Matrix: Jurnal Manajemen Teknologi dan Informatika
Volume 15 Issue 1 Year 2025 Pages 21-31

DOI: http://dx.doi.org/10.31940/matrix.v15i1.21-31
URL: http://ojs2.pnb.ac.id/index.php/matrix

Analysis of corn production in Indonesia using business intelligence technology based on Power BI

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Abstract: Corn production trends in Indonesia from 2020 to 2024 were analyzed to address regional disparities and enhance data-driven agricultural decision-making. Datasets from the Ministry of Agriculture and the Central Bureau of Statistics were integrated, transformed, and visualized using Microsoft Power BI, with a focus on evaluating fluctuations in harvested area, production volume, and productivity. Key objectives included identifying challenges linked to fragmented data and external disruptions. An Extract-Transform-Load (ETL) framework harmonized pre-2023 and post-2023 datasets, enabling standardized comparisons across 38 provinces. Results indicated a production peak of 486,000 tons in 2022, followed by a 4.5% decline in 2023 due to adverse climatic conditions and supply chain instability, and partial recovery to 15.2 million tons in 2024. Pronounced regional disparities emerged: West Java recorded 80 quintals per hectare productivity, while urbanized regions like Jakarta reported negligible output. The analysis underscores the efficacy of Business Intelligence (BI) tools in converting raw agricultural data into strategic insights, offering policymakers pathways to optimize resource allocation, mitigate inequities, and strengthen climate-resilient practices. These outcomes highlight BI's transformative potential in advancing sustainable agricultural development and adaptive governance frameworks.

Keywords: business intelligence, corn production, data analytics, ETL, Power BI

History Article: Submitted 6 January 2025 | Revised 26 March 2025 | Accepted 15 April 2025

How to Cite: M. K. Adesyahputra and E. P. Rachmawati, "Analysis of corn production in Indonesia using business intelligence technology based on Power BI", *Matrix : Jurnal Manajemen Teknologi dan Informatika*, vol. 15, no. 1, pp. 21–31, 2025. doi.org/10.31940/matrix.v15i1.21-31.

Introduction

Indonesia, as one of Southeast Asia's largest agricultural producers, plays a critical role in regional food security and economic stability [1]. Agriculture significantly contributes to the nation's GDP, employment, and socio-economic development. Among its key agricultural commodities, corn holds strategic importance as a dual-purpose crop: it serves as a staple food source for millions and a primary ingredient in livestock feed production [2]. Efficient corn production management is essential to ensure food security, support the livestock sector, and drive sustainable economic growth [3].

Despite its significance, Indonesia faces persistent challenges in optimizing corn production. Agricultural data crucial for policymaking are often fragmented, multidimensional, and inconsistently formatted across regions [4]. This lack of standardization hinders stakeholders from leveraging data effectively, resulting in suboptimal resource allocation, uneven productivity, and stark regional disparities [5]. External factors such as climate change, supply chain disruptions, and market volatility further complicate production planning, adding layers of complexity to agricultural management [6].

Technological advancements in information systems, particularly Business Intelligence (BI), offer transformative solutions. BI tools like Microsoft Power BI enable the integration, transformation, and visualization of complex datasets, empowering stakeholders to make data-driven decisions [7]. For instance, Microsoft Power BI a BI platform facilitates the creation of interactive dashboards and real-time analytics, allowing users to explore data dynamically [8]. Modern BI tools incorporate OLAP (Online Analytical Processing), a data analysis technique that organizes information rapid querying and aggregation, enabling stakeholders to dissect agricultural datasets across critical dimensions such as region, time period, and production scale and systematically uncover latent patterns and trends essential for strategic decision-making [9]. Together, these IT innovations empower users to identify trends, detect inefficiencies, and make data-driven decisions across a wide range of sectors, including agriculture [6].

Corn production in Indonesia is influenced by multiple interrelated factors, including harvested area, productivity per hectare, access to farming technologies, and external conditions such as weather and market dynamics [10]. Each of these factors contributes to the overall production landscape, and understanding their interactions requires sophisticated data analysis methods [4]. For instance, disparities in productivity between provinces are often linked to unequal access to resources such as high-quality seeds, fertilizers, and irrigation systems. Similarly, technological adoption, government support, and infrastructure availability play a crucial role in determining the efficiency of agricultural activities in different regions. Addressing these disparities is essential to achieving equitable development and ensuring that all regions can reach their full potential.

To tackle these challenges, this study focuses on applying Business Intelligence to analyze corn production data in Indonesia during the 2020–2024 period. The integration of Business Intelligence with large-scale agricultural datasets has been shown to enhance decision-making capabilities by leveraging advanced data processing and real-time analytics [11]. Microsoft Power BI is employed to process, analyze, and visualize the data, providing stakeholders with an intuitive and interactive platform to explore production trends and regional disparities. The research methodology incorporates an Extract, Transform, Load (ETL) process to ensure the accuracy, consistency, and reliability of the data. This process involves extracting data from official statistical sources, transforming it into a standardized format, and loading it into a BI platform for comprehensive analysis [12]. The OLAP-like features integrated within Power BI enhance the analysis by enabling users to drill down into detailed data dimensions, compare metrics across regions and time periods, and aggregate results at varying levels of granularity [9]. Using Power BI dashboards, stakeholders can interactively explore key metrics such as harvested area, production volume, and productivity per hectare across different regions [7]. These visualizations highlight patterns, identify underperforming regions, and enable targeted interventions to address productivity gaps.

