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Evaluation of Health Facilities Location to Support Accessibility to Essential Health Services in Bandar Lampung City, Lampung Province, Indonesia

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Abstract: Health remains one of the most important aspects of every human life, with access to quality healthcare services being a pivotal component of human well-being. In Indonesia, health facility distribution has been characterized by disparities, primarily concentrated on the populous Java Island. This distribution inequity underscores a significant challenge in achieving Sustainable Development Goals (SDGs) under Goal 3, which aims to ensure healthy lives and promote well-being for all. Bandar Lampung, the most densely populated city in Lampung Province and one of Sumatra's most populated cities, experiences an intensified demand for healthcare facilities due to its substantial population. However, the city grapples with numerous infrastructural challenges, including suboptimal road conditions that hinder accessibility to essential healthcare services. These challenges further underscore the urgency of assessing and addressing the healthcare infrastructure within Bandar Lampung. This research seeks to undertake a comprehensive evaluation of health facility availability in Bandar Lampung City, as well as an in-depth analysis of the accessibility of healthcare services in different areas of the city. To achieve this, the study employs the Network Analysis Tool, which leverages road network data to model travel distances and times. In addition to road network data, geospatial population data sourced is integrated into the analysis to gauge the demand for healthcare facilities within Bandar Lampung. This multifaceted approach is essential in comprehensively addressing the complex interplay between supply and demand in the healthcare sector. The combination of these datasets culminates in the creation of an accessibility model that unveils the disparities in healthcare access across Bandar Lampung. The model highlights areas where accessibility to healthcare facilities remains surprisingly low, despite the city's high population density. Conversely, it also identifies regions with high accessibility, potentially serving as templates for improving healthcare distribution in underserved areas. By revealing these disparities, this research contributes valuable insights to healthcare planning and policy formulation in Bandar Lampung and offers a template for addressing similar challenges in other regions with uneven healthcare distribution.

Keywords: *accessibility model, health facilities, spatial analysis*

Introduction

Health is undeniably one of the most vital aspects of human well-being, reflecting the overall quality of life. A key determinant of this quality is the accessibility of health facilities to all members of society [1-3]. In the context of Indonesia, a nation with a population of approximately 278 million people, ranking fourth in the world in terms of population [4], ensuring access to healthcare services has become an increasingly complex challenge. The continuous and rapid growth of Indonesia's population has given rise to a multitude of interconnected problems, particularly in the environmental sphere.

One of the significant repercussions of the surging population is the ever-increasing number of motor vehicles on the roads. As of 2021, there were over 22 million registered motor vehicles in Indonesia, representing a substantial surge in vehicular traffic [5]. This surge, in turn, poses a serious threat to Indonesia's air quality, which can have adverse effects on the health of its citizens. Furthermore, the escalating population has contributed to issues such as deforestation and urban sprawl, exacerbating global warming and adversely affecting public health [6-12]. These challenges underscore the urgent need for Indonesia to take action to achieve one of the Sustainable Development Goals (SDGs) under goal 3, which aims to ensure healthy lives and promote well-being for all [1].

One of the most densely populated cities in Indonesia is Bandar Lampung City, situated in the southernmost part of Sumatera Island and serving as the capital of Lampung Province. Lampung Province plays a critical role as a 'connector' for people traveling to Sumatera Island via land routes. The population of the Bandar Lampung metro area in 2023 has reached 1,162,000, marking a 2.11% increase from the previous year [13]. Given this population growth, ensuring the accessibility of health facilities for the residents of Bandar Lampung has become a primary concern. This challenge is further compounded by the deteriorating quality of the city's road infrastructure in certain areas [14] Consequently, it is imperative to conduct an evaluation of the accessibility of health facilities in Bandar Lampung to inform decision-makers about the necessity of establishing new healthcare facilities.

The objective of this study is to assess the accessibility of health facilities in Bandar Lampung by developing a spatial model that takes into account both accessibility and availability. This model leverages existing data, including the geographical locations of various types of health facilities and the road network. In addition, it integrates spatially-based population data to analyze the equilibrium between the supply and demand for healthcare services. The study utilizes Geographic Information System (GIS) and spatial analysis techniques to achieve these objectives.

While several studies have pursued similar goals, such as the work by Weiss et al [15], developed a global maps of travel time to healthcare facilities by utilizing Google and Open Street Map (OSM) data and managed to create 1km x 1km spatial product of the model, and the study by Hijriani and Putra [16], which developed an accessibility model for Bandar Lampung City using the ARIA method, there remains a noticeable gap in the literature – specifically, the lack of supply and demand analysis. Consequently, this study seeks to address this gap by conducting a spatial analysis of health facility supply and demand in Bandar Lampung.

Furthermore, the study aims to compare its model with the one developed by Weiss et al [15] as a form of validation. This comparison will involve employing statistical approaches to assess the accuracy and applicability of the proposed spatial model in the context of Bandar Lampung's healthcare accessibility. By doing so, this research aims to contribute to the improvement of healthcare infrastructure and accessibility in Bandar Lampung, ultimately promoting the well-being of its residents.

