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Water Quality Under Stress: Population Pressure, Environmental Degradation, and Climate Impact: Evidence from Refugee Camps in Cox's Bazar District, Bangladesh (2016-2024)

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Abstract

Providing safe water is a major challenge in refugee camps, where environmental and climatic conditions strongly shape living conditions. The Rohingya crisis, which peaked in 2017, displaced over 700,000 people to Bangladesh's Cox's Bazar district, where camps established in a confined area pose environmental and health challenges.

Remote sensing and environmental monitoring offer valuable insight into these evolving conditions, yet integrating heterogeneous data streams into high-quality, harmonised datasets remains difficult. This study addresses that gap by collecting, quality-controlling and integrating environmental, climatic and ecosystem-service data for the Cox's Bazar settlements.

We examine three stressors: (1) overpopulation and settlement dynamics, (2) reduced ecosystem services from land-use change, and (3) climate-related impacts from anomalies in the climate regime—while treating water, sanitation and hygiene (WASH) infrastructure as an intervening factor and water quality as the outcome. Following FAIR principles, the harmonised camp-level database is released as an open dataset alongside the article.

Keywords: water quality, refugee camps, environmental impact, ecosystem services, WASH, Landsat imagery, climate indicators, ecological indicators, Rohingya, Bangladesh

1. Introduction

The intricate dynamics between environmental factors, ecosystem services and the provision of clean water intersect with the issue of forced displacement in the context of refugee camps, giving rise to complex relationships. This is particularly evident in Bangladesh, a country facing the Rohingya refugee crisis. Since the mass exodus from Myanmar in 2017 (see the timeline of key political and environmental events in the Supplementary Material, Figure S1), refugees have encountered

substantial difficulties in securing safe water, sanitation and hygiene (WASH) conditions. The relocation of refugees to Bhasan Char in 2020 has been a controversial attempt to alleviate pressure on the camps in Cox's Bazaar (Islam and Siddika, 2022).

While studies have examined the relationships between water variability, environmental hazards, and migration (Xu and Famiglietti, 2023) and highlighted the importance of safe water for public health in refugee settings (Yasmin et al., 2023), the specific issue of environmental factors affecting the provision of clean water in refugee camps has not been fully investigated.

According to the UNDP (2018), the main water issues in Rohingya camps are saltwater intrusion, groundwater depletion, and contamination. Saltwater intrusion tied to salinization is increasingly understood as a systemic threat to drinking-water security, as evidenced in the Yucatan Peninsula, Narvaez-Montoya et al. (2025) and it emerges from interacting social, ecological and technological drivers even at low levels of watershed imperviousness (Grant et al. 2026).

In tropical regions, groundwater depletion, likewise, is increasingly understood as a compound outcome of intersecting pressures rather than any single cause, emerging where rising abstraction, land-use change and increasingly variable weather act together (Bierkens and Wada, 2019). In India, for instance, Asoka et al. (2017) showed that groundwater-storage change is governed jointly by pumping for irrigation and by variability in monsoon precipitation, so that storage falls fastest where heavy abstraction coincides with weak rainfall. This dependence on weather is equally pronounced elsewhere in the humid tropics: Taylor et al. (2013) found that groundwater recharge in East Africa is disproportionately sustained by intense rainfall events, leaving aquifers vulnerable when such events falter. These studies provide a framing for reading groundwater decline in settings such as refugee camps in Cox's Bazar District as the product of coupled human and climatic drivers, consistent with the multi-stressor perspective adopted here.

Water contamination in Rohingya refugee camps is mainly linked to occurrence of heavy metals, like arsenic and iron, faecal contamination from human sources, and inadequate WASH infrastructure (UNDP 2018). Many studies highlight water quality concerns in remote communities and refugee camps, including the Cox's Bazar district, namely contamination, poor taste and smell, and high levels of various pollutants, such as bacteria, turbidity, and chemicals (Alazzeh et al., 2019; Pompei et al., 2019; García et al., 2021; Khandaker, 2022) and the importance of conducting regular water testing and monitoring to ensure the safety of drinking water (Alazzeh et al., 2019; García et al., 2021; Khandaker, 2022).

Several studies have also investigated WASH conditions in Rohingya refugee camps. Akhter et al. (2020) found that better WASH infrastructure, lower population density, and shorter water collection times are associated with better water quality and lower prevalence of water-borne

diseases. However, more recent studies have reported inconsistent access to improved water sources, leading to rationing and longer storage times, which increase the risk of waterborne diseases (Butt et al., 2025).

A follow-up study in 2024 found improved access to chlorinated water, but also a decline in hygiene practices, leading to increased cases of diarrhoea and eye infections in children under 5 years old (Moghe et al., 2024). The study highlights the non-linear nature of WASH processes and the potential for setbacks with negative health impacts. More broadly, infrastructure provision alone may be insufficient to secure water quality: modelling global surface waters, Jones et al. (2022) found that even meeting the SDG 6.3 target of halving untreated wastewater would leave key quality thresholds unmet where treatment capacity is initially low, and Silva et al. (2024) argue that safeguarding water sustainability should primarily focus on pollution avoidance, monitoring, knowledge sharing, research into contamination removal and tightening of regulations.

For context, as reported by Alazzeh et al. (2019) the quality of treated drinking water in two Palestinian refugee camps, Aida Camp and Alazzah Camp deteriorated as it moved from community tanks to rooftop tanks, with Aida Camp having higher levels of contamination, including too high residual chlorine levels, and presence of total coliform bacteria and *E. coli*. Their study recommends more frequent and transparent water testing to ensure the safety of the drinking water in these camps, highlighting the need for improved water management practices to mitigate the impact of factors such as air temperature on water quality (Alazzeh et al., 2019).

Beyond water scarcity and contamination, the Rohingya refugee camps are vulnerable to severe weather events, such as heavy monsoon rains and cyclonic storms, which exacerbate the existing environmental and health challenges (A. Alam et al., 2020). In fact, climate change and weather conditions, are recognized as factors that can affect the quality of water and the effectiveness of water treatment systems (Alazzeh et al., 2019; Pompei et al., 2019; Ali and Shahreen, 2024; Egea-Corbacho et al., 2026) in Cox's Bazar refugee camps.

For instance, temperature regulation can have an impact on the provision of clean water in refugee camps. High temperatures can increase the rate of water evaporation, contamination, and bacterial growth, which can compromise the quality and safety of the water supply (WHO, 2011). Water storage containers and distribution systems can be exposed to direct sunlight, causing the water temperature to rise potentially leading to an increase in waterborne diseases (WHO, 2011; McCann et al., 2018).

This, in turn, can increase the demand for more efficient and effective treatment methods, such as advanced disinfection processes, to ensure the elimination of pathogens and other harmful microorganisms (McCann et al., 2018; Egea-Corbacho et al., 2026). In fact, in Drinking Water

Treatment Plants (DWTPs), the adaptation of disinfection processes, such as chlorination, ozonation, and ultraviolet radiation, is crucial to achieve effective pathogen elimination while minimising the formation of harmful byproducts (Egea-Corbacho et al., 2026).

Therefore, provision of adequate shelter and effective temperature regulation is essential in refugee camps both to ensure the provision of clean and safe drinking water but also to reduce the risk of heat-related illnesses, respiratory problems, and mortality (WHO, 2011; UNHCR, 2016; McCann et al., 2018).

To mitigate these risks, various strategies are employed, including the careful orientation of shelters and tents to optimise natural cross-ventilation and minimise direct solar exposure (UNHCR, 2016; McCann et al., 2018). The use of innovative materials, such as reflective coatings and insulated fabrics, can also help to block intense solar radiation, while the incorporation of green spaces and natural shade into camp layouts can help to reduce ambient temperatures and radiant heat, highlighting the importance of a holistic approach to temperature regulation in refugee camps (UNHCR, 2016; McCann et al., 2018). The vegetation's role extends well beyond shade: Anav et al. (2026) found that peri-urban forests measurably lower both temperature and air-pollution-related mortality in European cities, while Baker et al. (2026) quantified the rainfall-generating service of tropical forests, estimating that each square metre returns on the order of hundreds of litres to regional rainfall annually through evapotranspiration – regulating services whose loss during camp expansion bears directly on local water and thermal conditions.

In our analysis, we followed the plea to study the refugee camps “as dynamic social and environmental ecosystems where changes in the social and ecological spheres are interconnected and co-evolved” (Sobczak-Szelc et al. 2026) and the general guidelines of the One Health framework that implies joint analysis of human and environmental health (Gruetzmacher et al., 2021). Hence, the study aims to identify significant changes over time occurring in the refugee camps of Cox's Bazar, highlighting areas of vulnerability, and therefore, assess the resilience of living conditions in refugee camps.

In our analysis, we consider water quality parameters and WASH infrastructure data together with three key stressors impacting the Cox's Bazar refugee camps, i.e., (1) overpopulation and settlement dynamics, (2) climate related impacts stemming from anomalies in the climate regime, (3) reduced ecosystem services caused by land use changes. The analysis of environmental, infrastructural, and water quality data provide a robust foundation for understanding how refugee settlements respond to environmental and operational stressors, supporting evidence-based strategies and interventions to improve the health, well-being, and sustainability of these communities, particularly in relation to clean water access within these camps. Beyond these analyses, a key contribution of this work is the harmonised database itself: all environmental, climatic, ecosystem-service, infrastructural and

water-quality indicators were integrated to a common camp-and-year structure and are released as an openly accessible dataset (see Data Availability), providing a reusable evidence base for monitoring living conditions in protracted displacement settings.

2. Materials and Methods

2.1. Study Area

The study area is located along the coastal strip of southeastern Bangladesh in the district of Cox's Bazar, within the Chittagong division (Figure 1). The district southeast side borders Rakhine state in Myanmar and the Bay of Bengal on its west side. Before hosting the refugee camps, the area was characterized by broadleaf tree forest, with grasslands and croplands playing an important role (Rosińska and Teobaldelli, 2025; See Supplementary Material, Figure S2). The expansion of settlements, particularly in 2017-2019, has generated significant pressure on the local landscape both within the camps and in the surrounding areas, through deforestation (Mohammad E. Hasan et al., 2021; Sarkar et al., 2023), loss of vegetation cover (Rahman et al., 2019), soil instability (Ahmed, 2021; Chowdhury, 2023), and changes in surface hydrology (Zaman et al., 2020).

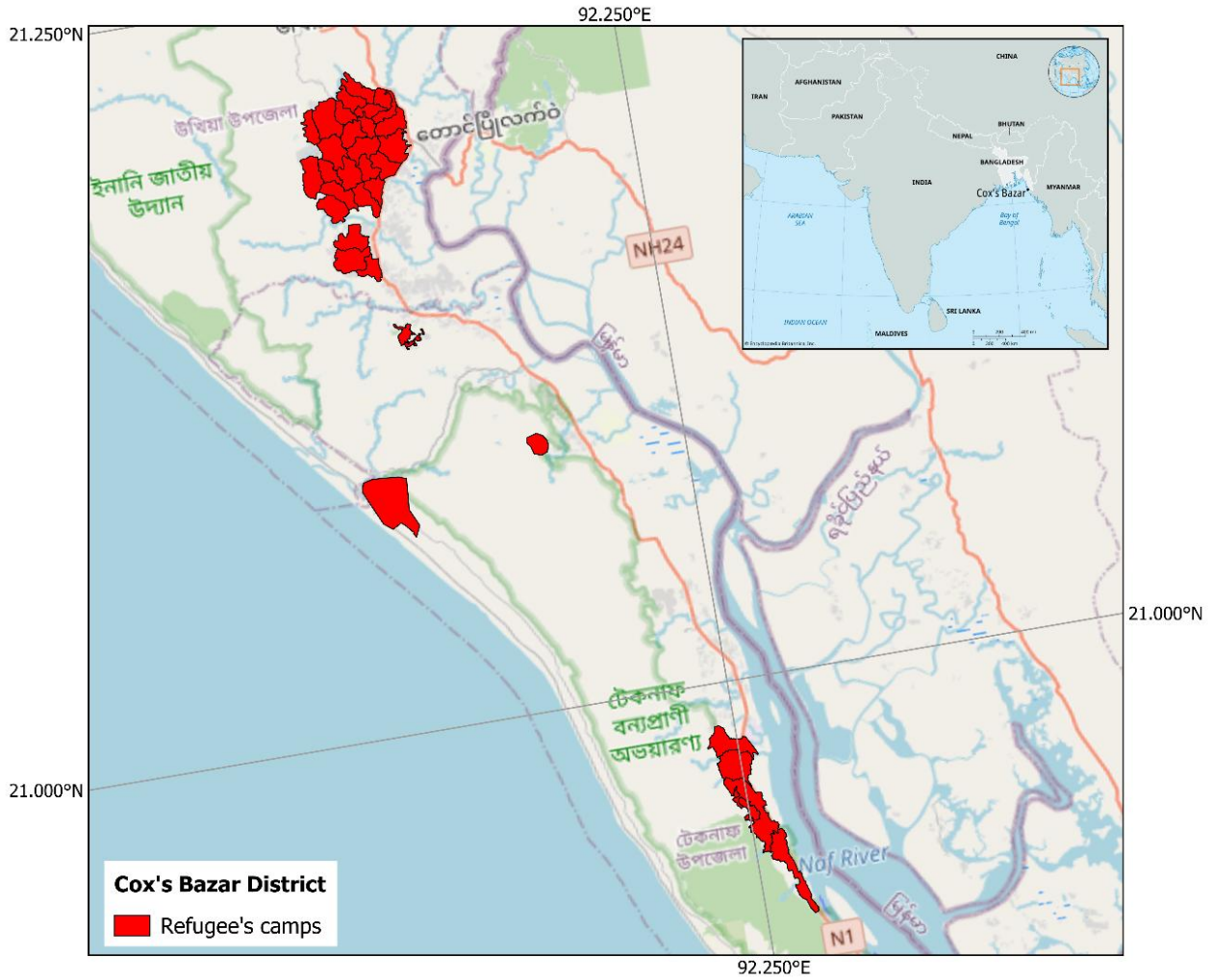


Figure 1. Refugee Camps (red shapes) in Cox's Bazar District (Bangladesh)

2.1.1. Climatic Conditions

Cox's Bazar is highly vulnerable to extreme weather events (monsoons, heavy rainfall, landslides, and mudslides) due to the steep terrain and geological composition (sandy hills and unstable soils), (Quader et al., 2021). Weather variability in Cox's Bazar is a complex phenomenon that manifests unevenly through seasonal and spatial variability, influenced by local and global factors.

Cox's Bazar has a tropical climate with relatively stable and warm temperatures year-round (ICIMOD, 2026), with a pronounced seasonal regime characterized by a dry winter and pre-monsoon period followed by intense rainfall in the monsoon season, between June and September, whereas rainfall remains minimal during the winter months (December–February).

Within the study period (2016-2024) considerable interannual variability in precipitation and associated environmental variables were recorded (See Supplementary Material, Figure S3 & S4). In particular, year 2020 saw an exceptionally dry pre-monsoon and early monsoon season and markedly reduced soil moisture relative to long-term averages. Several subsequent years showed

intensified monsoon activity, resulting in higher evapotranspiration (Figure S4-A) and soil moisture (Figure S4-B) values compared with the baseline. Among those years, 2024 exhibited the most pronounced anomalies in the dataset, with extremely dry and warm pre-monsoon months (i.e., March-May) (Figure S3) and extremely high rainfall during July–September, far exceeding the long-term monthly averages (Figure S3-B). These conditions were associated with very high soil moisture values (Figure S4-B), indicating prolonged surface saturation. Temperature values followed a typical seasonal cycle, with lower minimum temperatures during winter and peak maximum temperatures during the pre-monsoon period (Figure S3-A).

The analysis of data collected from different weather stations in Bangladesh reveals also significant spatial variability of total precipitation, from north (Chittagong Patenga, and Cox’s Bazar) to south (Sittwe) of the refugee camps (<https://meteostat.net/en>).

2.1.2. The Rohingya community

Rohingya refugees have fled persecution in Myanmar since the 70s, and it is estimated that about 671,300 people arrived in the Cox’s Bazar District short period after 25 August 2017 (UNHCR, 2018) (see Supplementary Material, Figure S1 and S5). The district hosts one of the world's largest concentrations of refugee camps, characterized by high population density and overcrowding. According to the 2011 census, the district had a total population of 2,289,990, with a density of 920 people per km². The most abrupt change in population density happened between 2017 and 2018; henceforth, the situation remained stable with mean values of land per capita—defined as the ratio between the area of each camp and its resident population—consistently below the standard category criterion of 45 m² (UNHCR, 2016) (see e.g., Supplementary Material, Figure S6).

At the end of 2025, UNHCR listed 1,177,962 Rohingya individuals in 33 camps in Cox's Bazar district, including 34,498 relocated to Bhasan Char. Overall, in 2024 the 33 camps, covering 23.6 km², have one of the highest population density in the world, with 46,573 people per km² (UNHCR, 2026a) (See Supplementary Material, Figure S5).

