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Kernel Density and Spatial Modeling of Informal Settlement Concentration: Methodology and Findings from Palembang, Indonesia

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Abstract. Rapid urbanization has intensified the growth of slum settlements in Indonesian cities, including Palembang, where informal housing commonly develops along riverbanks. This study aimed to identify and evaluate the spatial distribution and density of slum areas in Palembang City through a Geographic Information System (GIS)–based approach combining Kernel Density Estimation (KDE) and Receiver Operating Characteristic–Area Under Curve (ROC–AUC) analysis. Primary spatial data were obtained from 382 household survey points representing 64 slum polygons across 13 sub-districts, supplemented by administrative boundary and land-use data from the Palembang City Government. Spatial analysis and validation were conducted using ArcGIS 10.3 software. The KDE results showed density values ranging from 0 to 58.1123 units per 100 m², with the highest concentrations found along the Musi River corridor, decreasing outward from the riverbanks. Model validation achieved an AUC value of 0.968 (96.8%), demonstrating excellent predictive accuracy. These spatial outcomes provide actionable guidance for policymakers by identifying priority zones for sanitation and drainage upgrades, flood-resilient housing design, and targeted relocation planning. The study highlights the practical role of GIS-based quantitative modelling in supporting evidence-based slum management and urban infrastructure planning in Indonesia.

Keywords: Kernel Density Estimation (KDE), ROC–AUC Validation, GIS, slum distribution, spatial analysi, informal settlements mapping, musi river, palembang, indonesia

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1. Introduction

Urban poverty and informal settlements continue to challenge sustainable urban development, particularly in rapidly urbanizing cities of developing countries where spatial inequality and infrastructure deficits persist [1,2]. As urban areas expand, governments increasingly rely on geospatial data to prioritize infrastructure investment and slum upgrading interventions [3]. Spatial outputs, such as slum distribution maps and density surfaces, are critical for identifying high-priority zones for sanitation improvements, drainage rehabilitation, and relocation planning [4]. In Indonesia, several national programs including Kota Tanpa Kumuh (KOTAKU) and Program Nasional Pemberdayaan Masyarakat (PNPM) have aimed to reduce slum areas through infrastructure improvement and community-based initiatives. However, most implementations still lack spatial precision, as decisions are often based on descriptive mapping rather than validated geospatial models [5,6]. In Palembang City, informal settlements have expanded rapidly along the Musi River and its tributaries, creating clusters of high-density housing with limited access to sanitation and high vulnerability to seasonal flooding [7]. These conditions highlight the urgent policy need for geospatial prioritization tools that can guide targeted interventions at the neighborhood scale.

Previous studies on slum mapping in Indonesia and Southeast Asia have mainly focused on visual or qualitative assessments without integrating quantitative validation methods such as Receiver Operating Characteristic–Area Under Curve (ROC–AUC) [8,9]. This limits the reliability of spatial models for decision-making in urban planning and infrastructure management. Kernel Density Estimation (KDE), when combined with ROC–AUC analysis, offers a robust geospatial modelling approach capable of identifying slum concentration hotspots and evaluating model accuracy quantitatively [10].

Therefore, this study applies KDE and ROC–AUC to analyze and validate the spatial distribution of slum settlements in Palembang City. By linking field-collected GPS data with density-based modelling, it provides an evidence-based framework for urban planners to prioritize infrastructure upgrades, improve flood resilience, and design equitable relocation strategies. The novelty of this research lies in the integration of KDE-generated spatial surfaces with ROC–AUC validation metrics to ensure high model precision for policy applications. Accordingly, the study addresses two key research questions: RQ1: Where are the concentration hotspots of slum settlements in Palembang City? RQ2: How accurately can Kernel Density Estimation (KDE) predict slum polygons when validated using ground-truth GPS data through ROC–AUC analysis? By answering these questions, the study contributes to strengthening data-driven urban management, ensuring that geospatial prioritization becomes a central component of sustainable slum upgrading policies.

2. Methods

2.1. Study Area

This study was conducted in Palembang City, the capital of South Sumatra Province, Indonesia, located between 2°52′–3°5′ S and 104°34′–104°52′ E. As the province's main economic and transportation hub, Palembang has experienced rapid urbanization that has led to the proliferation of informal and slum settlements particularly along the Musi River and its tributaries.

