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Article

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Assessing inconsistency in global land cover products and a synthesis of studies on land use and land cover dynamics during 2001-2017 in the southeastern region of Bangladesh

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Abstract. The high-quality Land Use and Land Cover data is important for monitoring and analyzing environmental changes in the background of global warming. This study accessed the spatial and areal inconsistencies in the four most recent multi-resources land cover products in a complex manner using the common classification systems of IGBP-17, IGBP-9, IPCC-5 and TC (vegetation, wetlands and others only). Based on inconsistencies and multi temporal land cover datasets, a synthesis of study was triggered out on land use and land cover dynamics during 2001-2017 in the southeastern region of Bangladesh. The overall areal and spatial inconsistencies decreased from high to low levels of aggregation (IGBP-17 to TC), indicating that the inconsistencies are not only influenced by the level of thematic detail and landscape complexity but also related to the conversion uncertainties. Overall areal inconsistency in the comparison of the FROM-GLC and GlobeLand30 datasets was the smallest among the six pairs, while, the pair of MODISLC and LULC was observed the highest inconsistencies. Based on overall lower inconsistencies classification system (IGBP-9), the synthetic land use cover changes at the study area were assessed. During the period of study, the areal distribution of forest cover, built-up areas and water were found increased in annually by 0.4%, 1.32%, and 0.3% respectively, while the croplands and wetlands were respectively decreased by 0.5% and 0.3%. The dynamic changes of croplands, forest, and artificial surface were identified the prime cyclic land cover change. This research is helpful in providing training areas for the producer of land cover products.

Keywords: Areal and spatial inconsistency, multi-resource land cover products, common classification systems, land use and land cover change, Landsat.

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1 Introduction

Land use and land cover products are essential input datasets in land surface modeling or climate modeling [1-3] as of distinct land cover types and land cover datasets provides reliable information on carbon, water, and nitrogen processes for further ecology, climate, and hydrology studies [4-9]. With the advent of high-resolution imagery and more robust techniques, moderate-resolution remote sensing data sources have emerged in recent years, and the scientific community has witnessed a significant increase in the availability of land cover maps. Land cover products include the International Geosphere-Biosphere Program (IGBP) DIScover (IGBP-DIS) [10], the University of Maryland(UMD) Land Cover [11], the Global Land Cover (GLC) mapping project (GlobeLand30) [12], the Ecosystem Classification and Land Surface Parameters Database (ECOCLIMAP) [13], the Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Product (MODISLC) [14], and the newest Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC) [15]. The IGBP-DIS and UMD datasets belong to the first generation of 1 km global land cover maps, and are derived from 1981 to 1993 Advanced Very High Resolution Radiometer (AVHRR) data using the IGBP (17 land use types in total) and simplified IGBP (14 land use types in total) classification schemes, respectively [11]. The ECOCLIMAP classification scheme comes from the combination of the IGBP-DIS and UMD land cover types and has a spatial scale of 1 km [16]. MODIS provides global land cover with a spatial resolution of 500 m using six types of classification schemes [17]. Given the free availability of Landsat and similar resolution satellite data, a few 30 m GLC datasets had been developed and released in the past few years, including a decadal-scale wall-to-wall GLC data product (GlobeLand30) that shows change in ten land cover types and ten years [18]. These 30 m GLC datasets provide more details of land cover patterns, permit the detection of land cover change at the scale of most human land activities, and enable a better understanding of landscape heterogeneity, as well as increase the performance of modeling and simulations [19-20]. The open source FROM-GLC dataset is the first 30 m global land cover using Landsat data, developed with unique classification scheme based on land cover types from the Food and Agriculture Organization (FAO) of the United Nations and IGBP [15]. Despite the diversity of land cover products available, both data producers and users are frustrated with lack of adequate comparison between such products. Because these land cover products use different classification schemes and spatial resolutions and there is difficulty in selecting and comparing these products for a given application as land use and land cover (LULC) analysis. A specific way to compare datasets is to perform a relative comparison of various land cover maps, first reconciling their thematic classification systems into more aggregated categories after resampling the datasets to be into the same spatial resolution [21].

Using common classification systems based on the definition of each class in the original land cover products [22-23] or standards in reference to FAO [24], IGBP [11], or other dataset, some previous studies have highlighted general patterns of agreement, inconsistencies and accuracy among different land cover products at global [25-26], continental [24], national [22], and provincial scales [27]. Other studies not only demonstrated the compatibility and discrepancies between different datasets, but also qualitatively discussed the impacts of landscape in homogeneity, thematic resolution, spatial resolution, and mis-registration errors on product accuracy [26, 28]. However, few studies have focused on quantitatively examining the uncertainties of classification system conversion, and examined the inconsistencies in the complex land surface areas or approached the subject from the perspective of the complex landscape features.

Rapidly increasing population growth has resulted in high rates of deforestation and large tracts of forests transitioning into cultivated land; this transition has been recognized as a dominant land cover worldwide [29]. Asia has undergone the most rapid land cover changes in recent years; which has resulted in rapidly increasing cropland and large-scale deforestation in south Asian countries [30]. The area of per capita arable land in the south Asia is very low as compared to other continents. According to FAO (2014) [31], after the Maldives in south Asia, the 0.06 ha/person for Bangladesh is the lowest per capita land ratio worldwide. Clearly, the per capita agricultural land is decreasing as total population continues to increase. Among south Asian countries, Bangladesh potentially has the most serious conditions per capita agriculture land, with the rate decreasing 0.11, 0.09, 0.07, and 0.06 ha/person in 1981, 1991, 2001, and 2011 respectively [31-32]. In addition, due to the high population growth, per capita arable land was about 2122 person/km^2 in 2016 [33], which is the least area per person within the Asian countries outside of the Maldives. Therefore, it also called the land-hungry country [34]. Southeastern region of Bangladesh is a densely populated region with a complex landscapes basin of alluvial floodplain, tidal and coastal floodplain, terrace land, and hills where vegetation and trees outside of forests play an important role in the national economy and carbon sequestration [35]. The primary LULC classes in here are agricultural land, urban and built-up area, forest and vegetation, water bodies, and wetlands [36]. The natural vegetation of this region consists of tropical moist deciduous and semi-evergreen forests, mangroves, and fresh water wetlands [37]. The eastern forests belts of the study area, at the border with Myanmar, are related to the Indo-Burma biodiversity hotspot, one of the few globally significant areas with high species diversity and endemism [38].

Scientifically and systematically documenting land cover and land use changes over past several decades is important for understanding the consequences of these changes for human welfare [30]. Therefore, the objective of this paper is to assess the areal and spatial inconsistencies in different global land cover products and their synthesis analysis of land use and land cover dynamics. The four most recent global land cover products as the MODISLC, GlobeLand30, FROM-GLC, and LULC class of the Landsat satellite imagery data were compared with each other. Each of them used different classification schemes, supporting the present investigation. To assess the effects of diverse thematic details on the uncertainties and discrepancies in the datasets, we selected a 17-class IGBP classification system (IGBP-17), a 9-class IGBP classification system (IGBP-9), a 5-class IPCC classification system (IPCC-5) and finally at the highest level of aggregation, vegetation, wetlands and others only (TC) as common classification systems. The detailed research steps include the quantitatively analyzing the uncertainty caused by classification system conversion and pair wise each class and overall areal inconsistencies of the four land cover products in based on the uncertainties. Based on inconsistencies and above four different land cover products, a synthetic dynamics of land use and land cover changes at different spatial and temporal scale was also analyzed covering the study area from 2001 to 2017.

2 Materials and Methods

2.1 Study Area

This study incorporated data for the southeastern region of Bangladesh, between the latitudes 22°40′ - 24°10′ N and longitude 90°45′ - 92°40′ E with an area of 33,904 sq. km [39-40]. It shares land borders with Bay of Bengal in the south, India and Myanmar in the east and the locally largest river as well the Meghna River (based on water discharged) is in the north and west borders of the study area (Fig. 1). Geographically, it is the largest administrative division of Bangladesh out of eight [39-40] and a population of 29.15 million in consisting density of 884 persons per sq. km

[41]. The northern and western portions are listed as low-lying alluvial floodplains of the Meghna River that are less than 10 m above sea level, comprising 37.6% of the region. However, the remaining southern and eastern portion, where the elevation exceeds 200 m, comprises 62.4% of the area, mostly with a south–north distributed hilly nature [41]. The eastern portion hilly regions are mostly covered by dense forest with a variety wild life. The mega-river basin has played a crucial role in supporting agriculture, groundwater recharge, fish farming, and land building activities throughout history [42]. The vast areas of plain lands are mainly alluvial river floodplains, estuarine floodplains, wetlands, tidal floodplains, coastal plains, and a small portion of terraced land in nature.

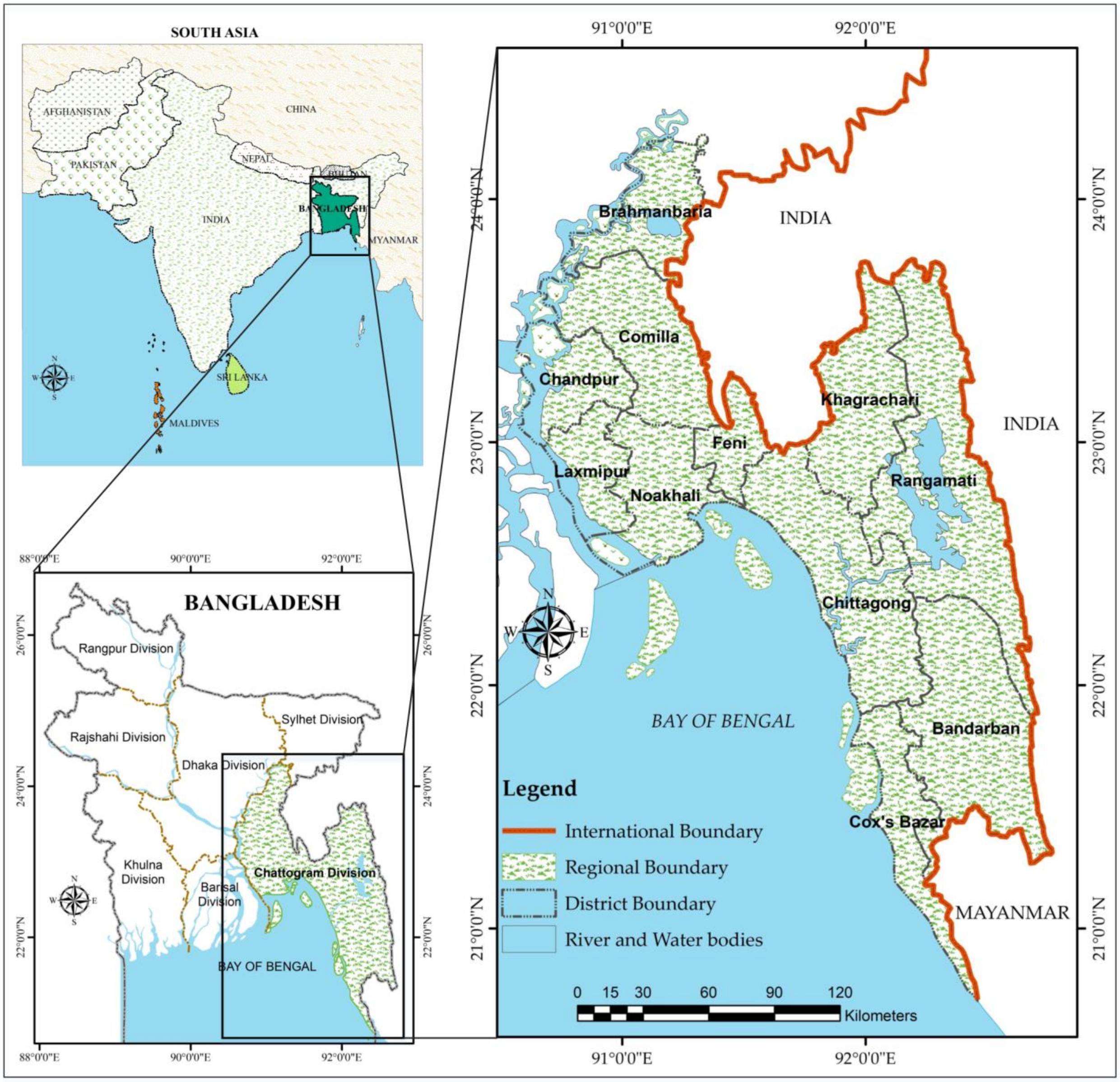


Fig. 1 Location of the study area the Southeastern region of Bangladesh

2.2 Datasets

To monitor and quantify the inconsistencies in global land cover products and heterogeneous landscapes and land cover change dynamics in the southeastern region of Bangladesh, high temporal and multiresolution recent global land cover products and remote sensing satellite imaginaries were used as datasets to be evaluated in this study. Three recent land cover products were the MODISLC, GlobeLand30, and FROM-GLC land cover datasets and LULC class images were collected from Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper Plus (ETM+). These products are derived from newer satellite images and are validated or assessed by the producers on worldwide scales in reference to Google Earth, Virtual Earth, Yahoo maps, and others. The usefulness of these four datasets to different regional investigators has rarely been reported. Fig. 2 has described the datasets products, processing and analysis in a flowchart.

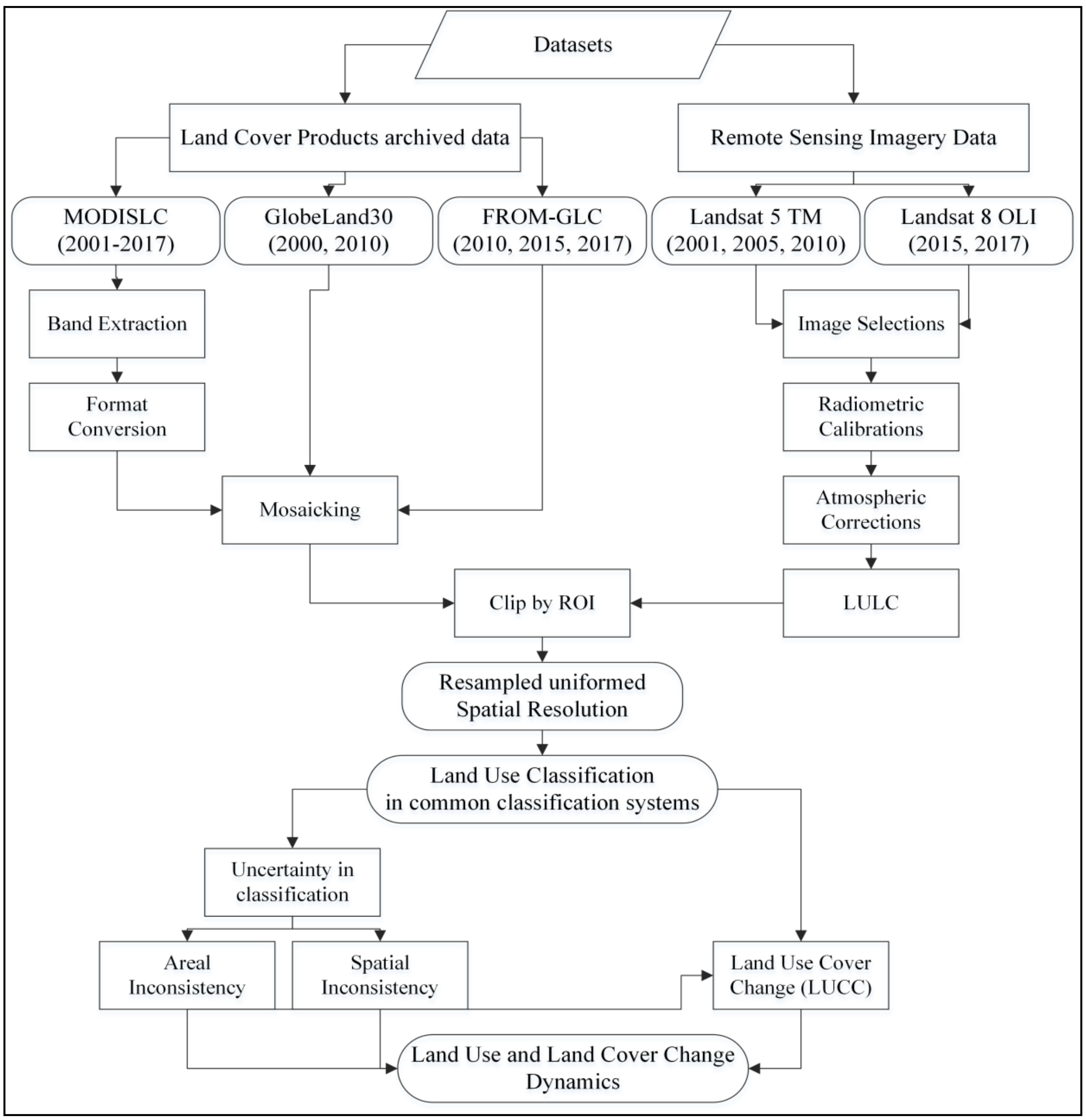


Fig. 2 Data analysis flowchart. ROI: Region of Interest; LULC: Land Use and Land Cover; LUCC: Land Use Cover Change.