2.1.3 Camps infrastructure

The shelters, typically made of lightweight materials (e.g., bamboo, plastic sheeting), are often temporary and vulnerable to natural phenomena (landslides, flooding, fires) (A. Alam et al., 2020). Similarly, WASH infrastructure presents critical issues regarding coverage and maintenance (Akhter et al., 2020; Moghe et al., 2024; Butt et al., 2025). Overall, there were more than 71,500 WASH, Solid Waste Management (SWMP) and Faecal Sludge Treatment (FSTP) infrastructure available in the refugee camps in July-August 2024 (See Supplementary Material, Figure S7).

2.2 Data Sources and Preprocessing

The analysis was conducted by collecting data for the study area over the period 2016–2024. Table 1 details the datasets and indicators used in the analysis, while Table S1 (Supplementary Material) details the list of camps included in the analysis. All heterogeneous sources listed in Table 1 were harmonised to a common camp (SSID) and year structure; this integrated, quality-controlled database is published as a standalone, openly accessible dataset – distinct from the Supplementary Material - to enable reuse and reproducibility according to the FAIR principles (see Data Availability).

Stressor 1 – overpopulation and settlement dynamics

Under stressor 1, data include population statistics and camp delineation, footprints and shelter numbers. Information on yearly estimates of resident refugee population for the period 2001 to 2024 was acquired from UNCHR Statistics (HDX, 2026; Table 1). Additional information was obtained by harmonizing survey reports and spatial dataset carried out by UN Refugees Agency (UNHCR), Resilient and Empowered African Community Health (REACH) Initiative, and International Organization for Migration (IOM) during the period 2017–2021, available in the Humanitarian Data Exchange platform (HDX, 2026) (Table 1).

Official camp boundary shapefiles (i.e., a common geospatial data format used in Geographic Information Systems to represent spatial features such as points, lines, or polygons) were only available from the Humanitarian Data Exchange platform for three points in time, May 2018, December 2023, and May 2024 (HDX, 2026). Because camp boundaries and their identification codes (SSID) were substantially revised in 2018, population data for the period 2018-2024 could not be directly linked to individual camps in 2017.

To address gaps in spatial data coverage, a refugee camp map from the September 2017 Inter-Sector Coordination Group document (Global Shelter Cluster, 2019) was georeferenced and used in QGIS (Nyall Dawson et al., 2026) and R-Studio (Posit, 2020) for analysis covering 2016 and 2017, while May 2018 shapefiles from the HDX platform were applied to the 2018-2022 period, assuming the refugee camps' overall extent in Cox's Bazar district remained largely stable.

Data on the camp structure footprint, including shelters, communal buildings sanitation facilities, and other built in infrastructure, were obtained from the United Nations Satellite Centre (UNOSAT) and REACH Initiative as shapefiles for 2018 – 2021 (HDX, 2026) and from UNHCR|GoB Population Data (UNHCR, 2026b) as tabular PDFs information for selected months in 2020 (March), 2023 (May and July) and 2024 (April and July) (Table 1).

Shelter counts for 2018-2021 were estimated by summing polygons reported in the UNOSTAT/REACH shapefiles (HDX, 2026) in QGIS (Nyall Dawson et al., 2026), while, for 2020-2024, they were retrieved by the UNHCR tabular dataset (2026c). Types of shelters were also covered in the study period, falling according to Carlevaro (2020) and UNHCR (2026c) in four categories: (1) Modular Transitional Shelter (MTS) (Phase 3) and MTS Single Storey, basic temporary shelter made of locally sourced materials; (2) Transitional Shelter Assistance (TSA) (Phase 3) and TSA I, more durable structures using bamboo, wood, and metal; (3) TSA II, upgraded shelters built from brick or concrete blocks; (4) SUM, a shelter upgrade and maintenance program, aiming to improve existing shelters.

Stressor 2 – climate-related impacts

Meteorological data were acquired from ERA5-Land gridded reanalysis produced by the European Centre for Medium-Range Weather Forecasts (Hersbach et al., 2020b), with monthly averaged data from 2016 to 2024 used to derive annual mean daily rates for precipitation and air temperature at 2 metres (Table 1). For each refugee camp, mean values were extracted by averaging the ERA5-Land raster grid cells overlapping the respective camp boundaries.

Stressor 3 – reduced ecosystem services caused by land-use changes

Ecosystem services (ES) refer to the benefits that ecosystems of any kind: terrestrial, marine or freshwater, and wild, anthropized, or even urban, provide to people (Millenium Ecosystem Assessment, 2005). These benefits include material flows, such as food, timber, or energy; better environmental conditions, such as clean air and water or climate change mitigation through carbon sequestration (Potschin and Haines-Young, 2016). Ecosystem services depend on the presence of biodiverse and healthy ecosystems, whose complex ecological structure, processes, and functions represent the foundation for providing ecosystem services to human societies.

To assess ecosystem service decline from land use change, an integrated approach was adopted combining ecological metrics, the Shannon and Evenness indices, measuring habitat heterogeneity and uniformity, with spectral and biophysical remote-sensing indices that reveal the condition and functional performance of the ecosystems observed. Digital images of land use/cover classes and ecosystem functional types for the years 2018–2022 generated as part of the ARICA project (Centrum UNEP/GRID-Warszawa, 2021; Table 1) were used to calculate ecological metrics (Supplementary Material, File S1). Spectral and biophysical remote-sensing indices were derived from Landsat-8 imagery for 2016-2024 (see Supplementary Material, Table S2). Dry-season imagery was selected for each year to minimize atmospheric and seasonal interference, and pixel-level indices (NDVI, NDBI, NDWI and Land Surface Temperature) were calculated and aggregated to the camp scale to characterize vegetation cover, built-up intensity, surface moisture, and thermal conditions, according to the equations reported in the Supplementary Material (File S2).

Water quality and WASH data

WASH infrastructure data for 2018–2024, drawn from UNHCR's Cumulative 4Ws Dataset, were used to track latrines, handpumps, and washrooms aggregated by year and camp (UNHCR, 2026b; Table 1). These were complemented by water quality measurements of Chemical Oxygen Demand (COD), Biological Oxygen Demand (BOD), *E. coli*, nitrate, phosphate, total nitrogen, Total Suspended Solids (TSS), and total coliforms collected from Faecal Sludge Treatment Plants (FSTPs) by multiple agencies over the same period (UNHCR, 2026b, Table 1).

Water quality data for 2018–2024 were obtained from the AFA (Analysis of Faecal and Abiotic Parameters) program, covering physicochemical and microbiological indicators (*E. coli*, turbidity, fluorides, TDS, etc.) collected across a range of water supply infrastructure types within the camps (Tanvir, 2026, Table 1).

Table 1. Datasets and indicators used in the analysis

Source	Category	Description	Temporal and/or Spatial Resolution	Stressors*
ERA5-Land	Precipitation	Mean daily precipitation rate (reanalysis; mm day ⁻¹)	Daily, (2016-2025); 9 km spatial resolution	2
	Air temperature	Mean daily 2 m air temperature (reanalysis; K)		2
Yearly raster dataset (ARICA)	Land use/land cover (LULC)	Thematic land cover classes	Annual (2018-2022)	3
	Ecosystem Functional Types (EFTs)	Ecological diversity indicators		3
Landsat 8 Thermal Infrared Radiance Sensor (TIRS) Collection 2 Level-2, Surface Temperature, U.S. Geological Survey (USGS)	Land Surface Temperature (LST)	Atmospherically corrected land surface temperature derived using the USGS single-channel algorithm. Converted to °C following official scaling documentation. Used to assess surface thermal dynamics within camp boundaries.	16-day revisit; December images (2016–2024); 100 m spatial resolution	3
Landsat 8 Operational Land Imager (OLI) Collection 2 Level-2, Surface Reflectance, U.S. Geological Survey (USGS)	Normalized Difference Vegetation Index (NDVI)	Vegetation index computed as (NIR – RED) / (NIR + RED). Proxy for vegetation density and photosynthetic activity. Values range from –1 to +1, with higher values indicating denser vegetation.	16-day revisit; December images (2016–2024); 30 m spatial resolution	3
	Normalized Difference Water Index (NDWI)	Moisture index computed as (GREEN – NIR) / (GREEN + NIR). Used to detect surface water presence and vegetation moisture content. Positive values indicate higher surface moisture or open water.		3
	Normalized Difference Built-up Index (NDBI)	Built-up index computed as (SWIR – NIR) / (SWIR + NIR). Used to identify impervious or built surfaces. Higher values indicate greater built-up or exposed soil presence.		3
Derived from Landsat 8 NDWI	NDWI Positive Fraction (NDWI_pos_frac)	Fraction of pixels within each camp boundary exhibiting NDWI > 0. Used as a proxy for the proportional surface area characterized by open water or high surface moisture conditions.		3
Derived from Landsat 8 NDVI	NDVI Bare Fraction (NDVI_bare_frac)	Fraction of pixels within each camp boundary exhibiting low NDVI values (threshold indicating bare soil or sparse vegetation). Proxy for exposed soil and non-vegetated surfaces.		3
Humanitarian Data Exchange platform (HDF)	Refugee Camp	Information on border and extension of refugee camps by year and SSID available as georeferenced shapefile.	Static and relative only to some date (May 2018, December 2023, May 2024)	1

Source	Category	Description	Temporal and/or Spatial Resolution	Stressors*
UNHCR GBD	Refugee Population, Camp Structure Footprint	Registered camp population	Tabular data with annual data (2001-2024)	1
UNHCR & REACH Settlement and Protection Profiling		Multi-Sectoral snapshots of demography, site conditions, risks, and needs in refugee camps.	PDF files reporting information collected during specific surveys (2017-2020)	1
IOM DTM		Registered camp population with spatial information	Data points based on reporting at block and camp levels during specific surveys (2017-2021)	1
UNOSAT and REACH Initiative		Total number and coverage area of shelters by camp and year	Data (Polygons) collected during specific surveys (2018-2021)	1
UNHCR GoB Population Data S/NFI Sector 4W S/NFI Phase 3 Tracker		Total number of shelters by camp	PDF files reporting information collected during specific surveys (2020, 2023-2024)	1
Water Quality & WASH data				
REACH WASH Site Profile	WASH	Registered camp population with shelters and WASH information	PDF files reporting information collected during specific surveys (2017-2018)	1
Multi Agency (2018-2024)	WASH	Cumulative 4Ws Dataset	Data points of WASH infrastructure (2018-2024)	-
Multi Agency	Faecal Sludge Treatment Plant (FTPs)	Waste Water Quality Monitoring Data by camp and year	Tabular data and FSTPs specifications (including spatial information) (2020-2024)	-
AFA Dataset	Water quality	Field samples of <i>E. coli</i> , Fe, Mn, TDS, Turbidity, etc.	Tabular data of annual averages related to specific camps and years (2018-2024)	-

Notes*: 1) overpopulation and settlement dynamics; 2) climate-related impacts; 3) reduced ecosystem services

2.2 Statistical Analysis and data treatment

Since the datasets varied in spatial scales, temporal resolutions and sampling frequency, all data were aggregated by year and camp ID (i.e., SSID), though this aggregation may mask temporal and within-group variability, associated with heterogeneous sampling conditions. Given that individual camps were not consistently sampled across years, the data were treated as a repeated cross-sectional design with independent observations. To test for temporal trends, one-way ANOVA were applied to ecological, satellite-derived, and water quality indicators, with Tukey's Honestly Significant Difference (HSD) test applied accordingly. When assumptions of normality and homoscedasticity were not met (Shapiro–Wilk and Levene tests, $p < 0.001$), Kruskal–Wallis tests with Dunn's post hoc comparisons (Holm correction) were performed as a sensitivity analysis.

For water quality data (Tanvir, 2026), the category “Raw Water” was excluded from the inferential statistical analysis due to unbalanced distribution of sampling groups across years, and temporal analyses were restricted to “Handpump Tubewell”, “Production Borehole” and “Tap Stand”.

The statistical analyses were performed using R (version 4.4.1) running in RStudio build 1.3.959 (RStudio, Boston, MA, USA; Posit, 2020). Data processing and visualization were conducted using packages from the *tidyverse* suite (Wickham et al., 2019). A significance level of $\alpha = 0.05$ was used for all statistical tests.

3 Results & Discussion

3.1 Stressor 1: Overpopulation and settlement dynamics

The total population of the refugee camps fluctuated during the observed years 2017-2024. A total increase recorded was from 3,987 in 2016 to 969,007 in 2024, it means that population increase was staggering and roughly 243-fold.

During the period 2017 – 2024 the area covered by the refugee camps which were included in this study (see Supplementary Material, Table S1), increased of about 56% passing from about 15.1 Km² to 23.6 Km² in 2024. Although this large increase in refugee camp's area, the population density in the same area was reduced by just 0.5%, passing from 46,820 (S.D.: $\pm 28,818$) person per km² in 2017 to 46,573 (S.D.: $\pm 21,219$) person per km² in 2024. On the other hand, during the period 2018 – 2024, the total refugee camp's area decreased of about 9% in front of a steady growth in the refugees as testified by an increase of total refugee population and population density, respectively by about 7.4% (see Supplementary Material, Figure S5), and 8.4%.

Accordingly, the average land available per capita has decreased over the years, from 57.70 m² in 2017 to 29.82 m² in 2024 (Figure 2). In parallel, despite the overall reduction in mean land per capita, a decreasing trend for standard deviation of land per capita (107.58 in 2017 to 23.04 in 2024) indicates less variability in land availability per person and a more uniform distribution of space across the camps.

The 2017-2024 shelter count showed an increasing trend over time, indicating a growing number of shelters in the refugee camps (Figure 3). The UNOSAT-REACH values show a significant increase in shelter counts from October 2017 to January 2019, with a growth rate of approximately 294% (from 48,673 to 192,050). The shelter count remained relatively stable from January 2019 to March 2020, with a slight increase to 204,688. From March 2020 to April 2021, the number of shelter polygons in the official shapefiles remained constant, with no differences in the shelter counts between the two dates.

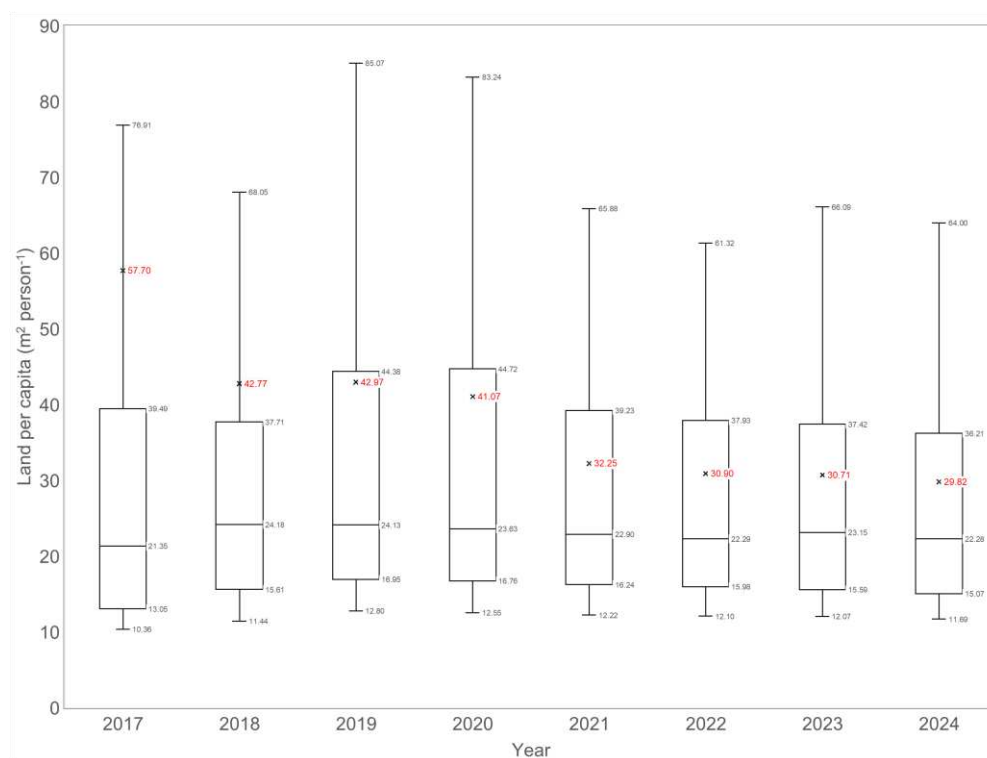


Figure 2. Land per capita in selected refugee camps in Cox's Bazar district during the years 2017-2024. The extension area of refugee camps in 2017 was georeferenced based on Global Shelter Cluster (2019), while those related to the years 2018, 2023, and 2024 were based on shapefiles from HDX (2026). The border camp definition of May 2018 has been used to estimate land per capita during the years 2019 -2022. The central line indicates the median, the cross marks the mean value (red text), and the box spans from the first quartile (Q1) to the third quartile (Q3), computed without including the median in the quartile calculation. Total population in selected camps was estimated using UNHCR data available from HDX (2026).

An analysis of shelter data, based on both spatial and tabular datasets, reveals a notable trend in the growth of shelters over time. Between 2017 and 2018, the number of shelters experienced a significant surge, followed by a period of relative stability from 2019 to 2021, and subsequently, a moderate increase from 2022 to 2024. Although the data presents some challenges in terms of comparability, it suggests a steady urbanization of the area, driven by a population growth rate of 6.4% between 2018 and 2024. In contrast, the area allocated to refugee camps expanded by only 1.73% during the same period, indicating a disproportionate increase in population density and potential pressure on existing infrastructure and resources.

