

Article

How Are Glacier-Dominated Himalayan River Corridors Responding to Climate Change in Terms of Relative Vegetation Cover? A Remote Sensing Investigation

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Highlights

What are the main findings?

- The dynamics of the riparian vegetation cover over the last few decades in the studied glacier-fed Himalayan Rivers appear to be strongly river-specific, and a single evolutionary trajectory related to the deglaciation phase is not evident.
- Both increasing and decreasing trends of riparian vegetation cover occurred in the studied rivers but such trends seem to be poorly related to the analyzed hydroclimatic drivers, suggesting a complex interplay among river runoff, sediment supply and vegetation resistance/erosion.

What are the implications of the main findings?

- This study contributes to the scientific understanding of how glacier-dominated Himalayan Rivers adjust their channel forms and sustain riparian vegetation across spatial and temporal scales. These results provide a reference point for interpreting future river-corridor changes in response to ongoing glacier retreat.
- By interpreting the structure through which climate-driven hydrological changes shape both vegetation stability and geomorphic dynamics, the results highlight critical pathways that can guide future predictions of climate-related hazards and lead the sustainable management of Himalayan river systems.

Abstract

The adjustments in channel morphology under influence of vegetation dynamics, impacting natural sediment and flow regimes at local, catchment, and regional scales, are primarily driven by natural and anthropogenic factors. Limited knowledge exists regarding the historical channel adjustments along Himalayan glacier-dominated rivers. This study specifically concentrates on three distinct glacier-dominated river segments: Nubra in Jammu and Kashmir, Ganga-Bhagirathi in India, and Langtang-Khola in Nepal. The research adopts a supervised classification model initially developed by Mukhtar and extends the technique by applying it to four additional sources of satellite data with spatial resolutions ranging from 2.4 m to 30 m. This extension of the model is accomplished using the Google Earth Engine (GEE) platform to extract three main macro-units (base-flow channels, emerged sediment bars and vegetated surfaces) in fluvial corridors. Across different locations, the behavior of the rivers exhibited variability; however, possibly cyclic behavior in riparian vegetation cover was observed during the studied period.



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Surprisingly, in the subsequent period of 2016–2020, noticeable channel widening was observed in almost all reaches of the three river segments. Notably, the high meltwater runoff periods from 1989 to 2003 in the Nubra River segment induced vegetation erosion and channel widening. On the contrary, flood events during the early 21st century possibly lacked the duration and intensity required to impact vegetation growth in river corridors. This trend was also evident in the Ganga-Bhagirathi River, where the stable vegetation cover showed no major effects from the 2012 flood event. Despite the susceptibility of the Langtang-Khola river to landslides and earthquakes, the study reaches in Langtang-Khola River remained unaffected by these catastrophic events. Briefly, this study contributes to an enhanced understanding of the intricate dynamics of channels and vegetation in Himalayan glacier-dominated rivers, spanning diverse spatial and temporal scales, and elucidates their correlation with factors related to climate change.

Keywords: Himalayan glacier-dominated rivers; channel adjustment; supervised classification model; satellite images classification; fluvial morphological macro-units

1. Introduction

Persistent ice loss because of global warming is significantly altering hydrological patterns in high-elevation mountain catchments in the Himalayas [1] as well as globally [2,3]. In recent decades, warmer air temperatures have led to decreased accumulations at lower elevations. Therefore, earlier spring snowmelt runoff is happening and glacier melt flows in mid to late summer have increased for most glaciers [4]. However, cryospheric fluctuations influence not only the water cycle but also the sediment supply to the channel network, and consequently the geomorphological impacts of glacier-dominated rivers responding to climate change are more consequential than those in nonglacial mountain rivers.

Glacier, ice sheet mass loss and permafrost degradation are causing the glacier-dominated river environments to become one of the most rapid shifting natural earth systems, a dynamic response that has emerged over the last three decades [5], and is expected to remain prominent for many decades, e.g., [6]. As a result, glacier-dominated river environments can be considered as natural laboratories to help understand short-term land stability and coupled sediment fluxes [7]. Glacier-dominated fluvial environments provide vital support to the study process, forming relationships for braided to single-thread rivers, due to the diurnal variations in the discharge hydrograph, and linked fluxes in the sediment supply, leading to swift channel changes [8]. In addition, channel morphology is directed by factors such as sediment load, channel adjustment [9], bedrock nature, discharge irregularity (highly variable and unpredictable flow patterns caused by glacier melt and seasonal changes specifically in rivers), floods [10], river bed slope and vegetation [11]. Rivers adjust from braided to single-thread channels based on changes in meltwater runoff and sediment fluctuations, so that major drivers of morphological changes are in turn responsive to the processes of deglaciation [12] and climatic conditions. The active channel is formed by the interplay of runoff from meltwater and precipitation that form submerged base-flow channels along with continuous sediment fluctuations that construct emerged bars. These processes of frequent flow and continuous sediment fluctuations also foster the growth of robust vegetation in fluvial corridors. In turn, vegetated surfaces resist changes due to their high elevation compared to islands and bars, aided by their distance from high-flow zones during floods in the active channel. Identifying vegetated surfaces as one of the major geomorphic units thus helps us to evaluate the longitudinal changes in river corridors over time.

Since Hickin [13] investigated the often overlooked aspects in fluvial geomorphology, there has been a prominent rise in research interest regarding the interpretation of the intricate relationship between vegetation and fluvial morphology. This amplified attention from the research community has improved the realization that understanding the control of vegetation is fundamental to comprehending the variety of processes shaping river dynamics. Keeping this concept in mind, research studies have focused on some specific aspects of vegetation river dynamics including island formation [14], channel adjustment [9,11], bank stability [15,16], as well as comprehensive vegetation function within channel dynamics [17]. The recent important contribution on conceptual modeling by Gurnell [18,19] highlights the role of different plant categories in controlling the channel formation and processes of change.

Vegetation plays a significant role in influencing river morphology across various spatial and temporal scales, leading to intricate feedback loops and connections [18,20]. The growth and spatial distribution of vegetation in upstream river zones are intricately connected to the hydrological regime, highlighting a robust linkage between the two. The river discharge, a key component of this regime, not only ensures water availability, nutrient cycling, and seed dispersal but also introduces challenges such as uprooting, excavation, and burial. Each riparian plant species, responding to specific optimal growth conditions, must strike a balance between moisture availability and the dynamic influence of river disturbances [21,22].

In addition to the intricate connection between vegetation and the hydrological regime in glacier-dominated river zones, flood events are integral components of the hydrological regime, exerting a profound influence on perennial vegetation and morphology of river channels [23]. Floods contribute to the transport and deposition of sediment, and foster nutrient-rich conditions for vegetation growth [24]. They also pose significant challenges, leading to uprooting, erosion, and variations in the distribution of plant species along the riverbanks due to their force and velocity [25]. The frequency and intensity of floods, closely tied to the hydrological regime, thus become critical determinants in the resilience and adaptation of vegetation [26], and they have formative impact on both the vegetation composition and morphological characteristics of river channels in glacier-dominated zones. Understanding these interconnected dynamics is crucial for effective river-corridor management in complex ecosystems [27].

Field observations have significantly boosted our understanding of sediment bar formation and vegetation as key components of the fluvial system. However, although the spatial resolution of acquired data has progressed with advances in remote sensing (RS) techniques, there is still a need to demonstrate novel analytical methods that can provide geomorphological change information at higher spatial and temporal resolutions. To map and quantify the broader riverscape, encompassing water, sediment, and vegetation, at an unprecedented spatiotemporal resolution, RS data and analysis hold significant potential for applications in fluvial geomorphology [28–30]. Considering the fluvial corridor as an integrated unit comprising river channels, fluvial deposits, riparian zones, and floodplains, time series of RS data can unveil fluvial dynamics and facilitate applications in bio-geomorphology [31].

Google Earth Engine (GEE), a cloud-based computing platform for geospatial analyses, provides access to vast amounts of remotely sensed Earth observation data, enabling geomorphological analyses at higher spatial and temporal resolutions and over larger spatial extents than previously achievable. GEE has been employed for monitoring river planform dynamics [32], including mapping wet parts and active sections of river channels, encompassing unvegetated gravel bars [33–36]. Supervised classification models in machine learning can be designed using labeled training data to classify morpholog-

ical features accurately in satellite imagery [28,37,38]. This approach can be applied to glacier-dominated river landscapes, allowing the identification and mapping of various elements like vegetation [39,40], water [41], and sediments [42]. By employing a supervised classification model based on diverse satellite images within GEE, we investigate changes in the glacier-dominated river environments over time, such as adjustments in channel morphology, sediment erosion and deposition, and vegetation growth [43,44]. The rationale behind this GEE approach is the absence of a single satellite source providing long-term data coverage. Our investigation describes the methods and results of classification change detection within three Himalayan glacier-dominated rivers (Nubra, Ganga-Bhagirathi and Langtang-Khola rivers) spanning from 1989 to 2020, with varying gaps according to data availability. The main objectives of this study are as follows: (i) to test the use of different sources of satellite images—featuring different resolution—with their relative remote sensing models to map macro-units in glacier-dominated Himalayan Rivers; (ii) to quantify the morphological changes (in terms of vegetated vs. active channel areas) within the study fluvial corridors from 1989 to 2020, to the hypothesis that during this period important variations occurred; and (iii) to examine the extent to which channel changes might be due to progressive hydrological variations (meltwater runoff changes) or disturbances (floods), with the hypothesis that vegetation progressively varies in association with meltwater runoff trends, but is punctuated more abruptly by floods.

2. Material and Methods

2.1. Study Area

The Karakoram-Himalaya (KH) mountain range extends for about 2500 km, from Yunnan province (China) in the east, and spanning westward to cross Bhutan, Nepal, Southern Tibet, North India and Pakistan [45]. The area is heavily glacierized, with about 37% of glacier cover, and thus it features a myriad of low-order streams and rivers which are glacier-dominated regarding their hydrological and coarse sediment transport regimes [46,47].

This study focuses on 3 glacier-dominated rivers: Nubra, Ganga-Bhagirathi, and Langtang-Khola. The Nubra River belongs to the Indus River basin whereas both the Ganga-Bhagirathi and the Langtang-Khola rivers belong to the Ganga River basin (Figure 1). Figure 2 shows the studied river segments in terms of their fluvial corridors (i.e., the valley bottom area occupied by floodplain/recent terraces, channels, after Belletti [48]).

The Nubra River originates from the Siachen glacier, the second-largest glacier system outside the polar region, and joins the Shyok River (a major tributary of the Indus River) after flowing southeast for around 76 km [49]. The mean annual precipitation in the Nubra valley is ~150 mm [50]. For this study, we investigated a segment, which lies about 48 km downstream of the Siachen glacier snout (Table 1). The total area of satellite images for this segment is 112 km² but includes slopes adjacent to the river and alluvial fans of tributaries. The actual fluvial corridor area is in fact 40 km². The basin area is 4334 km², which includes 1109 km² of Siachen glacier.

Ganga-Bhagirathi River originates from the Gangotri glacier, which is one of the largest glaciers in the Himalayas [51]. Meltwater from the Gangotri glacier is the main source of Bhagirathi River, which is a major tributary of Ganga River. The mean annual precipitation in the upper Bhagirathi basin is 1648 mm [52]. The part investigated in this study lies in the upper glacier-dominated reaches of the Bhagirathi River basin, which lies about 24 km downstream from the Gangotri glacier snout (Table 1). The total area of satellite image coverage for this segment is almost 25 km² and includes slopes adjacent to the river and alluvial fans of tributaries. The total basin area of the studied segment is 3218 km² and includes 179 km² of the Gangotri glacier.

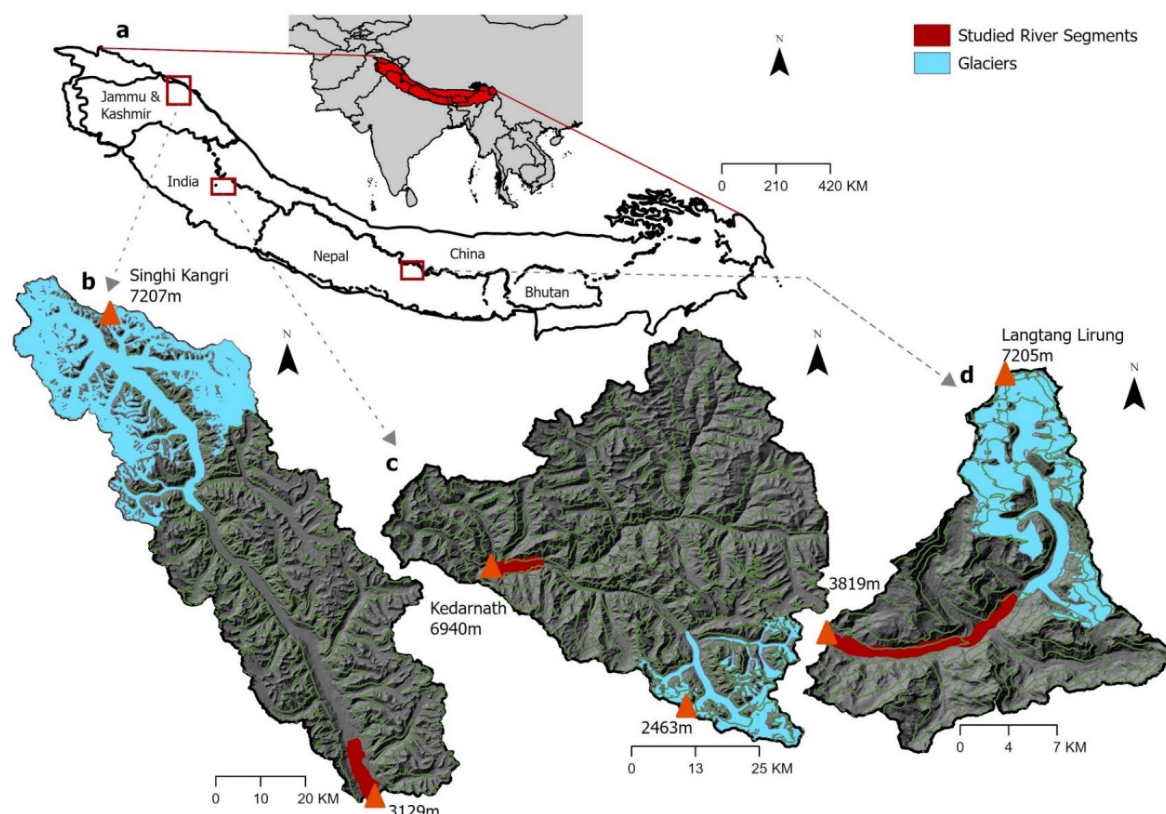


Figure 1. (a) Inset map showing the locations of the three study areas; (b) watershed divide area of Nubra River and Siachen glacier below Singhi Kangri, in Jammu and Kashmir; (c) watershed divide area of the Ganga-Bhagirathi River and Gangotri Glacier, India; (d) watershed divide area of Langtang-Khola River, Langtang Glacier, Nepal. Triangle marks indicate points of highest elevation and downstream elevation where studied fluvial corridor ends.

