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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

Shahidul Islam,^{a,b,c} Miao Zhang,^d Hong Yang,^{a,e,*} Mingguo Ma^{a,b,c,*}

^aChongqing Jinpo Mountain Field Scientific Observation and Research Station for Karst Ecosystem, School of Geographical Sciences, Southwest University, Chongqing 400715, China;

^bResearch Base of Karst Eco-environments at Nanchuan in Chongqing, Ministry of Nature Resources, School of Geographical Sciences, Southwest University, Chongqing 400715, China;

^cChongqing Engineering Research Center for Remote Sensing Big Data Application, School of Geographical Sciences, Southwest University, Chongqing 400715, China;

^dNorthwest Land and Resources Research Center, Shaanxi Normal University, No. 620, West Chang'an Avenue, Chang'an District, Xi'an 710119, China.

^eDepartment of Geography and Environmental Science, University of Reading, Whiteknights Reading, RG6 6AB, UK.

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.

*Corresponding Author: Hong Yang, E-mail: hongyanghy@gmail.com; Mingguo Ma, Email: mmg@swu.edu.cn

35 **1 Introduction**

36 Land use and land cover products are essential input datasets in land surface modeling or climate
37 modeling [1-3] as of distinct land cover types and land cover datasets provides reliable information
38 on carbon, water, and nitrogen processes for further ecology, climate, and hydrology studies [4-
39 9]. With the advent of high-resolution imagery and more robust techniques, moderate-resolution
40 remote sensing data sources have emerged in recent years, and the scientific community has
41 witnessed a significant increase in the availability of land cover maps. Land cover products include
42 the International Geosphere-Biosphere Program (IGBP) DIScover (IGBP-DIS) [10], the
43 University of Maryland(UMD) Land Cover [11], the Global Land Cover (GLC) mapping project
44 (GlobeLand30) [12], the Ecosystem Classification and Land Surface Parameters Database
45 (ECOCLIMAP) [13], the Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover
46 Product (MODISLC) [14], and the newest Finer Resolution Observation and Monitoring of Global
47 Land Cover (FROM-GLC) [15]. The IGBP-DIS and UMD datasets belong to the first generation
48 of 1 km global land cover maps, and are derived from 1981 to 1993 Advanced Very High
49 Resolution Radiometer (AVHRR) data using the IGBP (17 land use types in total) and simplified
50 IGBP (14 land use types in total) classification schemes, respectively [11]. The ECOCLIMAP
51 classification scheme comes from the combination of the IGBP-DIS and UMD land cover types
52 and has a spatial scale of 1 km [16]. MODIS provides global land cover with a spatial resolution
53 of 500 m using six types of classification schemes [17]. Given the free availability of Landsat and
54 similar resolution satellite data, a few 30 m GLC datasets had been developed and released in the
55 past few years, including a decadal-scale wall-to-wall GLC data product (GlobeLand30) that
56 shows change in ten land cover types and ten years [18]. These 30 m GLC datasets provide more
57 details of land cover patterns, permit the detection of land cover change at the scale of most human

58 land activities, and enable a better understanding of landscape heterogeneity, as well as increase
59 the performance of modeling and simulations [19-20]. The open source FROM-GLC dataset is the
60 first 30 m global land cover using Landsat data, developed with unique classification scheme based
61 on land cover types from the Food and Agriculture Organization (FAO) of the United Nations and
62 IGBP [15]. Despite the diversity of land cover products available, both data producers and users
63 are frustrated with lack of adequate comparison between such products. Because these land cover
64 products use different classification schemes and spatial resolutions and there is difficulty in
65 selecting and comparing these products for a given application as land use and land cover (LULC)
66 analysis. A specific way to compare datasets is to perform a relative comparison of various land
67 cover maps, first reconciling their thematic classification systems into more aggregated categories
68 after resampling the datasets to be into the same spatial resolution [21].

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

80 Rapidly increasing population growth has resulted in high rates of deforestation and large tracts
81 of forests transitioning into cultivated land; this transition has been recognized as a dominant land
82 cover worldwide [29]. Asia has undergone the most rapid land cover changes in recent years;
83 which has resulted in rapidly increasing cropland and large-scale deforestation in south Asian
84 countries [30]. The area of per capita arable land in the south Asia is very low as compared to other
85 continents. According to FAO (2014) [31], after the Maldives in south Asia, the 0.06 ha/person
86 for Bangladesh is the lowest per capita land ratio worldwide. Clearly, the per capita agricultural
87 land is decreasing as total population continues to increase. Among south Asian countries,
88 Bangladesh potentially has the most serious conditions per capita agriculture land, with the rate
89 decreasing 0.11, 0.09, 0.07, and 0.06 ha/person in 1981, 1991, 2001, and 2011 respectively [31-
90 32]. In addition, due to the high population growth, per capita arable land was about 2122
91 person/km² in 2016 [33], which is the least area per person within the Asian countries outside of
92 the Maldives. Therefore, it also called the land-hungry country [34]. Southeastern region of
93 Bangladesh is a densely populated region with a complex landscapes basin of alluvial floodplain,
94 tidal and coastal floodplain, terrace land, and hills where vegetation and trees outside of forests
95 play an important role in the national economy and carbon sequestration [35]. The primary LULC
96 classes in here are agricultural land, urban and built-up area, forest and vegetation, water bodies,
97 and wetlands [36]. The natural vegetation of this region consists of tropical moist deciduous and
98 semi-evergreen forests, mangroves, and fresh water wetlands [37]. The eastern forests belts of the
99 study area, at the border with Myanmar, are related to the Indo-Burma biodiversity hotspot, one of
100 the few globally significant areas with high species diversity and endemism [38].

101 Scientifically and systematically documenting land cover and land use changes over past
102 several decades is important for understanding the consequences of these changes for human

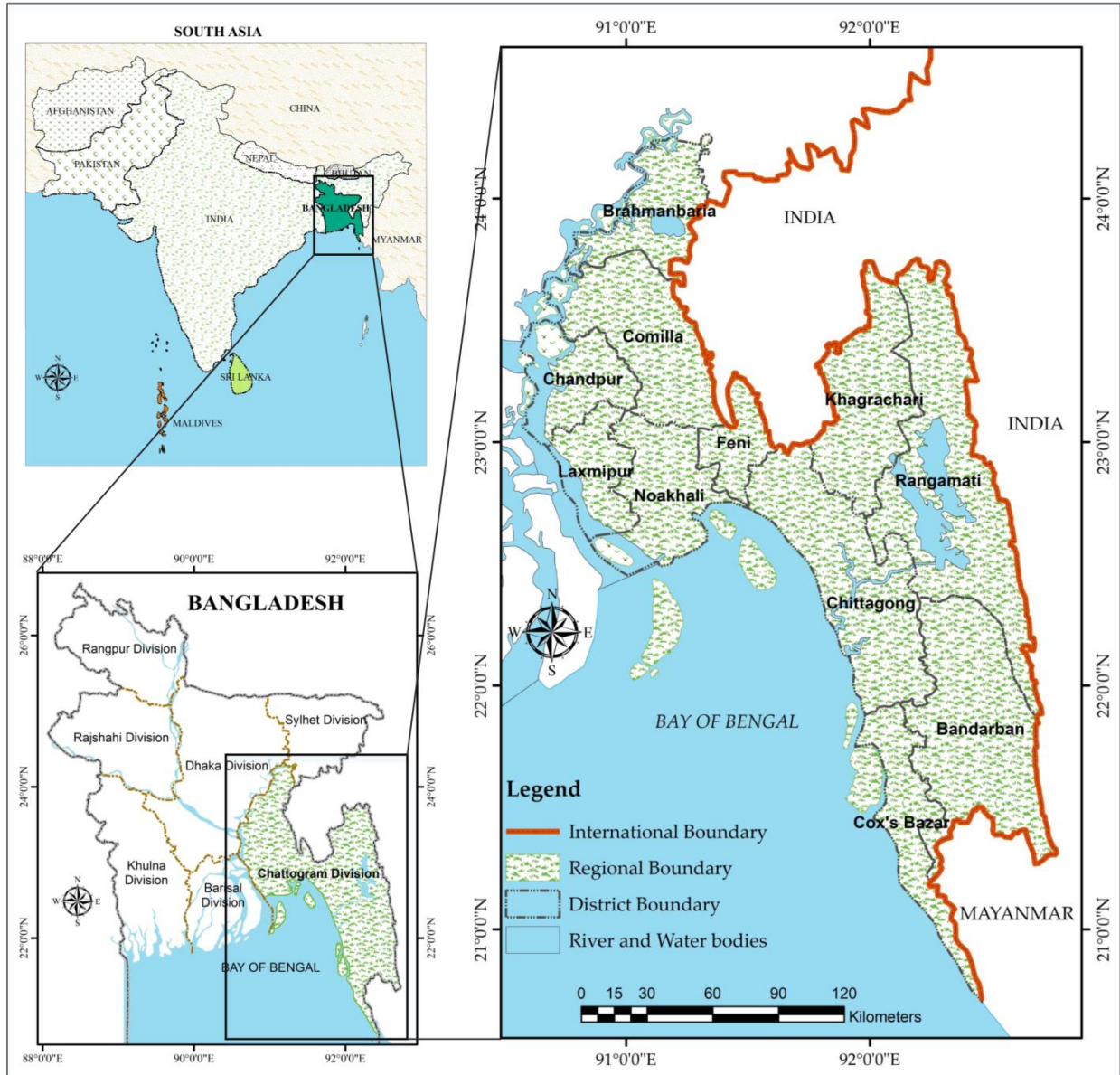
103 welfare [30]. Therefore, the objective of this paper is to assess the areal and spatial inconsistencies
104 in different global land cover products and their synthesis analysis of land use and land cover
105 dynamics. The four most recent global land cover products as the MODISLC, GlobeLand30,
106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

117 **2 Materials and Methods**

118 *2.1 Study Area*

119 This study incorporated data for the southeastern region of Bangladesh, between the latitudes
120 22°40' - 24°10' N and longitude 90°45' - 92°40' E with an area of 33,904 sq. km [39-40]. It shares
121 land borders with Bay of Bengal in the south, India and Myanmar in the east and the locally largest
122 river as well the Meghna River (based on water discharged) is in the north and west borders of the
123 study area (Fig. 1). Geographically, it is the largest administrative division of Bangladesh out of
124 eight [39-40] and a population of 29.15 million in consisting density of 884 persons per sq. km

125 [41]. The northern and western portions are listed as low-lying alluvial floodplains of the Meghna
126 River that are less than 10 m above sea level, comprising 37.6% of the region. However, the
127 remaining southern and eastern portion, where the elevation exceeds 200 m, comprises 62.4% of
128 the area, mostly with a south–north distributed hilly nature [41]. The eastern portion hilly regions
129 are mostly covered by dense forest with a variety wild life. The mega-river basin has played a
130 crucial role in supporting agriculture, groundwater recharge, fish farming, and land building
131 activities throughout history [42]. The vast areas of plain lands are mainly alluvial river
132 floodplains, estuarine floodplains, wetlands, tidal floodplains, coastal plains, and a small portion
133 of terraced land in nature.



134

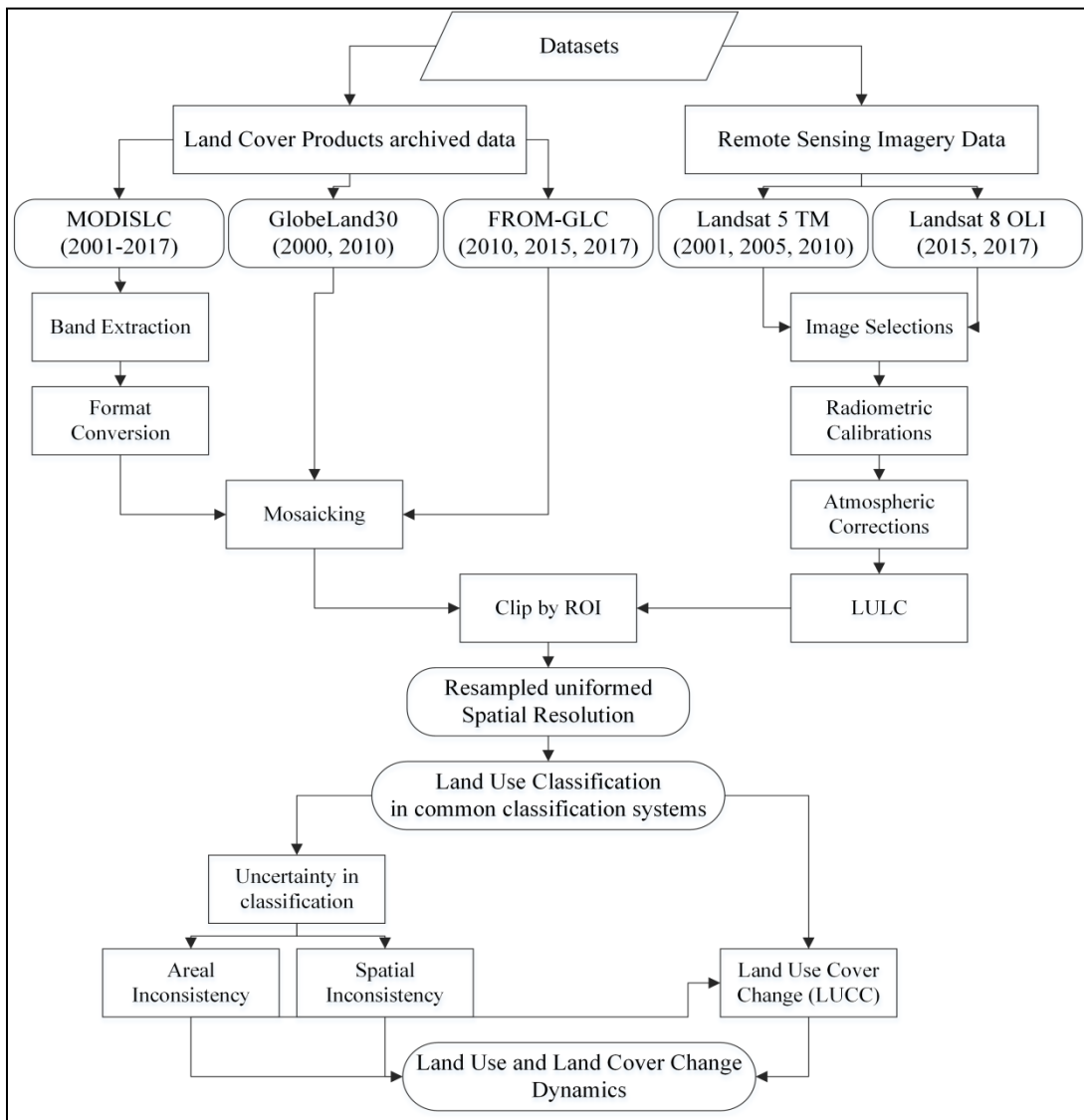
135

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

136 *2.2 Datasets*

137 To monitor and quantify the inconsistencies in global land cover products and heterogeneous
 138 landscapes and land cover change dynamics in the southeastern region of Bangladesh, high
 139 temporal and multiresolution recent global land cover products and remote sensing satellite
 140 imaginaries were used as datasets to be evaluated in this study. Three recent land cover products

141 were the MODISLC, GlobeLand30, and FROM-GLC land cover datasets and LULC class images
 142 were collected from Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper
 143 Plus (ETM+). These products are derived from newer satellite images and are validated or assessed
 144 by the producers on worldwide scales in reference to Google Earth, Virtual Earth, Yahoo maps,
 145 and others. The usefulness of these four datasets to different regional investigators has rarely been
 146 reported. Fig. 2 has described the datasets products, processing and analysis in a flowchart.



