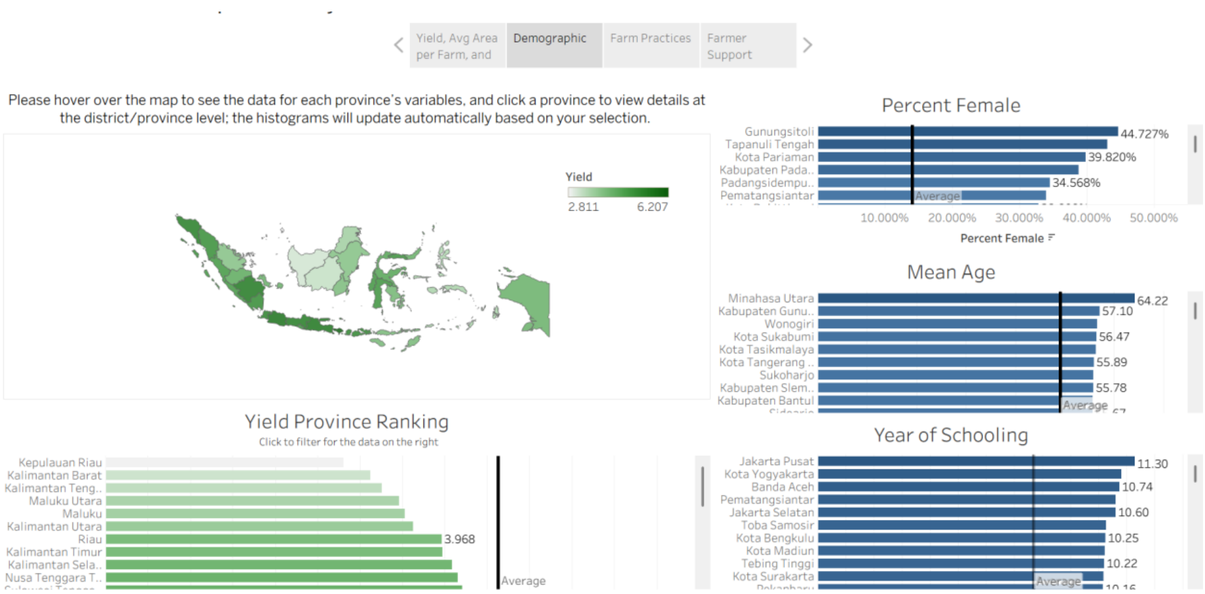


Source: Research Results
Figure 1. Dashboard view of district-level rice yield, average area per farm, and indeks risiko bencana

A choropleth map shows how yield productivity varies among districts/cities. As we could see, Java Island seems greener than the other islands. The farther it is from Java Island, the farther it is from green, which means the yield level decreases as the green fades. Looking at the histogram, some districts/cities are above the national average, while others are below. In the provincial yield histogram, we can see that Bali has the Highest Yield, whereas Kepulauan Riau has the lowest. The pattern in Figure 1 could lead to a combination of yield, average farm area, and disaster risk. Some districts may have higher yields, but low average farm area and low disaster risk, whereas other districts have a different combination. At a national level, the spatial view supports rapid identification of clusters and outliers before selecting areas for further analysis.

Demographic Characteristics of Agricultural Households

Figure 2 shows the demographic distribution, including the percentage of women farmers, farmer age, and year of schooling, along with comparisons with yield. Farmer age is a profile of a farmer's age that affects physical capacity, risk preferences, regeneration planning, and readiness for technological adoption and new practices; empirical studies show that aging farmer populations are slower to adopt innovations but have more experience (Budiyoko et al., 2023). Female Composition is the percentage of female farmers managed by females, indicating the role of gender and the potential for differences in access to land, inputs, information, and services that affect productivity (Doss, 2015). Education level (Years of Schooling) – is how long a formal education has been taken by a farmer, whether specifically joining a school in agriculture or not. It will build skills to process information, use financial access and digitalization, and adopt better agronomic practices; a higher education level is consistently associated with higher technical efficiency among farmers (Obianefo et al., 2021).



