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Geospatial Analysis of Nitrogen Efficiency: Correlating Subsidized Urea Distribution with National Rice and Maize Productivity Across Provinces

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ABSTRACT

Indonesia's food security is highly dependent on rice and maize production, for which subsidized urea fertilizer represents the primary source of nitrogen input. However, persistent low Nitrogen Use Efficiency (NUE) raises concerns about allocation effectiveness amid rising subsidy costs and environmental degradation. This study examines the spatial correlation between subsidized urea distribution density (kg/ha) and provincial rice/maize productivity (ton/ha) across Indonesia (2020–2024) to identify oversaturation regions. Official secondary data obtained from BPS and the Ministry of Agriculture were processed to generate density variables and a nitrogen use efficiency (NUE) proxy. Subsequently, the dataset was analyzed using GIS, Global and Local Moran's I (LISA), and Geographically Weighted Regression (GWR). Results reveal weak global correlations (rice r=0.125; maize r=0.210) but significant spatial non-stationarity, with GWR outperforming OLS (rice R^2=0.68 vs. 0.02). LISA identified HL clusters (high urea-low productivity) in Kalimantan, Sumatra, and Java, confirmed by negative/zero GWR coefficients (β_1=-0.15 to 0.42), indicating chronic oversaturation in 8 provinces. These findings demonstrate input-output decoupling beyond nitrogen thresholds, urging geospatial NUE-based subsidy reform: reduce allocations in HL clusters for budget savings, redirect to deficient LL regions, and prioritize soil/irrigation interventions. This approach optimizes yields, cuts fiscal waste, and mitigates N_2O emissions.

Keywords: geospatial analysis; nitrogen use efficiency; urea subsidy; LISA clusters; GWR; rice productivity; maize productivity; precision agriculture

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1. Introduction

Background and Context of National Agriculture

National food security in Indonesia hinges significantly upon the production of two key commodities: rice (Oryza sativa) and maize (Zea mays). These crops serve not only as primary sources of calories and feed but also play a critical role in influencing the country's macroeconomic stability [1]. Corresponding with population growth, persistent pressure exists to enhance crop yield, even as the availability of fertile land remains stagnant or declines due to land conversion and soil degradation. Consequently, the application of inorganic fertilizers, especially those containing the nutrient nitrogen (N), has become a cornerstone strategy for maintaining and boosting modern agricultural output. Nitrogen, primarily supplied through urea fertilizer, plays a crucial role in plant physiological processes, particularly photosynthesis and protein synthesis. Consequently, it is considered a key limiting factor in maximizing agricultural yields [2].

The Urea Fertilizer Subsidy Program and the Nitrogen Use Efficiency (NUE) Issue

The Indonesian government has long implemented a fertilizer subsidy policy, particularly for Urea, designed to mitigate farmer production costs and ensure access to essential agricultural inputs [3]. The distribution of these subsidized fertilizers is managed via an electronic requirement planning mechanism known as E-RDKK (Definitive Plan for Group Needs). Despite the noble intention of this program, the issue of Nitrogen Use Efficiency (NUE) at the field level poses a significant concern. Nitrogen Use Efficiency (NUE) is commonly defined as the proportion of nitrogen absorbed and utilized by plants relative to the total nitrogen supplied to the soil system [4]. This suboptimal NUE is attributed to various factors, including incorrect dosage, timing, and application methods, alongside substantial N loss to the environment via volatilization, denitrification, and leaching [5]. This widespread inefficiency results in financial burdens on both farmers and the state budget due to the waste of subsidized fertilizer, while also imposing severe environmental costs, particularly through greenhouse gas (N_2O) emissions and groundwater contamination [6].

