European Journal of Geography

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Received: 10/01/2024

Revised: 21/03/2025

Accepted: 08/04/2025

Published: 10/04/2025

Academic Editor:
Dr. Alexandros Bartzokas-Tsiompras

DOI: 10.48088/ejg.a.rai.16.2.091.107

ISSN: 1792-1341

Research Article

A Spatially-Informed Healthy Location Index for Assessing Urban Living Environment

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Abstract: Urban health outcomes are shaped by the complex interplay of environmental, social, and spatial factors. This study develops a Healthy Location Index (HLI) to assess spatial health risks by integrating health-promoting (HPSVs) and health-restraining (HRSVs) spatial variables using geospatial analysis and the Analytic Hierarchy Process (AHP). Taking Kolkata, India, as a case study, the HLI incorporates factors such as green and blue spaces, built-up density, air quality, and the distribution of alcohol and fast-food outlets to create a spatial model of urban health. The study utilizes remotely sensed and administrative datasets (e.g., Landsat-derived NDVI, NDBI, NDWI, Point-of-Interest data) and validates the HLI against COVID-19 containment zones (June 2020–January 2021) using Receiver Operating Characteristic (ROC) analysis. Results indicate that areas with high HLI scores—characterized by greater access to green spaces and lower exposure to environmental stressors—were less likely to be containment zones, suggesting a meaningful relationship between spatial health factors and urban resilience. However, the study acknowledges potential confounding variables, such as socioeconomic disparities, population density, and healthcare accessibility, which may influence health outcomes. The findings underscore the global applicability of the HLI framework in urban planning, public health policy, and epidemiological risk assessment, offering a scalable model for cities facing rapid urbanization and environmental challenges.

Keywords: GIS; Urban Health; Kolkata; India; Built Environment; Spatial Risk Analysis; Environmental Health; Urban Planning

Highlights:

- Proposed a scalable HLI framework with global implications for urban planning and targeted health interventions.
- Validation using COVID-19 containment zones and ROC analysis, demonstrating the utility of HLI in predicting health-risk areas.
- Policy implications for global urban planning and health interventions, emphasizing the need for improved green space access and environmental risk mitigation.

1. Introduction

Urban environments play a critical role in shaping public health, with the spatial distribution of health-promoting and health-restraining factors significantly influencing well-being. While the interplay between urban design and health has been widely acknowledged (Pineo, Glonti, & Davies, 2018), there remains a pressing need for tools that can systematically assess these factors and their interactions. The concept of a "healthy city," as defined by the World Health Organization (WHO), emphasizes continuous improvement in health outcomes through better social and physical environments, expanded community resources, and collaborative efforts among citizens (World Health Organization, 1985). However, achieving this vision requires a deeper understanding of how spatial variables—both positive and negative—interact to shape urban health (Marek et. al., 2021b).

In geography, the concept of "sense of place" significantly affects public health. The environment of a location impacts individuals across various dimensions, including spiritual, psychological, social, physical, and aesthetic aspects (Frumkin, 2003). Places can be categorized into two types: "good places," which promote better public health, and "bad places," which act as constraints to public health. Well-designed cities prioritize access to green spaces, safe transportation systems, and resilient infrastructure, which collectively reduce health risks and promote physical and mental well-being (Banay et al., 2017; Nieuwenhuijsen, 2018). With 70% of the global population projected to live in urban areas by 2050, the urgency to create healthy cities has never been greater. Moreover, healthy cities align with several Sustainable Development Goals (SDGs), including Zero Hunger, Clean Water and Sanitation, Sustainable Cities and Communities, and Climate Action (Pineo, Glonti, & Davies, 2018). As Aristotle stated, "A good city exists for the sake of a good life—not for the sake of life only" (Myerson, 2023). Urban planning and management are pivotal in this regard. There is growing concern among city officials and decision-makers regarding the impact of the urban environment on the health of its inhabitants. Practitioners in sectors such as housing, planning, and transportation are seeking new tools and guidance to better understand how existing policies can support the development of healthy cities (Zhou, Lengerke & Dreier, 2021a 2021b). In developed regions of Europe, the concept of "Healthy Cities" was established with a focus on both urban and local dimensions for promoting health. Healthy Cities initiatives in Europe have progressed through three five-year phases: 1988–1992, 1993–1997, and 1998–2002. The four primary strategies of Healthy Cities in Europe are: (i) prioritizing health on societal and political agendas, (ii) fostering partnerships for development within the health sector through good governance, (iii) advancing health priorities at both the European and global levels, and (iv) emphasizing the principles and determinants of health as essential components for sustainable development (Pineo, Glonti, & Davies, 2018).

In various regions of the Americas, the concept of Healthy Municipalities and Communities (HMC) is actively promoted. Countries that have adopted this initiative recognize that environmental quality and basic sanitation are fundamental to the development of any healthy city. HMC offers policies that not only support the health of local populations but also promote broader development goals, contributing to greater equity in public health (Pineo, Glonti, & Davies, 2018).

In the vast region of Southeast Asia, the inter-regional Healthy Cities Programme was launched in 1994, initially comprising six cities. However, the development of healthy cities in this region has been hindered by a lack of transparency surrounding the concept among local authorities and insufficient integration of urban infrastructure to support the initiative. Despite these early challenges, the programme has gradually expanded, and there are currently around 40 healthy cities in the region. In 2002, the Regional Office commissioned an evaluation of healthy cities projects in 12 cities across India, Nepal, Sri Lanka, and Thailand (Pineo, Glonti, & Davies, 2018).

Despite growing awareness, city officials and planners often lack the tools to evaluate the spatial dynamics of urban health. Existing frameworks, such as the Healthy Location Index (HLI) in New Zealand, have shown promise in mapping health-promoting and health-restraining factors but remain limited in their applicability to diverse urban contexts, particularly in low- and middle-income countries (LMICs) (Marek et al., 2021a and 2021b). This gap highlights the need for adaptable, spatially informed tools that can assess urban health comprehensively and guide evidence-based interventions.

2. Literature Review

The relationship between urban environments and public health has been a focal point of research, with increasing emphasis on the spatial dimensions of health-promoting and health-restraining factors. While earlier studies have explored the broad connections between urban planning and health, recent research has shifted toward understanding the spatial interplay of these factors and their cumulative impact on health outcomes (Marek et al., 2021a; Zhou, Lengerke, & Dreier, 2021). Urban environments are complex systems where health-promoting spatial variables (HPSVs) and health-restraining spatial variables (HRSVs) coexist and interact. HPSVs, such as green spaces, walkable neighborhoods, and access to healthcare, have been shown to improve mental health, reduce obesity, and enhance overall well-being (Banay et al., 2017; Twohig-Bennett & Jones, 2018). Conversely, HRSVs, including air pollution, inadequate sanitation, and poor housing conditions, exacerbate chronic diseases and mental health issues (Nieuwenhuijsen, 2018).

Recently, a study noted that children's BMI z-scores were correlated with green space availability, measured using the Normalized Difference Vegetation Index (NDVI). The study found that lower green space availability was associated with lower BMI, with the strongest correlations observed among boys and migrant children compared to girls and non-migrant children. This pattern was particularly evident in areas where green space availability was highest (Perdue Stone, & Gostin, 2003). Public health is also heavily influenced by the built environment, a relationship that was starkly evident during the Industrial Revolution when infectious diseases posed the most significant public health threat. Overcrowded, poor living conditions in urban areas contributed to the rapid spread of infections. In today's era, dominated by chronic diseases, there remains a significant connection between population health and the built environment (De and Rai 2024). Physical surroundings can expose individuals to pollutants and toxins, while also influencing lifestyle choices that contribute to conditions such as diabetes, coronary artery disease, and asthma. Public health advocates can drive improvements in the design of cities and suburbs to enhance public health outcomes, but it is crucial that they first understand the legal and regulatory frameworks that shape urban planning (Perdue Stone, & Gostin, 2003). Globally, initiatives such as the WHO's Healthy Cities Programme and the Healthy Municipalities and Communities (HMC) in the Americas have emphasized the importance of integrating health into urban planning (Pineo, Glonti, & Davies, 2018). These initiatives have promoted policies that address environmental quality, basic sanitation, and equitable access to resources.

Despite this understanding, there is limited research on how these variables interact spatially to influence health outcomes at the neighborhood or city level (Marek et al., 2021b). Recent studies have highlighted the importance of spatial analysis in urban health research. The use of Geographic Information Systems (GIS) and spatial statistics has enabled researchers to map health disparities and identify hotspots of health risks (Beyer et al., 2014; Chen et al., 2020). However, these studies often focus on isolated factors rather than integrating multiple HPSVs and HRSVs into a comprehensive framework. In New Zealand, an attempt is made to as a pioneering tool for mapping the influence of environmental factors on health. The HLI identifies healthy and unhealthy components within urban environments, providing actionable insights for urban planners and policymakers (Marek et al., 2021a). While the HLI has shown promise, its application has been limited to specific regions, and there is a need for adaptable frameworks that can be applied to diverse urban contexts, particularly in rapidly urbanizing regions of the Global South. Existing tools are often context-specific and lack scalability to other regions, particularly in low- and middle-income countries (LMICs) where urban health challenges are most acute (Marek et al., 2021b). There is also limited research on the role of spatial interconnections in shaping health outcomes, particularly in densely populated cities with complex urban morphologies.

