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Opportunities and Challenges in Applying Light-weight National-scale Spatial Network Models

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ABSTRACT

This paper explores the use of light-weight national-scale spatial network models in order to develop methods of understanding urban environments in developing contexts with limited data, budgets and time availability. The validity of national-scale analysis has been established in research focussed on the United Kingdom and United States of America, but not in other socio-economic and spatial landscapes. In order to evalute the extent to which this methodology still holds, Uruguay and The Maldives are taken as case studies. Open-source road-centre line data is used to construct spatial network models, which are analysed using space syntax analysis. First, each spatial network model is correlated with open-source population data to explore potential relationships between spatial network density (node count) and population. The study finds a notable relationship between national-scale population distribution and citywide node count, where the citywide radii of analysis is taken as the average global radii of the cities in each country under evaluation. Second, a comparative analysis of cities within each country is undertaken, finding that capital cities are consistently above the linear trendline. Potential uses of this approach in future applications are highlighted, for instance, in practical evidence-based decision making, and in research across larger samples of countries and variables. It is argued that, despite data, time and budget constraints, it is possible to construct light-weight national-scale spatial network models that are insightful in-and-of themselves, and in conjuction with other globally-available open-source data. This presents significant opportunities to equalise access to evidence-based urban design and policy.

KEYWORDS

National model, light-weight, developing nation, data-driven, spatial analysis

1 INTRODUCTION

In the last decade, there has been a significant progression in the technological advancements of GIS software, modelling, and computational capability which has broadened the opportunity for data-driven decision making. There has also been an increasing concern around inequality and forms of poverty – absolute and relative – within and between cities and nations. In response to these global challenges, the United Nations has set out 17 Sustainable Development Goals (SDG's) to "end all forms of poverty, fight inequalities and tackle climate change" which came into effect in 2016 (United Nations, no date b). Within this agenda, access to data provides a critical opportunity to create and assess policy, however "many governments still do not have access to adequate data on their entire populations. This is particularly true for the poorest and most marginalized" (United Nations, no date a). To this end, a paradox exists in that developing nations, where the need for evidence-based spatial decision making is often greatest, are also the locations where data, capacity and budgets are most limited. For sustainable development to occur, it is critical that we develop methods of understanding developing environments within the parameters of limited data sets.

Advances in open-source data availability, computational processing power and automated data cleaning have made it possible to rapidly construct spatial models of entire countries. The validity of national scale models has been established in research conducted by Serra et al. (2015) on three large-scale spatial network models of the United Kingdom. The study showed that "space syntax models and analysis hold their value at very-large territorial scales, being highly robust and producing coherent results between datasets of different sources, themes and dimensionalities" (Serra, Hillier and Karimi, 2015, p. 84:1). Additional research on the United Kingdom (Parham, Law and Versluis, 2017) and the USA (Bettencourt, 2013) has further affirmed the value and potential of national-scale models. Significant socio-spatial relationships were also found at a national scale in the United Kingdom, most notably the correlation between population distribution and node count at a radius of 10,000m.

To date, most of this national-scale work has been concentrated in data-rich nations and the extent to which the validity of this modelling holds in more data-sparse developing countries has not yet been established. The way in which this type of analysis can be utilised to address key urban challenges also requires investigation.

Using the existing studies conducted on the United Kingdom as a baseline, national-scale models of Uruguay – located on the southeastern coast of South America (Figure 1) – and the Maldives – an archipelagic country in the Indian Ocean, southwest of India and Sri Lanka (Figure 1) – will be explored to understand the extent to which these large-scale models, combined with minimal socio-economic data, can be successfully used in evidence-based spatial decision making.

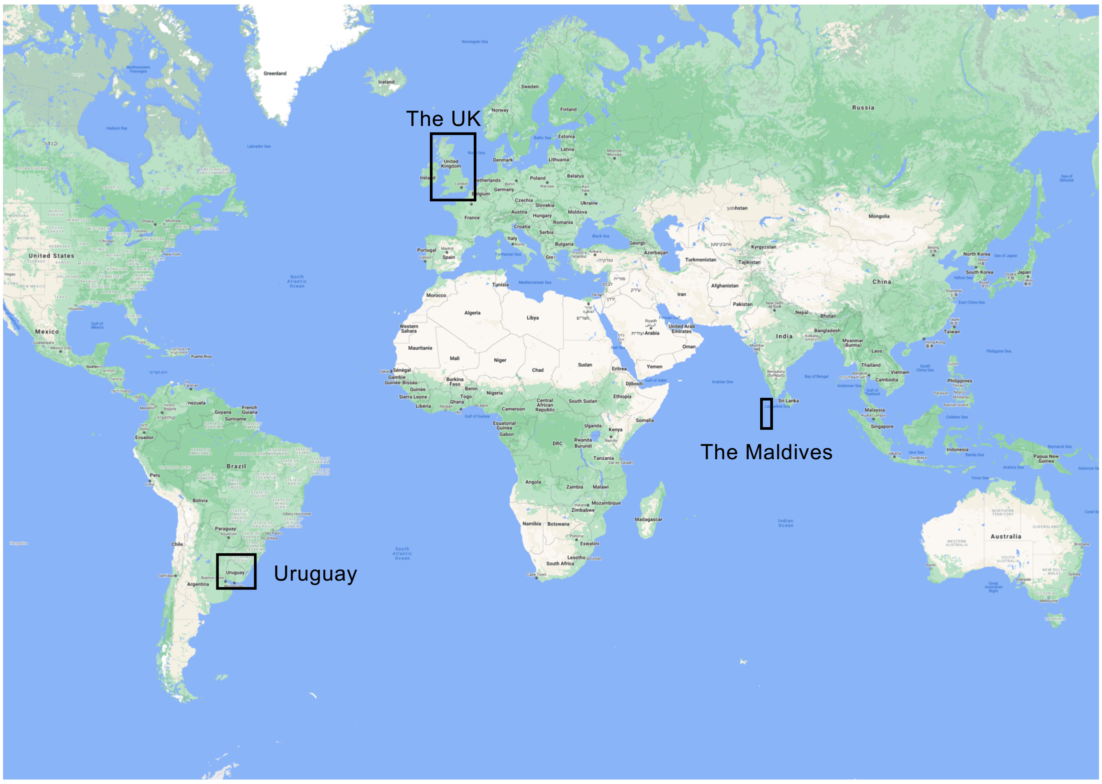

Figure 1 World Map showing the UK, the Maldives and Uruguay

Therefore, this study evaluates

1. The extent to which the methodology of using light-weight national-scale spatial network models still holds in differing developing socio-economic and spatial landscapes.
2. The relationship between population distribution and the size and shape of each national spatial network.
3. The relationship between population distribution and node count in individual cities and across each nation.
4. The potential of this approach in future applications and areas of development.