Beyond addressing agricultural challenges, this study emphasizes the broader role of advanced information systems in revolutionizing data management across various domains. Traditional methods of data analysis often rely on static reports and manual processing, which are time-consuming and prone to errors. In contrast, BI tools offer dynamic and automated solutions that significantly enhance the accessibility and usability of data [6]. By transforming raw data into actionable visual insights, these platforms enable stakeholders to make informed decisions based on real-time information. This capability is particularly valuable in a rapidly changing environment where timely and accurate data is essential for effective decision-making [13].

The integration of Business Intelligence into agricultural data management not only improves operational efficiency but also fosters collaboration among various stakeholders. Government agencies, private organizations, and local communities can leverage shared digital platforms to coordinate efforts, align strategic goals, and implement policies that address systemic challenges [14]. For example, insights derived from Power BI dashboards can guide policymakers in designing programs to support underperforming regions, allocate resources more effectively, and mitigate the impacts of external disruptions such as climate change and market volatility. This collaborative approach ensures that decision-making is inclusive, data-driven, and aligned with the broader goals of sustainable development.

Furthermore, this research highlights the potential of advanced information systems to drive innovation and sustainability in agriculture. By providing clear, data-driven insights, BI tools enable stakeholders to identify inefficiencies, optimize resource allocation, and develop strategies that promote resilience and adaptability [15]. This aligns with global efforts to achieve sustainable development goals, particularly those related to food security, economic growth, and environmental sustainability. The application of BI in agricultural data management demonstrates how cutting-edge technology can be harnessed to address complex challenges, unlock new opportunities, and improve the overall efficiency of critical sectors [6].

Ultimately, this study underscores the transformative power of information systems in enabling data-driven decision-making. By leveraging Microsoft Power BI to analyze and visualize corn production data, the research provides a blueprint for integrating advanced IT solutions into agricultural management practices [15]. The findings aim to equip stakeholders with actionable insights that can guide evidence-based strategies to enhance productivity, address regional disparities, and strengthen the resilience of Indonesia's agricultural sector. Moreover, the study serves as a testament to the broader relevance of modern information systems in driving innovation, fostering collaboration, and supporting sustainable development across diverse sectors.

Methodology

This study analyzes corn production data in Indonesia for the period 2020–2024 using a Business Intelligence approach based on Microsoft Power BI. Data were collected from official reports issued by the Ministry of Agriculture and the Central Bureau of Statistics (BPS). The process begins with the collection of secondary data on corn production, harvested area, and productivity from these official sources.

After collection, the next stage is the Extract, Transform, Load (ETL) process. In the extraction phase, data from two different periods (2020–2022, referred to as the Pre-2023 Dataset, and 2023–2024, referred to as the Post-2023 Dataset) are obtained. In the transformation phase, the two datasets are merged into one unified dataset. Common fields (for example, year, province, harvested area, production volume, and productivity) are aligned so that both datasets share the same column structure. Duplicate rows are removed to maintain data accuracy, and missing values for provinces not established in 2020–2022 are set as NULL or zero. Data gaps for newly established provinces in 2023–2024 are clearly marked, and province names are standardized across both periods to ensure consistency. In the loading phase, the cleansed and merged dataset is imported into Microsoft Power BI.

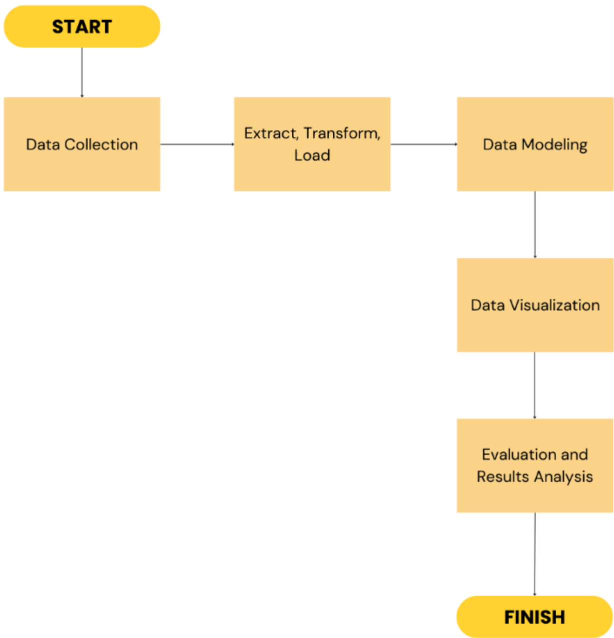
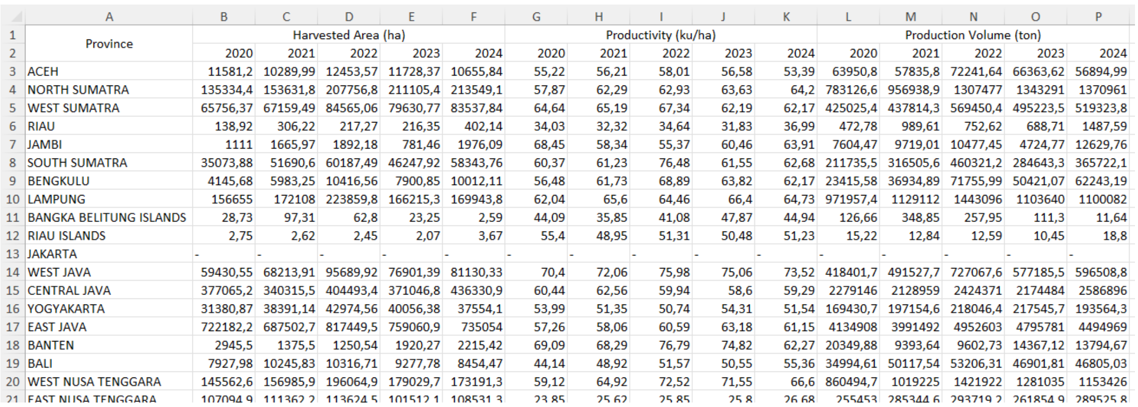


