Urban Infrastructure Inequalities in India

December 15, 2018

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Abstract

The present study examines (1) the capability of VIIRS NTLs to explain urban infrastructure access variations as observed from census data and (2) urban infrastructure inequalities in India. In the absence of detailed household-level infrastructure access and amenities data, we compiled a spatial database of ward-level household infrastructure access and amenities data that could be used to study multi-scalar infrastructure inequalities in association with other spatially explicit database. In addition, we applied a time series analysis algorithm to VIIRS time series data that summarizes the variation into four components: (1) intercept, (2) long-term trend, (3) phase, and (4) amplitude, which could be used to study the time series signal. In the present study, we analyzed the intercept term to understand how well VIIRS NTLs capture urban infrastructure access variations. We find that NTLs are limited in explaining infrastructure access variations across scales and that there is a nonlinear relationship between the two. Our results also show that infrastructure access/amenity levels follow a Kuznets-type relationship, which is consistent with a Bernoulli's process. In addition, our results show highest level of inequalities in the case of access to sewer system and lowest in the case of access to electricity. We show that these patterns in inequality could be linked to urbanization but there are significant inter-urban inequalities in case of fully urbanized regions, which are related to urban size. These patterns are indicative of a combined spatial and hierarchical diffusion process that will be examined in future research.

Contents

Introduction

A population of size roughly seven times the current population of US is expected to be added to urban areas globally, by the middle of the current century (United Nations, 2014). This increase in the share of population living in urban areas will occur mostly in Asia and sub-Saharan Africa. Considering the many benefits of urbanization, this ongoing and impending demographic change may accompany opportunities for socio-economic development (Glaeser, 2011; UN Habitat, 2013). Urban agglomerations bring positive socio-economic outcomes through providing higher access to infrastructure. In fact, previous research shows that level of infrastructure scale sub-linearly with urban (population) size whereas level of infrastructure access scale linearly (Bettencourt et al., 2007). One may infer from this that infrastructure is a necessary condition for urban centers and that there is economy of scale in infrastructure provisioning vis-à-vis urbanization levels. Importantly, the built urban environment brings positive not just socio-economic but also human health outcomes (Bettencourt and West, 2010; Dye, 2008).

Conversely, the ongoing and future urbanization poses significant multi-dimensional and multi-scalar sustainability challenges, including as an environmental change driver (Grimm et al., 2008; Seto et al., 2017). Our symmetric conceptualization of urbanization, however, undermines inequalities in the urban system that are often manifest across spatial scales and neglects the uncertainties in future urbanization scenarios and realizations. The "*science of inequality*" has made significant recent advances such that the nature and dynamics of economic inequality are well known and characterized (Chin and Culotta, 2014). Similar efforts to unravel multi-dimensional and multi-scalar urban inequalities are lacking (Sampson, 2017).

Besides being one of the sources of uncertainties, there are serious implications of this knowledge gap. First, several of the global change and sustainability concerns about urban areas cannot be rationally addressed with the knowledge gap. This is because underlying urban inequalities confounds extent of the problems due to distributional effects (Brelsford et al., 2017; Sampson, 2017). Second, without an understanding of the nature and dynamics of urban inequalities, urban-centered policies that are intended to mend existing inequalities cannot be rationalized. Third, reduction in inequalities forms a useful indicator of progress towards sustainable development (United Nations, 2016). Still, a lack of insight into urban inequalities thwarts a scientific assessment of sustainable urban development.

In developing countries, inequalities across multiple urban dimensions are still poorly understood, especially across scales. One such dimension is infrastructure access, which is important for several reasons. First, infrastructure access can potentially lock-in inequalities in socio-economic outcomes (Bettencourt, 2013; Calderón and Servén, 2014). Second, infrastructure access inequality is highly relevant for urban public policy in making effective interventions (Wellman and Spiller, 2012). *Third*, infrastructure access inequality is often argued to make communities differentially vulnerable to external shocks including, climate change impacts, in several ways (United Nations, 2016). Overall, understanding urban infrastructure inequalities has merits extending to all the sustainability dimensions.