Method

Study Area

The study area was located in Bandar Lampung City (**Figure 1**), which necessitates a systematic effort to improve health facilities access. Bandar Lampung is one of the most populated cities in Sumatera Island. Located in southernmost part of Sumatera Island, holding a critical role of connecting Sumatera and Java Island. According to the City Health Department [17], Bandar Lampung city have a total of 19 hospitals, 81 public health centers (puskesmas), 109 clinics, 495 independent practice doctors, and 333 pharmacies. These health facilities expected to accommodate the citizen of Bandar Lampung. As Bandar Lampung City maintains the highest population and urbanization in Lampung Province, coupled with its demographic diversity, a comprehensive approach is demanded to assess the accessibility of health facilities.

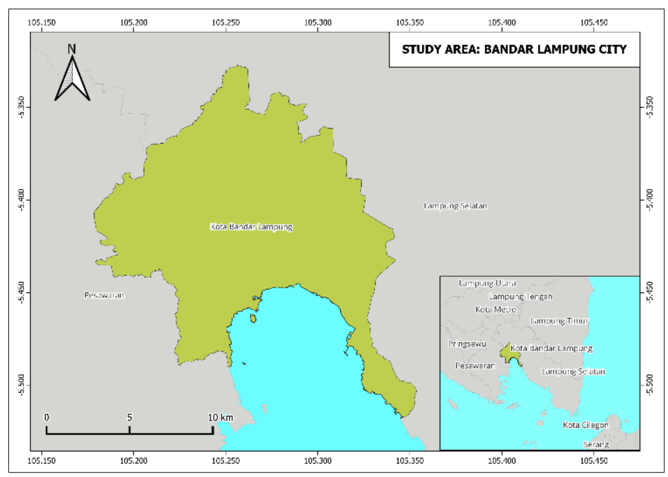

Figure 1. Study Area

Data

Various geospatial data were used and integrated to improve the quality of the results. **Table 1** summarizes the data that were used for this study.

The process of enhancing the health facilities dataset involved a dual-pronged approach, incorporating information from both the BIG data and OpenStreetMap sources to ensure a more comprehensive and exhaustive representation of healthcare services. The initial dataset from BIG data solely comprised hospital information, while the OpenStreetMap data enriched it by including details on clinics, doctors, dentists, and pharmacies. This amalgamation broatadened the scope of available health facilities, providing a more nuanced understanding of the healthcare landscape.

Table 1. Summary of data types and sources.

No	Dataset	Data Source	Data Type-Format	Reference
1	Health Facilities Location	Open Street Map and Indonesian Geospatial Agency (BIG)	Vector	[18-19]
2	Road Data	OpenStreetMap	Vector	[18]
3	Provincial and District Boundaries	BIG	Vector	[19]
4	WorldPop Population Density	WorldPop	Raster	[20]

Following the integration of data, a systematic categorization was applied, classifying the health facilities into five distinct types: Hospitals (encompassing major health facilities, whether private or public), Doctors, Dentists, Clinics, and Pharmacies. This categorization facilitated a more granular analysis, allowing for targeted insights into specific healthcare domains within the study area.

Simultaneously, road data was sourced from the OpenStreetMap website, forming the basis for constructing a comprehensive network dataset. This network data played a pivotal role in the development of an accessibility model, aiding in the assessment of the ease with which individuals could access different types of health facilities. The provincial and district boundaries were employed to delineate the geographical extent of the study area, adhering to a 1:50,000 scale for precise mapping and analysis.

To gauge the demand for health facilities within the study area, WorldPop population density data was incorporated. The population density information served as a key determinant, with higher densities indicating a greater demand for health facilities. This approach ensured that the accessibility model not only considered the spatial distribution of health facilities but also factored in the population dynamics, aligning the provision of healthcare services with the varying needs of different regions based on their population densities. In essence, the integration of diverse datasets and the application of a multifaceted analytical approach aimed to create a robust and insightful framework for understanding the healthcare landscape and accessibility within the specified geographic context.

Health Facilities Accessibility Analysis

This examination employs an adapted methodology, drawing inspiration from the approach outlined in Sakti et al. [21], which successfully devised a novel model for assessing the accessibility of school locations through GIS. The primary focus of this analysis centers on the utilization of the network analysis method to compute distances from health facilities (**Figure 2**). In an effort to delineate accessibility, this study introduces a categorization of distances into five variability levels: <1km, 1km – 2km, 2km – 3km, 3km – 4km, and >4km. Subsequently, these distance ranges are further segmented into five classes and were rasterized using the SAW method ranging from very low accessibility (class 1) to very high accessibility (class 5), as detailed in **Table 2**, displaying the corresponding classes and their respective scores. The outcomes of this classification are subsequently transformed into raster format to facilitate subsequent analyses. This comprehensive methodology not only adapts a proven approach from prior research but also introduces refined distance categorizations and accessibility classes, culminating in a detailed and nuanced assessment of health facility accessibility within the study area.

Table 2. Classes of The Health Facilities Accessibility.