2 EXISTING STUDIES AND DATA SOURCES

2.1 Existing studies

Research conducted by Serra et al. (2015) on three large-scale spatial network models of the United Kingdom reveals various socio-spatial relationships between UK cities. This study concludes significant correlations between employment distribution and node count at a 2,000m radius, and between population distribution and node count at a 10,000m radius (Serra et al., 2014 cited in Parham, Law and Versluis, 2017), where node count refers to the "number of segments encountered on the route from the current segment to all others" (Turner, 2004, p. 29) within the radius of analysis. This describes street network density.

Parham et al. (2017) further assesses the role of national models in spatially-driven growth strategies for existing cities. The study illustrates how, by understanding a city in relation to all other cities in a country, one can identify the areas in which a city is under or overperforming. This national-scale analysis also allows for the profiling of cities according to their spatial, social and economic characteristics. Cities can thence be grouped according to those with similar strengths and/or challenges, towards learning from spatial successes or finding solutions to common problems. For example, in areas where population is low relative to spatial network density, proposals could be made to target job creation and encourage movement into these areas, and vice versa.

This exemplifies the value of national-scale models in efficiently targeting infrastructure development and growth, by enabling consistent assessment of the relative performance of different settlements, cities and regions of a country. One reason for this is because national-scale models enable public transport and vehicular data to be assessed at the scale at which they are operating, rather than just looking at movement within an (often arbitrary) city boundary.

Thus, national-scale models can provide valuable insights and tools for understanding the spatiality of socio-economic factors within a country, which can help guide design and policy. This has been exemplified in the United Kingdom, however the question remains of the validity of these models outside of a developed, data-rich context.

2.2 Data sources

Historically, there has been a degree of isolation between disciplines within many traditional urban planning exercises. A challenge exists in how to integrate the design of various urban systems, so that the impact of each element on all others is truly considered within the proposed design. This is where integrated modelling practices become critical. The success of this approach is exemplified in the Nur-Sultan 2030 Masterplan (Space Syntax Ltd., 2021). This approach, however, relies on the existence and availability of critical datasets.

In addition to the technological advancements of the last few years, there has also been a shift towards promoting open-source data and development, which has resulted in great improvements to the coverage and resolution of open-source datasets. Since many developing nations do not have the resource to either commission extensive surveys or procure private data, the availability of open-source information is often the first step in opening up the possibility for data-driven design in this context.

The process of rapidly constructing spatial network models to a high degree of accuracy has become possible (and continues to become more efficient) due to advancements in open source data. In order to undertake space syntax analysis, road centre line data from OpenStreetMap, and the documentation of movement infrastructure from Google Maps and Google Earth satellite imagery can be utilised.

There has also been a rise in the availability of social, economic, and demographic datasets from local municipalities, governmental bodies such as the European Union, and non-governmental organisations such as the United Nations. There is also a growing desire from political parties in many nations to appear open and transparent, and to use open data to boost technological growth, inspired by successes such as the London Datastore. However, in developing contexts, many good intentions in this regard are yet to materialise into reliable and practical data sets. Until the availability and accuracy of local data progresses, the best option in these instances is usually to use globally-available data, such as the sources mentioned above.

The fourthcoming discussions evaluate the use of such data in two case studies, to explore new ways of working in countries with limited access to data.

3 DATASETS AND METHODS

The analysis is focussed on two primary case studies from real-world projects at Space Syntax Ltd in Uruguay and the Maldives. These countries have been selected as they are both developing nations with low data availability and coverage. Additionally, recently prepared spatial data from live project work and reasonable knowledge of local considerations exists within the company.

Previous studies on the United Kingdom will be used as a baseline, to compare and validate findings on Uruguay and the Maldives, as the UK national model is well-established with comprehensive datasets and extensive validation through use in professional practice.

Uruguay is spatially similar to the UK mainland, in that it is a single landform of a similar scale, with densely populated cities separated by rural landscape, but differs in terms of having a much lower total population. The Maldives differs from the UK mainland in both spatial form and population, being an archipelago with a much smaller overall land area, dispersed over a large area of ocean.

These similarities and differences support the task of establishing whether the methodology holds in differing socio-economic and spatial landscapes, as well as exploring the role of the overall size of the spatial network through correlation analysis.

Table 1. 2020 statistics on land area and population per case study (Worldbank, 2020a and 2020b)

Country	**Land area (sq. km)**	**Population**
United Kingdom	241,930	67,215,293
Uruguay	175,020	3,473,727
Maldives	300	540,542

Spatial models for Uruguay and the Maldives were generated from OpenStreetMap (OSM) road centre line data. This data was cleaned through an automated process using the Space Syntax Toolkit for QGIS, which simplifies angular changes and merges parallel lines into a single line, towards the principles of an axial map (Hillier and Hanson, 1984, pp. 17, 91; Turner, Penn and Hillier, 2005).

Uruguay population data is sourced from the open dataset of the European Commission's *Global Human Settlement layer* and is derived from the *Urban Centre Database UCBD R2019A*. This data is available at the city-level for settlements with over 50,000 (recorded) residents. For Uruguay, this data represents approx. 60% of the (recorded) national population; the rest of the population lives in settlements of less than 50,000 (recorded) residents.

The Maldives population data is sourced from the 2011 national census data and is available at the island-level. There are potential data inaccuracies in that some of the islands have a non-zero population count according to the census, but have no spatial infrastructure picked up from OSM. This is unlikely to be the case in reality and so further investigation is required, with similar challenges likely to be a common occurrence in data-poor contexts.

To investigate the extent to which national-scale population distribution follows spatial accessibility in Uruguay and the Maldives, space syntax analysis was processed on the respective cleaned spatial network models using DepthmapX, at multiple radii. Thereafter population data was spatially joined to each street segment of this processed spatial model.

The relationship between population and mean node count was assessed by Pearson correlations. Multiple correlations were run, based on different node count radii. Logarithmic mean node count and population values were used in order to control for data skewness.

4 EXPLORING THE SPATIAL DATA

The independent validity of spatial models across data-rich and data-sparse nations is explored in this chapter before assessing the correlation between the spatial network and population, in order to understand what insights the models can offer about the UK, Uruguay and the Maldives (see

Hillier et al., 1993 and Hillier, 2001 for an exploration of theories of spatial configuration and movement patterns).

