Trend Estimation of Child Nutrition Indicators at Micro-Level Administrative Units Using Night-Time Light Data

Sumonkanti Das[1], Bernard Baffour[1], Syed Abul Basher[2], Alice Richardson[3], Salim Rashid[4]

[1] School of Demography, Australian National University, Australia
[2] Department of Economics, East West University, Bangladesh
[3] Statistical Support Network, Australian National University, Australia
[4] Center for Urban Studies and Sustainable Development, East West University, Bangladesh

October 30, 2023

Extended Abstract

In this study, we apply a multilevel time-series modelling extension of small area estimation to estimate stunting trends for disaggregated domains over the period from 1997 to 2018. This analysis utilizes seven rounds of Demographic and Health Survey data and three Bangladesh Population and Housing censuses conducted within this period. The multilevel time-series models under consideration leverage strength by accounting for cross-sectional, temporal, and spatial correlations (Boonstra and van den Brakel, 2019; Boonstra et al., 2021). Furthermore, these models are designed in a way that allows for the interpolation of stunting levels for non-survey years. To enhance the direct survey-based estimates of stunting, our models incorporate spatially detailed nighttime light data. Satellite-detected nighttime light data are increasingly being used by researchers to measure localized economic activity in regions where traditional data, such as GDP or GNP, are either unavailable or untrustworthy. In such areas, the poor quality of data presents significant challenges in understanding economic growth, poverty, and the measurement of sustainable development, particularly at the subnational level. Numerous papers in applied economics have explored this topic, with the pioneering study by Sutton and Costanza (2002) demonstrating that the amount of light energy emitted (per square km) by a nation was highly correlated with its GDP. Since then, the use of nighttime light data has expanded into other disciplines, including health inequality (Ebener et al., 2005), ethnicity (Alesina et al., 2016), well-being (Ghosh et al., 2013), natural disaster management (Fabian et al., 2019), and studies on the Covid-19 pandemic (Elvidge et al., 2020). A key advantage of nighttime lights data is that they offer a unique dataset related to human activity, available for most of the globe at a very high resolution (Chen and Nordhaus, 2011). Numerous studies have employed nighttime light intensity data as a reliable proxy measure for economic activity (Henderson et al., 2012), economic development, urbanization, or income disparity (Weidmann and Theunissen, 2021) across various spatial and temporal scales (Levin and Duke, 2012). Key advantages of nighttime light data as a proxy for economic or development measures include their free availability, automatic daily collection, and the ability to easily derive aggregated values in a repeatable and consistent manner (Elvidge et al., 2012). Nighttime light data are particularly valuable for analyses at a subnational scale where the availability of economic data is often inconsistent (Basher et al., 2022).

While nighttime light intensity data are now commonly used as a proxy for analyses of economic

activity or urbanization, studies that extend this approach to predict child health outcomes have only recently emerged. Amare et al. (Amare et al., 2020) and Ameye and De Weerdt (Ameye and De Weerdt, 2020) demonstrated that nighttime light intensity can be used to predict child nutrition outcomes in East Africa. They noted that urbanization is generally positively correlated with child nutrition outcomes in developing countries. Urbanization may support better child nutrition outcomes due to an enhanced diversity of nutrition and access to markets, improved access to nutritional education, and the availability of health facilities, public infrastructure, and technology (Amare et al., 2020).

In numerous studies, environmental indicators such as the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), aridity (average monthly precipitation / average monthly Potential Evapotranspiration), and rainfall (precipitation) have been used to predict child malnutrition at country, regional, and grid cell levels (Du et al., 2013; Brown et al., 2014; Osgood-Zimmerman et al., 2018; Shaw et al., 2020; Seiler et al., 2021). Several studies have reviewed available remotely sensed and modeled data that could be linked to human health and nutrition (Brown et al., 2014; Seiler et al., 2021). Johnson et al. Johnson et al. (2013) used the Vegetation Continuous Fields (VCF) product (Hansen et al., 2003) to identify the association of forest cover with improved child health and nutrition in Malawi. Shaw et al. Shaw et al. (2020) provided evidence of child undernutrition attributable to drought conditions by examining the association of these conditions with under-5 child malnutrition (showing negative spatial autocorrelation) across districts in India.