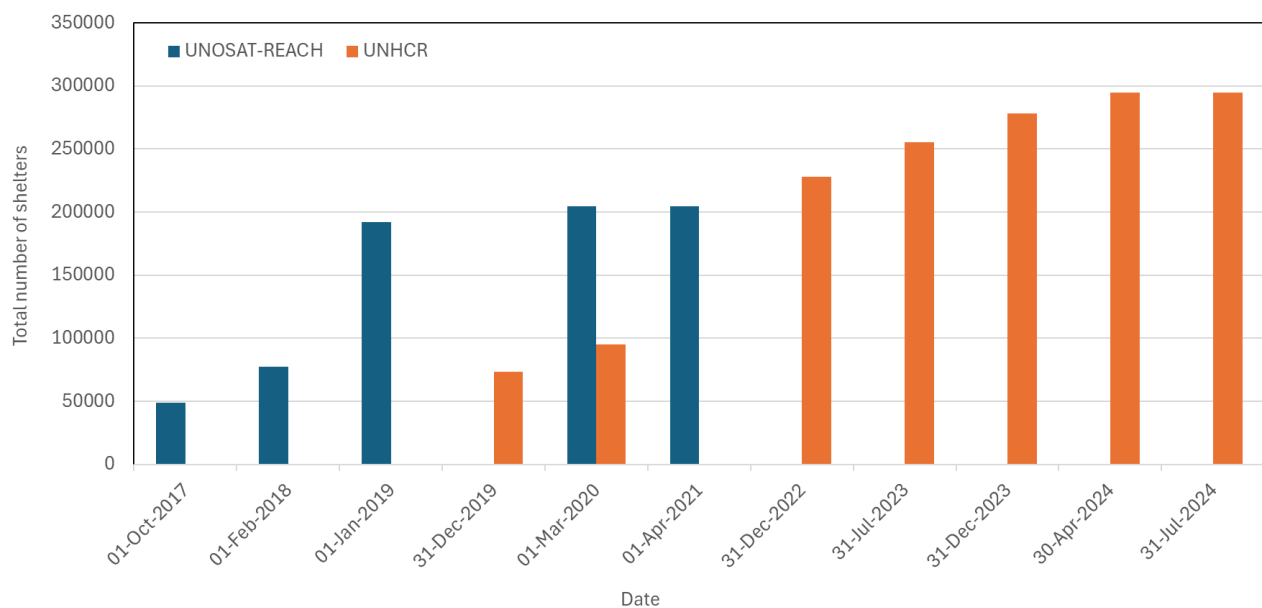


Figure 3. Total number of shelters in Cox's Bazar refugee camps estimated using UNOSAT-REACH shapefiles (HDX, 2026) and UNHCR tabular data (UNHCR, 2026c).

According to the UNHCR's reports, which span from March 2020 to July 2024, there was a significant expansion in the number of shelters reached, with a growth rate of around 210% (UNHCR, 2026c). Specifically, the number of shelters increased from 94,952 to 294,508 over this period, as illustrated in Figure 3. This represents a substantial increase in the provision of shelter, with the total number of shelters more than tripling during this time frame.

More precisely, in May 2020 (UNHCR, 2026c) the total numbers of shelters reached were 21,152 TSA I and 450 MTS shelters. Additionally, the UNHCR's report provides also a snapshot of the shelter provision efforts carried out during the period 2018-2019, i.e., 63,062 Phase 3 TSA shelters reached in 2019, and 10,288 Phase 3 MTS shelters reached during the period spanning 2018 and 2019.

During 2018-2019, most shelters (86%) built or delivered were of type TSA (Phase 3), with a small percentage (14%) of MTS (Phase 3) shelters (Figure 4). In 2020, most of the newly built shelters

(98%) were of type TSAI, with a tiny percentage (2%) of MTS Single Storey shelters. The overall distribution of shelters changed in 2022, with TSAI (43%) and TSAII (38%) being the most common types, followed by MTS Single Storey (10%) and SUM (9%). In 2023 there was a significant shift towards SUM shelters, accounting for 84% of the total new shelters, while MTS Single Storey shelters made up 16%. In 2024, the distribution of shelters continued to evolve, with SUM (70%) being the most common built in this period, followed by MTS Single Storey (27%) and TSAI (3%) shelters (Figure 4).

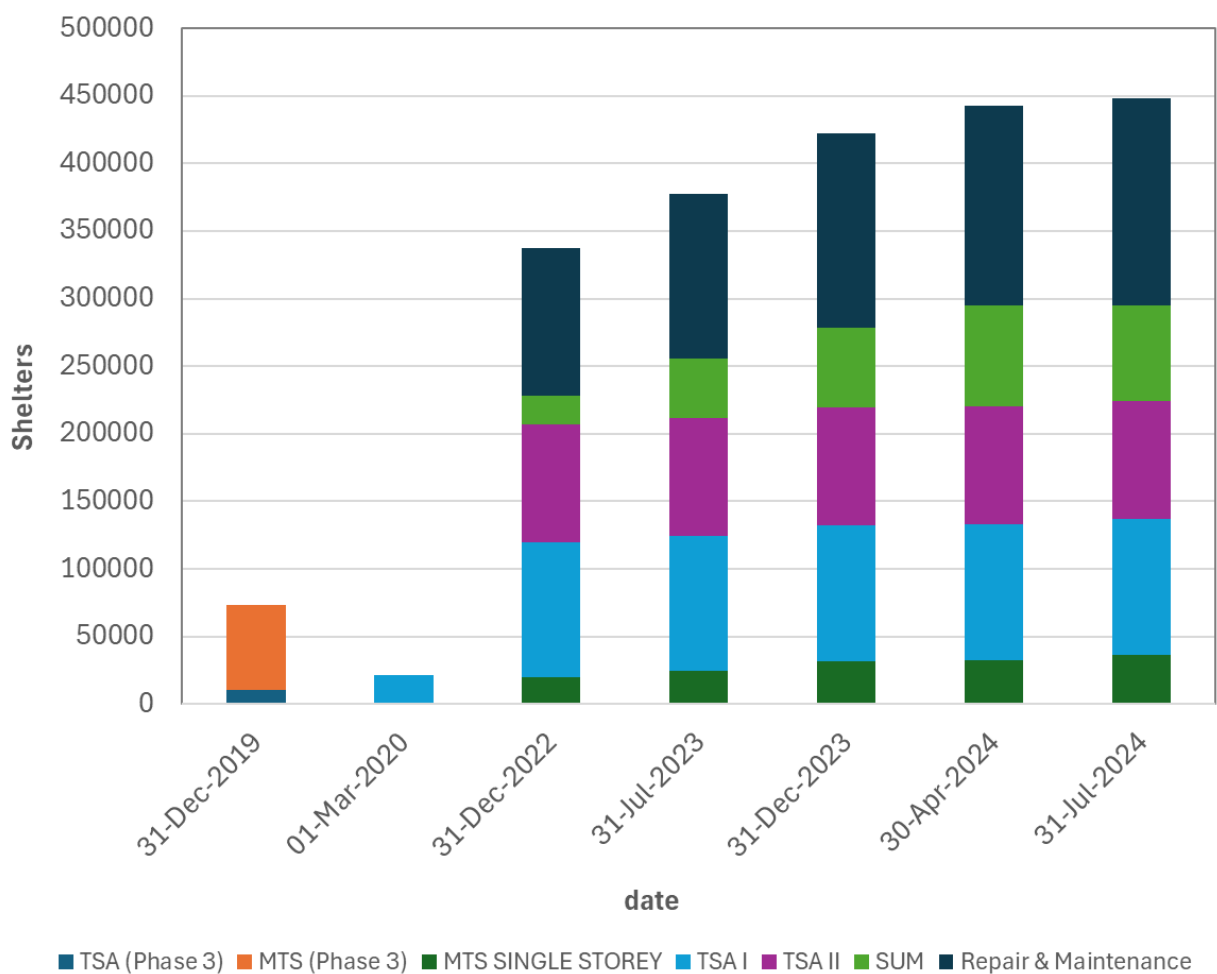


Figure 4. Types of shelters constructed, repaired, and/or maintained between 2019 and 2024 in Cox's Bazar refugee camps (UNHCR, 2026c).

The shift towards more upgraded or advanced shelter types, such as TSAII and SUM, follows the UNHCR guidelines to move away from basic or temporary shelter types in a prolonged displacement situation. This transition from emergency response to more sustainable and durable shelter solutions is a positive and more sustainable trend, especially in a situation of prolonged displacement conditioned by a lack of a durable political solution ensuring the security for the displaced population

in their country of origin. On the other hand, the decline in land per capita is a concern, as it indicates a decrease in available space per person, leading to more crowded living conditions. This trend suggests potential challenges in maintaining living standards and providing adequate services and amenities to the refugee population (M. J. Alam et al., 2021; Ramazani et al., 2022).

The population growth rate of 6.4% between 2018 and 2024 exceeded the expected natural population growth in humanitarian contexts, which typically ranges from 3-4% (UNHCR, 2019). The demographic trends in the refugee camps, including the age and gender structure, are influenced by various factors, such as new arrivals, births, and mortality rates. While we have information about the age and gender structure, we do not know if these changes or relative stability are due to new people coming and some leaving, new children born in the camp, or changes in mortality. These remain questions to be studied in the future.

3.2 Stressor 2: Climate-related impacts

Building on the broader climate analysis, ERA-5 reanalysis data were examined for Cox's Bazar to gain a more detailed view of local environmental conditions in the refugee camps. Overall, the mean daily rain rate fluctuated, with the lowest mean being 5.28 mm in 2022 and the highest mean being 8.74 mm in 2024 (Figure 5, bottom).

Minimum daily rain rate varied significantly across the years, ranging from 0.08 mm in 2019 to 1.26 mm in 2018, meaning some days had very little to no rain. On the other hand, the maximum daily rain rates showed a wide range, from 14.97 mm in 2022 to 28.34 mm in 2024, suggesting heavy rainfall on certain days. This indicates variability in rainfall patterns from year to year, as supported by the range of standard deviation of the daily rain rates (4.66 mm in 2022 to 9.37 mm in 2024; Figure 5, bottom).

The mean air temperatures were relatively consistent, ranging from 25.37°C in 2018 to 26.29°C in 2024, suggesting a tropical climate with minimal seasonal variation in temperature (Figure 6, top). The minimum air temperatures ranged from 20.37°C in 2020 to 21.93°C in 2023, indicating warm weather even at the lowest temperatures. The maximum air temperatures vary from 27.24°C in 2017 to 28.52°C in 2024. The standard deviation of the air temperatures was relatively low, ranging between 2.99°C in 2020 and 2.47°C in 2023 (Figure 5, top), thus suggesting a stable temperature regime throughout the year, typical of tropical climate near the equator.

When looking at individual years, maximum temperatures during the pre-monsoon season exceeded 37–39 °C (2023, 2024), suggesting enhanced thermal stress conditions prior to the onset of the monsoon. Overall, the climatic records reveal strong interannual variability superimposed on the monsoon-driven seasonal cycle, with alternating periods of drought and intense precipitation

affecting soil moisture availability and evaporative fluxes in the study area. This is also confirmed by other studies that have highlighted highly anomalous rainfall and land surface temperature for the study area, which exacerbate the effects of inadequate stream connectivity and a deficit in surface moisture (Roy et al. 2024). This local variability sits within a broader pattern in which land transformation itself reshapes climate: Tang et al. (2025) attributed increases in drought frequency, intensity and exposure to historical land-use and land-cover change, and Liu et al. (2025) projected that continued growth in impervious surfaces will raise local surface temperatures through 2100 independently of background warming.

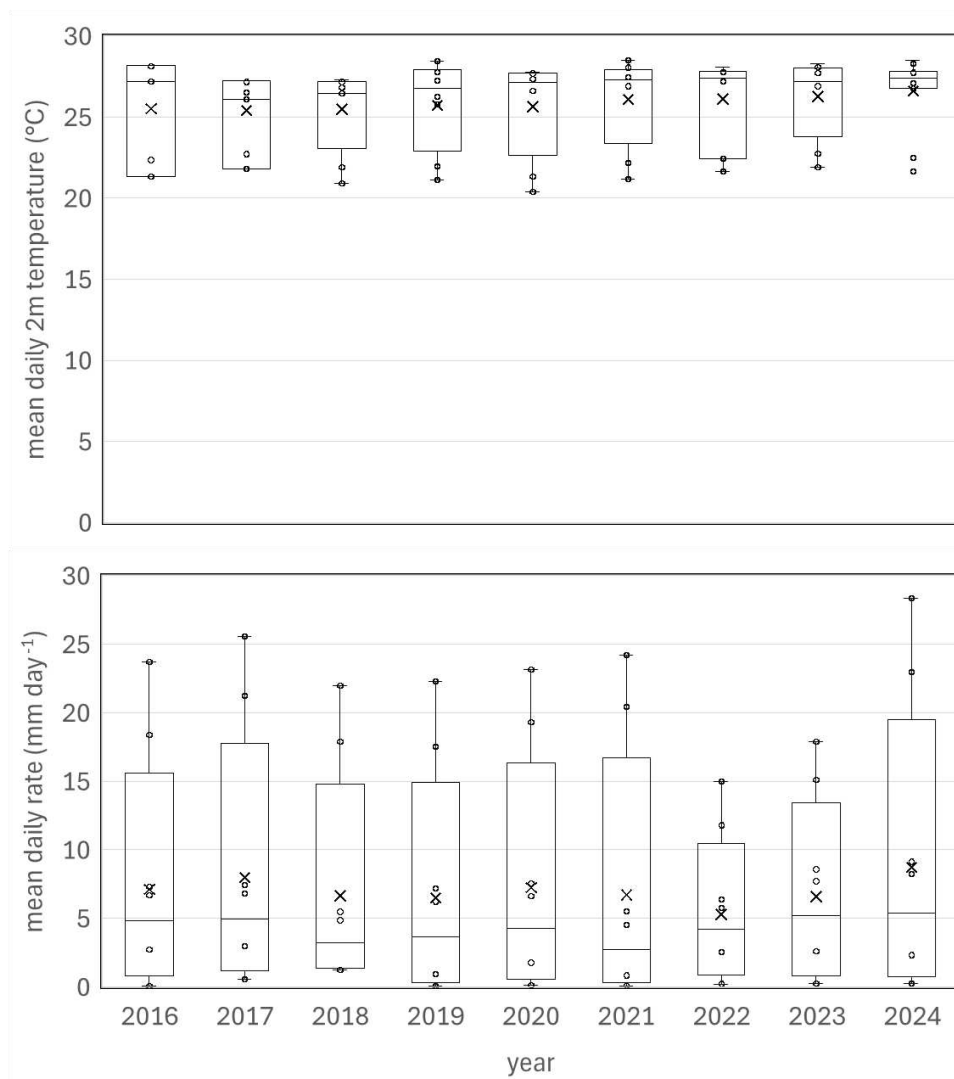


Figure 5. Interannual boxplot representation of the air temperature (°C, measured at 2 m) and daily rate of rain (mm/day) in Refugee camps of Cox's Bazar district. The central line indicates the median, the cross marks the mean value, and the box spans from the first quartile (Q1) to the third quartile (Q3), computed without including the median in the quartile calculation.

Overall, the analysis of climate data suggests that the region can experience seasonal shifts (like monsoons and droughts) and climate change (disruption of rainfall patterns and increase of extreme

weather events), highlighting the importance of effective water resource management. Climate change and weather conditions are recognized as factors that can affect water quality and the effectiveness of water treatment systems (Alazzeh et al., 2019; Pompei et al., 2019; Ali and Shahreen, 2024). Planning must therefore prioritize climate resilience to ensure consistent access to safe water via all the available water collection points and to absorb additional pressures on already limited water resources, thus avoiding shortages and contamination risks (see also Ali and Shahreen, 2024).

3.3 Stressor 3: Reduced ecosystem services caused by land-use changes

Ecological metrics

The analysis of the Evenness of the Ecosystem Functional Types (EFT) index, measuring the heterogeneity (Figure 6, right-bottom) showed a sharp decline during the years 2016-2019, followed by a recovery trend in the years 2020-2022 (U-shaped dynamic). The Shannon EFT index, measuring the uniformity (Figure 6, right-top), showed a similar trend, low in 2016-2019, then rising in 2020.

When the two indices were computed for the land use / land cover (LULC), the Evenness LULC (Figure 6, left-bottom), had quite stable values over time from 2018, with a median around 0.4-0.5, indicating a relatively constant land-use structure, although the internal composition of land-use types, such as forest, settlements, and bare soil, may not be evenly balanced. On the other hand, the Shannon LULC (Figure 6, left-top) showed consistently low values (<1.0) over time, indicating a landscape dominated by a few prominent land-use categories, likely due to natural ecosystem such as broadleaf forests (2016) then shifting abruptly to intense human activity and land use (from 2017 onwards).

A series of one-way ANOVAs were conducted to evaluate temporal differences (2016–2022) in Shannon diversity and Evenness derived from EFT and LULC classifications (Table 2).

