DYNAMICS AND DRIVERS OF LAND USE LAND COVER CHANGES IN BANGLADESH

BY

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THESIS

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ABSTRACT

Land is scarce in Bangladesh: Bangladesh occupies ~0.03 % of world's land area, but supports over ~2% of human population. This high population to land ratio, combined with socioeconomic development has placed tremendous pressure on Bangladesh's land resources for food, feed, and fuel. This study assesses the dynamics of land use land cover changes and its subsequent drivers at national and sub-national scales. We show contemporary spatial estimates of land change in Bangladesh using national-level analysis of Landsat imageries for 2000 and 2010. This analysis uses our newly compiled extensive socioeconomic database which covers ~480 sub-districts along with biophysical data. We also synthesized information from over 80 survey-based case studies on land use drivers in Bangladesh to complement our macro-scale analysis. We present a detailed analysis of contemporary land change both in terms of national extent and the use of detailed spatial information on land change, socioeconomic factors, and synthesis of case studies. Our results showed eight broad land cover types, of which majority is covered by agriculture (~70%), waterbody (rivers and shrimp ponds) (~10%) and forests (~8%). We found that agriculture, forest and mangrove areas showed a decreasing trend while bare soil, shrub land, waterbody and settlement showed an increasing trend. We identified three major land conversion types: agriculture to shrimp ponds, forest to shrub land and shrimp ponds to bare soil, and their hotspot regions at a sub-district level. Based on our analysis, we find both biophysical and socioeconomic variables contributing to the land conversions. We find that conversion of agriculture to shrimp ponds is driven by increasing rate of population, urban household size and rural household number, access to highways and variation in temperature. Drivers related to forest to shrubland conversion include increasing rate of population, access to rivers, highways and cities, and increaste rate of precipitation. Lastly, shrimp ponds to bare soil conversion is driven by access to highway, cities and rivers, elevation and increasing rate of precipitation.

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TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

Land-change studies aim to observe and monitor land cover and land use changes (LCLUC), explain its causes and consequences, and model its processes to predict future changes [*Robinson et al.*, 2013]. LCLUC can alter regional as well as global climate through changing characteristics of the Earth's surface and atmosphere [*Jain et al.*, 2013]. It can affect the behavior of the essential components of the climate system such as biophysical (e.g., surface temperature, albedo, evaporation), biogeochemical (e.g., carbon cycle) and biogeographical (e.g., species location and migration) components [*Robinson et al.*, 2013]. LCLUC is an important indicator to understand the interactions between anthropogenic activities and the environment [*Dewan et al.*, 2012]. Understanding the dynamics and drivers of LCLUC at local, regional and global scales will help policy-makers in effectively targeting areas of concern and implementing proper land use policies. Human activities have profound effect on land cover, especially observed in developing countries in the recent years where LCLUC are driven by socioeconomic development [*Dewan et al.*, 2012] . To assess the land cover changes, there is an increasing demand of detailed spatial coverages with high temporal frequency to assess land cover changes [*Thackway et al.*, 2013]. A large number of studies have been devoted to the LCLUC across the globe over different temporal and spatial time scales (E.g.: [*Meiyappan et al.*, 2016], [*Roy et al.*, 2015], [*Reddy et al.*, 2016], [*Huq et al.*, 2015], [*Islam and Hassan*, 2011], [*Zaman et al.*, 2010], [*Chowdhury and Koike*, 2010]). However, further study is required to find the relationship between the dynamics and drivers of LCLUC at local, regional and global scales.

One of the key challenges for Bangladesh is to ensure that there is enough agricultural production for the growing population while minimizing the potential land degradation from

LCLUC. The population in Bangladesh, according to the most recent census in 2011, is 144 million which is a sharp rise from 31 million in 2001 [*BBS*, 2011]. With rapid population growth in Bangladesh, it is estimated that more than 809 km^2 of agricultural land is converted to urban areas annually [*Dewan and Yamaguchi*, 2009]. For example, in Rajshahi district, the agricultural land is decreasing at the rate of 0.46% per year and the area under infrastructure use is increasing 5.86% per year [*Islam and Hassan*, 2011]. Between 1977-2010, the district lost about 14% of its arable land. If the agricultural decline and infrastructure incline continue at this rate, it is projected that the agricultural land will be completely wiped –out in the next 200 years [*Islam and Hassan*, 2011]

In the past eight decades (1930-2014), 9054 km^2 (~39%) of forests have been degraded to shrub land and transitioned to agricultural area [*Reddy et al.*, 2016]. In recent years, the annual deforestation rate in Bangladesh is ~1-3.3%, compared to the average deforestation rate of 0.6% in South Asia [*Reddy et al.*, 2016]. The increase in resource consumption due to population increase has further exacerbated the deforestation rates. It is estimated that forests in Bangladesh may disappear in the next 30-40 years or earlier [*Chowdhury and Koike*, 2010].

Increase of shrimp ponds and the rapid expansion of the industry is a rising concern for Bangladesh [*Ali*, 2006; *Paul and Vogl*, 2011; *Ahmed and Toufique*, 2015]. The shrimp industry in Bangladesh has expanded dramatically in recent decades. It increased from 200 km^2 in 1980 to 2100 km^2 in 2012-13, contributing to the economy however having negative environmental impacts such as land degradation, salt-water intrusion, sedimentation and pollution [*Paul and Vogl*, 2011; *Islam and Tabeta*, 2016].

To improve our understanding of the dynamics of LCLUC and its impact, there is a need in identifying the drivers of these changes. Moreover, it is essential to identify the socioeconomic drivers of LCLUC, specifically in developing countries like Bangladesh where such drivers play a major role. This study aims to understand the LCLUC of Bangladesh to: (1) analyze the spatial patterns of LCLUC at a decadal timescale (2000-2010), (2) identify the major biophysical and socioeconomic drivers of LCLUC, and (3) provide valuable information on the causes of LCLUC for land-use policy makers to mitigate its potential effects.

We first quantified land cover conversions (replacement of one land cover by another) at national scale using a wall-to-wall analysis of high-resolution (~30m) Landsat imageries at a decadal time interval (2000-2010) at national and sub-district levels. Our land use/cover definition is consistent with the Land Cover Classification System (LCCS) of the Food and Agriculture Organization (FAO)[*Di Gregorio and Jansen*, 2005]. Second, we investigated the spatial determinants of three major LCLUC types observed in Bangladesh. Third, we evaluated and reinforced the spatial determinants through collecting evidence from synthesis of case-studies that incorporate field knowledge of the causes of LCLUC in Bangladesh. Local case studies targeting at a few areas cannot generalize and quantify the causal relations between LCLUC and its driving factors for the entire region of Bangladesh with ~480 sub-districts with different socioeconomic conditions. We compiled over 30 socioeconomic variables at a decadal scale (2000 and 2010) using the two consecutive census years. We also incorporated contemporaneously biophysical variables which may also influence the spatiotemporal patterns of LCLUC in Bangladesh.

CHAPTER 2: DATA AND METHODOLOGY

2.1. Study area

Bangladesh located between 88° 10' N - 26° 38' N and 88° 10' E - 92° 41' E, covering an area of 144, 000 km^2. The elevation ranges from 0 m at the Indian ocean to 1502 m (Figure 1). It is divided into seven divisions: Chittagong, Rajshahi, Khulna, Barisal, Sylhet, Dhaka, Rangpur which is further divided into 64 districts (*zilas*) and 484 sub-districts (*upazilas*) [*BBS*, 2011] (Figure 2). Recently, there is a newly added division in Bangladesh: Mymensingh, dividing Bangladesh in eight divisions [*BBS*, 2011]. Our LCLUC estimates and analysis are based on the entire region of Bangladesh at a sub-district level.

2.2. Data

A summary of key input datasets used in this study is provided in Tables 1 and 2. In this section, we expand on rationale and processing of biophysical and socioeconomic variables used in our analysis of spatial determinants of LCLUC.

