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

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

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

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1 Introduction

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

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/km^2 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.

2   Materials and Methods

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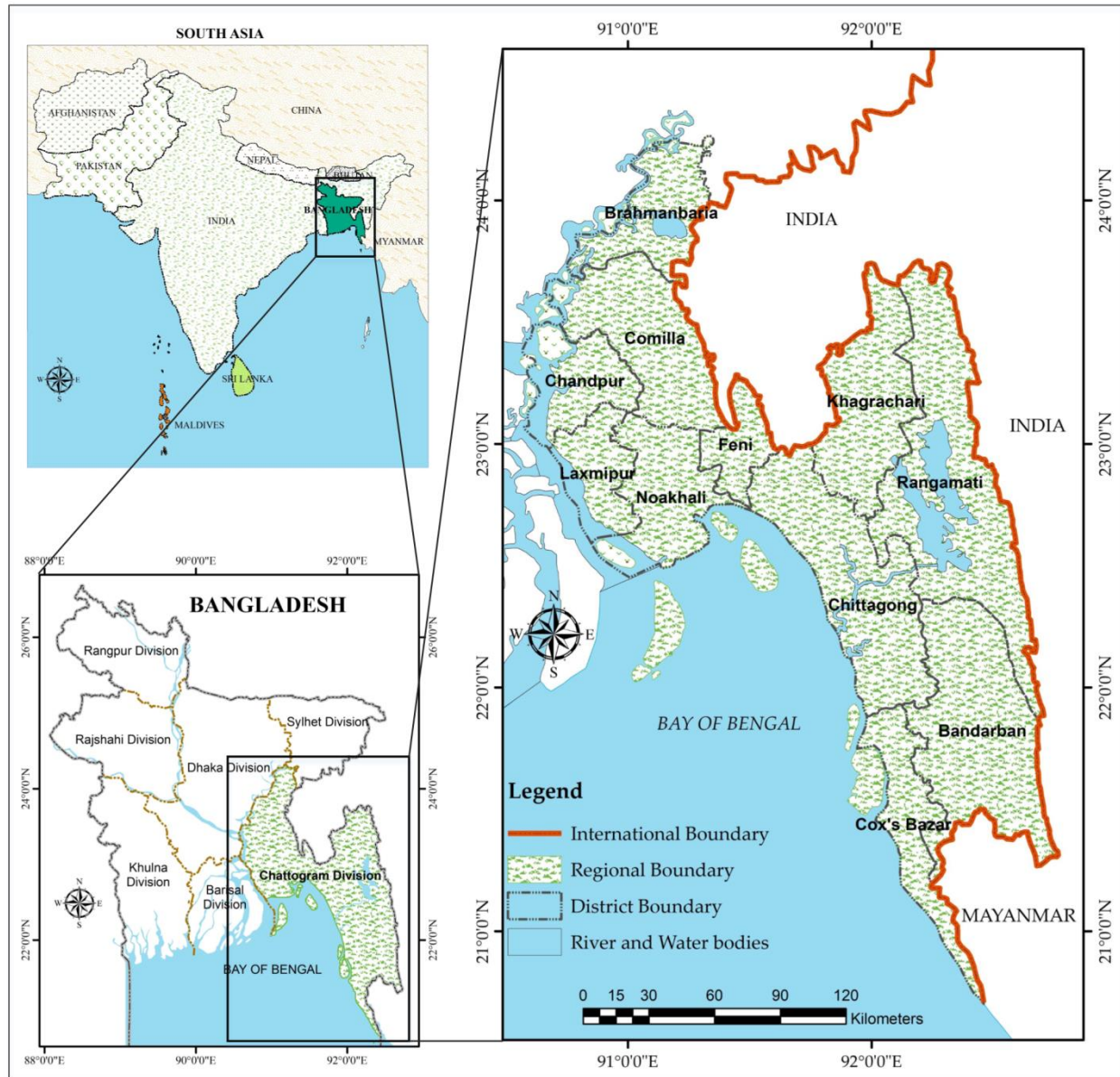
Fig. 1 Location of the study area the Southeastern region of Bangladesh

2.2 Datasets

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

7

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.
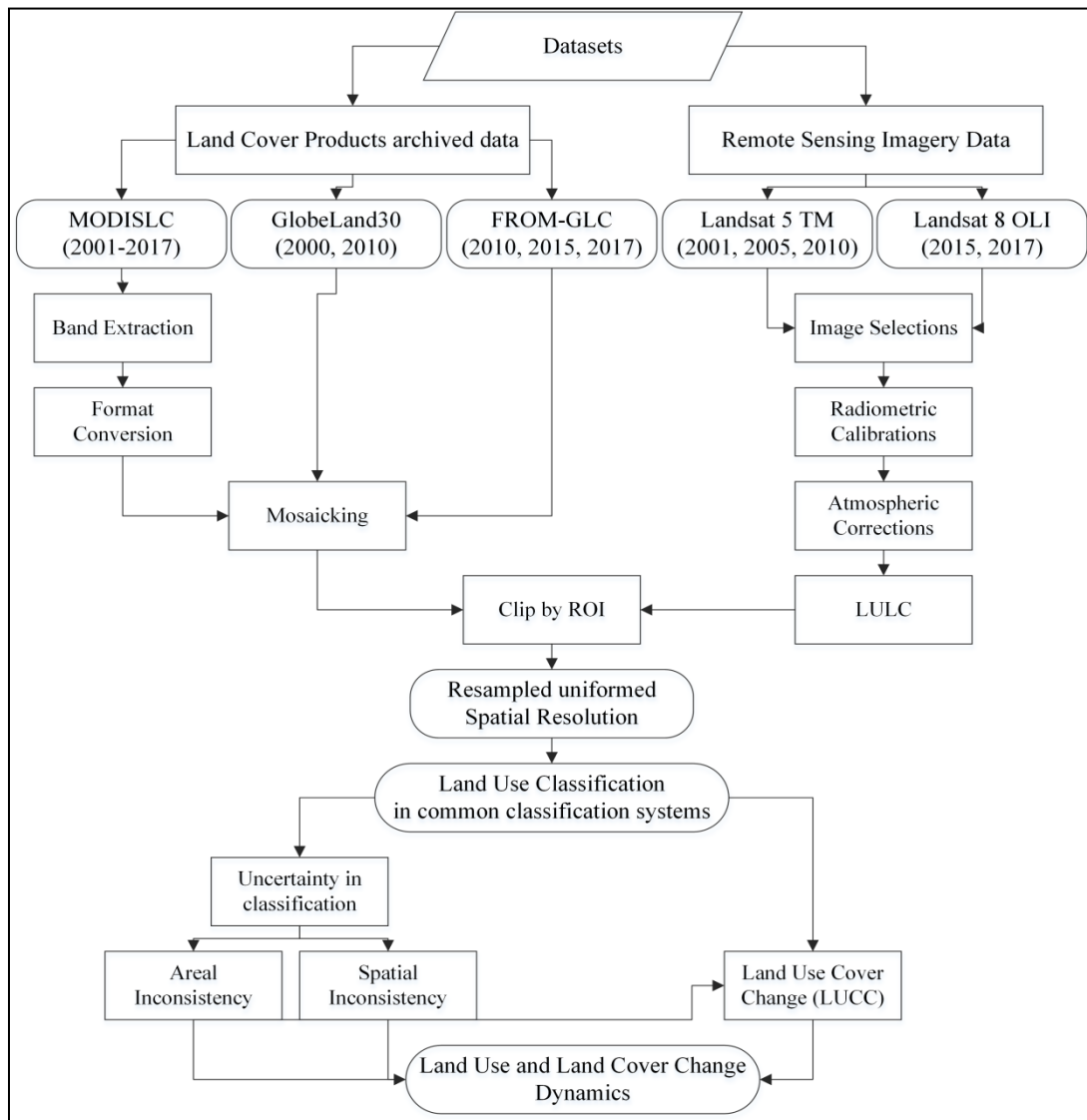
147

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

149   Change.

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.

