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# **A Geospatial Approach of Downscaling Urban Energy Consumption Density in Mega-city Dhaka, Bangladesh**

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## **Highlights:**

- Method for energy consumption density (ECD) estimation and mapping
- Adopted regression analytics to capture spatial variability of ECD
- Sensitivity analysis and visualization based on prediction error
- Identified statistically significant spatial clusters and outliers in ECD
- Geographical units (ward) are less effective than geometric grid in ECD estimation

# **A Geospatial Approach of Downscaling Urban Energy Consumption Density in Mega-city Dhaka, Bangladesh**

## **Abstract**

Lack of energy consumption data limits resource optimized urban structure and energy planning in developing countries like Bangladesh. Focusing on mega-city Dhaka as a case, this study applies a geospatial approach of using multi-source national and regional datasets and visual analytics to downscale and estimate energy consumption at a local scale (such as ward and gridcell). The energy consumption density (ECD), as a measure of end energy use in a unit area, was estimated and mapped by linking building floorspace data with residents' energy use indicators such as per capita energy consumption, household energy expenditure, and mobility (transportation) pattern. This study also evaluated the ECD modelling outputs, and their sensitivity to distance from central business district (CBD) and total building floorspace. Results found a positive correlation between the residential building floorspace and estimated ECD. Regression and sensitivity analysis also identified and mapped significant spatial clusters and outliers in estimated ECD pattern of Dhaka city. This approach and methodology could help similar cities in other developing countries adopt and implement energy focused urban development.

## **Keywords**

Urban energy, Energy consumption density, Spatial Analysis, GIS, Geo-spatial modelling

## 1. Introduction

Energy consumption and generation are key considerations in optimizing urban planning and constructing urban infrastructures. Evidence suggests that there is a strong connection between urban development process and energy consumption behavior and needs (Singh et al., 2015). According to Marique and Reiter, (2014), a well-planned feasible form of urban structure can influence energy efficient behavior and even enhance cleaner energy production in growing urban environment. On the other hand, unlike rural settlements, the urban areas can also offer more energy-efficient means of housing and transportation systems (Schubert, et al., 2013) if planned with data-driven process. However, lack of local level energy consumption data often limits resource optimized energy and urban planning in mega-cities. Literatures on energy-efficient urban forms emphasize the challenges of urban energy planning for growing megacities. Prominent research areas varies from the impact analysis of energy consumption pattern to the integrated urban planning nexus (Owens, 1985, Ewing and Rong, 2008, Liu and Shen, 2011, Madlener and Sunak, 2011 ; Makido et al., 2012, Wilson, 2013, Gudipudi et al., 2016). The recent global study on 40 mega cities (Kennedy et al., 2015) has reported positive correlations between the end use energy consumption and urban form (building floorspace). However, there are evidences of critical discussions about data availability and their quality, statistical methods, contexts and levels of uncertainty. In response to rapid urbanization in growing megacities, this is becoming an emerging challenge for urban development planning.

Better understanding of spatial and causal relationships between urban buildings and infrastructures, energy consumption behaviors, and lifestyle of the residents is crucial - (Madlener and Sunak, 2011; Howard et al., 2012; Wilson, 2013; Marique and Reiter, 2014; Resch et al., 2016). The resource efficient urban planning and design could be better promoted by use of detailed spatio-temporal data at a higher resolution (Howard et al., 2012, Allen et al., 2016). Deeper data-driven computational approach can explore more dynamics of cities and test new ideas although preferred

method and data for advancement of the traditional urban knowledge is still uncertain (Townsend, 2015, Voskamp et al., 2016).

The energy data related constraints are especially severe in the context of mega-cities of developing countries (Jayasinghe et al. 2017); like Dhaka, Bangladesh. One of the ways to track urban energy consumption pattern is measuring and mapping energy use. One of such measures called Urban Energy Density (UED) which is defined as “the annual total amount of end use energy (kWh) demanded, predicted or consumed in a single or group of buildings normalized by the total building area or its footprint area” (Pereira and Assis, 2013, Vaisi et al., 2015). This UED definition can be applied to a sub-regional scale and called, Energy Consumption Density (ECD) – which is - “the total amount of end use energy (kg oil equivalent: kgoe) consumed in a unit area (e.g. a local administrative unit such as ward or gridcell) normalized by the building floorspace (in square metre: sq.m)”. In this study, we focus on residential energy consumption density in mega city Dhaka where ECD (kgoe /sq.m of residential building floorspace) could be used as a metric to compare and conceptualize the level of energy use by residents between two unit areas. The data and information retrieved through this approach can be support future energy policy – for example, the recently commissioned energy master plan of Bangladesh (GOB, 2015) has included residential energy use as one of the potential sectors for energy efficient development.

Dhaka is one of the highest urban concentrations in south Asia; the resource constraints is very common like in other mega cities of global south. The existing planning and building regulations of Dhaka hardly address the energy dynamics rather focus on density and development control (Parveen, 2012, Alam, 2014, Sikder et al., 2016). Studies have already investigated urban structure phenomenon of Dhaka city by applying various scales and methods, including geospatial approaches (Ahmad et al., 2012, Byomkesh et al., 2012, Raja, 2012, Trotter et al., 2017); however, the dynamic aspect of energy issues are almost missing or were not addressed in a direct manner. To this end, a systematic analysis and visualization of energy consumption pattern and intensity has a potential to add value by stimulating the understanding on energy sensitive urban dimensions particularly at a

local scale. To conduct the visualization of energy consumption pattern and relevant spatial analysis, modelling can be an effective tool. Urban planning models can be classified as three levels namely micro, macro and meso (Robinson et al., 2009). For example, urban mobility investigations could be studied by modelling every vehicle and traffic features at a micro level, or by explicitly modelling major arteries (meso) or at an aggregation of regional level (macro). The level of modelling should be chosen in line with the research objectives. A meso-scale modelling has been widely used in urban planning (Couclelis, 1997; Torrens and O'Sullivan, 2001; Batty, 2009; Martilli, 2014). In this method, a problem under study (e.g. regions of Dhaka city) is represented using two-dimensional lattice or grid of cells. Ideally with access to micro building energy data (e.g. smart meters) and urban mobility data (e.g. smart cards), it is methodologically possible to use empirically calibrated micro simulation modelling approach for policy making (Howard et al., 2012; Kim et al., 2012; Angelidou, 2014; Mwasilu et al., 2014). Energy planning for mega-cities is often focused on a city scale rather than looking at sub-regional scale (e.g. districts, local administrative units - wards) for urban planning and infrastructure development (Bale et al., 2012, Phdungsilp, 2006). In the developing countries like Bangladesh, lack of micro-data in energy consumption at a building level poses challenge to develop and apply data-driven micro-simulation model and further pose difficulty for empirical data-driven policy implementation. In this context, a methodological approach is needed for ECD estimation at a sub-regional scale by using available energy consumption parameters and building information. The errors in data sources used for geo-spatial models (e.g. Kocabas and Dragicevic, 2006; Yeh and Li, 2006) can propagate further to the output variables and interpretation of results with sensitivity analyses for estimating ECD.

To address the challenges of spatial urban structure components in the context of energy, this study intend to develop a methodology for estimating and visualizing the analytics on urban energy consumption by using the available urban public datasets such as building information (floorspace, use), population census, household energy expenditure and mobility pattern of mega city-Dhaka. This study aims to answer the following research questions:

1. How to estimate urban energy consumption density in a smaller scale using available multi-sourced public sector urban dataset?
2. Which relationships exist between estimated ECD and explanatory variables such as distance from center business district (CBD) and building floorspace?

Estimation of ECD can help addressing many urban energy challenges especially at a local level. A downscaling approach of ECD estimates and further findings related to these research questions would facilitate decision making for spatial land use and energy infrastructure planning. Urban stakeholders including governments are often interested in understanding other energy-use such as transport/mobility issues for better development planning in addition to building energy consumption (Rahman et al., 2012). Although, local authorities are often key stakeholders in energy-efficiency initiatives, they have limited budgetary provisions; therefore, an analysis at local level of a city (e.g. wards, districts) can support the local city officials and policy makers in informed decision-making.

This paper begins by introducing the analytical scope of energy responsive urban development with a critical review on – planning for mega cities, energy density and modeling paradigms. Subsequently, section-2 (materials and methods) starts with a short description of the study area and datasets; afterwards the methodological process describes the data preprocessing steps and estimation of energy consumption density. Section 3 and 4 present the results and discussion of key findings, followed by empirical case study results including sensitivity analysis and spatial auto-correlation analysis. The paper ends with a conclusion highlighting key observations and findings, policy implication, limitations and further research indications to address even in other large cities.

## **2. Materials and Method**

### **2.1. Study area: The Mega city Dhaka**

Dhaka was a settlement with an area of only 1 sq. km and an estimated population of 20 thousand in 1640 during the Mughal Period. A rapid urbanization occurred after independence (1971), and Dhaka occupied 40 sq.km and became home to 1.6 million people (Kabir and Parolin, 2012). Dhaka city - the

capital of Bangladesh - is expected to become the world's third largest mega city by 2020, and has 38% of Bangladesh's urban population (UN, 2008). Land use conflicts have been an issue because of the topographical disadvantages of low-lying flat and wetlands in the city boundary (BBS, 2010, BBS, 2011). Land conversion has occurred with very little control (Ahmad et al., 2012, Ahmed and Ahmed, 2012, Alam, 2014); therefore urban planning and development for Dhaka has always been done in a haphazard and almost unregulated way (Fig. 1).

Rapid urbanization is one of the challenges for guiding a well-planned urban structure. Compounding this challenge of urban spatial structure, both building and transport sector of Dhaka city show an unsustainable and inefficient energy consumption portfolio (Ahsan, 2009). The residential building sector alone accounts for half of total electricity consumption; however, there are almost no visible initiatives for adoption of sustainable energy technology and efficient demand management (Parveen, 2012, GOB, 2015, Sikder et al., 2016). The city has a typical daily supply gap of 1000 MW, which is one of the root causes of regular blackouts (DESCO, 2012). The transport sector could also trigger higher energy consumption due to spatial urban structure of Dhaka. There are many factors (i.e. traffic congestion and malfunctioning traffic management systems) which often cause massive delays in covering even small distances, resulting in both higher travel time and energy consumption. So far, the most significant efforts in urban planning, spatial development and planning approaches have been: (i) Master Plan for Dhaka (1959); (ii) Dhaka Metropolitan Area Integrated Urban Development Project (1981); and (iii) Dhaka Metropolitan Development Planning - structure plan, urban area plan, and detailed area plan (DMDP: 1995-2015). The energy issue has never been an integrated topic in any planning and development efforts (Parveen, 2012) rather focused on physical development strategies (e.g. development directions, infrastructure services) and aesthetic density aspects (e.g. zoning, building height control).