4.1 UK National Spatial Model

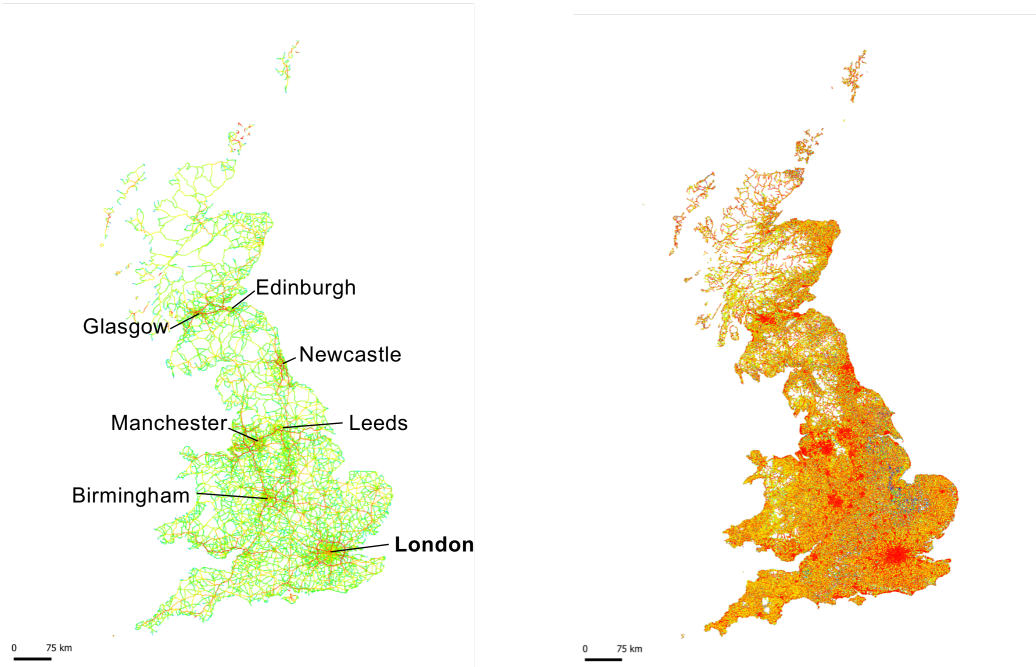

Figure 2. UK Spatial Model (a) Normalised Choice (100km) (b) Normalised Choice (2km). A selection of larger cities are labelled.

The results from the spatial model of the UK reveal the national-scale route hierarchy, which comprises of a network of dominant interconnecting routes. Although intuitive, this result objectively quantifies the relative significance and dominance of certain routes and their high movement potentials for journeys between cities across the UK. Normalised choice (100km) illustrates the dominance of London as a national centre for movement and activity. This is consistent with the perception that the UK is a centralised country in which London is especially dominant in a variety of economic, socio-economic and spatial parameters.

4.2 Uruguay National Spatial Model

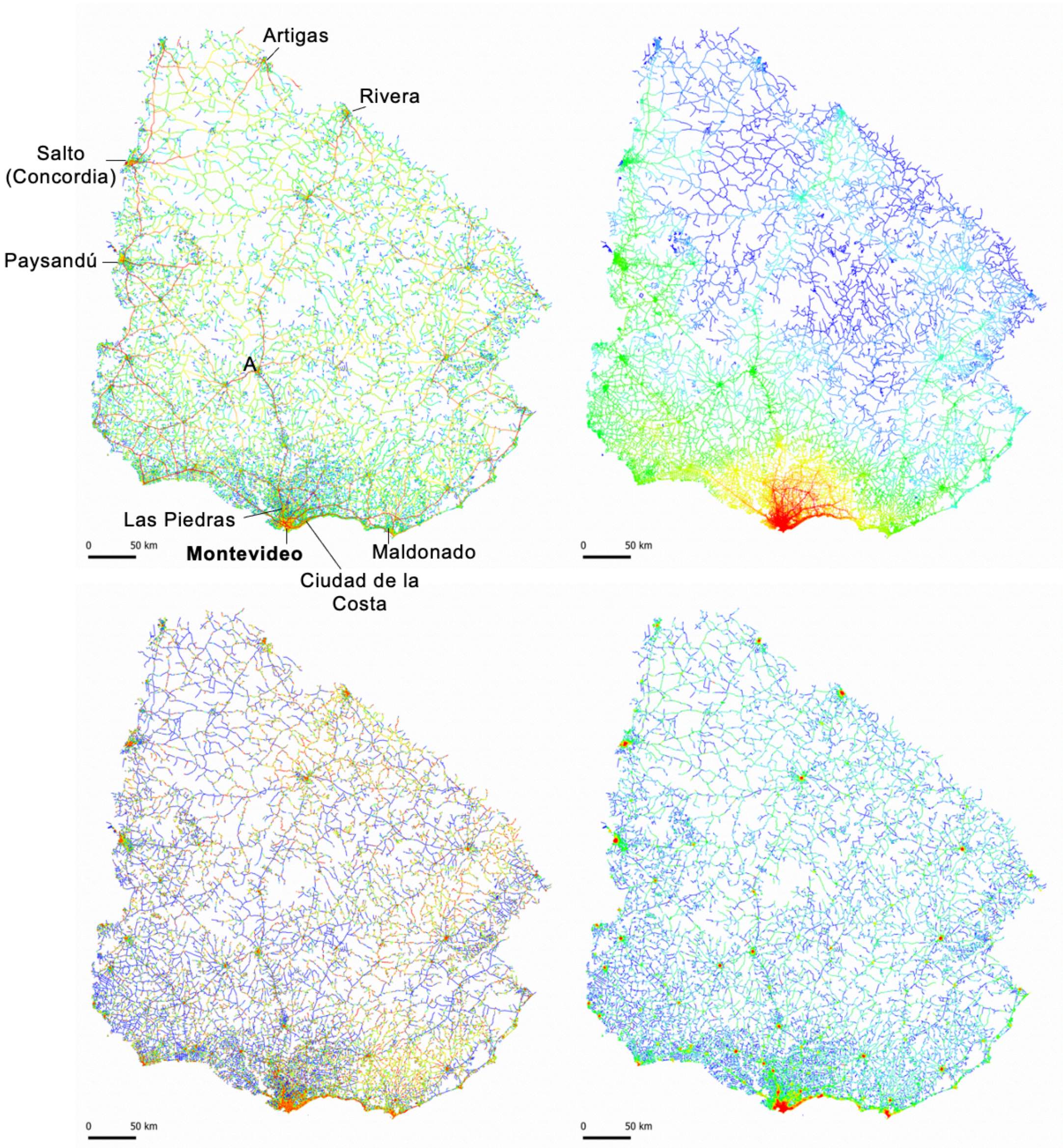

Figure 3. Uruguay Spatial Model (a) Normalised Choice (radius 100km) (b) Integration (radius 100km) (c) Normalised Choice (radius 2km) (d) Integration (radius 2km). Settlements with a recorded population of over 50,000 are labelled. Settlement 'A' marks Duranzo, the former capital of Uruguay (recorded population 30,000)