Shannon diversity based on EFT (Figure 6, right-top) showed a strong and highly significant temporal effect ($F(6, 212) = 21.95, p < 0.001$), with a large effect size ($\eta^2 = 0.38$). Assumptions of normality were met ($p = 0.336$), while homogeneity of variances showed mild deviation (Levene $p = 0.066$). Post-hoc comparisons indicated that values in 2016 were significantly higher than in most subsequent years, followed by a progressive increase toward 2022 (Table 2). This pattern was confirmed by the Kruskal–Wallis test ($\chi^2(6) = 81.31, p < 0.001$) (see Supplementary Material, Table S3).

Evenness derived from EFT (Figure 7, right-bottom) also varied significantly across years ($F(6, 212) = 14.07, p < 0.001$), with a moderate-to-large effect size ($\eta^2 = 0.28$). Residuals were normally distributed ($p = 0.226$), while variance homogeneity showed slight violation (Levene $p = 0.056$). It showed a significant temporal trend, with a marked decline from 2016 to 2019, followed by a partial recovery in subsequent years (2020–2022). Post-hoc comparisons confirmed significantly lower values in 2017–2019 relative to 2016, and significantly higher values in 2021–2022 compared to 2019 (Table 2). The Kruskal–Wallis test confirmed these differences ($\chi^2(6) = 63.88, p < 0.001$) (see Supplementary Material, Table S3).

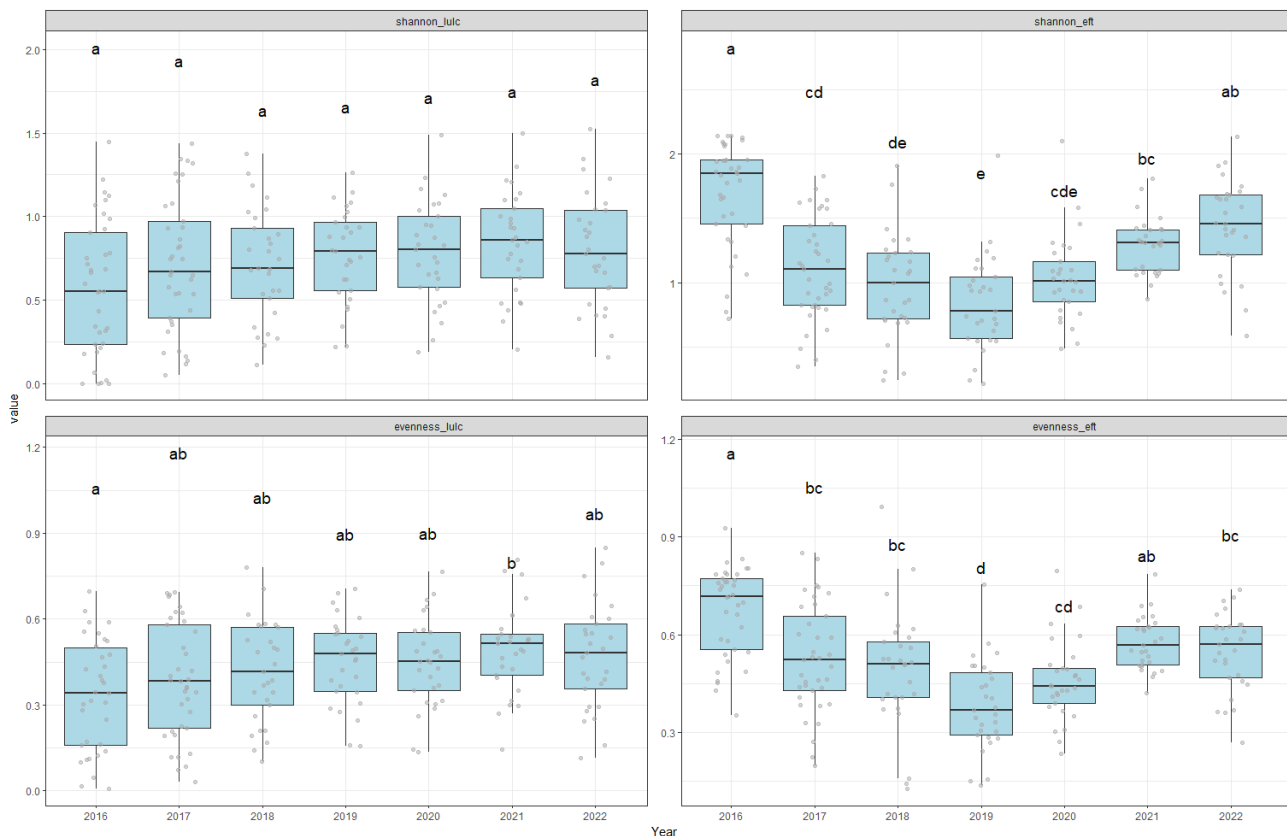


Figure 6. Distribution of diversity indices by year (2016–2022) in the refugee camps in Cox's Bazar (Bangladesh). Boxplots with different letters are significantly different from each other based on Tukey's HSD post hoc test ($p < 0.05$).

Shannon diversity based on LULC showed a weak but statistically significant effect of year, $F(6, 212) = 2.22, p = 0.042$, with a small effect size ($\eta^2 = 0.06$). However, residuals deviated from normality ($p = 0.029$), although homogeneity of variance was satisfied. Post-hoc comparisons revealed only one significant difference (2016 vs 2021) (Table 2). Importantly, the Kruskal–Wallis test was not significant ($\chi^2(6) = 11.04, p = 0.087$), suggesting that this effect is weak and not robust (see Supplementary Material, Table S3).

Evenness based on LULC showed a significant effect of year, $F(6, 209) = 3.06$, $p = 0.0069$, with a small effect size ($\eta^2 = 0.08$). Residuals slightly deviated from normality ($p = 0.032$), while homogeneity of variances was satisfied. Post-hoc comparisons indicated higher evenness in 2021 compared to 2016 (Table 2). The Kruskal–Wallis test confirmed this pattern ($\chi^2(6) = 13.61$, $p = 0.034$) (see Supplementary Material, Table S3).

Across all metrics, EFT-based indices showed stronger and more consistent temporal patterns compared to LULC-based indices. Shannon diversity and evenness derived from EFT exhibited large effect sizes and highly robust significance, whereas LULC-based metrics showed weaker or less consistent temporal signals.

Table 2. Results of variance-analysis for Shannon diversity and evenness across ecosystem functional types (EFT) and land-use/land-cover (LULC) categories (N = 312). The table reports One-Way ANOVA F-values, effect sizes (η^2), Shapiro-Wilk normality tests, Levene’s homogeneity tests, and Tukey post-hoc comparisons.

<i>Response</i>	<i>N</i>	<i>F(df)</i>	<i>p (ANOVA)</i>	<i>Effect Size (η^2)</i>	<i>p (S-W)</i>	<i>p (Levene)</i>	<i>Post-hoc (Tukey)</i>
<i>Shannon diversity (EFT)</i>	<i>312</i>	<i>21.95 (6,212)</i>	<i><0.001</i>	<i>0.38</i>	<i>0.336</i>	<i>0.0657</i>	<i>12</i>
<i>Shannon diversity (LULC)</i>	<i>312</i>	<i>2.22 (6,212)</i>	<i>0.042</i>	<i>0.06</i>	<i>0.0287</i>	<i>0.111</i>	<i>1</i>
<i>Evenness (EFT)</i>	<i>312</i>	<i>14.07 (6,212)</i>	<i><0.001</i>	<i>0.28</i>	<i>0.226</i>	<i>0.056</i>	<i>10</i>
<i>Evenness (LULC)</i>	<i>312</i>	<i>3.06 (6,209)</i>	<i>0.0069</i>	<i>0.08</i>	<i>0.0317</i>	<i>0.189</i>	<i>2</i>

Corroborating what has been reported for the study area during the period 2016-2019 by several authors (Rashid et al., 2021; Hasan et al., 2023), the results revealed that the diversity of land use/cover classes and ecosystem functional types in the refugee camps was moderate to high, indicating a relatively complex and diverse landscape. The results suggest that the greatest changes occurred in ecological functionalities, which are becoming less heterogeneous and more unevenly distributed, with some ecosystem functional types becoming less dominant, probably due to an increase in human-modified surfaces.

Previous studies conducted in the Ukhiya–Teknaf region following the 2017 Rohingya refugee influx into Bangladesh using remote sensing have documented a dynamic change in the spatial distribution of several types of flora and substantial reductions in vegetation cover, together with a rapid expansion of settlement areas (Rahman et al., 2019). Other studies also estimated considerable forest loss and degradation associated with the establishment and expansion of camps (Hassan et al., 2018; Mohammad Emran Hasan et al., 2021). Consistent with these findings Karim & Zhang (2021) identified a notable decline in vegetative cover and an increase in exposed soil areas between 2017

and 2019. Collectively, these studies highlight a rapid transformation of the landscape characterized by deforestation, expansion of built-up areas, and increasing human pressure on natural ecosystems (Hasan et al., 2023). These documented patterns of vegetation loss and expansion of built-up areas indicate a progressive simplification of the landscape structure, where natural land-cover classes become less dominant and human-modified surfaces increasingly prevail (Rashid et al., 2021; Hasan et al., 2023). Such changes suggest a shift toward a less heterogeneous and more unevenly distributed composition across the study area.

In our specific case, as the decrease of the Shannon and Evenness indices was observed specifically on Ecosystem Functional Types (EFTs) rather than on land-use/land-cover, it suggests that the area experienced in some years a functional homogenization, a reduction of ecological resilience, and likely a loss of niche diversity. Thus, the decline of the Shannon and Evenness EFT indices may indicate that certain ecological functional types have become dominant, while the recovery can be a sign of regeneration of ecological functionality or improved environmental management. The observed decline in Shannon diversity and evenness (particularly between 2016 and 2019) suggests a loss of functional complexity and balance in the ecosystem. Such a reduction indicates that the landscape may be operating in a more uniform way, with fewer alternative functional units available to buffer against disturbances. Consequently, the system could be more vulnerable to stressors such as pests, disease outbreaks, or extreme climatic events, potentially affecting its ability to maintain ecosystem services (e.g., water quality, flood control, biodiversity, presence and variety of non-timber forest products, NTFPs, etc.) which rely on a diverse set of functions (e.g., pollination, water regulation and soil fertility). For instance, Patwary et al. (2021) documented for the period 2017-2018 a loss of 2,486 ha of vegetation—20 % attributable to camp expansion and 80 % to deforestation—resulting in a 4.63 % reduction in annual ecosystem service value, from US 51.53 million to US 49.12 million.

Table 3. Interannual mean ($\pm$ standard deviation) of spectral reflectance bands (RED, GREEN, NIR, SWIR), land surface temperature (LST, °C), and derived surface indices (NDVI, NDBI, NDWI) within camp boundaries for the period 2016–2024 (December imagery acquisition; reference camp area related to a different acquisition date). NDWI fraction positive represents the fraction of pixels with NDWI > 0, indicating surface water or high moisture presence, while NDVI bare soil fraction denotes the fraction of pixels below the defined NDVI threshold for bare or sparsely vegetated surfaces. Values summarize within-camp spatial variability at 30 m resolution.

Camp area acquisition date	year	RED	GREEN	NIR	SWIR	LST	NDBI	NDVI	NDWI	NDVI bare soil fraction	NDWI fraction positive
September 2017	2016	0.058 (0.015)	0.067 (0.009)	0.261 (0.022)	0.167 (0.020)	28.72 (1.082)	-0.22 (0.074)	0.631 (0.098)	-0.58 (0.065)	0.00093 (0.00428)	0.0000 (0.000)
	2017	0.125 (0.032)	0.105 (0.023)	0.232 (0.015)	0.230 (0.032)	31.77 (0.898)	-0.01 (0.060)	0.322 (0.112)	-0.38 (0.085)	0.26973 (0.22243)	0.0003 (0.001)
May 2018	2018	0.117 (0.029)	0.104 (0.020)	0.236 (0.017)	0.222 (0.036)	29.98 (1.061)	-0.04 (0.061)	0.352 (0.093)	-0.39 (0.066)	0.13487 (0.13757)	0.0012 (0.003)
	2019	0.109 (0.020)	0.102 (0.014)	0.249 (0.016)	0.220 (0.028)	30.09 (0.980)	-0.07 (0.053)	0.399 (0.074)	-0.42 (0.051)	0.01648 (0.02388)	7.0049 (0.000)
	2020	0.104 (0.018)	0.096 (0.013)	0.243 (0.016)	0.207 (0.025)	28.74 (1.139)	-0.09 (0.051)	0.410 (0.074)	-0.43 (0.057)	0.05340 (0.03830)	0.0013 (0.004)
	2021	0.099 (0.017)	0.093 (0.013)	0.238 (0.015)	0.201 (0.022)	30.28 (1.195)	-0.09 (0.047)	0.422 (0.071)	-0.44 (0.056)	0.04109 (0.04963)	0.0015 (0.005)
	2022	0.094 (0.018)	0.092 (0.014)	0.268 (0.015)	0.211 (0.021)	34.00 (1.379)	-0.12 (0.047)	0.492 (0.076)	-0.49 (0.061)	0.01764 (0.02219)	0.0008 (0.002)
December 2023	2023	0.086 (0.013)	0.085 (0.010)	0.238 (0.015)	0.185 (0.016)	28.37 (1.259)	-0.13 (0.044)	0.477 (0.064)	-0.47 (0.052)	0.01099 (0.02185)	0.0004 (0.001)
May 2024	2024	0.096 (0.013)	0.090 (0.010)	0.232 (0.014)	0.192 (0.015)	28.67 (1.081)	-0.10 (0.040)	0.421 (0.062)	-0.44 (0.050)	0.02648 (0.04373)	0.0018 (0.009)

Spectral/biophysical remote-sensing indices

Analysis of satellite imagery reveals several trends in refugee camps over the years. The results obtained by analysing the imagery acquired in December from 2016 to 2024 by Landsat-8 OLI and TIRS are reported in Table 3.

The visible reflectance (RED and GREEN) exhibited a marked increase in 2017 (RED: 0.125 ± 0.032 ; GREEN: 0.105 ± 0.023) compared to 2016 (RED: 0.058 ± 0.015 ; GREEN: 0.067 ± 0.009), followed by a gradual decline through 2023. Elevated RED and SWIR reflectance in 2017 suggests greater exposure of bare soil or built surfaces during that year (Table 3).

Near-infrared (NIR) reflectance, indicative of vegetation vigour, was lowest in 2017 (0.2326 ± 0.015) and 2024 (0.2322 ± 0.018), and highest in 2022 (0.268 ± 0.015); standard deviations were generally modest (0.009 – 0.036), indicating relatively homogeneous surface conditions within camps, except for the higher heterogeneity in RED, GREEN and SWIR during 2017–2018 (Table 3).

Regarding the vegetation and built-up indices, NDVI displayed strong interannual variability, with the highest value reported in 2016 (0.631 ± 0.098) followed by a sharp decline in 2017 (0.323 ± 0.112) and, therefore, a progressive recovery through 2022 (0.492 ± 0.076), suggesting improved vegetation health or increased vegetation cover within the camps, and again in 2023–2024, a slight decrease (Table 3; Figure 7). The large SD in 2016 (0.098) and 2017 (0.112) suggests substantial within-camp heterogeneity in vegetation cover during those years.

The Normalized Difference Built-up Index (NDBI) values are generally low (Table 3; Figure 7), suggesting that refugee camps are characterized by areas of bare soil and sparse vegetation and therefore lack built-up areas with impervious surfaces such as concrete or asphalt. NDBI followed an inverse pattern relative to NDVI, with values nearly neutral in 2017 (-0.013 ± 0.060), indicating increased built-up or exposed surfaces, followed by progressively more negative values through 2023 (-0.133 ± 0.044), reflecting increasing vegetation dominance (Table 3; Figure 7). During the analysed period, there was a strong negative correlation (Pearson's product-moment) between NDVI and NDBI with $r(310) = -0.93$, $p = 0.000$. This inverse NDVI–NDBI dynamic supports a vegetation recovery trajectory after the 2017 disturbance peak, therefore indicating a direct trade-off between vegetation cover and urban infrastructure.

Concerning the bare surface fraction, the computed index exhibited substantial temporal variability with very low values in 2016 (0.0009 ± 0.004), a peak in 2017 (0.270 ± 0.222), and a progressive decline, thereafter, reaching a minimal value in 2023 (0.0109 ± 0.021) (Table 3). The high mean and large SD in 2017 indicate both expansion and spatial heterogeneity of bare or sparsely vegetated surfaces. The sharp decline after 2017 aligns with NDVI recovery trends.