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

174   [*]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)

11

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 GLCand 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)

14

MODISLC	GlobeLand30	FROM-GLC	LULC	
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
$$U = \frac{N_j}{\sum_i^n N_i} \times 100 \qquad (1)$$

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

247
248 $$OAI = \sum_i^n AIC \tag{3}$$

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

16

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

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.

3 Results

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.

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

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

(FG: FROM-GLC datasets; GL: GlobeLand30 datasets; MOD: MODISLC datasets; and LU: LULC of Landsat TM/ETM+ datasets)
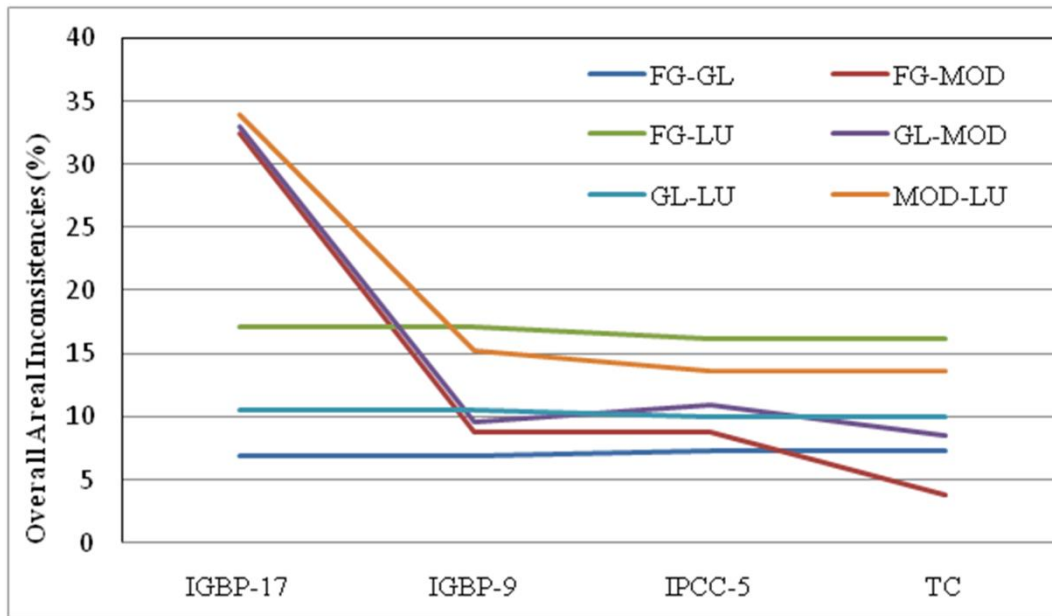
307   Overall areal inconsistencies between pairs of the FROM-GLC, GlobeLand30, MODISLC and

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).

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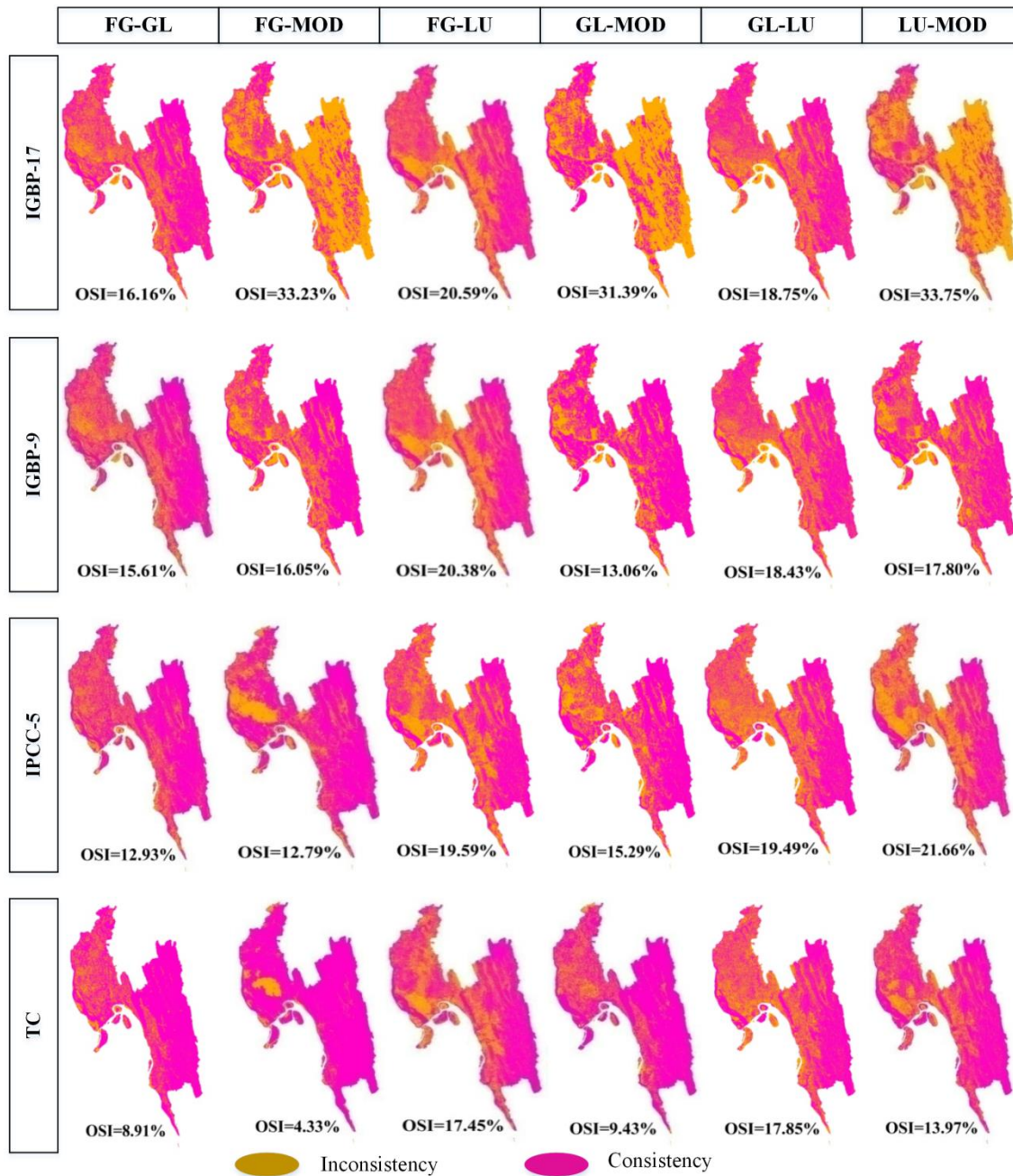
Fig.4 Overall spatial inconsistencies (OSI) in the pairwise comparison of FROM-GLC, GlobeLand30, MODISLC, and LULC datasets in the four common classification systems (FG: FROM-GLC datasets; GL: GlobeLand30 datasets; MOD: MODISLC datasets; and LU: Land use and land cover classes of remote sensing imaginary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

