TOWARD SPATIAL AND SOCIAL EQUALITY: INVESTIGATING AND MODELING THE LINK BETWEEN OPPORTUNITY AND URBAN INTENSITY IN METRO MANILA, PHILIPPINES

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KEY WORDS: AHP, GWR, OLS, opportunity mapping, spatial autocorrelation, spatial equality, urban intensity mapping neighborhood effects

ABSTRACT:

This paper employed an interdisciplinary mixed-method approach combining geomatics, geography, and sociology to investigate the link between opportunity and urban intensity across the 32 legislative districts of Metro Manila. Eighteen opportunity indicators, weighted within their opportunity dimensions using Analytic Hierarchy Process (AHP) were used to output Opportunity Scores, while annual VIIRS DNB nighttime light was used as proxy data to approximate the region's Urban Intensity Score. Two regression models were developed with different sets of explanatory variables: an AHP-based model that used the top two weighted indicators from each opportunity dimension, and a model that used Exploratory Regression Analysis (ERA) to determine the appropriate variable combination. Modeling via Ordinary Least Squares Regression (OLS) produced a properly specified global model, while OLS modeling of the ERA-based model exhibited non-stationarity between variables which necessitated performing Geographically Weighted Regression (GWR). Our quantitative findings, combined with insights from our mini focus group discussion (FGD), provided evidence of the unequal distribution of opportunities across Metro Manila and the spatially varying relationship between urban intensity and opportunity, which have significant implications for urban framework as well as housing choice.

1. INTRODUCTION

George Galster and Sean Killen coined the term "geography of opportunity" in 1995 to explain how an individual's level of opportunity is connected to the place they live in. Since then, various evidence-based approaches have been implemented to measure and visualize the geography of opportunity using socioeconomic variables including but not limited to physical, social, and geographic indicators.

Until this research, however, opportunity mapping in the Philippines has never been explicitly explored. While there exist perspectives on social inequality in the local context like that of a poverty map (Tingzon et al., 2019; see also Asian Development Bank, 2021), these approaches overlook the influences of external structures that can contribute to an individual's level of success or lack thereof in life. These structures may refer to socioeconomic systems and factors beyond an individual's control, such as gender-based discrimination, lack of access to education or healthcare, and limited job opportunities. These glaring gaps prompted us to produce never-before-seen opportunity maps in the Philippine setting that can engender a dynamic "place matters" look on social inequality.

Such a desire to fill this gap is particularly pressing and relevant for a densely populated and highly urbanized area like Metro Manila, Philippines. Comprising 16 cities and one municipality further divided into 33 legislative districts, the National Capital Region (NCR) poses several socioeconomic and physical challenges that contribute significantly to the development of each district (Porio, 2016). Social division, which is a manifestation of uneven development (Connell et al., 1999), is also palpably noticeable in Metro Manila despite perceived high levels of urbanization in the region.

All these set us in motion to investigate the relationship between the level of opportunity and urban intensity in Metro Manila, Philippines using an interdisciplinary mixed-method approach anchored on geography, sociology, and the principles of geomatics, and informed by insights from stakeholders and community members. To carry all these out, we based our procedures for opportunity mapping on conventional methods pioneered by the Kirwan Institute from Ohio State University in Columbus, Ohio. These involve the use of data from relevant socio-economic indicators to derive the opportunity scores of regions of interest.

The urban intensities of cities in Metro Manila were approximated using nighttime light (NTL) data, a commonly used method in urban mapping through remote sensing techniques (Bagan et al., 2018; Imran et al., 2019; Li & Zhou, 2017). Spatial modeling tools such as Ordinary Least Squares Regression (OLS) and Geographically Weighted Regression (GWR) were used to examine and explain the link between urban intensity and opportunity, as well as the spatial variability of said variables. Lastly, a mini focus group discussion (FGD) was also conducted to illuminate the quantitative findings and ground all results back to the bigger picture that involve policy formulation and interventions.

2. RESEARCH BACKGROUND

2.1 Life Chances Theory

Karl Marx was a key figure in advancing the idea that people's struggles are not only the result of personal failings or shortcomings, but rather are deeply rooted as well in the socio-economic structures of society that are historically "transmitted

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https://doi.org/10.5194/isprs-archives-XLVIII-4-W8-2023-211-2024

from the past" ([1869] 1972, p. 10) through existing state policies.