No	Distance (km)	Class/Score
1	0 – 1000	5
2	1000 – 2000	4
3	2000 – 3000	3
4	3000 – 4000	2
5	>4000	1

Health Facilities Demand Analysis

In this analysis, population density data serves as the basis for deriving the demand for health facilities, where elevated density values signify an increased demand [22]. The data is structured in a grid format with dimensions of 100m x 100m, aligning with the anticipated resolution of the resulting raster. To harmonize with the preceding analysis, the population density is categorized into five distinct classes by using SAW method. **Table 3** provides a comprehensive breakdown of this classification, along with the corresponding scores assigned to each class. By segmenting the population density into discrete classes, this approach enables a coherent comparison with earlier analyses, contributing to a unified and systematic

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understanding of the relationship between population density and the demand for health facilities.

Table 3. Classes of The Health Facilities Demand.

No	Population Density (person/100 km^2)	Class/Score
1	4 – 18	1
2	18 – 37	2
3	37 – 59	3
4	59 – 78	4
5	78 – 114	5

Health Facilites Supply-Demand Analysis

A comprehensive Supply-Demand analysis was undertaken to assess the overall availability of health facilities. Building upon the outcomes of the preceding two analyses, this approach involves a straightforward summation of the accessibility and demand values. The results of the Accessibility analysis serve as the supply, while the results of the Demand analysis represent the demand. To articulate the interplay between supply and demand, a nuanced scoring system is employed. Initially, the accessibility values are transformed into tens, ranging from 10 to 50, and then added to the demand values, which fall within the range of 1 to 5. Consequently, the cumulative results yield scores between 11 and 55, contingent upon the magnitude of the preceding accessibility and demand values. For instance, a score of 15 signifies very low accessibility but exceptionally high demand, whereas a score of 51 indicates extremely high accessibility but a minimal demand (noteworthy is the interpretation where the first digit pertains to supply or accessibility, and the second digit pertains to demand). Equation 1 outlines the formula elucidating the generation of these results. Importantly, these steps are systematically applied to all categories of health facilities individually, ensuring a nuanced and differentiated evaluation for each type.

$$SD = (Ac \times 10) + Dm \qquad \textbf{(1)}$$

Where *SD* is Supply-Demand score, *Ac* is accessibility score, and *Dm* is demand score.

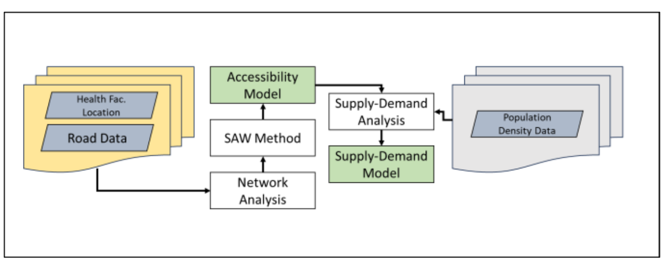

Figure 2. Analysis Flowchart

Results And Discussion

Accessibility Level

The findings from the accessibility analysis, as illustrated in **Figure 3-7**, shed light on the predominant distribution of high accessibility levels concentrated in the central region of Bandar Lampung. This trend is particularly evident when considering various facilities, with pharmacies exhibiting a notably higher accessibility level compared to doctors. The spatial representation reveals that private practice doctors and dentists occupy the smallest areas with high to very high accessibility levels. The abundance of pharmacies, dispersed widely across Bandar Lampung, contributes to their elevated accessibility levels compared to other healthcare facilities.

The lower accessibility levels, categorized as low to very low, may indicate either a deficiency in facility availability or a sparse population in those areas, rendering the services less essential. This aspect will be delved into further in the subsequent section of this discussion.

Interestingly, hospitals present a distinct pattern with high to very high accessibility observed primarily in the southeast part of the region. This anomaly is attributed to the presence of "Balai Pengobatan Lanal Lampung," a hospital situated in that locality. Similarly, clinics exhibit a unique accessibility pattern, with high to very high levels noted in the eastern part of the region, owing to the presence of "Klinik Nusantara." A comprehensive overview of the area and percentage distribution for each facility type is provided in **Table 4** for comparative analysis. The abbreviations used in the table include Pharmacies (PH), Hospitals (HP), Doctors (DC), Dentists (DS), and Clinics (CL), facilitating a concise understanding of the accessibility levels associated with each health facility type.

