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Research article

Carbon dioxide emission and bio-capacity indexing for transportation activities: A methodological development in determining the sustainability of vehicular transportation systems

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ABSTRACT

CO_2 emissions from urban traffic are a major concern in an era of increasing ecological disequilibrium. Adding to the problem net CO_2 emissions in urban settings are worsened due to the decline of bio-productive areas in many cities. This decline exacerbates the lack of capacity to sequestrate CO_2 at the micro and meso-scales resulting in increased temperatures and decreased air quality within city boundaries. Various transportation and environmental strategies have been implemented to address traffic related CO_2 emissions, however current literature identifies difficulties in pinpointing these critical areas of maximal net emissions in urban transport networks. This study attempts to close this gap in the literature by creating a new lay-person friendly index that combines CO_2 emissions from vehicles and the bio-capacity of specific traffic zones to identify these areas at the meso-scale within four ranges of values with the lowest index values representing the highest net CO_2 levels. The study used traffic volume, fuel types, and vehicular travel distance to estimate CO_2 emissions at major links in Dhaka, Bangladesh's capital city's transportation network. Additionally, using remote-sensing tools, adjacent bio-productive areas were identified and their bio-capacity for CO_2 sequestration estimated. The bio-productive areas were correlated with each traffic zone under study resulting in an Emission Bio-Capacity index (EBI) value estimate for each traffic node. Among the ten studied nodes in Dhaka City, nine had very low EBI values, correlating to very high CO_2 emissions and low bio-capacity. As a result, the study considered these areas unsustainable as traffic nodes going forward. Key reasons for unsustainability included increasing use of motorized traffic, absence of optimized signal systems, inadequate public transit options, disincentives for fuel free transport (FFT), and a decline in bio-productive areas.

1. Introduction

Urban transportation produces significant amounts of overall carbon dioxide (CO_2) emissions in urban areas (Li, 2011). Given an era of global warming and climate change, controlling CO_2 emissions, in support of sustainable development is a major concern in maintaining overall global sustainability and livability. According to the International Energy Agency (IEA), the transportation sector of the global economy was the second highest sectoral emitter of CO_2 emissions in year 2008; accounting for 22% of global CO_2 emissions (Loo and Li, 2012). Urban areas of the global economy with 54.5% (rising to 60% by 2030) of the global population are responsible for 75% of global CO_2 emissions, and intra-urban transportation contributed 17.5% of those CO_2 emissions (Fan and Lei, 2016). Dodman (2009), noted that, major cities around the world produced massive amounts of CO_2 from daily traffic movements. CO_2 emissions in representative cities such as: London (22 percent), New York (23 percent), Toronto (36 percent), and São Paulo (59.7%) support Dodman's observations. Additionally, fast developing countries with large populations such as India and China, are now experiencing steadily intensifying emissions of CO_2 from their burgeoning transportation sectors (Li, 2011; Dodman, 2009). It has long been projected that increasing traffic movements induced globally by

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both growth and increases in prosperity would be likely to increase transportation CO_2 emissions if energy consumption based on fossil fuels is not reduced (Li, 2011). Therefore, low CO_2 emissions and sustainable transportation initiatives are rising in importance in global agendas related to climate along with initiatives to change energy consumption patterns and production paradigms.

In addition to an ongoing global increase in transportation induced CO_2 emissions from urban areas, previous studies have identified a decline in bio-productive areas in cities, due to both a loss of area and both losses and degradation of vegetation in the remaining bio-productive area. Researchers have explored this reduction in bio-capacity, and concurrent increases in greenhouse gas (GHG) emissions (primarily CO_2) which jointly result in a widening deficit between the ecological footprint and bio-capacity, in turn resulting in a lack of environmental sustainability going forward (Mancini et al., 2016; Niccolucci et al., 2012). In a transport context, this can be a major indicator of the ability to maintain sustainability going forward. Several studies have linked transportation and CO_2 emissions; for example Shu and Lam (2011) studied traffic related CO_2 emissions and found spatial variations in CO_2 emissions from traffic activities correlated to differences in traffic intensity. Fan and Lei (2016), analyzed CO_2 emissions from traffic with a multivariate generalized Fisher index (GFI) decomposition model to examine the relation between energy structure, intensity and traffic turn-over. Zahabi et al. (2012) explored the effect of the built-environment on urban transport emissions. Labib et al. (2013) investigated the ecological footprint of urban transportation at city scale. Most of the existing transport-environment studies illustrated that growing populations, and the resulting demand for transportation when combined with a lack of available public transportation, influxes of new private vehicles to urban areas and a lack of energy efficient vehicles contributed to increases in CO_2 and other pollutant emissions (Perveen et al., 2017; Fan and Lei, 2016; Yigitcanlar and Kamruzzaman, 2014).

Currently, in the extant literature there is a paucity of research that studies specific locations, zones, and routes within urban transportation systems particularly those areas with high net CO_2. However, these same areas are those that would appear to require the most urgent near-term attention from policy-makers, to formulate and implement effective strategies for local CO_2 emissions reduction. This is a matter of particular urgency due to the ongoing decline of micro-climatic conditions in such areas as well as the need to address the decline in the already limited extent of bio-productive areas in cities (Shakil et al., 2014). Most often, transportation related studies have, in past, focused on mobility, accessibility, speed, or shifts in transport modes (Kamruzzaman et al., 2015). However, these studies do not provide data on existing conditions related to traffic related pollution as defined by net GHG emissions at particular locations. Nor do they provide data on co-located bio-productive areas with the capacity to diffuse or absorb emissions from local traffic.

Available ecological footprint studies at local scale (e.g. city or neighborhood level) have provided gross estimations of CO_2 emissions from residential energy, food, waste generation and fuel consumption, and compared these with area based bio-capacities (Shakil et al., 2014; Minx et al., 2013). However, such studies do not focus on the particulars of transportation related problems. Such studies have measured overall fuel consumption for transportation movements, without either breaking down transportation movements by types or making specific transportation related recommendations to improve transportation sustainability. Hence, there is a gap in the current literature in terms of understanding how traffic related carbon emissions correlate with local available bio-capacity particularly on the specific transportation routes or given zones in cities that have the highest net levels of CO_2.

In order to potentially create real world scenarios that implement sustainable transportation strategies, characterized by low CO_2 emissions and full carbon sequestration, it will be required to understand currently existing conditions related to CO_2 emissions from traffic as well as current carbon sequestration capacity. To facilitate such understanding the present study has rigorously utilized traffic volume and image-based remote sensing technologies to identify traffic zones which are critical, i.e. very heavily loaded, traffic nodes adjacent to bio-productive areas wherein the traffic zones are defined as the area within a 500 m radius of the critical traffic node as areas of interest (AOI). This study measured net CO_2 emissions from transportation activities/movements in these AOIs utilizing an inventory based carbon estimation methodology (Iqbal et al., 2016). The study specifically focused on the meso-scale level of analysis, in order to gain detailed insight into the differing characteristics of transport movement at study identified AOIs.

The present study presents a new index specifically created to correlate CO_2 emissions at critical traffic nodes with adjacent bio-capacity within the studied AOIs in order to calculate a net CO_2 emission value. This quantitative index will provide an opportunity to compare CO_2 emissions with sequestration capacity at specific locations in transport networks. In aggregate, data generated by applying this index to each critical node in a transport network will provide further data supporting policy and remediation both in real-time and as part of computer-simulations of 'what-if' scenarios. Furthermore, changes in the index values for a location based on either changes in traffic composition or changes in local vegetation will allow policy makers to easily grasp the effect of changes to environmental parameters which will, in turn, allow them to correlate index values to any costs of changing traffic or environmental parameters allowing for easier cost-benefit calculations.

2. Materials and methods

2.1. Conceptual design of "Emission, Bio-Capacity Index (EBI)"

Calculation of EBI values requires two types of activities; the first is related to the determination of CO_2 emissions from different vehicle types, based on different levels of activity, fuel type and emissivity (Fig. 1). EBI calculations determine the total daily and yearly CO_2 emissions from vehicular traffic activities for a given area AOI, and converts the yearly CO_2 emission value into the equivalent carbon uptake land measure (C, in global hectare) (Wiedmann and Barrett, 2010). The second type of activity requires determining the land cover types within the AOI and finding the corresponding bio-capacity for each land cover type. Index values are then generated by dividing the carbon uptake land estimated from yearly traffic CO_2 emissions by the total bio-capacity of the AOI, thus providing the value for the EBI for that AOI (Fig. 1). This relatively simple index combines the emissions of CO_2 emissions from traffic in a given area and co-located bio-capacity at the meso-scale into a single value. The basis of the model was derived from the concept of ecological footprints, and their relationship with biological capacities (Mancini et al., 2016; Ontl and Schulte, 2012; Wiedmann and Barrett, 2010).

The index developed for the present study is a new approach to providing tools that are easily and quickly comprehensible to policy-makers and non-experts and which will assist in determining the sustainability of a given transportation network as defined by net GHG emissions. Thus, this index will provide a sustainability-rating system for given locations and/or zones within a transportation network. Previously transportation networks' ecological footprints have been estimated by researchers; however combining the ecological footprint with co-located bio-capacity has heretofore only been explored in non-transport sectors such as housing, food and energy consumption (Nakajima and Ortega, 2016; Moore et al., 2013).