147
 148 **Fig. 2** Data analysis flowchart. ROI: Region of Interest; LULC: Land Use and Land Cover; LUCC: Land Use Cover
 149 Change.

150 2.2.1 Land cover products

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

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

169 **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]

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

173 **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.

174 Unclassified* 255 Has not received a map label because of missing inputs.
 *Land cover categories not present in the study area.

175 **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.

176 *Land cover categories not present in the study area

177 **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										

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

180 2.2.2 Remote sensing imagery data

181 Remote sensing satellite imageries were used to identify the land use and land cover (LULC) class
182 of the study area in some selective years of study. The images were acquired for 2001, 2005, and
183 2010 in between January and March of the year from Landsat 5 Thematic Mapper (TM L1T).
184 While in March 2015 and February 2017 of images were acquired from Landsat 8 OLI. All these
185 data were downloaded from the USGS Global Visualization Viewer (GloVis) archive
186 (<https://glovis.usgs.gov/>) [47]. The downloaded bands of Landsat 8 OLI and TM scenes were
187 superimposed (excluding the thermal band) to form multispectral images using ENVI5.1 software.
188 After the acquisition of the images, seven bands of OLI8 and five bands of TM except the thermal
189 bands of each image scene were superimposed to form a single multispectral image dataset using
190 the layer stack function. From the acquired data, if possible, only those images without cloud cover
191 were selected. Different remote sensing and GIS techniques were applied, such as digital image
192 processing using supervised classification and image indices. Supervised classification using a
193 maximum likelihood algorithm was applied to classify the LULC map. The classified images were
194 modified with the help of image indices and visual interpretation to produce a more accurate map.
195 Based on IGBP-9, FAO land cover classes and visible land cover of the study, we adopted a
196 classification scheme consisting of 6 first level classes, namely water, forests, wetlands, croplands,
197 artificial surfaces and others/bare lands (Table 5). The Universal Traverse Mercator (UTM) system
198 with the datum of WGS84 and Zone 46N was selected as projection for all data.

199 **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.

200 *2.3 Methodology*

201 *2.3.1 Classification system conversion*

202 The land cover datasets of MODISLC, GlobeLand30, FROM-GLC, and LULC classes are used
203 different classification schemes as well as common classification system of IGBP for MODISLC
204 [17], combined IGBP and FAO for FROM-GLC [15], and unique classification for GlobeLand30
205 [18] and LULC class distribution. However, differences in the classification system are prominent
206 (Table 2, 3, 4, and 5), for example, the FROM-GLC, GlobeLand30 and LULC class are the product
207 in which no distinction is made between evergreen and deciduous forest classes, while the LULC
208 is the only product in which no identification is made of shrublands and grasslands and MODISLC
209 is the only product having closed and open shrublands. To overcome the problem of conflicting
210 classification systems, the thematic classification system of the MODISLC, GlobeLand30, FROM-
211 GLC and the Landsat classified images as LULC were converted into four common classification
212 systems based on their original definition of classes in each land cover product, which defaults to
213 selecting the dominant category [11,20,22,24-26,48]. When some categories from the original
214 classification systems could not completely be attributed into any category in the common
215 classification systems due to conflicting definitions, we classified them into corresponding types
216 based on knowledge or by referring to data like the DEM, and labeled them as ambiguous types in

217 this study resulting in uncertainties during classification system conversion [48]. The IGBP-17,
 218 IGBP-9, IPCC-5 and TC common classification systems were used in this study. The detailed
 219 categories of the common classification systems and corresponding relationships were presented
 220 in Table 6.

221

222 **Table 6** The converting classification schemes of the MODISLC, GlobeLand30, FROM-GLC, and LULC classes in
 223 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

224 *Uncertain types when conversion was performed

225 2.3.2 Uncertainty during the classification system conversion

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

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

$$236 \quad U = \frac{N_j}{\sum_i^n N_i} \times 100 \quad (1)$$

237 Where, U = the uncertainty ratio caused by classification system conversion due to ambiguous types; N_j =
238 the total number of pixels of ambiguous types, n = the number of land cover types in the common
239 classification system, N_i = the total number of pixels of one type of common classification system, and
240 $\sum_i^n N_i$ = the total number of pixels of all land cover types.

241 2.3.3 *The method for assessing areal and spatial inconsistency*

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

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

$$246 \quad \quad \quad AIC = ABS (X_i - Y_i)/2 \quad \quad \quad (2)$$

$$247 \quad \quad \quad OAI = \sum_i^n AIC \quad \quad \quad (3)$$

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

253 Using the four common classification systems, the first step for obtaining the pairwise spatial
254 inconsistencies between the FROM-GLC (30 m), GlobeLand30 (30 m), LULC of remote sensing
255 images (30 m), and MODISLC (500 m) datasets level involved up-scaling higher spatial resolution
256 land cover into the corresponding datasets lower spatial resolution. A pixel in a low spatial
257 resolution usually represents only one type of land use type, whereas the corresponding high spatial
258 resolution pixel includes more than one land use type. In this study, a low spatial resolution pixel
259 was considered to be 100% correct when it agreed with the dominant type of the corresponding
260 high spatial resolution pixels and was considered to be 0% correct when it disagreed. Majority

261 filtering technology was used to upscale the high spatial resolution land cover into lower
262 resolutions. The Overall Spatial Inconsistency (OSI) between a given pair of these four land cover
263 products was calculated according to the formula below [20, 48]:

$$264 \quad OSI = \frac{N_{(i \neq j)}}{N} \times 100 \quad (4)$$

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

268 *2.3.4 Determination of land use classification system*

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

282 considered sufficiently representative and includes all land area within the study area, reducing
283 possible overlaps and omissions as far as practicable.

284 **3 Results**

285 *3.1 Areal Inconsistency*

286 Using four common classification systems, the areal inconsistencies of each land use type from
287 pairwise comparisons of the FROM-GLC, GlobeLand30, MODISLC, and LULC datasets were
288 shown in Table 7. During the classification system conversion to IGBP-17, the areal
289 inconsistencies were mainly present in mixed forests (up to 24.56%), woody savannas (up to
290 13.57%) and urban and built-up (up to 13.43%) classes. The areal inconsistencies in classification
291 system conversion to IGBP-9 were mainly caused by urban and built-up, croplands, and grasslands
292 (up to 12.35%, 7.90%, and 6.85% respectively) classes. During the classification system
293 conversion to IPCC-5, the areal inconsistencies were mainly caused by croplands, grassland, and
294 others (up to 7.90%, 6.85%, and 13.55% respectively). Mean while, during the classification
295 system conversion to TC system, the areal inconsistencies were mainly caused by vegetation (up
296 to 16.19%) and others (up to 13.55%). These land cover types were the dominant types in our
297 study area, illustrating that the different percentages of dominant types among land cover products
298 can greatly influence areal inconsistencies. The areal inconsistency of forests using IGBP-17,
299 IGBP-9, and IPCC-5 (24.56%, 4.87%, and 5.39% respectively) between the FROM-GLC and the
300 MODISLC were higher than the inconsistent result (0.2%, 1.33%, and 1.48%) from the paper [48],
301 but the areal inconsistencies for vegetation using TC (2.57%) was far less than the result (40.21%)
302 in the paper mentioned above.

303
304

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.

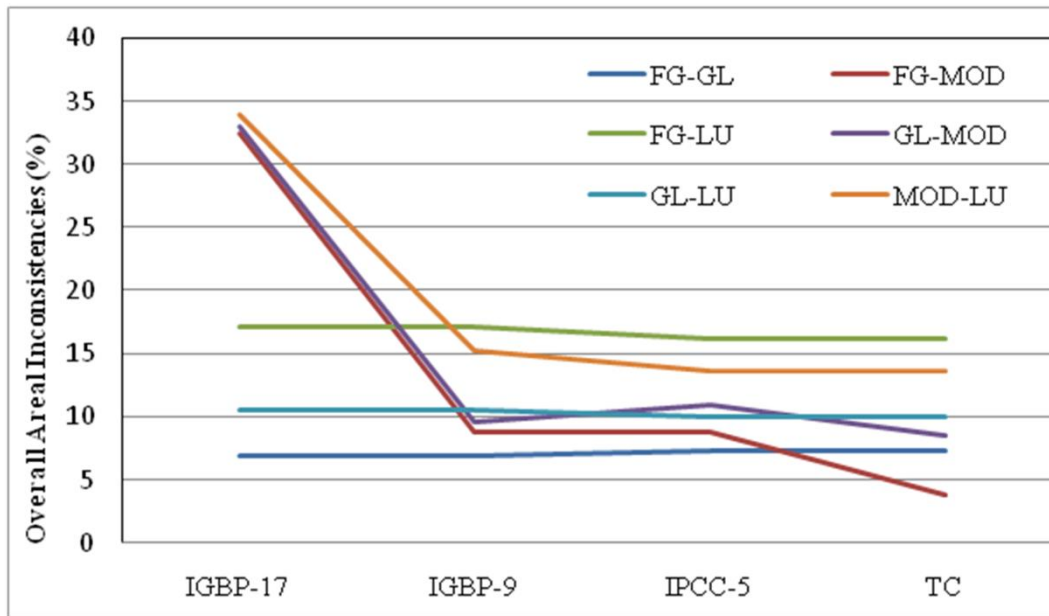
Classification System	Type	FG-GL (%)	FG-MOD (%)	FG-LU (%)	GL-MOD (%)	GL-LU (%)	MOD-LU (%)
IGBP-17	1	0.95	0.7	0.97	1.65	0.03	1.67
	2	0	0.01	0	0.01	0	0.01
	3	0	3.25	0	3.25	0	3.25
	4	0	0	0	0	0	0
	5	0	2.87	0	2.87	0	2.87
	6	4.09	24.56	5.94	20.47	1.85	18.62
	7	0	0	0	0	0	0
	8	0.02	0.52	0.52	0.5	0.5	0
	9	0	13.57	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
IGBP-9	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
	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
IPCC-5	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
	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
TC	1	6.15	2.57	16.19	3.58	10.04	13.62
	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

305
306

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

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

312 The largest overall areal inconsistency appeared in between the MODISLC and LULC of
 313 Landsat images aggregation using the common classification system IGBP-17 to TC (33.92%,
 314 15.30%, 13.63%, and 13.63% respectively) and the smallest in between the FROM-GLC and
 315 GlobeLand30 (6.87%, 6.87%, 7.29%, and 7.29% respectively). The pairwise inconsistencies were
 316 higher in related to MODISLC, indicating the accuracy of land cover datasets are depended on
 317 spatial resolution of the products.

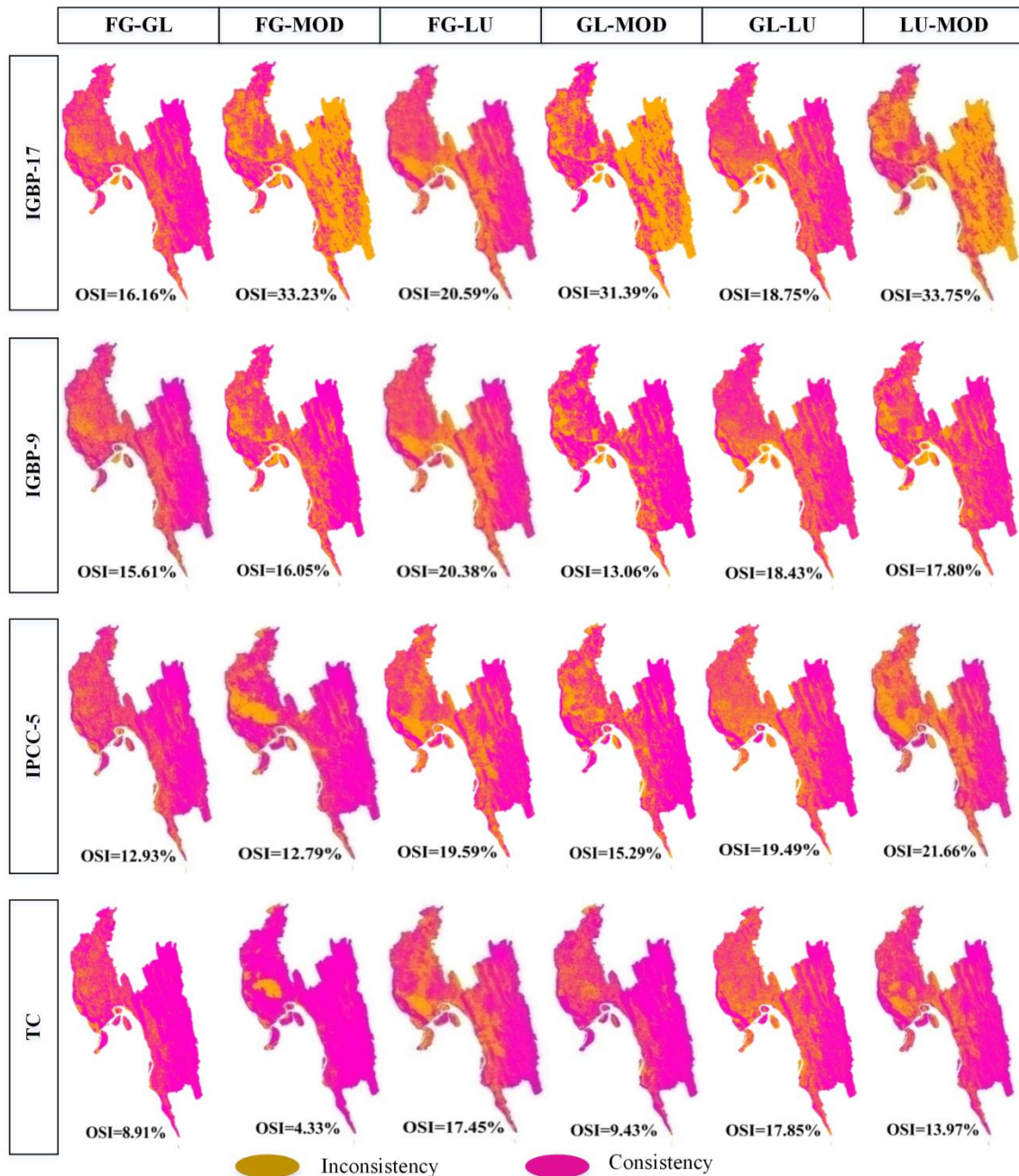


318
 319 **Fig. 3** Overall areal inconsistencies between pairwise of the FROM-GLC, GlobeLand30, MODISLC, and LULC
 320 class of Landsat TM/ETM+ datasets in four common classification systems (FG: FROM-GLC datasets; GL:
 321 GlobeLand30 datasets; MOD: MODISLC datasets; and LU: Land use and land cover classes of Landsat TM/ETM+
 322 datasets).