Table 4. Percentage of Total Area for Each Facilities Types Accessibility Level

Classes	Percentage of Total Area (%)				
	PH	HP	DC	DS	CL
Very Low	30.38	39.26	64.11	51.56	38.68
Low	6.98	11.86	12.09	12.25	7.87
Medium	10.21	14.66	10.55	14.22	16.39
High	21.27	19.29	9.29	15.60	23.55
Very High	31.16	14.93	3.96	6.37	13.50

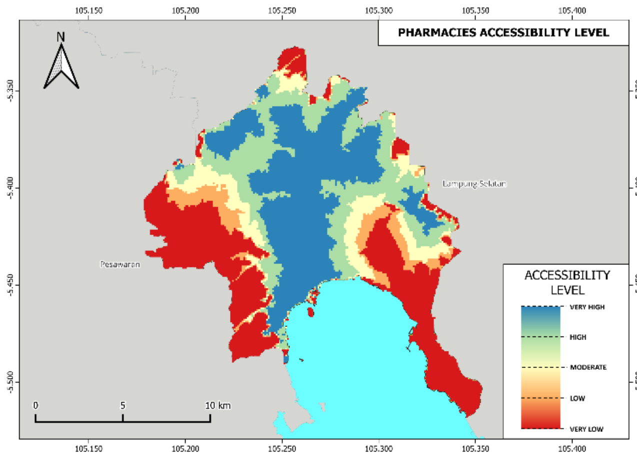

Figure 3. Pharmacies Accessibility Level

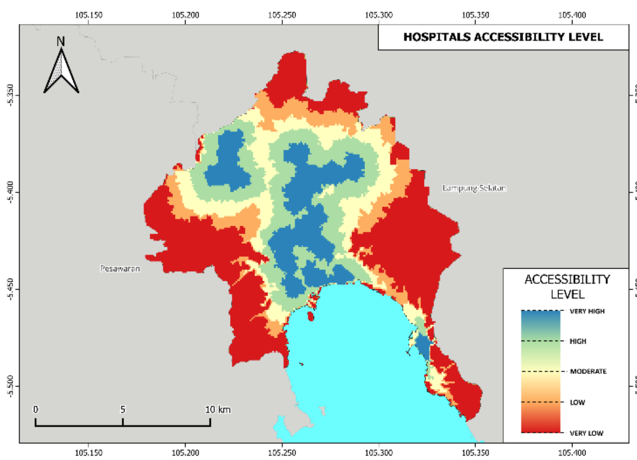

Figure 4. Hospitals Accessibility Level

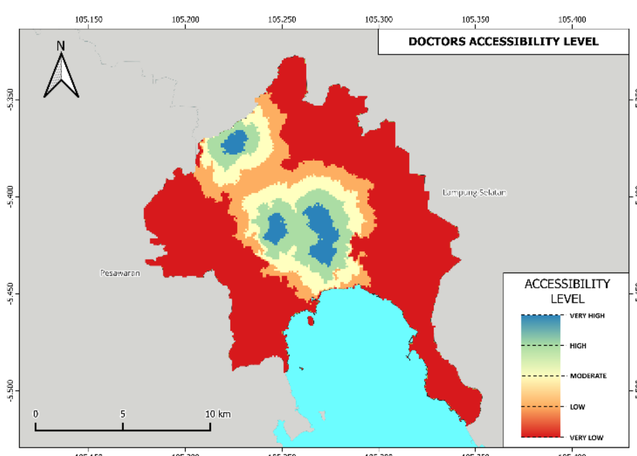

Figure 5. Doctors Accessibility Level

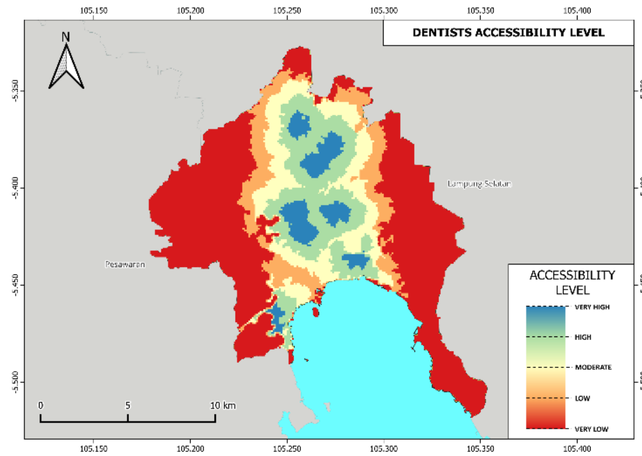

Figure 6. Dentist Accessibility Level

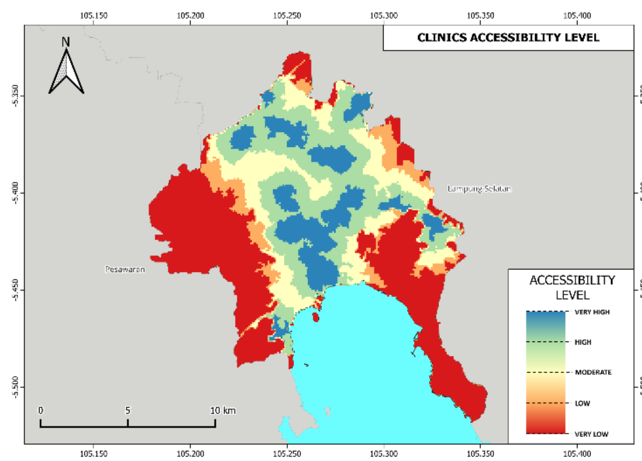

Figure 7. Clinics Accessibility Level

Demand Level

The demand analysis, as depicted in **Figure 8**, provides valuable insights into health facility demand, operating on the premise that higher population density correlates with increased demand. The vivid red hues on the map delineate areas with the highest demand, stemming from very high population density. Notably, the northern, middle, and southern regions of Bandar Lampung emerge as significant contributors to this heightened demand, constituting what is commonly regarded as the city center, despite the substantial population density.