2.2.1 Land cover products

The MODISLC is derived from the Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1) Version 6 data product, provides global land cover types at yearly intervals from 2001 to 2017. The MODISLC V6 data products is derived using supervised classifications then undergo additional post-processing that incorporate prior knowledge and ancillary information to further refine specific classes [17]. The GlobeLand30 land cover datasets were derived from National Geomatics Center of China (NGCC) is the 30 m GLC data product of the years 2000 and 2010. The images utilized for GlobeLand30 classification are multispectral images with 30 meters, including the TM5 and ETM+ of America Land Resources Satellite (Landsat) and the multispectral images of China Environmental Disaster Alleviation Satellite (HJ-1) [18, 43]. The FROM-GLC is the first fine scale global map product extracted from Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data with a spatial resolution of 30 m, covering the years of 2010, 2015 and 2017 [15].

In this study, the MODISLC dataset was downloaded from U.S. Geological Survey Land Processes Distributed Active Archive Center [44], the GlobeLand30 global land cover dataset was downloaded from the National Geomatics Center of China [45], and the FROM-GLC was downloaded from the Center for Earth System Science, Tsinghua University, China [46]. Detailed characteristics of these three datasets are summarized in Table 1, and the detailed classification schemes are individually listed in Tables 2, 3, and 4.

Table 1 Characteristics of the archive land cover products used in the study

	MODISLC	**GlobeLand30**	**FROM-GLC**
Sensor	Terra and Aqua	TM5, ETM+, HJ-1	TM/ETM+
Acquisition time	2001-2017	2000, 2010	2010, 2015, 2017
Classification method	Supervised classification of MODIS reflectance data	POK based classification	MLC, J4.8 decision tree, RF, and SVM classifier

Input data	7 Spectral bands LST/NDVI Normalized BRDF Adjusted Reflectance	20,000 Landsat and Chinese HJ-1 satellite images	8929 scenes TM/ETM+ data
Classification schemes	IGBP	GLC	FAO and IGBP
Thematic resolution	17	10	First level: 8 Second level: 26
Spatial resolution	500 m	30 m	30 m
Range	Global	Global	Global
Projection	Sinusoidal	UTM_WGS84	UTM_WGS84
Accuracy assessment	Cross validation	Sample based validation	Globally systematic unaligned sampling strategy
Overall accuracy	75%	80%	65.51%
Update rate	6 months	10 years	Unknown
Producer agency	LP DAAC U.S. Geological Survey	National Geomatics Center of China	Tsinghua University, China
Reference	[17]	[18, 43]	[15]

(POK: Pixel-object-knowledge; MLC: Maximum likelihood classifier; RF: Random Forest; SVM: Support Vector Machine; LST: Land Surface Temperature; NDVI: Normalized Difference Vegetation Index; BRDF: Bidirectional Reflectance Distribution Function)

Table 2 Classification scheme and class description of the MODISLC

Name	Value	Description
Evergreen Needleleaf Forests	1	Dominated by evergreen conifer trees (canopy >2m). Tree cover >60%.
Evergreen Broadleaf Forests	2	Dominated by evergreen broadleaf and palmate trees (canopy >2m). Tree cover >60%.
Deciduous Needleleaf Forests*	3	Dominated by deciduous Needleleaf (larch) trees (canopy >2m). Tree cover >60%.
Deciduous Broadleaf Forests	4	Dominated by deciduous broadleaf trees (canopy >2m). Tree cover >60%.
Mixed Forests	5	Dominated by neither deciduous nor evergreen (40-60% of each) tree type (canopy >2m). Tree cover >60%.
Closed Shrublands*	6	Dominated by woody perennials (1-2m height) >60% cover.
Open Shrublands*	7	Dominated by woody perennials (1-2m height) 10-60% cover.
Woody Savannas	8	Tree cover 30-60% (canopy >2m).
Savannas	9	Tree cover 10-30% (canopy >2m).
Grasslands	10	Dominated by herbaceous annuals (<2m)
Permanent Wetlands	11	Permanently inundated lands with 30-60% water cover and >10% vegetated cover.
Croplands	12	At least 60% of area is cultivated cropland.
Urban and Built-up Lands	13	At least 30% impervious surface area including building materials, asphalt, and vehicles.
Cropland/Natural Vegetation Mosaics	14	Mosaics of small-scale cultivation 40-60% with natural tree, shrub, or herbaceous vegetation.
Permanent Snow and Ice*	15	At least 60% of area is covered by snow and ice for at least 10 months of the year.
Barren	16	At least 60% of area is non-vegetated barren (sand, rock, soil) areas with less than 10% vegetation.
Water Bodies	17	At least 60% of area is covered by permanent water bodies.

Unclassified*	255	Has not received a map label because of missing inputs.

*Land cover categories not present in the study area.

Table 3 Classification schemes and class description of the GlobeLand30 land cover products

Land cover types	Value	Description
Cultivated Land	10	Lands used for agriculture, horticulture and gardens, including paddy fields, irrigated and dry farmland, vegetation and fruit gardens, etc.
Forest	20	Lands covered with trees, with vegetation cover over 30%, including deciduous and coniferous forests, and sparse woodland with cover 10 - 30%, etc.
Grassland	30	Lands covered by natural grass with cover over 10%, etc.
Shrub lands	40	Lands covered with shrubs with cover over 30%, including deciduous and evergreen shrubs, and desert steppe with cover over 10%, etc.
Wetland	50	Lands covered with wetland plants and water bodies, including inland marsh, lake marsh, river floodplain wetland, forest/shrub wetland, peat bogs, mangrove and salt marsh, etc.
Water bodies	60	Water bodies in the land area, including river, lake, reservoir, fish pond, etc.
Tundra*	70	Lands covered by lichen, moss, hardy perennial herb and shrubs in the polar regions, including shrub tundra, herbaceous tundra, wet tundra and barren tundra, etc.
Artificial Surfaces	80	Lands modified by human activities, including all kinds of habitation, industrial and mining area, transportation facilities, and interior urban green zones and water bodies, etc.
Bareland	90	Lands with vegetation cover lower than 10%, including desert, sandy fields, Gobi, bare rocks, saline and alkaline lands, etc.
Permanent snow and ice*	100	Lands covered by permanent snow, glacier and icecap
Not classified	255	Has not received a map label because of missing inputs.

*Land cover categories not present in the study area

Table 4 Classification Scheme of the FROM-GLC land cover products

L1T	L1C	L2T	L1/2C	L2T	L1/2C	L2T	L1/2C	L2T	L1/2C	L2T	L1/2C
Crop	10	Rice	10/11	Greenhouse	10/12	Other	10/13				
Forest	20	Broadleaf	20/21	Needleleaf	20/22	Mixed	20/23	Orchard	20/24		
Grass	30	Managed	30/31	Nature	30/32						
Shrub	40										
Wetland	50	Grass	30/51	Silt	90/52						
Water	60	Lake	60/61	Pond	60/62	River	60/63	Sea	60/64		
Tundra*	70	Shrub	40/71	Grass	30/72						
Impervious	80	High albedo	80/81	Low albedo	80/82						
Bareland	90	Saline-Alkali	90/91	Sand	90/92	Gravel	90/93	Bare-Cropland	10/94	Dry river/lake bed	90/95
Snow/Ice*	100	Snow*	100/101	Ice*	100/102						
Cloud	120										

*Land cover categories not present in the study area. (L1T: Level 1 Type, L1C: Level 1 Code, L2T: Level 2 Type, L1/2C: Level 1/2 Code)

2.2.2 Remote sensing imagery data

Remote sensing satellite imageries were used to identify the land use and land cover (LULC) class of the study area in some selective years of study. The images were acquired for 2001, 2005, and 2010 in between January and March of the year from Landsat 5 Thematic Mapper (TM L1T). While in March 2015 and February 2017 of images were acquired from Landsat 8 OLI. All these data were downloaded from the USGS Global Visualization Viewer (GloVis) archive (https://glovis.usgs.gov/) [47]. The downloaded bands of Landsat 8 OLI and TM scenes were superimposed (excluding the thermal band) to form multispectral images using ENVI5.1 software. After the acquisition of the images, seven bands of OLI8 and five bands of TM except the thermal bands of each image scene were superimposed to form a single multispectral image dataset using the layer stack function. From the acquired data, if possible, only those images without cloud cover were selected. Different remote sensing and GIS techniques were applied, such as digital image processing using supervised classification and image indices. Supervised classification using a maximum likelihood algorithm was applied to classify the LULC map. The classified images were modified with the help of image indices and visual interpretation to produce a more accurate map. Based on IGBP-9, FAO land cover classes and visible land cover of the study, we adopted a classification scheme consisting of 6 first level classes, namely water, forests, wetlands, croplands, artificial surfaces and others/bare lands (Table 5). The Universal Traverse Mercator (UTM) system with the datum of WGS84 and Zone 46N was selected as projection for all data.

Table 5 Classification schemes for LULC class distribution of 30m Landsat TM/ETM+ imaginary data

Land cover types	Value	Description
Water	1	Water bodies in the land area, including river, lake, reservoir, fish pond, sea water etc.
Forests	2	Lands covered with trees, with vegetation cover including deciduous and coniferous forests, and sparse woodland.

Wetlands	3	Lands covered with wetland plants and water bodies, including inland marsh, lake marsh, river floodplain wetland, forest/shrub wetland, peat bogs, mangrove and salt marsh, etc.
Croplands	4	Lands used for agriculture, horticulture and gardens, including paddy fields, irrigated and dry farmland, vegetation and fruit gardens, etc.
Artificial Surfaces	5	Lands modified by human activities, including all kinds of habitation, industrial and mining area, transportation facilities, and interior urban green zones and water bodies, etc.
Others/Bare lands	6	Lands with sandy fields, bare rocks, saline and alkaline lands, sea beach and shorelines etc.

2.3 Methodology

2.3.1 Classification system conversion

The land cover datasets of MODISLC, GlobeLand30, FROM-GLC, and LULC classes are used different classification schemes as well as common classification system of IGBP for MODISLC [17], combined IGBP and FAO for FROM-GLC [15], and unique classification for GlobeLand30 [18] and LULC class distribution. However, differences in the classification system are prominent (Table 2, 3, 4, and 5), for example, the FROM-GLC, GlobeLand30 and LULC class are the product in which no distinction is made between evergreen and deciduous forest classes, while the LULC is the only product in which no identification is made of shrublands and grasslands and MODISLC is the only product having closed and open shrublands. To overcome the problem of conflicting classification systems, the thematic classification system of the MODISLC,GlobeLand30,FROM-GLCand the Landsat classified images as LULC were converted into four common classification systems based on their original definition of classes in each land cover product, which defaults to selecting the dominant category [11,20,22,24-26,48]. When some categories from the original classification systems could not completely be attributed into any category in the common classification systems due to conflicting definitions, we classified them into corresponding types based on knowledge or by referring to data like the DEM, and labeled them as ambiguous types in this study resulting in uncertainties during classification system conversion [48]. The IGBP-17, IGBP-9, IPCC-5 and TC common classification systems were used in this study. The detailed categories of the common classification systems and corresponding relationships were presented in Table 6.

Table 6 The converting classification schemes of the MODISLC, GlobeLand30, FROM-GLC, and LULC classes in the four common classification systems

MODISLC	GlobeLand30	FROM-GLC	LULC	IGBP-17
17	60	61, 62, 63, 64	1	1 Water
1		22		2 Evergreen Needleleaf Forest (Coverage > 60% and Height > 2 m)
2		21		3 Evergreen Broadleaf Forest (Coverage > 60% and Height > 2 m)
3*				4 Deciduous Needleleaf Forest (Coverage > 60% and Height > 2 m)
4				5 Deciduous Broadleaf Forest (Coverage > 60% and Height > 2 m)
5	20	23	2	6 Mixed Forests
6*				7 Closed Shrublands (Coverage > 60% and Height < 2 m)
7*	40	40		8 Open Shrublands (10% < Coverage < 60% and Height < 2 m)
8				9 Woody Savannas (30% < Coverage < 60% and Height > 2 m)
9				10 Savannas (10% < Coverage <30% and Height > 2 m)
10	30	31, 32, 51		11 Grasslands
11	50	50	3	12 Permanent Wetland (transition zone between land and water bodies)
12	10	11, 12, 13	4	13 Croplands
13	80	80, 81, 82	5	14 Urban and Built-Up
14		94		15 Cropland/Natural Vegetation Mosaic (Any type of coverage < 60%)
15*	100*	101, 102		16 Snow and Ice
16	90	91, 92, 93, 95, 52	6	17 Barren or Sparsely Vegetated (Coverage < 10%)

MODISLC	GlobeLand30	FROM-GLC	LULC	IGBP-9
17	60	61, 62, 63, 64	1	1 Water
1, 2, 3*, 4, 5, 8	20	21, 22, 23	2	2 Forests
6*, 7*	40, 70*	40		3 Shrublands
9, 10	30	32		4 Grasslands
11	50	51, 52	3	5 Permanent Wetland
12, 14	10	11, 13, 94	4	6 Croplands (Crop/vegetation)

13	80	80, 81, 82	5	7 Urban and Built-Up
15*	100*	101*, 102*		8 Snow and Ice
16	90	91, 92, 93, 95	6	9 Others
MODISLC	**GlobeLand30**	**FROM-GLC**	**LULC**	**IPCC-5 classes**
12, 14	10	11, 13, 94	4	1 Croplands
1, 2, 3*, 4, 5, 6*, 7*, 8	20	21, 22, 23, 40	2	2 Forest lands
9, 10	30	32		3 Grasslands
11, 15*, 17	60, 100*	61, 62, 63, 64, 51, 52, 101*, 102*	1, 3	4 Water, snow, ice and wetland
13, 16	40, 50, 70*, 80, 90	80, 81, 82, 91, 92, 93, 95	5, 6	5 Others
MODISLC	**GlobeLand30**	**FROM-GLC**	**LULC**	**TC**
1, 2, 3*, 4, 5, 6*, 7*, 8, 9, 10, 12, 14	10, 20, 30	11, 13, 94, 21, 22, 23, 40, 32	2, 4	1 Vegetation
11, 15*, 17	60, 100*	61, 62, 63, 64, 51, 52, 101*, 102*	1, 3	2 Water, snow, ice and wetland
13, 16	40, 50, 70*, 80, 90	80, 81, 82, 91, 92, 93, 95	5, 6	3 Others

*Uncertain types when conversion was performed

2.3.2 Uncertainty during the classification system conversion

The classification schemes of the FROM-GLC, GlobeLand30, MODISLC and Landsat LULC datasets were converted into the four common classification systems. During the classification system conversion, some categories from the original classification systems could not completely be attributed into any category in the common classification systems due to differences in class definitions which were labeled as ambiguous types in this study. These were summarized into four main ambiguous types during classification system conversion, including (1) no dominant type; (2) different percentage of the dominant type; (3) the type definition broader than the corresponding type in the common classification system; and (4) labeling errors [48].