## **2.2. Description of Dataset**

Many building related geo-information are available from different public agencies and even open source volunteered geo-information services now a days (Hartmann et al., 2016). The combination of



attribute information like - building height, floorspace, and population density show higher usability even for constructing 3D city models using a 3DCityGML of recommended accuracy (Biljecki et al., 2017). In this research context, a multi-scale spatial analysis has been conducted after adopting compatible public sector datasets (both geospatial and statistical) and effective estimation methods (Table 1). The vector type geospatial data model allows the inclusion of geometry and geographical details of space more precisely in comparison to raster format or satellite imagery (Crooks, 2010). This article considered vector type building information and attribute type survey datasets for computing urban ECD (see also Fig 2).

### **2.3. Spatial data preprocessing**

The regular grid based computation method, with the aid of geographical information system (GIS) software, is considered a powerful way to store, and analyze urban structure, and spatial growth patterns (Yeh and Li, 2002, de Almeida et al., 2003, Gudipudi et al., 2016). The basic concept of such a method is to divide the whole space into continuous square grids after settling on a pre-defined cell size (henceforth gridcell); however, an appropriate selection has to be justified enough, which is always a critical step for initializing the geoprocessing environmental settings (Ahmed and Bramley, 2015). One of the popular arguments says the cell size has to be large enough to ensure precise computation results and interpretation. To find an optimum cell size, the coverage area of the largest physical feature was taken into consideration. There were very few buildings (8 out of 270,392) in Dhaka city with a coverage area greater than 10,000 sq.m. Hence, the gridcell size was settled as (100X100) m, which is also common in literature (Yeh and Li, 2002, Larondelle et al., 2014) and based on Dhaka city's building feature. The spatial variability of ECD has to be localized as per one of the basic requirements in spatial analysis, so it was assumed that man-made activities can be considered almost constant within a gridcell size of (100 × 100) sq.m ground area.

After determining gridcell size, a regular grid of cells (polygon type feature) was created with unique cell-IDs using GIS software. Afterwards, an overlay operation was conducted on the urban building structure layer (Fig. 2) to estimate gridcell-level information. The extent of area was set as Dhaka City

Corporation (DCC) area, which was comprised of 90 wards (smallest urban administrative unit). According to Saha (2011), the gridcell-based computation should be conducted with 3 distinct geographical settings, which emerged after overlaying the cellular lattice on the study area boundary and physical features. In this study, three geo-settings were considered as: (1) features contained within a gridcell; (2) features are divided by the gridcell boundary, falling in-between gridcells; and, (3) grid of cells affected by study area boundary. These three conditions provided data integrity check prior to further computations. The computational goal of all settings had to consider the gridcell-wise proportionate building structure and area of interest. The features that fell between multiple cells were divided in accordance to grid boundary line. The ground area outside of the study area boundary was excluded from individual gridcell area before storing estimated gridcell based information. In the next sections, the proposed method is presented as follows - Section 2.4 presents approach for building floorspace estimation. Section 2.5 presents the energy consumption density estimation procedure.

#### **2.4. Building floorspace estimation**

The building floorspace estimation procedure was conducted separately for both gridcell and ward level. For each ward, the building floorspace was calculated with known building footprint area (sq.m) and number of floors. For each gridcell, the building features has to overlay by following settings that mentioned in section 2.3. The spatial/attribute join type geospatial operations was performed during the estimations of floorspace by following extents and building use activities. It is assumed that all building floors have an identical floorspace, however, estimating total floorspace by including building height information (number of floors) still could be addressed spatial variability of urban building structure density (Huang et al., 2007, Stewart and Oke, 2012). The next section presents ECD estimation details and model assumptions.

#### **2.5. Estimation of energy consumption density**

Difficulty remains in estimating energy consumption due to lack of detailed data on related parameters. This study estimated the ECD by following an approach similar to population density

calculation (Yeh and Li, 2002, Khatun et al., 2015) – proportion of population per unit of sub-regional area; while also accounting for spatial variability of energy consumptions. In fact, the use of per-capita energy consumption was only to get an ECD estimation at each ward using census population. Thus, the ECD profile of a ward will be in proportion to population density of that particular scale. However, this ECD needs to be adjusted for mobility and building use. This adjustment was conducted for two key components of residential energy consumption relevant to resident's household and transport (mobility) use. Though, other energy uses (e.g. industry, service, etc.) are important but considered to be beyond scope of this article. In summary, the proposed estimation model calculates weights for each ward in order to obtain an adjusted ECD.

The proposed ECD modeling procedure has some important assumption that are explained below:

(i) The Dhaka City Corporation (DCC) ward boundary is the smallest administrative unit as per records of the national census agency. It is assumed that a building is completely located within only one administrative boundary of DCC ward. The census population was available for DCC wards and this was used to estimate total energy consumption (Per capita energy consumption\* Population of a Ward). This study included annual gross energy consumption per capita in Dhaka city; however, individual end-user sector was also considered such as household level energy expenditure (Domestic Energy: DE) and residents motorized travel expenditure (Transport Energy: TE).

(ii) The estimated amount of total building floorspace considered both building footprint (2D-horizontal) and building height (3D-vertical) dimension, as well as land use structure. There are eight major land-use structure types identified by local authorities in Dhaka. Out of which, only 4 types were included for classification of building use namely residential, commercial, services and mixed-use (i.e. a building has multiple use). Given the available datasets, the estimation model is flexible to extend further for industrial, service, commercial sector energy use.

(iii) The annual energy budget has been addressed so far where the seasonal variations on energy consumption are not being captured in the current estimation. Energy generation with local renewable sources (e.g. solar, geothermal) which should be account in the ECD estimation; that kind

of energy generation are very not yet significant in urban area rather providing as an island solution for rural Bangladesh.

The per capita energy consumption indicator for Dhaka city (i.e. Kennedy, et al., 2015: scaled energy consumption for greater Dhaka metropolitan area) was taken into consideration to estimate ECD rather than national level per-capita. In comparison to national energy consumption indicator (e.g. IEA indicator 2014.4 kgoe/cap: OECD/IEA, 2012), Dhaka is consuming about 607.08 kgoe/cap, which is 2.83 times more than national per-capita energy consumption (Kennedy et al., 2015). In this study, the unit of energy consumption density stands for kgoe/sq.m. The estimation was conducted for each ward and cell at multiple steps as explained in the following sections 2.5.1 and 2.5.2:

**2.5.1. ECD Estimation for each Ward**

After finalizing key assumptions and conducting geospatial processing, ECD was estimated for each ward (see also Annex-Table: 1). This involves the following equations:

$$ECD_i = \frac{\text{Per capita energy consumption} * \text{Population of Ward } i}{\text{Residential building floorspace of Ward } i} \dots\dots (1)$$

As discussed in Section 2.4, ECD estimated using equation (1) doesn't consider sector-wise energy uses such as domestic (household) and mobility and hence the proposed model will adjust ECD at each ward by using two weights:  $W_{DEi}$  and  $W_{TEi}$ . The generalized ECD adjustment is presented in equation (2) with further sub-sections discussed on the procedure for obtaining these two weights.

$$\text{Adjusted } ECD_i = ECD_i * W_{DEi} * W_{TEi} \dots\dots\dots(2)$$

Where,

$W_{DEi}$  indicates the weights for domestic energy use in ward i

$W_{TEi}$  indicates weights for transport energy use in ward i.

**(1) Weight for domestic energy use (DE)**

According to the income expenditure survey (HIES, 2010), the population was classified into 19 income groups (monthly per capita income between: <500 and 7000+ in BDT). For each group, the

monthly expenditure on various uses can be found in HIES database. Among that expenditure, only the percentage of monthly expenditure for ‘fuel and lighting’ is relevant for the end-use energy consumption at a household level. In this paper, this monthly fuel and lighting expenses for each spatial planning zone is used as a proxy for domestic energy use.

Based on HIES dataset, the average HH income was known for each spatial planning zone (A, B... H) and not at each ward. The average HH income for each ward i is assigned to the average HH income of spatial planning zone in which the ward is located. The procedure for calculating weights for domestic energy use for a particular ward is explained below.

Let  $HH_i$  denote number of households in Ward i

$Y_i$  denote average size of a HH in Ward i (according to STP zone statistics).

Average income of a HH in ward i,  $I_i = Y_i * \text{Average per-capita income of Ward i}$

$P_i = \%$  of monthly expenditure on fuel and lighting of a HH in Ward i using HIES.

For the entire Dhaka city, overall average monthly expenditure for HH was 15275.69 BDT. The average percentage (%) monthly expenditure for HH fuel and lighting was found to be 4.91 percent (HIES, 2010). Hence, overall average monthly expenditure for fuel and lighting was 750.04 BDT (i.e.  $15275.69 * 4.91/100$ ).

For each Ward i, weight for domestic energy use is obtained by following equation 3:

$$W_{DEi} = \frac{\text{Expenditure for household use at ward } i}{\text{Expenditure for household use in Dhaka city}} = \frac{HH_i * I_i * P_i}{750.04} \dots\dots\dots(3)$$

**(2) Weight for transport energy use (TE)**

The weight for adjusting ECD to transport energy use was obtained by using STP empirical survey dataset (see also Table 1). Among various modes of transport – motorized trips were collected as the usage of cars, buses, CNG, taxi and motor-cycle. As explained in section-2.2, motorized trips generation vary across different income groups – lower (LIG), middle (LMIG), higher middle (HMIG)

and higher (HIG). Hence to obtain the transport energy use variability at each ward; the trip generation patterns of various income groups need to be considered and this has been explained as follows:

Let,  $X = \{1, 2, 3, 4\}$  be index for income groups namely LIG, LMIG, HMIG, HIG

$HH_{xi}$  = Number of households of each income group in Ward i

$M_{xi}$  = % of motorized trip per HH for each income group in Ward i

$T_{xi}$  = Daily number of trips per HH for each income group in Ward i

DHH = Total number of households in Dhaka city

$T_i$  = Overall daily average number of trips per HH

Total daily average motorized trip for each income group x in Ward i,  $D_{xi} = M_{xi} * T_{xi} * HH_{xi}$

Annual average motorized trip for Ward i,

$$D_i = \sum_{x=1}^{x=4} D_{xi}$$

Total annual motorized trip for ward i,  $AMT_i = D_i * 365$

$ME_i$  denotes average expenditure per motorized Trip in Ward i (according to STP zone statistics).