2.2.1. Biophysical Data

Given the significant impacts of climate change on LCLUC in Bangladesh, we included seasonal mean temperature and precipitation as potential explanatory variables. Both precipitation and temperature data were collected for the country boundary of Bangladesh at 0.5°x 0.5° resolution from the CRU NCEP Reanalysis version 6 [*University of East Anglia Climatic Research Unit et al.*, 2014]. We calculated the average values, annual increased rate and standard deviation for temperature and precipitation from 2000-2010 as well as for monsoon months (June-September) and post-monsoon months (October-November). We also included the elevation profile using the Shuttle Radar Topography Mission (SRTM) one arc second (30 m) Digital Elevation Model (DEM) [*Yang et al.*, 2011]. To test the effects of soil conditions on land cover conversions, we included annual values and standard deviation of soil moisture data (at 0.5°x 0.5° resolution) [*Qu*, *Le et al.*, 2016].

2.2.2. Socioeconomic Data

Our geospatial socioeconomic database covers over 30 variables at the sub-district level, a total of 484 units. We collected tabular data for two consecutive census years (2001 and 2011) from the Bangladesh Bureau of Statistics (BBS)[*BBS*, 2011]. The census in Bangladesh is conducted once in 10-years and we assumed that the 2001 and 2011 censuses are reflective of the socioeconomic conditions of 2000 and 2010, respectively. We used the data provided in the census for our analysis of spatial determinants specific to the LCLUC for our study. We derived some variables by combining two or more census variables-for example we derived the percent change of population by subtracting "population of 2001" from "population of 2011" and divided it by "population of 2001."

Our sub-district level spatial database show high granularity which is important to explain the spatial variation in high-resolution land-cover conversion estimates (Figure 2). We collected the tabular data for each sub-district for both 2001 and 2011 census from the online digital database of the Bangladesh [*BBS*, 2011]. After compiling the data for each sub-district, we converted the sub-district level tabular data into geospatial data.

Data quality in some of the regions may be poor due to misreporting, human errors in computerization, quality of village/town boundaries, or unavailability of data due to separation and union of different sub-district boundaries. For sub-districts that had changes in the boundaries, we consulted the BBS to interpret the information for regions that are gone under boundary changes over the time-period.

2.2.3. Satellite Data

We used Landsat 5 thematic mapper (TM) images at 30 m spatial resolution for land cover mapping and identifying LCLUC between 2000 and 2010. The images were downloaded from the United States Geological Survey (USGS) website [*USGS*, 2015]. The entire region of Bangladesh lies within thirteen fully or partially covered Landsat images (each scene is 170 km by 183 km). We chose images from the winter months (October- February) to ensure they were cloud-free. Before image classification, we normalized all the spectral bands by reflectance to radiance conversion using the existing metadata information (gains, solar irradiance, solar elevation, acquisition time). We co-registered the spectral bands geometrically and layer stacked the spectral bands (1, 2, 3, 4, 5, and 7 at 30m) to make a multispectral image.

2.3. Overview of methodology

The overall approach for this study can be broken down into five steps. First, we quantified the land use/cover types for two years – 2000 and 2010. Second, we identified the aggregated areas of three major land use/cover conversion types using hotspot analysis. Third, we used Principle Component Analysis (PCA) to account for the multicollinearity across the drivers. Fourth, we used the logistic regression method to understand the relationship between the drivers and LCLUC. Finally, we explained and interpreted the dominant drivers of major LCLUC types (see Figure 3 for flow chart).

2.4. Quantifying Land Use/Cover Conversions

We interpreted Landsat images of 30 m spatial resolution to produce a national map of land use/cover. The entire country lies within 15 fully or partially covered Landsat images (each scene is 170 km by 183 km). We used a geographic object-based image analysis (GEOBIA) technique to extract the land cover and land use information from individual Landsat satellite scenes. GEOBIA partitions satellite imageries into image-objects by assessing their spatial, spectral and temporal characteristics [*Hay and Castilla*, 2008]. We classified Bangladesh into seven major land use/cover types: Agriculture, Shrubland, Barrenland, Forest, Waterbody, Settlement and Mangrove (Figure 4 and Table 3). Further, we divided the waterbody into two land cover types- flowing waterbody (rivers) and standing waterbody (shrimp ponds).

To verify the classification accuracy, we used 650 randomly-chosen reference points and compared the classified map with Google Earth Pro images [*Google Earth*, 2016]. For any misclassified land cover type, we used manual digitization for correction. In addition, we compared the land cover classification with three existing land cover/use classification studies (Table 4) [*SRDI*, 2013; *Reddy et al.*, 2016; *Hasan et al.*, 2017]. The three studies agree with each other with major land use/cover types such as agriculture, forest, although there are some land cover/use types that show differences in the spatial extent (e.g. settlement). This variation in spatial extent may be caused due to the differences in the methodology of the land cover classification.

For the land cover change analysis, we developed a land cover transition matrix based on areal changes. The diagonal values in the matrix show the unchanged area of the land cover class, while the other values show the area of the land cover class shifting from one class (row) to another (column) (Table 5). Using the matrix, we found many land use/cover conversions that took place between 2000 and 2010 however we study the three major land cover conversion types based on areal changes: agriculture to shrimp ponds, forest to shrub land and shrimp ponds to bare soil. We have not considered the LCLUC between rivers and other land use/cover types as these changes were mainly seasonal as well as the migration of river channel.

2.5. Hot spot analysis

To identify the hotspot areas for the three main conversion types, we used the Hot Spot Analysis (Getis-Ord Gi*) tool in ArcMap 10.4 [*ESRI*, 2016]. The resultant of Gi* statistic (formula given below) gives the z-scores of spatially clustered values analyzed within the context of neighboring features inside a specified distance band. Statistically significant larger positive z-scores correspond to more intense clustering of high values (hot spot) and smaller negative z-scores correspond to more intense clustering of low values (cold spot) [*Ord and Getis*, 1995]. For example, a score of ± 2 shows strong clustering as it represents 95% confidence level. We consider the hot spots having 95% confidence level to represent areas that have three major land cover/use conversions in this study.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{s \sqrt{\frac{\left[\sum_{j=1}^{n} w^2{}_{i,j} - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

$$s = \sqrt{\frac{\left[\sum_{j=1}^{n} x^2{}_j\right]}{n}} - (X)^2$$

where, x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between features i and j, and n is equal to the total number of features.

We randomly sampled each hotspot region for each of the three major conversion types to determine the biophysical and socioeconomic factors. The independent variables (biophysical and socioeconomic data) in our study have different units and scales. Thus, all the extracted values of the independent variable were standardized using z-score standardization technique by subtracting the mean value from the actual value and then dividing it by the standard deviation. After standardizing the variables, we used logistic regression method to model the relationship between the conversion types and its possible drivers. The logistic regression model is represented mathematically as:

$$Odds = ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \cdots + \beta_k \cdot X_k$$

where, odds indicate how likely an event is going to occur. In this case, how likely it is from a conversion to take place. *P* represents the probability that the conversion of LCLU type occurs (range=0 to 1), $\beta_0$is the intercept, β_1 - β_k represent the coefficient for different biophysical and socioeconomic factors (X_1 to X_k). The β_1 - β_k illustrate the relative importance of different driving factors for each individual LCLUC types.

It is also necessary to address the issue of multicollinearity where one or more explanatory variables can be dependent on each other in the study. High degree of multicollinearity can lead to high standard errors and misleading coefficient estimates (β_k). We used the PCA method to address this issue of multicollinearity. This method reduces the dimensionality of a data set consisting of many interrelated variables, and generates a new set of variables called the principle components [*Deng et al.*, 2008]. The new set of variables are ordered so that the first few retain most of the variation present in all the original variables. We selected the principle components that had the cumulative variance of ≥ 85% [*Du et al.*, 2014].

