Original Research Article

Evaluating equity for urban resilience in Hong Kong: integrating human-centric principle (HCP) with geospatial artificial intelligence (GeoAI)

Siwei Tang

Chengdu,Sichuan, 610000, China

Abstract: This research explores the intersection of the Human-Centric Principle (HCP) and Geospatial Artificial Intelligence (GeoAI) to evaluate the fairness of the urban environment in Hong Kong. As Hong Kong faces increasing challenges from social inequality and rapid urbanization, it is essential to develop inclusive strategies that prioritize the needs and voices of marginalized communities. This study proposes an integrated framework that leverages HCP to ensure citizen-centric approaches in the evaluation process of the urban environment while utilizing GeoAI to analyze spatial data and visualize community impacts. Through a mixed-methods approach, including case studies, data collection, and spatial analysis, this research aims to identify barriers to equity in urban resilience initiatives and propose actionable solutions. By engaging with diverse community members, the study seeks to enhance participatory design processes, ensuring that the benefits of resilience efforts are equitably distributed. The findings will contribute to a deeper understanding of how HCP and GeoAI can work synergistically to assess urban environments of Hong Kong, contributing to fostering not only a resilient but also an equitable city.

Keywords: Urban equity; Human-centric principle; Geospatial artificial intelligence; Hong Kong

1. Introduction

In the past decades, inequity in urban environment has become an increasing global concern. Inequality has remained ubiquitous with significant heterogeneity across different regions[1]. Previous research also reveals that inequity and marginality are shaped by relentless social forces and natural factors[2]. Multitudes of scholars have explored solutions to urban inequity, focusing on a wide range of strategies to create more inclusive cities. However, the scholars studying urban equity tend to concentrate on certain issues rather than acquire a comprehensive perspective of scientific and humanistic aspects, and the study of disparities is shaped by the researchers' situatedness[3].

This project intends to include Hong Kong as the case study region. Urban equity issues in Hong Kong are multifaceted, influenced by its unique socio-economic issues and environmental context. Hong Kong faces its distinct challenges related to inequity, reflecting the complex interplay between local factors and urban dynamics. Evidence indicates a significant increase in urban inequality in Hong Kong over the years[4]. The unequal dynamics have led to significant disparities in housing, education, and access to resources, perpetuating cycles of inequality. Since the late 1980s, the Gini coefficient of Hong Kong has rapidly increased and persisted above 0.5[5].

2. Exploring approaches for urban equity assessment

2.1. Human-centric principle (HCP)

The Human-Centric Principle (HCP) is an effective criterion that prioritizes the needs, preferences, and experiences of the citizens throughout the evaluation process. The HCP initiatives can raise awareness for urban inequality, fostering a culture of empathy and understanding within communities. According to the European Commission, Human-Centric Cities welcome people from all backgrounds and diversities, guaranteeing equal rights and opportunities, such inclusive cities can preclude inequalities[6]. In the review of HCP studies from 2020 to 2023, the cynosures of HCP scholars are interconnected with resilience and equity (**Figure 1**), which indicate the importance of HCP to advancing urban justice.