A chief reason for our lack of understanding of urban infrastructure access inequality in developing countries is data scarcity at the urban scale (Acuto and Parnell, 2016; Brelsford et al., 2017; Florida, 2017; Glaeser and Henderson, 2017; Pandey et al., 2016). National surveys in these countries are often comprehensive but lack the required granularity and temporal frequency to study urban variability as well as the rapidity of contemporary urbanization. New analytical lenses are subsequently required to understand urban infrastructure inequalities vis-à-vis urbanization (Brelsford et al., 2017)**.** Previous research has demonstrated the potential of using remotely-sensed nighttime lights (NTL) to uncover human development dimensions (Elvidge et al., 2012; Pandey et al., 2016; Zhang et al., 2013). Due to significant shortcomings in the data and failure of subsequent efforts to improve the data quality (Pandey et al., 2017), a more recent NTL product generated using data from Visible Infrared Imaging Radiometer Suite (VIIRS) sensor stands as an alternative. It promises to fill this data gap and advance our scientific understanding of the nature and dynamics of urban inequalities—particularly urban infrastructure access (Román et al., 2018). However, no study till date has characterized and measured urban infrastructure access using this new product. Therefore, this paper investigates the utility of using VIIRS NTL to study urban infrastructure access in India, a rapidly urbanizing country (Pandey et al., 2013), and inequalities therein. This research examines two specific research questions and are geared towards understanding urban infrastructural inequalities:

Question 1: How well does VIIRS-derived nighttime lights product explain urban infrastructure access variations as observed in census and other survey datasets?

Question 2: How do urban inequalities, in the form of infrastructure access differentials, vary within and between urban areas?

Methods

Data

In the present study, we use two sets of data sources: (1) Census Data and (2) VIIRS nighttime light images. We use census data to measure the level of infrastructure access at the household level. However, we found from our field visit that a spatially-detailed dataset for across the country is not available for public consumption. As an alternative, we compiled our own version of a spatialized dataset by combining a non-spatial dataset on household access to infrastructure amenities, available online from the census website at the ward/village level (http://www.censusindia.gov.in/2011census/HLO/HL_PCA/Houselisting-housing-HLPCA.html), with a spatial dataset containing census demographic attributes, available from the Yale library (InfoMap (Firm), n.d.). We first manually cleaned the data tables on household amenities for programmatic access. Next, we created a PostgreSQL database and using census codes combined the spatial dataset to generate a household infrastructural amenities data at the sub-district level (Figure S1). Here, we focused on six basic infrastructural amenities: (1) Access to electricity, (2) Access to liquefied petroleum gas (LPG), (3) Access to treated water, (4) Water provisioning in house premises, (5) Access to piped sewer, and (6) Waste water outlet to a closed drainage. For the purpose of the present study, we use the standard census definitions for the aforementioned amenities.

Next, we use VIIRS VNP46 daily time series images from 2012 to 2017 that have been corrected for atmospheric, terrain, snow, vegetation, lunar, and stray-light radiances. Due to the absence of high-quality images for a few dates, we interpolated the missing observations by applying a moving average filter on a per-pixel basis.

Time series analysis of VIIRS nighttime light images

We use daily VIIRS NTLs from (Román et al., 2018), over a period of five years (from 2012 to 2017) and fit an additive decomposition model to VIIRS NTL time series with a linearized single-term harmonic component to capture seasonality (Equation 1). We use a least-squares optimization algorithm to estimate model parameters by applying quality flags (Equation 1). We estimated the model parameters at the pixel level using Yale's high performance computing (HPC) environment.

$$f(t) = \mathrm{a} + \left(a_1\, Sin\left[\frac{2\pi t}{365.25}\right]\right) + \left(a_2\, Cos\left[\frac{2\pi t}{365.25}\right]\right) + mt + \varepsilon \tag{1}$$

where, a is the intercept, $a_1$and a_2 specifies intra-annual change, m is the linear inter-annual change, and ε is the residual term. Such time-series model specification has been applied to daytime remotely-sensed data (Pandey et al., 2018). In the present study, we use the intercept term (a) and the slope term (m) to understand the static and dynamic components of VIIRS NTLs, respectively. In other words, we focus on the modelled initial conditions and long term trend. Using a commonly-used sum of lights metric, we analyzed if the total NTLs radiance using the intercept (a) image (at the given spatial scale) can predict variations in level of infrastructure access (Elvidge et al., 2014). Here we corrected for the negative offset (negative intercept values) by rescaling the data for a lower bound of zero. Next, we subject the rescaled image to an unsupervised clustering algorithm with an objective to examine if varied NTL intensity levels captures infrastructure access and amenities variation in the census data (Memarsadeghi et al., 2007). We combined the initially obtained 17 clusters into four intensity classes by examining the mean and standard deviation values of the cluster: (1) very low, (2) low, (3) high, and (4) very high.