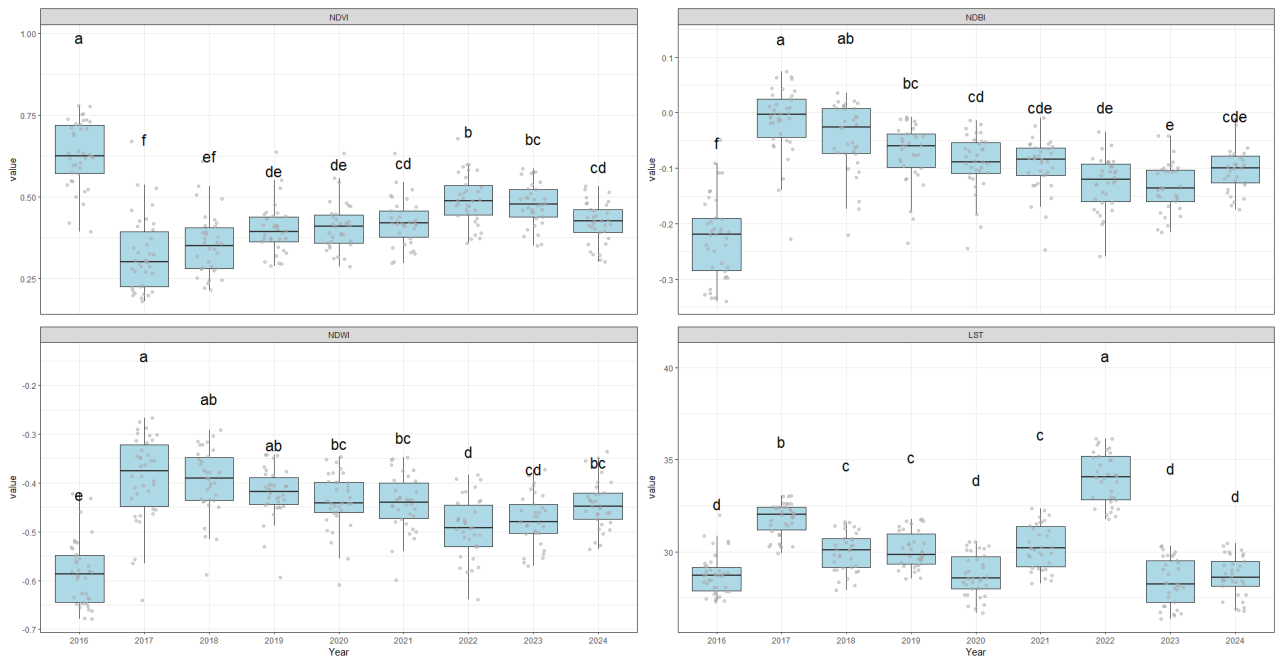


Figure 7. A comparative analysis of satellite-derived indices from the refugee camps in Cox's Bazar from 2016 to 2024. The plots display the NDBI, NDVI, NDWI, and LST indices calculated using Collection 2 Level-2 Landsat 8 OLI and TIRS data. Boxplots with different letters are significantly different from each other based on Tukey's HSD post hoc test ($p < 0.05$).

The Normalized Index Water Index (NDWI) values remained low (below -0.35) and relatively stable throughout the period examined, indicating drought conditions, dry soil, or the absence of vegetation and water in the winter, results those consistent with the acquisition carried out during the dry season (December) (Table 3; Figure 7). An extremely strong negative correlation between NDVI and NDWI was found with $r(310) = -0.99$, $p = 0.000$, indicating that areas with high vegetation cover tend to have low water presence, and vice versa. This could be due to the nature of the indices themselves, as areas with high vegetation might not necessarily have standing water, and areas with high water presence might have less vegetation. The analysis of surface moisture conditions based on NDWI showed consistently negative values across all years (-0.389 to -0.584) (Table 3; Figure 7). The most negative values occurred in 2016 (-0.584 ± 0.065) and 2022 (-0.49 ± 0.061), suggesting lower surface moisture relative to intermediate years.

The fraction of pixels with positive NDWI remained extremely low across all years, confirming the near absence of open water or saturated surfaces within camp boundaries during the dry season (Table 3). During the period 2017-2024, the values remained relatively low, with some fluctuations over the years. The standard deviations are relatively high, indicating variability in the data.

The highest Land Surface Temperatures (LST) values were observed in 2017 ($31.77 \pm 0.898^{\circ}\text{C}$) and particularly in 2022 ($34.0 \pm 1.4^{\circ}\text{C}$), while cooler conditions occurred in 2016, 2020, 2023, and 2024

($\approx 28\text{--}29^\circ\text{C}$) (Table 3; Figure 7). The LST values in 2023 and 2024 are relatively low, with values of 28.4°C and 28.7°C , respectively.

A moderate positive ($r(310) = 0.46$, $p = 0.000$) and negative ($r(310) = -0.40$, $p = 0.000$) correlation between LST and, respectively, NDBI and NDVI have been found during the observed period.

The analysis of the yearly relationship between NDVI and LST showed a strong inverse (negative) correlation between those two variables only during the years 2016, 2021–2024, while a decoupling was observed during the years 2017 – 2020 (See Supplementary Material, Figure S8).

The statistical analysis of temporal differences in satellite-derived indices was carried out using one-way analysis of variance (ANOVA), with year treated as a categorical predictor (Table 4). Before the analysis, assumptions of normality and homogeneity of variance were evaluated using Shapiro–Wilk and Levene’s tests.

Although Shapiro-Wilk tests ($p < 0.01$) and Levene’s tests ($p < 0.05$) confirm pervasive non-normality and heteroscedasticity, the large sample size ($N = 312$) renders the ANOVA F-tests fairly robust, and the concordant Kruskal–Wallis results (see Supplementary Material, Table S4) corroborate the main findings, i.e., temporal statistical differences found for all satellite-derived indices except NDWI fraction positive, a pattern that is consistent across both parametric ANOVA and the non-parametric Kruskal–Wallis test, indicating robustness to assumption violations.

Table 4. Results of variance-analysis for satellites-derived indices ($N = 312$). The table reports One-Way ANOVA F-values, effect sizes (η^2), Shapiro-Wilk normality tests, Levene’s homogeneity tests, and Tukey post-hoc comparisons.

Response	N	F(df)	p (ANOVA)	Effect Size (η^2)	p (S-W)	p (Levene)	Post-hoc (Tukey)
NDVI	312	43.56 (8, 303)	<0.001	0.53	<0.001	0.0189	24
NDBI	312	45.18 (8, 303)	<0.001	0.54	<0.001	0.0469	22
NDWI	312	33.5 (8, 303)	<0.001	0.47	0.00162	0.0377	20
LST	312	91.64 (8, 303)	<0.001	0.71	<0.001	0.101	27
NDVI bare soil fraction	312	31.46 (8, 303)	<0.001	0.45	<0.001	<0.001	15
NDWI fraction positive	312	0.89 (8, 303)	0.522	0.02	<0.001	0.522	0

The Tukey post-hoc test showed a clear temporal trajectory: 2016 differs significantly from subsequent years for NDVI, NDBI, and NDWI, suggesting an early baseline shift; the 2017–2020 interval exhibits mostly non-significant adjacent year differences, reflecting a transition phase; and the 2021–2024 period displays partial stabilisation, yet remains distinct from the early years.

Eventually, the year 2022 showed statistically significantly higher LST values than the other considered years (Table 4; Figure 7).

The sole exception, NDWI fraction positive, is non-significant in ANOVA ($p = 0.52$) and only marginally so in Kruskal–Wallis ($p = 0.042$), with no significant pairwise contrasts, likely owing to low variability or a sparse, zero inflated distribution, rendering it uninformative at the yearly scale.

Ecologically, the results imply a post-2016 decline in vegetation (NDVI) with incomplete recovery, a pronounced increase, then gradual stabilisation of built-up areas (NDBI), altered water dynamics (NDWI), and the strongest effect on land surface temperature (LST), consistent with thermal intensification driven by vegetation loss and urban expansion; bare soil fraction also rises, albeit with spatial variability, while water presence fraction shows no clear trend. This pattern mirrors process-based evidence from far larger domains: across more than 2,000 city clusters, Liu et al. (2022) showed that urban cores warm faster than their rural surroundings while vegetation greening partly offsets the signal, and Silveira et al. (2025) found, using satellite observations, that accumulated deforestation shifted regional climate toward higher land-surface temperatures and lower evapotranspiration where forest cover fell below about 60%, closely paralleling the coupled NDVI–LST dynamics we observe after the 2017 disturbance.

As reported by Hasan et al. (2023), for the Kutopalong Rohingya refugee camp of the Cox’s Bazar District, highest LST, lowest ET and dry soil conditions, registered in the area since 2017, are associated to highest level of deforestation (i.e., 80.32% decrease in forest area) and urbanization and the overall effect on the soil’s moisture retention capacity. Similarly, Mahi et al. (2021) report the loss of 12.2% of vegetation cover between 2013 and 2018 and a significant increase in areas with high temperatures as a consequence of the Rohingya influx in Teknaf Peninsula (Cox’s Bazar). Based on their analysis, they recommend an extensive regional environmental policy to address the issue, including hill conservation and tree plantation, to compensate for the loss of nature and mitigate the negative impacts of deforestation and climate change in the region.

The LST values indicate a period of cooler temperatures or changes in the camps’ microclimate, with moderate within-camp thermal heterogeneity. The relationship between LST and NDVI values is typically inverse, but—as we also observed in the period 2017–2020—can be decoupled by factors such as seasonal changes, land-use type, moisture availability, and urban heat island effects. This decoupling can have significant implications for humanitarian organizations, as it may indicate a need for more sustainable environmental management and cooling strategies such as reforestation projects or building strategies such as increasing the percentage of shelters made with more robust materials, such as brick or concrete blocks which have a higher albedo due to their lighter colour (e.g., TSAII shelter typology) and tend to reflect more solar radiation, thus determining a lower LST compared to models built with corrugated iron sheets or metal roofs, which can have a relatively low albedo and could lead to higher LST due to increased absorption of solar radiation (e.g., MTS Single

Storey). Interesting to note that the highest LST value in the refugee camps was observed in 2022, a year characterized by the lowest mean daily rate of precipitation (5.28 mm day⁻¹) and variability (4.66 mm day⁻¹).

Our results align with the findings of Karmakar et al. (2025), which report a substantial increase in LST in refugee camps of Cox's Bazar due to a 97% decrease in forest cover and around 162% of increase in built-up areas during the period 2013 – 2018. The analysis of NDVI values reveals a general decline from 2016 to 2017, followed by a gradual increase from 2017 to 2022, and a slight decrease from 2022 to 2024. The relationship between urbanization and NDVI values is complex and influenced by various factors, including climate, land use patterns, and management practices. For instance, water bodies and environmental processes (e.g., evapotranspiration) can have a significant effect in reducing LST, therefore underlining the importance of water resources in refugee camps (Karmakar et al., 2025).

Furthermore, the observed increase in the number of shelters built from 2017 to 2018 may have contributed to the decline in NDVI values during this period, while the recovery of NDVI values from 2018 to 2022 may be related to efforts to restore vegetation and implement sustainable land use practices. The implications for camp management with respect to the preserving of ecosystem services are multiple: the integration of green infrastructure (e.g., planting fast-growing, native trees and maintaining water bodies) can restore regulating services (temperature moderation, evapotranspiration) while also delivering cultural benefits, whereas adopting shelter designs that preserve vegetation (modular or elevated structures) can reduce ground-cover disturbance, mitigating the negative impact on NDVI and associated supporting services. Alongside, monitoring ecosystem service indicators such as regularly tracking LST, NDVI, and water body extent, will provide an early warning system for service degradation and informs timely mitigation measures.

3.4 Water, sanitation and hygiene (WASH) and faecal sludge treatment plant (FSTP) infrastructure

The analysis of the WASH dataset showed that several sanitation, solid waste and water infrastructures (up to 30,000) were built during 2018, following the first emergency period due to the arrival of the Rohingya population from Myanmar. In the following years, the number of new infrastructures gradually decreased (< 10,000) (Figure 8).

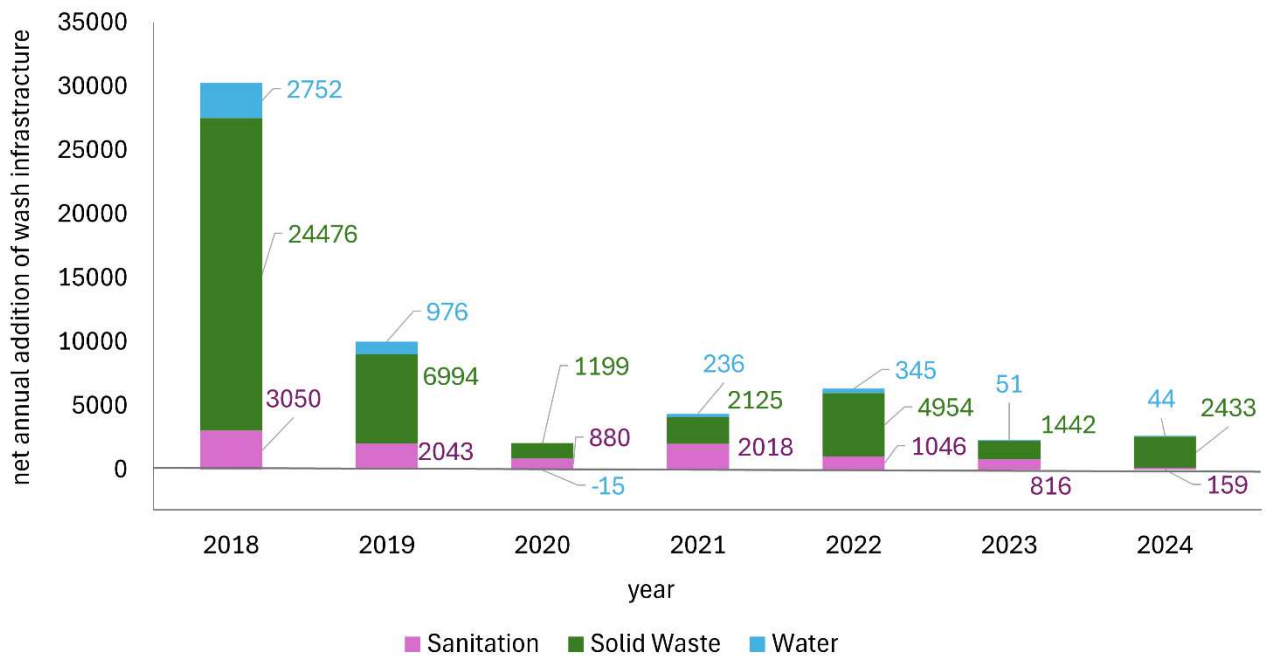


Figure 8. Net annual addition of WASH infrastructure in Cox's Bazar refugee camps from 2018 to 2024.

Similarly, analysis of WASH infrastructures for 2018-2024 showed a declining trend, with some yearly fluctuations in the net total annual number of water infrastructure reported for the refugee camps. Interestingly, during the year 2020, more water infrastructures were decommissioned than built (-15) (Figure 8).

Regarding the total number of faecal sludge treatment plants (FSTPs), in 2020, 55 FSTPs were present in the camps, but no weekly capacity data were reported. From 2021 onwards, capacity data were collected for a subset of FSTPs each year ($n = 4-32$). Their mean weekly capacities ranged from 33.6 to 168 m³ and maximum capacities reaching up to 700–900 m³ (Table 5).

Table 5. Total number of Faecal sludge treatment plants (FSTPs) and weekly capacity (m³) from 2020 to 2025 in Cox's Bazar refugee camps (Bangladesh)

year	Total number of FSTP	Capacity (weekly)			
		mean (FSTP sample)	sd	min	max
2020	55	-	-	-	-
2021	71	168 (4)	298	10	700
2022	597	38 (32)	89.4	0.68	900
2023	538	33.6 (32)	63.8	5	700
2024	168	35.8 (28)	69.6	5	700

The data on FSTP effluent in refugee camps in Cox's Bazar, including various effluent quality parameters of wastewater over a period of five years (2020-2024), are reported in Table 6 and Figure 9. The mean Chemical Oxygen Demand (COD) values ranged between 1166 mg/L in 2020 and 197 mg/L in 2023, indicating a significant decrease in organic matter over the years. Biochemical Oxygen

Demand (BOD) values spanned between 6048 mg/L in 2020 and 565 mg/L in 2023, also showing a substantial decrease in organic matter over the years.

Table 6. Summary statistics for FSTP effluent quality indicators in Cox's Bazar refugee camp, 2020-2024. The table presents mean values for a range of parameters, including Chemical Oxygen Demand (COD; mg/L), Biochemical Oxygen Demand (BOD; mg/L), Escherichia coli (E.coli; CFU/100 ml), Nitrate (mg/L), Phosphate (mg/L), Nitrogen (mg/L), Coliform (CFU/100 ml), and Total Suspended Solids (TSS; mg/L).

<i>year</i>	<i>COD</i>	<i>BOD</i>	<i>E.coli</i>	<i>Nitrate</i>	<i>Phosphate</i>	<i>Nitrogen</i>	<i>Coliform</i>	<i>TSS</i>
2020	1166	6,048	680,529	23.9	-	2070	-	7,866
2021	784	4,598	1,348,699	64.1	12.1	1857	206,775	5,000
2022	261	732	748,609	28.8	41.0	494	1,174,493	197
2023	197	565	145,477	28.0	36.6	489	320,345	188
2024	320	842	28,567	61.0	34.8	550	151,118	161

E. coli mean values ranged between 1,348,699 CFU/100 mL (2021) and 28,567 CFU/100mL (2024), indicating a significant variation in faecal contamination over the years (Figure 9). The mean nitrate values ranged from 23.9 mg/L (2020) to 64.1 mg/L (2021), with a notable increase in 2021. The mean phosphate values were only available from 2021 onwards, ranging from 12.1 mg/L (2021) to 41.0 mg/L (2022), indicating a significant variation in phosphate levels, whereas the total nitrogen showed a decrease in nitrogen levels over the years, with mean values ranging between 2070 mg/L in 2020 and 494 mg/L in 2022. The mean coliform values were also only available from 2021 onwards, ranging from 1,174,493 CFU/100 mL (2022) to 151,118 CFU/100 mL (2024), indicating, like what was observed for *E. coli*, a significant variation in coliform bacteria over the years. Eventually, the Total Suspended Solids (TSS) data showed a substantial decrease in suspended solids over the years, with mean values in the range between 7,866 mg/L (2020) and 161 mg/L (2024).