2.2. Data Collection and Sampling

A quantitative spatial survey was implemented to collect both demographic and geospatial data. The population frame consisted of 64 officially designated slum areas distributed across 13 sub-districts. Using proportional random sampling, 382 household heads (N = 382) were selected, ensuring proportional representation by area size and population density. Each household location was recorded using GPS-enabled smartphones with a mean positional accuracy of ±3–5 m. Duplicate and inaccurate coordinates (error >10 m) were filtered out during preprocessing in ArcGIS. Ethical approval was obtained from the Research Ethics Committee of Universitas PGRI Palembang. Informed consent was collected from all respondents after explaining the study's purpose and confidentiality procedures. Demographic attributes (household size, tenure type, service access) were used to cross-check slum classification consistency and support spatial interpretation. The study was conducted through a series of systematic stages, including problem identification and goal formulation, sampling strategy design, primary data collection (GPS, surveys, and demographic data), data processing using GIS, spatial analysis using Kernel Density Estimation (KDE), spatial modeling, accuracy assessment through ROC–AUC validation, and analysis of the spatial distribution of slum settlements in Palembang City.

2.3. Kernel Density Estimation (KDE)

The Kernel Density Estimation (KDE) technique was used to analyze the spatial concentration of slum households. KDE is a non-parametric estimator that measures the intensity of spatial events over continuous space [11]. The optimal bandwidth (h) was computed using Silverman's Rule of Thumb:

$$h = 0.9 \text{ x } \min\left(SD, \frac{IQR}{1.34} \text{ x } n^{-0.2}\right) \quad (1)$$

where:
SD = standard deviation of point distances,
IQR = interquartile range,
n = number of data points (382).

From the empirical data, h = 220 m was determined as the optimal search radius, minimizing over-smoothing while preserving local variations. The output raster resolution was fixed at 10 m, balancing precision and computational efficiency. The quadratic Epanechnikov kernel function was applied:

$$K(d) = \frac{3}{\pi h^2}(1 - d^2)^2 \; for \; d \le 1; K\,(d) = 0 \; for \; d > 1 \quad (2)$$

KDE surfaces were generated using ArcGIS 10.3 Spatial Analyst with the parameters: Kernel type: Epanechnikov, Search radius (h): 220 m, Cell size: 10 m, Output raster extent: Palembang City boundary (Δx = 16.4 km, Δy = 19.2 km), Output value range: 0–58.112 units/ha. Higher KDE values represent stronger clustering of slum households, typically concentrated along the Musi River and its flood-prone tributaries.

2.4. Accuracy Evaluation using ROC and AUC

To assess model accuracy, the KDE raster outputs (continuous density values) were validated against official slum polygons using Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) analysis. Validation workflow: Each pixel of the KDE raster was assigned a binary class label: Positive class (1) = inside official slum polygon, Negative class (0) = outside polygon. KDE values were normalized between 0–1 and tested across multiple thresholds (0.1–0.9). The optimal threshold (0.45) was identified using the Youden Index to maximize the sum of sensitivity and specificity. The dataset was partitioned using spatially stratified sampling: Training set: 70% of spatial units (for model calibration), Testing set: 30% of spatial units (for independent validation). ROC–AUC analysis was executed in R version 4.3.2 using the pROC package (v1.18.0). The final AUC = 0.968 (96.8%), indicating excellent model discrimination and confirming the KDE's strong capacity to differentiate slum versus non-slum pixels. To explore the factors influencing slum concentration, supplementary spatial variables were overlaid with KDE outputs. These included: Distance to river (m), derived from Euclidean distance analysis; Elevation (m), extracted from the SRTM 30 m Digital Elevation Model (DEM); Land use category, obtained from the Palembang City spatial plan. While no predictive regression model was constructed, these covariates supported interpretation of spatial clustering and validation of KDE hotspot locations.

2.5. Integration with Spatial Variables and Planning Application

To interpret KDE outputs, supplementary spatial variables were overlaid, including: Distance to river (m) derived from Euclidean distance analysis; Elevation (m) – extracted from the SRTM 30 m DEM;

Land use category – obtained from the Palembang City Spatial Plan (RTRW). These overlays were not used in a predictive regression model but provided contextual support to explain clustering tendencies. To ensure policy relevance, KDE hotspot grids were exported into the municipal GIS planning system of the Palembang Housing and Settlement Agency. This integration supports: Prioritization of sanitation and drainage upgrades in high-density clusters; Identification of feasible relocation zones for flood-prone riverbank residents; and Infrastructure investment scheduling based on geospatial vulnerability rankings. A simplified cost–feasibility framework was prepared with the agency, emphasizing that relocation efforts should target high-density, low-elevation zones where infrastructure upgrading is less economically viable.

