



Research Article

Candidate Dry-season Refugia and Recent Winter Open-water Decline in Hakaluki Haor, Bangladesh (1995–2026)

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Abstract

Hakaluki Haor is a major freshwater wetland in north-eastern Bangladesh, but the spatial concentration of persistent water and the consistency of recent winter open-water change remain poorly resolved. We combined JRC Global Surface Water v1.4 with Landsat Collection 2 surface reflectance in Google Earth Engine. A reproducible 164.410 km² analysis domain was defined from pixels with long-term water occurrence above 15%. At the 80% threshold, persistent permanent-water cores, mapped as candidate dry-season refugia, occupied 20.316 km² (12.357% of the domain). JRC monthly recurrence gave a mean of 7.378 recurrence-weighted water-month equivalents over ever-water pixels; 68.569% of that area fell in the 6–12-month-equivalent classes. Lost-water classes exceeded new-water classes in the original domain, two buffered domains and the full bounding box, although the ratio was strongly boundary-dependent (36.7–985.9). Of 32 Landsat winters from 1995 to 2026, 23 passed scene and clear-area requirements. The full Landsat record had no significant monotonic trend (Sen's slope +0.296 km² yr⁻¹; p=0.342), whereas 2016–2026 declined significantly (Sen's slope -1.939 km² yr⁻¹; p=0.008) at all three tested MNDWI thresholds. Sentinel-1 and Sentinel-2 winter areas covaried strongly during 2018–2026 (Pearson r=0.972), but their absolute extents differed. Published waterbird counts were available for nine matched winters; their moderate association with water area (r=0.413) became weak after adjustment for the number of beels surveyed (r=0.085). Published field studies support the ecological plausibility of retained-water refugia, but the mapped locations remain candidates for field verification.

Keywords

Wetland Monitoring, Dry-season Refugia, Surface Water Persistence, Google Earth Engine, Landsat, Sentinel-1, MNDWI, Waterbird Habitat

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1. Introduction

Seasonally inundated wetlands change rapidly across months and years. Their ecological and economic functions depend on where water persists during dry periods, not only on total wetland area. Satellite observations are therefore useful for separating persistent open-water cores from temporary inundation and for placing recent changes within a longer record. Recent work also shows the value of clearly defined, repeatable satellite indicators for practical wetland monitoring [1]. The JRC Global Surface Water dataset provides a consistent 30 m account of water occurrence, persistence and transition derived from the Landsat archive [2].

Hakaluki Haor is an Ecologically Critical Area in north-eastern Bangladesh and supports fisheries, agriculture and wetland-dependent livelihoods [3]. A recent fisheries assessment also identified continuing ecological and management concerns in the haor [4]. Earlier remote-sensing studies described substantial land-cover and water-body changes in Hakaluki Haor and the wider Sylhet wetland region [5-8]. Those

studies mainly compared multiple land-cover classes at selected dates or seasons. Their results show why continued monitoring is necessary, but they do not directly quantify the long-term frequency of permanent water within a fixed, reproducible water domain.

This study asks five questions. (1) How much of the analysis domain remained permanent water in most valid years, and how long did water recur across calendar months? (2) Does the predominance of JRC lost-water over new-water classes persist when the spatial domain is expanded? (3) Does winter open-water extent show a monotonic full-record trend, or a more recent directional change? (4) Do Sentinel-1 and Sentinel-2 independently corroborate recent interannual variation? (5) Do published midwinter waterbird counts show a simple association with mapped winter water after survey coverage is considered? The contribution is a reproducible water-persistence assessment that distinguishes satellite evidence from ecological context and tests sensitivity to thresholds, spatial domain and sensor choice.