2.6. Synthesis of case studies

We synthesized the existing ground-based studies on the causes of LCLUC in Bangladesh. Synthesis of case studies were useful for the following reasons: first, through the synthesis analysis, we could have a good understanding of the dynamics of LCLUC. Second, we could identify potential driving factors for LCLUC at a national scale as well as at a local scale. Third, we could identify the gaps in the existing studies (e.g. lack of understanding of driving factors at a sub-district level). The synthesis provides us with evidence to complement and evaluate the results from our study.

We reviewed the literature for LCLUC studies which focused on LCLUC in Bangladesh. The broad literature search for Bangladesh gave an understanding of the number of studies assigned to studying different LCLUC processes and type of analysis involved (e.g. inclusion of spatial determinants, broad or specific LCLUC type, and methods of data collection) (Table 6).

CHAPTER 3: RESULTS

The dominant land use/cover in Bangladesh are: agriculture (~70%), waterbody (~10%) and forests (~8%). Between 2000 and 2010, we find that there are transitions between the eight-land use/cover types (Figure 5). Among the transitions, major transitions include: agriculture to shrimp ponds, forest to shrub land and shrimp ponds to bare soil.

We present the LCLUC conversion and spatial determinants of three major LCLUC. LCLUC conversion estimates are based on analysis of satellite data and the determinants are based on the logistic regression analysis between LCLUC data and hypothesized biophysical and socioeconomic variables. We also present results from our synthesis analysis. We present the three major conversion types found in this study:

3.1. Agriculture to shrimp ponds

The overall agricultural area declined by ~3% and shrimp ponds area increased by ~10% over the 2000-2010 period (Table 3). A significant conversion from agricultural area to shrimp ponds was observed in this period. Major conversion was detected in the following districts: Habiganj, Sunamganj, Netrakona and Kishoreganj (Figure 6a).

Our results show that most socioeconomic and biophysical drivers were positively correlated with the conversion from agriculture area to shrimp ponds (Figure 6b), such as the variation of temperature during monsoon months and annual increasing rate of precipitation in post-monsoon months. The observed variation in temperature and increasing rate of precipitation can have an impact on the agricultural yield. Variability in the agricultural produce can lead farmers to switch to shrimp farming, which is a more stable income source. Additionally, the climatic conditions also favor shrimp production in the low-lying areas of Bangladesh.

Similar to our findings, *Amin et al.*, [2015] and *Huq et al.*, [2015] show that overall climate variability and change (changes in temperature, rainfall, humidity and sunshine) have an impact on the agriculture system in Bangladesh. This variability in agricultural yields affects the livelihood of people, especially in the rural areas. Likewise, [*Paul and Vogl*, 2011] also show that shrimp cultivation is a viable option for farmers as it has suitable agro-climatic conditions, adequate water resources and cheap labor force.

Additionally, our results show that an increase in overall population, urban household size and increasing rate of rural household number were positively associated with the conversion from agriculture area to shrimp ponds. Increasing rate of rural household number indicate that the population in rural areas play a role in the conversion of agriculture areas to shrimp ponds. Increase in the household number over the decade can indicate the need for more economic resources for people to support their families, resulting in the conversion of existing agricultural land to shrimp ponds.

Our results do not include economic variables indicating rise in shrimp demand however our synthesis analysis on existing studies show that the demand in the past three decades have increased significantly. The aquaculture industry has increased its export business, particularly to United States and European Union, making shrimp export the second largest export industry in Bangladesh [*Ahmed and Diana*, 2015]. *Ali,* [2006] shows that shrimp farming was 12 times more profitable than rice cultivation, leading farmers to choose shrimp farming rather than rice cultivation. Bangladesh earned 348.28 million dollars in 2009-2010 which increased to 453.93

million by 2012-2013 [*DCCI*, 2017]. Due to the high profitability, shrimp farming has become an attractive land use practice for the increasing population that contribute to economic development [*Ali*, 2006 ; *Rahman et al.*, 2013]. Most of the shrimp cultivation are concentrated in the rural areas of the country [*Ali*, 2006; *Ahmed and Diana*, 2015; *Islam and Tabeta*, 2016]. As local and international demand for shrimp is increasing, rural areas rapidly converted their agricultural areas for shrimp cultivation. The economic profitability of shrimp farming industries has led more farmers in rural areas to convert their agricultural lands to shrimp ponds.

3.2. Forest to shrub land

Forests cover ~8% of the total area and were concentrated largely in the southeastern region of the country, also known as Chittagong Hill Tract (CHT). During 2000-2010, Bangladesh lost ~9% of its forest area while shrub land gained ~21% (Table 3). Majority of the forest area were converted to shrub land area and observed in the southeastern region of the country. Major conversion of forest to shrub land occurred in Rangamati, Bandarban and Chittagong districts (Figure 7a).

The conversion from forest to shrub land was positively associated with the increasing rate of population and the increasing rate of urban household number (Figure 7b). This result can indicate that the increase in population and urban household number between 2000 and 2010 resulted in an increase in the demand of resources (in terms of forest products, agricultural land to produce more food). The distances to highways and cities had positive impacts, indicating this conversion mainly occurred in areas away from major cities and infrastructure.

Similar results are shown by *Uddin and Gurung*, [2010] and *Reddy et al.*, [2016] where increase of deforestation activities in Bangladesh occurred due to the increasing demand of land as a result of population growth. The deforestation occurred mainly due to agriculture expansion in Bangladesh caused particularly due to a practice known as shifting cultivation (locally known as *jhum*). In this practice, a certain patch of a forest is cleared by slashing and/or burning, followed by a short span of crop plantation and then a long span of fallow period [*Hossian*, 2011]. There is limited amount of fertile land for cultivation, thus local people have to clear forest areas to support the growing population [*Rahman et al.*, 2012]. In addition, due to high demand of land for agriculture, the fallow period was reduced to 3-4 years from 15-20 years, made it difficult for forest regeneration and increasing the risk of soil erosion [*Rahman et al.*, 2012].

Additionally, our results show that wetter conditions (annual overall increasing rate of precipitation and annual increasing rate of precipitation in monsoon months) were positively associated with the conversion of forest to shrub land. Majority of the forest areas are located primarily where there are favorable conditions for tree species to grow (i.e. wetter conditions rather than drier conditions). Our results show that areas in wetter conditions are observing the conversion of forest to shrub land area, implying that most of the forests are situated in the wetter areas of the country. [*Meiyappan et al.*, 2016] also show in their study that areas with wetter conditions are associated with forest loss.

3.3. Shrimp ponds to bare soil

The increase in bare soil area was mainly observed in the areas that were previously under shrimp cultivation. Hotspot areas of the conversion are mainly concentrated in sub-districts in the northeastern region and southwestern region of the country (Figure 8a). Positive association with distance to highways and cities (Figure 8b) suggested that these changes occurred in areas which were distant from highways and cities (i.e. rural areas). As most of the shrimp ponds were in rural areas (where highways and cities are not in distance), the conversion to bare soil is more likely to happen in such areas. The agricultural areas which were converted to shrimp ponds were mainly rice fields, which were heavily inundated with water through precipitation or irrigation.

Our study shows that there is a negative association between elevation and the conversion of shrimp ponds to bare soils. Most of the shrimp ponds are in the low-lying areas of the country, rather than higher-elevation areas (areas with higher elevation have difficulties in access and unfavorable conditions for shrimp cultivation). Positive association with increasing rate of rural household number and negative association with increasing rate of urban household number indicated that these changes were mostly occurring in rural areas. As discussed, majority of the shrimp farming areas were in the rural areas which indicated that such type of conversion was more likely to occur in rural areas.

