Assessing Spatial Equity and Potential Green Gentrification in Urban Farming Using GIS-based Machine Learning: A Case Study of Taipei's Garden City Program

Wei-Chun Chuang[1], Ching-Pin Tung[1], Wan-Yu Shih[2], Wen-Ray Su[3,4]*

[1] *Department of Bioenvironmental Systems Engineering, National Taiwan University, Taiwan*
[2] *MS Program in Disaster Risk Reduction and Resilience, National Taiwan University, Taiwan*
[3] *Department of Civil Engineering, National Taiwan University, Taiwan*
[4] *National Science and Technology Center for Disaster Reduction (NCDR), Taiwan*
william031430@gmail.com, cptung@ntu.edu.tw, wyshih@ntu.edu.tw, wrsu@ncdr.nat.gov.tw

Abstract

This study explores the spatial equity and socio-spatial implications of urban agriculture, focusing on the distribution of community gardens under Taipei's Garden City Program (TGCP) and their relationship to neighborhood-level income growth. By integrating unsupervised machine learning (DBSCAN) with spatial statistical methods (Moran's I and LISA), the analysis reveals that garden service density is highly concentrated in central districts, while peripheral areas exhibit significant service gaps. At the citywide scale, no significant correlation is found between garden density and income growth. This finding aligns with existing research suggesting that community gardens—being low-cost, small-scale, and decentralized—reflect the characteristics of the "just green enough" approach and are less likely to trigger conventional forms of green gentrification. However, several local areas do exhibit potential spatial coupling between garden presence and income change, highlighting the need for future policies to address distributional equity and neighborhood transition risks in urban agriculture planning.

Keywords: Urban agriculture, Spatial equity, Green gentrification, DBSCAN, GIS

1 Introduction

In recent years, urban agriculture has garnered increasing global attention as a multifunctional strategy for promoting sustainability, community resilience, and local food security [1-3]. Beyond its ecological and nutritional benefits, community gardening has been recognized for its potential to enhance social inclusion and foster place-based engagement in dense urban settings [4-7]. Against this backdrop, many cities—including Taipei—have launched garden-based initiatives aimed at embedding green infrastructure into the urban fabric. Launched in 2015, Taipei's Garden City Program (TGCP) reflects this trend, seeking to reintroduce green spaces through bottom-up, citizen-led farming across schools, communities, and public land [8-10].

However, as urban farming becomes more institutionalized, critical questions emerge regarding the spatial distribution and social impacts of these green interventions. Scholars have warned that urban greening, while environmentally beneficial, may inadvertently contribute to green gentrification—a process whereby ecological amenities raise neighborhood desirability, displace lower-income residents, and reinforce spatial inequality [11-16]. Within this debate, urban agriculture occupies an ambiguous position: although intended to promote equity, gardens may cluster in already privileged areas, thus exacerbating existing disparities in access to green space and social capital [17-18].

Building on this trend, a growing number of studies have employed GIS-based spatial statistical tools—such as Moran's I and LISA—to examine spatial associations related to urban risk, inequality, and green space accessibility [19-21]. Additionally, unsupervised machine learning algorithms, particularly DBSCAN, have been increasingly applied in urban spatial analysis for cluster detection and morphological classification. These techniques are especially effective in identifying non-linear or irregular spatial patterns that traditional statistical methods often fail to capture [22-23]. However, such methods have primarily been applied to domains such as accident analysis, pedestrian flow, natural disaster risk, and crime hotspot detection [24-28]. Their use in exploring the spatial coupling between urban agriculture and green gentrification remains relatively limited, highlighting the need for further empirical development and application in this emerging research area.

This study aims to examine whether urban farming initiatives in Taipei are equitably distributed, and whether they exhibit spatial patterns associated with potential green gentrification. Specifically, we analyze the spatial clustering of community gardens under the TGCP and assess their relationship to neighborhood-level income growth. To do so, we combine GIS-based spatial statistics (Moran's I, LISA) with unsupervised machine learning

*Corresponding Author: Wei-Chun Chuang; Email: william031430@gmail.com
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techniques (DBSCAN) to detect both macro- and micro-scale patterns in service distribution and socioeconomic change.

In Taipei, these debates are crystallised in the Taipei Garden City Program (TGCP), launched in 2015 as the city's flagship urban-agriculture initiative. The TGCP promotes edible landscapes across community spaces, schools and public buildings, and officially recognises four main types of gardens: community gardens on public open space, school gardens, rooftop gardens on public facilities, and allotment-style citizen farms. A city-wide 'garden bank' platform inventories eligible sites and coordinates adoption. Residents' associations, schools and non-governmental organisations can propose new garden bases or adopt existing ones through this platform, while the relevant managing agency reviews applications against criteria such as site safety and accessibility, minimum plot size, irrigation feasibility and the presence of a concrete management plan for ongoing maintenance and food- and ecology-related education activities.