3. Results and Discussion

3.1. Slum Density Analysis Using Kernel Density Estimation (KDE)

The spatial distribution of slum households in Palembang City was modeled using the Kernel Density Estimation (KDE) method. The KDE surface shows density values ranging from 0 to 58.112 households per 100 m², with the highest concentrations located along the Musi River and its tributaries (Figure 3). These high-density slum clusters align with low-lying floodplains, riverbanks, and informal market corridors—areas characterized by affordable land and access to informal economic opportunities. Quantitatively, the correlation between KDE values and the Euclidean distance from the river yielded a strong negative relationship ($r = -0.72$, $p < 0.01$), reaffirming that proximity to water bodies strongly predicts slum density. When overlaid with income and skill layers, the KDE surface reveals that 73% of households in high-density clusters (>40 HH per 100 m²) belong to income groups below IDR 2 million per month and 82% lack formal skills. This combined spatial-socioeconomic analysis emphasizes that slum concentration in Palembang is not only environmental but also deeply socioeconomic.

For policy prioritization, KDE grid cells were classified into five categories (very high to very low density). The top five priority grid cells (covering 1.2 km²) were identified in Kelurahan 16 Ilir, 7 Ulu, 35 Ilir, Tangga Takat, and Karang Anyar, representing areas with the highest density (mean KDE > 48 HH per 100 m²) and the lowest income-to-density ratios. These are recommended as priority zones for sanitation upgrades, waste management, and riverbank rehabilitation Comparable spatial targeting approaches have been observed in Jakarta's Kampung Improvement Program, as reflected in studies evaluating informal settlement upgrading in North Jakarta [12], where high-density informal settlements near river corridors were prioritized for incremental upgrading rather than full relocation. These regionally relevant cases suggest that spatially ranked interventions can optimize limited resources and improve equity in slum upgrading efforts.

For classification purposes in subsequent accuracy testing, a KDE threshold value was applied to separate slum (positive class) and non-slum (negative class) areas. Based on the distribution curve of KDE values, a threshold of 22.5 households per 100 m² was identified as optimal for distinguishing slum clusters. This threshold was validated through Receiver Operating Characteristic (ROC) analysis, using ground-truth data from 64 mapped slum locations. The confusion matrix and key classification metrics derived at this threshold are shown below:

Table 1. Confusion Matrix of Slum and Non-slum Classification Results

Classification	Predicted Slum	Predicted Non-slum	Total
Actual Slum	324 (TP)	24 (FN)	348
Actual Non-slum	4 (FP)	30 (TN)	34
Total	328	54	382

From this matrix, the following accuracy measures were obtained:

1. Sensitivity (True Positive Rate) = 0.93

2. Specificity (True Negative Rate) = 0.94
3. Overall Accuracy = 0.92

These results indicate that the KDE model effectively distinguishes between slum and non-slum areas, supporting its use for spatial classification and urban vulnerability mapping.