Inequality Measurement

Due to some of the limitations of the commonly used Gini coefficient (Cowell, 2011), we estimate the level of inequalities using an entropy-based measure (Equation 2).

$$T = \sum_{i=1}^{n}\left(\frac{y_i}{\sum_{i=1}^{n} y_i} \ln\left\{N\, \frac{y_i}{\sum_{i=1}^{n} y_i}\right\}\right) \tag{2}$$

Where T is Theil's index, n is the total number of observations, and y_i is the infrastructure access level for i^{th} observation. We use the *pysal* python package to derive within and between group inequalities (Rey and Anselin, 2010).

Results and Discussion

Predicting Infrastructure Access using NTLs

At the state level, our results show that sum of NTLs radiance are correlated with the level of infrastructure access. As expected, we find that the relationship was strongest in the case of electricity access and weakest in the case of access to sewer system (Table S1). On the other hand, we find that average NTL radiance is not correlated with the proportion of households with infrastructure access, with the exception of observed correlation with access to drainage and sewer system (Table S2). These two findings suggest that the relationship between NTLs and infrastructure could be due to a common variable with which both variables are potentially correlated including, population size, number of households, and population density. Nevertheless, the relationship between total NTLs radiance and number of households with infrastructure access suggest that NTLs could proxy for level of infrastructure access at the state-level.

Next, we analyze if total NTL radiance from different groups of NTLs intensities (very low, low, high, and very high) explain variations in infrastructural access levels. We find that variation in very low NTLs radiance between states does not explain the variation in infrastructural access (Table S3). Additionally, we find no stark differences in the correlations between NTL radiance groups but in general we observe that high and very high NTL radiance across states is more correlated with infrastructure access than low NTL radiance. This supports that fact that the basic infrastructural amenities considered in this study are concentrated in dense, brightly lit urban areas.

At the district level, we find that sum of NTL radiance was not correlated with the level of infrastructure access. Our results show that for five of the six infrastructural amenities considered there was weak or no statistically significant correlation. Particularly, in the case of Electricity (ρ = 0.23), LPG (ρ = 0.11), and Treated Water (ρ = 0.17), there was a weak correlation whereas for the remainder of the amenities the correlations were statistically insignificant (p-value > 0.01). However, in our analysis where we correlated the sum of NTL radiance from different groups of NTL intensities, we find that the sum of lights from very bright centers captured some of the variation in infrastructure access across districts (Table S4). Additionally, we find a weak linear relationship between satellite measurements and the level of access to infrastructure and amenities (Figure S2). From this finding, we infer that machine learning methods may be more suitable to predict infrastructure access using nighttime lights especially at finer spatial scales.

Infrastructure Access Inequalities

Our analysis of census data at the sub-district level revealed general patterns in the trajectories of changes in infrastructure access and amenities. We find that heterogeneities in infrastructure access levels follow a Kuznets-type relationship (Figure S3a and b). This observation is consistent with a recent study that conducted a similar analysis in Brazil and South Africa (Brelsford et al., 2017). The non-constant variance observed here is a property of a Bernoulli's process such that the standard deviation is $\sqrt{p(1-p)}$ where p is the mean. Additionally, we find that the level of infrastructure access is highest in case of access to electricity whereas lowest in the case of sewer system (Figure S3c).

Our inequality measurement using an entropy-based measure (Theil's Index), on the other hand, suggests highest level of inequalities in the case of sewer system and lowest in the case of access to electricity (Table S5). Lower levels of inequality in the case of access to electricity could be attributed to the fact that a majority of districts and sub-districts (Figure S1 and Figure S3) have been electrified (x̃ ~75%). Whereas, in the case of access to sewer system, access is limited to a few districts and sub-districts, which are potentially urbanized (Figure S1 and Figure S3).