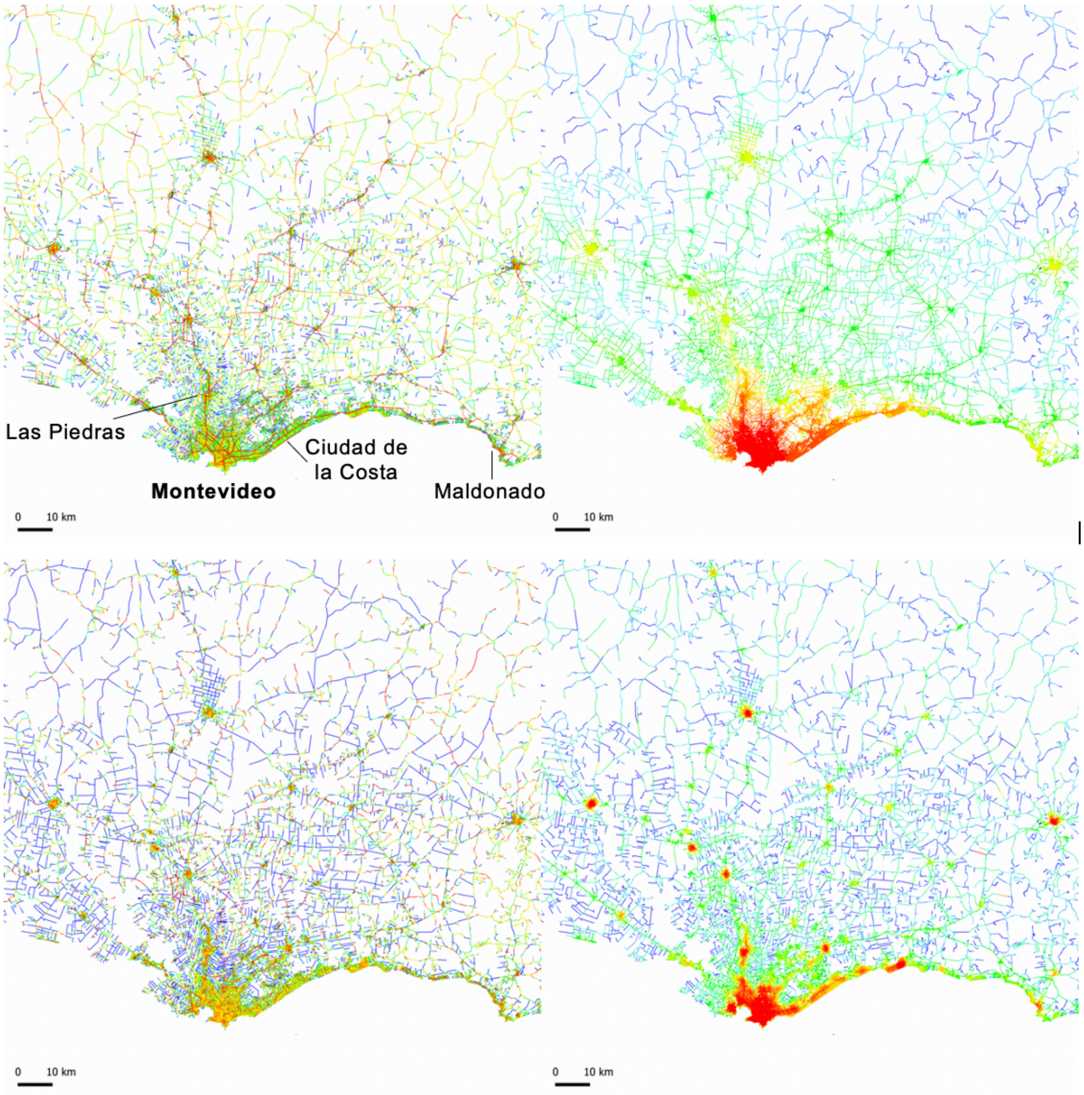

Figure 4. Montevideo, Ciudad de la Costa, Las Piedras and Maldonado (a) Normalised Choice (10km) (b) Integration (10km) (c) Normalised Choice (2km) (d) Integration (2km)

A visual review of the processed model of Uruguay reveals characteristics consistent with qualitative understanding of the country obtained during project work. Normalised Choice R100km (Figure 3 (a)) shows clearly the national-scale route hierarchy comprised of dominant connecting routes linking relatively large settlements. In particular, this route structure clearly converges on the capital city of Montevideo and is further supported by the strong centrality of Montevideo at national, citywide and local scales (Figure 3 (b), and Figure 4 (b) and (d)).

The finding of the spatial prominence of Montevideo corresponds to its economic dominance as well as perceptions of Uruguay as a highly centralised country from a socio-economic and political perspective, having strong similarities to the UK in this regard. There is also a spatial prominence to Duranzo (Figure 3 (a), labelled 'A'), the former capital of Uruguay which has a (relatively small) recorded population of 30,000 (UCBD database). It seems that the historic significance of Duranzo aligns with the hierarchy of movement potential at a national scale, despite its reduced socio-economic dominance in present-day Uruguay. This indicates the power of national spatial models to reveal spatial hierarchies. Such hierarchies are likely be related to and have consequences on social, environmental and economic outcomes for settlements and nations (Hillier, 1996).

Whilst this model appears to successfully describe how Uruguay functions internally, the role that national borders potentially play in the analysis should be noted. For example, the Argentinian city of Concordia sits only around 750m away from the city of Salto in north west Uruguay across the Uruguay River (Figure 3). While the spatial relationship of these two places is complicated by restrictions to movement as well as the physical barrier of the river itself, the location of these two settlements opposite each other is unlikely to be coincidental, indeed many of these ‘twin cities’ exist along the Uruguay border. This hints at the potential importance of cross-border proximity, and the need to consider these cases in detail when undertaking national modelling and using settlement-specific data. This is a consideration that will be explored later in the paper and requires further research in future studies.

