Shining a light on Dar es Salaam - 1992 to 2020: utilizing nightlight intensity data as a tool for modelling rapid urban growth patterns

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***Abstract*—This paper utilizes remotely-sensed nightlight intensity (NLI) data to construct and evaluate a multi-temporal urban growth model for Dar es Salaam, Tanzania, between 1992 and 2020. This contributes towards the creation of effective, globally-available modelling and monitoring tools to support urban planners, policy-makers and communities in contexts of data-sparsity and rapid urban growth: a duality often found in the global south. Findings reveal that multi-temporal NLI models can offer new, systematic insights into patterns of urban growth at multiple intra-city scales. For instance, this NLI model identifies and tracks parts of the city which are likely to have experienced different patterns of spatial and/or socio-economic development between 1992 and 2020.**

Keywords—rapid urban growth, remote sensing, nightlight intensity, sustainability, Dar es Salaam

I. Introduction

It is estimated that around two-thirds of the world's population will be living in cities by 2050 [1]. Urban expansion is likely to be especially striking throughout the global south, where exposure to climate-related disasters and migration-inducing social unrest is often disproportionately high [2]. This is likely to have consequences on the environmental, social and economic sustainability of cities. Unfortunately, without sufficient quality and consistency of data, it becomes very difficult to model, monitor and guide urban changes. For this reason, data insufficiencies often lie at the heart of problems associated with rapid urban growth.

The United Nation's Sustainable Development Goals (SDGs) and Global Urban Monitoring Framework (GUMF) are examples of frameworks which offer invaluable tools and metrics to support the monitoring of rapid urban growth across diverse contexts. However, the quality and consistency of available data vary considerably within and across nations.

In Tanzania, methods are in place to measure 5 of 14 indicators and 4 of 10 targets for SDG 11: 'make cities and human settlements inclusive, safe, resilient and sustainable' [3] [4]. Input data largely come from censuses. Whilst these data provide a range of useful statistics, and create quite a promising baseline, they are distorted by enumeration area boundaries, and collection methods are often unreported and inconsistent [5]. Existing data are insufficient to comprehensively model and monitor urban change: this is an example of data-sparsity.

In Dar es Salaam (Fig. 1), growth over the past 30 years has been rapid and uneven, with densification – 'a progressive trend towards infill development' – and sprawl – 'unplanned and haphazard outward expansion of development from the urban centre' – occurring simultaneously, and often in proximity [6] [7].

This paper utilizes nightlight intensity (NLI) data to construct and evaluate a multi-temporal urban growth model for Dar es Salaam between 1992 and 2020. NLI data is analyzed, supported by the k-means clustering approach. Findings suggest that NLI can reveal rapid urban growth patterns which may otherwise remain unseen. Having said this, without additional datasets (for instance, on population density, street network accessibility, or vegetation), subtleties at the intra-city scale are limited, and interpretating the meaning behind observed or predicted growth patterns can be challenging.

II. Growth in Dar es Salaam

Dar es Salaam's urban growth patterns can be largely attributed to the settlement decisions of individuals, collectively forming and consolidating informal settlements, which comprise approximately 65-90% of Dar es Salaam [8] [9]. Based on the UN definition, informal settlements are 'residential areas [with]…no security…[which] lack, or are cut off from, basic services and city infrastructure…may not comply with current planning and building regulations, and [are]…often situated in geographically and environmentally hazardous areas' [10].

These informal settlements can be found across the city, often in proximity to key arterial routes and local (usually informal) sub-centers. In some areas, settlements have, and continue to, become increasingly dense, whilst in others, particularly in less central areas, settlements continue to sprawl [11]. Both densification and sprawl can have negative impacts on social, environmental and economic sustainability. For instance, densification puts increasing strain on existing infrastructure, such as water or electricity, whilst sprawl increases the urgency with which new infrastructure is needed.

The prevalence of informal settlements, as in much of the global south, is likely to be the result of insufficiencies within formal housing and employment markets, which reflect longer-term 'low institutional capacity[ies]' to fund and manage urban and social infrastructure, and affordable housing [12].

Thus, Dar es Salaam exemplifies a compounding problem associated with rapid urban growth in data-sparse conditions:

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in cities where monitoring urban growth patterns is the most challenging, the need to effectively do so is often greatest.

