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Review

# Remote Sensing-Based Research for Monitoring Progress towards SDG 15 in Bangladesh: A Review

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**Abstract:** The Sustainable Development Goals (SDGs) have been in effect since 2015 to continue the progress of the Millennium Development Goals. Some of the SDGs are expected to be achieved by 2020, while others by 2030. Among the 17 SDGs, SDG 15 is particularly dedicated to environmental resources (e.g., forest, wetland, land). These resources are gravely threatened by human-induced climate change and intense anthropogenic activities. In Bangladesh, one of the most climate-vulnerable countries, climate change and human interventions are taking a heavy toll on environmental resources. Ensuring the sustainability of these resources requires regular monitoring and evaluation to identify challenges, concerns, and progress of environmental management. Remote sensing has been used as an effective tool to monitor and evaluate these resources. As such, many studies on Bangladesh used various remote-sensing approaches to conduct research on the issues related to SDG 15, particularly on forest, wetland, erosion, and landslides. However, we lack a comprehensive view of the progress, challenges, concerns, and future outlook of the goal and its targets. In this study, we sought to systematically review the remote-sensing studies related to SDG 15 (targets 15.1–15.3) to present developments, analyze trends and limitations, and provide future directions to ensure sustainability. We developed several search keywords and finally selected 53 articles for review. We discussed the topical and methodological trends of current remote-sensing works. In addition, limitations were identified and future research directions were provided.

**Keywords:** remote sensing; sustainability; SDG; forestry; wetland; erosion; landslide; Bangladesh

## 1. Introduction

Aggravating climate change impacts and increasing global population warrant the sustainable management of finite resources. This concern for sustainable development formed the basis of the ‘United Nations’ ‘Agenda 21’, a plan of action agreed in the 1992 Rio Summit to ensure global and local sustainable development practices. While the Agenda 21 was already in action, leaders of 189 countries realized the necessity of specific and measurable goals for development and thus, in 2000, they set eight ‘Millennium Development Goals’ (MDGs) to implement by 2015. Later, the success of MDGs inspired them to formulate and undertake a new set of goals after their expiration [1]. As such, the Rio+20 Conference in 2012 galvanized a process of setting a new set of goals, the ‘Sustainable Development Goals’ (SDGs), to continue the progress of the MDGs.

The successes of the MDGs, and the wider scope and measurable indicators of the SDGs encouraged both developed and developing countries to appreciate and include the SDGs in their

agendas [2]. Similar to many countries, Bangladesh—one of the most climate-vulnerable countries in the world—also incorporates the SDGs into its development objectives. Remarkable progress in some sectors (i.e., poverty alleviation, food security) of the MDGs influenced Bangladesh to assimilate the SDGs immediately after its inception into the national Five-Year Plan [3–5]. Furthermore, in order to track the progress of the SDGs, Bangladesh launched a web platform (<http://www.sdg.gov.bd/>) together with an android app (SDG BD). The Sustainable Development Solutions Network Survey 2019 found that Bangladesh is among the only two countries in the world that conducted an estimate of incremental financial needs to implement the SDGs [6]. Despite these attempts, attaining the SDGs may remain a challenge because of governance mechanisms, resource constraints, policy conflicts, and trade-offs among economic, social, and environmental components [7–9]. Continuously monitoring progress, identifying concerns, and evaluating the outcomes will be the key to achieving these goals. One of the few effective approaches to track the SDGs' accomplishment is to analyze specific targets and indicators as this approach can elucidate how much progress has been made and what further needs to be done [10,11].

In this study, we are particularly interested in monitoring and evaluating the progress on environmental goals because terrestrial and inland freshwater ecosystems are key factors in protecting millions of people from climate change induced environmental hazards, such as tropical cyclone, river bank erosion, flooding, etc. By sequestering carbon, serving as an abode to wide biodiversity, acting as a source of livelihood, and attenuating natural hazards (i.e., coastal protection, heat vulnerability, flooding), these ecosystems become key to human survival. In recent decades, climate change impacts, in addition to anthropogenic interventions, pose serious threats to these ecosystems. For instance, increasing droughts and fire risks would likely cause a decline in forest productivity in the Mediterranean region [12]. Again, climate change may accelerate the expansion of drylands globally by 23% by the end of this century and eventually induce more land degradation [13]. For this reason, there is a dedicated goal (SDG 15) in the SDGs to protect the terrestrial and inland freshwater ecosystems. In order to ensure the sustainability of these ecosystems, we need regular monitoring and evaluation as they can identify challenges, concerns, and progresses of ecosystem management.

Among various approaches to monitoring and evaluating terrestrial ecosystem management, remote sensing is a widely acknowledged and useful method. It allows detecting and analyzing changes of landscape dynamics over large areas including those areas that are not easily accessible or hazardous and facilitates extrapolation of expensive ground measurements [14]. Remote sensing further enables us to obtain information over a longer period of time at different spatial scales and associate this information with climate data [15]. Consequently, it is widely used in terrestrial ecosystem management and both at macro (i.e., changes in wetlands) and micro levels (i.e., forest insect disturbances). In this way, remote sensing can play a crucial role in monitoring and evaluating the SDG 15 components: forest, wetland, biodiversity, and land degradation.

Many studies adopted a remote-sensing approach to undertake analysis on the SDG 15 components in Bangladesh, particularly on forest, wetland, erosion, and landslides. Yet, we lack a comprehensive view of the progress, challenges, concerns, and future outlook of the goal and its targets. In this study, we attempt to address this dearth of knowledge. We seek to review systematically the remote-sensing studies related to SDG 15 components in Bangladesh. We present the developments, analyze the trends and limitations, and provide future directions that could ensure sustainability. We focus on the first three targets of SDG 15 (i.e., targets 15.1–15.3) as the rest of the targets in SDG 15 do not require a remote-sensing approach as the principal method of analysis (see Box 1). In the next section, we will elaborate on our review methods. Next, we will present the key findings of our review and then demonstrate the progress that has been made to date. Later, research gaps and future directions are discussed.

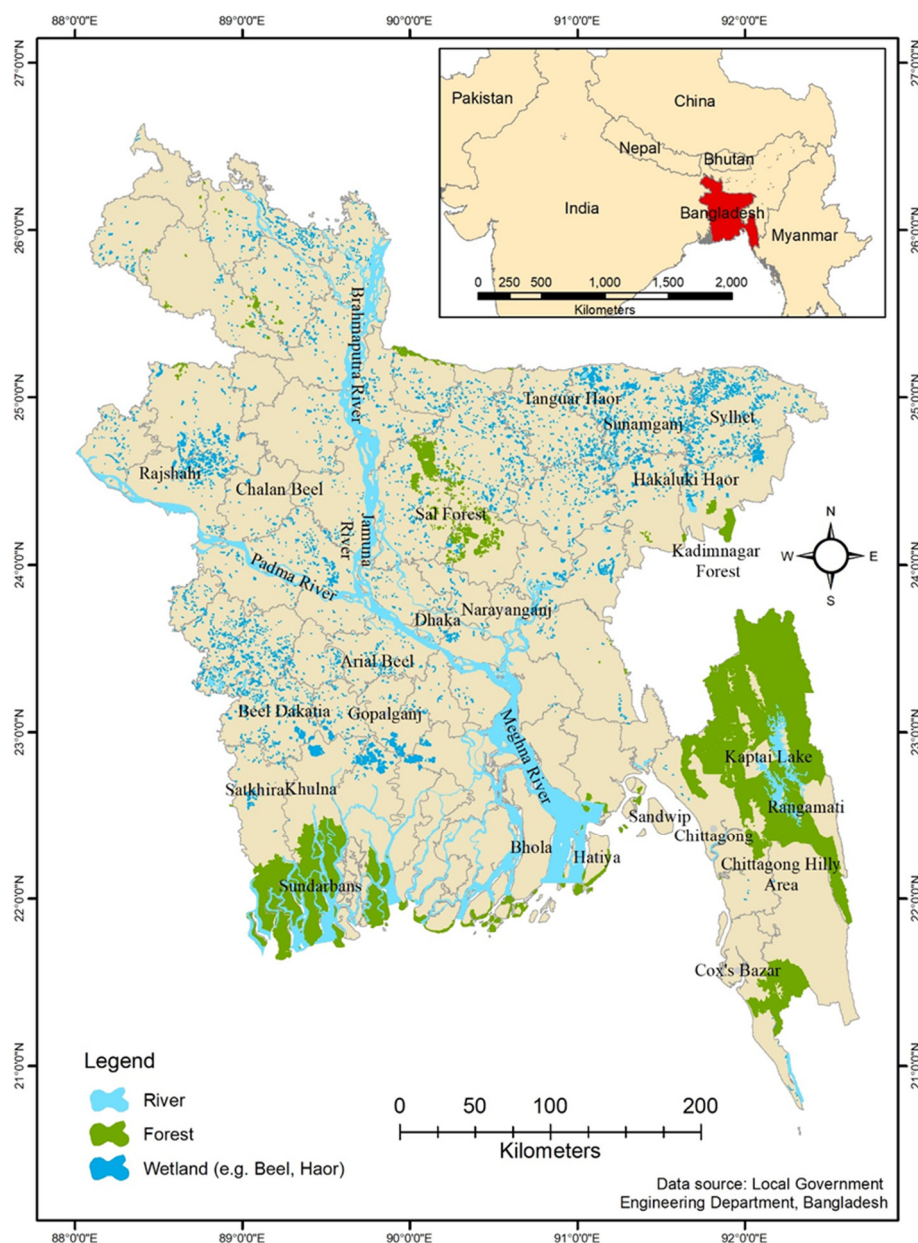
**Box 1.** Sustainable Development Goal 15 (complete list: <https://sustainabledevelopment.un.org/sdg15>)

- *Goal 15:* Protect, restore and promote *sustainable* use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss.
  - Target 15.1: By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements.
    - Indicator 15.1.1: Forest area as a proportion of total land area.
    - Indicator 15.1.2: Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type.
  - Target 15.2: By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally.
    - Indicator 15.2.1: Progress towards sustainable forest management
  - Target 15.3: By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world.
    - Indicator 15.3.1: Proportion of land that is degraded over total land area

**2. Methodology****2.1. Study Area**

Located only a few meters above the mean sea level, Bangladesh is a country of ~147,000 square kilometers (Figure 1). Geographically, it is located at the downstream of the Ganges-Brahmaputra-Meghna (GBM) river system, the highest sediment carrier river system in the world. The geology of the country is mostly sedimentary in nature. The eastern part, particularly southeast and northeast, is hilly but comprised of sedimentary layers of soils and rocks. The other part is mostly plain low-lying lands with little undulations in the northcentral region and stable platform in the northwest. These low lands are part of the geosynclinal basin, often termed as the 'Bengal Basin'. Numerous wetlands are located in this basin and it is estimated that nearly 50% of Bangladesh is wetlands that include seasonally inundated lowlands [16].