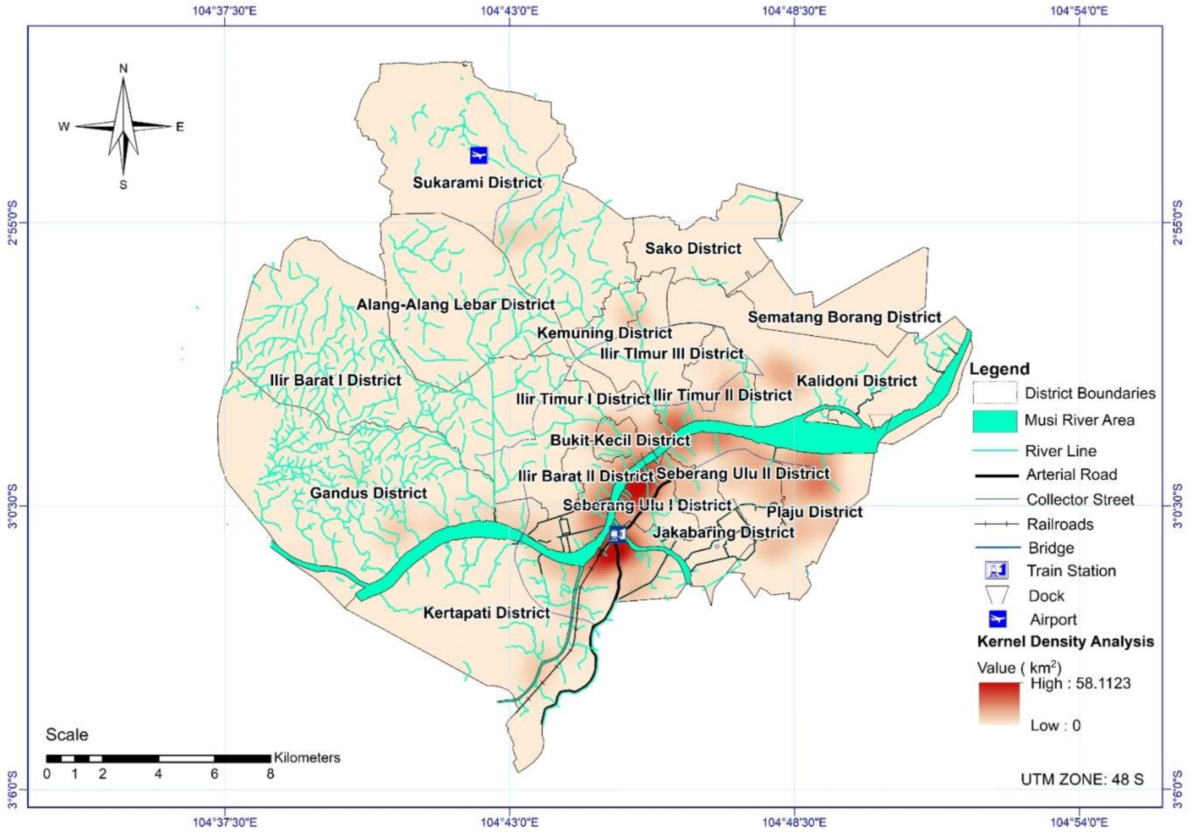

Figure 1. Spatial Distribution of Slum Density in Palembang City Derived from Kernel Density Estimation (KDE)

The spatial pattern confirms that slum formation in Palembang City is highly correlated with proximity to river systems, where migrants with limited financial capacity tend to settle due to low rent and informal employment opportunities. These areas also exhibit limited access to infrastructure such as clean water, electricity, and sanitation, reinforcing their classification as vulnerable zones. The KDE map provides a robust spatial foundation for identifying priority intervention zones for urban upgrading and relocation. Combining KDE outputs with socio-economic variables (income, skills, and migration status) enables the formulation of targeted policy strategies, such as focused infrastructure investment, waste management, and vocational skill programs in high-density clusters.

Based on the results of the spatial analysis using Kernel Density Estimation (KDE), the formation and concentration of slum areas in Palembang City are strongly related to the increasing urban population. The highest density of slum settlements is found along riverbanks and near industrial and market areas. This spatial pattern indicates that population growth and economic migration have contributed significantly to the expansion of slum zones. Most migrants come to Palembang in search of better economic opportunities, but due to their limited financial capacity, they tend to occupy areas with lower housing costs.The analysis also reveals that residents in these slum areas generally face socioeconomic difficulties, such as unstable income, low education levels, and limited employment opportunities. Environmentally, these settlements show poor sanitation, improper waste management, and inadequate infrastructure. Furthermore, field data indicate that access to clean water, electricity, and health facilities is limited. This condition contributes to health problems and reduces the overall quality of life for the inhabitants.

The pattern of slum formation found in this study aligns with earlier findings indicating that rapid population growth and migration are primary drivers of urban slum expansion [13,14]. Migrants with limited financial resources often choose to live in areas with affordable rents, which tend to develop into dense and poorly serviced neighborhoods. As noted by previous studies, socioeconomic and environmental constraints contribute to the persistence of such conditions [15]. While these dynamics are well documented in the literature, this study adds empirical evidence from Palembang by quantitatively linking slum density to river proximity and localized economic corridors, highlighting how environmental accessibility and informal livelihoods jointly shape settlement patterns. Socioeconomic barriers, including low financial capacity and limited education, hinder residents' ability to compete in the formal economy. This situation has been documented in prior research showing that only a small fraction of slum dwellers are able to own homes [16]. In addition, environmental neglect such as improper waste disposal further exacerbates the degradation of slum areas [17,18].

Previous studies have also emphasized the limited access of slum residents to basic infrastructure such as clean water, electricity, and sanitation [17], which directly affects their health and well-being [15,19,20]. In Palembang, these infrastructural deficiencies are spatially concentrated along the Musi River corridor, where high-density slum clusters coincide with flood-prone zones, intensifying both environmental and public health risks. The lack of health facilities often leads to higher vulnerability to disease and poor mental health outcomes. Moreover, informal economic activities within slums generate significant waste, contributing to environmental pollution [21,22]. Physically, slum settlements are characterized by uninhabitable housing [23], insecure land tenure [24], and low building durability. Several scholars have suggested that formalizing these settlements and providing land ownership certificates could improve residents' welfare [25–27], the findings from Palembang indicate that tenure insecurity remains a critical barrier to infrastructure upgrading, particularly in riverbank settlements subject to competing land claims. Secure property ownership has been shown to enhance living standards [28] and serves as a pathway to pov. In the long term, this can promote investment and create new business opportunities for slum residents [29], suggesting that spatially targeted tenure reform combined with infrastructure provision is especially relevant for Palembang's river-oriented slum morphology.