This study addresses critical gaps in urban health assessment by developing a novel Spatially-Informed Healthy Location Index (HLI). The HLI evaluates the complex interplay of health-promoting spatial variables (HPSVs) and health-restraining spatial variables (HRSVs) within urban environments. Using Kolkata as a case study, the research constructs an HLI that integrates diverse spatial factors, including green spaces, blue spaces, air quality, and the presence of unhealthy food and beverage outlets. The conceptual model not only identifies these contributing factors but also analyzes their spatial interrelationships, providing a holistic framework for urban health assessment. This work contributes to the expanding field of spatially informed urban health tools and offers a scalable model applicable to other cities, especially those in rapidly urbanizing regions of Asia, Africa, and Latin America. The HLI provides a practical framework for addressing urban health disparities and informing evidence-based interventions. By bridging the gap between local context and global applicability, this research advances geographical knowledge and offers actionable solutions for creating healthier urban environments worldwide.

https://doi.org/10.48088/ejg.a.rai.16.2.091.107

3. Materials and Methods

This study focuses on the spatial determinants of urban health, recognizing that the natural spaces, built environment and surrounding ambience play a significant role in shaping health outcomes. By developing a Spatially-Informed Healthy Location Index (HLI), this research aims to provide a comprehensive assessment of the spatial distribution of health-promoting and health-restraining factors within the urban environment. This index will integrate various spatial parameters, allowing for the identification of areas with both assets and challenges related to health, ultimately informing targeted interventions and urban planning strategies (Faka et. al., 2024). With this context in mind, the study pursues the following specific objectives:

- To develop a Spatially-Informed Healthy Location Index (HLI) for the selected study area.
- To identify and quantify the spatial distribution of health-promoting and health-restraining factors within the urban environment.
- To analyze the complex interplay between these factors and their influence on overall urban health.

This study selects specific parameters to construct the Healthy Location Index (HLI), categorizing them into Health-Promoting Spatial Variables (HPSVs) and Health-Restraining Spatial Variables (HRSVs). The chosen HPSVs include: (i) green spaces, recognized for their positive impacts on air quality, recreation, and mental well-being (Maulken et. al. 2023) (ii) blue spaces, encompassing ponds, lakes, and other water bodies, valued for their recreational opportunities and support of aquatic ecosystems. Access to blue spaces has been associated with improved mental and physical health, including stress reduction and increased physical activity (Gascon et.al. 2017); and (iii) recreational parks or open spaces, promoting physical activity and social interaction. Regular physical activity is crucial for preventing chronic diseases and improving overall health. The selected HRSVs, representing factors that negatively impact health, comprise: (i) the Normalized Difference Built-up Index (NDBI), often used as a proxy for urbanization and its associated environmental changes. High NDBI values indicate a greater concentration of built-up surfaces, which can lead to increased surface temperatures, reduced green space, and altered environmental processes (Maulken et. al. 2023). These changes can negatively impact human health and well-being; (ii) fast food and alcohol outlets have been linked to various social detriments, including increased crime rates, alcohol-related health problems, and community disruption (Fraser et al., 2010). Their inclusion as an HRSV acknowledges their potential negative impact on community health and safety.; (iii) the Air Quality Index (AQI), reflecting the level of air pollution and its associated health risks (Perdue, Stone, & Gostin, 2003). Air pollution is a significant threat to public health, contributing to respiratory illnesses, cardiovascular disease, and other adverse health outcomes. The AQI provides a standardized measure of air pollution levels and is a crucial indicator of environmental health.; and (iv) waterlogged areas, which can pose health risks due to the potential for disease transmission, particularly vector-borne diseases like malaria and dengue fever (Maulken et. al. 2023). These areas can also create unsanitary conditions and contribute to other environmental health hazards. The selection of these specific HPSVs and HRSVs aims to provide a comprehensive and balanced assessment of the spatial determinants of health within the study area. This approach recognizes that urban health is influenced by a complex interplay of both positive and negative environmental factors.

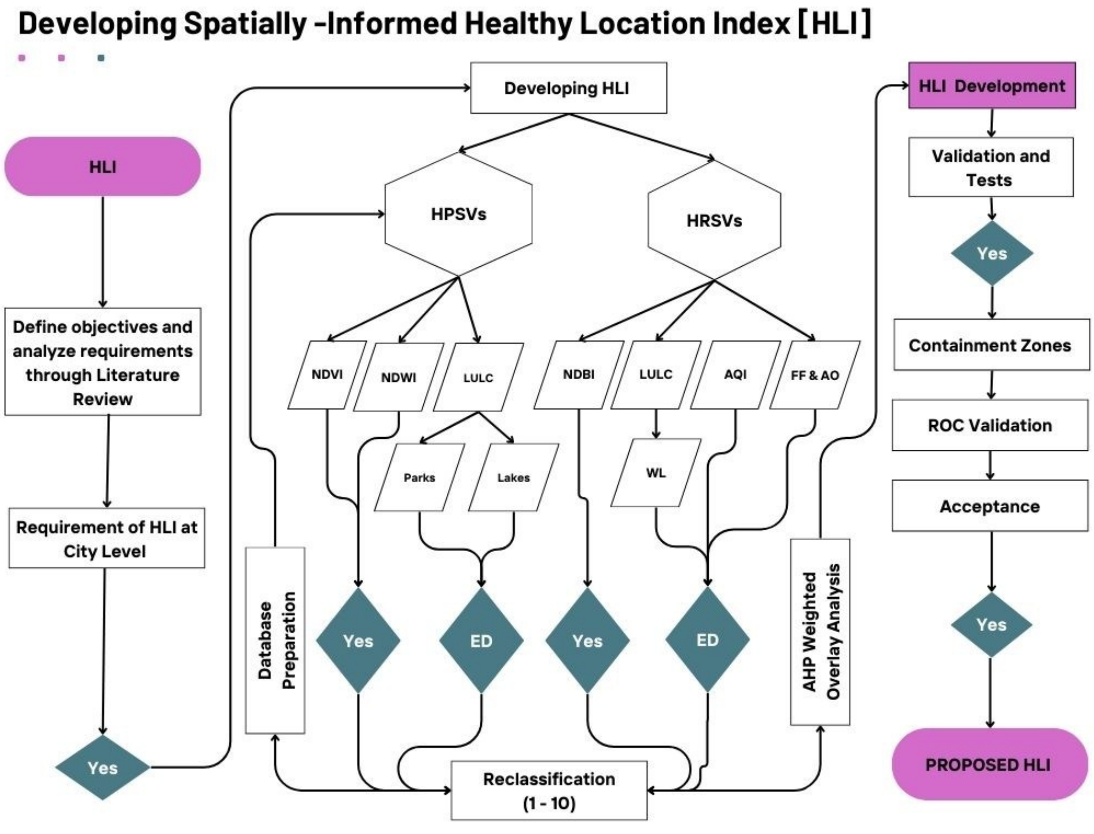

Figure 1. Research framework for developing a Spatially-Informed Healthy Location Index (HLI). Abbreviations used: HLI – Healthy Location Index, HPSVs – Health-Promoting Spatial Variables (NDVI: Normalized Difference Vegetation Index, NDWI: Normalized Difference Water Index, LULC: Land Use and Land Cover), HRSVs – Health-Restraining Spatial Variables (NDBI: Normalized Difference Built-up Index, WL: Waste Land, AQI: Air Quality Index, FF & AO: Fast Food and Alcohol Outlets.

https://doi.org/10.48088/ejg.a.rai.16.2.091.107

This study prioritizes spatial parameters over socio-economic factors due to their more direct and measurable influence on health outcomes. While socio-economic factors such as income, education, and employment are undeniably important, their impact on health is often mediated through complex and indirect pathways (Diez Roux & Mair, 2010; Arcaya et al., 2016). In contrast, spatial parameters—such as access to green spaces, proximity to unhealthy food outlets, and exposure to air pollution—exert a more immediate and tangible influence on individual and community health (Banay et al., 2017; Twohig-Bennett & Jones, 2018). Perhaps, spatial parameters are inherently measurable and spatially explicit, making them amenable to Geographic Information Systems (GIS) and spatial analysis techniques, which enable precise mapping and targeted interventions (Chen et al., 2020; Marek et al., 2021a). Socio-economic data, on the other hand, are often challenging to collect at fine-grained spatial scales, limiting their utility for localized health interventions (Zhou, Lengerke, & Dreier, 2021b).

The built environment plays a critical role in shaping health outcomes, and spatial parameters directly reflect these environmental characteristics (Nieuwenhuijsen, 2018). For example, the availability of green spaces has been linked to reduced stress, improved mental health, and lower rates of obesity (Twohig-Bennett & Jones, 2018), while proximity to fast-food outlets is associated with higher rates of diet-related diseases (Cobb et al., 2015). Interventions targeting spatial parameters, such as increasing green space or regulating unhealthy food environments, are often more directly actionable through urban planning and policy compared to broader socio-economic reforms, which require systemic changes and longer timeframes (Pineo, Glonti, & Davies, 2018).

While this study acknowledges the importance of socio-economic factors, it adopts a complementary approach by focusing on the spatial dimension of health. This approach recognizes the complex interplay between spatial and socio-economic influences but emphasizes the actionable nature of spatial interventions. By providing insights into the spatial distribution of health-promoting and health-restraining factors, this study aims to inform targeted interventions and contribute to the creation of healthier urban environments. Figure 1 illustrates the research framework adopted for this study.

3.1 A Case Study on Kolkata Municipal Corporation Area

Kolkata Metropolitan City (KMC) mapped in Figure 2, presents a critical case for the development of a Healthy Location Index (HLI) using geospatial tools due to its complex urban environment, poor air quality, and significant public health challenges. Recent studies have emphasized that Kolkata faces persistent environmental and living condition issues that adversely affect the quality of life in the city. According to a report by the Centre for Science and Environment (Centre for Science and Environment - CSE, 2020). Kolkata consistently ranks among the most polluted cities in India, with levels of particulate matter (PM10 and PM2.5) regularly exceeding permissible limits. This pollution is largely driven by vehicular emissions, industrial activities, and the combustion of solid fuels in densely populated areas, creating a hazardous urban environment for residents. Urban air quality studies (Kar et. al., 2024) show that Kolkata has a high burden of respiratory diseases, with air pollutants like nitrogen dioxide (NO_2) and particulate matter contributing to the rise of chronic obstructive pulmonary disease (COPD), asthma, and other respiratory ailments. A survey conducted in the city revealed that nearly 70% of respondents suffered from air pollution-induced illnesses, and lung cancer cases were reported to be among the highest in Indian cities (Central Pollution Control Board, 2018).