Figure 1. Flowchart of the research process

The flowchart in Figure 1 outlines the comprehensive research process, beginning with the collection of secondary data from official sources. Once the data are gathered, the process moves into the ETL phase, where data from two distinct periods (2020–2022 and 2023–2024) are extracted and merged into a unified dataset. During the transformation stage, the data undergo rigorous cleaning procedures including column alignment, duplicate removal, handling of missing values, and standardization of units and province labels to ensure consistency. After transformation, the cleaned data are loaded into Microsoft Power BI, where a robust data model is constructed by defining relationships and setting appropriate data types, utilizing Power BI's in-memory OLAP capabilities for multidimensional analysis. Finally, the process culminates in the creation of interactive dashboards and visualizations, which enable users to filter and explore trends in corn production such as variations in harvested area, production volume, and productivity across different provinces and time periods, ultimately transforming raw data into actionable insights for informed decision-making.

Figure 2. ETL process

Figure 2 presents an expanded view of the ETL process. It starts with the extraction of data from two separate datasets: the Pre-2023 Dataset (2020–2022) and the Post-2023 Dataset (2023–2024). The process then moves to the transformation phase, where several key steps are performed. First, the merging of datasets is executed to consolidate all records into one unified dataset; next, column alignment is carried out so that common fields are uniform; then, duplicate rows are identified and removed; afterward, missing values are handled by setting them as NULL or zero for provinces not present in the earlier period; subsequently, unit standardization is performed to ensure consistency in measurements (for example, converting harvested area to hectares and production volume to tons); finally, province labels are standardized to ensure uniform naming across the entire dataset. The final step in this flowchart is the loading of the processed data into Microsoft Power BI, where it is further modeled for multidimensional analysis. Once the data are loaded into Power BI, a data model is established by defining relationships and setting data types. This step, known as data modeling, utilizes Power BI's in-memory OLAP capabilities to support multidimensional analysis across regions and time periods. Data visualization is the next stage, where interactive dashboards and visual representations are created. These visualizations allow users to filter and explore trends in corn production, revealing changes in harvested area, production volume, and productivity across various provinces and time periods.



Province	Harvested Area (ha)					Productivity (ku/ha)					Production Volume (ton)				
	2020	2021	2022	2023	2024	2020	2021	2022	2023	2024	2020	2021	2022	2023	2024
ACEH	11581,2	10289,99	12453,57	11728,37	10655,84	55,22	56,21	58,01	56,58	53,39	63950,8	57835,8	72241,64	66363,62	56894,99
NORTH SUMATRA	135334,4	153631,8	207756,8	211105,4	213549,1	57,87	62,29	62,93	63,63	64,2	783126,6	956938,9	1307477	1343291	1370961
WEST SUMATRA	65756,37	67159,49	84565,06	79630,77	83537,84	64,64	65,19	67,34	62,19	62,17	425025,4	437814,3	569450,4	495223,5	519323,8
RIAU	138,92	306,22	217,27	216,35	402,14	34,03	32,32	34,64	31,83	36,99	472,78	989,61	752,62	688,71	1487,59
JAMBI	1111	1665,97	1892,18	781,46	1976,09	68,45	58,34	55,37	60,46	63,91	7604,47	9719,01	10477,45	4724,77	12629,76
SOUTH SUMATRA	35073,88	51690,6	60187,49	46247,92	58343,76	60,37	61,23	76,48	61,55	62,68	211735,5	316505,6	460321,2	284643,3	365722,1
BENGKULU	4145,68	5983,25	10416,56	7900,85	10012,11	56,48	61,73	68,89	63,82	62,17	23415,58	36934,89	71755,99	50421,07	62243,19
LAMPUNG	156655	172108	223859,8	166215,3	169943,8	62,04	65,6	64,46	66,4	64,73	971957,4	1129112	1443096	1103640	1100082
BANGKA BELITUNG ISLANDS	28,73	97,31	62,8	23,25	2,59	44,09	35,85	41,08	47,87	44,94	126,66	348,85	257,95	111,3	11,64
RIAU ISLANDS	2,75	2,62	2,45	2,07	3,67	55,4	48,95	51,31	50,48	51,23	15,22	12,84	12,59	10,45	18,8
JAKARTA	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
WEST JAVA	59430,55	68213,91	95689,92	76901,39	81130,33	70,4	72,06	75,98	75,06	73,52	418401,7	491527,7	727067,6	577185,5	596508,8
CENTRAL JAVA	377065,2	340315,5	404493,4	371046,8	436330,9	60,44	62,56	59,94	58,6	59,29	2279146	2128959	2424371	2174484	2586896
YOGYAKARTA	31380,87	38391,14	42974,56	40056,38	37554,1	53,99	51,35	50,74	54,31	51,54	169430,7	197154,6	218046,4	217545,7	193564,3
EAST JAVA	722182,2	687502,7	817449,5	759060,9	735054	57,26	58,06	60,59	63,18	61,15	4134908	3991492	4952603	4795781	4494969
BANTEN	2945,5	1375,5	1250,54	1920,27	2215,42	69,09	68,29	76,79	74,82	62,27	20349,88	9393,64	9602,73	14367,12	13794,67
BALI	7927,98	10245,83	10316,71	9277,78	8454,47	44,14	48,92	51,57	50,55	55,36	34994,61	50117,54	53206,31	46901,81	46805,03
WEST NUSA TENGGARA	145562,6	156985,9	196064,9	179029,7	173191,3	59,12	64,92	72,52	71,55	66,6	860494,7	1019225	1421922	1281035	1153426
EAST NUSA TENGGARA	107094,9	111362,2	113624,5	101512,1	108531,3	23,85	25,62	25,85	25,8	26,68	255453	285344,6	293719,2	261854,9	289525,8