Importantly, we note that within State and between Districts inequality levels are generally greater than between States and within District inequalities, respectively. This suggests that there are significant resource constraints that influence provisioning of infrastructure access and household amenities and that these may be reinforced due to existing urban gradient. In other words, since inequalities in infrastructure access are more pronounced between districts, these could be attributed to differences in urbanization levels across districts.

Urbanization and Infrastructure Access

As inferred previously from our results of infrastructure access inequalities, our results show that urbanization, i.e., the share of urban population to total population in a given sub-district is positively related to the level of infrastructure access and amenities, calculated as the share of households with access (Figure S4). However, there are two aspects of the relationship that our results also highlight. *First*, urbanization is not a strict condition for access to infrastructure and household amenities. Our results show that in case of some sub-districts there are higher levels of infrastructure access despite that fact that they are ~0% urbanized. Amongst such sub-districts, we note that access to electricity is particularly higher (μ = 55%) compared to other infrastructure and amenities where mean is relatively low (μ < 28%).

Second, there are significant inequalities in infrastructure access amongst sub-districts that are fully urbanized. Here also we note that inequalities (as measured by Theil's index) are higher amongst sub-districts in case of access to sewer systems compared to electricity and energy provisioning (Table S6). Clearly, agglomeration benefits are lacking in India in the case of access to sewer systems.

Conclusion

The present study examines (1) the capability of VIIRS NTLs to explain urban infrastructure access variations as observed from census data and (2) urban infrastructure inequalities in India. In the absence of detailed household-level infrastructure access and amenities data, we compiled a spatial database of ward-level household infrastructure access and amenities data that could be used to study multi-scalar infrastructure inequalities in association with other spatially explicit database. This spatial database is currently compiled to enable spatial analysis at the sub-district, district, and state level. Whereas, one can study within sub-district inequalities using the aspatial ward-level data. In addition, we applied a time series analysis algorithm at the per-pixel level that summarizes daily NTLs into four components: (1) intercept (i.e., average NTL value at t=0), (2) long-term trend, (3) phase, and (4) amplitude, which could be used to study the time series signal. In the present study, we analyzed the intercept term to understand how well VIIRS NTLs capture urban infrastructure access variations. We find that NTLs are limited in explaining infrastructure access variations across scales and that there is a nonlinear relationship between the two making machine learning algorithms more suitable. Whereas, our analysis suggest that remotely-sensed data could be useful when used in conjunction with census data to specifies hierarchies in the urban system and explain the relationship between the two. Our results show that infrastructure access/amenity levels follow a Kuznets-type relationship, which is consistent with a Bernoulli's process. In addition, our results show highest level of inequalities in the case of access to sewer system and lowest in the case of access to electricity. We show that these patterns in inequality could be linked to urbanization but there are significant inter-urban inequalities in case of fully urbanized regions, which are related to urban size. These patterns are indicative of a combined spatial and hierarchical diffusion process that will be examined in future research.