3.3 Land Use Classification

Land use and land cover of the study area southeastern region of Bangladesh from 2001 to 2017 are summarized in Fig. 5. This table is a combined result of land use classification of Landsat

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

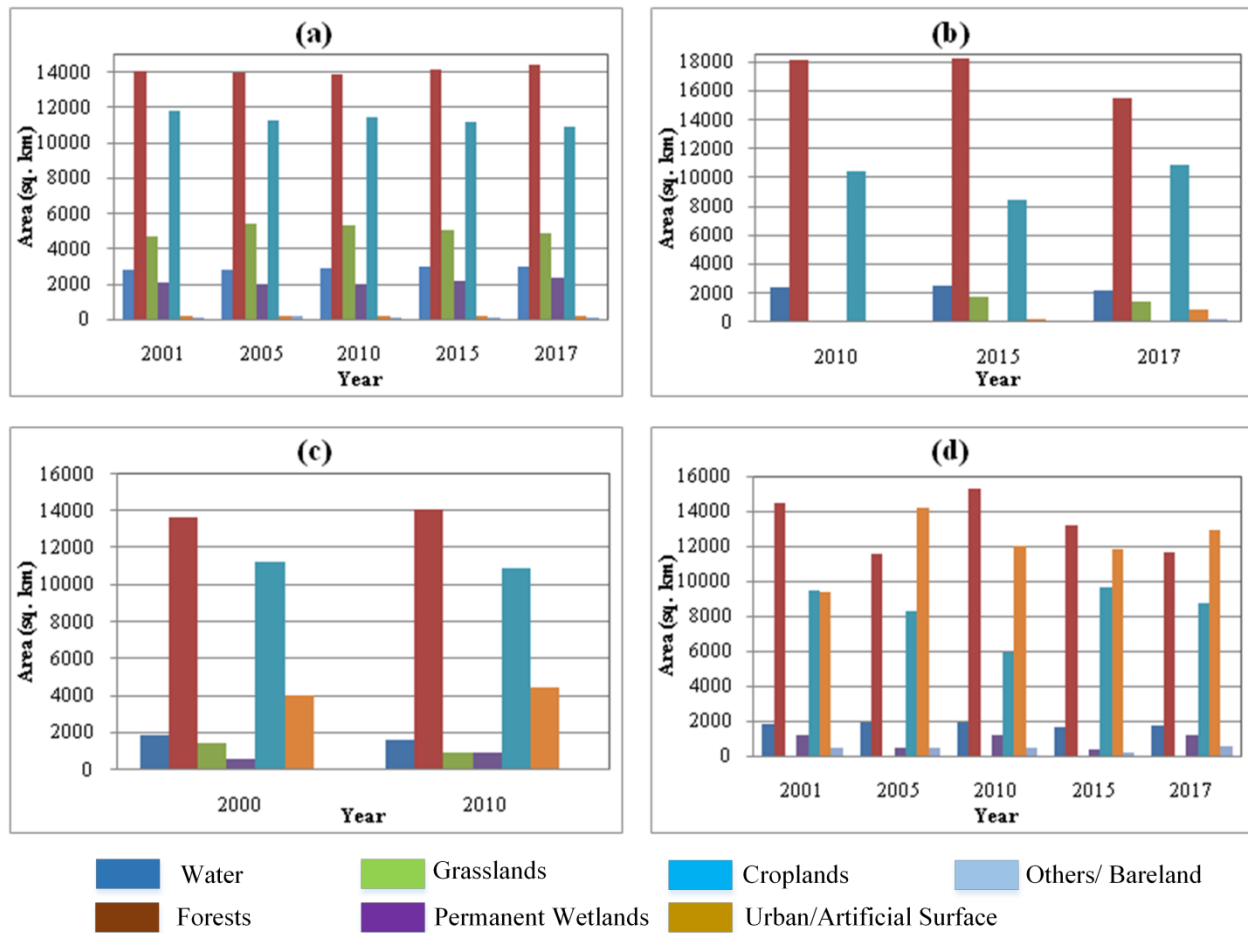367   difficult to definitely differentiate grasslands from agriculture on Landsat images.

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

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

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

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
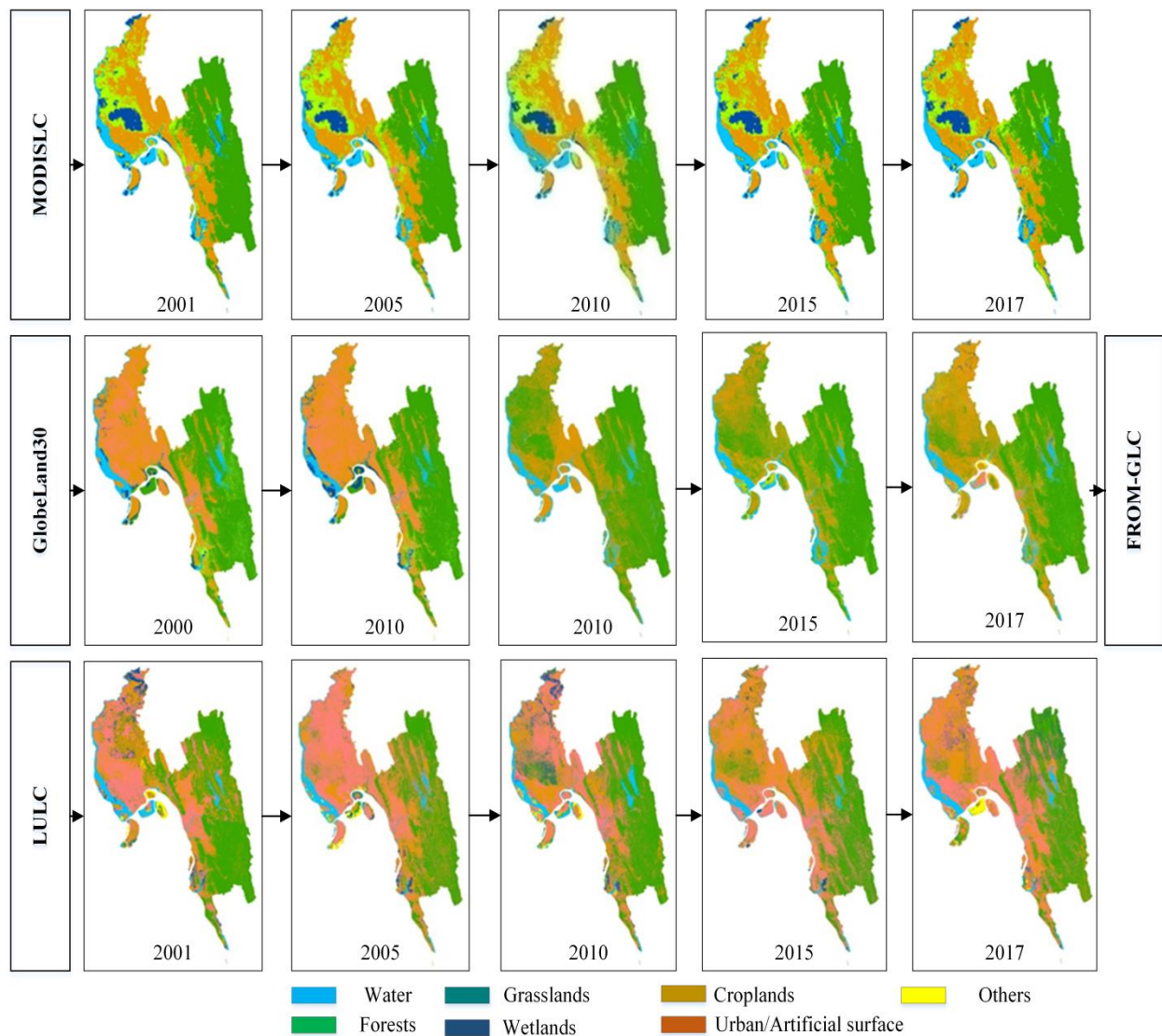
392 with grasslands.