Figure 3. Screenshot of raw data

Figure 3 displays a screenshot of the consolidated raw data used in this study. The dataset comprises data for 38 provinces and includes fields such as year, province, harvested area, production volume, and productivity. The rows represent individual records for each province and year, while the columns correspond to the key variables mentioned. This visual confirmation ensures that the data have been accurately integrated and are ready for detailed analysis.

The evaluation and results analysis phase follows visualization, where the insights derived from the interactive dashboards are interpreted to inform conclusions and recommendations for the agricultural sector. This systematic methodology, which integrates data consolidation within the transformation phase of the ETL process along with rigorous data modeling and advanced visualization in Power BI, ensures that the analysis is based on accurate, standardized data. The interactive dashboards developed enable users to explore trends in corn production across different regions and timeframes, ultimately supporting robust, data-driven decision-making in the agricultural sector.

Results and Discussions

Using Microsoft Power BI, this study thoroughly examined corn productivity data to generate interactive visualizations and dashboards that offer a comprehensive insight into regional trends. The analysis revealed notable patterns in harvested area, production volume, and productivity metrics, along with significant variations among provinces. These outcomes were discussed to assess their implications for agricultural policy and directions for future research.

Results

The data utilized in this study comprises annual corn productivity statistics, including harvested area, production volume, and productivity across various regions. It was obtained in Excel format from official sources. Preprocessing involved removing invalid or duplicate entries, normalizing formats, and grouping data by region and year. Data processed in the initial phase was then uploaded to Power BI, where visualizations were tailored to meet analytical needs. Graph types include bar charts to compare harvested areas, production volumes, and productivity across regions. An interactive dashboard was developed to integrate various visualizations and offer users the ability to filter data by year, region, or other categories.