2. Materials and Methods

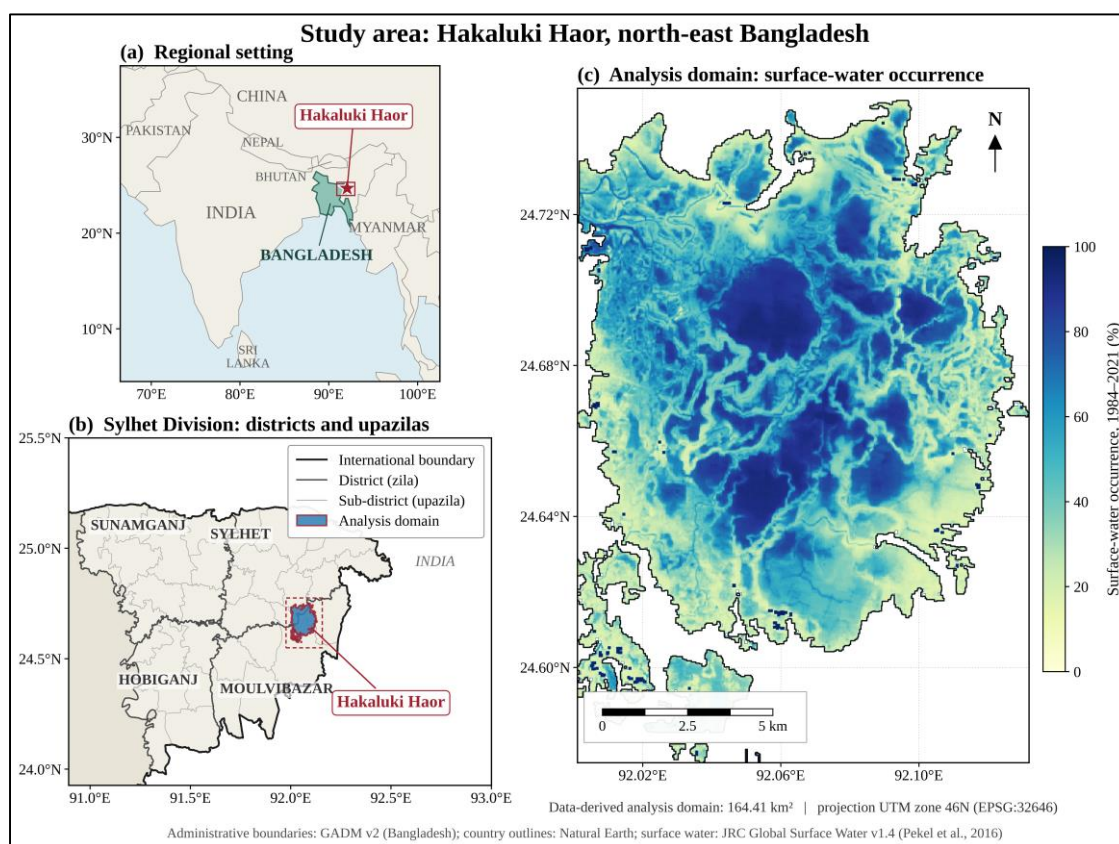


Figure 1. Location of Hakaluki Haor in Bangladesh and the 164.41 km² data-derived analysis domain. The local panel shows long-term JRC surface-water occurrence. The analysis boundary is reproducible but is not the legal Ecologically Critical Area boundary.

2.1. Study Area and Analysis Domain

Hakaluki Haor lies approximately between 24.55–24.85° N and 92.00–92.35° E in the Sylhet and Moulvibazar districts of north-eastern Bangladesh (Figure 1). An authoritative digital legal boundary was not available for this analysis. We therefore defined a reproducible analysis domain from the JRC Global Surface Water occurrence layer. Pixels with water occurrence above 15% were vectorized within the bounding box, and the largest contiguous polygon was retained. The resulting domain covered 164.410 km². It is an analytical water domain and should not be interpreted as the gazetted Ecologically Critical Area boundary.

2.2. JRC Water Persistence and Transitions

We used the JRC Global Surface Water v1.4 dataset, which summarizes the Landsat archive at 30 m resolution [2]. Long-term surface-water occurrence was used for domain construction and spatial context. Permanent-water frequency was calculated from the Yearly History image collection for 1984–2021. For each pixel, the number of valid years classified as permanent water was divided by the number of years with a valid water-history observation. Pixels with permanent-water frequencies of at least 60%, 80% and 100% were summarized to test sensitivity. The 80% threshold was selected as the main operational definition of a persistent permanent-water core.

Hydroperiod was represented with the JRC Monthly Recurrence collection for 1984–2021. For each of the 12 calendar months, monthly recurrence was converted from a percentage to a probability and summed over months with observations. The resulting 0–12 value is a recurrence-weighted water-month equivalent, not a direct count of inundated months in any particular year. Ever-water pixels were grouped into less than 3, 3 to less than 6, 6 to less than 9 and 9–12 equivalent-month classes.

The JRC transition layer was summarized using the official class meanings. Stable permanent water, stable seasonal water, new or lost seasonal water, new or lost permanent water, seasonal-to-permanent conversion, permanent-to-seasonal conversion and ephemeral classes were kept separate. Seasonal-to-permanent conversion was not counted as new water, and permanent-to-seasonal conversion was not counted as complete water loss.

Because the occurrence-derived domain can omit newly formed peripheral water, transition areas were recalculated in four domains: the original analysis domain, 1 km and 2 km buffers clipped to the bounding box, and the full fixed bounding box. For each domain, lost water was defined as lost permanent plus lost seasonal water, while new water was defined as new permanent plus new seasonal water. Ratios were used only to assess boundary sensitivity, not as annual rates.

2.3. Landsat Winter Open-Water Series

Landsat Collection 2 Level-2 surface-reflectance imagery

was processed in Google Earth Engine [9]. Landsat 5 TM covered the early record, Landsat 7 ETM+ was restricted to the 2012 and 2013 winters, and Landsat 8 and 9 OLI/OLI-2 covered the recent record. The surface-reflectance products build on LEDAPS for Landsat 5 and 7 and LaSRC for Landsat 8 and 9 [10, 11]. Surface-reflectance scale and offset factors supplied with Collection 2 were applied. Fill, dilated cloud, cirrus, cloud, cloud shadow, snow and radiometric saturation were masked using QA_PIXEL and QA_RADSAT.

Each winter was defined as 1 December of the previous calendar year through 31 January of the ending year. A median composite was calculated from the available clear observations. Open water was mapped using the Modified Normalized Difference Water Index, MNDWI=(green-SWIR1)/(green+SWIR1), following Xu [12]. The main threshold was MNDWI>0. A winter was retained when at least two scenes were available and at least 95% of the analysis domain had one or more valid observations. Twenty-three of 32 winters met these requirements. Excluded years were 1998, 2002–2006, 2008, 2012 and 2013. In 1996 and 1997, more than 95% of the domain had at least one clear observation, but less than 95% had two or more observations.

2.4. Trend and Uncertainty Analysis

Monotonic trends were tested with the Mann–Kendall statistic with continuity and tie correction [13], and trend magnitude was estimated as the median pairwise Sen slope [14]. The lag-1 correlation was inspected because serial dependence can alter Mann–Kendall significance [15]. No strong residual lag-1 dependence was detected in the fitted series. Tests were calculated for the full set of usable winters and for the continuous 2016–2026 period. Threshold sensitivity repeated all area and trend calculations at MNDWI>−0.10 and MNDWI>+0.10.

No field observations or independent historical reference archive covering the full study period were available. We therefore do not report a confusion matrix, area-adjusted accuracy or classification accuracy because these require an appropriate probability sample and more reliable reference labels [16]. Threshold sensitivity is used only as a robustness check, not as a replacement for independent validation. We did not apply an empirical transformation among TM, ETM+ and OLI sensors; small residual cross-sensor differences may therefore remain in the full record [17]. The recent 2016–2026 test is less exposed to this issue because it uses OLI and OLI-2 observations. The reported Landsat values represent mapped open water under the stated processing rules; they do not include water hidden beneath dense emergent vegetation.

