IN PURSUIT OF RESILIENT URBAN FORM TYPOLOGIES: TESTING A QUANTITATIVE APPROACH FOR MORPHOLOGICALLY BASED URBAN RESILIENCE.

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ABSTRACT

Urban systems which can absorb shocks, manage crises while simultaneously adapting to change can be regarded as being resilient. Furthermore, with the adoption of the New Urban Agenda by the UN, resilience has now been cemented as a key factor for sustainable urbanism. Yet, even with this the acknowledgement, there has been limited research into the role of urban form in building resilience. Through ongoing research into spatial resilience, several determinants which enhance the resilience of cities have been identified, namely connectivity, diversity, capital, redundancy and modularity. By using these spatial determinants as a basis, this paper aims to explore which urban typologies are most likely to enhance the spatial resilience of a city. To achieve this aim, we discuss each of the determinants and their related indicators. Next, using Manhattan, New York City, as a case study, we assess the performance of the city against the indicators. We then perform a Gaussian finite mixed model cluster analysis on these indictors and identify thirteen urban typologies. From there, we explore each of the typologies in terms of their general morphological properties and find that the grain of plots and blocks likely has a vital role to play in building spatial adaptive capacity.

Keywords: urban resilience, spatial resilience, access, urban grain

INTRODUCTION

Cities are facing increased uncertainties due to factors such as global climate change, economic instability, socio-political unrest and uncontrolled viral outbreaks, the latter of which has spread across the globe in the first half of 2020. In response to the increased uncertainty, many cities are turning to the concept of urban resilience in a bid to help plan for and mitigate future crisis (Coaffee and Lee, 2016; Shamsuddin, 2020). However, the concept of urban resilience is more than just the ability to resist and or recover from a disturbance. Instead, urban resilience, within the evolutionary resilience domain, also emphasises the capacity of an urban system to learn from and adapt to changing circumstances, and when needed, to transform into an alternative systems state which is better able to respond to future challenges (Carpenter et al., 2001; Meerow et al., 2016; Peres, 2016).

While there is a general increased interest into urban resilience (Zhang and Li, 2018), the spatial questions of resilience have received little attention with only a few authors having begun to explore the spatial qualities and form of cities which facilitate the emergence of resilient urban systems (Feliciotti et al., 2016; Marcus and Colding, 2014; Nel and Landman, 2015; Salat and

Bourdic, 2012). While some studies have focused on the impact of urban form in responding to specific threats; such as terrorism (Fischer et al., 2018), tsunamis (León and March, 2014; Tumini et al., 2017) and earthquakes (Allan et al., 2013), the focus on this paper is on the urban system properties which enhance the general capability of the system to adapt over time, or what we refer to here as the spatial adaptive capacity of cities. In this sense, we regard the ability of a city to adapt to changing circumstances to be a function of the city's urban form, as previous studies have shown a strong relationship to urban form and the location economic actives (Porta et al., 2011), distribution of land uses (Ozbil et al., 2011), environmental impacts (Mehaffy, 2015), pedestrian movement (Hillier et al., 1993) and adaptive potential (Moudon, 1986).

By making use of five spatial determinants for resilience, we set out to create and explore the *types* and *characteristics* of urban form, which might enhance the spatial adaptive capacity of cities. We do this by utilising a Gaussian mixture modelling (GMM) cluster analysis on our case study of Manhattan, New York City, to identify a series of typologies after which we explore the morphological characteristics of each type.

SPATIAL DETERMINANTS FOR RESILIENCE

Based on previous and ongoing research (Feliciotti, 2018; Nel et al., 2018; Nel and Landman, 2015), several spatial determinants have been identified which have been linked to improving the overall adaptive capacity, and therefore resilience of cities. These spatial determinants are connectivity, diversity, stored capital, redundancy and modularity. Each determinant and how they facilitate resilience are briefly discussed. This discussion is supplemented by providing spatial metrics which are used to describe each of the spatial determinants. As the focus of this study is only on the morphological aspects relating to cities, the social-economic distribution of urban characteristics are not considered here.