In addition to the city center, the southeastern part of the city exhibits a noteworthy concentration of high demand. However, the western and eastern sectors register more moderate to low demand values, resulting

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in a relative scarcity of healthcare facilities in these areas. This spatial distribution of demand levels has direct implications for the placement and concentration of health facilities, aligning with the demographic landscape of Bandar Lampung.

A key observation is the near homogeneity in the percentage of the total area corresponding to each demand level. This homogeneity stems from the classification methodology employed, utilizing the quantile method. This approach ensures a balanced classification by considering equal areas, contributing to a nuanced understanding of the spatial distribution of health facility demand throughout the city. The distribution pattern discerned from the demand analysis lays the groundwork for informed decision-making regarding the allocation and optimization of healthcare resources in Bandar Lampung.

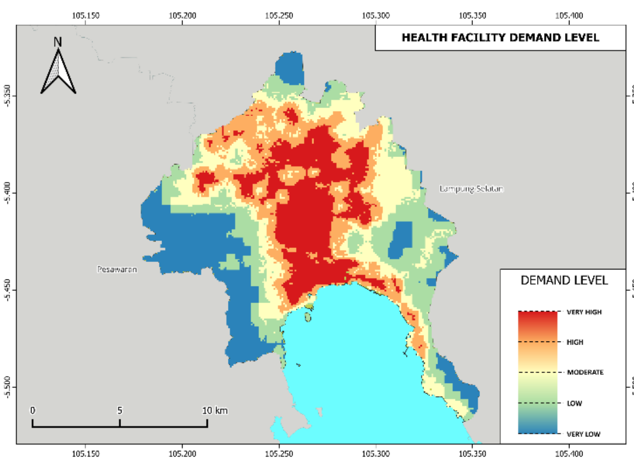

Figure 8. Health Facility Demand Level

Supply-Demand Level

Analyzing the supply-demand relationship is imperative to discern whether low accessibility to health facilities stems from a healthcare desert scenario or is rather a consequence of low population density leading to diminished demand in specific areas. **Figures 9-13** provide a comprehensive overview of the supply-demand levels for various types of health facilities. Notably, attention is directed towards key supply-demand scenarios, such as the juxtaposition of very high demand with very low accessibility denoted by a striking bright red, signifying a state of being very under-available. Conversely, the vibrant bright green hues represent instances of very low demand coupled with very high accessibility, emblematic of a situation where facilities are exceedingly over-available. Additionally, the very dark blue shades indicate areas characterized by both very high demand and very high accessibility.

Table 5 offers a detailed breakdown, elucidating the percentage of the total area classified as very under-available (VUA) and very over-available (VOA) for each health facility type. A noteworthy observation from the table is that doctors exhibit the highest percentage of very under-available areas compared to other health facility types. This insight underscores potential gaps in the accessibility of doctor services, signaling areas where the demand is notably high but the availability of doctors remains disproportionately low. In contrast, hospitals boast the lowest percentage of very under-available areas, indicative of a relatively well-distributed accessibility.

Furthermore, across all health facility types, the percentage of very over-available areas is remarkably low. The highest incidence of very over-available areas is found in pharmacies and clinics, each occupying a mere 0.03% of the total area. This indicates that, in general, the supply of healthcare facilities exceeds demand in only a negligible portion of the total area, reinforcing the need for strategic resource allocation and healthcare infrastructure planning to address localized discrepancies in accessibility and demand across Bandar Lampung.

Table 5. Percentage of Total Area for Each Facilities Types VUA and VOA

Classes	Percentage of Total Area (%)				
	PH	HP	DC	DS	CL
VUA	0.13	0.08	4.20	0.87	0.37
VOA	0.03	0.00	0.00	0.01	0.03

Comparison with Other Dataset

In order to validate our accessibility analysis, a comparison was conducted with the dataset provided by Weiss et al [15] titled "optimal travel time to healthcare with access to motorized transport." The underlying assumption is that travel time serves as an inverse measure of accessibility, where low accessibility corresponds to longer travel times. The Weiss et al. dataset, which delineates the optimal travel time to the nearest health facilities in Bandar Lampung, indicates that 45 minutes is the maximum travel time considered [15].

To facilitate a meaningful comparison, we reclassified the Weiss et al. dataset into five classes using the quantile method, aligning it with our accessibility model. The comparison was executed through the application of an "agreement pixel" metric [15]. Essentially, if a pixel in the accessibility model belongs to class 5, it is deemed in agreement if the corresponding pixel in the Weiss et al. dataset is also classified as class 5 [15]. This method allows for a pixel-level assessment of the agreement between the two datasets.