4.3 Maldives National Spatial Model

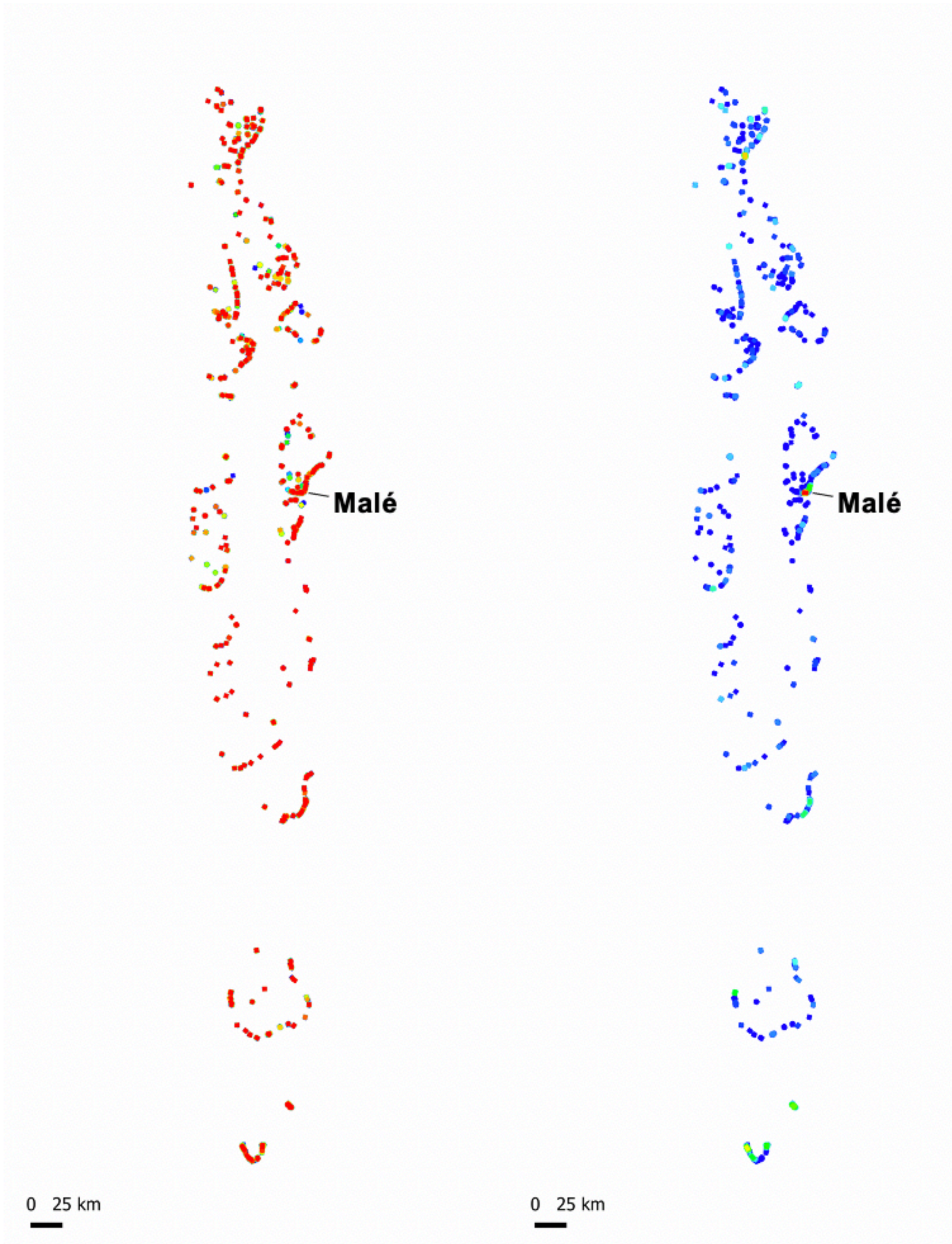

Figure 5. Maldives spatial model (a) Normalised Choice (radius 2km) (b) Integration (radius 2km). The capital, Malé is labelled.