Source: Research Results

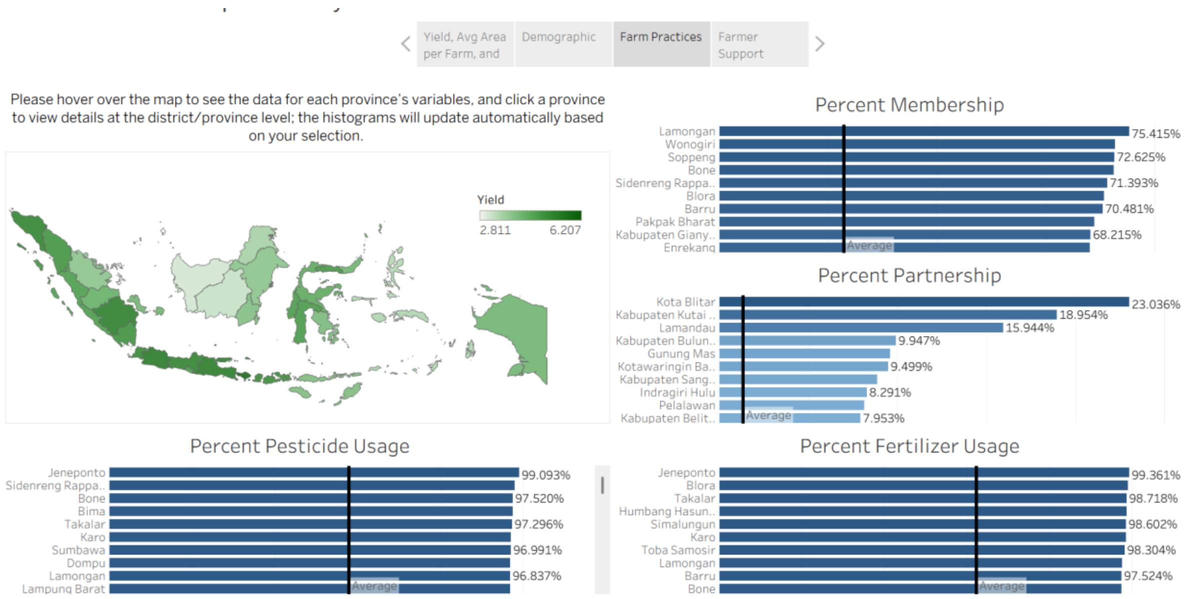
Figure 2. Dashboard view of district-level demographic indicators of agricultural households

Some districts/provinces have low yields but high percentages of women, farmer age, and year of schooling; other combinations are feasible. The figure could also track the progress of government interventions to increase education for farmers, lower the average age of farmers, and increase the percentage of women involved in agriculture. Therefore, the stakeholder could design the program to train, educate, or support farmer regeneration. For example, districts/cities with older farmers or fewer years of schooling may use a different education/training strategy than those with younger farmers and more years of schooling. This pattern suggests that demographic indicators may interact with structural conditions; therefore, these variables should be interpreted together with land structure and support indicators when screening priority areas. The highest of percent female of district is GunungSitoli, For mean Age variable is Minahasa Utara, and Year of Schooling is Jakarta Pusat.

Farming Practices

Figure 3 shows the percentages of farmer holdings that use fertilizer and pesticides, are part of a farmer group, and have formal partnerships, along with the comparison with yield.

Farmer group membership is a farmer's participation in a group or cooperation to facilitate learning together, share best practices, access services, and gain higher bargaining power in input and in selling the harvest, thereby leading to higher yields (Ali et al., 2023). Partnership participation involves schemes of formal partnerships, such as contract farming or offtaker patterns, that connect farmers and buyers, provide technical assistance, and sometimes involve KUR. This scheme has proven to increase salaries and access to markets for farmers in the rice value chain (Rochdiani et al., 2007). Pesticide use is the application of pest control products and disease control measures to protect crops and prevent loss of harvest. However, pesticides can reduce pest damage; however, overuse can risk the environment and health and may not lead to sustainable increases in productivity (Prihandiani et al., 2021). Fertilizer use provides nutrient inputs, such as nitrogen, phosphorus, and potassium, that can be combined with organic matter to improve yield, restore soil fertility, and support plant growth, and to increase harvest if the dosage and timing are matched (Sunarpi et al., 2021).