The results of this comparative analysis are summarized in **Table 6**, showcasing the agreement pixel percentage of the total area for each type of health facility. This analysis serves as a crucial step in validating the accuracy and reliability of our accessibility model by aligning it with an established dataset. The percentage agreement provides insights into the concordance between the two datasets, affirming the robustness of our accessibility analysis methodology and contributing to the overall credibility of our findings. This validation process bolsters the confidence in the accuracy of our accessibility model, enhancing its utility for informed decision-making in healthcare resource allocation and infrastructure planning in Bandar Lampung.

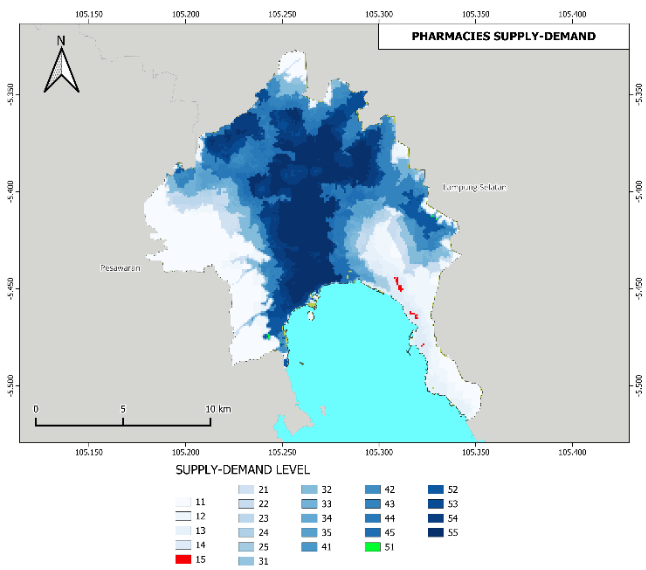

Figure 9. Pharmacies Supply-Demand

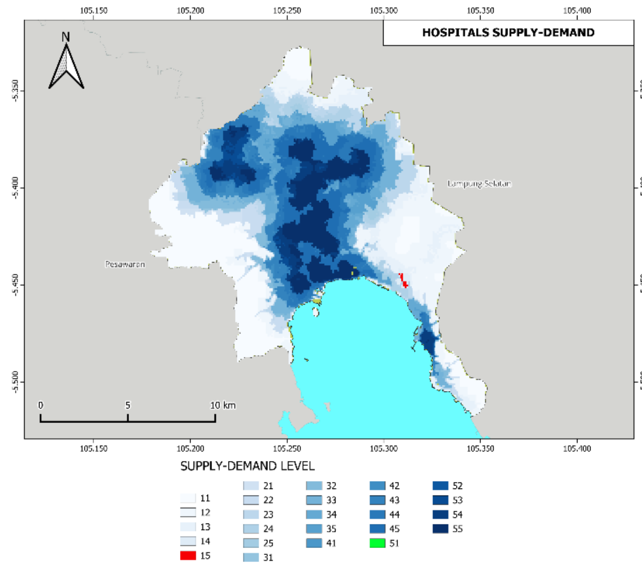

Figure 10. Hospitals Supply-Demand

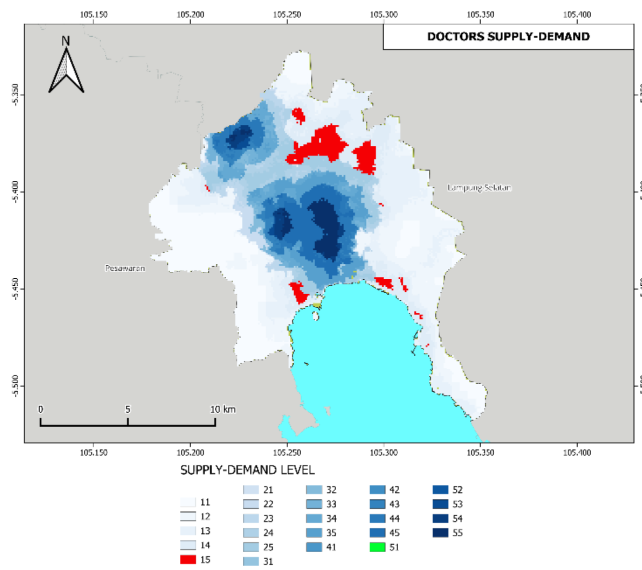

Figure 11. Doctors Supply-Demand

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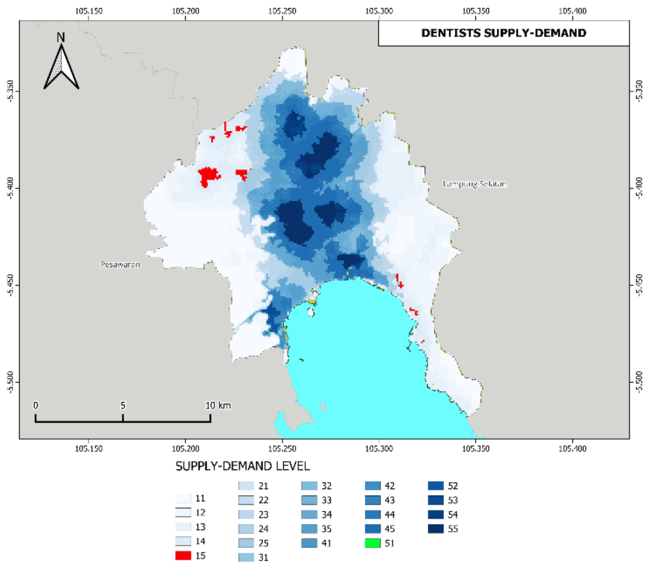

