



# Evaluating the role of wetlands in flood dynamics: A spatio-hydrodynamic assessment using Machine Learning and HEC-RAS of Koshi Tappu Wildlife Region, Nepal

Dikshit Chimoriya\* <sup>1</sup>, Bishal Khatri <sup>2</sup>, Subash Ghimire <sup>3</sup>

<sup>1</sup>Department of Civil Engineering, Kathmandu University, Dhulikhel 45200, Nepal

<sup>2</sup>Department of Geomatics Engineering, Karnali Secondary School, Jumla 21400, Nepal

<sup>3</sup>Department of Geomatics Engineering, Kathmandu University, Dhulikhel 45200, Nepal

## Abstract

Wetland ecosystems are critical for flood risk reduction, yet are experiencing rapid degradation, with serious implications for regional disaster resilience. This project evaluates the implications of wetland loss for flooding in Koshi Tappu Wildlife Reserve, a significant Ramsar site in Nepal. Using Sentinel-2 imagery and a Random Forest classifier, we mapped a substantial reduction in wetland area from 18.0 km<sup>2</sup> in 2019 to 13.8 km<sup>2</sup> in 2024, a net loss of 4.2 km<sup>2</sup>. Flood extent analysis using Sentinel-1 SAR imagery showed a corresponding increase in flood area from 20.6 km<sup>2</sup> to 24.6 km<sup>2</sup> between a flooding event in 2019 and a flooding event in 2024. To demonstrate a causal link between wetland loss and flooding, 1D and 2D HEC-RAS hydrodynamic model was developed to simulate flooding scenarios under both land cover conditions. We determined that the wetland loss contributed to the observed increase in flooding depth, velocity, and flood extent. This study provides empirical evidence supporting the protection and restoration of wetlands not only as an ecological issue, but a necessary and economically viable approach to nature-based flood risk reduction, disaster mitigation and climate adaptation.

**Keywords:** Wetland classification, Flood mitigation, HEC-RAS, Machine Learning, Koshi Tappu Wildlife Region

**Received:** Dec 28, 2025

**Revised:** Jan 31, 2026

**Accepted:** Feb 02, 2026

## Citation

Chimoriya, D., et al. 2026. Evaluating the role of wetlands in flood dynamics: A spatio-hydrodynamic assessment using Machine Learning and HEC-RAS of Koshi Tappu Wildlife Region, Nepal. *Int. J. Disast. Studies Climate Resil.* 2(1), 39–55.

<https://doi.org/10.64866/j.ijdsr.2026.10022>



## 1 Introduction

The Himalayan river systems' massive hydraulic power and sediment mobility are both indispensable yet sensitive lifelines for South Asia. The region is facing a climate crisis with warming rates that exceed the global average, causing accelerated ice loss along with a more intense hydrological cycle, which increases the chance of extreme flooding (Krishnan et al., 2019). A representative example is the Koshi River, a significant transboundary tributary of the Ganges, which regularly experiences catastrophic floods resulting in various socio-economic and environmental impacts (Sahani et al., 2023). In view of the increasing risk, natural infrastructure, especially floodplain wetlands, is being recognized as an important defense strategy against flooding risk. These ecosystems act as natural sponges and provide important hydrological services, such as stormwater retention,

peak flow reduction, and sediment reduction (Tang et al., 2020; Kumar et al., 2021).

The Koshi Tappu Wildlife Reserve (KTWR) is Nepal's first Ramsar site and represents one of the most important and diverse wetlands in the Himalayan foothills. The KTWR is comprised of a mosaic of marshes, reed beds, and oxbow lakes, all of which have performed as a natural hydraulic buffer for the Koshi River. However, despite its protected status, KTWR is severely and continuously threatened by anthropogenic and natural pressures, including agricultural encroachment, unsustainable groundwater extraction, and substantial sediment deposition from upstream areas, resulting in rapid degradation and loss of its water-spreading area (Chaudhary et al., 2016; Department of National Parks and Wildlife Conservation, 2024). Loss of water-spreading area is not only considered a biodiversity

\*Corresponding author. Email: [dikshitchimoriya17@gmail.com](mailto:dikshitchimoriya17@gmail.com) (DC), [bishalkhatri675@gmail.com](mailto:bishalkhatri675@gmail.com) (BK), [subash\\_ghimire@ku.edu.np](mailto:subash_ghimire@ku.edu.np) (SG)

crisis but also the direct reduction of ecosystem services that safeguard downstream communities and infrastructure.

Wetlands are recognized internationally for their role in flood alleviation, and the recent advancements in geospatial technology and hydrodynamic modeling have made it possible to measure these services (Van Coppenolle and Temmerman, 2020; Wing et al., 2022). However, there remains a notable research gap within the Himalayan region: absence of an empirical, high-resolution quantitative linking observed spatiotemporal wetland loss to changes in flood hydrology by using a combined observational and modeling approach. Although there are studies mapping wetland changes (Chaudhary et al., 2016) and modeling flooding (Feng et al., 2021), only a few studies have worked in a synergistic way and employed satellite-based flood observation (e.g. SAR) and process based hydraulic modeling (e.g. HEC-RAS) to differentiate the effect of wetland loss on flood parameters (depth, velocity, extent) in a dynamic and data sparse style (Uddin et al., 2019). This evidence gap contributes to the flood mitigation ‘invisible’ service not being revalued in policy and land use planning.

In order to fill this gap, this study uses an integrated approach of cloud-based remote sensing and 2D hydrodynamic modeling to quantitatively estimate the influence of recent wetland loss (2019–2024) on flood inundation dynamics in the KTWR. The specific objectives of this study are:

1. To map and quantify the spatiotemporal changes in wetland extent in the KTWR from 2019 to 2024 using multi-sensor satellite data in the Google Earth Engine (GEE) platform.
2. To assess the changes in actual flood extent before and after wetland loss (2019 vs 2024) using Sentinel-1 Synthetic Aperture Radar (SAR) imagery during significant flood events.
3. To quantify the causal impact of wetland loss on flood depth, velocity, and spatial extent using a calibrated 2D HEC-RAS hydrodynamic model for with-wetland and without-wetland scenarios.

With the goal of providing robust, science-based evidence to inform KTWR conservation and to develop a case for the strategic implementation of nature-based solutions into climate adaptive flood risk management practices across the Himalayan corridor, this research attempts to convert the notion of abstract ‘wetland loss’ into a concrete, quantified, observable change in flood hazard.

## 2 Materials and Methods

This research adopted a geospatial and hydrodynamic modeling approach to evaluate wetland loss impacts associated with flooding processes. The integrated process began with the collection of multi-temporal Sentinel-2 Multispectral Instrument (MSI) Level-2A derived surface reflectance data (COPERNICUS/S2\_SR\_HARMONIZED) using the Google Earth Engine (GEE) platform, along with Sentinel-1 SAR data for flood mapping, and an ALOS PALSAR DEM for topography. The Sentinel-2 imagery was pre-processed for deriving key spectral indices (NDVI, NDWI, MNDWI,

NDBI). A Random Forest classifier was then trained and implemented in GEE to delineate wetland extents for 2019 and 2024, allowing for spatiotemporal change detection analysis. The hydrodynamic impact of wetland loss was quantified using a two-dimensional HEC-RAS model configured with a 50 m x 50 m mesh and calibrated using historical discharge data and SAR-derived flood maps. Identical flood events were simulated in the model for the 2019 (with wetlands), and 2024 (without lost wetlands) scenarios, specifically to generate flood depth, velocity, and extent maps, and QGIS was used to analyze the differences of those maps to ascertain the specific contribution of wetland loss on flood vulnerability (Fig. 1).

### 2.1 Study area

The Koshi Tappu Wildlife Reserve (KTWR) (Fig. 2), located in the eastern Terai plains of Nepal (26.550°N–26.750°N, 86.900°E–87.100°E), is an excellent and crucial study site to explore the relationship between wetland loss and flood processes. The KTWR covers approximately 175 km<sup>2</sup>, straddling the districts of Sunsari, Saptari, and Udayapur and is a designated Ramsar Site of international significance because of its intricate patchwork of freshwater marshes, seasonally flooded grasslands, and oxbow lakes (Baral et al., 2020). Physiographically, the KTWR is determined by the flow regime of the Koshi River, one of the most sediment-laden rivers of the Himalayas. Geomorphic activity will create and sustain the wetland habitats that are being studied, which makes the KTWR a living laboratory of fluvial processes. It is also the same dynamic setting, when combined with social pressures, that may cause rapid change in the landscape through wetland erosion and sedimentation (Karki, 2010). Therefore, the KTWR presents an opportunity to quantify how these degraded ecosystems (e.g., grasslands, marshes, and ox-bow lakes) have diminished capabilities for flood pulse reduction, water storage, and downstream flooding risk mitigation—is fundamentally the question that this project seeks to address.

### 2.2 Data Acquisition and Preprocessing

This study obtained various remote sensing and hydrological data as presented in Table 1, to analyze wetland change and flood dynamics over Koshi Tappu Wildlife Reserve. The remote sensing data is given here, one of the primary sources this GEE refers to is an easy way of preprocessed-ready collections available on Google Earth Engine cloud computing platform. Comparable datasets for 2019 and 2024 were also used in this study, which enabled Spatio-temporal comparison. Sentinel-2 Multispectral Instrument (MSI) Level-2A surface reflectance data were used for both years, providing atmospherically corrected optical-band reflectance products that were processed using a consistent radiometric and atmospheric correction protocol for land-cover classification.

