Evaluating the effectiveness of nightlight intensity, population density, and spatial network analysis towards understanding rapid urban growth in data-sparse conditions: the case of Dar es Salaam, Tanzania.

by

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ABSTRACT

This research evaluates the effectiveness of nightlight intensity, population density, and spatial network analysis towards understanding rapid urban growth in the data-sparse context of Dar es Salaam, Tanzania between 1990 and 2020. This contributes towards solving the issue of data insufficiencies which often lie at the heart of problems associated with rapid urban growth; without good quality and availability of data, it is very challenging to grasp an understanding of how a city is evolving, and possible reasons for this. This makes it harder for communities and policy-makers to effectively implement changes which can support and enhance the sustainability and equality of cities. For example, investing in urban infrastructure in areas that are most infrastructurally deficient, or providing electricity supply to the most rapidly growing parts of a city.

With sufficient data, rapid urban growth in cities can be better understood, enabling better-informed local and citywide decision-making, and supporting analytical frameworks for monitoring past, present and future urban changes. This research reveals that open-source globally-available nightlight intensity, population density and spatial network analysis can help alleviate these data insufficiencies. This is achieved through evaluating the insights which can be drawn from each dataset independently, and when joined into a multi-temporal multi-variable cell-based layer. A new degree of divergence metric is proposed which enables more nuanced insights, and a comparative framework for analysing the performance of particular parts of the city is exemplified. Perhaps most crucially, this research offers a methodology which is easily replicable in numerous urban areas worldwide. This is a promising prospect in situations of rising environmental, social and economic insecurities.

KEYWORDS: Rapid urban growth, sustainability of cities, open-source data, data scarcity, methodological replicability, Dar es Salaam.

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CHAPTER 1: INTRODUCTION

1.1 Research Motivation

It is predicted that the world will become more populous and increasingly urbanised over the 21st century, with an estimated two-thirds of the world's population living in cities by 2050 (Vidal 2018; Revi and Rosenzweig 2013). Migration towards and between cities is likely to increase as more people, by choice and by force, respond to growing environmental, social and economic insecurities. The scale of urban expansion is likely to be particularly strong throughout the global south where exposure to climate-related disasters and life-threatening social unrest is often disproportionately high (see Randolph and Storper 2022). This is likely to have significant consequences for the environmental, social and economic sustainability of cities. Unfortunately, without sufficient quality and consistency of data, it becomes very challenging to understand, monitor and guide urban changes (such as the location and quality of infrastructure, housing, local centres and health facilities). Because of this, data insufficiencies tend to lie at the heart of issues associated with rapid urban growth.

Aiming to combat these challenges, the United Nation's Sustainable Development Goals (UN SDGs) adopted under the 2030 Agenda for Sustainable Development consist of 17 goals, 169 targets and 232 indicators, forming a 'shared blueprint for peace and prosperity for people and the planet, now and into the future' (United Nations n.d.). SDG 11 is central to the theme of sustainable urban growth: 'make cities and human settlements inclusive, safe, resilient and sustainable' (ibid.). To help achieve SDG 11, multiple comprehensive globally-applicable frameworks and monitoring and guidance tools have been put in place. For example, the New Urban Agenda (UN Habitat 2017), Global Urban Monitoring Framework (UN Habitat 2022) and National Sample of Cities (UN Habitat n.d.). Crucially, these frameworks require data for measuring and monitoring purposes.

To enable the performance of cities to be assessed over time, many municipalities and/ or central governments (often with the support of UN Habitat) establish metrics – from the size of different economic sectors or location of water pumps, to the proportion of children who receive education – and tools – such as City IQ or City Scan Data Tool (see UN Habitat 2021). Whilst such metrics are an invaluable resource for monitoring and potentially influencing urban changes, they are often particularly vulnerable to issues of data reporting, coverage and consistency both within and between settlements and nations (Worrall et al. 2017; Tanzania Urbanisation Laboratory 2019).

An opportunity to combat these data insufficiencies lies in globally-available open-source data. If such data can be utilised effectively and consistently in ways which can help understand rapid urban growth, then it creates the possibility of providing essential insights in settings where institutional capacity and financial constraints often limit systematic monitoring of key indicators (see Šliužas 2004). These insights could help support and empower communities and local policy-makers to improve the sustainability of, and quality of life within, their cities.

In light of this, this research focusses on evaluating the effectiveness of open-source nightlight intensity data, population density data, and spatial network analysis towards understanding rapid urban growth in Dar es Salaam in Tanzania over the period 1990 to 2020. These three datasets have been chosen based on their complementary insights into how an urban area is functioning at any given time. Nightlight intensity data reveals patterns of light-emitting activity, from transport and industrial activity, to household electricity consumption and commercial street activity. Population density data reveals where people are living to a high and consistent level of granularity (approximately 250m^2 grid cells). Spatial network analysis adopts space syntax methodology to reveal likely movement and activity potentials afforded by the configurational properties of the spatial network across multiple scales (see 3.3.1 Spatial network modelling and analysis).

Dar es Salaam (Fig. 1.1, Fig. 1.2 and Fig. 1.3) has been chosen as a case study because of its fast and uneven patterns of urban growth over the past 30 years (see Collier and Jones 2017; Tanzania Urbanisation Laboratory 2019) and data insufficiencies (see 2.3 Data in Dar es Salaam). Furthermore, community mapping initiatives (such as Zanzibar Mapping) have resulted in relatively well-documented spatial networks within Dar es Salaam's informal settlements (which form a large part of the city's urban structure (Hill and Lindner 2010a)). This makes Dar es Salaam a promising case study

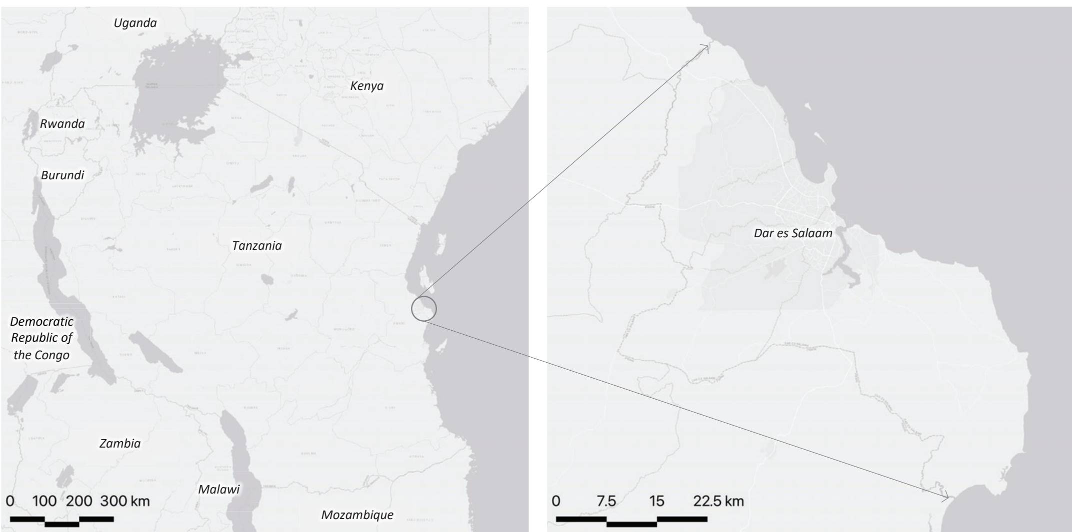


Fig. 1.1 Location of Dar es Salaam. *Basemap: ESRI Gray (light)*

because, without well-documented spatial networks, the potential to undertake accurate space syntax analysis is limited.

Fig. 1.2 Key routes and areas in Dar es Salaam. *Basemap: ESRI Gray (light)*

Fig. 1.3 Looking south-east, Dar es Salaam's central business district (CBD). *Source: iStock by Getty Images (standard license)*

1.2 Research Questions

This research therefore centres around an evaluation of how effective open-source datasets can be at offering new knowledge and insights into, and consistent monitoring of, patterns of rapid urban growth in data-sparse contexts. This is achieved through a study of Dar es Salaam from 1990 to 2020, examining the three chosen datasets – nightlight intensity, population density and spatial network analysis – independently and jointly. Thus, the following research questions are proposed:

1. To what extent can each dataset independently contribute to an understanding of rapid urban growth in Dar es Salaam?

   This is assessed through evaluating the insights about patterns of developmental, demographic and spatial changes in Dar es Salaam, 1990 to 2020, which can be independently drawn from each dataset.

2. To what extent can this understanding be enhanced by combining the datasets into a multi-temporal multi-variable cell-based model and 'degree of divergence' metric?

   This is assessed through evaluating the additional insights about patterns of developmental, demographic and spatial changes in Dar es Salaam, 1990 to 2020, which can be jointly drawn from a combined dataset of nightlight intensity, population density and spatial network analysis.

3. How can this methodology be used to effectively monitor rapid urban growth in Dar es Salaam and other contexts?

   This is assessed through evaluating how the research offers a replicable system for utilising open-source data in a way which offers new insights and methodologies towards understanding rapid urban growth in many contexts.

Thus, this research creates an opportunity to establish a new methodology which harnesses open-source data in a way that can help alleviate issues of data insufficiencies towards understanding and monitoring rapid urban growth (and achieving SDG 11). Of particular distinctiveness, the spatial network is examined as a central variable, and novel approaches for combining and jointly assessing multiple datasets are offered. Through this, existing methodological and knowledge-based limitations in understanding rapid urban growth can be reduced. This is not only applicable to Dar es Salaam but also to other urban environments around the world given the universality of open-source, globally-available datasets and systematic nature of this research.

1.2.1 Key definitions

It is important to highlight the confusion and contestation within academic and policy-making environments that often surrounds some key terms within the field of rapid urban growth. Due to the complexity and diversity of urban changes, the same terminology has often been used to refer to different phenomena. Table 1.1 clarifies the meaning of key terms used in this research.

Table 1.1 Key definitions

TERM	DEFINITION
RAPID URBAN GROWTH (VS. URBANISATION)	Rapid urban growth refers to natural population growth, migration-based population growth and expanding urban built form. This differs from the process of urbanisation which, in many cases, refers to urban expansion based on rural-urban migration alone (see World Bank 2021). In Tanzania, urban growth has been very high, but urbanisation has been relatively slow (ibid.; Castells-Quintana and Wenban-Smith 2020).
URBAN SPRAWL	Congedo and Macchi define urban sprawl as ‘a visible misalignment of population growth and the physical expansion of the city’ (Congedo and Macchi 2015, 5). That is, it is not physical expansion alone, but ‘unplanned and haphazard outward expansion of development from the urban centre’ (Bhanjee and Zhang 2018, 293; Brueckner 2000).
DENSIFICATION	In contrast to urban sprawl, densification is ‘a progressive trend towards infill development’ where population and built-form density both increase over time (Mustafa et al. 2018, 3289).
INFORMALITY	There are numerous interpretations of informality in the context of urbanism. It is important to note that there is no informal-formal binary, but a continuous scale on which urban areas with many combinations of characteristics lie (see Šliužas 2004). For the purposes of this research, the UN definition of informal settlements is adopted: ‘residential areas where 1) inhabitants have no security of tenure vis-à-vis the land or dwellings they inhabit, with modalities ranging from squatting to informal rental housing, 2) the neighbourhoods usually lack, or are cut off from, basic services and city infrastructure and 3) the housing may not comply with current planning and building regulations, and is often situated in geographically and environmentally hazardous areas’ (UN Habitat 2015, 1).

1.3 Document Structure

This paper begins with a review of literature in Chapter 2 and an exploration of the adopted methodologies in Chapter 3. Chapter 4 explores the first research question by investigating the independent effectiveness of each dataset towards understanding rapid urban growth in Dar es Salaam. Chapters 5 and 6 explore the second research question by investigating the additional effectiveness of the datasets when using a single multi-temporal multi-variable cell-based dataset (which combines all three datasets). Chapter 7 reflects on preceding analysis and explores the third research question before offering concluding remarks and suggestions for next steps.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This literature review focusses on four themes: growth and informality in Dar es Salaam, data in Dar es Salaam, existing methodologies towards understanding rapid urban growth, and open-source data. A brief history of urban development in Dar es Salaam is covered in section 4.2**.**

2.2 Growth and informality in Dar es Salaam

One key challenge associated with the rapid urban growth of Dar es Salaam is the 'low institutional capacity' to fund and manage essential developments such as urban infrastructure projects, electricity and water supply, and affordable housing (Šliužas 2004, 6). Consequentially, it is becoming increasingly challenging for these developments to keep up with the pace of urban growth. Because of this, informal development accelerates, fuelling the necessity of infrastructural improvements whilst simultaneously increasing the challenge of effectively and equitably doing so. Although estimates vary, most literature suggests that the majority of Dar es Salaam's population live in informal settlements, most likely between 65-90% (Bhanjee and Zhang 2019; Hill and Lindner 2010b). This has significant consequences on urban growth patterns.

Urban growth in Dar es Salaam since the 1990s has concentrated in a 'ribbon style' 'along the major highways' (Brennan and Burton 2007, 65; Bhanjee and Zhang 2019, 202). This reflects the expected pattern of urban growth centred on a balance between affordability and (social and spatial) accessibility (Kombe 2005; Hill and Lindner 2010b). As the city has extended and densified, spatial accessibility has increasingly become important not just in terms of access to the CBD (which lies within the historic core), but also in terms of access to informal sub-centres, which many residents 'strongly depend on' (Hill and Lindner 2010a, 112; Abebe 2011).

Links between emerging informal settlements and the wider city are also important for most people because they 'are economically and socially symbiotically inter-linked' (Kombe 2005, 128). Because of this, informal sub-centres often lie along the most well-connected parts of informal areas, near highways and 'along the borders of…settlements' which can adopt 'edge oriented commercial activity' (Rasmussen 2013, 4; Hillier et al. 2000, 94) (for example, the street along the bottom of Fig. 2.1). The quality of affordable public transport is also an important component of citywide links in these contexts (Kombe 2005). According to Hill and Lindner, this explains why 'southern parts of the city' which were hard to access developed more slowly compared to similar peripheral areas, despite being close to the CBD as-the-crow-flies (Hill and Lindner 2010a, 141).

Following these patterns, informal development has led to significant urban sprawl with ‘complex organic urban structures’ and varying population densities (Kombe 2005, 113; Bhanjee and Zhang 2019; Msuya et al. 2021). One reason for this is likely to be the proliferation of informal land markets which grew markedly since the 1990s in response to insufficient supply after land nationalisation in 1967 (Bhanjee and Zhang 2019). Consequentially, those looking for the most affordable housing options moved to capture cheap informal land, often relying on ‘kinship networks and social mechanisms for the enforcement of informal agreements’ (Kombe 2005, 120). This also attracted middle-income families with the prospect of home ownership, creating quite economically diverse neighbourhoods: ‘lack of planning is no longer synonymous with poverty’ (Brennan and Burton 2007, 55; Three City Land Nexus Research Team 2020).

Kombe argues that the ‘distort[ed]…spatial structure’ of Dar es Salaam has been exacerbated by land speculation, over time reducing the affordability of informal land (Kombe 2005, 131). This has occurred in a non-linear fashion because speculation has largely occurred in the most sought-after areas, where urban infrastructure quality is best, rather than based predominantly on proximity to the CBD. Thus, the cost of housing in different parts of Dar es Salaam seems to be a function of network accessibility to local sub-centres and the CBD, rather than proximity to the CBD alone.

This has impacted population densities across sprawling Dar es Salaam. Whilst, in general, informal parts of the city have ‘significantly lower population densit[ies] than the old urban areas’, some ‘highly consolidated’ areas – that is, locations where housing is particularly desirable – ‘are often more than three times more dense than planned areas within the same [as-the-crow-flies] radial band…from the centre’ (Bhanjee and Zhang 2018, 292; Three City Land Nexus Research Team 2020, 13). This contrast only increases the complexity of rapid urban growth in Dar es Salaam, and makes the need for understanding the spatial, social and economic conditions more pertinent. Fig. 2.2 illustrates differences in densities, from a low-density sprawling periphery to the city centre in the distance.

Despite this evolution of informal areas in Dar es Salaam, efforts to integrate settlements into ‘the formal urban structure…have been persistently insufficient’, and initial emergent network structures and built forms tend to endure (Kombe 2005, 115; Bhanjee and Zhang 2019; Karimi et al. 2007). This inflexibility can create extra costs and inefficiencies in the longer term because service supply in informal areas is ‘normally more expensive than via the public sector’ (Hill and Lindner 2010a, 43).

Overall, Msuya et al. suggest that ‘the city will continue to grow in a sprawling manner while also continuing to densify in the centre’ (Msuya et al. 2021, 180S). Although ‘Dar es Salaam…may be reaching peak informality’, and despite high ‘population turnover’ in central areas, the lasting impacts of rapid urban growth are likely to be significant and unsustainable (Three City Land Nexus Research Team 2020, 6; Congedo and Macchi 2015, 5; Msuya et al. 2021). Looking forward, patterns of rapid urban growth do not seem to be wavering, despite slowing rates of urbanisation (Castells-Quintana and Wenban-Smith 2020). Although some topographical constraints exist – sloping land to the west (Bhanjee and Zhang 2019) and flood plains within existing informal settlements (Brennan and Burton 2007) – there is still a lot of land yet to be engulfed by urban sprawl (Hill and Lindner 2010a).

Fig. 2.1 Informal settlement in Dar es Salaam. *Source: iStock by Getty Images (standard license)*

Fig. 2.2 Dar es Salaam's skyline from a peripheral sprawling informal settlement. *Source: iStock by Getty Images* (*standard* license)

2.3 Data in Dar es Salaam

In Tanzania, methods are in place to measure 5/14 indicators and 4/10 targets for SDG 11 (full list in Appendix 1: SDG 11 targets and indicators covered in Tanzania) (Goal Tracker Tanzania 2022). In Dar es Salaam, data for these indicators and targets largely comes from census data which is available at the enumeration area level (Fig. 2.3). Whilst the census data provides a range of useful statistics (from household size, to literacy levels, see Tanzania National Bureau of Statistics 2022) and creates quite a promising baseline, collection methods are often unreported, inconsistent and subject to inaccuracies (ibid.; Tanzania Urbanisation Laboratory 2019).

Fig. 2.3 Dar es Salaam enumeration area census boundaries. *Source: Tanzania National Bureau of Statistics 2022 ' 2012 PHC: Shapefiles - Level three'*

Given this, it is likely that open-source datasets will help to provide new insights and offer a systematic approach to collecting and comparing data towards understanding rapid urban growth. Moreover, such datasets are freely available and regularly updated and therefore likely to be a much more sustainable alternative. Table 2.1 offers a high-level comparison of multiple open-source datasets which are available in Dar es Salaam. Whilst not exhaustive, the listed datasets are likely to be the most useful for offering insights into rapid urban growth. It is important to highlight that inaccuracies and limitations within these datasets are unavoidable (see CHAPTER 3: methodology). For example, imperfect processes of data disaggregation or misalignment of time periods. Despite this, open-source data may still contribute towards understanding rapid urban growth in Dar es Salaam and elsewhere, particularly given the significant gaps in existing indicators and monitoring tools.

Table 2.1 Summary and comparison of key open-source datasets available for Dar es Salaam. Datasets used in this research are boxed in red

			AREA (UNIFORM SPATIAL UNIT OF ANALYSIS)	MEASURE-MENT	(MULTIPLE MEASURES/ INDICATORS)		
GHS-BUILT-S	satellite imagery	☒	☒	☒	☐	☒	
OPEN STREET MAP (**OSM**)	etwork – from e imagery + ndent reporting ımanitarian OSM, ıta Collect)	☒	☐	☐	☒	☒	;treetMap ɔutors n.d.
PROGRAM OPERATIONAL LINESCAN SENSOR (**DSMP-OLS**) + JOINT POLAR-ORBITING SATELLITE SYSTEM VISIBLE INFRARED IMAGING	ıtellite imagery and VIIRS)	☒	☒	☒	☐	☒	
SOCIO-ECONOMIC DATA AND APPLICATIONS CENTRE (SEDAC) GRIDDED POPULATION OF THE WORLD VERSION 4.10 (**GPW V4.10**)	ısed population ı – from census is)aggregation	☒	☒	☐	☐	☒	y-Whitfield et .5
APPLICATIONS CENTRE (SEDAC) DAR ES SALAAM LAND USE AND INFORMAL SETTLEMENT (**SEDAC-DAR**)	satellite imagery ı built form and aphy) + census survey data	☒	☐	☒	☒	☐	
UN WPP)	–	☒		☐	☒	☒	
GLOBAL HUMAN SETTLEMENT LAYER: **GHS-POP**	ısed population ı – from GHS-S + GPW v4.10	☒	☒	☒	☐	☒	et al. 2016

2.4 Existing research towards understanding components of rapid urban growth

Table 2.2 compares the methodologies of existing research towards understanding land-use types, urban sprawl and spatial dynamics in rapidly-growing urban contexts.

Table 2.2 Comparison of methodologies of existing research focussing on multiple components of rapid urban growth

STUDY	FOCUS AREA	DATA AND METHOD (SEE ALSO TABLE 2.1)	LIMITATIONS
HILL AND LINDNER (2010A; 2010B)	Land-use types and change in Dar es Salaam.	SEDAC-DAR + UN WPP Build a 'cell-based simulation model on land-use transformation' and logistic regression analysis (Hill and Lindner 2010b, 3) from 1982 to 2002 in order to predict informal and planned urban developments in Dar es Salaam in 2012 and 2022.	Land-use patterns are examined based primarily on as-the-crow-flies distance from the CBD, rather than network-based distance, and therefore only partially incorporate travel-time. Does not incorporate finer-grain data such as census data, or grid-based estimates.
BHANJEE AND C. ZHANG (2018)	Land-use types and urban sprawl in Dar es Salaam.	GHS-BUILT-S + GHS-POP + SEDAC-DAR Use regression techniques to identify relations between land-use types.	Theories of underlying mechanisms contributing to different land-use types could be further explored. Study relies on accuracy of building footprint information (from GHS-BUILT-S) which is subject to limitations given the diversity of built-form in the city which makes interpretation of built-forms from satellite imagery challenging.
BHANJEE AND S. ZHANG (2019)	Land-use types and urban sprawl in Dar es Salaam.	As above, but also incorporating land elevation and road distance measures.	As above.
PORTA ET AL. 2022	Extraction of 'urban form characters [which	Adopt a novel 'urban morphometrics' approach which applies machine	Heavily based on building footprint information. The accuracy of machine learning

	are] clustered into distinct homogenous urban types' (Porta et al. 2022, 2) across a selection of cities. Not yet in Dar es Salaam.	learning techniques to satellite imagery. This could enhance the accuracy of the aforementioned land-use type estimates, and offer quantitative insights into morphological patterns.	techniques in detecting urban form is likely to be limited in contexts such as Dar es Salaam, where built-form diversity and complexity is high.
THREE CITY LAND NEXUS RESEARCH TEAM 2020	'Seeks to understand key aspects of the structure and dynamics' of Dar es Salaam (Three City Land Nexus Research Team 2020, 4).	Space syntax analysis* + enumeration area (EA) census data.	Whilst the role of the city's spatial configuration can be explicitly analysed (unlike the other methodological approaches here), their analysis of socio-economic factors uses as-the-crow-flies distance from the CBD, rather than incorporating the spatial network. Even though the EA data contains many indicators such as socioeconomic class and proximity to water pipelines, it is subject to the modifiable areal unit problem (see Openshaw 1984), because the data is available in various sized polygons, which somewhat distorts the analysis.

*The space syntax approach sees settlements as configurational systems with local and global structures, the former reflecting the functionality and sustainability of the settlement itself, the latter reflecting its interactions with the wider context (Hillier 1996). Karimi and Parham (2012) argue that rapidly expanding settlements are particularly vulnerable to 'severe internal problems' because they 'do not have sufficient time to adjust, or self-correct their spatial structure' (Karimi and Parham 2012, 4). In this environment, space syntax techniques can offer an essential tool to objectively quantify the intra- and inter-connectedness of different areas of a city, which is fundamentally related to their socio-economic performance and sustainability (see Hillier 1996; Hillier 2009; Hillier et al. 2000).

2.5 Open-source data

2.5.1 Nightlight intensity data

Nightlight intensity data has been used across a range of studies concerning development, GDP and wealth. Most research has not focussed on the city or intra-city scale, but findings are fairly consistent. At the national and regional scale, nightlight can act as a good proxy for GDP, electrification rates and poverty rates (Chen and Nordhaus 2011; Proville et al. 2017; Elvidge et al. 2012). Nightlight may even perform better than GDP given it can indicate and account for the 'magnitude of the informal economy' (Ghosh et al. 2013, 4712).

Many studies find a strong relationship between nightlight, urbanisation rates and density at the city scale (Ma et al. 2015; Ch et al. 2021) and intra-city scale (Yin et al. 2019), although large settlements may be overestimated, whilst smaller ones are underestimated (Bagan et al. 2019). Bruederle and Holder compare local-level demographic and health surveys for 29 African countries (Bruederle and Holder 2018). They conclude that nightlight is a good proxy for development indicators at the local level, such as household wealth, education and health.

These findings suggest that nightlight intensity data has the potential to indicate different socio-economic conditions and levels of development at multiple scales. Issues of (dis)aggregation of datasets is likely to limit the frequent use of nightlight intensity data at the intra-city scale. However, given its consistent relation to many developmental indicators, the usefulness of nightlight intensity data when coupled with fine-grain measures has potential.

2.5.2 Population density data

Compared to nightlight intensity data, population density data is easier to interpret because it refers directly to one indicator. The Global Human Settlement Layer dataset enables spatially and temporally consistent population estimates across the globe (see 3.2.3 Population density). This is a potentially powerful tool towards understanding patterns of densification and sprawl in both more urban and more rural areas (see Melchiorri et al. 2018; Ehrlich et al. 2021). This can assist efforts to classify urban growth typologies both within and across cities (Mahtta et al. 2019).

Whilst other open-source datasets are available (e.g. topography, tree-cover), nightlight intensity and population density were chosen for this study given their relevance to rapid urban growth and potential to offer complimentary insights (see Table 2.1). Their creation and application is explored in the next section.

2.6 Interim conclusions

The chapter has revealed the complex nature of raid urban growth in Dar es Salaam, which can be largely attributed to limited urban infrastructure and a lack of affordable housing through formal land markets. As a result, the majority of Dar es Salaam's population lives in rapidly expanding informal settlements which are often not cohesively connected (spatially, socially and economically) to formal urban infrastructure and key movement corridors.

Combating these growth challenges is more difficult given existing data insufficiencies in Dar es Salaam, but open-source data is likely to help alleviate this problem. Whilst existing research offers methodologies and insights into urban growth patterns in Dar es Salaam and other data-sparse contexts, the potential benefits of applying nightlight intensity, population density, and spatial network analysis to explore rapid urban growth has potential.

CHAPTER 3: METHODOLOGY

3.1 Introduction

The methodology for this research consists of three key stages: data collection and rationale, data preparation, and analysis. Fig. 3.1 offers a summary of the methodology.

The period of analysis was chosen as 1990 to 2020 in order to maximise the period of urban growth being analysed, whilst considering limitations in data availability and quality. All data preparation was undertaken using QGIS.