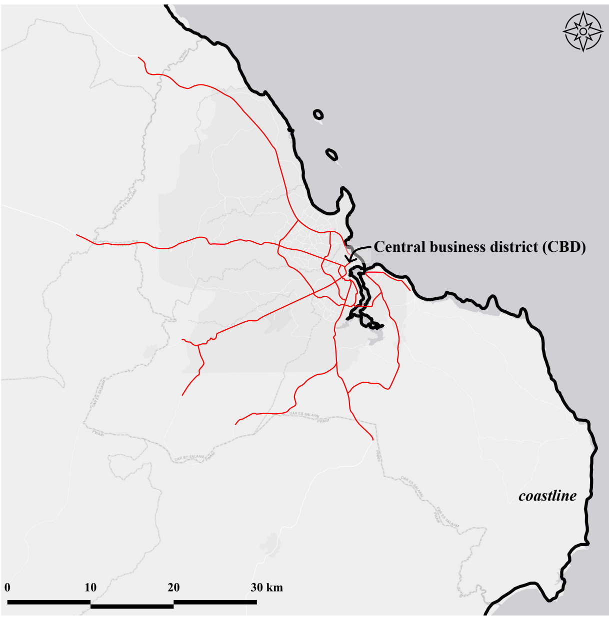

Fig. 1. Overview of Dar es Salaam, Tanzania. Key arterial routes shown in red. Source of coastline: Humanitarian Data Exchange [13].

III. Nightlight Intensity Data

NLI data is remotely-sensed and measured in digital numbers (DN) from 0 (no NLI detection) to 63 (maximum NLI detection) [14]. The data reveal night-time light emissions across the globe. The source of such emissions are manifold, from power plants to vehicles, commercial activity to people in their homes (when electricity is available). In the context of rapid urban growth, multi-temporal NLI can offer complete and temporally-consistent insights into actual patterns of urban change, revealing activity of some (unspecified) type, which could be useful for monitoring purposes. Having said this, interpretation of NLI data – that is, specifying the type of activity – is challenging, and requires theories of what NLI could suggest at different scales.

At the national and regional scale, NLI can act as a good proxy for gross domestic product (GDP), electrification rates and poverty rates [15] [16] [17]. NLI may even perform better than GDP given it can indicate and account for the 'magnitude of the informal economy' [18]. At the city scale, many studies find a strong relationship between NLI, rates of urbanization, and density [19] [20].

Fewer studies have explored the meaning of NLI at the intra-city scale, or at the scale of smaller spatially-consistent units (such as grid cells). In their 2018 study, Bruederle and Holder begin to fill this gap by synthesizing NLI data with demographic and health survey data for 29 African countries using two spatially-consistent units (circles around data hotspots and complete-coverage grid cells). They conclude that, at these local levels, NLI is a good proxy for development indicators such as wealth, education and health [21].

Thus, NLI can explicitly reveal actual patterns of activity. This is likely to be particularly beneficial in data-sparse conditions and/or contexts with notable informal/ undocumented commerce or residency, where existing knowledge of urban growth patterns is limited. However, it is likely to be very challenging to explain the specific causes and consequences of rapid urban growth using NLI data alone, given the association between NLI and many types of activities and metrics.

IV. Methodology

A. Data collection

NLI data 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 over 28 years were chosen in order to explore the effectiveness of NLI in a multi-temporal framework, whilst keeping time-costs and computational power low. In this paper, NLI data has been used from 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 [18].

For all four time periods, the 'stable lights average visibility' annual average NLI dataset was chosen – this compilation removes data distorted by cloud coverage, gas flares and other anomalies [22]. 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 1992 to 2020.

B. Data processing

The downloaded NLI data exists in global .tif files. Each file was cropped from the global layer to a 100km radius around the center of Dar es Salaam, vectorized and re-projected (to WGS84 UTM zone 37S – EPSG:32737). 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) were intercalibrated using a calibration matrix from Elvidge et al. [22]. This is necessary to control for different levels of NLI distortion across different satellites.

C. Data analysis

This dataset was visually and statistically explored to model citywide urban growth patterns. K-means clustering analysis was adopted to identify clusters based on NLI values of each 900m^2 grid cell in 1992, 2000, 2015 and 2020. The elbow method was used to choose to divide the data into 5 clusters. These clusters offer a mechanism to examine intra-city variation of NLI over time, and identify parts of the city which may be experiencing different types and rates of development (such as densification or sprawl).