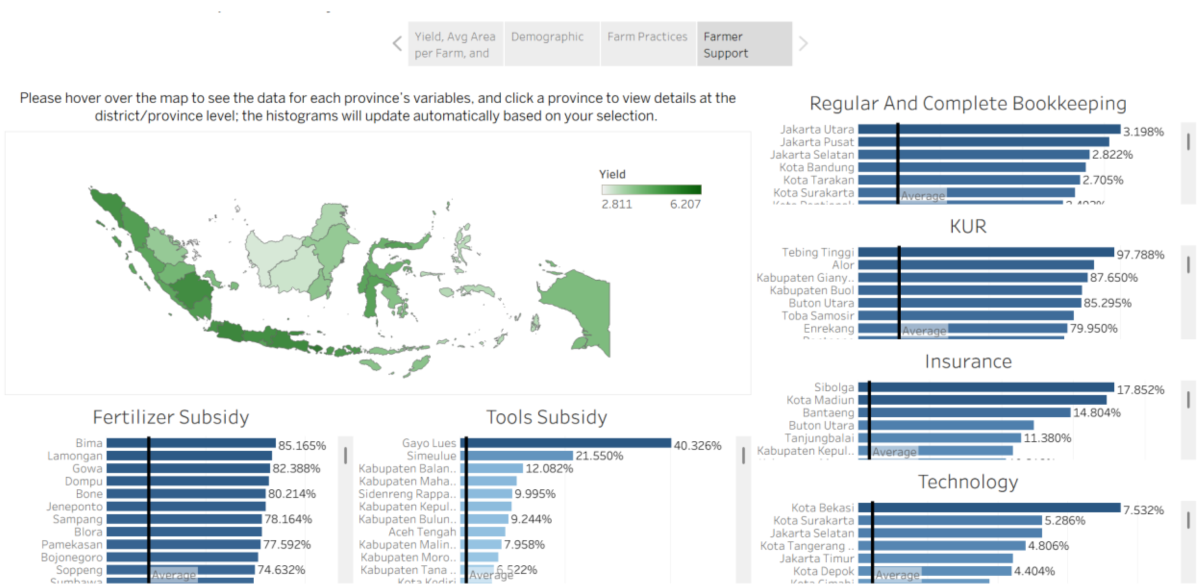
Source: Research Results

Figure 3. Dashboard view of district-level farming practice indicators

Some districts/cities achieve high yields with high fertilizer and pesticide use, farmer groups, and partnerships, while others achieve high yields with other combinations. The figure could also show how far the distribution of fertilizer and pesticides extends across districts within each province. Also, which district has low farmer groups and low partnerships, and how can we increase them in the next program? Maybe the current program is ineffective at increasing the percentage of farmer groups and partnerships. Overall, the dashboard helps reveal where input-use patterns align with higher yields and where exceptions occur, which can guide more targeted follow-up analysis.

Farmer Support and Services

Figure 4 shows the percentages of complete and regular bookkeeping, access to KUR, farming insurance, subsidy, and technology adoption, along with comparisons with yield. A fertilizer subsidy is government assistance that lowers the price of effective fertilizer, helping farmers, especially small farmers, obtain enough nutrients to protect or increase productivity, even though effectiveness depends on precision and distribution mechanisms (Maman et al., 2021). Tools and Machinery subsidy is government assistance to receive tools or machines (alsintan) like tractors, rice transplanter, or combine harvester, that will make it easier to process the field, planting, and harvest, and is explicitly promoted by the Ministry of Agriculture to increase yield and workforce efficiency (Kementerian Pertanian Republik Indonesia, 2024). Kredit Usaha Rakyat (KUR) is a formal subsidy lending program that enables farmers to allocate budget for inputs, tools, and other productivity investments; KUR is designed for small farmers, women farmers, and young farmers to access working capital and inclusive investment (Balai Besar Perpustakaan dan Literasi Pertanian, 2025). Agricultural insurance is insurance protection for farmers against production losses from natural disasters such as floods, droughts, pests, and diseases, thereby stabilizing income and reducing risk for investment in technologies that increase harvests (Purwadi et al., 2022). Technology adoption is the use of modern agricultural technologies, such as superior varieties, mechanization, precision input management, and information tools, and it is empirically associated with increased farmer productivity and welfare in the rice system (Ernawatiningsih & Sari, 2024). Bookkeeping is the practice of keeping regular, complete records of the activities, inputs, costs, income, and profits of agricultural holdings. Systematic bookkeeping will help farmers evaluate profitability and plan for the next season, or improve the quality of managerial decision-making (Yustriawan, 2021).