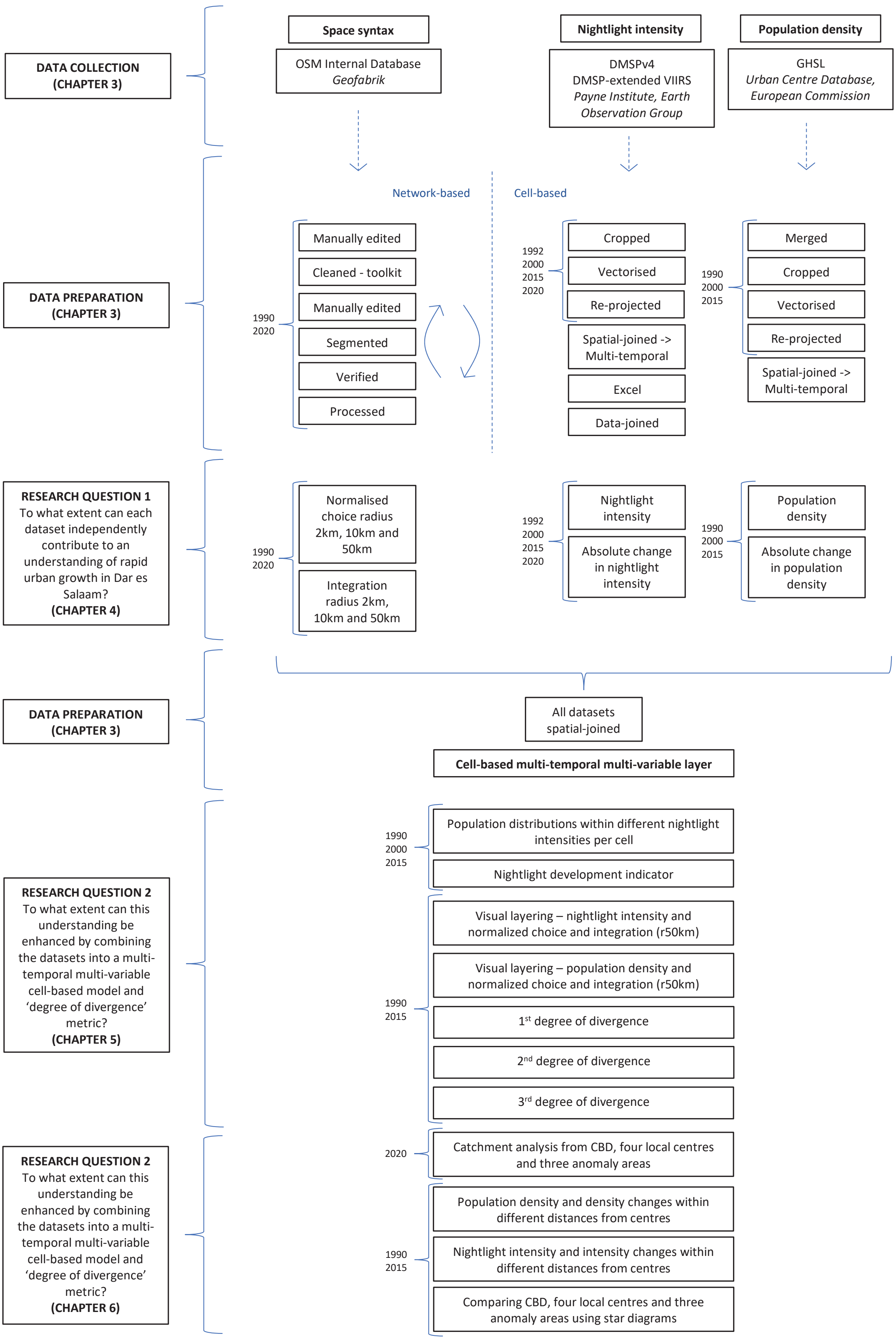


Fig. 3.1 Summary of methodology

3.2 Data collection and rationale

3.2.1 Spatial network modelling and analysis

Space syntax analysis (see Table 2.2) requires a spatial network. For this research, spatial network models for Dar es Salaam in 1990 and 2020 were created. Creating more spatial network models may have enabled a greater degree of understanding of rapid urban growth patterns. However, data preparation is time-consuming and requires increasing computing power to cope with the combined size of the data. Thus, including a third spatial network model is beyond the scope of this study and the years 1990 and 2020 were selected to book-end the points of analysis.

The 2020 spatial network model used OpenStreetMap (OSM) data extracted from the OSM Internal Database within Geofabrik (cropped for all data within 100km from the centre of Dar es Salaam using the osmium command line interface tool). This provides all network data as of 31st December 2020. On the basis of comparisons with Google Maps and Google Satellite, it seems as though this network data provides a fairly accurate picture of networks throughout Dar es Salaam. The mapping of informal settlements also seems accurate, particularly in comparison to most informal settlement mapping globally, which is sparse (Hill and Lindner 2010a).

Data for the 1990 spatial network model could not be collected in the same way. Given that OSM started in 2004, such network data does not exist for 1990. However, the 2015 network data seems to provide fairly accurate mapping of the central region of Dar es Salaam in 1990 when compared to historical maps (see 4.2 A brief history of urban development in Dar es Salaam). Thus, the 2015 OSM network data was used as a proxy for 1990 network data (extracted in the same way as the 2020 network data). Although gaps and inaccuracies are unavoidable in this scenario, other data can help to identify these issues. For example, using population density estimates to identify areas in which the spatial network is under-modelled.

3.2.2 Nightlight intensity

Nightlight intensity data is derived from satellite imagery. It is available in multiple formats depending on the desired time period(s), resolution and level of distortion. For this research, two datasets were chosen, each available using the WGS84 projection at a resolution of about 900m^2 cells (30-arc seconds). Four time periods were chosen in order to align with both space syntax and population density data whilst optimising the trade-off between benefits (detail and depth of research) and costs (time and computational power). Thus, nightlight intensity data was used in the years 1992, 2000, 2015 and 2020.

DMSP v4 satellite imagery was chosen for the years 1992 and 2000. Whilst higher-resolution VIIRS satellite imagery is available from 2012 onwards, comparisons with pre-2012 data would be hard in this instance. As a result, DMSP-extended VIIRS satellite imagery was chosen for the years 2015 and 2020, which matches the resolution of DMSP v4 (Ghosh et al. 2013). Because nightlight intensity data is only available from 1992, it has not been possible to perfectly match the population intensity data or spatial network data from 1990. Whilst this may limit the robustness of findings, misalignment does not lessen the significance of these efforts to assess the effectiveness of open-source data. Limitations are unavoidable and the aim of this research is to create a robust methodology that can withstand such limitations.

For all four time periods, the 'stable lights average visibility' annual average nightlight intensity dataset was chosen – this compilation removes data distorted by cloud coverage, gas flares and other anomalies (Elvidge et al. 2009). Use of annual average data seems apt for this research because monthly changes would likely be too subtle relative to the longer-term patterns from 1990 to 2020.

3.2.3 Population density

Population density data comes from the globally-available open-source Global Human Settlement Layer (GHSL) as part of the European Commission's Urban Centre Database. Baseline population estimates are taken from SEDAC's Gridded Population of the World (GPWv4.10) (based on census data disaggregation). This is then disaggregated into 9-arc second grid cells (approximately 275m^2 in Dar es Salaam, given the Earth's curvature) based on the GHS-BUILT-S layer (high-resolution extraction of built form density based on Landsat satellite imagery) (see Freire et al. 2016; Florczyk et al. 2019).

Data is available for the years 1975, 1990, 2000 and 2015. 1975 data was not used given the scope of the aforementioned datasets. Data for 1990, 2000 and 2015 was chosen using the WGS84 projection at a resolution of about 275m^2 (9-arc seconds).

3.3 Data preparation

3.3.1 Spatial network modelling and analysis

Both the 1990 and 2020 spatial network models were created using the following method. First, parts of the OSM network which do not form part of the movement network (such as rivers and administrative boundaries) were removed[1]. The network was then cleaned using the Space Syntax Toolkit (see Gil et al. 2015). This generates an unlinks file, an errors file, and a cleaned version of the OSM network in which the network is simplified by merging excess lines, snapping junctions together and simplifying angular changes.

Next, the cleaned network and unlinks files were manually edited: the foreground network was prioritised, informal settlements were examined to see if any large sections were missing that could be manually added, and the modelling of public (nature park) and institutional facilities (airport) were optimised. This model was then segmented and verified using the Toolkit. This was repeated until there were no errors left (see Fig. 3.1). The final spatial network models for 1990 and 2020 are shown in Fig. 3.2. Both models were processed (weighted by least angular change (metric)) at multiple radii, generating many space syntax measures. Table 3.1 Summary of space syntax measures explains the selected measures.

Table 3.1 Summary of space syntax measures

MEASURE *(ALSO KNOWN AS)*	**DESCRIPTION**	**SELECTED RADII**
INTEGRATION (INT) *(TO-MOVEMENT)*	Integration, also considered as 'relative asymmetry' 'compar[es] how deep the system is from a particular point with how deep or shallow it theoretically could be' (Hillier and Hanson 1989, 108). Intuitively, this can be thought of as the likelihood of travelling *to* that part of the network, from anywhere else in the network, within a given radius. The formula for integration is: **NC^2/TD** where NC is node count and TD is total depth, both of which are calculated when a spatial network model is processed in Depthmap (see Hillier et al. 2012).	2km (local), 10km (within-city), 50km (across-city)

[1] This included removing the Kigamboni ferry boat connection, as this is a different mode of transport which is not part of a typical spatial network model. Including the ferry connection would have required a time-based movement model, for which there is insufficient data.

NORMALISED CHOICE (NACH) *(THROUGH-MOVEMENT)*	Choice 'is exactly and only a function of the total depth of the system' (ibid., 159). Intuitively, this can be thought of as the likelihood of travelling *through* that part of the network, from anywhere else in the network, within a given radius. Normalised choice 'adjust[s] choice values according to the total angular depth of each segment, since the greater the segregation, the more the choice value will be reduced by being divided by a higher total depth number. This would seem to have the effect of measuring choice in a cost-benefit way' that is directly comparable across all spatial networks (ibid., 160). The formula for normalised choice is: **(LogCH+1)/(LogTD+3)** where CH is (non-normalised) choice and TD is total depth, both of which are calculated when spatial network models are processed in Depthmap (ibid., 2012).	2km (local), 10km (within-city), 50km (across-city)
NODE COUNT *(NETWORK DENSITY)*	Node count 'is the number of segments encountered on the route from the current segment to all others' (Turner 2004, 29).	2km (local), 10km (within-city), 50km (across-city)

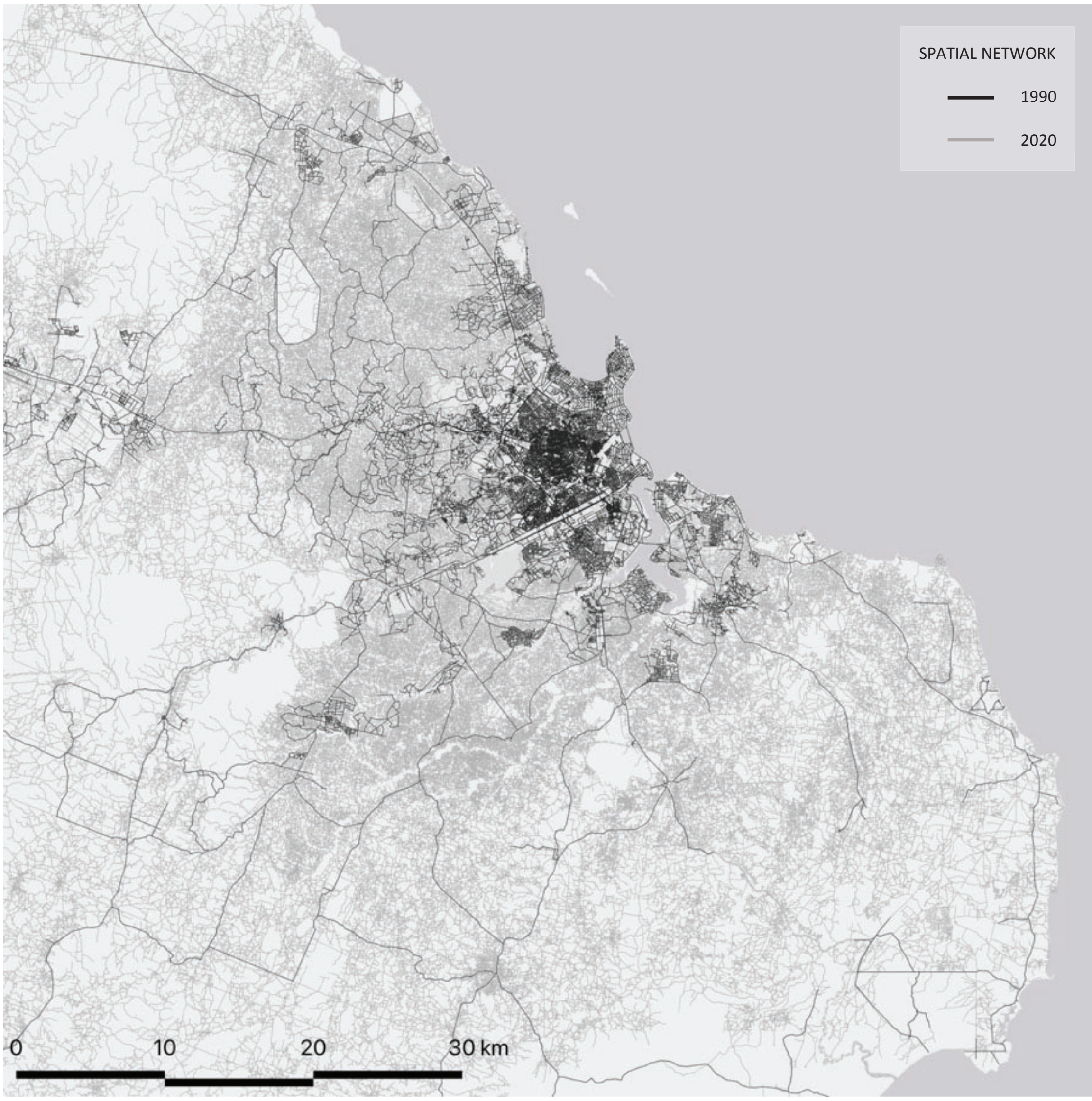


Fig. 3.2 Dar es Salaam spatial network models for 1990 (black) and 2020 (grey)

3.3.2 Nightlight intensity

The downloaded nightlight intensity data exists in global .tif files. Each file was cropped from the global layer to a 100km radius around the centre of Dar es Salaam, vectorised and re-projected (to WGS84 UTM zone 37S – EPSG:32737). This creates a layer of 900m^2 (30-arc seconds) cells for each time period, where nightlight intensity is measured in radiance units on a scale from 0 to 63 (Elvidge et al. 2021). To create a multi-temporal cell-based data layer, all four layers were joined using MMQGIS-generated grid cells. The DMSP v4 data (1992 and 2000) was intercalibrated in Excel using the Elvidge et al. 2009 calibration matrix. This is necessary to control for different levels of nightlight intensity distortion across different satellites (Elvidge et al. 2009). This .csv data was then joined to the multi-temporal cell-based nightlight intensity data layer (see Fig. 3.1).

3.3.3 Population density

Preparation of the population density data required the same process used for the nightlight intensity data with one additional step. The data is downloadable in .tif files for different sections of the globe. In order to have data for a 100km radius from the centre of Dar es Salaam, two .tif layers had to be merged before vectorisation and subsequent steps were possible. No intercalibration is necessary so Excel was not used for preparation of the population data. The resultant muti-temporal cell-based layer consists of 275m^2 cells, where population density is measured as the number of people per cell (see Fig. 3.1).

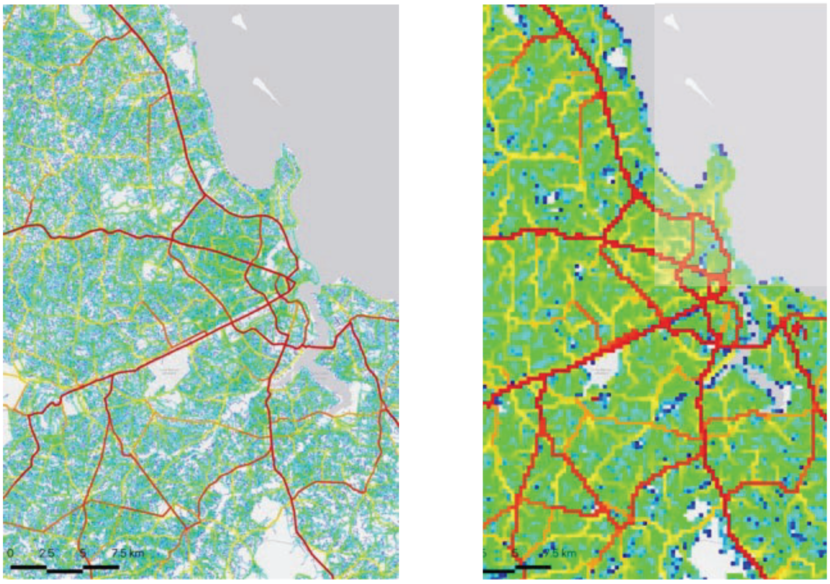
3.3.4 Combining data

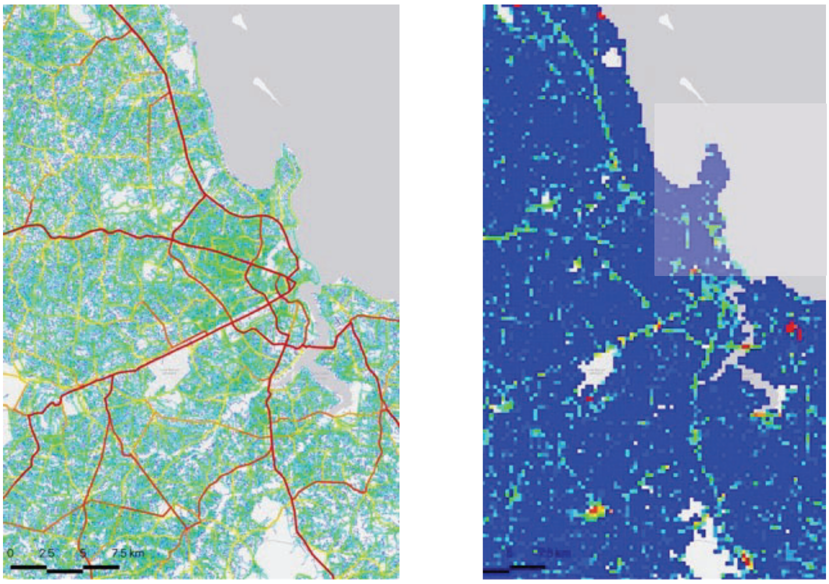
Data was combined in order to produce a single cell-based layer of 275m^2 cells. Taking the multi-temporal population density layer as the base, the multi-temporal nightlight intensity layer (900m^2 cells) was spatially joined using the 'feature with the largest overlap' QGIS setting.

The 1990 and 2020 spatial network models were then spatially joined. In this process, the count, minimum, maximum, range, sum and mean values of each space syntax measure for all segments within each cell were generated. As a result, one multi-temporal multi-variable cell-based layer (275m^2 cells) was created for use in both visual and statistical analysis (see Fig. 3.1).

Using cell-based space syntax analysis removes some of the nuance from a network-based model, in which insights can be drawn at the level of each street segment, as opposed to averaging over 275m^2 areas. Having said this, the cell-based space syntax analysis seems to perform fairly well relative to the network-based analysis. In Fig. 3.3, the results of normalised choice at radius 50km (NACHr50km) for the 2020 model of Dar es Salaam are shown on the network and also joined to cells (taking the maximum segment value within each cell). This reveals a fairly strong visual correspondence between the network-based and cell-based layers for higher-value NACHr50km segments/ areas (segments ranging from yellow to red). However, the correspondence is weaker if focus is placed on more segregated parts of the city (with lower NACHr50km values – segments ranging from blue to green).

In these instances, it may be more effective to draw insights from the mean segment value within each cell (Fig. 3.4). Although almost all differentiation is lost in this case, some differentiation in more segregated parts of the city can be found.





Similar conclusions can be drawn from a comparison of network-based and cell-based integration at radius 50km (INTr50km), although differences between maximum and mean cell values are more subtle. In general, maximum and mean values per cell respectively correspond better with higher-value and medium-to-lower value parts of the INTr50km network (Fig. 3.5 and Fig. 3.6).

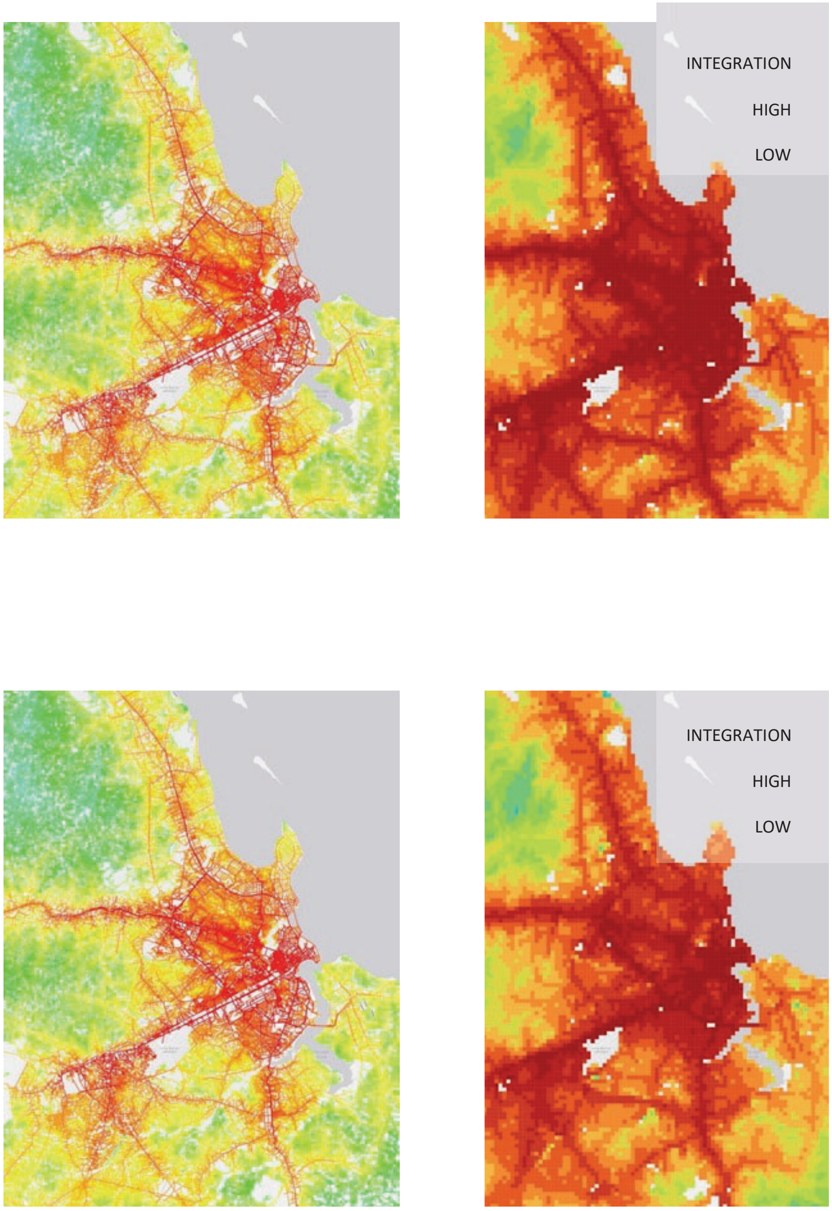


Fig. 3.6 Comparison of network-based (left) and cell-based mean (right) values of INTr50km using 2020 model (same scales)

Overall, cell-based space syntax analysis, whilst less nuanced and fine-grain, still provides insights into the spatial properties and patterns of movement and activity in Dar es Salaam which would otherwise be missing. Moreover, it is possible to use network-based space syntax analysis in conjunction with cell-based nightlight intensity and population density data through visual layering. This can enhance the robustness of analysis, as will be demonstrated in chapters 4, 5 and 6.

3.4 Analysis

A wealth of visual and statistical analysis was undertaken using QGIS and Microsoft Excel. Both software were used simultaneously to ensure feedback between findings from visual and statistical analysis, as opposed to considering them separate entities.

Table 3.2 lists key analytical steps which were used at least once.

Table 3.2 List of key analytical methods applied to research

QGIS	MICROSOFT EXCEL
Data join	Data averages
Spatial join	Graph plot
Merge cells	Correlation
Data averages	Pivot tables
Create new fields	Normalisation and percent-rank
Catchment analysis*	

***** Catchment analysis is a method of analysis which calculates metric distance from a point to all parts of a spatial network based on the network itself, rather than as-the-crow-flies distance. Because of this, the analysis can identify areas which may be quite hard to reach from a certain point, despite being quite close as-the-crow-flies. It is available through the Space Syntax Toolkit plugin on QGIS.

CHAPTER 4: INVESTIGATING THE EFFECTIVENESS OF SPATIAL NETWORK, NIGHTLIGHT INTENSITY AND POPULATION DENSITY DATA ANALYSIS AS PARALLEL, INDEPENDENTLY APPLIED METHODS

4.1 Introduction

This chapter first provides a brief history of urban development in Dar es Salaam in order to contextualise rapid urban growth in the city. Some independent findings from each dataset are then established: space syntax analysis, nightlight intensity, and population density. Using this, an assessment of the effectiveness of each independent dataset towards understanding rapid urban growth in Dar es Salaam is made. Full extents of each dataset can been seen in Appendix 2: Additional mapping.

4.2 A brief history of urban development in Dar es Salaam

The historic core of Dar es Salaam, today's central business district (CBD), lies nested in the sheltered coastline to the Indian Ocean (Fig. 4.1). By the early 1940s, Dar es Salaam had begun to densify along the proximate coastal edge and extend to serve surrounding agricultural land (Fig. 4.2). The 1949

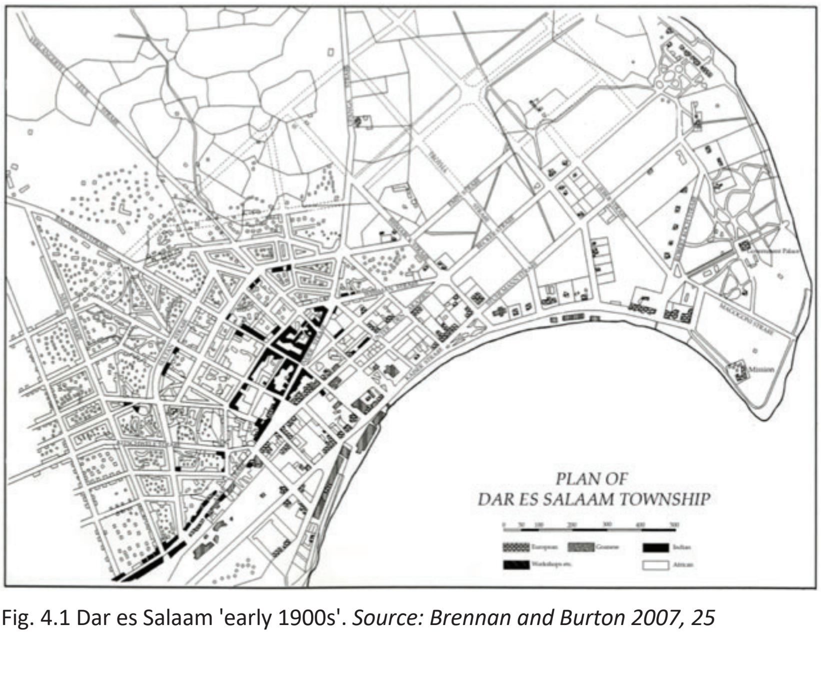


Fig. 4.1 Dar es Salaam 'early 1900s'. *Source: Brennan and Burton 2007, 25*

masterplan promoted low, medium and high density areas in relation to existing patterns of densification and extension.

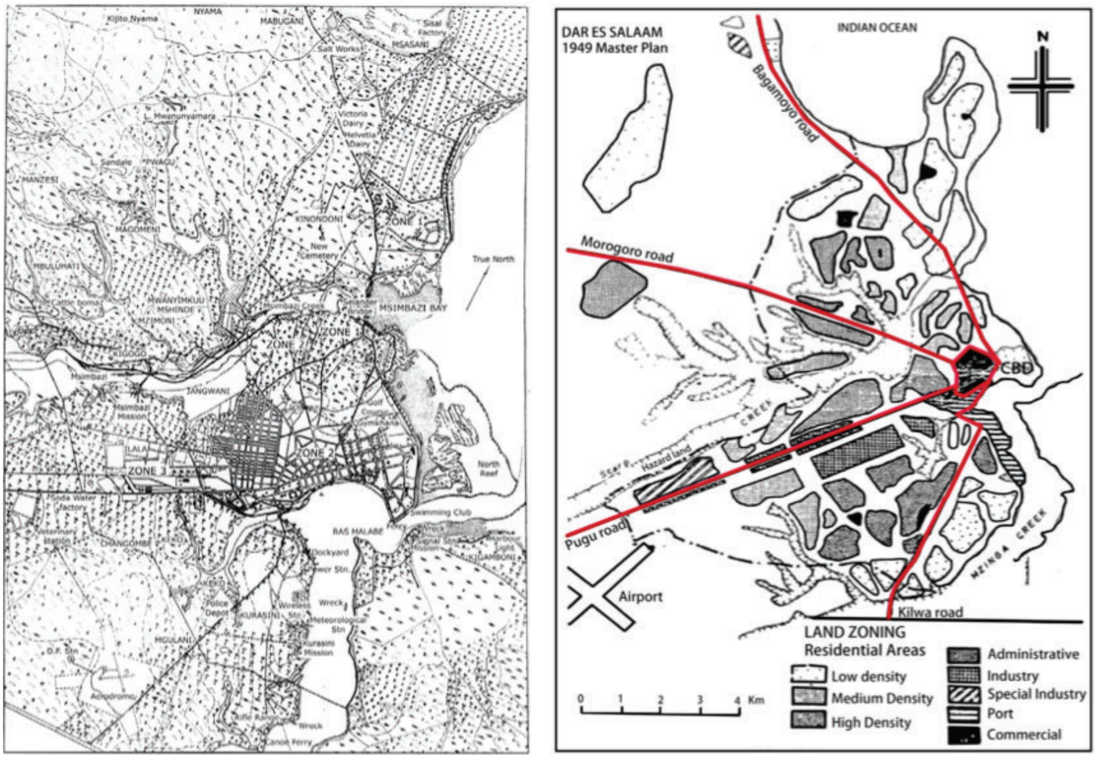


Fig. 4.2 Dar es Salaam: 1941 map (left) and 1949 masterplan (right). *Source: Brennan and Burton 2007, 40 (left) and Peter and Yang 2019, 365 (right). Note images not to same scale or rotation*

By the 1960s, urban development had encompassed most agricultural land surrounding the historic core, particularly in the port and industrial areas (Fig. 4.4). This prompted the development of the 1968 masterplan which envisioned the extension of the city, particularly to the north and south. By 1979, a newer iteration of the masterplan had evolved which promoted the consolidation of land between key arterial roads to the west of the historic core and lessened development to the north and south (Fig. 4.3). This is the 'latest approved zoning plan for Dar es Salaam…and as a consequence there is no up-to-date zoning plan in place' (Hill and Lindner 2010a, 125).