Uncertainties of classification system conversion caused by ambiguous types in the four common classification systems were quantitatively calculated by the following equation [48]:

$$\boldsymbol{U} = \frac{\boldsymbol{N_j}}{\sum_i^n \boldsymbol{N_i}} \times \mathbf{100} \quad (1)$$

Where, U= the uncertainty ratio caused by classification system conversion due to ambiguous types; N_j = the total number of pixels of ambiguous types, n = the number of land cover types in the common classification system, N_i = the total number of pixels of one type of common classification system, and $\sum_i^n \boldsymbol{N_i}$= the total number of pixels of all land cover types.

2.3.3 The method for assessing areal and spatial inconsistency

Areal and spatial inconsistencies were assessed using pixel-by-pixel comparisons between the different land cover products in the common classification systems.

Areal Inconsistency of each Class (AIC) and Overall Areal Inconsistency (OAI) in four common classification systems were computed by the following equations [20, 48]:

$$\boldsymbol{AIC = ABS\ (X_i - Y_i)/2} \tag{2}$$

$$\boldsymbol{OAI = \sum_i^n AIC} \tag{3}$$

where, AIC = areal inconsistencies of each class; n = the total number of land use types in the common classification systems; X_i = total area percentage of land use type i in one of the FROM-GLC, the GlobeLand30, the MODISLC, and the LULC; Y_i = total area percentage of class i one other four land cover products; and OAI = overall areal inconsistency in the common classification systems.

Using the four common classification systems, the first step for obtaining the pairwise spatial inconsistencies between the FROM-GLC (30 m), GlobeLand30 (30 m), LULC of remote sensing images (30 m), and MODISLC (500 m) datasets level involved up-scaling higher spatial resolution land cover into the corresponding datasets lower spatial resolution. A pixel in a low spatial resolution usually represents only one type of land use type, whereas the corresponding high spatial resolution pixel includes more than one land use type. In this study, a low spatial resolution pixel was considered to be 100% correct when it agreed with the dominant type of the corresponding high spatial resolution pixels and was considered to be 0% correct when it disagreed. Majority filtering technology was used to upscale the high spatial resolution land cover into lower resolutions. The Overall Spatial Inconsistency (OSI) between a given pair of these four land cover products was calculated according to the formula below [20, 48]:

$$\boldsymbol{OSI} = \frac{\boldsymbol{N_{(i \neq j)}}}{\boldsymbol{N}} \times \mathbf{100} \quad (4)$$

Where, *OSI*= Overall Spatial Inconsistency; $N_{(i \neq j)}$ = the number of pixels for which the type is different from another one at the same location when compared to different datasets (either FROM-GLC, GlobeLand30, LULC, or MODISLC), and *N* = the total number of pixels.

2.3.4 Determination of land use classification system

Different classification schemes were used in different land cover products of the MODISLC, the GlobeLand30, and the FROM-GLC datasets (Tables 2, 3, 4). In addition to image classification, a supervised classification method combined of IGBP and IPCC was used to build-up LULC map as a unique classification scheme (Table 5). All land classes of interest were selected and carefully defined to classify remotely sensed data successfully into land use and land cover categories in the study area. This requires the use of a classification scheme containing taxonomically clear definitions of classes. Classes in the system should normally be mutually exclusive, exhaustive, and hierarchical [49]. International Geosphere-Biosphere Program (IGBP) suggested nine broad categories for representing land areas within a country: water; forests; shrublands; grasslands; permanent wetland; croplands; urban and built-up; snow and ice; and others [10,48]. Based on these land use frames, the land areas in this study were classified/ reclassified as water, forests, grasslands, permanent wetland, croplands, urban and built-up/ artificial surface, and others/bare land, through field observation and by referencing preceding reports [34,36]. Each class is considered sufficiently representative and includes all land area within the study area, reducing possible overlaps and omissions as far as practicable.

3 Results

3.1 Areal Inconsistency

Using four common classification systems, the areal inconsistencies of each land use type from pairwise comparisons of the FROM-GLC, GlobeLand30, MODISLC, and LULC datasets were shown in Table 7. During the classification system conversion to IGBP-17, the areal inconsistencies were mainly present in mixed forests (up to 24.56%), woody savannas (up to 13.57%) and urban and built-up (up to 13.43%) classes. The areal inconsistencies in classification system conversion to IGBP-9 were mainly caused by urban and built-up, croplands, and grasslands (up to 12.35%, 7.90%, and 6.85% respectively) classes. During the classification system conversion to IPCC-5, the areal inconsistencies were mainly caused by croplands, grassland, and others (up to 7.90%, 6.85%, and 13.55% respectively). Mean while, during the classification system conversion to TC system, the areal inconsistencies were mainly caused by vegetation (up to 16.19%) and others (up to 13.55%). These land cover types were the dominant types in our study area, illustrating that the different percentages of dominant types among land cover products can greatly influence areal inconsistencies. The areal inconsistency of forests using IGBP-17, IGBP-9, and IPCC-5 (24.56%, 4.87%, and 5.39% respectively) between the FROM-GLC and the MODISLC were higher than the inconsistent result (0.2%, 1.33%, and 1.48%) from the paper [48], but the areal inconsistencies for vegetation using TC (2.57%) was far less than the result (40.21%) in the paper mentioned above.

Table 7 Areal inconsistencies for each land use type in four common classification systems in pair wise comparisons of the FROM-GLC, GlobeLand30, MODISLC, and Landsat TM/ETM LULC datasets.

Classification System	Type	FG-GL (%)	FG-MOD (%)	FG-LU (%)	GL-MOD (%)	GL-LU (%)	MOD-LU (%)
	1	0.95	0.7	0.97	1.65	0.03	1.67
	2	0	0.01	0	0.01	0	0.01
	3	0	3.25	0	3.25	0	3.25
	4	0	0	0	0	0	0
	5	0	2.87	0	2.87	0	2.87
	6	4.09	24.56	5.94	20.47	1.85	18.62
	7	0	0	0	0	0	0
	8	0.02	0.52	0.52	0.5	0.5	0
IGBP-17	**9**	0	13.57	0	13.57	0	13.57
	10	0	5.31	0	5.31	0	5.31
	11	0.92	0.29	1.83	0.63	0.91	1.54
	12	1.27	3.08	4.83	1.81	3.56	1.75
	13	0.615	5.92	7.9	5.3	7.29	1.99
	14	5.6	1.08	12.35	6.68	6.75	13.43
	15	0	3.71	0	3.71	0	3.71
	16	0	0	0	0	0	0
	17	0.27	0.14	0.02	0.13	0.25	0.12
	1	0.95	0.7	0.97	1.65	0.03	1.67
	2	4.09	4.87	5.94	0.78	1.85	1.07
	3	0.02	0.52	0.52	0.5	0.5	0
	4	0.92	5.02	1.83	5.94	0.91	6.85
IGBP-9	**5**	1.27	3.08	4.83	1.81	3.56	1.75
	6	0.62	2.21	7.9	1.59	7.29	5.7
	7	5.6	1.08	12.35	6.68	6.75	13.43
	8	0	0	0	0	0	0
	9	0.27	0.14	0.02	0.13	0.25	0.12
	1	0.62	2.21	7.9	1.59	7.29	5.7
	2	4.61	5.39	6.46	0.78	1.85	1.07
IPCC-5	**3**	0.92	5.02	1.83	5.94	0.91	6.85
	4	1.14	3.78	3.86	4.92	4.99	0.08
	5	7.29	1.22	12.33	8.5	5.05	13.55
	1	6.15	2.57	16.19	3.58	10.04	13.62
TC	**2**	1.14	3.78	3.86	4.92	4.99	0.08
	3	7.29	1.22	12.33	8.5	5.05	13.55

(FG: FROM-GLC datasets; GL: GlobeLand30 datasets; MOD: MODISLC datasets; and LU: LULC of Landsat TM/ETM+ datasets)

Overall areal inconsistencies between pairs of the FROM-GLC, GlobeLand30, MODISLC and LULC of Landsat images in four common classification systems are shown in the Fig. 3. Areal inconsistencies decreased with the increasing level of aggregation of the classification system, from IGBP-17 to TC as the higher areal inconsistencies were appeared IGBP-17 class conversion and smallest was found in TC.

The largest overall areal inconsistency appeared in between the MODISLC and LULC of Landsat images aggregation using the common classification system IGBP-17 to TC (33.92%, 15.30%, 13.63%, and 13.63% respectively) and the smallest in between the FROM-GLC and GlobeLand30 (6.87%, 6.87%, 7.29%, and 7.29% respectively). The pairwise inconsistencies were higher in related to MODISLC, indicating the accuracy of land cover datasets are depended on spatial resolution of the products.

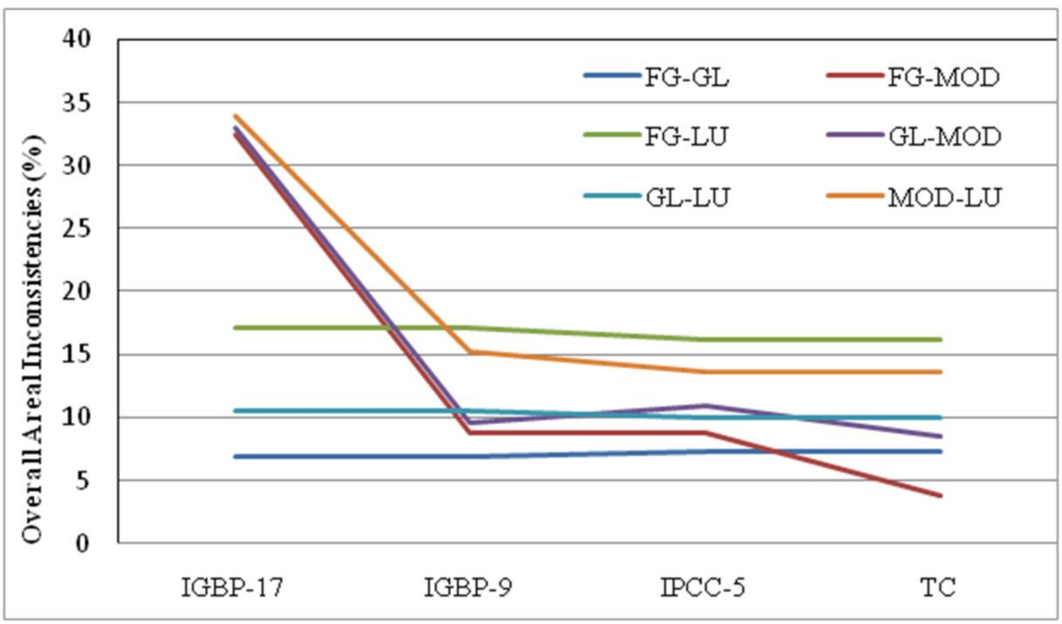


Fig. 3 Overall areal inconsistencies between pairwise of the FROM-GLC, GlobeLand30, MODISLC, and LULC class of Landsat TM/ETM+ datasets in four common classification systems (FG: FROM-GLC datasets; GL: GlobeLand30 datasets; MOD: MODISLC datasets; and LU: Land use and land cover classes of Landsat TM/ETM+ datasets).

3.2 Spatial Inconsistencies

The distribution and overall spatial inconsistencies in the pairwise comparisons of the FROM-GLC, GlobeLand30, MODISLC, and LULC datasets are shown in Fig. 4. The overall smallest spatial inconsistencies were between the FROM-GLC and the GlobeLand30 datasets as 16.16%, 15.61%, 12.93%, and 8.91% using the aggregation of common classification systems IGBP-17, IGBP-9, IPCC-5 and TC, respectively. While the overall higher spatial inconsistencies in comparison to other pair of land cover datasets were between the LULC and MODISLC as of 33.75%, 17.80%, 21.66%, and 13.97% using the four common classification systems respectively. In addition, the overall spatial inconsistency in IGBP-17 classification system between the FROM-GLC and MODISLC (33.23%) was slightly higher than the inconsistent result (18.57%) from the paper [48], but the overall spatial inconsistencies in the classification systems IGBP-9, IPCC-5, and TC (16.05%, 12.79%, and 4.33% respectively) were slightly less than the results (18.05%, 17.44%, and 14.95% respectively) in the paper mentioned above. The spatial inconsistencies decreased with the increasing level of aggregation of common classification systems from IGBP-17 to TC.

According to Fig. 4, the spatial inconsistencies in the pairwise comparison related to MODISLC were slightly higher than all other pairs of land cover datasets in IGBP-17, while they were smallest in TC classification system. On the other, the decreasing rates of overall spatial inconsistencies were lowest in the pairwise comparison related to LULC with the increasing level of aggregation. The overall spatial inconsistencies in pairwise comparison were almost regular results in IGBP-9 common classification system and as identified the better classification system in representing the study area land use and land cover change.