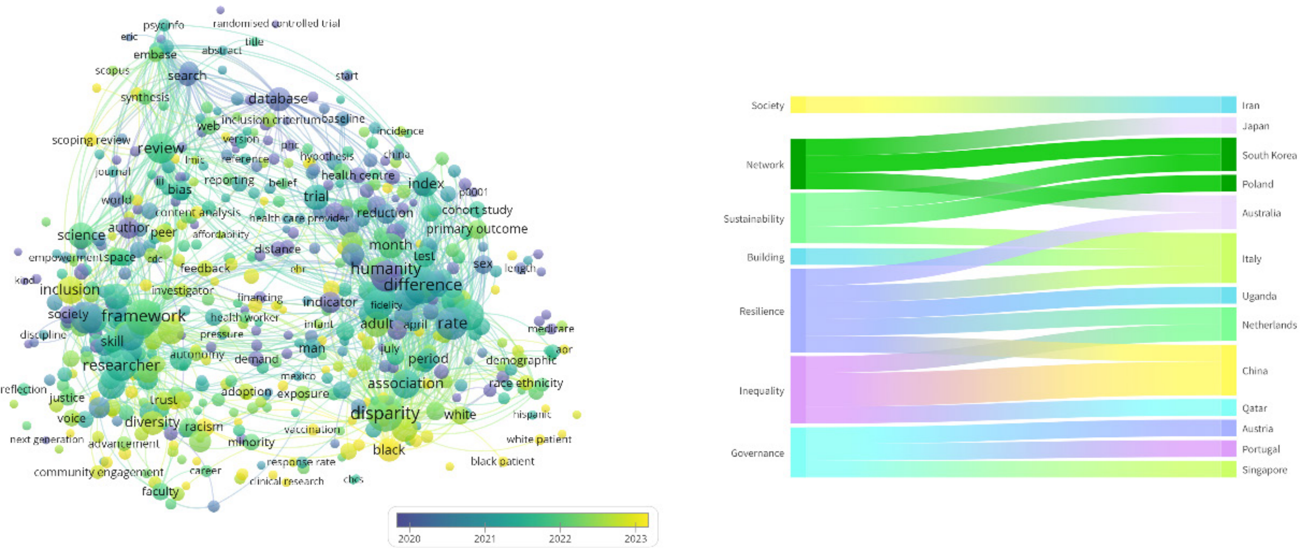

Figure 1. The Interconnected Fields in HCP Researches from 2020 to 2023.

(Source: Author)

2.2. Geographic artificial intelligence (GeoAI)

Besides the aforementioned HCP, another useful tool is Geographic Artificial Intelligence (GeoAI), which refers to the integration of artificial intelligence with geography. This interdisciplinary field combines geographic information systems (GIS), remote sensing, and machine learning, etc. The early interplay of AI and geography can be traced back to 1984, when Smith first proposed applying AI techniques to geospatial problem-solving tasks[7]. In the 1990s, Openshaw published the influential book Artificial Intelligence in Geography, marking the beginning of a broader AI revolution in geographic research[8]. Today, GeoAI is recognized as a critical enabler of urban resilience due to its ability to process large volumes of spatial data, uncover hidden patterns, and generate predictive insights. This capability allows cities to anticipate and respond to challenges such as climate change, infrastructure stress, and social inequality more effectively. By evaluating resource allocation and incorporating justice-oriented considerations, GeoAI helps to assess equity systems and contributes to enhancing overall resilience. Recent studies highlight its potential to discover space discrimination and boost cities' sustainability, ensuring that urban environments are not only spatially efficient but also socially equal (**Figure 2**).

2.3. The hybrid approach combing HCP with GeoAI

Despite the substantial studies in HCP and GeoAI respectively, there still remain unfilled gaps that combine HCP and GeoAI for enhancing urban resilience and equity. While GeoAI has shown great promise in addressing urban challenges, its rapid development raises concerns about potential harms, including discrimination and inequality resulting from biased or opaque algorithms. Additionally, the concept of super-intelligent AI, often referred to as singularity, poses risks of AI systems surpassing human control[9]. These concerns underscore the need to integrate Human-Centric principles into GeoAI applications, especially in the context of urban evaluation. By combining HCP and GeoAI, we can mitigate these risks and address the ethical and social challenges posed by AI in urban environments. HCP ensures that technology remains aligned with human values, emphasizing transparency, inclusivity, and justice in evaluation processes. When applied together, HCP can provide a necessary counterbalance to the purely data-driven nature of GeoAI, guiding the development of AI systems that are not only technically robust but also socially reasonable. This hybrid approach fosters a symbiotic relationship between humanity and technology, ensuring that evaluation contributes to qualified judgment in urban environments.