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Figures

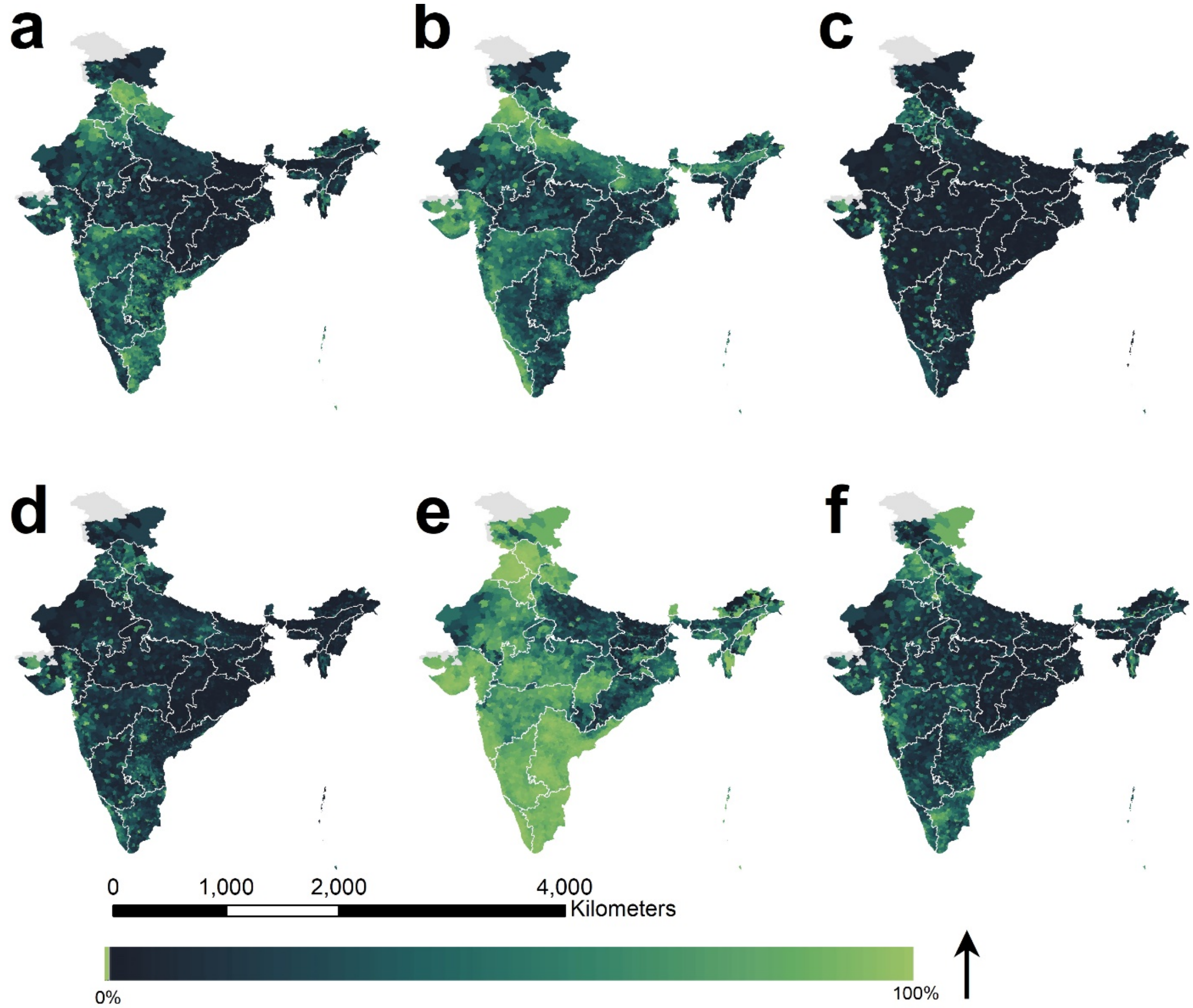

Figure S1: Spatial distribution of access to basic amenities (a) treated water, b) water in-premises, c) piped sewer, d) closed drainage, e) electricity, and f) cooking fuel (LPG). Data is shown at the sub-district level (*n* = 6054). White colored polygons represent State boundaries.