Connectivity might be regarded as the most important spatial determinant (Nel et al., 2018). This is because connectivity determines how things flow and interactions happen within cities (Salat, 2011). Connectivity is primarily determined by the form, distribution and strength of the network, and without good connectivity, cities would not be able to function (Marshall, 2005; Reggiani et al., 2015). For this study, we measure connectivity through two spatial metrics, access to plots and betweenness centrality of the pedestrian network. *Access to plots* describes the number and ease of which plots which can be reached within a specified threshold (Higgins, 2019a; Páez et al., 2012). The access to plots metric aids in identifying locations which are access poor and require higher costs (time or money) to reach the same number of locations. Areas with lower access are also less likely to adapt to changing circumstances as there are fewer opportunities available while also being more vulnerable to sudden loss in connectivity. *Betweenness centrality* indicates the potential through movement along a path (Rodrigue et al., 2013). Areas with higher betweenness centrality are likely to be able to adapt easier as there is more chance for interaction. However, too much betweenness centrality is also not desirable as places with high betweenness are also vulnerable to disruptions (Sharifi, 2018).

As one of the fundamental system properties within resilience theory, **diversity** provides the system with options and opportunities during times of change (Ferreira, 2016). To describe diversity, we use two modified location based measures of diversity proposed by Bobkova et al. (2017), namely, plot type heterogeneity and accessible plot density. *Plot type heterogeneity* describes how similar the plots are across within a specified reach. Areas with a higher degree of plot type heterogeneity are also likely to have a higher diversity of functions (ibid). *Accessible plot density* is a ratio between the number of plots accessible through the movement network in relation to those accessible through Euclidian distance. This metrics, therefore, indicates how effective the network is in allowing people to access opportunities.

Having access to spare **capital** or resources has long been regarded as being important within the resilience debate (Walker and Salt, 2012a). Within this context, we regard built volume as the potential to house activities, with more built volume providing more potential opportunities while encouraging additional interaction. When combined with accessibility measures, locations with a high degree of *accessible built volume* can more easily make use of the stored opportunities provided by the city and thereby able to access a diverse array of potential resources in a timely manner should circumstances change.

Redundancy implies a multiplicity of available functions, paths or components which can perform the same or similar functions (Anderies, 2014). Redundancy in urban systems is what allows a city to continue to function should one path or component cease to function. We consider redundancy in the form of *path redundancy*. Here, path redundancy is the number of alternative paths available for each location within a specified distance. Path redundancy provides an indication of the number of route options which the urban network provides.

Finally, **modularity** is a characteristic which describes how locations are decentralised and disaggregated into nested sub-places. Typically, modular areas are characterised by strong short-range internal connections and weaker long-range external connections. Additionally, modular areas can be described as semi-autonomous due to the decentralised and nested structure (Walker and Salt, 2012b). Two metrics are used to describe the modularity of the urban form. The first is a measure of the *internal connectedness* of the network, which is measured by counting the number of plots accessible within a given distance through a negative exponential impedance function. Locations which are closer to each other will have a higher score than those further away and indicates the strength of short-range connections. The second measure is that of *locational granularity*. Locational granularity indicates the nestedness of the urban form. It is calculated as the product of the number of accessible plots and blocks within a given distance. Summarised in Table 1 are the formula for each of the spatial metrics.

Spatial determinant	*Metric*	*Formula*
Connectivity	Access to plots	$A_i = \sum_j O_j e^{\left(-t_{ij}^2/40\right)}$ *Where accessibility, A, of origin i is the sum of all opportunities O available at destinations j accessible within travel time t and weighted by the impedance function impedance parameter 40 that accounts for the cost of travel. Adapted from (Higgins, 2019a)*
	Betweenness centrality	$\boldsymbol{BTW}(x) = \sum_{y \in N} \sum_{z \in R_y} W(y)W(z)P(z)OD(y,z,x)$ $OD(y,z,x) = \begin{cases} 1, & if\ x\ is\ on\ the\ first\ geodesic\ found\ from\ y\ to\ z \\ 1/2, & if\ x = y \neq z \\ 1/2, & if\ x = z \neq y \\ 1/3, & if\ x = z = y \\ 0, & Otherwise \end{cases}$ *Where the betweenness of x is the sum of the shortest geodesic paths which pass along x between y and z (Cooper, 2016).*