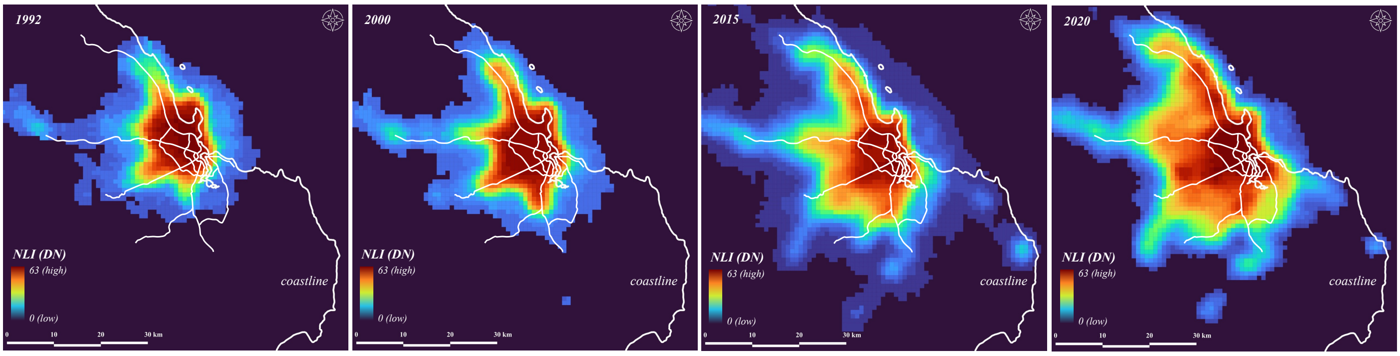

Fig. 2. Nightlight intensity (NLI) in 1992, 2000, 2015 and 2020.

V. Results

Fig. 2 shows NLI across Dar es Salaam in 1992, 2000, 2015 and 2020. From 1992 to 2000, NLI expands in a star-like pattern from the CBD; the central core maintains high NLI, and increases mainly occur along key radial routes. From 2000 to 2015, NLI continues to increase along key radial routes. NLI also increases between these routes (infill), particularly to the southwest of the CBD. These changes could reflect patterns of urban sprawl, densification along key routes, and/or increases in electrification rates. From 2015 to 2020, the processes of increasing NLI in both radial and infill locations continue, with a particular increase in NLI in infill locations to the northwest of the CBD. Within the central core – an area of approximately 10km around the CBD – NLI remains high from 1992 to 2020. In 1992 and 2000, taking data from older satellite sensors, uniformly high NLI is likely to be a consequence of light saturation [17]. In 2015, it is easier to spot particular hotspots of high NLI within the central area, suggesting that newer satellites have the potential to reveal more nuance in NLI. In 2020, NLI is, once again, uniformly high. This is likely to be due to greater NLI in 2020 relative to 2015, as opposed to light saturation, as is the case for earlier periods of analysis.

Fig. 3 maps the 5 clusters derived from k-means clustering analysis. These clusters have a strong spatial correspondence to observed NLI changes from 1992 to 2020. Fig. 4 tracks average NLI over time within the 5 clusters, and plots NLI in the CBD alongside a sample of local informal centers: Tandale, Rangitatu and Msongola [11]. This reveals the persistence of high NLI within cluster 1, the core of Dar es Salaam. Despite significant socio-economic differences between Tandale (a very dense, centrally-located informal settlement) and the CBD, NLI is almost identical in both areas. This exemplifies the lack of nuance in NLI data at this unit of analysis (900m^2 grid cells), particularly in central locations. Areas in cluster 2 (such as Rangitatu) have experienced two uplifts in NLI, with relative stability in NLI between 2000 and 2015. The 1992-2000 uplift could reflect urban expansion and electrification, whilst the 2015-2020 uplift is more likely to reflect densification, given the relatively central position of the cluster within Dar es Salaam by this time. Areas in cluster 3 experience increasing NLI over time, which is likely to reflect both spatial and socio-economic development. Cluster 4 encompasses areas on the urban-rural fringe of the city, such as Msongola. Cluster 5 encompasses rural surroundings.