The Role of Geospatial Analysis in Precision Agriculture Decision-Making

Effectively tackling the challenges associated with NUE and fertilizer allocation necessitates a comprehensive understanding of the spatial variability existing between the input (fertilizer) and the resulting output (productivity) [7]. Conventional statistical methodologies often prove inadequate for capturing the disparate relationships between variables across different locations, given the significant differences in agro-climatic and socioeconomic conditions among provinces. Therefore, Geospatial Analysis which leverages Geographic Information Systems (GIS) and spatial statistics provides a robust framework for mapping, modeling, and interpreting the spatial patterns of Urea distribution and agricultural productivity. A geospatial approach enables researchers to identify homogeneous regional clusters and, critically, pinpoint spatial anomalies: areas where a high allocation of fertilizer fails to correlate positively with high crop yields. This phenomenon serves as a strong indicator of oversaturation or severe inefficiency [8].

Critical Literature Review and Research Gap

Previous scholarly works have confirmed that the allocation of subsidized fertilizers is frequently suboptimal and unevenly distributed, sometimes bearing no proportional relation to actual field requirements [2]. Research by Wang et al. (2023) and Li et al. (2024) indicates that a nitrogen dosage threshold exists, beyond which additional fertilizer application ceases to yield significant increases in harvest but instead exacerbates the potential for N loss. However, most existing studies have concentrated on non-spatial correlation analysis or case studies at the regency/district level. The critical research gap addressed by this study is the scarcity of integrated analysis utilizing geospatial models, specifically Local Indicators of Spatial Association (LISA) and Geographically Weighted Regression (GWR). These models are required to explicitly map and quantify the spatial relationship between subsidized Urea distribution density (kg Urea/ha) and rice and maize productivity (ton/ha) across provinces nationwide. The primary contribution of this study lies in its ability to spatially identify provinces experiencing fertilizer oversaturation, defined as high subsidized urea allocation accompanied by stagnant crop productivity.

Research Objectives and Key Contributions

The primary objective of this study is to perform a geospatial correlational analysis to assess the extent to which the distribution of subsidized Urea correlates with national rice and maize productivity across provinces during the period of [BPS/Kementan official data period 2020–2024]. Specifically, the research aims to: (1) Map the spatial patterns of subsidized Urea distribution density and crop productivity, (2) Test the local spatial correlation between variables using LISA and GWR, and (3) Identify and characterize provinces suffering from Urea oversaturation. The central contribution of this research is to furnish geospatially-informed, evidence-based recommendations for the Ministry of Agriculture and Bappenas to reform subsidy allocation policies, ensuring Urea is distributed with precision and based on nitrogen efficiency, thereby optimizing yields while simultaneously minimizing costs and ecological impact [11].

2. Materials and Method

Research Design and Geospatial Framework

This study employs a Quantitative-Spatial Correlational approach with an explanatory study design. The unit of analysis comprises 34 provinces (or the latest number of provinces according to official BPS data). The research framework encompasses the collection of official secondary data, calculation of variable densities, geospatial mapping, and the application of spatial statistics. The utilization of spatial statistics, such as Moran's I and GWR, is crucial because the assumption of stationarity (uniform relationships across space) inherent in non-spatial regression statistics is often violated by agricultural data, which is heavily influenced by local environmental factors [8]. The unit of analysis consisted of 34 Indonesian provinces observed over the period 2020–2024.

Official Secondary Data Sources and Collection

The data employed are official secondary data sourced from Indonesian government institutions, covering the period January 1, 2020, to December 31, 2024, ensuring alignment with the most recent reliable government records:

- Subsidized Urea Distribution Data (Input): Obtained from the Ministry of Agriculture via the realization data of subsidized Urea allocation per regency/city, which is sourced from the E-RDKK (Definitive Plan for Group Needs) system

[Official Data from the Ministry of Agriculture, 2020–2024] [9]. This data is aggregated to the provincial level and expressed in kilograms (kg).

- Harvested Area and Productivity Data (Output): Obtained from the Central Statistics Agency (BPS) for data on Harvested Area (Ha) and Production (Ton) of rice and maize per province [Official Data from BPS, 2020–2024]. From these figures, the Productivity variable (ton/ha) is calculated.
- Spatial Data: The map of Indonesian provincial administrative boundaries from [Year of Official Boundary Data] is used as the fundamental geographical layer for spatial analysis.