By integrating geospatial analysis with machine learning, this study offers a novel empirical framework to assess whether urban agriculture—despite its inclusive rhetoric—may reinforce spatial injustice. In doing so, it contributes to a growing body of literature that interrogates the equity implications of green infrastructure, offering methodological tools and policy insights relevant for cities seeking to implement socially sustainable urban greening strategies. Concretely, the study addresses two research questions:

- RQ1: How are service intensities of TGCP gardens distributed across Taipei, and do they exhibit center–periphery disparities or localised clusters?
- RQ2: To what extent is village-level income growth spatially associated with the distribution of TGCP garden service intensity, and where do overlaps or mismatches between greening and income dynamics appear?

2 Literature Review

To situate this study within broader scholarly debates, this chapter reviews key literature at the intersection of urban greening, spatial justice, and socio-spatial change. Special attention is given to two domains: (1) the relationship between green space—particularly urban agriculture—and gentrification, and (2) the application of GIS and machine learning methods in urban spatial analysis. These strands of research provide both the theoretical grounding and methodological tools for analyzing the spatial equity implications of Taipei's Garden City program.

2.1 Green Space and Gentrification

Urban green space has long been promoted as a key strategy for improving environmental quality, public health, and social well-being. However, an expanding body of research has highlighted the paradoxical effects of greening in cities, wherein the introduction or enhancement of green amenities—such as parks, greenways, and waterfronts—can catalyze green gentrification. This process entails rising property values, demographic shifts, and the potential displacement of long-term or low-income residents, particularly in previously marginalized neighborhoods [11, 29-31].

While large-scale green infrastructure projects are often implicated in these dynamics [29, 32], the role of urban agriculture—and particularly community gardens—remains more ambiguous. On one hand, community gardens are frequently framed as tools for neighborhood empowerment, food justice, and grassroots placemaking [4-5, 33-35]. On the other hand, recent research suggests that while community gardens have the potential to welcome diverse participants, their prevalent framing around the "greater good" may unintentionally exclude food-insecure populations and reinforce food access inequalities [36].

Comparative analyses between traditional urban green spaces and urban agriculture suggest that while both can enhance local quality of life, they differ in scale, visibility, and institutional integration. Large parks or green corridors are often capital-intensive, top-down projects that attract real estate speculation [11, 37]. In contrast, community gardens are typically low-cost, small-scale, and decentralized—characteristics that align with the "just green enough" approach, which advocates for modest, community-led greening strategies aimed at avoiding speculative development and residential displacement [32, 38-39].

Although these characteristics suggest a lower risk of green gentrification, questions remain as to whether urban agriculture—particularly when scaled up or institutionalized—may still contribute to socio-spatial inequality. This study addresses this concern by examining the relationship between community gardens and neighborhood-level income change, with the aim of identifying whether the implementation of urban farming may inadvertently reinforce inequality or generate displacement pressures.

It is important to note that gentrification in general—and green gentrification in particular—is a multidimensional process that combines reinvestment in the built environment, changes in neighborhood social composition, and, in many cases, various forms of displacement or exclusion. Quantitative studies therefore often rely on multiple indicators, including trends in housing prices and rents, shifts in educational or occupational structure, changes in racial or ethnic composition, and evidence of residential turnover. In this study, we adopt a more restricted operationalization due to data availability and the need for citywide comparability: we use CPI-adjusted median household income growth at the administrative-village scale as an indicator of socio-economic uplift that may be consistent with early-stage green gentrification, while acknowledging that it does not capture the full dynamics of displacement or class restructuring. Accordingly, we interpret the results as patterns of socio-spatial association between urban-agriculture service intensity and income dynamics, rather than as definitive measurements of complete gentrification processes.

2.2 GIS and Machine Learning in Urban Research

The integration of Geographic Information Systems (GIS) and computational methods has significantly advanced research on spatial inequality and urban socio-spatial transformation. In particular, spatial statistical tools within GIS—such as Global Moran's I and Local Indicators of Spatial Association (LISA)—have been widely employed to detect clustering patterns and measure spatial autocorrelation in socioeconomic and environmental variables [40-43]. These methods have proven highly valuable for identifying spatial disparities in income distribution, green space accessibility, environmental risk, and patterns of urban redevelopment [4, 44-47].

Beyond conventional spatial statistics, unsupervised machine learning algorithms, especially DBSCAN (Density-Based Spatial Clustering of Applications with Noise), have gained growing attention in urban studies. DBSCAN does not require a predefined number of clusters and is capable of detecting non-linear and irregular spatial groupings—making it particularly suitable for analyzing fragmented or organically formed urban environments [22, 26, 43].