Capitalist institutions emerge and exist in urban cities where economic and political entities establish their authority and maintain influence over their residents and surrounding communities. Various literature found this phenomenon as evidence for how poverty levels increase in many urbanized places of developing countries: In an in-depth review by Okeke and Ahaoutu (2021), the Nigerian authors observed how urbanization creates imbalance in opportunities received, which drives "rural-urban migration [...] without commensurate provision for their economic opportunities for residents" (p. 9). The Marxist theory views this as an inevitable consequence of capitalism, as various institutions tend to concentrate wealth and power in the hands of a few, while leaving the majority of people in poverty.

Urban areas in Metro Manila are often unable to provide enough opportunities for everyone largely in part due to the inrush of migrants looking for better opportunities in Metro Manila, which increases competition for resources, jobs, and housing (Anderson et al., 2017). Such a phenomenon results in many Filipinos living in poverty in urban slums, which in any case is not a unique case in the country. Zhang (2016) also contended that while urbanization can help reduce poverty of migrating peasants, urbanization is also "positively correlated with urban poverty" (p. 23). Through a more general observation, Bayat & Biekart (2009) extended Marxist thinking by positing that "cities are increasingly shaped more by the logic of the market than the needs of their inhabitants" (p. 815) which in turn exacerbates disparities in urban areas, resulting in extremes of high level of urbanization and low level of opportunities for urban residents.

2.2 Neighborhood Effects Theory

While the spatiality of opportunity altogether is unexplored yet until this paper, manifestations of the theory in the Philippines are fortunately present in a significant number of studies. For instance, Mapa & Briones (2016) argued that a spatial variable like neighborhood effect is indeed a determinant for income growth in the Philippines because it injects "dynamics of how the regions/provinces' economic performance interact with each other" (p. 16). Connected to this is poverty mapping, which although is an easier and a more famous tool when quantifying inequality, is still deemed as a static methodology altogether that "fails to capture other important dimensions of neighborhood opportunity" (Brazil et al., 2022, p. 759) as this approach reveals only the "geography of people" (Dixon, 2020, p. 3) and not necessarily one's opportunity as it connects to vital spatial or "place" considerations.

All these studies converge to an understanding that where Filipinos live and how they live with their neighbors play an important role in their outcomes and choices in life, and that there is no way to deny that an individual's advancement is hinged on their collective struggle (knowingly or unknowingly) in achieving equality as determined also by the relationship of various opportunity measures.

2.3 Linking Opportunity & Urban Intensity

There have been notable local studies that explicitly linked opportunity with urban intensity or developments: Shatkin (2009) clarified that the "fragmented nature of Metro Manila's geography of economic and housing opportunity" (p. 404) makes it difficult for the underprivileged residents to make an appealing choice for their housing, employment, and even commuting needs. In the same manner, Baker & Watanabe (2017) also claimed that such a fragmentation in the metro hampers optimism among residents that eventually creates deteriorating mindset in job creation and livability. Other physical and spatial manifestations of development in Metro Manila have also been studied recently, especially their relation to opportunity indices such as crime (Mojica et al., 2017; Sanidad-Leones, 2010), filling up the urban space (Lorenzo, 2016), pedestrian wellbeing (Villanueva, 2019), health in terms of dengue incidence (Pangilinan et al., 2017), and land use (Murakami & Palijon, 2005).

What is lacking in these studies is explicitly conceptualizing and treating opportunity altogether as a spatial manifestation that can be linked to urban intensity. Thus, parallel to the study made by Imran et al. (2019), identifying patterns and clustering of opportunity as it relates to urban intensity made sense for the benefit of quantifying and visualizing the relationship between the two.

3. MATERIALS AND METHODS

3.1 Study Area

Metro Manila is the official National Capital Region (NCR) of the Philippines which comprises 16 highly urbanized cities and one municipality, further divided into 33 legislative districts. Analysis of the region was conducted at the legislative district-level, given its implications for policymaking. Combining the Municipality of Pateros and the City of Taguig into one district and separating the first district of Caloocan City into its northern and southern components gave us a total of 32 legislative districts for the first-ever opportunity mapping effort in the country.