Despite this, several subsequent projects have sought to improve the urban environment across Dar es Salaam: The 1992 Sustainable Dar es Salaam Project, the 1999 Sustainable Urban Development Project, and the 20,000 Plots Project of 'new self-sufficient, self-sustained satellite towns in the peri-urban areas' (ibid, 126). However, these projects have been criticised for only offering 'strategic polic[ies]…[rather] than a detailed planning document with concrete spatial designs' and for failing to provide affordable land and housing (ibid., 126; Kironde 2022).

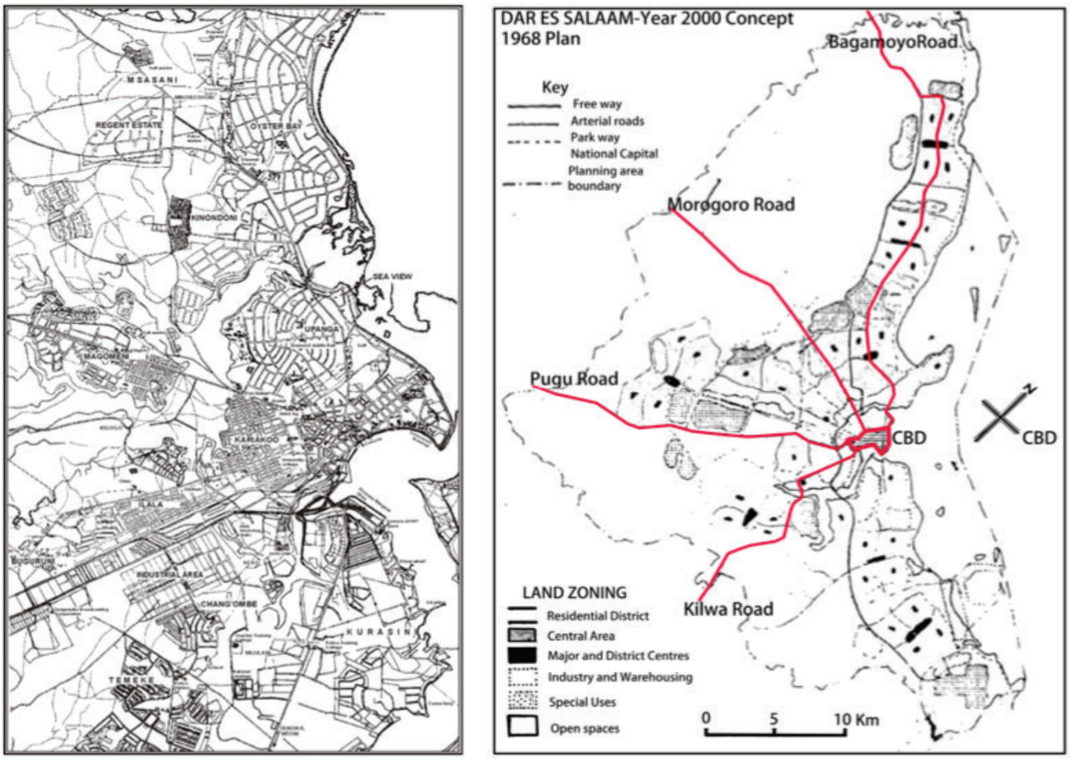


Fig. 4.4 Dar es Salaam: 1962 map (left) and 1968 masterplan (right). *Source: Brennan and Burton 2007, 50 (left) and Peter and Yang 2019, 366 (right). Note images not to same scale or rotation*

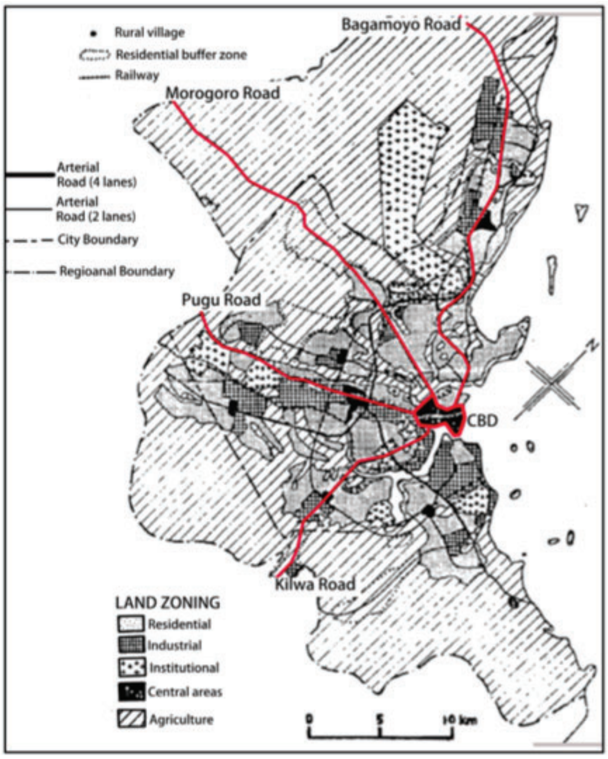


Fig. 4.3 Dar es Salaam 1979 masterplan. Source: Peter and Yang 2019, 366

The Dar es Salaam Transport Masterplan proposes: the dominance of Bus Rapid Transit (BRT) as 'the primary (or spine) public transport system in future', 'upgrades as part of the Nelson Mandela Ring Road', and improvements to infrastructure 'towards development of Kigamboni area' (Japan International Cooperation Agency 2008, 2, 18, 14). Whilst these developments have been, and continue to be, implemented and are likely to have notable impacts on growth trajectories for the city (Hill and Lindner 2010b), they are not keeping up with the pace of urban change (see Šliužas 2004). Consequentially, urban infrastructure across Dar es Salaam and the planning of further developments remains lacking.

Fig. 4.5 indicates areas of urban growth in Dar es Salaam from 1947 to 2001 (based on Peter and Yang 2019, 372). Whilst this may partially be a legacy of previous masterplans and projects, the high proportion of informal settlements in the city and rapid growth rates suggest that the landscape of Dar es Salaam today is largely the result of individual decision-making on where to settle and self-build (see Bhanjee and Zhang 2019). Fig. 4.6 shows the extent of urban growth from 1990 to 2020 as seen from satellite imagery.

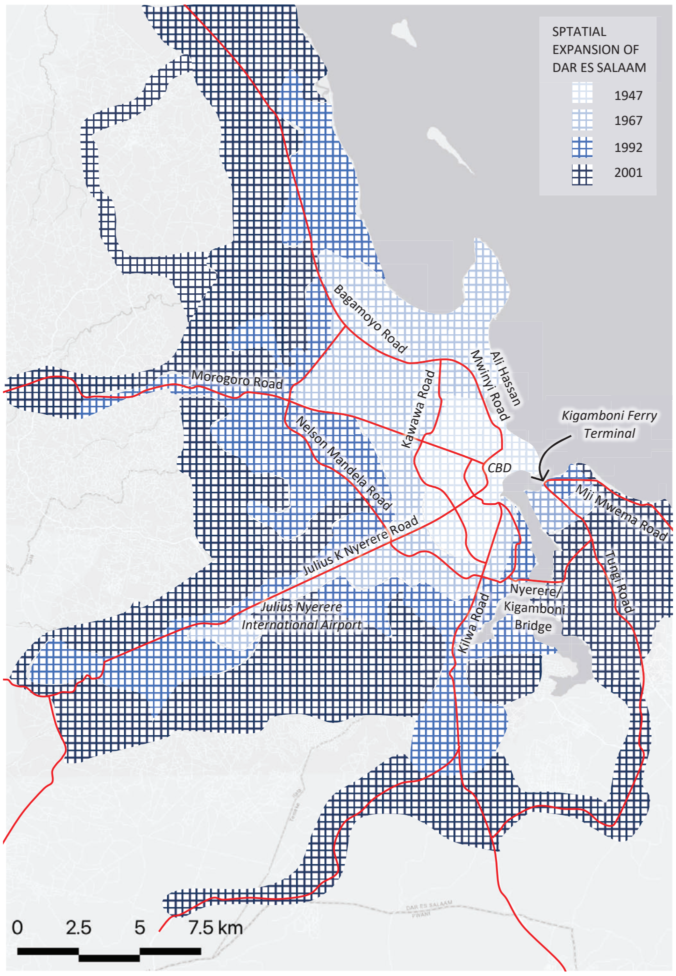


Fig. 4.5 Urban growth of Dar es Salaam, 1947 to 2001. *Source: Author's original image, based on Peter and Yang 2019, 370*


18km 18km

th June 2022

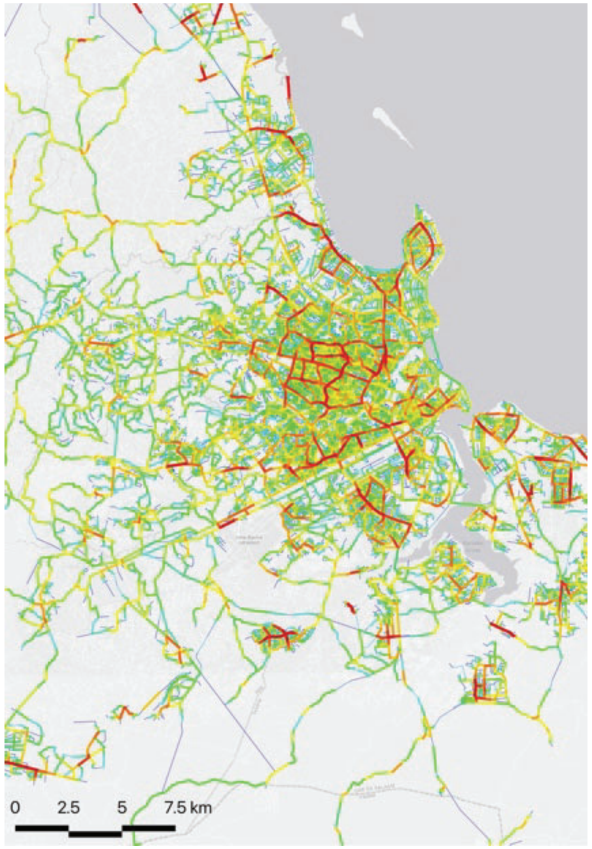
4.3 Space syntax analysis

4.3.1 Normalised choice and integration, 1990

Fig. 4.7 shows normalised choice (NACH) at three radii, where high and low values are shown towards the red and blue ends of the rainbow spectrum respectively. High values reveal segments with high through-movement potential at any given radii. Radii of 2km, 10km and 50km have been used to reflect likely patterns of through-movement at local (likely pedestrian), within-city, and across-city scales respectively. This also holds for the 2020 model (see 4.3.2 Normalised choice and integration, 2020). In 1990 Dar es Salaam, it seems that routes such as Julius K. Nyerere Road had high NACH values at radius 10km and 50km but not at radius 2km. This suggests there may have historically been a general misalignment of routes used for local- and citywide-scale journeys. One potential consequence of this could be over-crowded vehicular-dominant routes at radius 10km and 50km, whilst locally-dominant routes remained isolated from the wider movement network.

Integration (Fig. 4.8) reveals patterns of to-movement potential at the same radii. This suggests where network-based centres of activity are likely to be, as a result of street network density and depth (given by the metrics of node count and total depth). At radius 2km, the 1990 core of integration lied within the informal settlement of Tandale, reflecting its particular spatial density. At radius 10km and 50km, the most integrated routes fall along and around the high NACH routes, with a particular concentration in the CBD. This indicates that areas of 1990 Dar es Salaam which were likely to carry a lot of through-movement, were also likely centres of activity (to-movement). This may help to explain the long-standing phenomenon of street vendors which line many arterial routes in Dar es Salaam, despite the volume and speed of traffic (see Msuya and Mosha 2020; Rasmussen 2012). Such activity was also prevalent in Tandale, as reflected in 2km integration. See Fig. 2.1 for an example of street vendor activity along a dominant movement route.

In order to assess the extent to which these patterns have persisted into 2020, we can compare these findings with the 2020 analysis. Some caution must be taken with direct comparisons between the two models, given the unavoidable inconsistencies in mapping detail – the 1990 Dar es Salaam model seems to omit network in peripheral sub-centres (as will be explored later, with the assistance of other datasets).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2.5
5
7.5 km


NORMALISED
CHOICE
HIGH
LOW
2.5
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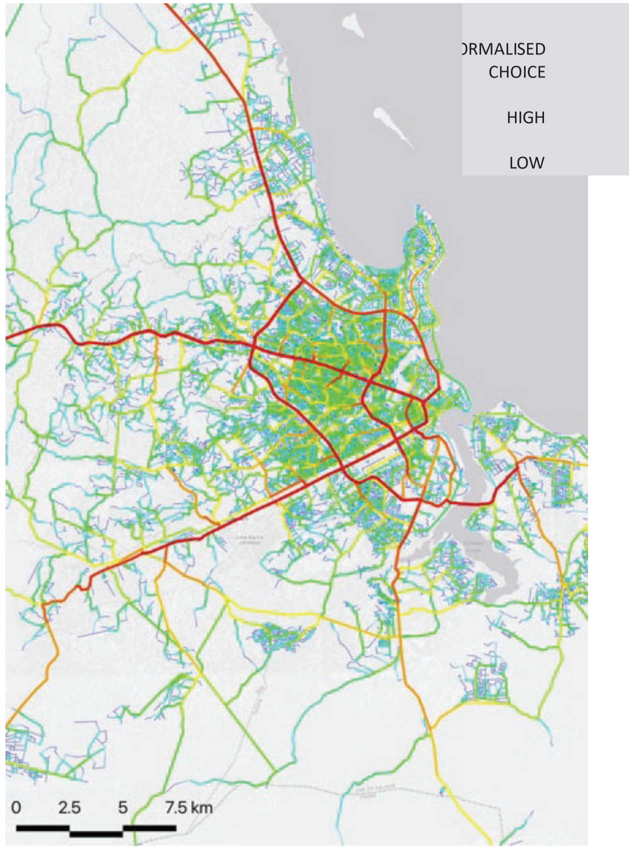
CHOICE
HIGH
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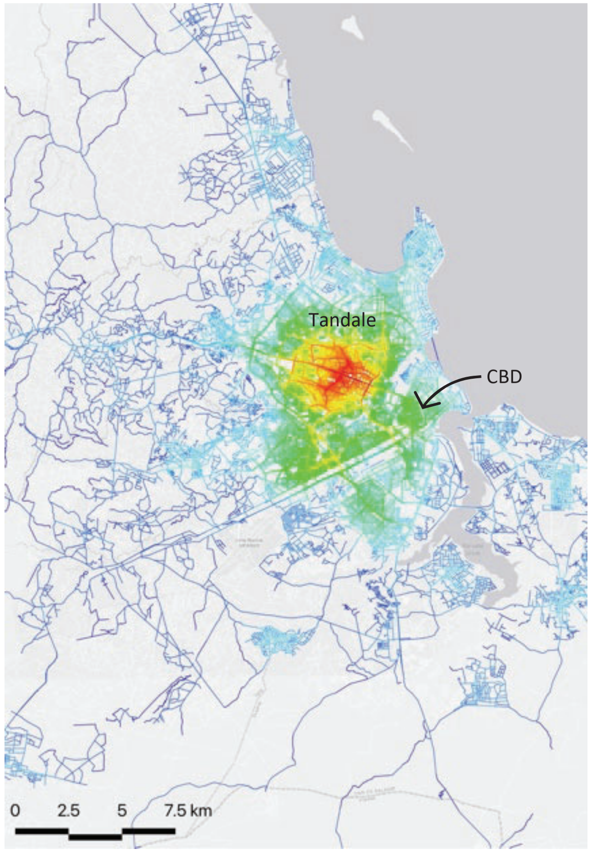
Tandale
CBD
0
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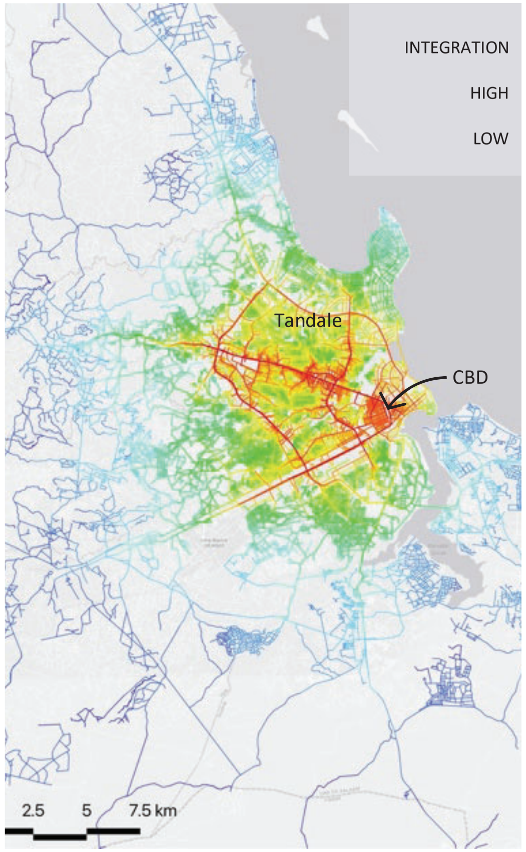
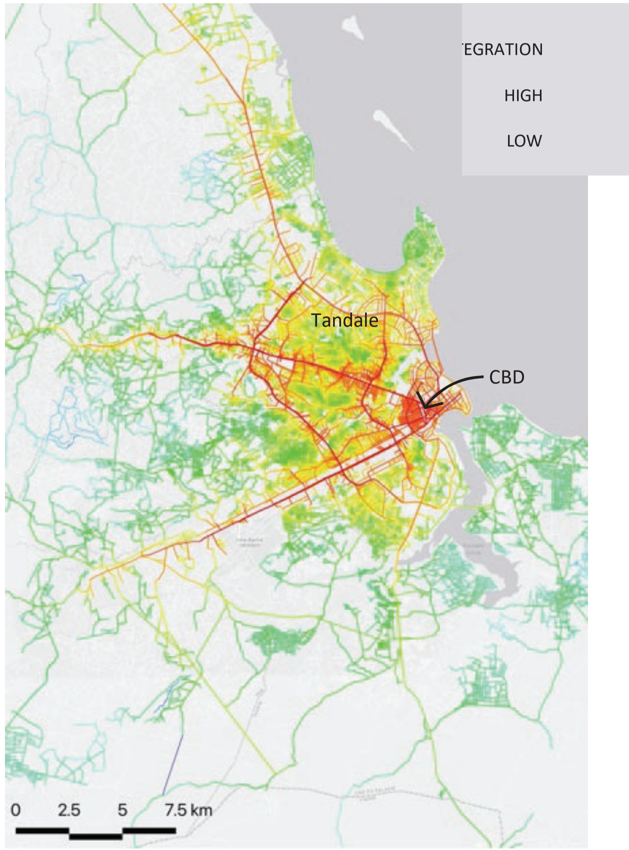
5
7.5 km


INTEGRATION
HIGH
LOW
Tandale
CBD
2.5
5
7.5 km


TEGRATION
HIGH
LOW
Tandale
CBD
0
2.5
5
7.5 km

4.3.2 Normalised choice and integration, 2020

Inspection of NACH at radii 2km, 10km and 50km for the 2020 model reveals the persistence of much of the 1990 spatial network (Fig. 4.10). Fig. 4.9 compares the top 20%-scoring NACHr50km segments from the 1990 model with their corresponding 2020 values. Most NACHr50km values for 2020 remain high (correlation of 0.733), indicating that most high-NACHr50km routes from the 1990 spatial network model have remained spatially dominant. No new routes seem to have significantly altered the overall patterns of movement at local (r2km), within-city (r10km) and across-city (r50km) scales.

Fig. 4.10 also indicates that a particularly high number of routes which have high through-movement potential at radii 10km and/or 50km have emerged to the south-west of the CBD. This could be a consequence of the relative accessibility of this part of the city to existing and emerging centres, as discussed in the literature review. However, without consulting other data, it is difficult to link these spatial properties to social and economic environments within different parts of the city.

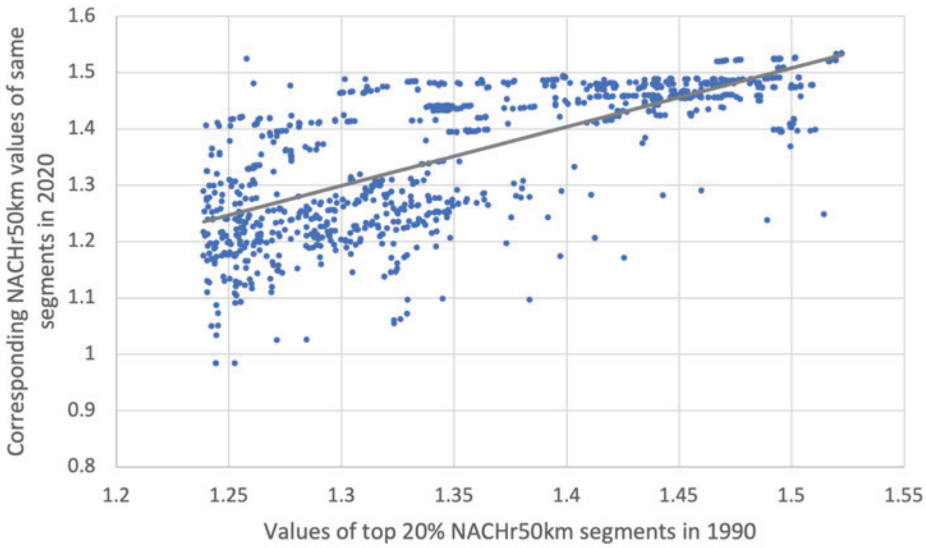
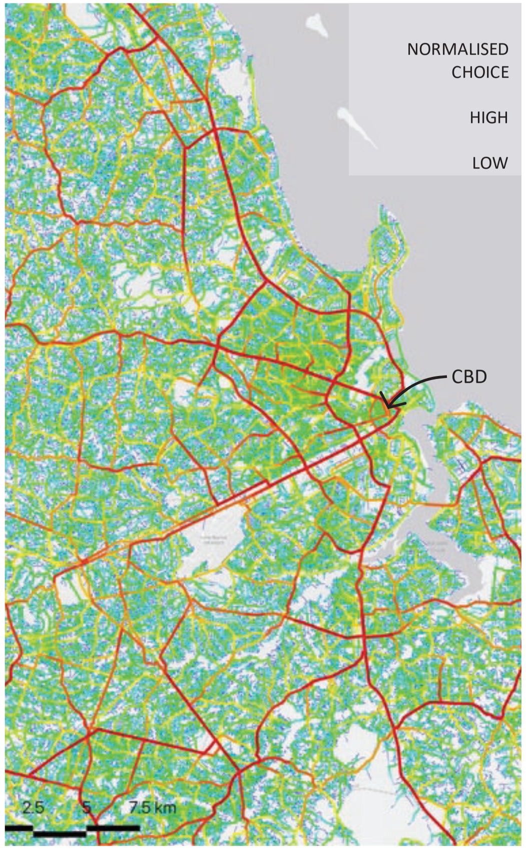
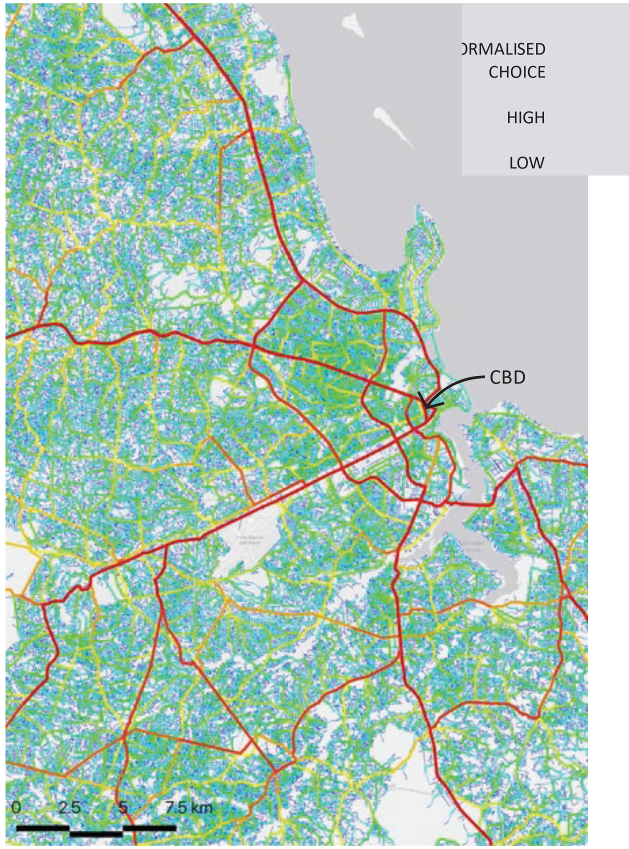


Fig. 4.9 Graph showing top 20% NACHr50km values for 1990, and their corresponding 2020 values. Linear trendline also shown.

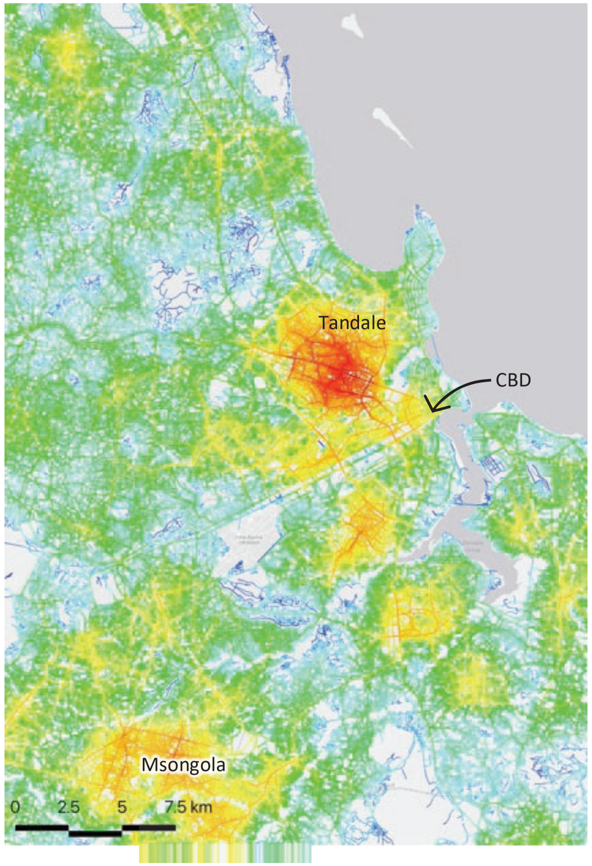

CBD
0
2.5
5
7.5 km

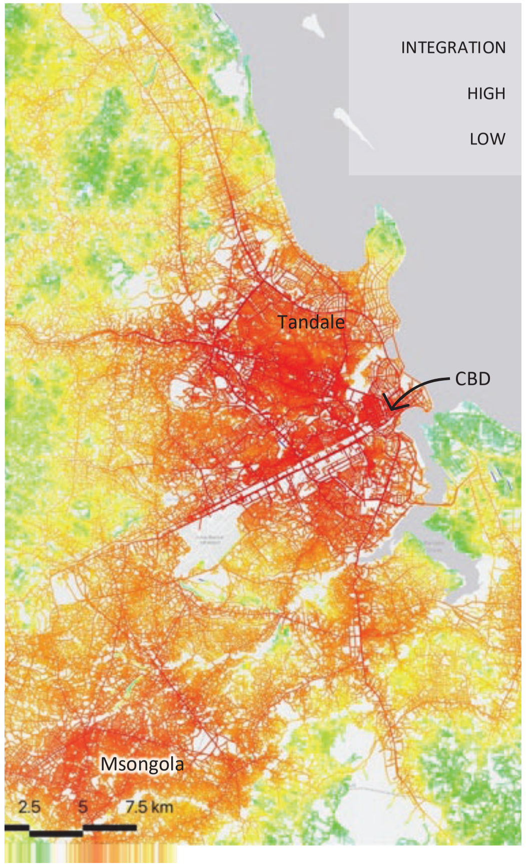

NORMALISED
CHOICE
HIGH
LOW
CBD
2.5
5
7.5 km

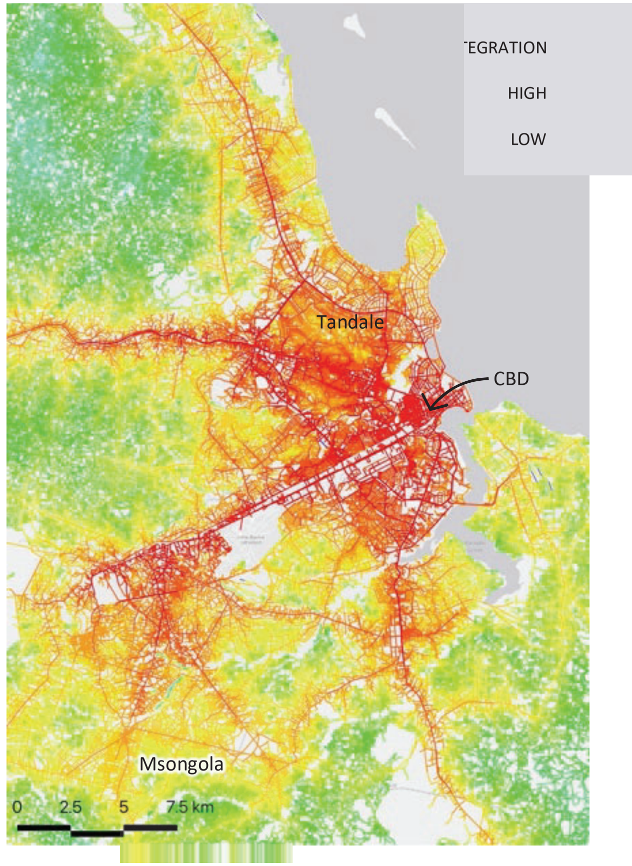

RMALISED
CHOICE
HIGH
LOW
CBD
0
2.5
5
7.5 km

This pattern of change to the south-west of the CBD is reinforced by the integration analysis (Fig. 4.11). Since 1990, multiple new clusters of high integration at radius 2km have emerged. Perhaps most notable is the cluster in the settlement of Msongola which, similar to Tandale (see Šliužas 2004), is fairly persistent across all radii, gravitating towards the high-NACH route of Julius K. Nyerere Road as the radius increases from 2km to 50km. The legacy of the historical network of Dar es Salaam is not only clear from a comparison of NACH in 1990 and 2020, but also by examining the core of integration at all radii: this has remained largely unchanged from 1990 to 2020. Multiple clusters of locally-integrated areas have also evolved, reflecting network densification.