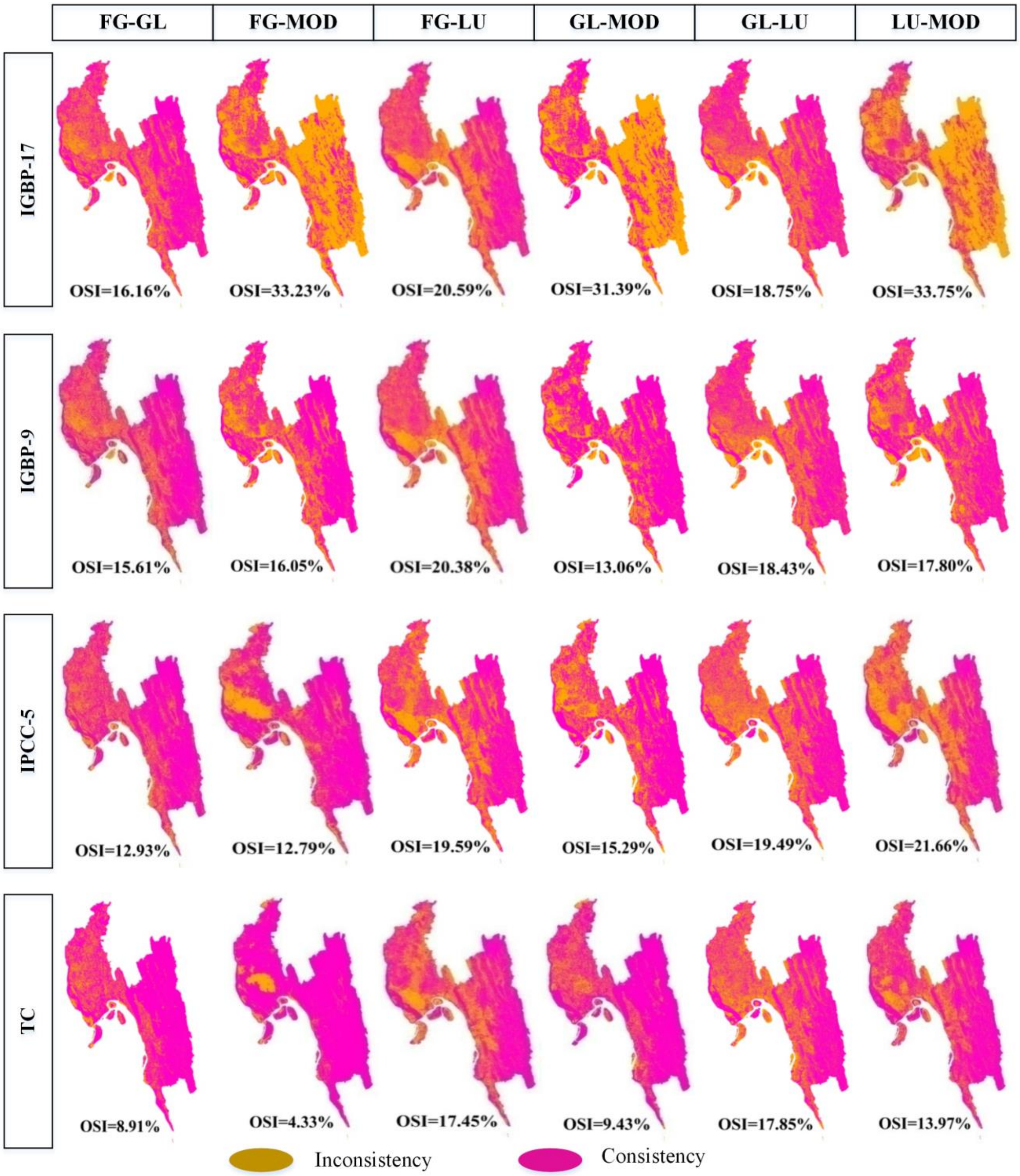


Fig.4 Overall spatial inconsistencies (OSI) in the pairwise comparison of FROM-GLC, GlobeLand30, MODISLC, and LULC datasets in the four common classification systems (FG: FROM-GLC datasets; GL: GlobeLand30 datasets; MOD: MODISLC datasets; and LU: Land use and land cover classes of remote sensing imaginary datasets)

3.3 Land Use Classification

Land use and land cover of the study area southeastern region of Bangladesh from 2001 to 2017 are summarized in Fig. 5. This table is a combined result of land use classification of Landsat satellite images as LULC and different land cover products of the FROM-GLC, the Globeland30, and the MODISLC datasets. The areas were arranged by some specific year (2001, 2005, 2010, 2015, and 2017) and by land use sub-categories based on IGBP-9 classification system as of lowest variation of overall areal and spatial inconsistencies were identified in Fig. 3 and 4. As of 2017, forests (lands covered with trees, with vegetation cover including deciduous and coniferous forests, and sparse woodland) dominated the land cover of this region; comprising 40.2%, 50%, and 31.7% of the total land cover area by MODISLC, FROM-GLC, and LULC respectively. In the GlobeLand30 land cover dataset, the same feature was the dominant category in their recent (2010) product as 42.6% of the total land cover area. Croplands (lands used for agriculture, horticulture and gardens, including paddy fields, irrigated and dry farmland, vegetation and fruit gardens, etc.) were the second dominant land cover class, covering approximately 30.4%, 34.8%, 23.8%,and 32.2% in the datasets respectively MODISLC, FROM-GLC, LULC, and GlobeLand30 of the land. Grasslands, occupying 4914 sq. km in MODISLC, 1461 sq. km in FROM-GLC, and 907 sq. km in Globeland30 datasets of the land area, appears around the transition zone and was not identified in LULC class. Because of their similar spectral reflectance signatures, it was difficult to definitely differentiate grasslands from agriculture on Landsat images.

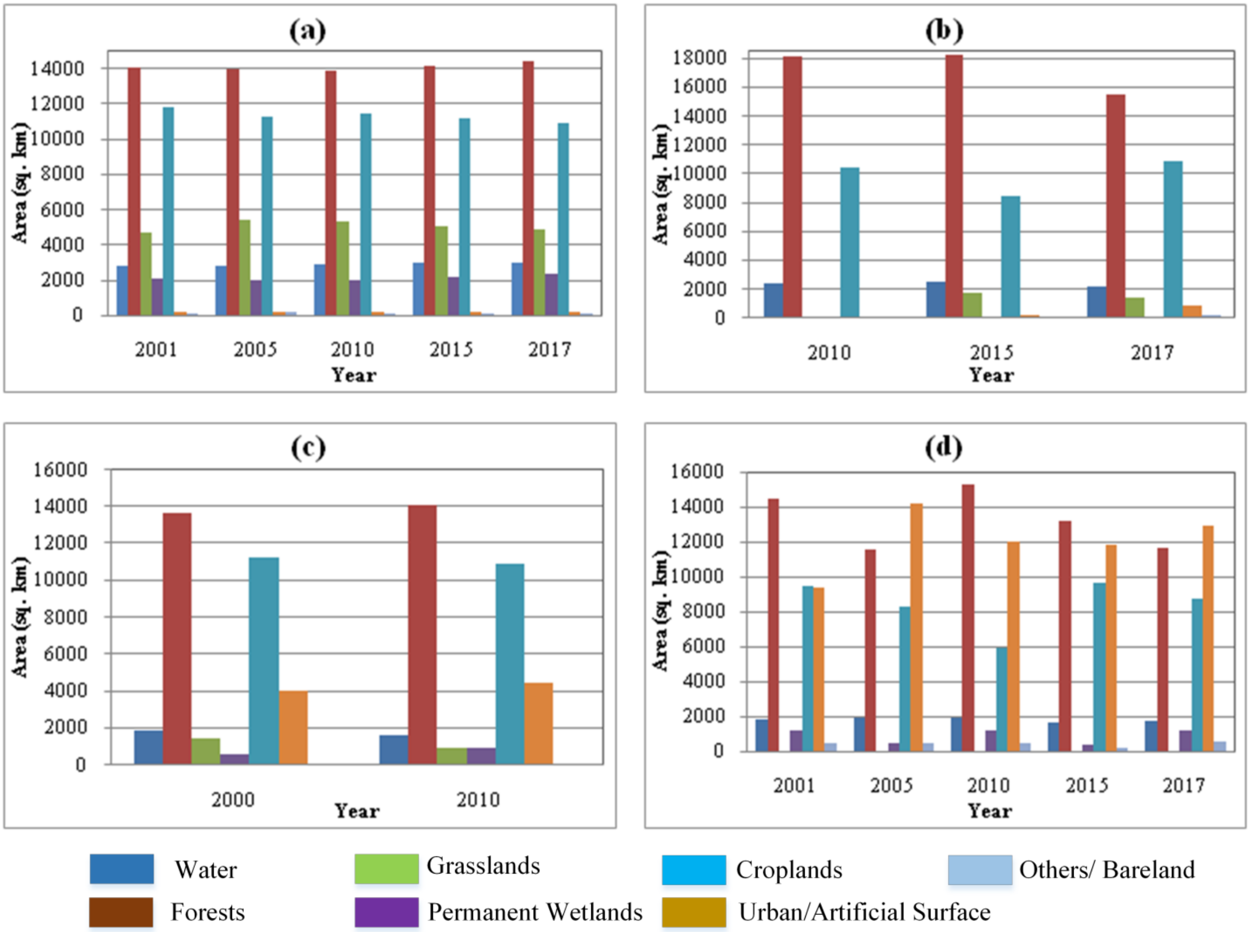


Fig. 5 Land use classification of the southeastern region of Bangladesh from (a) MODISLC, (b) FROM-GLC, (c) GlobeLand30, and (d) LULC of Landsat satellite images

Land use classification maps of some specific year of study from different land cover datasets are shown in Fig. 6. Based on reliability and available in access, the recent land cover products of the MODISLC in the year 2001, 2005, 2010, 2015 and 2017, the Globeland30 in the year 2000 and 2010, and the FROM-GLC in the year 2010, 2015 and 2017 were extracted. Based on supervised classification, Landsat images were used to prepare LULC maps in the year 2001, 2005, 2010, 2015, and 2017 of the study.

Water and forests were relatively well distinguished in land cover datasets and in Landsat imagery. Water in the southeastern region was mainly distributed western portion of the Meghna

River, southern part of the Bay of Bengal and inside lake water, while forests were in the southeastern hilly areas of high altitudes.

When attempting to identify agricultural croplands, the results may vary considerably depending on the date of image acquisition, because crops grow and are harvested according to seasonal and annual phenological cycles. The study area is a sub-tropical region with three distinct seasons and combination of low lying flat and undulating high topography (10 m to 200 m of sea level). The pre-monsoon hot season from March through May receive little rainfall, excessive rainfall and flooding in rainy monsoon season which starts from June through October, and a cool dry winter season from November through February [31]. In sufficient rainfall and alluvial floodplain areas as northern and western portion of the region, rice is cultivated in paddy fields from December until the following July [32]. Rice is often intercropped with grain and cash crops, beans, and vegetables. However, in other areas plants that do not require much water, such as corn, peanuts, and tobacco, are cultivated even in dry season. Croplands were often leading to confusion with grasslands.

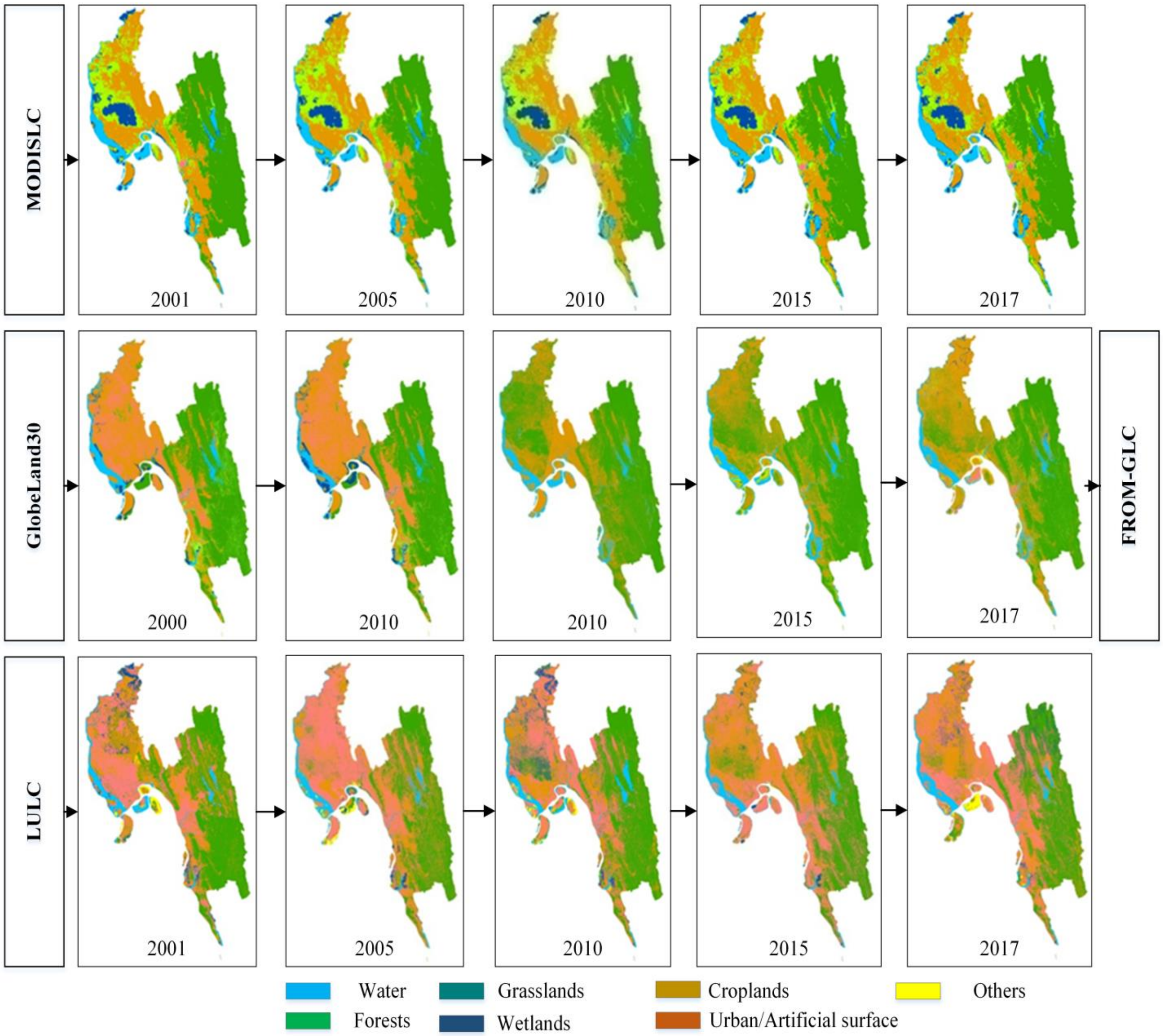


Fig. 6 Land use classification of the southeastern region of Bangladesh from the MODISLC, GlobeLand30, FROM-GLC, and LULC of Landsat imaginary datasets.

Wetlands were the common feature here of low lying flat topography at the floodplain region of northwestern areas and tidal floodplain lands of southern areas of the study. In seasonal variation, those were converted to croplands or water bodies as well as salt and shrimp cultivating nature. Therefore, the area of wetlands composition and distribution were identified high variation in different land cover datasets were different.

The MODISLC and the FROM-GLC datasets were presented the urban and built-up areas as of city centers areas only, while the GlobeLand30 and LULC classes described as artificial surfaces as well as rural and urban settlements, roads, and all other infrastructures in a broad category.

3.4 Composition, Distribution and Changes of Major LULC Classes

The study area is a predominantly agrarian region due to its fertile soil and favorable weather, which is suitable for many varieties of crops in a year [50]. Currently, around 60% of the land in Bangladesh is available for cultivation. However, agricultural land has been lost due to rapid urbanization, industrialization and soil salinization [51]. Suitability index mapping found that most areas across the country have potential for agricultural activities, except the southeastern, southwestern, and northeastern margins of the country [52]. However, LUCC research results (Fig. 7) suggest that in between 2001 to 2017, croplands, grasslands, and wetlands have decreased in area, concurrent with the significant increases in water bodies, forest cover, and artificial surfaces throughout the region. The LUCC results were mainly synthesized of the comprehensive evaluations in four different land cover classes of the MODISLC, FROM-GLC, GlobeLand30, and LULC classes of Landsat imaginary datasets.