Digital Elevation Models for 2019 and 2024 were acquired from open sources integrated within GEE (e.g., Shuttle Radar Topography Mission derivatives used as baseline topography, overwritten by recent acquisitions). Hydrological data, particularly discharge records were collected from

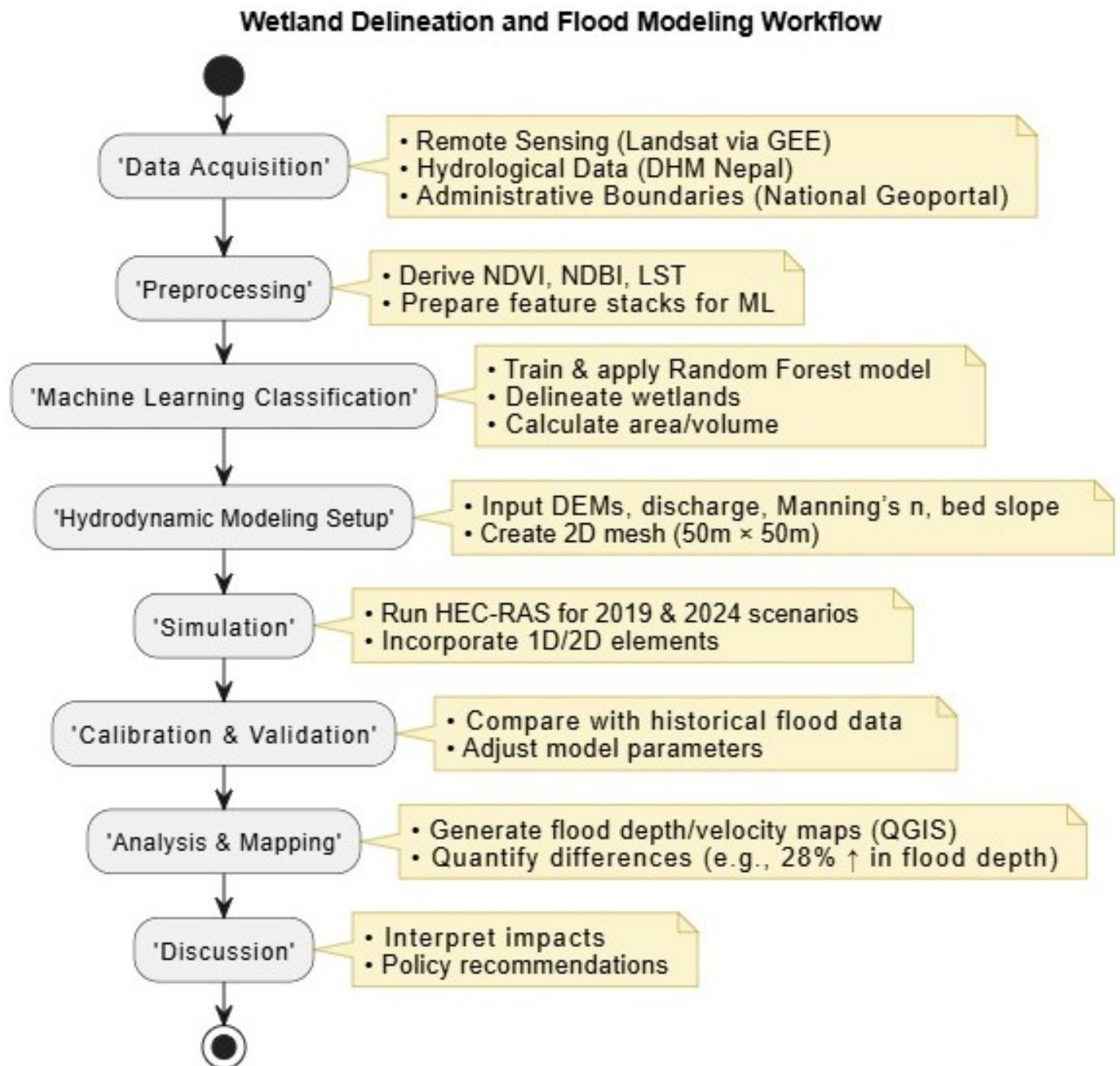


**Fig. 1.** Flow of chart of methodology.

the Department of Hydrology and Meteorology (DHM), Nepal. It is this data that will be used to simulate flood scenarios in HEC-RAS.

In the Google Earth Engine (GEE) platform, cloud-free composite images of 2019 and 2024 were produced using the Sentinel-2 MSI Level-2A surface reflectance dataset. Each year, all available scenes with cloud cover smaller than 10% were median-composited to create the most representative cloud-free image possible for land cover analysis. From the composites, key predictor variables were produced, including the Normalized Difference Vegetation Index (NDVI) from the Red (B4) and Near-Infrared (B8) bands, and the Modified Normalized Difference Water Index (MNDWI) using Green (B3) and Short-Wave Infrared 1 (B11) bands to

separate open water features, as well as the Normalized Difference Built-up Index (NDBI) using the SWIR1 (B11) and NIR (B8) bands. These predictor variables were selected, as they have been indicated to effectively separate the spectral signatures of water, wetland vegetation, and other categories of land cover. The Level-2A Sentinel-2 data were pre-processed for radiometric calibration and atmospheric correction. To guarantee the spatial consistency of the data, all data were geometrically aligned and reprojected to UTM Zone 45N coordinate reference system. The final input feature stack to classify consisted of the derived indices (NDVI, MNDWI, NDBI) with six of the core spectral bands (Blue [B2], Green [B3], Red [B4], NIR [B8], SWIR1 [B11], SWIR2 [B12]). All raster analyses were clipped to the exact bound-

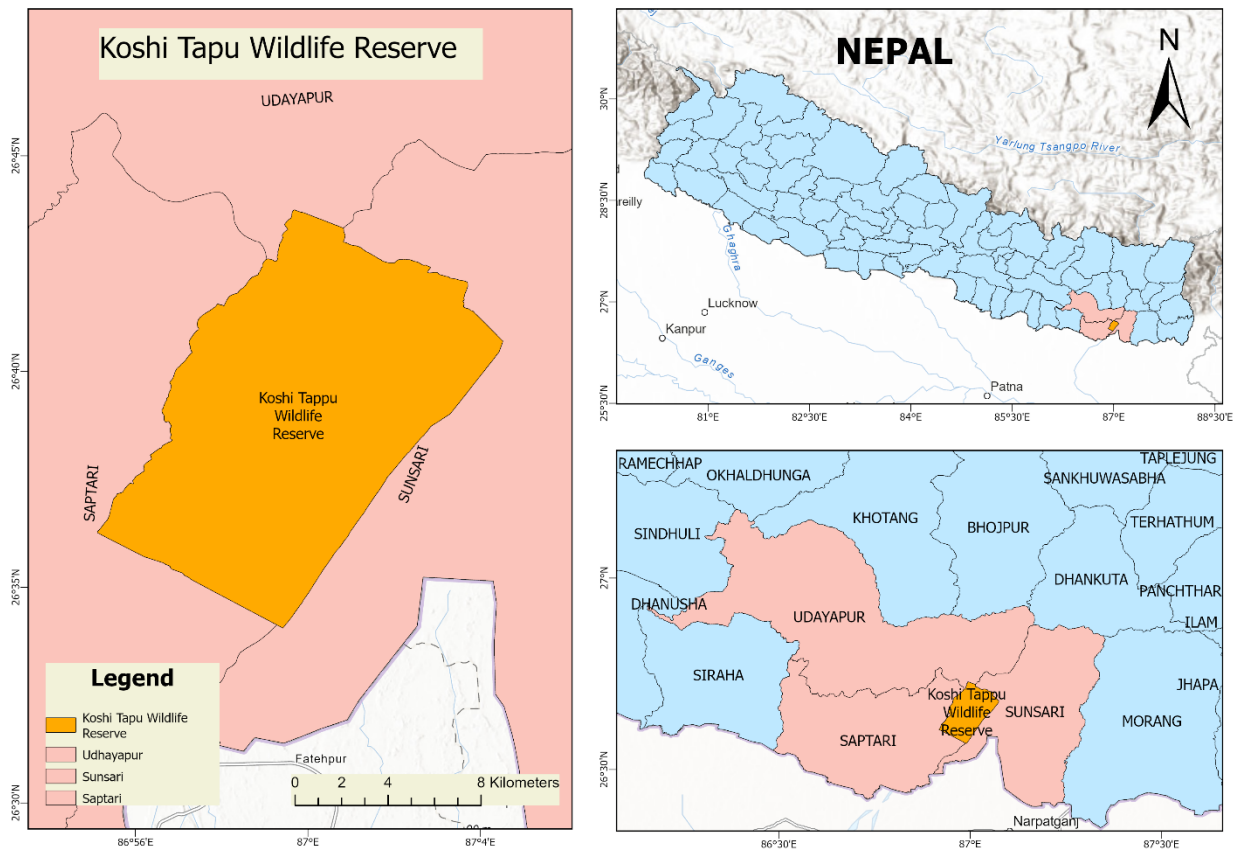


**Fig. 2.** Location of study area in eastern Terai of Nepal, Koshi Tappu wildlife reserve situated along the Sapta Koshi River in Koshi Province, Nepal.

**Table 1.** Description of data and their sources used in the study.

| S.No. | Data Type                                                                 | Source                                               | Date Accessed  |
|-------|---------------------------------------------------------------------------|------------------------------------------------------|----------------|
| 1     | Administrative Boundary                                                   | National Geoportal of Nepal                          | 12 August 2025 |
| 2     | Sentinel-2 MSI Level-2A (2019 & 2024)                                     | Google Earth Engine                                  | 15 August 2025 |
| 3     | Spectral Indices (2019 & 2024)                                            | Derived from Sentinel images                         | 18 August 2025 |
| 4     | DEM (2019 & 2024)                                                         | Google Earth Engine (SRTM derivatives and updates)   | 22 August 2025 |
| 5     | Hydrological Discharge Data                                               | Department of Hydrology and Meteorology (DHM), Nepal | 10 August 2025 |
| 6     | Sentinel-1 SAR GRD: C-band Synthetic Aperture Radar Ground Range Detected | Google Earth Engine                                  | 15 August 2025 |
| 7     | Secondary Discharge Data                                                  | GeoGlows Hydro Viewer                                | 10 August 2025 |

ary of the Koshi Tappu Wildlife Reserve which was sourced from the National Geoportal of Nepal.

To prepare the Geoportal for training, training samples were got with the help of high-resolution imagery from Google Earth Pro and field validation points collected during previous surveys carried out within that particular region. About 500 training points per class (wetland, water, vegetation, built-up, bare soil) were digitized every year. This ensured balanced representation. These samples helped in building the model by allocating 70% for training and 30% for validation.

The data sets used are summarized in Table 1.

2.3 Wetland Mapping and Change Detection

Machine learning played a key role in mapping and measuring changes in wetlands. It used supervised classification on the Google Earth Engine platform (Gorelick et al.,

2017). We chose a Random Forest (RF) algorithm because it effectively handles multi-spectral data and manages non-linear relationships between features (Breiman, 2001; Khattri et al., 2025). RF is an ensemble method that builds multiple decision trees, with 100 used in this study, and combines their predictions to improve accuracy and reduce overfitting.

The input feature space was the calculated indices (NDVI, NDBI, LST) and raw Landsat bands, forming a 9-band stack for each year. Training was carried out on the samples collected, with the tuning of hyperparameters through grid search: number of trees (50–200), maximum depth (none for full growth), and minimum samples per leaf (1). The model was run separately for the year 2019 and 2024 to include temporal variations, with an overall accuracy of 92% for 2019 (Kappa coefficient: 0.89) and 90% for 2024 (Kappa: 0.87) when tested against validation sets.

