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OBAN-AI: AI-Based Mapping of National Rice Surplus and Deficit Using LSTM Neural Network Algorithms for Distribution Optimization as Food Security

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Research Topic: Forecasting Rice Surplus and Deficit in Provinces of Java Using LSTM and Optimization Mapping

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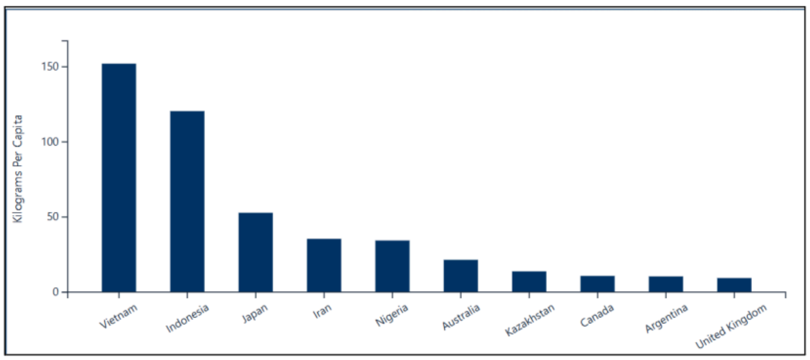
Introduction

Rice is a national strategic commodity in Indonesia, and it is not only a staple food for the majority of Indonesia but also as an economic commodity, which absorbs millions of job opportunities, especially in rural areas. Instability of rice supplies and prices have some consequences not only on economic activities but also on social and political stability in Indonesia. [1]

Indonesia's food security remains vulnerable, with 13.23% of districts still categorized as food insecure despite overall national production stability [2]. The rice supply chain plays a very important role in food security and involves various stages from production to consumption, as well as many actors, including farmers, traders, retailers, and consumers, with 5-7 business actors usually involved [1]. Effective strategies are needed to ensure stable, affordable, and efficient distribution from producers to consumers. Organized distribution can reduce costs, improve efficiency, and ensure quality and timeliness [3].

The National Food Agency (Bapanas) anticipates a surplus of 10.46 million tons of rice in Indonesia by the end of 2024. Even so, the data provided by the Head of the Nusa Tenggara Timur (NTT) Agriculture and Food Crops Office, Joaz Umbu Wanda, according to him, NTT experiences a rice deficit of approximately 200,000 tons per year out of a total requirement of around 622,000 tons per year [4]. The data presented by Umbu is confirmed by the field conditions. The distribution of rice at the provincial level is not evenly distributed. As of 2022, rice distribution across provinces in Indonesia remained uneven, with 11 provinces recording a surplus and 23 provinces experiencing a deficit [5].



Analysis of 2023 data on Global Rice Consumption Per Capita shows significant regional differences. Southeast Asian countries like Vietnam lead with high consumption at 152.08 kg per capita, while Indonesia follows with 120.5 kg per capita. In contrast, countries like Japan (52.82 kg), Iran (35.48 kg), and Nigeria (34.37 kg) depict moderate consumption. Western countries such as Australia (21.5 kg), Canada (10.79 kg), Argentina (10.47 kg), and the United Kingdom (9.38 kg) with the least consumption per capita [6].

Although there is a government program called Bulog rice, which is rice distributed by Perum Bulog, a state owned enterprise (BUMN) tasked with stabilizing the supply and price of staple foods in Indonesia. But, one of the challenges faced by Bulog is the inflexible government purchase price (HPP), which is not relevant to the market [7]. Bulog purchases national reserve rice but faces distribution difficulties, making it dependent on loans or government budgets [8]. The condition of rice in surplus provinces should be able to fill the needs of provinces experiencing a deficit by having a system that promotes equitable distribution [9]. Distribution of staple commodities is not only a regional problem, for example distribution of wheat in China, and its yield is directly related to the development of the national economy [10]. Indonesia's rice consumption per capita in 2022 was 185 kg/year, which is lower than Myanmar (279 kg), Vietnam (228 kg), Laos (227 kg), and Bangladesh (247 kg), but higher than China (134 kg), India (99 kg), and Malaysia (121 kg). This shows that Indonesia still holds high dependence on rice as a primary food source [11].

LSTM networks, renowned for their ability to capture long term dependencies in time series data, have demonstrated remarkable performance in various forecasting tasks [10]. Compared with traditional machine learning methods, deep learning techniques often achieve better performance [10]. CNN and recurrent neural network (RNN) are more widely used models in neural networks and have also been applied to crop yield estimation and prediction [10]. LSTM is a special kind of RNN, due to its recursive structure and gating mechanism that regulates the entry and exit of information into and out of cells, as well as its processing of sequential data [10]. The LSTM has feedback connections and can handle the input sequences of arbitrary length and is often preferred in the classification, processing, and prediction based on time series data [10]. While LSTM offers strong predictive ability, integration with AI based geospatial mapping and optimization algorithms can transform forecasts into actionable distribution strategies. In addition, a recent review by Ikram et al., shows that AI techniques (ANN, CNN, and other models) are increasingly being deployed to improve supply chain management in the food sector [12]. Including inventory control, transportation optimization, and demand forecasting. Thereby helping to make the chain more transparent, responsive, and less wasteful [12].