CHAPTER 4: SUMMARY AND CONCLUSIONS

Our results highlight the major conversion types in Bangladesh over the 2000 and 2010 time-period. Overall, we see that both biophysical as well as socioeconomic drivers play a role in the major conversion types discussed in this study. Major drivers found in this study are: population, urban household number, distance to cities, rivers and highways, precipitation and temperature. Distance to highways and rivers, increasing rate of urban household numbers and annual increasing rate of precipitation plays a role in all three major conversion types discussed in this study. Majority of these changes are seen mostly in the eastern and south-western part of the country at a sub-district level (Figure 6a, 7a, 8a). Forest conversions are mainly observed in the southeastern region where most of the forests occur in Bangladesh. Increase of shrimp cultivation is observed in the north-eastern region of the country. Existing studies in the literature on shrimp farming (e.g. [*Ali*, 2006; *Huq et al.*, 2015; *Islam and Tabeta*, 2016]) focus on the coastal regions of the country where certainly changes are occurring. In this study, we show that there has been sizable amount of conversion from agricultural area to shrimp ponds in the north-east area of the country mostly surrounded by land mass.

Major conversion types shown in this study represent how shrimp industries play a role in the LCLU transitions. We observed that agricultural land is decreasing in the account of shrimp farming. Our results show that such changes are occurring in the rural areas and an increase in population in these areas can facilitate this conversion as the growing population needs a stable source of income. Similarly, biophysical factors such as changing temperature and precipitation can affect the yield of the agriculture produce, leading farmers to switch to shrimp farming. Our synthesis analysis also shows that the major driver of increase in shrimp farming is the increase in economic profitability as compared to other farming produce as well as increase in the demand of shrimp internationally.

The conversion of forest to shrub land is also prominent in this study. As shown in our study, majority of the forest area lies in the southeastern part of the country. We see that these areas are converted into shrub land areas over 2000-2010 due to increase in population growth which increased the demand for resources. The prevailing tradition of shifting cultivation also accelerates deforestation activities and is continually accelerating to fulfill the demand of the growing population. Despite efforts from the local government and deforestation reports, forest areas continue to decrease as shown in our study as well as other studies in the literature (e.g. [*Rasul et al.*, 2004; *Chowdhury and Koike*, 2010; *Reddy et al.*, 2016; *Hasan et al.*, 2017].

Our study also shows the conversion of shrimp pond area to bare soil which is mostly occurring in the rural areas of the country. We find that the areas of shrimp ponds to bare soil conversion is similar to the areas of agriculture to shrimp pond conversion. Bare soil increase may be due to the seasonal changes or abandonment of shrimp pond areas once they maximize their use on a single pond.

TABLES

Table 1: List of biophysical variables

S.N.	Description	Spatial Resolution	Source
Climate Data			
1.	Digital Elevation Model	30m	[*Yang et al.*, 2011]
2.	Precipitation	0.5°x 0.5°	[*University of East Anglia Climatic Research Unit et al.*, 2014]
	Precipitation-Average for Monsoon Months (2000-2010)		
	Precipitation-Average for Post-Monsoon Months (2000-2010)		
	Precipitation-Averaged over the year (2000-2010)		
	Precipitation in Monsoon months -Trend (2000-2010)		
	Precipitation -Standard Deviation (2000-2010)		
	Precipitation-Trend (2000-2010)		
	Precipitation in Monsoon Months-Standard Deviation (2000-2010)		
	Precipitation in Post-Monsoon months -Trend (2000-2010)		
	Precipitation in Post-Monsoon Months-Standard Deviation (2000-2010)		
3.	Temperature	0.5°x 0.5°	[*University of East Anglia Climatic Research Unit et al.*, 2014]
	Temperature in Post-Monsoon months -Trend (2000-2010)		
	Temperature -Trend (2000-2010)		
	Temperature in Monsoon months -Trend (2000-2010)		
	Temperature in Monsoon Months-Standard Deviation (2000-2010)		
	Temperature in Post-Monsoon Months-Standard Deviation (2000-2010)		
	Temperature -Standard Deviation (2000-2010)		
	Temperature-Average for Monsoon Months (2000-2010)		
	Temperature-Average for Post-Monsoon Months (2000-2010)		
	Temperature-Averaged over the year (2000-2010)		
4.	Soil Moisture	0.5°x 0.5°	[*Qu, Le et al.*, 2016]
	Soil Moisture in Monsoon months -Standard Deviation (2000-2010)		
	Soil Moisture Average (2000-2010)		
	Soil Moisture -Trend (2000-2010)		

Table 2: List of socioeconomic variables

S.N.	Description	Spatial Resolution	Source
Socioeconomic Data			
1.	Percentage of Household with electricity	Sub-district	[*BBS*, 2011]
2.	Literacy	Sub-district	[*BBS*, 2011]
	Literacy 2001 Literacy 2011 Literacy increase rate		
3.	Rural household size	Sub-district	[*BBS*, 2011]
	Rural household size 2001 Rural household size 2011 Rural household size increase rate		
4.	Urban household size	Sub-district	[*BBS*, 2011]
	Urban household size 2001 Urban household size 2011 Urban household size increase rate		
5.	Rural household number	Sub-district	[*BBS*, 2011]
	Rural household number 2001 Rural household number 2011 Rural household number increase rate		
6.	Urban household size	Sub-district	[*BBS*, 2011]
	Urban household size 2001 Urban household size 2011 Urban household size increase rate		
7.	Population	Sub-district	[*BBS*, 2011]
	Population 2001 Population 2011 Increase Rate		
8.	Euclidean Distance	Sub-district	[*GADM*, 2012]
	Highway Cities Rivers		

Table 3: Comparison of land cover/use classes between 2000 and 2010

	2000	2010	2000-2010
Class Name	**Area (km2)**	**Area(km2)**	**% change**
Agriculture	110726	107613	-2.81
Shrub land	3134	3808	21.49
Bare Soil	2746	4643	69.07
Rivers	6899	7668	11.15
Forest	12147	11054	-9.00
Settlement	589	794	34.85
Mangrove	4513	4469	-0.97
Shrimp ponds	6816	7521	10.35
Total (sq.km)	147570	147570	

Table 4: Comparison of land cover/use classification with existing studies (in %)

Class	**This study**	**Reddy et al. (2016)**	**Hasan et al. (2017)**	**SRDI (2013)**
Agriculture	72.92	74.39	64.47	60.70
Shrub land	2.58	3.59	4.81	0.00
Bare soil	3.15	0.81	0.10	3.75
Waterbody	10.29	8.90	4.12	9.97
Forest	10.52	9.55	12.82	12.87
Settlement	0.54	1.11	13.68	12.72
Wetland	0.00	1.65	0.00	0.00

Table 5: LCLUC conversion matrix for 2000 and 2010

2000↓ 2010→	Agriculture	Shrub land	Bare Soil	Rivers	Forest	Settlement	Mangrove	Shrimp ponds
Agriculture	105235	209	586	1213	67	162	23	3232
Shrub land	532	2333	12	5	229	3	1	20
Bare Soil	495	5	30	1862	1	4	16	333
Rivers	651	3	1672	4387	3	20	49	113
Forest	142	1242	6	1	10749	1	0	7
Settlement	0	0	0	0	0	589	0	0
Mangrove	9	1	59	56	0	0	4380	9
Shrimp ponds	548	16	2279	144	5	16	1	3807