323 3.2 *Spatial Inconsistencies*

324 The distribution and overall spatial inconsistencies in the pairwise comparisons of the FROM-
325 GLC, GlobeLand30, MODISLC, and LULC datasets are shown in Fig. 4. The overall smallest
326 spatial inconsistencies were between the FROM-GLC and the GlobeLand30 datasets as 16.16%,
327 15.61%, 12.93%, and 8.91% using the aggregation of common classification systems IGBP-17,
328 IGBP-9, IPCC-5 and TC, respectively. While the overall higher spatial inconsistencies in
329 comparison to other pair of land cover datasets were between the LULC and MODISLC as of
330 33.75%, 17.80%, 21.66%, and 13.97% using the four common classification systems respectively.
331 In addition, the overall spatial inconsistency in IGBP-17 classification system between the FROM-
332 GLC and MODISLC (33.23%) was slightly higher than the inconsistent result (18.57%) from the
333 paper [48], but the overall spatial inconsistencies in the classification systems IGBP-9, IPCC-5,
334 and TC (16.05%, 12.79%, and 4.33% respectively) were slightly less than the results (18.05%,
335 17.44%, and 14.95% respectively) in the paper mentioned above. The spatial inconsistencies
336 decreased with the increasing level of aggregation of common classification systems from IGBP-
337 17 to TC.

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



345

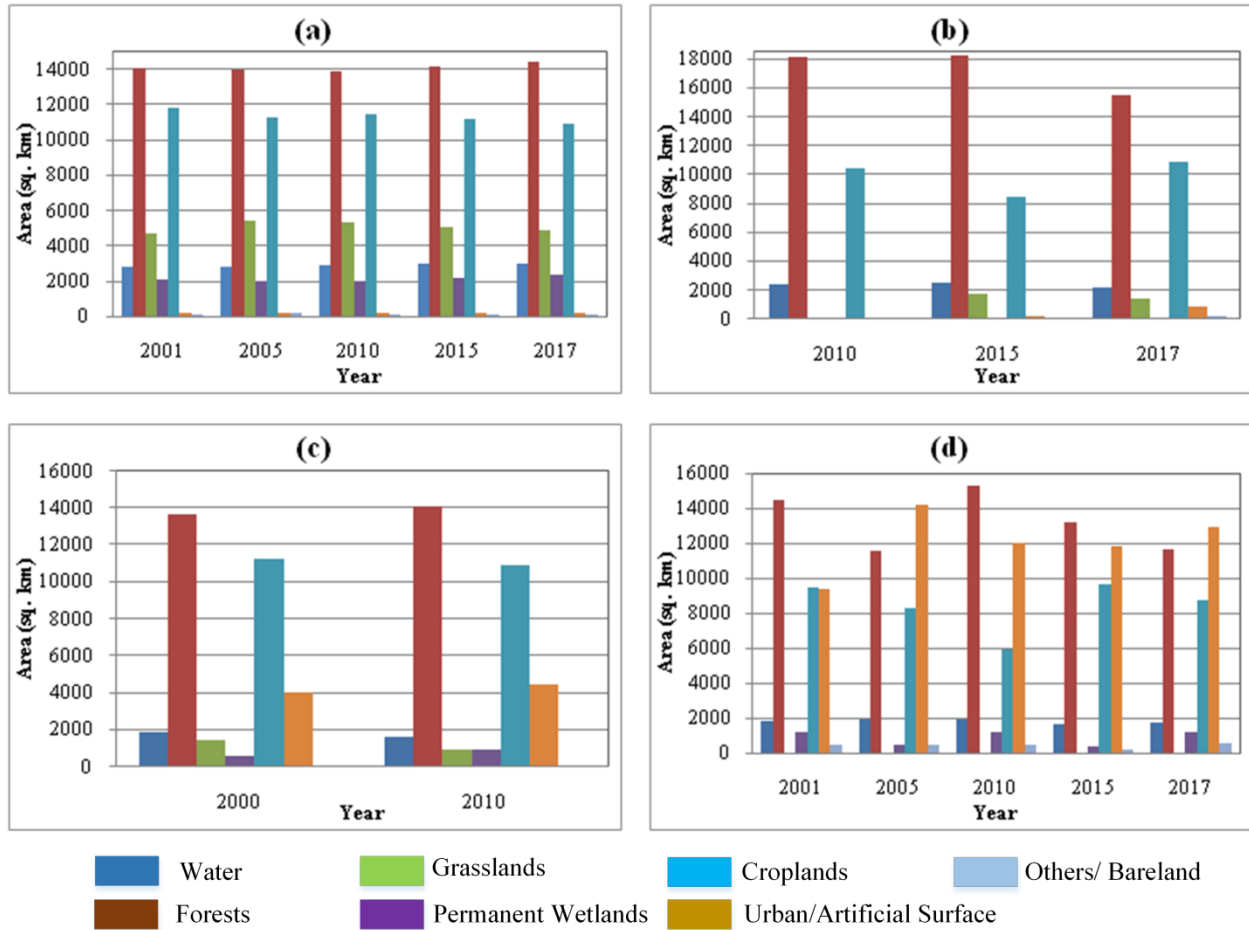
346 **Fig.4** Overall spatial inconsistencies (OSI) in the pairwise comparison of FROM-GLC, GlobeLand30, MODISLC,
 347 and LULC datasets in the four common classification systems (FG: FROM-GLC datasets; GL: GlobeLand30
 348 datasets; MOD: MODISLC datasets; and LU: Land use and land cover classes of remote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

349 *3.3 Land Use Classification*

350 Land use and land cover of the study area southeastern region of Bangladesh from 2001 to 2017

351 are summarized in Fig. 5. This table is a combined result of land use classification of Landsat

352 satellite images as LULC and different land cover products of the FROM-GLC, the Globeland30,
353 and the MODISLC datasets. The areas were arranged by some specific year (2001, 2005, 2010,
354 2015, and 2017) and by land use sub-categories based on IGBP-9 classification system as of lowest
355 variation of overall areal and spatial inconsistencies were identified in Fig. 3 and 4. As of 2017,
356 forests (lands covered with trees, with vegetation cover including deciduous and coniferous
357 forests, and sparse woodland) dominated the land cover of this region; comprising 40.2%, 50%,
358 and 31.7% of the total land cover area by MODISLC, FROM-GLC, and LULC respectively. In
359 the GlobeLand30 land cover dataset, the same feature was the dominant category in their recent
360 (2010) product as 42.6% of the total land cover area. Croplands (lands used for agriculture,
361 horticulture and gardens, including paddy fields, irrigated and dry farmland, vegetation and fruit
362 gardens, etc.) were the second dominant land cover class, covering approximately 30.4%, 34.8%,
363 23.8%, and 32.2% in the datasets respectively MODISLC, FROM-GLC, LULC, and GlobeLand30
364 of the land. Grasslands, occupying 4914 sq. km in MODISLC, 1461 sq. km in FROM-GLC, and
365 907 sq. km in Globeland30 datasets of the land area, appears around the transition zone and was
366 not identified in LULC class. Because of their similar spectral reflectance signatures, it was
367 difficult to definitely differentiate grasslands from agriculture on Landsat images.



368

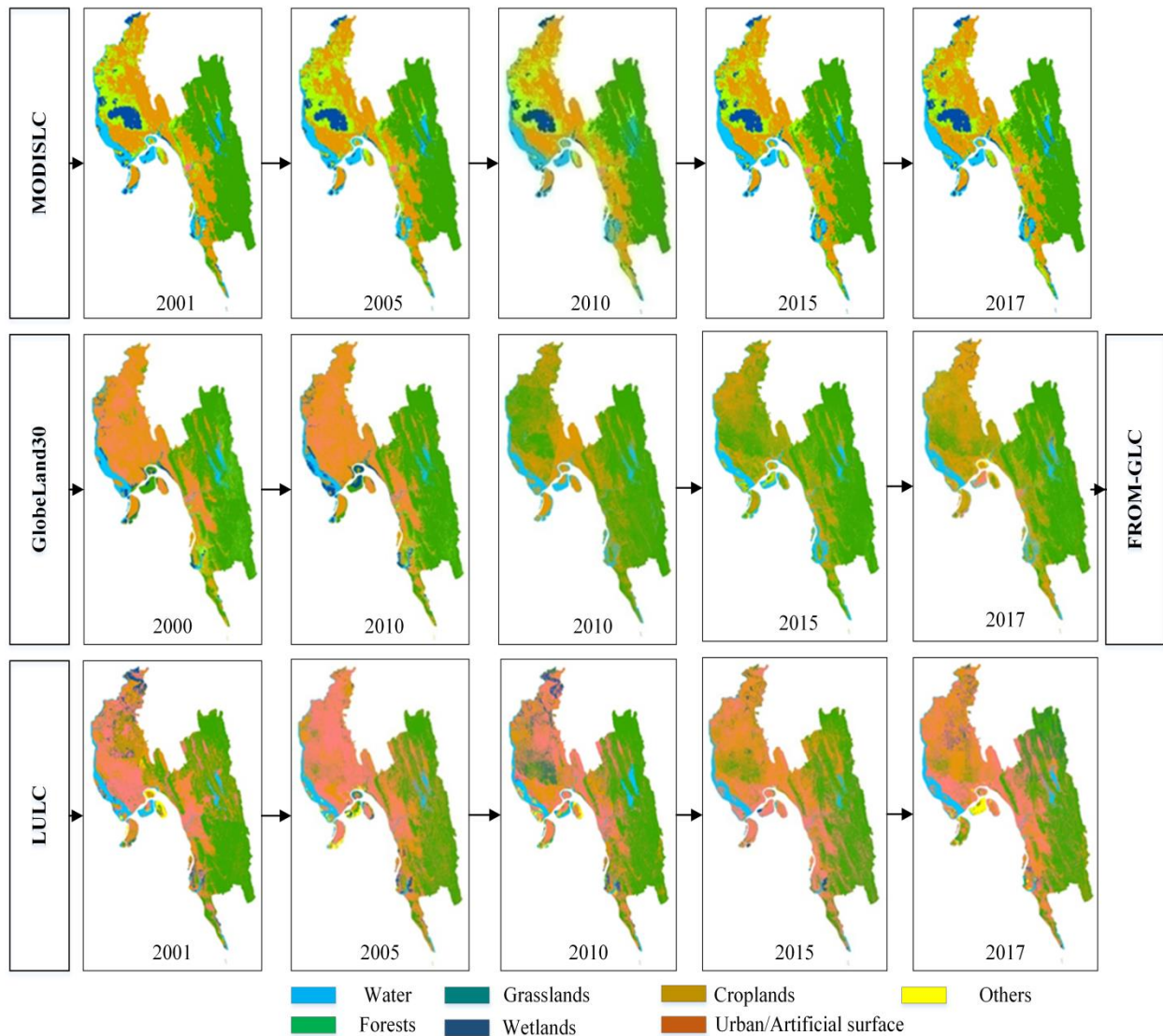
369 **Fig. 5** Land use classification of the southeastern region of Bangladesh from (a) MODISLC, (b) FROM-GLC, (c)
 370 GlobeLand30, and (d) LULC of Landsat satellite images

371 Land use classification maps of some specific year of study from different land cover datasets
 372 are shown in Fig. 6. Based on reliability and available in access, the recent land cover products of
 373 the MODISLC in the year 2001, 2005, 2010, 2015 and 2017, the Globeland30 in the year 2000
 374 and 2010, and the FROM-GLC in the year 2010, 2015 and 2017 were extracted. Based on
 375 supervised classification, Landsat images were used to prepare LULC maps in the year 2001, 2005,
 376 2010, 2015, and 2017 of the study.