Table 1. List of studied glacier-dominated rivers and associated details.

Rivers	Basin Area (km ²)	Glacier Area (km ²)	Fluvial Corridor (km ²)	Distance from Glacier Snout (km)	Average Width of Studied River Segment (m)	River Reach	Reach Area (km ²)	Reach Length (km)
Nubra River	4334	1109	68	48.19	1243	N1	28	14.12
						N2	40	14.87
Ganga-Bhagirathi River	3218	179	6	24	191	B1	2	3.63
						B2	3	6.65
Langtang-Khola River	312	57	4	--	149	K1	1	2.51
						K2	1	3.42
						K3	0.4	1.35

The third river studied is the Langtang-Khola, whose entire basin (354 km²) is located in central Nepal and fed by the Langtang glacier [53]. This debris-covered valley glacier is ~18 km in length and its elevation ranges from 4370 to 7119 m a.s.l [54]. The Langtang-Khola River joins the Trishuli River as part of the Ganga river system [55]. The mean annual precipitation in the basin is about 634 mm [56] and the mean annual temperature is 3.5 °C [53]. The acquired satellite images cover 25 km² of the Langtang-Khola River just downstream of the Langtang glacier snout. The investigated river segment drains an area of 360 km² including 57 km² of the Langtang glacier area (Table 1).

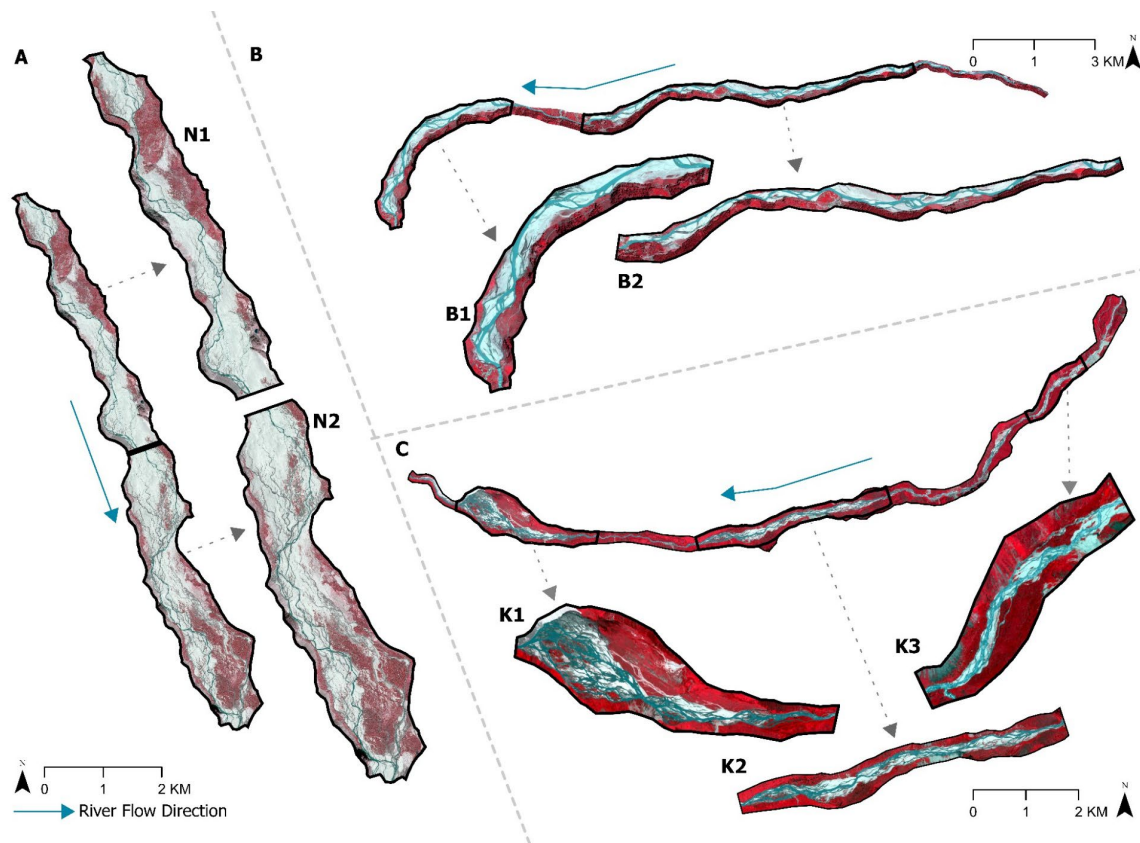


Figure 2. Map of three fluvial corridors divided in subsections (reaches): (A) Nubra River divided by upstream reach (N1) and downstream reach (N2); (B) Ganga-Bhagirathi River in downstream reach (B1) and upstream reach (B2); (C) Langtang-Khola River in downstream, central, and upstream reach (K1, K2 and K3).

2.2. Data Acquisition and Pre-Processing

2.2.1. Data Acquisition: RS Data

In order to investigate multi-decadal fluvial morphological changes, satellite images acquired at about the same time of the year throughout the analyzed period would be ideal, if high frequency (e.g., monthly) acquisitions are not possible. However, for these study rivers, the limited availability of images, along with presence of snow on the ground and frequent cloud cover, did not allow us to analyze images taken within the same specific month. Furthermore, it was necessary to use imageries from multiple platforms. In total, 13 images (Table 2) from different satellite sources and sensors were selected. Landsat-5 (LS-5) and Sentinel-2 (S-2) images during late/post monsoon period (August–November) are used from freely available data sources (easily accessible through Google Earth Engine), before 2000 (1989 and 1995) and of 2020 respectively. However, LS-5 images were used only for the very wide Nubra River, given their low resolution (30 m).

IKONOS, WorldView-2 and Quickbird-2 were selected for the years between 2000 and 2015, according to the availability of images spatially and temporally. Eight cloud-free georectified images were acquired mostly from the late/post monsoon period, but due to the constraints of limited suitable images in the archives, two images are from the months of March and May. However, for each study river, the time between two acquired images is adequate to detect fluvial changes in terms of macro-units (see Section 2.3). The selection of satellite images was made to optimize spatial, temporal and spectral properties while minimizing the cost.

Table 2. List of selected available satellite sources, acquisition dates and their resolutions. TM—Thematic Mapper, MS—Multispectral, LS-5—Landsat-5, QB-2—QuickBird-2, WV-2—WorldView-2, IK—IKONOS and S-2—Sentinel-2.

River	Satellite Source	Sensor	Acquisition Date	Spatial Resolution (m)
1	LS-5	TM	9 October 1989	30
2			11 November 1995	
3	QB-2	MS	5 March 2003	2.4–2.6
4			20 November 2009	
5	WV-2	MS	1 November 2014	2.4
6	S-2	MS	25 August 2020	10
7	QB-2	MS	9 May 2010	2.4–2.6
8	WV-2	MS	8 September 2014	2.4
9	S-2	MS	13 September 2020	10
10	IK	MS	October + November 2003	4
11	WV-2	MS	September + October 2011	2.4
12			7 September 2015	
13	S-2	MS	28 August 2020	10

Despite the small differences in the wavelengths of bands across all the satellite sources, we selected green and near-infrared bands, to maintain uniformity. The selection of bands was based on the efficacy of the Normalized Difference Water Index (NDWI), which is a spectral index that enhances the visibility of open water in satellite or aerial imagery [41]. It does so by calculating the normalized difference between the reflectance values in the green and near-infrared spectral bands. Water absorbs light in the red part of the spectrum and reflects strongly in the near-infrared region, while vegetation reflects strongly in both green and near-infrared bands. NDWI's formula boosts the contrast between water and non-water features. Higher NDWI values indicate the presence of water, allowing for effective mapping and monitoring of water bodies against soil and vegetation. This makes NDWI a valuable tool for various environmental and resource management applications. To train the algorithm for classification, two specific bands (green and near-infrared) from all 13 satellite images were used as input variables. This approach has been previously validated and successfully implemented in the published work for Sentinel-2 images [37]. The methodology ensures a reliable and quantifiable means for mapping and monitoring fluvial geomorphic features. The same methodology was applied for all other satellite images used in this study, keeping the parameters of spectral bands and index identical. To deal with the spatial resolution discrepancies, we applied five different models in total: one for each satellite source with individual calibration and validation datasets. The performance of each model was assessed and cross-validated with validation datasets and manual interpretation.

The ArcGIS Pro software (version 3.1) was used in this work to digitize fluvial corridors. Crucial for this delineation was the use of a Digital Elevation Model (DEM), and we used the freely available 12.5 m resolution Advanced Land Observing Satellite (ALOS) Phased Array Type L-Band Synthetic Aperture Radar (PALSAR) 2011 DEM, acquired by an ASF data search (Alaska.edu). Unfortunately, due to rectification problems encountered by some images, the margins of the fluvial corridors had to be digitized the same way for each single image of each river, to ensure that all the polygons were represented consistently and precisely (with an accuracy of about 20 m) in the same areas. Conversely, using a

single fluvial corridor polygon would have included erroneous areas such as slopes in some images.

2.2.2. Data Acquisition—Hydroclimatic and Glacier Inventory Data

Hydrological (glacier variations, meltwater runoff), climatic (Positive Degree Days, temperature and precipitation) and glacier area change data from the Randolph Glacier Inventory-RGI (GLIMS: Global Land Ice Measurements from Space, GLIMS.org [57]) were compiled to investigate the possible drivers of morphological changes in the study rivers. Most of the hydroclimatic data were derived from published papers available for the three river basins, and unfortunately, very few exist. The area has limited access due to the highly politically conflicted border region proximal to the Siachen glacier (Nubra River basin). A systematic approach was employed to extract pertinent information, ensuring consistency and accuracy in the assimilated data (Table 3).

Table 3. Collection of hydroclimatic data from peer-reviewed research papers. PDD—Positive Degree Days; TIA—Tribhuvan International Airport; SASE- Snow and Avalanche Study Establishment.

Glacier-Dominated River	PDD (°C)	Temperature (°C)	Precipitation (mm)	Meltwater Discharge (mm)	Stations	Reference
Nubra	1986–2018		1990–2013	1986–2018	SASE S-A1 & S-A2	[58]
Ganga-Bhagirathi		2010–2019	2010–2019		NASA platform SNOWMOD hydrological modeled data for Gangotri glacier basin	[59]
				2010–2019	Bhagirathi River—500 m downstream of glacier snout	[60]
				1999–2000		
Langtang-Khola		1981–2010	1981–2014	1985, 1988–2011	Kathmandu meteorological station	[61]
		2011–2017			TIA in Kathmandu valley	[62]
				2012–2013, 2016–2019	Kathmandu meteorological station	Raw data collection
			2015–2017		Kathmandu meteorological station	[63]

Negi [58] has recently conducted research on the hydrological mass balance of the Siachen glacier; they utilized the station data exactly as we did for our selected study site. In the Siachen region, a network of snow-meteorological observatories was established by the Snow and Avalanche Study Establishment (SASE) in India. From these observatories, we utilized data from two stations (S-A1; 3246 m a.m.s.l. and S-A2; 3687 m a.m.s.l.) out of a total of five stations. We collected Positive Degree Days, or PDDs (defined as the sum of daily average air temperatures above 0 °C for the specific time period), and precipitation data from both S-A1 and S-A2 stations and meltwater discharge observations from the S-A2 station from 1986 to 2018. Maximum and minimum temperature records were not publicly available, but by using the PDD time series as a starting point, we were able to extract the information from the data and compare it with our image analysis results. PDD data was available for the same years as meltwater runoff, but precipitation data was limited to the years 1990 to 2013.

Another relevant work published by Salim & Pandey [59] focused on temporal runoff measurements in the Gangotri glacier basin, where they used the SNOWMOD hydrological model to calculate glacier melt runoff, utilizing MODIS images and ALOS PALSAR DEM for the years from 2010 to 2019. Over the same interval, the modeled meltwater runoff data was compared with temperature and precipitation data that were derived from the NASA Prediction of Worldwide Energy Resources (POWER) platform (<https://power.larc.nasa.gov/>). Additional meltwater runoff data for the years 1999 and 2000 were collected from research conducted by Kumar [60].