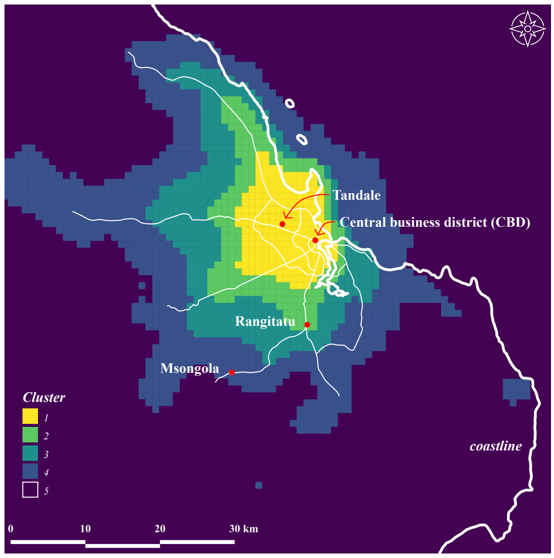

Fig. 3. Mapping of clusters from k-means clustering analysis. Location of central business district (CBD) and a sample of local informal centers (Tandale, Rangitatu and Msongola) are shown.

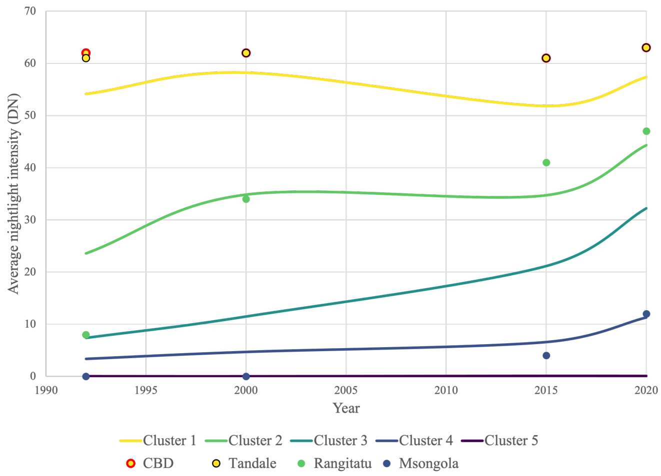

Fig. 4. Average nightlight intensity (NLI) across Dar es Salaam between 1992 and 2020. Lines represent average NLI of all cells per cluster (1 to 5) between 1992 and 2020. Points represent NLI for the central business district (CBD) and a sample of local informal centers (Tandale, Rangitatu and Msongola) between 1992 and 2020. Note that NLI for the CBD and Tandale is identical in 2000, 2015 and 2020, hence the overlap of points.

VI. Limitations

This analysis supports the use of NLI for modelling rapid urban growth patterns: it enables a spatially and temporally consistent view of activity across the city. However, the main limitation of NLI data in this context is, arguably, its ambiguity. It is challenging to draw meaning from NLI without additional data. For instance, increases in NLI in less central areas could reflect urban expansion and/or increases in electrification rates within existing parts of the city – most likely a mix of both. Whilst both interpretations offer insights into urban growth patterns, they are, alone, inconclusive.

VII. Conclusion

Overall, utilizing NLI as a tool for modelling rapid urban growth patterns seems to be a worthwhile endeavor, offering new insights into real activity across cities, in this case, Dar es Salaam, and enabling high-level monitoring of urban changes. This is particularly useful in data-sparse contexts, where completeness and accuracy of existing data is limited. In such contexts, modelling and monitoring rapid urban growth patterns is crucial in order to implement effective urban plans and policies, and help enable more sustainable development. Having said this, NLI-based models would significantly benefit from synthesis with alternative remotely-sensed and/or open-source data, which could be adopted in any data-sparse context. Doing so would a) help to validate and offer comparisons for NLI data, increasing the robustness of the NLI-based approach, and b) enable the creation of multi-variable models, increasing the subtlety and accuracy with which rapid urban growth patterns can be monitored. First, linking NLI with spatially-consistent estimates of population density (see the Global Human Settlement Layer – data since 1975), could help to alleviate some of the ambiguity in interpreting NLI data e.g. low NLI in a densely-populated area could signal low electrification rates and/ or informal growth [23]. Second, models of street networks could be incorporated to analyze spatial accessibility, revealing, for instance, the vibrant foreground and quieter background parts of cities [24], which likely contribute to, and are a consequence of, rapid urban growth patterns. Third, Landsat satellite data (data since 1972) could be incorporated to monitor crucial environmental changes related to rapid urban growth, such as the urban heat island effect, or biodiversity loss [25]. These approaches would help to alleviate data insufficiencies and equalize access to data-driven solutions for problems associated with rapid urban growth. This is an essential step towards creating more sustainable and equitable growth in cities.

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