Spatial determinant	*Metric*	*Formula*
Diversity	*Plot Type heterogeneity*	$$D_{Plot_R} = 1 - \sum_{i=1}^{C} (p_i)^2$$ *Where D_{Plot_R} is the accessible plot type diversity within a defined distance R; p_i is the proportion of plots within the ith category C to the total number of accessible plots. The index is close to 1 when a plot has higher accessible diversity of plot types and close to 0 when the plot type diversity is low and therefore relatively homogeneous. Adapted from (Bobkova et al., 2017)*
	Accessible plot density ratio	$$A_r = \sum \frac{N}{E}$$ *Where A_r is the plot accessibility ratio with a distance r; N is the number of plots accessible through the network within distance r; E is the number of plots accessible within a Euclidean distance r. Adapted from (Bobkova et al., 2017)*
Capital	*Accessible built volume*	$$C_i = \sum_j V_j e^{\left(-t_{ij}^2/40\right)}$$ *Where the accessible built volume, C, of origin i is the sum of all built volume V available at destinations j accessible within travel time t and weighted by the impedance function parameter 40 that accounts for the cost of travel. Adapted from (Higgins, 2019a)*
Redundancy	*Path redundancy*	$$\mu^r[i] = \sum_j e_j - v_j + 1$$ *Where the path redundancy, μ^r, of origin i, is the sum of the accessible links, e, minus the sum of accessible nodes, v, at destination j, plus 1 within distance r.*
Modularity	*Internal Connectedness of pedestrian network*	$$IC_i = \sum_j O_j . \varepsilon^{-0.1813 t_{ij}}$$ *Where IC is the accessibility of origin i; O opportunities available at destinations j; $\varepsilon^{-0.1813 t_{ij}}$ is the weighted function of the travel time t where -0.1813 is the impedance parameter which controls the strength of the distance decay. Modified from Higgins (2019b).*
	Locational granularity	$$G_i = \sum_j P_j f(t_{ij}) \times \sum_k B_k f(t_{ik})$$ $$f(t_{iz}) = \begin{cases} 1 & for\ t_{iz}\ \bar{t} \\ 0 & \text{otherwise} \end{cases}$$ *Where G is the accessible granularity for origin i at travel time t; P is number of plots available at destination j; B number of blocks available at destination k; $f(t_{ij})$ and $f(t_{ik})$ are the weighted function for plots (j) and blocks (k) for travel time t. z represents j or k in t_{iz}*

METHODOLOGY

To achieve our aim of identifying potentially 'resilient' urban typologies and their related characteristics, we conducted a case study using Manhattan, New York City, as a study area. While Manhattan is well known for its grid pattern, the local variations in its morphological units, namely plots, blocks and road structure, make it a compelling case study.

Data: For this study, several sources of data were used. The Pedestrian network was sourced from OpenStreetMap (OpenStreetMap contributors, 2019) through the OSMnx tool (Boeing, 2017). The public transportation network was obtained from New York's MTA corporation (MTA, 2019), the plots[1] data were obtained from NYC OpenData platform (City of New York, 2018). All the data was cleaned and prepared within the AcrGIS Pro environment.

Tools: To calculate our spatial metrics, several cutting edge tools were used. First, the Accessibility toolbox, developed by Higgins (2019a), was used to perform the various accessibility types of analysis utilised in the study. Additional analysis was performed using the Spatial Design Network Analysis (Cooper and Chiaradia, 2015) and Place Syntax (Ståhle et al., 2005) tools.

Analysis: For all metrics, a cut-off distance of 10 minutes travel time or 800 meters, depending on the type of calculation, was used. All results were standardised to have a score ranging between 0 and 1.

Clustering: As we are dealing with multivariate analysis, we first performed a principal component (PCA) analysis with varimax rotation to reduce the dimensionality of the data while retaining 90% of the variation within the data. From the rotated PCA we extracted four latent constructs which are labelled as 'Access LC', 'Options LC', 'Movement LC' and 'Efficiency LC'. Using the latent constructs as inputs, we then performed a Gaussian finite mixture model (GMM) clustering analysis using the MCLUST package (Scrucca et al., 2016) within R (R Core Team, 2020) to create an initial 24 clusters. Using the spatial distribution as well as the mean values of the identified latent constructs the initial clusters were aggregated into 13 secondary clusters, which were then ranked based on the sum of the mean scores of the original input metrics. The ranking indicate which type of cluster is likely to provide better spatial adaptive capacity. The results of the analysis are shown in the next section.