Total annual expenditure for motorized trip for ward i,  $AMTE_i = AMT_i * ME_i$  .....(4)

According to STP (2005) report, for the entire Dhaka city, the overall average daily average trips per household is 8.7 and average expenditure per motorized trip is 45.83 BDT.

Annual expenditure for motorized trips in Dhaka,  $DAMTE = 8.7 * DHH * 45.83 * 365$  ..... (5)

Thus, the weight for transport energy use for ward i is obtained by dividing equation (4) and (5):

$$W_{TEi} = \frac{\text{Expenditure for Transport use at ward i}}{\text{Expenditure for Transport use in Dhaka city}} = \frac{AMTE_i}{DAMTE} \dots\dots\dots(6)$$

Finally, the adjusted ECD using the proposed method factoring for domestic and transport energy use at each ward, can be rewritten as follows:

$$Adjusted\ ECD_i = ECD_i * \frac{HH_i * I_i * P_i}{750.04} * \frac{AMTE_i}{DAMTE} \dots\dots\dots(7)$$

**2.5.2. ECD Estimation for each gridcell**

For each DCC ward, the above procedure is repeated to obtain an adjusted ECD. At the gridcell level, ECD is calculated as a weighted proportion of residential building floorspace of the cell to the ward (see also Annex-Table: 2). The cell level estimation can be shown as following equation:

ECD for a cell j in a ward i is given by:

$$ECD_j = Adjusted\ ECD_i \times \frac{Residential\ building\ floorspace\ of\ Cell\ j}{Residential\ building\ floorspace\ of\ Ward\ i} \dots\dots\dots(8)$$

In summary, the equations 7 and 8 represent the proposed approach for down-scaling ECD at a ward and cell level respectively. The following section presents the results of above ECD estimation model in case of Dhaka city. It has begun with mapping spatial patterns and also co-relation analysis of estimated ECD to related building use. Afterwards, the regression analysis presents the sensitivity of ECD to two proxy parameters and error propagation. Finally, the spatial clustering are also presented after estimating spatial auto-correlation statistics.

**3. Results**

**3.1. Estimated ECD in relation to building use**

The resulted spatial pattern of ECD is visualized on thematic maps at two levels: ward and gridcell. The estimated ECD varied in terms of spatial distribution from Ward to gridcell due to respective Ward or cell's specific variables such as building floorspace, spatial landuse zone and others (Fig. 3).

For example, Ward 15 (the area to the left of cantonment) was within 4<sup>rd</sup> quantile of ECD distribution. However, gridcell model of the Ward 15 showed predominantly (about 50%) under 1<sup>st</sup> and 2<sup>nd</sup> quantile distribution of ECD. This variation could be due to comparatively less development of residential building floorspace. Similarly, the 3<sup>rd</sup> and 4<sup>th</sup> quantiles are also showing a relation to

high amount of building floorspace intensity. In fact, the functional land use zone (Annex-Fig: 1) based estimated weights for adjusted ECD may also have an effect.

Fig 4 show in the ward-wise share of building floorspace according to their use type. It should be noted that CBD (ward no 32) has major building floorspace for commercial and service sector but annual energy consumption density almost at the lower quartile. Interestingly, ward no 73 has majority of mixed use building floorspace and estimated ECD was very low. The ward-wise percentile distribution of total building floorspace confirmed that most wards were dominated by residential use. Mixed-use was second priority with higher shares than residential sectors in a few concentrated wards. With few exceptions, the service sector and commercial spaces had even shares in almost all wards. However, the aggregated result showed that the residential sector had the highest share of building floorspace (66.9%) compared to commercial (10.4%), service (10.2%) and mixed-use (12.3%). In fact, the mixed use also included residential activities; therefore, any dynamic energy related estimation should be included the residential building sector as a highly potential explanatory parameter.

The relationship between ECD and building floorspace (according to use type) was investigated further with closer looks at the analysis of Pearson's correlation coefficient ( $\rho$ ). First, at ward level a positive correlation existed for 3 types of use where residential sector ( $\rho = 0.13$ ) on top, but only mixed use remain as an exception (- 0.06) - more specifically, ECD is increasing by following building floorspace. Second, the gridcell-wise distribution of estimated ECD had a positive relationship only with residential (0.17); but, there is a slight increase in correlation between residential building floorspace and ECD. A negative and a very weak relation was found in all others sectors: commercial (-0.01), service (-0.02) and mixed-use (-0.01); however, this scenario confirmed the ECD estimation assumption about the residential energy consumption. In fact, the entire scenario confirmed very weak co-relations with an except for residential sector.



### 3.2. Regression Analysis and Error Propagation with GAM

Since one of the study goals is to analyze the ECD estimation sensitivity in consideration of explanatory energy consumption parameters. The distance from the CBD in reference Khatun, et al., (2015) and total building floorspace (Vaisi et al., 2015, Yeh, 2002 #235) showed high validity for explaining urban energy consumption aspects. By same principle, the local scale estimation of key variables has a potential for more insights, and support explaining sensitivity and uncertainties. The bivariate regression analysis was conducted and followed by estimating prediction errors.

In comparison between two levels of estimation (ward and gridded-cell), interesting findings were observed in their relationship with level of scale and resulted trend in ECD. The distance from CBD (Ward 32) was estimated as a straight-line air distance in consideration of extracted centroid of each polygon feature (for both DCC ward and cell). The total building floorspace simply obtained by adding 4 types of use type as introduced in section 2.4.

In Fig. 5, the ward-wise estimations showed positive correlation with both distance from CBD ( $\rho$ : 0.45) and total building floorspace ( $\rho$ : 0.009). A linear trend in regression fit that shows the spatial pattern of urban structure and higher transport energy consumption of residents in case of distance to CBD; but the total building floorspace had weak and non-linear relationship. On the other hand, the non-weak pattern was observed in cell-wise density in both parameters; however, the low  $R^2$  value shows poor model fit and explained low percentage of deviance (5.34 % and 26.1 %). Other than bivariate regression, the combined regression results in interaction terms with two parameter are slightly increased in  $R^2$  value (0.32) and followed by deviance explained up to 32.3%.

The prediction accuracy or uncertainty of models can be better explained by calculating errors (a difference between observed and predicted ECD value). The scatter plots show how model predictions are affected in relation to distance from CBD and building floorspace (Fig. 6). The regression fit shows almost non-linear trend in both ward and gridded model, but higher sensitivity was observed in case of the distance from CBD (e.g. at 5km). Similarly in case of gridded model, the predicted errors for the building floorspace are becoming larger at the value of 10000 sq.m.

The maps show the spatial pattern of prediction errors in a scale of equal quantile distribution (Fig. 7); it can be observed that the predictive accuracy from ward to cells varied while using different ECD models e.g. Ward 46 falls within 4<sup>th</sup> and 3<sup>rd</sup> quantile of ECD prediction error. However, due to the ward's explanatory variables (such as household expenditure, building floorspace, population), the cell level ECD estimation of Ward 46 falls predominantly 1<sup>nd</sup> and 2<sup>rd</sup> quantile (in distance to CBD). This example indicates that the error propagation and predictive accuracy varies ECD estimation from ward-level to gridded model.

It is often hard to explain complex urban system components in terms of static models. Therefore, the dynamic non-linear gaps have to be addressed with regard to the urban structure evolution (Chen, 1996). The discussion in previous sections pointed out that the spatial pattern of ECD could be investigated further in consideration of spatial dependency. In fact, the regression model fit may also be improved after identification of spatial autocorrelation clusters and statistically significant hot-spots of estimated ECD.

### **3.3. Spatial Auto-correlation analysis**

The auto-correlations extraction is one of the effective approaches for identification of statistically significant spatial clusters; therefore, it is possible to analyse the degree of dependency among similar/dissimilar observations in a geographic space. Following (Steiger et al., 2015), this study analyzed the spatial auto-correlation after combining Moran's I value and Getis  $G_i^*$ . In this study, the spatial pattern of ECD are indicated by the presence of significant spatial autocorrelation (Getis and Ord, 1992), that also quantifies Tobler's first law of geography: "Everything is related to everything else, but near things are more related than distant things" (Tobler, 2004). Typically, the Moran value appeared within a range of +1 (strong cluster), -1 (disperse) and 0 indicates randomness. In addition, the local indicators spatial association (Hellriegel and Teichmann) in reference to (Getis and Ord, 1992); that provides clusters in terms high-high (HH), low-low (HH) and associated spatial outliers (Low-high and High-Low) following statistical significance within estimated ECD. Similarly, Getis  $G_i^*$  results also provide hot spot and cold spot with a range of +1 and -1 value. By overlapping correlation of Local Moran's I (only High-High observations) and positive value gives all statistically significant

high value clusters. These results could be studied further for spatial association and sensitivity of ECD. This kind of approach can provide an efficient exploratory method for the detection spatially homogenous patterns with significant value of ECD. Maps in Fig. 8 show that statistically significant clusters and outliers at both ward and gridded model. The global Moran's I value clearly denotes strong clustering in gridcell wise estimation (0.73); however, the p-value is less than 0.01. It can be observed that the gridcell-wise high value clusters are showing a strong spatial correlation with the residential neighborhoods. Simply, the location that are residence of higher energy consumers; however, the outliers are also located at soundings area of high-high clusters. At least at gridcell-wise clusters have potential to conceptualize some degree of the density and decay profile under two different development scenarios of spatial urban structural (e.g. mono-centric and polycentric).

So far the classical regression models were considered in use of whole dataset for analyzing urban density function; however, such regression methods often criticized and called for adopting data-driven approaches in consideration of spatial clusters (Jiang, 2013; Jiang et al., 2016). In case of bivariate relation of sensitivity of ECD estimation, the poor model fit leads to many open questions regarding problem of spatial dependency and inclusion of multiple explanatory variables. Fig. 9 shows scatter plots after selecting two distinct type of clustering (e.g. LL and HH) and fitted two types of regression smooth lines (additive: GAM and polynomial: LOWESS). This approach helped to investigate on ECD sensitivity after removing statistical outliers, and identification of homogeneous set of observations. This analysis was only conducted for gridcell-wise ECD, because the Ward scale has only few statistically significant HH and LL observations.