Almost all these wetlands are somehow connected with the GBM river system [17]. In the southwest part, the largest contiguous mangrove forest, the Sundarbans, is located across Bangladesh and India. The forest is 10,000 square kilometers in size but 6000 square kilometers are within Bangladeshi territory. Along with mangrove forest, around 25 thousand square kilometers of forest stretched over the country that include southeastern hilly forests, coastal mangroves, northcentral Sal forests, broadleaved and bamboo forests, and social or village forests [18].

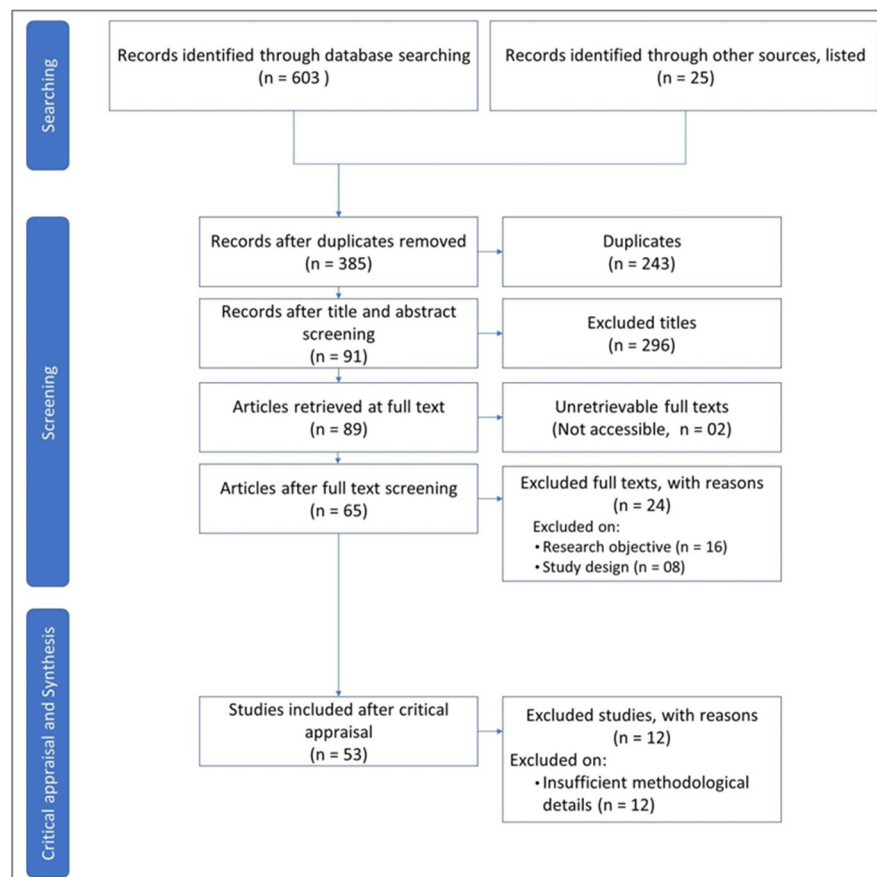


**Figure 1.** Study area. Key locations where remote-sensing studies have been conducted are included.

## 2.2. Systematic Literature Review

We conducted a systematic literature review (SLR) to distill studies that addressed the first three targets of SDG 15. These targets deal with the sustainability of three important aspects of the environment: terrestrial forest ecosystem, in-land freshwater ecosystem, and land degradation. Systematic reviews are conducted through transparent and repeatable processes, maximizing objectivity and attempting to minimize bias throughout the review [19]. The SLR, commonly used in healthcare and medicine research was found to be similarly useful in environmental conservation and management related works [20]. We adopted the ROSES (Reporting Standards for Systematic Evidence Synthesis in Environmental Research) protocol in the SLR process. The ROSES protocol updated another standard protocol, PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) and is specially designed for conservation and environmental management to synthesize different types of environmental evidence [21]. The ROSES protocol also ensures the replication of research. We began our search process using different combinations of keywords (see Appendix A for a detailed list of

search keywords) in the Web of Science platform (<https://www.webofknowledge.com>). We carefully attempted to include all possible subsets of search keywords based on our knowledge and experience so that we can select every relevant article. Each of our search queries provided a set of articles. We removed the duplicate articles and included only peer-reviewed journal articles that are published in the period of January 2000–August 2019. We selected this time frame because the MDGs were initiated in 2000 and the SDGs are a continuation of that. In order to ensure maximum inclusivity, we searched for articles using similar search keywords in the Google Scholar platform. At the end of our literature search process, we came up with 385 research articles for review (Figure 2).



**Figure 2.** Methodological flow based on the ROSES (Reporting Standards for Systematic Evidence Synthesis in Environmental Research) protocol.

In order to conduct SLR, we developed a set of inclusion and exclusion criteria based on which we selected relevant articles for synthesis (see Table 1). These criteria had been established to ensure the selection of articles that embraced remote-sensing approaches to undertake research on forest, wetland, river, and land degradation related issues. In the Step 1 and 2 of the review process, we screened the title and abstract of the 385 articles. We retained only those articles that topically focused on SDG 15 targets (e.g., forest cover estimation using remote sensing) and adopted remote sensing-based methods or materials. Articles that did not meet these two criteria were removed from our inventory. At the end of this stage, we obtained a total of 91 articles for full-text review (Figure 2). Next (Step 3), we performed a thorough review of these 91 articles. We removed those articles from our inventory that are not directly addressing SDG 15 issues or do not provide quantitative outputs on SDG 15 targets. Following this stage, we are left with 65 articles for a critical appraisal (Figure 2). In our critical assessment step (Step 4), we filtered out those articles that do not provide sufficient details of the remote-sensing method that they used. We performed this critical evaluation to avoid bias error in our



analysis. This final step of our SLR process yielded 53 articles which were included in our synthesis (Figure 2). Note that, we were not able to perform a meta-analysis on the findings extracted from these 53 articles since they employed a variety of methods with differential geographic and temporal contexts. To obtain information on the articles we reviewed, we created a matrix that contained detailed information on the objective, study area, remote-sensing products, methodological approach, results, limitations, uncertainties etc.

**Table 1.** Inclusion and exclusion criteria.

Steps	Inclusion Criteria	Exclusion Criteria	Accepted	Rejected
Step 1: Title screening	Title of the article includes a topic related to the use of remote sensing or geospatial techniques in the issues regarding Sustainable Development Goal (SDG) 15; Title that includes topic areas of SDG 15 (i.e., 15.1–15.3), but may not explicitly mention remote sensing as primary approach of analysis.	Title of the article does not include a topic related to the use of remote sensing or geospatial techniques in the issues regarding SDG 15; title that is not related to SDG 15 targets (i.e., forest, wetland, dryland, land degradation), regardless of the use of remote sensing or geospatial approach; title with study area outside Bangladesh or excluding Bangladesh.	91	296
Step 2: Abstract screening	Abstract that clearly mentions the use of remote sensing or geospatial approaches in addressing issues related to the first three targets of SDG 15 in Bangladesh.	Abstract that may focus on SDG 15 targets but does not mention the use of remote sensing or geospatial approaches; abstract with study area outside Bangladesh or excluding Bangladesh.		
Step 3: Full text review	Article that develops or uses remote sensing products or algorithms to address issues related to SDG 15.1–15.3.	Article that may use remote sensing approach in the analysis but is not directly related to the SDG 15 targets; article that does not provide quantitative outputs using remote sensing techniques.	65	26
Step 4: Critical appraisal	Article that provides sufficient details of methodology.	Article that does not provide enough details of methodology and thus the output cannot be validated.	53	12

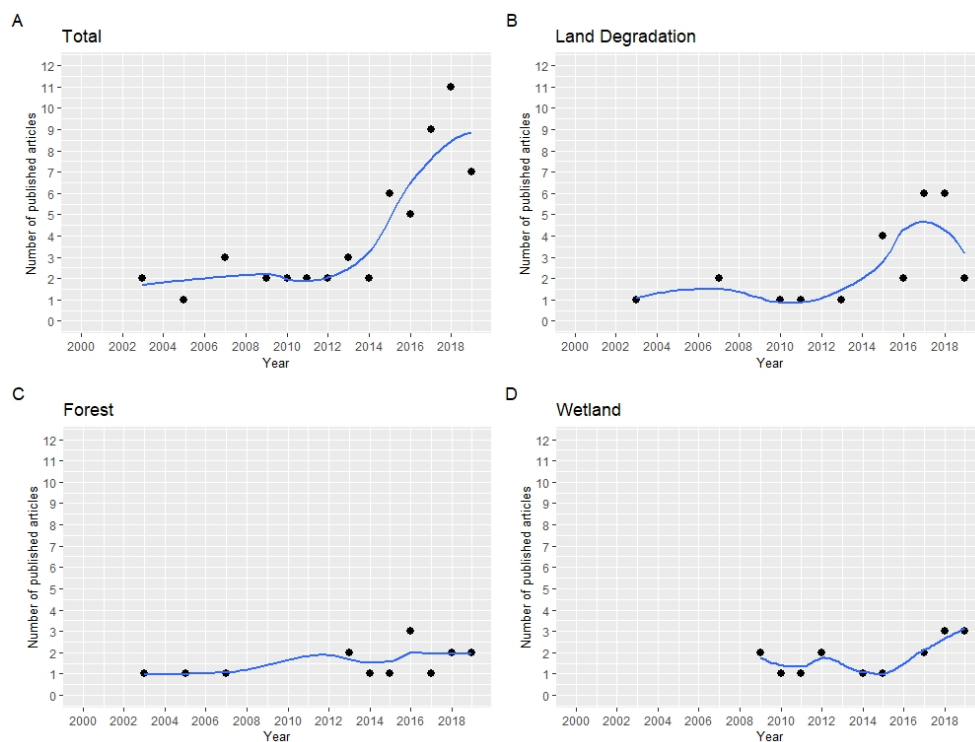
### 3. Results: Current Status of Monitoring Sustainable Development Goal (SDG) Targets

#### 3.1. Research Frequency

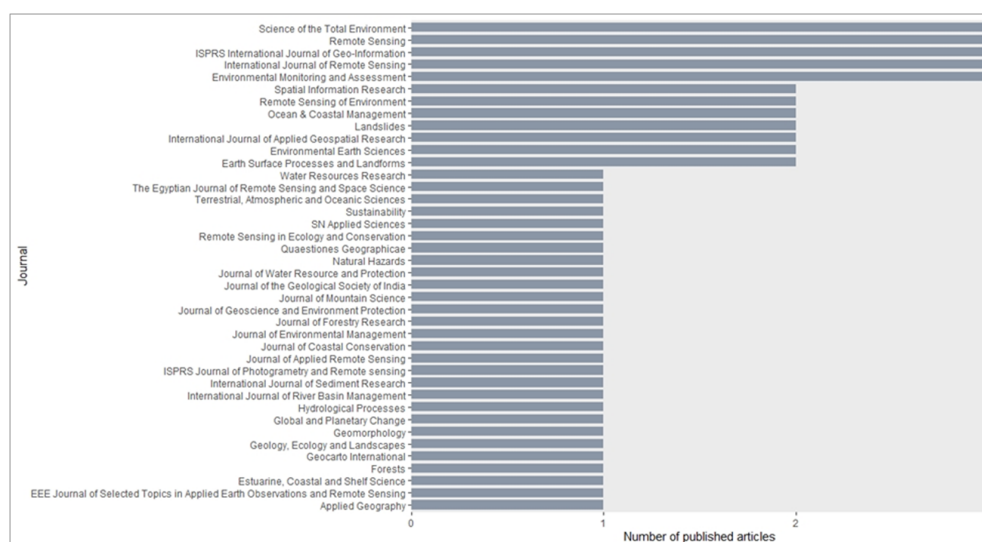
We found that remote-sensing research on SDG 15 components was conducted throughout our study period (2000–2019). The frequency of studies significantly increased after 2010 potentially because Landsat data was made freely available in 2008 (see Figure 3A). This increase in number is particularly evident in land degradation-related studies (Figure 3B). A concern over landslide-related deaths in recent years might have led to more research works on land degradation using remote sensing approaches. On the contrary, publications of forest related studies are static throughout the study period (Figure 3C). We found that wetland related studies started to publish in 2009 and onwards (Figure 3D). This is rather interesting that despite having the presence of numerous wetlands across the country and a growing significance of wetlands in attaining environmental sustainability, no research on wetlands using remote sensing was conducted in the first eight years of our study period. We assume that the coarse resolution of Moderate Resolution Imaging Spectroradiometer (MODIS) data discouraged its use in wetland analysis when Landsat was not freely available.