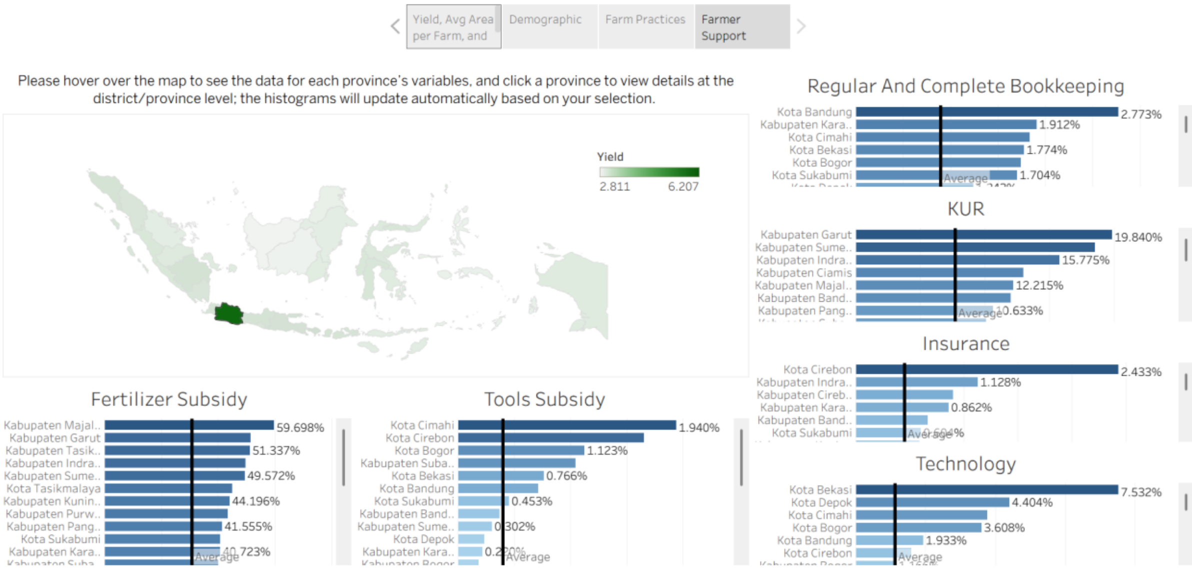
Source: Research Results

Figure 4. Dashboard view of district-level farmer support and service indicators

Some districts/cities have high yields with low percentages of subsidy, technology adoption, insurance, and KUR, while others have different combinations. The figure could also show how far the effectiveness of distributing KUR, insurance, or subsidies for the company varies across provinces and districts. Also, it could be determined for each province which district has the lowest percentage of KUR, Insurance, and other indicators that need improvement in the next program, or whether the current program is ineffective or needs more evaluation and monitoring. This non-uniform alignment between yield and programme coverage can be used to flag potential targeting gaps and to prioritise districts for deeper review.

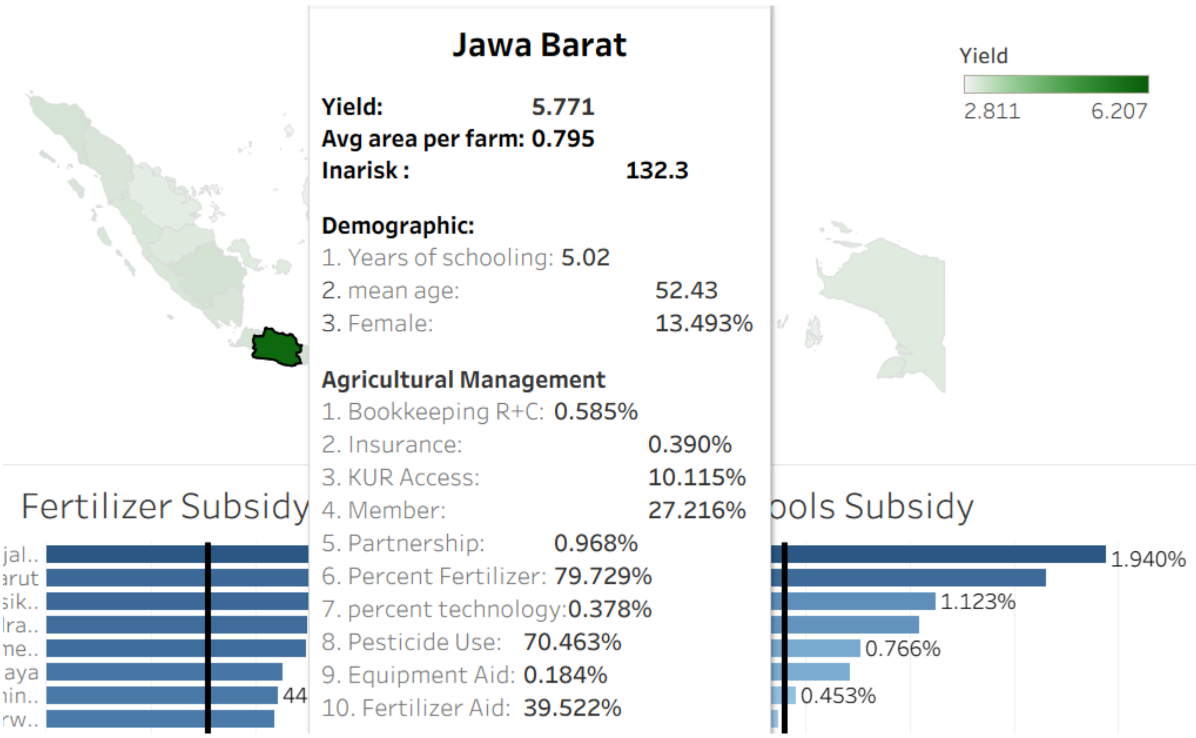
Province hover summary for quick profiling