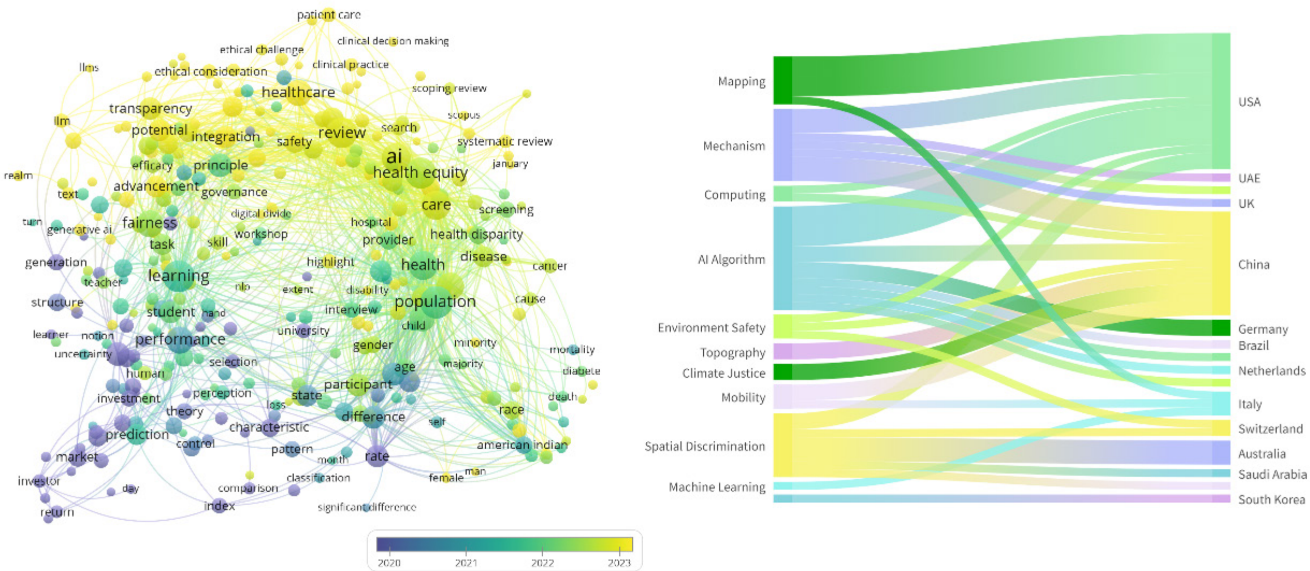

Figure 2. The Interconnected Fields in GeoAI Researches from 2020 to 2023.

(Source: Author)

2.4. The evaluative framework

The proposed research outline aims to form a rotative, responsive and retrospective framework (**Figure. 3**). Through evaluative methods, the scheme employs an iterative process based on machine learning and GIS. The HCP-GeoAI evaluation framework and design strategy are flexible and adaptable, allowing the system to respond effectively to evolving data and environmental conditions, resulting in more well-informed and practical assessments.

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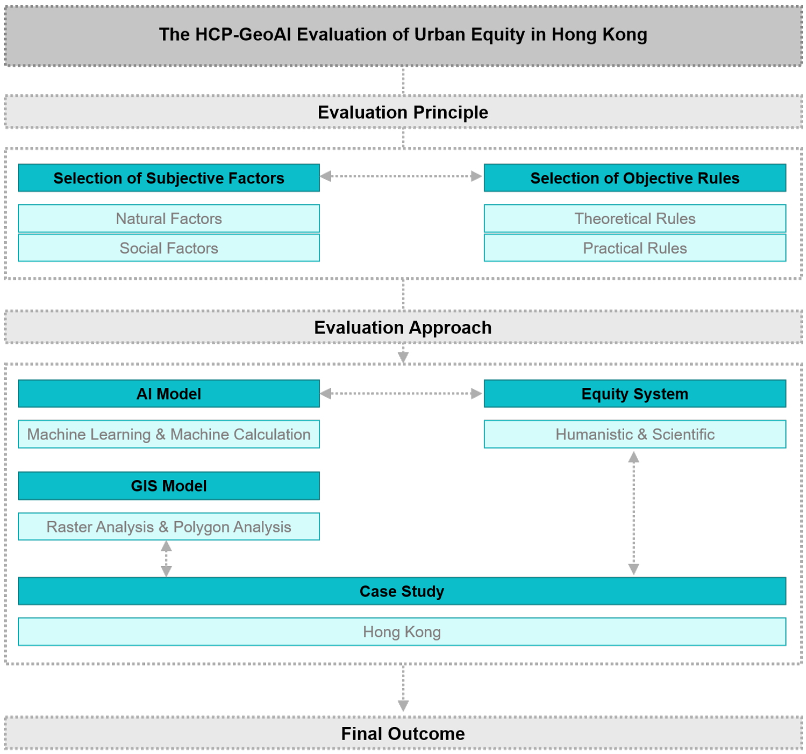