The gridded data has only 586 High-HIGH (HH) but 3191 LOW-LOW (LL) observations. The regression models shows comparatively better fit rather than considering whole dataset - at least by looking at  $R^2$  value, deviance explained and smooth lines. A negative correlation can be found in relation of ECD and distance to CBD for both LL ( $\rho$ : 0.25) and HH ( $\rho$ :-0.37). Simply, ECD decreases as the distance from the CBD increases; however, the location of HH clusters are observed at 4km from CBD centroid that followed a positive trend till 6 km; however, a negative downward trend was observed up to

10km. The ECD vs. total building floorspace shows a positive correlation and in regression fits; but the regression smooth lines show a rise and fall within range of 5000 to 15000 sq.m. In case of HH clusters, a wide degree of confidence also appeared after 20000 sq.m. Regression modeling by considering interaction of both predictors (distance to CBD and total floorspace) to ECD gives a higher  $R^2$  value (38.5%) and explained a deviance up to 40.1%.

Within the gridded model, the HH clustered observations shows a positive relationship only with residential (0.15) and commercial (0.01) type building use activity. It indicates a slight increase in correlation terms between residential building floorspace and ECD after considering only statistically significant HH clusters. A negative and also very weak relationship observed in both mixed use (-0.09) and service use (-0.01). Additionally, the vertical building floorspace for residential activity showed a higher correlation with ECD ( $p$ : 0.17), where correlation coefficient for horizontal building floorspace found only negative 0.003. Above outcomes partially confirmed that the estimated ECD has significant validity in relation to spatial location of intensified residential energy consumption. In fact, the weak correlation in the whole scenario may need further explanation in consideration of potential candidate predictors.

#### **4. Discussions on key findings**

This study presented a geospatial approach to estimate residential energy consumption density in the context of data constrained and fast growing cities like Dhaka. The initial results of this study show that local scale estimation of ECD captured some detail insight of urban density and decay function at gridded model rather than administrative unit - ward. This is consistent with findings observed with the phenomenon of natural cities (Jiang et al., 2015) where estimated topological units are more effective for learning detailed insights than basic geographic units (census - ward). We should acknowledge that in large cities like Dhaka, apart from the proxy parameters (e.g. distance to CBD, total building floorspace), there might be a need for predictor variables that may have a major explanatory power to conceptualize the function of density and decay of urban structure development. Within the proposed ECD modelling approach, the residential building floorspace had

a significant influence on gridded-cell wise energy density estimation. The share of residential activity was considered for disaggregation purpose; one of justifications is that the residential use is highest among the four land use classes in Dhaka and identification of high density energy consumption could help for effective urban management decisions. Similarly, it should be noted that the residential sector is one of the highest energy consumers in comparison to commercial, service and mixed-use activity in Dhaka and even beyond (while considering the report of electricity suppliers e.g. DESCO, 2012).

The results show that spatial distribution of ECD was not uniform and this variation was due to level of building development in each ward predominantly with residential use. Identifying ECD levels in wards provide an empirical basis for targeting energy efficiency initiatives in high consumption wards. There were two distinct type of clusters namely Low-Low (LL) and High-High (HH). ECD showed increasing trend up to 4km from CBD beyond which ECD showed a decreasing trend. This trend variation could be linked to usage of high energy consuming transport choice when within 4km of CBD and with prominent usage of low per-capita fuel consumption (e.g. Bus) while travelling from distance further to CBD. While modelling ECD with both domestic consumption and residential mobility parameters, the model deviation explained about 40.1%.

Spatial computational literature also suggest that more urban aspects including energy needs to be realized instead of only two dimensional urban characteristics. Much uncertainty could be emerged due to assumptions related to building shapes, rooftops, orientations, building skin and many more. This study estimated ECD by gathering official dataset that are currently available and accessible. The dataset used for the case study ranges in between 2005 to 2011, - including latest available 2011 Census, it seems to be outdated for representing current energy budget in the context of rapid urbanization pattern of Dhaka city. However, the proposed ECD estimation method and visualization provides an opportunity to study energy budget further in the case of Dhaka city and other data constrained county contexts. In that respect, the availability of new/updated dataset will open up a

scope of further monitoring of resident's energy consumption based on finding and knowledge from this kind of study.

The spatial auto-correlation statistics in combination of Local Moran's I provided advantages for efficient exploratory analysis after finding statistical significant clusters and reducing randomness within the ECD observations. The visualization of maps and scatters plots also partially show the in-depth learning in use of official dataset and related shortcoming; which may need further investigation as a new avenue of potential research in adoption of new and/or alternative source of dataset (e.g. Steiger, 2015). The findings from proposed approach clearly seems to be powerful for conceptualizing the understanding of urban structure on multi-scale dimension in the context of data constrained large city like Dhaka; however, further work should be conducted to fine tune the non-linear model fit by including more predictors and beyond the spatial autocorrelations. Several comparatively modern methods - such as Eigenvector spatial filtering (e.g. Murakami, 2017), bootstrap resampling base machine learning approach (e.g. Wood, 2006) exist that can be included in the model fit so that accuracy and statistical significance could be improved for better productivity.

The results could not be detailed on a direct micro-level energy aspects due to lack of building-level energy consumption information; however, the results offer value for better integration of energy and urban planning research. Recent studies showed interesting links between urban density and carbon emission by applying City Clustering Algorithm (CCA) on a gridded dataset of USA cities (Gudipudi et al., 2016) and studying spatial distribution of end-user energy intensity in New York city (Howard et al., 2012); however this micro scale dataset on energy consumption do not exist in many growing cities of the developing world. In this regard, the proposed methodology could be adopted potentially using public sourced data and software packages (Liang et al., 2015, Hartmann et al., 2016, Lansley and Longley, 2016, Biljecki et al., 2017, Lloyd and Cheshire, 2017) that can capture some of the complexities in spatial analytics of urban structure.

## 5. Conclusion and Policy Implication

In the context of many developing countries including Bangladesh, lack of energy consumption data remains one of the limitations for energy concerned urban development. This study estimated energy consumption density of Dhaka city at a local scale by considering urban building structures information, population census, household income-expenditure and urban trip generation pattern. The definition of urban energy density (UED) has been extended for urban sub-regional scale. The case study considered only the administrative area of Dhaka city corporation (DCC) because of the availability of data regarding ward-level population, mobility pattern and degree of physical development. The findings from this study and concluding remarks that can contribute to urban development and energy planning:

- The gridded model could be better conceptualized in some degree of spatial variability in urban residential ECD; however, many uncertainties and related assumption are remain open. As illustrated for Dhaka, the sub-regional geospatial estimations could be used to support for extensive analysis of vector type building information. However, more specific type of development model can be recommended through further investigations of key functions and related dynamic predictors.
- Within four types of building use categories, the mixed-use building should have residential activity as well; however, this has not been captured within the ECD estimation. Generation with renewable are not part of this estimation, which assumed to be non-significant in urban Bangladesh. The proposed residential ECD estimation model could be extend further after computing weights for energy use in industrial, service as well as commercial sector. The annual energy budget has been addressed so far where the seasonal variations on energy consumption are not being considered in the current estimation, which could also be addressed in, further studies.
- Considering residential building footprint and population census in estimation of ECD has showing the ability to analyses and visualize the spatial energy consumption variation of

resident's, but similar approach could be adapted for investigating many other human-environment interactions. The proxy variables added value to spatial dimensions of urban energy consumption such as income group-wise energy expenditure and motorized travel behavior of residents. The registered (residential) population was considered only in the population census; however, the diurnal mobility (e.g. working hours) can increase the actual population of a ward for particular hours per day and hence this can affect energy consumption estimation by using only resident population at each ward. However, the generalization of our study results need to be done carefully as the assumptions may differ in other context of dynamic urban structure components and definition of empirical input data sources.

These findings can contribute to further advancements in urban planning and to support urban planners, professionals and decision makers. This research found great potential in this approach to explore in-depth urban structure form for resource efficient decision-making; however, the quality and reliability of data are acknowledged as limitations in the scope of this study. The proposed approach could be improved to address the lack of future scenario optimization and open-source data integrated application development after solving validation issues. One can argue within the call of new urban science, there are commitments for having more accessible traditional public sector big/open datasets (which are already known sometimes to the local urban actors). In most cases, financial constraints do not allow to collect huge data and buy recent technologies. Open data and technologies enable data-driven decision making and management in many developing countries. However, the capacity building of professionals and public officials (Sikder et al., 2016) need to take a serious turn to maximize future generation of open government and public urban services related human resources.

Future research could extend ECD estimation with detailed data on building use and sector-wise energy consumption. There are scope for further explorative study in consideration of spatial dynamics, energy consumption, renewable energy and resident's structure. In fact, the spatial