2.2. Case study area

In order to conduct the present study of traffic-related CO_2 emissions and co-located carbon sequestration capacity, a detailed spatial extent was selected. The present study was conducted at meso-scale, at ten major intersections (nodes) within the transportation network of

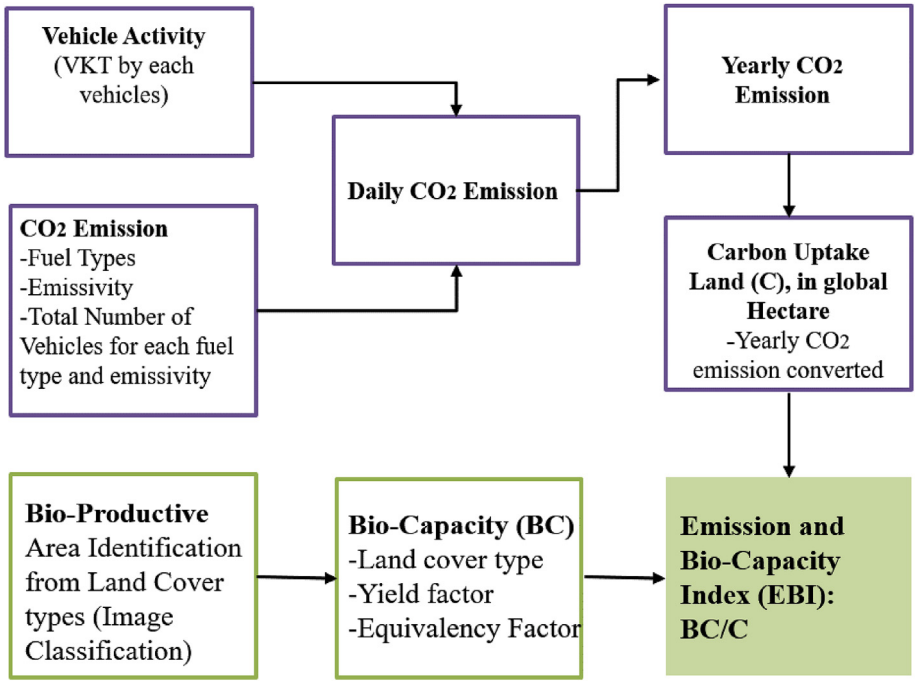

Fig. 1. Conceptual design of EBI.

Dhaka. Dhaka, is one of the fastest growing mega-cities globally and a major area of urban agglomeration. As a result, the city generates millions of trips every day, and traffic activity is both intense and intensifying (Iqbal et al., 2016). A complex network of roads of varied capacity, growing demands for private vehicles, and overall increase in motorization from year to year due to better economic growth and prosperity, are driving commensurate increases in CO_2 emissions. Dhaka's major arteries are characterized by chronic traffic congestion further exacerbating fuel consumption and related CO_2 emissions (Labib et al., 2013; Karim, 1999).

In addition to traffic emissions, the city is experiencing a loss of bio-productive areas capable of sequestering CO_2 emissions. Dewan and Yamaguchi (2009) found that the city was changing its land cover types, and built up areas were increasing with concomitant decreases in vegetation, bodies of water and fallow land (Hassan and Southworth, 2017; Dewan and Yamaguchi, 2009). For example, in the period from 1999 to 2009 built up areas within Dhaka increased by 16.86% of the total urban area, while vegetative cover, bodies of water and fallow land decreased by 3.23%, 1.98% and 10.80% respectively (Ahmed and Ahmed, 2012). Each of these declines could also be understood as a decline in available bio-productive areas. Thus, the continuing increases in CO_2 emissions combined with decreases in capacity to sequestrate carbon within city boundaries are resulting in continual increases in net CO_2 generation (Labib et al., 2013).

The ten study zones selected for the present study are major nodes in Dhaka's urban transportation network. The researchers delineated a buffer of one half of a kilometer radius around each node to create study zones/AOIs that allowed explicit determination of the spatial domain of measurement. The sites selected were: Mirpur 10 no., Technical Morh, Shymoli, Framgate, Mohakhali, Gulshan 1, Mog bazaar, Science lab, Motijheel and Jatrabari (Fig. 2). While city-level macro scale studies (Labib et al., 2013) can provide a general overview of overall emissions and extant bio-capacity, they are lacking in the specificity and detail required for meso-level analysis (Iqbal et al., 2016; Dias et al., 2016). Therefore, the present study focused on specific sites for detailed examination of GHG emissions as well as associated bio-capacity. Study site selection was focused on traffic nodes characterized by high levels of traffic volume, connectivity and diverse trip type generation. (Labib et al., 2014).

2.3. Vehicular emission estimation method

2.3.1. Emission modeling

In order to determine the amount of CO_2 emitted due to vehicular activity in Dhaka at selected AOIs; an inventory based emission model was utilized based on vehicular travel within the AOIs. In such models "bulk" emission factors (emissivity) and vehicle activity (distance travelled) are considered in determining an emission level from each different class of vehicles. This creates an aggregate, top-down, approach to estimating transport related CO_2 emissions (Kamruzzaman et al., 2015; Wadud and Khan, 2011; Afrin et al., 2012). The specific model that was utilized to estimate carbon dioxide emissions is given in eq (1) (Pan et al., 2016; Kamruzzaman et al., 2015; Neema and Jahan, 2014).

$$E_i = \sum_{j=1}^{n} \sum_{k=1}^{n} EF_{ijk} A_{jk} \tag{1}$$

Where,

i = Type of a pollutant (in this case CO_2)
j = Fuels consumed (e.g. CNG, Gasoline)
k = Emitting Vehicular type (Volume survey)
E_i = Emissions from pollutant
EF_{ijk} = Emission Factor (g/km)
A_{jk} = Activity level for each pollutant source.

The activity level for each pollutant source within a particular study site has been determined by the following relationship in eq (2);

$$A_{jk} = VKT = L \times AADT \tag{2}$$

where,

A_{jk} = Activity level for each pollutant source for each study area (km/day)
VKT = Vehicle Kilometers Traveled (km/day).
L = Road length (km) of the selected links within the study area

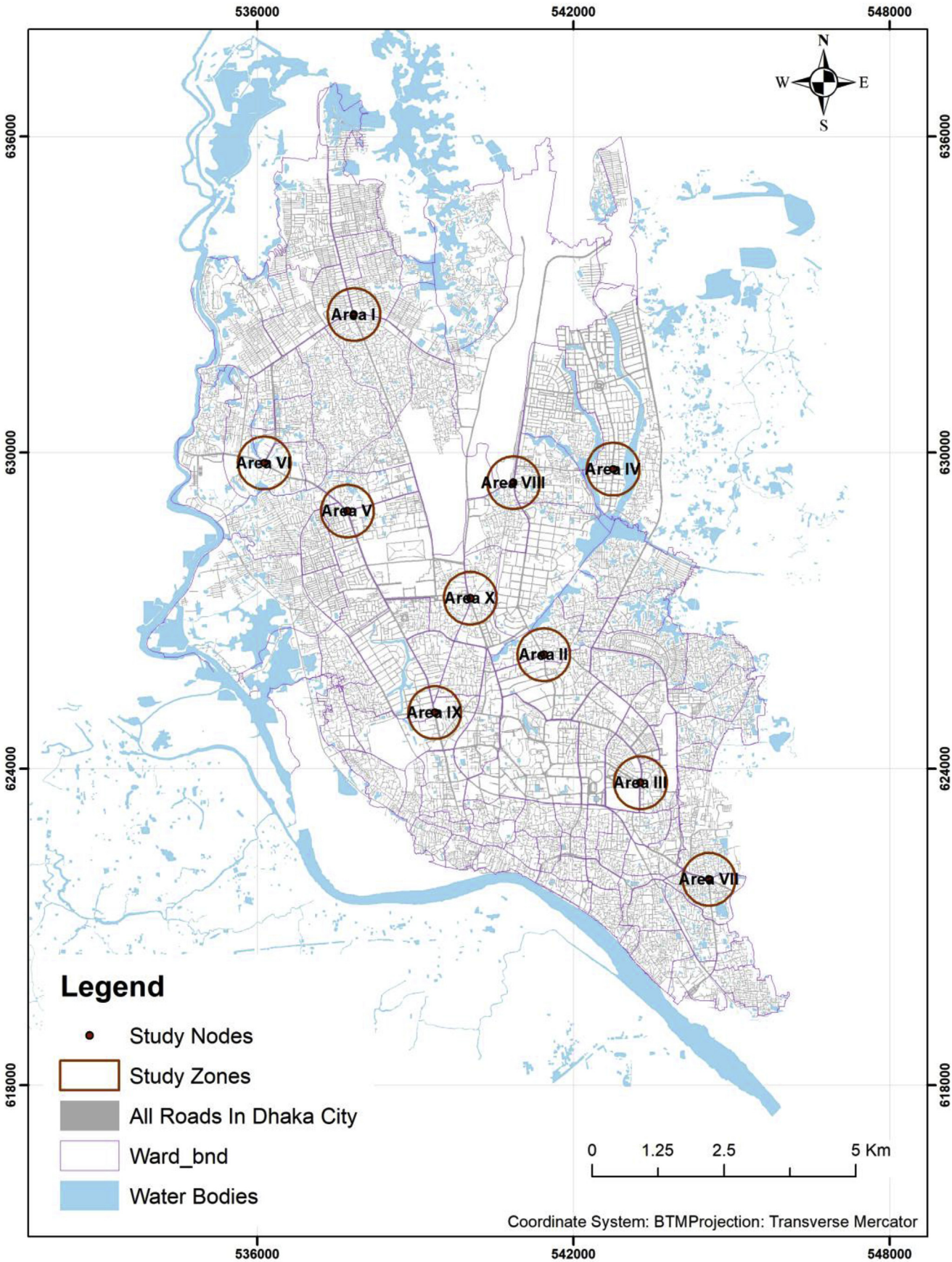

Fig. 2. Study areas, area of interest (AOIs).

AADT = Annual Average Daily Traffic (traffic volume/day)

2.3.2. Vehicle Kilometers Traveled (VKT)

The three methodological processes typically used to measure CO_2 emissions in aggregate, top-down, approaches to emissions modeling, are: (i) fuel consumption, (ii) specific vehicle tagging/tracking, or (iii) travel distance methods (e.g. VKT). In the present study vehicle activity level was determined by measurement of VKT, the most widely used method in determining CO_2 emissions at meso or micro scales (Kamruzzaman et al., 2015; Iqbal et al., 2016). For each study area, the selected road links' lengths were determined using GIS data for the Dhaka city traffic network drawn from the Detailed Area Plan database, developed by RAJUK, the city development authority. The present study made the assumption that, once a vehicle entered the study zone, and traveled the zone's road links, that this travel represented their total distance or VKT within the AOI zone(s).