Subsequent to classification, we separated wetlands through morphological operations (e.g., opening/closing filters) to filter noise as well as a threshold on the output probability ( $>0.7$  for class wetland). We extracted and vectorized three large wetland polygons (A, B, and C). Although volumes were approximated with  $\text{Volume} = \text{Area} \times \text{Average Depth}$  using elevations from the DEM as a benchmark with neighboring terrain (e.g., Polygon A: 93.5 m in 2019 compared to 93 m in 2024 showing shallowing), we calculated areas directly from classified raster. Accuracy validation was by confusion matrices and points verified in the field, vouching for good producer's accuracy (95% for wetlands) and user's accuracy (91%). Sensitivity analysis identified NDVI as the most important feature (importance score: 0.35), followed by LST (0.25), echoing vegetation and thermal signatures as discriminators (Talukdar and Pal, 2017). This ML approach enabled precise quantification of wetland loss: from 16.10 sq. km in 2019 (A: 9.30, B: 3.80, C: 3.00) to 12.70 sq. km in 2024 (A: 4.80, B: 4.00, C: 3.90), to directly drive HEC-RAS inputs.

## 2.4 Flood Extent Analysis using SAR Imagery

The major 2019 event and a similar 2024 event flood extents were mapped using Sentinel-1 C-band Synthetic aperture radars (SAR) Ground Range Detected (GRD) data in Google Earth Engine collection (Gorelick et al., 2017; Uddin et al., 2019). For each yearly event, a pre-flood baseline image (dry season) was masked and compared to an image taken during peak flooding (UN-SPIDER, 2021; Pandey et al., 2022). VH polarization band was used for analysis due to its sensitivity to smooth open water surfaces which has a characteristic low backscatter (Twele et al., 2016). This polarization was chosen to improve the detection of floodwater in the reserve's common vegetated areas, like grasslands and shrublands. The cross-polarized signal is better at getting through sparse vegetation compared to co-polarized VV (Tsyganskaya et al., 2018). The change detection algorithm classified a pixel as flooded if the ratio of flood image to baseline image exceeded a calibrated threshold of 1.25, which has been established as useful in differentiating inundated areas from other land cover (Pandey et al., 2022). The resulting binary flood maps were converted into vector layers and the total flooded area within each year's boundary for the Koshi Tappu Wildlife Reserve was calculated in square kilometers. The SAR flood mapping provided an empirical, spatially-explicit dataset to support model calibration and comparative analysis of flood extent for both time periods.

## 2.5 Hydrodynamic Modeling Setup

### 2.5.1 HEC-RAS 1D Model

The 1D hydrodynamic model shown in Figs. 3–5, included a 1D component using HEC-RAS version 6.0 to simulate channel flow hydraulics and graph river cross-sections and flood depths along the Koshi River within the Koshi Tappu Wildlife Reserve. The 1D component complemented the 2D model by dealing with in-channel hydraulics, providing descriptive profiles of water surface elevations and

velocities along rivers during floods. The main inputs were:

- **Topography:** Cross-sections from 2019 and 2024 DEMs, with periodic sampling for characteristic geometry of river.
- **Hydrological Data:** Peak occurrence of floods in each of the years represented as hydrographs from DHM Nepal.
- **Slope of Bed:** From terrain analysis of river reach.

A single 1D river reach was delineated by cross-sections that were orthogonal to the direction of flow. Boundary conditions were upstream inflow hydrographs and downstream assumptions of outflow as normal depth. The model solved the 1D Saint-Venant equations using a finite-difference method under unsteady flow mode, and the time step size was set at 1 minute for numerical stability.

### 2.5.2 HEC-RAS 2D Model

The hydrodynamics simulation was carried out using HEC-RAS 6.7 beta, which is a widely used software package used for simulating over natural and artificial systems. The model configuration utilized both 1D and 2D modules in order to capture the complex flood hydraulics of the Koshi Tappu Wildlife Reserve. Priority was assigned to the 2D model to simulate overland flow and inundation trends influenced by wetland storage. The most important inputs were:

- **Topography:** DEMs for 2019 and 2024 years, down sampled to 50 m resolution for computational efficiency.
- **Hydrological Data:** Discharge hydrographs by Department of Hydrology and Meteorology (DHM), Nepal, marking years of peak flood for both.
- **Land Use Parameters:** Manning's roughness coefficients, taken from literature survey as well as ML-classified land cover (0.05 in 2019 for vegetated surface; 0.025 in 2024 considering reduced wetland cover and smoother surfaces).
- **Bed Slope:** Calculated in HEC-RAS via terrain analysis, along the reserve.
- **Wetland Incorporation:** Wetlands were represented in HEC-RAS using machine learning (ML)-delineated polygons, which were incorporated as internal boundary conditions. These polygons, classified and selected based on ML analysis, were assigned precise locations and coordinates on the map and overlaid in the HEC-RAS model.

A 50 m x 50 m 2D numerical grid was defined, and this was discretized at wetland edges and river channels for accuracy. Downstream normal depth assumptions and upstream inflow hydrographs were used as boundary conditions. Careful cross-sections and boundary lines were sketched to represent the reserve terrain. The model solved the full 2D Saint-Venant equations by a finite-volume approach and with a 30-second time step for stability (Courant number  $< 1$ ).

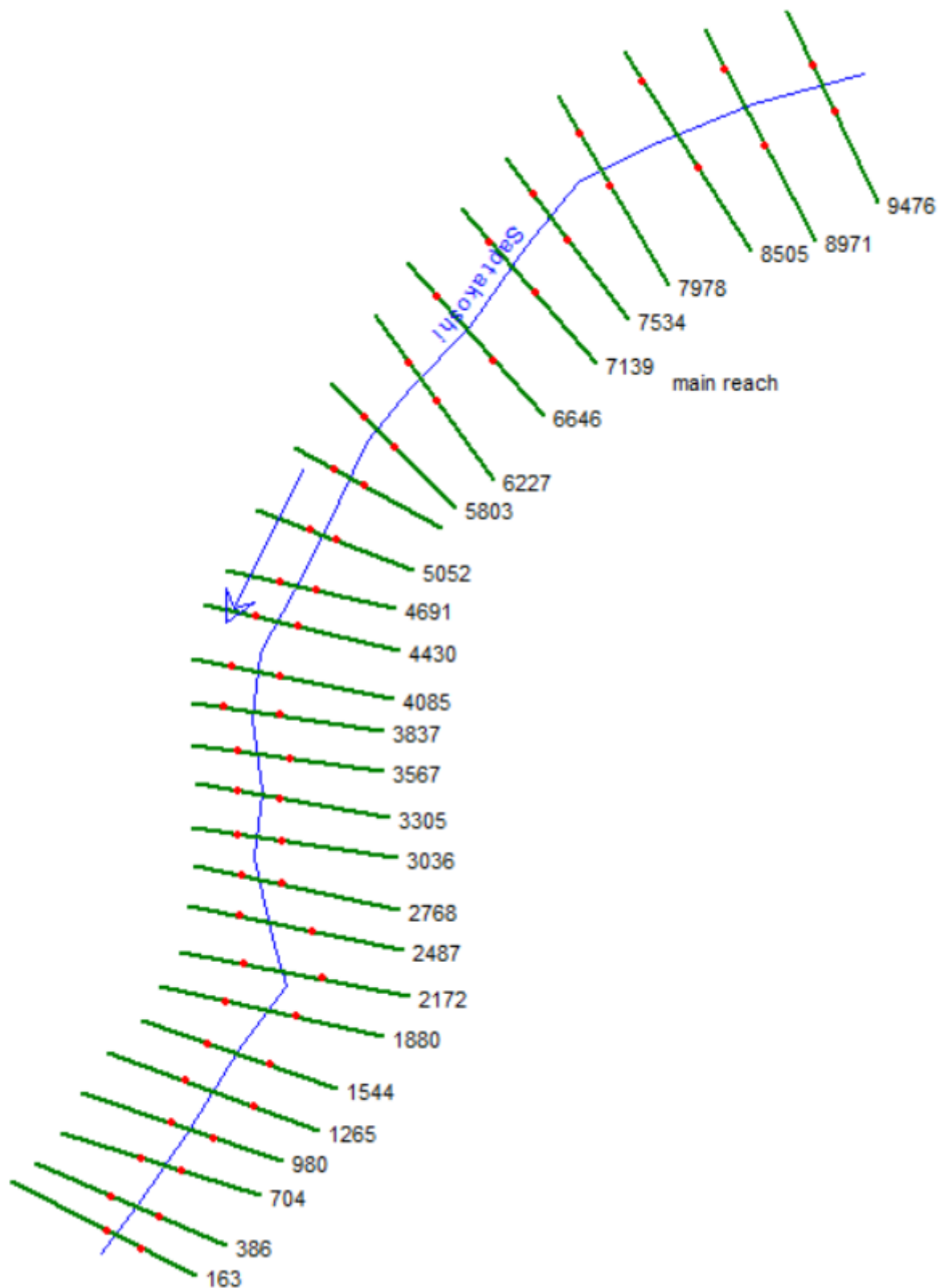


**Fig. 3.** Cross-section of the Sapta Koshi River covering the entire area of the Koshi Tappu Wildlife Region where the study was conducted.

**Validation Process.** Parameter calibration (e.g., Manning's  $n$  derived from ML land cover) was performed to maximize simulated results against DHM's historical flood records. The 2019 calibration used gaged water levels

at main stations, and this led to Nash-Sutcliffe Efficiency (NSE) of 0.82 as well as Root Mean Square Error (RMSE) of 0.45 m for depths of floods. The 2024 validation used cross-validation on independent records of discharges, and

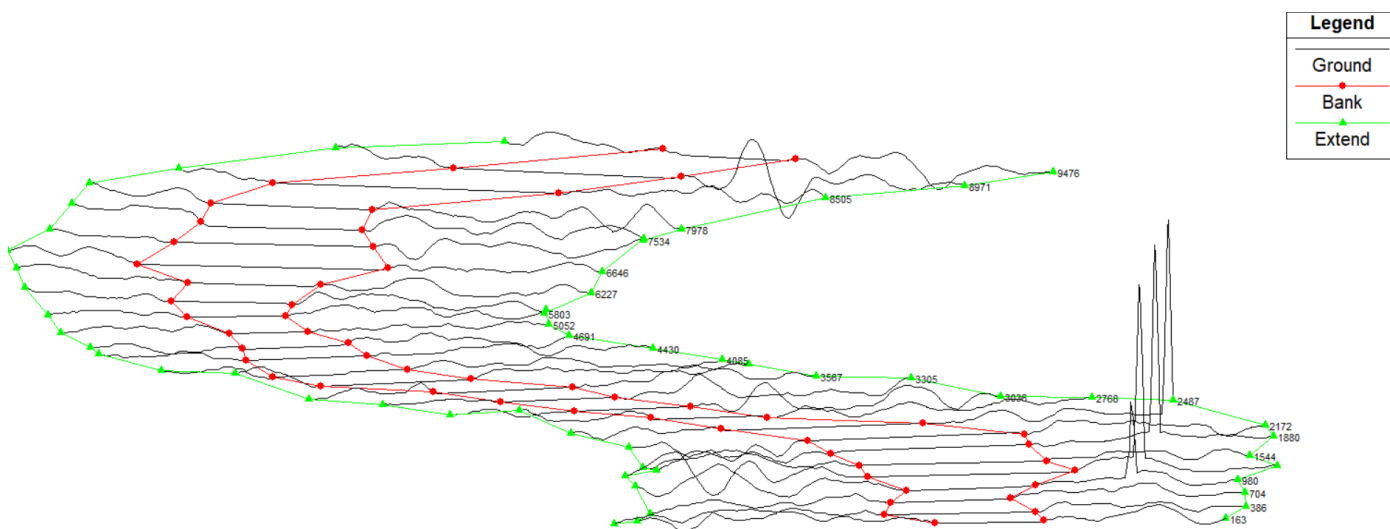


**Fig. 4.** River bed profile of the Sapta Koshi River, encompassing the entire Koshi Tappu Wildlife Reserve, where the study was conducted.