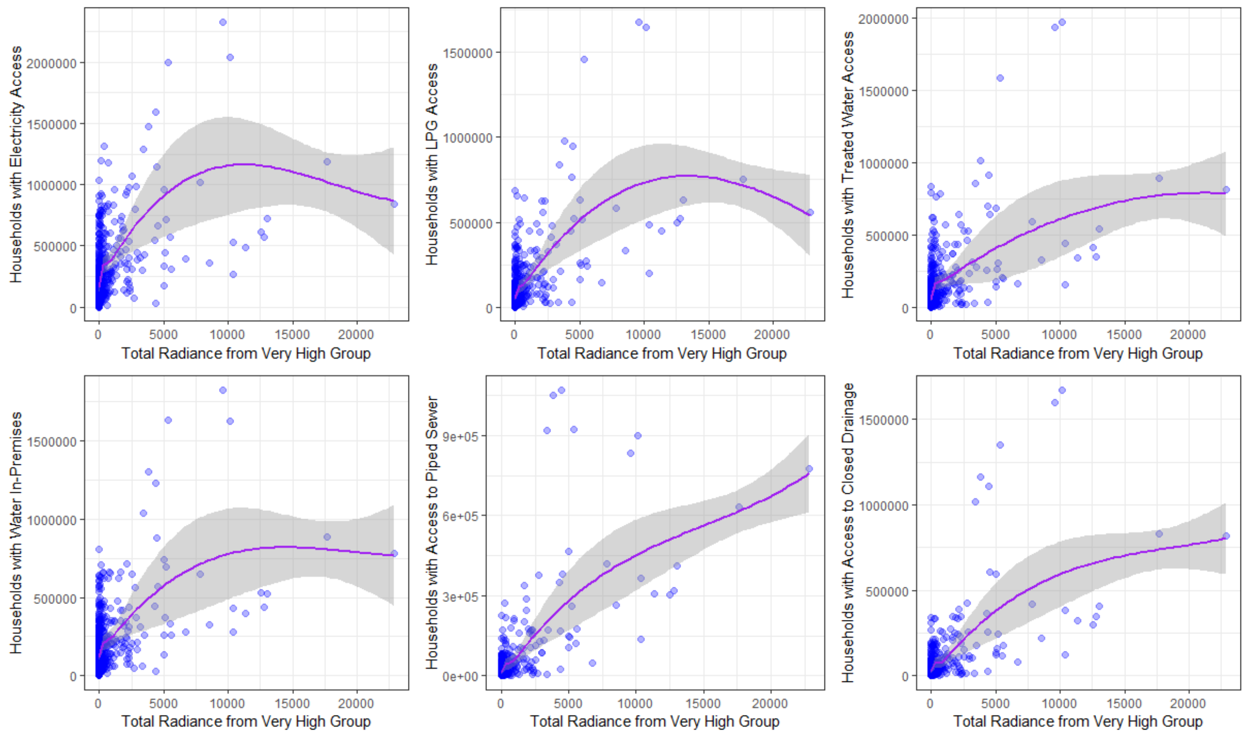

Figure S2: Relationships between household's access to infrastructure amenities and total radiance from very high group at the district level. Note that this figure has been generated after removing Bangalore district that was identified as a significant outlier with very high brightness level and relatively lesser number of households with access to infrastructural amenities.