In this study, the Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Precipitation Condition Index (PCI) have been extracted from multi-source remote sensing data and used as climatic or environmental indicator variables to account for climate change information over the considered reference period of about two decades. Following Du et al. Du et al. (2013), these three-dimensional climatic variables are combined into one index through Principal Component Analysis and referred to as the Synthesized Drought Index (SDI), which is then utilized in the multilevel model. Population density grids (number of people per km^2), available every five years (2000, 2005, 2015, 2020), have been utilized by Osgood-Zimmerman et al. (Osgood-Zimmerman et al., 2018) for estimating stunting, underweight, and wasting prevalence in five-year intervals. However, as this study aims to estimate stunting prevalence at an annual frequency, remote-sensed data available at space and time have been used in this study.

The inclusion of remotely sensed information in the trend prediction analysis of stunting is motivated by their increased availability and recent studies that highlight the importance of variables related to climate, environment, and socio-economic conditions, for which remotely sensed data products exist.

The main objectives of this study are twofold. Firstly, we provide model-based estimates of stunting at the second (64 districts) and third (544 sub-districts) administrative hierarchy levels in Bangladesh for the period of 2000-2018. Secondly, we examine how remote-sensed data, reflecting changes in socio-economic conditions and climate change at local levels over the last two decades, can aid in estimating trends of stunting prevalence when information on the target variable is too sparse over time and space. These two objectives aim to be achieved by developing a Bayesian multilevel time-series model of stunting at the sub-district level in Bangladesh.

The developed model utilizes temporal strength over time, spatial strength over a geographical area, and accounts for unobserved differences (heterogeneity) in stunting over time and space. To exploit temporal strength, we define smooth or local level trends at various aggregation levels, such as sub-district, district, and division, in addition to linear time trends via night-time light score. Spatial strength is incorporated by including spatial effects of neighbouring districts and sub-districts in the area-level models at district and sub-district levels, respectively. Spatial effects are considered only at the detailed level to avoid double smoothing of estimates. Cross-sectional correlation is accounted for by incorporating fixed effects of division and night-time light, random effects of the intercept at the domain level, and correlated random effects of children's age group varying over districts and divisions.

Furthermore, an overall or age-specific smooth trend at the division level is defined for the detailed level domains belonging to the same division to exploit spatio-temporal strength. The incorporation of such temporal and spatio-temporal components allows for a more robust multilevel time-series model to predict the trends of stunting at the considered detailed level domains. We interpolate the stunting levels in non-survey years from the model output to estimate trends in stunting for the target small domains. Subsequently, we obtain trends at higher aggregation levels (such as national and division levels) through aggregation of the detailed level predictions. The comparison of the estimated higher aggregation level trends with the corresponding survey-weighted direct estimates provides evidence of consistency for the detailed level estimates. We have investigated a number of model diagnostics to evaluate the fitted models and the corresponding trends at various aggregation levels. The estimated trends are useful in identifying districts that remain over the threshold of "very high" prevalence at the end of the considered time period. The novel contributions of this study to the malnutrition literature include (i) developing a spatio-temporal model at the administrative level 3 in Bangladesh, a level at which approximately half of the domains are not covered in the survey, and (ii) predicting the stunting prevalence for non-survey time points by accounting for the relationship between remote-sensed data and the outcome variables, in addition to underlying spatial and temporal relationships.

Keywords: MCMC simulation, Multilevel time series model, Small area estimation, Remote-sensed data, Stunting.

References

Alesina, A., S. Michalopoulos, and E. Papaioannou (2016). Ethnic inequality. *Journal of Political Economy 124*(2), 428–488.

Amare, M., C. Arndt, K. A. Abay, and T. Benson (2020). Urbanization and child nutritional outcomes. *The World Bank Economic Review 34*(1), 63–74.

Ameye, H. and J. De Weerdt (2020). Child health across the rural–urban spectrum. *World Development 130*, 104950.