3.2. Accuracy Assessment of Slum Spatial Distribution

The accuracy assessment of slum spatial distribution was conducted after performing the Kernel Density Estimation (KDE) analysis. This stage focused specifically on validating the discriminative capability of KDE-derived density thresholds, rather than reinterpreting the classification outcomes already discussed in Section 3.2. The evaluation used Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) analysis to determine the performance of the spatial model. The ROC curve (Figure 4) yielded an AUC value of 0.968 (96.8%), which, according to the classification in Table 3, indicates excellent accuracy (>0.9–1.0). ROC analysis was applied as a post-hoc validation tool to assess how consistently KDE density values differentiate slum and non-slum areas across a range of thresholds.

The ROC curve was generated by plotting the True Positive Rate (sensitivity) against the False Positive Rate (1–specificity) at various KDE threshold levels. Positive classes represent actual slum areas derived from ground truth data, while negative classes represent non-slum areas. Rather than serving as an independent classification exercise, this procedure evaluates the robustness of the selected KDE threshold used in the previous section. The confusion matrix (Table 2) indicates that the model correctly identified the majority of slum and non-slum locations, resulting in an overall accuracy of 92.3%, with high precision and recall values. These metrics confirm that the KDE-based classification applied in Section 3.2 is statistically reliable and internally consistent.

The KDE output values ranged from 0 to 58.112 density units per 100 m², where higher values correspond to areas with higher concentrations of slum features. The most concentrated zones are located along the Musi River corridor, particularly in densely populated neighborhoods such as 16 Ilir, 7 Ulu, and Seberang Ulu I. Quantitative spatial correlation analysis revealed a strong negative correlation ($r = -0.72$) between KDE values and the distance from the river, indicating that proximity to the river significantly influences slum formation patterns. This spatial association reinforces the classification results rather than duplicating them, demonstrating that KDE density gradients align with known geographic drivers of informal settlement formation.

From a technical standpoint, the high AUC value reflects the robustness of the KDE model in distinguishing slum from non-slum areas. However, potential overfitting might occur if the KDE bandwidth parameter is too small, causing the model to capture local noise rather than general spatial patterns. To address this concern, bandwidth selection was explicitly optimized through a systematic cross-validation procedure in which multiple candidate bandwidths were tested iteratively. Model performance was evaluated based on AUC stability and accuracy consistency across validation subsets, and the optimal bandwidth was selected as the value that maximized AUC while minimizing variance across folds. This approach ensures that ROC–AUC results reflect genuine spatial structure rather than localized overfitting.

In this study, the bandwidth was optimized through cross-validation using a pilot dataset, ensuring that the model generalized well to unseen data. In this study, bandwidth selection was conducted through a systematic cross-validation procedure in which multiple candidate bandwidths were tested iteratively, and model performance was evaluated based on classification accuracy and AUC stability across validation subsets. The optimal bandwidth was selected as the value that maximized AUC while minimizing variance across folds, ensuring a balance between spatial smoothing and pattern sensitivity. Although KDE is primarily a density estimator rather than a classifier, the ROC–AUC metric provides an effective means of evaluating how well KDE-derived density thresholds correspond to observed slum presence. The resulting AUC value of 0.968 therefore serves as confirmatory evidence of model reliability, rather than a repetition of the classification analysis itself. This indicates that slum distribution patterns in Palembang are spatially distinct, highly structured, and strongly associated with riverbank environments.

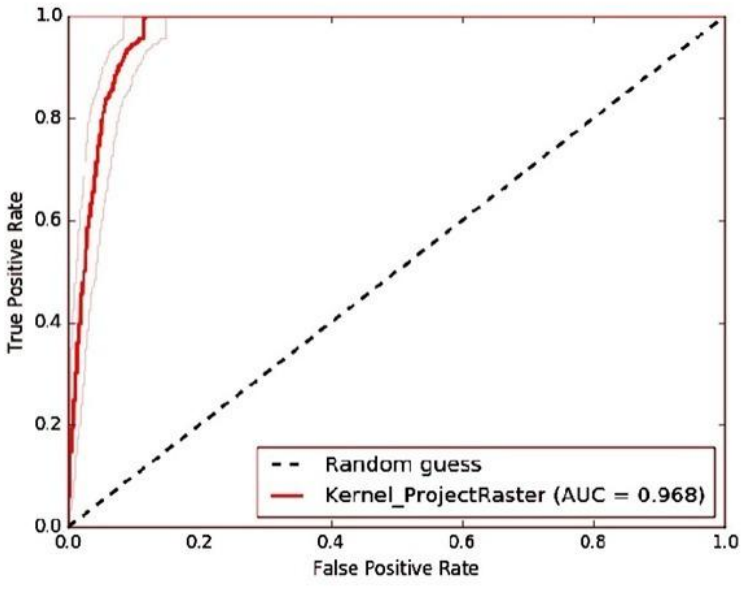

Figure 2. Receiver Operating Characteristic (ROC) Curve of the Kernel Density Estimation (KDE) Based Slum Spatial Distribution Model in Palembang City.