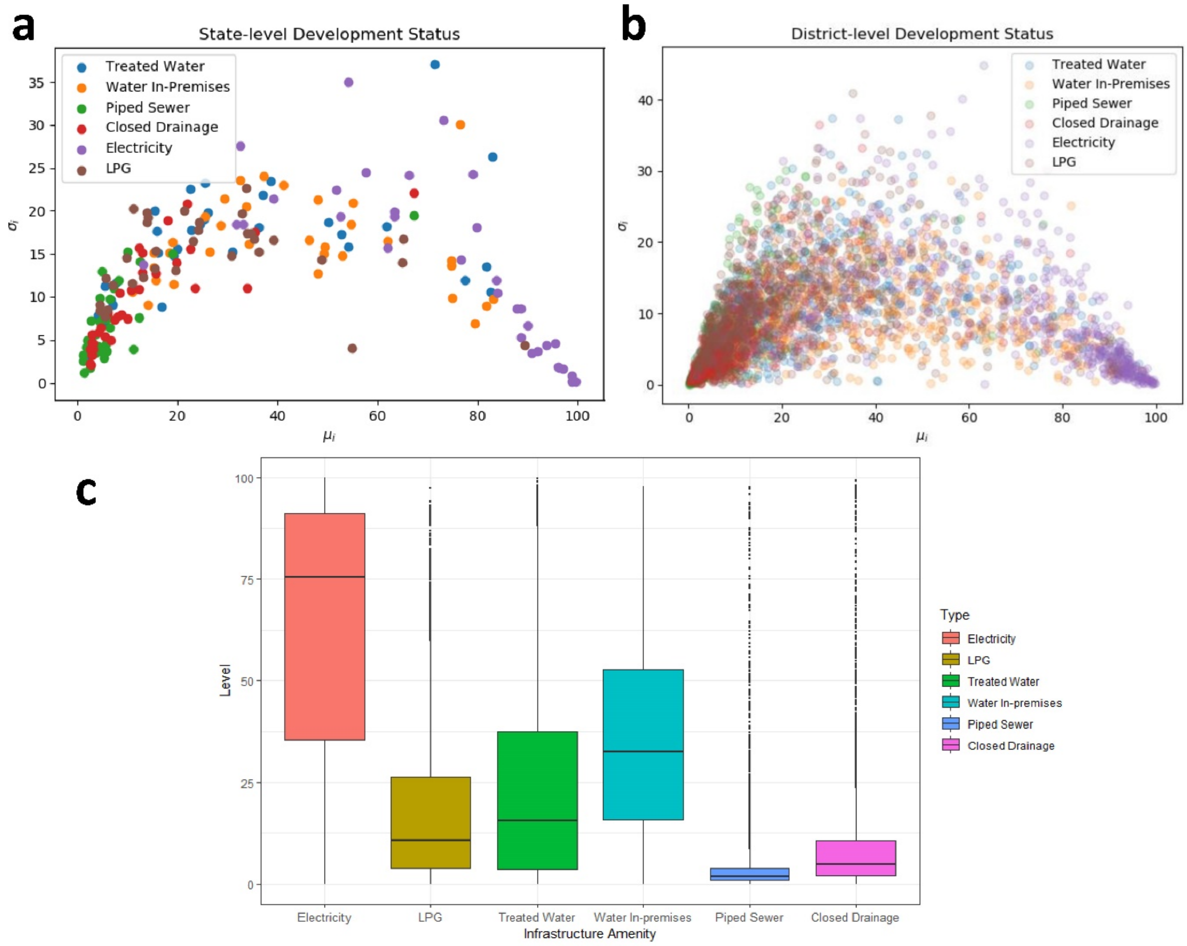

Figure S3: Relationship between mean level of infrastructure access and standard deviation observed from analyzing sub-district level observations aggregated at a) state and b) district levels. c) Distribution of the level of infrastructure across 6094 sub-districts.