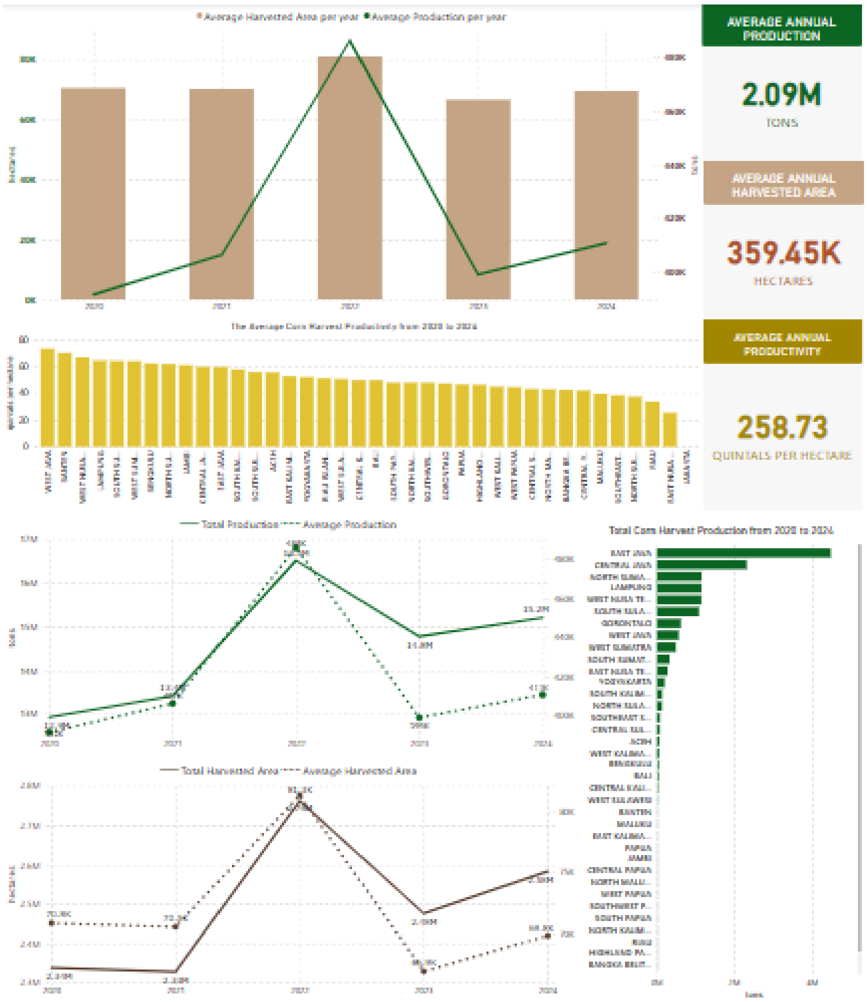


Figure 4. Corn productivity dashboard

The dashboard includes key visualizations such as the average harvested area per year, the average production volume per year, and the average productivity per hectare, all of which work together to provide critical insights into corn production trends. These visualizations offer a comprehensive overview of production metrics that are essential for understanding performance over time. Figure 4 illustrates this dashboard, which is designed to allow users to interact with the data dynamically, thereby enabling them to explore and analyze production trends across different regions and years in a highly intuitive manner.

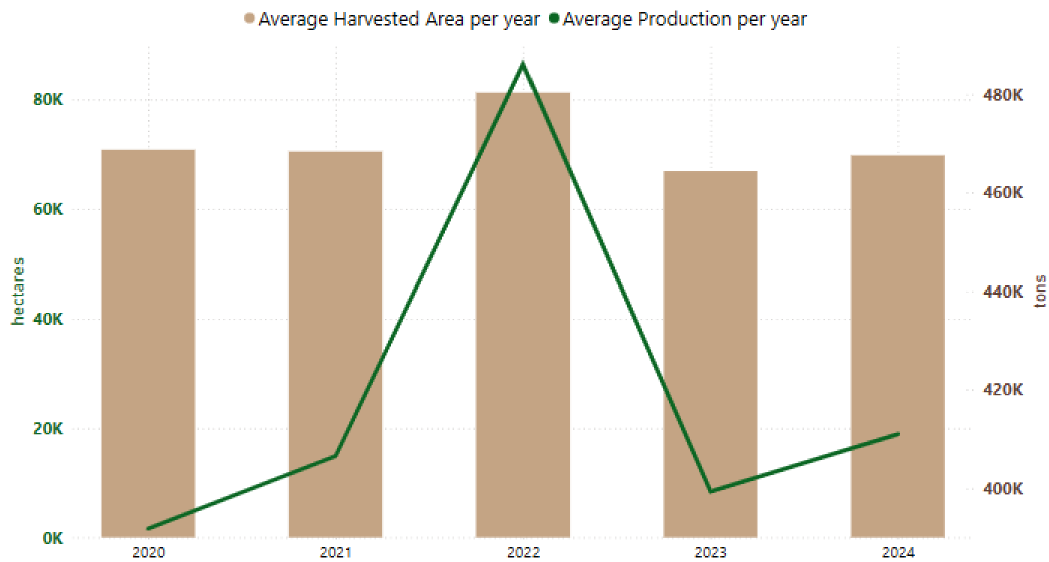


Figure 5. Average harvested area and production trends

Figure 5 delineates the temporal progression of the average harvested area and production volume from 2020 to 2024 and elucidates the inherent responsiveness of the corn production system to external perturbations. The peak observed in 2022, characterized by an 81.3 thousand-hectare harvested area and a production volume of 486 thousand tons, serves as a benchmark for optimal production conditions. In contrast, the marked decline in 2023 underscores the susceptibility of the production process to adverse meteorological events and supply chain disruptions, thereby highlighting systemic vulnerabilities. The subsequent, albeit incomplete, recovery in 2024 indicates that while remedial measures may ameliorate some adverse impacts, a latent fragility persists that warrants further intervention.

This visualization provides a critical empirical foundation for advocating enhanced risk management practices, infrastructural investments, and the integration of advanced forecasting technologies. Such measures are imperative for sustaining production stability and mitigating the effects of exogenous shocks, thereby reinforcing the strategic value of Business Intelligence tools in agricultural decision-making.

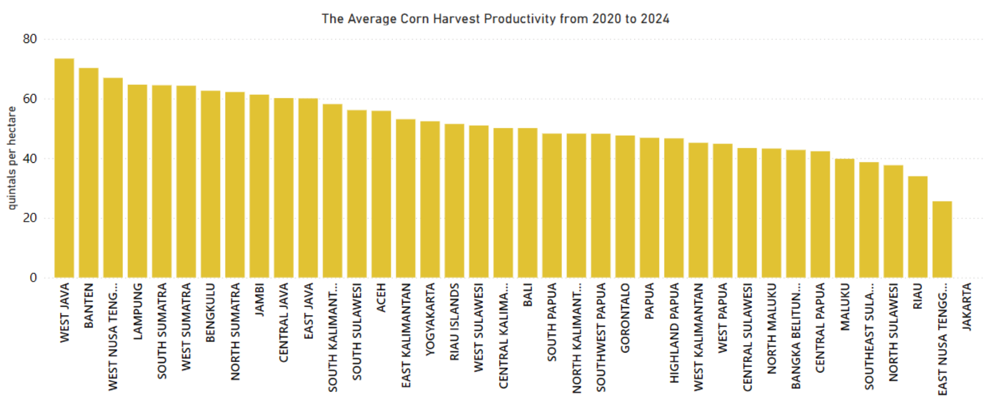


Figure 6. Average corn productivity per province

This chart clearly highlights significant productivity differences across provinces. For instance, West Java recorded the highest productivity, achieving an impressive level of around 80 quintals per hectare, while Jakarta registered no production data due to its completely urban landscape lacking any agricultural land. Additionally, East Nusa Tenggara exhibited the lowest productivity, with levels falling below 40 quintals per hectare. These variations not only reflect differing efficiencies in land use influenced by factors such as soil quality, access to modern technology, and overall resource management practices but also offer critical insights into regional disparities within the agricultural sector. Figure 6 provides a detailed visual comparison of these productivity levels, serving as an empirical foundation for further investigation into the effectiveness of localized agronomic practices and supporting targeted interventions aimed at optimizing production efficiency across diverse regions.