Lastly, the datasets (meltwater, temperature and precipitation) collected for the Langtang-Khola River were extracted from different research articles and complemented by adding unpublished data to obtain continuous series for the analyzed period. Meltwater discharge data was available from 1985 to 2011 with a two-year gap from 1986 to 1987 [61] and raw data collection from 2012 to 2019 again showed that two years of data was missing, from 2014 to 2015. Because the meteorological station available in Langtang does not provide a continuous dataset spanning the study period, we utilized temperature data collected in Kathmandu located 70 km away from the Langtang river segment analyzed. Temperature records came from two sources: from 1981 to 2010 by Yao & Shi [61] and from 2011 to 2017 by Thapa [62]. Similarly, the datasets were merged for precipitation records: 1981–2014 by [61] and 2015–2017 by Khanal [63].

2.3. Image Classification and Change-Detection Analysis

We initially developed a model to delineate fluvial morphological features of glacier-dominated rivers in the Himalayas, continuing the procedure developed by [37]. The model is based on fluvial morphological macro-units defined in the Geomorphic Unit System (GUS) proposed by Belletti [48]. Our study is based on few major spatial units derived from GUS, within the channel and its borders, including (i) submerged base-flow channels; (ii) emerged and unvegetated sediments (bars); and (iii) vegetated surfaces.

The spatial unit “vegetated surface” is free from taxonomical (plant species) and structural (height) classes, including all the vegetated areas within the fluvial corridor. Working with high-resolution data enables detection of small-sized ponding water patches within vegetated surfaces that can lead to misclassifying morphological macro-units. To overcome this issue, we created different training polygons by grouping mixed-water plus vegetation pixels into a single vegetated surface (yellow polygons) category-unit (Figure 3). On the other hand, wet and dry channels were grouped into one same macro-unit class as base-flow channels (purple polygons). The third unit covers unvegetated emerged sediments recognized as bars (blue polygons). Retaining these three macro-units to describe glacier-dominated rivers in consideration enables us to quantify changes in the spatial expansion of each unit over time as a function of changing bedload transport processes and to better understand how the river hydrology is modified through time by deglaciation and rainfall events in Himalayan river basins.

The selected river segments were further divided into reaches (Table 1 to investigate if and how much morphological change might be associated with different morphological settings and/or with upstream/downstream conditioning at the reach scale. The Nubra River segment was divided into two reaches: reach N1 (28 km²) is comparatively less braided than reach N2 (40 km²). The Ganga-Bhagirathi River segment was also split into 2 reaches, B1 and B2, of around the same size (2 km²). Finally, the Langtang-Khola River was subdivided into 3 reaches: K1, K2 and K3 with 1, 1 and 0.4 km² area, respectively.

GEE platform was used to develop a classification model by using a supervised classifier algorithm. The 13 images were used as reference layers for the calibration and validation of the model. Because the selected images are from different satellite sources constituting different wavelength ranges, separate models for each source were developed with individual calibration and validation datasets. The LS-5-based model comprised two images (years: 1989 and 1995) for the Nubra River. We also experimented with using LS-5 images for the other two confined rivers (Ganga-Bhagirathi and Langtang-Khola) locations, but these rivers are too narrow for the low-resolution LS-5 data to classify the river channels well. However, the results of the Nubra River classification were satisfying, which is why LS-5 data was used for this wider river. The IKONOS-based classification model contains just one image from the year 2003 for the Langtang-Khola River; we followed the

classification process and avoided manual delineation of geomorphic units to keep the process consistent for all satellite sources throughout the time period. QB-2 has provided us with two images (for the years 2003 and 2009) of the Nubra River and one image (year: 2010) of the Ganga-Bhagirathi River. The WV-2 model used one 2014 image for the Nubra River, one 2014 image for the Ganga-Bhagirathi River and two (2011 and 2015) images for the Langtang-Khola River. Lastly, S-2 provides one image from the year 2020 for each studied river.

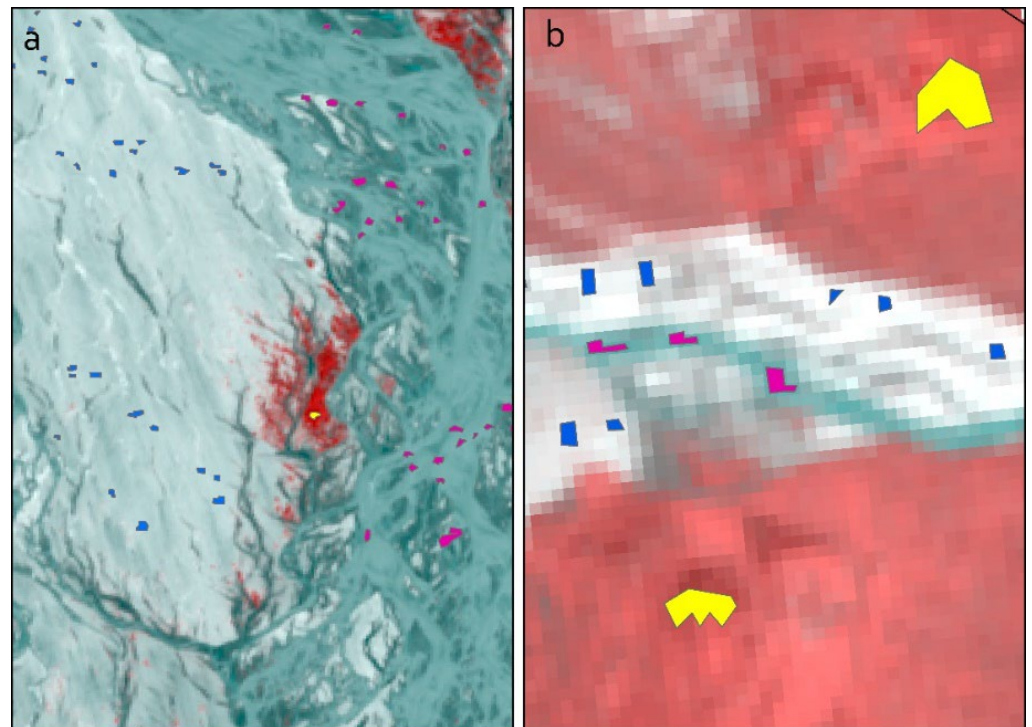


Figure 3. Sample training polygons taken for 3 different macro-units: vegetated surfaces (yellow); base-flow channels (pink); and bars (blue). Panels: (a) Nubra River; (b) Ganga-Bhagirathi River.

We have developed a single supervised random forest (RF) classifier, merging all the calibration datasets from different locations and dates, within each of five satellite sources. Reference data from all 13 images was organized and then divided, with a ratio of 70% for model training and 30% for accuracy assessment for each satellite source analyzed separately (Table 3). The number of sample data collection sites selected from each glacier-dominated river segment was based on the idea of balance and the area investigated. For example, the area of the Nubra River used for model development was 112 km² (which is 4 times wider than other sites), and 150 sample polygons for each geomorphic unit were taken from all six images of the Nubra River. On the other hand, a 25 km² area of both Ganga-Bhagirathi and Langtang-Khola Rivers was investigated with 50 sample polygons for each geomorphic unit from all seven images (three for Ganga-Bhagirathi and four for Langtang-Khola River). Overall, our Landsat-based model was calibrated with 590 calibration and 310 validation polygons. We took 101 calibration sample polygons, and 49 polygons were assigned for validation of the IKONOS image. The QB-2 model was designed with a total of 704 training polygons, and 346 polygons were separated for accuracy assessment. Similarly, WV-2 and S-2 models feature calibration/validation polygon ratios of 632/268 and 525/225, respectively. The collection of training data was based on manual interpretation of the satellite images. Manual interpretation entails visual examination of drawn polygons to detect macro-units within them. It permits the thorough analysis and identification of landforms, registering nuances that may not be detectable

through automated methods only. A simple random sampling technique was performed to collect three macro-unit classes samples, as it involves picking polygons from the study area in a way that confirms each polygon has an equal chance of being chosen. Simultaneously, the pixel quantity (on which accuracy assessment is based) also varies considerably due to the larger polygon sizes within the wider river (Nubra) compared to the narrower river segments (Ganga-Bhagirathi and Langtang-Khola).

The RF classifier was applied to obtain morphological classification maps for each site and every single selected year. As described above, the GEE platform was utilized to train the algorithm and perform classification, and the geomorphic macro-unit area-change calculation was also performed using GEE. After training models for all satellite sources and performing image classification processes, maps were clipped using fluvial corridor shapefile (Section 2.2). Furthermore, the extracted fluvial corridor was clipped in reach sections, and change-detection analysis was performed by calculating the pixel area of all three macro-units for each classified image. The calculated area was further compared from one year to the next for all the river segments to calculate the differences in geomorphic macro-units experienced throughout the studied period. Along with this, accuracy assessment was performed for all reaches separately (Table 3). Classified maps were taken to ArcGIS pro software to perform final map-making of river morphological change analysis. The results were examined and justified through the validation datasets and through visual interpretation of original satellite images for temporal trajectories as well as the model-validation process.

To assess the model's performance, the supervised classification of macro-units underwent accuracy evaluation using a confusion or error matrix. Utilizing the validation dataset (30% of total training dataset from each river segment), the classifier's effectiveness was tested. This effectiveness was calculated twice (1) to calculate the reach-scale precision for all selected river segments (Table 4, Tables S1 and S2) and (2) to calculate the individual accurateness of models (Table S3) for all satellite sources utilized in this study. A 2D confusion matrix was generated for morphological macro-unit classes, incorporating computed metrics such as overall accuracy (OA) and the kappa index. OA represents the percentage of accurately classified pixels over the entire dataset, while the kappa index gauges the agreement between the classification and the truth value, with 1 indicating perfect agreement and 0 indicating no agreement. Additionally, the producer's accuracy (PA) is presented, quantifying the error of omission, reflecting the model's precision in excluding pixels not belonging to a specific class. Furthermore, the user's accuracy (UA) is provided, assessing the error of commission, indicating the model's accuracy in correctly identifying pixels belonging to a specific class.

Table 4. List of satellite images with fluvial corridor-scale classification training and validation polygons, and reach-scale validation pixels.

Satellite	River	Year	Polygons Before Clipping Fluvial Corridor		Model-Based OA %	Pixels After Clipping Reach Sections			Reach-Scale OA %	Kappa Coefficient
			Calibration		Validation		Correctly Classified			
Landsat	Nubra	1989	290	160	0.84	N1	75	66	88	0.81
						N2	91	71	78	0.67
		1995	300	150		N1	75	54	72	0.57
						N2	91	82	90	0.85
IK	Langtang-Khola	2003	101	49	1	K1	53	53	1	1
						K2	78	78	1	1
						K3	12	12	1	1

Table 4. Cont.

Satellite	River	Year	Polygons Before Clipping Fluvial Corridor		Model-Based OA %	Pixels After Clipping Reach Sections			Reach-Scale OA %	Kappa Coefficient
QB2	Nubra	2003	291	159	0.85	N1	377	232	62	0.41
						N2	577	409	71	0.55
	Nubra	2009	314	136		N1	374	316	84	0.76
						N2	568	486	85	0.77
	Ganga-Bhagirathi	2010	99	51		B1	157	157	100	1
						B2	234	234	100	1
WV2	Nubra	2014	315	135	0.86	N1	4040	3972	98	0.95
						N2	6659	6629	99	0.99
	Ganga-Bhagirathi	2014	111	39		B1	130	130	100	1
						B2	321	321	100	1
	Langtang-Khola	2011	103	47		K1	66	64	97	0.95
						K2	91	72	79	0.69
						K3	11	11	100	1
						K1	77	49	64	0.44
	Langtang-Khula	2015	103	47		K2	87	60	69	0.52
						K3	19	18	95	0.88
S2					Nubra	2020	316	134	0.99	N1
	N2	663	663	100						1
	Ganga-Bhagirathi	2020	109	41	B1	26	26	100		1
					B2	52	51	98		0.97
	Langtang-Khola	2020	100	50	K1	51	51	100		1
					K2	43	43	100		1
					K3	8	8	100		1

3. Results

3.1. Accuracy Assessment

From Table 4, it can be observed that the overall accuracy of reach-scale classified images for all the river segments ranges between 86% and 92% of the classified maps, demonstrating the effectiveness of the model in extracting morphological macro-units, with an overall accuracy/kappa coefficient of around 86%/0.86, 99%/0.96 and 92%/0.87 for Nubra, Ganga-Bhagirathi and Langtang-Khola Rivers, respectively. The lowest accuracy (N1: 62%) was obtained in the Nubra River for QB-2 image 2003 (Table S1); a considerable amount of water (base-flow channel) pixels (120) were misclassified as emerged sediment bars. Similarly, in the Langtang-Khola River, the lowest accuracy (K1 64% and K2 69%) for WV-2 image 2015 (Table S2) was observed, with 20 emerged sediment bar pixels misclassified as vegetated surfaces in K1 and 12 vegetated surface pixels misclassified as base-flow channel in K2.

Table S3 shows the error matrix based on the classified images of all studied fluvial corridors, i.e., the model performance as well as the accuracy of fluvial corridors' classified images. The overall model-based accuracy of all the images from different satellite sources are as follows: LS-5 84%, IKONOS 100%, QB-2 85%, WV-2 86% and S-2 99%. The image featuring the lowest accuracy (68%) is the WV-2 in 2011 for Langtang-Khola, with 27 emerged sediment bar pixels misclassified as vegetated surfaces. The overall accuracy for all the developed models turned out to range between 84% and 99%, providing quite a high level of accuracy that is suitable for further research [64].