Spatio-temporal studies revealed that in 2001, the total area of cropland was 31% of the study area and in 2017 it has revealed 29.7%. The study pointed out that croplands areas were substantially decreased about 1.3% with a contraction rate of 0.1-0.8% per year (R^2 = 0.019) during 2001-2017 period of study. On the other hand, overall the urban and built-up areas as well as artificial surfaces of the southeastern region of Bangladesh increased significantly between 2001 and 2017. In 2001, the built-up areas were listed as 11.8%, which as increased to 13.8% in 2017 of the mutually distributed over the study area. Overall about 2% of the urban land cover areas were increased with a rate of 1.2% (R^2 = 0.347) per year during this period of study.

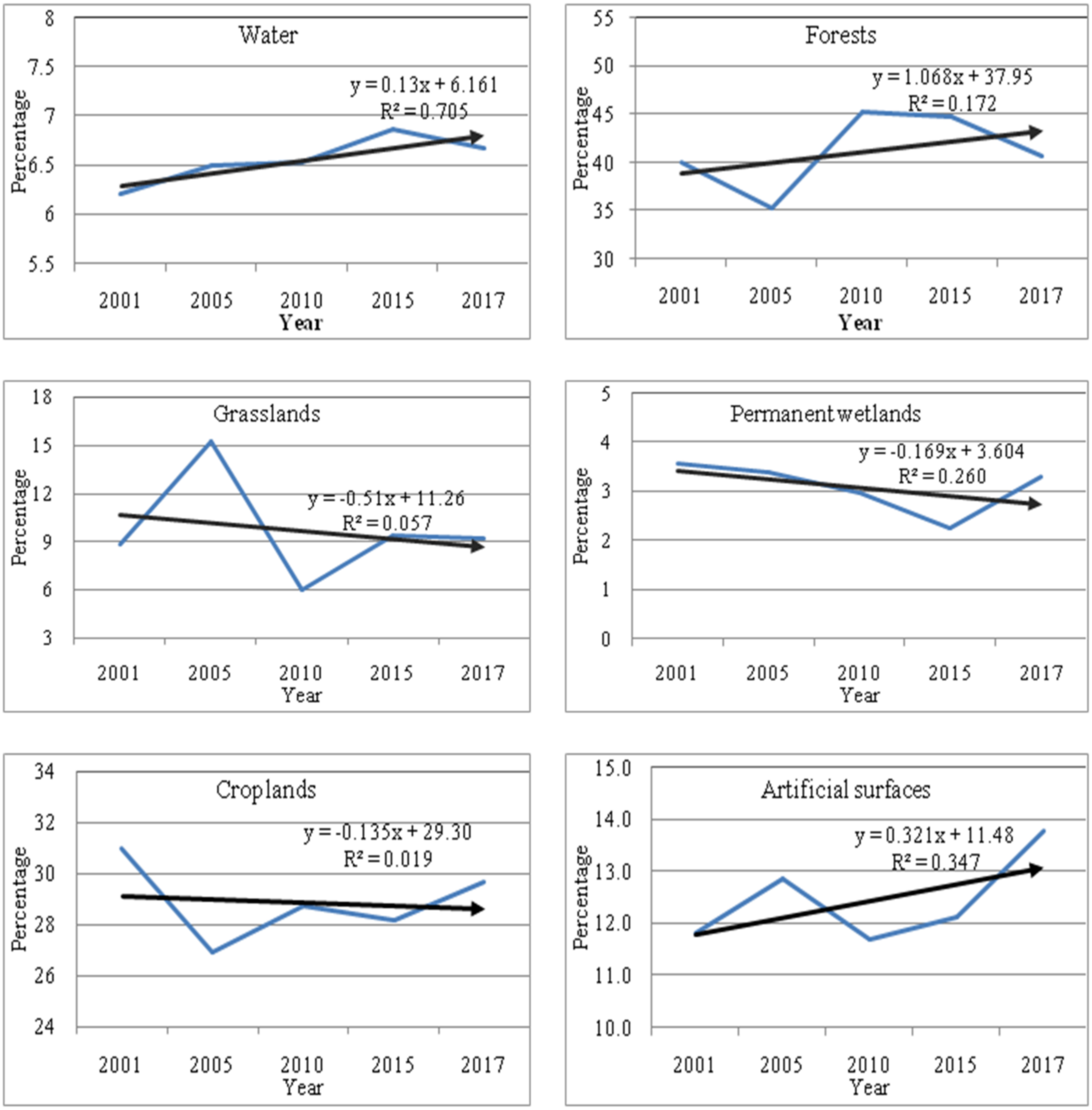


Fig. 7 The different LUCC status at the southeastern region of Bangladesh from different land cover products in average of the MODISLC (2001 to 2017), FROM-GLC (2010, 2015, 2017), GlobeLand30 (2000, 2010), and Landsat imaginary (2001, 2005, 2010, 2015, 2017) datasets.

In the southeastern region of Bangladesh, the sources of water are primarily surface and ground waters such as rivers and *khals*, lakes, *beel*, *haor*, *char*, and wetlands. *Beel* refers to low lands mainly lying in the floodplains and deltaic region. *Haor* refers to the low-lying vast depression areas that flooded during the monsoon and dried out in winter [53, 54]. The *haor* areas are mostly located in the north-eastern part of the study area that plays significant roles in the livelihoods of surrounding communities as well maintenance of biodiversity [55]. The study area has around 37.6% of land below 10 m elevation [41]. Therefore, during monsoon season; rainfall, flooding, and surges have converted agricultural land to water bodies in the various low lands across the active floodplain areas of the study. From 2001 to 2017 on an average, the total water bodies' area increased from 6.2 to 6.7% across the study area by 0.3% annually. On the other hand, the total areas of *beel* and *haor* as well as wetlands have slightly decreased. On the basis of the comprehensive evaluations of four different land cover datasets in an average, the total area decreased from 3.6 to 3.3%, about 0.3% annually from 2001 to 2017.

Spatial analysis has shown that the total forest cover was increasing in area and quality. The different land cover products have indicated that forest cover increased about 0.6% from 2001 to 2017. The substantial changes have identified that the tree cover in reserve forest as well as natural forest is decreasing but tree outside of forest was increasing. Some other research also identified that vegetation coverage at the southeastern region of Bangladesh was increased by 0.43 SINDVI indexed value during 2001-2016 [35] and the total tree canopy cover increased 4.3% during the 2000-2014 time interval [56]. However, there are noticeable inconsistencies in between the various national level studies regarding forest change. The grasslands are primarily situated north eastern part of the study area. However, the area has in decreasing trend considerably 0.1% per year from 2001 to 2017.

The change matrixes for the different land cover products of the MODISLC (2001-2017), the FROM-GLC (2010-2017), the GlobeLand30 (2000-2010) and LULC classes (2001-2017) were produced by post-classification comparison from the classification results, which yield "from-to" change information identifying where, and how much, change has occurred (Table 8). As seen in the matrix table of different land cover datasets, 85.5%, 60.7%, 75.3%, and 38.7% of land covers remained unchanged of the MODISLC, FROM-GLC, GlobeLand30, and LULC class distributions between the years.

Since historical time period, the agricultural land has transforming to non-agricultural land use at different spatio-temporal scales. Clearly, previous research has shown that agricultural land has been primarily transformed into urban land in recent decades [31, 57, 58, 59]. According to the transfer matrix table (Table 8), cropland area losses have been due to transformations to built-up areas and tree plantation outside of forest cover areas. Different transformation of land areas in cropland were seen in different land covers products. It was seen that 282.9 and 600 sq. km land areas of croplands have decreased in GlobeLand30 (2000-2010), and LULC (2001-2017) class, other than increased in MODISLC (2001-2017) and FROM-GLC (2010-2017) by 917.8 and 358.1 sq. km respectively.

Based on a comprehensive review of previous LULC studies, rapid population growth has resulted in high urbanization across all over Bangladesh [36]. Spatial analysis indicates that the built-up area expanded primarily by replacing agricultural land, water bodies and forest areas. Chittagong city, located in the southeast, is the second largest city in Bangladesh has also a high rate of population growth and urban expansion [60]. The transfer table here has identified the urban and built-up areas were expanding mainly by aggregation of croplands and forests areas over the period of study.

Table 8 Land cover transition matrix in the southeastern region of Bangladesh in different land cover products of the MODISLC (2001-2017), FROM-GLC (2010-2017), GlobeLand30 (2000-2010), and LULC (2001-2017)

		Land Types	**2017**						
			W	F	GL	PW	CL	UB	Others
MODISLC	**2001**	Water	2764.5	0	0.5	5.7	0	0	2.0
		Forests	0.3	13526.7	436.9	23.9	95.6	0	0.0
		Grasslands	43.2	353.5	2770.9	336.1	1206.1	2.3	16.7
		Permanent Wetland	95.8	21.5	118.5	1799.9	25.5	0	29.7
		Croplands	58.1	503.5	1569.9	112.5	9565.1	0.5	2.0
		Urban and Built-Up	0	0	0	0	0	166.7	0

		Land Types	W	F	GL	PW	CL	IS	Others
		Others	13.7	0	7.7	63.9	1.5	0	57.4
		Land Types	**2017**						
			W	F	GL	PW	CL	IS	Others
FROM-GLC	**2010**	Water	1337.7	163.7	78.0	21.3	446.4	233.6	103.1
		Forest	268.7	11900.8	777.8	38.6	4537.2	215.6	11.9
		Grassland	1.8	52.5	1.8	0.3	15.9	0.5	0.1
		Wetland	0.2	1.1	0.1	0.03	1.24	0.04	0
		Croplands	489.9	3125.6	571.9	52.9	5619.4	353.3	56.0
		Impervious	0.9	0.3	0.1	0.01	0.8	0.3	0.2
		Others	4.5	0.8	1.2	0.1	6.2	1.7	1.5
		Land Types	**2010**						
			W	F	GL	PW	CL	AS	Others
GlobeLand30	**2000**	Water	1169.8	118.5	18.4	262.9	137.1	10.7	0.1
		Forests	49.0	11491.7	298.0	200.8	191.3	106.4	0.2
		Grasslands	39.6	667.5	376.4	33.1	76.7	65.8	4.0
		Permanent Wetlands	55.8	72.0	0.6	324.0	56.1	5.4	0.1
		Croplands	134.4	316.6	29.1	33.2	8638.5	982.7	0.5
		Artificial surface	21.5	14.1	4.9	5.1	751.9	2877.7	0.4
		Others	0.8	0.9	3.5	1.9	0.5	0.7	5.2
		Land Types	**2017**						
			W	F	GL	PW	CL	AS	Others
LULC	**2001**	Water	979	17	-	8	92	212	195
		Forests	66	7125	-	425	1882	2164	19
		Grasslands	-	-	-	-	-	-	-
		Permanent Wetlands	44	40	-	94	495	260	11
		Croplands	112	1438	-	284	2081	3705	48
		Artificial surface	204	802	-	118	2485	3887	101
		Others	21	16	-	3	33	233	49

The study area has large sources of water resources from various channels and vast areas of wetlands due to low lying topography. From the four different land cover in between 2001 and 2017, water bodies' areas were increased considerably while decreasing wetlands. Water areas were mainly increased in transformation of wetlands in the northern part of the region, while southern part has aggregated the croplands areas.

4 Discussion

4.1 Pattern of Inconsistencies in Different Land Cover Mapping

The comparisons of land cover products in previous studies have been made only at global [25,26], continental [24], national [22], or provincial scales [27], since they focused on general patterns of inconsistencies or indirect validation accuracy of the products, which is meaningful to large scale studies. To our knowledge, in small scale area as well in southeastern region of Bangladesh, this is the first study to evaluate the amount of pair wise level of inconsistencies in different land cover products (the MODISLC, FROM-GLC, GlobeLand30, and LULC of Landsat images) from different view of spatial resolutions. It was found that the overall areal inconsistency and spatial inconsistency of the FROM-GLC and GlobeLand30 is relatively small among the pairs of the four products. While the pair of MODISLC and LULC was the highest overall areal and spatial consistency in relative to others. The overall areal inconsistency other than spatial inconsistency result is consistent with the conclusions in similar studies [20,22-24]. Both in overall areal and spatial consistencies, the pair relation to the MODISLC were the highest inconsistencies. The product of MODISLC was only land cover of 500 m spatial resolution other than 30 m of FROM-GLC, GlobeLand30 and Landsat images. The second largest values of areal and spatial inconsistencies were identified in pair related to LULC class of Landsat imaginary datasets. However study in a small area may use the lower spatial resolution of land cover datasets as well as FROM-GLC and GlobeLand30 land cover products.

The FROM-GLC had the smallest uncertainties due to the explicit relationships between different classification levels. However, we quantitatively highlighted the uncertainties in classification system conversion in this study. On the other hand in the classification system conversion, IGBP-9 class was the lowest variation of uncertainties and inconsistencies, which were recommended for later part of comprehensive evaluations of land use and land cover changes analysis of the study. Although the study also recognized that a number of external factors (like map projections, resolution unifications and mis-registration) are also the sources of the uncertainties and discrepancies among the four products, which were not the focus of this paper.

4.2 *Impacts of Major LUCC Classes*

4.2.1 The impacts of agricultural land contraction

Since the independence of Bangladesh, the increasing population resulted the widely LUCC across the country. The contractions of agricultural land to non-agricultural land resultant the various consequences over the country. At the study area southeastern region of Bangladesh, on an average of the four land cover products, overall about 0.5% croplands has decreased annually between 2001 and 2017. The contraction rate has been slightly lower as decreased up to 1.45% annually after 2000 in different divisions of the country [31,57].

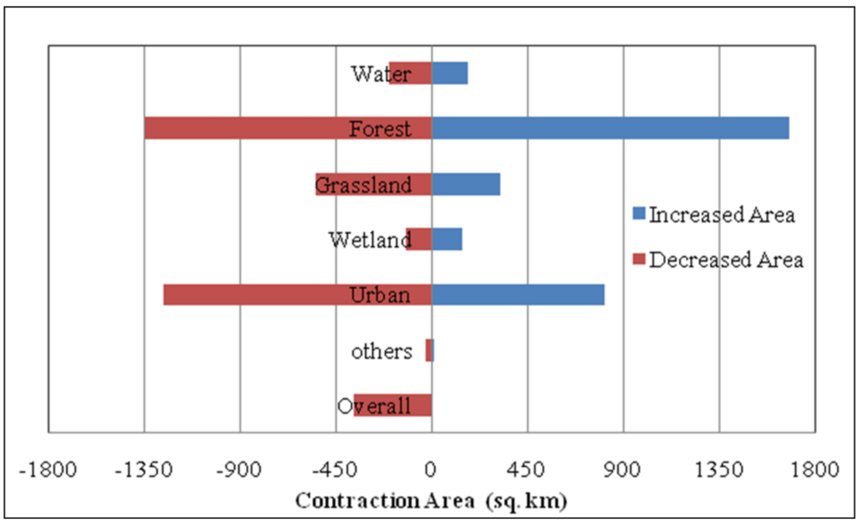


Fig. 8 The contraction of croplands area with all other LUCC classes at the southeastern region of Bangladesh from 2001 to 2017.