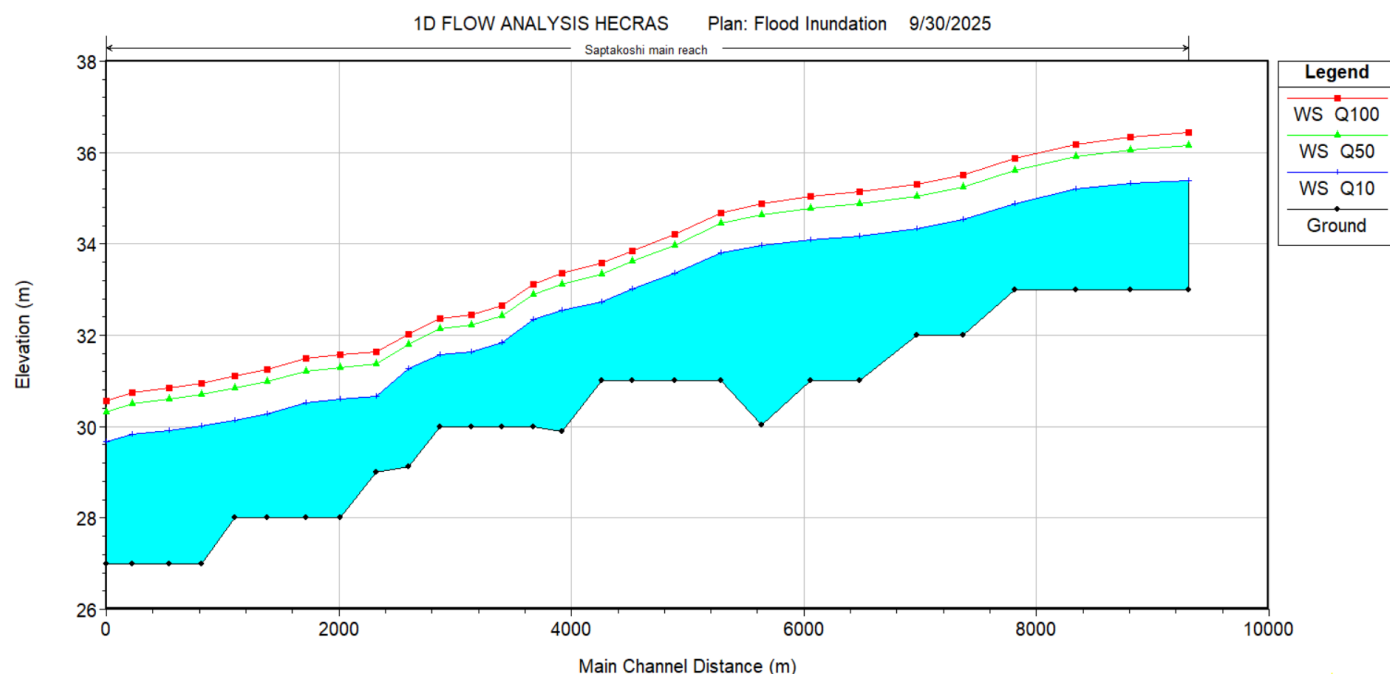


**Fig. 5.** Flood mapping of the Sapta Koshi River within the Koshi Tappu Wildlife Reserve, illustrating the maximum discharge corresponding to 10, 50 and 100-year return periods.

this led to NSE of 0.78 as well as RMSE of 0.52 m. Sensitivity analysis confirmed that ML-calculated wetland volume reductions were the dominant driver of flood depth increases, and Manning's  $n$  was a secondary one. Parameter selection was guided by literature benchmarks (e.g., benchmarking against similar Himalayan floodplain studies) to establish valid models and observed rainfall and river stage data were primarily obtained from DHM, including records from stations surrounding the Koshi Tappu Wildlife Reserve (i.e. Station 695 at Chatara) serving as the principal reference and secondary datasets from GeoGlows Hydro viewer were also used to support validation. HEC-RAS Model validation was carried out using a point-based comparison approach, with three validation points distributed across

upstream, midstream, and downstream sections of the study area.

### 3 Results

#### 3.1 Spatiotemporal Dynamics of Wetland Changes (2019–2024)

The spatiotemporal assessment shows significant change of the landcover within the Koshi Tappu Wildlife Reserve between 2019 and 2024 as illustrated in the classification maps (Figs. 6 and 7). Quantitatively, the most significant change was the reduction in the area of wetland from approximately 17.99 km<sup>2</sup> to 13.77 km<sup>2</sup>, representing a net loss (or ~23%) of 4.22 km<sup>2</sup> wetland area over a 5-year study period. The conversion of wetland to other land cover

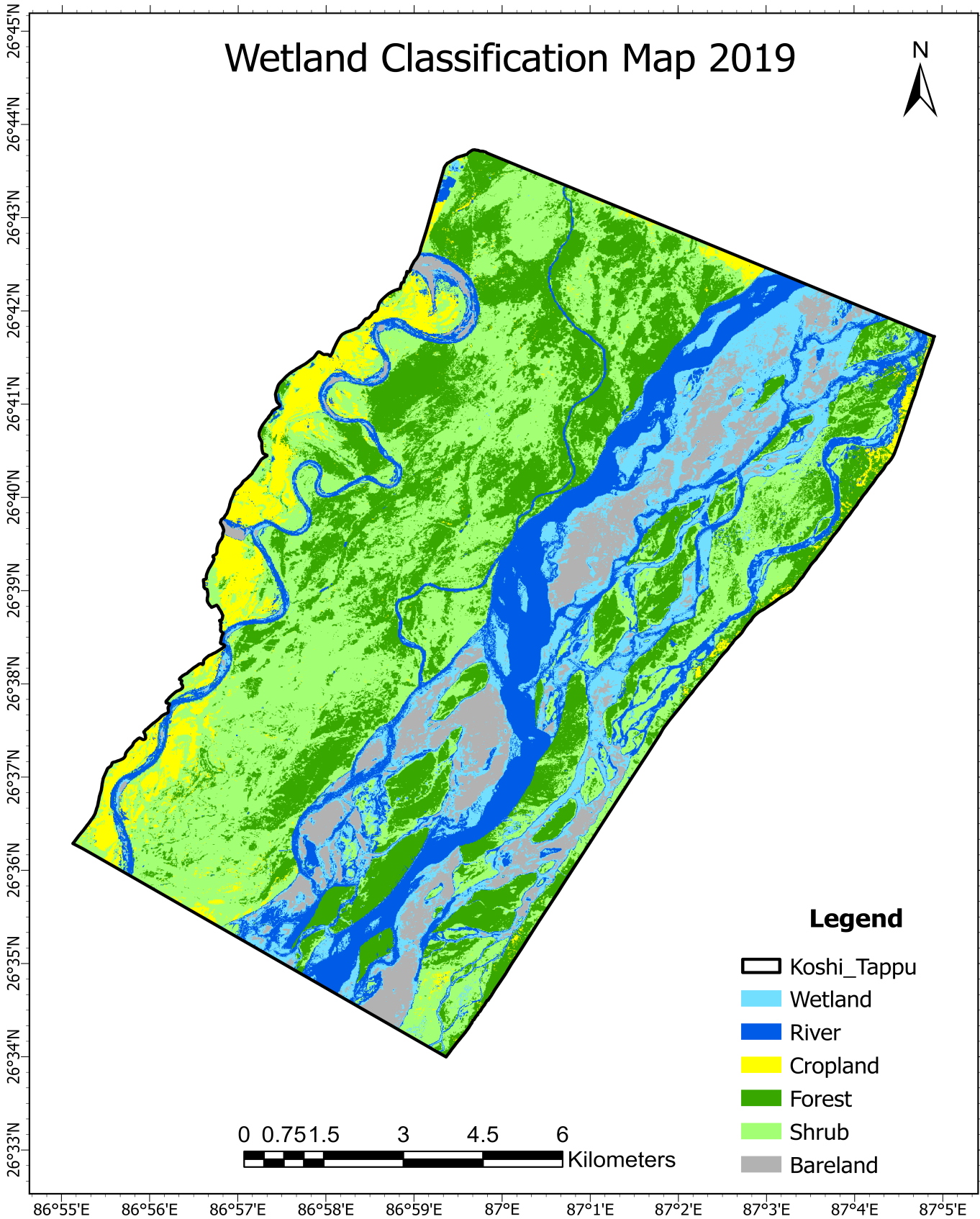


**Fig. 6.** Wetland map of 2019 in the Koshi Tappu Wildlife Reserve, showing the spatial distribution of wetlands.

types accompanied other significant alterations in land-cover. Specifically, the area of the Koshi River channel increased by nearly 4.93 km<sup>2</sup>, indicating significant geomorphic activity occurred between 2019 and 2024. In parallel,