2.5. Sentinel Cross-Sensor Corroboration

Recent winter water was mapped independently from Sentinel-1 GRD and Sentinel-2 surface reflectance for the same December-January window [18, 19]. Sentinel-1 Interferometric Wide swath VV scenes from 2016–2026 were restricted to

incidence angles of 31–45°, composited by the median and classified with a winter-specific edge-Otsu backscatter threshold; slopes of 5° or more were excluded. Thresholds ± 1 dB were retained as a sensitivity check. Sentinel-2 Harmonized surface reflectance from 2018–2026 was masked with Cloud Score Plus ($cs_cdf \geq 0.65$) and the Scene Classification Layer, composited by the median and classified with $MNDWI > 0$, with -0.05 and $+0.05$ thresholds retained for sensitivity [20].

Cross-sensor corroboration was assessed descriptively. Pearson and Spearman correlations compared annual Sentinel-1 and Sentinel-2 winter-water areas over their matched years. The 2026 binary masks were also placed on the same 20 m export grid to calculate intersection, union and the share of Sentinel-1 water pixels also classified as water by Sentinel-2. The sensors were not treated as interchangeable or as independent accuracy reference data.

2.6. Published Waterbird Evidence

Midwinter waterbird totals and survey coverage were taken from the CREL Technical Report 2, which compiled Asian Waterbird Census surveys of Hakaluki Haor for 2006–2011 and 2014–2018 [21]. The number of beels surveyed varied from 18 to 43, and no survey was conducted in 2012 or 2013. We matched the census record to Landsat winters that passed the satellite-data requirements. Nine winters overlapped: 2007,

2009–2011 and 2014–2018. Pearson and Spearman correlations were calculated for total waterbirds against mapped winter water. The calculations were repeated after dividing the count by the number of beels surveyed as a simple survey-effort adjustment. These correlations are descriptive because the sample is small, coverage was not identical and the report notes differences in survey timing, habitat conditions and bird groups among years. The census evidence was not used to validate the satellite classification.

3. Results

3.1. Candidate Dry-Season Refugia

Permanent-water frequency produced a spatially concentrated network of retained-water cores (Figure 2). At the main 80% threshold, these satellite-identified candidate dry-season refugia covered 20.316 km², equivalent to 12.357% of the analysis domain and 12.384% of the ever-water area. Threshold choice affected the mapped extent: 22.767 km² met the 60% definition, whereas 7.836 km² remained permanent in every valid year (Table 1). Here, refugia is an operational landscape-screening term for highly persistent water that may retain ecological function during seasonal contraction; it does not indicate field confirmation of every mapped pixel.

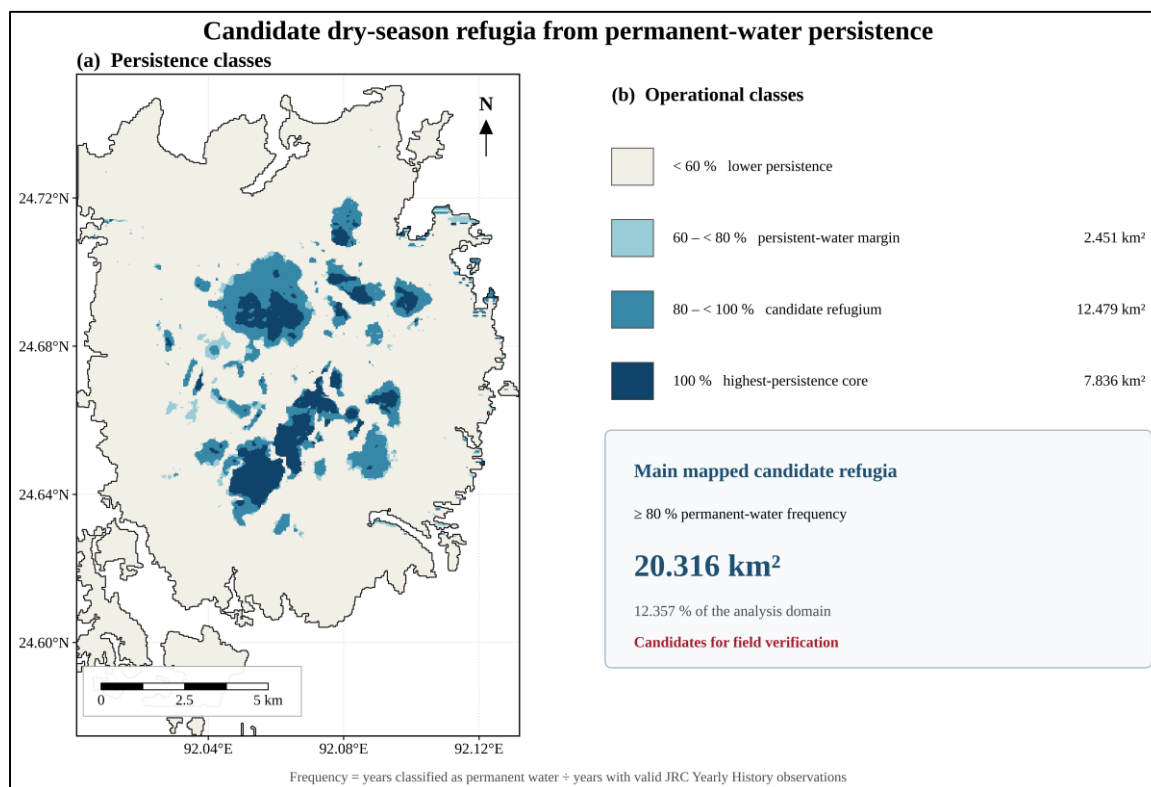


Figure 2. Candidate dry-season refugia identified from JRC permanent-water frequency. The main candidate class contains pixels classified as permanent water in at least 80% of years with valid Yearly History observations; the 100% class is the highest-persistence core. These are priorities for field verification, not confirmed ecological refugia.