The studies we identified were published in journals with a wide range of scope (see Figure 4). A significant number of articles (37%) were published in remote-sensing or geospatial analysis-focused journals (e.g., *Remote Sensing*, *Remote Sensing of Environment*). It indicates that the focus of these articles was the utilization or development of a new remote-sensing approach to examine SDG 15 components. Only 15% of articles were published in subject-specific journals (e.g., *Landslides*, *Forests*). Many of these

articles used remote sensing techniques as an ancillary tool. Nearly half of all articles were published in interdisciplinary journals (e.g., *Science of the Total Environment*, *Sustainability*). The target audience of these journals is often broad and comprises various backgrounds and interests. As such, the articles published in these journals attempted to balance between the technical aspect of remote sensing and its applications.



**Figure 3.** (A) Number of articles on SDG 15 components, (B) land degradation, (C) forest, (D) wetland, using remote sensing published each year between January 2000 and August 2019.



**Figure 4.** Number of articles on SDG 15 components using remote sensing published each year.

### 3.2. SDG 15.1—Forests

We found that there were 15 remote-sensing articles published on forests during the study period. Two-third of these studies used Landsat data in their analyses, while a few used MODIS [22,23],



Sentinel-2 [24], and radar products (e.g., ALOS-PALSAR, TanDEM-X) [25,26]. The availability of moderate resolution (i.e., 30 m) Landsat imageries made it a popular choice of data products among the researchers. SDG 15 focuses on forest area (i.e., forest cover) as a proportion to total area. We found that almost half of the forest-related studies focused on estimating forest cover change over time. These studies largely assessed the forest cover extent in the period between 1975 and 2015. They reported that the annual deforestation rate ranged from 0.04% to 4.0%; however, most of the studies reported an annual loss of forest at the rate of 0.34–0.81%. We found that the annual deforestation rate varies with region. For example, using a hierarchical classification approach on Landsat imageries, Quader et al. (2017) found that the Sundarbans mangrove forest, the largest contiguous mangrove forest in the world sized around 10,000 square kilometers, was encountering 0.38% annual loss in forest cover over the period of 1975–2010 [27]. However, Ghosh et al. (2016) used a supervised maximum likelihood classification (MLC) approach and reported that the Sundarbans was experiencing a 0.81% annual loss in the period 1977–2015 [28]. We think that considering the dynamic nature of the intertidal environment [26,27] and the image classification accuracy [29], the deforestation rate in the Sundarbans may not be worrisome.

In addition to the Sundarbans, forest cover loss estimations have been conducted in the southeast part of the country as well. While assessing locational suitability for mangrove afforestation, Hossain et al. (2003) found that mangrove in Cox's Bazar is encountering 0.34% loss every year [30]. However, this scenario is different in the hilly part of southeastern Bangladesh. For instance, in the hilly areas, forest cover increased with an annual rate of 0.45% in the period between 1989–2014 [31]. This supervised MLC analysis indicated that forest cover gain was prominent until 2003 but started to experience loss since then. Forest loss in certain locations of the southeast part is much higher than the average loss of the country that can be attributed to the forced international migration. Because of the Rohingya influx from neighboring Myanmar, forests were cleared in the southeastern part of the country [24]. Hassan et al. (2018) estimated that the forest loss was as high as 4.0% annually in the places where refugee camps are established [24].

Overall, Bangladesh is losing forests historically at a slow but static rate. Reddy et al. (2016) conducted a historical analysis on the forest cover in Bangladesh and found that from 1930 to 2015, the annual deforestation rate was 0.46% [32]. They found that the deforestation rate was highest (0.75%) during 2006–2014 in their 85-year time period. Unlike Ahammad et al. (2019) [31], they found that hilly areas of southeastern parts are facing more deforestation than other parts, particularly due to agriculture. They also found forest gain in the south-central coastal zone, which can be attributed to the afforestation programs. Figure 5 represents the forest cover loss/gain estimated by different studies.

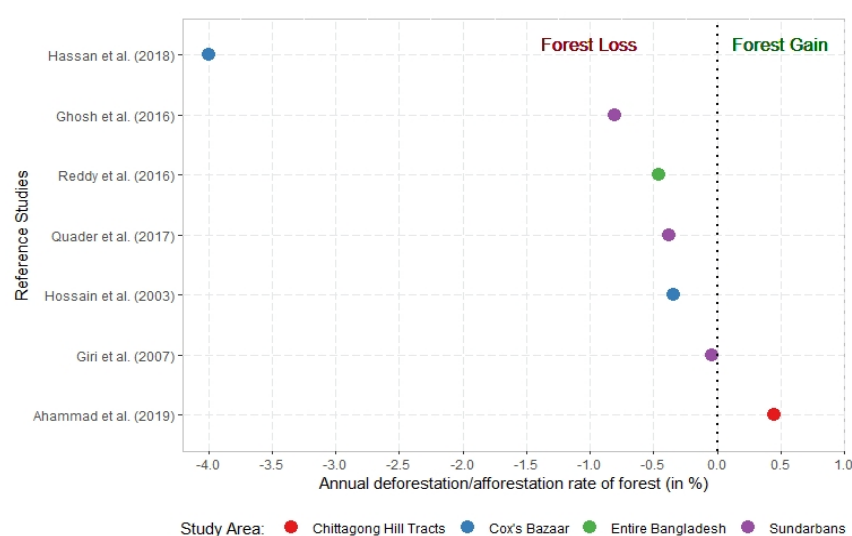
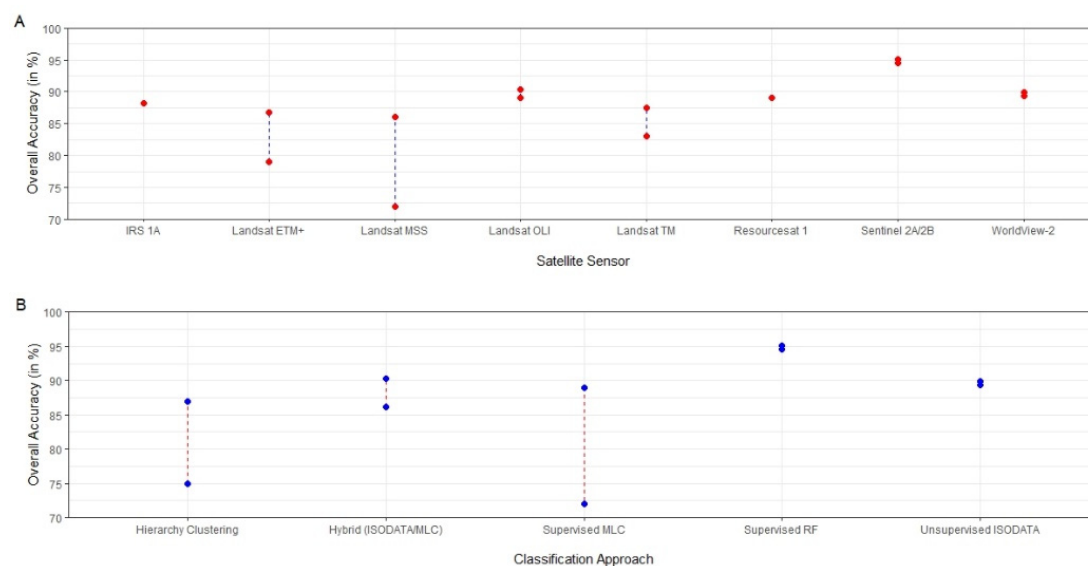


Figure 5. Forest cover loss/gain estimation by different studies [24,27,30–34].

Although the rate of forest cover loss in Bangladesh may seem smaller than many other parts of South Asia [35,36], the concerning issue in Bangladesh is that the conversion of dense forest into medium dense or open forest may lead to an overestimation of forest sustainability. For instance, Redowan et al. (2014) reported that dense forest in Sylhet decreased at a rate of 0.36% per year from 1988 to 2010 while medium dense forest increased at a rate of 0.91% [37]. Loss of dense forest was reported higher than other types of forests by [27] and [32] as well. Ishtiaque et al. (2016) found that despite no significant change in the areal extent of the Sundarbans, the forest is encountering fragmented degradation in biomass and other forest health parameters (i.e., percent tree cover, evapotranspiration) [22]. Cornforth et al. (2013) also found the presence of fragmented degradation in the Sundarbans [26]. Furthermore, Ghosh et al. (2016) identified the dominant most species, *H. fomes*, in the Sundarbans decreased over time and Islam and Ma (2018) found that land surface temperature is increasing in the southeastern forested parts, potentially because of fragmented deforestation [23,28]. These studies indicate that only focusing on total forest cover may keep us in the fallacy of forest sustainability, we need more evidence on other aspects of forests as well (see Section 4.1 for details).