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

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

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



393

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

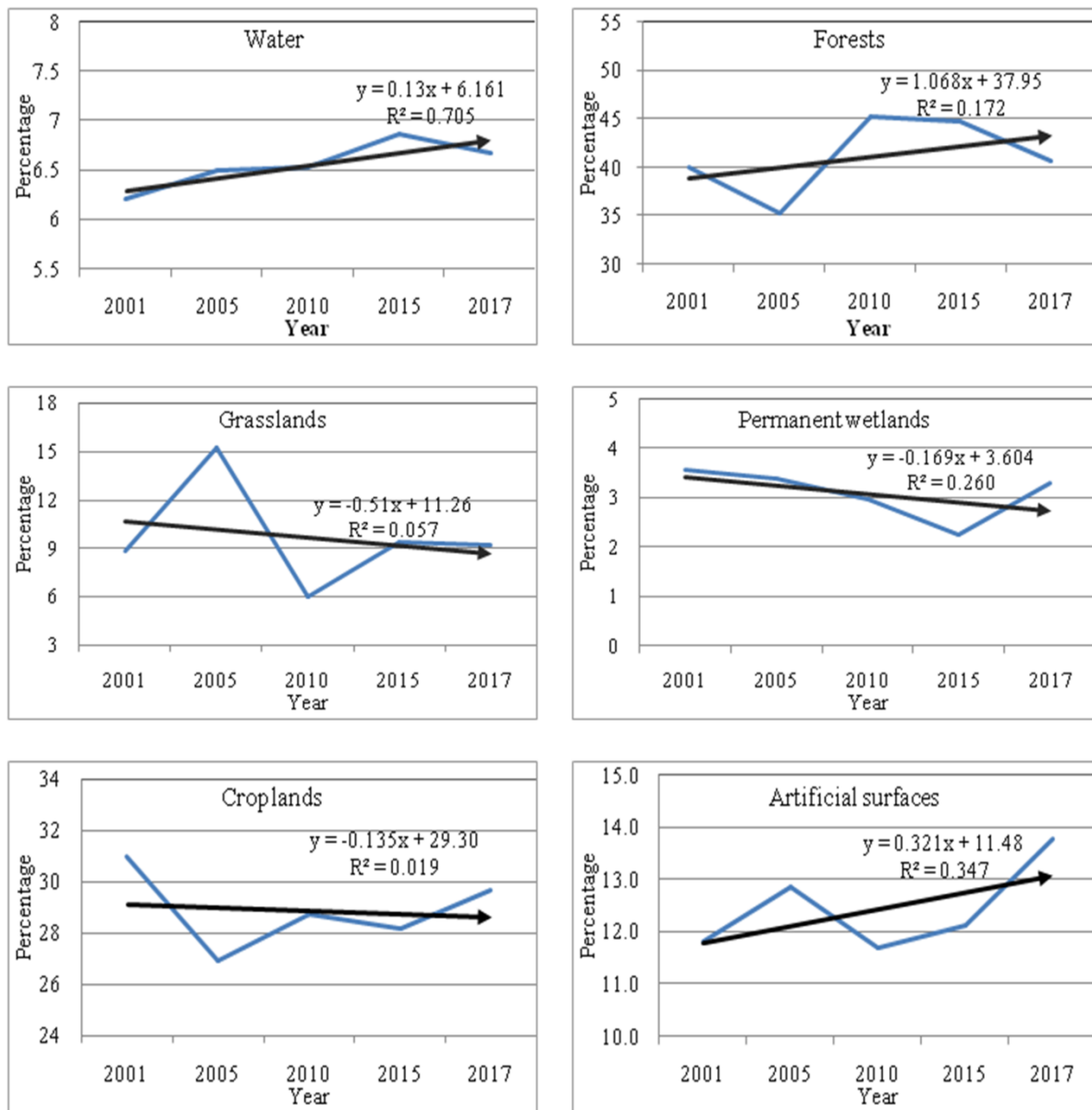
396 Wetlands were the common feature here of low lying flat topography at the floodplain region
 397 of northwestern areas and tidal floodplain lands of southern areas of the study. In seasonal
 398 variation, those were converted to croplands or water bodies as well as salt and shrimp cultivating
 399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

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

404 *3.4 Composition, Distribution and Changes of Major LULC Classes*

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

416 Spatio-temporal studies revealed that in 2001, the total area of cropland was 31% of the study
417 area and in 2017 it has revealed 29.7%. The study pointed out that croplands areas were
418 substantially decreased about 1.3% with a contraction rate of 0.1-0.8% per year ($R^2 = 0.019$) during
419 2001-2017 period of study. On the other hand, overall the urban and built-up areas as well as
420 artificial surfaces of the southeastern region of Bangladesh increased significantly between 2001
421 and 2017. In 2001, the built-up areas were listed as 11.8%, which as increased to 13.8% in 2017
422 of the mutually distributed over the study area. Overall about 2% of the urban land cover areas
423 were increased with a rate of 1.2% ($R^2 = 0.347$) per year during this period of study.



424

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

428 In the southeastern region of Bangladesh, the sources of water are primarily surface and ground
 429 waters such as rivers and *khals*, lakes, *beel*, *haor*, *char*, and wetlands. *Beel* refers to low lands
 430 mainly lying in the floodplains and deltaic region. *Haor* refers to the low-lying vast depression
 431 areas that flooded during the monsoon and dried out in winter [53, 54]. The *haor* areas are mostly
 432 located in the north-eastern part of the study area that plays significant roles in the livelihoods of

433 surrounding communities as well maintenance of biodiversity [55]. The study area has around
434 37.6% of land below 10 m elevation [41]. Therefore, during monsoon season; rainfall, flooding,
435 and surges have converted agricultural land to water bodies in the various low lands across the
436 active floodplain areas of the study. From 2001 to 2017 on an average, the total water bodies' area
437 increased from 6.2 to 6.7% across the study area by 0.3% annually. On the other hand, the total
438 areas of *beel* and *haor* as well as wetlands have slightly decreased. On the basis of the
439 comprehensive evaluations of four different land cover datasets in an average, the total area
440 decreased from 3.6 to 3.3%, about 0.3% annually from 2001 to 2017.

441 Spatial analysis has shown that the total forest cover was increasing in area and quality. The
442 different land cover products have indicated that forest cover increased about 0.6% from 2001 to
443 2017. The substantial changes have identified that the tree cover in reserve forest as well as natural
444 forest is decreasing but tree outside of forest was increasing. Some other research also identified
445 that vegetation coverage at the southeastern region of Bangladesh was increased by 0.43 SINDVI
446 indexed value during 2001-2016 [35] and the total tree canopy cover increased 4.3% during the
447 2000-2014 time interval [56]. However, there are noticeable inconsistencies in between the various
448 national level studies regarding forest change. The grasslands are primarily situated north eastern
449 part of the study area. However, the area has in decreasing trend considerably 0.1% per year from
450 2001 to 2017.

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

456 remained unchanged of the MODISLC, FROM-GLC, GlobeLand30, and LULC class distributions
 457 between the years.

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

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

474 **Table 8** Land cover transition matrix in the southeastern region of Bangladesh in different land cover products of
 475 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

	Others	13.7	0	7.7	63.9	1.5	0	57.4	
FROM-GLC		2017							
	Land Types	W	F	GL	PW	CL	IS	Others	
	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	
GlobeLand30		2010							
	Land Types	W	F	GL	PW	CL	AS	Others	
	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	
LULC		2017							
	Land Types	W	F	GL	PW	CL	AS	Others	
	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	

476 The study area has large sources of water resources from various channels and vast areas of
477 wetlands due to low lying topography. From the four different land cover in between 2001 and
478 2017, water bodies' areas were increased considerably while decreasing wetlands. Water areas
479 were mainly increased in transformation of wetlands in the northern part of the region, while
480 southern part has aggregated the croplands areas.

481 **4 Discussion**

482 *4.1 Pattern of Inconsistencies in Different Land Cover Mapping*

483 The comparisons of land cover products in previous studies have been made only at global [25,26],
484 continental [24], national [22], or provincial scales [27], since they focused on general patterns of
485 inconsistencies or indirect validation accuracy of the products, which is meaningful to large scale

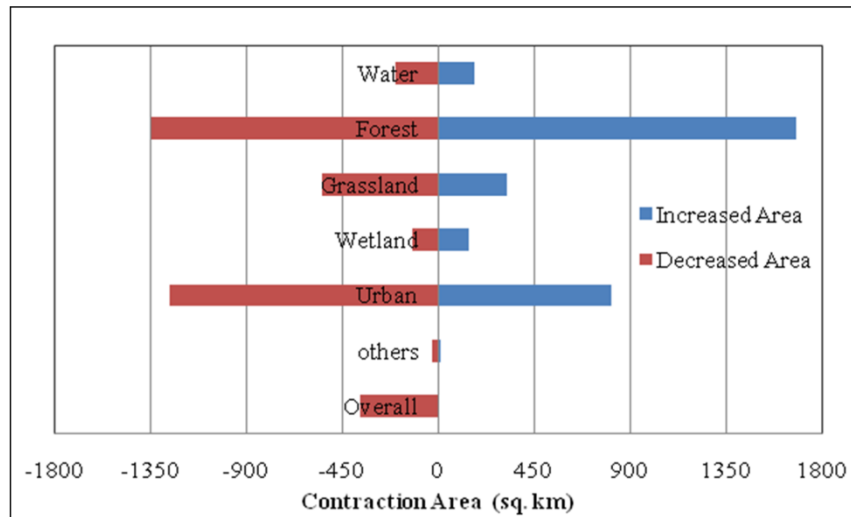
486 studies. To our knowledge, in small scale area as well in southeastern region of Bangladesh, this
487 is the first study to evaluate the amount of pair wise level of inconsistencies in different land cover
488 products (the MODISLC, FROM-GLC, GlobeLand30, and LULC of Landsat images) from
489 different view of spatial resolutions. It was found that the overall areal inconsistency and spatial
490 inconsistency of the FROM-GLC and GlobeLand30 is relatively small among the pairs of the four
491 products. While the pair of MODISLC and LULC was the highest overall areal and spatial
492 consistency in relative to others. The overall areal inconsistency other than spatial inconsistency
493 result is consistent with the conclusions in similar studies [20,22-24]. Both in overall areal and
494 spatial consistencies, the pair relation to the MODISLC were the highest inconsistencies. The
495 product of MODISLC was only land cover of 500 m spatial resolution other than 30 m of FROM-
496 GLC, GlobeLand30 and Landsat images. The second largest values of areal and spatial
497 inconsistencies were identified in pair related to LULC class of Landsat imaginary datasets.
498 However study in a small area may use the lower spatial resolution of land cover datasets as well
499 as FROM-GLC and GlobeLand30 land cover products.

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

508 4.2 Impacts of Major LUCC Classes

509 4.2.1 The impacts of agricultural land contraction

510 Since the independence of Bangladesh, the increasing population resulted the widely LUCC across
511 the country. The contractions of agricultural land to non-agricultural land resultant the various
512 consequences over the country. At the study area southeastern region of Bangladesh, on an average
513 of the four land cover products, overall about 0.5% croplands has decreased annually between
514 2001 and 2017. The contraction rate has been slightly lower as decreased up to 1.45% annually
515 after 2000 in different divisions of the country [31,57].



516
517 **Fig. 8** The contraction of croplands area with all other LUCC classes at the southeastern region of Bangladesh from
518 2001 to 2017.

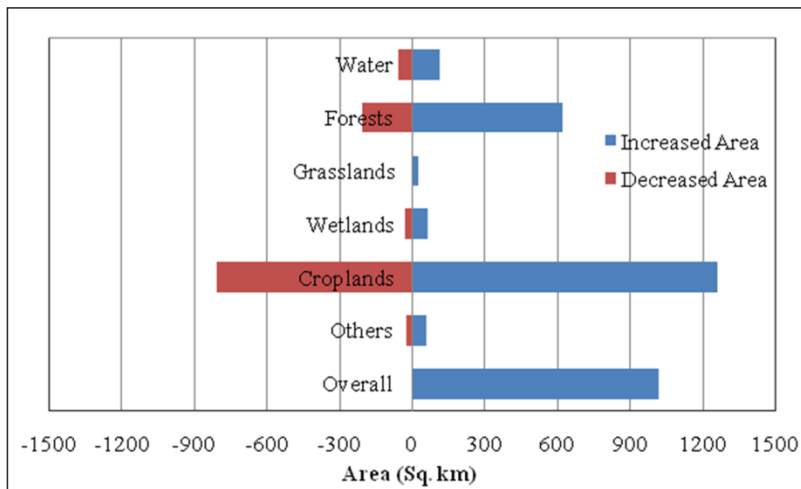
519 The contraction of croplands with major land cover classes between 2001 and 2017 has shown
520 in Fig. 8. In an average of the four different land cover products, cropland was mainly decreased
521 to forest as well as tree cover (1346 sq. km) and urban and built-up areas (1260 sq. km), while the
522 land areas was increased by aggregation of forest (1677 sq. km) and artificial surface areas (809
523 sq. km). Overall about 59.6% of the croplands were unchanged during the period of study. With
524 the time and introduced new farming technology, the study area adopted various ways to increase

525 food production and minimize food insecurity. The start of agro-technological advancement
526 increased the production with crop intensity, which increased per capita income more than 130%
527 and reduced the poverty level 50% [61-62]. However, overall, the gross production of rice and
528 wheat increased significantly during the period between 1971/72 and 2010/11 from 10.46 to 35.3
529 million metric tons [61-63]. On the other hand, in 2005, Bangladesh's net AFOLU emissions were
530 61.3 million tCO₂e, accounting for over 52% of the total net national emissions [64]. Agriculture
531 emitted 43.1 million tCO₂e or about 35% of all emissions and 66% of AFOLU emissions, while
532 LULUCF constituted the remaining 34% of AFOLU emissions with a net emission of 18.2 million
533 tCO₂e. The three most important emission sources in the agriculture sector were manure
534 management (representing 41% of agricultural emissions), enteric fermentation (24%) and rice
535 cultivation (18%) [65]. However the country requires of 23.64 million of metric tons (MMT) rice
536 and wheat for the total population [63]. Still, 40% of the rural populations live with a landless
537 status [22]. Furthermore, around 60% of farmers are functionally landless with about 62% of
538 farming households having less than 0.4 ha of farmland [66]. Therefore, food production is not
539 enough for all household. Due to decline in agriculture land, the overall production declined and
540 the problem of food insecurity is becoming more intense and they have to import food from
541 neighboring countries.

542 *4.2.2 The effects of urban land development*

543 Rapid population growth is a major component of urban land development, historically, those
544 growth have been increasing significantly over the southeastern region of Bangladesh. Multiple
545 driving factors are responsible for the LUCC and artificial surface expansion [67]. Since 1990s,
546 the study area's population has grown rapidly by 20.5 to 28.4 million in between 1991 and 2011
547 [68]. The high rate of economic and population growth, massive infrastructure development, and

548 impact of climate change have been major causes of rapid LUCC across the area [69]. The study
 549 on LUCC of different land cover products has identified the urban and a built-up as well as
 550 artificial surface at study area was increased mainly by accretion of croplands and forest
 551 degradation (Fig. 9). From 2001 to 2017, about 1260 sq. km and 622 sq. km of croplands and
 552 forest cover respectively have converted to urban and built-up areas. On the other hand, artificial
 553 surface was converted to croplands and tree cover as well of 809 and 204 sq. km respectively
 554 during this period. Overall about 1017 sq. km of urban and built-up areas was increased between
 555 2001 and 2017 period of study with an annual rate of 1.32%. However, Hasan et al. (2013) [31]
 556 found that the urban area increased 401 sq. km during 2000-2010 and Reddy et al. (2016) [70]
 557 found that settlement area had increased 1643 sq. km (1.1%) in 2000-2014, which were in agreed
 558 with the results.