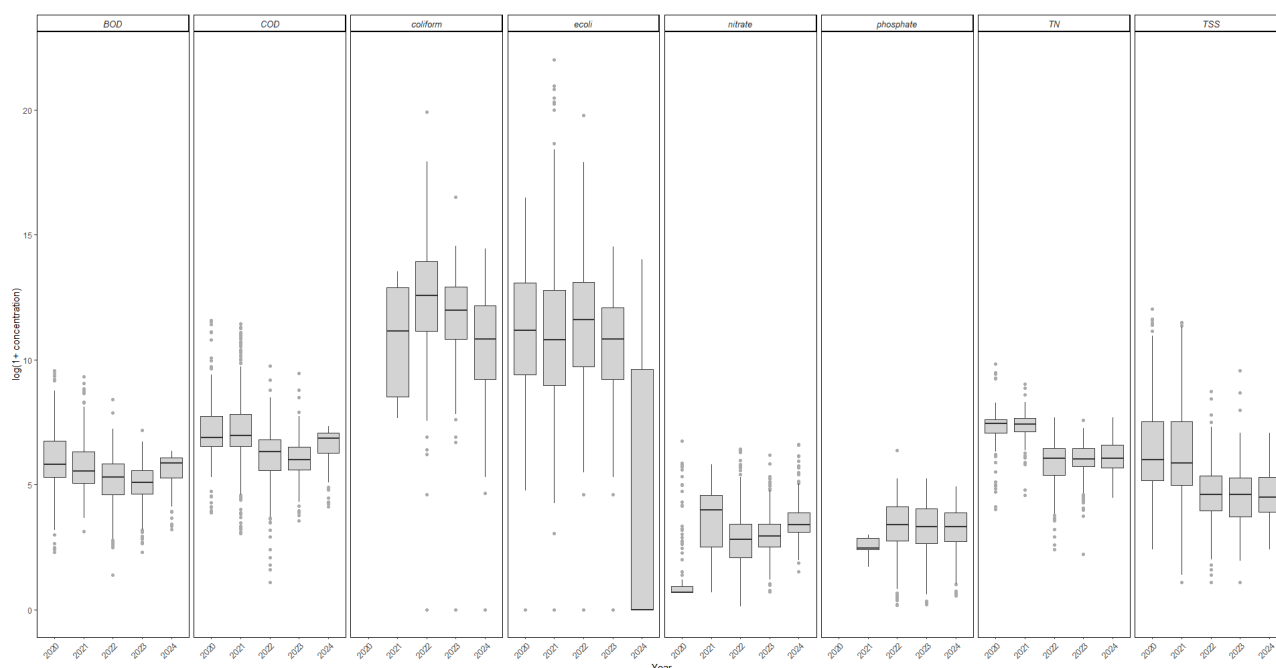


Figure 9. Boxplots of effluent quality indicators measured in Cox's Bazar refugee camps based on samples collected in FSTPs from 2020 to 2024; values are shown in $\log(1 + x)$ scale.

Although improved infrastructure and technology, such as water treatment plants and innovative water purification systems, are needed to ensure access to safe and clean water (M.-U. Alam et al., 2020; García et al., 2021; Ali and Shahreen, 2024), the analysis of WASH and FSTP infrastructure reveals a declining trend in sanitation infrastructure, while solid waste infrastructure shows significant fluctuations over the years likely linked to changes in waste management practices or the implementation of new waste management strategies.

Our analysis suggests that the initial emergency response to the Rohingya refugee crisis led to a rapid increase in WASH infrastructure, but this momentum has not been sustained over time. The decline in sanitation infrastructure is concerning, as it may indicate a decline in access to safe and hygienic toilets for the refugee population. At the same time, there remains the need for community engagement and education to promote safe water practices and improving water quality, to avoid the secondary contamination of previously treated drinking water (M.-U. Alam et al., 2020; Faruque et al., 2022; Ali and Shahreen, 2024; Sobczak-Szelc et al., 2026).

The quality of FSTP wastewater is improving over time, with a reduction in organic matter and suspended solids. However, high levels of faecal contamination recorded in some years are concerning, as they may indicate inadequate treatment or management of the FSTP wastewater. This represents an environmental concern, as treated liquid effluent disposed of via infiltration does not meet the Bangladesh Department of Environment standards for discharge to surface water, and no national standards currently exist in Bangladesh to regulate infiltration-based disposal (ARUP et al., 2022). The persistence of contamination despite improving effluent metrics echoes Jones et al. (2022), whose global modelling indicated that meeting wastewater-treatment targets alone leaves

quality thresholds unmet where baseline capacity is low, and supports the argument of Silva et al. (2024) that source control and continuous monitoring, rather than infrastructure expansion alone, are decisive.

3.5 Water Quality as the outcome of the stressors' impact , mediated by the WASH infrastructure

The water quality parameters (Figure 10; Table 7) exhibited varying trends over the years. *E. coli* concentrations showed a significant decrease in 2020, with mean values ranging from 59.5 CFU/100 mL in 2019 to 1.04 CFU/100 mL in 2020. However, the high standard deviations indicate substantial variability in these concentrations. In contrast, fluoride levels remained relatively stable, with mean values fluctuating between 0.81 mg/L in 2022 and 0.57 mg/L in 2023. The low standard deviations suggest consistent fluoride concentrations over the years (Table 7). Free Residual Chlorine (FRC) levels demonstrated an increasing trend, with mean values ranging from 0.16 mg/L in 2019 to 0.39 mg/L in 2020. Manganese and iron concentrations also showed notable trends, with manganese levels remaining relatively stable between 0.20 mg/L in 2022 and 0.06 mg/L in 2024, and iron levels decreasing from 1.69 mg/L in 2020 to 0.48 mg/L in 2023. The Total Dissolved Solids (TDS) and turbidity levels exhibited more pronounced variability. TDS values declined significantly in 2020, with mean values ranging from 391 mg/L in 2019 to 120 mg/L in 2020. Turbidity levels, meanwhile, remained relatively stable, with mean values ranging from 8.14 NTU in 2021 to 3.38 NTU in 2023. Despite these overall trends, the high standard deviations for TDS and turbidity (Table 7) indicate substantial variability in these parameters. The elevated TDS and salinity signals are consistent with salinization increasingly reported for stressed aquifers - such as the seawater-intrusion, dissolution and nitrate drivers documented by Narvaez-Montoya et al. (2025) and the coupled socio-technical drivers identified by Grant et al. (2026) - underscoring that these outcomes reflect interacting human and environmental pressures rather than isolated events.

Table 7. Summary statistics for drinking water quality parameters in Cox's Bazar refugee camp, 2020-2024. The table presents mean values and standard deviation (reported in parentheses) for Escherichia coli (E.coli; CFU/100 ml), Fluoride (mg/L), Free Residual Chlorine (FRC; mg/L), Iron (mg/L), Manganese (mg/L), Total Dissolved Solids (TDS; mg/L), and Turbidity (NTU).

year	<i>E. coli</i>	Fluoride	FRC	Iron	Manganese	TDS	Turbidity
2019	59.55 (74.7)	0.69 (0.14)	0.16 (0.19)	1.15 (1.25)	0.16 (0.49)	391.7 (899.2)	4.92 (1.89)
2020	1.04 (2.2)	-	0.40 (0.24)	1.69 (1.87)	0.16 (0.06)	120.4 (73.3)	5.44 (0.94)
2021	2.90 (5.1)	0.64 (0.39)	0.21 (0.24)	0.92 (0.77)	0.11 (0.09)	162.4 (38.2)	8.15 (19.3)
2022	4.07 (14.0)	0.82 (0.25)	0.36 (0.26)	0.70 (0.81)	0.21 (0.30)	171.9 (51.8)	6.73 (12.2)

2023	3.00 (5.8)	0.57 (0.28)	0.35 (0.23)	0.48 (0.43)	0.10 (0.13)	201.3 (83.1)	3.38 (2.81)
2024	2.20 (5.9)	0.65 (0.25)	0.37 (0.21)	0.82 (2.02)	0.06 (0.03)	191.5 (95.3)	3.47 (2.36)

Given violations of normality and homoscedasticity assumptions (Shapiro–Wilk and Levene tests, $p < 0.001$ in several cases), non-parametric analyses were additionally performed. Kruskal–Wallis tests confirmed the presence of significant differences among years (Figure 10) within water collection point types, and post hoc pairwise comparisons using Dunn’s test with Holm correction showed patterns consistent with those observed in the parametric ANOVA framework (Table 8).

The statistical analysis of 1,058 waterpoint samples revealed marked heterogeneity among the three water source categories (Table 8; Figure 10).

For *E. coli* concentration measured in samples collected in hand-pump/tubewell samples ($n = 344$), Shapiro-Wilk and Levene tests indicated non-normality and heteroscedasticity ($p < 0.001$), yet the overall ANOVA was highly significant ($F_{5,388} = 41.95$, $p < 0.001$) with a large effect ($\eta^2 = 0.383$); post hoc Tukey tests identified five pairwise differences and the Kruskal-Wallis test confirmed heterogeneity ($\chi^2 = 118.85$, $p < 0.001$, Dunn $p < 0.001$). Fluoride ($p = 0.055$, $\eta^2 = 0.310$), manganese ($p = 0.052$, $\eta^2 = 0.210$), free residual chlorine ($p = 0.011$, $\eta^2 = 0.118$), Total Dissolved Solids ($p = 0.126$, $\eta^2 = 0.075$) and turbidity ($p < 0.001$, $\eta^2 = 0.225$) also showed significant variation within this group, supported by corresponding Kruskal-Wallis tests (all $p < 0.05$).

In contrast, Production Borehole samples displayed non-normal distributions and yielded non-significant ANOVA and Kruskal-Wallis results for all parameters ($p > 0.2$).

Tap stand samples similarly exhibited non-normality for all the response variables analysed; *E. coli* ($p = 0.267$, $\eta^2 = 0.037$) and most chemical parameters were non-significant, except Iron ($p = 0.009$, $\eta^2 = 0.179$) and free residual chlorine ($p = 0.005$, $\eta^2 = 0.069$), with the later displaying modest but significant differences also in the Kruskal-Wallis test ($\chi^2 = 18.01$, $p = 0.003$ for chlorine).

Overall, the greatest practical heterogeneity was observed in bacterial load and several chemical constituents for handpump/tubewell water, whereas borehole water was largely homogenous, and tap stand water showed limited but detectable variation in residual chlorine. Hand-pump/tubewell bacterial load variability might be linked with the shallower depth of the wells, thus higher exposure to surface transport of faecal material (Luby et al., 2008) or longer transport and storage times depending on the distance to the well (Goel et al. 2023). This can be exacerbated by the lack of buffer zones, allowing contamination by animals or human contact, or poor structural engineering solutions systems. Singh et al. (2022) demonstrated that structural interventions that limit risks of breakage or malfunctioning can consistently reduce microbial contamination at point-of-use, all the

while not neglecting the importance of proper hygiene and sanitation practices to reduce contamination. In a densely populated camp, microbiological point-of-use contamination can trigger rapid diarrhoeal disease transmission after a storm or when hygiene facilities are overwhelmed, thereby eroding community resilience.

Variations in chlorine at tap-stand water might be explained by distribution network travel distance, since residual chlorine has been shown to decrease significantly with distance from the treatment facility (Kulmedov et al. 2025). Adequate chlorination is a key resilience factor because it provides a buffer against sudden microbial surges following heavy rainfall or contamination events. The overall consistency suggests that the chlorination programme is functioning, but the few outliers should be targeted for corrective action.

Fluoride levels also vary markedly across handpump/tubewell sources (Table 8; Figure 10). Because excess fluoride can cause skeletal fluorosis, the presence of high fluoride sites may compromise long-term health, reducing the population's ability to cope with additional stressors. Tap stand water shows smaller but still significant fluoride differences, indicating that even treated supplies can harbour local variations.

Eventually, Total Dissolved Solids (TDS) and turbidity are statistically different for handpump/tubewell water, yet the effect sizes are negligible (Table 8; Figure 10). This means that, while measurements can detect a difference, the practical impact on taste, aesthetic quality, or treatment requirements is minimal. Nevertheless, the presence of any significant variation signals that the water distribution network is not homogeneous, which could become problematic if a supply interruption forces reliance on a single source. As reported by several authors, human activities, such as land use changes, agricultural practices, and urbanization, are identified as significant contributors to water quality degradation in many of the studies (Gyimah et al., 2020; Camara et al., 2019; Yao et al., 2023; Weng et al., 2024). Our study highlights how water quality in the refugee camp has improved over the years, with decreased values of *E. coli*, iron, and TDS levels. However, there are still concerns regarding the variability of *E. coli*, iron, and turbidity levels, which may indicate issues with water treatment and distribution. In fact, our results indicate that the quality of water supplied to the refugee camps in Cox Bazar is uneven, and this heterogeneity has direct implications for the camps' resilience – i.e., their capacity to maintain health and basic services in the face of shocks such as floods, disease outbreaks, or supply chain disruptions. In this situation, the need for alternative water sources, such as rainwater harvesting, and climate-resilient water management strategies, should be emphasized (M.-U. Alam et al., 2020; García et al., 2021; Ali and Shahreen, 2024).

Resilience can therefore be strengthened by targeted monitoring and identification of high variability points (elevated *E. coli* or fluoride, handpump/tube-wells) through more frequent testing and rapid

remedial measures (e.g., wellhead protection, point of use chlorination). Moreover, infrastructure upgrades (e.g., standardising pump construction and maintenance across the camps) can reduce the observed heterogeneity, strengthening the system's ability to withstand environmental shocks. Community engagement (e.g., training residents to recognise and report water quality issues at specific taps or pumps) can also enhance early warning capacity and promotes adaptive management and, eventually, during emergencies, water from the most reliable sources (low microbial load, adequate chlorine residual) can be earmarked for vulnerable groups (children, pregnant women), preserving health-related resilience. As a reminder, any presence of *E. coli* is above the WHO and EU threshold value of 0 CFU/100 mL (see Supplementary Material, Table S5). The TDS values during the studied period exceeded the recommended threshold of 300 mg/L.

In summary, the data reveal that while overall disinfection is satisfactory, the pronounced variability in microbial contamination and fluoride concentrations at hand-pump/tubewell sites represents a weak point in the water-supply system, therefore undermining safe drinking water provision and the community resilience. Addressing these disparities through focused monitoring, infrastructure standardisation, and community participation will improve the camps' capacity to maintain safe water under adverse conditions, thereby bolstering overall resilience.

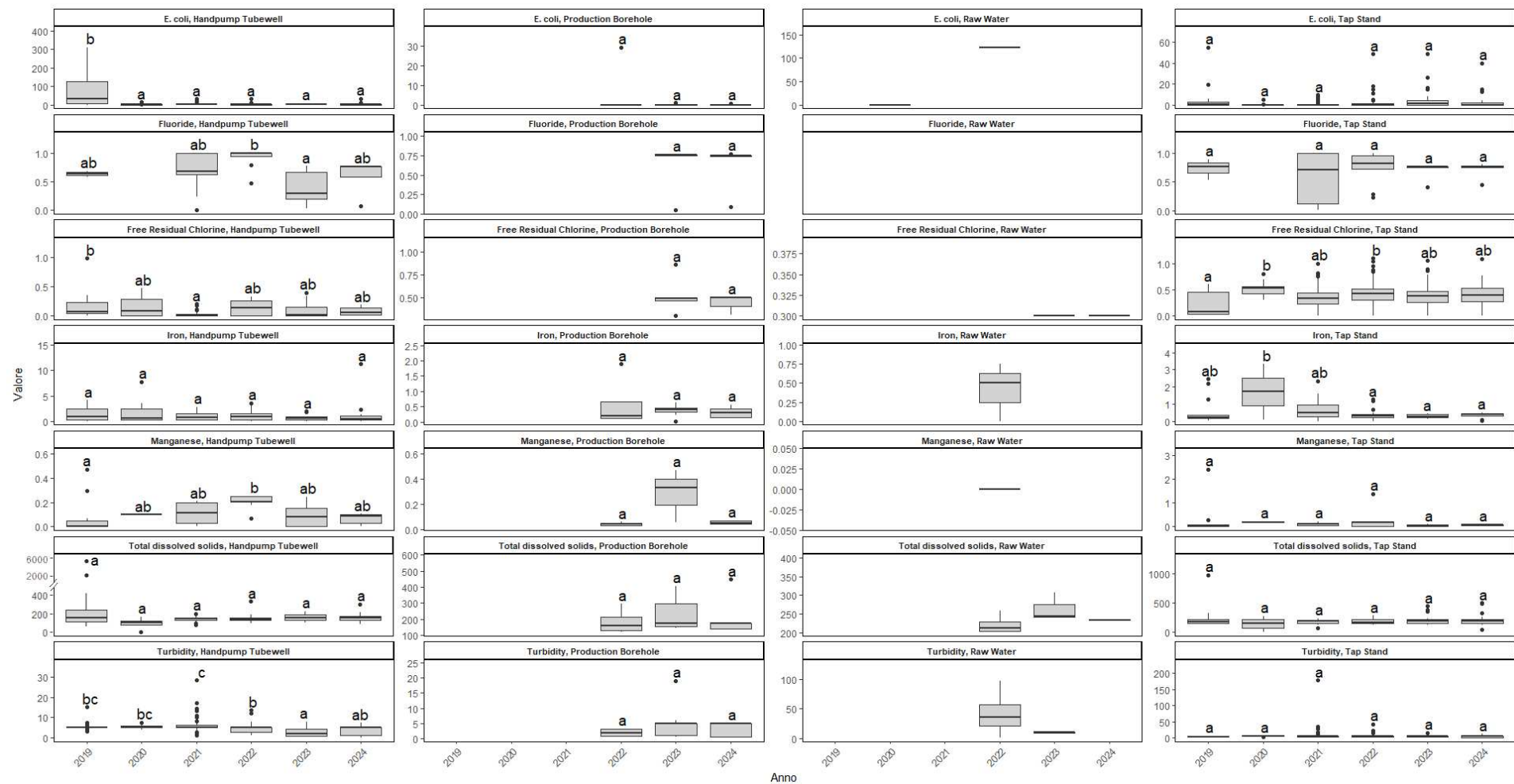


Figure 10. Water quality measurements from 2019 to 2024 of *E. coli* (CFU/100 ml), fluoride concentration (mg/L), Iron concentration (mg/L), free residual chlorine (mg/L), Manganese concentration (mg/L), Total Dissolved Solids (mg/L) and turbidity (NTU) in refugee camps of Cox's Bazar from sample collected in four different water collection point type. Different letters denote significant differences among boxplots according to Tukey's HSD test ($p < 0.05$), limited to "handpump tubewell", "production borehole", and "tap stand" water collection point type samples.