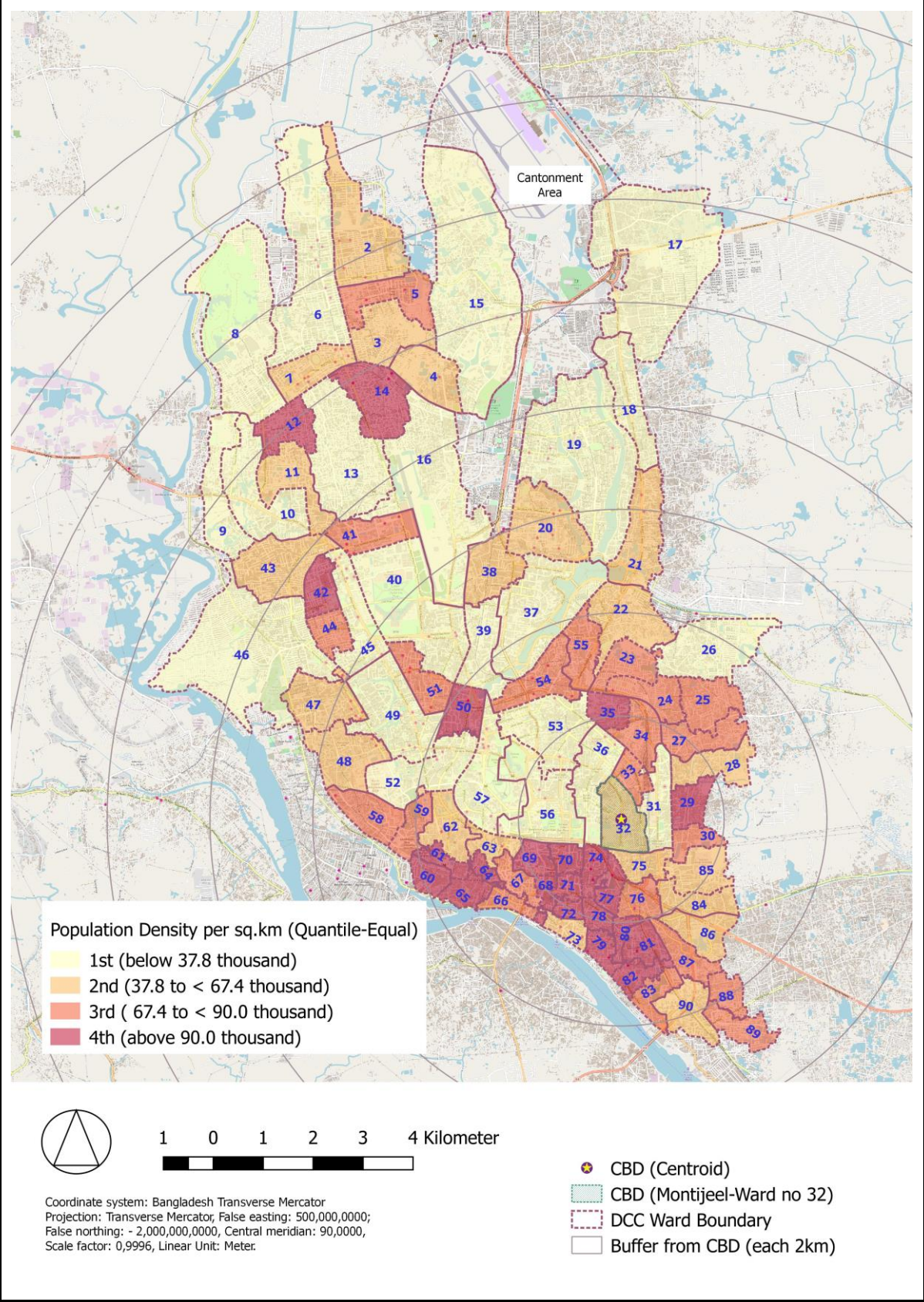
dynamic of energy consumption at a micro level need to be explored further for long-term projection models. Many energy use behavior literature shows significant influence of diverse set of socio-economic variables where multivariate sensitivity analysis could also add value after including real time data on building components, transportation and household lifestyle. These methods could lead to a better climate change and urban planning approach to achieve sustainable development goals.

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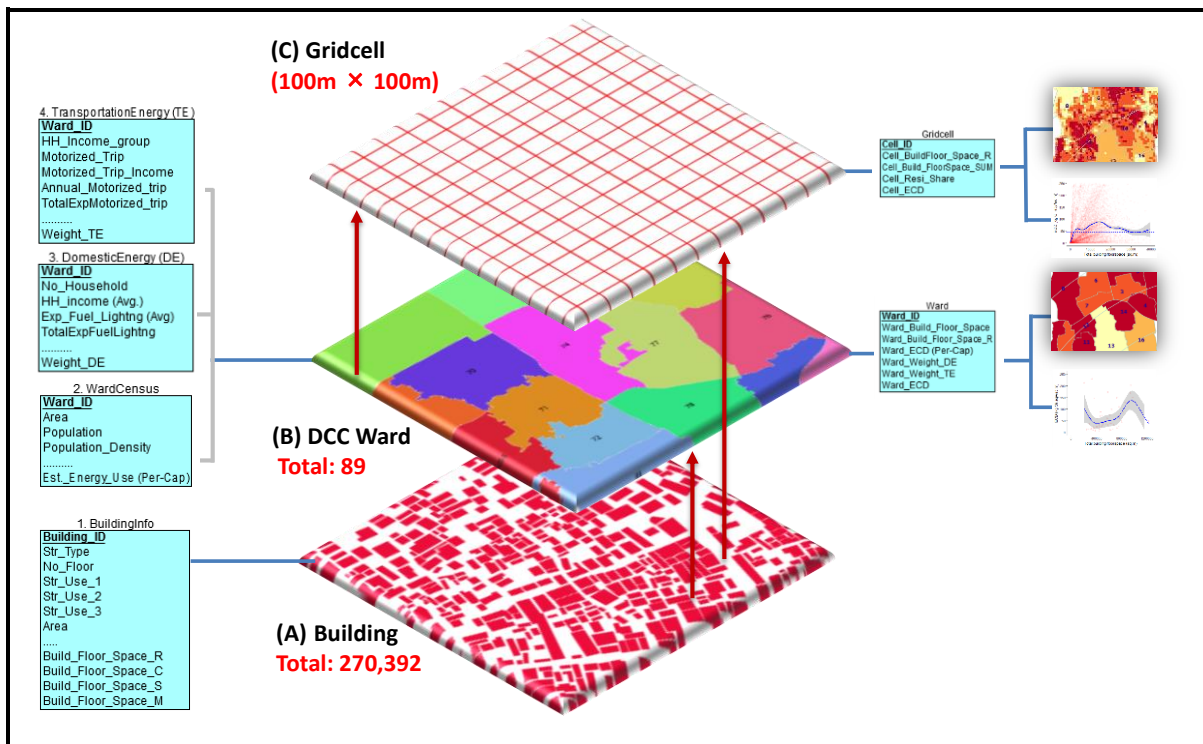
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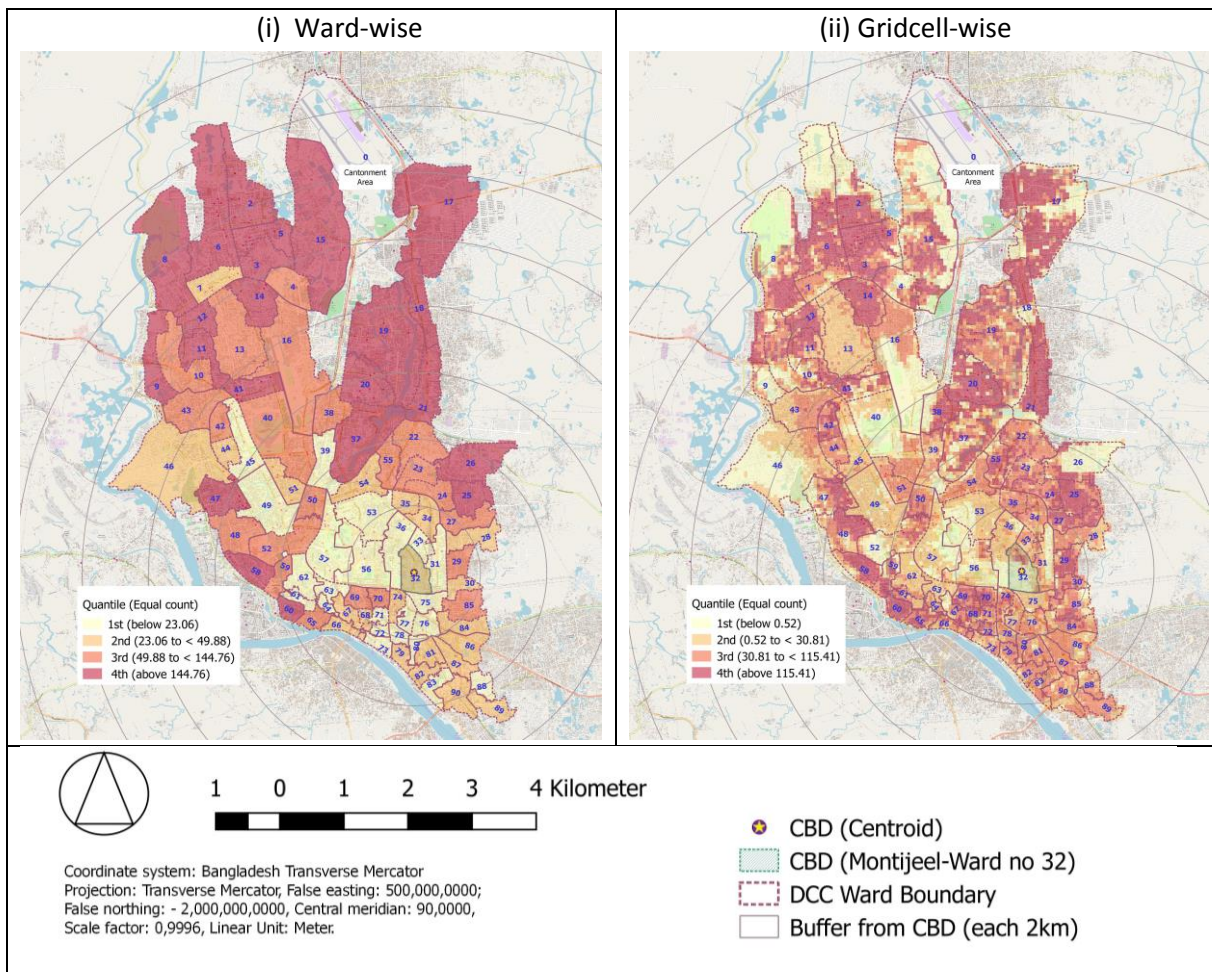