3.2. Channel Changes

3.2.1. Nubra River

For the Nubra River, 6 images (1989, 1995, 2003, 2009, 2014 and 2020) were used to quantify the change over a period of 31 years, with an average of 85% of reach-based accuracy calculation (Table 4). As shown in Figures 4–6, marked changes took place in the analyzed fluvial corridor for both the analyzed reaches (N1 and N2), with the exception of

the period 2014–2020 (Figure 4). In fact, in reach N1, a noticeable trend was the substantial decrease (15%) in vegetation (and resulting increase in active channel area (i.e., the sum of emerged sediments and base-flow channels)) until 2003, followed by an increase in vegetation (and thus channel narrowing) of 18% until 2020. In N2, the same initial trend described for N1 is also observed, but in the later phase vegetation decreased (6%), which is in contrast to what occurred in N1. From 1989 to 2020, N2 displays both increases and decreases in vegetation cover (with the complementary narrowing and widening of the active channels), possibly indicating cyclic behavior. However, a long-term investigation is necessary to conclude that these changes are cyclic.

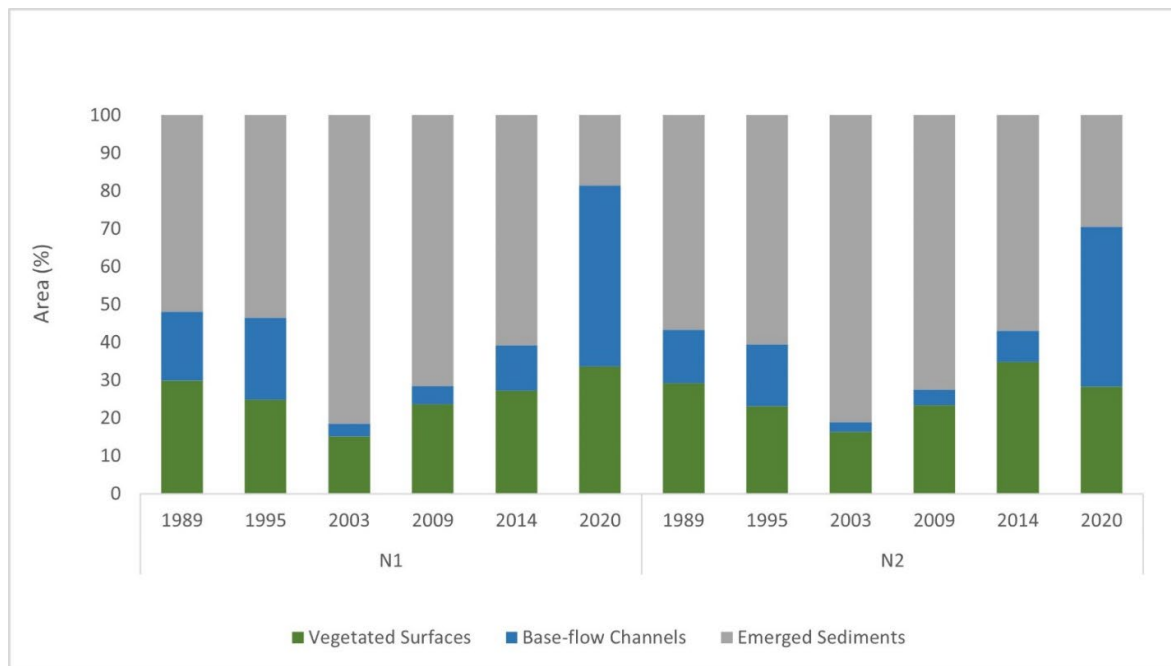


Figure 4. Reach-scale area changes in macro-units (vegetated surfaces, base-flow channel and emerged sediments) of Nubra River.

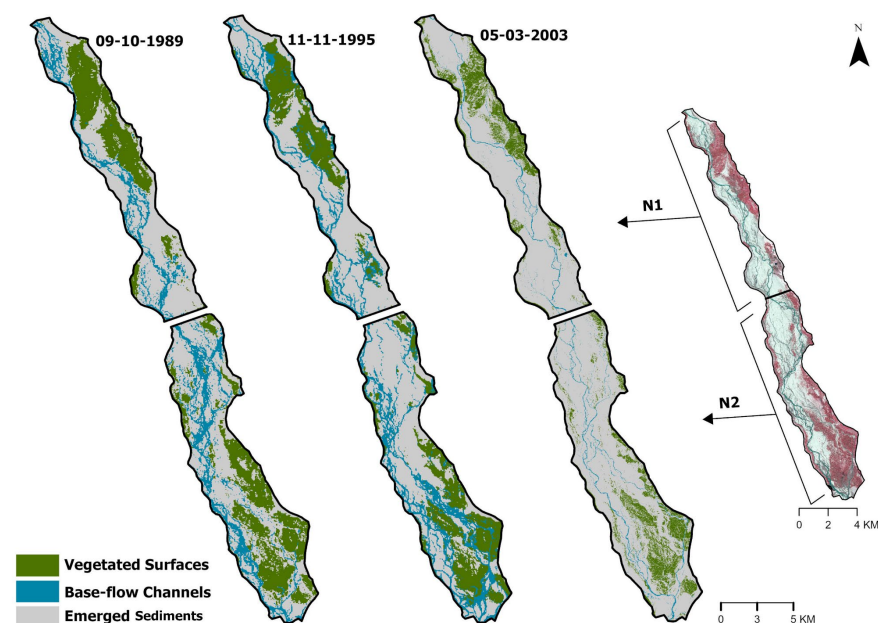


Figure 5. Classified images relative to the Nubra River, presenting reach-scale fluvial morphological changes from 1989 to 2003. The Infrared WV2 image on the right shows the entire study segment.

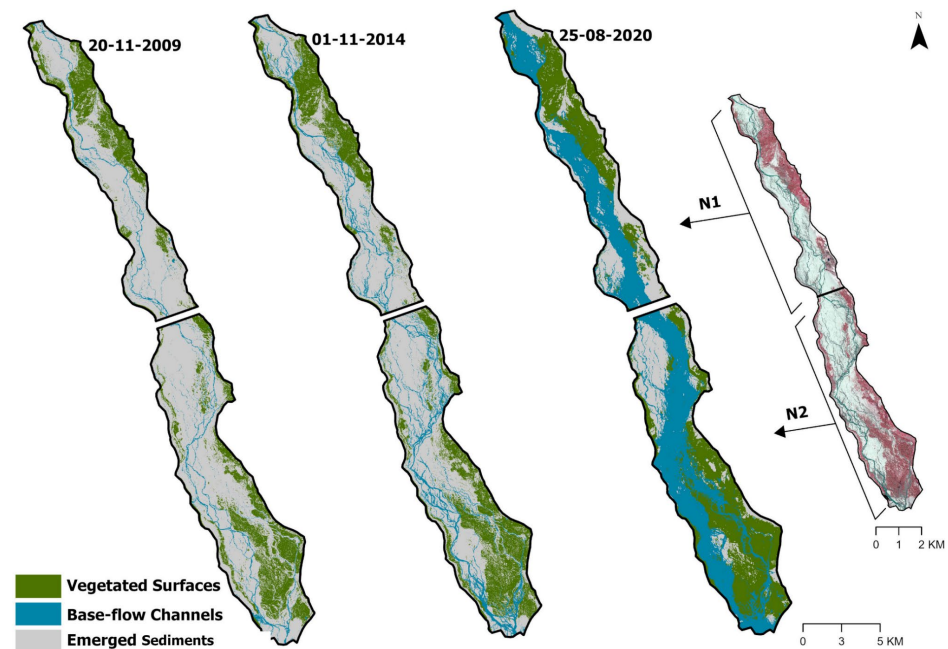


Figure 6. Classified images relative to the Nubra River, presenting reach-scale fluvial morphological changes from 2009 to 2020. The Infrared WV2 image on the right shows the entire study segment.

3.2.2. Ganga-Bhagirathi River

For the Ganga-Bhagirathi River segment, satellite images were available for years 2010, 2014 and 2020, thus allowing us to quantify morphological changes over 10 years, and rely on an average reach-based accuracy of 99% (Table S2). Both reaches (B1 and B2) show similar planform changes, but B1 features gentler variations compared to B2, especially for the period 2014–20. The active channel area (i.e., the sum of emerged sediments and base-flow channels) shown in Figures 7 and 8 for B1 and B2 represents little decreases in area of almost 1% and 4%, respectively, for the period 2010–2014. Vegetated areas of both reaches followed the same level of increase as the active channel area, which decreased in 2014–2020. An opposite picture was exhibited from 2014 to 2020, with a slight decrease of 3% and 19% in vegetated areas of B1 and B2, respectively, while the active channel area in both the reaches correspondingly increased.

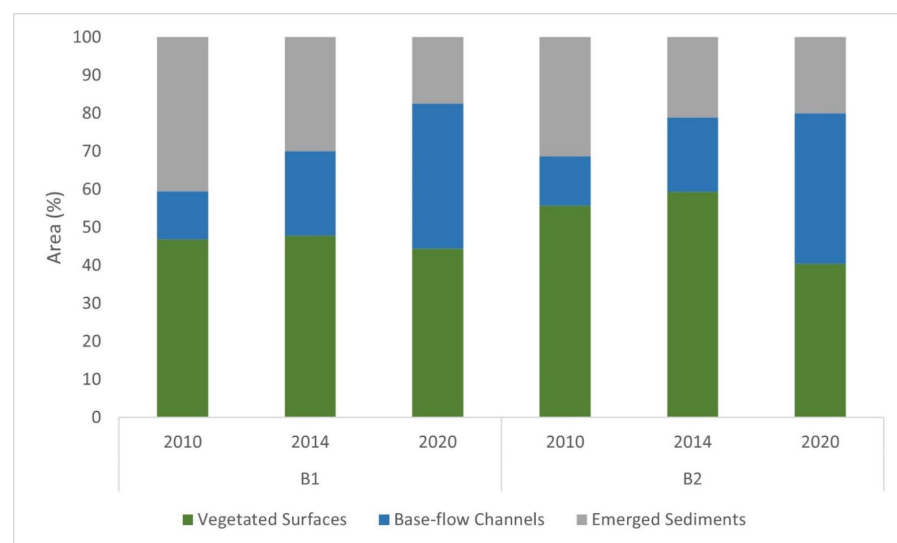


Figure 7. Reach-scale area changes in macro-units (vegetated surfaces, base-flow channel and emerged sediments) of Ganga-Bhagirathi River.

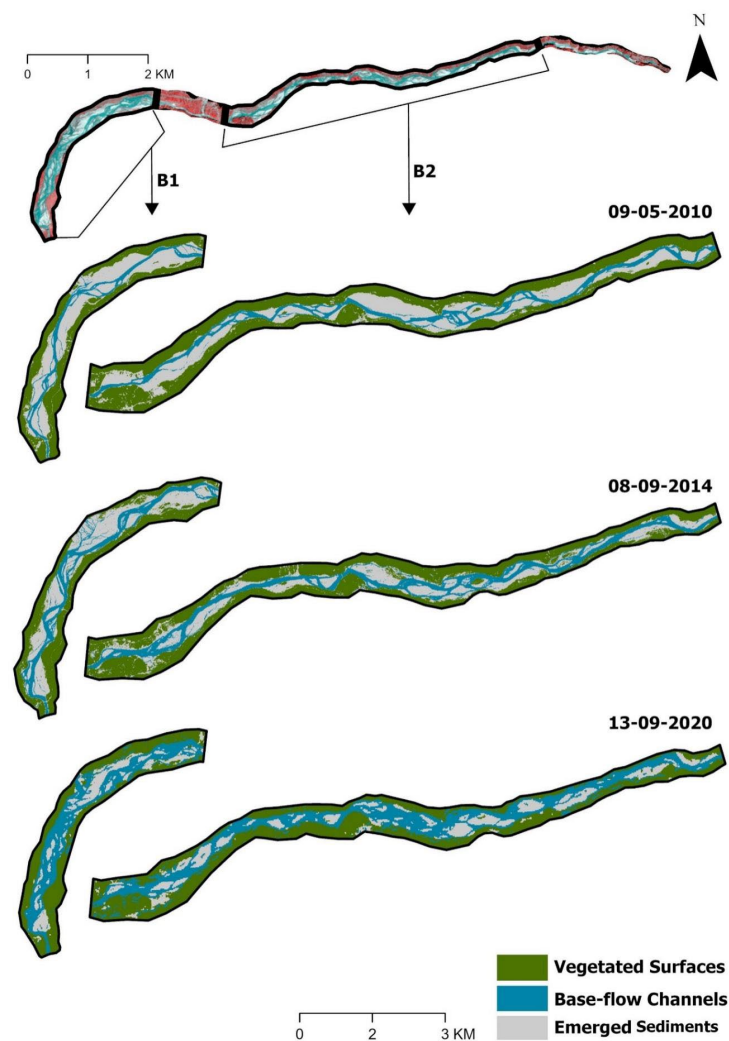


Figure 8. The classified images for the Ganga-Bhagirathi River presenting reach-scale fluvial morphological changes from 2010 to 2020. The Infrared WV2 image above shows the entire study segment.

3.2.3. Langtang-Khola River

The reach-scale dynamics are used to visualize changes in river segment planform morphology, using four images (2003, 2011, 2015, 2020) for the period of 18 years, attaining an average reach-based precision of 92% (Table S2). The analyzed river segment was subdivided into three reaches: K1 (braided), K2 (wandering) and K3 (single-thread). In general, similar patterns of change can be observed for all the reaches. All the reaches have behaved uniformly for active channel and vegetated surfaces area. As shown in Figure 9, vegetated surface area increased from 2003 until 2015 for the whole studied river segment by 16% in K1 and 11% in K2 and K3, and thus the active channel (base-flow channels + emerged sediments) decreased by the same amount in this period. Vegetated surfaces were significantly increasing in marginal areas. Conversely, decreased vegetated surface values of 7%, 3% and 5% were observed during the period from 2015 to 2020, for K1, K2, and K3, respectively (Figures 10 and 11).