2.3.3. Vehicle fuel usage type

Emission levels and emissions factors for each vehicle type depend on the fuel usage as well as fuel types consumed by that particular type of vehicle (Andrews, 2008). The emission estimation model suggests that while fuel usage is a factor of major significance in determining the total amount of emissions, the type of fuel a vehicle consumes during the process of combustion also impacts on the levels of CO_2 emitted. Thus, for the present study a detailed database summarizing the type of fuel used by each different type of vehicle found in the present study was necessary. Table 1 presents the fuel types each class of vehicle found in the present study could use and the percentage of use of each fuel type within each vehicle class. The table also correlates the fuel type usages for each vehicle class with the grams per kilometer of CO_2 emitted (Neema and Jahan, 2014; Wadud and Khan, 2011).

The specific fossil fuel types identified in Table 1 are: diesel, gasoline (petrol) and compressed natural gas (CNG). Among different vehicle classes, 100% of motorcycles observed used only gasoline, while 100% of all auto rickshaws, taxi cabs, and legunas (a partially open microbus converted to increase capacity) observed in the AOIs used CNG. A comparison of fuel usage values shows that CNG is the most used fuel amongst all vehicle classes in Dhaka due to the wide availability of natural Gas within Bangladesh.

Table 1
Fuel use type by different vehicle classes in Dhaka, percentage of usage and Emission factors (EFs).
Source: ([1]Neema and Jahan, 2014, [2]Wadud and Khan, 2011).

Vehicle Class	Fuel Type	Percentage of Usage[1]	CO_2 Emission Factor (gm/km)[1,2]
Car	Petrol	13.80%	258
	CNG	86.20%	237
Bus	Diesel	24.20%	887
	CNG	75.80%	968
CNG Auto Rickshaw	CNG	100%	75
Motorcycle	Petrol	100%	40
Microbus/Ambulance	Petrol	6.50%	331
	CNG	85.50%	162
	Diesel	8%	344
Jeep/Station wagon	Petrol	24.70%	331
	CNG	57.80%	363
	Diesel	17.50%	332.5
Taxicab	CNG	100.00%	237
Leguna/Tempo/Human Hauler (Para-transit)	CNG	100.00%	450
Pick up/Minitruck	Diesel	9.00%	500
	CNG	91.00%	450
Truck	Diesel	82.60%	887
	CNG	17.40%	450

2.3.4. Emissivity of various vehicles based on different fuel types

In the inventory based emission model, emissivity represents per unit emissions expressed in grams per kilometer of vehicle travel (gm/km) (Pan et al., 2016; Kamruzzaman et al., 2015). In order for the emissions model to provide valid results it requires the emission factors (EFs) to be accurately measured. Studies conducted by: Labib et al. (2013), and Neema and Jahan (2014) of Dhaka's transport network used emission factors developed by Wadud and Khan (2011) and showed that these EFs do provide acceptable level of accuracy for emissions from vehicles, operating under typical traffic conditions in Dhaka. Table 1 presents the corrected emission factors correlated with the relevant different vehicles categories and fuel types. It should be noted that, Table 1 shows that for some vehicle classes (e.g. buses and jeeps) have higher emission factors associated with combustion of CNG compared to diesel or petrol. However, most vehicle classes (e.g. cars, micro-buses, pickups) had lower values for their emissions factors when fueled with CNG compared to diesel and petrol. The researchers note, that the efficiency of internal combustion engines under varying fuel regimes is a complex topic impacted by many factors beyond the scope of this study and further note that both the potential quality of liquid fuel to CNG conversions (Diesel-to-CNF, Petrol-to-CNG) and overall vehicle maintenance are impacted by both parts availability and economic constraints that many vehicle operators in developing countries face (Wadud and Khan, 2011).

Overall, the researchers suggest that it may be argued that these EFs are an estimate of per-unit emissions for different modes where the vehicles involved are at least likely to have reached normal engine operating temperatures. They also note that different per-unit emission values might be calculated if all factors including: fuel efficiency, engine type, age of vehicle, quality of engine conversion from liquid to CNG fuel, and hot/cold emission values could be provided for detailed emissions modeling. However, failing the ability to do such data-intense modeling, and in light of the fact that the emissions data gathered by the current study was analyzed utilizing empirically based values for Dhaka emissions from the Wadud and Khan (2011), where they estimated and validated the EFs for the vehicle classes by their field observation and tests. The researchers are confident that EF values derived for vehicular emissions for this study represent values based on the real world traffic composition found in Dhaka by taking account of vehicle condition, fuel use and vehicle efficiency in terms of traffic operation in Dhaka.

Furthermore, as the presents study was focused on the meso-scale and based on the aggregate method of data collection, The EF values used were a necessary compromise to cover larger volume of traffic in the major streets of Dhaka city. Therefore, intensive emission modelling (usually micro-scale) was not adopted in this case study, also other issues related to congestion emission (i.e. idle emission), vehicle speed based emission variations was not considered. Such details are primarily considered for micro level studies, where in this case mesoscopic studies focused on spatial variation across transportation network at selected areas (Dias et al., 2016).

2.3.5. Traffic volume data collection

Traffic volume data in the AOIs was captured manually on weekdays from February to March, 2014. Utilizing the peak hour volume survey data for each area the peak hour traffic (7.00 a.m.–10.00 a.m.) value was converted to a value for daily traffic by multiplying the data captured by an empirically derived conversion factor developed for previous traffic studies in Dhaka conducted by Jahan (2013) and Neema and Jahan (2014). These conversion factors were validated by Jahan (2013) by comparing the annual average daily traffic (AADT) at the time of Jahan's study with emissions and traffic data found in the strategic transportation plan (2005) for Dhaka (STP, 2005). Therefore, the estimated daily weekday traffic was assumed to be representative of the annual average day daily traffic (AADT) for the surveyed links within the study areas. It should be noted that, due to AADT data

unavailability during the study period, this research required the application of such a conversion factor. However, if AADT data were available for the study period for the nodal sites under study, being based on yearly observed traffic data, using actual AADT data instead of applying a conversion factor, would provide more robust results.

Based on volume of vehicular traffic, vehicle activity levels, and the fuel types of the observed vehicles, the corresponding emission factors, eq (2), and eq (1) were estimated for each AOI for a single day. This data was then converted to an annual carbon dioxide emissions value by multiplying the average number of days in a year with the daily value for each study area.

2.4. Carbon uptake land estimation

The calculated total CO_2 emissions for each year were used for the estimation of the hectares of carbon uptake land that would be required to wholly neutralize these emissions. In order to determine the total biologically productive hectares of area needed to sequestrate total emissions a soil carbon sequestration factor was used (Moore et al., 2013; Ontl and Schulte, 2012; Monfreda et al., 2004; Wackernagel and Rees, 1998). A soil carbon sequestration factor of 1.6175 per acre of land was applied (Xu and Martin, 2010) and it was then converted to local hectare values by multiplying the resulting value by 0.4047 (Shakil et al., 2014). The obtained local hectare values were then converted to global hectare (gha) by an equivalence factor (EQF) of 1.26 (Ewing et al., 2010; Monfreda et al., 2004). In this case, eq (3) summarizes the calculations required to determine the carbon uptake land value for the relevant AOIs (Moore et al., 2013; Xu and Martin, 2010).

$$C = \left(\frac{TC}{S}\right) \times EQF \tag{3}$$

where,

C = Carbon uptake land (in global Hectare, gha)
TC = Total CO_2 in tons in a year (in tons)
S = Soil carbon sequestration factor (tons CO_2/acre/year)
EQF = Equivalency factor (gha/hectare)

Using eq (3) total CO_2 produced in each study area could be converted to a carbon foot print expressed in gha (Global Hectare) units. This calculated area was then utilized to estimate the EBI value.

2.5. Bio-capacity estimation process

2.5.1. Bio-capacity estimation

Bio-capacity (BC) is the capacity of an ecosystem to produce biological materials of use to humans and also to absorb waste they generate (including CO_2 emitted by combustion of fossil fuels) (Mancini et al., 2016). Land areas that contribute to bio-capacity may include cropland, grazing land, fishing grounds, forest and built up areas (Wackernagel et al., 2005; Monfreda et al., 2004), eq (4) is the equation for bio-capacity estimation for each AOIs considered in the present study (Mancini et al., 2016).

$$BC = \sum_{i=1}^{n} Ar_i * YF_i * EQF_i \tag{4}$$

where,

BC = Bio-capacity (in global hectare, gha)
Ar_i = Area of i land use type (hectare)
YF_i = Yield factor i type land use type (ratio of national yield and world average yield)
EQF_i = Equivalency factor for i type land use type

In this case, BC represents the total bio-capacity within an AOI. This BC is a summation of the bio-productivity of each land use type based on their yield and equivalence factor. Here, 'i' indicates the specific type of land use, for example forest, or water. For each land use type, there is an associated specific Yield factor (YFi) calibrated to Bangladeshi conditions, and the specific equivalency factor (EQFi) has been accounted for in the estimation process. Satellite image analysis was used to determine the area devoted to each identified land use type (Ar). The amounts of land devoted to built-up areas, vegetation and water bodies in the AOI were estimated utilizing the following image classification method. It should be noted that, Bangladesh specific yield factor and equivalency factors were obtained from Shakil et al. (2014) and Labib et al. (2013), based on Global Footprint Network, 2011, and the YF and equivalency factors for different land cover types as listed in Tables 1S and 2S in the supplementary document.

2.5.2. Land use classification

Detailed land use type information for each AOI was derived by applying a supervised classification-maximum likelihood algorithm to high resolution satellite images of the areas of interest (Lillesand et al., 2014; Ahmed and Ahmed, 2012). In this case, *DigitalGlobe* satellite images (25, November 2013) were obtained and geo-referenced, as universal transverse Mercator (UTM) within the zone 46 N–datum world geodetic systems (WGS) 84. The per pixel size of the satellite images resolved at 0.6 m. The present study's scale of analysis required higher spatial resolution images in order to identify detailed land use types. Vegetation, water bodies, vacant land, buildings, and other infrastructure (e.g. the transport network) were land use classes utilized to determine bio-capacity. Details of these land use classes can be found in Table 3S in the supplementary document.