Figure 12. Dentists Supply-Demand

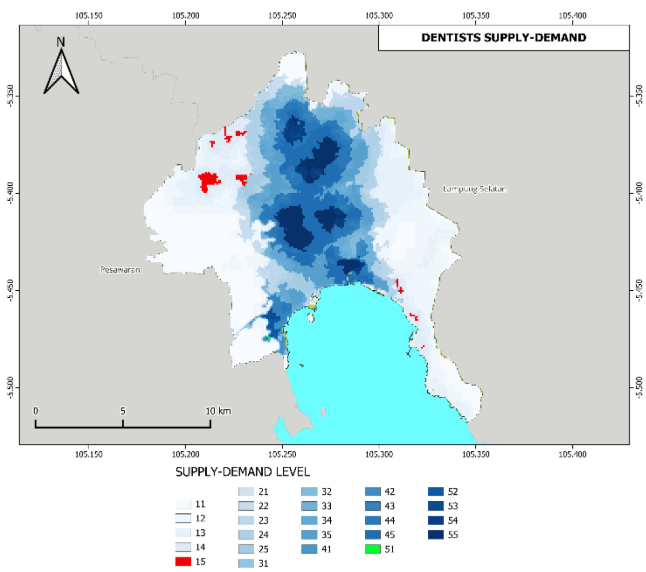

Figure 13. Dentists Supply-Demand

Table 6. Agreement Pixel (AP) Compared to Weiss et al. [15] Percentage of Total Area for Each Facilities Types

Classes	Percentage of Total Area (%)				
	PH	HP	DC	DS	CL
AP	14.6	16	26.1	18.6	15.5

The findings presented in **Table 6** reveal a relatively low level of agreement between our accessibility model and the dataset provided by Weiss et al. [15]. One plausible explanation for this disparity lies in the discrepancy in the level of detail between the two datasets. Our accessibility model operates at a higher resolution, with a grid size of 100m x 100m, whereas the Weiss et al. dataset utilizes a coarser resolution of 1km x 1km. This difference in granularity can lead to an underestimation of the comparison results, as the coarser dataset might overlook nuances captured by our more finely detailed model [15].

Despite the observed lower agreement levels, it's crucial to interpret these results with consideration for the inherent limitations associated with dataset resolution disparities. The highest level of agreement, noted in the case of the doctors' category at 26.1%, suggests that even within the constraints of the coarser dataset, there is some alignment between the two sources regarding accessibility to doctor services.

This discrepancy underscores the importance of selecting datasets with resolutions that align with the granularity required for the specific analysis at hand. While our model excels in capturing fine-grained details at the local level, the Weiss et al. dataset, with its coarser resolution, may not fully capture the intricacies of accessibility variations [15]. It's imperative to acknowledge these limitations when interpreting the agreement levels, emphasizing the need for caution in drawing definitive conclusions solely based on the comparison percentages. Further refinement and validation efforts, perhaps with higher-resolution external datasets, could enhance the precision of our accessibility model and contribute to a more nuanced understanding of healthcare accessibility in Bandar Lampung.

Conclusions

In the pursuit of understanding and optimizing healthcare accessibility, this study has successfully developed a spatial model to assess the accessibility levels of five distinct types of health facilities within the Bandar Lampung City area. The outcomes of this research hold significant implications for policymakers, providing a solid foundation upon which strategic developmental strategies, particularly in the healthcare sector, can be formulated.

The observed spatial distribution of high accessibility areas aligning with high demand underscores the interplay between service availability and population needs. However, the nuanced revelation that certain regions exhibit a persistent lack of accessibility despite heightened demand introduces a critical dimension to the discussion. The identification of very under-available (VUA) healthcare facilities, spanning from 0.13% to 4.20% of the total area of Bandar Lampung, serves as a clarion call for targeted interventions to bridge these accessibility gaps. Addressing such discrepancies is paramount to ensuring that healthcare services are not only available but also equitably distributed, thus meeting the diverse needs of the population.

Beyond its immediate implications for Bandar Lampung, the results of this study hold broader significance. The established model and its insights can be extrapolated to inform developmental strategies in other Indonesian regions or even countries sharing similar demographic and geographic characteristics. By leveraging the methodology and findings of this research, policymakers and stakeholders in healthcare planning can tailor interventions to enhance accessibility, fostering a more resilient and responsive healthcare infrastructure.

Conflicts of interest

The authors declare no conflict of interest.

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References

[1] "Goal 3 | Department of Economic and Social Affairs," United Nations, https://sdgs.un.org/goals/goal3 (accessed Nov. 1, 2023).