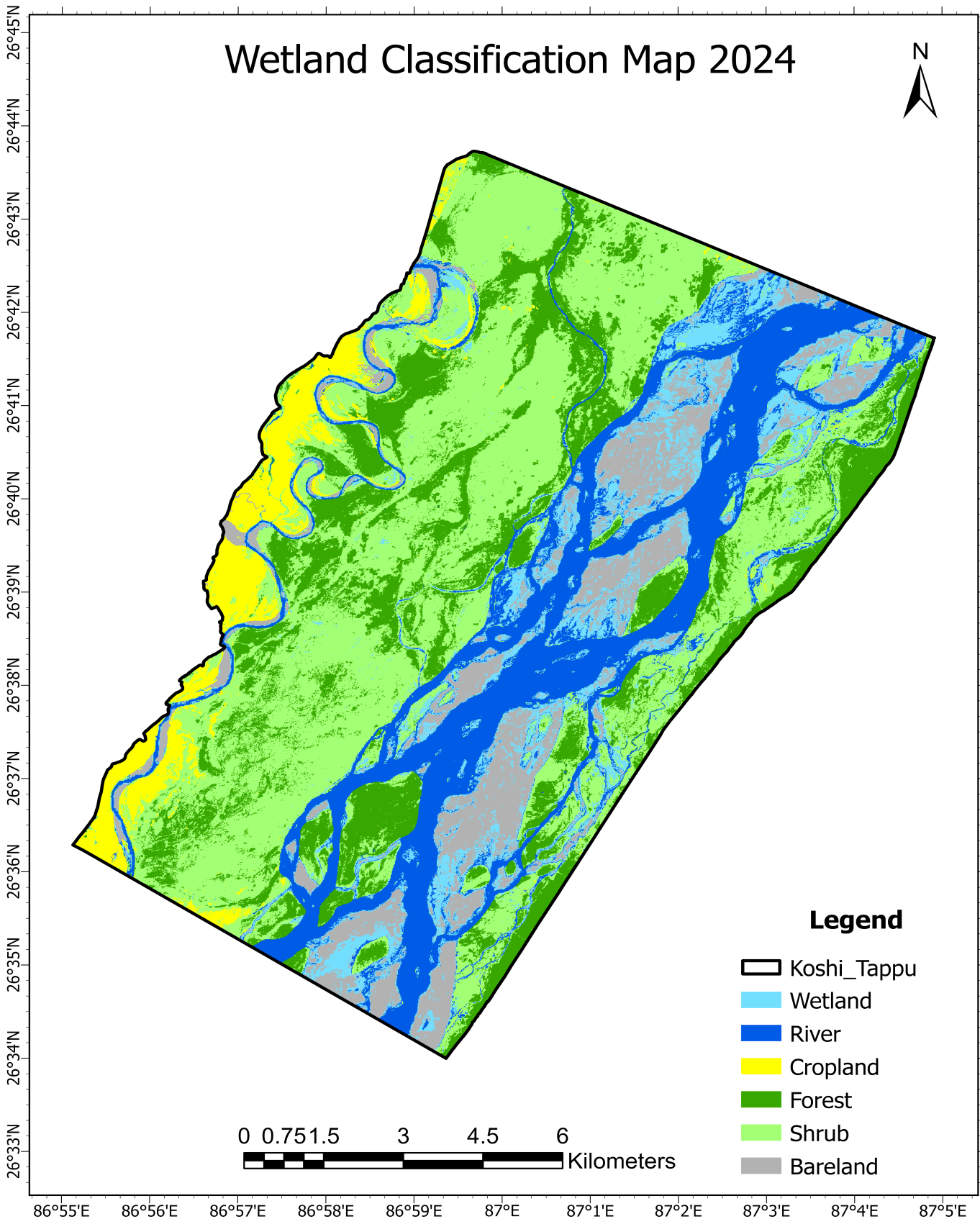


**Fig. 7.** Wetland map of 2024 in the Koshi Tappu Wildlife Reserve, showing the spatial distribution of reduced wetlands.

forest area reduced by over 9.37 km<sup>2</sup>, and areas of shrubland and bare land expanded.

The summary land cover data for all land cover class is presented in [Table 2](#). The spatial extent of wetland area

**Table 2.** Land cover change in the Koshi Tappu Wildlife Reserve over the 2019–2024 period, showing the percentage change and net change in area (km<sup>2</sup>) for each land cover class.

| Class    | 2019 Area (km <sup>2</sup> ) | 2024 Area (km <sup>2</sup> ) | Net Change(km <sup>2</sup> ) | % Change |
|----------|------------------------------|------------------------------|------------------------------|----------|
| Wetland  | 17.99                        | 13.77                        | -4.22                        | -23.46%  |
| River    | 22.20                        | 27.13                        | +4.93                        | +22.21%  |
| Cropland | 8.22                         | 8.31                         | +0.09                        | +1.10%   |
| Forest   | 38.68                        | 29.31                        | -9.37                        | -24.22%  |
| Shrubs   | 50.06                        | 56.39                        | +6.33                        | +12.64%  |
| Bareland | 12.16                        | 14.76                        | +2.60                        | +21.38%  |

**Table 3.** Wetland polygons in the Koshi Tappu Wildlife Reserve for 2019 and 2024, highlighting the spatial variability and dynamics of wetland alterations over the five-year period.

| Year | Polygon | Area (sq. km) | Elevation (m) | Estimated Volume Change (%)              |
|------|---------|---------------|---------------|------------------------------------------|
| 2019 | A       | 9.3           | 93.5          |                                          |
| 2019 | B       | 3.8           | 91            |                                          |
| 2019 | C       | 3.0           | 87            |                                          |
| 2024 | A       | 4.8           | 93            | -48.4 (area decrease and elevation drop) |
| 2024 | B       | 4.0           | 90            | +5.3 (area increase but elevation drop)  |
| 2024 | C       | 3.9           | 88            | +30.0 (area increase but elevation drop) |

loss, portrayed in the associated maps, was not complete and seems to be occurring in particular areas, primarily the central and northern regions of the Reserve, indicating the process of area degradation and loss is not evenly distributed throughout the landscape. This pattern fits with the Koshi being a dynamic river system full of sediment. Floods lead to strong sediment movement, shifting channels, and quick changes to the floodplain. In these areas, wetland loss and widening channels can show sediment buildup and changes in land shape, rather than just direct land use changes. As a result, the grouped wetland losses in the central and northern reserve may point to areas where sediment is actively deposited and where channels are moving, which affects the survival and storage capacity of wetlands (ICIMOD, 2021).

### 3.2 SAR-derived Flood Extent Analysis

The evaluation of Sentinel-1 SAR imagery in (Figs. 8 and 9) showed a clear increase in floods within the Koshi Tappu Wildlife Reserve from 2019 to 2024, as shown in Figs. 8 and 9. In 2019, the flooded area was 20.56 km<sup>2</sup>, which covered 13.74% of the study area. In 2024, the flooded area increased to 24.55 km<sup>2</sup>, covering 16.41% of the Reserve. Overall, the increase in flood extent showed an increase of 3.99 km<sup>2</sup> (~19.4%) over five years and this indicates an increase in the severity and spatial extent of flooding within the protected area.

### 3.3 HEC-RAS Flood Simulation Outcomes

Results of HEC-RAS 2D modeling as shown in Figs. 10–13 indicated substantial flood behavior variability from 2019 to 2024 that was possibly induced through machine learning-based quantification of wetland degradation. The spatial variation in flood impact between the 2019 and 2024 events is attributed to differences in rainfall intensity, spatial distribution of precipitation, antecedent moisture conditions, manning's coefficient and wetland storage response. Rainfall records indicate that the initial 24-hour rainfall prior to flooding in 2019 and 2024 were approximately 291

m<sup>3</sup>/s and 320 m<sup>3</sup>/s respectively. The depth of flood heightened modeled by about 28%, from max depth of 3.17 m in 2019 up to 4.02 m in 2024 within the reserve as shown in Figs. 10 and 11. The results show that wetland degradation alone significantly increased flood depths, underscoring the critical role of wetland storage in flood regulation.

Figs. 12 and 13 depict the flow velocities. These velocities showed variations with mean velocities up from 2019's 1.2 m/s to 2024's 1.8 m/s with reduced frictional resistance (lower Manning's n) and reduced wetland attenuation. Inundation extent from space maps developed within QGIS also showed variations: 2019 floodwaters as a general practice happened within wetland buffers, whereas 2024 cases showed increased flooding to neighboring habitats. Specific changes for wetlands are presented in Table 3, while reduced area with corresponding elevation changes that reduced storage capacity are revealed.

These outcomes highlight the wetlands' role in reducing floods. Simulations show that the volume losses measured by ML are directly linked to increased flood risks.

## 4 Discussion

### 4.1 The Direct Impact of Wetland Loss on Flood Regimes

The results of this research provide measurable evidence associating extensive wetland loss in the Koshi Tappu Wildlife Reserve with increased flooding conditions. The net loss of 4.2 km<sup>2</sup> of wetlands from 2019 to 2024 also reflects a continual regional trend of wetland conversion due to sediments, agriculture, and water resource projects (Chaudhary et al., 2016). The net loss of wetlands has a direct hydraulic implication, as it decreases areas needed for temporary storage of floodwater and flow retardation. The observed +3.99 km<sup>2</sup> increase in flood extent was derived from the SAR, while the modeled increases in flood depth and velocity were likely a result of the diminished capacity of this natural buffer. The results provide support for more global studies that showed loss of natural floodplains and wetlands contributed to higher and faster peak flows