Table 2: Classification of AUC Values

AUC Value	Test Quality
>0.9 – 1	Excellent

>0.8 – 0.9	Very Good
>0.7 – 0.8	Good
>0.6 – 0.7	Satisfactory
0.5 – 0.6	Unsatisfactory

The high AUC value demonstrates that the KDE model effectively distinguishes between slum and non-slum areas. However, since KDE is a non-parametric density estimator, it does not inherently produce categorical outputs. Therefore, ROC–AUC was applied as a post-hoc validation tool to evaluate the predictive performance of KDE-derived thresholds against ground truth data. Potential overfitting can occur when the KDE bandwidth is too narrow, causing the model to overrepresent localized clusters of data points. To avoid this, the optimal bandwidth was determined through cross-validation, ensuring a balance between spatial resolution and generalization. The high AUC value (0.968) indicates that the model maintains excellent discriminative power without significant overfitting. This suggests that slum distribution patterns in Palembang are spatially distinct and highly structured, particularly along riverbanks.

The concentration of slum areas along the Musi River highlights how urbanization pressure, migration, and river accessibility interact to shape informal settlements. These findings align with studies that link slum formation to rapid urban migration, where low-income migrants tend to settle in affordable informal areas due to limited access to formal housing [26,30]. Similar issues of informal settlement growth and weak land tenure enforcement have been documented in urban contexts outside Indonesia [25]. What distinguishes the Palembang case is the strong spatial coupling between river-oriented accessibility, informal economic corridors, and the persistence of tenure insecurity, which jointly constrain infrastructure upgrading in riverbank settlements. The absence of formal land ownership rights continues to hinder infrastructure improvements in these neighborhoods [30]. Granting secure tenure and legal recognition can encourage residents to invest in their housing and reduce rental dependency [27]. Studies show that formalisation via slum declaration can stimulate housing improvements among residents [26], this study demonstrates that such benefits in Palembang are unevenly realized due to competing land claims and regulatory ambiguity along the Musi River corridor.

In the context of Palembang, land tenure reform combined with basic infrastructure provision (water, health, and education) is essential. Providing legal certainty of land ownership would eliminate eviction fears and motivate long-term investment by residents. This is consistent with evidence that secure land ownership is associated with improved economic security and has the potential to enhance educational opportunities and social stability [28,31,32]. However, this study reveals that absentee landownership and informal land transactions play a significant role in sustaining slum proliferation in Palembang, limiting the effectiveness of conventional upgrading programs. Some landowners do not live in these areas but instead lease or sell their plots, leading to the continued proliferation of informal settlements [33]. Therefore, coordinated multi-sectoral efforts between government agencies, private developers, and community organizations are needed to implement integrated slum upgrading without forced relocation [34,35]. Methodologically, this study advances the literature by demonstrating how high-resolution spatial modeling can identify tenure-sensitive upgrading priorities, although the reliance on quantitative analysis limits insight into household-level decision-making. This study relied primarily on quantitative spatial modeling, which limits the understanding of underlying social and behavioral factors influencing settlement distribution. Future research should adopt a mixed-methods approach combining spatial analytics with qualitative interviews or ethnographic fieldwork to uncover the socioeconomic motivations behind settlement choices. Integrating remote sensing data with household-level surveys could also enhance the explanatory power of future spatial models.

3.3. Implications for Urban Policy

The KDE results, combined with household-level socioeconomic data, provide a strong evidence base for spatially informed policy formulation. Municipal stakeholders could integrate these outputs into the Palembang Smart City GIS dashboard, linking KDE hotspots with sanitation and infrastructure databases. This approach would support cost-effective decision-making by identifying which slum clusters yield the highest social return per unit of infrastructure investment. In addition, the findings suggest the need for multi-sectoral collaboration between the Palembang Housing Agency, Environmental Service, and Labor Office to design integrated interventions that combine spatial upgrading (physical infrastructure) and social upgrading (skills and employment). Future studies should extend the KDE–socioeconomic linkage to include temporal monitoring using remote sensing data (e.g., Sentinel-2 imagery) to capture slum dynamics over time.