Despite these advances, the application of machine learning to urban agriculture and green infrastructure remains relatively underexplored [48]. This study therefore applies an integrated approach combining spatial statistics and machine learning to analyze the spatial characteristics of Taipei's Garden City program. Specifically, DBSCAN is used to detect service clustering patterns of community gardens. Given the large number and heterogeneous, often random spatial distribution of garden sites, this method is especially well-suited to the analysis [43]. Furthermore, Global Moran's I and LISA are applied to assess spatial associations between garden distribution and socioeconomic changes, such as income growth [49]. Together, this integrated method offers a more nuanced understanding of the spatial structure and social effects of urban agriculture, while contributing to both the methodological and empirical dimensions of urban sustainability research.

3 Methodology

3.1 Study Area and Data Collection

The study area encompasses the entirety of Taipei City, a high-density metropolitan region of 2.5 million residents characterized by steep topography, strong center–periphery contrasts, and a long history of land-use pressure on agricultural land. Since 2015, the city has implemented the Taipei Garden City Program (TGCP) as a key policy instrument for promoting urban agriculture and enhancing green infrastructure. Under this program, edible gardens are created on a diverse set of sites, including community gardens on public open space, rooftop gardens on public buildings and school grounds, and allotment-style citizen farms. These gardens are embedded within a broader policy agenda that links food production to environmental education, social cohesion and climate adaptation.

Institutionally, the TGCP is operationalised through a 'garden bank' system that inventories potential garden bases and coordinates public adoption. Residents' associations, schools, social organisations and other civic groups may apply to establish or adopt a garden base; applications are reviewed by the relevant managing agency in accordance with the city's Garden City implementation guidelines, which specify criteria related to site suitability, public accessibility, safety, basic infrastructure (e.g. water access) and long-term management capacity. Official statistics indicate that by the end of 2016 the city had integrated 401 garden bases—58 'Happy Farms' on public vacant land, 31 green roofs, 295 'small gardens' in schools and 17 citizen farms—totalling approximately 101,898 m² and engaging 26,584 participants. Within five years, the program had expanded to more than 730 gardens city-wide, covering nearly 20 hectares of edible green infrastructure and involving over 50,000 citizens. Our analysis focuses on all TGCP gardens established between 2014 and 2018, capturing the core expansion phase of the program while aligning the timing of garden implementation with the available income data used in the socio-spatial analysis.

Primary data were collected through structured surveys administered to 130 TGCP gardens, comprising 38 community, 33 rooftop and 59 school gardens. The questionnaire was specifically designed for the managers or coordinators of Taipei Garden City gardens and focused on operational characteristics such as monthly opening days, daily operating hours, average weekly usage frequency and accessibility restrictions. The survey was implemented during the study period using a combination of telephone interviews and on-site visits. One response was obtained for each sampled garden; all 130 contacted garden managers completed the questionnaire, resulting in a response rate of 100% for the targeted sample. Secondary spatial data were obtained from the Government's Open Data Platform, specifically the Garden City spatial dataset provided by the Parks and Street Lights Office, Public Works Department. These data included garden locations, sizes, dates of establishment and closure, as well as garden types (community, rooftop, or school). Additionally, village-level household counts and median household incomes for 2015 and 2018 were sourced from the Fiscal Information Agency, Ministry of Finance. Administrative boundary data for villages were obtained from the National Land Surveying and Mapping Center (NLSC) under the Ministry of the Interior, providing official polygon datasets essential for accurate spatial analysis and aggregation.

3.2 Research Design and Workflow

A five-stage analytical workflow was implemented in Python 3.10, leveraging specialized geospatial and spatial statistical libraries to assess spatial equity and potential green gentrification within Taipei's Garden City Program (TGCP). The workflow is explicitly organized so that Stages 1–3 diagnose the spatial distribution and clustering of TGCP garden service intensity (addressing RQ1), while Stages 4–5 evaluate its spatial association with village-level income growth (addressing RQ2). GeoPandas was utilized for all spatial data handling, geographic projections, and spatial joins. Scikit-learn provided the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, essential for objectively identifying spatial clusters without prior assumptions regarding shape or number. Spatial autocorrelation diagnostics, including global and local bivariate Moran's I, were conducted using the PySAL stack. Auxiliary Python libraries (pandas, numpy, matplotlib, folium, etc.) supported data preprocessing, visualization, and interactive mapping. This integrated methodological framework combines primary field surveys, spatial simulations, machine-learning clustering, and robust spatial statistical analysis to provide a rigorous evaluation of the spatial distribution of urban gardening services and their socioeconomic implications.