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

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

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

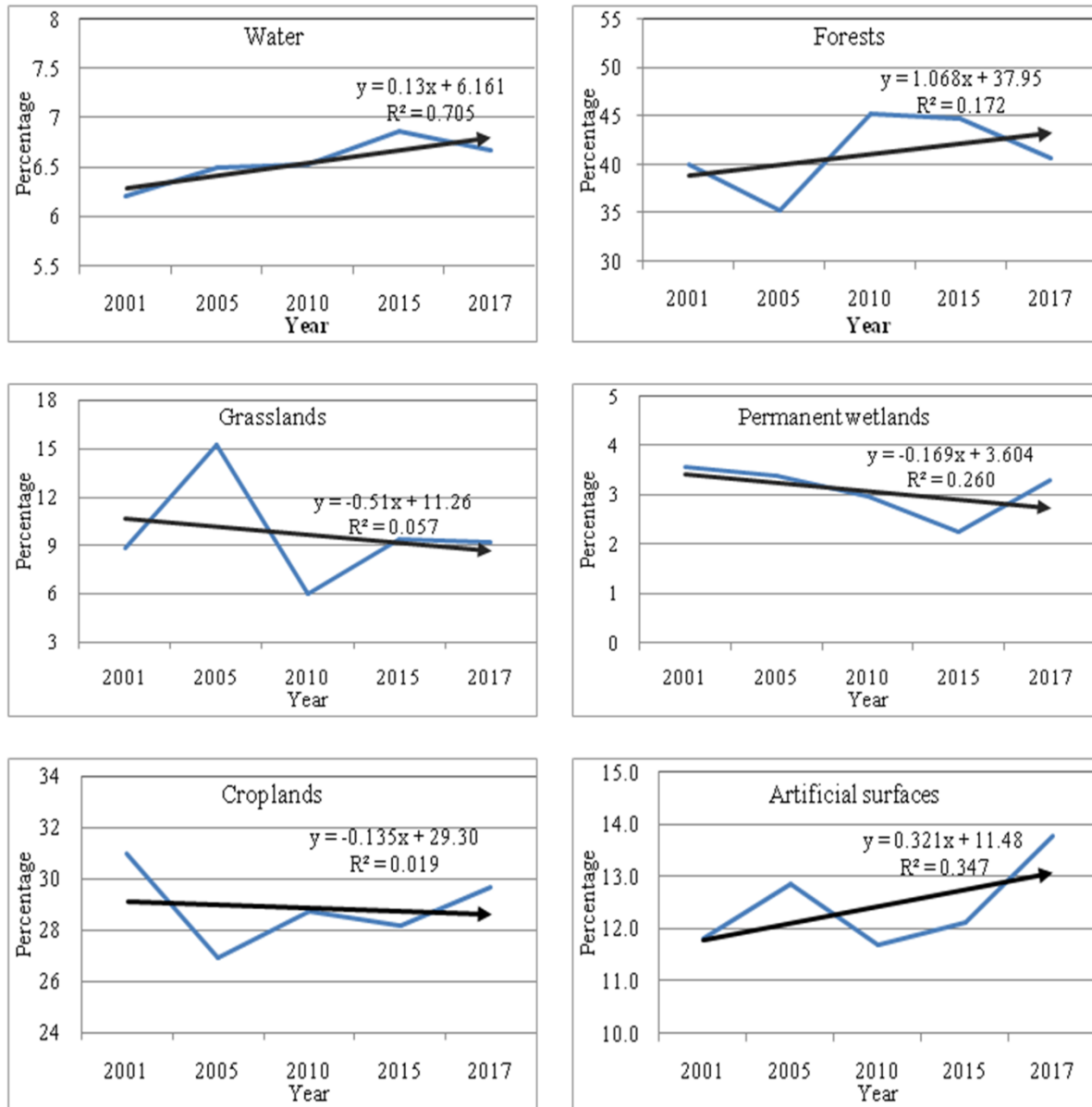423   were increased with a rate of 1.2% ($R^2 = 0.347$) per year during this period of study.

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

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

28

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

| | | **Land Types** | 2017 | | | | | | |
			W	F	GL	PW	CL	IS	Others
FROM-GLC	**2010**	Water	1337.7	163.7	78.0	21.3	446.4	233.6	103.1
		Forest	268.7	11900.8	777.8	38.6	4537.2	215.6	11.9
		Grassland	1.8	52.5	1.8	0.3	15.9	0.5	0.1
		Wetland	0.2	1.1	0.1	0.03	1.24	0.04	0
		Croplands	489.9	3125.6	571.9	52.9	5619.4	353.3	56.0
		Impervious	0.9	0.3	0.1	0.01	0.8	0.3	0.2
		Others	4.5	0.8	1.2	0.1	6.2	1.7	1.5

| | | **Land Types** | 2010 | | | | | | |
			W	F	GL	PW	CL	AS	Others
GlobeLand30	**2000**	Water	1169.8	118.5	18.4	262.9	137.1	10.7	0.1
		Forests	49.0	11491.7	298.0	200.8	191.3	106.4	0.2
		Grasslands	39.6	667.5	376.4	33.1	76.7	65.8	4.0
		Permanent Wetlands	55.8	72.0	0.6	324.0	56.1	5.4	0.1
		Croplands	134.4	316.6	29.1	33.2	8638.5	982.7	0.5
		Artificial surface	21.5	14.1	4.9	5.1	751.9	2877.7	0.4
		Others	0.8	0.9	3.5	1.9	0.5	0.7	5.2

| | | **Land Types** | 2017 | | | | | | |
			W	F	GL	PW	CL	AS	Others
LULC	**2001**	Water	979	17	-	8	92	212	195
		Forests	66	7125	-	425	1882	2164	19
		Grasslands	-	-	-	-	-	-	-
		Permanent Wetlands	44	40	-	94	495	260	11
		Croplands	112	1438	-	284	2081	3705	48
		Artificial surface	204	802	-	118	2485	3887	101
		Others	21	16	-	3	33	233	49