Methodologically, studies that detected a change in forest cover mostly used supervised MLC algorithm for classifying images and performed post-classification change detection. Additionally, the supervised random forest [24], hierarchical [27], hybrid [30,32] and classification approaches have been used by some. Forest health assessment, habitat degradation, species composition related studies used various approaches, in addition to supervised MLC, in their analysis including OLS Ordinary Least Square (OLS) regression [22,23], unsupervised Iterative Self-Organizing Data Analysis Technique (ISODATA) [25], and Refined Gamma Maximum-A-Posteriori (RGMAP) filtering [26]. In change detection studies, classification accuracy is very important to ensure the correct estimation of land cover change [38]. However, classification accuracy depends on a variety of factors, such as satellite sensor, spatial resolution, ground truth information, validation approach, noise, time period, software used, and even classification algorithm. From our analysis, we found that Sentinel-2, with 10 m resolution, provides the highest overall accuracy (~95%) in assessing forest-cover change followed by another high-resolution (2 m) satellite sensor, the WorldView-2. This indicates that high resolution imageries may provide better classification accuracies than moderate resolution Landsat or coarse resolution MODIS imageries. However, as Hassan et al. (2018) used Sentinel-2 for only two years and also used high-resolution QuickBird imageries for validation, we do not claim that the overall accuracy will be this high for other contexts [24]. We further observed that Landsat TM performed better than Landsat ETM+ in different studies in terms of accuracy, thus we advocate for using Landsat TM over ETM+. Landsat MSS showed a wide range of accuracy measures. Low accuracy can be attributed to a relatively coarser resolution (60 m) and validation technique. Compared to other Landsat sensors, OLI provided better accuracies. Figure 6, generated by summarizing the literature, demonstrates a comparative presentation of overall accuracy based on satellite sensors (A) and classification algorithms (B). We found that supervised Maximum Likelihood Classifier (MLC) has a wide range of accuracy which may partly depend on the time period of the satellite imageries- the latest images have higher accuracies (see Appendix B as well). Hybrid classification (ISODATA/MLC) and supervised Random Forest (RF) also showed a good prospect in achieving high accuracy.

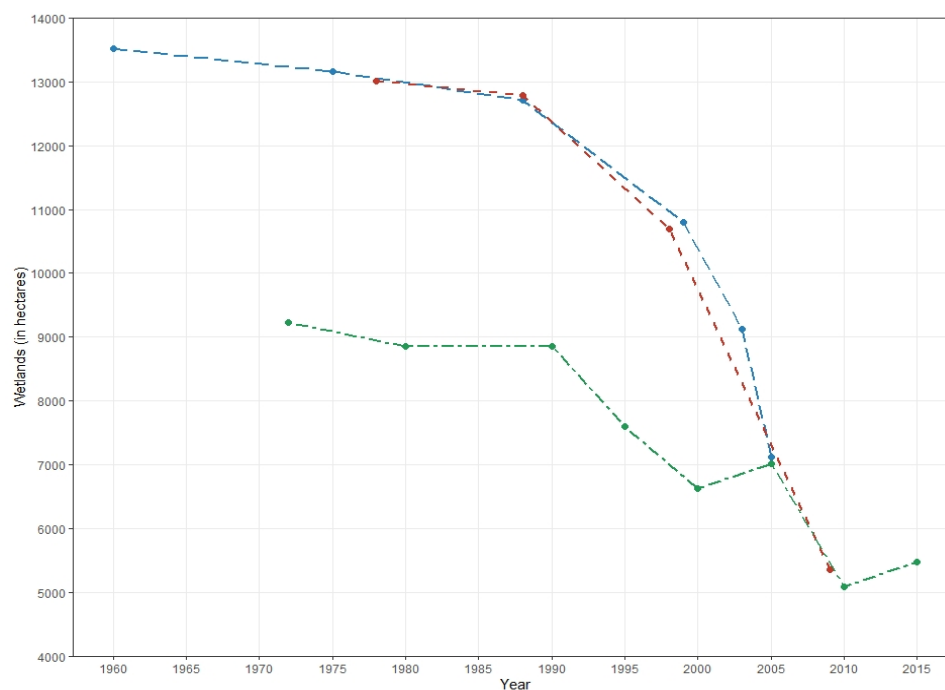


**Figure 6.** Range of overall classification accuracy in forest related studies based on satellite sensor (A) and classification approach (B).

### 3.3. SDG 15.2—Wetland

We found 15 articles pertaining to wetland analysis using satellite images and geographic information system (GIS) techniques. For clarification, as found in the articles we reviewed, this wetland category includes both the water bodies (e.g., lake, ponds, lagoons, rivers, and aqua fishing) and the lowlands/wetlands (e.g., permanent and seasonal wetlands, marshy land, rills and gullies, swamps). Among these 15 articles, five articles directly focused on analyzing wetlands whereas the rest of them focused on analyzing land-use changes in general with a particular focus on identifying spatio-temporal patterns of wetlands in different areas of Bangladesh.

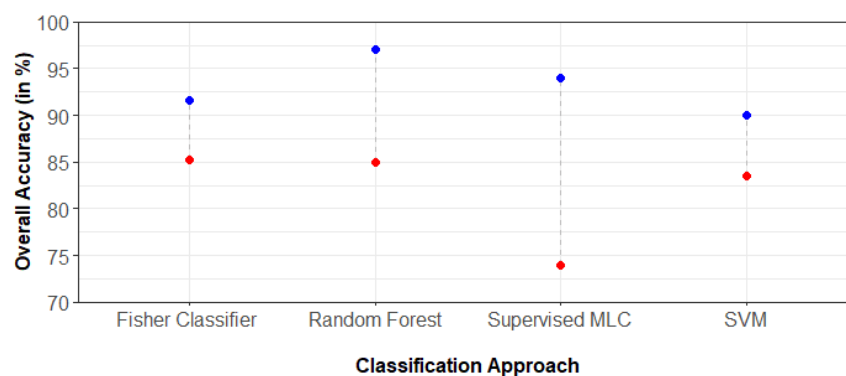
Almost half of the articles on wetland conducted research on Dhaka, the capital of Bangladesh, and its surrounding areas. This is because Dhaka is the home to more than 10 million people and the existence of wetlands and water bodies in Dhaka is intrinsically important to its drainage and flooding condition. In one of the early attempts, Dewan and Yamaguchi (2009a, 2009b) found that due to urban expansion the wetlands and water bodies of the Dhaka Metropolitan Area (DMA) decreased about 6385 hectares and 864 hectares respectively during the period of 1960–2005 [39,40]. Similarly, Mahmud et al. (2011) estimated a loss of 7657 hectares of wetlands in the DMA between 1978 and 2009 [41]. A more thorough estimation has been done by Hassan and Southworth (2017). Analyzing eight periods of land cover maps, they found that the areas under lowland/water bodies in the Dhaka City Corporation (DCC) shrunk from 9225 hectares to 5479 hectares between 1972 and 2015, a net decrease of 41% over the 44-year period [42] (Figure 7). Paul et al. (2019) recently found a similar estimation for Dhaka City: 33% of surface water bodies have been depleted during 1967 and 2008 [43]. The losses of wetlands or conversion to different land covers can be attributed particularly to landfilling or encroachment for urban expansion [41,44]. Hassan and Southworth (2017) found that urban expansion took place in the north, northwest, and southwest regions of Dhaka [42]. However, Ahmed and Ahmed (2012) claimed that the northern part of the city experienced some gains in wetlands, although northeast and southwest parts encountered a massive transformation of wetlands to built-up areas [45]. Similarly, Griffiths et al. (2010) identified a profound expansion of urban areas in Dhaka city using a multi-sensor and multi-temporal mapping approach [46]. Their results coincide to some extent with those of Hassan and Southworth (2017)—changes in wetlands in the early 1990s were characterized by filling up spaces within the urban fabric, whereas, the later changes were triggered by the urban expansion process. These findings highlight the increasing vulnerability of ecologically sensitive wetlands in the Dhaka city and surrounding peri-urban areas (e.g., Savar, Narayanganj).



**Figure 7.** Trend of wetlands change in Dhaka metropolitan area and its surroundings as reported by [39] (blue line), [41] (red line), and [42] (green line).

Besides Dhaka city, other areas of Bangladesh received attention in terms of quantifying water bodies using remotely sensed data. For example, the study by Tseng et al. (2019) focused on surface water area (WA) quantification of the Sylhet-Mymensingh Haor Area that receives the highest annual precipitation in Bangladesh [47]. Their primary focus was to develop a surface WA quantification method (i.e., flood chance modeling) by combining multiple satellite data including MODIS, Landsat optical satellite image, Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), Gravity Recovery and Climate Experiment (GRACE) observations, Sentinel-1A images, and Ice, Cloud, and land Elevation Satellite (ICESat) elevation products. It appears that the fusion of multiple imageries with varying spatial resolution improved the measurement of surface water area although there is a seasonality effect; for example, monsoon season WA measurement accuracy (84%) was higher than that of the dry season (50%). Huq, Bruns and Ribbe (2019) assessed long-term (1973–2014) and short-term (pre- and post-monsoon) quantities, values, and changes of freshwater ecosystem services (FES) in the “beel” areas (i.e., large-surface water body that accumulates surface runoff water) of the middle-south and south-west regions (e.g., Khulna-Gopalganj beel) of Bangladesh [48]. Sikdar and Hossain (2015) studied the geophysical sources of uncertainty for satellite interferometric (SRTM)-based discharge estimation in the river deltas of Bangladesh [49].

Methodologically, for analyzing wetland or land-use change most of these studies used a two-step workflow: multi-temporal land-use/land-cover (LULC) classification and change detection. Multiple studies used the MLC algorithm [39,41,50,51] which usually performs best when each land use class has Gaussian distribution. However, when both the study area and land use class size are larger, class membership often does not follow the Gaussian distribution. In such cases, the MLC algorithm demonstrates poor performance in accurately classifying LULC classes. Therefore, few studies that focused on analyzing larger and spatially heterogeneous landscapes (e.g., the greater Dhaka city) used other classification algorithms such as Fisher’s classifier [45], support vector machine [46], random forest [42], and a combination of extreme gradient boosting and random forest [52]. Figure 8, generated by summarizing the literature, shows that these algorithms yielded high and less variant classification accuracy than the supervised MLC algorithm (see Appendix C for details).