Thus, it seems that the spatial network of Dar es Salaam has significantly densified and extended since 1990 in ways that reinforce the historic network and support the emergence and solidification of important movement corridors and sub-centres. This can help enhance understanding of rapid urban growth by providing an objective measure of through- and to-movement potentials at different scales, and changes between 1990 and 2020. Whilst it is possible to draw tentative insights into the social life of different parts of the city from this analysis, without other data to reinforce these claims, the extent to which more concrete understanding can be drawn is limited.


Tandale
CBD
Msongola
0
2.5
5
7.5 km


INTEGRATION
HIGH
LOW
Tandale
CBD
Msongola
2.5
5
7.5 km

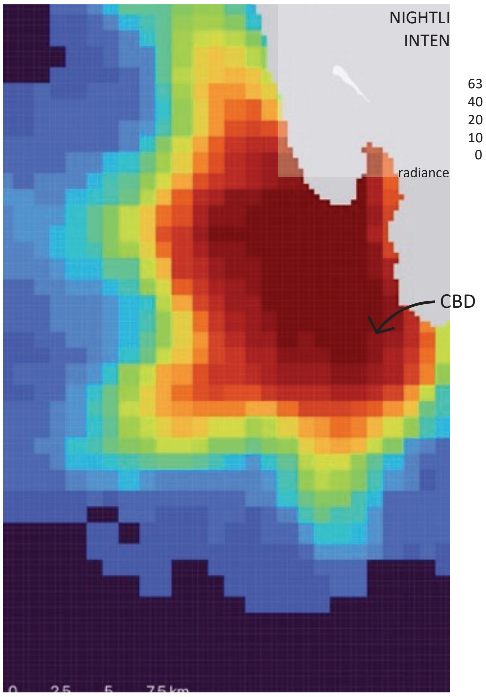

HIGH
LOW
Tandale
CBD
Msongola
0
2.5
5
7.5 km

4.4 Nightlight intensity

Nightlight intensity seems to follow a fairly radial pattern of expansion and intensification (Fig. 4.12). From 1992 to 2020, nightlight intensity creates a star-like pattern from the CBD outwards – this may be in-line with the fingers of high NACHr50km and INTr50km segments but, independent from the other datasets, it is hard to be certain.

In 1990 and 2000, there is a lack of nuance in the city centre nightlight intensity. This is likely to be a consequence of light saturation in older satellite sensors (see Elvidge et al. 2012). In 2015, it is easier to spot the particular hotspots of intensity within the central area. In 2020, this pattern disappears which is likely to be due to a greater intensity of nightlight in 2020 relative to 2015, as opposed to light saturation.

Areas which have seen an apparent absolute fall in nightlight intensity from 1992 to 2015 are most likely to be areas impacted by the 1992 light saturation issue (Fig. 4.13). Outside of the historic centre, areas have almost wholly experienced a significant absolute increase in nightlight intensity. These nightlight intensity patterns could be the result of factors such as: greater access to electricity; greater population; greater economic/ industrial activity; greater use of vehicles. Thus, examining nightlight intensity data alone can highlight interesting overall patterns of change. However, without examining spatial and population dynamics, it is hard to infer specific meaning from these characteristics towards understanding patterns of urban growth in different parts of Dar es Salaam.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INTEN
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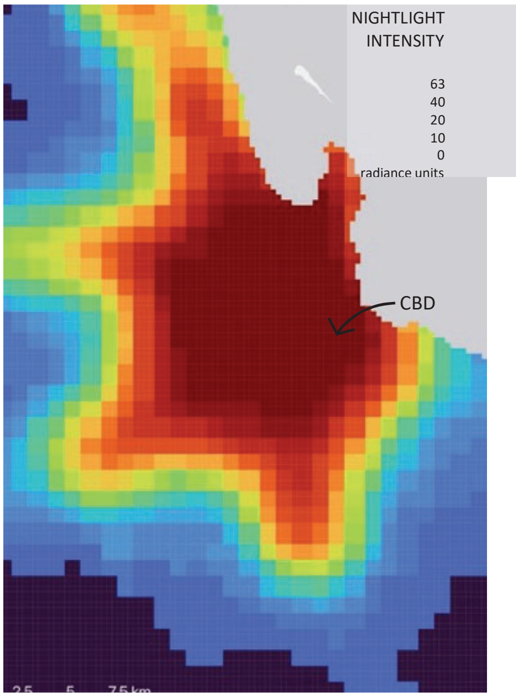
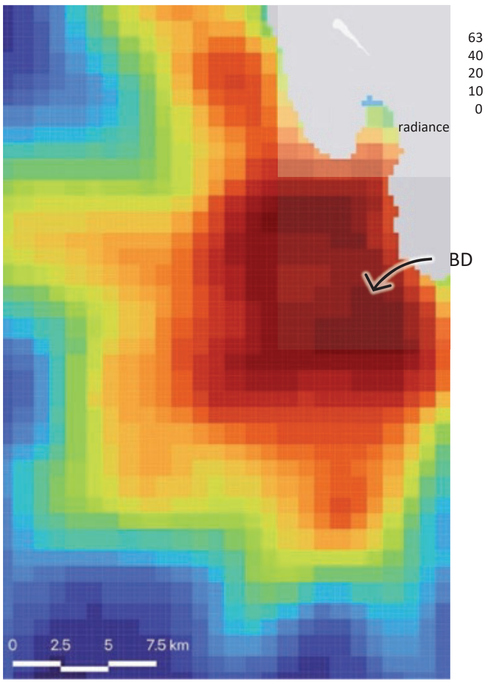
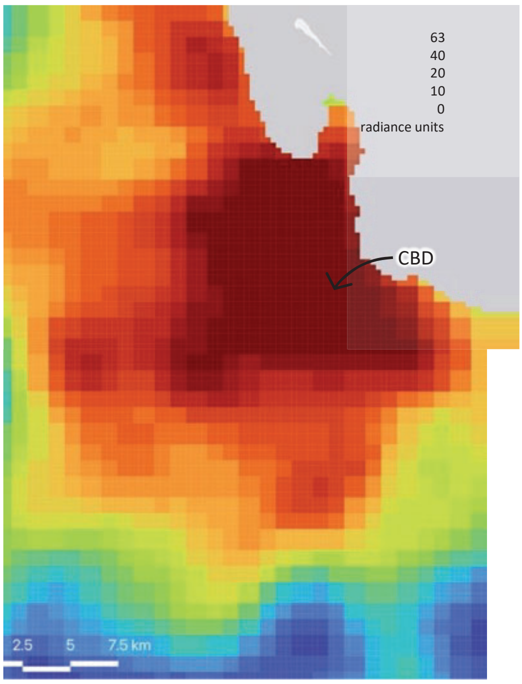
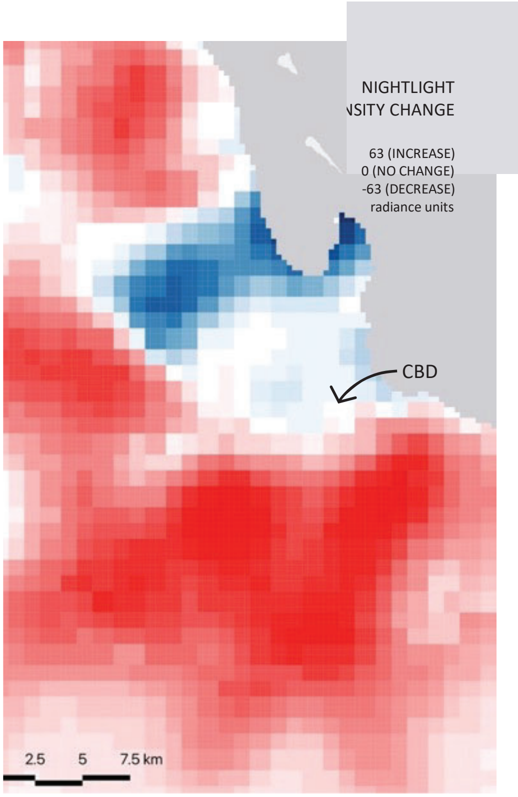
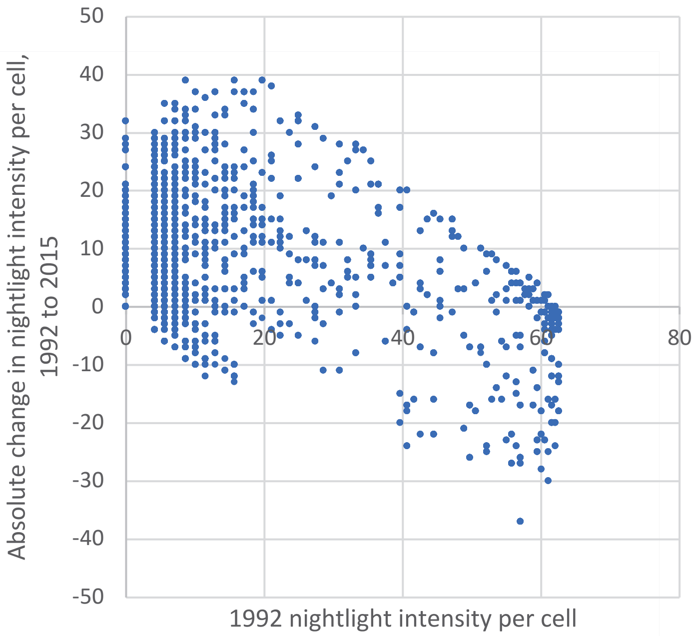
40
20
10
0
radiance
CBD


NIGHTLIGHT
INTENSITY
63
40
20
10
0
radiance units
CBD


63
40
20
10
0
radiance
BD
0 2.5 5 7.5 km


63
40
20
10
0
radiance units
CBD
2.5 5 7.5 km

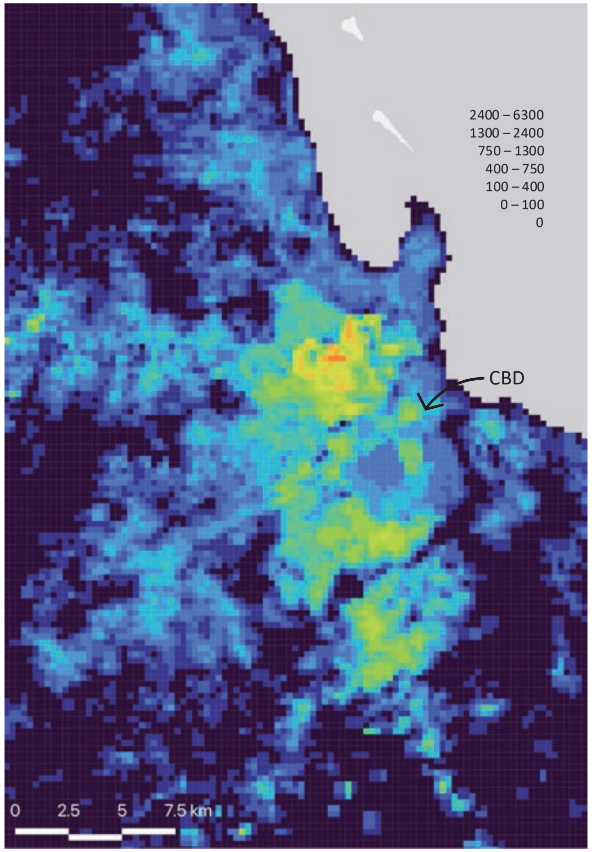


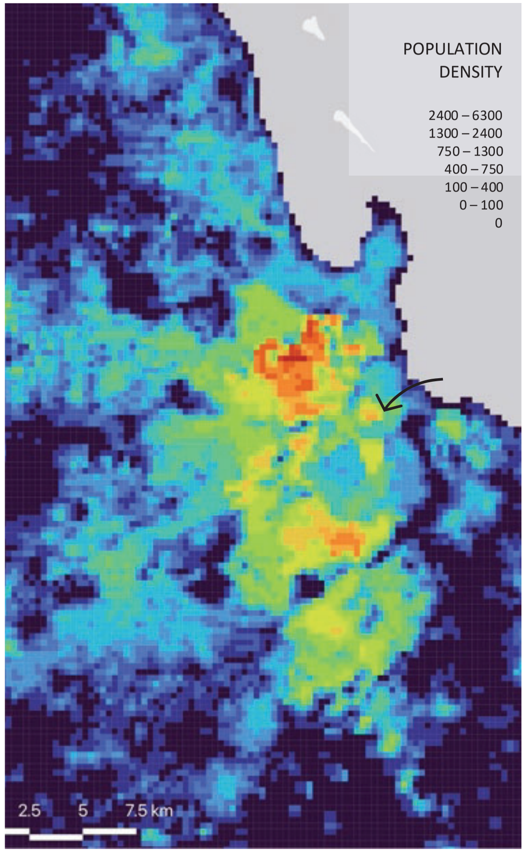


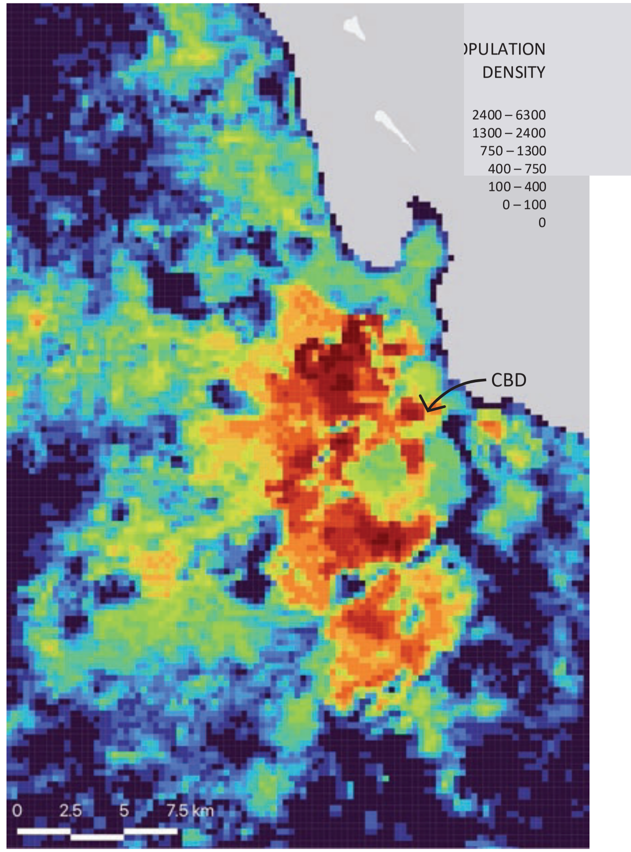
4.5 Population density

Visual examination of population density shows that cells with both non-zero and zero population in 1990 have become more populated, suggesting that population has densified and also sprawled (Fig. 4.14). Within each time-period, it seems that population density does not follow a linear pattern based on proximity to the CBD. As discussed in the literature review, population patterns are likely to reflect individuals' trade-offs between spatial accessibility, proximity to centres, and affordability (see Kombe 2005; Hill and Lindner 2010a).

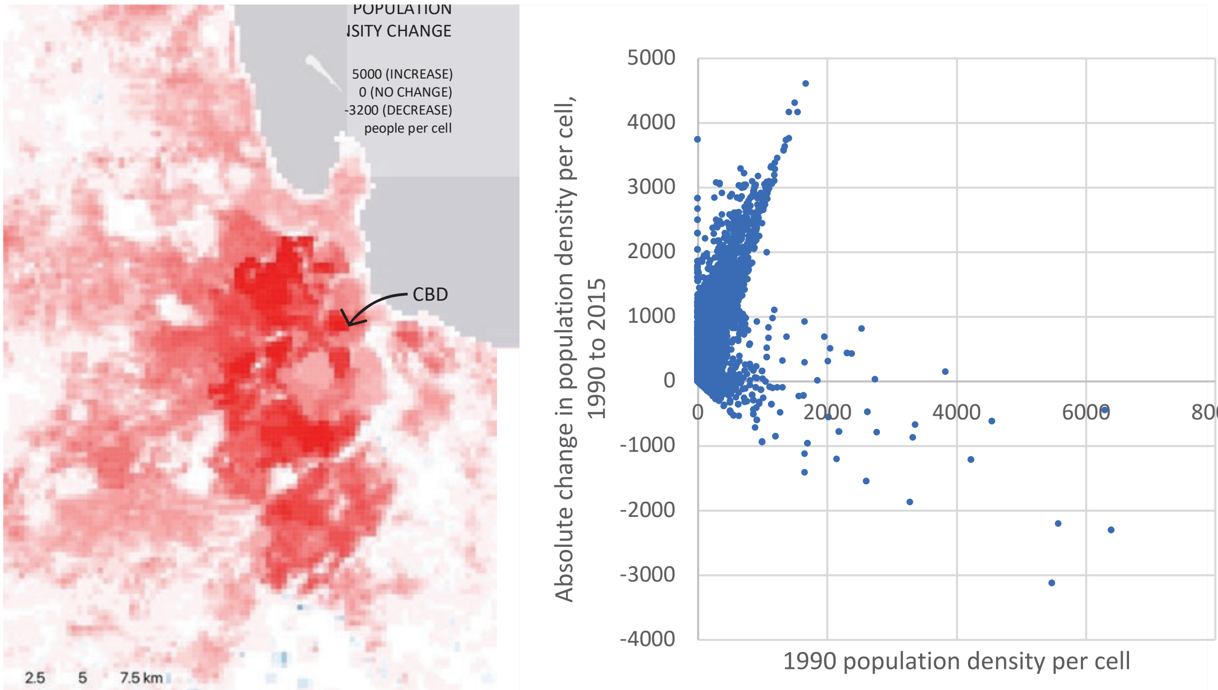
Fig. 4.15 shows that, overall, cells which were most densely populated in 1990 are also those that have seen the largest absolute growth in population density. This suggests that the process of densification may be more intensive than that of sprawl. This aligns with other research which highlights 'compact growth' in the centre, particularly in central informal areas, alongside sprawl (Msuya et al. 2021, 165S; Three City Land Nexus Research Team 2020).


2400 – 6300
1300 – 2400
750 – 1300
400 – 750
100 – 400
0 – 100
0
CBD
0
2.5
5
7.5 km


POPULATION
DENSITY
2400 – 6300
1300 – 2400
750 – 1300
400 – 750
100 – 400
0 – 100
0
2.5
5
7.5 km


DENSITY
2400 – 6300
1300 – 2400
750 – 1300
400 – 750
100 – 400
0 – 100
0
CBD
0
2.5
5
7.5 km

Whilst this data can reveal who is living in different parts of Dar es Salaam to quite a fine-grain level, it does not say anything about how people are living. For instance, the area may not be well-connected to other parts of the city (and, thus, greater employment opportunities), or it may not have access to secure electricity or water. Without this, it is hard to posit reasons for the observed population dynamics, limiting understanding of rapid urban growth beyond historic observation.



;. 4.15 Absolute change in population density, 1990 to 2015, map (left), scatter (right)

4.6 Interim conclusions

Table 4.1 summarises the pros and cons of each independent dataset towards understanding rapid urban growth in Dar es Salaam. Despite their limitations, each dataset independently offers new insights into the city from spatial, developmental and demographic perspectives. The next chapter explores how these datasets may be combined in order to enhance understanding of rapid urban growth.

Table 4.1 Summarising pros and cons of each independent dataset

DATASET	PROS	CONS
SPACE SYNTAX ANALYSIS 1990, 2020	Offers a very nuanced network-based picture of how the city functions in terms of through- and to-movement potentials. Offers multi-scale analysis, facilitating a greater understanding of how different parts of the city function and connect at multiple scales. Provides insights into spatial changes over time.	Not fully accurate with some network missing (particularly within informal settlements). Time-consuming to validate and check the models given the need for historical records, and given the sizes of models . Requires other data to interpret the causes and consequences of the spatial network properties. Models are not multi-model, i.e. do not incorporate other modes of traffic (bus, ferry, rail)
NIGHTLIGHT INTENSITY 1992, 2000, 2015, 2020	Results indicate actual activity (access to electricity, industrial activity, vehicles etc.) rather than one specific measure (population). This may create a more comprehensive understanding of actual 'development' when combined with other data.	Cell-based so less fine-grain than network-based data. Can be hard to interpret when used alone. Pre-2012 data has quite a lot of light saturation in settlement centres, making it hard to draw conclusions from city-centre data. Must forego accuracy in newer data in order to consistently compare to older data.
POPULATION DENSITY 1990, 2000, 2015	Easy to interpret. Consistently accurate across time-periods.	Cell-based so less fine-grain than network-based data. Does not tell you how people are living, only where they are.

CHAPTER 5: INVESTIGATING THE EFFECTIVENESS OF SPATIAL NETWORK, NIGHTLIGHT INTENSITY AND POPULATION DENSITY DATA ANALYSIS WHEN COMBINED INTO A SINGLE MULTI-TEMPORAL MULTI-VARIABLE CELL-BASED DATASET

5.1 Introduction

This chapter develops on preceding analysis in order to enhance the understanding of rapid urban growth in Dar es Salaam. This is achieved by combining the datasets through visual layering and visual and statistical analysis of the joined multi-variable multi-temporal cell-based dataset (see 3.3.4 Combining data). Section 5.2 explores overall trends and section 5.3 proposes a new degree of divergence metric.

5.2 Overall trends

Fig. 5.1, Fig. 5.2 and Fig. 5.3 show the distribution of population per cell within different nightlight intensity bands in 1990, 2000 and 2015 respectively. Comparing these, the relation between nightlight intensity and average population density seems to get stronger over time – shown by an increasingly strong upwards trend in the boxplots (which represent the inter-quartile range of population densities). This reveals overall population densification over time, particularly in (and contributing to) areas with greater nightlight intensity. This could reflect many urban changes, from electrification to commercial activity to use of vehicles and could therefore be associated with both benefits and problems associated with rapid urban growth. Given that the quantity and magnitude of population density outliers with zero nightlight reduces over time, it is more likely that the observed increasing

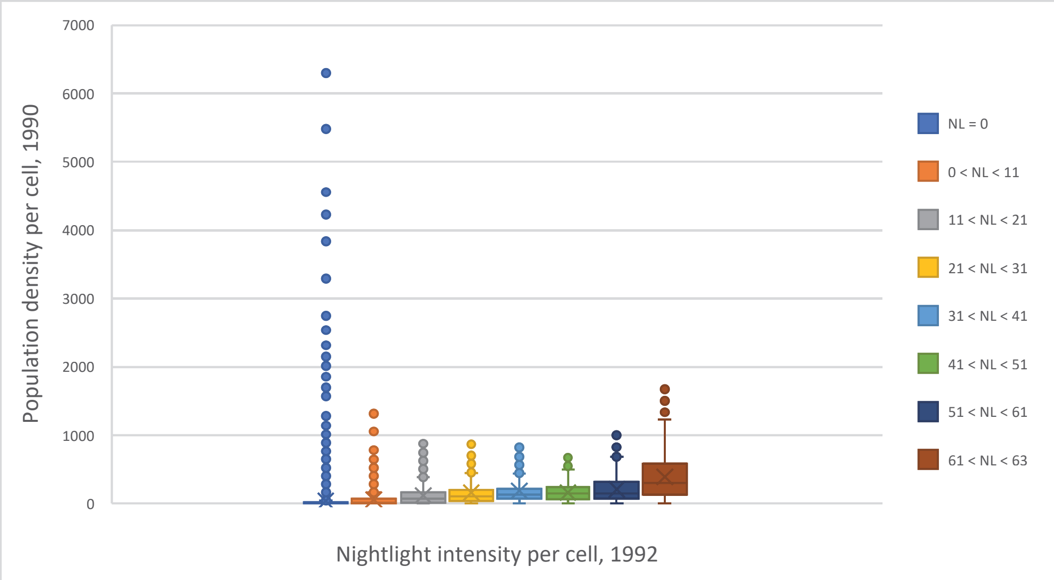


Fig. 5.1 Distribution of population per cell within different nightlight intensity bands, 1992

upwards trend at least partially reflects electrification, transitioning these cells into higher nightlight intensity bands.

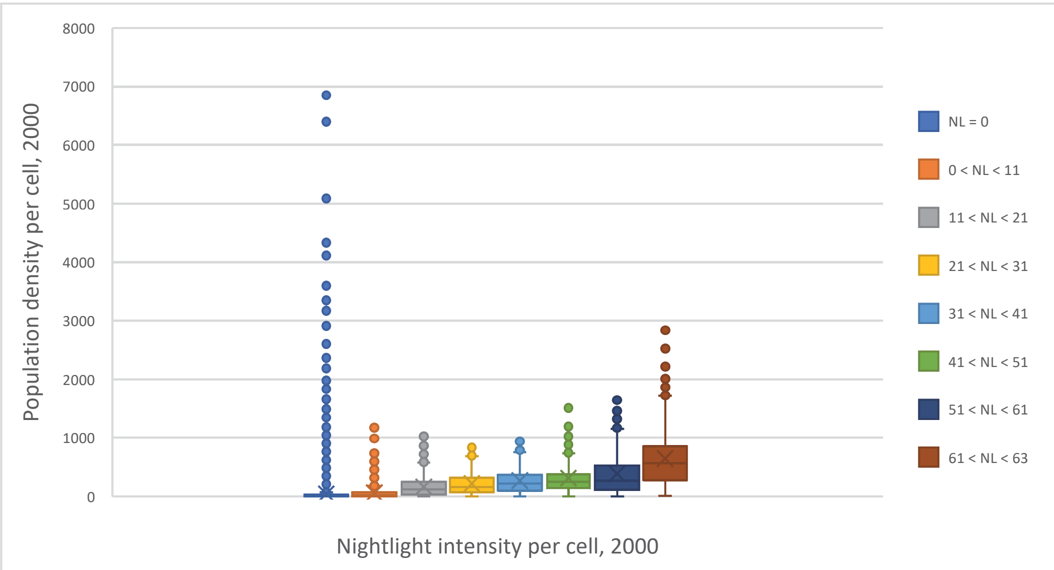


Fig. 5.2 Distribution of population per cell within different nightlight intensity bands, 2000

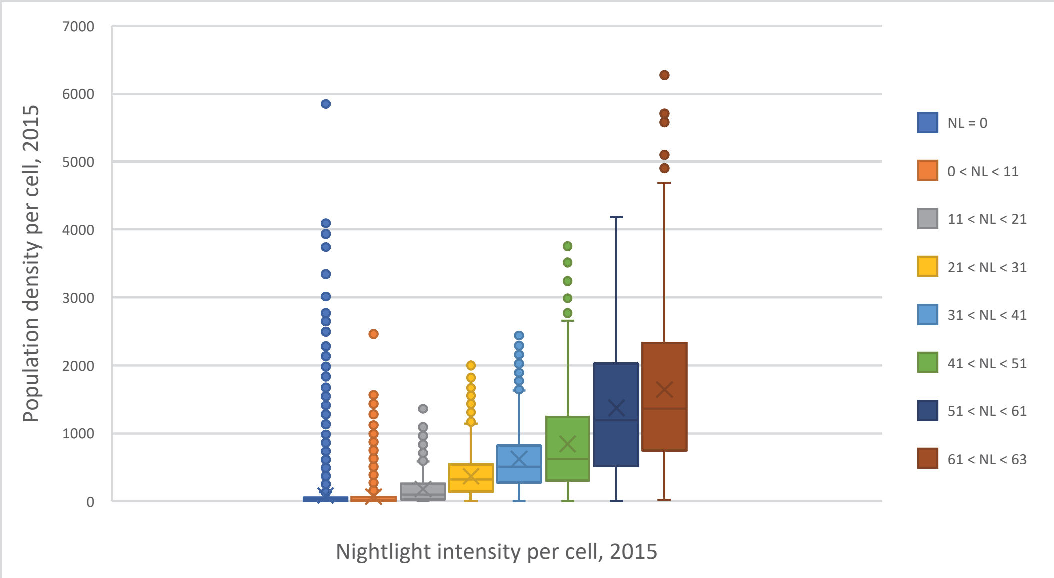


Fig. 5.3 Distribution of population per cell within different nightlight intensity bands, 2015

These findings are supported by Fig. 5.4 which plots cumulative population and nightlight intensity for 1990, 2000 and 2015, echoing the work of Elvidge et al. (2012). Perfect equality of population density and nightlight intensity – that is, equal distribution of nightlight amongst the population – would be represented by a perfect 45-degree line. The straightening of the curve towards a 45-degree line in each time period therefore reflects increasing equality in access to electricity. This is an important finding for understanding the overall relation between population and nightlight across Dar es Salaam overtime. However, given that it is not possible to trace the cause of particular nightlight emissions, these results may be distorted by other sources of nightlight. For instance, populations living close to a power station or industrial plant may appear to be consuming electricity, but may in fact be without power. Thus, when used at an intra-city level, the conclusiveness of this approach may be weakened.