The contraction of croplands with major land cover classes between 2001 and 2017 has shown in Fig. 8. In an average of the four different land cover products, cropland was mainly decreased to forest as well as tree cover (1346 sq. km) and urban and built-up areas (1260 sq. km), while the land areas was increased by aggregation of forest (1677 sq. km) and artificial surface areas (809 sq. km).Overall about 59.6% of the croplands were unchanged during the period of study. With the time and introduced new farming technology, the study area adopted various ways to increase food production and minimize food insecurity. The start of agro-technological advancement increased the production with crop intensity, which increased per capita income more than 130% and reduced the poverty level 50% [61-62]. However, overall, the gross production of rice and wheat increased significantly during the period between 1971/72 and 2010/11 from 10.46 to 35.3 million metric tons [61-63]. On the other hand, in 2005, Bangladesh's net AFOLU emissions were 61.3 million tCO_2e, accounting for over 52% of the total net national emissions [64]. Agriculture emitted 43.1 million tCO2e or about 35% of all emissions and 66% of AFOLU emissions, while LULUCF constituted the remaining 34% of AFOLU emissions with a net emission of 18.2 million tCO_2e. The three most important emission sources in the agriculture sector were manure management (representing 41% of agricultural emissions), enteric fermentation (24%) and rice cultivation (18%) [65]. However the country requires of 23.64 million of metric tons (MMT) rice and wheat for the total population [63]. Still, 40% of the rural populations live with a landless status [22]. Furthermore, around 60% of farmers are functionally landless with about 62% of farming households having less than 0.4 ha of farmland [66]. Therefore, food production is not enough for all household. Due to decline in agriculture land, the overall production declined and the problem of food insecurity is becoming more intense and they have to import food from neighboring countries.

4.2.2 The effects of urban land development

Rapid population growth is a major component of urban land development, historically, those growth have been increasing significantly over the southeastern region of Bangladesh. Multiple driving factors are responsible for the LUCC and artificial surface expansion [67]. Since 1990s, the study area's population has grown rapidly by 20.5 to 28.4 million in between 1991 and 2011 [68]. The high rate of economic and population growth, massive infrastructure development, and impact of climate change have been major causes of rapid LUCC across the area [69]. The study on LUCC of different land cover products has identified the urban and a built-up as well as artificial surface at study area was increased mainly by accretion of croplands and forest degradation (Fig. 9). From 2001 to 2017, about 1260 sq. km and 622 sq. km of croplands and forest cover respectively have converted to urban and built-up areas. On the other hand, artificial surface was converted to croplands and tree cover as well of 809 and 204 sq. km respectively during this period. Overall about 1017 sq. km of urban and built-up areas was increased between 2001 and 2017 period of study with an annual rate of 1.32%.However, Hasan et al. (2013) [31] found that the urban area increased 401 sq. km during 2000-2010 and Reddy et al. (2016) [70] found that settlement area had increased 1643 sq. km (1.1%) in 2000-2014, which were in agreed with the results.

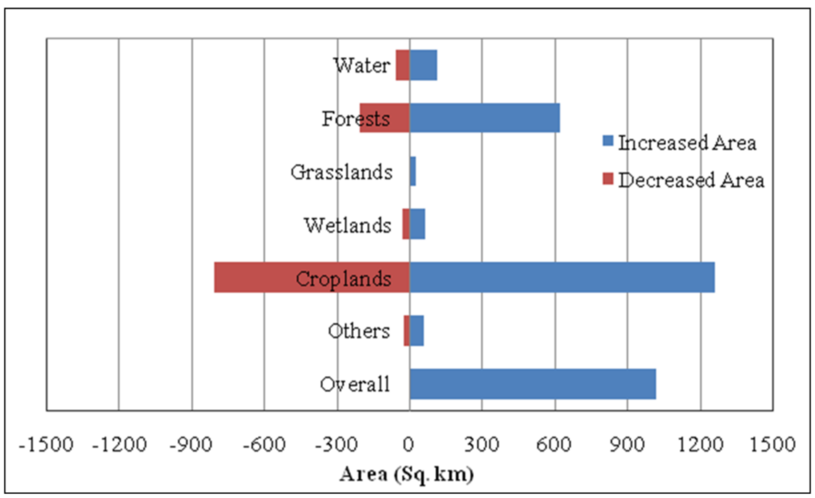


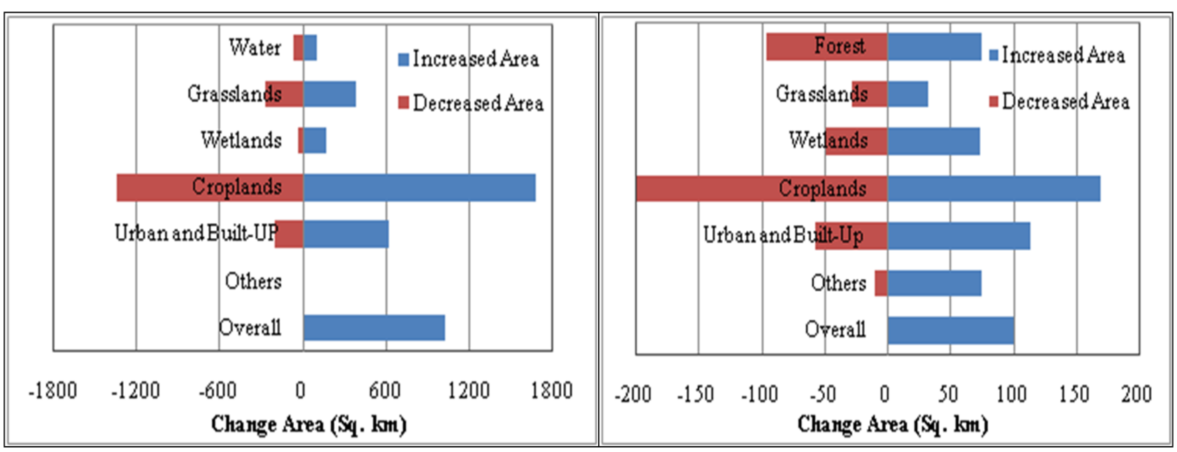
Fig. 9 The impacts of urban and built-up areas by major land cover classes of the study area from 2001 to 2017 in combination of four different land cover products

Approximately one-fourth of the national population lives in urban area [68] and increasing urban population growth has resulted the urban expansion speedily, mostly in the city areas. As result, infrastructure development with unplanned urbanization processes encroached on agricultural land, forestland, low-lying areas, and water bodies, resulting in the transformation from vegetation cover to concrete built-up areas. These types of changes are incorporated to vulnerable capital city as well other big cities from natural disasters and LUCC issues. One of the obvious impacts of urban growth at the cost of agricultural land is the increasing problem of food security. Similarly, the conservation of other land uses such as forest and water bodies has several environmental and socio-economic consequences.

4.2.3 The effects of forest cover and water bodies changes

With the combination of hilly areas (62.4%) and low elevation deltaic floodplain (37.6%), the southeastern region of Bangladesh has a tropical monsoon climate characterized by heavy seasonal rainfall, high temperatures and high humidity [41]. Forest cover is mostly distributed in south-east part of the study area of hilly region (Fig. 6). The impacts of forest cover and water bodies in the southeastern region of Bangladesh in an average of the four different land cover of the MODISLC, FROM-GLC, GlobeLand30, and LULC classes has described in Fig. 10. In between 2001 and 2017, forest cover at the study area was mainly affected by croplands as of 1346 sq. km was aggregated. Forest cover was also found changed to grasslands and build-up areas. Overall the forest cover at the study area has increased by 1022 sq. km as 0.4% annually during this period. However, Patopov et. al. (2017) [56] was also identified; tree cover outside of forest was increased as of overall 4.3% total canopy cover increased over the country during 2000-2014 period and Islam et. al. (2018) [35] found 0.43 indexed value of increased SINDVI at the study during 2001-2016, which support the study results. Although overall tree cover is increasing, spatial distribution of forest cover showed that tree canopy cover in reserve forest at the south-east region of the study area was decreased, while increased plantations in settlement and cropland areas. However, due to the high demand for wood and wood products, the overall forest cover status is increasing rate after 2000 which also shows very less per capita forest land in the world. According to FAO

(2010b) [71], the average per capita forest land is 0.60 ha globally; however, in recent decades, Bangladesh has only reached 0.12 ha per capita forest land. The forest department has implemented several massive programs and projects to regenerate and reforest after the devastating cyclone of 1960.The impacts of these programs have been observed since 2000. Furthermore, illicit felling of forest cover also improved after 2000. Bangladesh is considered the world's most vulnerable country to the negative impacts of climate change, facing particularly high risks from tropical cyclones and floods specially the study area southeastern region of Bangladesh. In response, the country has prioritized adaptation and has invested over US$ 10 billion of its own resources to increase its climate resilience [72]. Nonetheless, Bangladesh has also implemented mitigation activities, including in the AFOLU sector. Current and planned AFOLU mitigation activities include afforestation/ reforestation, REDD+, climate resilient agriculture, lowering methane emissions in agricultural production, crop diversification, fertilizer management and improved livestock management. The country has several NAMAs under development in the industry and waste sectors and is exploring potential in other sectors [72].



(a) (b)

Fig. 10 The impacts of (a) forest covers and (b) water bodies in major LUCC classes in four different lands cover products from 2001 to 2017

Due to foothills of the Himalayas and low lying riverine the country shares 57 trans-boundary rivers. The rivers play the important role for agriculture as the well high risk of floods and river erosion within the study area. In an average of four different land cover products, overall the water areas in the study has increased 100 sq. km. Water area was mainly increasing by logged and flooded of cropland and built-up areas. In recent decades, due to the high rate of population growth and urbanization process, the wetlands surrounding the built-up areas have seriously degraded [58].This wetlands change and unplanned urbanization as well as development have made the drainage system in the urban areas vulnerable to water logging problems and their consequences. Moreover, due to high profit from shrimp and salt cultivation, water bodies at the southern coastal areas have increased up to 500% after 1980s in the southern regions [51]. On the one hand the shrimp farming improved the local livelihood; but on the other hand, intensive shrimp farming has impacted coastal land use with creating saline water intrusions, which may destruction the wetlands as well as water bodies and rice ecosystems as well decrease of rice production.

5 Conclusion

Bangladesh has undergone rapid LUCC due to speedy population growth and urbanization that resulted sharp contractions in agricultural land. Using the common classification systems, this study tried to assess the spatial and areal inconsistencies in the four most recent multi-resource land cover products and based on this inconsistencies, a synthesis of study was triggered out on land use and land cover dynamics during 2001-2017 in the southeastern region of Bangladesh. The four recent land cover products of the MODISLC, FROM-GLC, GlobeLand30, and LULC class of Landsat imaginary datasets were used in different time frame on the basis of their data sources availabilities.

The overall areal and spatial inconsistencies in the widely used classification system conversion decreased with the decreasing of the thematic detail in the classification scheme as from IGBP-17 to TC. This indicates that the assessment of areal and spatial inconsistencies is primarily influenced by the thematic detail of the common classification systems. In compared to different pair of land cover datasets, the pairs related MODISLC land cover product were the highest areal and spatial inconsistencies while the FROM-GLC and GlobeLand30 was the smallest one. However, in referenced datasets, spatial resolution might be one of the prime concerns of land cover data validation; the lower the spatial resolution is the better of land cover indication. The foregoing pair-wise comparative analyses provide insight for both data produces and users. For data producers, the identified areas of lower inconsistencies may serve as a reference data for training areas selection. Likewise, areas of higher inconsistencies may receive special attention in future land cover characterization and mapping. Users also will have an opportunity to examine the similarities and differences in their area of interest, and make informed decisions based on their thematic applications. Learning from past experience and building on the existing infrastructure (e.g., regional network), the consistency and accuracy of global land cover data are expected to improve in the future.

The four different land cover products used in land use cover changes in the study were in different classification schemes. This study was reclassified them into a common classification system and were discussed the LUCC status by their comprehensive changing results. For land use classification, IGBP-9 (as identified lower variations of inconsistencies) suggests adopting nine land use categories: water; forests; shrublands; grasslands; wetland; croplands; urban and built-up; snow and ice; and others. All land cover products and Landsat satellite images of the land areas of southeastern region of Bangladesh was classified/reclassified in accordance with this suggested land use categories. As of 2017, forests and croplands were the principle dominates the land cover of this region, comprising 40.2%, 50%, 31.7%, and 42.6% of forests and 30.4%, 34.8%, 23.8%, and 32.2% of croplands in the four different land covers of MODISLC, FROM-GLC, LULC, and GlobeLand30 datasets respectively. Based on the systematic assessment in an average of the four different land cover products in the southeastern region of Bangladesh, this study concluded that the land areas of water, forests, and artificial surfaces were increased in different spatial and temporal dynamics, while croplands, grasslands, and wetland were decreased. The major effects of LUCC dynamism were mainly circulated in the changing pattern of croplands, forests, and artificial surfaces of the study area. However, the historical spatio-temporal LUCC results are inconsistent between studies. Although the research was focuses on uncertainty in the land cover data, it would be useful to highlight the contribution of the AFLOU sector in Bangladesh to the GHG emissions and would be further helpful to understand the consequence of climate change mitigation. Further LUCC study is needed to examine the historical data with new methods, tools, and data resources in the context of environmental change at the national and regional scale. The trans-boundary river basin is one of the most important water resources in South Asian countries for agriculture and human needs, yet few studies have addressed this area. Further LUCC study is needed to improve accuracy, eliminate uncertainties and discrepancies in the spatio-temporal changes.

Author Contributions:

S.I. and M.M. conceived and designed the experiments and research; S.I. and M.Z. performed the experiments and analyzed the data; and S.I., H.Y. and M.M. jointly revised the paper.

Conflicts of Interest:

The authors declare no conflict of interest.