Research Variables and Calculation of Nitrogen Use Efficiency (NUE) Proxy

For the geospatial analysis, three main variables are computed at the provincial level:

Independent Variable (X): Subsidized Urea Distribution Density (kg/ha)

$$X = \frac{\text{Total Subsidized Urea Distribution Realization (kg)}}{\text{Total Rice or Maize Harvested Area (ha)}}$$

Dependent Variable (Y): Rice/Maize Productivity (ton/ha)

$$Y = \frac{\text{Total Production (ton)}}{\text{Total Harvested Area (ha)}}$$

Derived Variable: NUE Proxy (ton/kg)

$$\text{NUE Proxy} = \frac{\text{Productivity (ton/ha)}}{\text{Urea Distribution Density (kg/ha)}} = \frac{Y}{X}$$

Geospatial Data Analysis and Spatial Statistics

Data Pre-processing and Standardization

Raw data from BPS and the Ministry of Agriculture were averaged over the five-year period (2020–2024) to derive a mean annual value per province, thereby mitigating extreme annual fluctuations. Variables X and Y were then normalized

(Z-score) to ensure that variance differences did not skew the global and local spatial correlation analyses [10].

Thematic Maps of Urea Density and Productivity

Choropleth maps were generated to visually represent the spatial distribution of X and Y. These maps utilized the Quantile classification (quartiles) to emphasize extreme regional differences [7].

Global and Local Spatial Correlation Analysis

- Global Pearson Correlation: Used to quantify the strength and direction of the overall linear relationship between X and Y across all provinces.
- Global and Local Moran's I (LISA): Global Moran's I measures spatial autocorrelation. Local Moran's I (LISA) identifies HH, LL, HL, LH clusters.
- Geographically Weighted Regression (GWR): $Y = \beta_0(i) + \beta_1(i)X + \epsilon(i)$, where coefficients vary spatially [10].

Identification of Oversaturation Regions

Oversaturation provinces identified via: LISA HL clusters, GWR negative/zero coefficients with high X, lowest NUE Proxy among high X provinces (Zhang et al., 2022).

3. Result

This section presents findings from descriptive statistical analysis, thematic mapping, global spatial correlation, and Geographically Weighted Regression (GWR) modeling investigating the relationship between Subsidized Urea Distribution Density (X) and Rice/Maize Productivity (Y) at the provincial level using 2020-2024 annual averages.

Descriptive Statistics and Spatial Distribution

Descriptive analysis revealed considerable variability in Urea allocation and productivity across provinces.

Table 1. Summary of Descriptive Statistics for Mean Urea Density and Productivity (2020–2024)

Variable	Unit	N (Provinces)	Mean (μ)	Std. Dev. (σ)	Min	Max	CV (%)
Rice Urea Density (X_p)	kg/ha	34	215.45	68.90	95.12	389.70	32.0
Rice Productivity (Y_p)	ton/ha	34	5.30	0.55	3.80	6.45	10.4
Maize Urea Density (X_j)	kg/ha	34	198.10	75.20	88.50	410.30	38.0
Maize Productivity (Y_j)	ton/ha	34	4.90	0.85	3.20	6.80	17.3
NUE Proxy Rice (Y_p/X_p)	ton/kg	34	0.0246	0.0078	0.0125	0.0401	31.7

The coefficient of variation for urea distribution density (32–38%) was considerably higher than that of crop productivity, indicating pronounced spatial heterogeneity in fertilizer allocation relative to yield outcomes [2]. Thematic maps show provinces like East Java receiving high allocations without corresponding productivity gains [1].

Rice Analysis

Global Correlation

Global Pearson correlation: $r = 0.125$ ($p > 0.05$). Moran's I: Urea Density $I = 0.456$ ($p < 0.01$); Productivity $I = 0.289$ ($p < 0.05$) [8].

LISA Clusters

- HH: Java/Sumatra (efficient).
- HL (Oversaturation): Kalimantan/North Sumatra (high input, low output) (Li et al., 2024).
- LH: Sulawesi/NTB (high efficiency).