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

4 Discussion

4.1 Pattern of Inconsistencies in Different Land Cover Mapping

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

31

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].
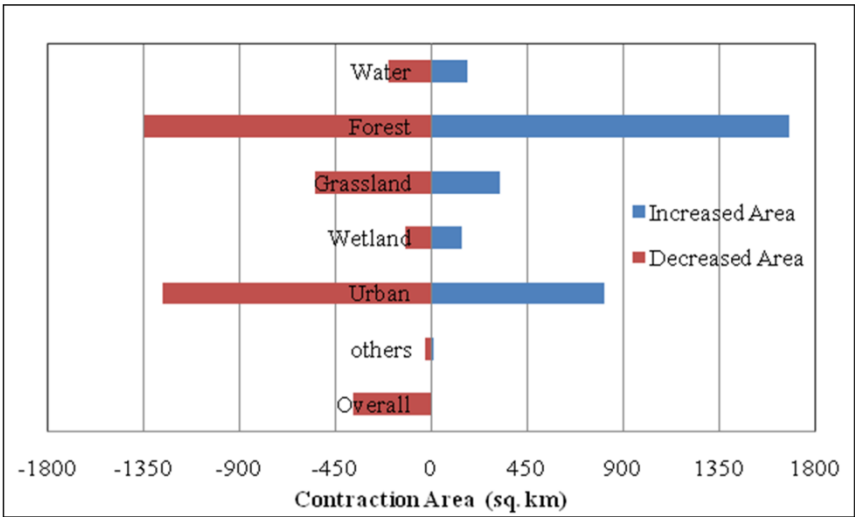
516

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

33

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 tCO_2e, 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   tCO_2e. 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
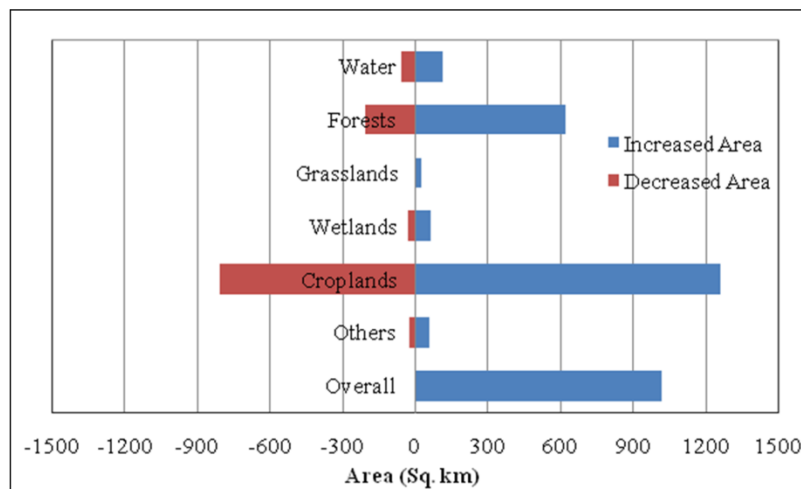
558   with the results.

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

35

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

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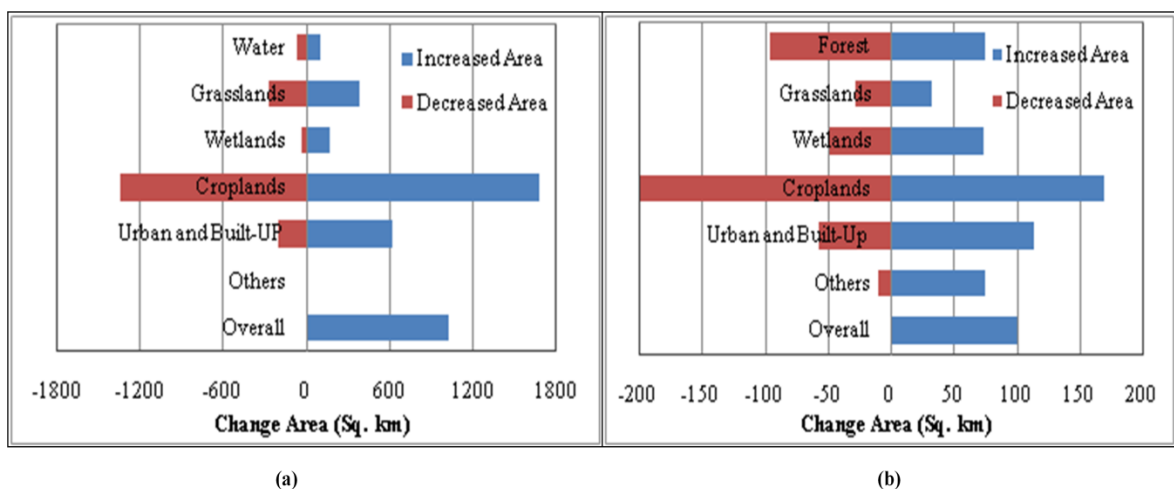

(a)　　　　　　　　　　　　　　　(b)

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

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 imaginary 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.

674 **Acknowledgements:**

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 UNFCC, 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-