FINDINGS AND DISCUSSION

The results of the analysis are shown in the figures below. Figure 1 shows the results of the analysis of the eight metrics used to describe the determinants of spatial resilience. As shown in Figure 1, there is significant variation in the performance of locations across the study area. Generally, the lower portions of Manhattan (from 14th Street) tend to have higher scores for all metrics. This trend is further reflected in the four smaller maps in Figure 2, which show the latent constructs derived from the rotated PCA. The latent construct maps are visualised using the standard deviation, with locations shown in white reflecting areas with average scores. While warmer and cooler colours represent locations with high and low scores respectively. The large map on the right in Figure 2 shows the 13 different urban typologies identified from the aggregated ranked cluster analysis. While Figure 3 shows the distribution of values for each of the eight metrics per cluster. As the aim of this study is exploratory, the clusters have been labelled according to their rank and not been given any specific names.

[1] As the access tools make use of the polygon centroids, Central Park, as well as any large or very long plots, were split into smaller plots. This allows locations which are far from the polygons geometric centre but close to its edge to still be counted in the analysis

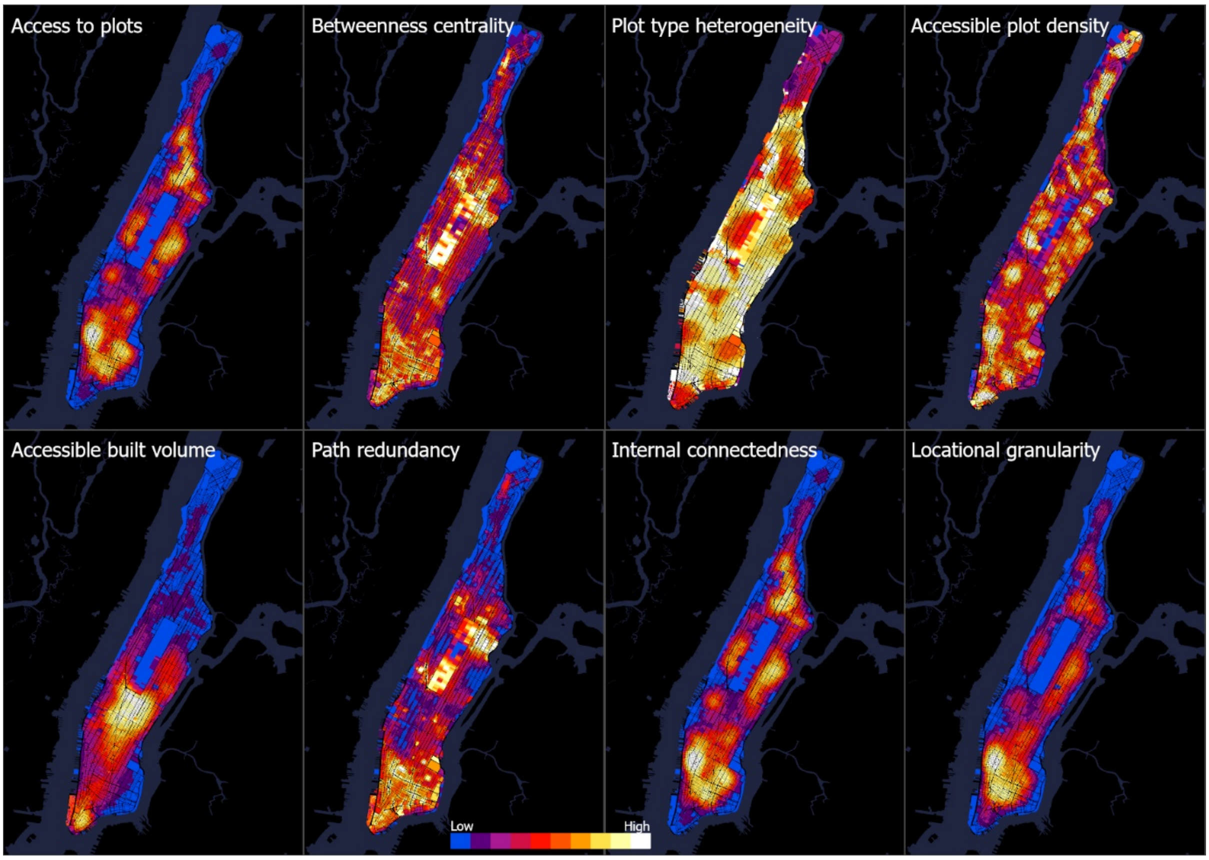

Figure 1: The results of the analysis of the eight metrics of the resilience spatial determinants.