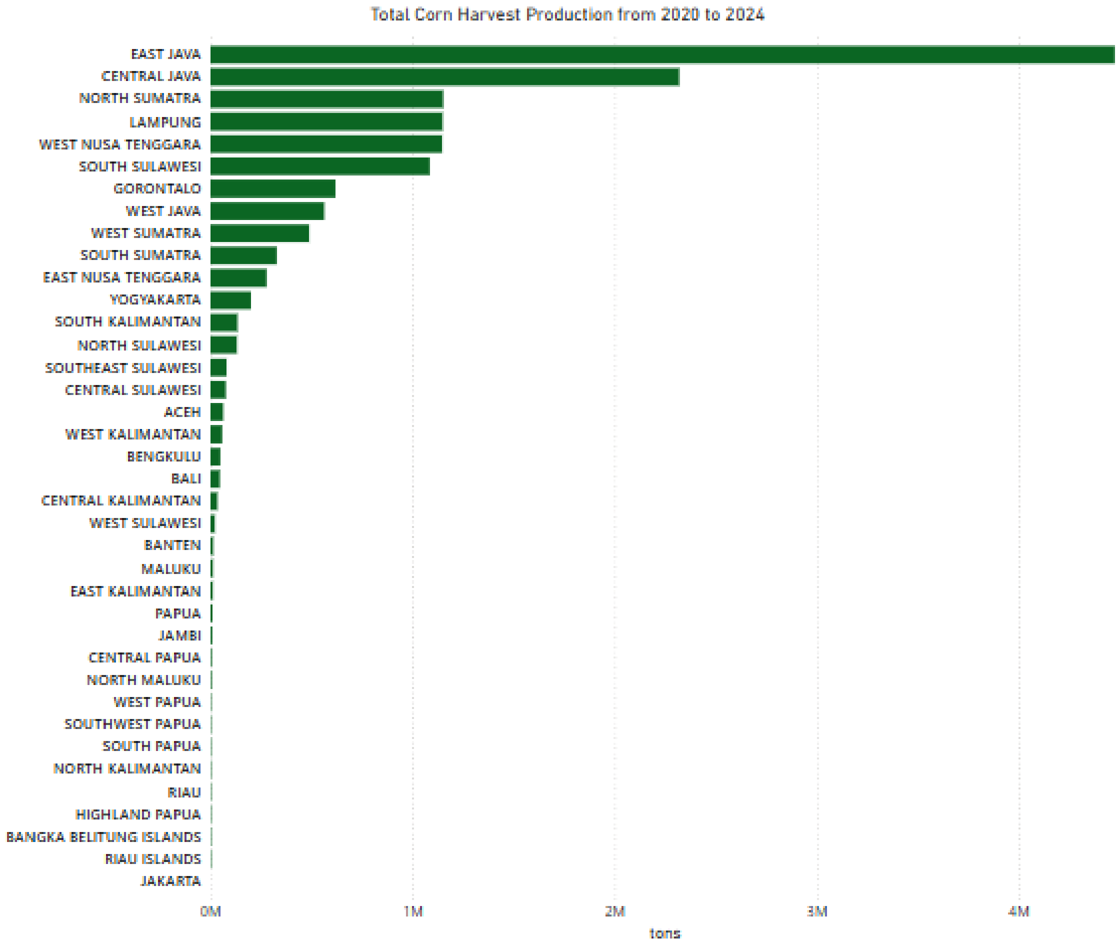


Figure 7. Corn production by province

Horizontal bar charts vividly illustrate the production capacities of various provinces over the period from 2020 to 2024. For instance, East Java led with a production exceeding 4 million tons, followed by significant contributions from Central Java and North Sumatra. In contrast, regions such as Jakarta showed no production data due to its urbanized landscape that lacks agricultural land, and several provinces in Papua (including Southwest Papua, South Papua, Central Papua, and Highland Papua) have missing data for 2020–2022 as they were newly established administrative regions. These visualizations provide not only a clear differentiation of regional production capacities but also serve as a critical indicator for identifying areas that may benefit from focused developmental strategies. By pinpointing these disparities, the chart offers valuable insights into where infrastructural investments and tailored policy interventions could bolster agricultural development and enhance regional productivity. Figure 7 , therefore, acts as a foundational reference for both researchers and policymakers aiming to understand and address the spatial imbalances in corn production across the nation.