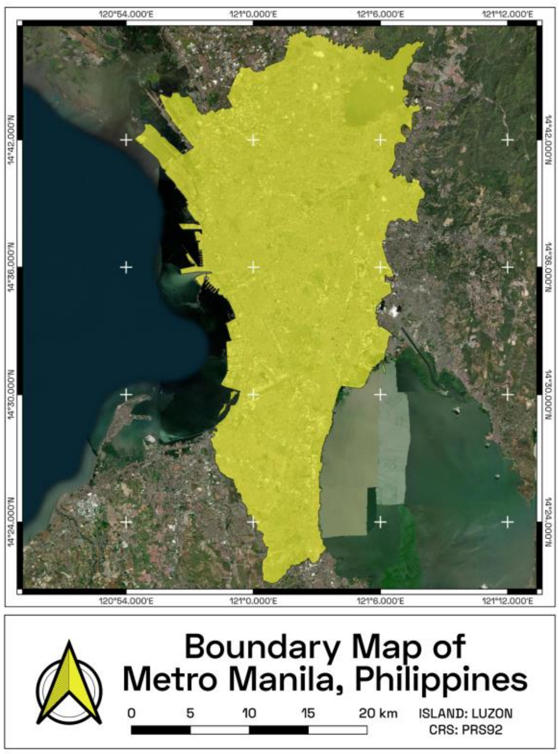

Figure 1. Boundary Map of Metro Manila
Note. Base map from Google.

3.2 Research Design

The research employed a mixed-method research (MMR) design of both quantitative and qualitative approaches. The quantitative approach allowed us to provide evidence-based facts about our key variables. Spatial analyses and modeling were conducted through rigorous data analysis, variable selection methods, diagnostic tests, and statistical inferences. Google Sheets, Microsoft Excel, and QGIS Desktop 3.22.2 were used for all data processing and mapping procedures. SPSS Statistics, a software used for analytics, was used to conduct multivariate correlation analysis. ArcGIS 10.8.1. was utilized solely for the purpose of performing Local Moran's I, Global Moran's I, OLS and GWR. The qualitative approach was employed through the conduct of a mini focus group discussion (FGD), whose outputs allowed us to understand the context of the maps and models we created.

3.3. Data Acquisition

The research performed GIS-based opportunity mapping from opportunity indicators, urban intensity mapping with the use of nighttime light (NTL) as proxy data, and spatial analysis and modeling using the opportunity and urban intensity scores derived from the mapping procedures. Table 1 shows the data requirements utilized for these processes.

Data	Description and Source
Metro Manila Boundary Shapefiles	Used to determine the boundaries of the study area's legislative districts. *Sources: PSA, NAMRIA, HDX*
NTL Data	VIIRS DNB NTL data, used to approximate the urban intensity levels of Metro Manila. *Source: Earth Observation Group*
Opportunity Indicator Data	Socio-economic variables categorized into four opportunity dimensions, used to determine the opportunity levels of Metro Manila. *Sources: TSIP, OSM, eFOI, government agencies and reports*

Table 1. Data Requirements and Sources

Table 2 shows the 18 indicators considered in estimating the opportunity levels in Metro Manila, classified under four different dimensions adapted from Knaap (2017). The indicators were chosen depending on their relevance in the Philippine context and their availability and accessibility.

Dimension	Indicators
Institutional	Teacher to student ratio
	Academic performance rate
	Literacy rate
	High school completion rates
	High school dropout rates
Geographic	Ownership of private vehicles
	Access to health care facilities
	Access to gendered and queer facilities
	Access to social organizations
Environmental	Crime rate
	Number of traffic accidents
	Existence of toxic release sites
	Share of vacant housing units
	Access to parks and open space
Social-Interactive	House ownership and occupancy rates
	Residents with at least a college diploma
	Poverty incidence
	Employment rate

Table 2. Opportunity Dimensions and Indicators

3.4 Opportunity Mapping

Adapted from the procedures laid out by Imran et al. (2019) and The Kirwan Institute (2016), four general steps were undertaken to output the opportunity map: (i) weighting, (ii) standardizing indicator values, (iii) computing the composite opportunity dimension scores (CODS), and (iv) determining the comprehensive opportunity score (COS).

Opportunity indicators were weighted within their respective dimensions via Analytical Hierarchy Process (AHP) to determine their significance in determining one's opportunity as reflected by the opinion of community members selected via judgment and snowball sampling. Data per indicator were then standardized to represent them in values relative to those of other legislative districts' and to allow for convenience in combining them later on. The CODS were computed by taking the sum of the products of the standardized scores and their respective weights:

$$CODS_j = \sum_{i=1}^{n} w_i z_i \quad (1)$$

where z = standardized score
i = an opportunity indicator
j = an opportunity dimension
w = weight of the opportunity indicator

Meanwhile, the COS were derived from the simple average of the CODS of each opportunity dimension. A total of five opportunity maps were generated–one for each opportunity dimension and one for comprehensive opportunity. CODS and COS values were rescaled from 0-100% using the Min-Max method. These were used to classify the legislative districts of Metro Manila into five levels of opportunity (Very Low, Low, Moderate, High, and Very High Opportunity). Classification was done using QGIS's Equal Counts (Quantile) feature following Knaap's (2017) method, so that each level contains around or the same number of districts which helps in identifying visual patterns.