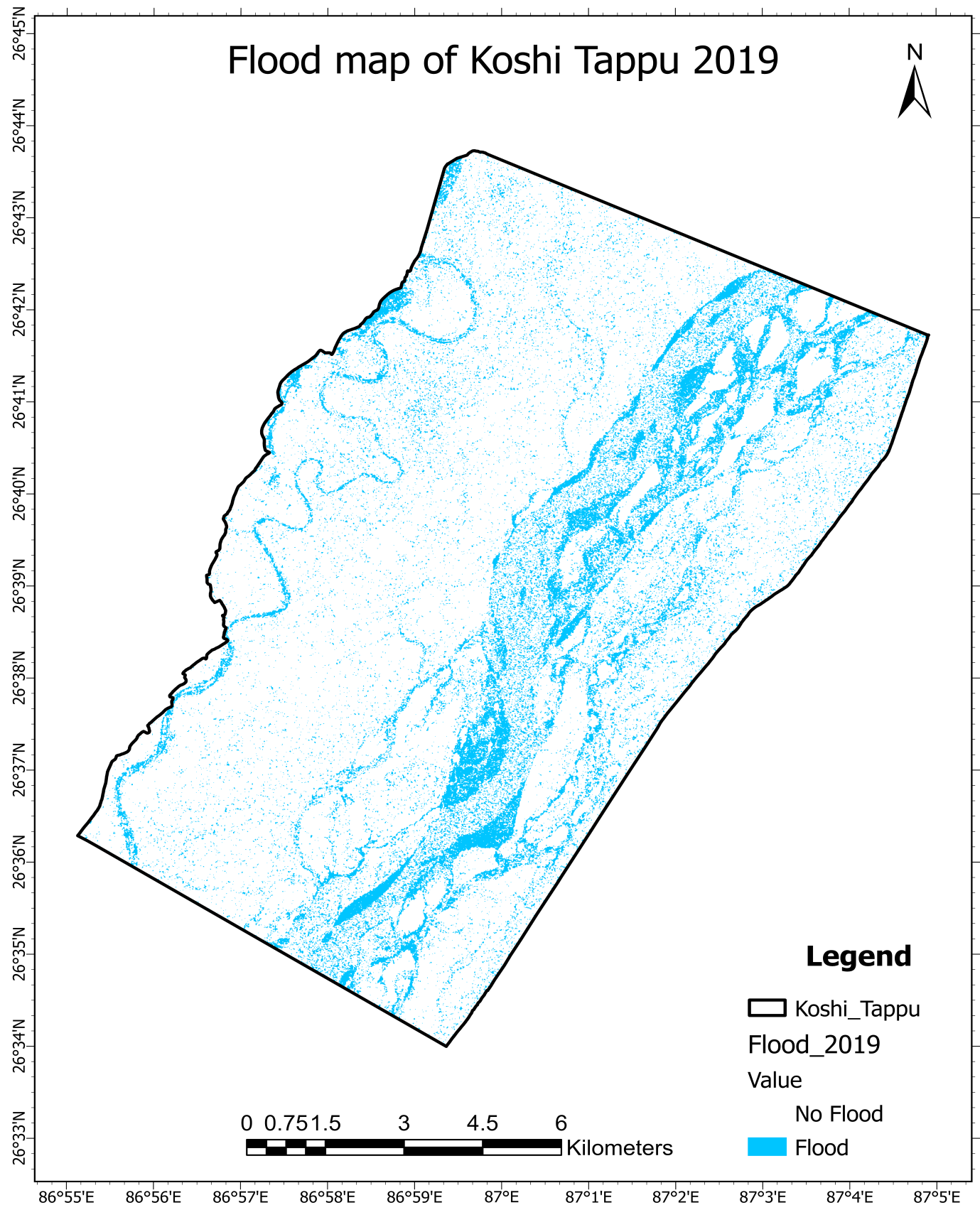


**Fig. 8.** Flood extent map of 2019 in the Koshi Tappu Wildlife Reserve, showing areas inundated based on Sentinel-1 SAR imagery.

downstream (Tang et al., 2020). Converting these natural sponges to other land covers (mainly the expanding river channel and shrublands) likely decreases roughness, leading to flood wave propagation being more efficient and increas-

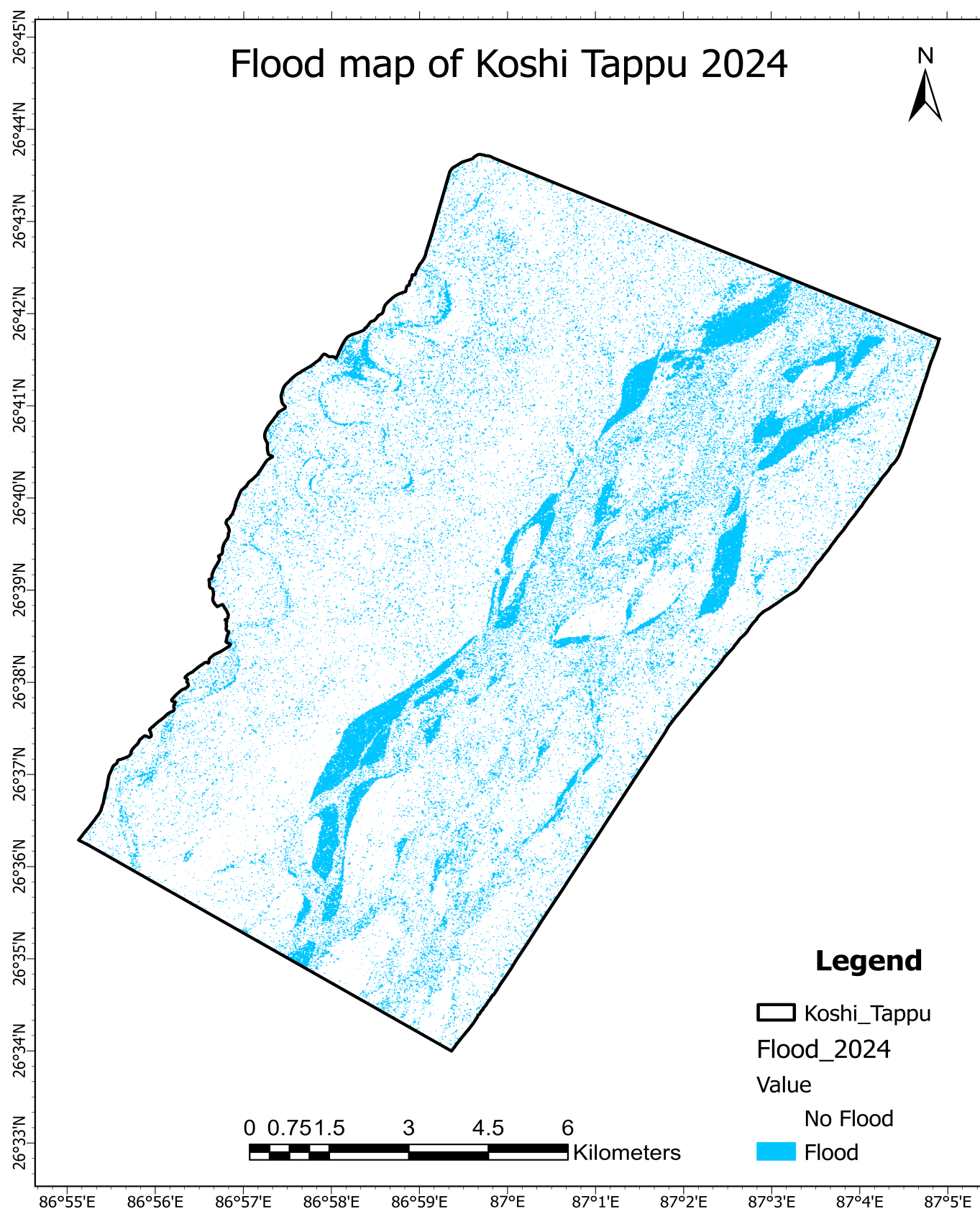


**Fig. 9.** Flood extent map of 2024 in the Koshi Tappu Wildlife Reserve, showing increased inundated areas based on Sentinel-1 SAR imagery.

ing flood risk for ecosystems in the reserve area and for adjacent communities (Kumar et al., 2021). This empirical evidence indicates that conserving wetlands is not only an ecological aspiration, but an essential climate adaptation

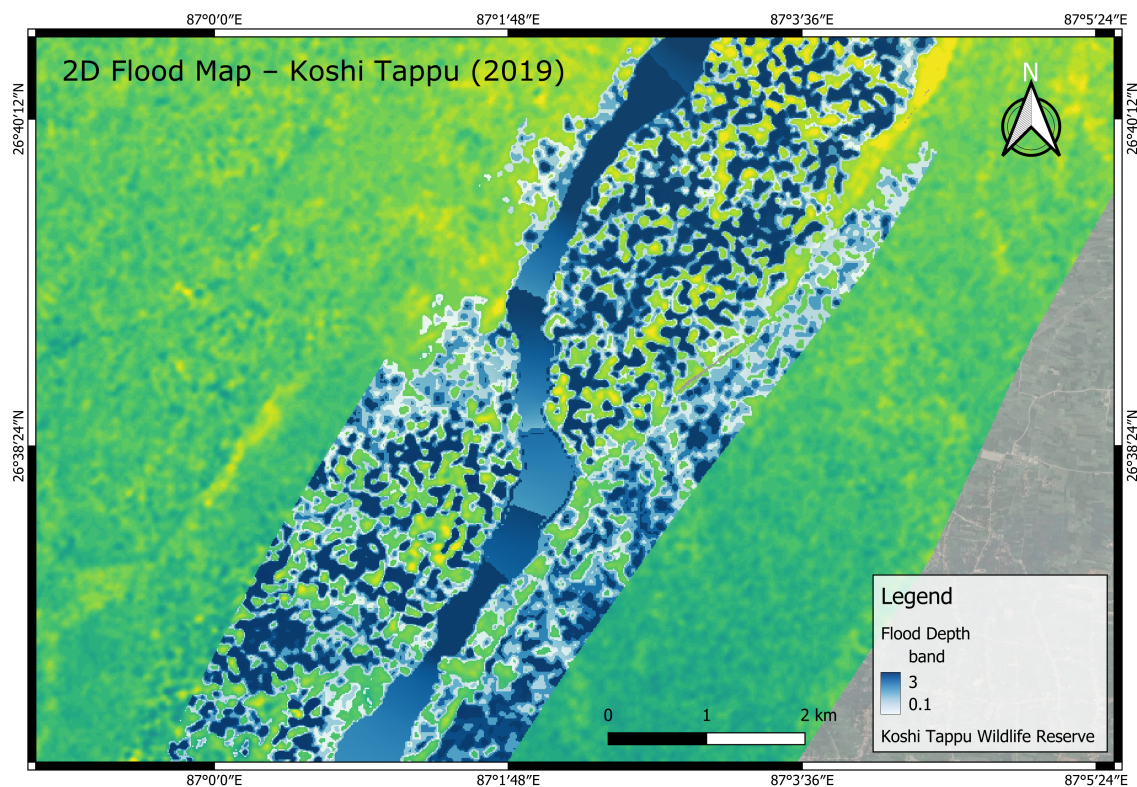


**Fig. 10.** Flood depth map of 2019 in the Koshi Tappu Wildlife Reserve, illustrating inundated areas and the spatial distribution of water depths based on HEC-RAS 2D hydrodynamic modeling.