**Figure 8.** Range of overall classification accuracy in wetland-related studies based on classification approach.

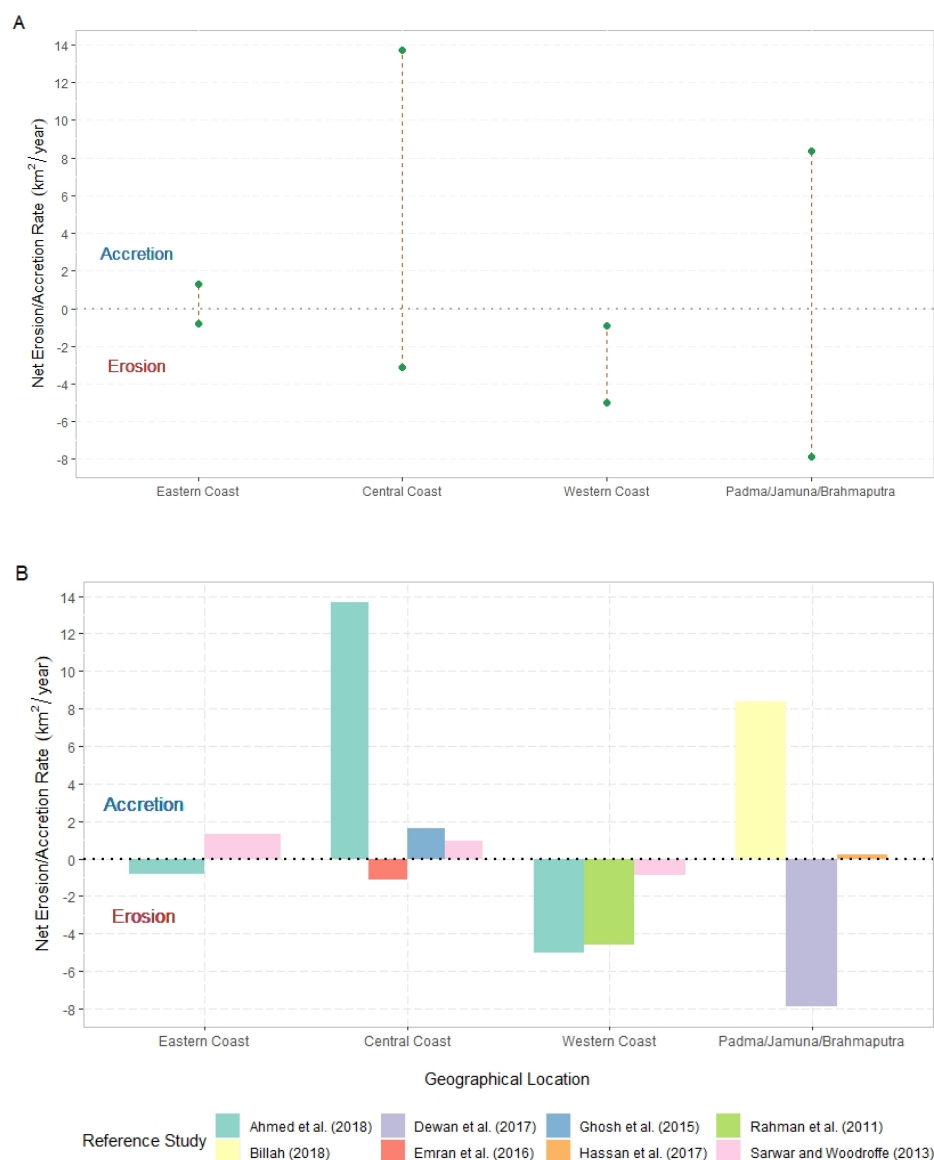
### 3.4. SDG 15.3—Land Degradation

We adopted the IPCC's (Intergovernmental Panel for Climate Change) definition of land degradation in this study: it is a negative trend in land condition, caused by direct or indirect human-induced processes including anthropogenic climate change, expressed as long-term reduction or loss of at least one of the following: biological productivity, ecological integrity or value to humans [53]. The IPCC identified various physical, chemical, and biological land degradation processes that include erosion, subsidence, compaction, salinization, flooding, pest outbreak etc. Landslides are also identified as a form of land degradation. In this study, we focused on riverbank and coastal erosion and landslides to represent land degradation related research as remote sensing is predominantly used in these research areas in Bangladesh. Therefore, the results of land degradation are presented in the following two sections: erosion and landslides.

#### 3.4.1. Erosion

We found that at least 15 articles were published that focused on land degradation through erosional processes. These articles mostly analyzed the erosion and accretion rates using satellite imagery and GIS techniques. These studies found a variety of estimates. For instance, Rahman et al. (2011) found that the southwestern coastal region, forested by the Sundarbans mangrove forest, encountered 170 km<sup>2</sup> of net erosion between 1973 and 2010, while Ahmed et al. (2018) reported 82 km<sup>2</sup> net loss of lands in this region during 1985–2010 and Sarwar and Woodroffe (2013) claimed at least 19 km<sup>2</sup> net erosion in the seaward margin of this coast in the period of 1989 and 2010 (see Figure 9) [54–56]. High erosion in this part indicates a low supply of sediment from the upstream and increased dynamics of sea wave erosion. Upstream embankments and dikes prevented the regular water flow in southwest Bangladesh which led to water-logging, river bed upheaval in certain parts [57]. Studies found that erosion is particularly dominant in the central coastal region as this part is facing as high as 14.7 km<sup>2</sup> loss of lands per year [55]. However, the estuary of the GBM river system, one of the highest sediment carrier river systems in the world, is located in this region which causes enormous amounts of sedimentation in this part of coastal areas. Sarwar and Woodroffe (2013) found that some parts of this region faced as high as 150 km<sup>2</sup> accretion in just 20 years (1989–2009) and Ahmed et al. (2018) claimed that the central coastal region gained around 410 km<sup>2</sup> land during 1985–2010 (see Figure 9) [55,56]. As such, new islands have been formed and existing islands are stretched further southward. These islands may encounter erosion in the northern parts, but deposition in the southern part compensates for it. Ghosh et al. (2015), for example, found that Hatiya Island in the central coastal region experienced 34 km<sup>2</sup> of net land accretion every year in the period of 1989 and 2010, particularly in the southern tip [58]. However, in the central-eastern coastal region, erosion can happen in southern parts as Emran et al. (2015) found that Sandwip Island encountered 39 km<sup>2</sup> of net land loss between 1980 and 2004, particularly in the southern locations [59]. Contrary to the western or central part,

the eastern coastal region faced the least amount of erosion, 1.2 km<sup>2</sup>/year [55] and 0.63 km<sup>2</sup>/year [56]. However, the accretion rate estimation is rather disputed as Ahmed et al. (2018) claimed a net loss of 24 km<sup>2</sup> during 1985–2015 but Sarwar and Woodroffe (2013) found an increase of 28 km<sup>2</sup> land between 1989 and 2010 [54,55]. Apart from coastal areas, studies have been conducted on the GBM river system as well. For instance, Baki and Gan (2012) found that Jamuna River, the lower part of Brahmaputra, is undergoing a net accretion of 44 m/year on its left bank and a net erosion of 39 m/year on its right bank during 1973–2003 [60]. Similarly, Dewan et al. (2017) analyzed the locations of the Padma River (the Ganges) where erosion and accretion took place and estimated that the net loss for the left bank is 155 km<sup>2</sup> and for the right bank is 28 km<sup>2</sup> in the period of 1973–2011 [61]. Billah (2018) found a high amount of accretion in the confluence of the Padma and Jamuna (*aka* the Brahmaputra) rivers and that resulted into the formation of numerous islands totaling of more than 300 km<sup>2</sup> of lands [62]. However, Khan and Islam (2003) claimed that the Brahmaputra River is shifting westward with a rate of 50 m/year during the period of 1830 and 1992 [63].



**Figure 9.** Net erosion and accretion rate (in square kilometer) per year. (A) represents the location-wise range of erosion/accretion rate. (B) demonstrates study and location-wise specific erosion/accretion rate [54–56,58,59,61,62,64].



Methodologically, many of these studies used remote sensing products as supporting tools to identify land degradation prone areas and calculate land loss or gain (e.g., [33,64,65]). These studies used digitization techniques on satellite imageries (i.e., on-screen digitization). This technique involves collection of satellite imageries over a specific time period and later manual digitization is undertaken on each of the images. Subsequently, these digitized layers are overlaid and compared. Digital Shoreline Analysis System (DSAS) has been used as a popular tool to compare these layers and analyze shoreline changes [54,56,59]. The studies that adopted on-screen digitization technique use various high to moderate resolution remote sensing imageries including aerial photographs [65,66], Sentinel-2 [65], and Landsat [54,58,63] products. The identification of the land-water boundary is a critical step in this technique. While some studies used visual inspection or direct digitization on the cloud-free, rectified imageries [62,63,66], others developed new approaches to demarcate the land-water boundary. For instance, Rahman et al. (2011) found that normalized difference vegetation index (NDVI) useful to distinguish land and water in a forested region [54]. Again, Ghosh et al. (2015) and Emran et al. (2016) developed modified normalized difference water index (MNDWI) and classified images in order to identify the land-water boundary in coastal regions [58,59]. Ahmed et al. (2018), on the other hand, used band 4 of Landsat ETM+ images to distinguish land and water [55]. Sarwar and Woodroffe (2013) found that creating the ratio of bands 5 and 2 in Landsat TM and ETM+ images is a useful approach to delineate the land-water boundary in coastal areas of Bangladesh [56]. Dewan et al. (2017) used Landsat bands 1, 6, and 7 to estimate bank line change in the Padma river [61]. Alternatively, Hazra et al. (2016) compared the fractal dimension index and shape index while analyzing the changes in shapes of islands over time [33]. Instead of demarcating the land-water boundary, Hassan et al., (2017) used a classification approach to calculate the amount of land converted to water [64]. Some of the studies used remote sensing products as ancillary information sources. For instance, Bonnema et al. (2015) used a satellite-based elevation product (i.e., SRTM) and a precipitation product (i.e., Tropical Rainfall Measuring Mission (TRMM)) in their hydrologic model to demonstrate shifting in Kaptai reservoir basin [67]. Similarly, Maswood and Hossain (2015) used bathymetric data calculated from SRTM, Landsat, and MODIS data to improvise the simulation of river dynamics [68].

### 3.4.2. Landslides

We found that seven articles have so far been published on landslide inventory and susceptibility mapping. These articles used remote sensing as a supporting tool to extract information that has been later employed to different models or analysis. Landslides can occur in areas where land has been degraded and, at the same time, a landslide can cause land degradation. As such, landslide inventory shows the locations of land degradation [66,67]. On the other hand, landslide susceptibility maps (LSM) show the spatial probability of landslides based on the relationship of previous landslides and their causal factors, such as slope, aspect, geology, and land use/land cover [68–71]. In this way, LSMs can also indicate locations prone to land degradation.

In Bangladesh, landslides occur mainly in the hilly south-eastern region known as the Chittagong Hilly Areas (CHA). We found that out of seven studies only one study produced landslide inventory for the entire CHA [72]. Other studies focused on creating LSMs for the two largest urban parts of the CHA-Chittagong Metropolitan Area (CMA) [73,74] and Cox's Bazar municipality [75], as well as for landslide prone Rangamati district [76]. Landsat TM and OLI images and MLC approach were used for mapping land use land cover change and developing indices (i.e., NDVI) [73,77], while Advanced Spaceborn Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) (30 m) and ALOS-PALSAR DEM (12.5 m) were used for preparing topographic causal factors such as slope, aspect, profile and plan curvature using the GIS platform [76,78]. In these studies, study areas and methods for creating LSMs were different, so it is difficult to say whether the use of different remote sensing products affected the prediction of the LSMs.