Stage 1– Garden-Level Service Capacity Assessment

Operational openness was first quantified per garden type from the questionnaire survey (38 community, 33 rooftop and 59 school gardens). For each type t we calculated four normalised openness components—mean share of open days $\bar{d}_t / 30$, open-hours ratio $\bar{h}_t / 24$, mean weekly-use ratio $\bar{u}_t / 7$ and proportion of gardens with unrestricted access $\bar{s}_t$. The four components were averaged to obtain a type-specific Openness Coefficient (**OC_t**):

$$OC_t = \frac{1}{4}\left(\frac{\bar{d}_t}{30} + \frac{\bar{h}_t}{24} + \frac{\bar{u}_t}{7} + \bar{s}_t\right), t \in \{\text{community, rooftop, school}\}. \quad \textbf{(1)}$$

Next, all TGCP gardens established between 2014 and 2018 (inclusive) were retrieved from the municipal GIS database, supplying each garden's polygon area A_i and centroid coordinates. A garden-specific Service-Strength Index (SSI) was then assigned by multiplying its physical supply by the openness characteristic of its type:

$$SSI_i = A_i \times OC_{t(i)} \quad \textbf{(2)}$$

where $t(i)$ denotes the type of garden i. This formulation links field-validated operational accessibility to the complete pre-COVID garden inventory, yielding a spatially comparable measure of service capacity that feeds into the subsequent point simulation and clustering stages.

Stage 2 – Service-Weighted Spatial Point Simulation

All TGCP gardens established between 2014 and 2018 (N = 577) were transformed from discrete polygons into a continuous surface of service-intensity points. Each garden's Service Strength Index (SSI) was first classified into one of five equal-interval classes (with breakpoints every approximately 88 units, up to a maximum SSI of around 440). Based on its class, garden i was assigned a specific number of simulation points $n_i \in \{1,3,5,7,9\}$, such that higher-capacity gardens contributed proportionally more points to the spatial surface. These points were randomly generated within a circular buffer centered on each garden's coordinates, where the radius was calculated as $r_i = \sqrt{A_i / \pi}$, with A_i denoting the area of garden i. This approach ensured that the spatial footprint of simulated points captured both operational service strength and physical parcel extent. The final simulation yielded a total of 12,807 service-weighted points, providing a high-resolution, intensity-preserving input surface for density-based clustering and village-level aggregation in subsequent analytical stages.

Stage 3 – Density Estimation and Cluster Detection via DBSCAN

The service-weighted points generated in Stage 2 were reprojected to TWD97/TM2 coordinates (EPSG:3826) and analyzed using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN), a non-parametric unsupervised machine learning algorithm. The clustering parameters were set to reflect Taiwan's urban planning context: a search radius of 800 meters was adopted to correspond with the standard service radius of neighborhood parks, and the minimum number of points required to form a cluster was set to 27, equivalent to three gardens from the highest service class.

This approach allowed for the detection of spatially cohesive clusters of high urban farming service intensity, without imposing assumptions about the number, size, or shape of clusters. Each identified cluster was assigned a unique label, and service points were appended with their corresponding cluster membership.

To support comparison with village-level socio-economic indicators, DBSCAN-generated cluster points were spatially aggregated to administrative boundaries. This point-to-polygon transformation enabled alignment with official income statistics. For each of Taipei's 456 villages, five indicators were computed: total clustered points, cumulative service intensity, average and maximum cluster density, and number of distinct clusters. These metrics constituted the urban farming service layer used in subsequent spatial equity and green gentrification analyses.

Stage 4 – Income Growth Layer and CPI Adjustment

Village-level median household-income statistics for 2015 and 2018 were obtained from Taiwan's Fiscal Information Agency. The 2015–2018 window was selected for two reasons: (i) it lies entirely before the economic disruptions associated with the COVID-19 pandemic (from 2019 onward); and (ii) it overlaps exactly with the study's garden cohort, which comprises all TGCP sites established between 2014 and 2018, thereby maximising temporal consistency between service-capacity and income data.

To ensure temporal comparability, nominal household incomes were converted to real values using the Consumer Price Index (CPI), with 2015 as the base year ($CPI_{(2015)}$ = 100.0; $CPI_{(2018)}$ = 101.8). The adjustment was performed using the following formula:

$$\text{Real Income}_{2018} = \frac{\text{Nominal Income}_{2018}}{1.018} \quad (3)$$

Subsequently, the percentage change in income between 2015 and 2018 was computed for each village. The growth rate was calculated as:

$$\text{Income Growth (\%)} = \left(\frac{\text{Real Income}_{2018} - \text{Income}_{2015}}{\text{Income}_{2015}} \right) \times 100 \quad (4)$$

Citywide benchmarks were derived using household-weighted median incomes to produce aggregate growth rates for calibration.