Table 1. Sensitivity of persistent permanent-water area to the frequency threshold.

Frequency threshold	Core area (km ²)	% analysis domain	% ever-water area
60%	22.767	13.848	13.878
80%	20.316	12.357	12.384
100%	7.836	4.766	4.777

The complementary monthly-recurrence analysis covered 164.050 km² of ever-water pixels and produced a mean of 7.378 recurrence-weighted water-month equivalents. Only 0.034 km² fell below 3 equivalents; 51.528 km² fell between 3 and less than 6, 73.032 km² between 6 and less than 9, and 39.456 km² between 9 and 12. Thus, 112.488 km² (68.569% of ever-water area) occupied the 6–12-equivalent-month classes. These values summarize long-term monthly recurrence and are not observed months in an individual year.

3.2. Surface-Water Transitions

The transition layer was dominated by stable seasonal water (107.672 km²) and stable permanent water (15.198 km²). Lost seasonal water covered 33.957 km², while new seasonal water

covered 0.034 km². A further 6.214 km² changed from permanent to seasonal water. This indicates reduced persistence, not complete loss. Seasonal-to-permanent conversion covered 0.680 km² (Figure 3; Table 2). Lost permanent water and ephemeral classes occupied small areas. These categories describe change between the JRC comparison periods and are not annual rates.

The direction of the lost-versus-new comparison persisted when the analysis domain was expanded, but its magnitude changed sharply. Lost water exceeded new water by 985.9:1 in the original occurrence-defined domain, 104.8:1 in the 1 km buffer, 74.9:1 in the 2 km buffer and 36.7:1 in the full fixed bounding box. Total mapped new water increased from 0.034 km² in the original domain to 4.411 km² in the full box. This confirms the predominance of lost-water classes while showing that no single loss-to-gain ratio is boundary-invariant.

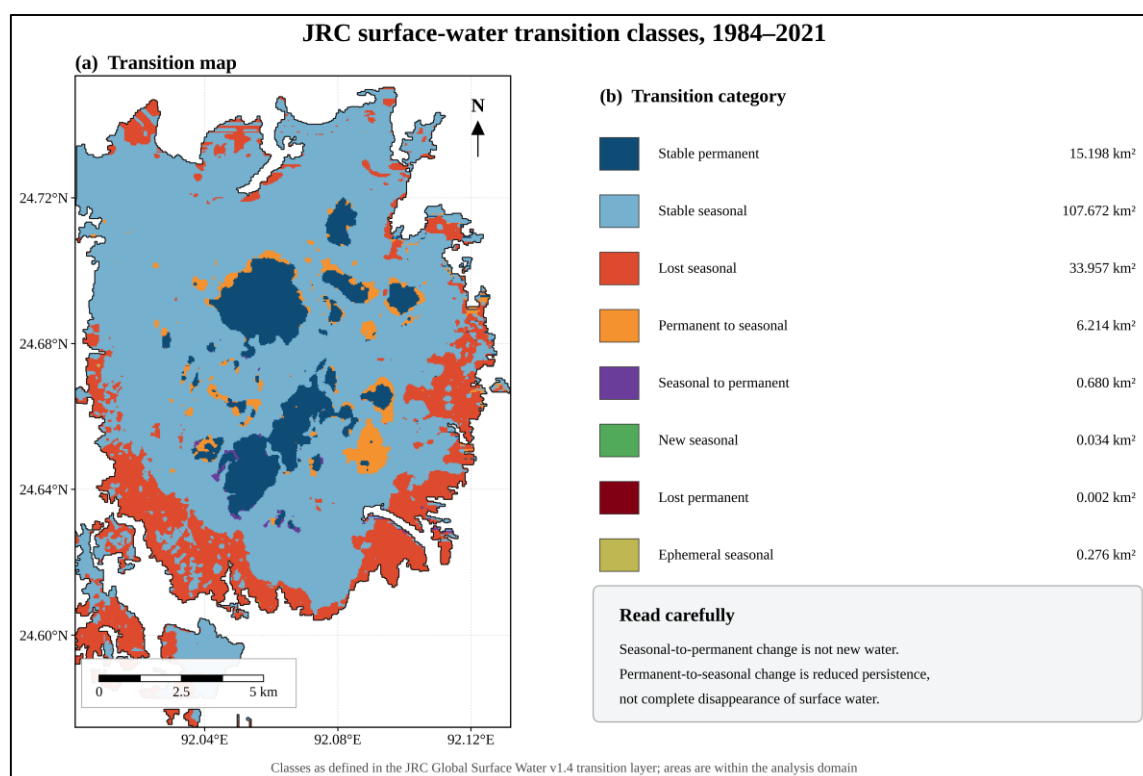


Figure 3. Official JRC Global Surface Water transition classes within the analysis domain. Categories are reported separately to avoid treating seasonal-to-permanent conversion as new water or permanent-to-seasonal conversion as complete water loss.

Table 2. JRC transition categories and mapped areas.

Transition category	Area (km ²)
Stable permanent	15.198
Stable seasonal	107.672
Lost seasonal	33.957
Permanent to seasonal	6.214
Seasonal to permanent	0.680
New seasonal	0.034
Lost permanent	0.002
Ephemeral seasonal	0.276

Categories describe change between the JRC comparison periods (1984–2021); they are not annual rates.

3.3. Winter Open-Water Dynamics

Across the 23 usable winters, mapped open water averaged 84.126 km² (SD 14.065 km²; coefficient of variation 16.719%). Values ranged from 54.015 km² in 1997 to 113.673 km² in 2011. The full record did not show a significant monotonic trend at the main threshold (Sen's slope +0.296 km² yr⁻¹;

$Z=0.951$; $p=0.342$). Full-record slopes were also non-significant at thresholds of -0.10 and $+0.10$ (Table 3).