3.3. Possible Drivers of the Observed Changes Within the Fluvial Corridors

3.3.1. Nubra River

The hydroclimatic and glaciological data available for the Nubra River basin and the Siachen glacier (see Methods Section) are quite limited; nonetheless, they enable us to attempt to link the trends in vegetation/active channel area over time to variations in

glacier area, meltwater runoff, and precipitation. The period from 1989 to 2003 exhibited marked fluctuations in Positive Degree Days (PDDs) and precipitation at the annual scale, but a rising trend in PDD and a decreasing one in precipitation are apparent, with the increasing PDD leading to higher meltwater runoff (Figure 12). During the same period, vegetated surfaces within the Nubra fluvial corridor were in decline, and thus the active channel expanded. Therefore, higher meltwater runoff due to warmer temperatures might have been highly effective in eroding vegetation during this period, in both reaches. Later, during the period 2004–2014, PDD increased further while meltwater runoff remained quite constant, probably because of concomitant glacier variations (Figure 12). Interestingly, during this period, vegetation recovered in both reaches by steadily encroaching on former emerged sediment areas, such that in 2014, its area attained values higher than in 1989. It is likely that the constant (i.e., not increasing) meltwater runoff facilitated vegetation expansion and thus active channel contraction. Such a trend was not altered even by three flood events which occurred in the Nubra River basin in 2010 and 2014 [65,66]. Despite the 2010 flood being one of the most intense floods ever recorded in the history of Pakistan [67], its effects on the Nubra fluvial corridor are not visible in terms of channel widening due to vegetation erosion. For the next 6 years (2015–2020) covered by satellite images, PDD and meltwater runoff data are available only until 2018. Remarkably, reach N1 underwent expansion (i.e., vegetation reduced), while in reach N2, an opposite trend occurred in response to years (2015–2018) featuring meltwater runoff similar to the previous period (with the exception of 2016) and to a large flood event which occurred in 2015 [68]. Unfortunately, we do not have any plausible explanation for such contrasting trends.

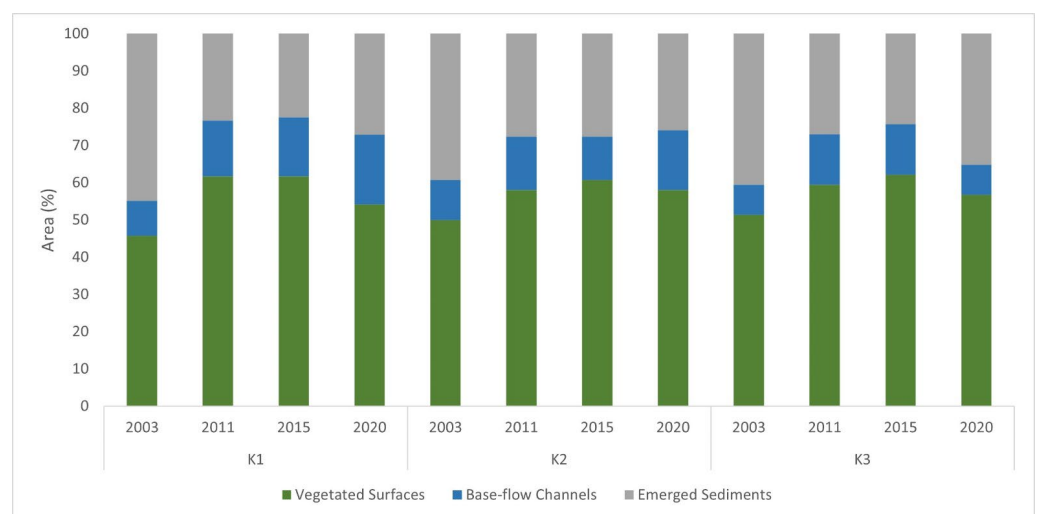


Figure 9. Reach-scale area changes in macro-units (vegetated surfaces, base-flow channel and emerged sediments) of Langtang-Khola River.

3.3.2. Ganga-Bhagirathi River

Similarly to what was observed for the Nubra River basin, the Ganga-Bhagirathi River basin trends in temperature and precipitation are opposed. Interestingly, if the entire period is considered, meltwater runoff has been declining, but the reduction has been mostly occurring between 2010 and 2011, whereas from 2012 to 2019, changes in meltwater runoff were less marked and not monotonic (Figure 13). In terms of morphological changes (i.e., changes in vegetated areas within the fluvial corridor), between 2010 and 2014, vegetation increased—although only slightly—in both reaches, possibly in response to the sharp reduction in meltwater runoff described above. In contrast, both reaches feature less vegetation cover in 2020, with a more marked decline in reach B2 (the same reach exhibits a larger vegetation expansion than B1 between 2010 and 2019). Such a variation (i.e., an

expansion of active channel areas) might be associated with the increasing meltwater runoff observed between 2012 and 2016 (when runoff was quite relatively large). This explanation would imply that the subsequent (2017–2019) relatively-low-runoff years were not able to make an impact on vegetation encroachment, which was already visible in the 2020 images. Major flood events reported for this river in 2000 and 2012 [69] seemingly did not cause any long-lasting, detectable effect on active channel vs. vegetated areas, or at least their effects cannot be detected by our analysis.

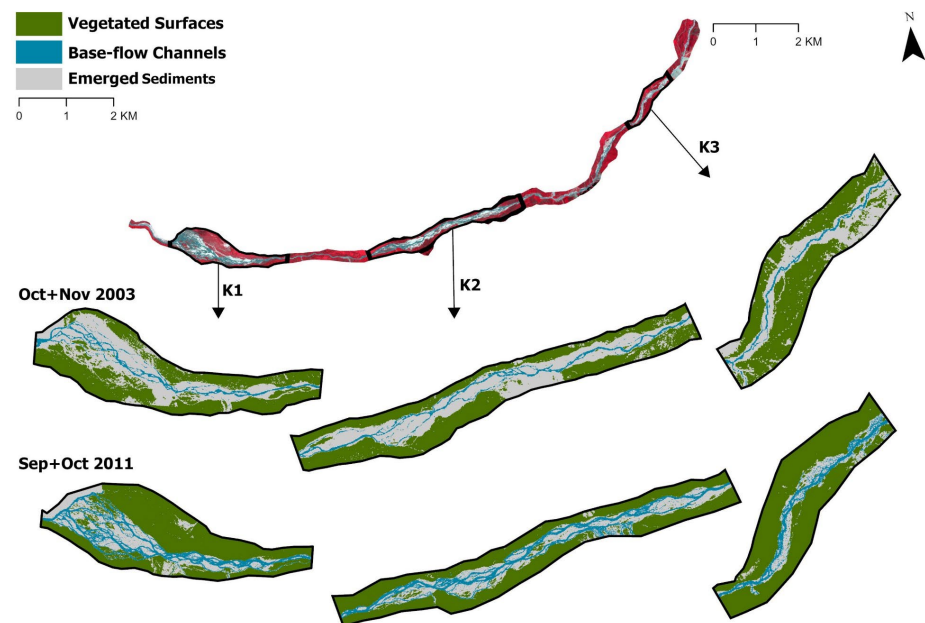


Figure 10. Langtang-Khola River, Langtang Glacier, Nepal. Classified images present reach-scale fluvial morphological changes from 2003 to 2011. The Infrared WV2 image on the top highlights the presence of water (blue color) and vegetation (red color).

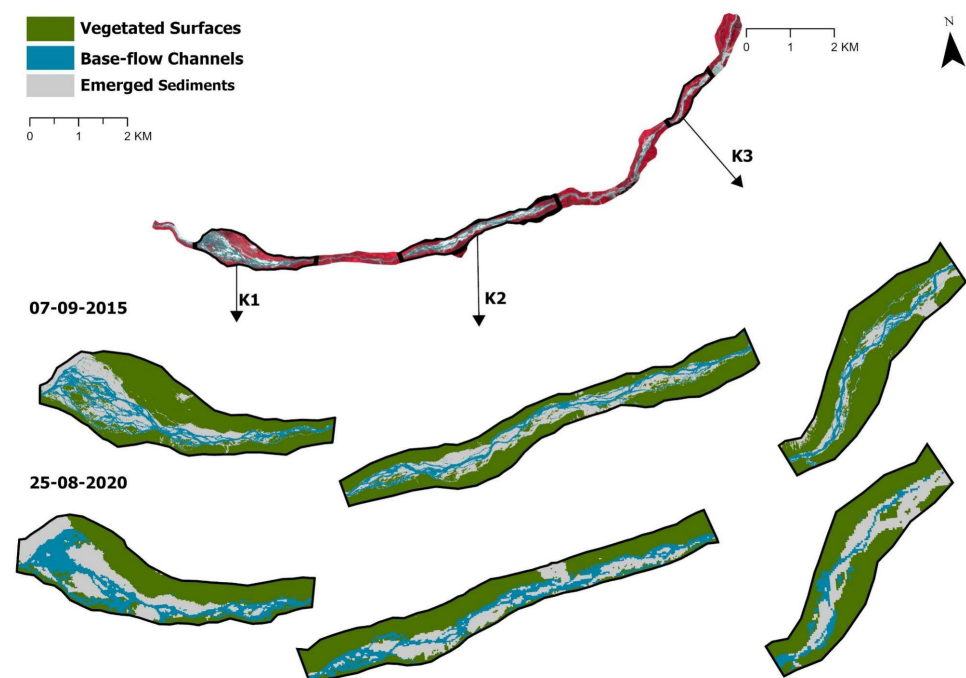


Figure 11. Langtang-Khola River, Langtang Glacier, Nepal. Classified images present reach-scale fluvial morphological changes from 2015 to 2020. The Infrared WV2 image on the top highlights the presence of water (blue color) and vegetation (red color).

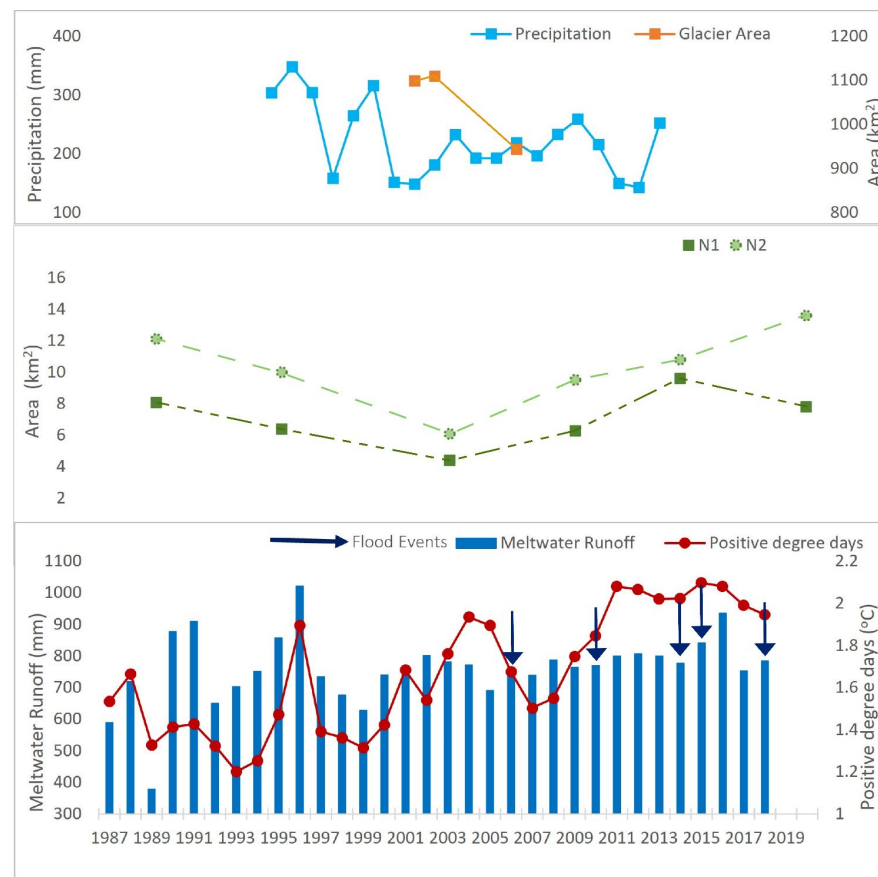


Figure 12. Comparison of hydro-meteorological data with vegetated surfaces changes in Nubra River. The top panel represents precipitation and glacier area changes data, the middle panel represents area of vegetated surface, and the bottom panel shows meltwater runoff and Positive Degree Days data.

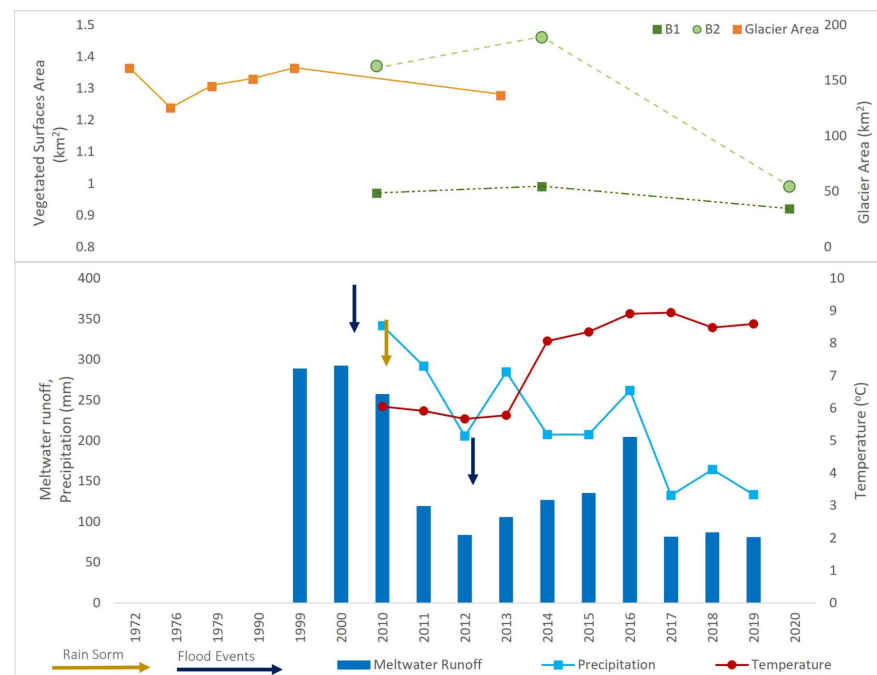


Figure 13. Comparison of hydro-meteorological data with vegetated surfaces changes in Ganga-Bhagirathi River. The top panel shows glacier area changes data, and area of vegetated surface in the fluvial corridor for the two reaches B1 and B2, and the bottom panel shows meltwater runoff, precipitation and temperature data.