Table 6: Synthesis of case-studies in Bangladesh

Case #	Research Type	Research notes	Region	Time Period	References
B-1	LCLUC Conversions	Forest to Agriculture Agriculture to Urban	Dhaka	1975-2005	[*Dewan et al.*, 2012]
B-2	LCLUC Conversions	Agriculture to Urban	Dhaka	1975-2003	[*Dewan and Yamaguchi*, 2009]
B-3	LCLUC Conversions	Forest to Agriculture Forests to Urban	Entire Country	1977-2001	[*Uddin and Gurung*, 2010]
B-4	LCLUC Conversions	Forest to Urban	Mirzapur Union of Gazipur District (Mid-Bangladesh)	1989-2009	[*Yesmin et al.*, 2014]
B-5	LCLUC Conversions	Agriculture to Urban	Coastal Area of Bangladesh	1989-2000-2010	[*Islam et al.*, 2016]
B-6	LCLUC Conversions	Forest to Agriculture	Entire Country	1930-2014	[*Reddy et al.*, 2016]
B-7	LCLUC Conversions	Agriculture to Urban	Coastal Area of Bangladesh	1950s-2000s	[*Ahmed*, 2011]
B-8	LCLUC Conversions	Forest to Agriculture	Chittagong Hill Tracts	~1860s-1990s	[*Rasul et al.*, 2004]
B-9	LCLUC Conversions	Agriculture to Urban	Dhaka	1960s-2000s	[*Dewan*, 2013]
B-10	LCLUC Conversions	Agriculture to Urban	Dhaka	1975 and 2003	[*Dewan and Yamaguchi*, 2009]
B-11	Shifting cultivation	-	Khagrachhari district	-	[*Rahman et al.*, 2012]
B-12	Urbanization	-	Entire Country – focus on Dhaka	~1980s-2010s	[*Zaman*, 2010]
B-13	LCLUC Conversions	-	Entire Country	1976-2010	[*SRDI*, 2013]
B-14	Shrimp farming	-	Entire Country	1999-2008	[*Paul and Vogl*, 2011]
B-15	Land degradation	-	Entire Country	1970s-2000s	[*Hasan and Alam*, 2006]

Table 6 (Cont.): Synthesis of case-studies in Bangladesh

B-16	**LCLUC Conversions**	**Forest to Agriculture**	**Chittagong Hill Tracts**	**1970s-2000s**	**[*Ahammad and Stacey*, n.d.]**
B-17	LCLUC Conversions	-	Chakaria Sunderbans	1974-2012	[*Rahman and Hossain*, 2015]
B-18	LCLUC Conversions	Forest to Shrimp Farms	Chakaria Sunderbans	1977-1990s	[*Hossain and Lin*, 2001]
B-19	Landlessness	-	Bangladesh	1960-1984	[*Rahman and Manprasert*, 2006]
B-20	Agriculture	Declining productivity	Bangladesh	~1960s - 2015	[*Hossain*, 2015]
B-21	Forest Resources	-	Bangladesh	1959-1996	[*FRA*, 2000]
B-22	Overall Report	-	Bangladesh	1970-2009	[*FAO*, 2011]
B-23	Forest Conversation	-	Bangladesh	1962-2007	[*Chowdhury and Koike*, 2010]
B-24	Forest and forest management	-	Bangladesh	1961-2004	[*Biswas and Choudhury*, 2007]
B-25	LCLUC	Agricultural land	Rajshahi	1977-2010	[*Islam and Hassan*, 2011]
B-26	Land cover mapping	-	Bangladesh	1985-1993	[*Giri and Shrestha*, 1996]
B-27	Shifting cultivation	-	Bangladesh	1990s-2000s	[*Hossian*, 2011]
B-28	Managing Coastal Area	-	Coastal Area of Bangladesh	2001-2015	[*Islam et al.*, 2016]
B-29	Shrimp farm	Rice farms to Shrimp farming	Damarpota, Southwestern Bangladesh	1985-2003	[*Ali*, 2006]
B-30	Agriculture land use	-	Bangladesh	1999-2000s	[*Rahman et al.*, 2013]

FIGURES

Figure 1: Elevation Map of Bangladesh (in meters)