The continuous 2016–2026 period showed a significant decline at the main threshold (Sen's slope -1.939 km² yr⁻¹; $Z=-2.647$; $p=0.008$; Figure 4a). The decline remained significant at MNDWI thresholds of -0.10 and $+0.10$, with slopes from -1.939 to -2.465 km² yr⁻¹ (Figure 4b; Table 3). The recent direction was therefore robust to the tested threshold range, although the exact magnitude varied.

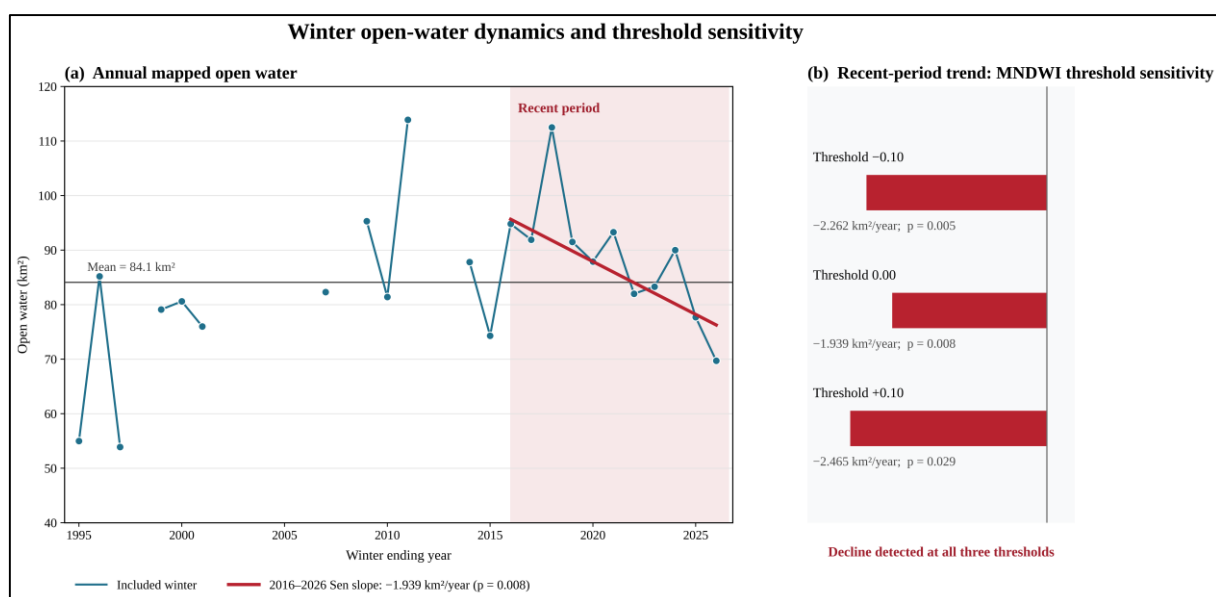


Figure 4. Annual winter mapped open-water extent and threshold sensitivity. Lines join consecutive usable winters; gaps indicate winters excluded by scene or valid-area requirements. The recent decline was significant at all three tested MNDWI thresholds.

Epoch summaries provide a complementary spatial comparison, with the number of usable winters stated for each panel (Figure 5). Mean annual mapped water rose from 70.712 km² in 1995–2000 to 95.089 km² in 2016–2020, then was

82.608 km² in 2021–2026. These values are descriptive rather than equal-support trend estimates: the panels contain 5, 1, 3, 3, 5 and 6 usable winters, respectively, and the 2001–2005 panel represents only one winter.

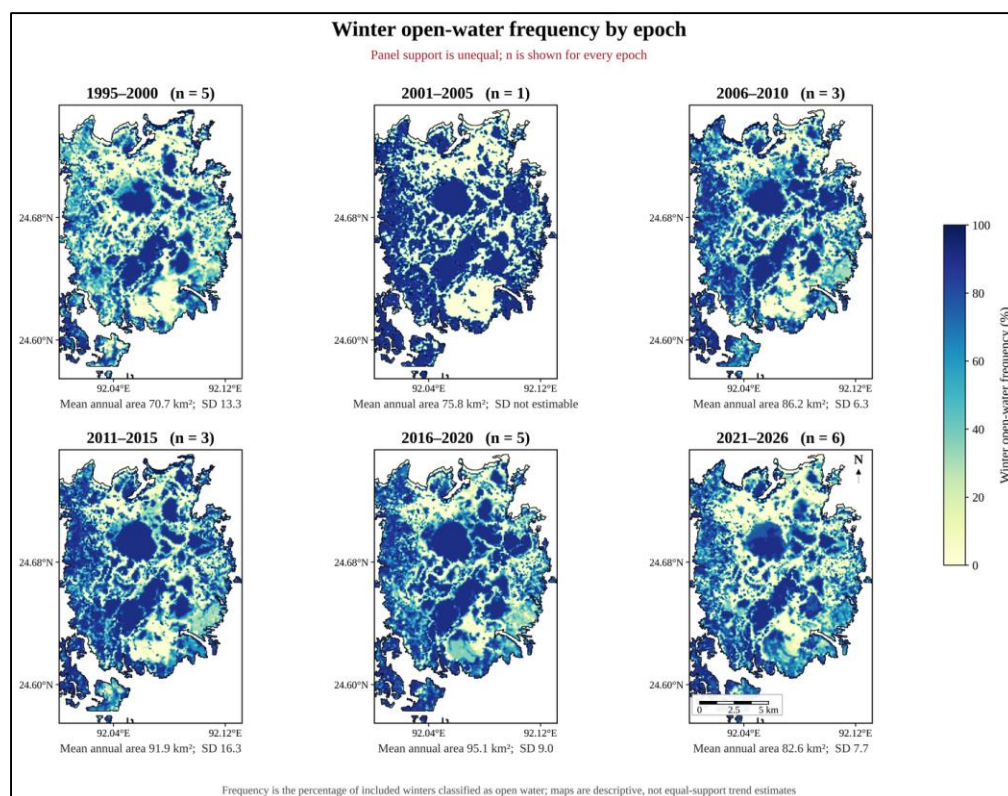


Figure 5. Winter open-water frequency within six epochs. Colour represents the percentage of usable winters classified as open water; and *n* is reported for every panel. Because epoch support is unequal, the maps are descriptive spatial summaries and are not used as equal-support evidence of temporal change.