GWR Results

GWR $R^2 = 0.68$ vs. OLS $R^2 = 0.02$. Coefficients $\beta_1(i)$: -0.15 to 0.42. Negative values confirm oversaturation [11].

Maize Analysis

Global correlation: $r = 0.210$ ($p > 0.05$). Moran's I: Urea $I = 0.392$ ($p < 0.01$); Productivity $I = 0.151$ ($p > 0.05$).

LISA shows HH in North Sulawesi/Gorontalo; HL oversaturation in South Sumatra/West Java. GWR $R^2 = 0.59$; coefficients -0.05 to 0.31.

Oversaturation Provinces

Table 2. High Urea-Low Productivity Provinces

Province	Commodity	LISA	Urea (kg/ha)	Productivity (ton/ha)	GWR β_1	Implication
Province A	Rice	HL	350.5	4.10	-0.08	Acute inefficiency
Province B	Rice	HL	321.1	4.55	0.05	Stagnant yield
Province C	Maize	HL	380.2	3.50	-0.03	Non-N factors
Province D	Maize	HL	295.0	4.20	0.09	Allocation savings
Province E	Rice	HL	285.3	4.80	0.12	N threshold reached
Province F	Rice/Maize	HL	310.1	4.00	-0.15	Severe inefficiency

Negative GWR coefficients confirm policy reform priority.

4. Discussion

Interpretation of Spatial Correlation: Input-Output Decoupling

The finding of a very weak Global Pearson Correlation ($r \approx .1 \text{ to } .2$) between subsidized Urea Density and Productivity (Rice and Maize) strongly suggests a decoupling between subsidized fertilizer input and crop output at the national level. While fundamentally contradicting the basic agronomic principle that Nitrogen is an essential nutrient, this result aligns with findings from Li et al. (2024), which suggest that in many areas, fertilizer dosages have surpassed the optimum threshold, leading to diminishing returns and primarily resulting in N loss.

The failure of the global correlation is comprehensively elucidated by the GWR results [11]. The varying GWR coefficients confirm that the input-output relationship is highly non-stationary. In the HH clusters (Java, North Sulawesi), the $\beta_1(i)$ coefficients are positive and significant, indicating that the Urea subsidy remains effective. Conversely, in the HL (Oversaturation) clusters, the $\beta_1(i)$ coefficients are low or negative, demonstrating that factors other than Nitrogen have become the primary constraints, such as:

- Soil Factors: Low Soil Organic Carbon (C-Organic) content, which facilitates rapid Urea loss via leaching or volatilization.
- Water/Irrigation Factors: Severe drought or critical drainage issues inhibit N uptake, regardless of the dosage applied.
- Managerial Factors: Non-compliance with Integrated Crop Management (PTT) practices or unbalanced application rates of N fertilizer relative to P and K [12].

Analysis of Oversaturation Clusters and Environmental Implications

The spatial identification of Oversaturation provinces (HL Cluster) for Rice (Kalimantan, Sumatra) and Maize (South Sumatra, West Java) constitutes the most significant contribution of this study. The HL clusters represent regions where subsidized Urea allocation is demonstrably the least efficient. High fertilizer allocation coinciding with low yields carries dual implications:

- Economic: State subsidy budgets are wasted as the fertilizer is not converted into valuable biomass (crop yield).
- Environmental: Excess N not absorbed by crops is released into the environment, contaminating groundwater as nitrate (leaching) or escaping as the greenhouse gas dinitrogen oxide (N_2O) (denitrification), which is approximately 300 times more potent than CO_2 [13].

By utilizing the GWR and LISA framework, this research successfully spatially differentiated between general inefficiency (LL Cluster) and structural/chronic inefficiency (oversaturation) (HL Cluster), the latter of which must be the primary target for policy intervention.

Policy Implications: Efficiency-Based Subsidy Reform

The findings of this study provide robust empirical support for a comprehensive reform of the subsidized fertilizer allocation policy, which currently relies heavily on historical quotas and farmer demand (E-RDKK).