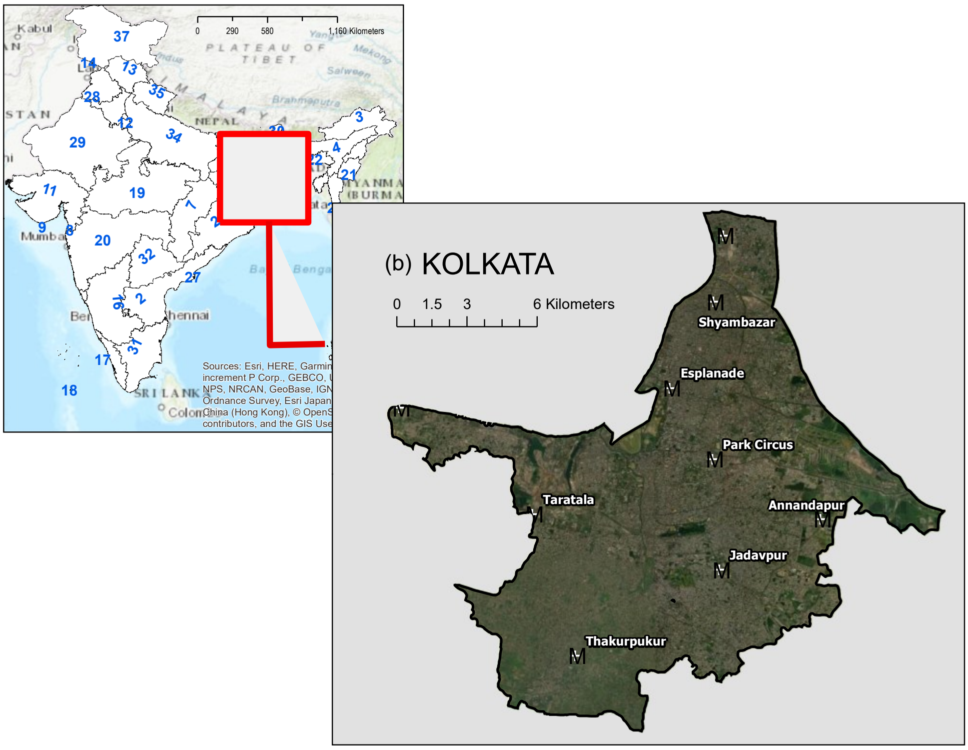

Figure 2. Map of the Study Area (a) India—1. Andaman and Nicobar; 2. Andhra Pradesh; 3. Arunachal Pradesh; 4. Assam; 5. Bihar; 6. Chandigarh; 7. Chhattisgarh. 8.Dadra and Nagar Haveli; 9.Daman and Diu; 10. Goa; 11. Gujarat; 12. Haryana; 13. Himachal Pradesh; 14. Jammu and Kashmir; 15. Jharkhand;16. Karnataka; 17. Kerala; 18.Lakshadweep; 19. Madhya Pradesh; 20. Maharashtra; 21.Manipur; 22. Meghalaya; 23.Mizoram; 24. Nagaland; 25.NCT of Delhi; 26. Odisha; 27. Puducherry; 28. Punjab; 29. Rajasthan; 30. Sikkim; 31.Tamil Nadu; 32. Telangana; 33.Tripura; 34. Uttar Pradesh; 35.Uttarakhand; 36. West Bengal.

https://doi.org/10.48088/ejg.a.rai.16.2.091.107

In terms of living conditions, the city is marked by overcrowding, inadequate housing, and limited access to green and blue spaces, which are essential for mental and physical well-being. According to the Global Liveability Index 2022, Kolkata scored low on quality-of-life indicators such as healthcare access, infrastructure, and environmental sustainability (Economist Intelligence Unit, 2022). Studies show that while Kolkata has some health-promoting areas, such as green parks and water bodies, these are unevenly distributed and inaccessible to a large portion of the population. The lack of adequate urban planning, particularly in the allocation of green spaces, exacerbates the health risks posed by pollution and limited recreational spaces. Given this context, Kolkata is an ideal location for conducting an HLI using geospatial tools, as it provides a unique opportunity to map both health-promoting and health-restraining spatial variables (Sen & Guchhait, 2021). Tools like NDVI, NDWI, and NDBI can highlight the disparities in access to healthy environments across the city, such as proximity to parks, water bodies, and air quality hotspots. Recent studies (Ghosh & Banerjee, 2020; Mukherjee et al., 2019) have highlighted the need for urban planning interventions that prioritize the creation of "healthy locations" by promoting access to green spaces, reducing pollution, and improving overall living conditions. By integrating spatial health data, the HLI will not only pinpoint areas of high risk but also inform policy interventions aimed at improving public health, promoting sustainable urban living, and mitigating environmental hazards. Thus, Kolkata's combination of severe air pollution, poor urban infrastructure, and limited access to healthy spaces makes it a prime candidate for developing and applying the HLI framework to enhance the quality of life for its residents.

3.2 Data Acquisition, Database Creation and Distribution Mapping

The geospatial analysis for computing the Healthy Location Index (HLI) utilized a diverse range of data sources. Satellite imagery from Landsat 8, dated December 2021 to December 2023, was employed to extract key indices such as average NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), and NDBI (Normalized Difference Built-up Index). Land Use and Land Cover (LULC) data were obtained from Bhuvan, an Indian geo-platform providing detailed environmental and infrastructural data. Locations of alcohol and food outlets, as well as AQI stations, were sourced from Google Earth. The analysis involved Euclidean Distance calculations and reclassification of spatial variables, followed by an AHP (Analytic Hierarchy Process) pairwise comparison to derive weights and assess the health impact of various locations. Alcohol outlet data was further cross verified from the West Bengal Excise Department, including the addresses of registered alcohol outlets along with their zip codes. Using ArcGIS 10.8, image classification was performed to calculate the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Built-up Index (NDBI).

In the weighted overlay analysis, a standardized 1–10 scale was employed, where 1 denotes the least healthy locations and 10 signifies the most-healthy. This uniform scaling facilitates the integration of various spatial variables influencing urban health. Following a “Greater is Better” principle, NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index) were reclassified such that higher values (greater vegetation and water presence) corresponded to healthier locations (score closer to 10), while lower values were associated with less favorable conditions (score closer to 1). Several studies have established that higher NDVI and NDWI values correlate with improved air quality, reduced urban heat island effects, and enhanced mental well-being. Recent studies have demonstrated that increased vegetation and water presence correlate with improved mental and physical health outcomes (Gascon et al., 2016; Gascon et al., 2017).

Conversely, spatial variables following a “Lower is Better” approach were reclassified such that areas closer to health-supportive environments received higher scores. Euclidean distance calculations were performed for open spaces, recreational parks, and blue spaces (ponds/lakes), and reclassified using the same 1–10 scale. Locations nearer to these amenities (lower Euclidean distance) were assigned higher scores, as research has demonstrated that proximity to green and blue spaces significantly improves physical activity levels, mental health, and overall well-being (Van den Berg et al., 2015).

Further Euclidean distance calculations were applied to health-restraining spatial variables (HRSVs), including wasteland, alcohol outlets, fast food outlets, and poor air quality index (AQI) locations (Figure 6). These were reclassified using the same 1–10 scale, where areas closer to these features were assigned lower scores, reflecting their negative influence on urban health. Proximity to wastelands has been linked to increased exposure to environmental hazards, while alcohol and fast-food outlet density is associated with higher rates of non-communicable diseases (Richardson et al., 2015; Thornton et al., 2016). Likewise, poor AQI values indicate increased exposure to respiratory and cardiovascular risks, further justifying their classification as health-restraining factors (Maulken et.al., 2023).

Table 1. Reclassification of Health-Promoting and Health-Restraining Spatial Variables Based on the "Greater is Better" and "Lower is Better" Approach for Healthy Location Index (HLI) Assessment

Category	Spatial Variable	Approach Adopted	Reclassification Scoring Scale (1-10)
HPSVs	NDVI (Normalized Difference Vegetation Index)	Greater is Better	Higher NDVI = Higher Score (10 = Most Healthy)
	NDWI (Normalized Difference Water Index)	Greater is Better	Higher NDWI = Higher Score (10 = Most Healthy)
	Distance to Open Spaces/Parks	Lower is Better	Closer Distance = Higher Score (10 = Most Healthy)
	Distance to Blue Spaces (Ponds/Lakes)	Lower is Better	Closer Distance = Higher Score (10 = Most Healthy)
HRSVs	NDBI (Normalized Difference Built-up Index)	Lower is Better	Lower NDBI = Higher Score (10 = Most Healthy)
	Distance from Wastelands	Greater is Better	Higher Distance = Higher Score (10 = Most Healthy)
	Distance from Alcohol Outlets	Greater is Better	Higher Distance = Higher Score (10 = Most Healthy)
	Distance from Fast Food Outlets	Greater is Better	Higher Distance = Higher Score (10 = Most Healthy)
	Distance from Poor AQI Areas	Greater is Better	Higher Distance = Higher Score (10 = Most Healthy)

https://doi.org/10.48088/ejg.a.rai.16.2.091.107

The threshold selection for each variable was informed by prior empirical research and policy guidelines emphasizing urban environmental health determinants. By integrating these "Greater is Better" and "Lower is Better" principles, the weighted overlay analysis effectively delineates spatial patterns of urban health in a scientifically robust manner. Table 1 provides a clear distinction between variables that promote health (HPSVs) and those that restrain it (HRSVs), along with their adopted reclassification approach and scoring scale.