3.3.3. Langtang-Khola River

The meteorological data gathered in Kathmandu (see methods) indicate also for this region a marked increasing trend for air temperatures and slightly declining precipitation values, although with strong annual variations. During the period for which satellite images are available (2003–2020), meltwater runoff data from the Langtang glacier increased—more markedly after 2009—and peaked in 2016, and thereafter decreased, attaining a value much lower than the average in 2019 (Figure 14). The observed changes in vegetated areas within the fluvial corridor do not seem to reflect in a clear way the meltwater runoff trends, as vegetation increased from 2003 until 2011 in all the three reaches (although quite slightly in reach K3), which contrasts what was found in the other studied rivers. The subsequent (from 2015 to 2020) decline in vegetated areas visible from K1 and K2 reaches is also poorly justifiable in terms of decreasing meltwater runoff. Rather, the reduction in vegetation within the fluvial corridor might be due to the occurrence in 2019 of a rock avalanche triggered by an earthquake, which was 7 km away from the studied river segment. Most likely, the coarse sediment transport in the Langtang-Khola River increased substantially right after this event, and this might have caused more pronounced lateral channel mobility and thus the erosion of marginal vegetation.

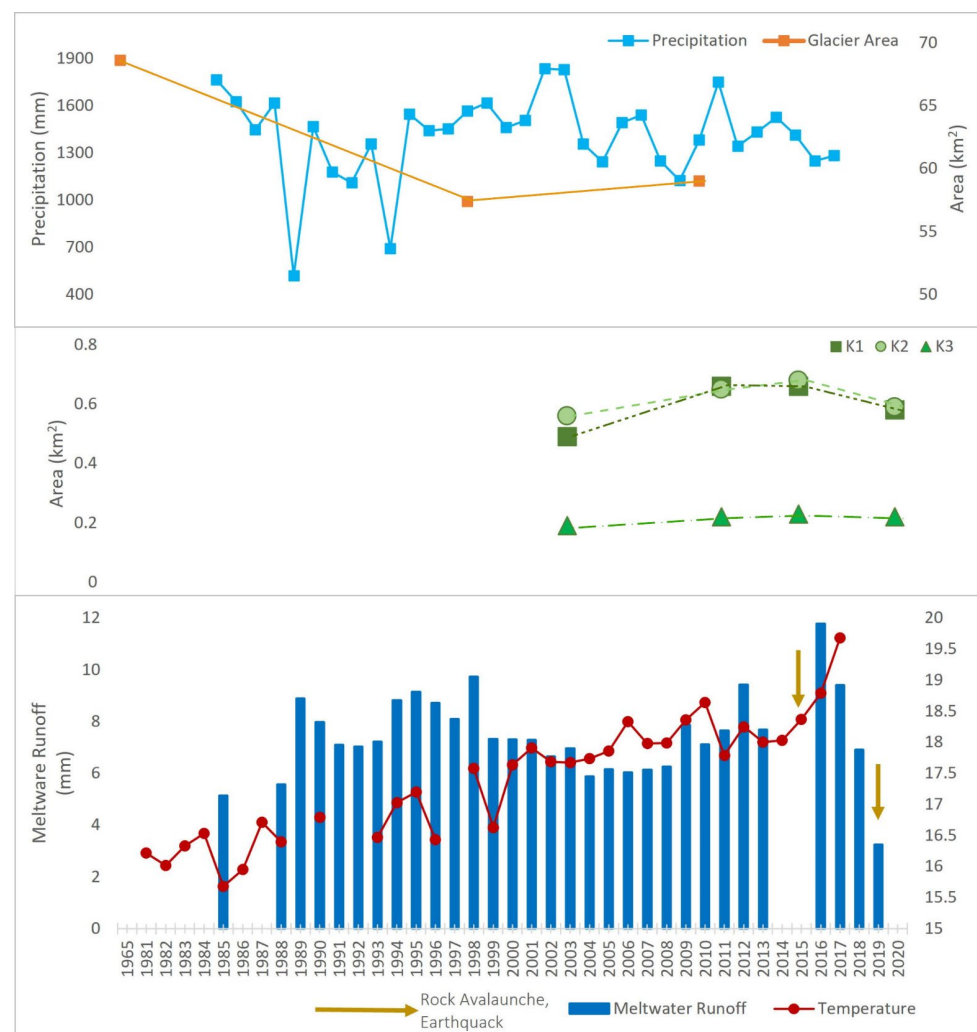


Figure 14. Comparison of hydro (meltwater runoff) and meteorological (PDDs and precipitation) data with reach-scale (K1, K2 and K3) vegetated surface changes in Langtang-Khola River, Langtang Glacier, Nepal. The top panel shows precipitation and changes in glacier area data, the middle panel represents vegetated surface area and the bottom panel shows meltwater runoff, temperature and catastrophic event data.

4. Discussion

The current study used GEE to determine the changes in fluvial corridors of selected glacier-dominated rivers using different satellite sources from 1989 to 2020. As stated in the introduction, three goals of the present paper were (1) to test the use of different sources of satellite images—featuring different resolutions—with their relative remote sensing models to map macro-units in glacier-dominated Himalayan Rivers; (2) to quantify the morphological changes (in terms of vegetated vs. active channel areas); and (3) to establish whether channel changes might be due to hydrological progressive variations (meltwater runoff changes) and disturbances (floods).

4.1. Model's Performance

This study utilized a supervised classification model [37] approach for delineating fluvial macro-units in glacier-dominated rivers within the Himalayan region, utilizing imagery from five different resolutions (2.4 m-WV2, 2.4–2.6 m-QB2, 4 m-IKONOS, 10 m-S2, and 30 m-LS5). While existing methodologies for monitoring river planforms in the Himalayas have been proposed, they predominantly focus on single-river systems, downstream segments, or basin-scale analyses. The Himalayan region, marked by ongoing deglaciation, serves as a critical hotspot where significant variations in runoff, sediment supply, and river dynamics are expected. Our study is based on reach-scale investigations of diverse morphological patterns of three glacier-dominated rivers, and it is the first of its kind regarding the Himalayan region at such spatial and temporal scales. The classification analysis considers diverse river morphological patterns, ranging from wide braided rivers (Nubra) to relatively narrow channels (Ganga-Bhagirathi & Langtang-Khola), thereby capturing a transitional spectrum of fluvial configurations.

Remarkably, the accuracy of the classified images underscores the applicability of the model to Himalayan glacier-dominated rivers, and they are highly satisfactory, demonstrating an impressive average overall accuracy (OA) of 90%. Notably, the IKONOS-based model is trained on a single location and image due to cost constraints and availability limitations during the study period. Conversely, other models, particularly those based on WV2 and S2, are trained using images from different times and locations, encompassing training samples from all three studied locations. High-resolution images, ranging from 2.4 to 4 m, exhibit consistent performance in both wider and narrower rivers. Medium-resolution images (10 m) yield highly satisfactory results, achieving an impressive average OA of 99%. However, it is noteworthy that the model's performance is superior in wider rivers, such as Nubra, whereas narrower river channels, notably in Ganga-Bhagirathi and Langtang-Khola, present more shadow effects from the hillslope, intensifying uncertainties in water–sediment and water–vegetation pixel classification. LS5 images with a 30 m resolution lack the ability to analyze channel spectra, shape, and features [70], necessitating manual extraction of macro-units in narrower glacier-dominated rivers. Consequently, the classification results demonstrate the model's efficacy and its potential for accurately monitoring fluvial morphological changes in glacier-dominated rivers within this region. The analysis can be rerun or updated as new remote sensing data layers, automatically acquired by GEE, allowing for identifying and monitoring changes in river size and pattern. This is particularly useful with the freely available and continuously covering S2 images over the Himalayan region.

The spectral signatures of water, exposed sediment, and vegetation are markedly different; therefore, a supervised classifier can normally distinguish these classes easily within a single image. However, classification across different rivers and acquisition dates becomes more challenging due to varying atmospheric conditions, different vegetation

phenological stages, and changes in water turbidity factors that are particularly significant in proglacial environments such as the one investigated here.

Considering the number of dates and locations included in each classifier developed for the different satellite sensors, the accuracies reported in Table 4 are expected and fully consistent. On average, the classifiers perform very well, as they are trained using samples from all available dates (i.e., no image is classified without at least some training polygons derived from that specific date).

While this approach limits the direct transferability of the models in terms of other locations or dates for each sensor without needing a recalibration phase using new training data, it substantially increases the reliability of the classifications used in this study, as they are specifically tailored to the study areas and periods. For this reason, we consider the proposed classifiers sufficiently robust to support the analysis of multi-annual changes in the mapped morphological units.

This robustness is also evident from visual inspection of the classified rasters (e.g., Figures 5, 6, and 10), where geomorphic trajectories emerging over time are clear and their magnitude is substantially greater than the classification uncertainty. The validity of satellite-based classifiers, such as the one proposed in this paper, for analyzing river geomorphic trajectories over time has also been demonstrated and discussed in recent studies, including Bozzolan [71].

4.2. Is There a Single Evolutionary Trajectory During the Study Period?

Regarding the spatiotemporal patterns of morphological changes, we observed dynamic vegetation growth over the studied period in all the glacier-dominated river segments and all reaches of selected glacier-dominated river segments. More prominently, since 2003, the channels are exhibiting clear narrowing and increased vegetation growth, except in 2020, where the widening of river channel is most prominent. A potential reason for this change could be the differences between hydro-meteorological drivers. During the periods of 1989–1995 and 1995–2003, Nubra River widening was most pronounced with a sharp and continuous decrease in vegetated surfaces, while N2 experienced a steady increase in vegetated surfaces from 2003 onwards. All three reaches of the Langtang-Khola River behaved in a similar way, showing an evident vegetation increase over the channel during the study period (2003–2011 and 2011–2015). Ganga-Bhagirathi River was studied in just two periods; the first period shows a vegetation increase while the second features a decrease. All the reaches in three glacier-dominated river segments, excluding N1, show a sharp decrease in vegetation during the last studied period (2015–2020 for Nubra and Ganga-Bhagirathi; 2016–2020 for Langtang-Khola). The contrasting trends in vegetation cover dynamics observed in the period 2015–2020 between the upper and lower reaches of the Nubra River may be due to a variety of causes, such as preferential deposition of coarse sediment during downstream sediment transfer, in turn driving lateral erosion and thus vegetation removal, as well as reach-based differences in relative groundwater table elevation which may affect tree growth rate and thus their resistance against floods [72].

This investigation prompted an inquiry into the potential correlation between changes in vegetation cover and variations in meltwater runoff or flood occurrences. This question arises in the context of the observed morphological changes in the fluvial corridor, impacting the surrounding vegetation. A few parameters may help explain the influence of hydroclimatic variations on channel dynamics, including (i) number of Positive Degree Days (PDDs); (ii) precipitation including high intensity extreme events, defined by threshold of >100 mm/h over a geographical region around 20–30 km² [68]; (iii) meltwater runoff fluctuations; and (iv) catastrophic events including floods.

As to the number of PDDs, in Nubra valley, the value gradually increased throughout the study period (1987–2018). The year 1996 showed the sharpest increase in PDDs, leading to high meltwater runoff, along with some other peak meltwater runoff years (1990 and 1991). When comparing this with vegetation cover changes, eroding of vegetation is clearly experienced until 2003. Interestingly, there are few high-intensity (2010 and 2014) and low-intensity floods (2006 and 2015) in the next period, but these are not strong or long enough to affect vegetation in the Nubra River fluvial corridor. During the last few years subject to investigation, there are frequent flood events with little gaps in between, causing the vegetated area to decline in N2. More specifically, in 2018 a flood occurred near Panamik and affected Tirisha village [68], located on the eastern side of reach N1. The stream affected by the flood event joins the Nubra River at the reach N1 and probably caused vegetation erosion.

Floods in the Shyok-Nubra region were reported for 2006, 2010, 2014, and 2015. These events led to significant erosion in specific areas and substantial sediment and debris deposition in others [73]. So, the studied site is probably not influenced much by these short-term (e.g., 11 h duration in 2018) flood events. Similarly, in the Ganga-Bhagirathi River, despite the occurrence of a rainstorm in 2010 and a flood event in 2012, both of which were relatively moderate in intensity, the subsequent period from 2011 to 2014 witnessed a comparatively low meltwater runoff. This hydrological activity created favorable conditions for the substantial increase in vegetation on exposed sediments. In a recent study conducted by Swarnkar [74], findings indicate a notable reduction of -21.3% in post-1995 extreme flows at various return periods within the Ganga-Bhagirathi basin.