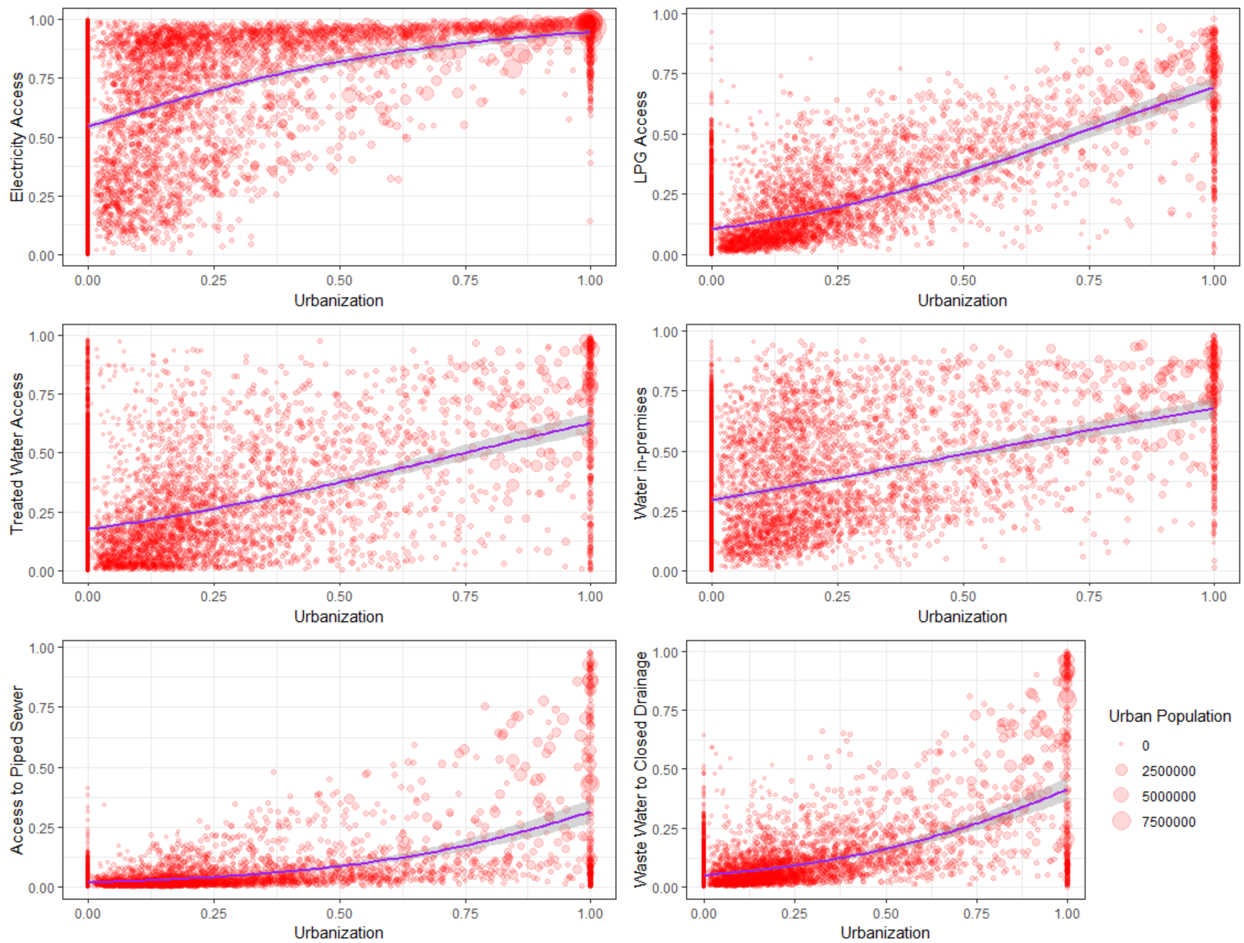

Figure S4: Distribution of sub-districts (n = 6054) across urbanization and infrastructure access levels. Trend line is a binomial fit and confidence interval is at 0.05 level.

Tables

Table S1: Correlations between total nighttime lights radiance and number of households with access to a given infrastructure at the state level.

Infrastructure Type	Pearson's Correlation Coefficient
Electricity	0.74*
LPG (Cooking Fuel)	0.64*
Treated Water	0.66*
Water in-premises	0.63*
Piped Sewer System	0.59*
Closed Drainage	0.62*
***Significant at 0.01 level**	

Table S2: Correlations between average nighttime lights radiance and proportion of households with access to a given infrastructure at the state level.

Infrastructure Type	Pearson's Correlation Coefficient
Electricity	0.03
LPG (Cooking Fuel)	0.29
Treated Water	0.17
Water in-premises	-0.07
Piped Sewer System	0.64*
Closed Drainage	0.45*
***Significant at 0.01 level**	

Table S3: Correlations between total nighttime lights radiance and number of households with access to a given infrastructure by nighttime lights radiance groups at the state level.

	Nighttime Lights Radiance Groups			
	Very Low	**Low**	**High**	**Very High**
Electricity	0.37	0.63*	0.74*	0.66*
LPG (Cooking Fuel)	0.26	0.55*	0.64*	0.65*
Treated Water	0.21	0.52*	0.66*	0.65*
Water in-premises	0.36	0.66*	0.63*	0.63*
Piped Sewer System	0.32	0.62*	0.59*	0.71*
Closed Drainage	0.27	0.58*	0.62*	0.64*
*Significant at 0.01 level				

Table S4: Correlations between total nighttime lights radiance and number of households with access to a given infrastructure by nighttime lights radiance groups at the district level.

	Nighttime Lights Radiance Groups			
	Very Low	**Low**	**High**	**Very High**
Electricity	0.06	0.23*	0.23*	0.32*
LPG (Cooking Fuel)	0.04	0.18*	0.10	0.42*
Treated Water	0.03	0.19*	0.17*	0.37*
Water in-premises	0.05	0.21*	0.09	0.33*
Piped Sewer System	0.02	0.20*	0.03	0.48*
Closed Drainage	0.02	0.18*	0.06	0.44*
*Significant at 0.01 level				

Table S5: Inequalities in access to infrastructure at two spatial scales (state and district) measured using Theil's index.

		Inequalities in Access to					
Scale	**Theil Index**	**Electricity**	**LPG**	**Treated Water**	**Water in-premises**	**Piped Sewer System**	**Waste Water to Closed Drainage**
District	**Total**	0.16	0.49	0.50	0.22	0.97	0.63
	Between	0.13	0.27	0.34	0.15	0.60	0.39
	Within	0.03	0.22	0.16	0.07	0.37	0.24
State	**Between**	0.10	0.18	0.27	0.08	0.30	0.23
	Within	0.06	0.31	0.22	0.14	0.67	0.40

Table S6: Between urban inequalities amongst sub-districts that are fully urbanized.

Infrastructure Type	**Theil's Index**
Electricity	0.01
LPG	0.11
Treated Water	0.20
Water In-premises	0.09
Piped Sewer System	0.61
Waste Water to Closed Drainage	0.48