3.3 AHP Weighted Overlay Model for a Healthy Location Index

The Analytical Hierarchy Process (AHP), a multi-criteria decision-making technique, plays a crucial role in aiding complex decision-making by deconstructing a challenging problem into a hierarchical structure (Rai, 2019). This structure descends from the main goal to criteria, sub-criteria, and potential solutions, arranged across successive tiers. The AHP method operates on the principle that decision-making is more effective when a small number of factors are considered in relation to a specific property, without the distraction of other unrelated factors or properties. These pairwise comparisons are based on Thomas Saaty's "scale of relative importance," a nine-point comparative scale designed to measure intangible properties cited in many literatures (Rai, 2019). In this study, pairwise comparisons (Table 1) between NDVI, NDWI, Land Use and Land Cover, NDBI, alcohol outlets, food outlets, and the air quality index (AQI) were conducted using matrix representations (square and reciprocal) derived from the consensus of nine experts with backgrounds in urban planning, geography, public health, industry consulting, spatial analysis, and related research. The following parameters were used: n1 = Proximity to higher NDVI values; n2 = Proximity to higher NDWI values; n3 = Proximity to open spaces/recreational parks; n4 = Proximity to blue spaces/ponds/lakes; n5 = Distance from areas with higher NDBI values; n6 = Distance from waterlogged zones; n7 = Distance from fast food and alcohol outlets; n8 = Distance from poor AQI

Table 2 results from multiple pairwise comparisons using Saaty's nine-point scale of relative importance. This method, suitable for measuring intangible properties, employs a reciprocal matrix based on expert opinions. The matrix satisfies the reciprocal property ($A=(a_{ij})$, *where* $a_{ij}=w_i/w_j$), and relative weights are derived by normalizing the largest eigenvalue (λ_{max}, *where* $Aw=\lambda_{max}$). Consistency analysis ensures logical judgments ($a_{jk}=a_{ik}/a_{ij}$), with a Consistency Ratio (CR) below 0.10 indicating acceptable consistency. If CR exceeds 0.10, reassessment is required (Rai 2019).

Table 2. Pair Wise Comparison and Reciprocal Matrix[1]

		n1	**n2**	**n3**	**n4**	**n5**	**n6**	**n7**	**n8**
	Spatial Variables	**Near Higher NDVI value**	**Near Higher NDWI value**	**Near Open Space/Recreational Park**	**Near Blue space/pond/lake**	**Away from Higher NDBI**	**Away from Waterlogged zone**	**Away from fast Food and Alcohol Outlets**	**Away from higher AQI**
n1	**Near Higher NDVI value**	1	1	1	1	2	1/3	1/4	1/3
n2	**Near Higher NDWI value**	1	1	3	1	2	1/3	1/3	1/4
n3	**Near Open Space/Recreational Park**	1	1/3	1	1	2	1/3	1/3	1/4
n4	**Near Blue space/pond/lake**	1	1	1	1	3	3	1/3	1/3
n5	**Away from Higher NDBI**	1/2	2	1/2	1/3	1	1/4	1/3	1/4
n6	**Away from Water-logged zone**	3	3	3	1/3	4	1	1/3	1/3
n7	**Away from fast Food and Alcohol Outlets**	4	3	1/3	3	3	3	1	1/2
n8	**Away from higher AQI**	3	4	4	3	4	3	2	1

[1] A reciprocal matrix is a key component of the Analytic Hierarchy Process (AHP) used in pairwise comparisons. It ensures that the relative importance of different criteria is logically consistent. A reciprocal matrix AAA is a square matrix where each element a_{ij} represents the ratio of the importance of criterion *i* over criterion *j*, and it satisfies the reciprocal property:

$A=(a_{ij})$, where $a_{ij}=w_i/w_j$ and $a_{ji}=1/a_{ij}$

where: • *W_i and w_j are the relative weights of criteria i and j.* • *A_{ij} indicates how much more important i is compared to j.* • *$a_{ji}=1/a_{ij}$ ensures reciprocity, meaning if one criterion is twice as important as another ($a_{ij}=2$), then the reverse is half ($a_{ji}=1/2$).*

4. Results and Discussion

4.1 Distribution mapping of HPSVs and HRSVs

An analysis of Health Promoting and Health Restraining Spatial Variables (HPSVs and HRSVs) in Kolkata, providing valuable insights into the spatial distribution of health-related environmental factors within the city. Figure 3 illustrates key Health Promoting Spatial Variables (HPSVs), including the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Water Index (NDWI), open spaces, and blue spaces. NDVI and NDWI are widely used indicators for assessing the availability of vegetation and water bodies in urban areas. The NDVI in Kolkata predominantly ranges between -0.056 and 0.2573, indicating relatively low vegetation coverage across much of the city. Similarly, the NDWI values, which reflect the presence of water bodies, fall between -0.183 and 0.25, with higher values observed in areas such as the East Kolkata Wetlands and Anandapur, which are known for their water resources. Open spaces, including parks and recreational areas, are sparse, with notable concentrations around the East Kolkata Wetlands, while blue spaces, representing water bodies such as lakes and ponds, are more evenly distributed. As evident from Figure. 3, the Euclidean distance analysis illustrates the spatial distribution of ponds and lakes, ranging from 0 to 2,244.39 meters, and parks and open spaces, extending up to 11,239.9 meters. These HPSVs are crucial for urban health, as proximity to green and blue spaces has been strongly linked to improved physical and mental health outcomes in urban populations (Sarkar, Webster and Gallacher, 2018, Gascon et.al. 2017).

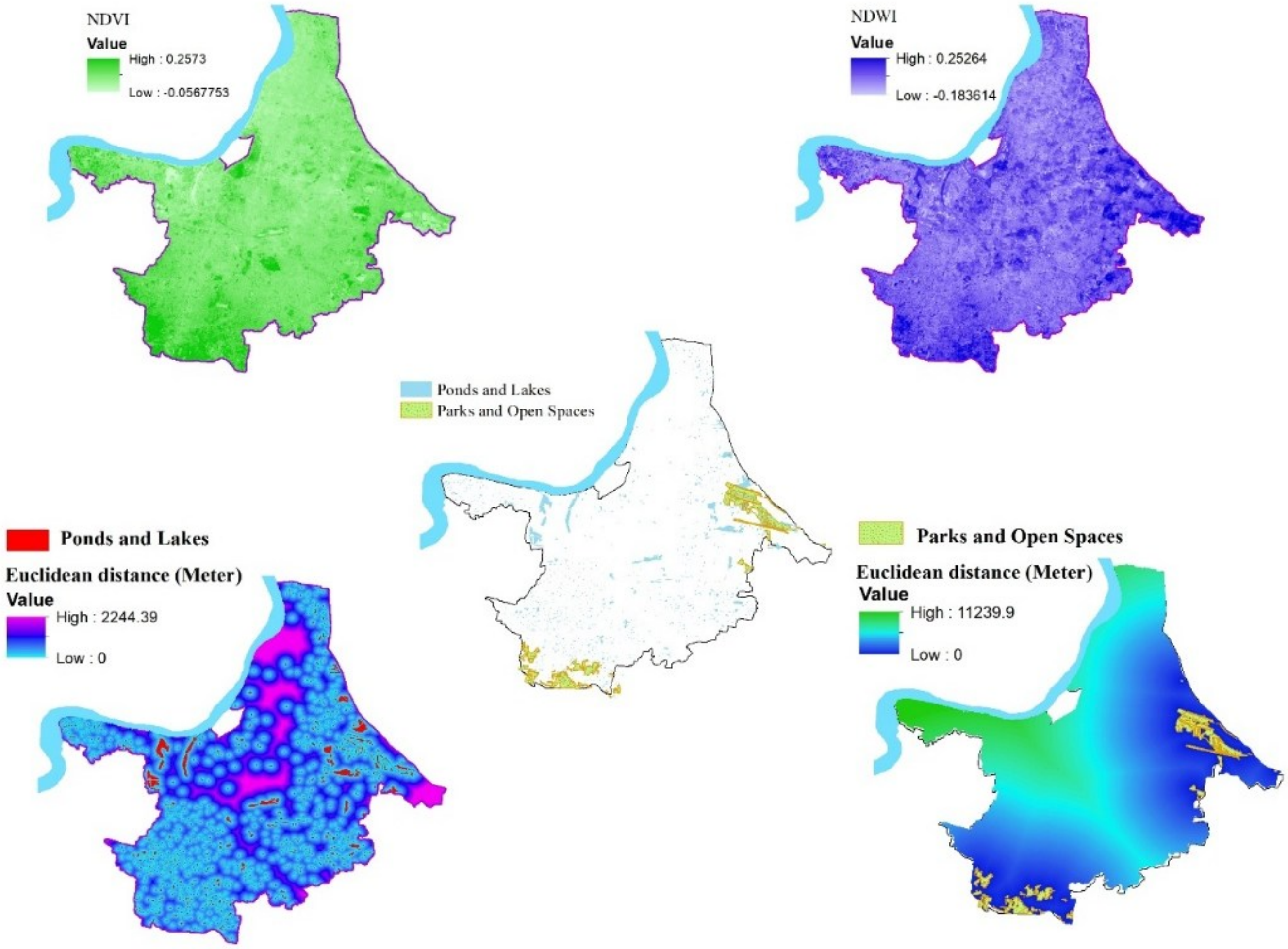

Figure 3. Health promoting spatial variables (HPSVs) and their distribution

Figure 4 displays the Health Restraining Spatial Variables (HRSVs), which include the Normalized Difference Built-up Index (NDBI), wasteland areas, alcohol outlets, and the Air Quality Index (AQI). The NDBI highlights Kolkata's built-up areas, with darker shades representing denser urbanization. The highest NDBI values, ranging from -0.25264 to 0.183614, are concentrated in central and northern Kolkata, areas characterized by high-density development. Wasteland is relatively limited, though small patches are present in the southern parts of the city. Fast Food and Alcohol outlets are predominantly located in the central and northern regions. Figure 4 also presents the Euclidean distance analysis of key health-restraining spatial variables. The distance from waterlogged zones ranges from 0 to 10,167.2 meters, while the Euclidean distance from major fast food and alcohol outlets varies between 0 and 4,581.36 meters. Additionally, the interpolated air quality surface exhibits values between 56.77 and 198.77, indicating moderate to severely poor air quality across Kolkata. AQI values across the city point to severe air quality issues, consistent with other studies that emphasize Kolkata's poor air quality as a significant public health concern (World Health Organisation, 2020; Haque and Singh, 2017). Kolkata has been repeatedly ranked among the most polluted cities globally, with vehicular emissions and industrial activities as primary contributors (Haque and Singh, 2017).