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Figure Caption

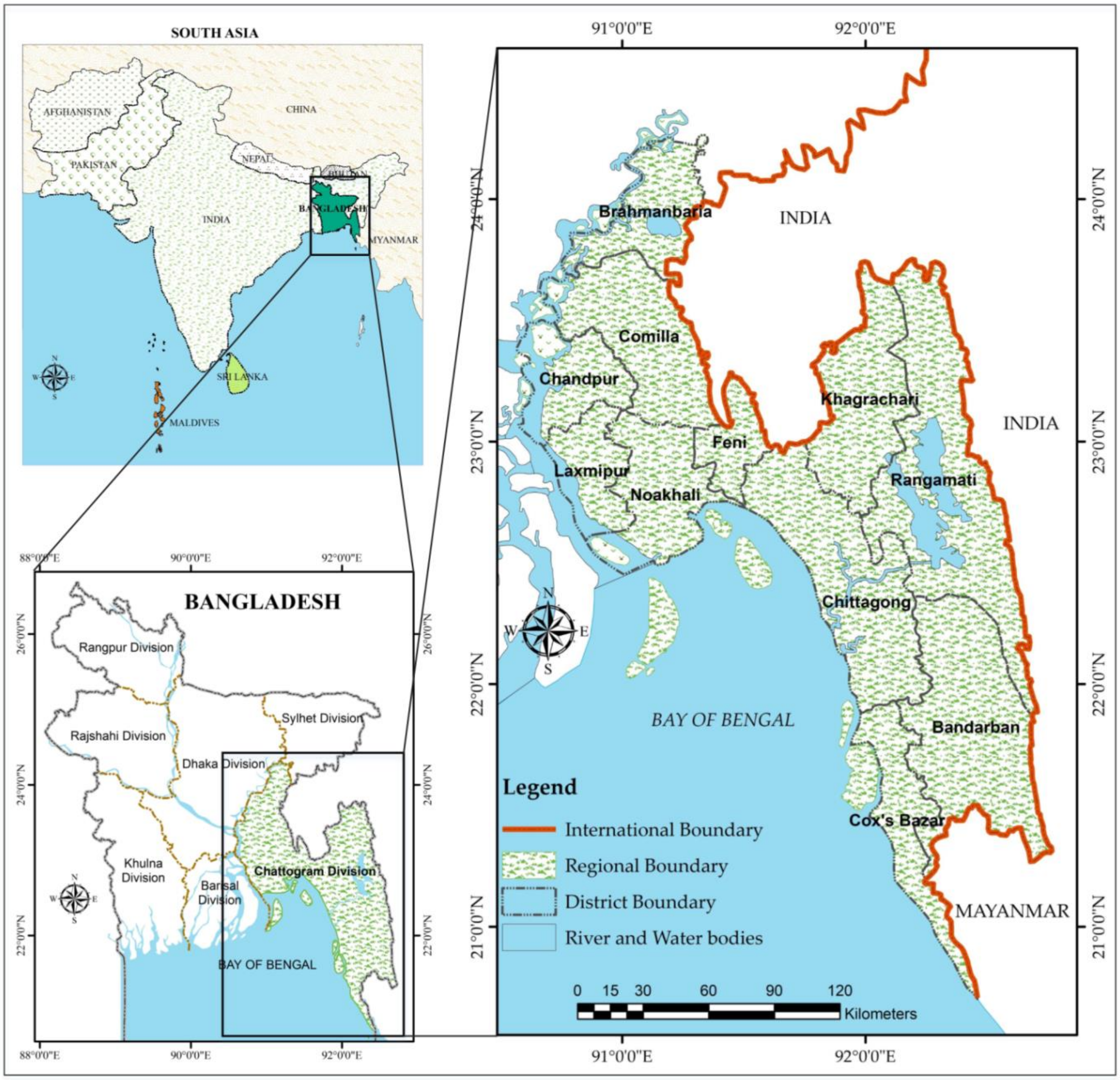

Fig. 1 Location of the study area the Southeastern region of Bangladesh

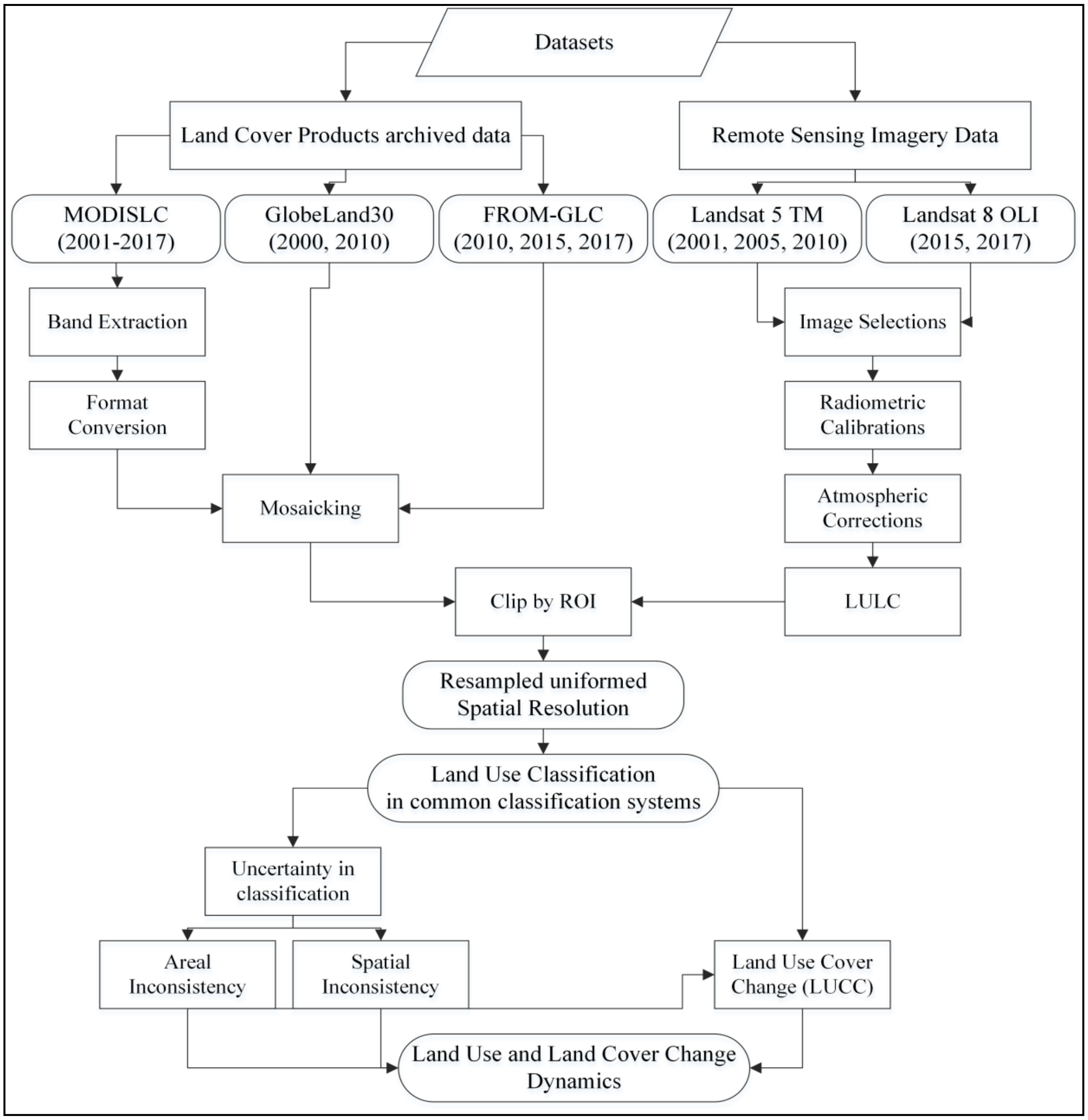

Fig. 2 Data analysis flowchart. ROI: Region of Interest; LULC: Land Use and Land Cover; LUCC: Land Use Cover Change.

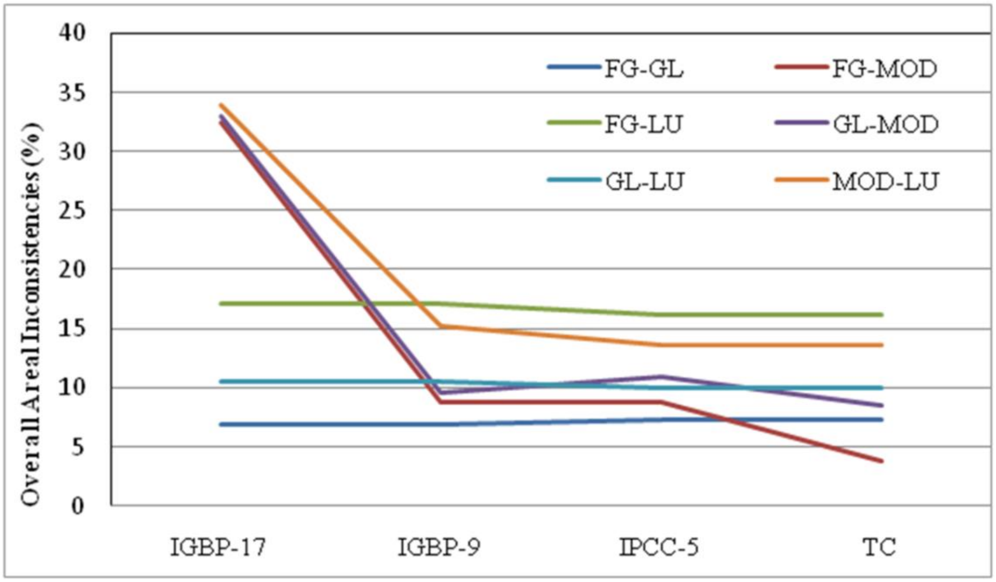

Fig. 3 Overall areal inconsistencies between pairwise of the FROM-GLC, GlobeLand30, MODISLC, and LULC class of Landsat TM/ETM+ datasets in four common classification systems (FG: FROM-GLC datasets; GL: GlobeLand30 datasets; MOD: MODISLC datasets; and LU: Land use and land cover classes of Landsat TM/ETM+ datasets).

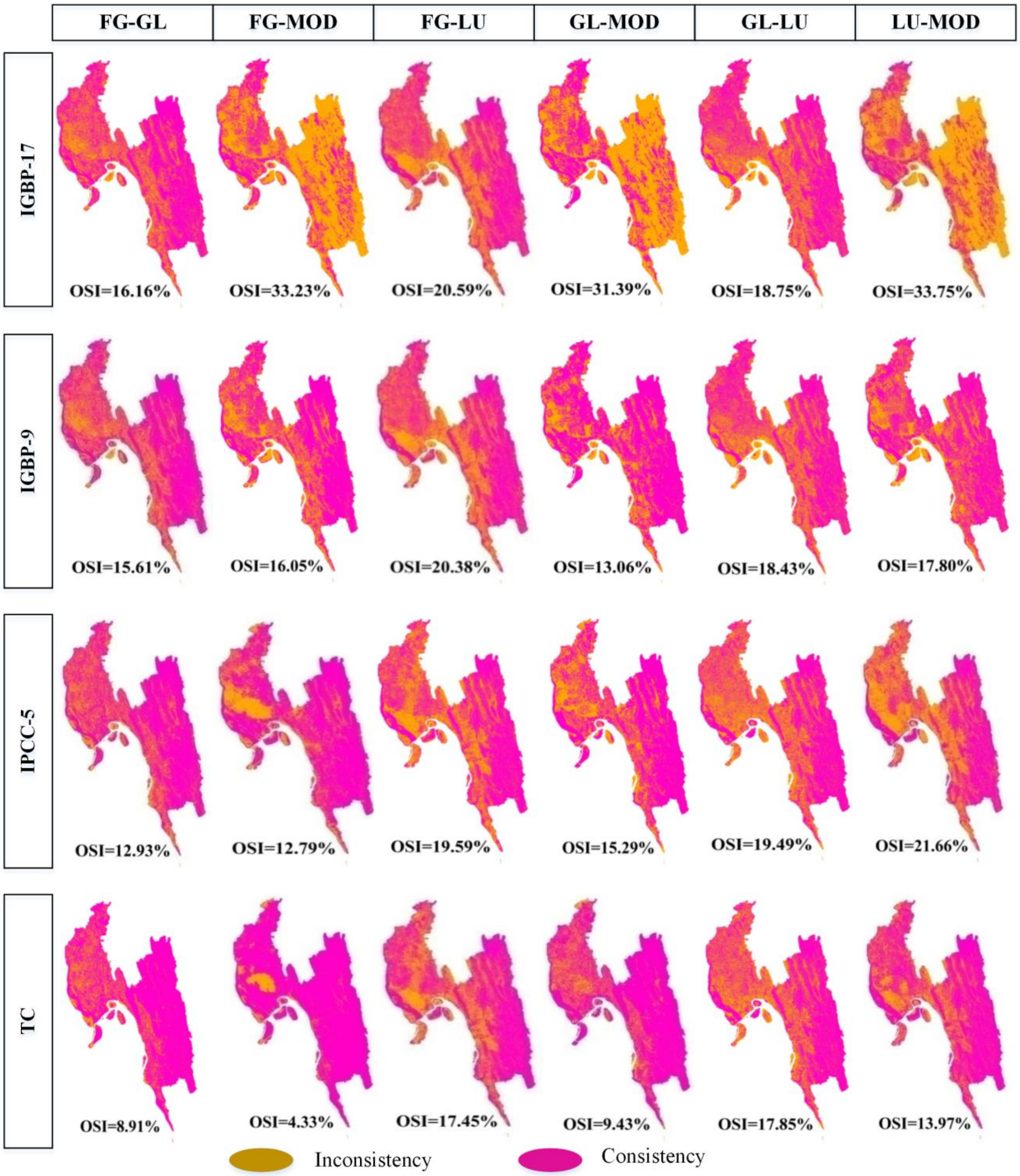

Fig.4 Overall spatial inconsistencies (OSI) in the pairwise comparison of FROM-GLC, GlobeLand30, MODISLC, and LULC datasets in the four common classification systems (FG: FROM-GLC datasets; GL: GlobeLand30 datasets; MOD: MODISLC datasets; and LU: Land use and land cover classes of remote sensing imaginary datasets)

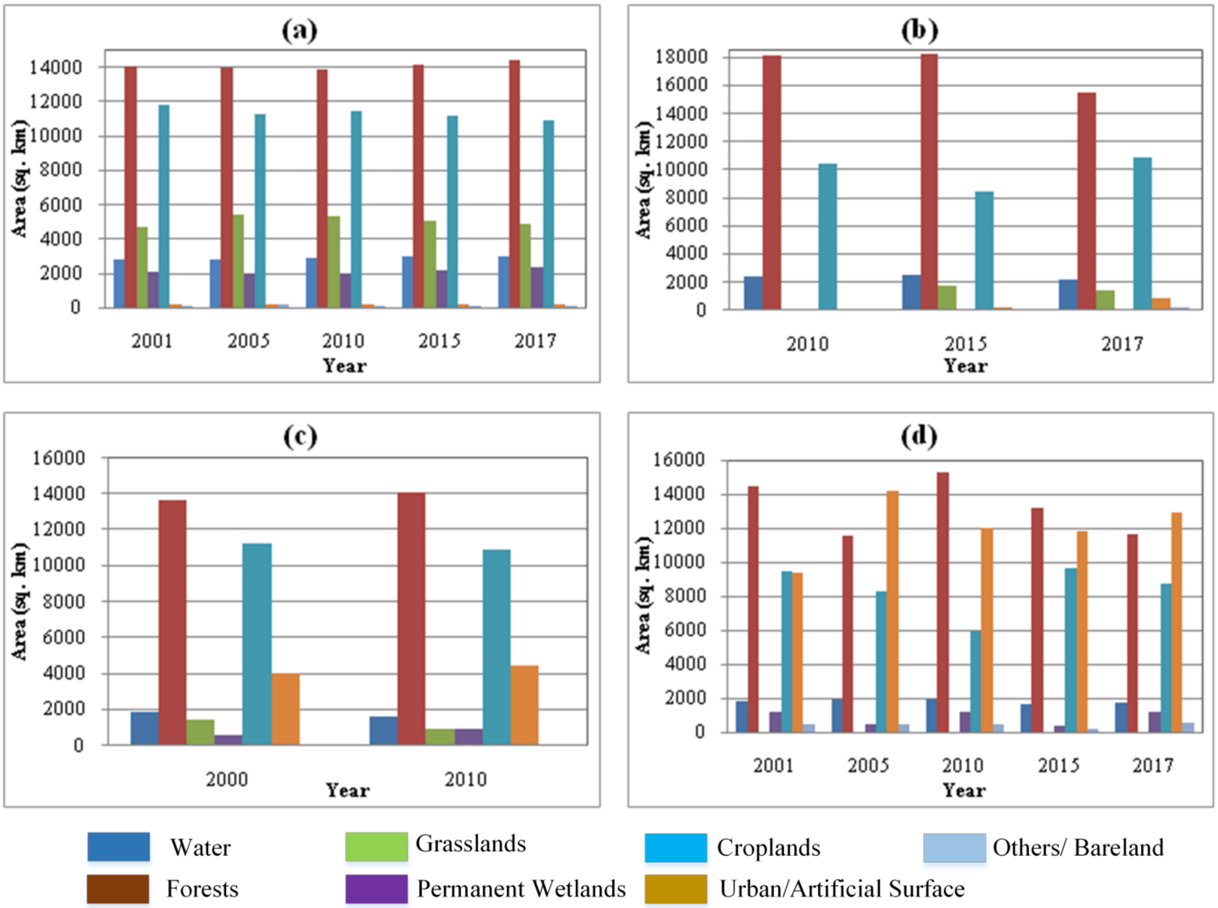

Fig. 5 Land use classification of the southeastern region of Bangladesh from (a) MODISLC, (b) FROM-GLC, (c) GlobeLand30, and (d) LULC of Landsat satellite images