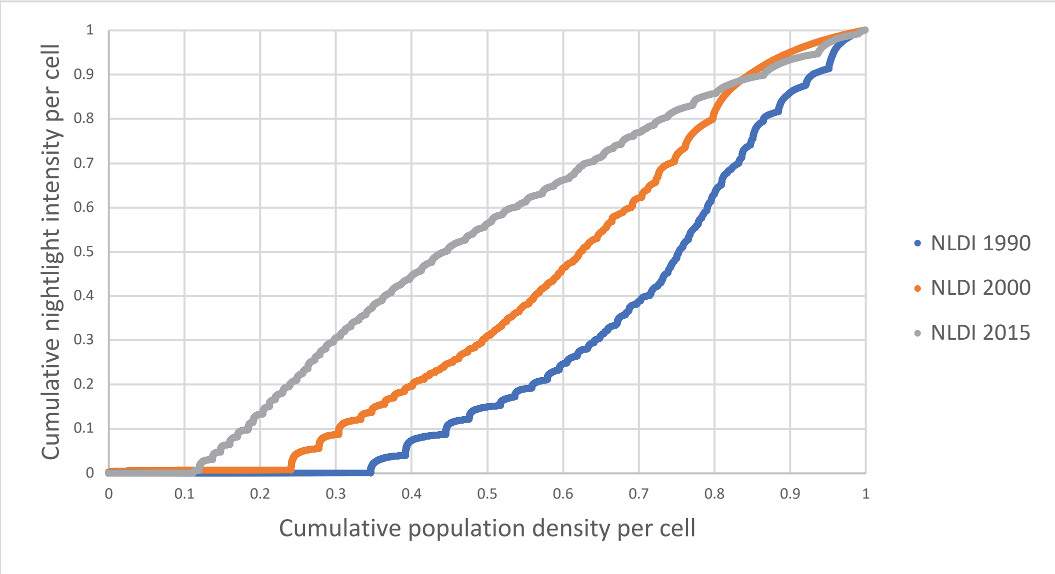
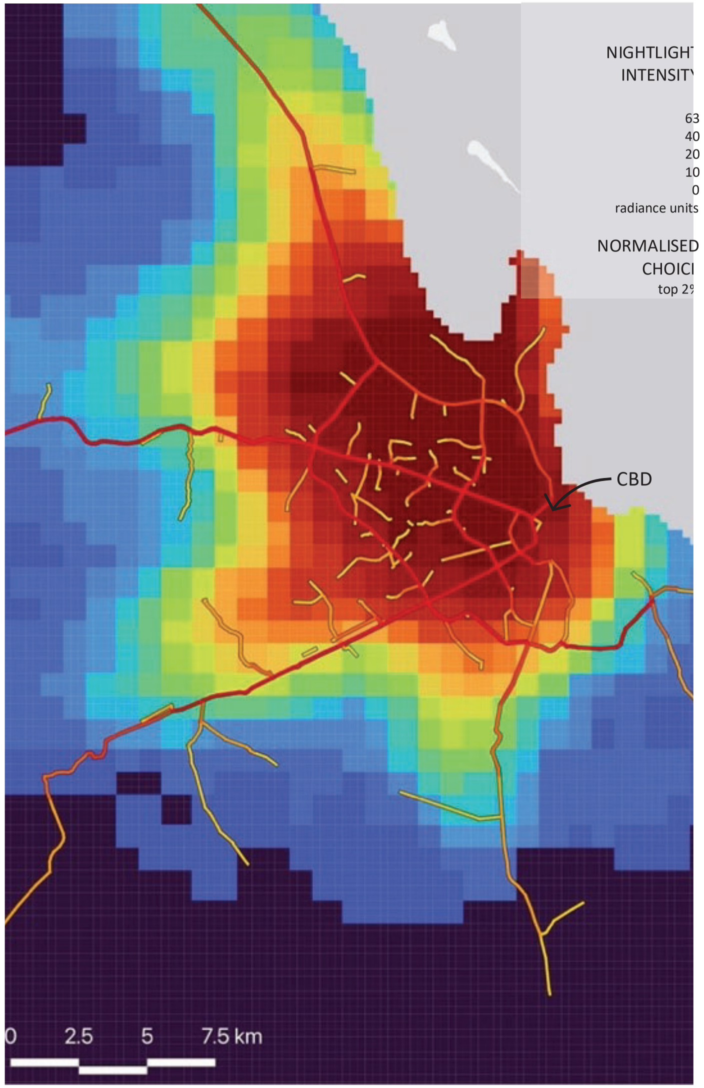
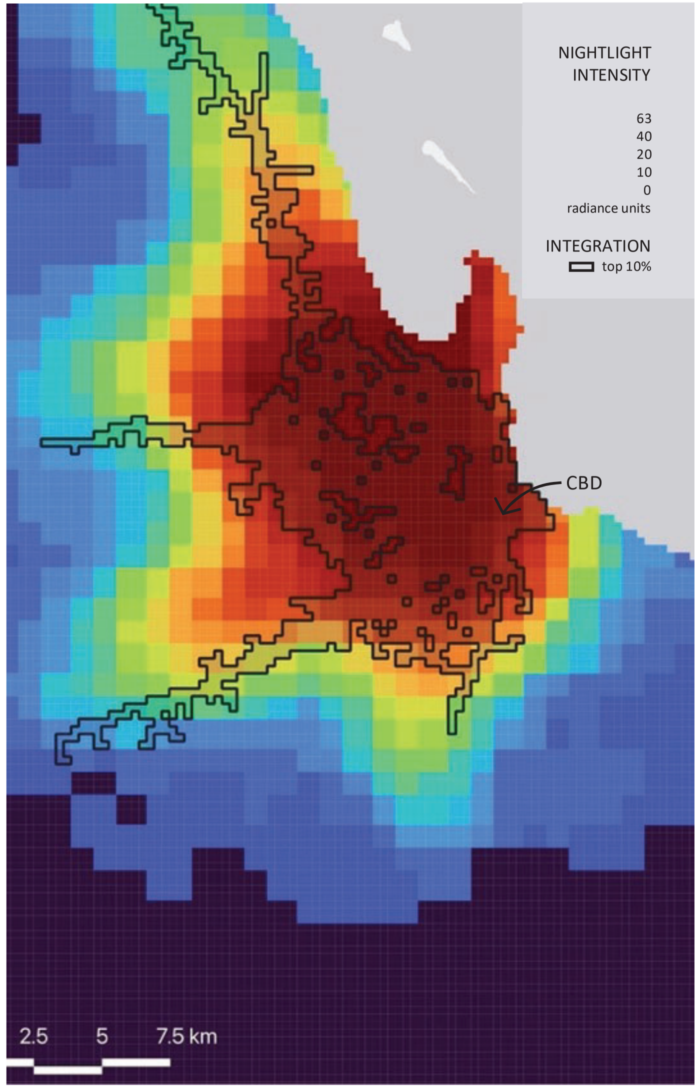
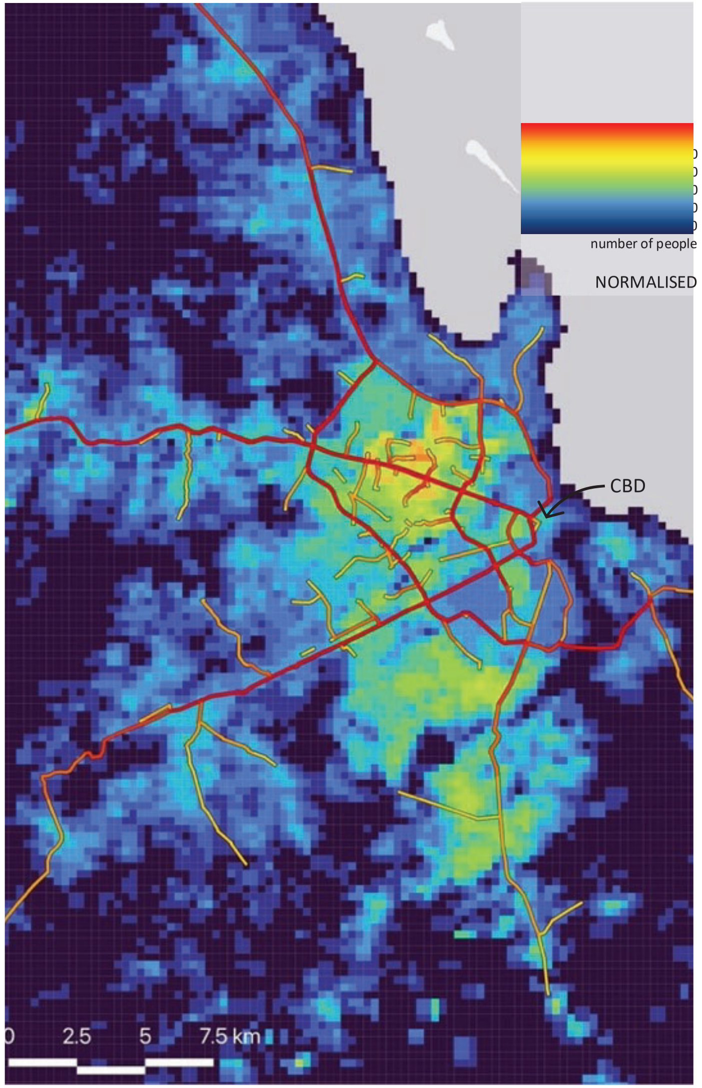


Fig. 5.4 Nightlight development indicator (based on Elvidge et al. 2012) - cumulative population and nightlight intensity

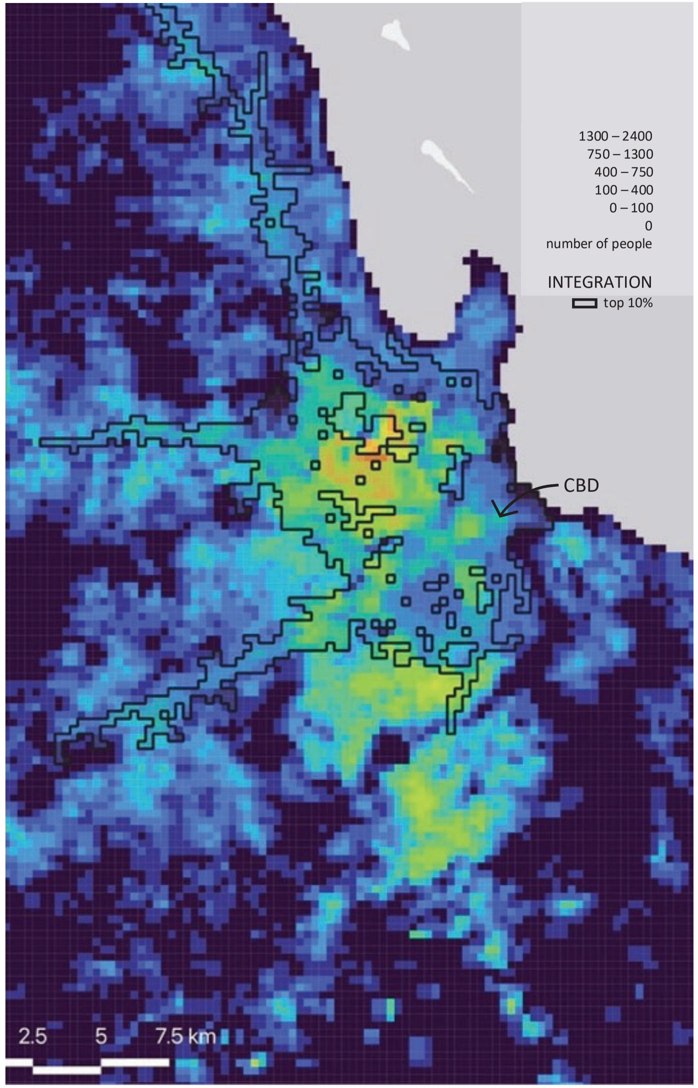
To begin incorporating space syntax analysis into the combined analysis, visual layering can offer some new insights. Fig. 5.5 reveals the connection between nightlight intensity in 1992, and routes with the top 2% across-city movement potential values (NACHr50km) and top 10% centrality values (INTr50km). Fig. 5.6 reveals that population density is greatest along routes with the top 2% NACHr50km values, although not in a perfectly linear pattern. Population density seems less related to the top 10% INTr50km values overall, although the most densely populated areas do lie within this highly-integrated area.


NIGHTLIGHT
INTENSITY
63
40
20
10
0
radiance units
NORMALISED
top 2
CBD
0
2.5
5
7.5 km


NIGHTLIGHT
INTENSITY
63
40
20
10
0
radiance units
INTEGRATION
top 10%
CBD
2.5
5
7.5 km



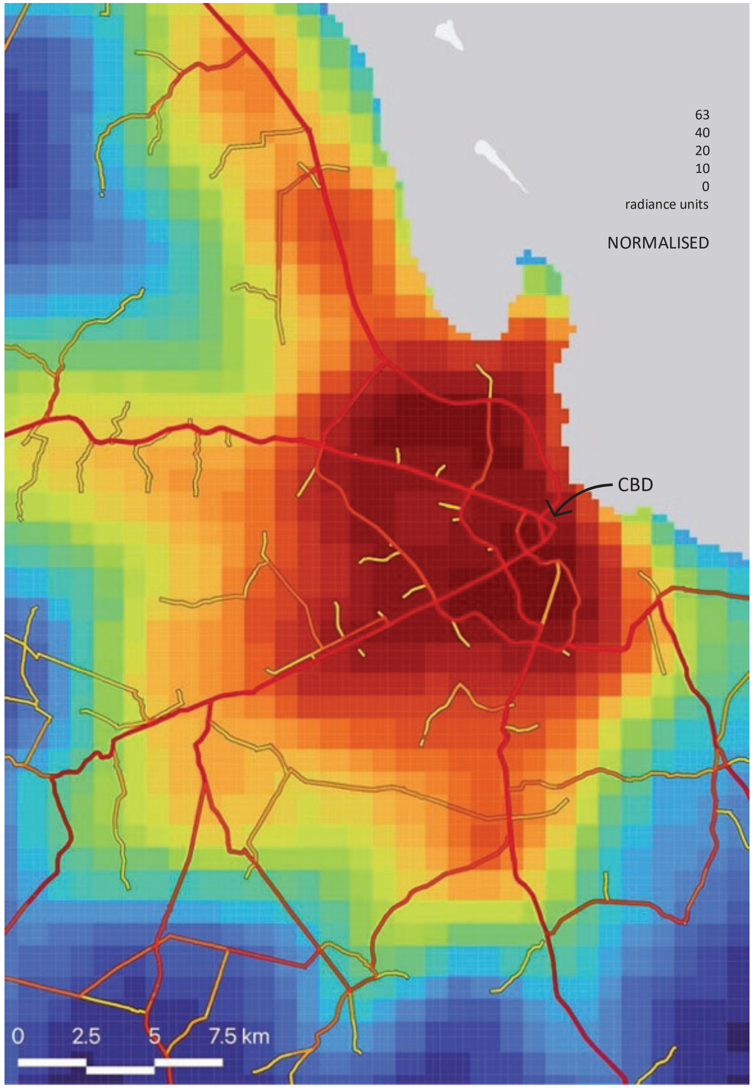
number of people
NORMALISED
CBD
0
2.5
5
7.5 km



1300 – 2400
750 – 1300
400 – 750
100 – 400
0 – 100
0
number of people
INTEGRATION
top 10%
CBD
2.5
5
7.5 km

Fig. 5.7 reveals how the 1990 relation between nightlight intensity and top 2% NACHr50km values has persisted into 2015. As the spatial network has expanded, nightlight intensity seems to have followed these key movement corridors fairly consistently. The top 10% INTr50km values also bear a close relation to patterns of nightlight intensity. One anomaly seems to be in the south-west part of the city (labelled A) which has high INTr50km but relatively low nightlight intensity. This could reflect limited access to electricity in this part of Dar es Salaam, which could indicate lower socio-economic development, particularly given that population density is quite high in this area (Fig. 5.8).

Population density in 2015 seems to follow top 2% NACHr50km routes to less of an extent than in 1990, although it does seem to follow the top 10% INTr50km area more than in 1990. This could reflect the idea that areas which are most densely populated are a result of demand to be close to centres of activity. At the same time, those who cannot afford this try to at least prioritise accessibility to routes with high movement-potential. This logic reflects the patterns of lower-density sprawl between key movement corridors, alongside densification around centres. This is unpacked further in section 6.3 Catchment analysis.


63
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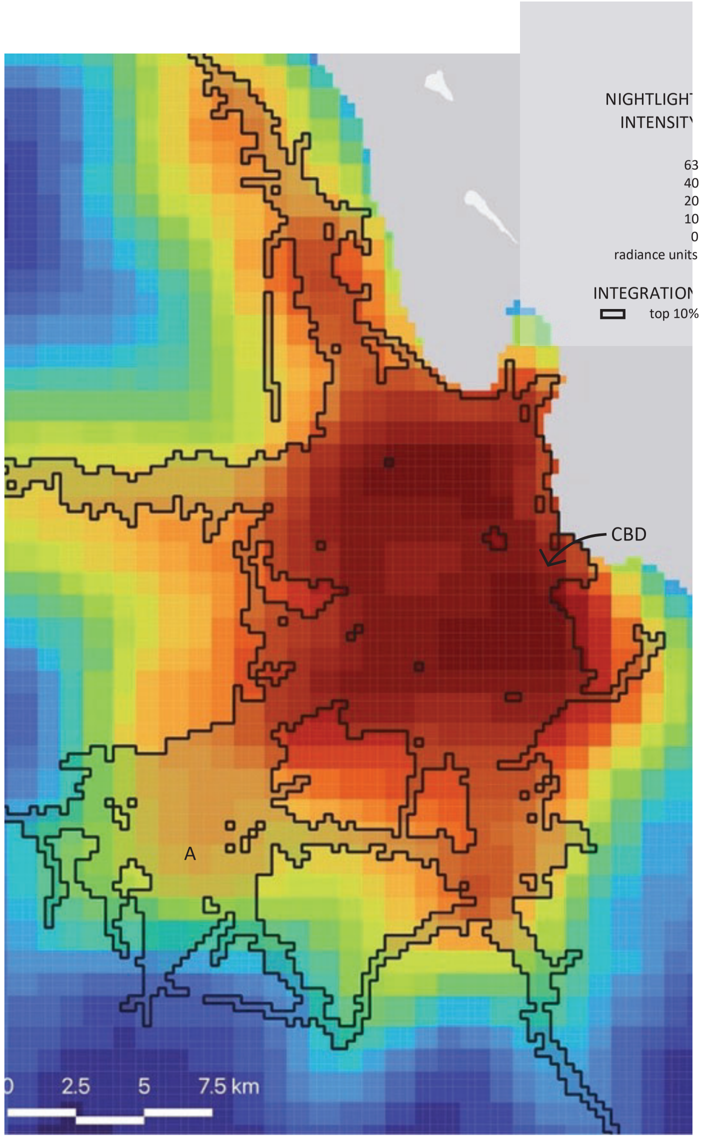
radiance units
NORMALISED
CBD
0 2.5 5 7.5 km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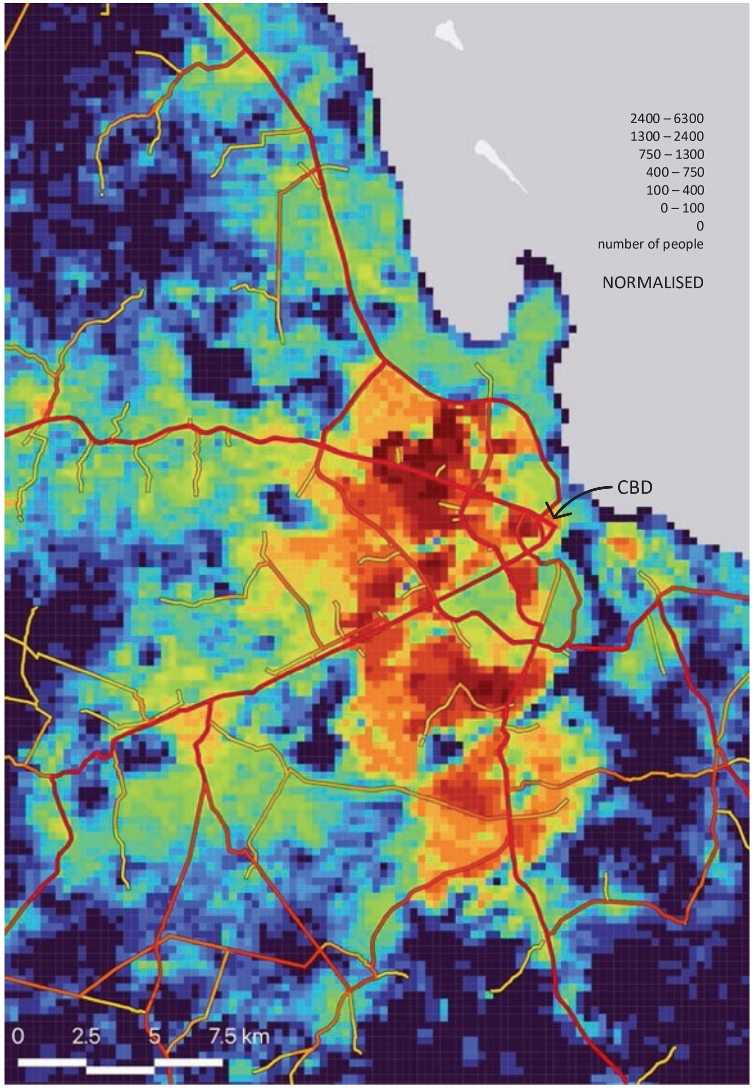
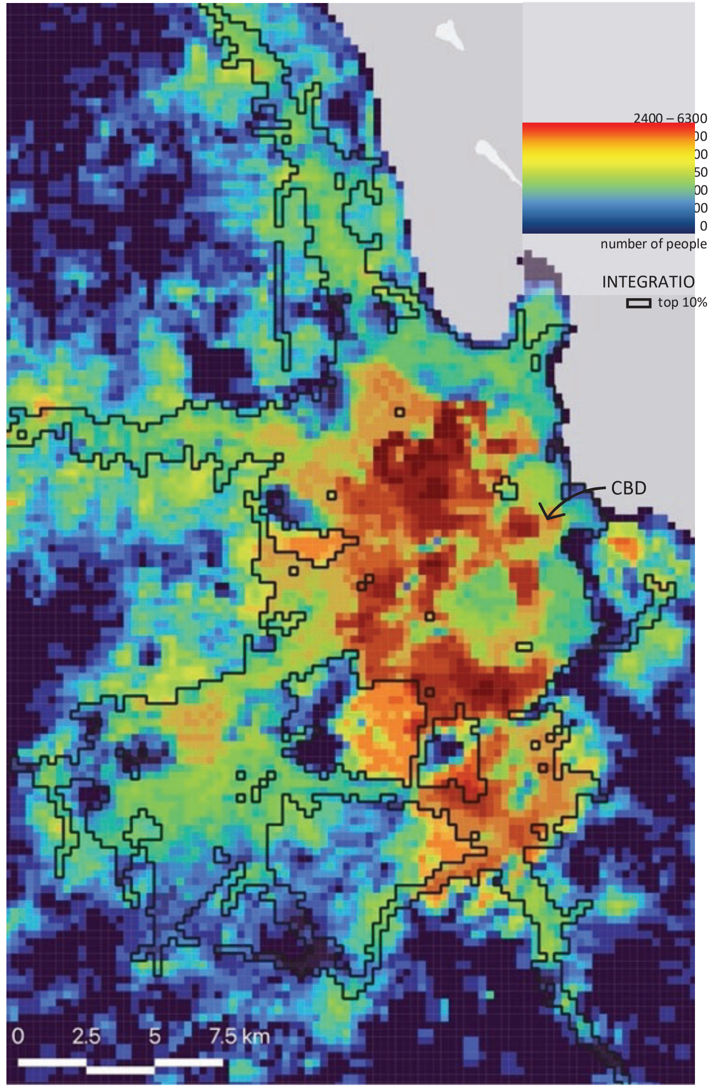

2400 – 6300
1300 – 2400
750 – 1300
400 – 750
100 – 400
0 – 100
0
number of people
NORMALISED
CBD
0
2.5
5
7.5 km


2400 – 6300
0
number of people
INTEGRATIO
top 10%
CBD
0
2.5
5
7.5 km

5.3 Degrees of divergence

Using cell-based space syntax analysis (see 3.3.4 Combining data), it is possible to directly explore patterns and compare attributes. Given that time-periods do not quite align, 1992 nightlight intensity data is used in conjunction with 1990 population density data and space syntax analysis, and 2015 nightlight intensity data is used in conjunction with 2015 population density data and 2020 space syntax analysis. The decision of the latter was based on the fact that spatial network changes are likely to be much slower than population density changes.

A degree of divergence metric has been created which explores the size of the difference (or divergence) between two values. This offers a tool to identify existing connections between spatial, socio-economic and demographic characteristics within different cells. Fig. 5.9 illustrates this.

For this research, three degree of divergence indicators have been made. Each indicator has been calculated for 1990 and 2015. Table 5.1 summarises each indicator. Particular caution should be taken with the 1st and 2nd degrees of divergence for 1990 because limitations in the spatial network model reduce the accuracy of the results – for instance, some cells have a lower node count because that area is insufficiently modelled. The distributions of each degree of divergence can be found in the Appendices**:** Scatterplots for each degree of divergence**.**

Table 5.1 Summary of each degree of divergence indicator

DEGREE OF DIVERGENCE	PARAMETERS	RATIONALE	INTERPRETATION
1ST	Population density per cell Mean node count per cell r2km (indicates network density)	Highest correlation 1990: r = 0.66 2015: r = 0.54	Positive scores: the percentile rank of population density exceeds that of mean node count r2km, which could indicate that there is too much pressure on that network i.e. it may be overcrowded. Negative scores: the percentile rank of population density is less than that of mean node count r2km, which could indicate that there is spare capacity in the network to support a larger population i.e. it may be underpopulated.

2ND	Nightlight intensity per cell Mean node count per cell r10km (indicates network density)	Highest correlation 1990: r = 0.88 2015: r = 0.60	Positive scores: the percentile rank of nightlight intensity exceeds that of mean node count r10km, which could indicate a very active or busy area. Negative scores: the percentile rank of nightlight intensity is less than that of mean node count r10km, which could indicate areas which do not have access to electricity.
3RD	Population density per cell Nightlight intensity per cell	The third relationship to explore in the space syntax – nightlight intensity – population density triangle.	Positive scores: the percentile rank of population density exceeds that of nightlight intensity, which could indicate that access to electricity is unequal, or the area is not very active or busy. Negative scores: the percentile rank of population density is less than that of nightlight intensity, which could indicate that the cell is very active, busy, or near light-emitting industrial activity.

Fig. 5.10, Fig. 5.11 and Fig. 5.12 show the 1990 and 2015 maps for each degree of divergence.