Table 3. Mann–Kendall and Sen’s slope sensitivity results.

Period	MNDWI threshold	n	Sen slope (km ² yr ⁻¹)	Z	p
1995–2026 usable winters	−0.10	23	+0.028	0.053	0.958
1995–2026 usable winters	0.00	23	+0.296	0.951	0.342
1995–2026 usable winters	+0.10	23	+0.433	1.479	0.139
2016–2026	−0.10	11	−2.262	−2.803	0.005
2016–2026	0.00	11	−1.939	−2.647	0.008
2016–2026	+0.10	11	−2.465	−2.180	0.029

n = number of usable winters; Z = Mann–Kendall test statistic.

3.4. Sentinel Cross-Sensor Corroboration

Sentinel-1 mapped winter water declined from 42.296 km² in 2016 to 27.822 km² in 2026, while the adaptive VV thresholds remained within −16.10 to −16.70 dB. Sentinel-2 mapped 123.816 km² in 2018 and 81.948 km² in 2026 at MNDWI>0;

the 2019–2026 values ranged from 78.833 to 94.391 km². Absolute Sentinel-2 areas were consistently larger than Sentinel-1 areas, so the two products are not directly interchangeable.

Despite the magnitude difference, interannual variation was strongly aligned across the nine matched winters of 2018–2026 (Pearson $r=0.972$; Spearman $\rho=0.867$). The association remained strong after excluding the high-water 2018 winter (2019–2026: Pearson $r=0.842$; Spearman $\rho=0.810$). On

the common 20 m grid in 2026, 99.7% of Sentinel-1 water pixels also occurred within Sentinel-2 water, although the intersection-over-union was only 0.327 because Sentinel-2

mapped a much broader water extent (Table 4).

Table 4. Descriptive Sentinel-1 and Sentinel-2 cross-sensor comparison.

Comparison	Result
Annual area, 2018–2026 (n=9)	Pearson $r=0.972$; Spearman $\rho=0.867$
Annual area, 2019–2026 (n=8)	Pearson $r=0.842$; Spearman $\rho=0.810$
2026 common 20 m grid	$S1=27.072 \text{ km}^2$; $S2=82.468 \text{ km}^2$; intersection= 26.991 km^2
2026 spatial agreement	99.7% of S1 water within S2 water; intersection-over-union=0.327

S1 = Sentinel-1; S2 = Sentinel-2.

3.5. Waterbird–Water Association

Across the nine matched winters, total waterbird abundance had a moderate positive association with mapped winter water (Pearson $r=0.413$; Spearman $\rho=0.533$). However, the rela-

tionship became weak when counts were divided by the number of beels surveyed (Pearson $r=0.085$; Spearman $\rho=0.183$; Table 5). The secondary census data therefore do not support a simple interpretation in which total open-water extent alone controlled waterbird abundance.

Table 5. Exploratory association between published waterbird counts and mapped winter water (n=9 matched winters).

Census measure	Pearson r	Spearman ρ
Total waterbirds	0.413	0.533
Waterbirds per surveyed beel	0.085	0.183

Counts from the Asian Waterbird Census compiled in CREL Technical Report No. 2 [21]. Associations are exploratory and do not validate the satellite classification.

4. Discussion

4.1. A Spatially Concentrated Permanent-Water Core

The main long-term result is the concentration of persistent permanent water. Only 20.316 km^2 met the 80% definition, and the 100% core was less than 8 km^2 . The ecological use of refugia is well established in seasonally flooded wetlands: permanent water can allow remnant fish populations to survive dry periods and contribute to recolonization after reflooding [22]. Hakaluki-specific field and fisheries studies make the interpretation locally plausible. Retained-water beels are described as winter shelter, feeding, breeding and nursery habitat, and annual beel drying is reported as a pressure on fish assemblages. The CREL surveys show that waterbird importance is

concentrated in particular beels rather than distributed evenly across the haor [3, 21, 23, 24]. This triangulation supports the ecological relevance of persistent water, but it does not prove that every mapped core pixel performed a refugial function. We therefore use candidate dry-season refugia or persistent-water cores rather than field-confirmed refugia.

The monthly-recurrence result adds a seasonal dimension to this pattern. More than two-thirds of ever-water area occupied the 6–12 recurrence-weighted water-month classes, but only 20.316 km^2 met the stricter 80% permanent-water-frequency definition. Recurring seasonal inundation is therefore widespread, whereas highly persistent permanent water is spatially concentrated. The water-month equivalent is a long-term probability summary and should not be read as a direct annual hydroperiod.

The waterbird comparison reinforces this caution. Raw bird totals rose moderately with mapped water across the nine matched winters, but the relationship nearly disappeared after a simple adjustment for the number of beels surveyed. The CREL report also shows that high water can reduce exposed mud and short wet grass used by shorebirds, while individual

beels fluctuate with water level, fishing and drainage [21]. Habitat configuration, water depth and the mix of bird groups therefore matter alongside total open-water area.