Despite experiencing landslides in almost every monsoon, Bangladesh lacks an official inventory of landslides hampering the preparation of LSMs [72]. Furthermore, unavailability of

cloud-free images hinders actual mapping of landslide prone locations though the incidence of landslide is high during the monsoon [78]. Landslide removes vegetation and the regrowth rate of vegetation is usually very high in the affected areas. Therefore, detecting landslides using automated techniques in moderate resolution (30 m) satellite images is difficult [72,76]. We found that only two studies attempted to use remote sensing methods [72,76], while other studies used field mapping for landslide inventory generation. Rabby and Li (2019) integrated field mapping and remote sensing-based Google Earth mapping to map 730 landslides over the whole CHA [72]. Google Earth provides an excellent platform in this regard because it contains an array of satellite images, including moderate resolution Landsat imagery (30 m), orthophotos, high resolution (0.5–3 m) Satellite Pour l'Observation de la Terre (SPOT), FORMOSAT-2, World View 1 and 2 imagery. Rabby and Li (2019) used field mapping to validate Google Earth mapping and found an overall accuracy of 88% [72]. Sifa et al. (2019) used Synthetic Aperture Radar (SAR) images to detect landslides [76]. They measured displaced mass between two images for four sub-districts of Rangamati district from pre and post-event (the 2017 Rangamati landslide) images. They detected 420 landslides and used them to generate LSM.

Other studies used field mapping to prepare landslide inventory and used it for LSM generation. These studies created LSMs with a fare (>70%) prediction capability [73,75,77]. Topographic causal factors such as slope, aspect, geology, and curvatures were used in those studies, although they may not have a direct connection with land degradation [73], but land use/land cover change has a direct connection with land degradation [78]. A MLC supervised classification method was used for land use and land cover mapping in these studies. The overall accuracy of these maps was >85%. To reveal the impact of hill cutting on landslides, Rahman et al. (2017) introduced a new causal factor called the distance from hill cutting locations in their study [78]. They used remote sensing methods to detect hill cutting with Landsat TM images of 1990 and 2010. Therefore, remote sensing helped showing the relationship of land degradation activities like removal of vegetation and hill cutting with landslide susceptibility of an area.

#### 4. Discussion

Monitoring and addressing the SDGs require a concerted effort from government, research organizations, non-government organizations, and local stakeholders. The availability of remote sensing data enables these actors to take better decisions. Recent developments of big data, cloud computing, and artificial intelligence provide enormous opportunities to obtain and analyze micro level data and address the SDGs accordingly [79,80]. Building of an integrated geospatial information infrastructure should be a priority for every country [81]. However, for a developing country, one of the biggest challenges would be effective and sustained access to this technology [82]. In order to address this concern, government and other stakeholders ought to think spatially and establish infrastructures that organize and share spatial information required for decision making [80,83]. As SDGs are interconnected, a geospatial infrastructure would demystify the interrelation and facilitate the connectivity [84]. However, along with these developments by the government, researchers and other stakeholders are required to produce impactful contributions that would assist the SDG related decision making. While current remote sensing research on Bangladesh brings forth interesting outcomes, we think this is inadequate. In the following sub-sections, we intend to provide directions for future research based on the limitations we identified in this work.

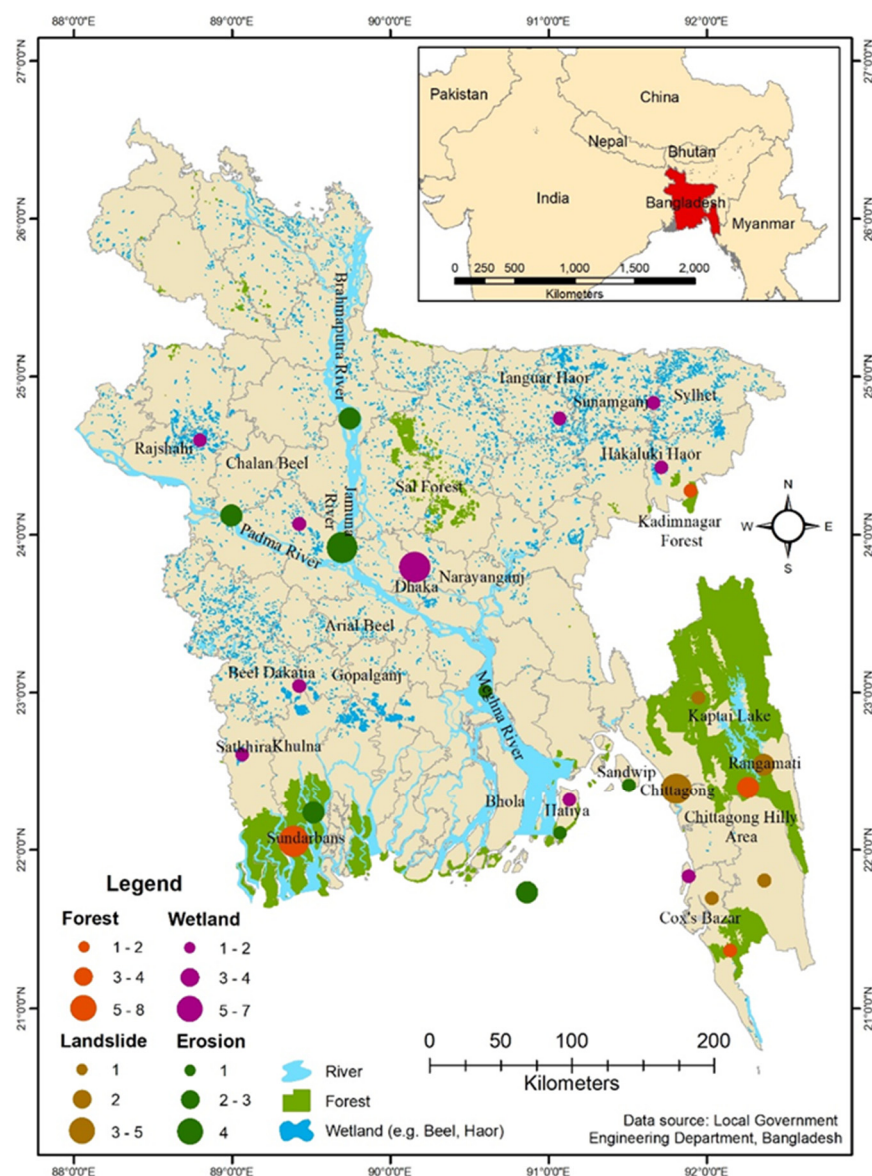
##### 4.1. Forest

Forest related research in Bangladesh mostly focused on change detection in their areal extent. They mostly used one satellite image per decade with a classification approach from which they calculated forest cover change. Despite this is an important contribution, only focusing on changes in forest boundary may not be sufficient to properly track SDG 15, hence more in-depth analysis on different aspects of forest health and ecosystem is required. Different ecological, biogeochemical, plant physiological traits can serve as indicators of forest health [85]. For instance, forest carbon sequestration

assessment can inform us about carbon stock in aboveground biomass, understory vegetation, litter, woody debris, and soil organic matter (see [86,87]). Also, canopy chemistry analysis (e.g., chlorophyll, nitrogen, lignin, carotene) can demonstrate forest functionality (see [88–90]). Net/gross primary productivity and fragmentation analysis have the potential to indicate specific locations of forest degradation (see [91,92]). The largest forest of Bangladesh, the Sundarbans, is encountering ‘top-dying’ disease in the dominant most tree- *H. fomes* which leads to forest degeneration [93]. Approaches of analyzing insect disturbances in forest using remote sensing may be useful for analyzing defoliation of *H. fomes* trees (see [94]). Furthermore, Biswas et al. (2007) and Uddin et al. (2013) identified the presence of invasive species in the forest ecosystem of Bangladesh [95,96]. Although those species are not ubiquitously abundant, they still remain as threats to native species. For regular and historical monitoring of invasive species distribution, remote sensing can act as an important tool (see [97]).

In Bangladesh, most of the forest related studies have been conducted on the Sundarbans (see Figure 10). This forest comprises of around 25% of the forested area of Bangladesh (DOE 2015). Similarly, the southeastern hilly part contains more than 25% of the forested area, yet there are only very few studies that have been conducted on this hilly forest. Illegal logging and shifting agriculture pose a threat to this hilly forest [98] and remote sensing estimation of forest cover and other forest attributes in this area could be a useful contribution. Also, Bangladesh has forests in part of the northcentral and southeastern zones of the country that never received enough attention. These forests are often smaller in size and people usually dwell in these forests. Many of these forests are used as ‘picnic or outing spots’ and forest biodiversity is not well taken care of. Remote sensing research can evaluate the changes in these forests. Because of smaller size and fragmentation, a remote sensing approach will require high-resolution data products to assess forest cover change or other attributes. In addition to traditional forests, social forestry is also prevalent in Bangladesh. Social forestry expands the forest cover of the country and it can serve important livelihood source to the local villagers as well [99]. DOE (2015) identified that more than 10% of the forested area is under social or village forests [18]. As integration of social science data with remote sensing becomes a more useful approach to deal with societal challenges, we postulate that remote sensing of social forestry can serve as an important topic of interest.

Methodologically, the supervised MLC classification approach is popular among the studies in Bangladesh. These studies mostly used Landsat images because of their availability. We think although supervised MLC or unsupervised ISODATA algorithms can provide a decent accuracy, other classification algorithms that provide a better accuracy could be used. For instance, based on a meta-analysis of pixel-based analysis of land cover classification, Khatami et al. (2016) reported that the support vector machine provided a greater accuracy followed by artificial neural network and random forest algorithms [100]. Similarly, Qian et al. (2014) found that support vector machine and normal Bayes classifiers were superior to classification and regression tree and k-nearest neighbor in an object-based land cover classification process [101]. In regard to satellite image usage, future studies can utilize freely available Sentinel images that have a better spatial resolution (10 m); however, Sentinel is a recently launched satellite and doesn’t have coverage before 2014. Moreover, the use of radar and LiDAR has been increased lately for forest attributes assessment (see, for instance, [102,103]). Synthetic aperture radar (SAR) sensor uses microwave signals that can penetrate vegetation and water and are less attenuated by the cloud. SAR images could be very useful in Bangladesh as they will be less constrained by the monsoon cloud and the effect of tide-ebb in mangrove forests. SAR images can also provide a good classification accuracy in the large-scale analysis (see [104]). As such, we highly recommend using SAR, particularly L-band (i.e., ALOS PALSAR) data, for forest attribute analysis.



**Figure 10.** Geographical coverage of the research articles published on forest, wetland, erosion, and landslide related issues in Bangladesh.

#### 4.2. Wetland

Existing remote sensing and GIS-based wetland (i.e., lowlands, rivers, and canals) and LULC change analysis research in Bangladesh focused mainly on ‘change detection’ elucidating spatio-temporal patterns of the change in LULC classes. Existing research provided knowledge of the state of wetlands in different parts of Bangladesh. Although this knowledge may generate insights on the state of wetlands and SDGs, to the best of our knowledge there exists no study that explored progress toward SDGs in Bangladesh based on analyzing spatio-temporal dynamics of wetlands using remote sensing. Although wetlands as nutrient-based-solution are essential to achieving many of the SDGs [105], existing RS-based studies on wetlands in Bangladesh do not depict a comprehensive picture on the nation’s progress toward these goals. For a country with vast wetlands, remote sensing data and techniques are undoubtedly useful than the traditional in-situ techniques. Existing studies only provide fragmented and episodic pictures on the SDG status by focusing on specific regions and timelines (see Figure 10).