3.5 Urban Intensity Mapping

Urban intensity mapping was performed to determine the levels of urbanization of the legislative districts relative to each other. Three general steps were performed to generate the urban intensity map: (i) pre-processing of NTL data, (ii) summarization of values, and (iii) determining the urban intensity score (UIS).

Pre-processing of NTL data included image clipping, vectorization, boundary clipping, and merging–all to generate a vectorized layer of NTL data pixels clipped to follow the boundaries of the legislative districts of Metro Manila. For data summarization, notable data statistics such as the minimum and maximum digital radiance values, the mean, and the standard deviation of the NTL data were recorded to aid in further analyses.

Lastly, the UIS was computed by: (i) taking the means of the digital radiance values present in each legislative district, and (ii) standardizing the means to get a better sense of how the values are related to each other. These standardized means were used as each district's UIS.

One urban intensity map was generated for the region. Similar mapping procedures from opportunity mapping were done using the UIS values, with the five levels of urban intensity being: Very Low, Low, Moderate, High, and Very High Urbanization.

3.6 Data Analysis

Patterns and visualization of clusters and outliers were generated to elicit evidence on where level of opportunities and urban intensity may be clustered or not. This was done through readily available tools in ArcMap called Global Moran's I and Anselin's Local Moran's I using the Queen's case Contiguity as the neighborhood definition.

3.7 Spatial Modeling

The relationship between opportunity and urban intensity was analyzed using spatial regression and autocorrelation tools. We utilized Exploratory Regression Analysis (ERA), Ordinary Least Squares (OLS), and Geographically Weighted Regression (GWR) in this order, using ArcMap 10.8.1. Two approaches were used in developing a model, where urban intensity (UIS) was designated as the dependent variable and selected opportunity indicators (weighted scores) were designated as explanatory variables.

3.7.1 AHP-based Modeling: The first approach used the top two opportunity indicators per dimension as the explanatory variables, based on the results of the weights computed from AHP, hence the name AHP-based model. This was an attempt to test if a model considering the results of weighting would produce acceptable statistics and explanatory powers in linking urban intensity and opportunity in Metro Manila.

3.7.2 ERA-based Modeling: This approach made use of a combination of explanatory variables deemed the most appropriate from the ERA results. IBM SPSS Statistics software was used to conduct bivariate analysis, wherein variables whose correlation values were not highly correlated (0.8 to -0.8) were included in ERA.

3.8 Focus Group Discussion

Involvement of community members in designing the opportunity mapping process was of paramount consideration in this study. With this we conducted a mini FGD after finalizing the preliminary results of the analyses. It was conducted with three community members of Metro Manila, each representing the employee and the LGU sector, and the private community members such as the student population. All were chosen from the AHP survey respondent pool. The discussion was conducted to illuminate the results of the analyses by comparing the results with perceived patterns on spatial inequality and deliberating on what can be improved in the methodology used.

4. RESULTS AND DISCUSSION

4.1. Opportunity Mapping Outcomes

Results of opportunity mapping showed that environmental opportunity is highest at the northwestern part of Metro Manila, while social-interactive opportunity is highest at the eastern and southwestern parts. No trend in the spatial variability of the institutional and geographic dimensions was observed. These combine to form the comprehensive opportunity map shown in Figure 2, where the highest opportunity levels are clustered at the eastern area of the region and the lowest at its northwestern parts.

These observed patterns in comprehensive opportunity are the result of the eastern districts (e.g. Makati, Taguig/Pateros, Pasig) having mostly high opportunity dimension scores. Meanwhile, although northwestern districts (e.g. southern districts of Caloocan, Valenzuela, Districts 1 and 6 of Manila) have high environmental opportunity scores, they also had low scores in the other three dimensions.