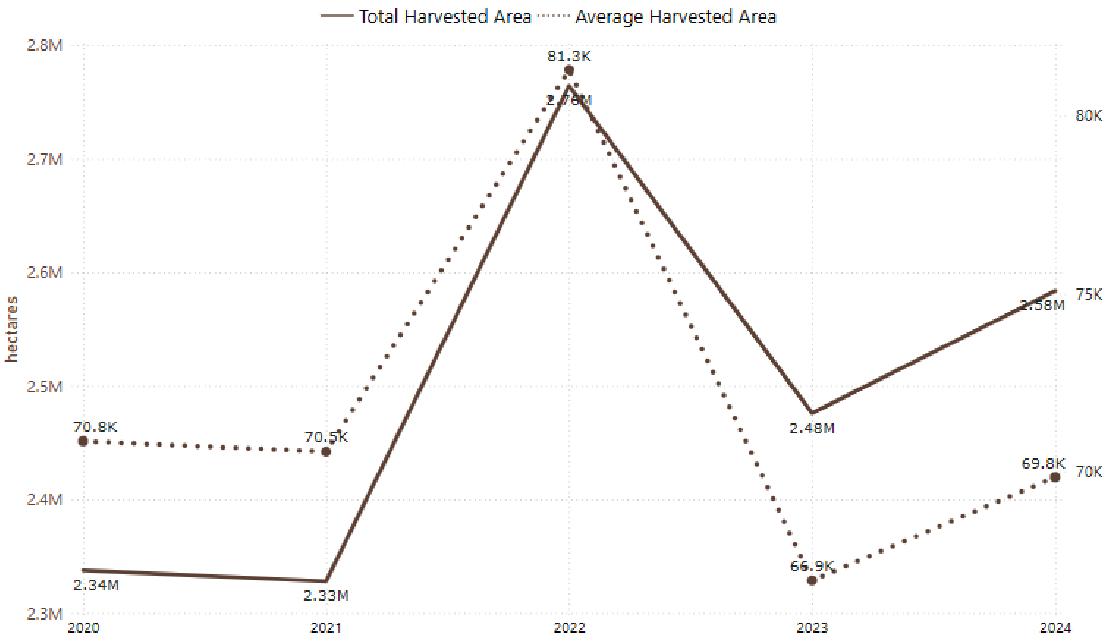


Figure 8. Annual harvested area trends

Annual trends in harvested area from 2020 to 2024 exhibit fluctuations driven by factors such as climate change and land allocation policies. In 2022, the harvested area peaked at 2.81 million hectares, followed by a decline to 2.48 million hectares in 2023, and a slight recovery in 2024. This pattern is significant because it reflects how environmental conditions and policy decisions directly affect agricultural land use. The decline in 2023 may indicate the impact of adverse weather conditions or shifts in land management practices, suggesting vulnerabilities in the current agricultural framework. Moreover, the partial recovery in 2024 implies that while some corrective measures may have been effective, the system has not yet returned to its previous optimal state. Figure 8 offers a clear view of these temporal trends and anomalies, serving as a vital empirical basis for further investigation into the dynamics between environmental factors, land policy, and agricultural productivity.

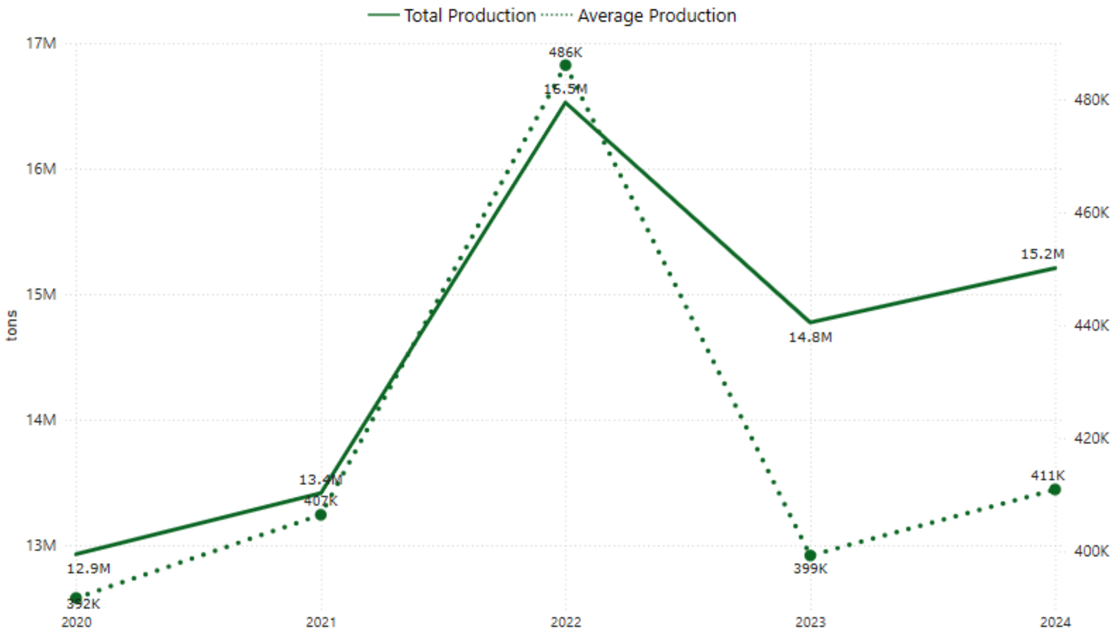


Figure 9. Annual corn production trends

Production trends mirror those observed in the harvested area, with 2022 achieving the highest output at 15.5 million tons, a decline to 14.8 million tons in 2023, and a partial recovery to 15.2 million tons in 2024. This pattern is significant because it underscores the direct influence of external factors such as climate variability, market dynamics, and infrastructural constraints on corn yields. The drop in production in 2023 may reflect the adverse effects of unfavorable weather and supply chain disruptions, while the recovery in 2024 suggests that mitigation strategies and adaptive practices are beginning to yield positive results. Figure 9 provides a visual representation of these fluctuations and serves as an empirical foundation for analyzing the resilience of corn production systems, highlighting the need for continuous monitoring and targeted policy interventions to stabilize yield performance over time.