The results of our study indicate that, at least in the glacier-fed rivers investigated here, it is not possible to delineate a single evolutionary trajectory associated with the recent deglaciation dynamics that occurred in the Himalayas-Karakorum, in contrast to our expectations based on existing conceptual models proposed for proglacial streams [75]. Such evidence calls for the need to monitor such river systems at a higher temporal resolution (currently limited by the availability of cloud- and snow-free satellite images), as well as at higher spatial resolution for the narrower rivers. However, besides the remote sensing-based monitoring of future morphological changes, the implementation of standard hydrometric monitoring in the upper reaches of such rivers—ideally integrated by a sediment transport monitoring scheme where possible—would provide essential information to relate the future fluvial changes to the hydro-sedimentary forcings generated by each river basin.

4.3. Limitations

The availability of data poses a significant challenge, encompassing not only high-resolution satellite images but also hydro-meteorological data. Regarding historical satellite imagery, a notable obstacle is the absence of a comprehensive overview of image archives, particularly concerning their spatial and temporal coverage when undertaking a long-term analysis of past changes. Moreover, numerous archives housing high-resolution images are not freely accessible. The 30 m resolution of LS5 images proves inadequate for studying narrow glacier-dominated rivers within complex topographies categorized by steep gradients, deep valleys and dynamic glacial landscapes causing complex hydrological interactions. The S2 imagery lacks continuous coverage of the Himalayan region before 2019. Between 2000 and 2016, other satellite sources utilized are prohibitively expensive and offer limited coverage. In certain instances, the necessity arose to merge images from different dates to achieve complete coverage of the river-corridor area. For instance, the Langtang-Khola image of 2011 was assembled by combining WV2 images from September and October. Similarly, the IKONOS 2003 image is a composite of images from October

and November. Two of the three glacier-dominated rivers, namely the Nubra River in the disputed territory of Jammu and Kashmir (controlled by India) and the Ganga-Bhagirathi River in India, have highly confidential hydrological data. Notably, due to variations in spectral, temporal, and radiometric resolutions across different satellite sources, a single classification model proved insufficient for the classification of all 13 images, necessitating the development of distinct training datasets for various supervised classification models.

Concerning the intervals between acquisition dates of satellite imageries, the research work aligns with standard practices for the long-term morphological change analysis in the fluvial systems, where temporal coverage provides critical understandings into the aggregate impact of glacier retreat and hydrological dynamics [76]. The 4–5-year gap between satellite image acquisition was followed to analyze significant morphological adjustments, which is seemingly obvious over a multi-annual timeframe in such critical environments. Furthermore, considering the harsh glacier-dominated climatic conditions and limited vegetation growth in such zones, seasonal effects on vegetation detection and river morphology are supposed to be negligible [77]. The fact that the imageries used for the multitemporal analysis feature varying time intervals is quite a common issue in fluvial morphological studies. Evolutionary trajectories based on few “snapshots” in time are surely less informative compared to those built with frequent (in the order of few years) images, especially because the effects of single flood events cannot be reliably discerned, as it is for our study. However, the aim of this work was to identify the possible changes in river corridors occurring in response to the most recent deglaciation phase, and we were thus constrained to use the only available imageries covering these recent time scales, which included those we used in our analysis, to provide the necessary insights.

Using separate models for each satellite source to confirm valid image classification is both reliable and crucial because of the different competencies and resolutions of various sources. The major limitation of employing multiple sources in a single study is in making it challenging to intercompare results. The unique properties of each source can introduce irregularity in the data that can affect the uniformity of results. According to the experimental investigation, single models with specified instructions for using consistent spectral bands (green and near-infrared) and sampling datasets from all satellite image sources, gives a direct error without giving any classified or misclassified resultant images, because of varying frequency range even within the same bands. To alleviate this issue, careful calibration and validation processes were executed, making sure that the models account for these variations and standardize the data proficiently. Regardless of the challenges, the combination of high spatial resolution (IKONOS, QB-2 and WV-2) with wide-ranging temporal coverage (LS-5) improves the overall analysis, permitting more comprehensive and nuanced interpretations of the study area. In conclusion, despite these complexities, the rigorous methodological framework used confirms that the data is comparable and the results are reliable.

5. Conclusions

Our study explored, for the first time, the temporal variations in morphological macro-units (base-flow channels, emerged sediments and vegetated areas) within the fluvial corridors of three Himalayan glacier-dominated rivers through the application of remote sensing methods applied to time series of images from multiple satellite sources. The principal findings of our work are the following: (i) the most significant morphological changes (in terms of vegetation vs. active channel areas) took place in the very wide and highly braided Nubra River, whereas the relatively narrow Langtang-Khola River showed the most limited variations. Intermediate magnitudes of changes occurred in the Ganga-Baghirati River, and (ii) channel narrowing and expansion (i.e., vegetation expansion and

contraction) are not related in a simple manner to meltwater runoff trends and/or the occurrence of flood events. Although a link between higher runoff and vegetation erosion is apparent—at least for the Nubra and the Ganga rivers—it seems that massive sediment input from hillslopes (from the 2019 rock avalanche in the Langtang-Khola river basin) as well as single years of exceptionally high meltwater runoff might impact vegetation erosion, as previously observed by other studies. In conclusion, this research underscores the critical importance of examining both structural and functional connectivity in sediment transport to comprehensively grasp the complex vegetation dynamics in highly dynamic environments such as glacier-dominated rivers, as well as the extreme value of satellite-based monitoring of such processes in remote areas like the Himalayan Rivers. The discernible influence of climatic and hydrological anomalies on morphological changes in these regions emphasizes the significance of continued studies in understanding and managing these environments.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18040556/s1>, Table S1: Reach-scale confusion matrix of Nubra River with three morphological macro-unit classes (number in metrics are pixels of validation datasets); vegetated surface (veg), base-flow channels (water), and emerged sediment units (sed) for the years 1989–2020; Table S2: Reach-scale confusion matrix of Ganga-Bhagirathi and Langtang-Khola River with three morphological macro-unit classes (number in metrics are pixels of validation datasets); vegetated surface (veg), base-flow channels (water), and emerged sediment units (sed) for the years 2003–2020; Table S3: Model-based confusion matrix of Nubra, Ganga-Bhagirathi and Langtang-Khola River with three morphological macro-unit classes (number in metrics are pixels of validation datasets); vegetated surface (veg), base-flow channels (water), and emerged sediment units (sed) for the years 1989–2020.

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Data Availability Statement: GEE code is available at “GitHub—ZarkaMukhtar/Classification-Modeling-of-Himalayan-Proglacial-Rivers”, and the raw data supporting the conclusions of this article will be made available by the authors upon request.

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References

1. Yao, J.; Chen, Y.; Guan, X.; Zhao, Y.; Chen, J.; Mao, W. Recent climate and hydrological changes in a mountain–basin system in Xinjiang, China. *Earth-Sci. Rev.* **2022**, *226*, 103957. [CrossRef]
2. Pepin, N.C.; Arnone, E.; Gobiet, A.; Haslinger, K.; Kotlarski, S.; Notarnicola, C.; Palazzi, E.; Seibert, P.; Serafin, S.; Schöner, W.; et al. Climate changes and their elevational patterns in the mountains of the world. *Rev. Geophys.* **2022**, *60*, e2020RG000730. [CrossRef]
3. Rasouli, K.; Pomeroy, J.W.; Janowicz, J.R.; Carey, S.K.; Williams, T.J. Hydrological sensitivity of a northern mountain basin to climate change. *Hydrol. Process.* **2014**, *28*, 4191–4208. [CrossRef]
4. Doyle, S.H.; Hubbard, A.; van de Wal, R.S.W.; Box, J.E.; van As, D.; Scharrer, K.; Meierbachtol, T.W.; Smeets, P.C.J.P.; Harper, J.T.; Johansson, E.; et al. Amplified melt and flow of the Greenland ice sheet driven by late-summer cyclonic rainfall. *Nat. Geosci.* **2015**, *8*, 647–653. [CrossRef]
5. IPCC. *Summary for Policymakers. In Climate Change and Land: An IPCC Special Report*; IPCC: Geneva, Switzerland, 2019. Available online: <https://www.ipcc.ch/srccl/chapter/summary-for-policymakers/> (accessed on 12 January 2025).
6. Shannon, S.; Smith, R.; Wiltshire, A.; Payne, T.; Huss, M.; Betts, R.; Caesar, J.; Koutroulis, A.; Jones, D.; Harrison, S. Global glacier volume projections under high-end climate change scenarios. *Cryosphere* **2019**, *13*, 325–350. [CrossRef]

7. Carrivick, J.; Heckmann, T.; Fischer, M.; Davies, B. An inventory of proglacial systems in Austria, Switzerland and across Patagonia. In *Geomorphology of Proglacial Systems: Landform and Sediment Dynamics in Recently Deglaciated Alpine Landscapes*; Heckmann, T., Morche, D., Eds.; Springer International Publishing: Cham, Switzerland, 2019; pp. 43–57. [\[CrossRef\]](#)
8. Marren, P.M. Magnitude and frequency in proglacial rivers: A geomorphological and sedimentological perspective. *Earth-Sci. Rev.* **2005**, *70*, 203–251. [\[CrossRef\]](#)
9. Gumiero, B.; Rinaldi, M.; Belletti, B.; Lenzi, D.; Puppi, G. Riparian vegetation as indicator of channel adjustments and environmental conditions: The case of the Panaro River (Northern Italy). *Aquat. Sci.* **2015**, *77*, 563–582. [\[CrossRef\]](#)
10. Ruiz-Villanueva, V.; Piégay, H.; Scorpio, V.; Bachmann, A.; Brousse, G.; Cavalli, M.; Comiti, F.; Crema, S.; Fernández, E.; Furdada, G.; et al. River widening in mountain and foothill areas during floods: Insights from a meta-analysis of 51 European rivers. *Sci. Total Environ.* **2023**, *903*, 166103. [\[CrossRef\]](#)
11. Comiti, F.; Da Canal, M.; Surian, N.; Mao, L.; Picco, L.; Lenzi, M.A. Channel adjustments and vegetation cover dynamics in a large gravel-bed river over the last 200 years. *Geomorphology* **2011**, *125*, 147–159. [\[CrossRef\]](#)
12. Marren, P.M.; Toomath, S.C. Channel pattern of proglacial rivers: Topographic forcing due to glacier retreat. *Earth Surf. Process. Landf.* **2014**, *39*, 943–951. [\[CrossRef\]](#)
13. Hickin, E.J. Vegetation and river channel dynamics. *Can. Geogr.* **1984**, *28*, 111–126. [\[CrossRef\]](#)
14. Picco, L.; Comiti, F.; Mao, L.; Tonon, A.; Lenzi, M.A. Medium- and short-term riparian vegetation, island and channel evolution in response to human pressure in a regulated gravel-bed river (Piave River, Italy). *Catena* **2017**, *149*, 760–769. [\[CrossRef\]](#)
15. Krzeminska, D.; Kerkhof, T.; Skaalsveen, K.; Stolte, J. Effect of riparian vegetation on stream bank stability in small agricultural catchments. *Catena* **2019**, *172*, 87–96. [\[CrossRef\]](#)
16. Van de Wiel, M.J.; Darby, S.E. A new model to analyse the impact of woody riparian vegetation on the geotechnical stability of riverbanks. *Earth Surf. Process. Landf.* **2007**, *32*, 2185–2198. [\[CrossRef\]](#)
17. Surian, N.; Barban, M.; Ziliani, L.; Monegato, G.; Bertoldi, W.; Comiti, F. Vegetation turnover in a braided river: Frequency and effectiveness of floods of different magnitude. *Earth Surf. Process. Landf.* **2015**, *40*, 542–558. [\[CrossRef\]](#)
18. Gurnell, A.M.; Bertoldi, W.; Corenblit, D. Changing river channels: The roles of hydrological processes, plants and pioneer fluvial landforms in humid temperate, mixed-load, gravel-bed rivers. *Earth-Sci. Rev.* **2012**, *111*, 129–141. [\[CrossRef\]](#)
19. Gurnell, A.M.; Corenblit, D.; García de Jalón, D.; González del Tánago, M.; Grabowski, R.C.; O'Hare, M.T.; Szewczyk, M. A conceptual model of vegetation–hydrogeomorphology interactions within river corridors. *River Res. Appl.* **2016**, *32*, 142–163. [\[CrossRef\]](#)
20. Camporeale, C.; Perucca, E.; Ridolfi, L.; Gurnell, A.M. Modeling the interactions between river morphodynamics and riparian vegetation. *Rev. Geophys.* **2013**, *51*, 379–414. [\[CrossRef\]](#)
21. Tabacchi, E.; Lambs, L.; Guillo, H.; Planty-Tabacchi, A.-M.; Muller, E.; Décamps, H. Impacts of riparian vegetation on hydrological processes. *Hydrol. Process.* **2000**, *14*, 2959–2976. [\[CrossRef\]](#)
22. Zhou, S.; Zhang, W.; Wang, S.; Zhang, B.; Xu, Q. Spatial–temporal vegetation dynamics and their relationships with climatic, anthropogenic, and hydrological factors in the Amur River Basin. *Remote Sens.* **2021**, *13*, 684. [\[CrossRef\]](#)
23. Russell, A.J.; van Tatenhove, F.G.M.; van de Wal, R.S.W. Effects of ice-front collapse and flood generation on a proglacial river channel near Kangerlussuaq (Søndre Strømfjord), West Greenland. *Hydrol. Process.* **1995**, *9*, 213–226. [\[CrossRef\]](#)
24. Greet, J.; Cousens, R.D.; Webb, J.A. Seasonal timing of inundation affects riparian plant growth and flowering: Implications for riparian vegetation composition. *Plant Ecol.* **2013**, *214*, 87–101. [\[CrossRef\]](#)
25. Bendix, J.; Hupp, C.R. Hydrological and geomorphological impacts on riparian plant communities. *Hydrol. Process.* **2000**, *14*, 2977–2990. [\[CrossRef\]](#)
26. Garssen, A.G.; Baatrup-Pedersen, A.; Voesenek, L.A.C.J.; Verhoeven, J.T.A.; Soons, M.B. Riparian plant community responses to increased flooding: A meta-analysis. *Glob. Change Biol.* **2015**, *21*, 2881–2890. [\[CrossRef\]](#)
27. Milner, A.M.; Gloyne-Phillips, I.T. The role of riparian vegetation and woody debris in the development of macroinvertebrate assemblages in streams. *River Res. Appl.* **2005**, *21*, 403–420. [\[CrossRef\]](#)
28. Piégay, H.; Arnaud, F.; Belletti, B.; Bertrand, M.; Bizzi, S.; Carbonneau, P.; Dufour, S.; Liébault, F.; Ruiz-Villanueva, V.; Slater, L. Remotely sensed rivers in the Anthropocene: State of the art and prospects. *Earth Surf. Process. Landf.* **2020**, *45*, 157–188. [\[CrossRef\]](#)
29. Smith, M.J.; Pain, C.F. Applications of remote sensing in geomorphology. *Prog. Phys. Geogr.* **2009**, *33*, 568–582. [\[CrossRef\]](#)
30. Tamminga, A.D.; Eaton, B.C.; Hugenholtz, C.H. UAS-based remote sensing of fluvial change following an extreme flood event. *Earth Surf. Process. Landf.* **2015**, *40*, 1464–1476. [\[CrossRef\]](#)
31. Henshaw, A.J.; Gurnell, A.M.; Bertoldi, W.; Drake, N.A. An assessment of the degree to which Landsat TM data can support the assessment of fluvial dynamics, as revealed by changes in vegetation extent and channel position along a large river. *Geomorphology* **2013**, *202*, 74–85. [\[CrossRef\]](#)
32. Tobón-Marín, A.; Cañón Barriga, J. Analysis of changes in river planforms using Google Earth Engine. *Int. J. Remote Sens.* **2020**, *41*, 8654–8681. [\[CrossRef\]](#)