While income dynamics represent only one dimension of gentrification, income is the only socio-economic indicator consistently available at the village scale citywide during this period. The 2015–2018 window enables us to detect early patterns of socio-spatial association between urban-agriculture service intensity and income change during the program's formative years. We therefore interpret the income-growth layer as an indicator of short-term socio-economic uplift potentially associated with greening, rather than a comprehensive measure of displacement or fully developed gentrification processes.

Stage 5 – Spatial Coupling and Statistical Evaluation

To examine potential links between urban farming service intensity and local economic trajectories, the village-level garden-service indicators (Stage 3) were spatially joined with real income growth data (Stage 4) across 456 administrative villages in Taipei. Spatial autocorrelation was assessed using two complementary diagnostics implemented via libpysal 4.9:

Global Bivariate Moran's I was calculated using a row-standardized Queen contiguity weights matrix to evaluate the city-wide spatial association between cumulative garden-service intensity and real income growth. To formally define the statistic, the global bivariate Moran's I is expressed as:

$$I = \frac{n}{S_0} \cdot \frac{\sum_i \sum_j w_{ij} \left(x_i - \bar{x}\right)\left(y_j - \bar{y}\right)}{\sqrt{\sum_i (x_i - \bar{x})^2 \cdot \sum_j (y_j - \bar{y})^2}} \quad (5)$$

where x_i is the garden service intensity at location i, y_j is the income growth in neighboring unit j, w_{ij} is the spatial weight (based on Queen contiguity), n is the total number of spatial units, and S_0 is the sum of all spatial weights. This statistic indicates whether areas of high or low garden intensity are systematically aligned with higher or lower income growth outcomes across the city as a whole.

Local Bivariate Moran's I (LISA) was then applied to identify statistically significant clusters of spatial co-variation at the village level. The local bivariate Moran's I for each unit i is computed as:

$$I_i = \left(x_i - \bar{x}\right) \sum_j w_{ij} \left(y_j - \bar{y}\right) \quad (6)$$

where I_i measures the local spatial association between garden service intensity in unit i and income growth in neighboring units j. Based on this calculation, each village was classified into one of four spatial types: High–High (HH), Low–Low (LL), High–Low (HL), or Low–High (LH), according to the directional concordance between garden-service intensity and income change. Statistical significance was assessed via 9,999 Monte Carlo permutations with a threshold of $p < 0.05$.

This comprehensive analytical framework enables precise measurement of TGCP service intensity at fine spatial resolutions, delineation of statistically significant service hotspots and coldspots, and rigorous assessment of potential co-evolutionary patterns between urban farming services and socioeconomic trajectories indicative of green gentrification.

4 Results

4.1 Spatial Distribution of Urban Gardens

Figure 1 presents the spatial distribution of service-weighted points derived from Taipei's urban farming program, analyzed using the DBSCAN clustering algorithm (see Methods, Stages 1 to 3). These points do not correspond to the physical locations of individual gardens; rather, they were generated through probabilistic simulation based on each garden's Service Strength Index (SSI). Gardens with higher service strength were assigned a greater number of points. Each point's color and radius represent the size of the DBSCAN cluster to which it belongs, providing a high-resolution spatial representation of service intensity.

The clustering results reveal four distinct spatial typologies across Taipei:

High-Intensity Hotspots – The most cohesive and densely populated clusters are located in the city's historic core, particularly along the boundary between Wanhua and Zhongzheng districts. These areas contain a high concentration of service-weighted points, reflecting large and intensively managed urban gardens.

Moderate-Density Aggregations – Medium-sized clusters are found in central districts such as Datong, Zhongshan and Daan. These clusters are smaller and less dense than those in the core, representing a secondary level of service accessibility.

Low-Density Clusters – Small, peripheral clusters are observed in areas such as Songshan, Xinyi, and Wenshan. These clusters barely meet the DBSCAN density threshold, indicating a limited or emerging presence of urban gardens.

Non-Clustered Zones – In outer districts such as Beitou, Nangang, and the fringes of the city, many service-weighted points failed to form any cluster. These areas represent zones of extremely low urban agriculture service intensity, effectively functioning as "service voids."