Figure 10. Summary metrics

A scorecard in Figure 10 summarizes key performance indicators such as average production (2.09 million tons per year), average productivity (258.73 quintals per hectare), and average harvested area (359.45 thousand hectares per year). These aggregate metrics not only provide a snapshot of overall corn production performance but also offer a robust framework for benchmarking agricultural outcomes. The integration of these indicators allows policymakers to evaluate production efficiency and identify critical areas for improvement. Furthermore, the summary metrics serve as a basis for comparing historical trends and projecting future performance under varying policy scenarios and environmental conditions. This empirical foundation is essential for designing targeted interventions and optimizing resource allocation within the agricultural sector.

Discussions

The results highlight significant trends and disparities in corn productivity across regions and years, offering insights into various factors that affect production performance. The peak in harvested area and production volume in 2022 likely reflects favorable conditions, including improved weather and government interventions, whereas the subsequent decline in 2023 underscores the vulnerabilities of agricultural production to external disruptions such as climate change and supply chain issues [5]. The partial recovery in 2024 suggests that corrective measures have been effective, yet it emphasizes the need for sustained efforts to maintain stability in production levels.

Regional disparities in productivity are evident; for example, West Java's high productivity points to the benefits of advanced agricultural technologies, robust infrastructure, and efficient resource management [4], [6]. In contrast, areas with lower productivity encounter challenges such as poor soil quality, limited access to modern farming methods, and insufficient infrastructure. While Jakarta's lack of corn production is an anticipated outcome due to its predominantly urban landscape and limited agricultural zones, this phenomenon warrants a deeper exploration of urbanization's broader implications on regional agricultural dynamics. Urban expansion often precipitates significant changes in land use, influencing not only the availability of arable land but also altering food supply chains and economic relationships between urban centers and their rural peripheries. For instance, Jakarta's case can be seen as a microcosm of how rapid urban development may lead to increased dependency on food production from surrounding regions, potentially creating vulnerabilities in local food security and contributing to socio-economic disparities. Further research should investigate these urban-rural linkages, examining how shifts in demographic patterns, land use policies, and infrastructure development collectively impact agricultural productivity and regional sustainability. Such insights would provide a more nuanced understanding of how urbanization, while expected to reduce local production, also plays a pivotal role in shaping broader agricultural and economic landscapes. Similarly, the lack of data for Papua, Southwest Papua, South Papua, Central Papua, and Highland Papua during 2020–2022 is attributed to their recent administrative establishment rather than a failure in production, underscoring the impact of evolving regional boundaries on data reporting.

Integrating these findings with established agricultural theories reinforces the importance of adopting precision agriculture techniques and data-driven policymaking. The use of Power BI in this study demonstrates how modern Business Intelligence tools can transform raw data into actionable insights, thereby supporting more efficient decision-making. These insights suggest that targeted policies are needed to address regional disparities, improve data collection in newly established regions, and prioritize technological advancements. Future research should explore the long-term impacts of these interventions and expand the application of data visualization tools to additional crops and regions, further contributing to sustainable agricultural development across Indonesia [7], [8], [14].

Conclusion

This study underscores the transformative role of Business Intelligence in addressing Indonesia's agricultural challenges, particularly in analyzing corn production trends and regional disparities between 2020 and 2024. Using Microsoft Power BI, the research revealed critical insights into production volatility linked to climate disruptions, such as a 4.5% decline in 2023, and stark productivity contrasts between high-performing agrarian regions like West Java, which achieved 80 quintals per hectare, and non-agrarian zones such as Jakarta. However, the study has limitations, including data gaps in newly established provinces such as Southwest Papua and reliance on a single BI platform, which may affect the generalizability of findings. Additionally, the simplification of external factors like interactions between climate and market dynamics may underestimate systemic risks. Future research should expand temporal and spatial granularity by integrating IoT and satellite data, employ machine learning to model compound risks such as simultaneous drought and inflation, and compare BI tools including Power BI and Tableau for agricultural applications. Exploring urban farming models in densely populated regions and tracking policy impacts through real-time BI dashboards could further bridge rural-urban divides. By addressing these limitations, interdisciplinary collaborations can advance equitable, data-driven agricultural governance, ensuring resilience across Indonesia's diverse landscapes.

Acknowledgments

We extend our heartfelt gratitude to Universitas Semarang for their unwavering support, which has been instrumental in facilitating this research. Their commitment to fostering academic innovation has enabled us to delve deeply into the intersection of technology and financial behavior. We also wish to express our sincere appreciation to P3M Politeknik Negeri Bali for providing an excellent platform to publish this journal. The opportunity to share our findings through such a reputable publication is greatly valued. The collective support from these institutions has been pivotal in making this study possible and advancing knowledge in the field of financial technology and risk assessment. We are truly grateful for their collaboration and encouragement.

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