559
 560 **Fig. 9** The impacts of urban and built-up areas by major land cover classes of the study area from 2001 to 2017 in
 561 combination of four different land cover products

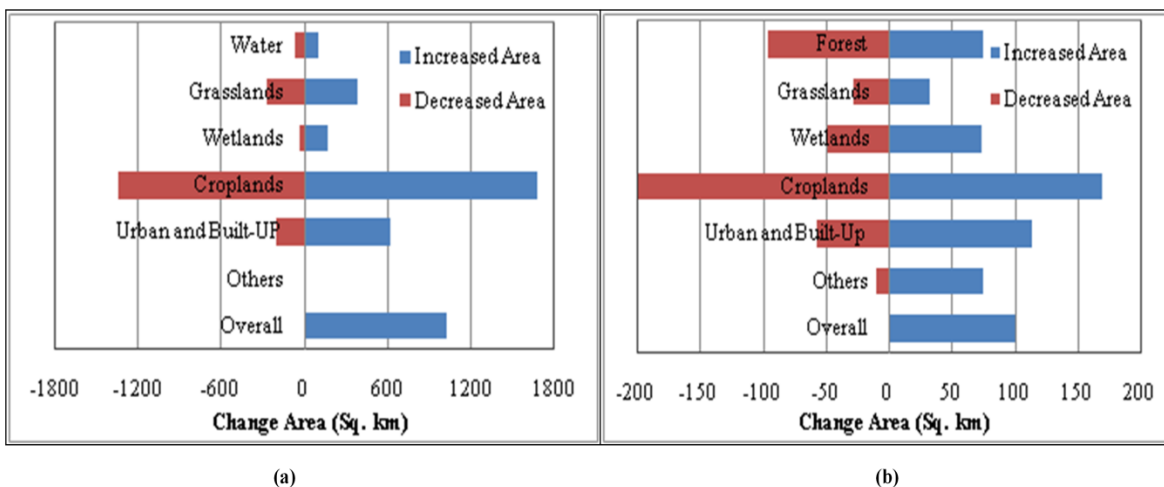
562 Approximately one-fourth of the national population lives in urban area [68] and increasing
 563 urban population growth has resulted the urban expansion speedily, mostly in the city areas. As
 564 result, infrastructure development with unplanned urbanization processes encroached on
 565 agricultural land, forestland, low-lying areas, and water bodies, resulting in the transformation

566 from vegetation cover to concrete built-up areas. These types of changes are incorporated to
567 vulnerable capital city as well other big cities from natural disasters and LUCC issues. One of the
568 obvious impacts of urban growth at the cost of agricultural land is the increasing problem of food
569 security. Similarly, the conservation of other land uses such as forest and water bodies has several
570 environmental and socio-economic consequences.

571 *4.2.3 The effects of forest cover and water bodies changes*

572 With the combination of hilly areas (62.4%) and low elevation deltaic floodplain (37.6%), the
573 southeastern region of Bangladesh has a tropical monsoon climate characterized by heavy seasonal
574 rainfall, high temperatures and high humidity [41]. Forest cover is mostly distributed in south-east
575 part of the study area of hilly region (Fig. 6). The impacts of forest cover and water bodies in the
576 southeastern region of Bangladesh in an average of the four different land cover of the MODISLC,
577 FROM-GLC, GlobeLand30, and LULC classes has described in Fig. 10. In between 2001 and
578 2017, forest cover at the study area was mainly affected by croplands as of 1346 sq. km was
579 aggregated. Forest cover was also found changed to grasslands and build-up areas. Overall the
580 forest cover at the study area has increased by 1022 sq. km as 0.4% annually during this period.
581 However, Patopov et. al. (2017) [56] was also identified; tree cover outside of forest was increased
582 as of overall 4.3% total canopy cover increased over the country during 2000-2014 period and
583 Islam et. al. (2018) [35] found 0.43 indexed value of increased SINDVI at the study during 2001-
584 2016, which support the study results. Although overall tree cover is increasing, spatial distribution
585 of forest cover showed that tree canopy cover in reserve forest at the south-east region of the study
586 area was decreased, while increased plantations in settlement and cropland areas. However, due to
587 the high demand for wood and wood products, the overall forest cover status is increasing rate
588 after 2000 which also shows very less per capita forest land in the world. According to FAO

589 (2010b) [71], the average per capita forest land is 0.60 ha globally; however, in recent decades,
 590 Bangladesh has only reached 0.12 ha per capita forest land. The forest department has implemented
 591 several massive programs and projects to regenerate and reforest after the devastating cyclone of
 592 1960. The impacts of these programs have been observed since 2000. Furthermore, illicit felling of
 593 forest cover also improved after 2000. Bangladesh is considered the world's most vulnerable
 594 country to the negative impacts of climate change, facing particularly high risks from tropical
 595 cyclones and floods specially the study area southeastern region of Bangladesh. In response, the
 596 country has prioritized adaptation and has invested over US\$ 10 billion of its own resources to
 597 increase its climate resilience [72]. Nonetheless, Bangladesh has also implemented mitigation
 598 activities, including in the AFOLU sector. Current and planned AFOLU mitigation activities
 599 include afforestation/ reforestation, REDD+, climate resilient agriculture, lowering methane
 600 emissions in agricultural production, crop diversification, fertilizer management and improved
 601 livestock management. The country has several NAMAs under development in the industry and
 602 waste sectors and is exploring potential in other sectors [72].



603 (a) 604 **Fig. 10** The impacts of (a) forest covers and (b) water bodies in major LUC classes in four different lands cover
 605 products from 2001 to 2017

606 Due to foothills of the Himalayas and low lying riverine the country shares 57 trans-boundary
607 rivers. The rivers play the important role for agriculture as the well high risk of floods and river
608 erosion within the study area. In an average of four different land cover products, overall the water
609 areas in the study has increased 100 sq. km. Water area was mainly increasing by logged and
610 flooded of cropland and built-up areas. In recent decades, due to the high rate of population growth
611 and urbanization process, the wetlands surrounding the built-up areas have seriously degraded
612 [58]. This wetlands change and unplanned urbanization as well as development have made the
613 drainage system in the urban areas vulnerable to water logging problems and their consequences.
614 Moreover, due to high profit from shrimp and salt cultivation, water bodies at the southern coastal
615 areas have increased up to 500% after 1980s in the southern regions [51]. On the one hand the
616 shrimp farming improved the local livelihood; but on the other hand, intensive shrimp farming has
617 impacted coastal land use with creating saline water intrusions, which may destruction the
618 wetlands as well as water bodies and rice ecosystems as well decrease of rice production.

619 **5 Conclusion**

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

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

644 The four different land cover products used in land use cover changes in the study were in
645 different classification schemes. This study was reclassified them into a common classification
646 system and were discussed the LUCC status by their comprehensive changing results. For land use
647 classification, IGBP-9 (as identified lower variations of inconsistencies) suggests adopting nine
648 land use categories: water; forests; shrublands; grasslands; wetland; croplands; urban and built-up;
649 snow and ice; and others. All land cover products and Landsat satellite images of the land areas of
650 southeastern region of Bangladesh was classified/reclassified in accordance with this suggested

651 land use categories. As of 2017, forests and croplands were the principle dominates the land cover
652 of this region, comprising 40.2%, 50%, 31.7%, and 42.6% of forests and 30.4%, 34.8%, 23.8%,
653 and 32.2% of croplands in the four different land covers of MODISLC, FROM-GLC, LULC, and
654 GlobeLand30 datasets respectively. Based on the systematic assessment in an average of the four
655 different land cover products in the southeastern region of Bangladesh, this study concluded that
656 the land areas of water, forests, and artificial surfaces were increased in different spatial and
657 temporal dynamics, while croplands, grasslands, and wetland were decreased. The major effects
658 of LUCC dynamism were mainly circulated in the changing pattern of croplands, forests, and
659 artificial surfaces of the study area. However, the historical spatio-temporal LUCC results are
660 inconsistent between studies. Although the research was focuses on uncertainty in the land cover
661 data, it would be useful to highlight the contribution of the AFLOU sector in Bangladesh to the
662 GHG emissions and would be further helpful to understand the consequence of climate change
663 mitigation. Further LUCC study is needed to examine the historical data with new methods, tools,
664 and data resources in the context of environmental change at the national and regional scale. The
665 trans-boundary river basin is one of the most important water resources in South Asian countries
666 for agriculture and human needs, yet few studies have addressed this area. Further LUCC study is
667 needed to improve accuracy, eliminate uncertainties and discrepancies in the spatio-temporal
668 changes.

669 **Author Contributions:**

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

672 **Conflicts of Interest:**

673 The authors declare no conflict of interest.

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679 DAAC, National Geomatics Center of China (NGCC), Tsinghua University of China, and USGS respectively.
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681

682 **References**

- 683 1. J. F. Yin, X. W. Zhan, Y. F. Zheng, C. R. Hain, M. Ek, J. Wen,; L. Fang, and J. C. Liu, “Improving
684 Noah land surface model performance using near real time surface albedo and green vegetation
685 fraction,” *Agric. For. Meteorol.* **218**, 171–183 (2016).
- 686 2. X. H. Wen, S. H. Lu, and J. M. Jin, “Integrating remote sensing data with WRF for improved
687 simulations of oasis effects on local weather processes over an arid region in northwestern China,” *J.*
688 *Hydro meteorol.*, **13**, 573–587 (2012).
- 689 3. GCOS, *The second report on the adequacy of the Global Observing System for Climate Support of*
690 *the UNFCCC, GCOS-82*. Secretariat of the World Meteorological Organization: Geneva, Switzerland,
691 74 pp (2003).
- 692 4. R. A. Houghton, J. I. House, J. Pongratz, G. R. van der Werf, R. S. DeFries, M. C. Hansen, C.
693 LeQuere, and N. Ramankutty, “Carbon emissions from land use and land cover change,”
694 *Biogeosciences* **9**, 5125–5142 (2012).

- 695 5. S. W. Running, D. D. Baldocchi, D. P. Turner, S. T. Gower, P. S. Bakwin, and K. A. Hibbard, “A
696 global terrestrial monitoring network integrating tower fluxes, flask sampling, ecosystem modeling
697 and EOS satellite data,” *Remote Sens. Environ.* **70**, 108–127 (1999).
- 698 6. M. Herold, J. S. Latham, A. DiGregorio, and C. C. Schmullius, “Evolving standards inland cover
699 characterization,” *J. Land Use Sci.* **1** (2–4), 157–168 (2006).
- 700 7. M. E. Andrew, M. A. Wulder, and T. A. Nelson, “Potential contributions of remote sensing to
701 ecosystem service assessments,” *Prog. Phys. Geogr.* **38** (3), 328–353 (2014).
- 702 8. J. J. Feddema, K. W. Oleson, G. B. Bonan, L. O. Mearns, L. E. Buja, G. A. Meehl, and W. M.
703 Washington, “The importance of land-cover change in simulating future climates,” *Science*, **310**,
704 1674–1678 (2005).
- 705 9. C. Zhang, C. Li, X. Chen, G. Luo, L. Li, X. Li, Y. Yan, and H. Shao, “A spatial-explicit dynamic
706 vegetation model that couples carbon, water, and nitrogen processes for arid and semiarid
707 ecosystems,” *J. Arid Land* **5**, 102–117 (2013).
- 708 10. T. R. Loveland, B.C. Reed, J. F. Brown, D. O. Ohlen, Z. Zhu, L. Yang, and J. W. Merchant,
709 “Development of a global land cover characteristics database and IGBP DISCover from 1 km
710 AVHRR data,” *Int. J. Remote Sens.* **21**, 1303–1330 (2000).
- 711 11. M. Hansen, and B. A. Reed, “A comparison of the IGBP discover and university of Maryland 1 km
712 global land cover products,” *Int. J. Remote Sens.* **21**, 1365–1373 (2000).
- 713 12. H. Xie, X. Tong, and W. Meng et al. “A multilevel stratified spatial sampling approach for the quality
714 assessment of remote-sensing-derived products,” *IEEE Journal of Selected Topics in Applied Earth
715 Observations and Remote Sensing*, **8**(10): 4699–4713 (2015) [DOI: 10.1109/JSTARS.2015.2437371].
- 716 13. S. Faroux, A. T. KaptuéTchuenté, J. L. Roujean, V. Masson, E. Martin, AND P. Le Moigne,
717 “ECOCLIMAP-II/ Europe: A twofold database of ecosystems and surface parameters at 1 km
718 resolution based on satellite information for use in land surface, meteorological and climate models,”
719 *Geosci. Model Dev.*, **6**, 563–582 (2013).

- 720 14. M. A. Friedl, D. Sulla-Menashe, B. Tan, A. Schneider, N. Ramankutty, A. Sibley, and X. Huang,
721 “MODIS Collection 5 global land cover: Algorithm refinements and characterization of new
722 datasets,” *Remote Sens. Environ.*, **114**, 168–182 (2010).
- 723 15. P. Gong, J. Wang, L. Yu, Y. Zhao, Y. Zhao, L. Liang, Z. Niu, X. Huang, H. Fu, S. Liu et al. “Finer
724 resolution observation and monitoring of global land cover: First mapping results with Landsat TM
725 and ETM+ data,” *Int. J. Remote Sens.*, **34**, 2607–2654 (2013).
- 726 16. J. L. Champeaux, V. Masson, and F. Chauvin, “Ecoclimap: A global database of land surface
727 parameters at 1 km resolution,” *Meteorol. Appl.*, **12**, 29–32 (2005), *ISPRS Int. J. Geo-Inf.*, **6**, 112 17
728 of 17(2017).
- 729 17. M. Friedl, and D. Sulla-Menashe, *MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3*
730 *Global 500m SIN Grid V006* [Data set], NASA EOSDIS Land Processes DAAC,
731 (2015), [doi:10.5067/MODIS/MCD12Q1.006]
- 732 18. J. Chen, J. Chen, A. Liao, X. Cao, L. Chen, X. Chen, C. He, G. Han, S. Peng, M. Lu et al. “Global
733 land cover mapping at 30 m resolution: A POK-based operational approach,” *ISPRS J. Photogramm.*
734 *Remote Sens.*, **103**, 7–27 (2015).
- 735 19. J. J. Arsanjani, A. Tayyebi, and E. Vaz, “GlobeLand30 as an alternative fine-scale global land cover
736 map: Challenges, possibilities, and implications for developing countries,” *Habitat Int.*, **55**, 25–
737 31(2016).
- 738 20. C. Giri, B. Pengra, J. Long, and T. R. Loveland, “Next generation of global land cover
739 characterization, mapping, and monitoring,” *Int. J. Appl. Earth Obs. Geoinf.*, **25**, 30–37(2013).
- 740 21. A. H. Strahler, L. Boschetti, G.M. Foody, M. A. Friedl, M. C. Hansen, M. Herold, P. Mayaux, J. T.
741 Morisette, S. V. Stehman, and C. E. Woodcock, “Global Land Cover Validation: Recommendations
742 for Evaluation and Accuracy Assessment of Global Land Cover Maps,” *European Communities:*
743 *Luxembourg City, Luxembourg*, (2006).