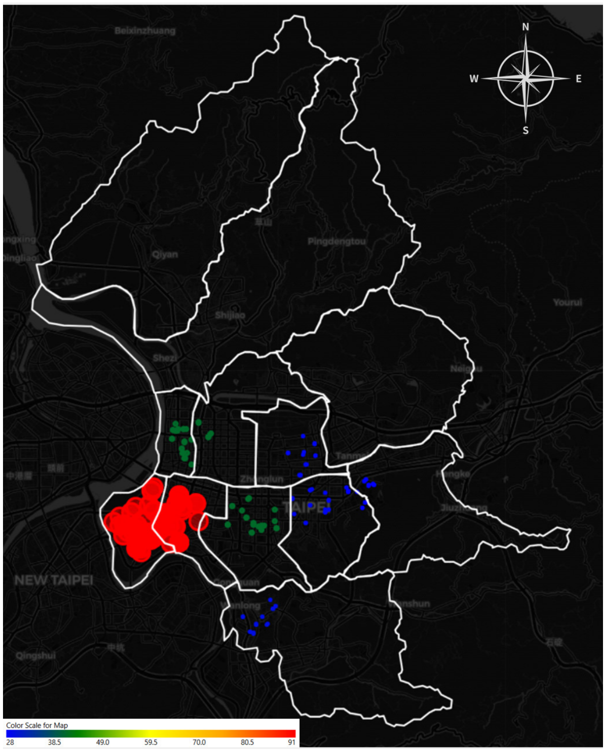

Figure 1. Spatial clusters of simulated service-weighted points representing urban farming intensity in Taipei, detected using the DBSCAN algorithm

While Figure 1 provides a detailed depiction of cluster patterns at the point level, further analysis of the relationship between urban farming service intensity and socioeconomic conditions requires aggregation to the administrative scale. This transformation enables direct comparison with village-level income data. Figure 2 presents the results of this spatial aggregation, illustrating cumulative service intensity per village using a graduated color ramp from light yellow (low density) to dark red (high density). Several key patterns emerge:

High-Intensity areas, including Zhongzheng and Wanhua, exhibit the highest density values (>500), aligning with the prominent high-intensity clusters identified in Figure 1.

Moderate-density areas, including parts of Datong, Zhongshan, and Daan districts (secondary-level aggregations), along with Songshan, Xinyi, and Wenshan districts (third-level aggregations), exhibit moderate to low density values (50–500) as identified in the point-based analysis.

Low-density areas, including peripheral villages in the north, east, and southeastern parts of the city, fall into the lowest density class (<50), once again highlighting spatial service gaps and inequities in distribution.

Taken together, Figure 1 and Figure 2 reveal a pronounced spatial bias in the allocation of urban farming resources across Taipei. While central neighborhoods benefit from dense and interconnected networks of garden infrastructure, many peripheral villages remain underserved. This spatial disparity provides an empirical foundation for the subsequent analysis of the potential emergence of green gentrification processes.

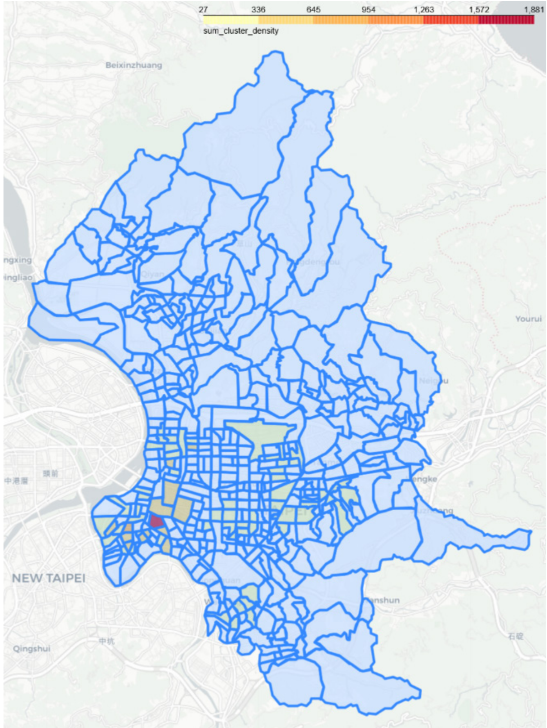

Figure 2. Village-level cumulative service intensity of urban farming infrastructure in Taipei

4.2 Spatial Coupling Findings

To examine the spatial association between urban farming service intensity and local economic change, village-level real income growth rates were aligned with aggregated garden service metrics (see Methods, Stages 4 and 5). Two complementary spatial autocorrelation techniques were employed to capture both global and local dynamics: Global Bivariate Moran's I assessed overall spatial alignment across the city, while Local Indicators of Spatial Association (LISA) identified statistically significant neighborhood-level clusters.

4.2.1 Global Spatial Autocorrelation

The Global Bivariate Moran's I statistic (Figure 3) was 0.0203 with a p-value of 0.2250, indicating a weak and statistically non-significant positive spatial association between garden service density and income growth. This suggests that, at the citywide scale, there is no consistent spatial pattern in which high garden intensity areas are clustered alongside high-income-growth villages—or vice versa.