Figure 3. The HCP-GeoAI Evaluation Framework.

(Source: Author)

3. Evaluating urban equity in Hong Kong

3.1. Acquiring relative factor weights

First, Stepwise Regression Method is applied. Proposed by Efroymson[10], Stepwise regression is a statistical method which can be used for selecting a subset of evaluation factors for use in a regression model. After datasets are collected, all evaluation factors for equity prediction with the highest p-value (indicating the least significance) are removed until the remaining predictors meet the exit criteria. Finally, the evaluation factors are weighed and selected from the keywords (**Figure 4** and **Figure 5**).

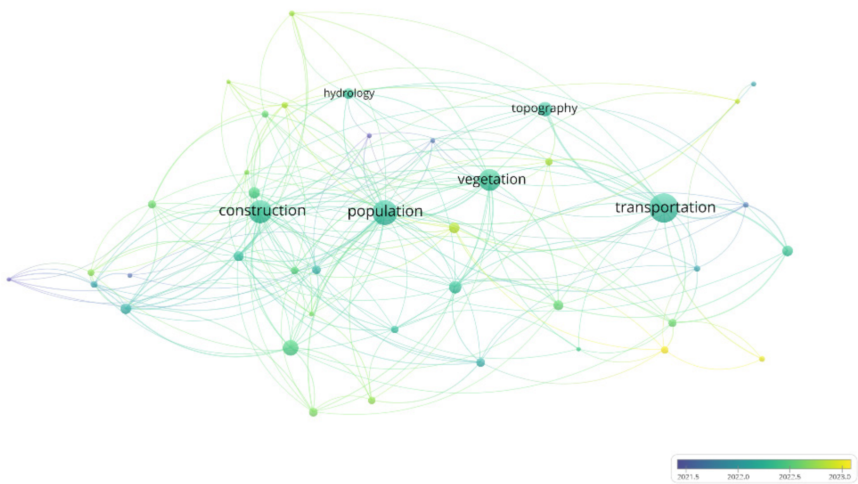


Figure 4. The Selected Evaluation Factors from Equity-Evaluative Researches from 2021 to 2023.

(Source: Author)

Figure 5. The Weight Chart of Evaluation Factors according to Researches from 2020-2024.

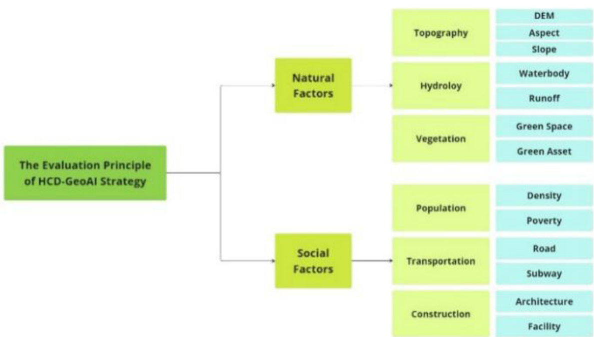
(Source: Author)

Base on the selected evaluation factors and weight reference from the Stepwise Regression Method, this step combines the Delphi Method with the Pairwise Comparison Method to compare each alternative factor directly with every other alternative factor in pairs[11]. Then, we identify and recruit a diverse group of experts with relevant knowledge and experience related to the topics. Distribute the questionnaire more than two rounds to the experts to gather their insights into the gradings of the evaluation factors (**Figure 6**).