A sufficient number of training samples that are representative of the area under analysis are critical for accurate image classification using ERDAS Imagine software as used in the present study. Training sites within the image are required to calibrate the software to accurately identify each land cover type found within a given image being analyzed (Campbell and Wynne, 2011). The sites used for the training samples were chosen based on reference data and ancillary information collected from secondary sources; in this case Detailed Area Plans for Dhaka, 2010 maps, and Dhaka City Corporation (DCC) Ward maps. After training sites development, signature creation, and running maximum-likelihood classification algorithms in ERDAS Imagine, five classified land cover types in the AOI's were identified. These five land cover types were merged into three broader types for the purpose of analyzing bio-capacity they comprised: built-up areas, vegetation, and water bodies. In turn areas in the images identified as one of these three types were assessed for classification accuracy. In the present study, this accuracy assessment was conducted by a ground truthing cross check process. For each land use class, GPS readings at five points were taken during field visits at each AOI. Therefore, a total fifty points were available for the ten study areas (Table 45S, supplementary document), with known land use for each point and these were then geo-referenced as point features in GIS. Finally, from the error matrix, producers' accuracy, user accuracy and overall accuracy was estimated (Labib and Harris, 2018). The classified images were then utilized to find the total area of each land cover type within each study area. These total areas were then inputted into the bio-capacity estimation equation (eq (4)) and the bio-capacity of each study area was determined.

2.6. Emission and bio-capacity index estimation

After completing the calculation of the amount of carbon uptake land that would be required to completely neutralize a given study area's CO_2 emissions versus the bio-capacity in global hectares (gha) for each of the ten AOIs an "Emission and bio-capacity index" value was calculated for each AOI. The calculation of the index value is shown in eq (5).

$$EBI = \frac{BC}{C} \quad (5)$$

where,

EBI = Emission bio-capacity index (EBI)
BC = Total bio-capacity of an area (gha)
C = Carbon Uptake land of that particular area (gha)

The emission bio-capacity index value represents the over or undershoot between the value of carbon uptake land equivalent to 100% sequestration of GHG emissions and the actually measured bio-capacity. Thus, EBI values of ≥1 imply that the bio-capacity is adequate to sequestrate observed CO_2 emissions produced from vehicle operations within the AOIs. EBI values of < 1 indicate that bio-capacity or bio-productivity are not great enough for full CO_2 sequestration and or not producing enough bio-products of a value to offset the CO_2 impact of traffic related CO_2 emissions. It should be noted that, Carbon uptake land have only been estimated for traffic related CO_2 emissions, other CO_2 emissions such as industries, household waste not been considered. Therefore, EBI values in this case only represent the traffic CO_2 emissions situation and related bio-capacities. If other emission sources (e.g. Industries) been considered, the overall EBI values may have changed, and then comprehensive bio-capacity and emission scenarios might be identified, which is beyond the scope of this study.

For current study, EBI values less than 1 are categorized into three classes. These classes are generated using the equal class interval method. Based on these classes, index values are translated into an easy to understand single digit, whole number emission bio-capacity score (EBS) value (1–4) and equivalent color code (e.g. red, orange, yellow, and green), in which the value one which correlates with red represents very high net CO_2 emissions and correspondingly low bio-capacity as illustrated in Table 2. As presented in Table 2, the EBI value ranges and corresponding scores have descriptors to that convert the number values into easily interpretable descriptions for wider audiences. The researchers chose the equal class interval method as other approaches to classification such as the natural breaks method. Despite natural break method provide better fit for the studied AOIs by optimizing the classes based on EBI values, however this classification approach do not let standardization of this method for other study areas, such as other cities. Nonetheless, the details of utilizing the natural breaks method of classification can be found in Table 4S in the Supplementary document.

3. Results

3.1. Vehicular CO_2 emission scenario in study areas

Bio-productive areas in the AOI's was generally fixed or in decline (Ahmed and Ahmed, 2012). Thus, the significant variable governing changes in net CO_2 emissions and the EBI index value was derived from vehicular exhaust. In turn, the composition of such exhaust was dependent upon three sub-variables: vehicle type, fuel use and activity levels. The results for these major sub-variables are discussed for each AOI in the following sections.

3.1.1. Vehicle type composition

Volume survey data represents the vehicle composition in the AOI under study. Fig. 3 depicts the vehicle type composition in different study areas. Fig. 3 shows that in most areas automobiles generated the highest share of traffic volume. It also indicated that the highest automobile usage was observed in areas V, VI and VIII (namely Gulshan 1, Science lab and the Farm-gate area). By contrast, the greatest concentration of bus traffic was observed in areas I, VII, X, IX (namely Mirpur 10, Mog-bazaar, Jatrabari and Motijheel area). CNG auto-rickshaw and motorcycle were a moderately dominant mode of travel in all study areas. Other modes (jeep, pick-up, leguna, and taxi) comprised an insignificant share of overall traffic composition.

3.1.2. Vehicle classes aggregate share of CO_2 emissions and per-capita emissions

Each vehicle class has different emission characteristics and emission factors based on its engine type and power, age of engine, type of fuel consumed, fuel efficiency etc. Fig. 4 shows variations in CO_2 emissions from different vehicle types in all AOIs. It is clear that except Area V the highest levels of CO_2 emissions observed were derived from bus service, followed by automobiles. CNG fueled buses were found to have the highest per vehicle emission factor (968 gm/km) among all the types of vehicles observed. For example, the emission factor for CNG fueled automobiles was less than one-third (237 gm/km) as much as that for CNG fueled buses. Despite automobiles comprising the majority of traffic, due to their lower emission factors they contributed less CO_2 emission compared to buses on a per vehicle basis. Overall, however, Fig. 4 makes clear that automobiles and buses generated between 60 and 70% of all CO_2 emissions in the AOIs.

Emissions per vehicle is an insufficient measure of CO_2 emissions versus person-miles traveled in urban traffic. What is key to understanding traffic volume versus emissions observed is to examine the value for the *per-capita* emissions for different vehicle classes in the AOIs. For example a full bus may have a much lower per-capita emissions value than other classes of vehicles in traffic despite having the largest per vehicle emissions value. Per-capita emissions for each vehicle class (Fig. 1S, supplementary document), have been estimated using vehicle occupancy data obtained from Labib et al. (2014). Analysis of estimates of per-capita vehicle usage show that emissions per passenger are highest from automobiles. By contrast, public transit buses have the lowest per-capita emissions. Aggregating all the AOIs studied, the per-capita emissions generated by automobiles were ten times higher than the per capita value for buses. This result is consistent with other studies such as Wang et al. (2017) and Wang et al. (2015), whose reported results were similar to those in the present study, with buses having the highest occupancy and thus the lowest per-capita CO_2 emission levels.

3.1.3. Total CO_2 emissions in each AOI

This section provides estimates of total CO_2 emissions from the transportation sector for the studied AOIs. In order to determine the total daily CO_2 emissions from each AOI, emissions data for traffic on all links within each study area were combined. Annual emissions were projected by multiplying the number of days in a non-leap year by the net CO_2 emissions calculated for each AOI daily, as shown in Table 3. Details of daily and yearly CO_2 emission for all AOIs can be found in Table 47S, in the supplementary document. As illustrated in Table 3 'Total tons of CO_2 in a year' column, the lowest CO_2 emissions occurred

Table 2
Emission and bio-capacity index classification.

Emission bio-capacity index (EBI)	Emission bio-capacity score (EBS)	Descriptor	Color Code
≥1.0	1	Bio-capacity is very good and capable of sequestrating all CO_2 emissions in area.	Green
0.67–1.0	2	Bio-capacity is not adequate to absorb all CO_2 emissions.	Yellow
0.33–0.67	3	Bio-capacity is extremely low in comparison to net CO_2 emissions.	Orange
< 0.33	4	Bio-capacity is in critically short supply in area and net CO_2, emissions are extremely high.	Red

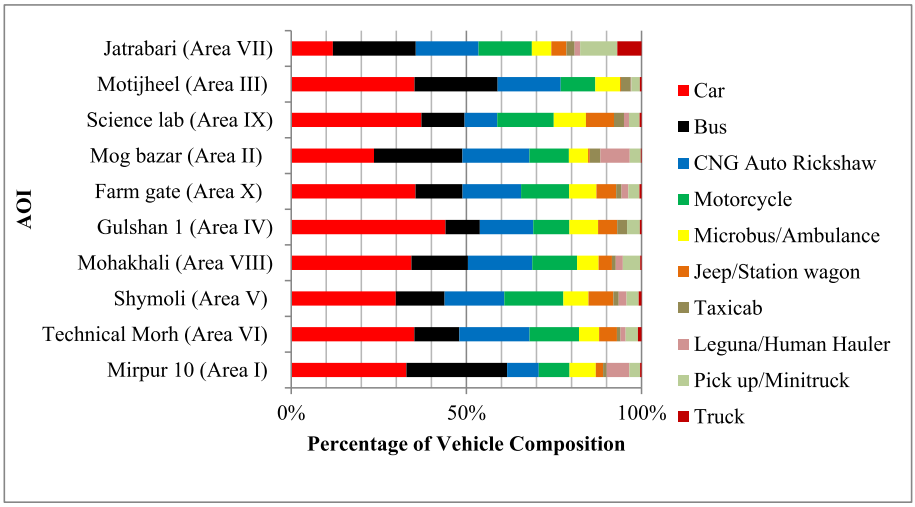

Fig. 3. Vehicle type composition in selected study areas from volume survey data.