**Fig. 1.** Dhaka city showing the absolute population density distribution.

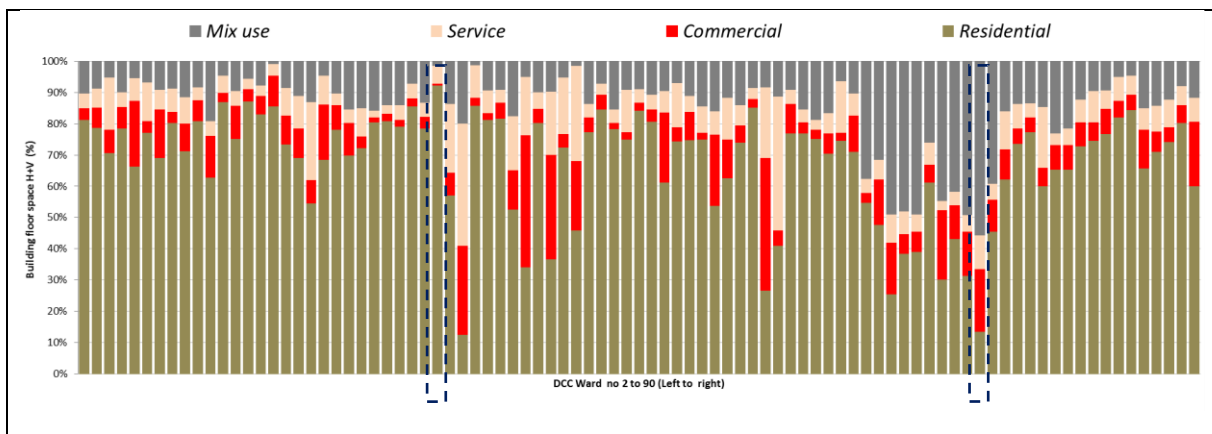




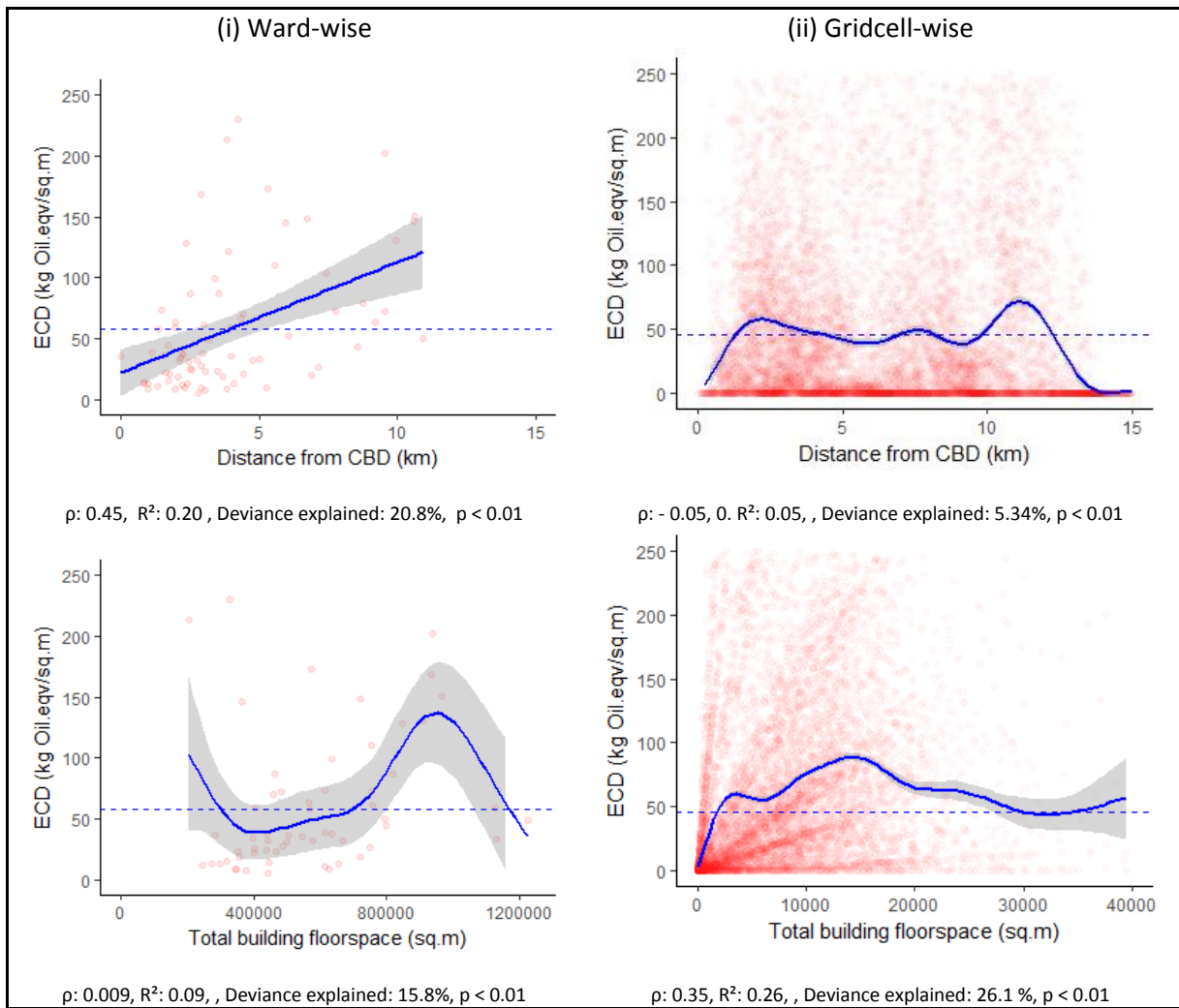
**Fig. 2.** Flow chart shows the steps of data processing, estimation and visualization



**Fig. 3.** Spatial distribution of energy consumption density pattern. Buffer rings indicate an air distance of 2km each from the CBD. The distance from CBD (i.e., Motijeel commercial area - DCC ward no. 32) was estimated as a straight line air distance (as like Makido, et al., 2012) in consideration of extracted centroid of each polygon feature (i.e., DCC ward and gridded-cell).