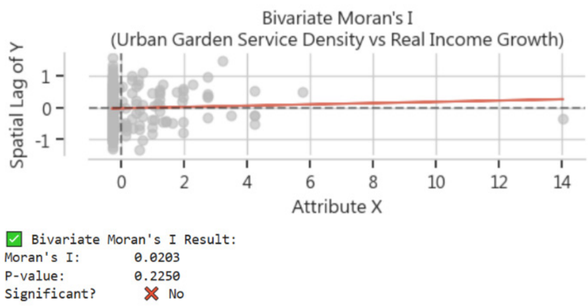

Figure 3. Global Bivariate Moran's I scatterplot assessing the spatial association between urban garden service density and real income growth

4.2.2 Local Spatial Clusters

In contrast, the LISA results (Figure 4) reveal several statistically significant local clusters ($p < 0.05$), providing a more nuanced understanding of spatial co-variation:

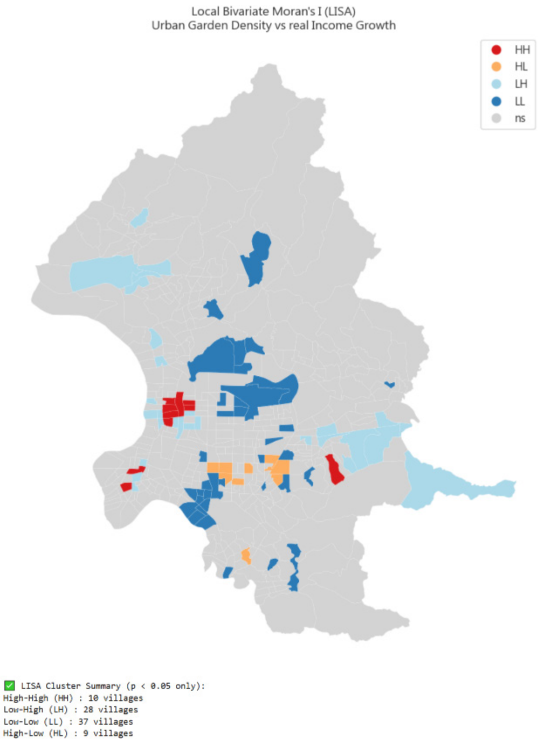

Figure 4. Local Bivariate Moran's I (LISA) cluster map showing the spatial relationship between urban garden service density and real income growth in Taipei

High–High (HH): 10 villages exhibit both high garden service density and high income growth in adjacent areas. These clusters are concentrated along the Datong–Zhongshan corridor and may signal early-stage green-induced uplift, with implications for gentrification dynamics.

High–Low (HL): 9 villages, mainly located in Daan and Xinyi districts, show high garden service intensity but are adjacent to low-growth areas, suggesting that increased urban agriculture alone does not immediately translate into local economic gains.

Low–High (LH): 28 villages, particularly in Nangang and Beitou, exhibit low garden service intensity but are surrounded by high-income-growth neighbors, indicating a spatial mismatch between urban agriculture and local economic trajectories.

Low–Low (LL): 37 villages, located along the northern edges of Zhongshan and Songshan districts and in a riverside sector of Zhongzheng that extends into the south-western portion of Daan, notably display both low garden-service density and low income growth, highlighting areas where limited urban agriculture coincides with weaker economic performance.

Overall, the evidence points to a spatially uneven distribution of urban farming services in Taipei. At the citywide scale, garden-site density is not significantly correlated with real income growth, suggesting that—unlike capital-intensive green projects such as large parks—community gardens do not, in and of themselves, follow or induce the conventional trajectories of green gentrification. This finding underscores their potential as a relatively inclusive and socially sustainable form of urban greening.

At the neighborhood scale, however, bivariate LISA analysis reveals spatial patterns that merit targeted policy responses. A handful of high–high (HH) clusters combine dense garden provision with rapid income gains, which may signal the early stages of green-driven uplift. By contrast, low–low (LL) and low–high (LH) clusters highlight areas where community garden services are scarce—either in tandem with slow economic growth (LL) or adjacent to faster-growing neighborhoods (LH). These configurations expose structural gaps in the distribution of urban farming sites that require differentiated strategies. In LL areas, characterized by both limited garden access and weak economic performance, priority should be placed on foundational investments in urban farming infrastructure to address dual disadvantages. In LH areas, where low garden density coincides with neighbouring income growth, interventions should combine the expansion of community garden facilities with proactive monitoring to avoid exacerbating socio-spatial disparities through uneven development.

Taken together, the results argue for spatially differentiated urban-agriculture policy rather than uniform greening targets. When planned through a spatial-justice lens, initiatives such as Taipei's Garden City Program can enhance environmental quality while simultaneously advancing social equity within the city's broader sustainability agenda.

5 Conclusion

This study examined the spatial equity and potential socio-spatial impacts of urban agriculture by analyzing the distribution and clustering of community gardens under Taipei's Garden City Program (TGCP) and their association with neighborhood-level income growth. By integrating spatial statistics (Moran's I, LISA) with machine learning (DBSCAN), we developed a replicable methodological framework to assess whether garden-based greening initiatives exhibit spatial patterns indicative of green gentrification or reinforce spatial exclusion.