Table 8. Results of within-group analyses across years (from 2019 to 2024) for *E. coli* (CFU/100 ml), fluoride concentration (mg/L), Iron concentration (mg/L), free residual chlorine (mg/L), Manganese concentration (mg/L), Total Dissolved Solids (mg/L), and turbidity (NTU). The table includes one-way ANOVA outputs (*F*-values and effect sizes, η^2), Shapiro–Wilk normality tests, Levene’s tests for homogeneity of variances, Tukey HSD post hoc comparisons, and corresponding non-parametric results from Kruskal–Wallis tests (χ^2) and Dunn (with Holm correction) post hoc analyses.

response	water point sample type	<i>N</i>	<i>p</i> (S-W)	<i>p</i> (Levene)	<i>F</i> (<i>df</i>)	<i>p</i> (ANOVA)	Effect Size (η^2)	Post-hoc (Tukey)	χ^2 (K-W)	<i>p</i> (K-W)	Post-hoc (Dunn)
<i>E. coli</i>	Handpump Tube well	344	<0.001	<0.001	41.95 (5, 338)	<0.001	0.383	5	118.85	<0.001	<0.001
Fluoride		29	0.053	0.459	2.7 (4, 24)	0.055	0.310	1	9.98	0.041	0.033
Iron		118	<0.001	0.274	0.95 (5, 112)	0.450	0.041	0	2.78	0.733	0.886
Manganese		51	<0.001	0.607	2.39 (5, 45)	0.052	0.210	1	14.66	0.012	0.003
Free Residual Chlorine		123	<0.001	0.020	3.13 (5, 117)	0.011	0.118	1	24.14	<0.001	<0.001
Total Dissolved Solids		115	<0.001	0.103	1.77 (5, 109)	0.126	0.075	0	16.01	0.007	0.009
Turbidity		272	<0.001	0.013	15.46 (5, 266)	<0.001	0.225	6	105.53	<0.001	<0.001
<i>E. coli</i>	Production Borehole	25	<0.001	0.225	1.6 (2, 22)	0.225	0.127	0	0.8	0.669	0.793
Fluoride		11	<0.001	0.919	0.01 (1, 9)	0.923	0.001	0	0.3	0.583	
Iron		25	<0.001	0.135	1.01 (2, 22)	0.380	0.084	0	1.02	0.600	0.748
Manganese		10	0.018	0.109	4.54 (2, 7)	0.054	0.565	0	3.19	0.203	0.296
Free Residual Chlorine		10	0.122	0.782	0.46 (1, 8)	0.518	0.054	0	0.01	0.906	
Total Dissolved Solids		16	<0.001	0.935	0.25 (2, 13)	0.785	0.037	0	1.16	0.559	0.696
Turbidity		25	<0.001	0.615	0.83 (2, 22)	0.447	0.071	0	1.69	0.429	0.662
<i>E. coli</i>	Tap Stand	177	<0.001	0.269	1.3 (5, 171)	0.267	0.037	0	10.42	0.064	0.178
Fluoride		30	0.004	0.072	0.39 (4, 25)	0.817	0.058	0	1.53	0.822	0.965
Iron		82	<0.001	<0.001	3.31 (5, 76)	0.009	0.179	3	6.53	0.258	0.408

<i>Manganese</i>	33	<0.001	0.864	0.29 (5, 27)	0.916	0.051	0	7.4	0.193	0.850
<i>Free Residual Chlorine</i>	241	<0.001	0.675	3.49 (5, 235)	0.005	0.069	2	18.01	0.003	0.011
<i>Total Dissolved Solids</i>	121	<0.001	0.225	1.47 (5, 115)	0.207	0.060	0	2.57	0.765	0.985
<i>Turbidity</i>	149	<0.001	0.320	1.11 (5, 143)	0.360	0.037	0	10.88	0.054	0.042

4 Conclusion

In conclusion, our study analyzed the trends and patterns of climatic, environmental, ecological, and functional factors, as well as population indicators, over a period of nine years (2016-2024) in the refugee camps in Cox's Bazar District, Bangladesh. The aim was to identify evidence-based strategies and interventions to improve health, well-being, and sustainability of these communities, with a particular focus on the provision of clean water. Our analysis examined three key stressors impacting the Cox's Bazar refugee camps, including overpopulation and settlement dynamics, reduced ecosystem services, and climate-related impacts. Filtered by the limited availability of WASH and FSTP infrastructures, we examined the water quality outcomes.

Our findings show that the rapid population growth in the area has driven deforestation and/or forest degradation, loss of vegetation, and intensified urbanization, resulting in a decline in the provision of safe drinking water, and ecosystem services such as temperature control, and climate regulation. For instance, the decline in vegetation is reflected in higher land surface temperatures, which might be related to specific microclimatic conditions, such as drought conditions and reduced evapotranspiration (Hasan et al., 2023). These ecosystem services are interconnected with supporting services such as soil formation, nutrient cycling, and primary production, and can be affected by the reduction of the ecosystem functional types. Remotely derived biodiversity indices, such as Shannon and Evenness, can guide restoration and conservation planning (Giri and Qiu, 2016), especially when integrated with information on ecosystem functional types. The observed decline in vegetation reflected in higher land-surface temperatures represents a vegetation-climate coupling now corroborated at regional scale by satellite evidence (Silveira et al., 2025; Tang et al., 2025).

Water-quality trends reveal reductions in *E. coli*, iron, and TDS, yet faecal contamination still exceeds WHO/EU limits, underscoring the need for continuous monitoring of WASH and FSTP systems. These findings corroborate earlier studies (Mahmud et al., 2019; Akhter et al., 2020; Faruque et al., 2022; Sarkar et al., 2023; Ali and Shahreen, 2024) and highlight the importance of improved infrastructure and technology in sustaining a range of ecosystem services essential for health, resilience, and long-term sustainability of the camps. This need is reinforced by broader evidence that infrastructure targets alone are insufficient to secure water quality (Jones et al., 2022; Silva et al., 2024) and that salinization and related pressures are best understood as coupled human-environment processes (Narvaez-Montoya et al., 2025; Grant et al., 2026).

Overall, our study demonstrates the complexity of issues related to the provision of clean water and environmental factors in the context of mass displacement. Water quality and availability are fundamental to the living conditions, health outcomes, and habitability of a settlement, and understanding the patterns of water quality parameters and environmental impact of large-scale refugee camps is crucial for informing humanitarian action.

Taken together, these results position the refugee camps of Cox's Bazar District, Bangladesh, as a case study of a coupled human–environment system under stress. The rapid settlement of a large population onto a small area — coupled with the deforestation — compresses into less than a decade, and a few square kilometres, the same land-change–climate–water cascade that the wider literature documents across regions and decades: vegetation loss, built-up expansion and land-surface warming move together rather than independently, and their interaction — not any single pressure — propagates to water availability and quality. This coupling reproduces at settlement scale the feedback reported for far larger domains (Silveira et al., 2025; Liu et al., 2022; Tang et al., 2025), while the WASH trajectory shows that gains in such systems are non-linear and partly reversible, with early improvements followed by stagnation or decline. Water quality, in this reading, is best understood as a system-level outcome downstream of land, climate and sanitation drivers acting jointly (Jones et al., 2022; Silva et al., 2024; Narvaez-Montoya et al., 2025; Grant et al., 2026), rather than as an isolated infrastructural problem.

The methodological contribution follows directly from this systems view: the harmonised, multi-stressor database assembled here (see Data Availability) offers a transferable template for monitoring other protracted-displacement settings, linking environmental, climatic, ecosystem-service and water indicators at the camp-and-year scale. We stress, however, that the present design is descriptive and ecological; the observed couplings are consistent with, and parallel, the process-based studies cited above rather than demonstrating causation within the camps. Establishing those mechanisms, and capturing conditions as experienced by residents themselves, is the necessary next step.

Further analyses are needed to model the processes shaping living conditions and environmental impact, and to strengthen data collection to better understand the conditions from the perspective of the residents of the camps. Currently, there is a lack of in-depth knowledge about the population, including stability over time, population movement, natality, mortality, and assessment of conditions by the refugees themselves. Addressing these knowledge gaps is essential for tailoring effective strategies to improve the health, well-being, and sustainability of refugee communities.

Data Availability

The harmonised database generated for this study integrates, for each camp (SSID) and year over 2016–2024, the environmental, climatic, ecosystem-service, infrastructural (WASH, solid-waste and faecal-sludge) and water-quality indicators described in Table 1, together with the derived remote-sensing indices (NDVI, NDBI, NDWI, LST and associated bare-soil and water fractions) and ecological metrics (Shannon and Evenness for ecosystem functional types and land-use/land-cover). It is provided in GeoPackage and xlsx formats with accompanying metadata and is deposited in the JRC Open Data Catalogue under a CC BY 4.0 licence at <https://doi.org/10.2905/JRC.MT8GR2R>.

This database is distinct from the Supplementary Material. The source datasets remain available from their original providers as cited in Table 1, and the contribution of the present release is the quality-controlled harmonisation and linkage of these heterogeneous streams into a single, analysis-ready resource.

References

- Ahmed, B., 2021. The root causes of landslide vulnerability in Bangladesh. *Landslides* 18, 1707–1720. <https://doi.org/10.1007/s10346-020-01606-0>
- Akhter, M., Uddin, S.M.N., Rafa, N., Hridi, S.M., Staddon, C., Powell, W., 2020. Drinking Water Security Challenges in Rohingya Refugee Camps of Cox's Bazar, Bangladesh. *Sustainability* 12. <https://doi.org/10.3390/su12187325>
- Alam, A., Sammonds, P., Ahmed, B., 2020. Cyclone risk assessment of the Cox's Bazar district and Rohingya refugee camps in southeast Bangladesh. *Science of The Total Environment* 704, 135360. <https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.135360>
- Alam, M.J., Habib, M.A., Pothier, E., 2021. Shelter locations in evacuation: A Multiple Criteria Evaluation combined with flood risk and traffic microsimulation modeling. *International Journal of Disaster Risk Reduction* 53, 102016. <https://doi.org/10.1016/j.ijdr.2020.102016>
- Alam, M.-U., Unicomb, L., Ahasan, S.M.M., Amin, N., Biswas, D., Ferdous, S., Afrin, A., Sarker, S., Rahman, M., 2020. Barriers and Enabling Factors for Central and Household Level Water Treatment in a Refugee Setting: A Mixed-Method Study among Rohingyas in Cox's Bazar, Bangladesh. *Water* 12. <https://doi.org/10.3390/w12113149>
- Alazze, S., Galaiti, S., Bishara, A., Al-Azraq, N., Durant, J., 2019. Impacts of Intermittent Water Supply on Water Quality in Two Palestinian Refugee Camps. *Water* 11, 670. <https://doi.org/10.3390/w11040670>
- Ali, M., Shahreen, T., 2024. Climate-resilient water resource management for Rohingya refugee camps in Bangladesh. *Int. J. Sci. Res. Arch.* 12, 2661–2694. <https://doi.org/10.30574/ijrsra.2024.12.1.1139>
- Anav, A., Gualtieri, M., Sorrentino, B. et al. (2026). Leveraging peri-urban forests to reduce temperature and air pollution-related urban mortality in European cities. *Communications Earth & Environment* 7, 62. <https://doi.org/10.1038/s43247-025-03079-2>
- ARUP, OXFAM, UNICEF, 2022. Technical assessment of faecal sludge management in the Rohingya response (Phase 2 final report). OXFAM.
- Asoka, A., Gleeson, T., Wada, Y., Mishra, V., 2017. Relative contribution of monsoon precipitation and pumping to changes in groundwater storage in India. *Nature Geoscience* 10, 109–117. <https://doi.org/10.1038/ngeo2869>
- Baker, J. C. A., Smith, C., Veiga, J. A. P. et al. (2026). Quantifying tropical forest rainfall generation. *Communications Earth & Environment* 7, 150. <https://doi.org/10.1038/s43247-025-03159-3>
- Bierkens, M.F.P., Wada, Y., 2019. Non-renewable groundwater use and groundwater depletion: a review. *Environmental Research Letters* 14, 063002. <https://doi.org/10.1088/1748-9326/ab1a5f>
- Butt, S., Chowdhury, Md.S.R., Sadique, S., Faisal, A.A., Mahama, A., Gorski, A., Pop-Stefanija, B., Beversluis, D., Lochokon, J.M., Velivela, K., Uadiale, K., Rahman, Md.M., Worku, T.G., Billiew, T.J.G., Keating, P., 2025. Assessment of water, sanitation and hygiene services within nineteen Rohingya camps in Cox's Bazar, Bangladesh in 2022. *BMC Health Services Research* 25, 814. <https://doi.org/10.1186/s12913-025-12874-8>
- Carlevaro, N., 2020. COX's BAZAR | 2019 (technical review mission of swiss solidarity supported projects shelter support and public buildings No. RO17 & JRZ18- October 2019). mobilstudio, Geneva.
- Chowdhury, M.S., 2023. A review on landslide susceptibility mapping research in Bangladesh. *Heliyon* 9, e17972. <https://doi.org/https://doi.org/10.1016/j.heliyon.2023.e17972>

