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Mapping urban night lights at a fine spatial resolution: downscaling VIIRS using geographically weighted area-to-point regression Kriging

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Abstract:

In order to extract useful geospatial information, cartographers are constantly challenged to respond to new sources and types of spatial data, such as satellite remote sensing imagery. Many different satellite remote sensing systems monitor the surface of the Earth, but only a small number of them are suitable for mapping or are even specifically made to record human activity, which is closely related to socioeconomic activities. Remote sensing observations of night-time light (NTL) give us a timely and spatially precise measure of human activity, enabling a wide range of applications at the global or national level. The use of NTL data for socioeconomic measurement is predicated on the notion that areas with brighter lights are probably more prosperous economically than areas with dimmer lights. (Henderson et al. 2016).

While at the global scale, night lights from Visible Infrared Imaging Radiometer Suite (VIIRS) were found as a useful proxy for socioeconomic activities, such analyses are yet to be undertaken at finer level due to restriction of the spatial resolution of the sensor (~460m) (Levin et al. 2014). Therefore, higher spatial resolution night-time imagery is required to examine socioeconomic phenomena within cities and to comprehend local-scale urban dynamics.

A feasible solution to the problem of enhancing the spatial resolution of NTL and thus, provide a more accurate night-time light source for mapping, is spatial downscaling. Downscaling refers to reducing the pixel size (i.e., increasing the spatial resolution) of remotely sensed images in the context of remote sensing (Wang, et al. 2016). Increasing the spatial resolution in remote sensing, just as with increasing the number of sample points within the same spatial area, leads to the potential for more information and detail, despite "full coverage" at the measurement resolution(s). Area-to-Point Regression Kriging (ATPRK) is one of the most extensively used spatial downscaling techniques (Wang et al. 2016). ATPRK, and its variants in the regression part of the method, has been used, mainly, to enhance the spatial resolution of multispectral data (Wang et al. 2016; Jin et al. 2018). Attempts to spatially downscale NTL data are rare; in fact, only the work of Ye et al., (2021) exists to date. To address this research gap, this paper proposes a new framework for downscaling VIIRS NTL data to a fine spatial resolution of 100 m motivated because a plethora of fine-scale applications, such as city-scale applications, are possible, but only with this spatial resolution. To the best of the authors' knowledge, no previous study has used Geographically Weighted Area-to-Point Regression Kriging (GWATPRK) to disaggregate NTL data.

In this research, only open-source spatial data were utilised, including Suomi-NPP VIIRS (variable to be downscaled) and Landsat 8 product (covariate). The area of interest was New Delhi, India's most densely populated metropolis with about 10,400 people per square kilometre living in an area of 1,483 km^2 (Bhanarkar et al. 2018). Improved geographic information regarding the spatial distribution of the downscaled urban lights using GWATPRK in New Delhi is made possible thanks to the design and cartography used in Figure 1's map. To emphasise the geographic distribution of areas with more and less light, the city's administrative boundaries (districts) were included on the map. A data classification approach has been used for the cartographic visualisation of the night-time lights. Before displaying the data, it is best to arrange it logically by classifying the data, or aggregating it (Kraak and Ormeling 2010). Head/tail breaks classification scheme is specifically designed for data which exhibit a heavy-tailed distribution (Jiang 2013). In this study, the head/tails classification adopted because the distribution of lights is heavily tailed. Night light data from the downscaled VIIRS was broken down into 7 categories of light. The symbology of these categories are lighter and darker yellows to indicate the presence of light. Categories 4, 5, 6 and 7 offered suitable darkness with category 7 being the darkest. A light to dark grey scale represents the darkness levels. Using the heads/tails classification method, the brightest areas are separated from the rest and this is an indicator of wealth and those lit geographic locations are in line

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with the research of Telle et al. (2021) where they mapped the most prosperous locations in New Delhi based on economic indicators.