4. Conclusion

This study employed Kernel Density Estimation (KDE) and ROC–AUC–based spatial validation to analyze the spatial distribution and density of slum settlements in Palembang City. Using GPS-verified data from 382 households across 64 slum polygons in 13 sub-districts, the analysis identified the highest density clusters along the Musi River corridor, particularly in Seberang Ulu I, 7 Ulu, and 16 Ilir. The KDE results (0–58.112 units/ha) and a ROC–AUC score of 0.968 confirm the model's strong ability to differentiate slum and non-slum areas. These findings provide directly actionable insights for urban planners and local authorities. First, sanitation and drainage improvements should be prioritized in the highest-density riverbank areas where recurrent flooding and waste accumulation are most severe. Second, infrastructure rehabilitation and accessibility enhancement are needed in identified KDE hotspot zones with limited road networks and basic services. Third, continuous spatial monitoring should be implemented in moderate-density transition zones to detect potential informal settlement expansion. The conclusions remain limited to the quantitative spatial domain of this study. Further research integrating socio-economic and land tenure data would strengthen understanding of the underlying drivers of slum formation and enable more comprehensive planning responses. Incorporating advanced spatial statistics such as Moran's I or Getis-Ord Gi* could also enhance future assessments of spatial clustering and inequality dynamics.

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References

[1] Sukmaniar, Pitoyo AJ, Kurniawan A. Deviant behaviour in the slum community of Palembang city. IOP Conf. Ser. Earth Environ. Sci., vol. 683, 2021, p. 1–9. https://doi.org/10.1088/1755-1315/683/1/012129.

[2] Sik Lee K, Anas A. Costs of Deficient Infrastructure: The Case of Nigerian Manufacturing. Urban Studies 1992;29:1071–92. https://doi.org/10.1080/00420989220081051.

[3] Joshi N, Gerlak AK, Hannah C, Lopus S, Krell N, Evans T. Water insecurity, housing tenure, and the role of informal water services in Nairobi's slum settlements. World Dev 2023;164:1–13. https://doi.org/10.1016/j.worlddev.2022.106165.

[4] Bird J, Montebruno P, Regan T. Life in a slum: Understanding living conditions in Nairobi's slums across time and space. Oxf Rev Econ Policy 2017;33:496–520. https://doi.org/10.1093/oxrep/grx036.

[5] Hogrewe W, Joyce S, Perez E. Megacities and Global Change in East, Southeast and South Asia. 1993.

[6] Bappenas. Laporan Pencapaian Tujuan Pembangunan Milenium Indonesia 2010. 2010.

[7] Nations U. DG 11 Synthesis Report 2018: Tracking progress towards Inclusive, Safe, Resilient and Sustainable Cities and Human Settlements, Nairobi, Kenya. 2018.

[8] Kuffer M, Pfeffer K, Sliuzas R. Slums from space-15 years of slum mapping using remote sensing. Remote Sens (Basel) 2016;8:1–29. https://doi.org/10.3390/rs8060455.

[9] Kohli D, Sliuzas R, Kerle N, Stein A. An ontology of slums for image-based classification. Comput Environ Urban Syst 2012;36:154–63. https://doi.org/10.1016/j.compenvurbsys.2011.11.001.