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4.2 Delineating health-influencing spatial relationships based on proximity to HPSVs and HRSVs

In this study, a standardized 1–10 reclassification scale was employed to assess spatial health variables, where 1 represents the least healthy locations and 10 denotes the healthiest. As outlined in Section 5 and Table 1, this standardized approach enables the integration of diverse spatial determinants of urban health. The uniform scaling methodology aligns with previous studies on urban health indices, where classification scales are utilized to ensure comparability across heterogeneous spatial attributes (Perdue, Stone, & Gostin, 2003). This reclassification framework normalizes the influence of each variable, facilitating the development of a composite Healthy Location Index (HLI) by incorporating both health-promoting spatial variables (HPSVs) and health-restraining spatial variables (HRSVs). The mapped results, presented in Figures 5 and 6, depict the spatial distribution of health-related factors influencing urban well-being. Figure 5 illustrates the reclassified HPSVs, applying a "Greater is Better" approach for NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index), while employing a "Lower is Better" approach for the Euclidean distance-based distribution of green and blue spaces. These methodological choices align with proximity-based health modeling, which demonstrates the positive health impacts of increased access to vegetation and water bodies, contributing to psychological well-being, improved air quality, and urban cooling (Roy et al., 2022). Conversely, Figure 6 presents the spatial distribution of HRSVs, including alcohol outlets, waterlogged areas, and regions with poor air quality. A "Greater is Better" approach was applied, where locations farther from these variables received higher scores. Proximity to alcohol outlets, waterlogged zones, and poor AQI areas is associated with adverse health outcomes, such as increased crime rates, vector-borne diseases, and respiratory conditions (Haque & Singh, 2017). The classification of these variables highlights the role of environmental stressors in shaping urban health risks.

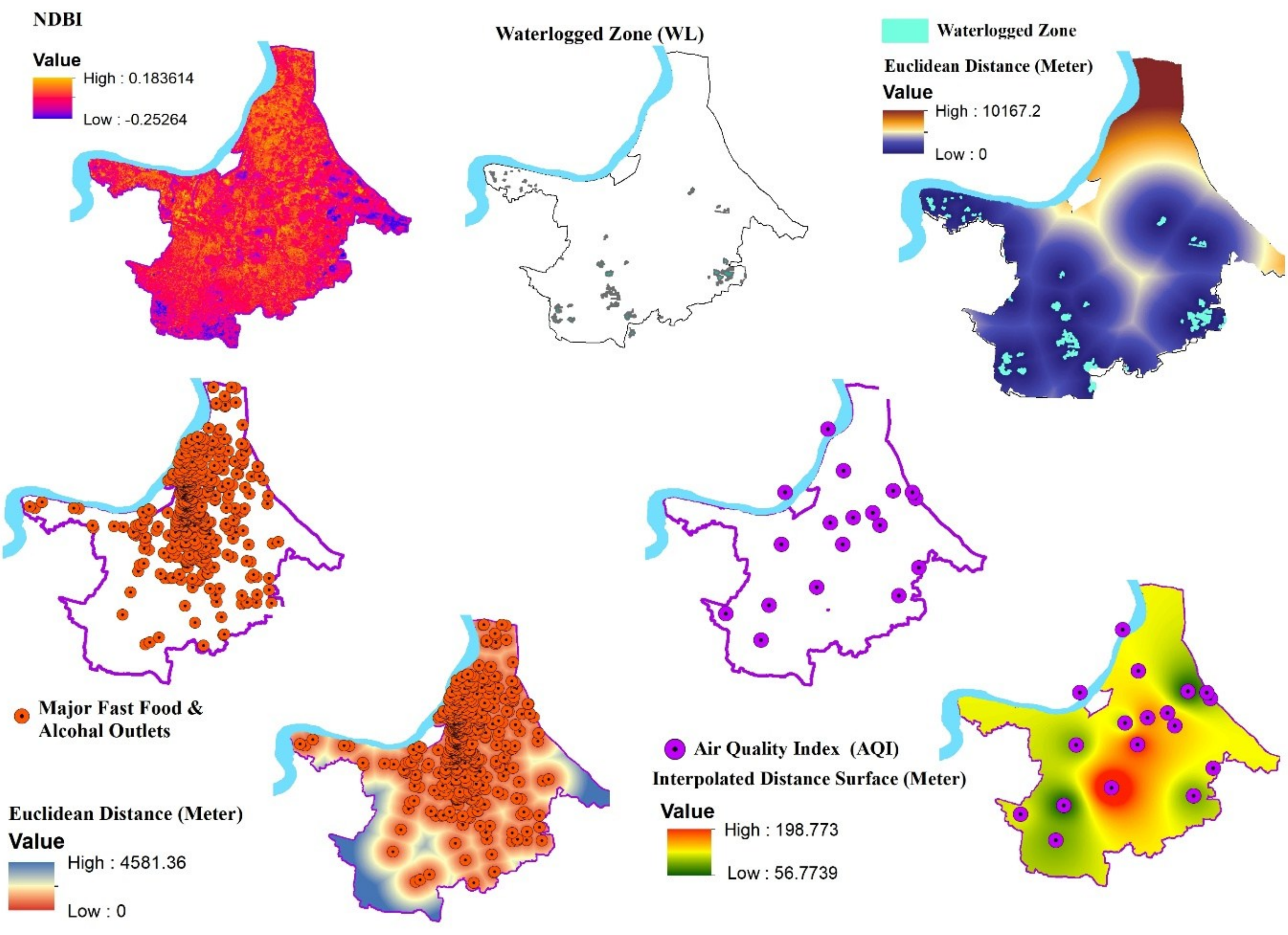

Figure 4. Health Restraining Spatial Variables (HRSVs) and their distribution

The spatial analysis underscores significant heterogeneity in the distribution of health-promoting and health-restraining factors across Kolkata. Healthier areas are characterized by proximity to green and blue spaces, while regions with high built-up density, poor air quality, and accessibility to alcohol outlets exhibit lower health scores. These findings reinforce the need for urban planning interventions that enhance access to green infrastructure and mitigate environmental health risks. Prior research emphasizes that strategic urban planning and policy interventions—

such as improving urban green space accessibility and reducing exposure to environmental hazards—are critical to fostering healthier urban environments (Sen & Guchhait, 2021; Roy et al., 2022; Spiroska, Rahman & Pal, 2011; Rai, 2019; Sarkar, Webster & Gallacher, 2018; Gason et al., 2017).

4.3 Healthy Location Index (HLI) for Kolkata

The primary objective of this study is to develop a Healthy Location Index (HLI) for Kolkata using the Analytic Hierarchy Process (AHP) model, a multi-criteria decision-making approach that allows for the systematic evaluation of various health-related spatial variables. In this framework, health indicators are classified into two major categories: Health Promoting Spatial Variables (HPSVs) and Health Restraining Spatial Variables (HRSVs). The HPSVs, such as the NDVI, NDWI, proximity to open spaces, and blue spaces (e.g., lakes and ponds), are reclassified based on an index scale ranging from 1 to 10, where higher values indicate healthier locations. Similarly, the HRSVs, including proximity to alcohol outlets, waterlogged areas, and air quality (measured through the Air Quality Index, AQI), are also reclassified on the same scale. In this case, lower index values correspond to less healthy areas, while higher values denote healthier locations.

The AHP model facilitated a detailed pairwise comparison of these variables, allowing for the assignment of priority weights to each indicator based on its relative importance in determining the healthiness of a location. The study's priority matrix, outlined in Table 3, provides a detailed ranking of various spatial variables that contribute to the development of the Healthy Location Index (HLI) for Kolkata. This ranking was derived using the Analytic Hierarchy Process (AHP) model, which allowed for the systematic evaluation of both HPSVs and HRSVs factors.