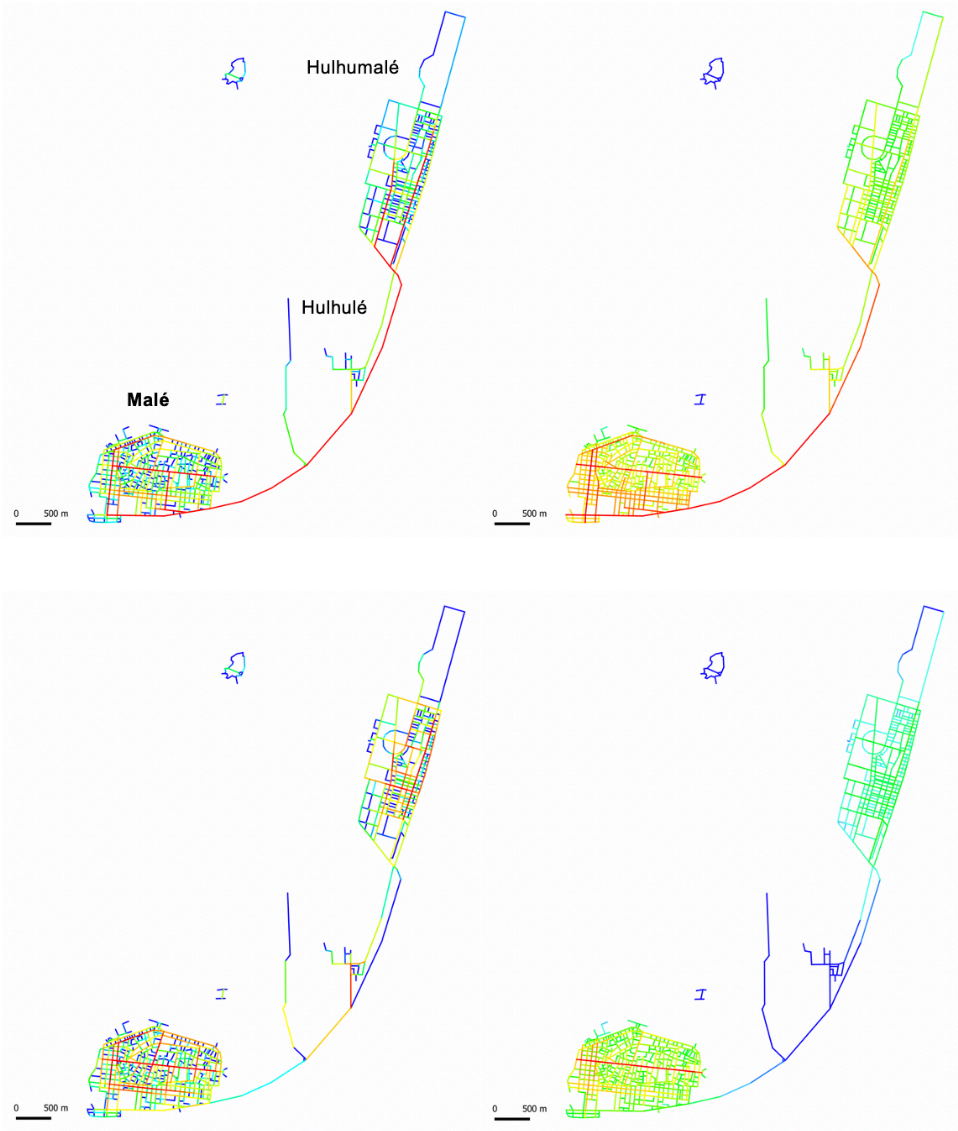

Figure 6. Malé, Hulhulé and Hulhumalé (a) Normalised Choice (10km) (b) Integration (10km) (c) Normalised Choice (2km) (d) Integration (2km)

Visual review of the Maldives at a national-scale is less instructive due to the highly dispersed nature of the country and the lack of national-scale networks relative to more traditional (non-archipelagic) nations. However more can be learned when looking in greater detail at particular islands or atolls. The capital Malé, for example, has very recently been joined to the neighbouring islands of Hulhulé and the recently reclaimed Hulhumalé via the Chinese-funded Sinamalé bridge. The spatial network changes that result from the Sinamalé bridge are picked up by analysis at different scales, with local measures (R2km) suggesting how Malé functioned prior to the construction of the bridge, and larger scale analysis describing the prominence of the bridge for longer-range movement today (Figure 6). These observations have been verified during field trips by Space Syntax Limited and project partners 4D Island before and after the construction of the bridge.

Such analysis can be highly instructive in assessing potential issues the city may experience as it adapts to the significant spatial changes caused by the bridge, including a significant disconnect between how the city has evolved spatially in terms of route hierarchy and corresponding land use and how it works since the construction of the bridge. Insights relating to this have been seen to be valuable by Malé City Council and interest from the Local Government Authority has been shown in using the national model elsewhere, given that it can be used quickly and cheaply.

Using these examples, it has been shown that the spatial models can identify local and global centres, and national-scale movement structures which show primary connections between urban settlements. From this, it can be concluded that the models in-and-of themselves are a suitably accurate representation of on-the-ground conditions for high-level analysis, and thus offer meaningful insights into the spatial structure of these nations. Although the spatial network model of the Maldives is somewhat different to most national spatial models (due to its achipelagic nature), this presents an opportunity to see what relationships may hold across diverse landscapes.

It should be noted that care needs to be taken to ensure that the accuracy of the models is represented correctly, with on-the-ground or other forms of verification required should more detailed conclusions be required than those intended by high-level national and city-scale studies. Misconceptions regarding this can be a risky particularly in contexts where institutional capacity and understanding of evidence-based processes is low.

5 EXPLORING THE RELATIONSHIP BETWEEN NODE COUNT AND POPULATION DISTRIBUTION

5.1 Uruguay

In the case of Uruguay, the results reveal consistencies with the findings for the UK (Parham, Law and Versluis, 2017), where population correlates most strongly with mean node code at R10,000m (Figure 7), with R = 0.6517. It is important to note that, in conjunction to this, the metric size of cities in Uruguay is largely similar to that of the UK, whereby R10,000m is an appropriate radius to capture the spatial extents of the urban settlements.

In terms of population distribution, Montevideo, the capital of Uruguay, and Salto, which lies on the Uruguay-Argentina border, sit well above the linear trendline. Maldonado and Ciudad de la Costa sit significantly below this (Figure 7).

The divergence of these cities from the linear trendline offer the potential for insights into how these cities function. There is reason to suspect that capital cities, for example, may have a tendency to be denser in comparison to other cities in a way that is not purely explained by spatial properties, as the city is likely to be attractive based on expectations around employment opportunities and lifestyle factors. There may also be geographical constraints on settlement expansion, limiting urban sprawl and making densification of the urban network and morphology more likely. The cities of Maldonado and Ciudad de la Costa, on the other hand, lie in close proximity to Montevideo and the low population relative to node count could suggest these are acting as peripheral or satellite cities, with Montevideo, to some extent, functioning as their centre.

The position of Salto relative to the trend line also offers potential insight into its spatial relationship to Concordia, across the Uruguay-Argentina border. With the two cities being separated by only around 750m, the likely increase in node count at 10,000m if Concordia were included in the spatial model would move Salto closer to the trend line and may explain a significant portion of its divergence.

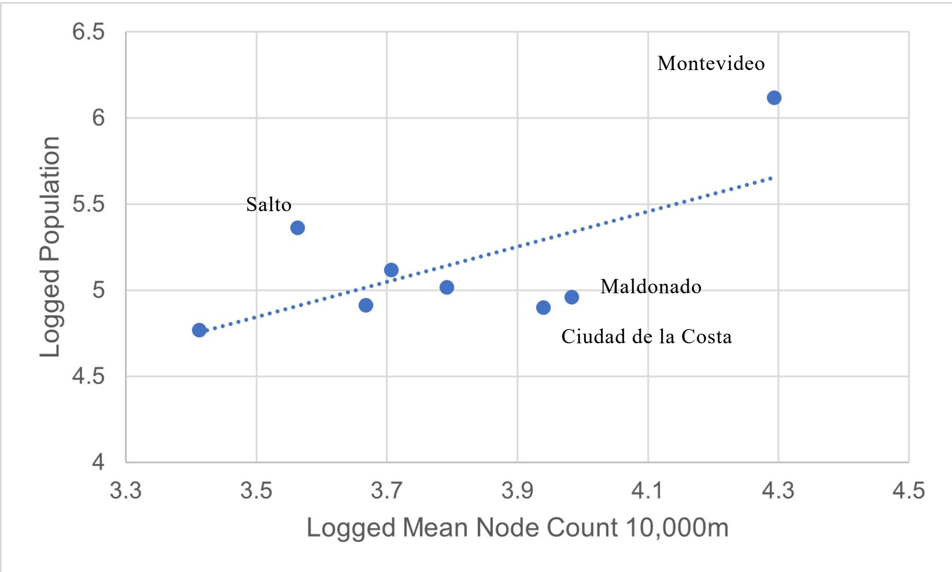

Figure 7. Uruguay relationship between population and mean node count at R10,000m. R = 0.6517

5.2 The Maldives

In the case of The Maldives, the relation between population and mean node count at R10,000m does not hold as strongly (Figure 8).