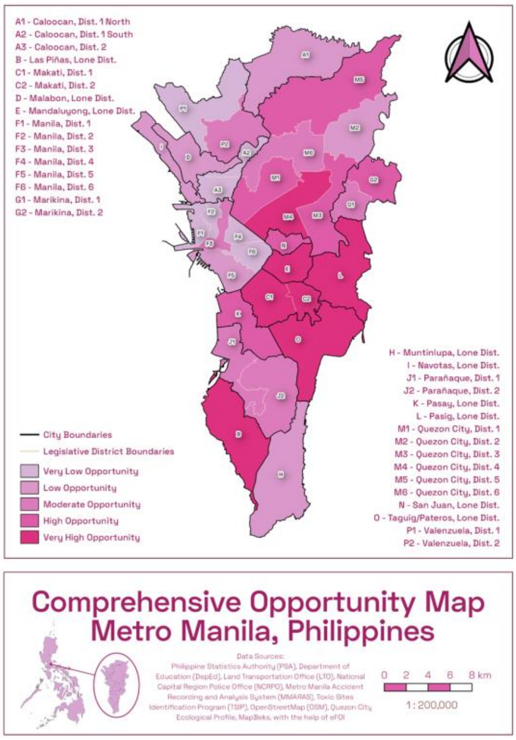

Figure 2. Comprehensive Opportunity Map of Metro Manila

These maps and results were presented in our mini FGD for the evaluation of the participating residents of Metro Manila. Primary discussion revolved around the observation that aside from opportunity as a whole being multifaceted, opportunity levels derived reflect the current observed situation in the region in that districts with high opportunity levels are usually those with large establishments and economic and industrial activity, e.g. Makati and Las Piñas, while districts with low opportunity levels are usually those with fewer establishments and are difficult to access via public transportation, e.g. Caloocan and Valenzuela.

4.2. Urban Intensity Mapping Outcomes

Figure 3 shows that the most urbanized districts are at the central and western end of the region, i.e. Makati districts, Pasay's lone district, District 1 of Manila, and Mandaluyong's lone district. Meanwhile, the least urbanized districts are found at the northern part, i.e. District 1-South of Caloocan, District 1 of Valenzuela, Districts 2 and 5 of Quezon City, and the lone district of Navotas.

A general trend of urbanization decreasing in intensity as we go from the center of the region outwards can be observed. This aligns with the economic situation in the region, where most business centers and establishments can be found in the general vicinity of Makati. It can be observed from visual comparison of the two maps that there are varying relationships between opportunity and urban intensity per district. Our results showed that despite being a highly urbanized city, there seems to be low opportunities present in the districts of Manila. Meanwhile, a nearby city, Makati, manifested a direct relationship with urban intensity and opportunity. This may be due to differences in the

https://doi.org/10.5194/isprs-archives-XLVIII-4-W8-2023-211-2024 |

effectiveness of implementing local policies which provide opportunities to the residents of the cities. Given these implications, we now move on to discussing the spatial patterns and clusters found in the region to further give light on which localities were found to have a significant concentration of high and low opportunities.

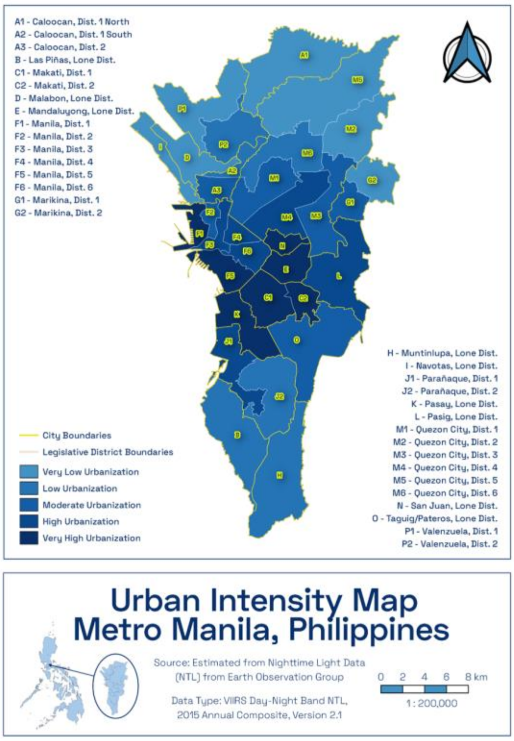

Figure 3. Urban Intensity Map of Metro Manila

4.3 Spatial Analysis via Moran's Statistics

Spatial autocorrelation of the variables was investigated using Global Moran's I. This was done to identify if there is notable clustering of opportunities in the region, and to determine where these clusters are located. It was revealed that institutional and geographic dimensions of opportunity had a random spatial distribution, while both environmental and social-interactive dimensions and the COS and UIS exhibited clustered patterns. To better contextualize this, results of the Local Moran's I tool were mapped, wherein high-high and low-low clusters and high-low and low-high outliers for each variable were visualized.

Given the presence and abundance of clusters and outliers in the region, and upon discussion of the results with our mini FGD participants, our findings imply a domino effect on the distribution of opportunities in the region. That is, a district with low opportunity may impact neighboring districts to behave the same way. This aligns with neighborhood effects theory, i.e. how these districts exchange (or not exchange) resources with each other affects the opportunities their residents receive. Implementation of policies in a nearby district may also influence how one district executes their own. All these point to a region-wide framework for better cooperation among districts to increase chances for equitable distribution of opportunity across Metro Manila.