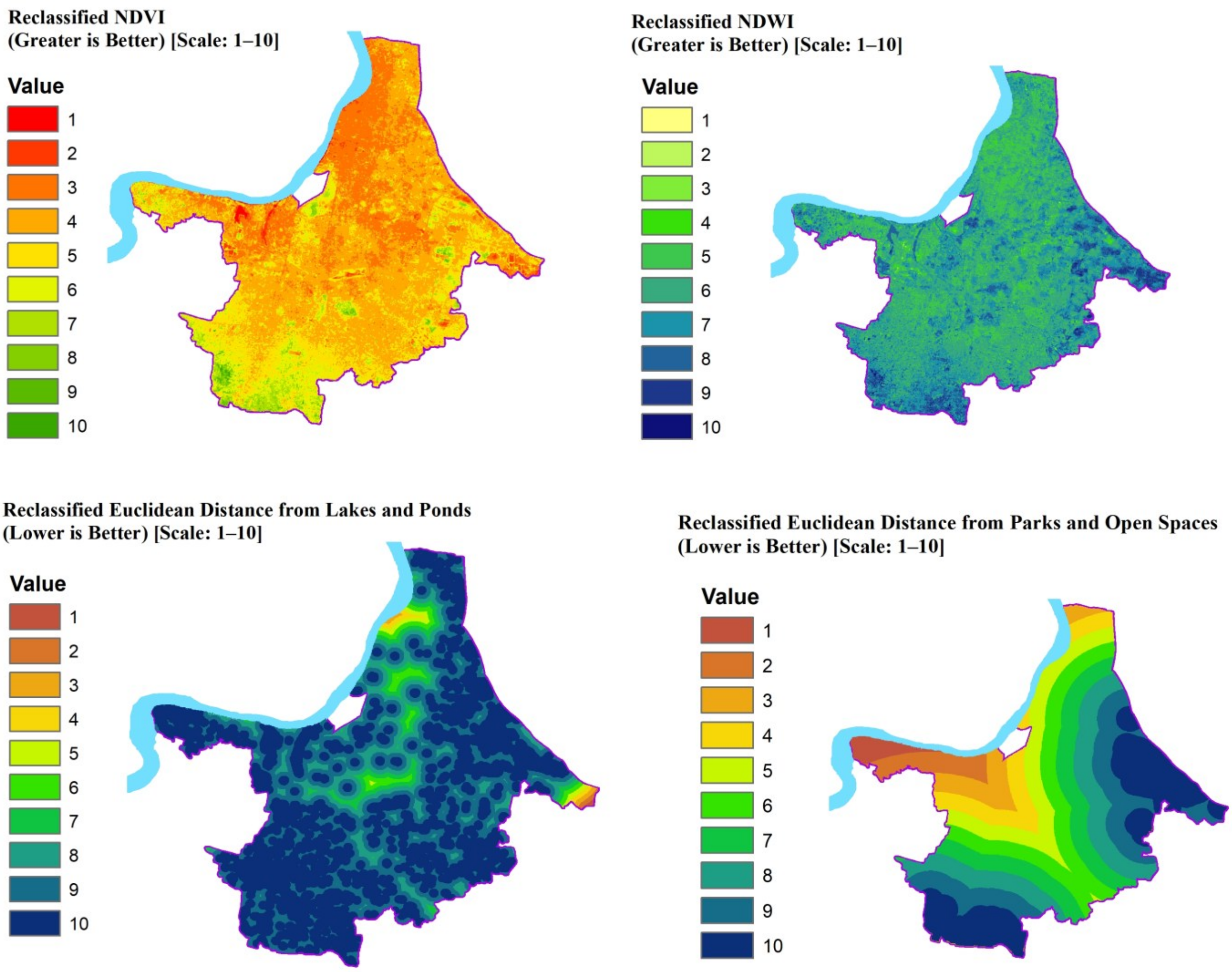

Figure 5. Reclassified map of key Health-Promoting Spatial Variables (HPSVs) for the Healthy Location Index (HLI) using a 1–10 scale, where higher values indicate stronger contributions to urban health. NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index) follow a "Greater is Better" approach, with higher scores assigned to areas with greater vegetation and water presence. Euclidean Distance from Ponds & Lakes and Parks & Open Spaces follow a "Lower is Better" approach, with higher scores assigned to areas closer to these features, reinforcing their positive impact on HLI.

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The spatial variables were assigned priority percentages based on their relative importance in determining the healthiness of different locations across the city (Table 3). These priorities reflect the weight each factor has in contributing to either positive or negative health outcomes, aligning with recent urban health research (Lowe, Boulange, & Giles-Corti, 2014).

Table 3. Result of Priority Matrix

Spatial Variables	Priority (%)	Rank
Near Higher NDVI value	6.8	6
Near Higher NDWI value	8.5	5
Near Open Space/ Recreational Park	6.1	7
Near Blue Space/Pond/ Lake	11.3	4
Away from higher NDBI	3.9	8
Away from Waterlogged Zone	12.8	3
Away from fast food and Alcohol Outlets	21.1	2
Away from Higher AQI	29.4	1

The highest-ranked spatial variable, distance from areas with higher Air Quality Index (AQI), received a weight of 29.4%, indicating that air quality is the most critical factor in determining a healthy location in Kolkata. This finding is consistent with numerous studies showing the significant impact of air pollution on respiratory and cardiovascular diseases, especially in dense urban areas like Kolkata (Haque and Singh, 2014; Manisalidis et. al., 2020). Given that Kolkata ranks among the most polluted cities in India, poor air quality remains a substantial public health concern, particularly in areas with dense vehicular traffic and industrial activity (Lowe, Boulange, & Giles-Corti, 2014). The second most critical factor is proximity to alcohol outlets, which is associated with a 21.1% priority. This aligns with existing research suggesting that areas with a higher concentration of fast food and alcohol outlets tend to exhibit poorer health outcomes, due to the increased prevalence of lifestyle-related diseases such as obesity, liver disease, alcohol dependency, and violence-related injuries (Ganasegeran, et.al. 2024).

The high weight of this factor underscores the importance of regulating alcohol availability in urban areas to improve public health outcomes. Proximity to waterlogged zones was ranked third, with a weight of 12.8%. This is significant in the context of Kolkata's vulnerability to monsoon flooding, which exacerbates the spread of waterborne diseases like cholera and dengue fever, posing serious health risks in certain parts of the city (Mukhopadhyay et. al. 2019). Waterlogged zones in Kolkata frequently suffer from stagnant water and poor drainage systems, leading to an increased prevalence of these diseases, particularly in low-income neighborhoods where infrastructure may be lacking. Proximity to blue spaces (ponds/lakes) was assigned a weight of 11.3%, reflecting the positive health impact of access to natural water bodies, which are known to promote mental well-being, reduce stress, and encourage physical activity (Ganasegeran, et.al. 2024). Blue spaces, such as the East Kolkata Wetlands, play a crucial role in enhancing the environmental and aesthetic quality of urban areas, contributing to overall health improvements. In contrast, proximity to open spaces and recreational parks received a lower priority, with a weight of 6.1%. Although green spaces are known to have a positive impact on physical and mental health, the relatively low availability and uneven distribution of such spaces in Kolkata likely reduce their overall influence on public health outcomes (Sarkar, Webster, & Gallacher, 2018). Despite this, open spaces remain important for promoting outdoor activities and mitigating the urban heat island effect, especially in the context of climate change (Sen & Guchhait, 2021). The Normalized Difference Vegetation Index (NDVI), which measures vegetation density, was weighted at 6.8%, ranking sixth. While NDVI is indicative of green coverage, its lower weight compared to AQI and alcohol outlets suggests that, although important, vegetation cover in Kolkata does not have as immediate or significant an impact on health as other factors. This is likely due to the limited availability of high-quality green spaces in core urban areas, where the negative effects of pollution and urban density outweigh the benefits of green cover. Conversely, proximity to areas with high Normalized Difference Built-up Index (NDBI)—an indicator of built-up, urbanized areas—was assigned the lowest priority, with a weight of 3.9%. This finding suggests that while urban density contributes to health concerns, its impact is less direct compared to other spatial variables such as air quality and access to open spaces. The moderate weight assigned to NDBI may also reflect the fact that, despite high levels of urbanization, Kolkata's compact urban form and relatively high use of public transport can mitigate some of the negative health impacts associated with urban sprawl (Lowe, Boulange, & Giles-Corti, 2014).

The priority matrix highlights a clear distinction between the health-promoting and health-restraining factors in Kolkata. Notably, air quality, proximity to alcohol outlets, and waterlogged areas emerge as the most critical health-restraining variables, reflecting their profound and immediate impact on public health. These findings are consistent with the literature on urban health risks, where air pollution, lifestyle factors, and environmental hazards are commonly cited as major contributors to health inequities in cities (Maji, Dikshit, & Deshpande, 2017). In contrast, access to blue spaces, open spaces, and vegetation are health-promoting variables, though their relative influence is less pronounced in the context of Kolkata's urban environment. This suggests that while the presence of natural spaces contributes positively to health, their distribution and availability are insufficient to offset the negative impacts of pollution and urban density in many parts of the city. The analysis yielded a Consistency Ratio (CR) of 8.4%, well within the acceptable threshold of 10%. The CR is a key measure in AHP to ensure the reliability of the pairwise comparisons; a CR above 10% would render the results unreliable (Saaty, & Kearns, 1985). In this study, the consistency of the judgments underscores the robustness of the final HLI outcomes.

After performing the reclassification and pairwise comparison, the HLI was developed by integrating the weighted values of each health-promoting and health-restraining variable. The Healthy Location Index (HLI), displayed in Figure 7, reveals significant spatial heterogeneity in the healthiness of different parts of Kolkata. As highlighted before on a scale of 1-10, lower index values correspond to less healthy areas, while higher values denote healthier locations. Most areas within the city fall under an index value of 5, indicating a moderate level of health, where locations are neither strongly health-promoting nor severely health-restraining. This aligns with other urban studies highlighting the challenges of balancing urban development with health sustainability, especially in dense megacities (Harpham and Werna, 1996). Key areas, such as Esplanade, Park Street, Topsia and Badartala, fall under the lower end of the index, suggesting these are health-restraining locations. These areas are characterized by higher levels of urbanization, poor air quality, and proximity to health-restraining variables like alcohol outlets and waterlogged areas, contributing to a less favorable living environment. Studies from similar urban contexts highlight the cumulative negative effects of built density and limited access to green spaces, which exacerbate public health risks (Sarkar, Webster, & Gallacher, 2018). In contrast, areas like Cossipore, Anandapur part of south-west Kolkata show relatively higher index values, between 6 and 8, indicating health-promoting locations. These areas benefit from proximity to green and blue spaces and lower concentrations of built-up areas, which enhance their overall health quality. Similar findings have been reported in other urban studies, where access to green and open spaces significantly correlates with better public health outcomes, especially in reducing stress and promoting physical activity risks (Sarkar, Webster, & Gallacher, 2018).