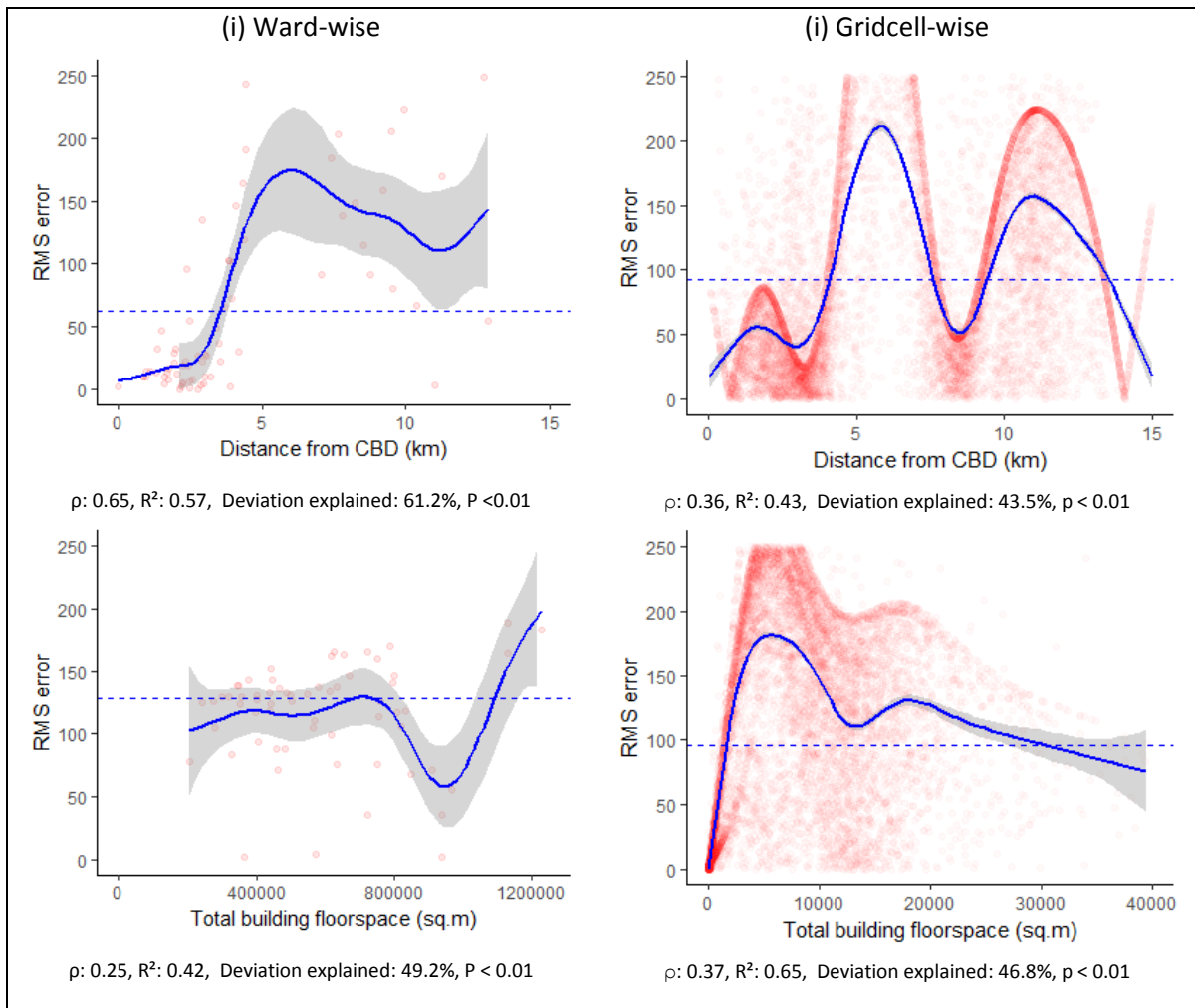


**Fig 4:** Distribution of building floorspace according to use at each ward

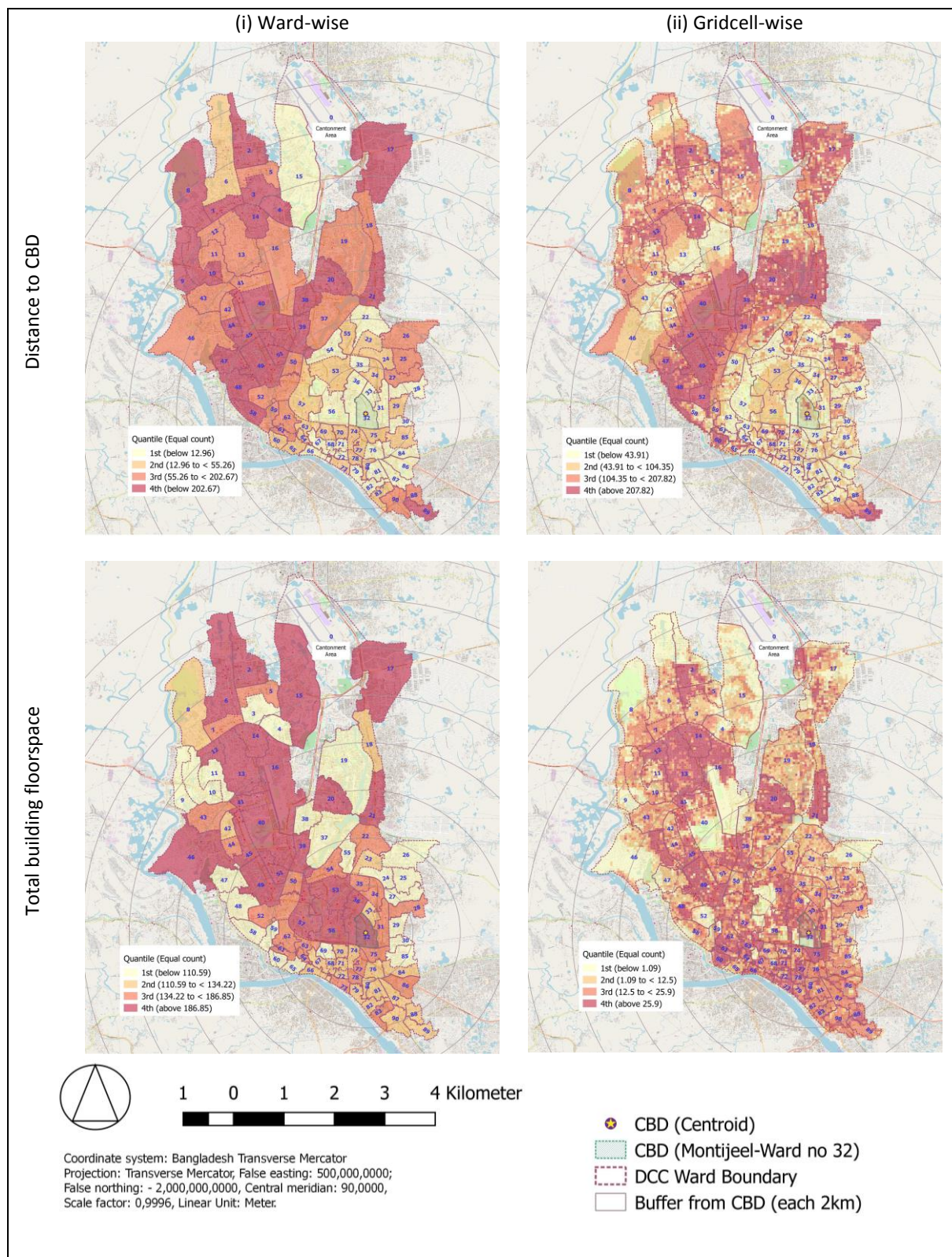


**Fig. 5.** GAM fit showing bivariate spatial relationship of ECD with distance to CBD and total building floorspace. The generalized additive model (GAM) used a formula:  $y \sim s(x)$ . Wood (2006) discussed detail theoretical insights on GAM with practical examples.



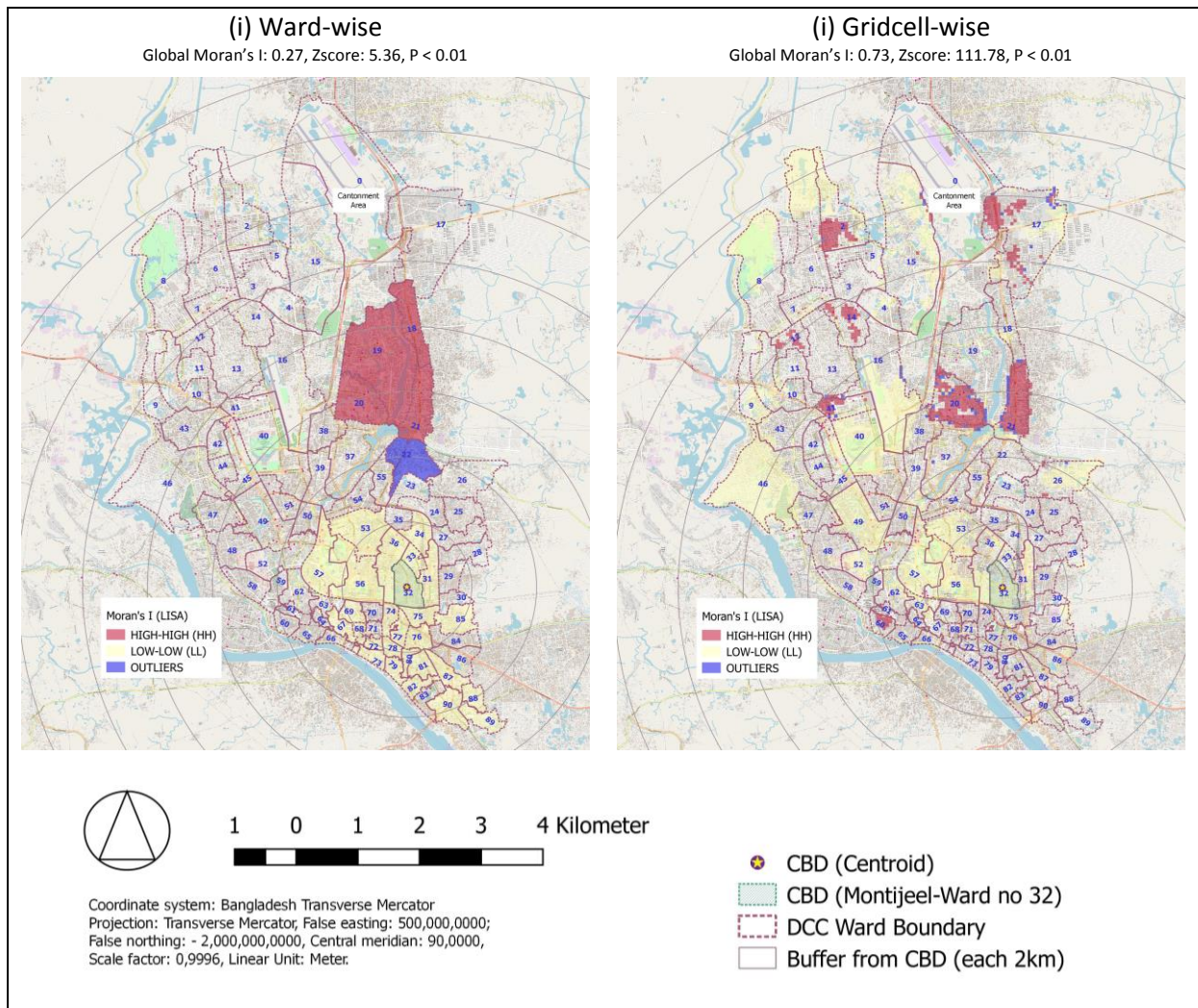


**Fig. 6.** Prediction sensitivity using GAM according to distance from CBD and total building floorspace.



**Fig. 7.** Spatial variation of model accuracy according to prediction errors (RMS).





**Fig. 8.** Spatial Autocorrelations showing local Moran's I clustering and outliers. The parameter for Moran's I and Getis G<sub>i</sub> calculation were settled as Euclidian distance, K=4 and 95% statistical significant.

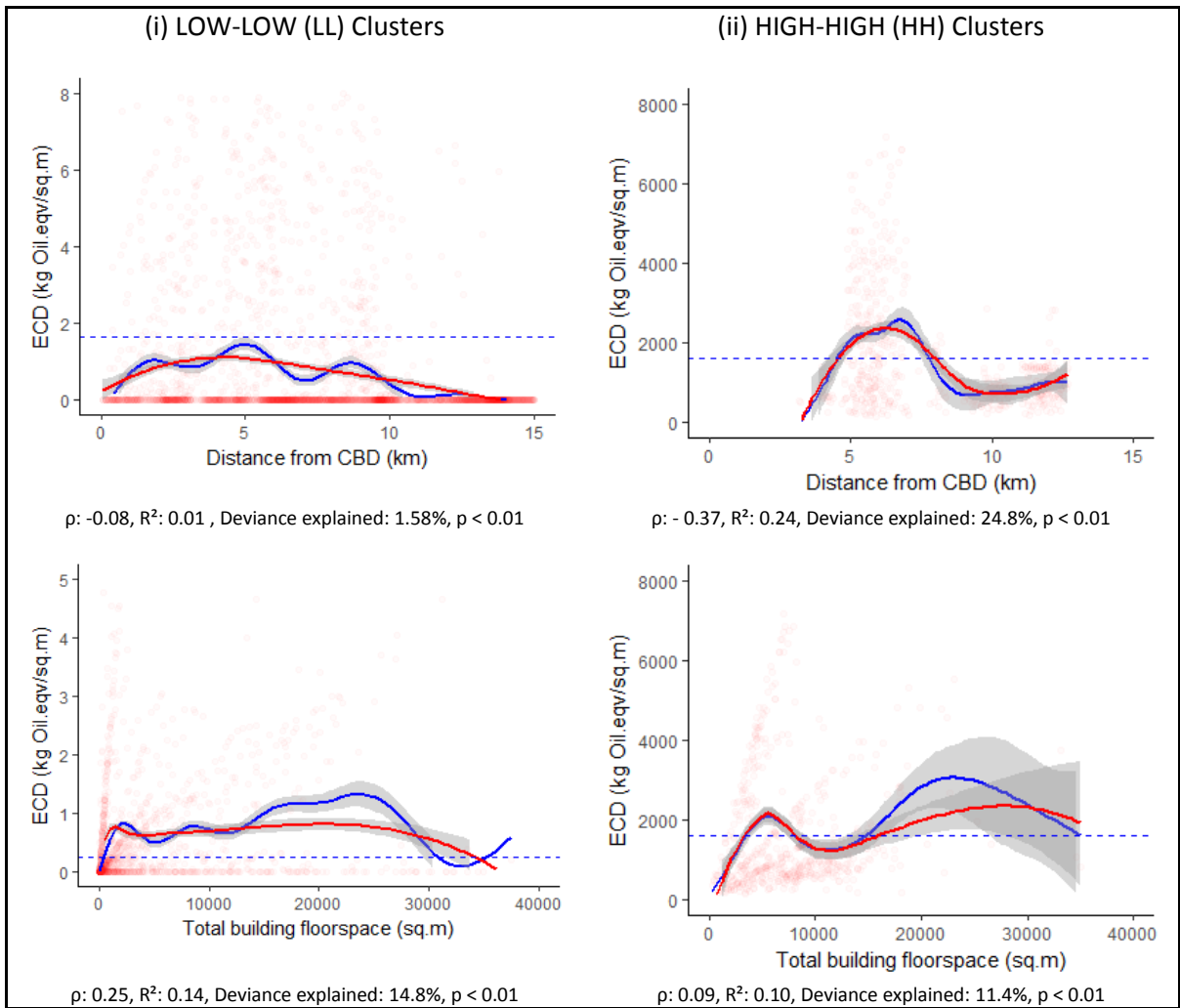
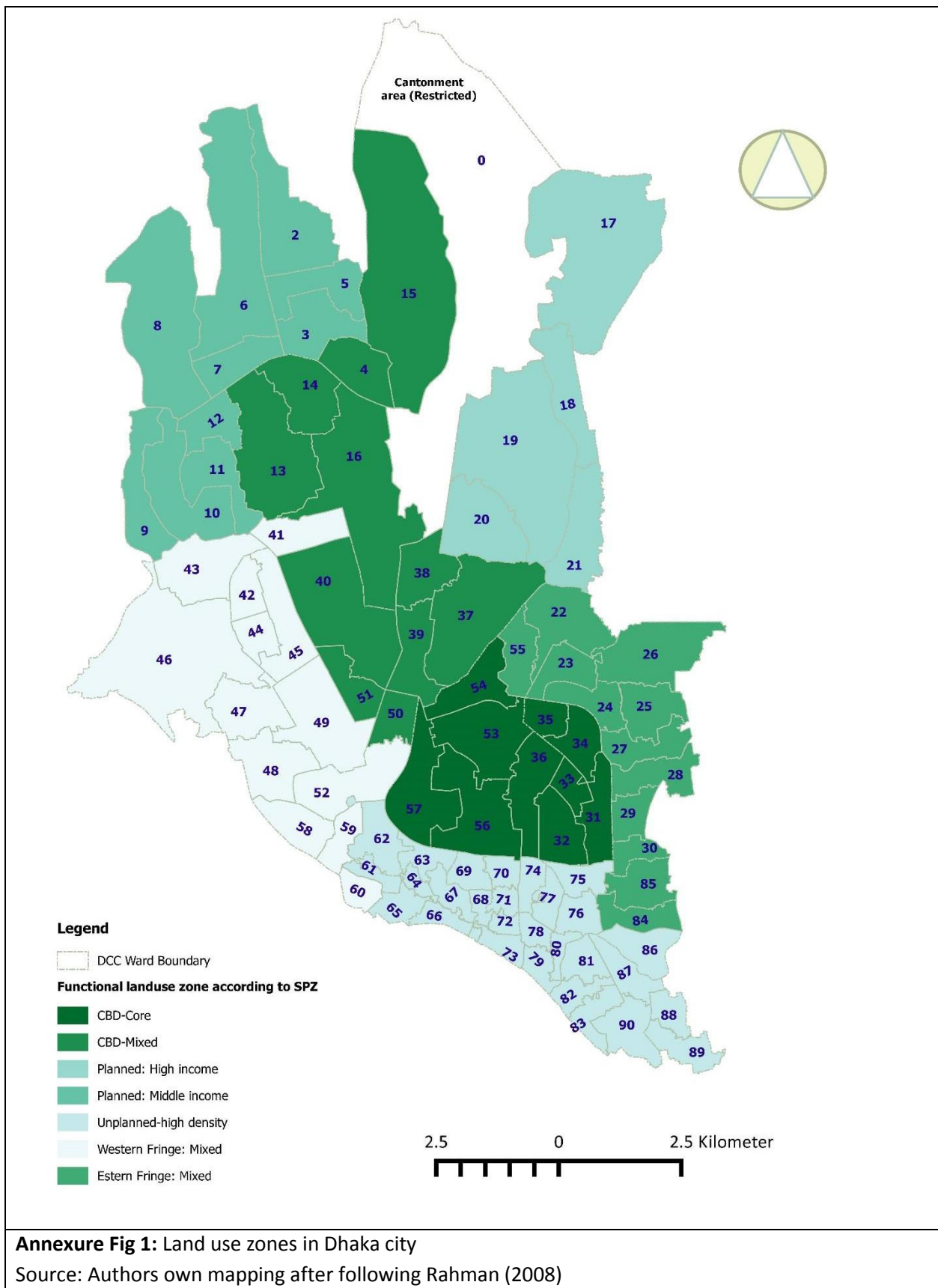