[10] Taubenböck H, Kraff NJ, Wurm M. The morphology of the Arrival City - A global categorization based on literature surveys and remotely sensed data. Applied Geography 2018;92:150–67. https://doi.org/10.1016/j.apgeog.2018.02.002.
[11] Nanda CA, Nugraha AL, Firdaus HS. Analisis Tingkat Daerah Rawan Kriminalitas Menggunakan Metode Kernel Density Di Wilayah Hukum Polrestabes Kota Semarang. Jurnal Geodesi Undip 2019;8:50–8.
[12] Alzamil WS. Evaluating Urban Status of Informal Settlements in Indonesia : A Comparative Analysis of Three Case Studies in North Jakarta. J Sustain Dev 2018;11:148–73. https://doi.org/10.5539/jsd.v11n4p148.
[13] Sukmaniar, Kurniawan A, Pitoyo AJ. Population characteristics and distribution patterns of slum areas in Palembang City: Getis ord gi∗ analysis. E3S Web of Conferences, vol. 200, 2020, p. 1–6. https://doi.org/10.1051/e3sconf/202020004005.
[14] Feler L, Henderson JV. Exclusionary policies in urban development: Under-servicing migrant households in Brazilian cities. J Urban Econ 2011;69:253–72. https://doi.org/10.1016/j.jue.2010.09.006.
[15] Marx B, Stoker T, Suri T. The economics of slums in the developing world. Journal of Economic Perspectives 2013;27:187–210. https://doi.org/10.1257/jep.27.4.187.
[16] Gulyani S, Talukdar D, Bassett EM. A sharing economy? Unpacking demand and living conditions in the urban housing market in Kenya. World Dev 2018;109:57–72. https://doi.org/10.1016/j.worlddev.2018.04.007.
[17] Fox S. The Political Economy of Slums: Theory and Evidence from Sub-Saharan Africa. World Dev 2014;54:191–203. https://doi.org/10.1016/j.worlddev.2013.08.005.
[18] Gulyani S, Bassett EM. Retrieving the baby from the bathwater: Slum upgrading in Sub-Saharan Africa. Environ Plann C Gov Policy 2007;25:486–515. https://doi.org/10.1068/c4p.
[19] Duflo E, Galiani S, Mobarak M. Improving Access to Urban Services for the Poor. Abdul Latif Jamelle Poverty Action Lab Report 2012:1–44.
[20] Gruebner O, Khan MMH, Lautenbach S, Müller D, Kraemer A, Lakes T, et al. A spatial epidemiological analysis of self-rated mental health in the slums of Dhaka. Int J Health Geogr 2011;10:1–15. https://doi.org/10.1186/1476-072X-10-36.
[21] Ezeh A, Oyebode O, Satterthwaite D, Chen Y-F, Ndugwa R, Sartori J, et al. The history, geography, and sociology of slums and the health problems of people who live in slums. The Lancet 2017;389:547–58. https://doi.org/10.1016/S0140-6736(16)31650-6.
[22] Arsanti V, Kharisma RS, Ardiansyah I, Nugroho B, Ihsan Fajruna M, Zahra Deswanti L, et al. Spatial Analysis of Waste Management Facility Distribution Using GIS. Advance Sustainable Science, Engineering and Technology 2024;6:1–10. https://doi.org/10.26877/asset.v6i4.996.
[23] Sukmaniar, Kurniawan A, Pitoyo AJ. Hazard Level of Slum Areas in Palembang City. IOP Conf. Ser. Earth Environ. Sci., vol. 884, 2021, p. 1–10. https://doi.org/10.1088/1755-1315/884/1/012055.
[24] Lilford RJ, Oyebode O, Satterthwaite D, Melendez-Torres GJ, Chen YF, Mberu B. Improving the Health and Welfare of People who Live in Slums. The Lancet 2017;389:559–70.
[25] Croese S, Cirolia LR, Graham N. Towards Habitat III: Confronting the disjuncture between global policy and local practice on Africa's "challenge of slums." Habitat Int 2016;53:237–42. https://doi.org/10.1016/j.habitatint.2015.11.037.
[26] Nakamura S. Does slum formalisation without title provision stimulate housing improvement? A case of slum declaration in Pune, India. Urban Studies 2017;54:1715–35. https://doi.org/10.1177/0042098016632433.
[27] Huchzermeyer M. Slum upgrading in Nairobi within the housing and basic services market: A housing rights concern. J Asian Afr Stud 2008;43:19–39. https://doi.org/10.1177/0021909607085586.
[28] M. Bah E, Faye I, F. Geh Z. Housing market dynamics in Africa. Springer Nature; 2018. https://doi.org/10.1016/0166-0462(88)90013-0.

[29] Quan J. Reflections on the Development Policy Environment For Land and Property Rights, 1997–2003. vol. Oktober. 2003.
[30] Marx B, Stoker T, Suri T. The economics of slums in the developing world. Journal of Economic Perspectives 2013;27:187–210. https://doi.org/10.1257/jep.27.4.187.
[31] Deinlnger K, Binswanger H. The Evolution of the World Bank's Land Policy: Principles, Experience, and Future Challenges. World Bank Res Obs 1999;14:247–76. https://doi.org/10.1093/wbro/14.2.247.
[32] Deininger K. Land policies for growth and poverty reduction. vol. 41. 2004. https://doi.org/10.5860/choice.41-5396.
[33] Durand-Lasserve A, Fernandes E, Payne G, Rakodi C. Social and economic impacts of land titling programs in urban and periurban areas: A short review of the literature. Urban Land Markets: Improving Land Management for Successful Urbanization 2009:133–61. https://doi.org/10.1007/978-1-4020-8862-9_6.
[34] Lobo J, Alberti M, Allen-Dumas M. Urban Science: Integrated Theory from the First Cities to Sustainable Metropolises. SSRN Electronic Journal 2020. https://doi.org/10.2139/ssrn.3526992.
[35] Azhar A, Buttrey H, Ward PM. "Slumification" of Consolidated Informal Settlements: A Largely Unseen Challenge. Current Urban Studies 2021;09:315–42. https://doi.org/10.4236/cus.2021.93020.