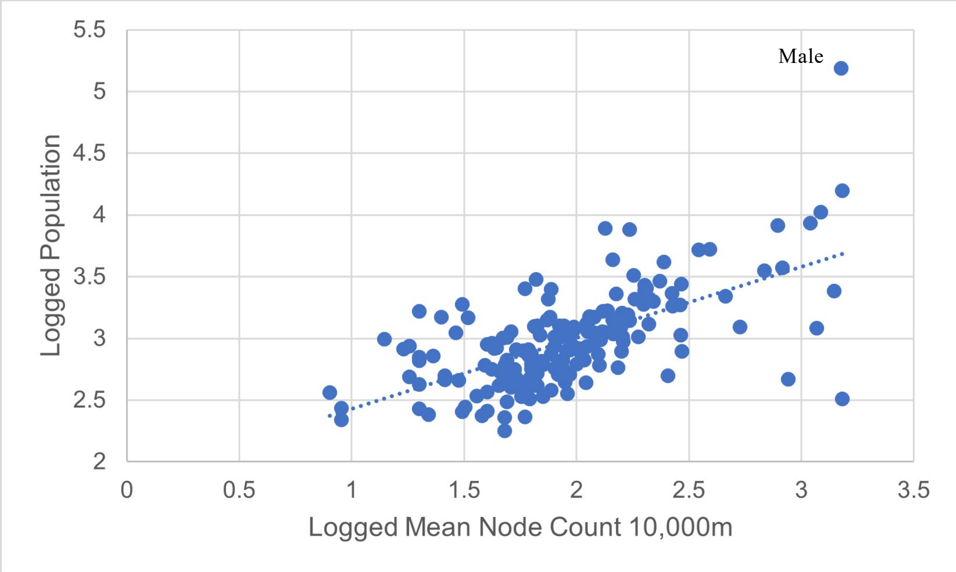

Figure 8. Maldives correlation between population and mean node count at R10,000m. R = 0.6333

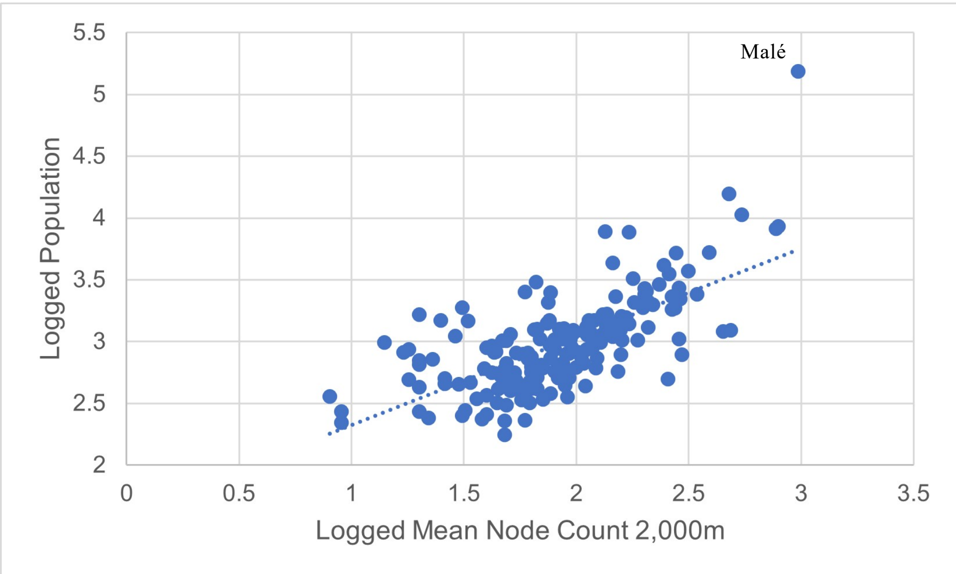

Figure 9 Maldives correlation between population and mean node count at R2,000. R = 0.6818

The R values for the correlations between population and mean node count at R10,000m (R = 0.6333) and R2,000m (R=0.6818) are within 0.05 of each other. This closeness is likely to be due to the geography of the archipelago as the majority of the islands are less then 3km^2. As a result, a radius of R10,000m runs far beyond the bounds of the island spatial network meaning that, for most islands, the mean node count at R10,000m is similar to the mean node count at R2,000m as there is little spatial network beyond this radius.

R10,000m is larger than the global radius relative to the size of the island-level spatial network[1]. R2,000m, which has a higher correlation with population and lower average deviation from the trendline, is more accurately indicative of global island-level movement potentials. A correlation between population and mean node count at R400m was also calculated to explore how population relates to local-scale movement potentials. This correlation was 0.4822. Thus, despite its spatial differences to Uruguay and the UK, this evidence from the Maldives supports the argument that population corresponds most closely to city-scale/global movement.

In terms of population distribution, Malé in the Maldives is significantly far above the linear trendline, with a population notably in excess of where one may expect it to be, based on the node count at R2,000m. While this may seem anomalous based on this data alone, it is in fact potentially reflective of the local conditions and challenges. Malé is one of the most densely populated cities on earth. The overcrowded island is almost bursting at the edges with land being 'reclaimed' from the ocean to accommodate the population. Therefore, the potential conclusion from the data that Malé has less network per person than it should, would seem to be consistent with more detailed observations and on-site observations. Improving our quantitative understanding of these problems could prove useful, particularly when considering large-scale infrastructure and growth strategies.

Further, more detailed analysis of individual settlements and cities would be beneficial to understand the extent to which the inference of the data tallies with on-the-ground observations and the relationship to long-term outcomes.

5.3 Summary of correlations

The table below summarises the results from linear correlation analyses between population and mean node count across all cities in both Uruguay and the Maldives.

Uruguay		The Maldives		
Population with mean node count 10,000m (4dp)	Population with mean node count 2,000m (4dp)	Population with mean node count 10,000m (4dp)	Population with mean node count 2,000m (4dp)	Population with mean node count 400m (4dp)
0.6517	0.4707	0.6333	0.6818	0.4822

[1] The inhabited islands of the Maldives are not fully isolated, but connected by multiple ferry, boat and sea-plane networks. The ways in which this impacts movement between islands is an important but complex factor for future consideration.