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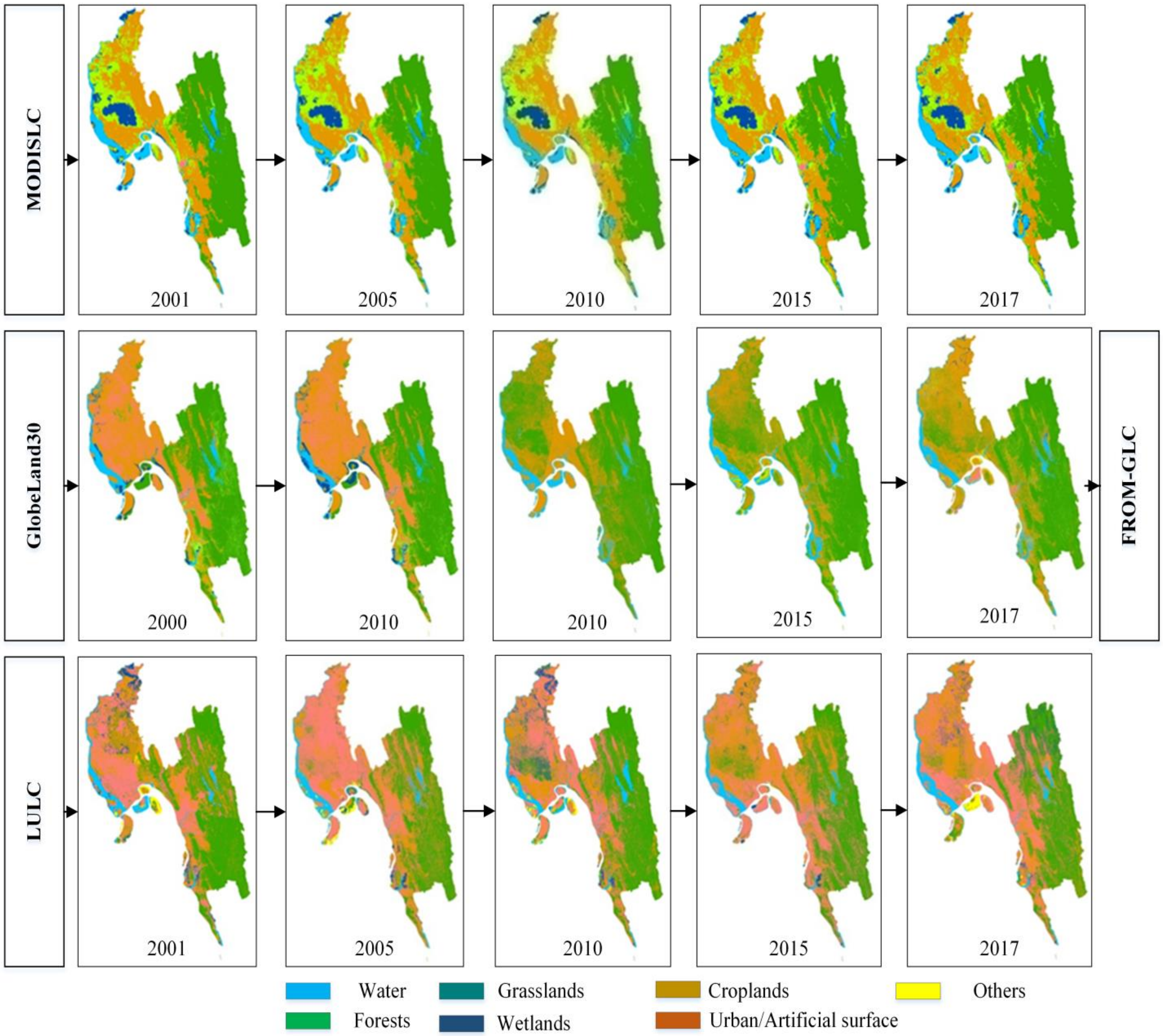


896 **Fig. 6** Land use classification of the southeastern region of Bangladesh from the MODISLC, GlobeLand30, FROM-
897 GLC, and LULC of Landsat imaginary datasets.

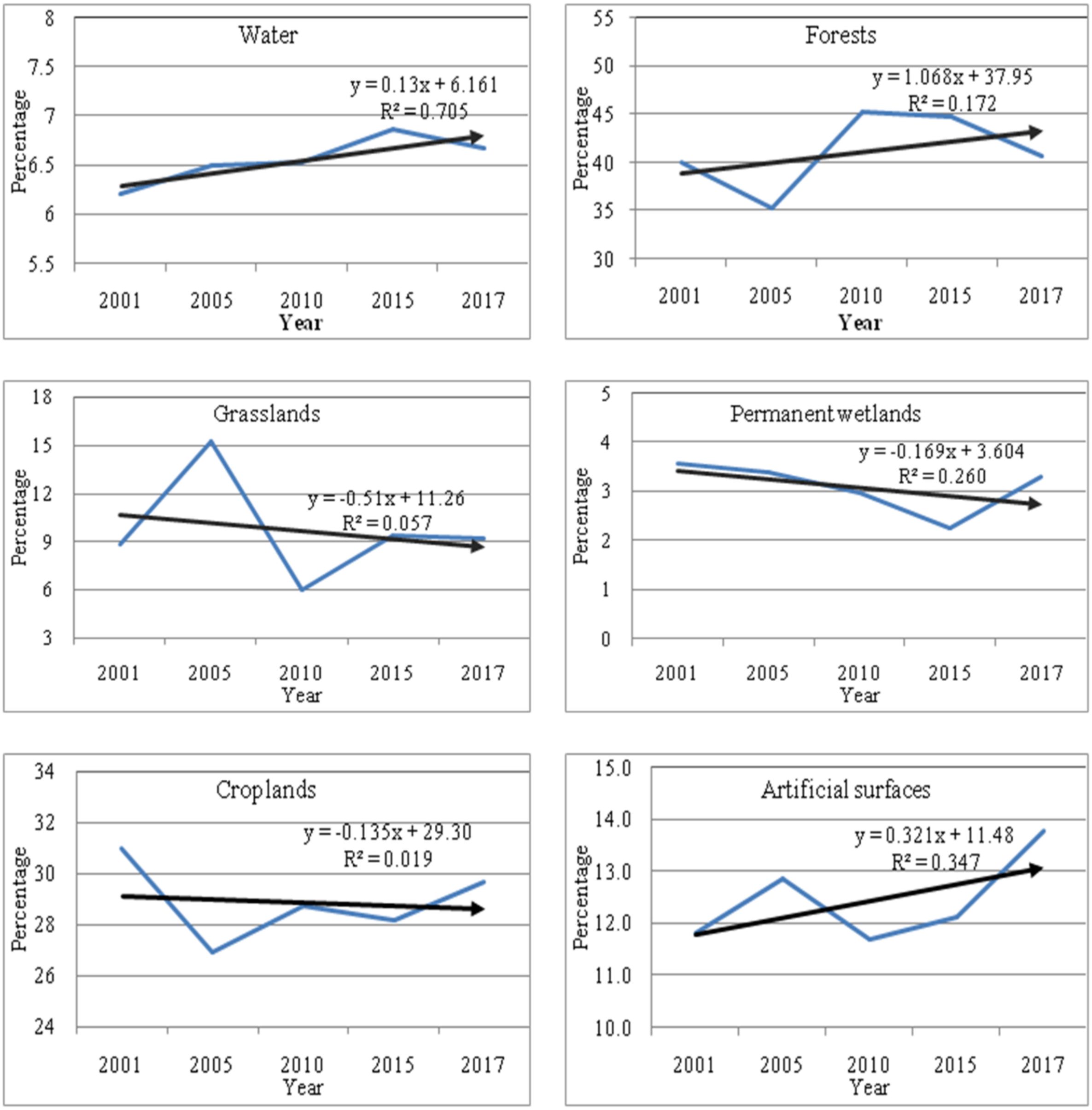


Fig. 7 The different LUCC status at the southeastern region of Bangladesh from different land cover products in average of the MODISLC (2001 to 2017), FROM-GLC (2010, 2015, 2017), GlobeLand30 (2000, 2010), and Landsat imaginary (2001, 2005, 2010, 2015, 2017) datasets.

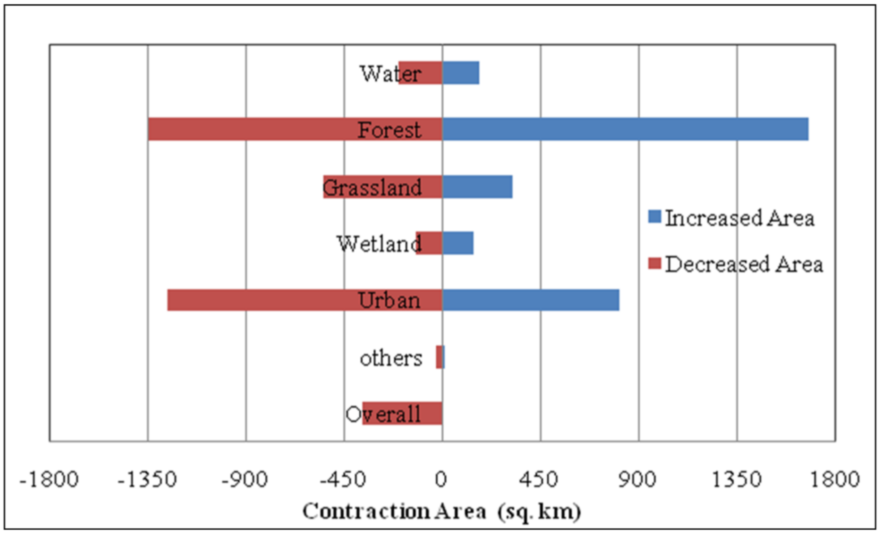


Fig. 8 The contraction of croplands area with all other LUCC classes at the southeastern region of Bangladesh from 2001 to 2017.

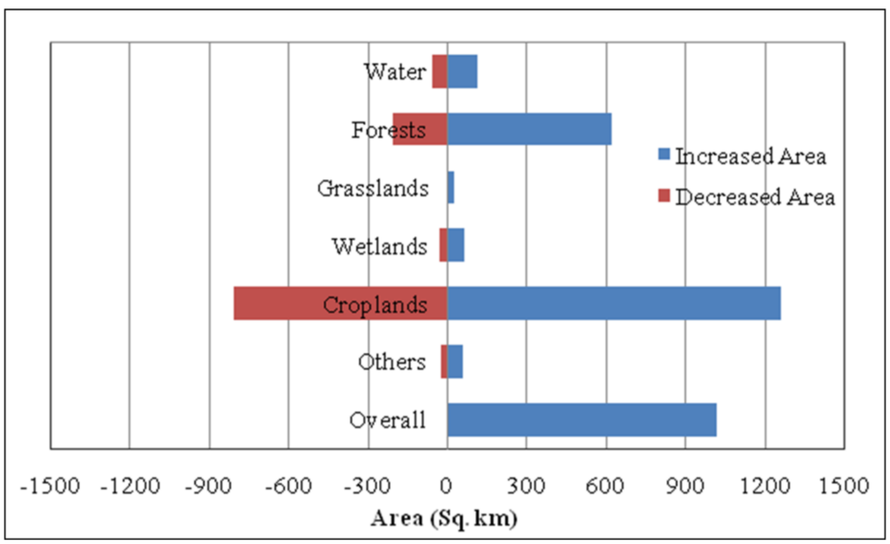
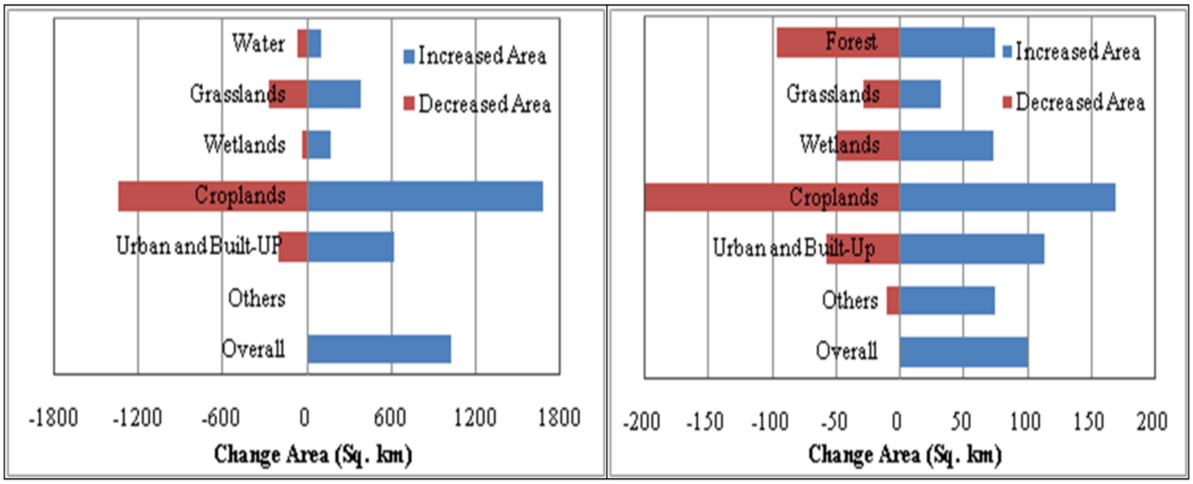


Fig. 9 The impacts of urban and built-up areas by major land cover classes of the study area from 2001 to 2017 in combination of four different land cover products



(a) (b)

Fig. 10 The impacts of (a) forest covers and (b) water bodies in major LUCC classes in four different lands cover products from 2001 to 2017.