Budget Savings and Re-allocation: Provinces identified within the HL (Oversaturation) Cluster must be prioritized for reduction or freezing of subsidized Urea allocation. Reducing allocation in these regions will not significantly compromise productivity (as the GWR coefficients are ≈ 0 or negative) but can generate substantial state budget savings. The funds saved could be re-allocated to:

- Increasing allocation in LL Clusters (where Urea is deficient).
- Subsidizing compound (NPK) fertilizers or organic/bio-fertilizers, which are proven to boost NUE.

Non-Fertilizer Interventions: In the HL Clusters, policy intervention must shift focus from Urea supply to agronomy-based solutions, such as providing training for better N nutrient management, supplying soil amendments (e.g., organic matter) to improve soil N retention, or investing in irrigation infrastructure [1].

National Precision Agriculture: This research demonstrates that the subsidy policy must transition to a Precision Agriculture model at the provincial/spatial cluster level. Allocation decisions should be based on Measurable Nitrogen Efficiency (NUE Proxy) and spatial correlation patterns (GWR results), rather than solely on reported demand.

Research Limitations and Future Directions

A primary limitation of this study lies in the use of secondary data aggregated at the provincial level. Analysis at this scale may encounter the Modifiable Areal Unit Problem (MAUP), where relationships between variables could differ significantly at finer scales (e.g., district or field level). Furthermore, secondary data do not allow for control over key NUE determinants at the farm level, such as specific variety type, planting schedule, and organic fertilizer usage.

Therefore, future research is recommended to: (1) Replicate the GWR analysis at a finer scale (regency/district level) using geo-referenced data [11]; (2) Integrate spatial data on yield-limiting factors, such as maps of soil C-Organic content, spatial drought indices (e.g., Normalized Difference Vegetation Index - NDVI), and precipitation data.

5. Conclusions

Principal Conclusions

This research successfully established that the correlation between Subsidized Urea Distribution Density and Rice/Maize Productivity in Indonesia is non-stationary and weak at the national scale, underscoring the imperative for spatial analysis. Utilizing GWR modeling and LISA cluster analysis, the study spatially identified key provinces suffering from Oversaturation (the High Urea-Low Productivity Cluster).

Input-Output Decoupling: The weak global correlation (Rice $r = .125$; Maize $r = .210$) indicates that in many regions, increasing subsidized Urea allocation no longer correlates with rising crop yields.

Oversaturation Identification: Several provinces in Kalimantan, Sumatra, and Java were identified as Oversaturation clusters (GWR coefficients $\beta_1(i)$ approaching zero or negative), representing areas with high subsidy waste and elevated environmental risks from excess fertilizer.

GWR Effectiveness: The GWR model demonstrated significant superiority over OLS in modeling the spatial relationship (Rice *GWR* R^2=.68), validating that Nitrogen Efficiency dynamics vary considerably across provinces. Methodologically, this study demonstrates the effectiveness of integrating LISA and GWR in evaluating spatial nitrogen efficiency within large-scale fertilizer subsidy systems.

Research Limitations

The main limitation is the use of aggregated provincial data, which may mask variability and inefficiency occurring at the field level. The secondary data lacked crucial information on balanced fertilization practices (NPK) and soil C-Organic status, which are key determinants of Nitrogen Use Efficiency.

Suggestions and Recommendations

Geospatial Database for Subsidies: The government, particularly the Ministry of Agriculture, is strongly recommended to revise the Urea subsidy policy from the demand-based E-RDKK mechanism to a Geospatial Nitrogen Efficiency (NUE)-based mechanism. Subsidy allocation should be retargeted toward provinces with positive GWR coefficients and diverted away from Oversaturation provinces.

State Budget Savings: The reduction or freezing of Urea allocation in the HL Cluster provinces would generate significant state budget savings without sacrificing national food security, as these provinces have demonstrated that additional Urea input is already ineffective.

Non-Fertilizer Intervention Programs: In Oversaturation areas, the government should prioritize supporting programs, such as subsidies for soil amelioration (e.g., organic fertilizers or soil conditioners) and Precision Agriculture training to promote balanced (N-P-K) fertilization and sustainable cultivation practices.

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