- 744 22. Y. Bai, M. Feng, H. Jiang, J. Wang, Y. Zhu, and Y. Liu, "Assessing consistency of five global land
745 cover data sets in China," *Remote Sens.*, **6**, 8739–8759 (2014).
- 746 23. Y. Ran, X. Li, and L. Lu, "Evaluation of four remote sensing based land cover products over china,"
747 *Int. J. Remote Sens.*, **31**, 391–401(2010).
- 748 24. A. T. KaptuéTchuenté, J. L. Roujean, and S. M. de Jong, "Comparison and relative quality
749 assessment of the GLC2000, GLOBCOVER, MODIS and ECOCLIMAP land cover data sets at the
750 African continental scale," *Int. J. Appl. Earth Observ. Geoinf.*, **13**, 207–219 (2011).
- 751 25. I. McCallum, M. Obersteiner, S. Nilsson, and A. Shvidenko, "A spatial comparison of four satellite
752 derived 1km global land cover datasets," *Int. J. Appl. Earth Obs. Geoinf.*, **8**, 246–255 (2006).
- 753 26. R. Latifovic, and I. Olthof, "Accuracy assessment using sub-pixel fractional error matrices of global
754 land cover products derived from satellite data," *Remote Sens. Environ.*, **90**, 153–165 (2004).
- 755 27. X. Ye, J. Zhao, L. Huang, D. Zhang, and Q. Hong, "A comparison of four global land cover maps on
756 a provincial scale based on China's 30 m globeland30," *In Proceedings of the International
757 Conference on Geo-Informatics in Resource Management and Sustainable Ecosystems*, Hong Kong,
758 China, 18–20 November; pp. 447–455 (2016).
- 759 28. S. Fritz and L. See, "Identifying and quantifying uncertainty and spatial disagreement in the
760 comparison of global land cover for different applications," *Glob. Chang. Biol.*, **14**, 1057–1075
761 (2008).
- 762 29. E. Lambin, B. Turner, H. Geist, S. Agbola, A. Angelsen, J. Bruce, O. Coomes, R. Dirzo, G. Fischer,
763 C. Folke et al. "The causes of land-use and land-cover change, moving beyond the myths," *Glob.
764 Environ.Chang.*, **11**, 261–269 (2001).
- 765 30. E. Lepers, E. Lambin, A. Janetos, R. DeFries, F. Achard, N. Ramankutty, and R. A. Scholes, "A
766 synthesis of information on rapid land-cover change for the period 1981–2000," *BioScience*, **55**, 115–
767 124 (2005).

- 768 31. Food and Agriculture Organization of the United Nations Regional Office for Asia and the Pacific,
769 FAO, *Statistical Yearbook 2014: Asia and the Pacific Food and Agriculture*, Food and Agriculture
770 Organization of the United Nations Regional Office for Asia and the Pacific: Bangkok, Thailand,
771 (2014).
- 772 32. M. Hasan, M. Hossain, M. Bari, and M. Islam, “Agricultural Land Availability in Bangladesh, *SRDI*,
773 *Ministry of Agriculture*, Dhaka, Bangladesh, p. 42. ISBN 978-984-33-6141-7 (2013).
- 774 33. Population Reference Bureau, *World Population Data Sheet with a Special Focus on Human Needs*
775 *and Sustainable Resources*, Population Reference Bureau: Washington, DC, USA, (2016).
- 776 34. S. S. Hasan, X. Deng, Z. Li, and D. Chen, “Projections of Future Land Use in Bangladesh under the
777 Background of Baseline, Ecological Protection and Economic Development,” *Sustainability*, **9**, 505
778 (2017).
- 779 35. S. Islam and M. Ma, “Geospatial Monitoring of Land Surface Temperature Effects on Vegetation
780 Dynamics in the Southeastern Region of Bangladesh from 2001 to 2016,” *ISPRS Int. J. Geo-Inf.*, **7**,
781 486 (2018) [doi:10.3390/ijgi7120486].
- 782 36. R. Rai, Y. Zhang, B. Paudel, S. Li, and N. R. Khanal, “A Synthesis of Studies on Land Use and Land
783 Cover Dynamics during 1930–2015 in Bangladesh,” *Sustainability*, **9**, 1866 (2017).
- 784 37. D. M. Olson, “Terrestrial Ecoregions of the World: A new map of life on earth,” *Bioscience*, **51**, 933–
785 938 (2001).
- 786 38. N. Myers, R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, and J. Kent, “Biodiversity
787 hotspots for conservation priorities,” *Nature*, **403**, 853–858 (2000).
- 788 39. Bangladesh National Portal, *Chittagong Division*, Cabinet Division, Government of the People’s
789 Republic of Bangladesh. Available online: [http://www.chittagongdiv.gov.bd/site/page/98079ea0-](http://www.chittagongdiv.gov.bd/site/page/98079ea0-2144-11e7-8f57-286ed488c766)
790 [2144-11e7-8f57-286ed488c766](http://www.chittagongdiv.gov.bd/site/page/98079ea0-2144-11e7-8f57-286ed488c766) (accessed on 11 May 2018).
- 791 40. S. Miah, *Banglapedia: National Encyclopedia of Bangladesh*, 2nd ed., Islam, S., Ahmed, A.J., Eds.;
792 Asiatic Society of Bangladesh: Dhaka, Bangladesh (2012).

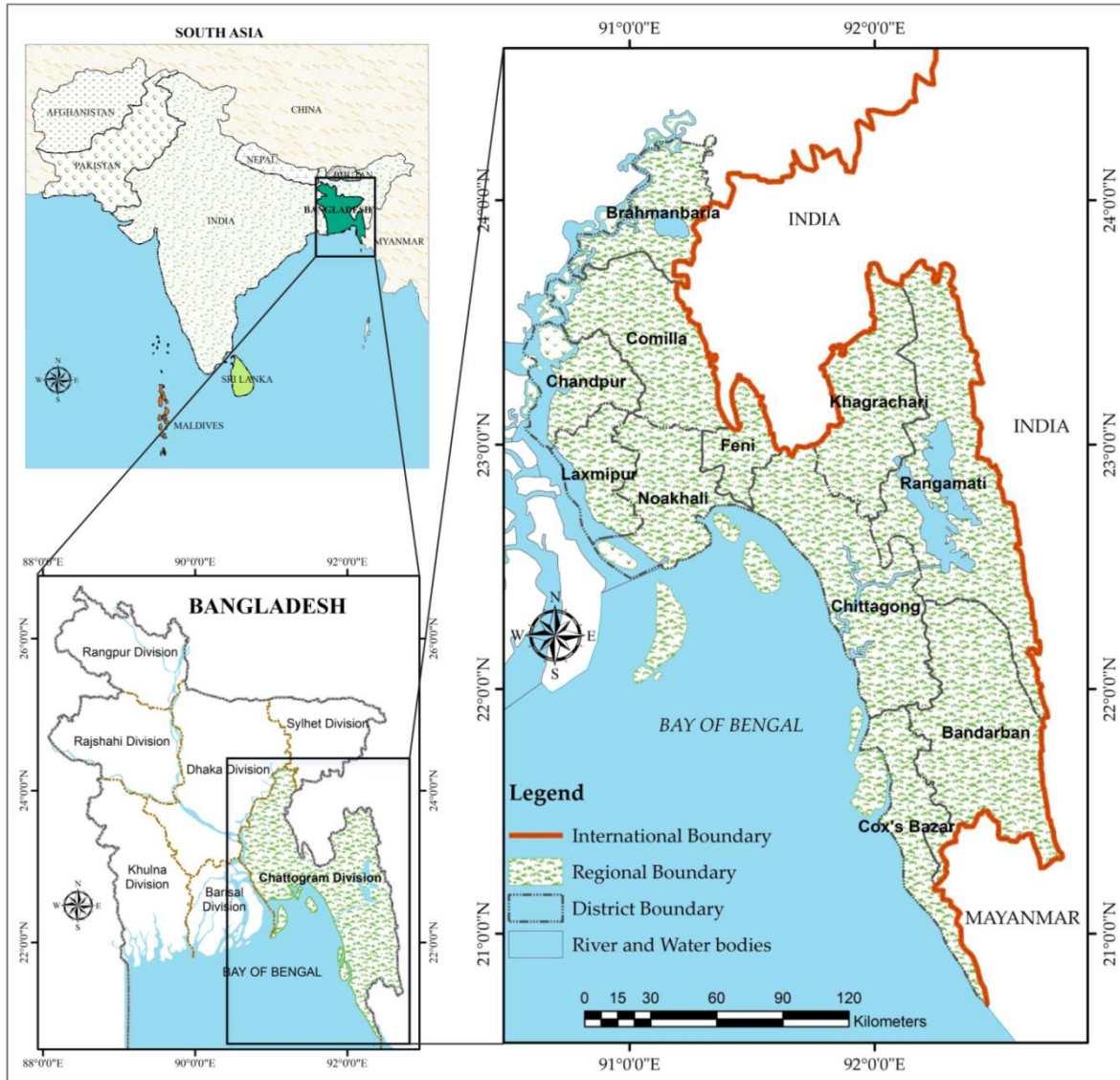
- 793 41. BBS, *Population Census 2011*, Bangladesh Bureau of Statistics, Government People’s Republic of
794 Bangladesh, Dhaka, Bangladesh (2011).
- 795 42. A. Dewan and R. Corner, “Dhaka Megacity: Geospatial Perspectives on Urbanisation, Environment
796 and Health,” *Springer*, New York, NY, USA (2014).
- 797 43. J. Chen, X. Cao, S. Peng, and H. Ren, “Analysis and Applications of GlobeLand30: A
798 Review,” *ISPRS Int. J. Geo-Inf.*, **6**, 230 (2017).
- 799 44. NASA’s Earth Observing System Data and Information System, Available online:
800 <https://search.earthdata.nasa.gov/search?q=MCD12Q1&ok=MCD12Q1> (assessed on 12 January
801 2019)
- 802 45. National Geomatics Center of China, Available online:
803 <http://www.globallandcover.com/GLC30Download/download.aspx> (assessed on 7 December 2019)
- 804 46. Center for Earth System Science, Tsinghua University, Available online:
805 <http://data.ess.tsinghua.edu.cn/> (assessed on 15 January 2019)
- 806 47. USGS Global Visualization Viewer (GloVis). Available online: <https://glovis.usgs.gov/> (assessed on
807 21 January 2019)
- 808 48. M. Zhang, M. Ma, P. De Maeyer, and A. Kurban, “Uncertainties in Classification System Conversion
809 and an Analysis of Inconsistencies in Global Land Cover Products,” *ISPRS Int. J. Geo-Inf.*, **6**, 112
810 (2017).
- 811 49. J. R. Jensen, *Introductory digital image processing: a remote sensing perspective*, 3rd ed., Bergen
812 (NJ): Pearson Prentice Hall (2005).
- 813 50. Bangladesh Bureau of Statistics, *Yearbook of Agricultural Statistics-2015*, Bangladesh Bureau of
814 Statistics (BBS), Statistics and Informatics Division (SID): Dhaka, Bangladesh, (2016).
- 815 51. G. M. Islam, A. K. Islam, A. A. Shopan, M. M. Rahman, A. N. Lazar, and A. Mukhopadhyay,
816 “Implications of agricultural land use change to ecosystem services in the Ganges delta,” *J. Environ.*
817 *Manag.*, **161**, 443–452 (2015).

- 818 52. M. Malek, M. Hossain, R. Saha, and F. Gatzweiler, "Mapping Marginality Hotspots and Agricultural
819 Potentials in Bangladesh," *University of Bonn*, Bonn, Germany, pp. 1–30 (2013).
- 820 53. A. Alam, M. Chowdhury, and I. Sobhan, *Biodiversity of Tanguar Haor: A Ramsar Site of*
821 *Bangladesh*, Wildlife: International Union for Conservation of Nature, **Volume I**, Dhaka,
822 Bangladesh, pp. 1–234 (2012).
- 823 54. S. Khondoker, M. L. Hossain, and K. A. H. Moni, "Wetland management in Bangladesh: A study on
824 BeelBakar," *Agric. For. Fish.*, **3**, 320–328 (2014).
- 825 55. T. Majumder, S. K. Mazumder, M. M. Monwar, and L. Basak, "Towards climate change resilient of
826 Hail Haor, Sylhet: Reviewing the role of the co-management approach," *IOSR J. Agric. Vet. Sci.*, **5**,
827 59–66 (2013).
- 828 56. P. Potapov, "Comprehensive monitoring of Bangladesh tree cover inside and outside of forests,
829 2000–2014" *Environ. Res. Lett.*, **12**, 104015 (2017).
- 830 57. M. A. Quasem, "Conversion of agricultural land to non-agricultural uses in Bangladesh: Extent and
831 determinants," *Bangladesh Dev. Stud.*, **34**, 59–85 (2011).
- 832 58. M. Uddin, M. Anwar, M. Rahman, and M. Mobin, "An investigation on the pattern of land use
833 change in Dhaka city using remote sensing and GIS application," *J. Environ. Sci. Nat. Resour.*, **7**,
834 105–109 (2014).
- 835 59. A. Ahmed, and S. H. Hussain, "Changing Urban Land use and Agricultural Land Transformation: A
836 Case Study of Narayanganj City," *ASA Univ. Rev.*, **6**, 237–284 (2012).
- 837 60. S. Roy, K. Farzana, M. Papia, and M. Hasan, "Monitoring and Prediction of Land Use/Land Cover
838 Change using the Integration of Markov Chain Model and Cellular Automation in the Southeastern
839 Tertiary Hilly Area of Bangladesh," *Int. J. Sci. Basic Appl. Res.*, **24**, 125–148 (2015).
- 840 61. Food and Agriculture Organization of the United Nations FAO, *Bangladesh Food Security Brief;*
841 *World Food Programme, Vulnerability Analysis and Mapping Unit WFP*, Dhaka, Bangladesh,
842 (2005).