	Hydrology	Vegetation	Population	Transportation	Construction	Topography
Hydrology		1/4	1/3	1/3	1/3	2
Vegetation			1	1/4	1/4	3
Population				1/4	1/3	3
Transportation					1	4
Construction						4
Topography						

Figure 6. The Pairwise Comparison Matrix of Evaluation Factors (Source: Author).

Analytic Hierarchy Process allows for the incorporation of both qualitative and quantitative factors, making the combination of humanistic aspects and scientific aspects applicable in this research. Once there are numerical values from the Pairwise Comparison Matrix, it is possible to derive weights for each criterion based on the comparison matrices (**Figure 7**).



Primary Factor	Weight
Transportation	0.3123
Construction	0.2951
Vegetation	0.1350
Population	0.1279
Hydrology	0.0763
Topography	0.0532

Secondary Factor	Weight
(Transportation) Road	0.2082
(Transportation) Subway	0.1041
(Construction) Architecture	0.1967
(Construction) Facility	0.0984
(Vegetation) Green Space	0.1013
(Vegetation) Green Asset	0.0338
(Population) Density	0.0320
(Population) Poverty	0.0960
(Hydrology) Waterbody	0.0254
(Hydrology) Runoff	0.0509
(Topography) DEM	0.0090
(Topography) Aspect	0.0236
(Topography) Slope	0.0206

Figure 7. The AHP Model and the Factor Weights.

(Source: Author)

3.2. Proceeding raster overlay process

Accompanied by the Reclassified Method and AI Digital Simulation Method, the Raster Overlay Process is based on mathematical operations, which can include addition, subtraction, multiplication, or division according to the factor weights to analyze relationships between different layers. After that, values in the raster layers can be reclassified or grouped into categories to simplify analysis. Continuous data can be categorized into low, medium, and high to measure equity and provide guidance for resilient design based on human-centric principles and AI-generated rules (**Figure 8**).

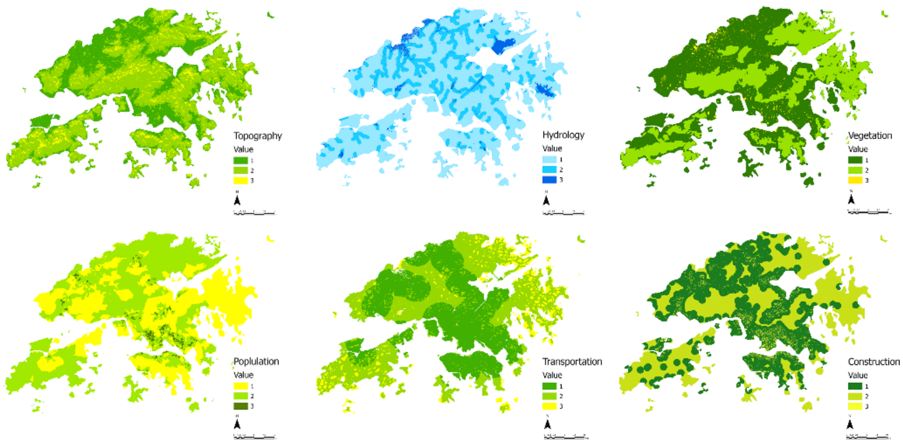


Figure 8. The Reclassification Maps of Equity Factors of Hong Kong.

(Source: Author)

3.3. Generating final equity indices

The six thematic sub-grid maps generated in this study reflect the spatial variation of data and the spatial relationship of equality characteristics. By using raster calculators in GeoAI to weigh and overlay these six thematic raster maps, an ideal equity index map was produced, which utilized artificial intelligence data correction and raster overlay techniques to generate the final equity index map. Through raster overlay and weighted calculations, it can be observed that equality in Hong Kong's urban areas is significantly influenced by construction and transportation. Areas with dense construction have a lower equity index, while areas with convenient transportation have a higher equity index (**Figure 9**). Overall, the equity index in northern Hong Kong is higher than in the south, indicating that urban development should be inclined towards the southern regions in the future.