The 1st degree of divergence (Fig. 5.10) reveals that, in 1990, peripheral areas seem to be largely highly populated relative to node count r2km (positive scores, shown in shades of red). This may be due to inaccuracies in the spatial network model. Having said this, some central areas have positive scores despite being well-modelled. Thus, this metric can identify areas within the centre of 1990 Dar es Salaam which may be at risk of over-crowdedness. In 2015, Fig. 5.10 shows the potential pressures on peripheral parts of Dar es Salaam – these areas are very densely populated given the density of the spatial network. This is likely to be fairly accurate given the quality of the 2020 spatial network model, thus offering powerful insights into how population is supported by the spatial network.

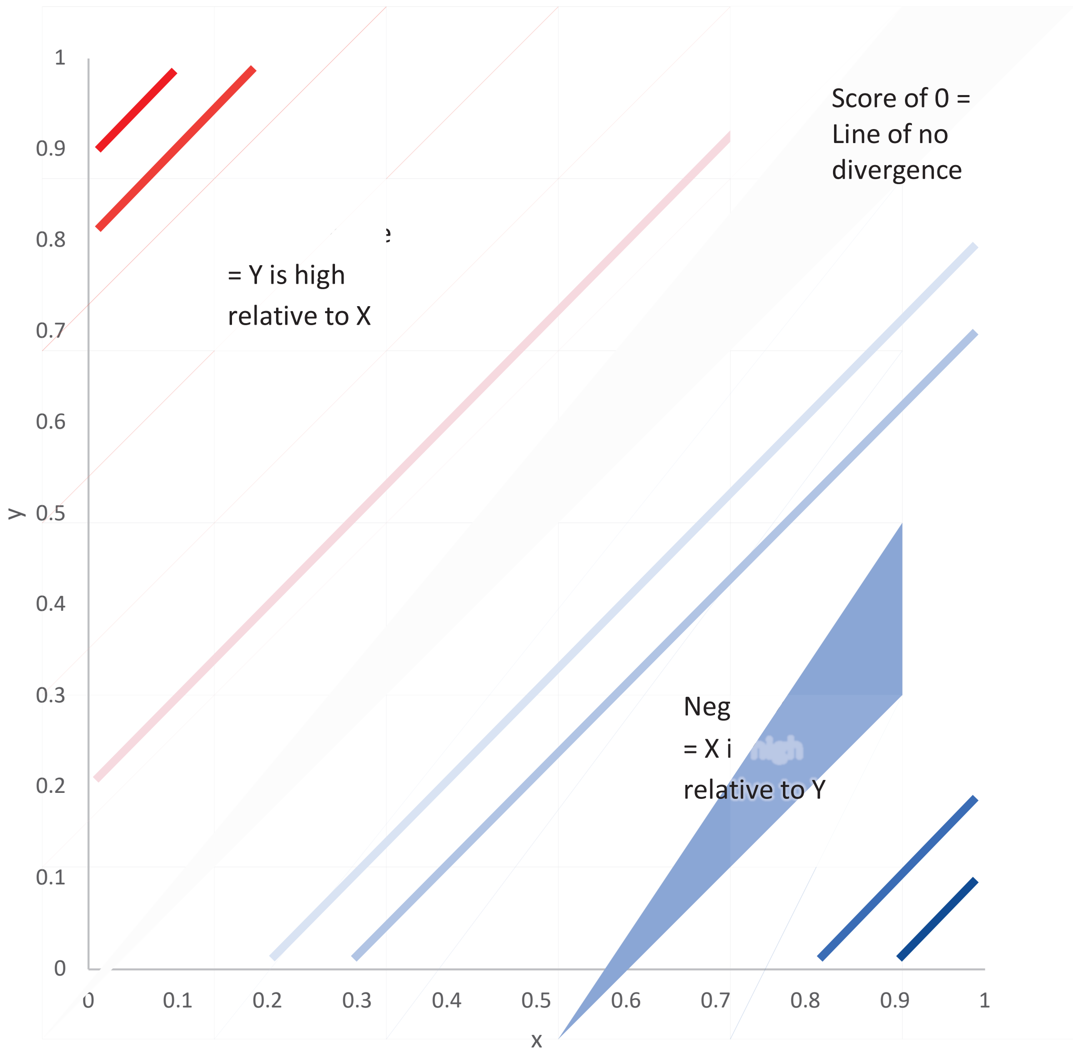
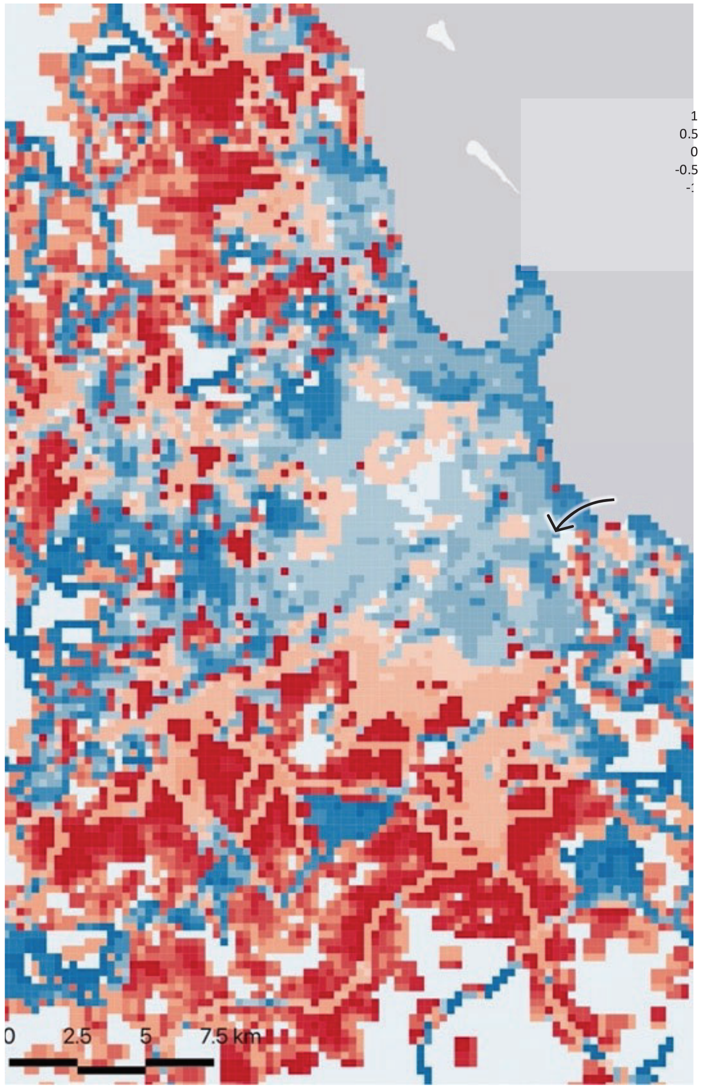


Illustration of the degree of divergence

Fig. 5.11 suggests that, in 1990, more south-western parts of the city had limited use of electricity relative to the density of the network. Despite inaccuracies with 1990 data, this suggests there may have been a particular inequality of access to electricity in some central parts of the city. In 2015, the map identifies interesting areas where nightlight is low relative to spatial density. This is likely to be highlighting parts of the city where electrification rates are lower, particularly given some of these areas (in blue) have busy roads running through them, which will only enhance nightlight values.


1
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0
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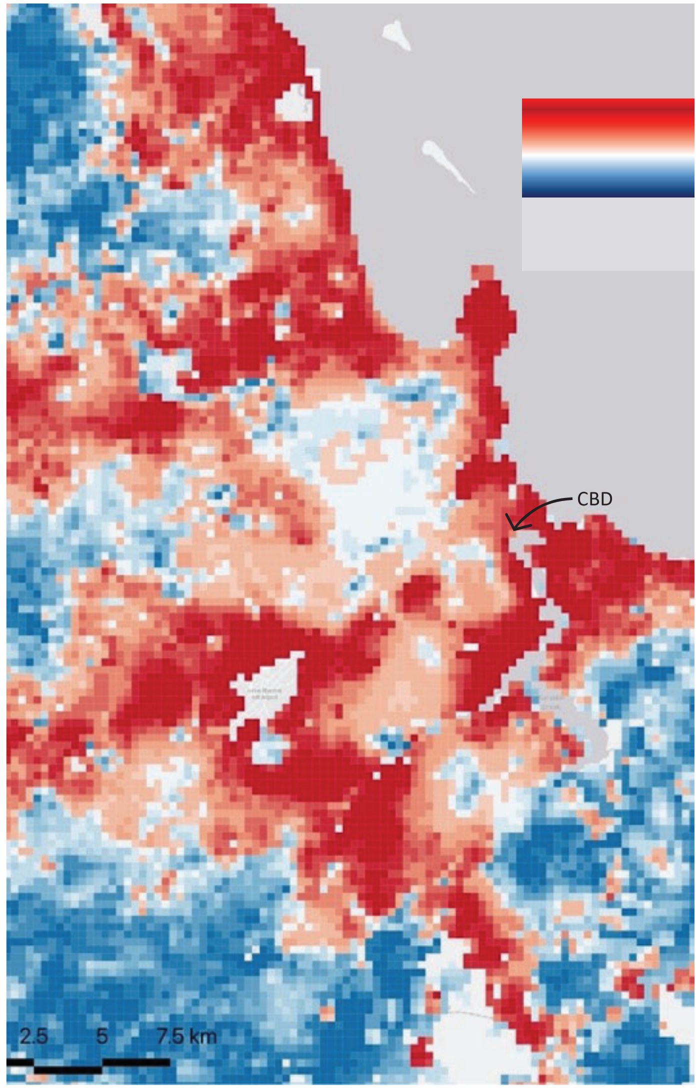
CBD
2.5
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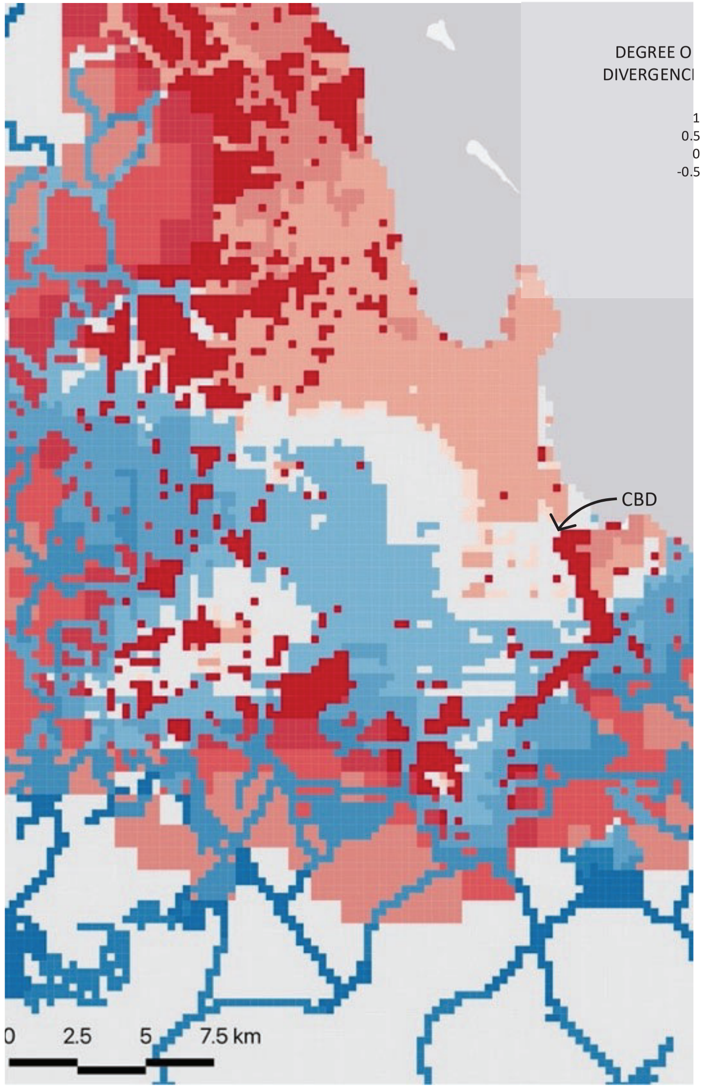
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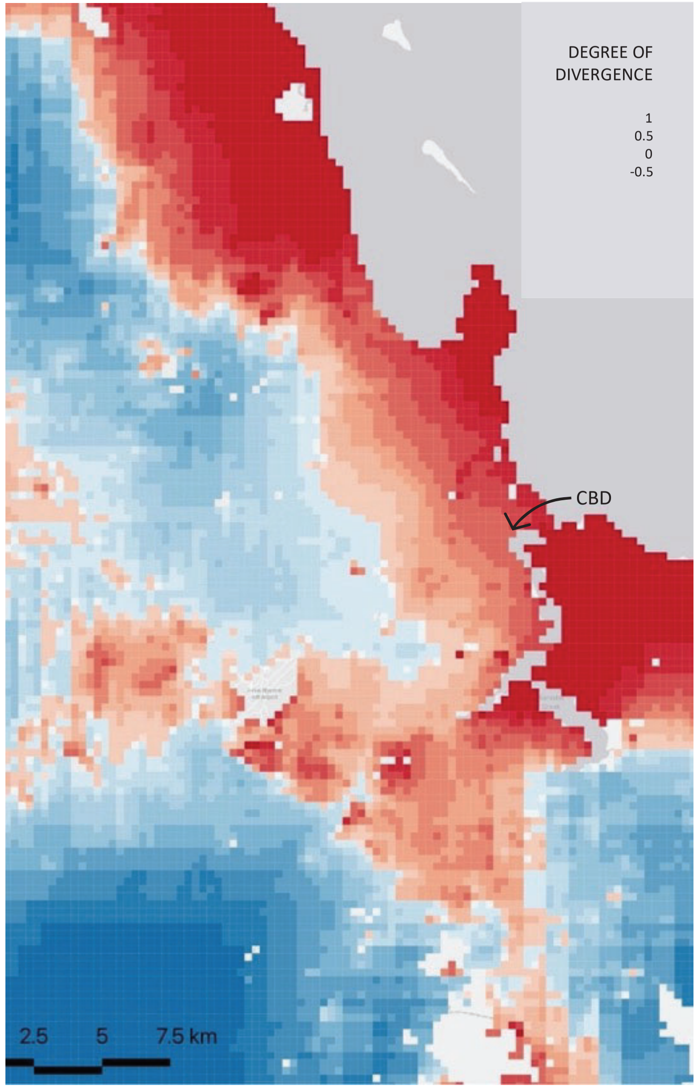
DEGREE OF
DIVERGENCE
1
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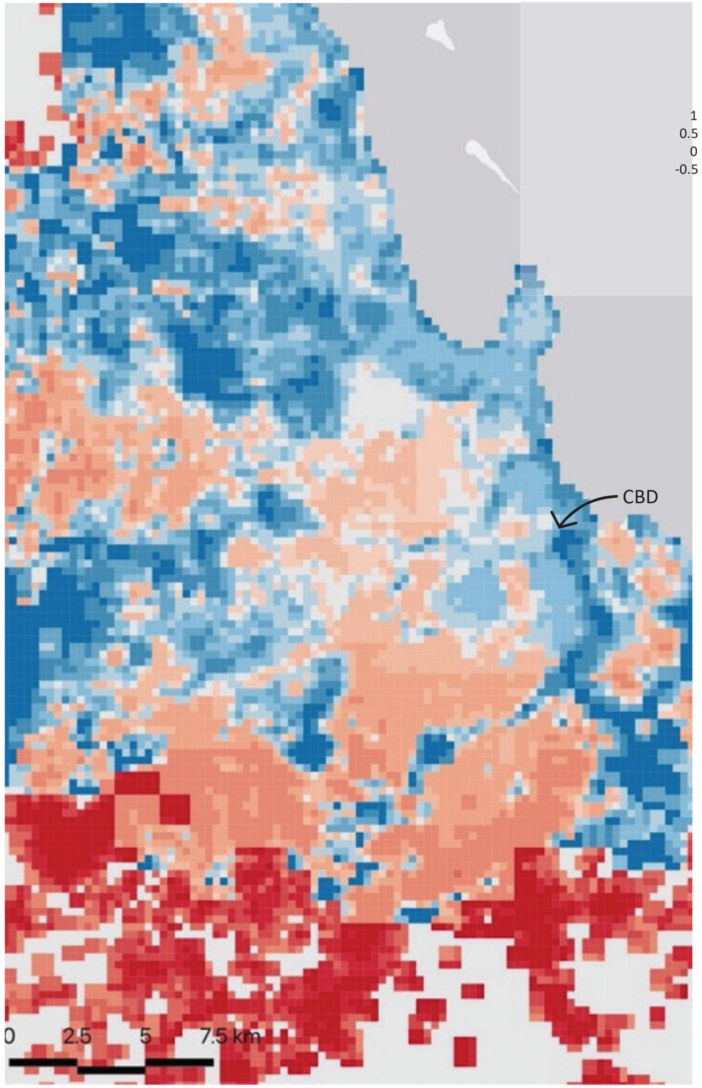
-0.5
CBD
2.5
5
7.5 km

Finally, Fig. 5.12 reveals areas which have (positive and negative) imbalances between population density and nightlight intensity. Given this metric does not use space syntax analysis, the quality of the 1990 results are of higher quality. Most notably, in both 1990 and 2015, the south-western part of Dar es Salaam has a high negative degree of divergence value. This suggests that population is particularly high relative to nightlight intensity, which may suggest low electrification rates.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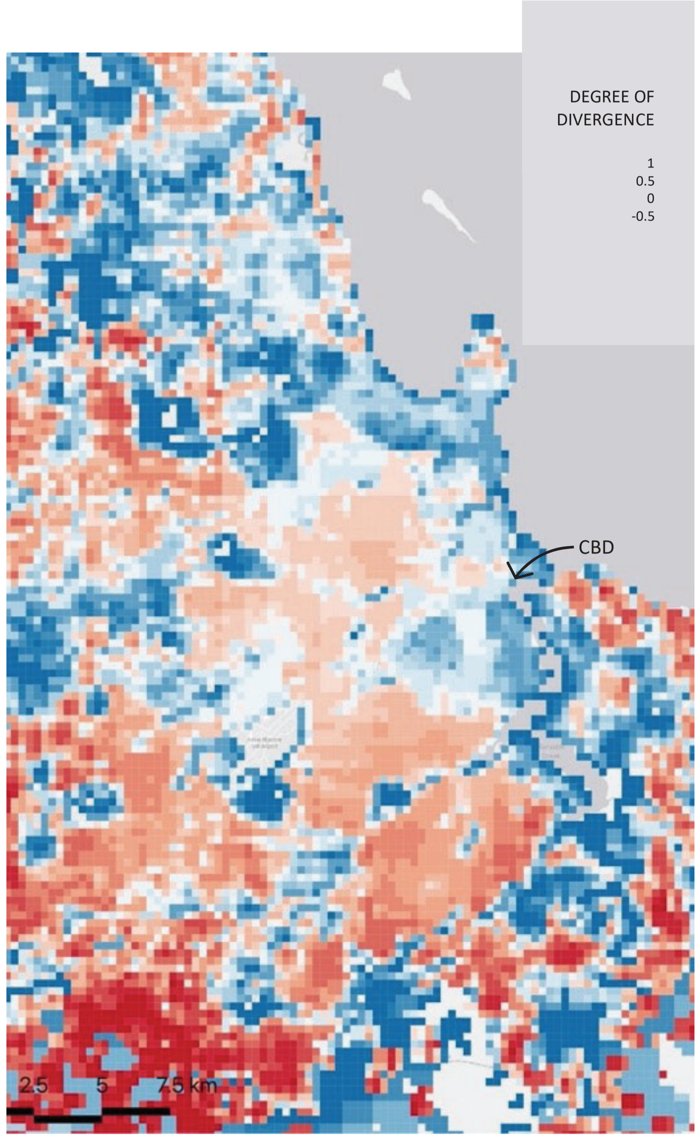

DEGREE OF DIVERGENCE
1
0.5
0
-0.5
CBD
2.5
5
7.5 km

5.4 Interim conclusions

This chapter has used graphical analysis, visual layering and the creation of a degree of divergence metric to illustrate that combining city-wide data can provide a great analytical tool to identify strengths and weaknesses in the city. In particular, the degree of divergence metric can consistently identify areas based on spatial, developmental and demographic imbalances. Whilst there are inaccuracies that should not be disregarded, the analysis offers considerable new insights and knowledge about rapid urban growth in Dar es Salaam. Furthermore, the methodology used is easily replicable in other contexts and time-periods. The next chapter applies and extends this work to create a comparative framework for particular parts of the city.

CHAPTER 6: APPLYING THE MULTI-TEMPORAL MULTI-VARIABLE CELL-BASED DATASET TO CREATE A COMPARATIVE FRAMEWORK

6.1 Introduction

This chapter zooms-in to eight focus areas in order to illustrate how this research offers a comparative framework for understanding (through new insights and knowledge) and monitoring urban changes over time. The selected focus areas are introduced and then explored using catchment analysis before synthesising the findings using star diagrams. This may be particularly useful for communities and policy-makers who want to compare the performance of particular areas, and unpack why this may be the case.

6.2 Selection of local sub-centres and anomaly areas

Fig. 6.1 and Fig. 6.2 respectively show the location and birds-eye view of each of the eight focus areas, categorised by 'types' (Table 6.1).

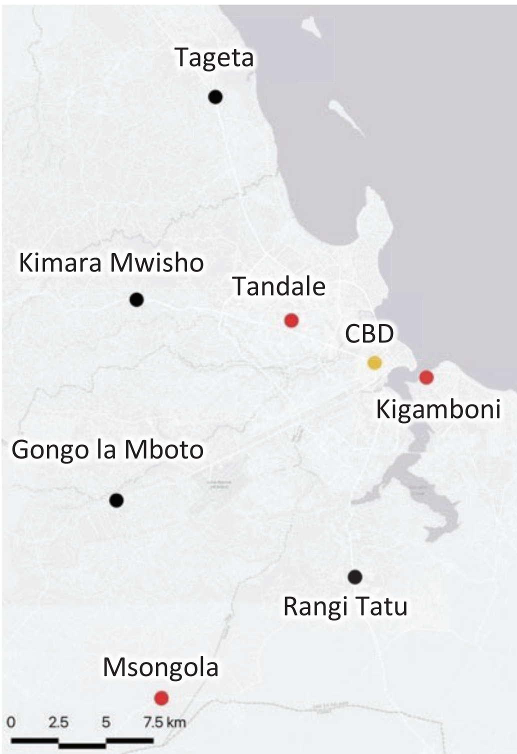


Fig. 6.1 Map of locations of CBD (yellow), local centres (black) and anomaly areas (red)

Table 6.1 explains the rationale behind the selection of each focus area. The precise location point for each focus area aligns as closely as possible to Kombe (2005), Hill and Lindner (2010a) and Google Maps. Data for each area was extracted from the multi-temporal multi-variable cell-based layer using a 2km network-based buffer from each location point – this is generated through catchment analysis (see 3.4 Analysis). These areas are shown in Appendices: Catchment analysis 2km focus areas – 1990 and 2020 spatial networks.

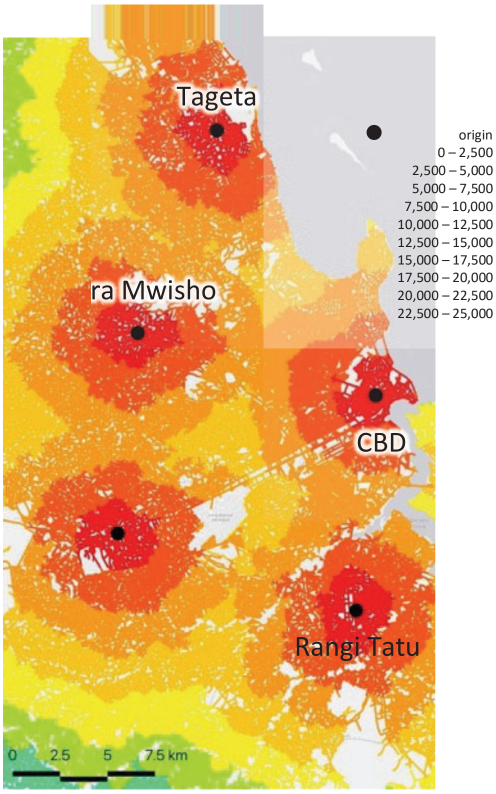
Table 6.1 Focus area selection and rationale

<table>
<tr><th>FOCUS AREA</th><th>RATIONALE</th><th>TYPE OF FOUCS AREA</th></tr>
<tr><td>CBD</td><td>Significant historic and present-day dominance.</td><td>CBD</td></tr>
<tr><td>RANGI TATU</td><td rowspan="5">Identified as important sub-centres by Kombe (2005) and Hill and Lindner (2010a). Stand out in preceding analysis because they lie on key arterial routes with higher nightlight intensities and population densities.</td><td rowspan="5">Local centre</td></tr>
<tr><td>GONGO LA MBOTO</td></tr>
<tr><td>KIMARA MWISHO</td></tr>
<tr><td>TAGETA</td></tr>
<tr><td>TANDALE</td><td>A clear anomaly based on preceding analysis. It is a very dense, centrally-located informal settlement.</td><td rowspan="3">Anomaly</td></tr>
<tr><td>KIGAMBONI</td><td>A clear anomaly based on preceding analysis. It is a less dense mixed-income neighbourhood which is poorly connected to other parts of the city, despite close as-the-crow-flies distance to the CBD. Despite being ‘an attractive prospect for a new city…plans have been put on hold indefinitely’ (Three City Land Nexus Research Team 2020, 33).</td></tr>
<tr><td>MSONGOLA</td><td>A clear anomaly based on preceding analysis. It is a sprawling, more recently-developed informal settlement.</td></tr>
</table>

5.2 Satellite images of focus areas. *Source: ESRI Satellite*

6.3 Catchment analysis

Using the 2020 spatial network model, catchment analysis was undertaken from the CBD and local centres, and from anomaly areas (Fig. 6.3). Using this, each cell was given a value of mean minimum distance to a local centre or the CBD. This offers a mechanism through which insights about the socio-economic performance of each centre can be made.



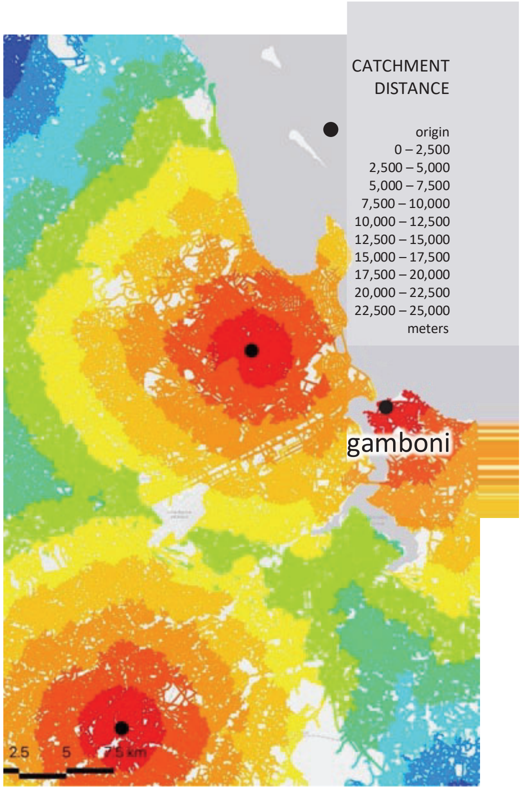


Fig. 6.4 and Fig. 6.5 reveal how total population and average population density (per cell) change with distance from each centre. Although total population peaks at around 5km from each centre, average population falls fairly linearly as distance increases. This suggests that, whilst the most densely populated areas are often around centres, most people live around 5km from them. These patterns are fairly consistent for all centres, although areas 4-6km from the CBD are approximately the same density as areas within 1km of it.