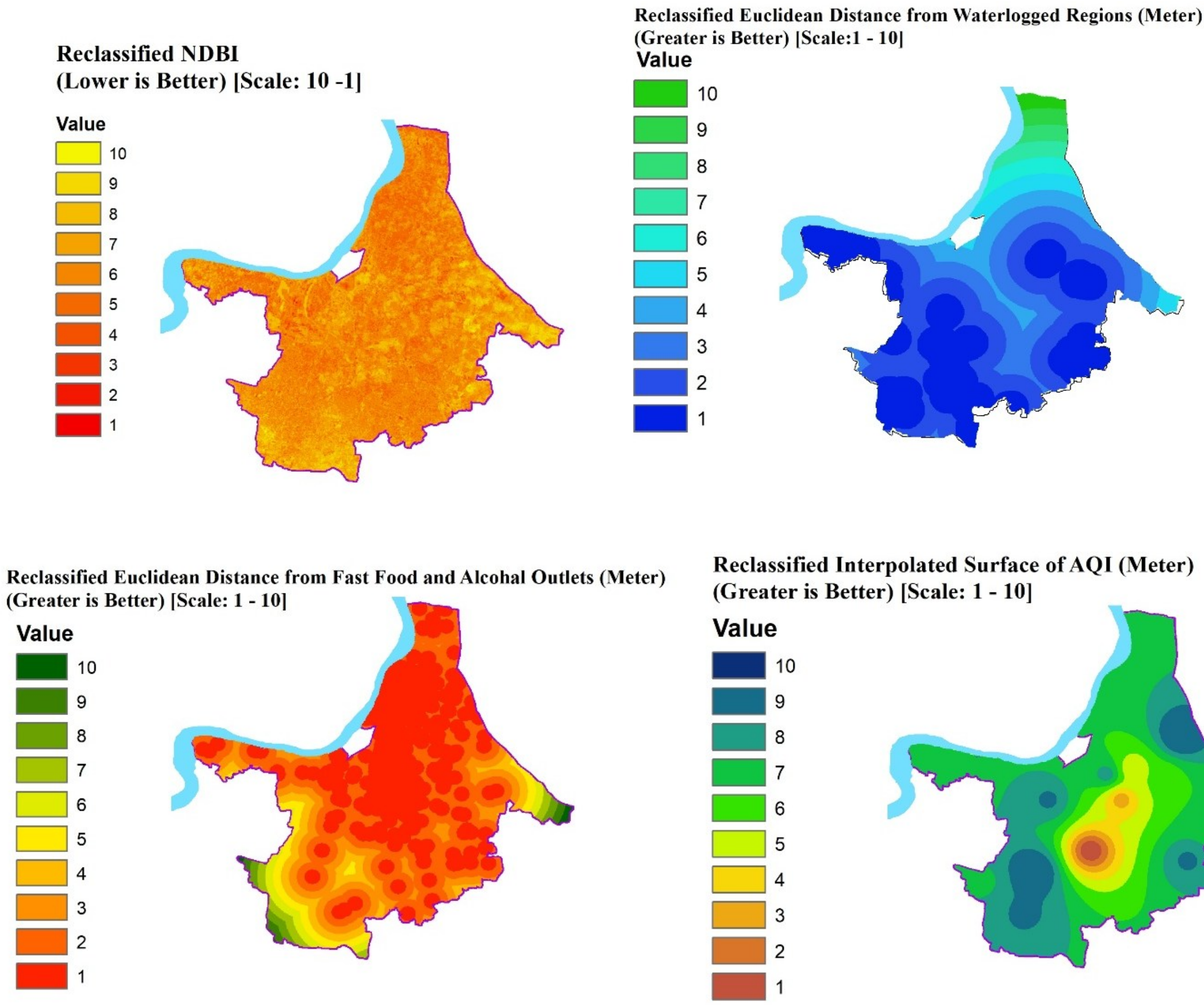

Figure 6. Reclassified Health-Restricting Spatial Variables (HRSVs) Map – Demonstrating Inverse HLI Contributions Based on Proximity: Greater distances from HRSVs (e.g., high-density built-up areas, alcohol outlets, zones of poor air quality) contribute positively to HLI

5. Validation of HLIs using Post Lockdown containment zones of 2020 - 2021

To validate the HLI's performance, we used containment zones designated by the West Bengal State Government as a precautionary measure during the COVID-19 lockdown from June 2020 to January 2021. Containment zones, as defined by public health and government agencies, are geographically demarcated areas established to curb the spread of infectious diseases, like COVID-19, through localized restrictions and enhanced surveillance. Within these zones, strict control measures are implemented, such as movement restrictions, compulsory testing, and isolation protocols, designed to prevent community transmission from identified hotspots to surrounding areas. These zones are typically designated based on criteria such as population density, number of confirmed cases, and environmental factors contributing to higher transmission risks (Routh, Rai, & Bhunia, 2023). In the context of this study, containment zones marked by the West Bengal State Government from June 2020 to January 2021 were used to validate the Healthy Location Index (HLI) developed for Kolkata. The hypothesis assumes that "healthy" areas, as indicated by higher HLI scores, would be less likely to be designated as containment zones due to favorable environmental and spatial conditions that potentially lower disease transmission risks. By comparing containment zone locations with HLI rankings (Figure 8), this study employs containment zones as a real-world indicator of urban health risk, corroborating the index's accuracy in delineating health-promoting versus health-restraining urban areas (Lak, Shakouri Asl, Maher, 2020; Clark et.al. 2024).

To assess the reliability of the HLI in predicting healthiness, a Receiver Operating Characteristic (ROC) curve was employed (Figure 9). The ROC curve, a diagnostic tool commonly used in epidemiology and geospatial health studies, measures the classifier's performance by plotting

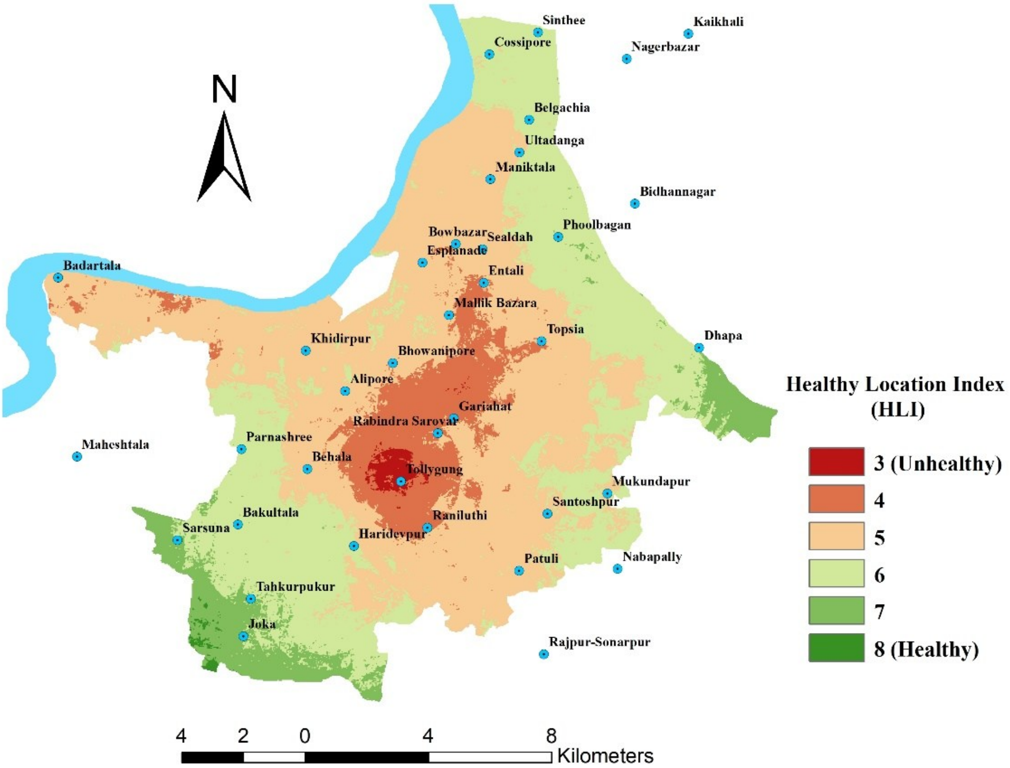

Figure 7. Healthy Location Index Map of Kolkata

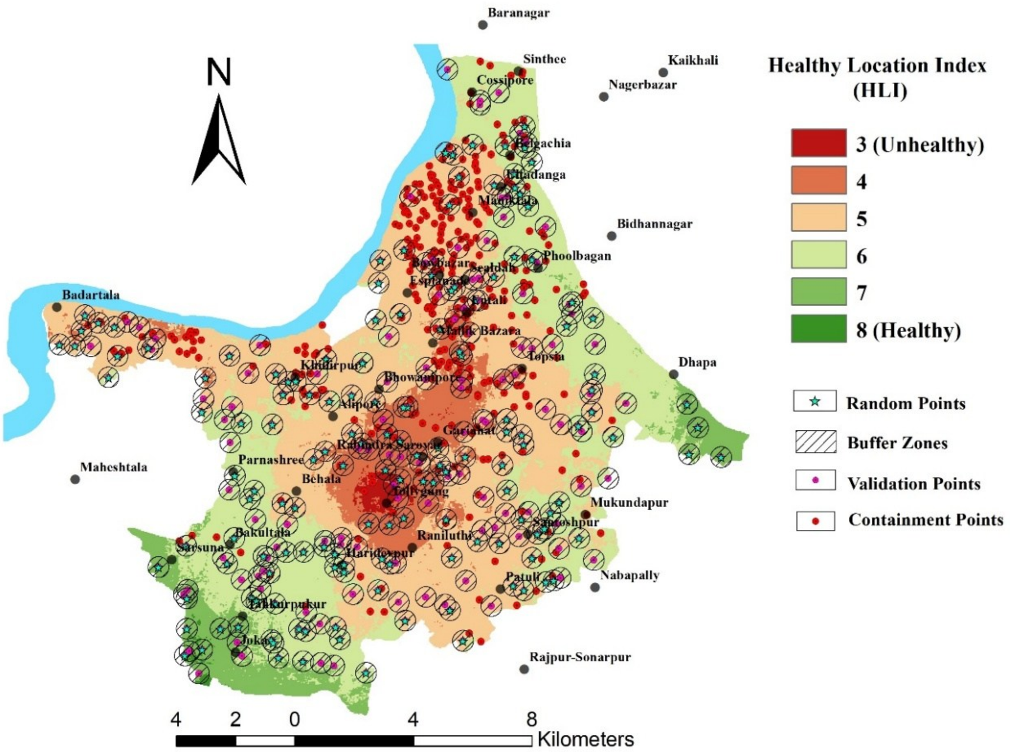

Figure 8. Overlay map of 2020-2021 containment zones on the Healthy Location Index (HLI) map of Kolkata, with 200-meter buffers around randomly generated points to identify co-occurrences between containment zones and health restraining zones.