4.4 Spatial Modeling Outcomes

With the varying spatial autocorrelation results of the opportunity dimensions and comprehensive opportunity, it follows that the distribution of each opportunity indicator in the region must also be diverse. Jumping from spatial analysis to spatial modeling was warranted given the need to explain the spatial variability of opportunity across the legislative districts of Metro Manila, and in connection, its relationship with urban intensity.

4.4.1 AHP-based Model: For this model, the following variables that ranked first and second in terms of their perceived importance via AHP were selected as explanatory variables: (i) LR (Literacy Rate) and APR (Academic Performance Rate) from the institutional dimension, (ii) HC (Access to Health Care) and SO (Access to Social Organizations) from the geographic dimension, (iii) CR (Crime Rate) and POS (Parks and Open Spaces) from the environmental dimension, and (iv) PCD (Population with a College Diploma or Greater) and ER (Employment Rate) from the social-interactive dimension. Shown are the results of relevant statistics using OLS modeling.

Variable	Coeff	Std. Error	*t*-statistic	*p*-value	VIF
Constant	0.000000	0.104268	0.000000	1.000000	-
			Institutional		
LR	-1.028849	0.477166	-2.156164	0.041766*	1.340033
APR	1.678532	0.656699	2.556016	0.017662*	1.521767
			Geographic		
HC	-1.363143	0.315720	4.317566	0.000254*	1.830739
SO	3.457957	1.346552	2.568009	0.017197*	1.648156
			Environmental		
CR	0.529597	0.625216	0.847061	0.405690	1.670546
POS	-1.069956	1.117681	-0.957301	0.348372	1.881186
			Social-Interactive		
PCD	0.812500	0.694659	1.169638	0.254126	3.111413
ER	1.130717	0.477615	2.367425	0.026703*	2.663679

**statistically significant at 1% level of significance*

Table 3. Summary of the AHP-based OLS model diagnostics

No issues with multicollinearity were found as indicated by the VIF values which were all less than 7.5. The model produced an adjusted R^2 value of 0.652102, implying that the selected independent variables can predict variances in the urban intensity of Metro Manila more than 65% of the time. The model also had an overall significant Joint F- and Joint Wald values, 8.263316 and 331.894885, respectively, which are indicators of overall model significance.

As indicated by the coefficients produced for each independent variable, a positive relationship between urban intensity and the following opportunity indicators exists: APR (Academic Performance Rate), SO (Access to Social Organizations), CR (Crime Rate), PCD (Population with a College Diploma or Greater), and ER (Employment Rate). Meanwhile, a negative relationship between urban intensity and the following opportunity indicators exists: LR (Literacy Rate), HC (Access to Health Care), and POS (Parks and Open Spaces).

The Koenker (BP) statistic value was not statistically significant, implying that the relationships generated by the model are consistent globally. Further, conducting a spatial autocorrelation analysis on the residuals of the model revealed spatial randomness. Overall, this implies that there is little to no chance of the AHP-based model making under- or over-predictions of the dependent variable.

Given the implication of stationarity and the good spatial autocorrelation results on the model's residuals, we hence ended the spatial statistics for the AHP-based model at OLS, as the global model generated was already acceptable.

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4.4.2 ERA-based Model: Bivariate Analysis. For this model, bivariate analysis was first performed to determine if there are any variables that are highly correlated. Results showed that out of 18 variables, only POS (Parks and Open Spaces) under the environmental opportunity dimension was found to have been highly negatively correlated (-0.801) with GQF (Access to Gendered and Queer Facilities) and highly positively correlated (0.821) with VHU (Share of Vacant Housing Units). Omitting POS was therefore necessary for including this variable in the models may result in multicollinearity, difficult identification of the important effects of this variable, or cause bias in the model (Shrestha, 2020).

Exploratory Regression Analysis Results. We then proceeded to ERA with a criterion of 1 minimum and 17 maximum number of explanatory variables. A total of 352 models were generated using the criteria shown below.