Although previous studies have used LSTM to predict rice prices, analyze food security issues, or examine long term consumption patterns, none have combined AI based predictions with optimization models to solve specific problems by integrating AI to address the imbalance of rice surpluses and deficits between provinces. This study fills that gap by using a stacked LSTM model to estimate provincial level rice surpluses and deficits, and combining it with minimum cost flow optimization and geospatial mapping to propose real solutions for rice distribution in Java, Indonesia.

Existing Literature

Estimating rice yields and prices using deep learning has become an important research focus in supporting food security. Predicting rice surpluses and deficits using Long Short Term Memory (LSTM) architecture shows great potential in agricultural planning and policy making. This literature review discusses three studies that explore the implementation of LSTM for rice related predictions using different approaches.

Zhou et al. (2023) investigated rice yield prediction in Hubei Province, aiming to predict district level rice yields using remote sensing and deep learning while taking into account spatial heterogeneity [13]. The data sources used in this study were MODIS remote sensing indices (EVI, GPP, SAVI), ERA5 air temperature, rice yield statistics, and dummy variables for spatial heterogeneity [13]. The data type used was a combination of remote sensing images, climate, and crop yield statistics [13]. The CNN-LSTM model achieved the highest performance, reducing prediction error (RMSE) by approximately 20–46% compared to CNN and ConvLSTM [13]. In addition, by incorporating spatial heterogeneity into the model, prediction accuracy increased significantly because it allowed predictions to take account of variations in environmental conditions across different districts [13]. However, this study did not consider economic variables, focusing only on land. In the context of food security, the finding of this study supports planning by identifying spatial variations in crop yields. This reinforces the growing evidence that hybrid models outperform single architecture approaches in agricultural forecasting. While previous approaches often relied solely on statistical or remote sensing data, this study combined climatic, spatial, and temporal information for improved prediction accuracy.

The focus of study done by Sunoto & Siahaan was to compare MLP Regressor and LSTM in predicting rice productivity in 34 provinces [14]. The data source used was BPS data on rice productivity, harvest area, productivity, and production per province [14]. The type of data used was statistical productivity data presented in tabular form [14]. The models used were MLP Regressor and LSTM, and the best model for predicting rice productivity was LSTM [14]. LSTM achieved an accuracy of 94.12% (MSE 0.0030), outperforming MLP (91.18%, MSE 0.0047) [14]. LSTM excels at capturing temporal or seasonal patterns on a national scale, even though this study utilizes statistical inputs and not spatial or remote sensing data [14]. These findings are useful for national agricultural planning and food policy because accurate predictions can anticipate potential rice shortages or surpluses thereby strengthening food security planning.

The research conducted by Hidayat and Wibisonya discusses rice price predictions in Indonesia by incorporating weather variability into the modeling process [15]. The data used comes from daily data between 2015 to 2023, including rice prices, rainfall, temperature, humidity, crop yields, and land area from BMKG, BPS, and the Ministry of Industry and Trade (Disperindag) [15]. The type of data used is time series information covering economic and climatic factors [15]. The model used is Long Short Term Memory (LSTM) with four layers (256–128–64–32 neurons), tested with different training testing splits (80:20 and 70:30) and the number of epochs (100 and 200) [15]. The best performance was achieved with a 70:30 split and 100 epochs, resulting in an RMSE of 0.054 [15]. The advantage of LSTM lies in its ability to capture long term dependencies in sequential data, allowing the model to predict price fluctuations influenced by seasonality and climate [15]. However, this study did not include spatial features or policy related variables. These findings are important because accurate rice price forecasts support market stabilization strategies and provide information for trading decisions.

Deep learning models such as LSTM and CNN-LSTM are preferred because of its ability to capture complex temporal and spatial patterns, handle nonlinear relationships, and deliver higher prediction accuracy compared to conventional statistical methods. This proposal aims to fill the gap by developing a deep learning model that enhances rice forecasting accuracy, therefore supporting food security planning and policy decisions.

Research Question:

1. What are the historical patterns of rice production, consumption, and distribution that create surplus and deficit dynamics across Java's provinces from 2019 to 2024?
2. How can a min-cost flow optimization model be applied to forecasted surplus and deficit data to improve the efficiency of rice distribution across Java?
3. How accurate can an LSTM model forecast rice surplus and deficit using MAPE as the evaluation metric?

Research Aims: The aim of this research is to develop and evaluate an AI based forecasting system to map and predict rice surpluses and deficits in several provinces in Java as an effort to increase the effectiveness of food security through smart technology based on the LSTM algorithm.