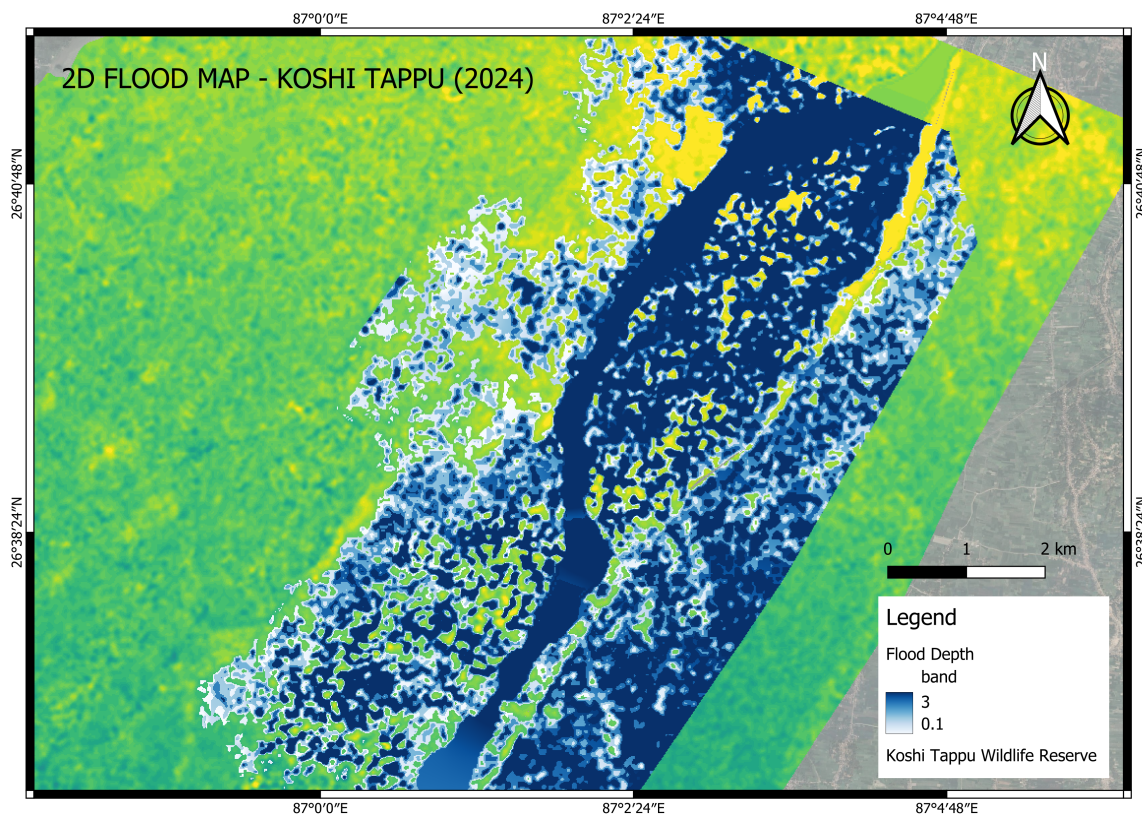


**Fig. 11.** Flood depth map of 2024 in the Koshi Tappu Wildlife Reserve, illustrating the increased inundated areas and spatial distribution of water depths based on HEC-RAS 2D hydrodynamic modeling.

and disaster risk reduction strategy. Recent reporting from Reuters highlights the frequency of high-flow events in the

Koshi system. It describes repeated instances where large gate openings were necessary at the Koshi Barrage. For in-

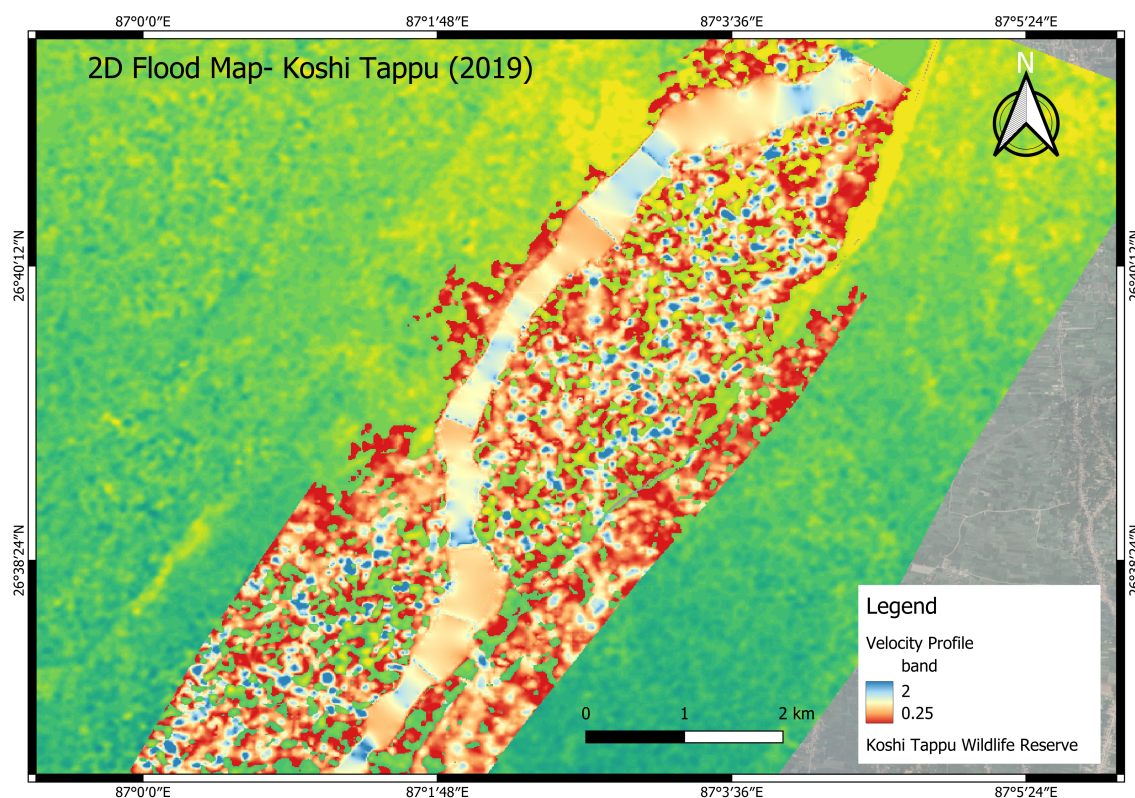


**Fig. 12.** Velocity profile map of 2019 in the Koshi Tappu Wildlife Reserve, showing the spatial distribution of flow velocities across the river and floodplain, derived from HEC-RAS 2D hydrodynamic modeling.

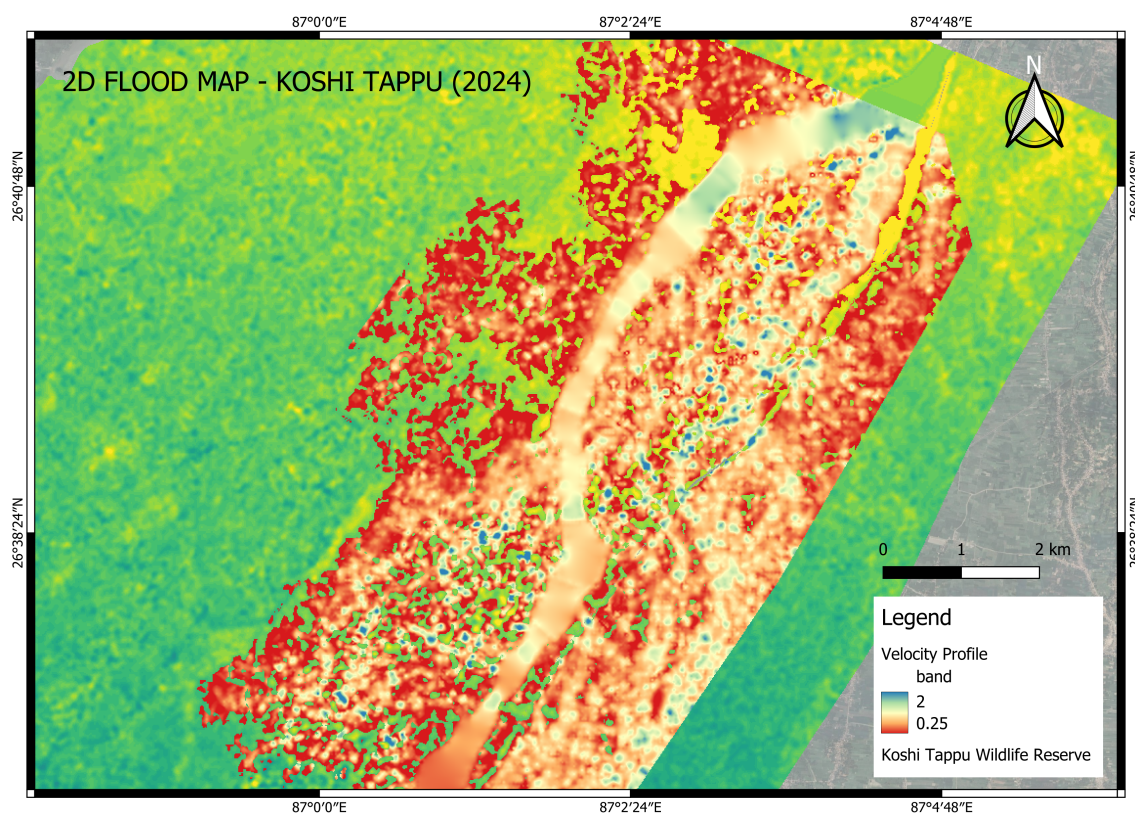


**Fig. 13.** Velocity profile map of 2024 in the Koshi Tappu Wildlife Reserve, showing the spatial distribution of increased flow velocities across the river and floodplain, derived from HEC-RAS 2D hydrodynamic modeling.

stance, during heavy rains in 2024, Reuters reported that the Koshi River flowed above the danger level. All 56 sluice gates were opened, and traffic was restricted on the barrage bridge. Similar responses to open all gates and issue public

warnings occurred during significant monsoon flooding in 2024 (Sharma, 2024).

#### 4.2 Policy Implications for Wetland Conservation and Flood Management

The influence of wetland loss on the increasing risk of flooding requires a basic change to policy related to water resource and disaster management in the Koshi Basin and similar Himalayan regions. Current flood management strategies tend to focus on structural approaches like embankments that can harm hydrologic function by isolating rivers from their natural floodplains and increasing sedimentation and flood risk elsewhere (Devkota et al., 2012; Acharya and Hori, 2019). We firmly recommend that ecosystems, and in the particular cases of this research—wetland restoration and conservation, be prioritized in policy documents and explicitly embedded as natural infrastructure or nature-based public safety infrastructure (Van Coppenolle and Temmerman, 2020). Policymakers should consider strategies that protect wetlands in the KTWR site, undertake restoration of degraded wetlands and incentivize sustainable land uses in the buffer zone to enhance flood mitigation and ameliorate sediment loads. Effective management of the Koshi River and its sediment regime will require cross-border cooperation between Nepal and India, as flooding and excessive sedimentation rather than overtopping of embankments is an operational hurdle that should be approached with a basin-wide management schema (Bagale, 2020; ICIMOD, 2021). Finally, leveraging the flood mitigating values of wetlands identified through this study into national and regional climate adaptation strategies, can be used to attract funding, delimit the appropriate scales of benefit, and create a more resilient socio-ecological system in response to future extremes and climate change effects.

#### 4.3 Linking Wetland-loss Drivers to Actionable Management Interventions

In addition to changes in landforms and land use, local biological factors and usage pressures can gradually harm wetland function in KTWR. This happens by narrowing wetland areas and damaging habitat structure. Recent evidence from Koshi Tappu Wildlife Reserve shows that invasive plants are already changing local plant communities. This issue is becoming a significant concern for conservation in the reserve (Bhattarai et al., 2024). Similarly, grazing pressure in KTWR's lowland grasslands has emerged as a management challenge. Studies show that more intense grazing can negatively impact plant life and soil quality. This highlights the need for controlled grazing practices (Tuladhar et al., 2022). These factors can be addressed. Focused control of invasive species in key wetland and grassland areas, along with seasonal or rotational grazing regulations, and improved land-use rules in buffer zones can help preserve the vegetation structure and roughness needed for wetland storage and flow management. Presenting these as practical steps offers recommendations that go beyond vague calls to 'protect wetlands' and connects conservation goals with local resource use.