To assess Bangladesh's progress towards achieving SDGs using remote sensing data and GIS techniques, future wetland research can focus on two crucial aspects: broadening the topical scope and covering all wetlands including lowlands, rivers, and canals. For example, wetland pollution is a serious issue, particularly in the city areas. Addressing the drivers of wetland loss and degradation, ensuring wise use of wetlands, maintaining ecological characters of wetlands are one of the key goals that can contribute to the achievement of the SDGs, upon implementation, as outlined in the 4th Ramsar Strategic Plan 2016–2024. Although current literature on wetland analysis provides important knowledge and insights on the spatio-temporal dynamics of wetland loss in Bangladesh primarily driven by increased urbanization, more research should focus on elucidating how and/or whether wetlands are contributing to achieving specific SDGs set by the United Nations.

#### 4.3. Land Degradation

Land degradation related research in Bangladesh mostly focused on erosion and accretion rate assessment of rivers or islands or coasts. However, considering the dynamic deltaic and coastal environment we need more research on erosion and accretion of rivers and sea. Riverbank erosion is considered as a major natural hazard in Bangladesh [106]. Despite having some large scale research on the GBM river system (i.e., [60,61,107]), we are in dire need of more research on how channels are shifting, to which directions these channels are migrating, and hotspots of erosion and accretion. In addition to trend analysis, we need predictive modeling based on remote sensing data. In the coastal areas, especially in the estuary zones, erosion/accretion is often very much context-dependent. As such, studies provided variable estimates of net land gain or loss. We need more research on economically and environmentally important coastal islands and areas.

Soil erosion *aka* land degradation is a threat to agricultural and land use sustainability and food production [108,109]. Although agriculture is an important part of the economy, we found no research on soil erosion in agricultural lands or its impacts on agriculture or land use sustainability using remote sensing. However, worldwide remote sensing has been used as an effective tool for measuring soil erosion due to agricultural activities and other natural or anthropogenic reasons (see, for instance, [110,111]). Studies often factored remote sensing information into (Revised) Universal Soil Loss Equation (USLE) in a GIS environment to obtain soil loss estimation (e.g., [112,113]). Remote sensing is usually used as an ancillary tool to provide important information in these research works. Studies developed land use land cover maps, derived slope and elevation data, obtained precipitation data from remote sensing products and later integrated those with field-collected information. Considering the dearth of knowledge in this research area, we believe conducting research on soil loss under different land cover types could provide information needed to ensure agricultural and land use sustainability.

Landslide related research in Bangladesh mostly focused on landslide susceptibility mapping. These studies used remote sensing as a supporting tool. In these studies, land use land cover has been used as a causal factor. So, we need an in-depth analysis of land use land cover change and its role in landslide susceptibility. We particularly need predictive modeling as future scenarios of land use land cover may have different effects on landslide susceptibility [114]. Even though land use land cover has been identified as a vital factor in landslide incidences, no study, as yet, has assessed the impact of future land use/land cover scenarios on landslide susceptibility in the Chittagong Hilly Area (CHA) [73]. Different urban growth, forest cover reduction, and hill-cutting scenarios can be modeled based on the past pattern using deep-learning and machine-learning methods. Landslide susceptibility scenarios can be assessed based on these future scenarios to understand the effects of land degradation on landslides. Land-use and land-cover scenario modeling can be done in a variety of ways using different techniques and software tools, such as cellular automata (CA), markov chain (MC), hybrid CA-MC (IDRISI software), logistic regression (CLUE-S model), FORE-SCE model (United States Geological Survey recommended), TerrSet software (Land Change Modeler, Geomod), Dinamica EGO software (weight of evidence) etc. Land-use/land-cover change is a dynamic landslide causal

factor but most of the casual factors are static (e.g., slope) and takes hundreds or thousands of years to change. This modeled future land-use/land-cover map will help to understand the future landslide susceptibility scenarios in CHA. In the study area, land-use zonation has not been implemented yet and future research can assess the effects of different urban growth, forest cover reduction and hill cutting scenarios for example, in Chittagong Hill Tracts (CHT) from 2010–2040 built-up area will increase by 156.29% in business as usual scenario and 19.20% in the environmental protection priority scenario [115]. Therefore, future research can assess the landslide susceptibility of CHT based on these changes of land use/land cover. Different cities of CHA, for example, Rangamati municipality has a proposed land-use map that has not been implemented yet. Future research can assess the impact of proposed land-use maps of landslide susceptibility and can give necessary suggestions to urban planners so that new plans do not bring slope instability in CHA.

In Bangladesh, most of the landslide related studies were on Chittagong Metropolitan Area (CMA), Cox's Bazar municipality and Rangamati district (see Figure 10). Landslide susceptibility mapping for the entire CHA has not been done yet, particularly due to the unavailability of landslide inventory. Field-based mapping would not be viable to create an inventory for such a large and mostly inaccessible area. Using remote sensing techniques some attempts have already been made to prepare landslides inventories [72,76], yet we need more studies on landslide inventory preparation using high-resolution imageries. Because Rabby and Li (2019) reported that 61% of the 730 landslides that they identified are relatively smaller ( $<500\text{ m}^2$ ) in size and cannot be detected in moderate resolution satellite images [72]. They also opined that due to topography and geology in Bangladesh small-sized landslides are dominant. As such, we recommend the use of both high-resolution remote sensing and field-based mapping for the preparation of landslide inventories. Since the CHA has a long history of land use conflicts, landslide susceptibility mapping using the landslide inventories would help government for more appropriate land use planning.

Methodologically, bivariate, multivariate, machine learning and deep learning methods were adopted for landslide susceptibility mapping. However, accuracy of the landslide susceptibility maps depends on the quality of the remote sensing products. Most of the studies used ASTER GDEM and Landsat products while Sifa et al. (2019) used ALOS PALSAR products that have better resolution [76]. However, as the study areas were different, we were not able to compare the accuracy of landslide susceptibility maps produced using different DEMs. We suggest that future studies can compare the accuracy of landslide susceptibility maps produced from different freely available DEMs, such as ASTER DEM, Shuttle Radar Topography Mission (SRTM) and ALOS PALSAR.

## 5. Conclusions

With the advent of 2020, assessing the progress of the SDGs becomes more important as many goals are planned to be achieved by this year. In this paper, we tracked and evaluated the progress made in SDG 15 components (i.e., forest, wetland, land degradation) using remote-sensing techniques. We focused on the research works conducted in Bangladesh, one of the most climate-vulnerable countries in the world. We systematically reviewed the peer-reviewed articles that were published between 2000 and 2019. We discussed the trends of research on forest, wetland, erosion, and landslide-related issues. We identified that research is geographically clustered in some areas and we urge more research on ecologically important areas that have not received attention yet. We found that land-use/land-cover analysis is a key approach of research in all research areas of SDG 15, except erosion. Most of the studies used moderate-resolution Landsat images because of its free availability and longer temporal coverage. The use of high-resolution images (e.g., SPOT, QuickBird, Sentinel) showed that better resolution can provide better accuracy. We observed that a supervised MLC classification approach is the most utilized method for land-use/land-cover classification. We recognized that support vector machine and random forest classification algorithms have better potential to provide higher accuracies. In erosion research, identifying the land-water boundary is important and we acknowledged that combining different bands or indices can be effective.



In addition to tracking the trends of current research, we provided guidelines and directions for future research. We suspect that if the current trend of research is continued, we may not have achieved satisfactory progress at the end of 2030, when the SDGs will reach their completion. We suggested some specific research areas to ensure the advancement of current research. The availability of high-resolution optical imageries, use of radar images, and development of machine-learning methods provide us a window of opportunity to fulfill current research gaps and advance our current knowledge. We acknowledge that we had some limitations in our research. We focused only on erosion and landslides in the land degradation section, while land degradation encompasses salinity, flooding, subsidence etc. Considering the large scope, we recommend addressing only land degradation-related research in a separate study. Furthermore, we only considered peer-reviewed journal articles for SLR, and thus disregard non-refereed reports and articles. Also, we did not consider non-English research in this study. Despite these limitations, the review approach we have taken in this paper is methodologically sound and can be replicated for other parts of the world. We think similar analysis on different countries would be useful for researchers and policy makers that could provide important information for sustainable development.

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**Note:** The R codes used to create the graphs can be found here: [https://github.com/asif-ishti/SDG\\_Bangladesh\\_graphs](https://github.com/asif-ishti/SDG_Bangladesh_graphs). The maps are created using ArcGIS 10.7.1.

## Appendix A

**Table A1.** Search queries for systematic literature review. (Platform: Web of Science. Time span: January 2000–August 2019.)

Topic	Search Queries	Number of Articles	Total Number (Removing Duplicates)
Forest cover	TS = (remote sensing) AND TI = (mangrove* OR forest* OR deforest*) AND TI = (Bangladesh)	07	48
	TS = (remote sensing) AND TS = (mangrove* OR forest* OR deforest*) AND TI = (Bangladesh)	17	
	TS = (remote sensing) AND TS = (mangrove* OR forest* OR deforest*) AND TS = (Bangladesh)	39	
	TS = (remote sensing) AND TS = (mangrove* OR forest* OR deforest* OR Bangladesh) AND TI = (Sundarban* OR Sunderban*)	21	
	TS = (remote sensing) AND TS = (forest* OR deforest* OR forest cover) AND TI = (Bangladesh)	16	
	TS = (remote sensing) AND TS = (forest* OR deforest* OR forest cover) AND TS = (Bangladesh)	36	
Wetlands	TS = (remote sensing) AND TS = (wetland OR canal* OR river*) AND TS = (Bangladesh)	76	76
	TS = (remote sensing) AND TI = (wetland OR canal* OR river*) AND TS = (Bangladesh)	27	

Table A1. Cont.

Topic	Search Queries	Number of Articles	Total Number (Removing Duplicates)
Land degradation (Erosion)	TS = (remote sensing) AND TI = (river* OR erosion OR coast*) AND TS = (Bangladesh)	42	79
	TS = (remote sensing) AND TI = (degradation* OR erosion OR accretion) AND TS = (Bangladesh)	07	
	TS = (remote sensing) AND TS = (degradation* OR erosion OR accretion) AND TS = (Bangladesh)	39	
	TS = (remote sensing) AND TS = (river bank OR erosion OR coast*) AND TS = (Bangladesh)	56	
Land degradation (Landslides)	TS = (remote sensing) AND TS = (landslide* OR avalanche* OR mudslide* OR earthfall OR landslip) AND TS = (Bangladesh)	05	05
Land use land cover change	TS = (remote sensing) AND TI = (land use OR land cover OR change detect*) AND TS = (Bangladesh)	21	82
	TS = (remote sensing) AND TS = (land use OR land cover OR change detect*) AND TS = (Bangladesh)	82	
Erosion (due to flood or river flow)	TS = (remote sensing) AND TS = (river discharge OR river flow OR river morpho* OR water flow OR water resource) AND TS = Bangladesh	45	78
	TS = (remote sensing) AND TS = (inundation OR flood hazard* OR flood OR flood vul*) AND TS = Bangladesh	55	
Land degradation (agriculture)	TS = (remote sensing) AND TS = (agriculture) AND TS = (erosion OR land degrad* OR soil degrad*) AND TS = (Bangladesh)	02	0
	TS = (remote sensing) AND TS = (land degrad* OR soil degrad*) AND TS = (Bangladesh)	10	
	TS = (remote sensing) AND TS = (soil erosion) AND TS = (Bangladesh)	02	
Total			368
Inclusion of external articles in the initial review (Google Scholar search)			17
Total for initial review			385

## Appendix B

Table A2. Details of the forest-related remote-sensing studies that conducted forest cover classification.