A recent geostatistical approach, GWATPRK, was applied to disaggregate NTL images for the first time. To demonstrate the performance of the proposed downscaling prediction, two benchmark approaches, GWR and Machine Learning with Splines from the regression and hybrid-based downscaling families, were used to compare with GWATPRK. With an RMSE of 7.18, an MSE of 50.65, and a Pearson's correlation of 0.94, the GWATPRK model predicted more accurately than the GWR and Machine Learning with Splines models, when downscaling conducted at 1600 m spatial resolution (Table 1). At the 100 m spatial resolution, GWATPRK achieved perfect coherence with the original NTL data, that is, the downscaled result is identical to the original image when upscaled (Table 2).

The following is a summary of the findings. (1) GWATPRK outperformed the two benchmark algorithms, indicating its value in spatial downscaling NTL data and improving the geographic information interpretation. (2) In contrast to the benchmarks, GWATPRK achieved complete coherence with the original coarse data. (3) Because of its non-stationary character, the GWATPRK technique is ideal when the covariates are insufficient to explain the variation observed (i.e., there are missing variables).

The final downscaled NTL image is shown in Figure (1).

GWATPRK			GWR			Splines		
RMSE	**MSE**	**PCC**	**RMSE**	**MSE**	**PCC**	**RMSE**	**MSE**	**PCC**
7.18	**50.65**	**0.94**	8.81	76.72	0.91	9.08	82.44	0.91

Table 1: Quantitative assessment of the downscaling methods at 460m (reference is the original NTL)

Pearson's Correlation Coefficient		
GWATPRK	**GWR**	**Splines**
0.99	0.98	0.98

Table 2: Coherence results through PCC

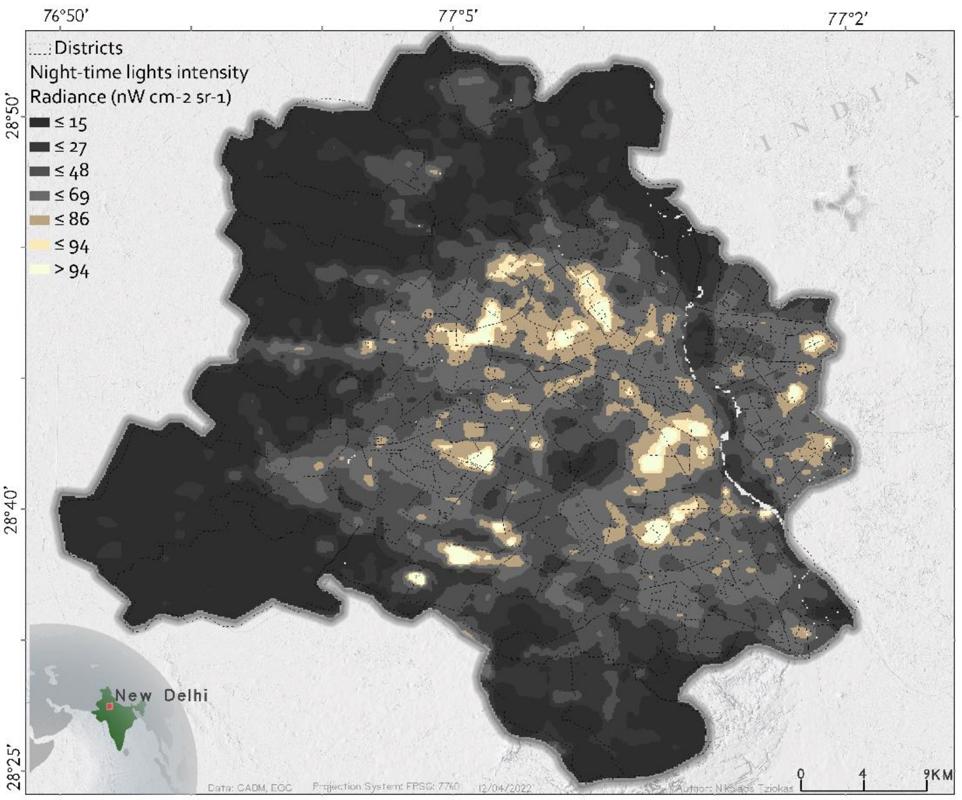

Figure 1: Map of night-time lights of New Delhi for March 2016, with a spatial resolution of 100 m. The map shows the night-time lights after disaggregating the raw VIIRS image using GWATPRK.

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