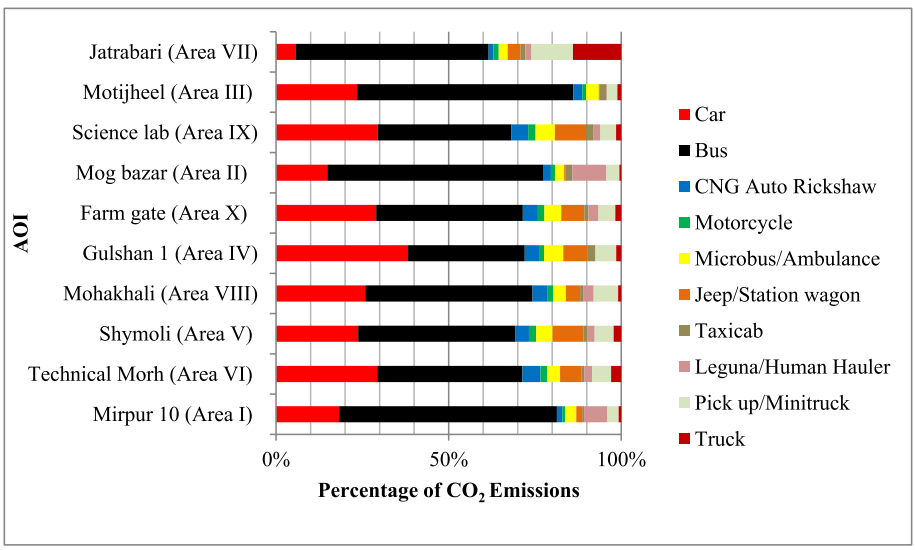

Fig. 4. CO_2 emission levels from different vehicle types in each AOI.

in Area I; by contrast the highest CO_2 emissions were observed in Area X the most active node in the city transportation network. Higher CO_2 emissions levels correlated with higher levels of transportation activities in the AOI's in the present study. This was not only illustrated by very high levels of traffic in Area X but also by the low levels of traffic in Area I. Detailed Area Plan land use data supported this as well as our findings that Area I was predominantly residential and thus supporting fewer commercial and administrative activities (Labib et al., 2014). As a result, Area I generated less transportation activity and hence fewer emissions. Its predominantly residential nature also meant that it was an area of trip production, rather than trip attraction. Combining all AOIs in the present study generated an average value for CO_2 emissions of thirteen tons of CO_2 emitted per day. Figs. 5 and 6 show the quantity of CO_2 emissions mapped to the AOI's in the present study. The emissions calculation for each link within each AOI is presented in Tables 5S–46S, Supplementary Document.

3.2. Carbon uptake land equivalent to CO_2 emissions in AOIs

Utilizing the estimated CO_2 emissions from transportation activities in each AOI, the carbon uptake land value that would be required to absorb all CO_2 emissions in each AOI was determined. Table 3 presents a summary of the estimated amount of carbon uptake land that would be required to neutralize and sequester all CO_2 emissions at the time of the present study. The table shows that the largest carbon uptake land value would be required for areas IV and VIII (Farm-gate and Science Lab). By contrast the lowest carbon footprint was found in areas I and VII (Mirpur 10 and Mog-bazaar). For all cases, the carbon uptake land value required was calculated by multiplying total net annual CO_2 production with the appropriate conversion factors, first for sequestration of all CO_2 emitted expressed in tons per acre per year, followed by a conversion of this value to hectares and finally a conversion of the hectare value to global hectares to arrive at the estimated carbon uptake land area expressed in global hectares. These estimated carbon uptake land (C) values were then utilized as input values to eq (5) in determining the EBI values.

3.3. Bio-capacity of each AOI

Bio-capacity is one of the major constituents of the EBI. Therefore, the value for the biological capacity of each AOI was estimated utilizing eq (4) in the methodology section. The outcomes of the bio-capacity estimation process are described below.

3.3.1. Bio-productive areas

For bio-capacity estimation three broad categories of land use types

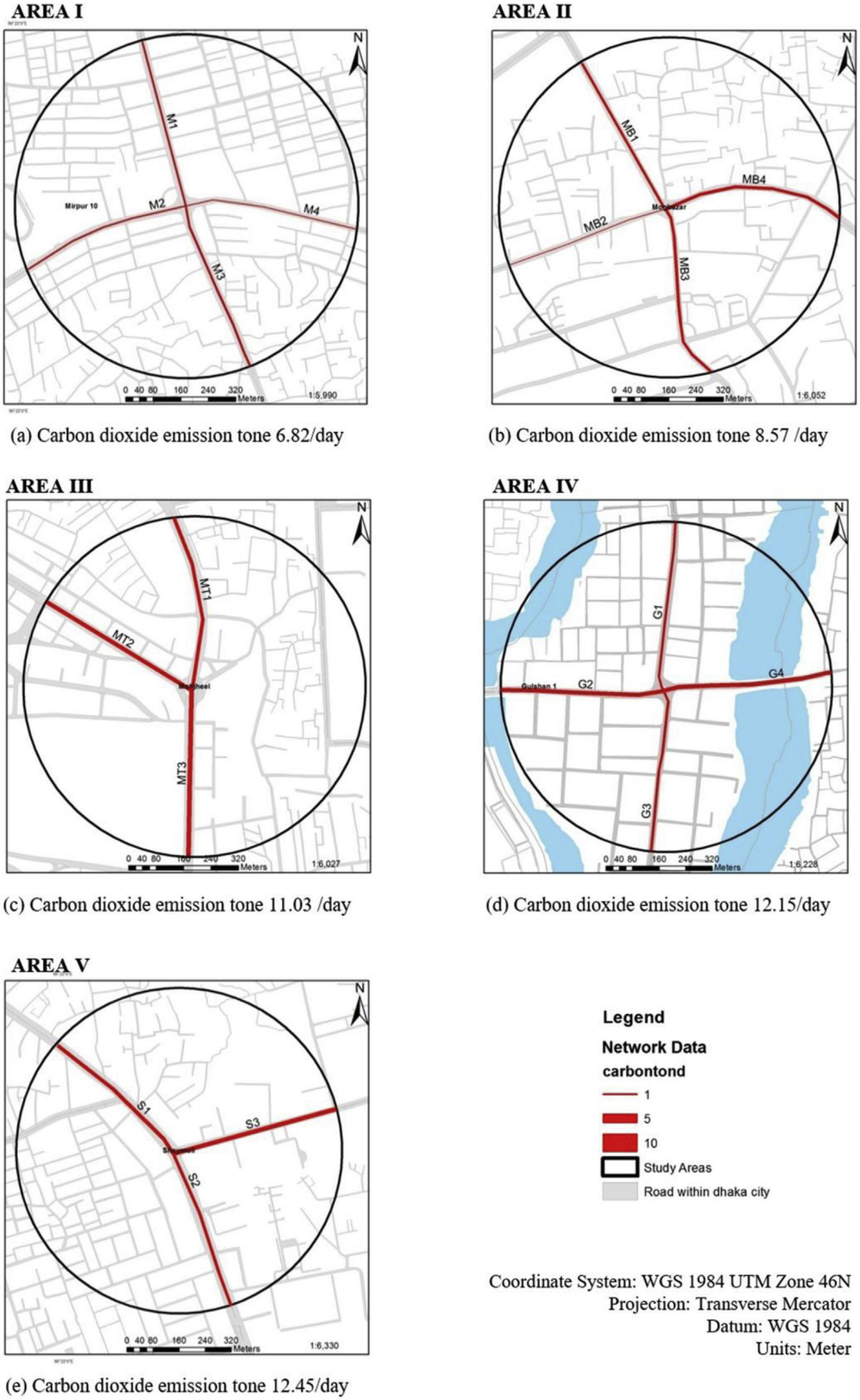

Fig. 5. Average daily CO_2 emission map for the transport links found within the AOIs.