Search Criterion	Cutoff	Trials	No. of Passing Models	% Passed
Min Adjusted R^2	> 0.50	262143	222385	84.83
Max Coefficient *p*-value	< 0.05	262143	367	0.14
Max VIF Value	< 7.50	262143	154556	58.96
Min Jarque-Bera *p*-value	> 0.10	262143	257908	98.38
Min Spatial Autocorrelation *p*-value	> 0.10	226	218	96.46

Table 4. Exploratory Regression Global Summary

Extensive and rigorous trial runs were employed to screen for the best-performing OLS model that could be suitable for GWR analysis. 15 models, all with omitted variables, were chosen for a diagnostic test via OLS based on the aforementioned criteria, the resulting Koenker's studentized Breusch-Pagan (BP) *p*-value which measures for the non-stationarity of the variables, and the Jarque-Bera (JB) *p*-value which determines whether the model has bias or not.

Choosing the Best Model. From these 15 models, five OLS models advanced to the next round, chosen based on the number of explanatory variables (at least four) and the significance of the K (BP) statistic, to maintain considerable explanatory powers and as bases for non-stationarity, respectively. All five models had no multicollinearity issues, exhibited non-stationarity, and were not biased, i.e., the residuals were normally distributed. To choose the best model, we employed Global Moran's I to test for spatial autocorrelation of the residuals. A clustered pattern of residuals is preferred in this case, given that this is one criterion to justify the need for a GWR. Given that 4 of 5 models had a clustered spatial autocorrelation, we decided to choose Model No. 335 as the global model for further analysis primarily because it had the highest number of explanatory variables, making it the model with more explanatory powers, thereby rendering it more effective in policy implications.

OLS Modeling Results. Using Model No. 335, the following indicators were selected as explanatory variables: (i) APR (Academic Performance Rate) and HDR (High school Dropout Rate) from the institutional dimension, (ii) GQF (Access to Gendered and Queer Facilities) and SO (Access to Social Organizations) from the geographic dimension, (iii) CR (Crime Rate), VHU (Share of Vacant Housing Units), and NTA (Number of Traffic Accidents) from the environmental dimension, and (iv) PI (Poverty Incidence) from the social-interactive dimension. Shown in Table 5 are the results of relevant statistics using OLS modeling.

VIF values were less than 7.5, indicating no issue at all with multicollinearity. All eight variables were statistically significant at the 0.01 level of significance, which means that these opportunity indicators help in explaining the urbanization or activity in the legislative districts of Metro Manila. An adjusted R^2 value of 0.547093 was outputted, meaning that the variability in urban intensity can be explained by the eight variables with an accuracy level of more than 54%.

Variable	Coeff	Std. Error	*t*-statistic	*p*-value	VIF
Constant	0.000000	0.118968	0.000000	1.000000	-
Institutional					
APR	1.888597	0.703372	2.685063	0.013221*	1.340999
HDR	-3.613388	1.191063	-3.033751	0.005904*	2.069798
Geographic					
GQF	-2.588782	1.065586	-2.429444	0.023342*	4.703273
SO	6.633643	2.185097	3.035858	0.005875*	3.333779
Environmental					
CR	2.262353	1.061437	2.131405	0.043962*	3.698536
VHU	-2.239212	0.903745	-2.477703	0.021001*	2.213863
NTA	3.152917	0.884084	3.566311	0.001639*	3.756913
Social-Interactive					
PI	4.527758	1.360633	3.327685	0.002929*	4.336889

**statistically significant at 1% level of significance*

Table 5. Summary of the ERA-based OLS model diagnostics

Notably, the Koenker (BP) statistic value was 16.199287 ($p < 0.01$), indicating that this model exhibited spatial non-stationarity, which was one criterion in justifying the need for a GWR analysis. Testing the model's residuals for correlation was conducted, the result exhibiting a clustered pattern. Reiterating the interpretation provided by ArcMap, such a pattern indicates that "there is a less than 10% likelihood that this clustered pattern could be the result of random chance." In other words, this could mean that the global OLS model may under- or over-perform when predicting or specifying a relationship. This was the second criterion for the need to perform GWR analysis.

GWR Modeling Results. Important outputs of the local GWR model revealed the spatial variability of the coefficients and their significance based on the calculated *t*-values across the 32 legislative districts of Metro Manila. Sample maps of said outputs are shown in Figure 5.

A darker shade of orange in the coefficient map indicates a stronger relationship between the corresponding opportunity indicator and urban intensity while a lighter shade indicates a relatively weaker link. The significance of these coefficient values was also calculated through *t*-test to measure the reliability of these relationships using the following conditions: level of significance = 0.025 and degrees of freedom = 31, with a critical value of 2.04. The coefficient estimates were divided by their standard errors to derive the ratio value equivalent to the *t*-value per se.