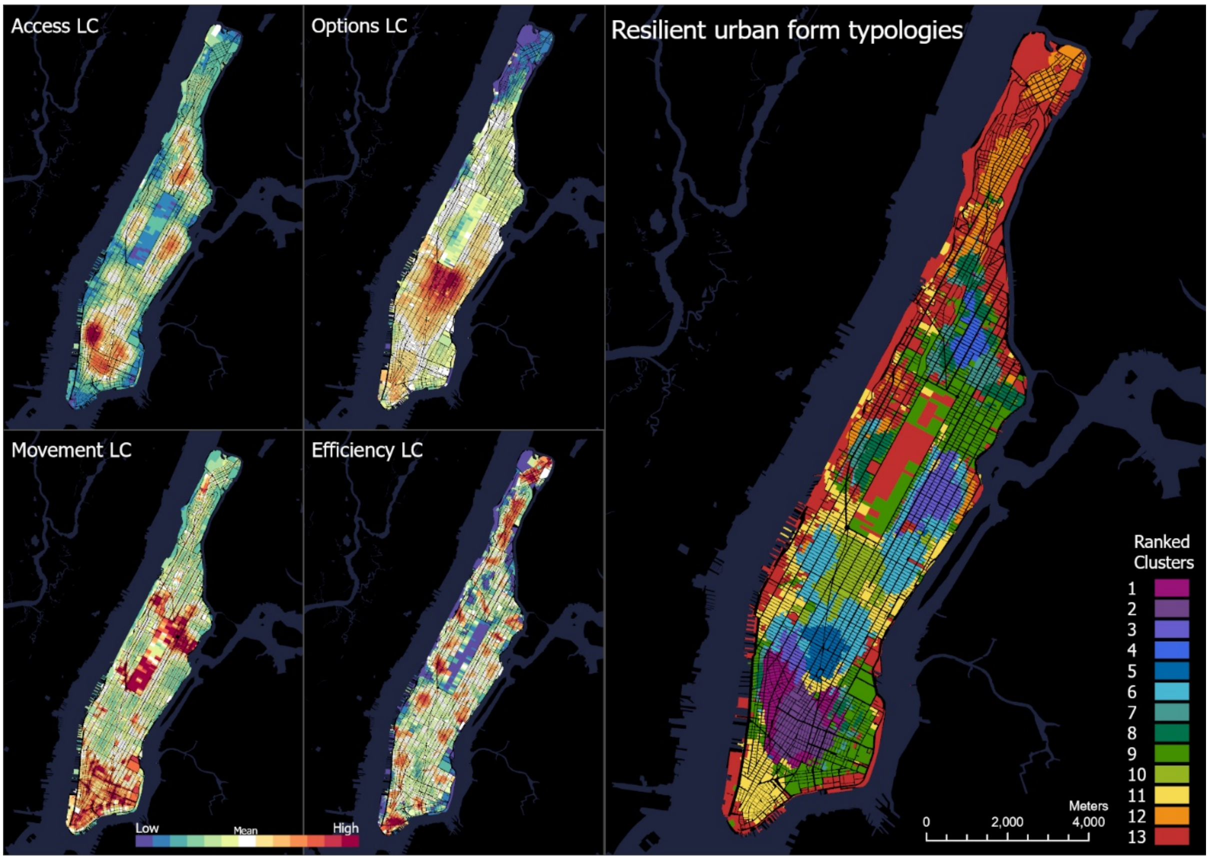

Figure 3: (Left) The four latent components derived from the rotated PCA. (Right) Shows the final ranked clusters for Manhattan.