Basher, S. A., J. Behtarin, and S. Rashid (2022). Convergence across subnational regions of Bangladesh–what the night lights data say? *World Development Sustainability 1*, 100001.

Boonstra, H. J. and J. van den Brakel (2019). Estimation of level and change for unemployment using multilevel and structural time-series models. *Survey Methodology 45*(3), 395–425.

Boonstra, H. J., J. van den Brakel, and S. Das (2021). Multilevel time-series modeling of mobility trends in the Netherlands for small domains. *Journal of the Royal Statistical Society: Series A 184*(3), 985–1007.

Brown, M. E., K. Grace, G. Shively, K. B. Johnson, and M. Carroll (2014). Using satellite remote sensing and household survey data to assess human health and nutrition response to environmental change. *Population and environment 36*(1), 48–72.

Chen, X. and W. D. Nordhaus (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences 108*(21), 8589–8594.

Du, L., Q. Tian, T. Yu, Q. Meng, T. Jancso, P. Udvardy, and Y. Huang (2013). A comprehensive drought monitoring method integrating modis and trmm data. *International Journal of Applied Earth Observation and Geoinformation 23*, 245–253.

Ebener, S., C. Murray, A. Tandon, and C. C. Elvidge (2005). From wealth to health: modelling the distribution of income per capita at the sub-national level using night-time light imagery. *international Journal of health geographics 4*(1), 1–17.

Elvidge, C. D., K. E. Baugh, S. J. Anderson, P. C. Sutton, and T. Ghosh (2012). The night light development index (nldi): a spatially explicit measure of human development from satellite data. *Social Geography 7*(1), 23–35.

Elvidge, C. D., T. Ghosh, F.-C. Hsu, M. Zhizhin, and M. Bazilian (2020). The dimming of lights in china during the covid-19 pandemic. *Remote Sensing 12*(17), 2851.

Fabian, M., C. Lessmann, and T. Sofke (2019). Natural disasters and regional development–the case of earthquakes. *Environment and Development Economics 24*(5), 479–505.

Ghosh, T., S. J. Anderson, C. D. Elvidge, and P. C. Sutton (2013). Using nighttime satellite imagery as a proxy measure of human well-being. *sustainability 5*(12), 4988–5019.

Hansen, M., R. DeFries, J. Townshend, M. Carroll, C. Dimiceli, and R. Sohlberg (2003). Global percent tree cover at a spatial resolution of 500 meters: First results of the modis vegetation continuous fields algorithm. *Earth Interactions 7*(10), 1–15.

Henderson, J. V., A. Storeygard, and D. N. Weil (2012). Measuring economic growth from outer space. *American economic review 102*(2), 994–1028.

Johnson, K. B., A. Jacob, and M. E. Brown (2013). Forest cover associated with improved child health and nutrition: evidence from the malawi demographic and health survey and satellite data. *Global Health: Science and Practice 1*(2), 237–248.

Levin, N. and Y. Duke (2012). High spatial resolution night-time light images for demographic and socio-economic studies. *Remote Sensing of Environment 119*, 1–10.

Osgood-Zimmerman, A., A. I. Millear, R. W. Stubbs, C. Shields, B. V. Pickering, L. Earl, N. Graetz, D. K. Kinyoki, S. E. Ray, S. Bhatt, et al. (2018). Mapping child growth failure in Africa between 2000 and 2015. *Nature 555*(7694), 41–47.

Seiler, J., K. Harttgen, T. Kneib, and S. Lang (2021). Modelling children's anthropometric status using Bayesian distributional regression merging socio-economic and remote sensed data from South Asia and sub-Saharan Africa. *Economics & Human Biology 40*, 100950.

Shaw, S., J. Khan, and B. Paswan (2020). Spatial modeling of child malnutrition attributable to drought in india. *International Journal of Public Health 65*, 281–290.

Sutton, P. C. and R. Costanza (2002). Global estimates of market and non-market values derived from nighttime satellite imagery, land cover, and ecosystem service valuation. *Ecological Economics 41*(3), 509–527.

Weidmann, N. B. and G. Theunissen (2021). Estimating local inequality from nighttime lights. *Remote Sensing 13*(22), 4624.