- 843 62. M. Begum, and L. D’Haese, “Supply and demand situations for major crops and food items in
844 Bangladesh,” *J. Bangladesh Agric. Univ.*, **8**, 91–102 (2010).
- 845 63. M. Kashem, and M. A. Faroque, “Country Scenarios of Food Security and Governance in
846 Bangladesh,” *J. Sci. Found*, **9**, 41–50 (2011).
- 847 64. MOEF (2012), “Government of the People’s Democratic Republic of Bangladesh. Second National
848 Communication to the UNFCCC,” Ministry of Environment and Forests.
849 <http://unfccc.int/resource/docs/natc/bgdnc2.pdf>.
- 850 65. A. Zeleke, “Role of Agriculture, Forestry and Other Land Use Mitigation in INDCs and National
851 Policy in Asia,” *LEDS, Agriculture, Forestry and Other Land Use (AFOLU) Working Group*, (2016).
- 852 66. R. Magnani, L. Oot, K. Sethuraman, G. Kabir, and S. Rahman, “USAID Office of Food for Peace
853 Food Security Country Framework for Bangladesh (FY 2015–2019),” *Food and Nutrition Technical
854 Assistance III Project*, Washington, DC, USA, pp. 1–69 (2015).
- 855 67. B. Rimal, L. Zhang, H. Keshtkar, N. Wang, and Y. Lin, “Monitoring and Modeling of Spatiotemporal
856 Urban Expansion and Land-Use/Land-Cover Change Using Integrated Markov Chain Cellular
857 Automata Model,” *ISPRS Int. J. Geo-Inf.*, **6**, 288 (2017).
- 858 68. Bangladesh Bureau of Statistics, *Population and Housing Census-2011; Bangladesh Bureau of
859 Statistics (BBS)*, Ministry of Planning, Statistics and Informatics Division (SID), Dhaka, Bangladesh,
860 pp. 1–640 (2014).
- 861 69. K. Uddin, D. Gurung, “Land cover change in Bangladesh- a knowledge based classification
862 approach,” *In Proceedings of the 10th International Symposium on High Mountain Remote Sensing
863 Cartography ICIMOD*, Kathmandu, Nepal, 8–11 September, pp. 41–46 (2008).
- 864 70. C. S. Reddy, S. V. Pasha, C. S. Jha, P. G. Diwakar, V. K. Dadhwal, “Development of national
865 database on long-term deforestation (1930–2014) in Bangladesh,” *Glob. Planet. Chang*, **139**, 173–
866 182 (2016).

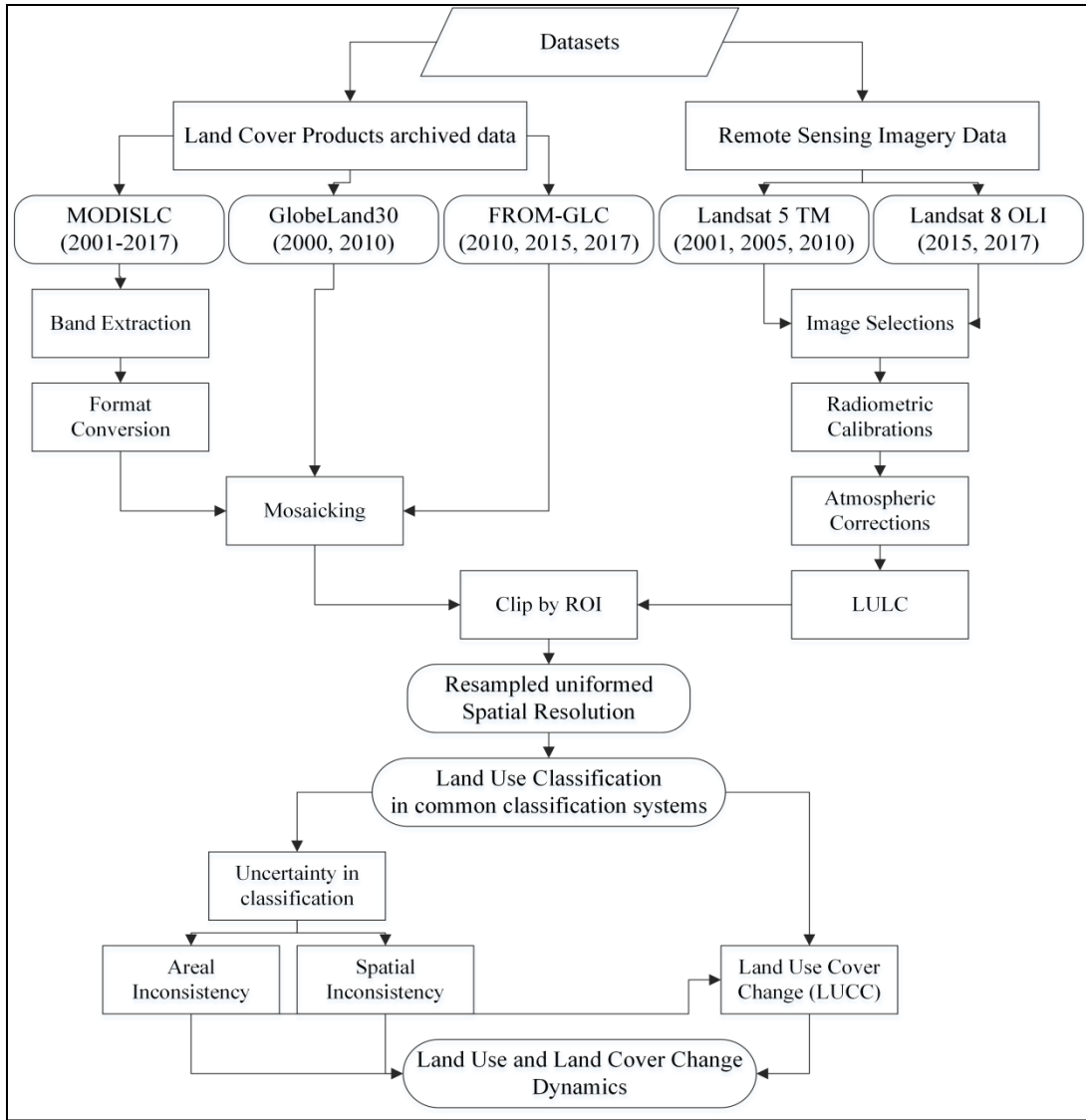
- 867 71. Food and Agriculture Organization of the United Nations (FAO), *Global Forest Resources*
868 *Assessment 2010 Country Reports, Bangladesh*, Forestry Department, Food and Agriculture
869 Organization of the United Nations: Rome, Italy (2010).
- 870 72. Anita, Wahida Musara. Status of Climate Finance and NAMA in Bangladesh. Ministry of
871 Environment and Forest. Regional Workshop on NAMA.
872 http://unfccc.int/files/focus/mitigation/application/pdf/bangladesh_regional_workshop_on_nama.pptx
873 [- revised.pdf](#).
- 874 73. MOEF (2009), Government of the People's Republic of Bangladesh. Bangladesh Climate Change
875 Strategy and Action Plan (BCCSAP) for 2009- 2018. Ministry of Environment and Forests.
876 https://cmsdata.iucn.org/downloads/bangladesh_climate_change_strategy_and_action_plan_2009.pdf.

877 **Figure Caption**



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

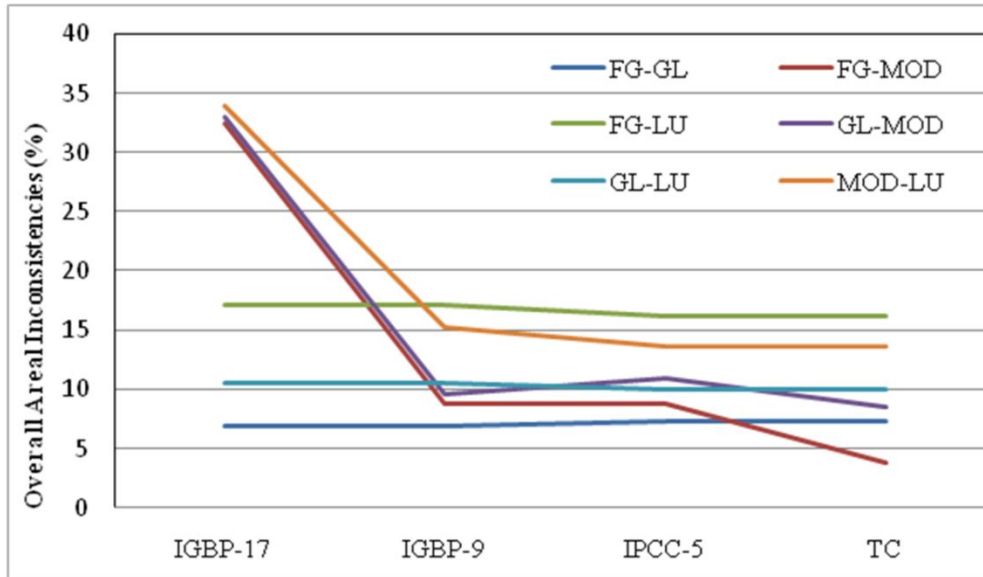


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881 **Fig. 2** Data analysis flowchart. ROI: Region of Interest; LULC: Land Use and Land Cover; LUCC: Land Use Cover

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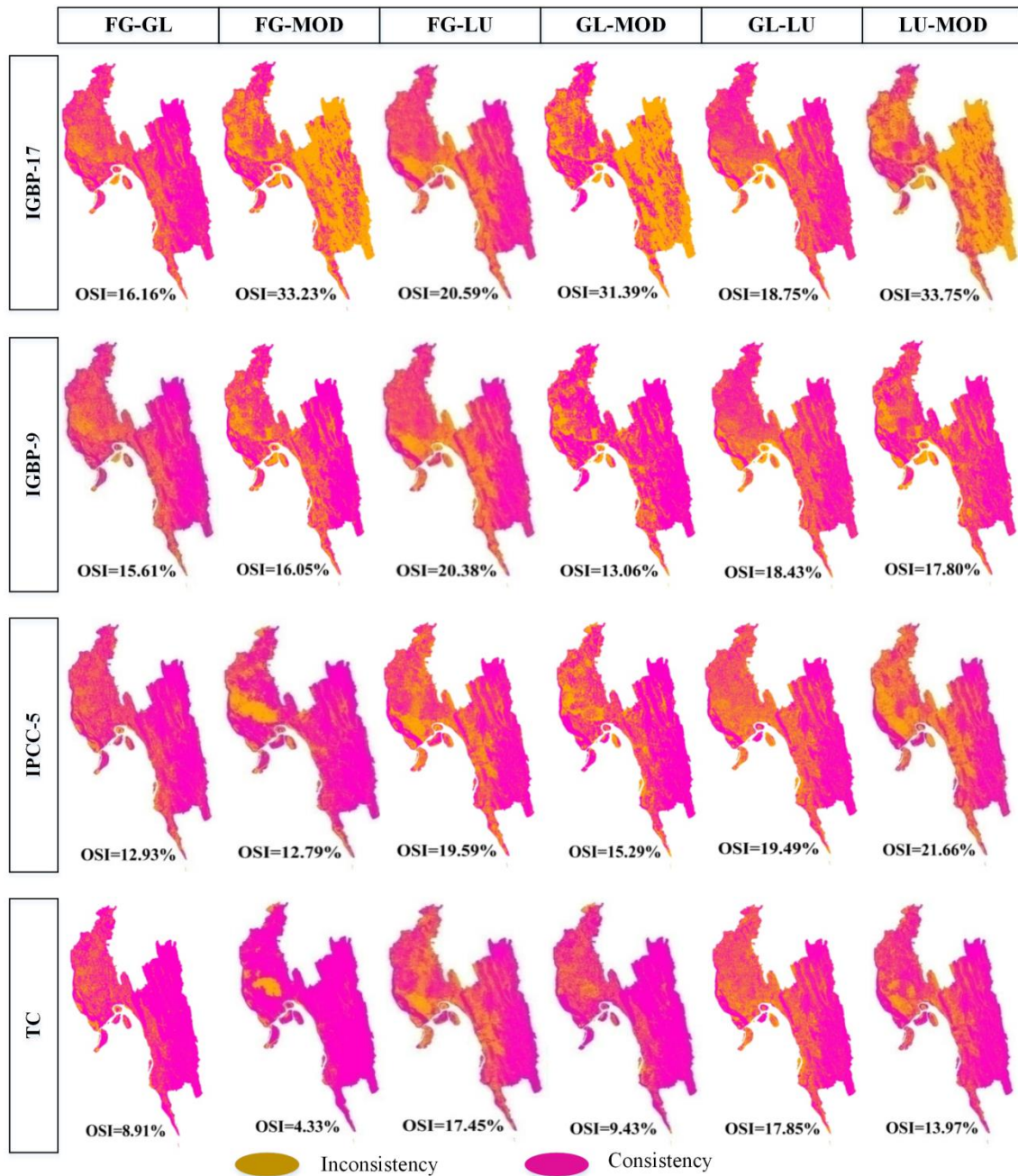
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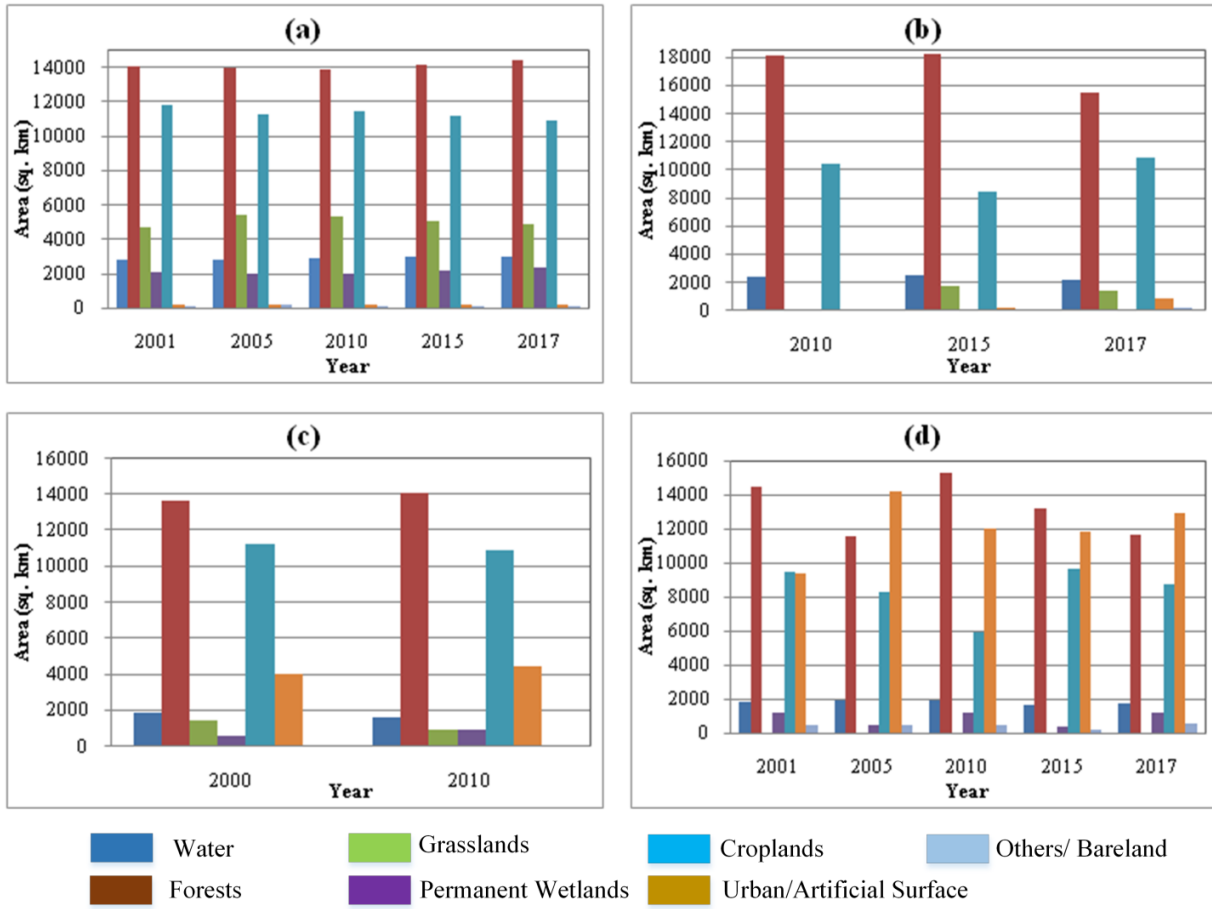
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Fig. 3 Overall areal inconsistencies between pairwise of the FROM-GLC, GlobeLand30, MODISLC, and LULC class of Landsat TM/ETM+ datasets in four common classification systems (FG: FROM-GLC datasets; GL: GlobeLand30 datasets; MOD: MODISLC datasets; and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