Reference	Study Period	Remote Sensing Product	Classification Approach	Accuracy Obtained	Primary Software	Remarks
Redowan et al. (2014) [37]	1988 2010	Landsat TM	Supervised MLC	84.6% 87.5%	ERDAS Imagine 9.2	<ul style="list-style-type: none"><li>Images were cloud free.</li><li>Image differencing was used as change-detection algorithm.</li></ul>
Hassan et al. (2018) [24]	2016 2017	Sentinel-2	Random Forest (RF)	94.53% 95.14%	R-studio	<ul style="list-style-type: none"><li>QuickBird (2.4 m) image was used to identify land-cover features.</li><li>As non-parametric machine-learning classifiers (e.g., RF) require a large number of reference data, they collected ground training data using GPSs and a GPS camera.</li></ul>
Rahman et al. (2019) [25]	2019	WorldView-2 (2 m) TDX SAR (12 m)	Unsupervised ISODATA	89.33% (WV2) 89.89% (WV2-TDX)	Arc GIS 10.2.1	<ul style="list-style-type: none"><li>TDX-SAR data was primarily used for canopy height measurement.</li><li>Google Earth image was used for accuracy assessment.</li><li>The NDVI-Red Edge (NDVI<sub>re</sub>) has shown to be a good measure of biophysical plant traits and has been helpful in discriminating mangroves from non-mangroves.</li></ul>
Ahammad et al. (2019) [31]	2003 2014	Landsat	Supervised MLC	83% 79%	ENVI 5.0	<ul style="list-style-type: none"><li>Digital Globe image was used for accuracy assessment.</li></ul>
Quader et al. (2017) [27]	1975 1989 2000 2010	Landsat MSS Landsat TM Landsat ETM+ Landsat TM	Hierarchical classification (NDVI threshold), Unsupervised ISODATA	75.8% 84.4% 86.8% 78.1%	N/A	<ul style="list-style-type: none"><li>Due to heterogeneity of the area, the whole study area was first subdivided into land (i.e., mangroves) and water areas based on a NDVI threshold considering all negative NDVI values as water.</li><li>Google Earth and SPOT images were used for accuracy assessment.</li><li>Post-classification change detection algorithm was used.</li></ul>
Giri et al. (2007) [29]	1977 1989 2000	Landsat MSS Landsat TM Landsat ETM+	Supervised MLC	79% 85% 86%	N/A	<ul style="list-style-type: none"><li>QuickBird (2.4 m) image and aerial photographs were used for accuracy assessment.</li></ul>
Rahman et al. (2013) [116]	1999–2000	Landsat ETM+	Supervised MLC Unsupervised ISODATA Band Ratio/Supervised	89% 86% 90%	N/A	<ul style="list-style-type: none"><li>They used Optimum Index Factor for band ratio and found the value high for the ratio- B1, B4, B7.</li><li>Google Earth images were used for accuracy assessment.</li></ul>

## Appendix C

**Table A3.** Details of the wetland related studies based on remote sensing data and techniques.

Reference	Study Period	Remote Sensing Product	Classification Approach	Accuracy Obtained	Primary Software	Remarks
Mahmud et al. (2011) [41]	1978	Landsat MSS	Supervised MLC, parallelepiped	87–92.5%	ERDAS Imagine 9.2; ArcGIS 9.3.1	<ul style="list-style-type: none"> <li>Images represent wet season (June to August).</li> <li>Parallelepiped as non-parametric rule improved the classification accuracy.</li> </ul>
	1988	Landsat MSS				
	1998	Landsat TM				
	2009	Landsat TM				
Dewan & Yamaguchi (2009) [39]	1975	Landsat MSS	Supervised MLC	85.6%	ERDAS Imagine	<ul style="list-style-type: none"> <li>Robust accuracy assessment of LULC maps using field data, geographic features on land use maps, high-resolution images (i.e., SPOT and IKONOS), and topographic map.</li> <li>Additionally, rule-based post-classification refinement was used.</li> </ul>
	1989/90	SPOT Pan (10 m)		NA		
	1992	Landsat TM		89.6%		
	2003	Landsat ETM+ IKONOS Pan (1 m)		90%		
Dewan & Yamaguchi (2009) [40]	1960	Topographic maps (scale 1:50,000)	Supervised MLC	NA	ERDAS Imagine and ArcGIS 9.1	<ul style="list-style-type: none"> <li>Only winter time data was used. Therefore, use of other seasonal data could highlight seasonal dynamics.</li> <li>Field-based and high resolution images were used as reference data.</li> <li>Post-classification refinement was useful to achieve better classification accuracy.</li> </ul>
	1975	Landsat MSS		85.6%		
	1988	Landsat TM		86.4%		
	1999	Landsat TM		90.4%		
	2003	Landsat ETM+		90%		
	2005	IRS-1D LISS III		88.2%		
Griffith et al. (2010) [46]	1990	Landsat TM ERS-1	Support Vector Machine (SVM)	83.5%	imageSVM, LibSVM ERDAS Imagine	<ul style="list-style-type: none"> <li>Multi-source data and knowledge-based post-processing strategy yielded best overall accuracy.</li> <li>Some land-use classes (e.g., wetland) are better delineated with multi-temporal information rather than sole use of their spectral information.</li> <li>SVMs suited for classifying heterogeneous RS data with non-linear class distribution.</li> </ul>
	2000	Landsat ETM+ ERS-2		83.8%		
	2006	Landsat ETM+ ASAR		84.7%		
Kumar and Ghosh (2012) [51]	1977	Landsat MSS	Supervised ML	86%	Idrisi 32; Arcview 3.2; Cartalinx	<ul style="list-style-type: none"> <li>Spectral confusion due to coarse spatial resolution as well as use of training samples from paper-based maps seem to have impacted the classification accuracy of older images.</li> </ul>
	1989	Landsat TM		90%		
	1997	Landsat TM		92%		
	1999	Landsat ETM		94%		

Table A3. Cont.

Reference	Study Period	Remote Sensing Product	Classification Approach	Accuracy Obtained	Primary Software	Remarks
Ahmed and Ahmed (2012) [45]	1989	Landsat TM	Fisher’s linear discriminant	85.2%	ERDAS Imagine 9.1	<ul style="list-style-type: none"><li>Seasonality of collected images, lower spatial and spectral resolution caused issues such as mixed pixels among landuse classes and spectral mixing or confusion which contributed to some misclassifications.</li><li>Temporal incongruence of reference maps and Landsat images may have resulted in producing spurious ground truth data.</li></ul>
	1999	Landsat ETM+		86.8%		
	2009	Landsat TM		91.6%		
Rahman et al. (2017) [78]	1972	Landsat MSS	Supervised MLC	82%	ENVI 5.0; ArcGIS 10.1	<ul style="list-style-type: none"><li>Agriculture and forest classes were less accurately classified than the water class in all study years.</li><li>Various reference data were used to increase the overall classification accuracy of LULC mapping in different years.</li></ul>
	1978			89%		
	1989	Landsat TM		90%		
	2009			86%		
	2013	Landsat 8 (OLI)		82%		
Hassan and Southworth (2017) [42]	1972	Landsat MSS	Random Forest (RF)	87%	ERDAS Imagine; R-studio	<ul style="list-style-type: none"><li>Large number of reference data was used from diverse sources.</li><li>Large number of predictor variables was used in the RF model including topographic, spectral bands and indices, and infrastructure information (e.g., road density, distance to main road and river/lake).</li><li>DMSP-OLS night-light reflectance, elevation, tasseled cap greenness, and red, NIR and thermal band were identified as most important variables for accurate prediction of LULC classes.</li><li>The user accuracy for classes including water bodies were higher (over 90%).</li><li>Relatively lower user accuracy was reported for wetland and agricultural classes due to misclassification for 1972–1990.</li><li>Land-cover information extracted from Google Earth imagery helped minimize misclassifications for more recent years.</li></ul>
	1980			86%		
	1990	Landsat TM		89%		
	1995			86%		
	2000	Landsat ETM+		85%		
	2005	Landsat TM		91%		
	2010			97%		
	2015	Landsat OLI-TIRS		94%		
	1989	Landsat TM				
	2001	Landsat ETM				
2010	Landsat TM					
Jahan et al. (2018) [117]	2014	Landsat 8	Supervised ML	NA	ERDAS Imagine 9.1 ArcGIS 10.2	<ul style="list-style-type: none"><li>Landsat, SRTM, and topographic datasets were used to delineate river basin catchment area, drainage, slope, and LULC.</li><li>LULC analysis was secondary focus; no indication of classification accuracy.</li></ul>
		SRTM DEM				

Table A3. Cont.

Reference	Study Period	Remote Sensing Product	Classification Approach	Accuracy Obtained	Primary Software	Remarks
Tareq et al. (2018) [118]	1989	Landsat TM	Supervised ML	NA	ERDAS Imagine ArcGIS	<ul style="list-style-type: none"> <li>Cloud free winter (November to December) images were used.</li> <li>Focus group discussion, key informant interviews and informal discussion were used in identifying ground truth data.</li> <li>Focused on evaluation of waterlogging hazard scenario based on results from LULC change analysis.</li> <li>No indication of classification accuracy.</li> </ul>
	2000	Landsat TM				
	2011	Landsat TM Rapid Eye Google Earth Pro				
Huq et al. (2019) [48]	1973	Landsat 1	Object-based	NA	QGIS	<ul style="list-style-type: none"> <li>Accuracy assessment of study years, except for 2014, could not be performed due to lack of ground-truth data.</li> <li>Land cover change analysis results served as proxy indicators for assessing changes of freshwater ecosystem services.</li> </ul>
	1994	Landsat 5				
	1995	Landsat 5		>83		
	2014	Landsat 8		NA		
	2015	Landsat 8		NA		
Paul et al. (2019) [43]	1967	CORONA (Pan, 8 m)	Unsupervised ISODATA	NA	NA	<ul style="list-style-type: none"> <li>Only dry season images were used.</li> <li>Manual editing on raster layers was done to identify seasonal waterbodies previously not detected by ISODATA analysis.</li> </ul>



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