A closer look at each coefficient map presents interesting trends. For example, in the case of CR (crime rate) as shown in Figure 5, a positive relationship was observed between this variable and urban intensity throughout the entire region. A stronger relationship manifested in central Metro Manila, i.e., all six districts of Manila City, the two districts of Valenzuela City, and the first, third, and fourth districts of Quezon City. A relatively weak relationship presented in the southern portion of the region, i.e., lone district of Taguig/Pateros City, lone districts of

Muntinlupa City and Las Piñas City, the two districts of Parañaque City, and the two districts of Makati City. Significant relationships were notably those districts found in the central part of the region going to the north. Non-significant coefficients started from Makati City going south, with the lowest *t*-value of 1.3091.

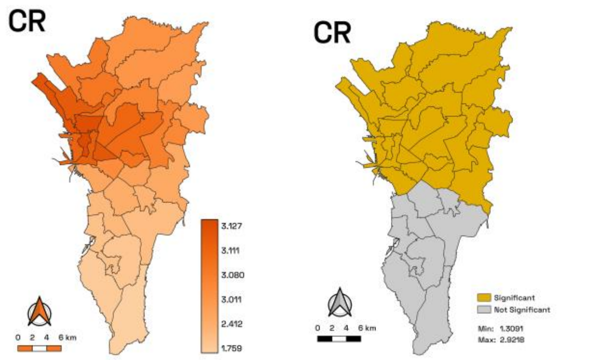

Figure 5. GWR Coefficient (left) and *t*-statistic (right) Maps for Crime Rate

Extensive discussion and interpretation of our maps help explain in detail the spatial variability of opportunity as it relates to urban intensity. Such can provide evidence to help policymakers in their efforts for equitable urban development, especially with the opportunity indicators that they might take into consideration when crafting such measures. More so, the intersection of the importance of these eight indicators cannot be stressed enough, that is everything affects everything: one's opportunity is not dependent on one factor only.

4.4.3 Final Global and Local Models: We now summarize the relevant parameters produced by the final global (AHP-based) and local (ERA-based) models. Both the global and local models offer strong implications for policy making. The strength of basing policies on a global OLS AHP-based model relies on the fact that the variables used here were those that ranked first and second during the weighting process via AHP. The participation of the community and their evaluation on which indicators have more impact on their opportunities in life were taken into consideration. It also makes sense that this model would be appropriate globally, as responses to the AHP were collected from a wide range of individuals from the region.

Parameter/ Statistic	AHP-based Global Model	ERA-based Local Model
Dependent Variable	UIS	UIS
Explanatory Opportunity Indicators	LR, APR, HC, SO, CR, POS, PCD, ER	APR, HDR, GQF, SO, CR, VHU, NTA, PI
R^2	0.741882	0.760492
Adjusted R^2	0.652102	0.599556
Spatial Autocorrelation of Residuals	Random	Random

Table 6. Summary of Relevant Parameters of the Final Global and Local Models

Meanwhile, compared to the AHP-based OLS model, the findings from the GWR model help provide enough evidence as to the spatially varying nature of opportunity indicators as they relate to urban intensity. This means that LGUs and policymakers can base their policies on attributes from the GWR, especially coefficient values and *t*-statistics maps. In general, policymakers must take note that there is no need to choose between a global (regional) or a local (district-level) model; if anything, both are usable and must be integrated together to account for the limitations of our methodology, especially on the part of having to rescale down the values of citywide data to legislative district data. It is of policy implication as well to take note of the variables involved and how they vary across space as they relate to urban intensity, and how reliable the relationships are.

5. CONCLUSIONS AND RECOMMENDATIONS

The results of this paper put in place compelling and never-before-explored insights on the levels of opportunity and urban intensity in Metro Manila, Philippines. Acute and indispensable findings based on the performed spatial analysis and models were useful in telling the first ever story in the country of how and why place matters in understanding one's opportunity in Metro Manila, Philippines.

Our maps and models offer versatile uses: They pinpoint areas needing attention, highlight locations needing interventions, and help derive place-based policy implications. For instance, GWR modeling revealed that a high poverty incidence correlates with urban intensity in all districts. From this type of analysis, LGUs can derive data on which opportunity indicators are important to consider in reviewing existing urban policies, and formulating interventions to improve the quality of life in their districts. Further, combined with spatial autocorrelation tools, our maps help suggest a much-needed collaboration among neighboring districts to improve opportunity distribution. Notably, the comprehensive opportunity cluster map reveals limited opportunities in northwestern Metro Manila, necessitating policy revisions for residents' well-being. Most importantly, our maps in conjunction with existing housing cost and land value maps can also aid in identifying advantageous residential locations in Metro Manila.

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