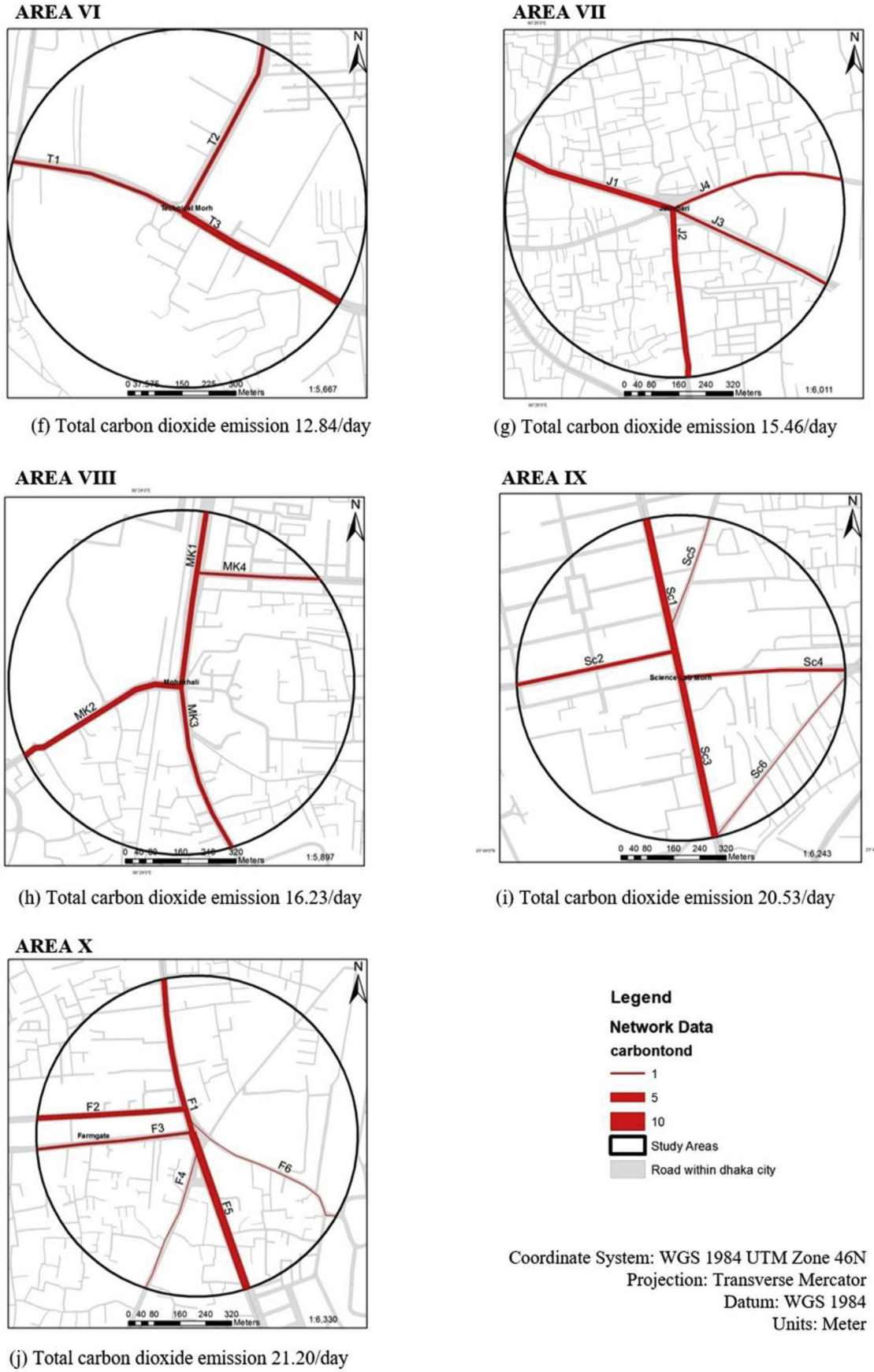

Fig. 6. Average daily carbon dioxide emission map in different transport links within AOIs.

Table 3
Estimated Carbon Uptake land for AOIs.
Source:[1]Ewing et al. (2010); [2]Shakil et al. (2014); [3]Xu and Martin (2010).

Area	Total tons of CO_2 in a year	Sequestration (tons CO_2/acre/year)[1]	Acre to Hectares conversion factor[2]	Hectares	Hectares to global hectares conversion factor[3]	Carbon Uptake Land (C, gha)
	I	II	III	IV = (I/II)*III	V	VI = IV*V
Area I (Mirpur 10)	2489	1.6175	0.4047	622.83	1.26	784.76
Area II (Mogbazaar)	3128			782.64		986.13
Area III (Motijheel)	4025			1007.30		1269.19
Area IV (Gulshan 1)	4434			1109.58		1398.07
Area V (Shymoli)	4544			1136.98		1432.59
Area VI (Technical Morh)	4686			1172.59		1477.47
Area VII (Jatrabari)	5642			1411.86		1778.94
Area VIII (Mohakhali)	5923			1482.18		1867.54
Area IX (Science lab)	7493			1874.87		2362.33
Area X (Farm gate)	7738			1936.05		2439.43

were identified namely: i) built-up areas (comprising buildings, infrastructure, roads), ii) vegetation, and iii) bodies of water. Figs. 7 and 8 represent the results of the present study's land surface classifications in each AOI. It is evident that, among the three classes, built-up land represented most of the hectarage in each AOI with the exception of areas V (Gulshan 1) (Fig. 7d) and II (Technical Morh) (Fig. 8f). Nine of the AOIs had limited areas of open water and area VI (Farm-gate) within the selected buffer range (Fig. 8j) had no open water area whatsoever. The greatest quantities of vegetation were found in areas II (Technical morh) as shown in Fig. 8 (f) and I (Mirpur 10) as shown in Fig. 7 (a). The lowest quantity of vegetation was found in area X (Jatrabari area) as presented in Fig. 8 (g). The hectarage values calculated for each of the three classes of land use types were utilized to determine the actual bio-capacity of the AOIs.

Employing an error matrix accuracy test on the classified images was required to check the accuracy of the classification process. Correlating the error matrix producer's accuracy and the user's accuracy provided a determination of overall accuracy (Table 49S, Supplementary Document). The Kappa coefficient was also verified. Producers' and users' accuracies were found to be over 80% for the built-up and vegetation classes. Overall accuracy of image classification was 84% and the kappa coefficient value was 0.75 (Table 50S, Supplementary Document). Kappa values. Generally a kappa value of more than 0.80 indicates that image classification was both very good and highly acceptable, however values of more than 0.75 are widely acceptable (Lillesand et al., 2014; Campbell and Wynne, 2011). Accuracy Test points, with GPS coordinate values for UTM zone 46 N for the AOIs are presented in Table 48S in Supplementary Document.

3.3.2. Bio-capacity of selected areas

Utilizing the land use areas identified from the analyzed images and eq (4), the bio-capacity (BC) value for each AOI was determined. As an example, Table 4 illustrates the calculation process utilized to calculate the bio-capacity for Area I (Mirpur 10). It was found that the total bio-capacity was approximately 267.8 gha. Employing this calculation methodology the bio-capacity for each AOI was determined. The results for each AOI are summarized in Table 5 under the 'Bio-capacity Area' column. The actual bio-capacity estimation calculations for each AOI are provided in Table 51S in the supplementary document.

Table 4 illustrates that, the yield factors for built-up areas are greater than those for forest or bodies of water, hence the estimated bio-capacities of built-up areas have higher values than those for vegetation and water bodies. This apparently counter-intuitive result can cause confusion for readers not familiar with the theory supporting the concept of National Footprint Accounts (NFA) and bio-capacities. According to the NFA bio-capacity is defined as "the biosphere's supply (bio-capacity) of ecosystem products and services in terms of the amount of bio-productive land and sea area needed to supply these products and services." (Borucke et al., 2013, p 518). However, due to lack of data unavailability regarding the bio-productivity of built-up areas, built-up land is considered the *equivalent* of cropland in terms of world average productivity (Galli, 2015; Borucke et al., 2013). This assumption is developed on the basis of the observation that, in general human settlements (e.g. Urban areas, built infrastructure) are located in fertile areas which may had the potentials for high yielding cropland (Borucke et al., 2013; Wackernagel et al., 2002). As a result of this assumption, despite having no photosynthesis and thus no direct bio-productivity from built-up land, considering yield factor of cropland as yield factor for built-up areas over or underestimates total bio-capacity.

In this case, as cropland in Bangladesh has a higher yield factor than either forest or bodies of water (Table S1, Supplementary document), and cropland is used as a value equivalent for built-up areas, the consequence is that built-up areas have a higher yield factor than forest's or bodies of water. Nonetheless, this equivalence allows to create a dummy-value for the productivity that occurs in these areas. It should be noted that, due to inherent theoretical limitation of NAF's bio-capacity estimation process, current study may over/under estimated the bio-productivity of built-up areas compared to vegetation and water-bodies. In reality to improve overall bio-capacity, more vegetation cover and water bodies with greater yields would act as positive contributors, in contrast increasing built-up areas would only reduce overall bio-capacity.

3.4. Emission and bio-capacity index values

Dividing the bio-capacity (BC) area by the estimated carbon uptake land value (C) allows the EBI to be determined. Table 5 shows that nine out of ten areas possess EBI value of < 0.33 which equates to a EBS of 4, both of these values imply that bio-capacity is in critically short supply in these areas and net CO_2, emissions are extremely high. With the exception of Area I (Mirpur 10) all other AOIs would require the addition of very large amounts of bio-productive land within their geographical boundaries if they were to have the capacity to absorb all the net CO_2 emissions currently emitted by the transportation sector in each respective AOI. The very high amounts of net CO_2 emissions are strongly related to high and continuously increasing traffic volumes and high usage levels for private vehicles but may also suggest that there are inefficiencies inherent in operating old or poorly maintained vehicles, related to poorly tuned engines, nonfunctioning or ineffective pollution controls on engines and related issues pertaining to excessive use of fuel. Overall, Table 5 conclusively demonstrates that the amount of bio-productive area within the AOI's is inadequate to sequester all emitted CO_2, and illustrates the serious gap between levels of CO_2 production and CO_2 sequestration.

Both the raw data-take and the calculated EBI values are highly indicative of the very high levels of CO_2 emissions from transportation