- Egea-Corbacho, A., Godino-Ojer, M., Somolinos, S., Ripoll, V., 2026. Climate change–driven alterations in water quality and their impact on trihalomethane formation: A review of treatment technologies. *Journal of Water Process Engineering* 86, 109894. <https://doi.org/10.1016/j.jwpe.2026.109894>
- Faruque, A., Alam, B., Nahar, B., Parvin, I., Barman, A.K., Khan, S.H., Hossain, M.N., Widiati, Y., Hasan, A.M., Kim, M., Worth, M., Vandenent, M., Ahmed, T., 2022. Water, Sanitation, and Hygiene (WASH) Practices and Outreach Services in Settlements for Rohingya Population in Cox’s Bazar, Bangladesh, 2018–2021. *IJERPH* 19, 9635. <https://doi.org/10.3390/ijerph19159635>
- García, R., Naves, A., Anta, J., Ron, M., Molinero, J., 2021. Drinking water provision and quality at the Sahrawi refugee camps in Tindouf (Algeria) from 2006 to 2016. *Science of The Total Environment* 780, 146504. <https://doi.org/https://doi.org/10.1016/j.scitotenv.2021.146504>
- Giri, S., Qiu, Z., 2016. Understanding the relationship of land uses and water quality in Twenty First Century: A review. *Journal of Environmental Management* 173, 41–48. <https://doi.org/10.1016/j.jenvman.2016.02.029>
- Global Shelter Cluster (2019), Shelter Projects 2017–2018, www.shelterprojects.org. Accessed on 2026-08-06 at URL: <https://reliefweb.int/report/world/shelter-projects-2017-2018-case-studies-humanitarian-shelter-and-settlement-responses>
- Goel, V., Chan, B., Ziaide, M., Yunus, M., Ali, M.T., Khan, M.A.F., Alam, M.N., Faruque, A., Babu, S., Kabir, M.M., Delamater, P.L., Serre, M., Sobsey, M.D., Islam, M.S., Emch, M., 2023. Deep tubewell use is associated with increased household microbial contamination in rural Bangladesh: Results from a prospective cohort study among households in rural Bangladesh. *Environmental Pollution* 324, 121401. <https://doi.org/10.1016/j.envpol.2023.121401>
- Grant, S. B., Bhide, S. V., Spiesman, A. et al. (2026). Social-ecological-technological drivers of freshwater salinization in the Occoquan Reservoir, United States. *Communications Earth & Environment* 7, 133. <https://doi.org/10.1038/s43247-025-03152-w>
- Grizzetti, B., Lanzaova, D., Liqueite, C., Reynaud, A., Cardoso, A.C., 2016. Assessing water ecosystem services for water resource management. *Environmental Science & Policy* 61, 194–203. <https://doi.org/10.1016/j.envsci.2016.04.008>
- Hasan, Md.A., Mia, Md.B., Khan, M.R., Alam, Md.J., Chowdury, T., Al Amin, Md., Ahmed, K.M.U., 2023. Temporal Changes in Land Cover, Land Surface Temperature, Soil Moisture, and Evapotranspiration Using Remote Sensing Techniques—a Case Study of Kutupalong Rohingya Refugee Camp in Bangladesh. *J geovis spat anal* 7, 11. <https://doi.org/10.1007/s41651-023-00140-6>
- Hasan, Mohammad Emran, Zhang, L., Dewan, A., Guo, H., Mahmood, R., 2021. Spatiotemporal pattern of forest degradation and loss of ecosystem function associated with Rohingya influx: A geospatial approach. *Land Degrad Dev* 32, 3666–3683. <https://doi.org/10.1002/ldr.3821>
- Hasan, Mohammad E., Zhang, L., Mahmood, R., Guo, H., Li, G., 2021. Modeling of Forest Ecosystem Degradation Due to Anthropogenic Stress: The Case of Rohingya Influx into the Cox’s Bazar–Teknaf Peninsula of Bangladesh. *Environments* 8, 121. <https://doi.org/10.3390/environments8110121>
- Hassan, M.M., Smith, A.C., Walker, K., Rahman, M.K., Southworth, J., 2018. Rohingya Refugee Crisis and Forest Cover Change in Teknaf, Bangladesh. *Remote Sensing* 10, 689. <https://doi.org/10.3390/rs10050689>
- HDX, 2026. Humanitarian Data Exchange | Find & Use Crisis Data | HDX [WWW Document]. The Humanitarian Data Exchange. URL <https://data.humdata.org/> (accessed 3.9.26).
- Islam, M.D., Siddika, A., 2022. Implications of the Rohingya Relocation from Cox’s Bazar to Bhasan Char, Bangladesh. *International Migration Review* 56, 1195–1205. <https://doi.org/10.1177/01979183211064829>
- Jones, E. R., Bierkens, M. F. P., Wanders, N. et al. (2022). Current wastewater treatment targets are insufficient to protect surface water quality. *Communications Earth & Environment* 3, 221. <https://doi.org/10.1038/s43247-022-00554-y>
- Karim, M.F., Zhang, X., 2021. Analysis of Vegetative Cover Vulnerability in Rohingya Refugee Camps of Bangladesh Utilizing Landsat and Per Capita Greening Area (PCGA) Datasets. *Remote Sensing* 13, 4922. <https://doi.org/10.3390/rs13234922>

- Karmakar, S., Rahman, M., Meng, L., 2025. Land Cover Changes and Land Surface Temperature Dynamics in the Rohingya Refugee Area, Cox Bazar, Bangladesh: An Analysis from 2013 to 2024. *Atmosphere* 16, 250. <https://doi.org/10.3390/atmos16030250>
- Keeler, B.L., Polasky, S., Brauman, K.A., Johnson, K.A., Finlay, J.C., O'Neill, A., Kovacs, K., Dalzell, B., 2012. Linking water quality and well-being for improved assessment and valuation of ecosystem services. *Proc. Natl. Acad. Sci. U.S.A.* 109, 18619–18624. <https://doi.org/10.1073/pnas.1215991109>
- Khandaker, N., 2022. Assessing the Groundwater Quality of Rohingya Refugee Camp Cox Bazar Bangladesh. *Bhutan Journal of Research and Development*. <https://doi.org/10.17102/bjrd.rub.10.2.020>
- Kulmedov, B., Eroglu, E., Kandymov, N., 2025. Modeling the factors affecting residual chlorine decay in the water distribution network of Abuja, Nigeria. *Water Quality Research Journal* 60, 482–497. <https://doi.org/10.2166/wqrj.2025.006>
- Liu, S., Li, X., Shi, Z. et al. (2025). Urbanization is projected to increase local surface temperature by 2100. *Communications Earth & Environment* 6, 988. <https://doi.org/10.1038/s43247-025-02947-1>
- Liu, Z., Zhan, W., Bechtel, B. et al. (2022). Surface warming in global cities is substantially more rapid than in rural background areas. *Communications Earth & Environment* 3, 219. <https://doi.org/10.1038/s43247-022-00539-x>
- López-Monzalvo, M., Batllori-Sampedro, E., Ayala-Godoy, J., Guerrero-Ruiz, E., Hernández-Terrones, L., 2024. Connecting Water Quality and Ecosystem Services for Valuation and Assessment of a Groundwater Reserve Area in South-East Mexico. *Water* 16, 1358. <https://doi.org/10.3390/w16101358>
- Luby, S.P., Gupta, S.K., Sheikh, M.A., Johnston, R.B., Ram, P.K., Islam, M.S., 2008. Tubewell water quality and predictors of contamination in three flood-prone areas in Bangladesh. *Journal of Applied Microbiology* 105, 1002–1008. <https://doi.org/10.1111/j.1365-2672.2008.03826.x>
- Mahi, M.M., Sharif, Md.S., Rudra, R.R., Haque, Md.N., 2021. The Geo-Spatial Approach to Detect the Change in Vegetation and Land Surface Temperature (LST) after Formation of Rohingya Settlements in Bangladesh. *JCEST* 12, 288–241. <https://doi.org/10.33736/jcest.3986.2021>
- Mahmud, Z.H., Islam, M.S., Imran, K.M., Hakim, S.A.I., Worth, M., Ahmed, A., Hossan, S., Haider, M., Islam, M.R., Hossain, F., Johnston, D., Ahmed, N., 2019. Occurrence of *Escherichia coli* and faecal coliforms in drinking water at source and household point-of-use in Rohingya camps, Bangladesh. *Gut Pathogens* 11, 52. <https://doi.org/10.1186/s13099-019-0333-6>
- McCann, M., Knudsen, C., Sphere Association (Eds.), 2018. The Sphere handbook: humanitarian charter and minimum standards in humanitarian response, Fourth edition. ed. Sphere Association, Genf.
- McFeeters, S.K., 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing* 17, 1425–1432. <https://doi.org/10.1080/01431169608948714>
- Moghe, C.S., Jalon, O., Samiha, M., 2024. Assessment of water, sanitation, hygiene services and communicable disease among the populations of 33 camps in Cox's Bazar, Bangladesh: A follow up study. *Médecins Sans Frontières*.
- Narvaez-Montoya, C., Mondragon Bonilla, R., Goldscheider, N. et al. (2025). Groundwater salinization patterns in the Yucatan Peninsula reveal contamination and vulnerability of the karst aquifer. *Communications Earth & Environment* 6, 468. <https://doi.org/10.1038/s43247-025-02456-1>
- Nyall Dawson, Jürgen Fischer, Matthias Kuhn, Alessandro Pasotti, mhugent, Denis Rouzaud, Alexander Bruy, Tim Sutton, Martin Dobias, Mathieu Pellerin, Even Rouault, Víctor Olaya, Paul Blottiere, Werner Macho, Radim Blazek, Loïc Bartoletti, Gary Sherman, Harrissou Sant-anna, Julien Cabieces, ... Borys Jurgiel. (2026). *qgis/QGIS: 4.0.0 (Versions final-4_0_0)* [Computer software]. Zenodo. <https://doi.org/10.5281/zenodo.18889261>
- Patwary, M.M., Ashraf, S., Shuvo, F.K., 2021. Estimation of Ecosystem Services Loss due to Rohingya Influx in Eastern Coast of Bangladesh using Multi-Temporal Satellite Data. <https://doi.org/10.1002/essoar.10508194.1>
- Pompei, C., Alves, E., Vieira, E., Campos, L., 2019. Impact of meteorological variables on water quality parameters of a reservoir and ecological filtration system. *International Journal of Environmental Science and Technology* 17. <https://doi.org/10.1007/s13762-019-02552-8>

- Posit, 2020. RStudio Desktop. Middlemist Red.
- Quader, M.A., Dey, H., Malak, Md.A., Sajib, A.M., 2021. Rohingya refugee flooding and changes of the physical and social landscape in Ukhiya, Bangladesh. *Environ Dev Sustain* 23, 4634–4658. <https://doi.org/10.1007/s10668-020-00792-0>
- R Core Team, 2024. R: A Language and Environment for Statistical Computing. Race for Your Life.
- Rahman, M., Islam, M., Chowdhury, T., 2019. Change of Vegetation Cover at Rohingya Refugee Occupied Areas in Cox's Bazar District of Bangladesh: Evidence from Remotely Sensed Data. *Journal of Environmental Science and Natural Resources* 11, 9–16. <https://doi.org/10.3329/jesnr.v11i1-2.43360>
- Ramazani, R., Ostadtaghizadeh, A., Yari, A., Hanafi-Bojd, A.A., Soltani, A., Rostami, S.B., Heydari, A., 2022. Criteria for Locating Temporary Shelters for Refugees of Conflicts: A Systematic Review. *ijph*. <https://doi.org/10.18502/ijph.v51i4.9236>
- Rashid, K.J., Hoque, Md.A., Esha, T.A., Rahman, Md.A., Paul, A., 2021. Spatiotemporal changes of vegetation and land surface temperature in the refugee camps and its surrounding areas of Bangladesh after the Rohingya influx from Myanmar. *Environ Dev Sustain* 23, 3562–3577. <https://doi.org/10.1007/s10668-020-00733-x>
- Rosińska, A., Teobaldelli, M., 2025. How much pressure is too much pressure? The environmental impact of the refugee and IDPs camps in Cox Bazar District: case study. *CLIMATE (IM)MOBILITY IMPACTS & OUTCOMES: Impacts of mobility, Environmental and Climate Mobilities Network*.
- Sarkar, S.K., Saroar, M., Chakraborty, T., 2023. Navigating nature's toll: Assessing the ecological impact of the refugee crisis in Cox's Bazar, Bangladesh. *Heliyon* 9, e18255. <https://doi.org/https://doi.org/10.1016/j.heliyon.2023.e18255>
- Silva, F., Al Bakain, R., Pradeau, G. et al. (2024). Protection over restoration to ensure water sustainability. *Communications Earth & Environment* 5, 638. <https://doi.org/10.1038/s43247-024-01798-6>
- Silveira, M. V. F. et al. (2025). Observed shifts in regional climate linked to Amazon deforestation. *Communications Earth & Environment* 6, 948. <https://doi.org/10.1038/s43247-025-02900-2>
- Singh, N.P., Kulshrestha, M., Shukla, N., Mishra, V., Kulshreshtha, M., 2022. Management of risk factors for breaking localised pathways of microbial contamination in tubewells with handpump: a case study from India. *Modeling Earth Systems and Environment* 8, 2513–2523. <https://doi.org/10.1007/s40808-021-01242-0>
- Tang, T., Ge, J., Shi, H. et al. (2025). Drought frequency, intensity, and exposure have increased due to historical land use and land cover changes. *Communications Earth & Environment* 6, 398. <https://doi.org/10.1038/s43247-025-02392-0>
- Tanvir, A., 2026. Water Quality Dashboard (2019 - 2025) - Field Agencies.
- Taylor, R.G., Todd, M.C., Kongola, L., Maurice, L., Nahozya, E., Sanga, H., MacDonald, A.M., 2013. Evidence of the dependence of groundwater resources on extreme rainfall in East Africa. *Nature Climate Change* 3, 374–378. <https://doi.org/10.1038/nclimate1731>
- Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment* 8, 127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0)
- UNDP, 2018. Impacts of the Rohingya Refugee Influx on Host Communities. United Nations Development Programme, Dhaka.
- UNHCR, 2026a. 31 Dec 2025 (Monthly), Rohingya refugee population dashboard. Joint Government of Bangladesh - UNHCR.
- UNHCR, 2026b. Shelter-CCCM [WWW Document]. Rohingya Refugee Response - Bangladesh. URL <https://rohingyaresponse.org/sectors/coxs-bazar/shelter-cccm/#workinggroups> (accessed 3.9.26).
- UNHCR, 2026c. WASH: Water, Sanitation, and Hygiene [WWW Document]. Rohingya Refugee Response - Bangladesh. URL <https://rohingyaresponse.org/sectors/coxs-bazar/wash/> (accessed 3.9.26).
- UNHCR, 2026d. Bangladesh: Rohingya Refugee Response: Operational partner presence (3W) in camps and host communities as of March 2025 [WWW Document]. Rohingya Refugee Response - Bangladesh. URL <https://rohingyaresponse.org/>
- UNHCR, 2018. Bangladesh, 07 – 21 March 2018 (Situation Reports / Updates), Operational Update. UNHCR Bangladesh, Cox's Bazar, Bangladesh.

- UNHCR, 2016. 4th edition of the UNHCR Emergency Handbook: Camp planning standards (planned settlements).
- WHO (Ed.), 2011. Guidelines for drinking-water quality, 4. ed. ed. World Health Organization, Geneva.
- Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the Tidyverse. *JOSS* 4, 1686. <https://doi.org/10.21105/joss.01686>
- Xu, L., Famiglietti, J.S., 2023. Global patterns of water-driven human migration. *WIREs Water* 10, e1647. <https://doi.org/10.1002/wat2.1647>
- Yasmin, T., Dhesi, S., Kuznetsova, I., Cooper, R., Krause, S., Lynch, I., 2023. A system approach to water, sanitation, and hygiene resilience and sustainability in refugee communities. *International Journal of Water Resources Development* 39, 691–723. <https://doi.org/10.1080/07900627.2022.2131362>
- Zaman, S., Sammonds, P., Ahmed, B., Rahman, T., 2020. Disaster risk reduction in conflict contexts: Lessons learned from the lived experiences of Rohingya refugees in Cox’s Bazar, Bangladesh. *International Journal of Disaster Risk Reduction* 50, 101694. <https://doi.org/https://doi.org/10.1016/j.ijdrr.2020.101694>
- Zha, Y., Gao, J., Ni, S., 2003. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing* 24, 583–594. <https://doi.org/10.1080/01431160304987>.

List of Acronyms

ANOVA: analysis of variance

BOD: Biological Oxygen Demand

CFU: Colony Forming Unit (bacterial load)

COD: Chemical Oxygen Demand

EFT: ecosystem functional type

EPSG: 4-5 digit identifiers for Coordinate Reference Systems (CRS), datums, and projections

FSTP: Faecal Sludge Treatment Plant

GIS: Geographical Information System

HSD: (Tukey's) Honestly Significant Difference

IOM: International Organization for Migration

LST: Land Surface Temperature

LULC: Land Use / Land Cover

MTS Single Storey ("Modular Transitional Shelter"): it is a type of shelter designed for temporary use, typically made of locally sourced materials such as bamboo, wood, and corrugated iron sheets. These shelters are intended to provide a basic level of protection from the elements and are often used as an interim solution until more permanent housing can be constructed.

NDVI: Normalized Difference Vegetation Index

NDBI: Normalized Difference Built-up Index

NDWI: Normalized Difference Water Index

REACH: Resilient and Empowered African Community Health

SSID: Refugee camp alphanumeric code identifier

SUM ("Shelter Upgrade Maintenance"): programme to improve or refurbish shelters during a year, to make them more safe, durable, and comfortable for the beneficiaries

TSA I ("Transitional Shelter Assistance"): they are a type of shelter designed to be more durable and resilient than the MTS Single Storey. Typically made of materials such as bamboo, wood, and metal are designed to provide a more robust structure, better protection from wind, rain, and extreme temperatures. They may include features such as windows, doors, and a roof that can withstand moderate weather conditions

TSA II: upgraded version of the TSA I often made of more robust materials, such as brick or concrete blocks. They are designed to provide even better protection and durability and may include additional features such as improved ventilation, lighting, and insulation, therefore, providing a higher level of comfort and safety for refugees, and may be used as a more permanent solution in areas where refugees are likely to remain for an extended period

TSS: Total Suspended Solids

UNHCR: United Nations High Commissioner for Refugees

UNOSAT: United Nations Satellite Centre

WASH: Water, sanitation and hygiene.

Credit authorship contribution statement

Maurizio Teobaldelli was the lead author of the analysis and writing, responsible for 40% of the article. The remaining authors contributed as follows: Anna Rosińska (initial idea, social science input, draft writing and revision, 20%), Caterina Cacciatori (water quality input, draft writing and revision, 20%), Bernd Manfred Gawlik (overseeing the work, draft revision, 10%), and Jan Loeschner (overseeing the work, draft revision, 10%).

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used GPT@JRC for checking of grammar and for coding some algorithms in R-Studio. We also asked for literature suggestions to compare with our results. After using this tool, we reviewed and edited the content and take full responsibility for the content of the publication.

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Declaration of competing interest

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