4.2. Different Forms of Surface-Water Change

Keeping the official transition classes separate changes how the change should be interpreted. The 0.680 km² seasonal-to-permanent class represents increased persistence, not newly created water. Conversely, the 6.214 km² permanent-to-seasonal class represents reduced persistence rather than total disappearance. The domain-sensitivity test supports the direction of loss dominance: lost-water classes exceeded new-water classes in all four tested domains. However, the ratio declined from 985.9 in the occurrence-defined domain to 36.7 in the full box as peripheral gains were admitted. The direction is robust, but no single loss-to-gain ratio is. Conversion of seasonal margins and weakening of permanent-water persistence are different processes and require different field investigation.

The satellite record cannot identify why these transitions occurred. Independent studies nevertheless document beel siltation, annual drying, destructive fishing and drainage or dewatering in Hakaluki Haor, and report improvements where beels and canals were re-excavated [3, 24]. These pressures are plausible mechanisms that are consistent with weakening water persistence, but they are not proven causes of the mapped pixels. The CREL report separately documents hunting and poisoning as threats to waterbirds [21]; hunting is therefore treated as a biodiversity pressure, not as a cause of water-area change.

4.3. Full-Record Stability and Recent Decline

The Landsat series did not show a significant monotonic trend across all usable winters, but the continuous 2016–2026 record declined significantly. The recent result was retained at all three MNDWI thresholds, which supports the direction of change even though the exact slope remains threshold-dependent. This pattern also explains why conclusions can differ among studies that use selected years, different seasonal windows or broad land-cover classes. Waleed et al. [7] used a regional machine-learning, multi-class assessment for Sylhet, whereas Siddique et al. [8] examined selected-date and seasonal land-cover patterns in Hakaluki Haor. In contrast, this study measures JRC permanent-water frequency and annual winter open water within one fixed water-derived domain. It is therefore a complementary water-persistence assessment, not a competing full land-cover map.

The Sentinel results provide genuine cross-sensor corroboration of recent interannual variability. Sentinel-1 and Sentinel-2 annual areas were strongly correlated even after the high-water 2018 winter was omitted, and nearly all 2026 Sentinel-1 water pixels were nested within the broader Sentinel-2 water mask. This supports the direction and timing of recent

variation, but not equality of mapped area: Sentinel-2 consistently classified substantially more water than Sentinel-1. Optical MNDWI and radar backscatter respond to different surface and vegetation conditions, so agreement in temporal pattern is more defensible than treating either absolute extent as ground truth.

4.4. Limitations

This assessment has eight main limitations. First, no independent reference archive was available for historical accuracy assessment, so the Landsat series is not presented as a validated habitat map. Second, optical MNDWI represents exposed water and may omit water beneath dense emergent or floating vegetation, while Sentinel-1 backscatter uses a narrower operational water definition; their areas are therefore not interchangeable. Third, nine Landsat winters failed the scene or clear-area requirements, and two early included winters had limited repeat clear coverage. Fourth, the JRC products and the Landsat series are both derived from Landsat observations; their agreement cannot be treated as independent confirmation. Fifth, the occurrence-derived analysis domain does not reproduce the legal ECA boundary and suppresses peripheral gains; any exact loss-to-gain ratio is therefore boundary-dependent. Sixth, residual differences among Landsat sensors may affect exact full-record magnitudes because no empirical cross-sensor harmonization was applied [17]. Seventh, the recurrence-weighted water-month metric is a long-term monthly probability summary, not a direct observation of annual inundation duration. Eighth, the secondary waterbird counts had variable spatial coverage and were not linked to mapped water at individual beels. These limitations restrict causal and ecological interpretation but do not alter the transparent product-based summaries reported here.

5. Conclusions

Within a reproducible 164.410 km² analysis domain, 20.316 km² was classified as permanent water in at least 80% of valid JRC Yearly History observations. Monthly recurrence showed widespread seasonal inundation but a much more concentrated permanent-water core. Field-based publications show why retained-water beels can have refugial importance, but the mapped cores remain candidate dry-season refugia rather than field-confirmed ecological refugia. Lost-water classes exceeded new-water classes in every tested spatial domain, although no exact loss-to-gain ratio was stable to boundary choice. The 23-winter Landsat series showed no significant full-record trend, whereas 2016–2026 declined significantly at all three tested MNDWI thresholds. Strong Sentinel-1/Sentinel-2 temporal correspondence corroborated recent interannual variation while also showing that absolute sensor-derived areas differ. Published waterbird totals did not retain a clear relationship with water area after simple adjustment for census

coverage. The paper therefore supports a stronger but still defensible conclusion: persistent water is spatially concentrated, recent winter open water declined, and the ecological consequences depend on habitat condition and management rather than water area alone.

Abbreviations

CREL	Climate-Resilient Ecosystems and Livelihoods
ECA	Ecologically Critical Area
ETM+	Enhanced Thematic Mapper Plus
GRD	Ground Range Detected
JRC	Joint Research Centre
MNDWI	Modified Normalized Difference Water Index
OLI	Operational Land Imager
SAR	Synthetic Aperture Radar
SD	Standard Deviation
TM	Thematic Mapper
VV	Vertical Transmit–Vertical Receive

Author Contributions

Md. Imran Hossain: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing

Md. Atiqur Rahman: Investigation, Validation, Writing – review & editing

Nafia Muntakim: Formal Analysis, Validation, Writing – review & editing

Tomalika Biswas: Validation, Writing – review & editing

Md. Mujibor Rahman: Supervision, Validation, Writing – review & editing

Md. Redwanur Rahman: Supervision, Project administration, Validation, Writing – review & editing

Data Availability Statement

All satellite products used in this study are publicly available through Google Earth Engine: JRC Global Surface Water v1.4 [2], Landsat Collection 2 Level-2 surface reflectance, Sentinel-1 GRD [18] and Sentinel-2 Harmonized surface reflectance [19]. Waterbird census data were taken from a published report [21]. The Google Earth Engine scripts and the derived CSV, GeoJSON and GeoTIFF outputs underlying the reported results are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Biography



Md. Imran Hossain is a PhD fellow at the Institute of Environmental Science, University of Rajshahi, Bangladesh, and the Founder and Lead Researcher of GRID Bangladesh (Geospatial Research & Insight for Development). His research focuses on the application of geographic information systems (GIS), remote sensing and Earth observation to environmental monitoring and natural-resource assessment. His work particularly involves cloud-based geospatial analysis using Google Earth Engine, multi-temporal and multi-sensor satellite imagery, land-use and land-cover change, vegetation dynamics, river and coastal processes, and spatial data visualisation. A major focus of his research is the long-term assessment of environmental change in the Sundarbans mangrove ecosystem using satellite observations. His broader research interests include spatial data quality, environmental change detection, and the use of open Earth observation archives to support land, water and ecosystem management in Bangladesh.