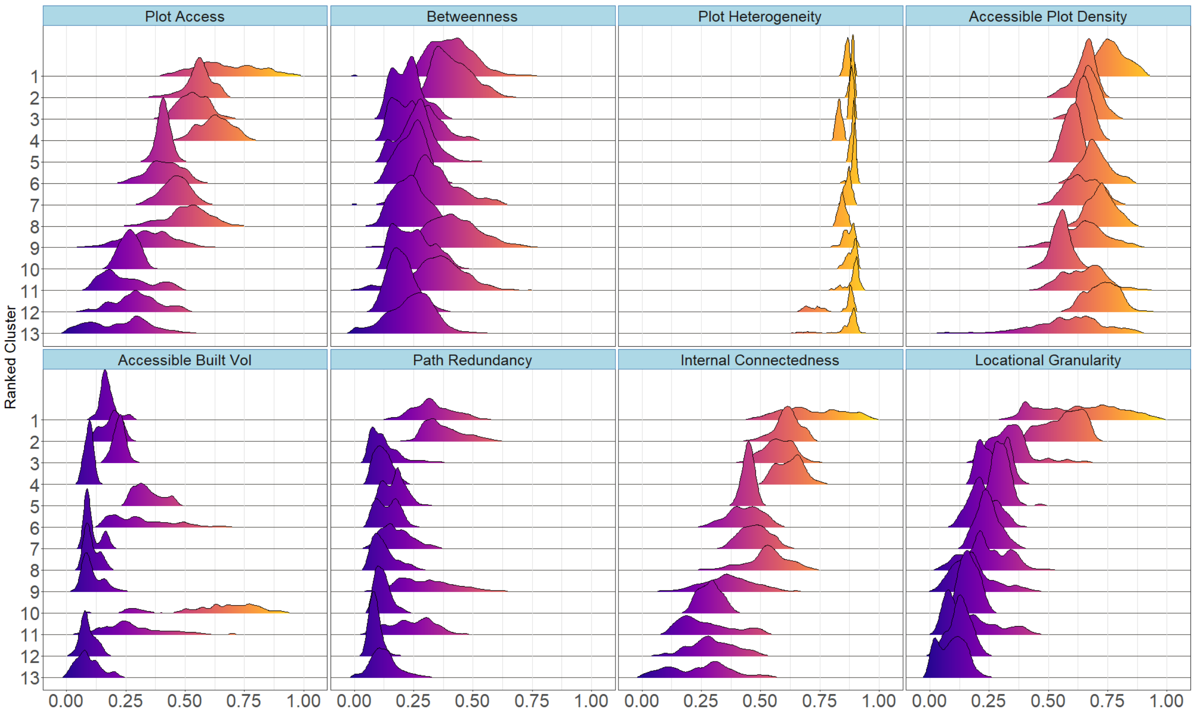

Figure 2: The normalised distribution of each spatial metric per cluster. Cluster 1 is the top row of each block.

The results of the cluster analysis suggest that, generally, locations near the centre of the island tend to form clusters which have better overall performance. In contrast, locations located on the island's edge the tended to form clusters which performed poorly overall. This result might be attributed to the natural edge effect caused by the island's edge; however, other factors are also likely to contribute to this. Possible factors include access to public transport, network density, the presence of diagonal streets and the plot and block sizes.

Plots and blocks, being among the fundamental elements of urban form (Moudon, 1994), have been found to have an impact on the ability of a location to change over time (Moudon, 1986;). We investigated this possibility further by comparing the plot sizes of the three top ranked clusters to those of the bottom three ranked clusters. The top three clusters had an average plot size which was between 1.23 and 1.6 times smaller than those of the bottom three clusters. This finding tentatively supports the existing literature showing the relationship between plot size and adaptive potential (Salat, 2017). However, plots size alone may not be enough to account for the results. Indeed, smaller blocks also seem to be an important factor. For example, when comparing cluster 1 (the area around Greenwich Village) and cluster 4 (upper Manhattan – Harlem) with each other, we observed that, although both clusters tend to have small plots, with cluster 4 having the smallest mean plots size of all clusters, cluster 1 tends to have smaller blocks. The result of the mix of small plots and blocks is reflected clearly in the locational granularity metric (see Figure 3) introduced in this paper. While this is an intriguing finding, further analysis is needed.

CONCLUSION

With the increasing uncertainty, coupled with the expected increased urban growth in the coming years (UN-DESA, 2018), cities are facing unprecedented pressures to adapt. Urban resilience has been suggested as a possible avenue to help cities to overcome these challenges. However, there is currently little guidance in the form of urban design for resilient cities.

This study has begun to make a small step towards design for urban resilience by introducing several metrics which are guided by the determinants that enhance the spatial adaptive capacity of cities. Furthermore, by performing a GMM cluster analysis, we have identified several urban typologies, with some typologies performing well against all spatial metrics. The best performing typologies were further characterised by a fine grain plot and block system. Lastly, the exploration of resilient urban typologies also begins to open a path for urban design to impact existing and future urban form to become more spatially adaptive through improved access and intervention into the plot and block patterns.

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