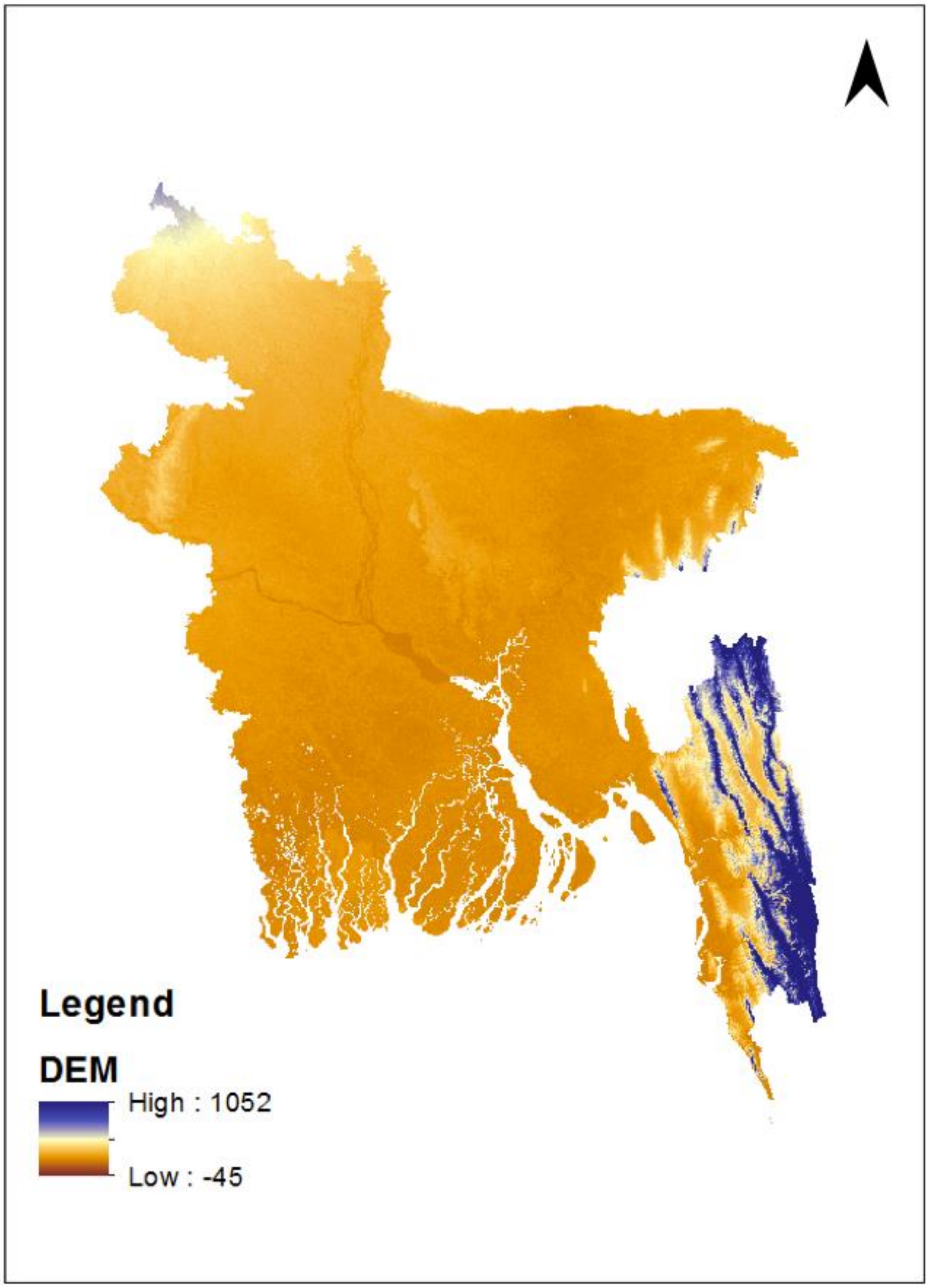


Figure 2: Administrative regions of Bangladesh

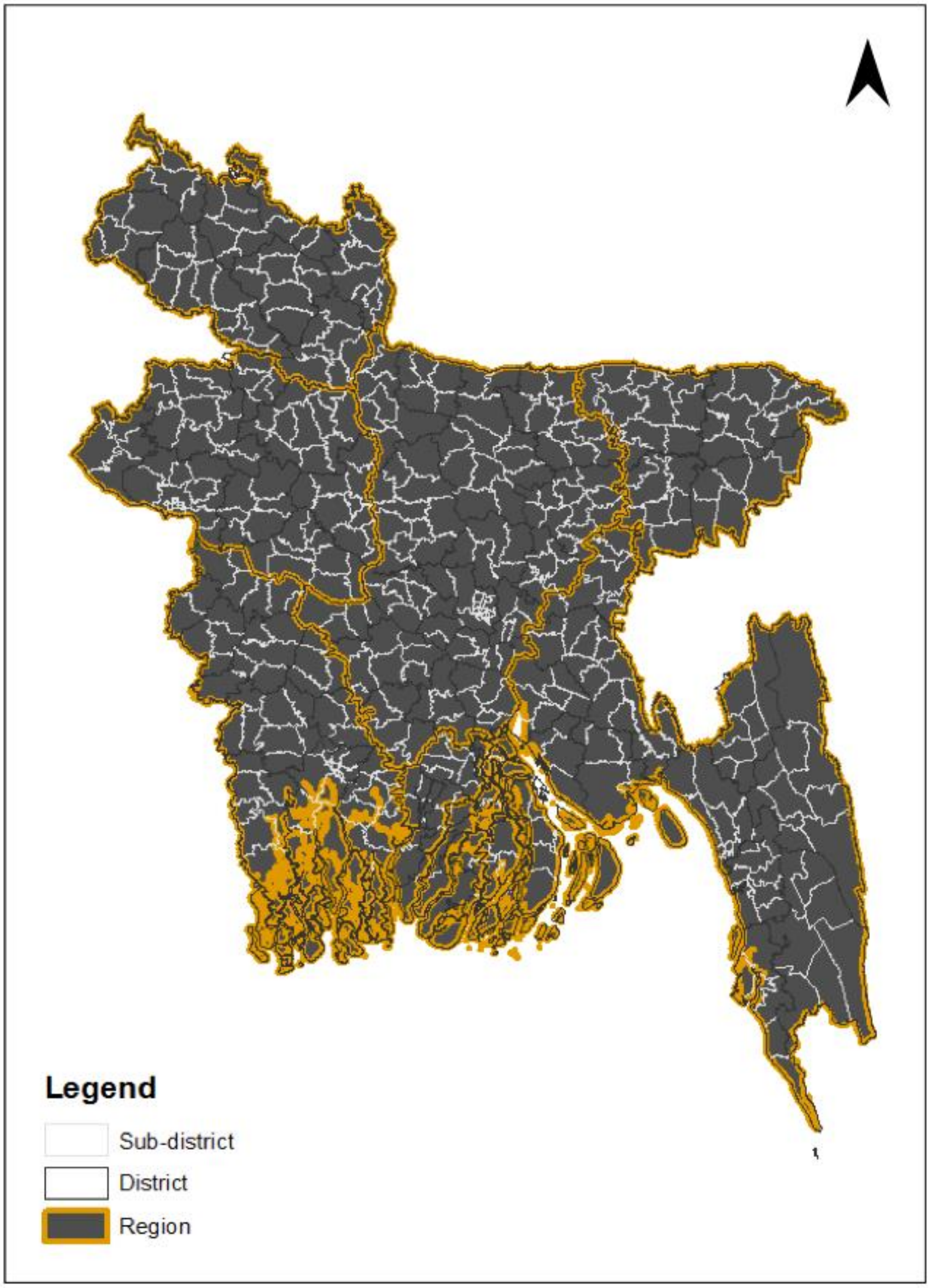


Figure 3: Flowchart diagram of methodology

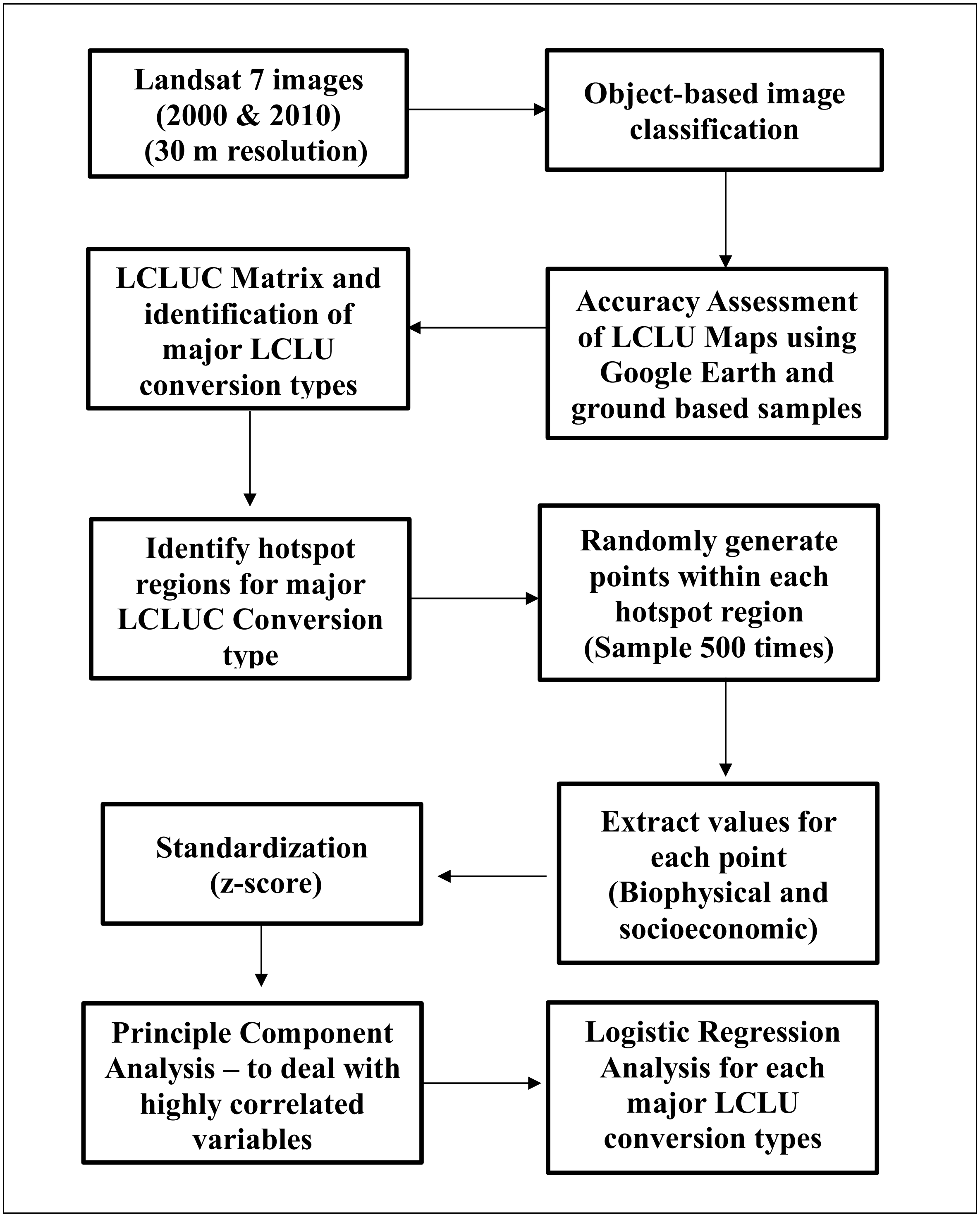
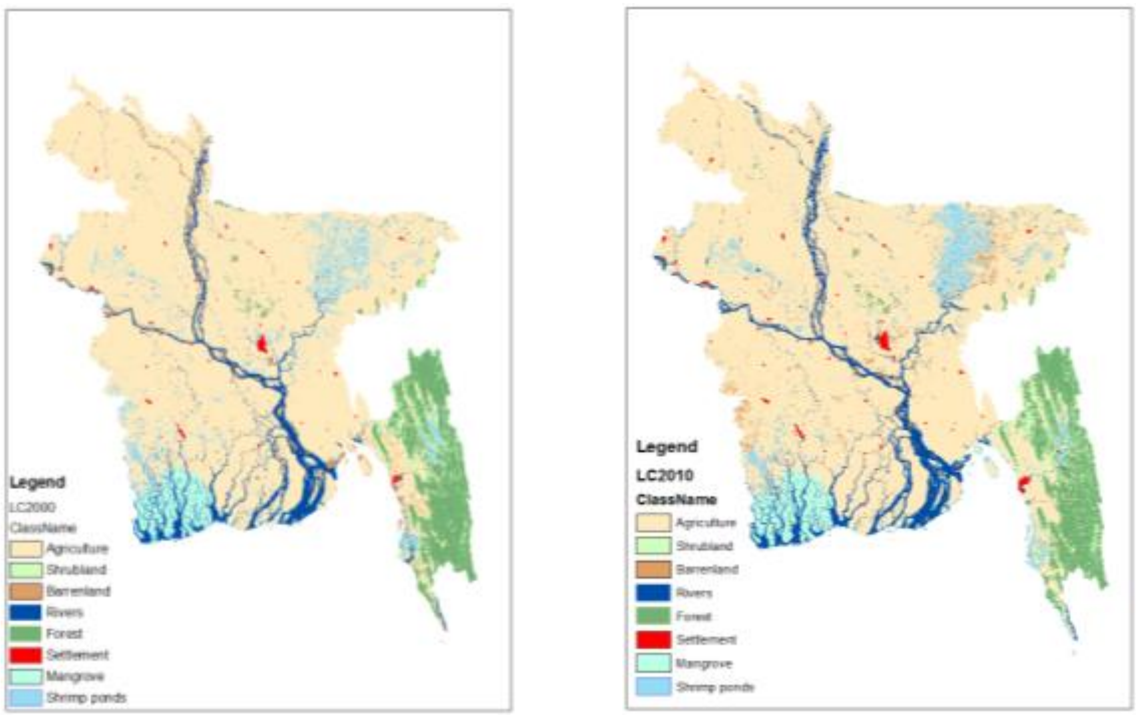