Our results reveal a pronounced spatial imbalance in garden service intensity across Taipei. High-density clusters are concentrated in the urban core, while large peripheral areas remain underserved. At the citywide scale, we find no statistically significant correlation between garden density and income growth, suggesting that urban agriculture may not follow the gentrification trajectories typically associated with large-scale green infrastructure. However, local patterns identified through LISA show more nuanced dynamics: High–High clusters may indicate early-stage uplift pressures, whereas Low–High and Low–Low clusters expose structural disparities in community garden provision. These findings highlight the need for spatially differentiated urban-agriculture policies. Programs such as the TGCP hold promise as socially inclusive forms of urban greening, but their outcomes depend on whether implementation strategies explicitly address distributional equity and avoid reproducing existing spatial inequalities.

These results also clarify how our study contributes to the broader green gentrification literature. Much existing work focuses on large, capital-intensive greening projects—such as waterfront parks or flagship ecological corridors—that are strongly associated with real-estate speculation and socio-economic displacement. By contrast, our citywide analysis of community-oriented urban agriculture in Taipei reveals a different pattern: although garden service intensity is uneven and clustered, we do not observe strong citywide coupling between urban agriculture and income growth. This suggests that small-scale, community-led greening efforts, as implemented under the TGCP, may be more compatible with 'just green enough' strategies, producing milder socio-economic impacts than major park projects, even though certain High–High areas still warrant monitoring. Additionally, the Taipei case introduces an East Asian perspective to a literature dominated by North American and European contexts. Studying a high-density Asian metropolis where urban agriculture is institutionalised through municipal planning illustrates how concerns about green gentrification unfold in a setting shaped by long-standing land pressure and state-led governance. Methodologically, by combining a survey-based Service Strength Index, service-weighted point simulation, DBSCAN clustering and bivariate Moran's I/LISA, the study provides a transferable diagnostic toolkit for future research on urban agriculture, environmental justice and green gentrification in rapidly urbanising regions.

This study also highlights several limitations. Our analysis relies on CPI-adjusted median household income growth over a relatively short period (2015–2018) as the sole socio-economic indicator. Although this measure enables consistent citywide comparison at the administrative-village scale, it does not capture other dimensions of (green) gentrification, including housing-market changes, demographic turnover, or displacement pressures. Consequently, we refrain from interpreting our results as evidence of complete gentrification processes, framing them instead as patterns of spatial co-variation between urban-agriculture service intensity and short-term income dynamics. Future research could build on this work by incorporating multi-indicator socio-economic datasets, longitudinal data, and finer-grained demographic information to more fully trace the complex trajectories of green gentrification.

A second limitation concerns the choice of administrative villages as the sole spatial unit of analysis. While this scale is dictated by data availability and aligns with how neighborhood-level policies and community programs are implemented in Taipei, it also entails a classic modifiable areal unit problem (MAUP). The village-level LISA clusters and bivariate spatial associations identified in this study are therefore inherently dependent on this particular zoning scheme, and different spatial frameworks (for example, alternative administrative boundaries or regular grid cells) could yield somewhat different local cluster configurations. Future research could address this issue more directly by conducting grid-based or multi-scale sensitivity analyses to evaluate the robustness of spatial patterns across multiple spatial resolutions and boundary definitions.

By offering a transparent, adaptable analytical framework and empirical evidence from a rapidly expanding urban-agriculture initiative, this study contributes to the growing interdisciplinary dialogue at the intersection of urban sustainability, spatial justice, and machine learning–assisted spatial planning.

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Biographies

Wei-Chun Chuang is CEO of Sustainable Future Impact Co., Taiwan, and a researcher in GIS, NLP, and built-environment decarbonization. His work focuses on net-zero pathways, carbon accounting, life-cycle carbon footprints, and low-carbon buildings and infrastructure, including CBAM and GRESB-related applications.

Ching-Pin Tung is Professor, Department of Bioenvironmental Systems Engineering, National Taiwan University. He received his PhD in Civil and Environmental Engineering from Cornell University. His research spans ESG governance, climate risk assessment and adaptation, environmental systems analysis, and sustainable water and soil resources planning and management.

Wan-Yu Shih is Associate Professor, Master Programme in Disaster Risk Reduction and Resilience (MDR3), National Taiwan University, and Director of Taipei GR Lab. Her research addresses urban green/blue infrastructure, heat risk mitigation, and climate adaptation and governance. She holds a PhD in Planning and Landscape from the University of Manchester.

Wen-Ray Su is a Project Leader at the National Science and Technology Center for Disaster Reduction (NCDR), Taiwan. He holds a PhD in Civil Engineering from National Central University. His expertise includes disaster management, systems analysis, and geospatial information, and he led development of a national disaster information service platform.