790   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**
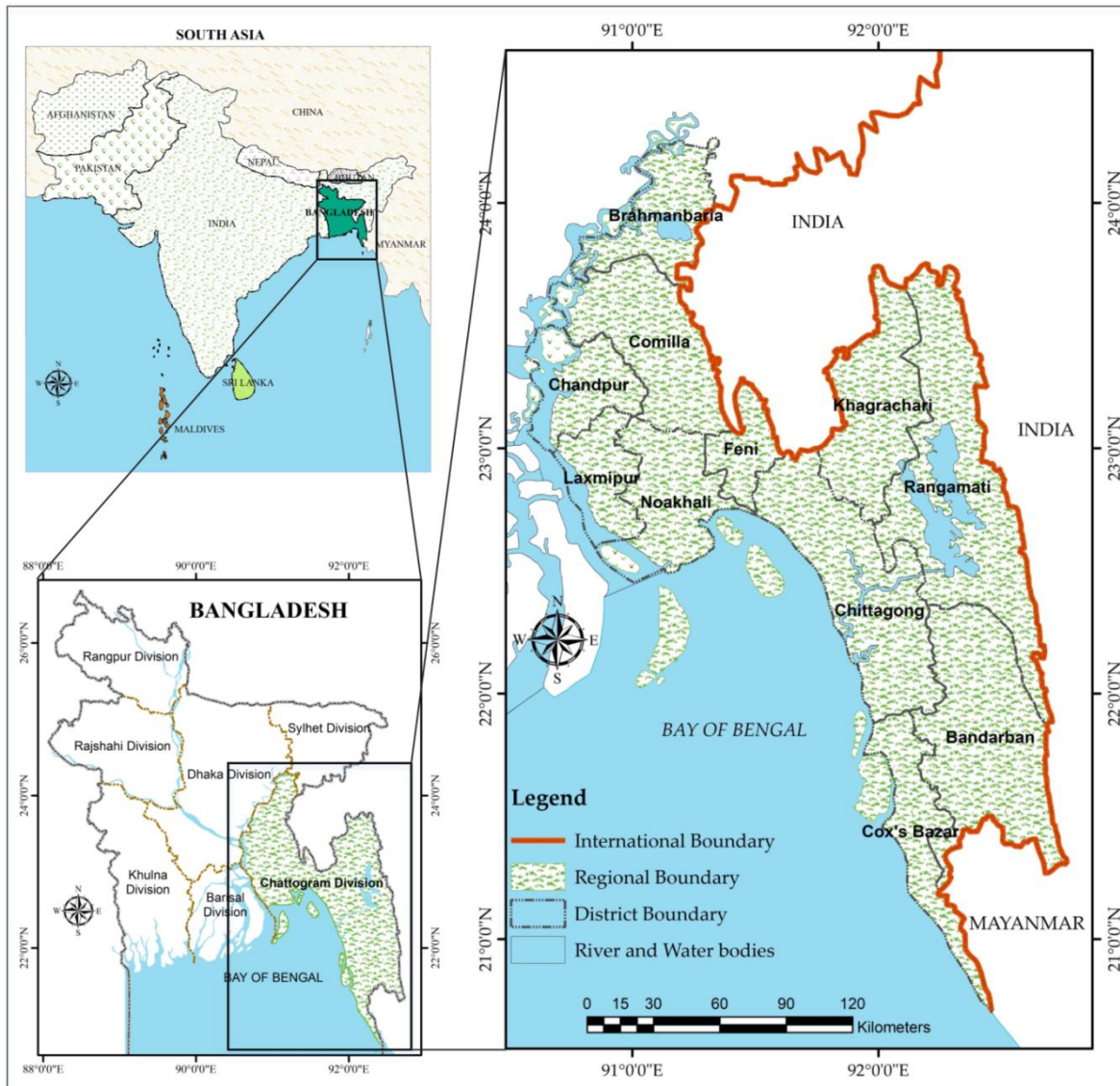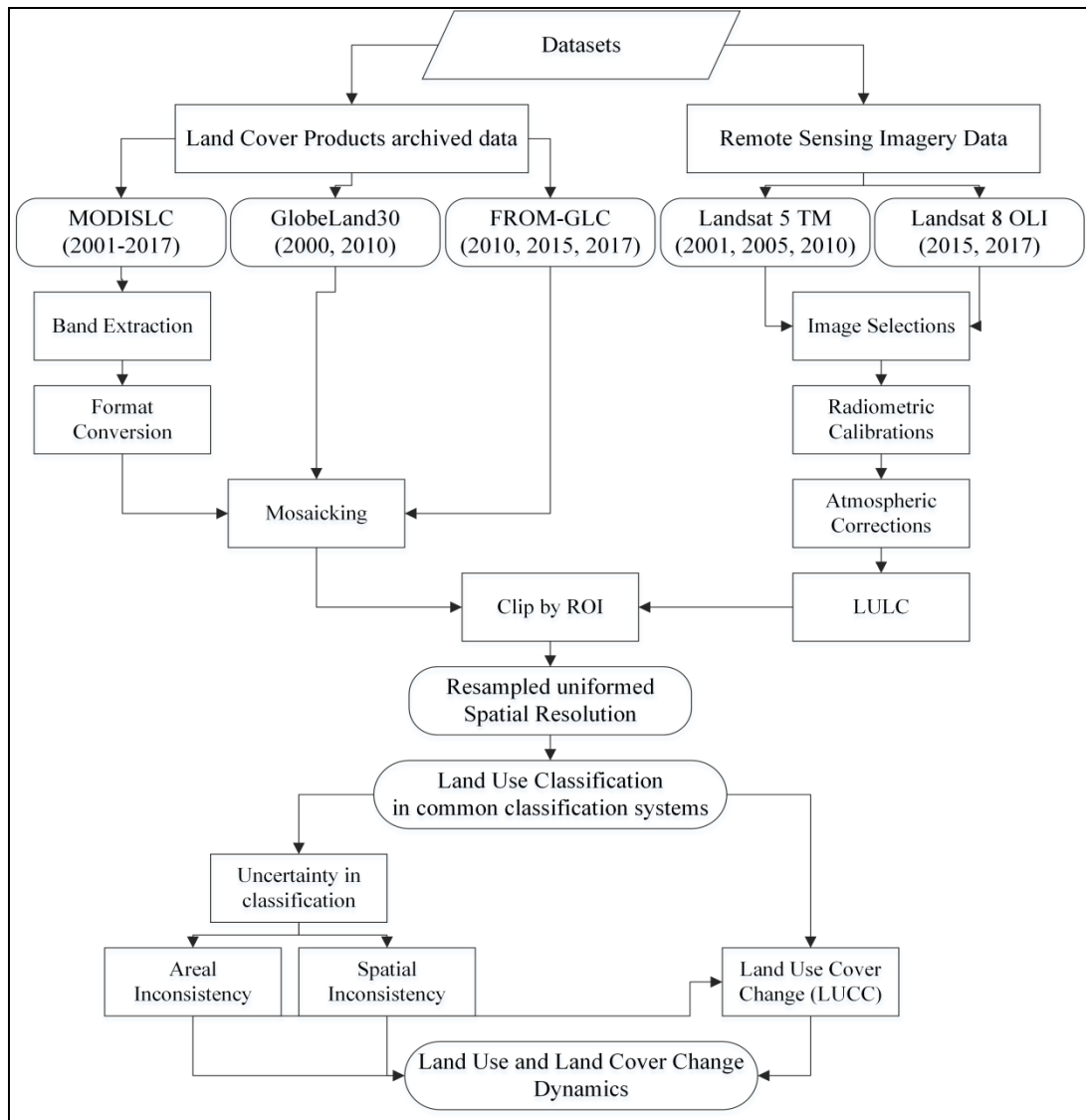
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879　　　　　　　　　　　　**Fig. 1** Location of the study area the Southeastern region of Bangladesh

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

882　　　　　　　　　　　　　　　　　　　　　　　　　Change.

883
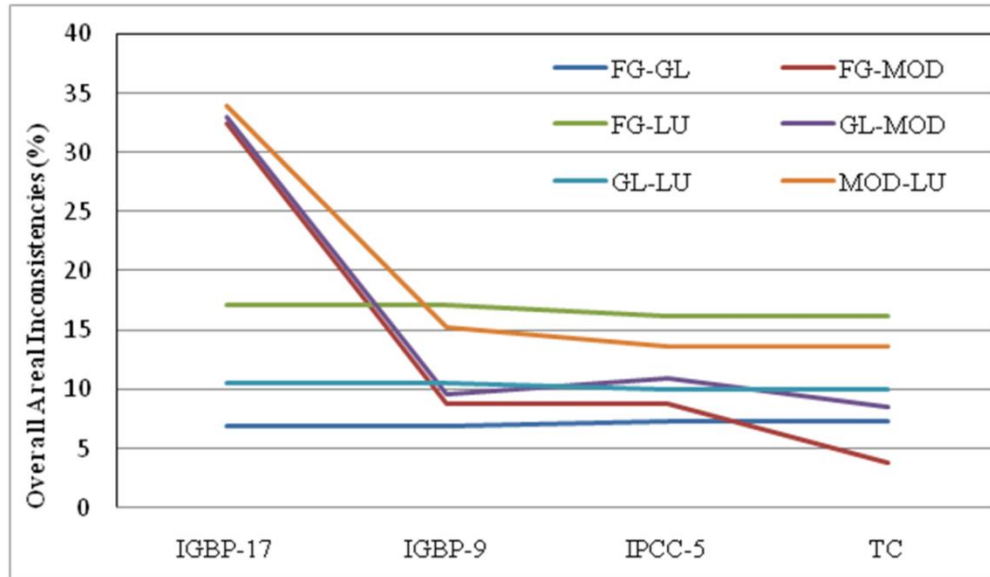
Fig. 3 Overall areal inconsistencies between pairwise of the FROM-GLC, GlobeLand30, MODISLC, and LULC
class of Landsat TM/ETM+ datasets in four common classification systems (FG: FROM-GLC datasets; GL:
GlobeLand30 datasets; MOD: MODISLC datasets; and LU: Land use and land cover classes of Landsat TM/ETM+
datasets).