[2] W. E. CUNNINGHAM et al., "Access to medical care and health-related quality of life for low-income persons with symptomatic human immunodeficiency virus," MEDICAL CARE, vol. 33, no. 7, pp. 739–754, 1995. doi:10.1097/00005650-199507000-00009

[3] K. Bogart et al., "Healthcare access, satisfaction, and health-related quality of life among children and adults with rare diseases," Orphanet Journal of Rare Diseases, vol. 17, no. 1, 2022. doi:10.1186/s13023-022-02343-4

[4] "Indonesia population (live)," Worldometer, https://www.worldometers.info/world-population/indonesia-population/ (accessed Nov. 4, 2023).

[5] "Indonesia Registered Motor vehicles," CEIC, https://www.ceicdata.com/id/indicator/indonesia/motor-vehicle-registered (accessed Nov. 9, 2023).

[6] P. Panja, "Deforestation, carbon dioxide increase in the atmosphere and global warming: A modelling study," International Journal of Modelling and Simulation, vol. 41, no. 3, pp. 209–219, 2019. doi:10.1080/02286203.2019.1707501

[7] P. M. Fearnside, "Tropical deforestation and global warming," Science, vol. 312, no. 5777, pp. 1137–1137, 2006. doi:10.1126/science.312.5777.1137c

[8] X. Zhang and B. Arellano Ramos, "Urban sprawl and warming – research on the evolution of the urban sprawl of Chinese municipalities and its relationship with climate warming in the past three decades," The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XLIII-B4-2022, pp. 209–215, 2022. doi:10.5194/isprs-archives-xliii-b4-2022-209-2022

[9] F. Estrada and P. Perron, "Disentangling the trend in the warming of urban areas into global and local factors," Annals of the New York Academy of Sciences, vol. 1504, no. 1, pp. 230–246, 2021. doi:10.1111/nyas.14691

[10] A. Rossati, "Global warming and its Health Impact," The International Journal of Occupational and Environmental Medicine, vol. 8, no. 1, pp. 7–20, 2017. doi:10.15171/ijoem.2017.963

[11] A. Singh and B. M. Purohit, "Public health impacts of global warming and climate change," Peace Review, vol. 26, no. 1, pp. 112–120, 2014. doi:10.1080/10402659.2014.876326

[12] J. Calleja-Agius, K. England, and N. Calleja, "The effect of global warming on mortality," Early Human Development, vol. 155, p. 105222, 2021. doi:10.1016/j.earlhumdev.2020.105222

[13] "Bandar Lampung, Indonesia metro area population 1950-2023,"MacroTrends, https://www.macrotrends.net/cities/21446/bandar-lampung/population (accessed Nov. 10, 2023).

[14] M. H. Wismabrata, "Keluh Kesah warga Kota Bandar lampung Jalan Rusak Tak Kunjung Diperbaiki Halaman all," KOMPAS.com, https://regional.kompas.com/read/2023/05/25/152503078/keluh-kesah-warga-kota-bandar-lampung-jalan-rusak-tak-kunjung-diperbaiki?page=all (accessed Nov. 16, 2023).

[15] Weiss, D.J. et al., "Global maps of travel time to healthcare facilities," Nat Med 26, 1835–1838 (2020). https://doi.org/10.1038/s41591-020-1059-1

[16] A. Hijriani and R. I. Putra, "Measuring spatial accessibility of healthcare services using ARIA Method, Case Study at Bandar Lampung City," IOP Conference Series: Earth and Environmental Science, vol. 739, no. 1, p. 012094, 2021. doi:10.1088/1755-1315/739/1/012094

[17] Dinas Kesehatan Kota Bandar Lampung, "Profil Kesehatan Kota Bandar Lampung Tahun 2021", Bandar Lampung: Dinas Kesehatan Kota Bandar Lampung, 2021 (accessed Nov. 9, 2023). [Online]. Available: https://dinkeskotabalam.com/prof/DINAS_KESEHATAN.pdf

[18] "Bandar Lampung City Map" OpenStreetMap, https://www.openstreetmap.org/#map=11/-5.4034/105.2834 (accessed Nov. 4, 2023).

Published by: Lembaga Penelitian dan Pengabdian Masyarakat (LPPM) Institut Teknologi Sumatera, Lampung Selatan, Indonesia

[19] "Data Peta RBI Kota Bandar Lampung" Badan Informasi Geospasial, https://tanahair.indonesia.go.id/portal-web/download/perwilayah (accessed Nov. 4, 2023).

[20] "Indonesia Population Density 2020 UN Adjusted" WorldPop Organization, https://hub.worldpop.org/geodata/summary?id=44750 (accessed Nov. 4, 2023).

[21] A. D. Sakti et al., "School location analysis by integrating the accessibility, natural and biological hazards to support equal access to education," ISPRS International Journal of Geo-Information, vol. 11, no. 1, p. 12, 2021. doi:10.3390/ijgi11010012

[22] A. Ghorbani, "Demand for health and Healthcare," Healthcare Access, 2022. doi:10.5772/intechopen.98915