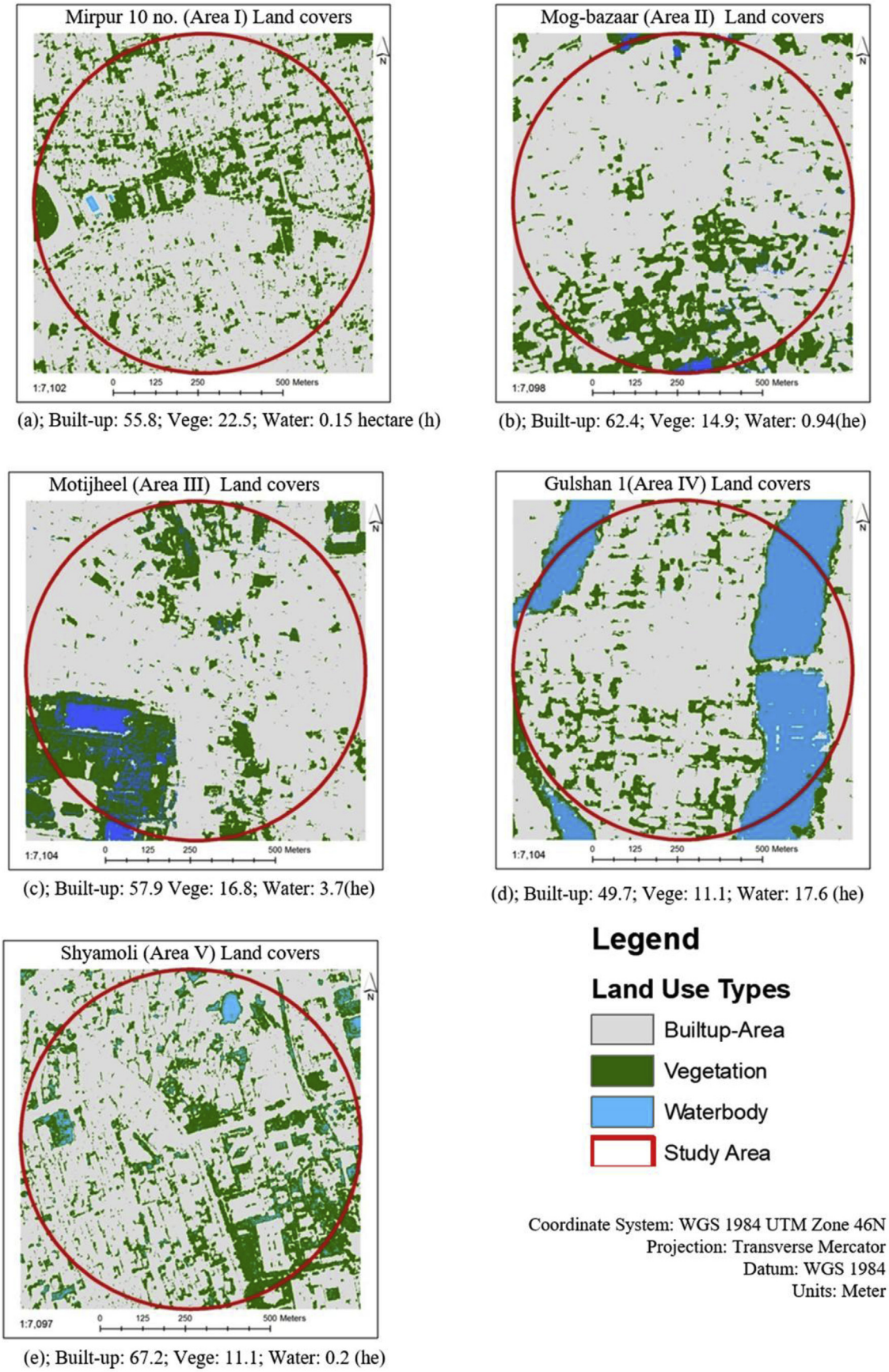

Fig. 7. Land use classification maps in different AOIs.

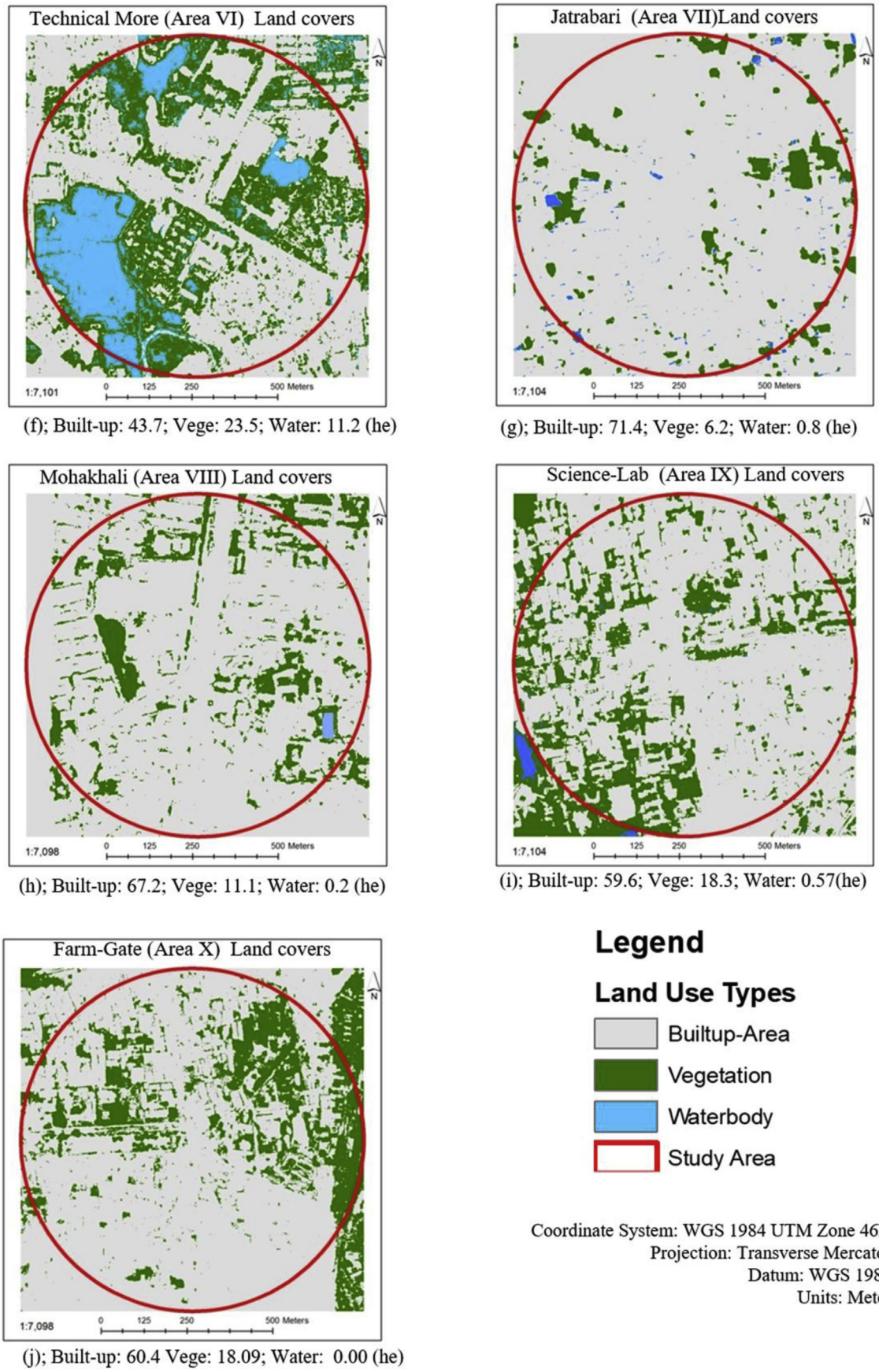

Fig. 8. Land use classification maps in different AOIs.

Table 4
Bio-capacity estimation for area I (Mirpur 10).

AOI	Land Class	Area (Hectare) (Ar)		Yield Factor (YF)		Equivalency Factor (EQF) (gha/hectare)		Bio-capacity (gha)
Mirpur 10 (Area I)	Built-Up Land	55.80	×	1.85	×	2.51	=	259.40
	Forestland/Vegetation	22.58	×	0.35	×	1.26	=	9.99
	Fishing Ground/Water body	0.15	×	1.00	×	0.37	=	0.06
	Total Bio-capacity in Mirpur 10						=	269.44

Table 5
Emission and bio-capacity Index and Score values for each AOI.

Area	Carbon Uptake Land (gha)	Bio-capacity Area (gha)	EBI	EBS	Color Code
Area I (Mirpur 10)	785.20	269.43	0.343	3	Orange
Area II (Mog bazaar)	987.08	298.06	0.302	4	Red
Area III (Motijheel)	1269.36	278.20	0.219	4	Red
Area IV (Gulshan 1)	1398.43	242.60	0.173	4	Red
Area V (Shymoli)	1432.89	233.91	0.163	4	Red
Area VI (Technical Morh)	1477.91	217.92	0.147	4	Red
Area VII (Jatrabari)	1779.99	335.08	0.188	4	Red
Area VIII (Mohakhali)	1868.61	317.41	0.170	4	Red
Area IX (Science lab)	2363.18	285.57	0.121	4	Red
Area X (Farm gate)	2440.20	289.00	0.118	4	Red

activities in nine of the ten AOIs. It clearly indicates that the overall emissions of CO_2 from the transportation sector in Dhaka are well in excess of levels that available bio-capacity can remediate or counter balance. Indeed, the carbon uptake land value that equates to the ability to sequester all CO_2 emissions from the transportation sector in Dhaka is a hectare value larger than the hectare value for all land within the city limits (Labib et al., 2013).

4. Discussions

4.1. Major factors contributing to higher CO_2 emissions and lower EBI values

The present study's analysis highlighted several factors responsible for the high net CO_2 emissions in Dhaka. Results showed that both the composition of vehicular traffic and the limited bio-capacity of extant land cover types contributed to observed high net emissions. Those AOIs with lower EBI values closely correlated with higher levels of vehicular activity and more built-up land use area within the AOI. In these areas, the volume of daily vehicular traffic through the links of each AOI was quite large. These AOIs were exemplified by high traffic volume, host intersections characterized by intermittent spikes in volume, and differentiation between trip originating and terminating traffic. Traffic nodes in AOIs such as Farmgate (Area X) and Science Lab (Area IX) explicitly exhibit these characteristics. Therefore, it can be implied that, intermittent nodes (usually having higher connectivity) which connect more trips need careful design, and more effective traffic regulations to assist in controlling CO_2 emissions, as higher traffic density would likely raise levels of such emissions (Ferreira and d'Orey, 2012).

The results of the present study also indicate that lower EBI value (and corresponding high EBS score) traffic network nodes are characterized by high levels of private vehicle usage (e.g. automobiles and motor bikes) versus the use levels of public transit such as buses. This finding is common to a number of recent studies including Iqbal et al. (2016), Kamruzzaman et al. (2015); and Druckman and Jackson (2008). Equally, it is clear from the present study's results combined with that increases in motorized traffic both public and private are the driving force for increases in overall net CO_2 emissions from the transportation sector in Dhaka (Labib et al., 2013). As Bangladesh continues to experience a growing economy, the affordability of private vehicles increases in lock-step among private citizens (Islam et al., 2016). Furthermore, until now there has been no effort made to control the usage of private vehicles in Dhaka, and no restrictions for private vehicles on busy and crucial nodes. Thus, a large and increasing component of the increase in motorized traffic comprises of personal vehicles which are becoming a major component in future increases in CO_2 emissions in Dhaka from transportation.