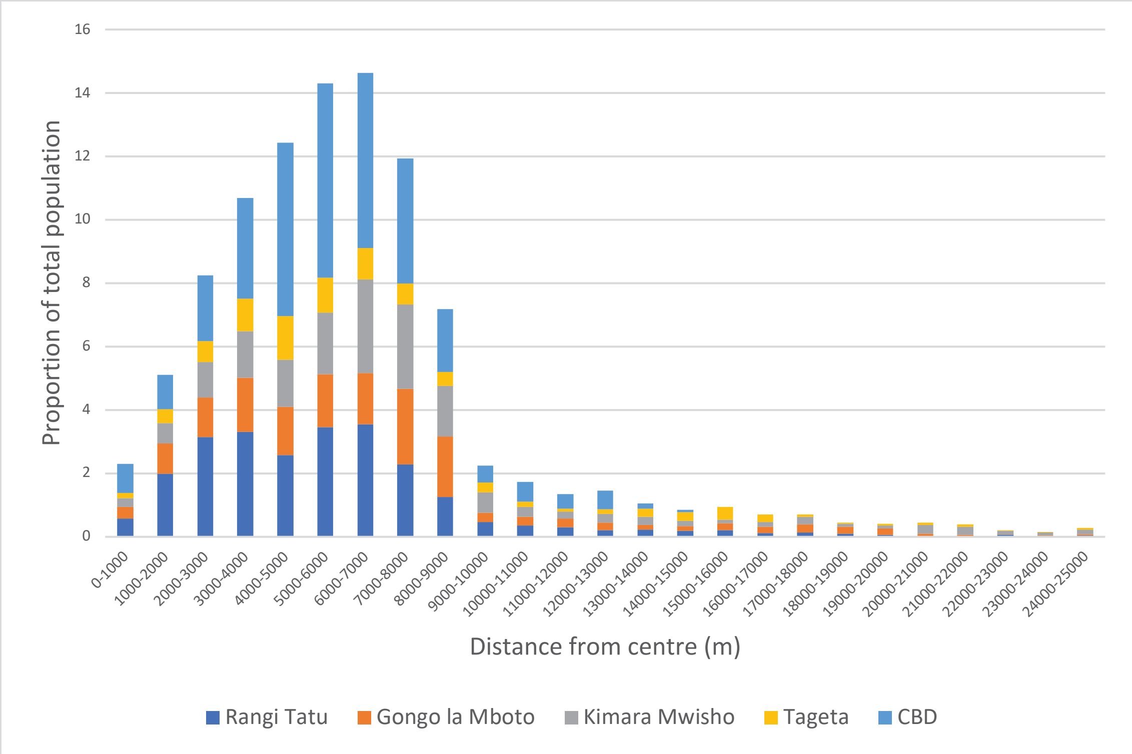


Fig. 6.4 Proportion of total population within different distance bands from each centre

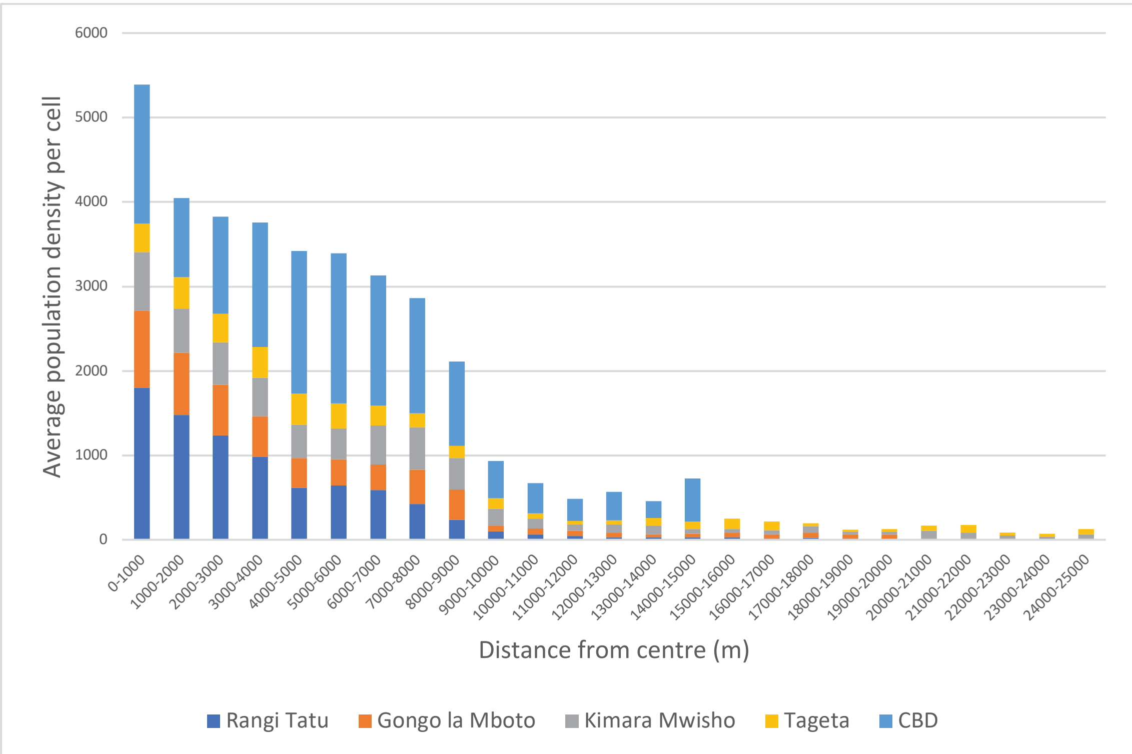


Fig. 6.5 Average population density per cell within different distance bands from each centre

Fig. 6.6 shows how population density has changed since 1990 in distances from each centre. These patterns likely reflect expected patterns of densification and sprawl. Areas around the CBD seem to have largely been areas of densification, with significant density increases closest to the CBD and also in surrounding areas, up to about 8km away. In contrast, the local centres are likely to have acted as central points for both densification and sprawl, with some households trying to live as close to the centre as possible, whilst being affordable. This trend may explain the notably higher population increases closer to the local centres, exemplifying the importance to most people of living near a local centre.

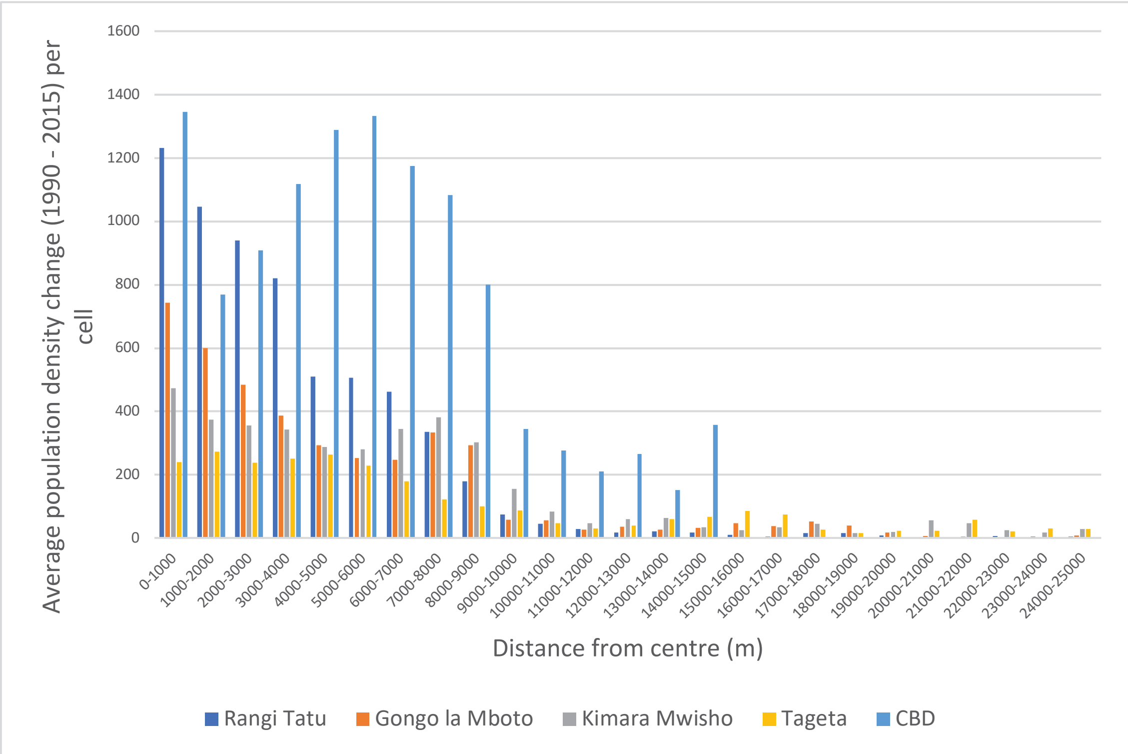


Fig. 6.6 Average population density change (1990 – 2015) per cell within different distance bands from each centre

Nightlight intensity also seems to decrease with distance from centres (Fig. 6.7). This suggests that more activity happens closer to centres. This makes intuitive sense and supports the use of nightlight intensity as an indicator of activity. Moreover, centres which see a greater fall in nightlight intensity as distance increases may be those where electrification rates outside of the local centres are lower. Whilst inconclusive, these findings could support and be supported by local knowledge in order to understand patterns of nightlight intensity as the city undergoes rapid urban expansion. The persistently high values for distances from the CBD reflects its overall centrality.

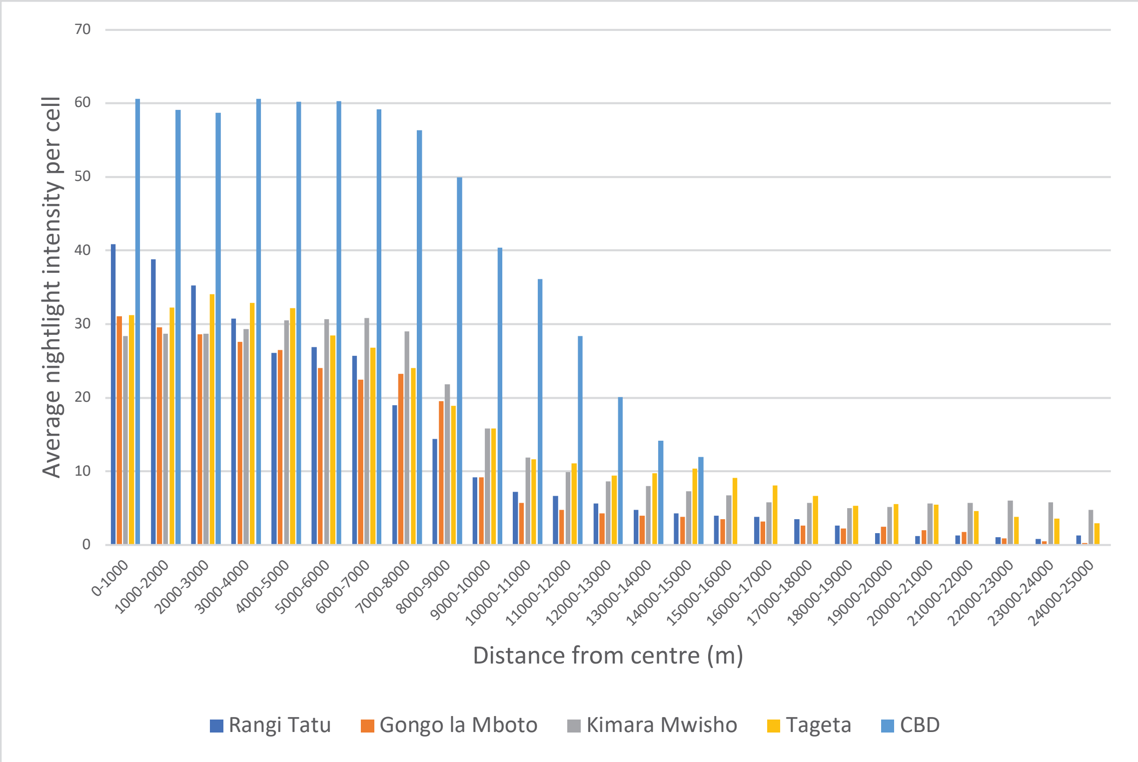


Fig. 6.7 Average nightlight intensity per cell within different distance bands from each centre

This is further supported by examining average changes to nightlight intensity from 1990 (Fig. 6.8). Local centres which had low electrification rates in 1990 show the biggest changes (e.g. Rangi Tatu). Areas around the CBD have seen smaller increases, and even decreases closest to the centre. This is likely to reflect the distortion of nightlight intensity values in the centre of Dar es Salaam in 1990, but also suggests a slower overall change in nightlight. This is likely to be because the centre of Dar es Salaam has historically had access to electricity and been a centre of activity.

Overall, the use of catchment analysis in-and-of-itself offers insights into how different parts of Dar es Salaam are actually connected to centres, rather than relying on as-the-crow-flies distances. By incorporating these results into the multi-temporal multi-variable cell-based layer, the ways in which nightlight intensity and population density change with distances from (or accessibility to) centres can be examined. This provides insights into how Dar es Salaam has evolved under rapid urban growth, and offers a methodology towards comparing the characteristics of different areas.

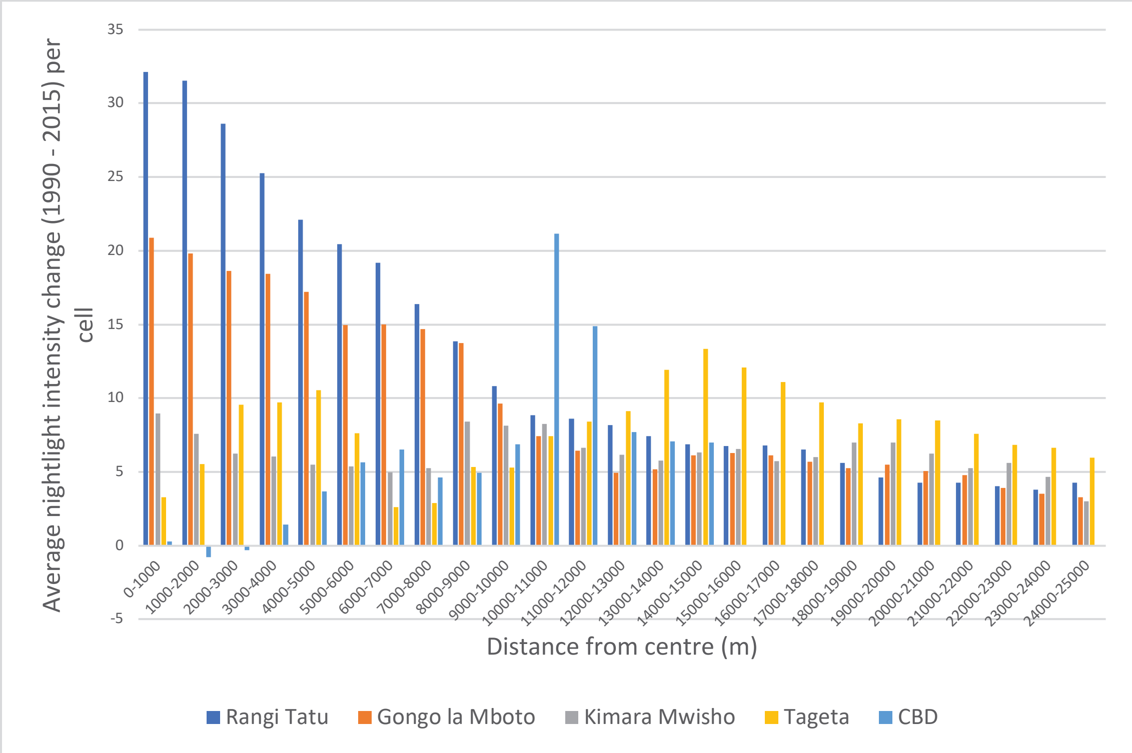


Fig. 6.8 Average nightlight intensity change (1990 – 2015) per cell within different distance bands from each centre

6.4 Comparative framework for assessing the CBD, sub-centres and anomaly areas

Based on the previous analysis, this section offers an overall comparison of the characteristics of the eight focus areas using star diagrams. The three degrees of divergence are compared alongside local (r2km) and across-city (r50km) integration. Integration has been chosen because the literature and supporting analysis of centres have both highlighted the importance of local and citywide centrality in patterns of rapid urban growth.

Each integration score is the percentile rank from 0 to 1, where 1 represents the highest value in Dar es Salaam. Each degree of divergence score lies between -1 and 1, where 0 is the lowest divergence. Comparisons are shown in Fig. 6.9 (1990) and Fig. 6.10 (2015), and insights are offered in Table 6.2. As in the previous section, results were calculated based on the mean of all cells within a 2km catchment of each centre.

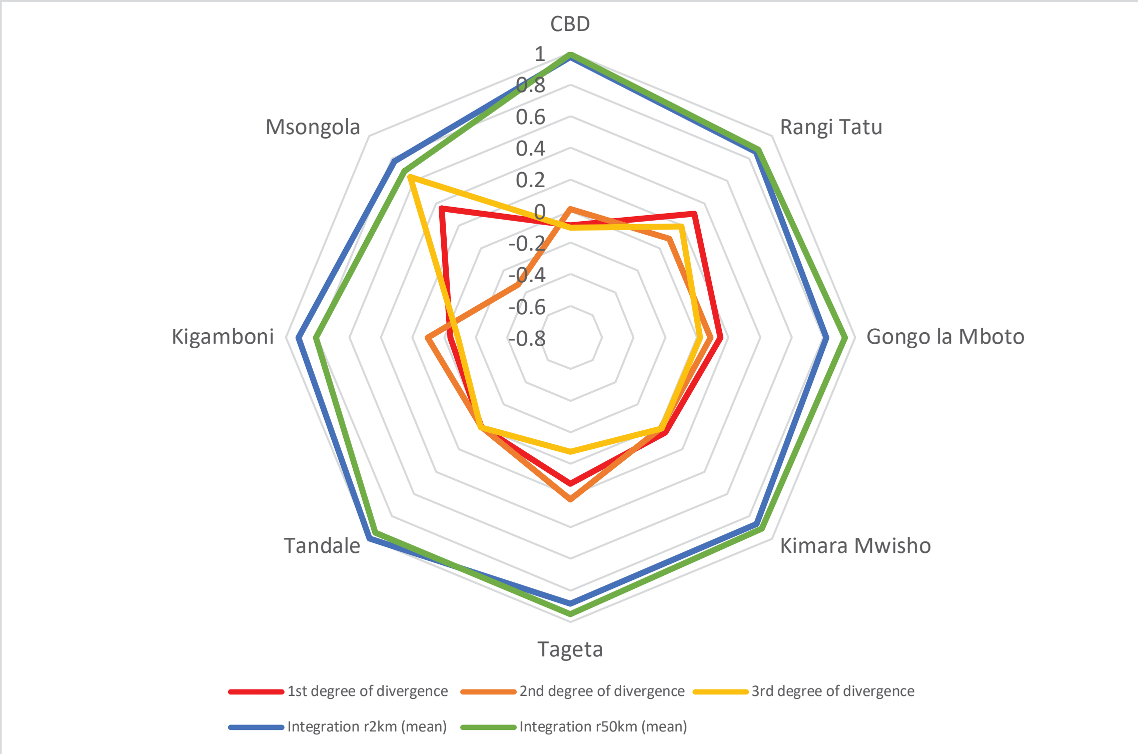


Fig. 6.9 Average values for key indicators within 2km catchment of each centre, 1990

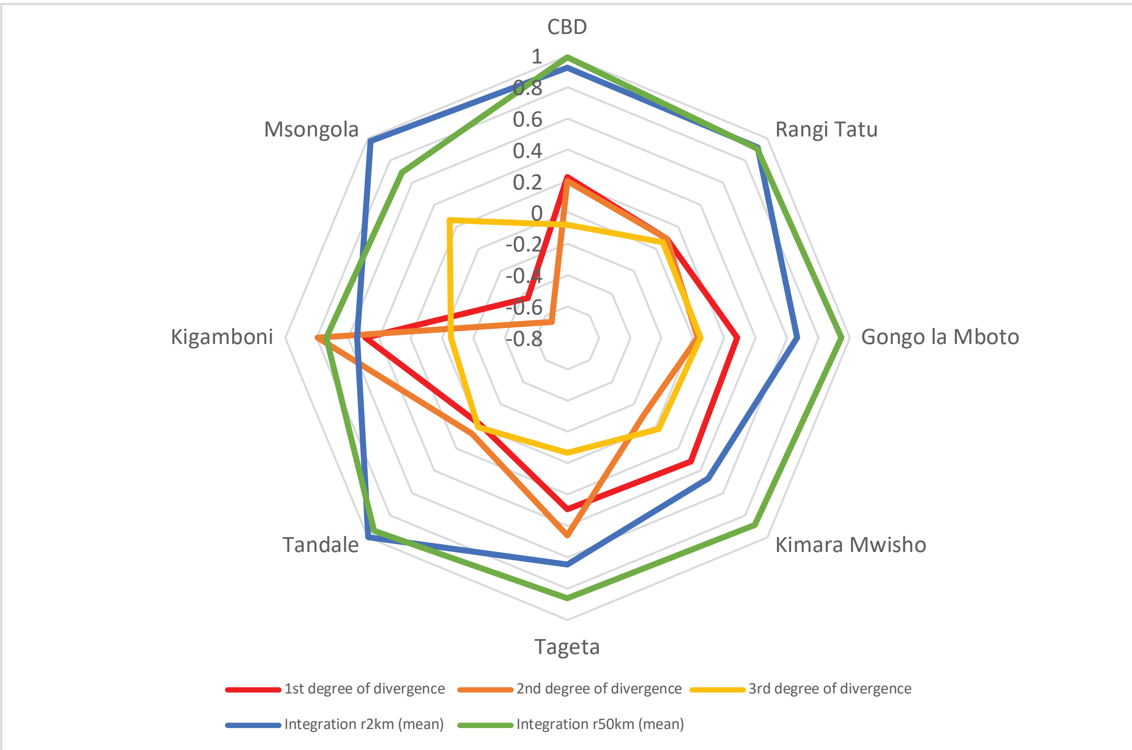


Fig. 6.10 Average values for key indicators within 2km catchment of each centre, 2015

Table 6.2 Summary of insights from star diagrams, 1990 and 2015

FOCUS AREA	1990 INDICATORS	2015 INDICATORS
CBD	Very high and similar local and global integration Low degrees of divergence	Similar local and global integration Increase in 1st and 2nd degrees of divergence, possibly reflecting greater pressures on the spatial network
RANGI TATU	High and similar local and global integration 1st degree of divergence value suggests high population relative to network density	Similar local and global integration Better alignment of degrees of divergence towards 0, suggesting a good balance between network density, population and activity
GONGO LA MBOTO	High local and global integration. Lower local integration suggests a lack of continuity in local networks Low degrees of divergence	Greater disparity between local and global integration, suggesting a lack of improvement in the continuity of local networks Increase in 1st degree of divergence, possibly reflecting greater pressures on the spatial network
KIMARA MWISHO	High and quite similar local and global integration Low degrees of divergence	Greater disparity between local and global integration, suggesting a lack of improvement in the continuity of local networks Increase in 1st degree of divergence, possibly reflecting greater pressures on the spatial network Fall in 2nd degree of divergence suggests a lack of activity and/or electrification relative to network density
TAGETA	High and quite similar local and global integration Relatively high 1st and 2nd degrees of divergence suggest high population and activity and/or electricity consumption relative to network density	Greater disparity between local and global integration, suggesting a lack of improvement in the continuity of local networks Increase in 1st degree of divergence, possibly reflecting greater pressures on the spatial network

		Increase in 2^{nd} degree of divergence, suggesting a lot of activity and/or consumption of electricity (could be industry and/or affluence)
TANDALE	Very high and similar local and global integration Low degrees of divergence	Local integration above global integration, suggesting a well-functioning internal network, which could be more connected to global movement networks Increase in 2^{nd} degree of divergence, suggesting a lot of activity and/or consumption of electricity
KIGAMBONI	High local and global integration. Lower global integration suggests a lack of connection to global movement networks Relatively high 2^{nd} degree of divergence suggests high activity/ electricity consumption relative to network density	Global integration above local integration, suggesting an improved connection to citywide movement networks, but lack of local network continuity Increase in 1^{st} degree of divergence, possibly reflecting greater pressures on the spatial network Increase in 2^{nd} degree of divergence, suggesting a lot of activity and/or consumption of electricity (could be industry and/or affluence)
MSONGOLA	High local and global integration. Lower global integration suggests a lack of connection to global movement networks Very high 3^{rd} degree of divergence suggests low electricity consumption relative to population, perhaps indicating lack of electrification Other degrees of divergence are especially skewed by spatial network inaccuracies	Local integration above global integration, suggesting a well-functioning internal network, which could be more connected to global movement networks Low 1^{st} and 2^{nd} degrees of divergence suggests some under-utilisation of the spatial network. A slightly lower 3^{rd} degree of divergence suggests a better alignment of population and electricity consumption

	Note: caution should be taken with positive degree of divergence values in 1990 given limitations in the spatial network model, which will give an upwards bias to peripheral areas

Overall, creating a diagrammatic comparison of key indicators across identified focus areas helps to unpack patterns of rapid urban growth within different parts of the city.

6.5 Interim conclusions

This chapter has zoomed-in to eight focus areas in order to illustrate the effectiveness of nightlight intensity, population density and spatial network analysis when used jointly within a clear comparative framework. As with preceding analysis, this method is easily replicable across numerous other contexts. Many new insights have been made about the nature of rapid urban growth across Dar es Salaam and in particular locations. By analysing the city from multi-scalar and multi-temporal perspectives, the nuance that can be provided by combining open-source datasets is notable.

CHAPTER 7: DISCUSSION AND CONCLUSION

7.1 Reflection on research questions

This research has thoroughly evaluated the effectiveness of nightlight intensity, population density, and spatial network analysis towards understanding rapid urban growth in the data-sparse context of Dar es Salaam, Tanzania between 1990 and 2020. This has been achieved by asking three research questions whose answers have provided new knowledge and insights into Dar es Salaam's patterns of rapid urban growth and established a replicable framework for monitoring rapid urban growth across numerous contexts.

7.1.1 To what extent can each dataset independently contribute to an understanding of rapid urban growth in Dar es Salaam?

This research has illustrated the insights that can be drawn from each dataset independently.

Spatial network analysis using space syntax techniques has enabled the configurational properties of Dar es Salaam's spatial network to be consistently and objectively assessed at multiple scales for both 1990 and 2020. Through this, routes with different levels of movement potential at local, within-city and across-city scales have been identified (NACHr2km, NACHr10km and NACHr50km). Potential centres of activity at local, within-city and across-city scales have also been identified (INTr2km, INTr10km and INTr50km). Both movement potentials and centres of activity have been compared between 1990 and 2020, revealing the persistence of the city's historic spatial configuration. Despite some unavoidable shortfalls in the accuracy of the spatial network models, particularly in 1990, these findings suggest that spatial network analysis can effectively offer some new insights into the likely movement and activity patterns of the city.

Analysis of nightlight intensity has enabled an assessment of different levels of activity across the city in 1990, 2000, 2015 and 2020. Whilst earlier data is subject to distortion in the city centre, patterns of nightlight intensity changes over time offer new insights into growth trajectories within different parts of the city, and can help identify actual hotspots of activity.

Analysis of population density across the city in 1990, 2000 and 2015 has provided clear knowledge on the number of people living in different parts of the city. This has enabled insights into the demography of Dar es Salaam at quite a fine-grain and consistent level (275m^2 grid cells).

7.1.2 To what extent can this understanding be enhanced by combining the datasets into a multi-temporal multi-variable cell-based model and 'degree of divergence' metric?

This research has shown that knowledge and insights into rapid urban growth in Dar es Salaam can be considerably enhanced by jointly analysing spatial network, nightlight intensity and population density data.

Initially, this research studied the relationship between nightlight intensity and population density using box-and-whisker plots and a cumulative line graph. This revealed areas which, historically and more recently, have no or limited access to electricity. It also revealed changes to electrification, activity and population density which have happened across Dar es Salaam since 1990.

Secondly, visual layering was undertaken to reveal relationships between spatial network analysis (movement potentials and centres of activity) and nightlight intensity and population density in 1990 and 2015. This provided insights into how spatial, developmental and demographic changes have evolved along interconnected trajectories.

Thirdly, a degree of divergence metric was created. This novel contribution provides a method to systematically compare the performance of the entire city using three metrics at a resolution of $275m^2$ grid cells. The 1st degree of divergence calculates differences between local spatial network density (node count radius 2km) and population density. The 2nd degree of divergence compares differences between within-city network density (node count radius 10km) and nightlight intensity. The 3rd degree of divergence compares differences between population density and nightlight intensity. Through these metrics, new, more nuanced insights can be made about the relative performance of different parts of the city, and how this has changed over time (in this case, from 1990 to 2015). For instance: whether an area is over-crowded relative to local spatial network density, whether activity is surprisingly high relative to within-city spatial network density, or whether activity is low relative to its population density.

Fourthly, preceding analysis was utilised in order to create a comparative framework for identifying and studying focus areas (the CBD, 4 local sub-centres and 3 anomaly areas). Catchment analysis was undertaken using the 2020 spatial network model. This enabled an accurate assessment of population densities, nightlight intensities and their changes over time using network-based distances from the CBD and 4 local sub-centres.

Finally, the analysis was synthesised into star diagrams for 1990 and 2015. This compared the values of all three degrees of divergence alongside local and across-city integration (INTr2km and INTr50km) for each focus area.

Therefore, the analysis undertaken in this research has shown that, in the case of Dar es Salaam, spatial network analysis, nightlight intensity and population density all independently offer new knowledge and insights – that is, greater understanding – into rapid urban growth to some non-negligible extent. The extent to which this understanding can be enhanced by combining the datasets into a multi-temporal multi-variable cell-based model and new degree of divergence metric is significant. Joint analysis of all three datasets has generated new, nuanced insights across the whole city at a good degree of accuracy and granularity.