Figure 4: LCLU Classification in Bangladesh for (a) 2000 and (b) 2010



(a) (b)

Figure 5: Gross gain, gross losses, and net changes in land use and land cover at a national scale (km^2) for 2000-2010

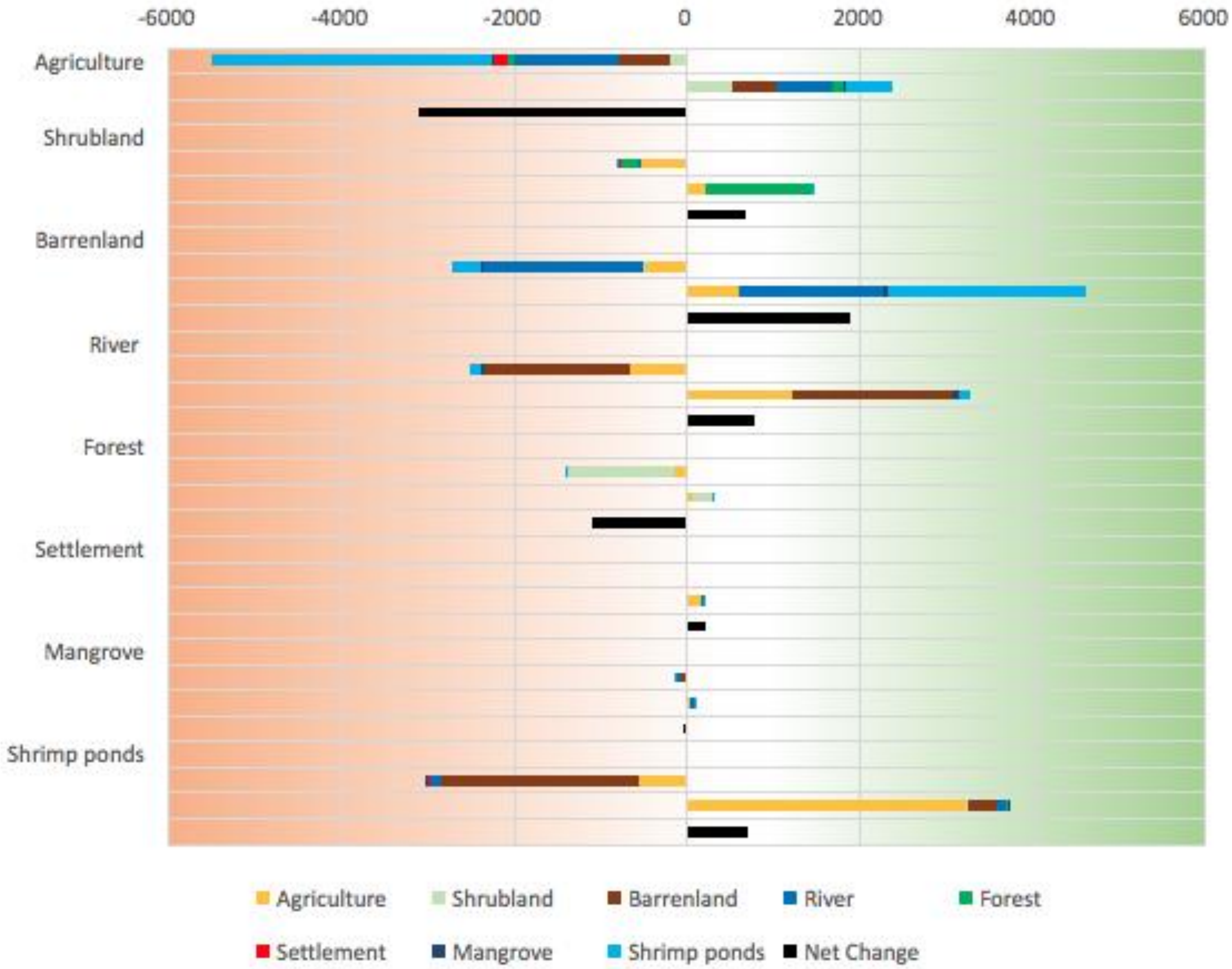
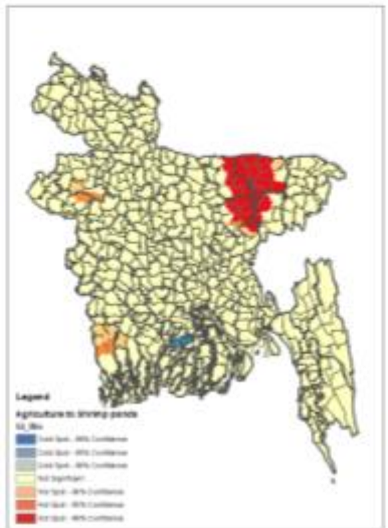
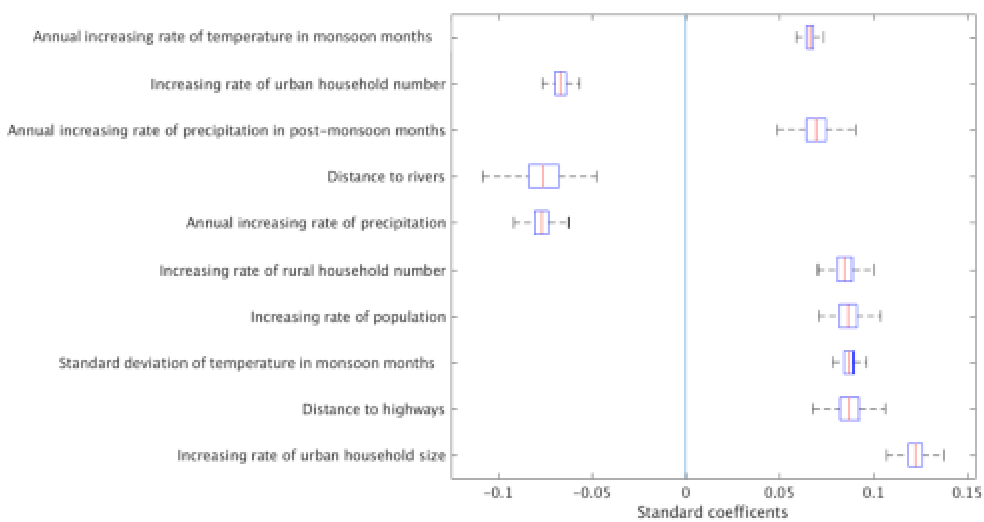