In addition to the filter function shown in Figure 5, the dashboard also includes a hover function that provides a brief profile for each profile, keeping the district/cities as the main unit of analysis. When the cursor hovers over a province on the map, the panel displays information, which is an aggregation of the whole province (Figure 6). This panel will show the full indicator/variable, including average yield, average farmer area, demography, farmer practices, and farmer support. By doing this, the user could compare the average at the provincial, district, and national levels simultaneously. Some provinces may have all their districts below the national average in certain variables/indicators. Some provinces have higher or lower rates than the national average, which may be due to one or two districts/cities.



Source: Research Results

Figure 5. Example of province-based filtering of district-level farmer support indicators in the dashboard (ST2023)



Source: Research Results

Figure 6. Example of province hover summary panel for rice productivity and structural indicators

Overall Discussion

Based on those four, display different groups of indicators/variables on the dashboard to easily view the different district structures in Indonesia. The combination of a Choropleth map and a histogram allows the user to explore multiple dimensions simultaneously, especially when structured into a story (four displays). For example, to compare the results of demographic and other support indicators.

The contribution of this research is to develop and document a set of district-level visualization tools based on the national census. For stakeholders, this research can serve as a benchmark for the national or provincial average, or for comparing one district with another within the same province or nationally. Also, it could identify the priority or potential district/province to be further analyzed. For example, Bali has the highest yield among provinces and could be analyzed to see what makes it so. By reducing the complexity of checking the raw data for ST2023, this dashboard is easily used for many meetings/events among stakeholders as a single evidence resource.

Potential practical uses of the dashboard include:

- supporting national and provincial coordination meetings by providing a shared reference for district benchmarking;
- helping provincial and district governments scan which indicators are consistently below the national average and where targeted support may be prioritised;
- helping researchers select districts/provinces for deeper follow-up analysis by shortlisting outliers and contrasting profiles.

From an academic perspective, the dashboard functions as an exploratory data analysis tool that helps users quickly inspect distributions, heterogeneity, and potential outliers before moving to formal modelling (Tukey, 1977). In visual analytics, interactive views and user-driven filtering support iterative sensemaking by combining visualization with human judgement, which can guide hypothesis generation and the selection of suitable follow-up methods (Keim et al., 2008). In this research, the map–histogram–ranking combination, together with filters and hover summaries, is designed to complement (not replace) subsequent quantitative approaches such as clustering or regression once stakeholders have identified priority districts or unusual profiles.

CONCLUSION

This research shows that the agricultural census (ST2023) and the disaster risk index (Inarisk) can be useful in an interactive dashboard for analyzing variation in rice productivity and agricultural structure at the district/city level, with four domain indicators: Yield and field structure, demographic, farm practices, and farm support. This dashboard shows the specific variety of architectural structures that will be displayed when the analysis is at the national or provincial level. This analysis is only for descriptive purposes; to be causative, it needs more research or further analysis.

For stakeholders, this dashboard can be a simple, practical tool to compare distributions at the national and provincial levels, identify regions with specific indicators, and also inform policy priorities for further intervention. By reducing the complexity of reading the raw data ST2023, this dashboard will be a good initial step for further development through assessment resources and other quantitative analyses, such as clustering or regression analyses based on the visual patterns identified.

This research relies entirely on aggregate census and risk-index data at the province and district/city levels. Therefore, it does not capture within-district heterogeneity, plot-level management, or seasonal dynamics, and the dashboard should be interpreted as a descriptive exploration rather than a causal explanation.

- incorporate time-series indicators (e.g., prices, production, climate shocks) to monitor changes over time and support forecasting;
- extend the analysis with clustering, regression, and spatial econometric approaches to test hypotheses suggested by the visual patterns;
- triangulate the dashboard insights with field validation or stakeholder consultation to refine interpretation and prioritisation.

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