Another factor contributing to CO_2 emissions in Dhaka is an obsolescent traffic signal system. In Dhaka no coordinated system of traffic signals geared to optimizing traffic patterns and traffic throughput exists. The current signal system was not designed for either current or projected levels of traffic. Indeed, the current signal system has such limited capacity that in the AOIs researchers observed traffic police manually attempting to coordinate traffic signals during periods of high traffic volume, for example Farmgate (Area X) experiences massive traffic congestion the majority of each day. This congestion is abetted by the fact that the signal systems on different links in the area are not coordinated with each other. As a result, traffic police are required to assist in controlling traffic. However, they must use their personal judgment, uninformed by conditions at other intersections, as to how much time ought to be allocated to each phase of the signal cycle in order to optimize overall traffic flow in all links in the intersection they are attempting to control. These inadequacies of the present system observed during the present study appear to actually contribute to inducing massive congestion on some links in the AOIs. Unfortunately, such congestion is associated with increased trip times, increased costs to human health and much increased CO_2 emissions (Iqbal et al., 2016; Labib et al., 2013). Ferreira and d'Orey (2012) demonstrated that, a well-organized intelligent transportation system (ITS) based traffic signaling system is effective in mitigating CO_2 emissions in high density traffic areas.

The major arterial roads of Dhaka do not provide access for fuel free transport modes such as bicycles or rickshaws (Mahmud et al., 2012). In this study, the nodes examined in the AOIs were connecting major arterial roads, It must be noted that FFTs do not emit CO_2, and they are widely used in secondary or access roads in Dhaka city (Labib et al., 2016). However, while it might be speculated that the absence of FFTs on major roads might be a reason for greater CO_2 production in these nodes due to the increased use of motorized alternatives there is the issue highlighted by the present study that major arteries in Dhaka are near, at, or over their capacity limits. Injecting slow-moving FFTs with limited passenger carrying capacity into arterial traffic could actually lower overall passenger throughput on these arteries and increase emissions due to further increasing congestion caused by mixing FFTs with motorized traffic on major arteries. Furthermore, mixing FFT's and motorized transport on major roadways causes serious safety issues and is a practice discouraged world-wide in urban settings. However, given the popularity of FFT's in Dhaka and their environmentally benign nature it is possible that exploring the possibility of providing dedicated lanes for FFTs might provide the path to an effective solution.

Another major problem existing in Dhaka's traffic is related to the abundance of unfit vehicles on the road. During the traffic volume survey the researcher observed a predominance of older vehicles often exhibiting major deficiencies in maintenance, both public (e.g. bus) and

private (e.g. jeep, station wagon) in traffic. Field observation showed, that often these vehicles had been marked by the traffic police as unfit. Upon inquiry as to why so many such vehicles were to be seen in traffic it became apparent that irregular inducements provided by the owners of the vehicles to avoid formal legal action were common. Thus, weaknesses both in the practice of policing and in the justice system are transport issues insofar as they contribute to allowing both unsafe and high emitting vehicles to remain on the road in Dhaka.

A final issue is the levels of vegetation growing in the AOIs. Neema and Jahan (2014), found that the presence of increased amounts of road side vegetation correlates with higher levels of CO_2 sequestration along such roadsides. However, the AOIs in the present study had little greenery growing directly along their links or, indeed, anywhere within their overall areas.

4.2. Impacts and way forward

From an ecological point of view, the transportation system in Dhaka is not sustainable due to the fact that its extant bio-productive areas cannot sequester even a large fraction of current CO_2 emission levels. Furthermore, the areas of the city devoted to land uses that support what bio-capacity exists are shrinking (Hassan and Southworth, 2017). Further shrinkage of bio-capacity in a city whose population and hence, traffic levels continue to increase suggest that net CO_2 emissions both from traffic activities and other activities will also continue to increase. Such increases will, in turn intensify heat-island effects as well as supporting increases in other air pollutants besides CO_2 (Harlan and Ruddell, 2011; Han and Naeher, 2006).

4.2.1. Policy implications

The rating system created for the present study may aid in both planning professionals and policy makers being able to more easily grasp the severity of the CO_2 emissions problem under current and projected conditions. The index may also act as a surrogate value for the negative impact emissions have on health, livability and the environment in Dhaka. Based on the results of the current, several policy initiatives recommended to improve the overall sustainability, livability and environment of Dhaka.

4.2.1.1. Public transit. The Strategic Transport Plan 2005 for Dhaka recommended introducing bus rapid transit (BRT) in the main corridors of the city as an effective and efficient solution to resolve the poor service quality and capacity constraints of current bus systems in Dhaka. Despite having been recommended as long ago as 2005 this is an excellent suggestion with even greater merit, due to urban growth, than when it was first mooted (Rahman et al., 2012). Additionally, as of 2017 the authors note that a new Mass Rapid Transit is under construction in Dhaka in association with JICA, and this may change the composition of traffic in Dhaka with a greater emphasis on public transit. However, experience in other major cities particularly in developing economies suggests that as long as the numbers of private vehicles continues to increase; a highly likely scenario in a country with a growing economy and a growing middle-class, any reduction in overall CO_2 emissions and congestion on surface routes will likely be a transitory one.

4.2.1.2. Low emissions zones. Apart from attempts to engender a travel demand shift by promoting public transit (e.g. Metro, BRT), FFTs, and encouraging mixed land use (McBain et al., 2017; Nakamura and Hayashi, 2013) in Dhaka, low-emission zone initiatives could be an effective solution to calm traffic intensities and CO_2 production in key nodes (or highly connective nodes). For example, nodes in AOIs VIII, IX, and X might have low emission zoning strategies implemented to discourage the number of trips with private vehicles. Despite having potential political difficulties in implementation, low emission zoning policy could be implemented with relatively little cost and within a short period of time. Implementation of low emission zones appears a reasonable solution, similar to the low emission zones in London (Ellison et al., 2013) and other European cities (Dias et al., 2016; Holman et al., 2015).

4.2.1.3. Improved traffic management. Another policy intervention might be needed in improving the traffic management system. A key component to minimizing both emissions and maximizing quality of life is the design of a modern traffic management plan for Dhaka supported by a high-capacity and fully functional traffic signaling system optimized to maximize traffic throughput. The authors strongly recommend replacing the current obsolete system requiring continuous human intervention by traffic police with a new optimized signaling system using ITS (Satyanarayana et al., 2018). Gains in economic efficiency and productivity within Dhaka may well yield more than the cost of such a system.

4.2.2. Other potential low-carbon interventions

In addition to a traffic calming strategy, a ride-share program may be an effective solution in the context of Dhaka's needs. Labib et al. (2013) suggested that, carpool or car share initiatives might be effective in Dhaka and as of 2016 such services have been implemented in the city in with relatively limited coverage. Additionally, private rideshare services such Uber and Pathao-Moving Bangladesh (a local ride-sharing company providing motor-cycle rides), both introduced in 2017, have been gaining popularity among those needing transportation in Dhaka. At least two recent studies had results suggesting that ride-share services have successfully reduced private/personal vehicle usage and congestion in urban areas in which such services were introduced (Li et al., 2017; Alexander and González, 2015). Thus, officially encouraging and monitoring ride-share services may to some extent, assist in ameliorating traffic induced CO_2 emissions.

Urban greening initiatives including road side tree plantation, green roof creation, green wall installation and other green infrastructure creation would not only assist in CO_2 sequestration but also in overall improvements in living conditions, quality of life and even storm water control. In particular among the studied AOIs due to their extremely low EBI values, Area V, VI, IX, and X would appear to require immediate action to improve their vegetative coverage utilizing some rapid measure such as Green roofs and green walls (Rowe, 2011).

5. Conclusion and further development

With the growing concern for CO_2 emissions resulting from vehicular traffic it has become necessary to better understand and identify the areas within cities such as Dhaka where CO_2 emissions from vehicles have outstripped the local capacity to absorb and sequester such emissions along with associated emissions that can be a direct threat to human health. In light of this need the present study has as one of its key purposes the development of an EBI rating system that would assist in identifying the traffic routes and zones within an urban transportation network that are deemed ecologically unsustainable due to high net CO_2 emissions and low local bio-capacity. This rating system combines the domain of traffic emission related studies with ecological footprint and bio-capacity related studies. In turn this has allowed the establishment of index values for the previously missing relationship between urban transportation systems and their local environments.

The present study utilizing the EBI successfully mapped and measured net CO_2 emissions at key traffic nodes in Dhaka. As a result, it provided an understanding of the CO_2 sequestration capacity associated with each AOI but more importantly it created a map overlaying the traffic network highlighting problem areas using an index that is easy to grasp for policy makers. The EBI rating system found very high (level 4, code red) index values correlated with very low CO_2 absorption and high net CO_2 emissions at nine out of ten key nodes. Thus of the ten nodes only one was moderately sustainable as defined by having the

capacity to absorb a considerable amount of the CO_2 emissions in its local area. Based on the results, it is reasonable to conclude that the nodes with lowest EBI values require urgent attention to ameliorate both their current net CO_2 emissions as well as control future increases in such emissions.

While identifying critical nodes as ecologically unsustainable as they currently stand, in the Dhaka road network was one proximate reason for conducting the present study a wider goal was to create an index that reduces the many potential factors impacting net emissions to a single digit number and associated colour. This, in turn, allows the creation of coloured map overlays for urban areas highlighting problem areas clearly while also showing their relationship to one another and to the underlying transportation networks at a glance. It is the opinion of the authors that it is not enough to know the facts but necessary to be able to convey them clearly and easily especially to policy makers and potentially to other interested groups and/or the wider urban population. Finally, given sufficient data and adequate simulation software the EBI could be valuable as one output modality for modeling different outcomes in 'What-if' scenarios of CO_2 emissions, with the EBI value and color changing as parameters such as: traffic intensity, signal optimization, different road surfaces and differing levels of vegetation inter alia are varied.

Despite the careful attention of the authors, this study is not presented as being comprehensive. It would benefit from further testing of the new index as well as potentially improving on the measurement techniques used in the index creation process in order to further refine the index to ensure the most robust results.

Conflict of interests

No potential conflict of interest was reported by the authors.

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Appendix A. Supplementary data

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