Methodology

Research Approach: This research will use quantitative methods, incorporating statistical and mathematical data analysis approaches. A predictive model is utilized to forecast rice surpluses and deficits, enabling the development of AI based mapping analysis for visualizing food distribution. The primary data consists of annual time series rice production records (2019–2024) across Indonesia's 34 provinces, sourced from Badan Pusat Statistik (BPS). The mapping analysis involves AI driven visualization techniques, leveraging Geographic Information Systems (GIS) to map food distribution patterns effectively. All analyses are conducted using the Python programming language within the Google Colab environment.

Methodological Framework: The preparation stage began with identifying food security issues and distribution gaps, as discussed in the Introduction. Next, the scope of the study was defined, covering all 34 provinces in Indonesia during the period 2019 to 2024. Finally, rice production data is collected from reliable sources such as the Central Statistics Agency (BPS) to form a solid basis for further analysis.

Project Practicalities: In the model development stage, annual production data is preprocessed through cleaning and normalization to ensure data quality and consistency. LSTM (Long Short Term Memory) models are then trained and tested using the 2019–2024 time series data. The evaluation metric employed is MAPE (Mean Absolute Percentage

Error), selected for its ability to express accuracy as a percentage, which makes it more intuitive for interpretation. Additionally, MAPE facilitates easier comparisons across provinces with varying production scales and is particularly suitable for communicating how far predictions deviate from actual values.

The optimization stage involves applying Min-Cost Flow optimization to the forecasted surpluses and deficits. Surplus provinces are assigned as supply nodes, while deficit provinces serve as demand nodes. Transport costs and capacity constraints are incorporated into the model to reflect real world logistics. The optimization is run to minimize overall distribution costs, utilizing tools such as Python in Google Colab.

During the evaluation stage, the forecasting model's accuracy is validated by calculating MAPE on the test data. To demonstrate the superiority of the LSTM approach, it is compared against baseline models such as ARIMA and regression. Furthermore, the optimization results are validated by comparing distribution costs and balance metrics before and after applying the min-cost flow algorithm, ensuring the framework's effectiveness in addressing food security challenges.

Research Design: Exploratory research used to analyze rice surplus and deficits patterns from rice consumption and production data from 2019-2024. Then, predictive research develops an LSTM based forecast to predict rice demand/supply. Applied research by implementing optimization algorithm for distribution simulation and visualizing results.

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In this study, data was obtained from the Central Statistics Agency (BPS), covering all 34 provinces. However, for analysis, a smaller sample of five provinces was selected, as they are all located on the island of Java. Java was chosen as the sample because it is considered the national economic center, thanks to adequate infrastructure that supports economic growth [16]. In addition, according to the Central Statistics Agency (BPS), Java accounts for 56.10% of Indonesia's total population. The agency also noted that Indonesia's economy remained concentrated in Java in 2021 [17].

Risk management: In the process of making this research, several potential risks such as data availability and quality, overfitting, and bias in the data. Mitigation measures that have been identified for these risks include collecting data from a variety of valid sources, such as government or market reports, applying a dropout layer to the LSTM model to randomly "turn off" some neurons during training, thereby preventing the network from memorizing patterns, combining official government datasets with independent sources, and transparently disclosing identified biases in reporting.

Potential Limitations & Roadblocks: This model relies on historical production and consumption data, but food security is also influenced by external factors such as changes in government policy, extreme weather events, and rice imports and exports, and these factors cannot be fully predicted by models. While LSTM models are effective in capturing temporal dependencies, they may be prone to overfitting on specific periods of historical data. To address this, validation with new and unseen datasets will be necessary.

Integrating an AI model into the national food distribution system requires coordination between different organizations even if the model works well for predictions, matching policies, and proper use of resources. These challenges related to organization and policy could delay the actual implementation.

Conclusion

Rice is Indonesia's main staple food and is very important for socio economic stability. Although national production is sufficient to meet demand, uneven rice distribution has caused a persistent gap between surplus and deficit regions. The absence of integrated, data driven decision making tools exacerbates this inequality and threatens food security.

This study developed an artificial intelligence (AI) based mapping system to predict and improve the allocation of rice surpluses and deficits, using annual data (2019-2024) from the Central Statistics Agency (BPS), the Ministry of Agriculture, and Kaggle. A Long Short Term Memory (LSTM) neural network is used to predict provincial surpluses and deficits, and the results are combined with a minimum cost flow optimization model to design effective distribution strategies. The accuracy and reliability of the model's performance are evaluated using Mean Absolute Percentage Error (MAPE).

This research advances knowledge by developing an AI based predictive system that forecasts supply and demand trends and translates them into efficient distribution maps. This integration provides practical insights for policymakers to improve food distribution efficiency, reduce costs, and strengthen food security. Additionally, this framework can be adapted for other essential commodities, offering broader applications in food strategies.

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