Md. Atiqur Rahman is a researcher affiliated with the Institute of Environmental Science, University of Rajshahi, Bangladesh, where he completed his M. Phil in 2016, and a member of the institute's Ecology and Biodiversity Research Laboratory. He holds bachelor's and master's degrees in Botany from the University of Rajshahi and serves as Assistant Professor at Puthia Mohila Degree College, Rajshahi. He is also affiliated with GRID Bangladesh (Geospatial Research & Insight for Development). His research applies GIS and remote sensing to the forest environment, with ongoing work on multi-decadal forest-cover dynamics across the Sal-dominated national parks of northwestern Bangladesh.



Nafia Muntakim is affiliated with the Institute of Environmental Science, University of Rajshahi, Bangladesh. Her research focuses on climate change and adaptation, heatwave vulnerability, urban resilience, human–environment interactions, water quality assessment, GIS, and remote sensing. She applies geospatial analysis, satellite remote sensing, statistical methods, and machine-learning approaches to investigate environmental and climatic problems. In the present study, she was responsible for conceptualization, methodology, formal analysis, and writing the original draft. Her broader research experience includes industrial effluent pollution, particulate air pollution, climatic drivers of lightning casualties, land-cover dynamics, surface urban heat islands, and compound hydroclimatic extremes. Her

research interests particularly emphasize the application of geospatial and Earth observation data to environmental assessment and climate-resilient planning in Bangladesh.



Tomalika Biswas is a graduate student pursuing a Master of Science in the Department of Geosciences, Colorado State University, Fort Collins, USA. She earned her BSc and MS degrees in Geology and Mining from the University of Rajshahi, Bangladesh. Her expertise spans applied and field geology, geophysics, geotechnical engineering and remote sensing. Her recent work applies geospatial analysis to environmental monitoring in Bangladesh, including mangrove change in the Sundarbans, urban thermal environments in Rajshahi and land-cover change in Altadighi National Park. In the present study, she contributed to validation and manuscript review.



Md. Mujibor Rahman is a Professor and Head of the Environmental Science Discipline at Khulna University, Bangladesh. He received his Ph. D. in GIS in 2007 and completed a Postgraduate Diploma in Remote Sensing and GIS from the Indian Institute of Remote Sensing, Dehradun, India. He also holds master's and bachelor's degrees in Geography and Environmental Studies from the University of Rajshahi, Bangladesh. His research interests include GIS and remote sensing, physical and coastal environments, environmental planning and management, climate-change vulnerability, and disaster-risk assessment. He has extensive experience in teaching, postgraduate research supervision, and multidisciplinary environmental and geospatial research, with numerous journal articles, book chapters and

funded research projects focusing particularly on the coastal and environmentally vulnerable regions of Bangladesh.



Md. Redwanur Rahman is a Professor at the Institute of Environmental Science, University of Rajshahi, Bangladesh, with more than 25 years of research and applied research experience in ecology, biodiversity and environmental science. He received his B. Sc. in Zoology, M. Sc. in Ecology and Ph. D. from the University of Rajshahi, where he also conducted postdoctoral research supported by the Ministry of National Science, Information and Communication Technology, Government of Bangladesh. He has also served as a technical advisor for ecology and biodiversity programmes in Bangladesh. His research interests include ecology and biodiversity, environmental pollution, environmental impact assessment, ecosystem and natural-resource management, and environmental change. More recently,

his research has incorporated GIS, remote sensing and geospatial approaches for assessing vegetation dynamics, land-cover change and environmentally sensitive ecosystems, including the Sundarbans. He has supervised 25 completed M. Phil. and Ph. D. degrees and currently supervises several postgraduate researchers. His scholarly contributions include approximately 150 research papers, five books, three book chapters and three encyclopedia entries.

Research Field

Md. Imran Hossain: Geographic Information Systems, Google Earth Engine analysis, Wetland and Coastal Monitoring, Remote Sensing Image Processing, Spatial Data Quality Assessment, Cartography

Md. Atiqur Rahman: Forest Ecology and Biodiversity, Forest-cover Change Detection, Geographic Information Systems and Remote Sensing, Protected-area Monitoring, Satellite Time-series Analysis

Nafia Muntakim: Climate Change and Adaptation, Heatwave Vulnerability and Urban Resilience, Geographic Information Systems and Remote Sensing, Hydroclimatic Extremes, Environmental Pollution and Water Quality, Human–environment Interactions

Tomalika Biswas: Applied Geology, Field Geology, Geophysics, Geotechnical Engineering, Remote Sensing, Environmental Monitoring, Land-cover Change Analysis

Md. Mujibor Rahman: Geographic Information Systems and Remote Sensing, Physical and Coastal Environments, Environmental Planning and Management, Climate-change Vulnerability, Disaster-risk Assessment

Md. Redwanur Rahman: Ecology and Biodiversity, Environmental Pollution, Environmental Impact Assessment, Ecosystem and Natural-resource Management, Environmental Change, Geographic Information Systems and Remote Sensing