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



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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

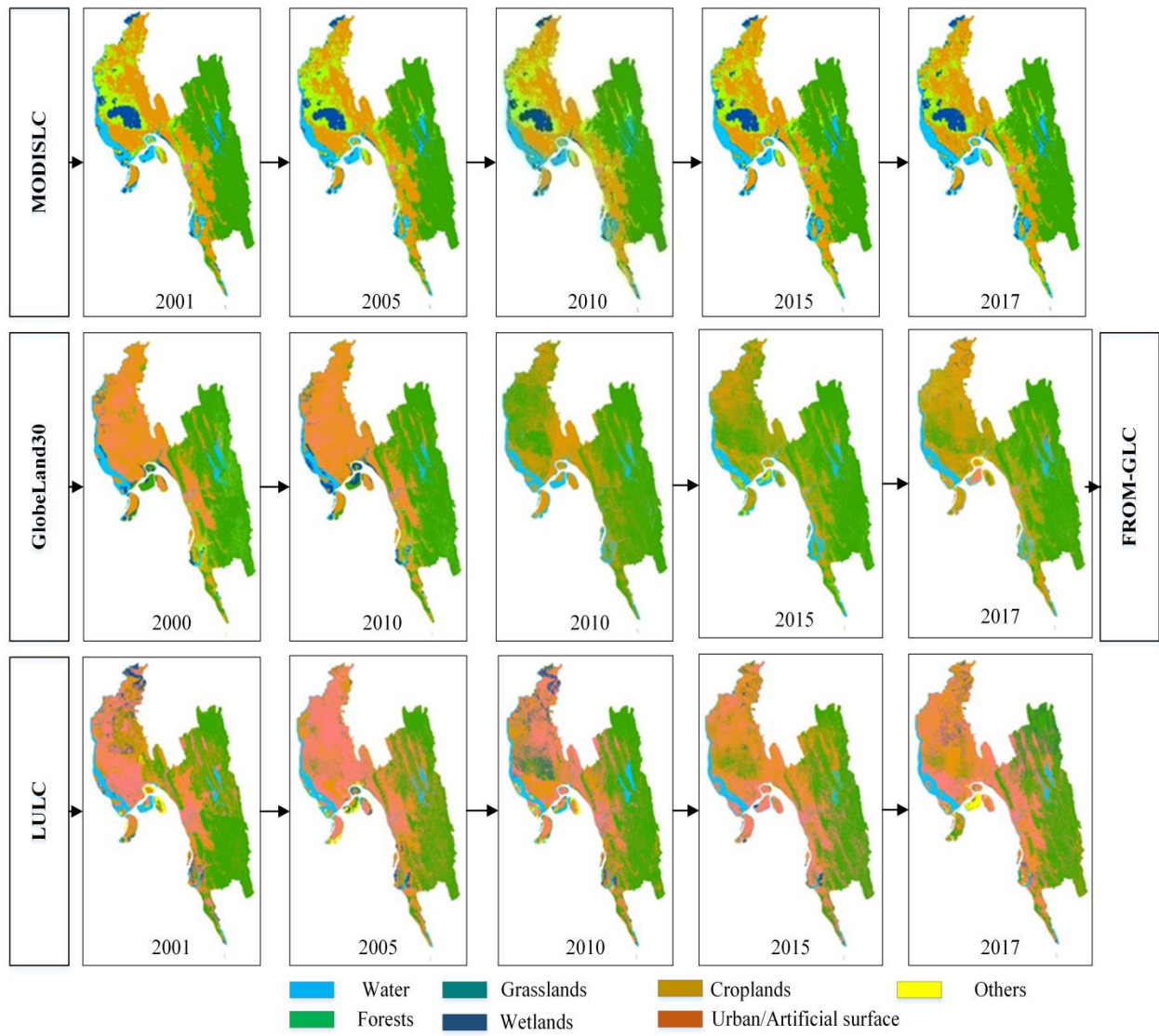
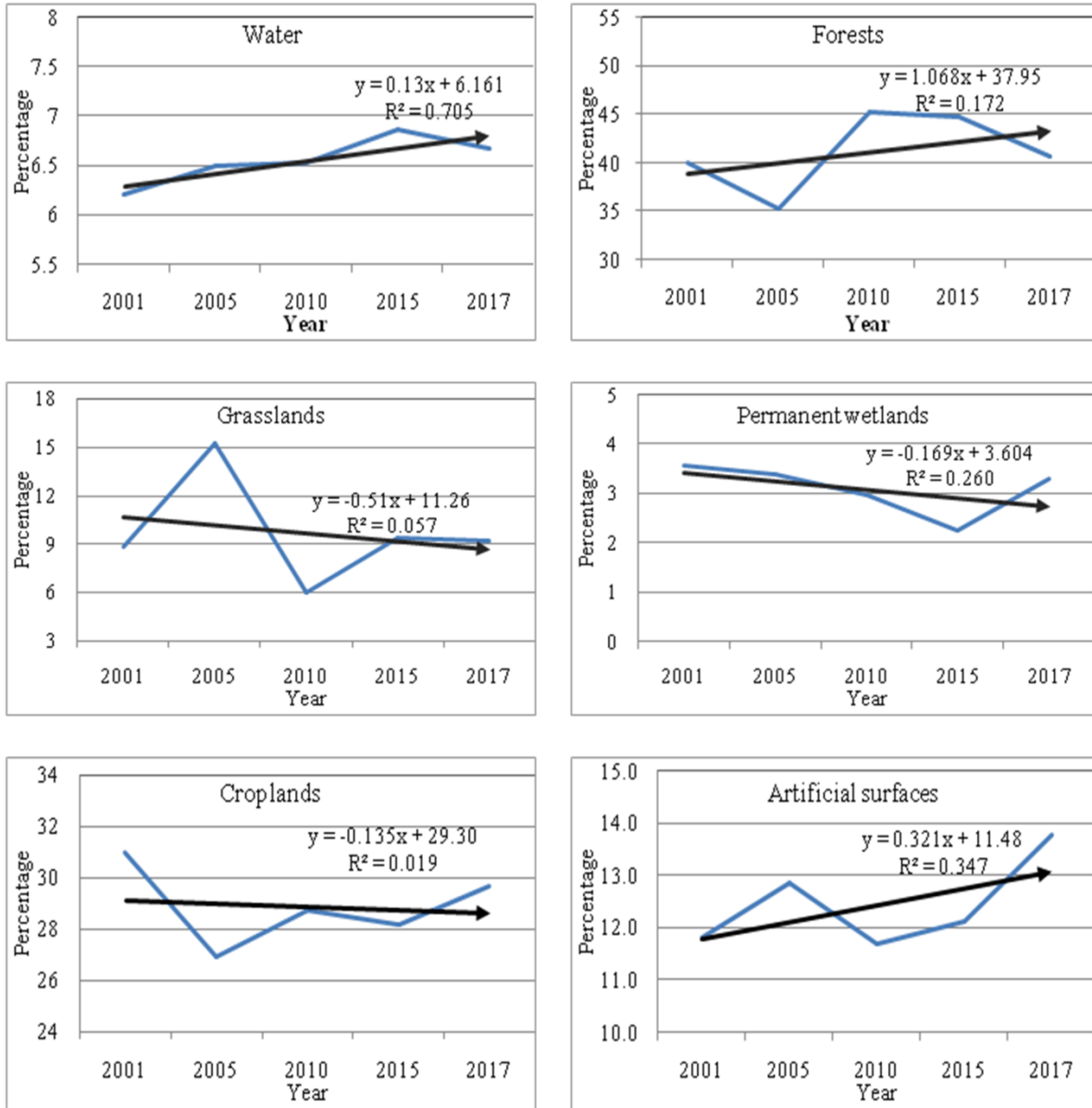


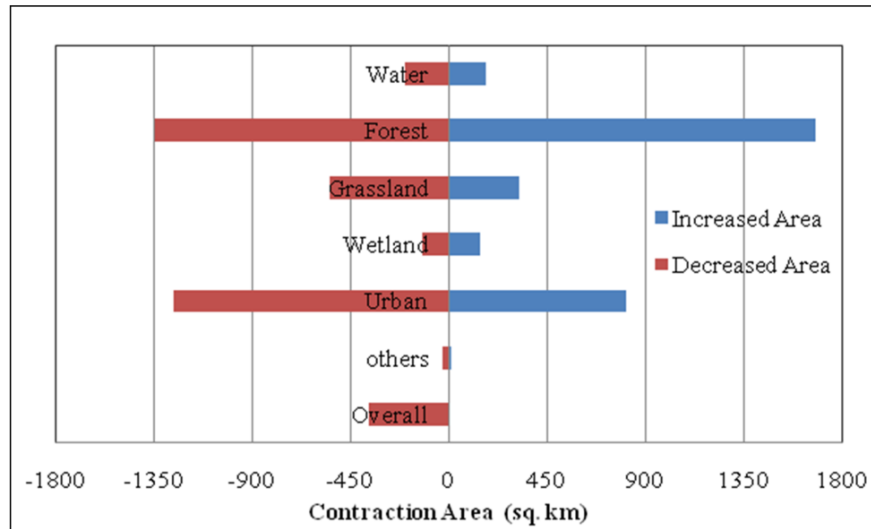
Fig. 6 Land use classification of the southeastern region of Bangladesh from the MODISLC, GlobeLand30, FROM-GLC, and LULC of Landsat imaginary datasets.



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Fig. 7 The different LUC 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 imagery (2001, 2005, 2010, 2015, 2017) datasets.

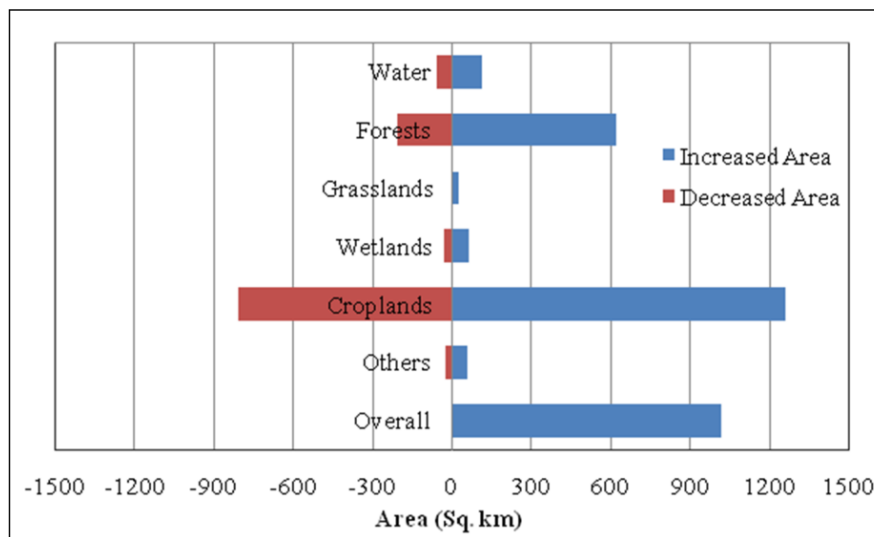


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Fig. 8 The contraction of croplands area with all other LUC classes at the southeastern region of Bangladesh from 2001 to 2017.

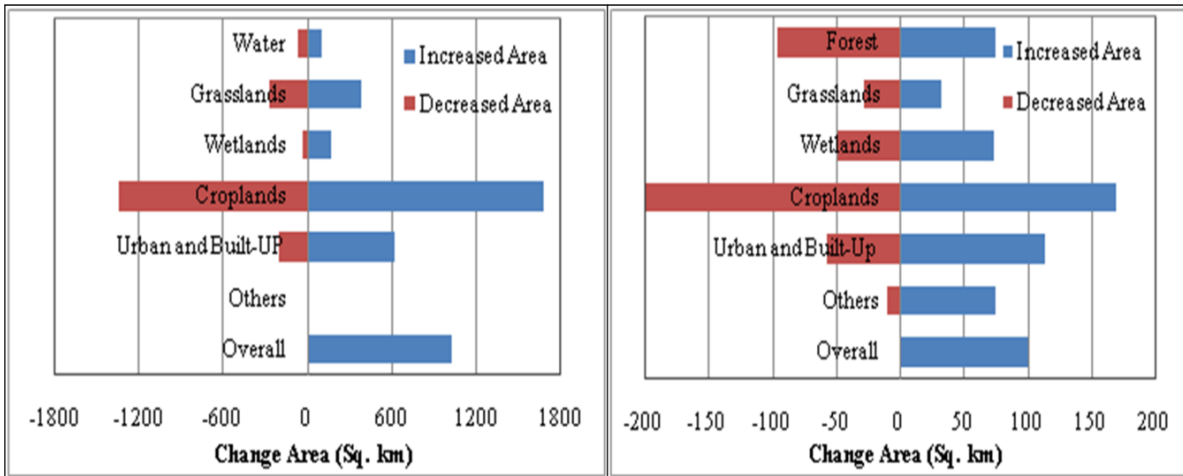


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Fig. 9 The impacts of urban and built-up areas by major land cover classes of the study area from 2001 to 2017 in combination of four different land cover products



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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.