## 5 Conclusion

This study shows that converting natural wetlands weakens a landscape's basic ability to reduce flooding. This change increases ecological loss and creates a measurable risk to society and water resources. The transformation of these essential ecosystems harms their natural roles as sponges and buffers, resulting in larger and more severe floods during heavy rain events. This evidence highlights that protecting and restoring wetlands is not just about conservation goals. It's important for public safety and climate resilience. Therefore, including wetland integrity in flood management and land-use planning is essential to protect vulnerable communities and ecosystems.

## 6 Recommendation

Despite these findings, the research is limited in many ways that provide avenues for future research. The validity of the hydrodynamic model is mainly based on the resolution of the DEMs applied and the computation of spatially varying Manning's roughness coefficients. Flood events simulated in the research are just examples. A better model would have been achieved if various flood events were simulated with different return periods. Due to the lack of consistent historical flood boundary data and inundation points, the validation of the HEC-RAS simulated inundation areas using the spatial overlay method was not feasible. Future research should be conducted to integrate high-resolution data on soil infiltration and hydrology to improve the hydrology of the wetlands within the basin. From the management point of view, the research findings would be very instrumental to policymakers and conservation agencies within the region to ensure that the provisions of the Ramsar Convention on the protection of wetlands are fully implemented. The integration of nature-based solutions to transboundary flood management approaches within the Koshi River Basin is critical to enhance the socio-ecological resilience within the region.

## Acknowledgement

We would like to acknowledge all the researchers who have contributed previously to similar projects.

## Conflict of interest

The authors declare that there are no known conflicts of interest associated with this publication.

## Data availability

All data used in this study are derived from primary as well as freely available open-access sources, which are fully cited within the manuscript. Additional processed datasets can be made available from the corresponding author upon reasonable request.

## CRedit statement

**Dikshit Chimoriya:** Conceptualization, modeling, methodology development, manuscript preparation, GIS-based mapping, reference management. **Bishal Khatri:**

Data sorting and preparation, conceptualization, wetland classification, study area delineation, validation procedures, writing. **Subash Ghimire:** Supervision, technical inputs, review and editing, modeling and validation.

## AI-use statement

No AI tool was used for data analysis, interpretation, or drawing of conclusions. All responsibility for the content rests with the authors.

## References

- Acharya, S., Hori, T., 2019. Revisiting flood management process in transboundary Koshi river in Nepal and India. *Annals of the Disaster Prevention Research Institute, Kyoto University* 62, 640–649. <https://www.dpri.kyoto-u.ac.jp/nenpo/no62/ronbunB/a62b0p34.pdf>
- Bagale, D.R., 2020. Nepal–India water cooperation: Consequences of mutuality or hegemony? *Water Policy* 22, 1098–1108. <https://doi.org/10.2166/wp.2020.135>
- Baral, H.S., Bhatt, T.R., Giri, S.R., Ram, A.K., Shah, S.K., Poudyal, L.P., Chaudhary, D., Bhattacharya, G., Amin, R., 2020. Status of the critically endangered Bengal Florican *Houbaropsis bengalensis* in Koshi Tappu Wildlife Reserve, Nepal. *Journal of Threatened Taxa* 12, 16006–16012. <https://doi.org/10.11609/jott.4832.12.9.16006-16012>
- Bhattarai, D., Lamichhane, S., Regmi, A.R., Joshi, K.P., Pandeya, P., Dhimi, B., Gautam, A.P., Adhikari, H., 2024. Impact of invasive alien plants on the resident floral diversity in Koshi Tappu Wildlife Reserve, Nepal. *Ecology and Evolution* 14, 70316. <https://doi.org/10.1002/ece3.70316>
- Breiman, L., 2001. Random forests. *Machine Learning* 45, 5–32. <https://doi.org/10.1023/A:1010933404324>
- Chaudhary, S., Chettri, N., Uddin, K., Khatri, T.B., Dhakal, M., Bajracharya, B., Ning, W., 2016. Implications of land cover change on ecosystem services and people's dependency: A case study from the Koshi Tappu Wildlife Reserve, Nepal. *Ecological Complexity* 28, 200–211. <https://doi.org/10.1016/j.ecocom.2016.04.002>
- Department of National Parks and Wildlife Conservation, 2024. *Koshi Tappu Wildlife Reserve and its Buffer Zone Management Plan (2081/82–2085/86)*. Government of Nepal, Ministry of Forests and Environment. [https://giwmcdnone.gov.np/media/pdf\\_upload/Koshitappu%20WR%20Management%202081-2085\\_orxz2c0.pdf](https://giwmcdnone.gov.np/media/pdf_upload/Koshitappu%20WR%20Management%202081-2085_orxz2c0.pdf)
- Devkota, L., Crosato, A., Giri, S., 2012. Effect of the barrage and embankments on flooding and channel avulsion: Case study Koshi River, Nepal. *Journal of Rural Infrastructure Development* 3, 124–132. <https://resolver.tudelft.nl/uuid:b9026f10-e9b8-4cc6-9e27-93416804eac5>
- Feng, B., Zhang, Y., Bourke, R., 2021. Urbanization impacts on flood risks based on urban growth data and coupled flood models. *Nat. Hazards* 106, 613–627. <https://doi.org/10.1007/s11069-020-04480-0>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- ICIMOD, 2021. *Sediment Management in the Koshi Basin* (Policy Brief). International Centre for Integrated Mountain Development. [https://www.icimod.org/wp-content/uploads/2021/12/1200g\\_20211202\\_PB\\_SedimentManagementInTheKoshiBasin\\_AF.pdf](https://www.icimod.org/wp-content/uploads/2021/12/1200g_20211202_PB_SedimentManagementInTheKoshiBasin_AF.pdf)
- Karki, J.B., 2010. Koshi Tappu Ramsar site: Updates on Ramsar information sheet on wetlands. *The Initiation* 2, 10–16. <https://doi.org/10.3126/init.v2i1.2513>
- Khatri, B., Kharel, B., Dhakal, P., Acharya, S., Thapa, U., 2025. Spatio-temporal dynamics of urban heat island using Google Earth Engine: Assessment and prediction—a case study of Kathmandu Valley, Nepal. *Climate Services* 38, 100560. <https://doi.org/10.1016/j.cliser.2025.100560>
- Krishnan, R. et al., 2019. Unravelling climate change in the Hindu Kush Himalaya: Rapid warming in the mountains and increasing extremes, in: Wester, P., Mishra, A., Mukherji, A., Shrestha, A. (Eds.), *The Hindu Kush Himalaya Assessment*. Springer, Cham. [https://doi.org/10.1007/978-3-319-92288-1\\_3](https://doi.org/10.1007/978-3-319-92288-1_3)
- Kumar, S., Agarwal, A., Villuri, V.G.K. et al., 2021. Constructed wetland management in urban catchments for mitigating floods. *Stoch Environ Res Risk Assess* 35, 2105–2124. <https://doi.org/10.1007/s00477-021-02004-1>
- Pandey, A.C., Kaushik, K., Parida, B.R., 2022. Google Earth Engine for large-scale flood mapping using SAR data and impact assessment on agriculture and population of Ganga–Brahmaputra Basin. *Sustainability* 14, 4210. <https://doi.org/10.3390/su14074210>
- Sahani, R.K., Badiger, S., Samrat, A., Krishnan, S., 2023. Flood frequency and flood intensity changes in the post-embankment period in the Kosi sub-basin, India: Impact of location, caste, and class on the flood vulnerability of marginal communities. *Frontiers in Water* 5, 1017945. <https://doi.org/10.3389/frwa.2023.1017945>
- Sharma, G., 2024-07-07. *Heavy Rains Trigger Landslides in Nepal, 11 Killed, 8 Missing*. Reuters. <https://www.reuters.com/world/asia-pacific/heavy-rains-trigger-landslides-nepal-11-killed-8-missing-2024-07-07/>
- Talukdar, S., Pal, S., 2017. Impact of dam on inundation regime of flood plain wetland of Punarbhaba river basin of Barind Tract of Indo-Bangladesh. *International Soil and Water Conservation Research* 5, 314–325. <https://doi.org/10.1016/j.iswcr.2017.05.003>
- Tang, Y., Leon, A.S., Kavvas, M.L., 2020. Impact of size and location of wetlands on watershed-scale flood control. *Water Res. Manag.* 34, 1693–1707. <https://doi.org/10.1007/s11269-020-02518-3>
- Tsyganskaya, V., Martinis, S., Marzahn, P., Ludwig, R., 2018. Detection of temporary flooded vegetation using Sentinel-1 time series data. *Remote Sensing* 10, 1286. <https://doi.org/10.3390/rs10081286>
- Tuladhar, R., Sapkota, R.P., Parajuli, A., Gautam, B., 2022. Impacts of livestock grazing on vegetation and soil in lowland grassland ecosystem of Nepal. *Journal of Institute of Science and Technology* 27, 39–48. <https://doi.org/10.3126/jist.v27i2.43568>
- Twele, A., Cao, W., Plank, S., Martinis, S., 2016. Sentinel-1-based flood mapping: A fully automated processing chain. *International Journal of Remote Sensing* 37, 2990–3004. <https://doi.org/10.1080/01431161.2016.1192304>
- Uddin, K., Matin, M.A., Meyer, F.J., 2019. Operational flood

- mapping using multi-temporal Sentinel-1 SAR images: A case study from Bangladesh. *Remote Sensing* 11, 1581. <https://doi.org/10.3390/rs11131581>
- UN-SPIDER, 2021. *Step-By-Step: Recommended Practice: Flood Mapping and Damage Assessment using Sentinel-1 SAR Data in Google Earth Engine*. UN-SPIDER Knowledge Portal. <https://www.un-spider.org/advisory-support/recommended-practices/recommended-practice-google-earth-engine-flood-mapping/step-by-step>
- Van Coppenolle, R., Temmerman, S., 2020. Identifying global hotspots where coastal wetland conservation can contribute to nature-based mitigation of coastal flood risks. *Global and Planetary Change* 187, 103125. <https://doi.org/10.1016/j.gloplacha.2020.103125>
- Wing, O.E.J., Lehman, W., Bates, P.D. et al., 2022. Inequitable patterns of US flood risk in the Anthropocene. *Nat. Clim. Chang.* 12, 156–162. <https://doi.org/10.1038/s41558-021-01265-6>