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

892

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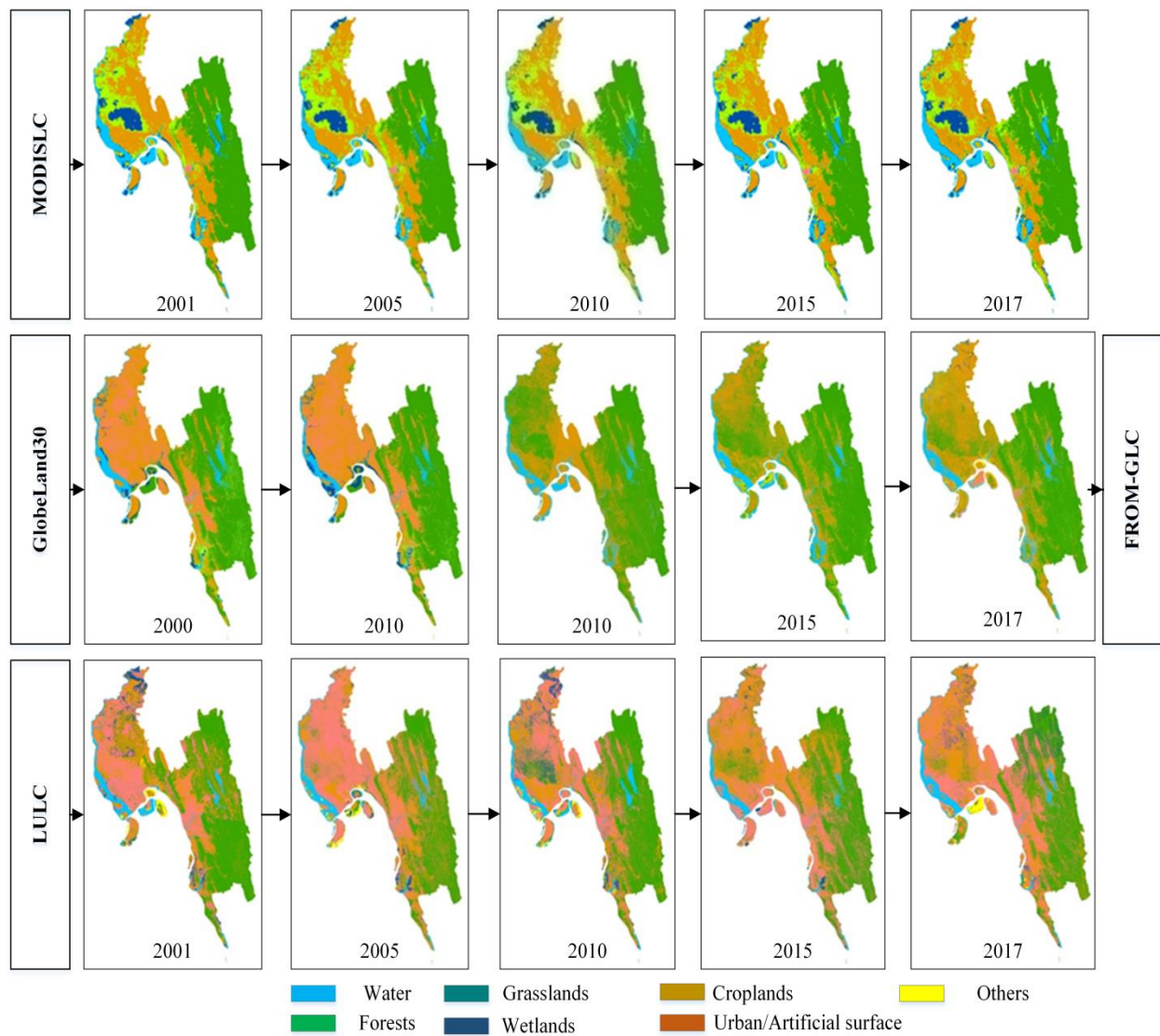894 GlobeLand30, and (d) LULC of Landsat satellite images

Water   Grasslands   Croplands   Others

Forests   Wetlands   Urban/Artificial surface

895

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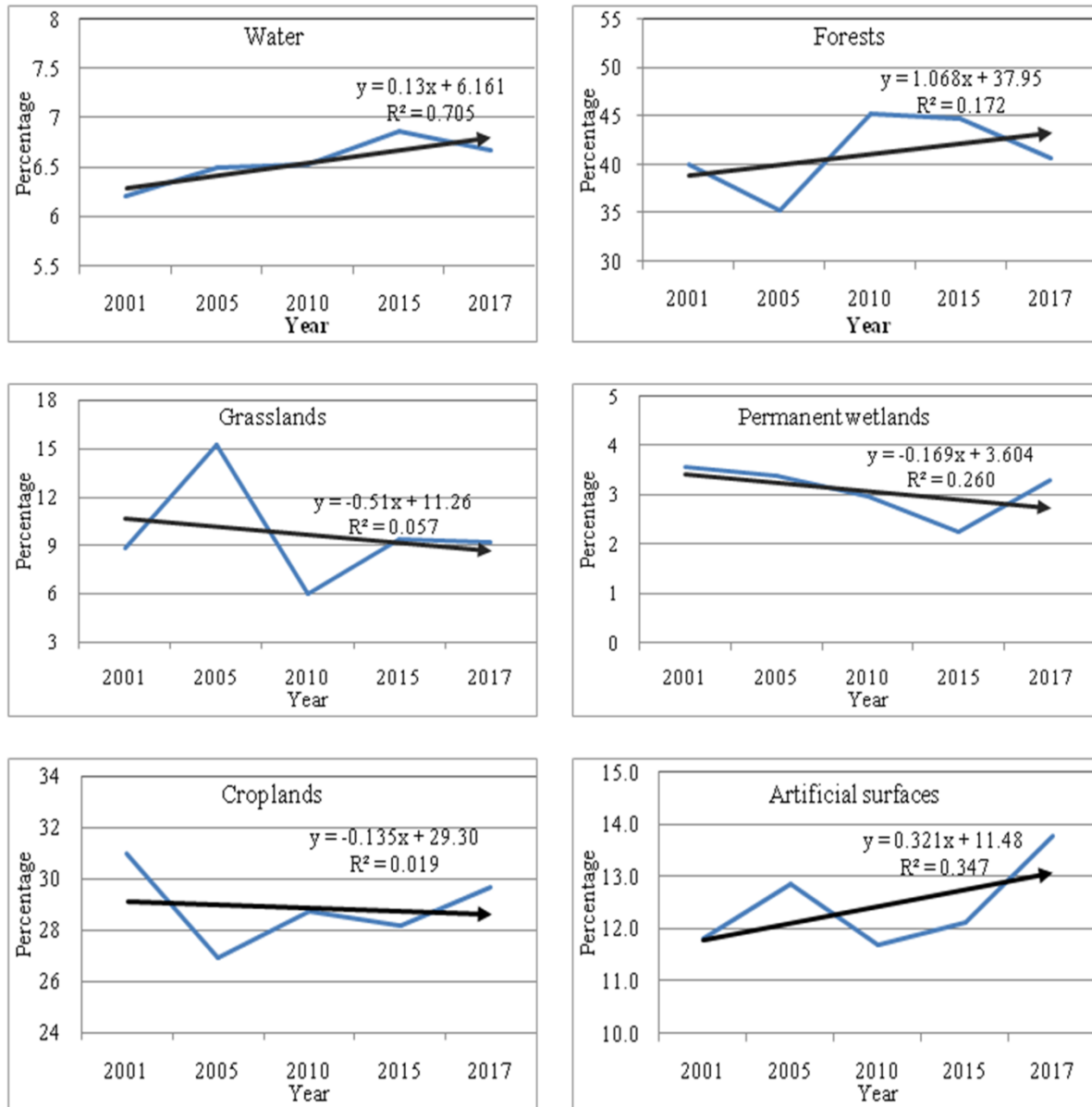897   GLC, and LULC of Landsat imaginary datasets.