7.1.3 How can this methodology be used to effectively monitor rapid urban growth in Dar es Salaam and other contexts?

This research has undertaken multiple analyses in order to build a methodology which can offer crucial new insights and knowledge about patterns and trends of rapid urban growth in Dar es Salaam. This approach could be used not only to enhance understanding of rapid urban growth, but also to monitor rapid urban growth by repeating the analysis over time. Given that the datasets are regularly updated and are consistent over time, there is, on the basis of this research, considerable potential to adopt a monitoring framework. Furthermore, because the datasets are all open-source and globally-available, this methodology is widely replicable across the world. In conjunction with existing comprehensive monitoring tools such as the Global Urban Monitoring Framework (UN Habitat 2022), this research can make real contributions in alleviating issues of data insufficiencies towards understanding and monitoring rapid urban growth in data-sparse conditions.

7.2 Conclusion and next steps

In conclusion, this research has dived deeply into the analytical possibilities of open-source data in order to offer new insights and knowledge into rapid urban growth in data-sparse contexts, offering a novel and easily replicable methodological framework. This is a crucial step towards alleviating data insufficiencies that are so often associated with rapid urban growth. In particular, this research has utilised the full benefits of the space syntax approach in visual and statistical analysis, and in generating accurate distance measures i.e. not just as-the-crow-flies distances. Compared to other studies, the combined dataset contains cells of the same size and is therefore less subject to the modifiable areal unit problem (it is still a risk, however).

Having said this, this research by no means offers a mechanism for completely understanding rapid urban growth. The value of local-level knowledge should not be underestimated or pushed aside, and other datasets are likely to only enhance the nuance of the findings presented here. Uniquely, this method has the potential to be applied in the same manner anywhere in the world, providing an opportunity for systematic comparisons and deeper understanding of rapid urban growth. This is essential in order to move towards more sustainable and equitable patterns of growth in cities.

There are lots of potential streams of research that could evolve from this study. The adoption of this methodology in other contexts would help to establish its general effectiveness and streamline the approach. For instance, explorations into all urban settlements in Tanzania, or a selection of large cities in other countries. In particular, looking at secondary cities may be more useful for policy-makers because, as population densities are usually lower and urban changes not yet so permanent, there may be more room to make changes and at lower costs. With a larger sample of cities, causal regression analysis could be used to provide deeper understanding of mechanisms involved in rapid urban growth. In addition, more research to establish the effectiveness of the degree of divergence or similar metrics is essential in order to solidify methods which relate spatial network properties to demographic and socio-economic data. One such metric could be a measure of severance which directly compares disparities between local and global integration (as alluded to in section 6.4 Comparative framework for assessing the CBD, sub-centres and anomaly areas). The importance, and perhaps even urgency, of research in this field continues to expand as cities continue to grow and environmental, social and economic insecurities become more far-reaching.

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Appendices

Appendix 1: SDG 11 targets and indicators covered in Tanzania

Table 0.1 Full list of SDG 11 targets and indicators covered in Tanzania. *Source: United Nations n.d.; Goal Tracker Tanzania 2022.*

TARGET	DEFINITION	NUMBER OF INDICATORS COVERED IN TANZANIA
11.1	'By 2030, ensure access for all to adequate, safe and affordable housing and basic services and upgrade slums'	1/1
11.2	'By 2030, provide access to safe, affordable, accessible and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons'	1/1
11.3	'By 2030, enhance inclusive and sustainable urbanization and capacity for participatory, integrated and sustainable human settlement planning and management in all countries'	1/2
11.4	'Strengthen efforts to protect and safeguard the world's cultural and natural heritage'	0/1
11.5	'By 2030, significantly reduce the number of deaths and the number of people affected and substantially decrease the direct economic losses relative to global gross domestic product caused by disasters, including water-related disasters, with a focus on protecting the poor and people in vulnerable situations'	0/2
11.6	'By 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management'	0/2
11.7	'By 2030, provide universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities'	0/2
11.A	'Support positive economic, social and environmental links between urban, peri-urban and rural areas by strengthening national and regional development planning'	0/1

11.B	‘By 2020, substantially increase the number of cities and human settlements adopting and implementing integrated policies and plans towards inclusion, resource efficiency, mitigation and adaptation to climate change, resilience to disasters, and develop and implement, in line with the Sendai Framework for Disaster Risk Reduction 2015-2030, holistic disaster risk management at all levels’	2/2
11.C	‘Support least developed countries, including through financial and technical assistance, in building sustainable and resilient buildings utilizing local materials’	0/0

Appendix 2: Additional mapping

Full extent of each dataset

Fig. 0.1 shows the full extent of each dataset.

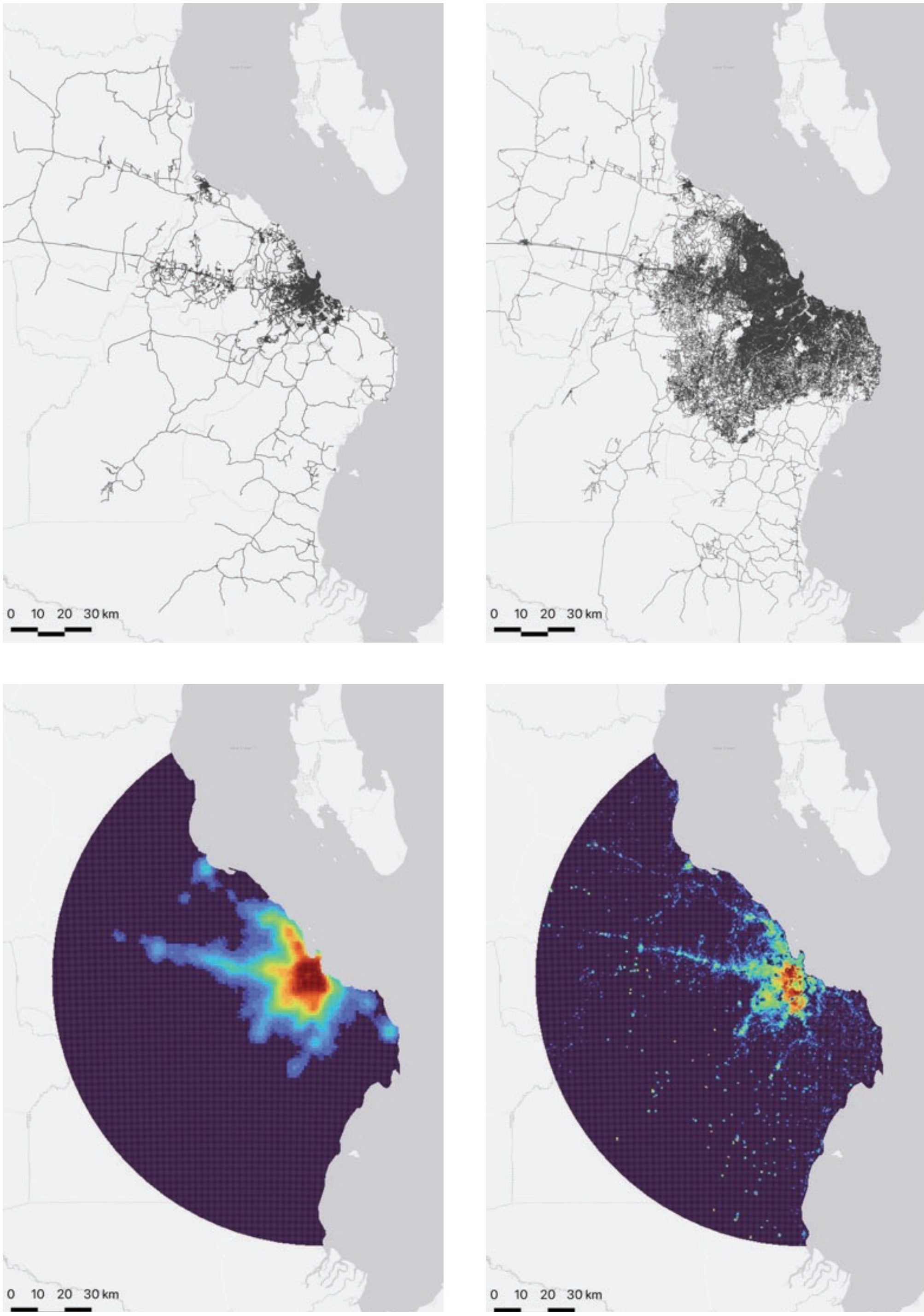

Fig. 0.1 Full extent of each dataset: 1990 spatial network model (top left); 2020 spatial network model (top right); nightlight intensity (bottom left); population density (bottom right)

Nightlight intensity and population density data

Fig. 0.2 and Fig. 0.3 show the evolution of nightlight intensity and population density respectively at a larger scale, revealing how nightlight intensity has changed at the peripheries of the city.

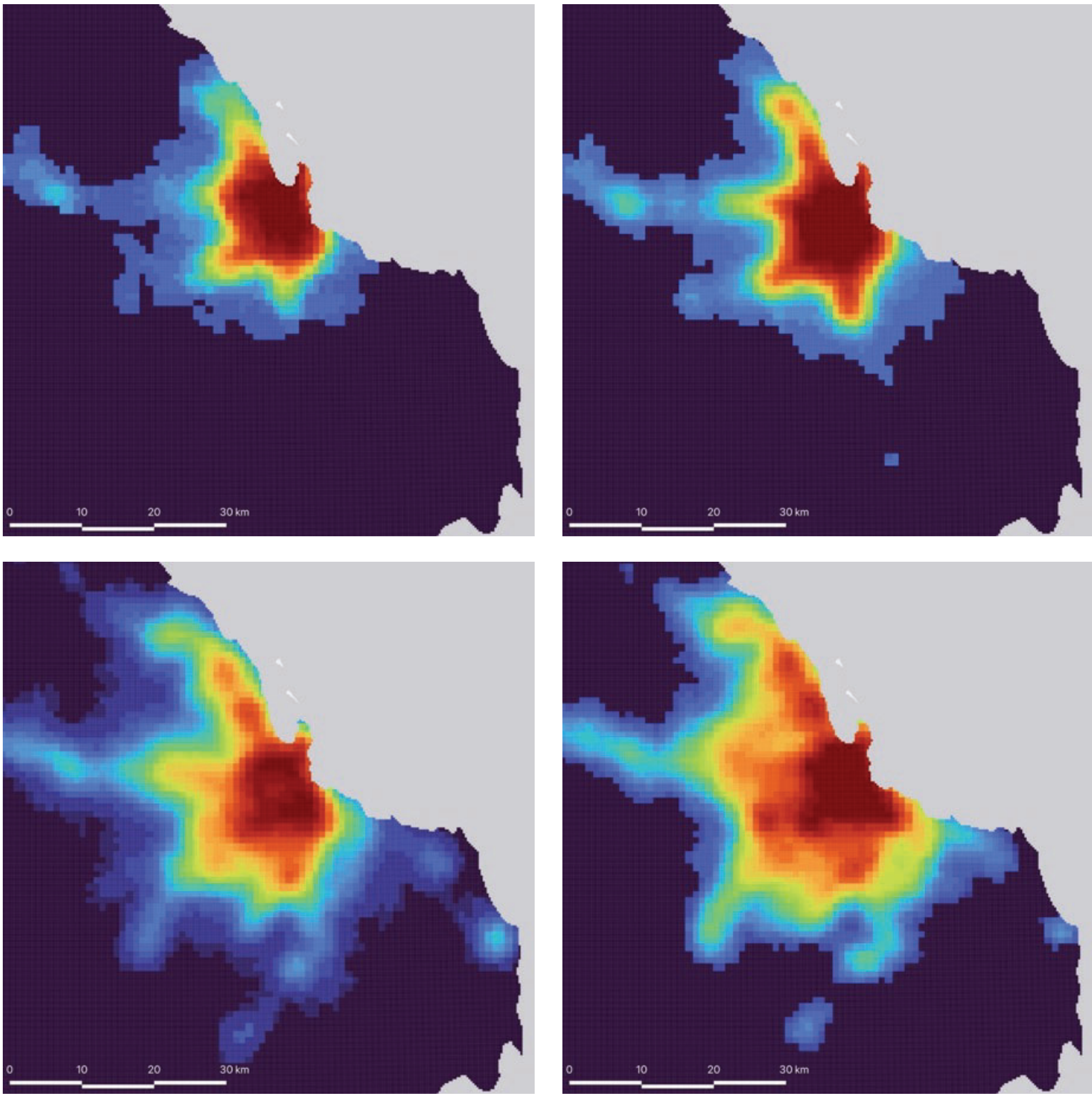

Fig. 0.2 Evolution of nightlight intensity: 1992 (top left); 2000 (top right); 2015 (bottom left); 2020 (bottom right)

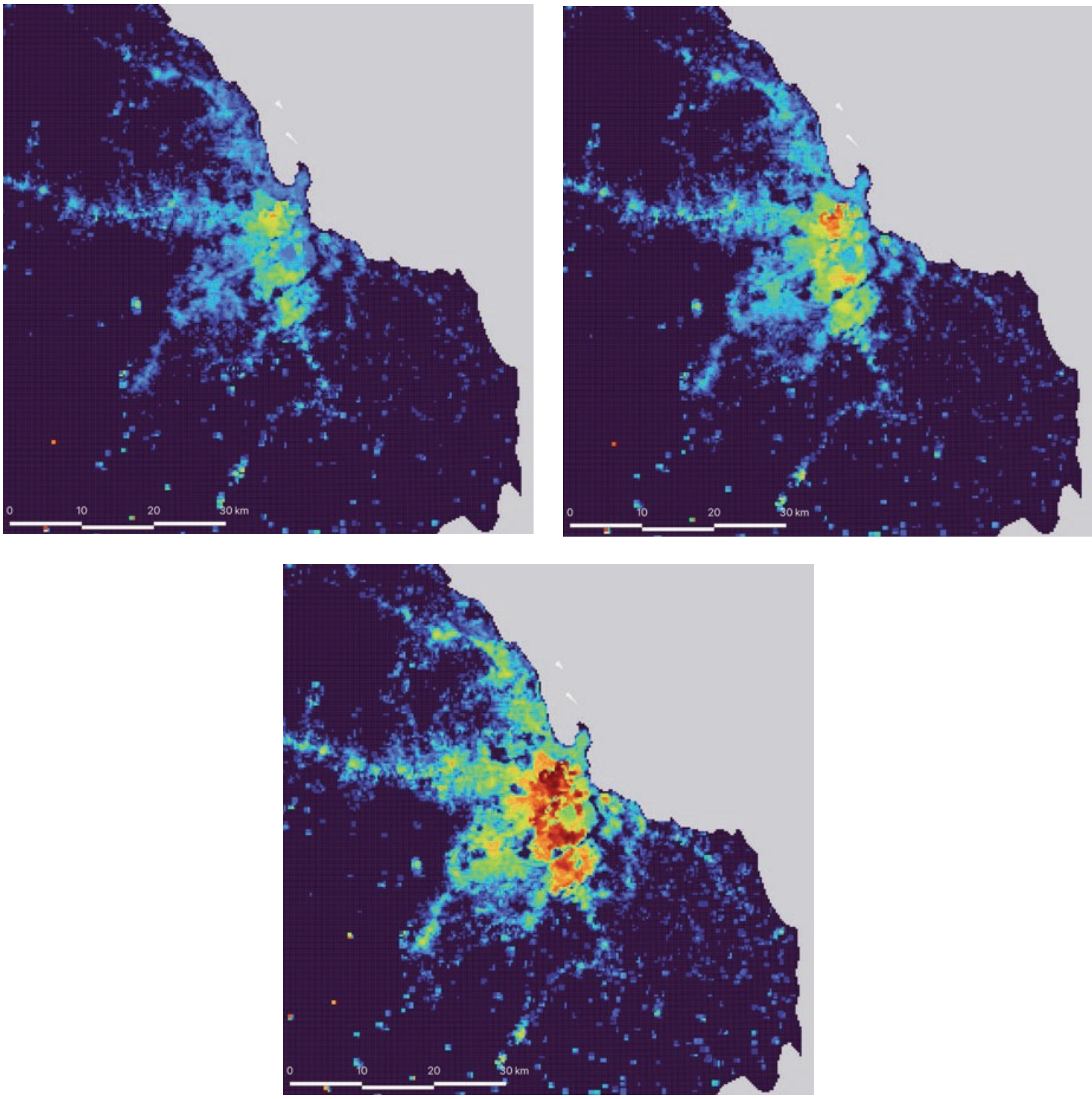

Fig. 0.3 Evolution of population density: 1990 (top left); 2000 (top right); 2015 (bottom)

Fig. 0.4 shows the absolute change in nightlight intensity (1992 to 2015) and population density (1990 to 2015) at a larger scale.

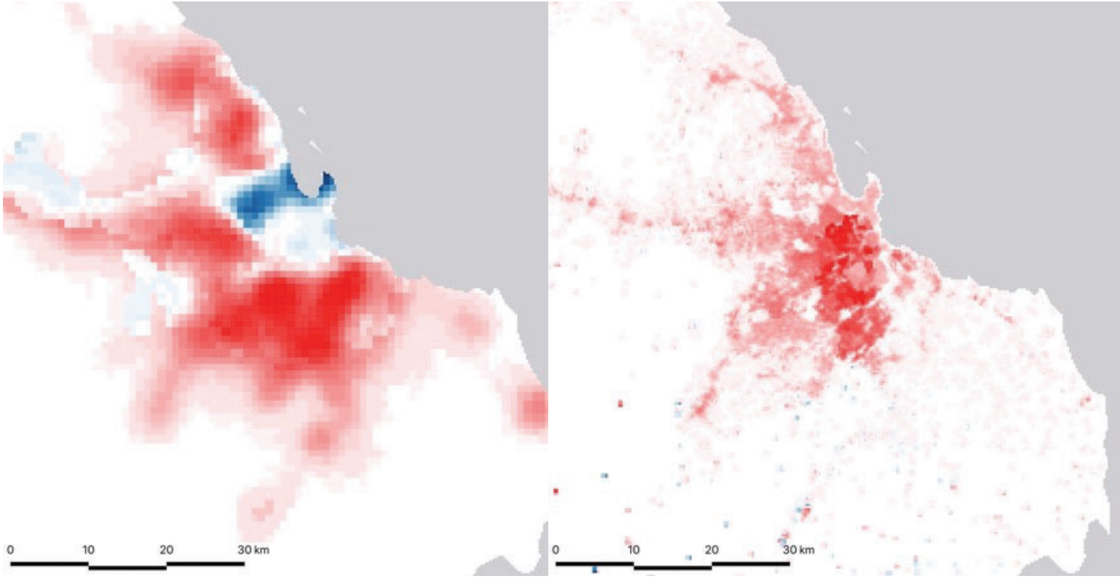

Fig. 0.4 Absolute change in nightlight intensity (1992 to 2015 - left) and population density (1990 to 2015- right)

Scatterplots for each degree of divergence

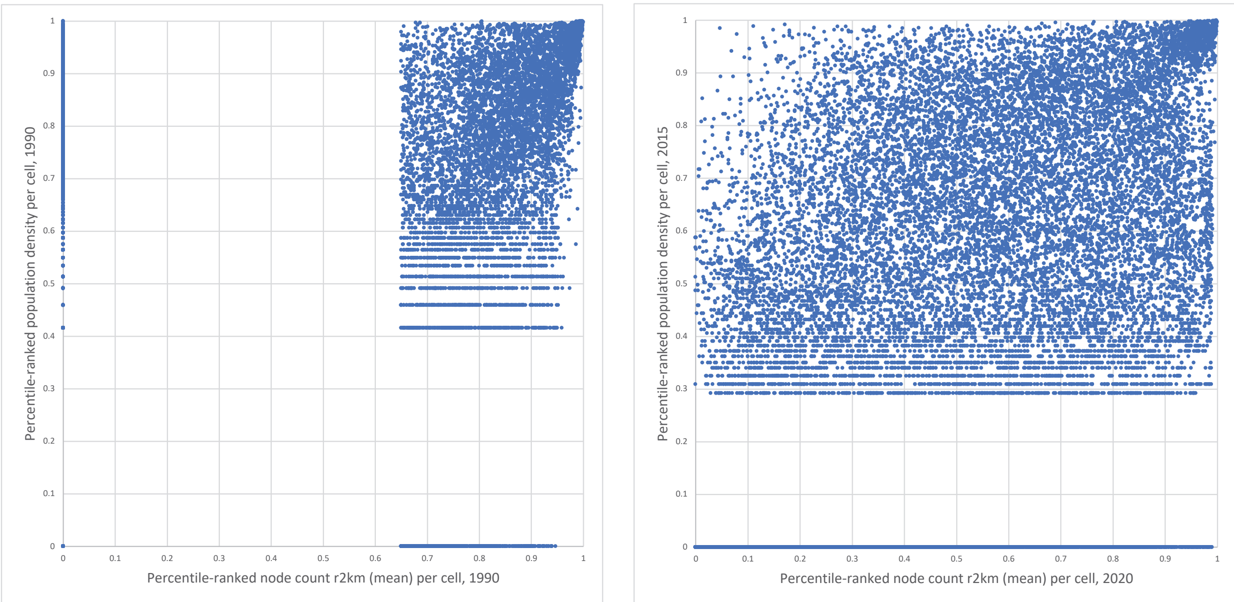

Fig. 0.5 Scatterplots of the 1st degree of divergence - node count r2km and population density, 1990 (left) and 2015 (right)

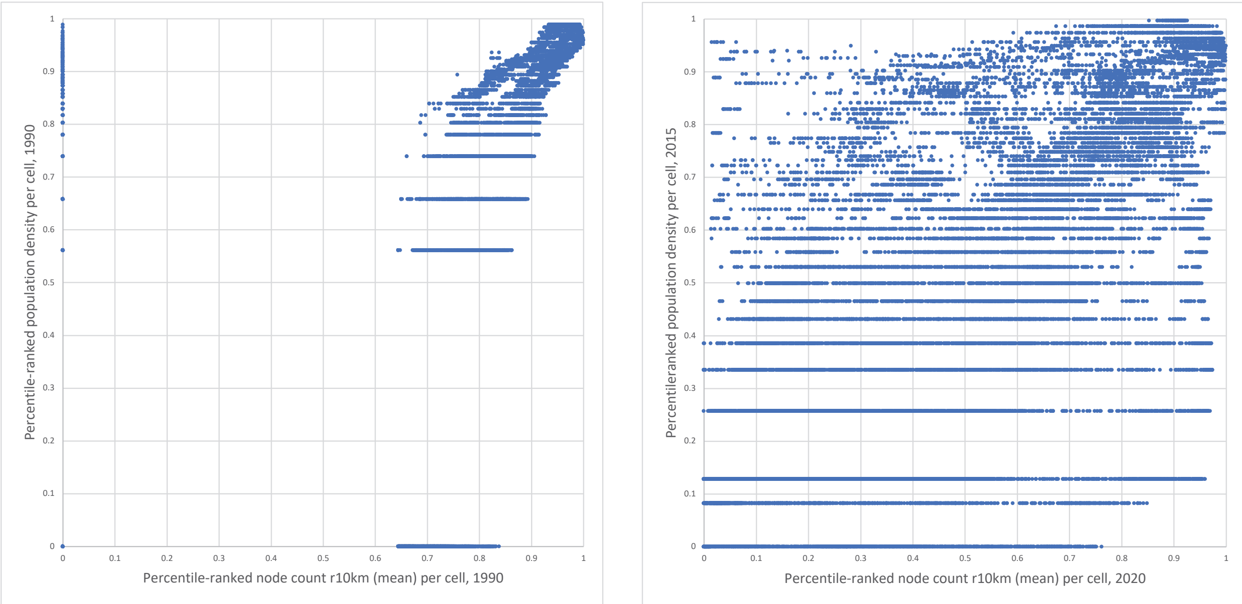

Fig. 0.6 Scatterplots of the 2nd degree of divergence - node count r10km and nightlight intensity, 1990 (left) and 2015 (right)

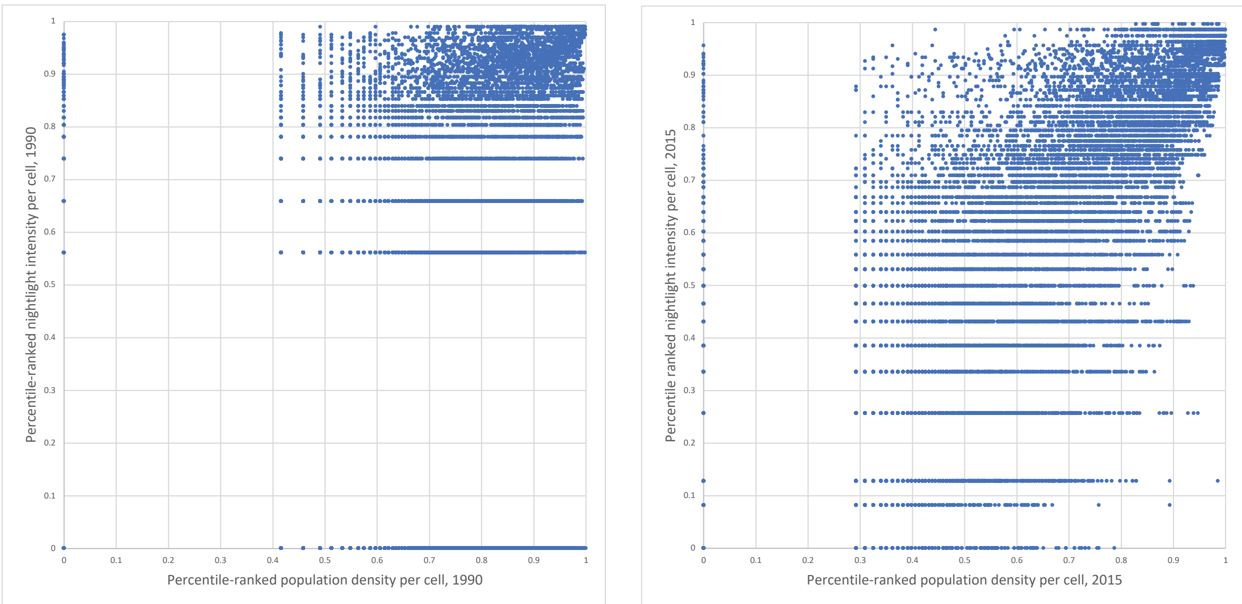

Fig. 0.7 Scatterplots of the 3rd degree of divergence - population density and nightlight intensity, 1990 (left) and 2015 (right)

Catchment analysis 2km focus areas – 1990 and 2020 spatial networks

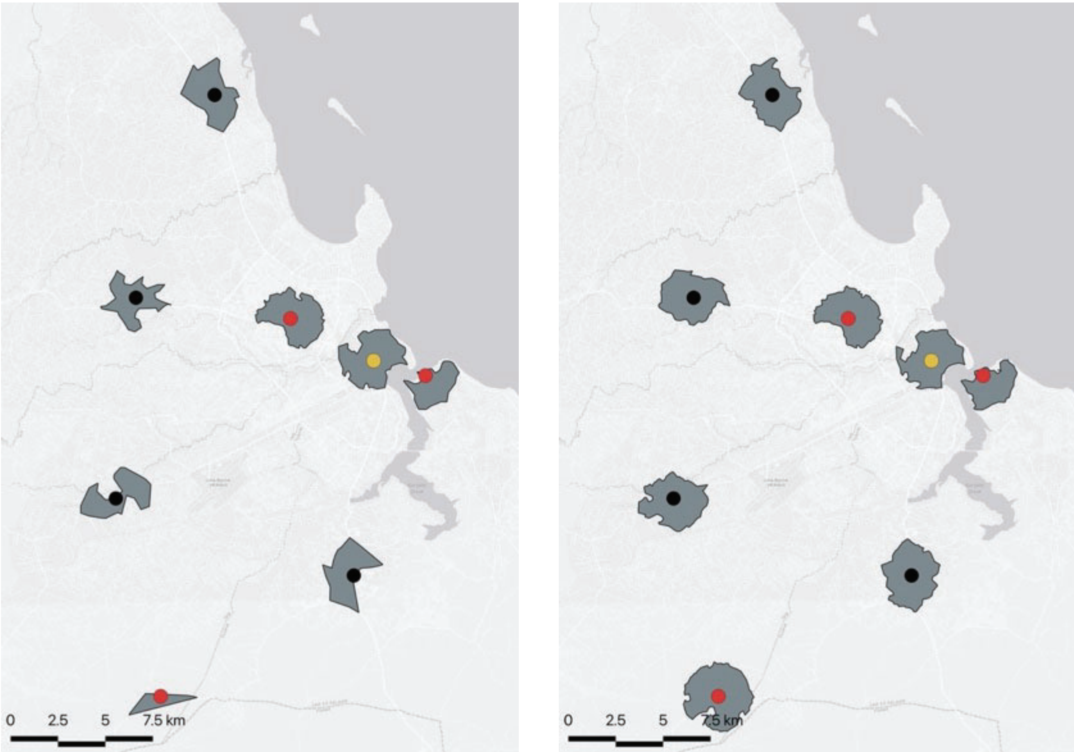

Fig. 0.8 2km network catchment areas from focus areas and anomalies, 1990 and 2020