Figure 6: (a)Hotspot regions at sub-district scale for agriculture to shrimp pond conversion. (b)Factors most prominent in explaining: a conversion of agricultural area to shrimp ponds (2000-2010). The plots show the standardized regression coefficients of the ten most important variables (largest absolute mean estimates across coefficients) estimated using the logit model. Standardized coefficients refer to how many standard deviations a dependent variable will change, per standard deviation increase in the independent variable. Standardized coefficients allow comparisons of the relative effects of independent variables measured on different scales. Results from resampling with 500 replicates: central red line shows mean estimate; error boxes (blue) show 25–75% confidence interval; whiskers show 5–95% confidence interval**.**

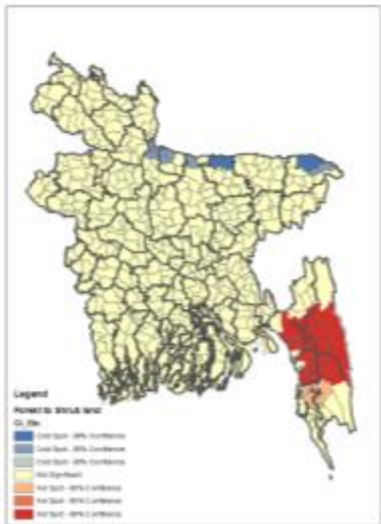


(a)

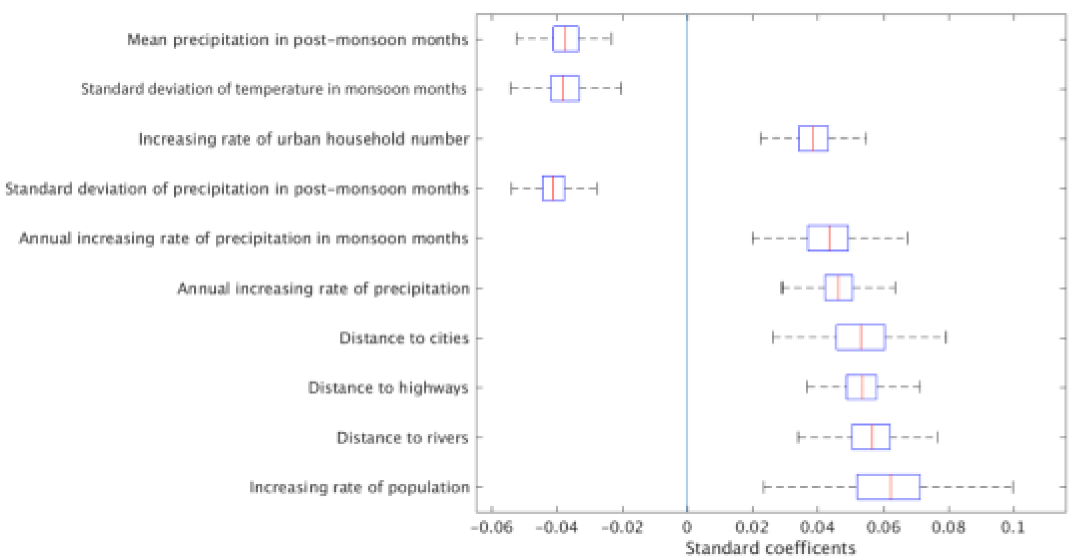


(b)

Figure 7: (a) Hotspot regions at sub-district scale for forest to shrub land conversion (b) Factors most prominent in explaining: a conversion of agricultural area to shrimp ponds (2000-2010). The plots show the standardized regression coefficients of the ten most important variables (largest absolute mean estimates across coefficients) estimated using the logit model. Standardized coefficients refer to how many standard deviations a dependent variable will change, per standard deviation increase in the independent variable. Standardized coefficients allow comparisons of the relative effects of independent variables measured on different scales. Results from resampling with 500 replicates: central red line shows mean estimate; error boxes (blue) show 25–75% confidence interval; whiskers show 5–95% confidence interval.

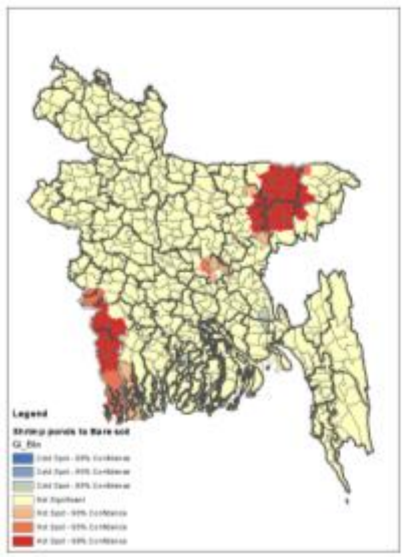


(a)

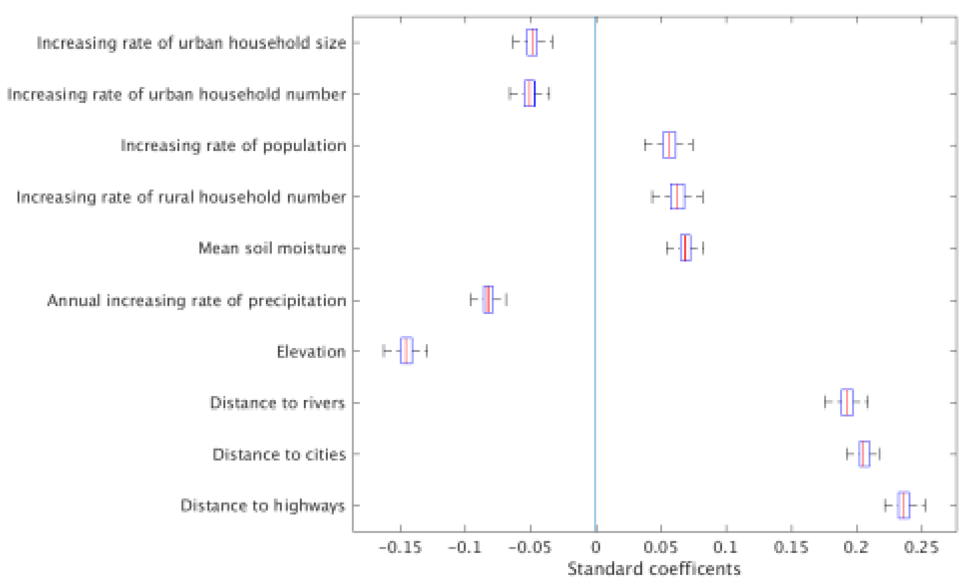


(b)

Figure 8: (a) Hotspot regions at sub-district scale for shrimp ponds to bare soil conversion (b)Factors most prominent in explaining: a conversion of shrimp ponds to bare soil (2000-2010). The plots show the standardized regression coefficients of the ten most important variables (largest absolute mean estimates across coefficients) estimated using the logit model. Standardized coefficients refer to how many standard deviations a dependent variable will change, per standard deviation increase in the independent variable. Standardized coefficients allow comparisons of the relative effects of independent variables measured on different scales. Results from resampling with 500 replicates: central red line shows mean estimate; error boxes (blue) show 25–75% confidence interval; whiskers show 5–95% confidence interval.



(a)



(b)

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