898

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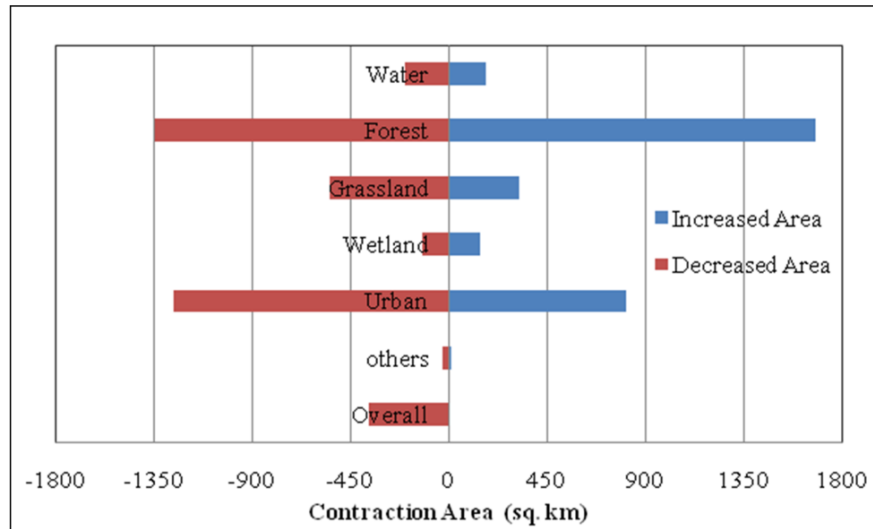901 Landsat imaginary (2001, 2005, 2010, 2015, 2017) datasets.

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902

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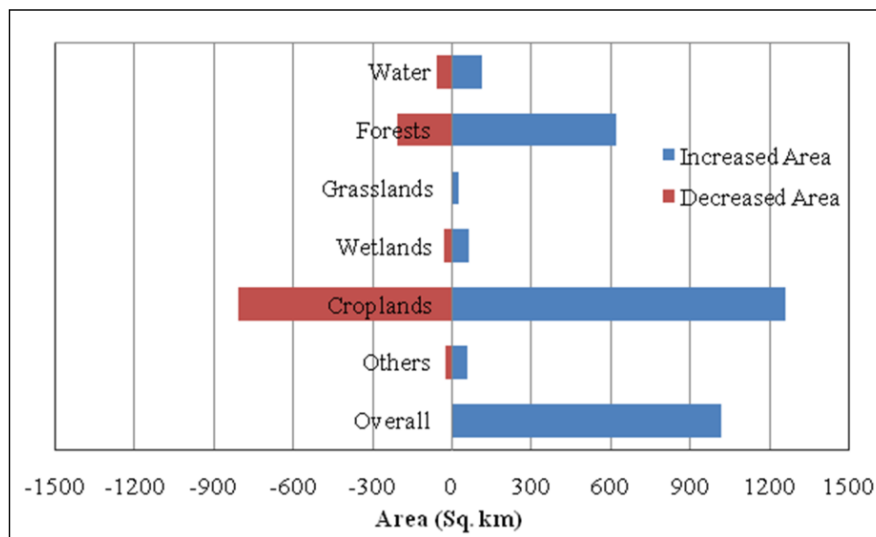

905

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
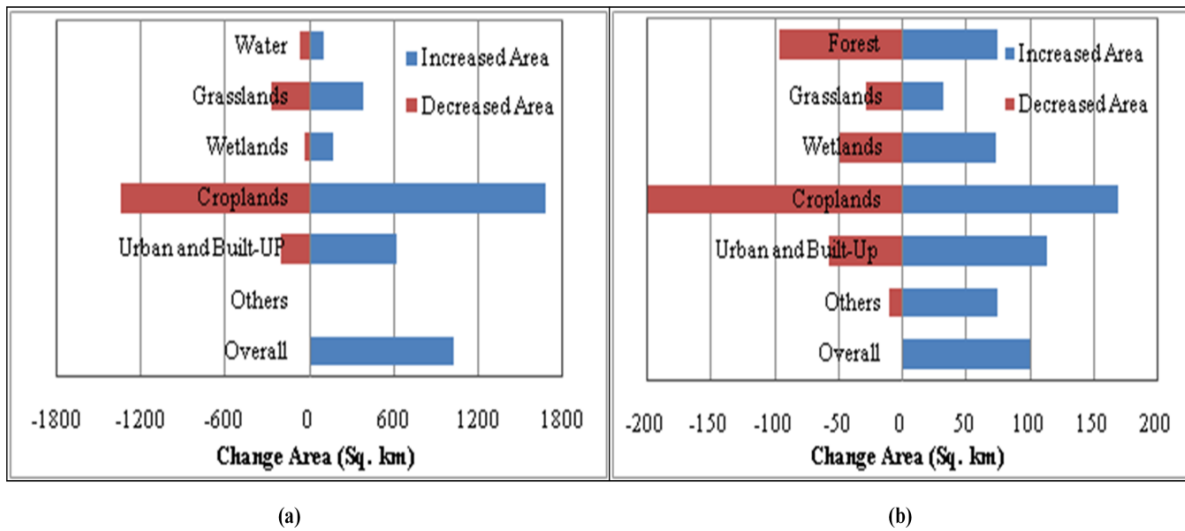
908

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.