6 DISCUSSION

6.1 Spatial analysis findings

Findings from both Uruguay and The Maldives thus suggest that population distribution follows the citywide mean node count, and not necessarily a strict node count of R10,000m. Overall, the correlations are slightly lower than those of Serra et Al (2014) and Parham (2017), which may be due to limited or low resolution data, however the results are still consistent with previous findings and significant enough for consideration.

In both cases, the population of capital cities of each nation was above the linear trendline. This is consistent with the results seen in (Parham, Law and Versluis, 2017) whereby London also deviated from the linear trendline. As discussed in relation to Montevideo, this may be explained by additional, non-spatial, pressures on the spatial density and population of capital cities in particular. However, more analysis and a larger data set would be required to draw significant conclusions.

As illustrated by Parham (2017), potentially useful insights can be gained from the relative positions of settlements to the linear trendline, to understand what element of the city needs improvement and/or development. For example, in Ciudad de la Costa and Maldonado, the density of the street network assessed against the linear trendline suggests that these settlements may be able to support a higher population than they currently do. Conversely, Salto in Uruguay and Malé in the Maldives have a total population that is above the linear trendline, suggesting there may be potential to improve infrastructure and intensify the movement network in these locations to better support the existing population.

It is worth reiterating here that these investigations are highly exploratory in nature and the study has various limitations. First, the sample size is limited and the study would ideally need to be expanded to 10 – 20 other nations. Second, the data is aggregated to a city level and thus the nuances of street-to-street differences (Hillier, 1996) that space syntax analysis can draw crucial insights from will not be taken into consideration. Third, the boundary definitions of the *UCBD* data are highly simplified and the polygons appear to be derived from tiles. This means that the edges have a degree of inaccuracy. Last, a challenge to national scale modelling is that the current processing time on DepthmapX is still extensive.

However, limitations considered, the consistency of the relationship between population and mean node count across such geographically, economically and socially different countries shows potential. The findings of this paper suggest that significant opportunities for policy and practice are possible through the creation and analysis of light-weight national-scale spatial network models.

6.2 Implications of the results for policy and practice

One implication of this study is an increasing confidence to use national models in commercial proposals for the development and growth of new and existing cities, as well as in national or regional spatial plans. With this understanding, population and employment can be distributed according to the spatial density of the street network, as measured by node count, and potential areas for improvement can be highlighted. This should be undertaken in conjunction with other relevant studies considering economic, environmental and other factors.

The opportunities of rapid, national scale modelling lie in the fact that with little input – time, data, money – widely available spatial network models can be used to draw out valuable insights. Such insights can inform evidence-based decision-making and can be used in rapidly changing urban and rural environments where the costs of poor decisions are often greatest and institutional capacity to assess the situation holistically is low. Insights here can be particularly valuable in high-level strategy and assessment as well as prioritisation of key elements and areas for interventions, which can then be targeted by governments, local authorities, and NGOs.

While the potential is high, the use of these techniques poses several challenges. In many contexts, the data available is limited, so where spatial modelling is possible, careful thought needs to be given to how this can be paired with other data or insights to draw conclusions. Low-resolution models also bring up challenges of how to ensure models are matched to the questions, with clear boundaries set on the level of detail that can be extracted, particularly when asking questions relating to causality. Lastly, it is important that models and insights are usable in the contexts concerned. This not only means that insights are tailored to the key questions at hand but also that they are tailored to the institutional capacity and level of understanding present so that arguments can be understood and communicated by decision makers and used as part of a successful engagement and delivery process.

7 CONCLUSIONS AND POTENTIAL FOR FUTURE WORK

The analysis of light-weight national-scale spatial network models has produced significant correlations which provide useful insights into the spatial functioning of Uruguay and the Maldives and their socio-spatial properties: specifically, the interplay between spatial network density and population. On this basis, it can be concluded that the established methodologies of assessing countries at a national scale in order to unpack socio-spatial relationships still holds in developing socio-economic landscapes, where the resolution of spatial models and data are limited.

The study found that population distribution follows citywide mean node count, as opposed to a fixed radius of 10,000m, affirming the hypothesis that the size of the spatial network is directly related to socio-spatial correlations. This finding suggests that the local and global radii used for drawing such insights should be aligned to the scale of the urban settlements.

There is potential to expand the study to better understand the relationship between population and the spatial network of cities, as well as to expand the variables being assessed. For example, researching the correlation between income and the spatial configuration of urban systems at multiple scales. Preliminary analysis on Uruguay finds correlations between GDP per capita and mean node count at R2,000m (R = 0.6422), and between GDP per capita and the closeness of cityide (R10,000m) and local (R2,000m) accessibility (R = 0.6089). These findings indicate potential relationships between economic and spatial properties, however this requires further exploration and is not conclusive at this stage.

Future research should also incorporate other useful open-source global data sets. This is likely to be beneficial by increasing our understanding of how the spatial network relates to a wider range of socio-economic and environmental variables. For instance, using open-source NASA satellite night light imagery may enhance understanding of living standards and wealth distribution within and between countries (Elvidge et al., 2012; Zongguang et al., 2016; Weidmann and Schutte, 2017). This could be synthesised with analysis of spatial networks to understand the spatiality of social and economic circumstances. Also, open-source environmental data sources such as Global Forest Watch could be used to draw insights about how spatial networks may relate to environmental injustices.

As open-source data continues to expand in coverage and accuracy, the breadth of questions which relatively quick and low-cost analysis can answer will increase. Given this, the opportunities of using light-weight national-scale spatial network models are significant, and increasingly so. Using spatial network models and open-source data is a mutually beneficial process; each can enhance the capacity for analysis of the other.

Finally, future research should seek to establish methods and aggregate measures that can provide a high level diagnostics of the inherent spatial structure of cities. This includes exploration into a measure of severance, as well as a revision of the original (axial) synergy measure (Hillier, 1996) to understand the interaction of foreground and background spatial networks, which has long been shown to be an important indicator of sustainability and resilience in cities (Hillier, 2009).

We acknowledge again the exploratory nature of these studies within a limited sample size, however the significance of the correlations suggests that the use of this type of analysis to offer insights into urban systems, on projects operating within stringent data, time and budget constraints, is promising and worth further investigation. The use of light-weight national-scale spatial network models may help to equalise access to evidence-based design, whilst simultaneously enhacing the depth of understanding of the role of spatial networks in social, economic and environmental outcomes.

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