As for the affordable building, the high cost of housing is a significant barrier to urban equity, efforts to provide affordable housing, such as public rental housing and subsidized homeownership schemes, are crucial. Besides, A well-developed public transportation system can enhance access to jobs and services for all residents, reducing inequalities. Achieving urban equity in Hong Kong requires a multifaceted approach that addresses housing, transportation, public services, and community engagement. By leveraging technology and fostering inclusive policies, Hong Kong can work towards a more equitable urban environment for all its residents.

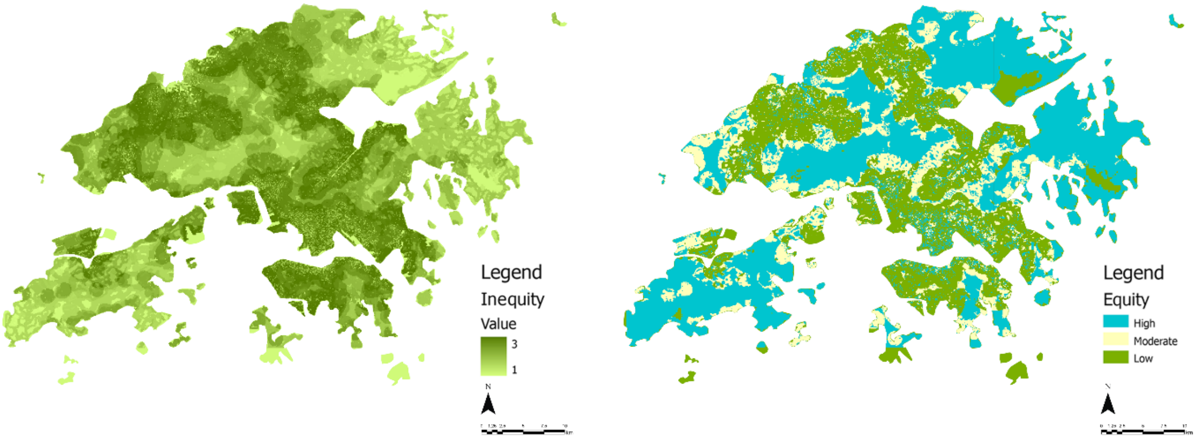


Figure 9. The Equity Index Maps of Hong Kong.

(Source: Author)

4. Conclusion and discussion

A Multi-Criteria Decision-Making (MCDM) approach in this research utilizes a pairwise comparison matrix of parameters to define an objective and is a key component of the Analytic Hierarchy Process (AHP) technique. The method indicates the importance of each criterion, and serves as the basis for evaluating judgments. Using the pairwise comparison matrix and normalized weights, methodologies were employed to determine the weights of various criteria for identifying equity-prone zones. These weights were established based on insights from experts. The final delineation of high-equity and low-equity zones in GeoGIS is derived from these weights through a weighted overlay analysis. By integrating HCP with artificial intelligence correction and raster overlay techniques, it is possible to quickly generate the equity sub-factor maps. Furthermore, by combining this with correlation analysis, high-precision equity index maps can be produced. Therefore, the method of generating the equity base map through raster overlays in conjunction with HCP is an ideal approach that combines GIS technology with artificial intelligence. The paper presents various improvements to the proposed method, but certain issues remain, such as the selection of equity factors for measurement. Compared to other methods, the literature review and the HCP's selection of equity sub-factors demonstrate a significant accuracy advantage. However, due to the limitations of the method itself, biases may arise, and the lack of multidimensional factors can lead to a misrepresentation of the actual equity distribution. It is necessary to assess whether to retain or remove factors based on field investigations, which require sociological knowledge and can impact the correction of the maps to some extent. Thus, further field exploration is needed on how to reasonably and appropriately utilize the information provided by artificial intelligence elements for automatic correction. Additionally, when calculating with weights, the determination and selection of these weights can significantly affect the results and should be established based on the researcher's understanding of the macro relationships of equity distribution and the density of sampling districts.

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