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sensitivity (true positive rate) against specificity (1 - false positive rate). In this case, the ROC curve evaluates how effectively the HLI values correlate with the likelihood of an area being marked as a containment zone. An Area Under the Curve (AUC) close to 1 would signify a strong predictive capacity, confirming the HLI's relevance for assessing spatial health risks within urban environments (Mas. Et. al. 2013; Nath et.al. 2021). The assumption underlying this validation is that locations classified as "healthy" by the HLI would have a lower likelihood of being marked as containment zones, as the spatial factors associated with health-promoting areas—such as higher greenery, better air quality, and reduced urban density—are likely to limit viral transmission and improve resilience to outbreaks (Lak, Shakouri Asl, Maher, 2020). The ROC (Receiver Operating Characteristic) curve for the Healthy Location Index (HLI) serves to assess its classification accuracy in predicting containment and non-containment zones within Kolkata (Figure 9). By plotting “1 - Specificity” along the x-axis against “Sensitivity” on the y-axis, the ROC curve illustrates the model's performance, with points above the diagonal indicating accuracy better than random chance and points below indicating worse performance (Clark et. al. 2024). The “Positive if Greater Than or Equal to” values are considered as cut-offs. For any location if the cut off values is less than 6.50 the “Sensitivity” and “1-Specificity” percentage is considered as Unhealthy and get drafted as Containment Zone. Any Location which is greater than 6.50 is considered as Healthy and will not get drafted as containment zones (A1 and A2). The cut-off was derived using the Youden’s Index (J = Sensitivity + Specificity - 1), which is a widely accepted method in ROC analysis for selecting the optimal threshold that maximizes both true positive rate (sensitivity) and true negative rate (specificity). This ensures that the classification of healthy and unhealthy zones achieves the best possible balance between false positives and false negatives. The asymptotic significance level of .000 ($p < 0.001$) confirms the robustness of the cut-off selection, indicating a meaningful differentiation between the two categories. In this study, the ROC curve shows a positive classification, represented by a blue line above the diagonal, affirming that the HLI’s distinction between health-promoting and health-restraining zones is meaningful (Figure 9). The Area Under the Curve (AUC) is statistically significant with an asymptotic significance level of .000, demonstrating a strong association between the containment status and HLI values (Table A1).

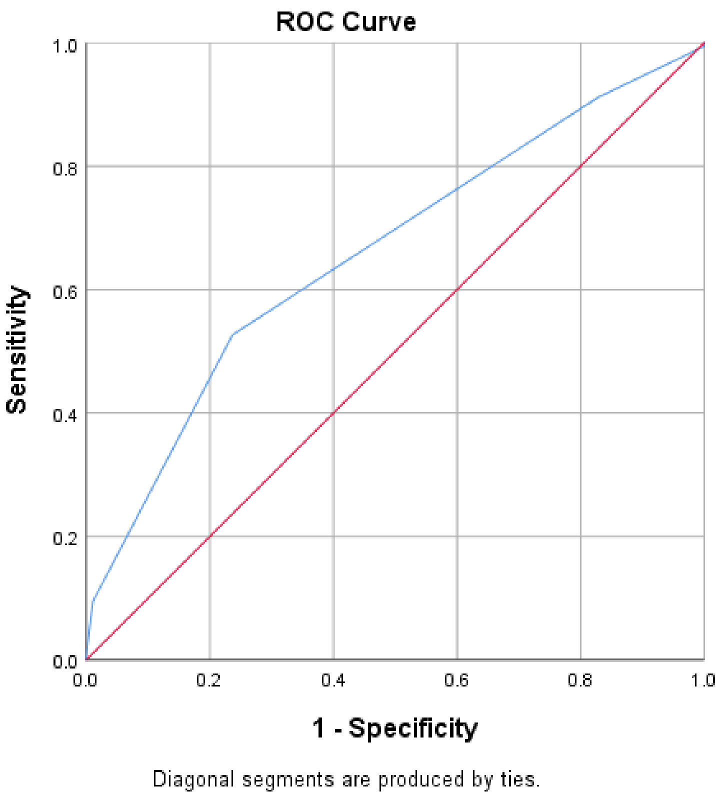

Figure 9. ROC validation curve

An AUC of 0.66 in this context indicates that 66% of the instances of containment and non-containment zones correspond directly to the HLI scores, supporting the hypothesis that higher HLI scores align with healthier, non-containment areas and lower HLI scores align with areas more likely to be containment zones (Table 5). Although, the ROC analysis with AUC of 0.66 suggests that the Healthy Location Index (HLI) has moderate predictive ability in distinguishing between healthy and unhealthy zones, this value is statistically significant, it indicates that 66% of instances of containment and non-containment zones align with HLI scores, which is above random chance (AUC = 0.5) but below the threshold considered strong predictive performance (AUC ≥ 0.8). These findings highlight the utility of the HLI as a geospatial health metric in identifying and assessing spatial health risks across urban zones.

6. Conclusions

The Healthy Location Index (HLI) developed in this study establishes a rigorous geospatial framework for assessing health heterogeneity across urban landscapes, considering both health-promoting and health-restraining spatial variables. The methodology leverages the Analytic

Hierarchy Process (AHP) for assigning weighted importance to each variable and utilizes Euclidean distance to model spatial relationships effectively, providing a refined analysis of localized health conditions. This approach enabled an in-depth view of health vulnerability at a granular level, as validated by ROC curve analysis using COVID-19 containment zones—a strategy representing recent urban health risk—thereby underscoring the HLI's validity in capturing spatial health disparities (Nath et.al. 2021). Results demonstrated significant spatial variation within Kolkata, with areas like Cossipore, Patuli, Santoshpur, Parnashree, Tahkurpukur, Nabapally, Sarsuna etc. emerging as more health-promoting, due in large part to their proximity to natural elements such as green and blue spaces. In contrast, areas with high levels of urbanization and poor air quality, including Esplanade, Topsia, Tollygung, Baowbazar, Sealdah, Entali, Mullickbazar etc., were highlighted as health-restraining zones. These insights underscore the potential of HLI as a tool for directing targeted public health measures, urban planning policies, and sustainable development efforts that aim to reduce health inequalities and enhance urban liveability.

In the academic sphere, this study contributes significantly by advancing the methodology for health index modeling in urban settings, validated by empirical health data, and setting a standard for combining geospatial analytics with health metrics in urban studies (Ozdenerol, 2016). However, limitations arise from the reliance on static spatial data, which does not fully capture temporal health variations or account for the dynamic nature of urban environments and emerging health trends. Additional limitations include potential bias from the subjective weights assigned in the AHP process, as well as challenges in accessing high-resolution data on health-restraining features such as real-time air quality or socio-economic deprivation indices (Lowe, Boulange, Giles-Corti, 2014). The moderate predictive ability of an AUC of 0.66 implies that while HLI provides valuable insights into spatial health risks, it should be used in conjunction with other health indicators rather than as a standalone metric. Additional inclusion of spatial, demographic, and epidemiological factors, such as population density, socioeconomic status, healthcare accessibility, and acute disease incidence rates may further enhance predictive accuracy. While HLI is informative in identifying areas at risk, targeted interventions should be validated with field data. Containment strategies, or resource allocation for disease prevention or air pollution control, can be prioritized in areas with lower HLI scores. However, decision-makers must also consider potential biases in geospatial data, the role of unmeasured confounding variables (socio-economic factors, demographic, behavioural and life style factors, policy and governance factors etc.) and the need for adaptive modeling based on real-time health outcomes (Kirkbride et al., 2024). Research should focus on enhancing the temporal sensitivity of the HLI by integrating time-series geospatial datasets, possibly utilizing real-time satellite data or IoT sensor networks to capture dynamic health variables like air quality, noise levels, or even crowd density. Incorporating machine learning algorithms could further refine the weighting process and increase objectivity. Expanding HLI validation by comparing it with health outcomes from longitudinal data could also strengthen its reliability and applicability across various urban environments. This would help develop a more resilient model that can better inform urban health policies and allow adaptation to rapidly changing urban health landscapes.

Funding: This research was supported by a Grant-in-Aid for SEED Fund Research project titled “Restoration to Revitalization: Modelling Post COVID Medical Tourism Economy of Kolkata!” (No: AU/R&D/SEED/22/03-2020-21) from Adamas University, awarded to Dr. Anu Rai, Assistant Professor, Department of Geography, Adamas University, Kolkata, as the Principal Investigator, for pursuing research on this subject.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: The authors would like to extend their sincere gratitude to all the experts and respondents who participated in the pairwise comparison survey for their valuable insights and contributions. Additionally, we thank the anonymous reviewers for their constructive feedback and suggestions, which greatly improved the quality of this work.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

AI Assistance Declaration: The authors declare that AI assistance was used solely for language modifications and grammatical corrections in this research document. The content, ideas, and analyses remain the original work of the authors, with no substantive changes or intellectual contributions from AI tools. The use of AI was limited to enhancing readability and ensuring linguistic clarity.

Appendix

Table A1. Result of ROC validation

(a) Case Processing Summary

Containment	Valid N (listwise)
Positive[a]	169
Negative	93

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

[a.] The positive actual state is 0.

(b) Area Under the Curve (AUC)

Test Result Variable(s): HLI

Area	Std. Errora	Asymptotic Sig.b	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.660	.034	.000	.593	.727

The test result variable(s): HLI has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Table A.2 Coordinates of the Curve

Positive if Greater Than or Equal To	Sensitivity	1 - Specificity	Sensitivity	1 - Specificity
2.00	1.000	1.000	100.00%	100.00%
3.50	.994	1.000	99.41%	100.00%
4.50	.911	.828	91.12%	82.80%
5.50	.527	.237	52.66%	23.66%
6.50	.095	.011	9.47%	1.08%
7.50	.006	0.000	0.59%	0.00%
9.00	0.000	0.000	0.00%	0.00%

Note: The "Positive if Greater Than or Equal to" values are considered as cut-offs. For any location if the cut off values is less than 6.50 the "Sensitivity" and "1-Specificity" percentage is considered as Unhealthy and get drafted as Containment Zone. Any Location which is greater than 6.50 is considered as Healthy and will not get drafted as containment zones. The cut-off was derived using the Youden's Index (J = Sensitivity + Specificity - 1), which is a widely accepted method in ROC analysis for selecting the optimal threshold that maximizes both true positive rate (sensitivity) and true negative rate (specificity). This ensures that the classification of healthy and unhealthy zones achieves the best possible balance between false positives and false negatives. The asymptotic significance level of .000 (p < 0.001) confirms the robustness of the cut-off selection, indicating a meaningful differentiation between the two categories.

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