Fig. 9. Model fit after taking only statistically significant clusters according to Autocorrelation

statistics. The blue line shows GAM fit and red one is showing LOWESS fit.

**Annexure:**



**Annexure Fig 1:** Land use zones in Dhaka city

Source: Authors own mapping after following Rahman (2008)

Table 1: A brief overview on datasets from Dhaka city

<b>Dataset</b>	<b>Brief description</b>
Building Information (2007)	A vector type geodatabase built by the RAJUK through direct topographic survey in 2005-2006 for preparing Detail Area Plan (DAP) that were included features such as: building structures and other land uses. The building structures were also attributed with number of floors and use activities. This dataset were used in this study for extracting building floorspace (see section 2.3 and 2.4).
Population Census (2011)	BBS publish results from official population census, where ward is the smallest urban administrative and census unit in Dhaka. This information was used in this article for estimating initial energy consumption at each ward (section 2.5) and number of household.
Income Expenditure Survey - HIES (2010)	Since 1973, BBS has conducted urban income-expenditure survey and presented analysis including sector-wise monthly expenditure for fuel and lighting at the household level. The systematic statistical sampling was reported including large cities. In reference to this dataset, the annual residential energy expenditures for each Ward are estimated that also included the income profile variability of SPZ (section 2.5.1).
Transportation Survey - STP (2005)	Under initiative of STP, an intensive travel pattern interview was conducted with large number of samples (approx. 20,150 city dwellers). The survey aimed at determining how the residents' personal travel demand pattern related with transportation system parameters, trip expenditure, and income profile. Using this dataset, this article estimated an annual expenditure for motorized trip for each ward that also considered the variability of SPZ in Dhaka city (section 2.5.1).

Source: RAJUK (2007); HIES (2010); BBS (2011); STP (2005)

Notes: RAJUK - Capital Development Authority, BBS - Bangladesh Bureau of Statistics, SPZ - Spatial Planning Zone, STP- Strategic Transportation Planning

**Annexure-Table 1: ECD calculation – Example of DCC Ward 69**

Items	Values				Unit	Data Source
<b>Initial Energy consumption density (ECD) calculation:</b>						
Annual consumption in Greater Dhaka in 2011	9480427235.31				kgoe	Kennedy et. al. 2015
Per-cap energy consumption in greater Dhaka	607.08				kgoe	Estimated
Population of Dhaka (study area)	5253192				person	BBS
Average HH size	4.8				person	BBS
Population of Ward 69	62039				person	BBS
Area of ward 69	444087.4				sq.m	DAP
Total energy consumption of Ward 69	37662337.52				kgoe	Estimated
Total energy consumption of Dhaka	3132724966				kgoe	Estimated
% share in total energy consumption for Ward 69	1.179629875				%	Estimated
Building floor space for Ward 69	563950				sq.m	DAP
Residential floor-space for ward 69	345325.23				sq.m	DAP
Initial ECD <sub>i</sub> = Total energy consumption / Residential floor-space for ward 69	109.0633821				kgoe/sq.km	Estimated
<b>Weight calculation for Residential energy use:</b>						
Number of HH in Dhaka	1095665					BBS-Estimated
Average HH monthly expenditure of Dhaka city	15275.69				BDT	HIES, 2011 - Estimated
Average % HH monthly expenditure for fuel and lighting of Dhaka city	4.31%				%	HIES, 2011 - Estimated
Average HH monthly expenditure for fuel and lighting of Dhaka city	750.04				BDT	HIES, 2011 - Estimated
Annual Total expenditure for fuel and lighting of Dhaka city	9861510919				BDT	HIES, 2011 - Estimated
<b>For ward 69</b>						
Average HH size of Ward 69	5.17				Person	BBS
Number of households of Ward 69	12000				frequency	HIES, 2011 - Estimated
Average income of Ward 69					BDT	HIES, 2011 - Estimated
Average HH monthly expenditure for fuel and lighting of Ward 69	666.16	STP			BDT	HIES, 2011 - Estimated
Annual Total expenditure for fuel and lighting of Ward 69	95925493.79				BDT	HIES, 2011 - Estimated
% share of energy expenditure in Ward 69	0.9727261	%	<-- W <sub>DEI</sub>			Estimated
<b>Weight calculation for Transportation energy use</b>						
Average Annual Trip Motorized trip/HH for the entire Dhaka	1870.4				Trips	
Annual motorized trips for the entire Dhaka city	2049331816				Trips	
Average cost per trip for Dhaka city	45.83				BDT/trip	
Annual expenditure for Mobility use for Dhaka city	93920877127				BDT	
<b>For ward 69</b>						
Income groups	LIG	LMIG	HMIG	HIG		
% HH with in diff income groups for ward 69	33	37	26	4	Percentage	STP -2005
% Motorized trip for ward 69	41.2	30.5	48.1	68.6	Percentage	STP -2005, Estimated
Daily number of trips/HH per income group	7.8	9	3.8	10.4	Count	STP -2005, Estimated
Number of HH in diff income groups for ward 69	3960	4440	3120	480	Count	STP -2005, Estimated
Annual motorized trip for ward 69 per HH/ income group	1173	1002	1721	2604		STP -2005, Estimated
Annual motorized trip for ward 69/income group	4644863	4448475	5367989	1249927		STP -2005, Estimated
Annual motorized trip for ward 69 in grand-total	15711253.51				Trips	STP -2005, Estimated
Average cost per trip in Ward 69	35.65				BDT/trip	STP -2005, Estimated
Annual Expenditure for Mobility use in Ward 69	560106187.7				BDT	STP -2005, Estimated
% share of mobility expenditure in Ward 69	0.596359622		<-- W <sub>TEI</sub>		%	Estimated
<b>Adjusted ECD for Ward 69: (values used are from cells with Yellow colour)</b>						
ECD for Ward 69	109.0633821					Estimated
% share of energy expenditure in Ward 69	0.972726133	%	<-- W <sub>DEI</sub>			Estimated
% share of mobility expenditure in Ward 69	0.596359622	%	<-- W <sub>TEI</sub>			Estimated
<b>Adjusted ECD for Ward 69 = ECD for Ward 69 * W<sub>DEI</sub> * W<sub>TEI</sub></b>						
Thus, Adjusted ECD for Ward 69	63.26708	<-- final example answer for Ward 69			kgoe/sq.m	Estimated

**Annexure-Table 2: ECD calculation – Example of gridcell at ward no. 69**

<b>Cell level disaggregation example:</b>		
ECD <sub>i</sub> (i= 69)	63.26708	kg.oil equivalent /sq.m
Residential floor-space cell j (j=1228)	8374.96	sq.m
Residential floor-space i (i=69)	345325.23	sq.m
Share of residential floor-space at cell j	2.4252	%
ECD for Cell j in ward i	153.43775	kgoe/sq.m