33. Boothroyd, R.J.; Nones, M.; Guerrero, M. Deriving planform morphology and vegetation coverage from remote sensing to support river management applications. *Front. Environ. Sci.* **2021**, *9*, 657354. [\[CrossRef\]](#)
34. Boothroyd, R.J.; Williams, R.D.; Hoey, T.B.; Barrett, B.; Prasojo, O.A. Applications of Google Earth Engine in fluvial geomorphology for detecting river channel change. *WIREs Water* **2021**, *8*, e1496. [\[CrossRef\]](#)
35. Pu, G.; Quackenbush, L.J.; Stehman, S.V. Using Google Earth Engine to assess temporal and spatial changes in river geomorphology and riparian vegetation. *JAWRA J. Am. Water Resour. Assoc.* **2021**, *57*, 789–806. [\[CrossRef\]](#)
36. Vercruyse, K.; Grabowski, R.C. Human impact on river planform within the context of multi-timescale river channel dynamics in a Himalayan river system. *Geomorphology* **2021**, *381*, 107659. [\[CrossRef\]](#)
37. Mukhtar, Z.; Bizzi, S.; Comiti, F. Supervised geomorphic mapping of Himalayan rivers based on Sentinel-2 data. *Remote Sens.* **2023**, *15*, 4687. [\[CrossRef\]](#)
38. Zhai, X.; Oliver, A.; Kolesnikov, A.; Beyer, L. S4L: Self-supervised semi-supervised learning. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, Republic of Korea, 27 October–2 November 2019; pp. 1476–1485. [\[CrossRef\]](#)
39. Shorewala, S.; Ashfaq, A.; Sidharth, R.; Verma, U. Weed density and distribution estimation for precision agriculture using semi-supervised learning. *IEEE Access* **2021**, *9*, 27971–27986. [\[CrossRef\]](#)
40. Tooke, T.R.; Coops, N.C.; Goodwin, N.R.; Voogt, J.A. Extracting urban vegetation characteristics using spectral mixture analysis and decision tree classifications. *Remote Sens. Environ.* **2009**, *113*, 398–407. [\[CrossRef\]](#)
41. Yu, H.; Wang, Z.; Zhang, H.; Guo, Y. Water body extraction methods study based on RS and GIS. *Proc. Environ. Sci.* **2011**, *10*, 2619–2624. [\[CrossRef\]](#)
42. Chen, Z.; Liu, X.; Yang, J.; Little, E.; Zhou, Y. Deep learning-based method for SEM image segmentation in mineral characterization: An example from Duvernay Shale samples in the Western Canada Sedimentary Basin. *Comput. Geosci.* **2020**, *138*, 104450. [\[CrossRef\]](#)
43. Camalan, S.; Cui, K.; Pauca, V.P.; Alqahtani, S.; Silman, M.; Chan, R.; Plemmons, R.J.; Dethier, E.N.; Fernandez, L.E.; Lutz, D.A. Change detection of Amazonian alluvial gold mining using deep learning and Sentinel-2 imagery. *Remote Sens.* **2022**, *14*, 1746. [\[CrossRef\]](#)
44. Wieland, M.; Martinis, S. Large-scale surface water change observed by Sentinel-2 during the 2018 drought in Germany. *Int. J. Remote Sens.* **2020**, *41*, 4742–4756. [\[CrossRef\]](#)
45. Azam, M.F.; Wagnon, P.; Berthier, E.; Vincent, C.; Fujita, K.; Kargel, J.S. Review of the status and mass changes of Himalayan–Karakoram glaciers. *J. Glaciol.* **2018**, *64*, 61–74. [\[CrossRef\]](#)
46. Comiti, F.; Mao, L.; Penna, D.; Dell’Agnese, A.; Engel, M.; Rathburn, S.; Cavalli, M. Glacier melt runoff controls bedload transport in Alpine catchments. *Earth Planet. Sci. Lett.* **2019**, *520*, 77–86. [\[CrossRef\]](#)
47. Coviello, V.; Vignoli, G.; Simoni, S.; Bertoldi, W.; Engel, M.; Buter, A.; Cavalli, M. Bedload fluxes in a glacier-fed river at multiple temporal scales. *Water Resour. Res.* **2022**, *58*, e2021WR031873. [\[CrossRef\]](#)
48. Belletti, B.; Rinaldi, M.; Bussettini, M.; Comiti, F.; Gurnell, A.M.; Mao, L.; Nardi, L.; Vezza, P. Characterising physical habitats and fluvial hydromorphology: A new system for the survey and classification of river geomorphic units. *Geomorphology* **2017**, *283*, 143–157. [\[CrossRef\]](#)
49. Pisit, R. Shyok River in Nubra Valley, Ladakh, Jammu and Kashmir, India. Dreamstime. Available online: <https://www.dreamstime.com/stock-photo-shyok-river-nubra-valley-ladakh-jammu-kashmir-india-september-image48758641> (accessed on 12 January 2025).
50. Ganju, A.; Nagar, Y.C.; Sharma, L.N.; Sharma, S.; Juyal, N. Luminescence chronology and climatic implication of the Late Quaternary glaciation in the Nubra Valley, Karakoram Himalaya, India. *Palaeogeogr. Palaeoclimatol. Palaeoecol.* **2018**, *502*, 52–62. [\[CrossRef\]](#)
51. Jain, S.K. Impact of retreat of Gangotri Glacier on the flow of Ganga River. *Curr. Sci.* **2008**, *95*, 1012–1014.
52. Bhambri, R.; Bolch, T.; Chaujar, R.K.; Kulshreshtha, S.C. Glacier changes in the Garhwal Himalaya, India, from 1968 to 2006 based on remote sensing. *J. Glaciol.* **2011**, *57*, 543–556. [\[CrossRef\]](#)
53. Pradhananga, N.S.; Kayastha, R.B.; Bhattarai, B.C.; Adhikari, T.R.; Pradhan, S.C.; Devkota, L.P.; Shrestha, A.B.; Mool, P.K. Estimation of discharge from Langtang River basin, Rasuwa, Nepal, using a glacio-hydrological model. *Ann. Glaciol.* **2014**, *55*, 223–230. [\[CrossRef\]](#)
54. Wijngaard, R.R.; Steiner, J.F.; Kraaijenbrink, P.D.A.; Klug, C.; Adhikari, S.; Banerjee, A.; Pellicciotti, F.; van Beek, L.P.H.; Bierkens, M.F.P.; Lutz, A.F.; et al. Modeling the response of the Langtang Glacier and the Hintereisferner to a changing climate since the Little Ice Age. *Front. Earth Sci.* **2019**, *7*, 143. [\[CrossRef\]](#)
55. Shiraiwa, T.; Yamada, T. Glacier inventory in the Langtang Valley, Nepal Himalayas. *Low Temp. Sci. Ser. A Data Rep.* **1991**, *50*, 47–72.

56. Adhikari, T.R. Impact of Climate Change on Flow Regime in Himalayan Basins, Nepal. Doctoral Dissertation, Faculty of Hydrology, Tribhuvan University, Kathmandu, Nepal, 2014. Available online: <https://elibrary.tucl.edu.np/handle/123456789/15236> (accessed on 13 January 2025).
57. RGI Consortium. *Randolph Glacier Inventory—A Dataset of Global Glacier Outlines (Version 7)*; NASA National Snow and Ice Data Center Distributed Active Archive Center: Boulder, CO, USA, 2023. [\[CrossRef\]](#)
58. Negi, H.S.; Gusain, H.S.; Dhahiya, T.; Kumar, A. Hydrological mass balance study of Siachen Glacier, East Karakoram. *J. Earth Syst. Sci.* **2022**, *131*, 33. [\[CrossRef\]](#)
59. Salim, M.; Pandey, A.C. Estimation of temporal snowmelt runoff using geospatial technique in Gangotri Glacier Basin, Uttarakhand, India. *Remote Sens. Appl. Soc. Environ.* **2021**, *24*, 100660. [\[CrossRef\]](#)
60. Kumar, K.; Miral, M.S.; Joshi, V.; Panda, Y.S. Discharge and suspended sediment in the meltwater of Gangotri Glacier, Garhwal Himalaya, India. *Hydrol. Sci. J.* **2002**, *47*, 611–619. [\[CrossRef\]](#)
61. Yao, R.; Shi, J. Precipitation differences cause contrast patterns of glacier-meltwater-supplied discharge of two glacier basins between northern and southern Third Pole. *Sci. Bull.* **2019**, *64*, 431–434. [\[CrossRef\]](#)
62. Thapa, A.; Silwal, A.; Sharma, P.; Gautam, S.; Nepal, C.; Bhattarai, S.; Timsina, D. Surface air temperature trends in Kathmandu Valley for 2011–2017. *Bibechana* **2021**, *18*, 95–104. [\[CrossRef\]](#)
63. Khanal, S.; Thakuri, S.; Dhakal, M.; Sharma, S.; Wagle, L. *Proceedings of Research Seminar on Climate Change*; Tribhuvan University: Kathmandu, Nepal, 2019.
64. Rwanga, S.S.; Ndambuki, J.M. Accuracy assessment of land use/land cover classification using remote sensing and GIS. *Int. J. Geosci.* **2017**, *8*, 611–622. [\[CrossRef\]](#)
65. Atta-ur-Rahman; Khan, A.N. Analysis of 2010 flood causes, nature and magnitude in the Khyber Pakhtunkhwa, Pakistan. *Nat. Hazards* **2013**, *66*, 887–904. [\[CrossRef\]](#)
66. Siddiqui, M.J.; Haider, S.; Gabriel, H.F.; Shahzad, A. Rainfall–runoff, flood inundation and sensitivity analysis of the 2014 Pakistan flood in the Jhelum and Chenab River Basin. *Hydrol. Sci. J.* **2018**, *63*, 1976–1997. [\[CrossRef\]](#)
67. Hashmi, H.N.; Siddiqui, Q.T.M.; Ghumman, A.R.; Kamal, M.A.; Mughal, H.u.R. A critical analysis of 2010 floods in Pakistan. *Afr. J. Agric. Res.* **2012**, *7*, 1054–1067. [\[CrossRef\]](#)
68. Thayyen, R.J.; Singh, M.K.; Dimri, A.P. Visual evidence of constrained area of a cloudburst, 12 June 2018, Tirisha Village, Nubra Valley, Ladakh, India. *J. Clim. Change* **2020**, *6*, 47–57. [\[CrossRef\]](#)
69. ReliefWeb. India: Floods—June 2012 (FL-2012-000110-IND). ReliefWeb, 2012. Available online: <https://reliefweb.int/disaster/fl-2012-000110-ind> (accessed on 15 January 2025).
70. He, Y.; Yao, S.; Yang, W.; Yan, H.; Zhang, L.; Wen, Z.; Zhang, Y.; Liu, T. An extraction method for glacial lakes based on Landsat-8 imagery using an improved U-Net network. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2021**, *14*, 6486–6498. [\[CrossRef\]](#)
71. Bozzolan, E.; Brenna, A.; Surian, N.; Carbonneau, P.; Bizzi, S. Quantifying the impact of spatiotemporal resolution on the interpretation of fluvial geomorphic feature dynamics from Sentinel-2 imagery. *Water Resour. Res.* **2023**, *59*, e2023WR034699. [\[CrossRef\]](#)
72. Gurnell, A.M.; Petts, G.E. Trees as riparian engineers: The Tagliamento River, Italy. *Earth Surf. Process. Landf.* **2006**, *31*, 1558–1574. [\[CrossRef\]](#)
73. Hakhoo, N.; Bhat, G.M.; Pandita, S.; Hussain, G.; Haq, A.U.; Hafiz, M.; Ahmed, W.; Singh, Y.; Thusu, B. Natural hazards—Their drivers, mechanisms and impacts in the Shyok–Nubra Valley, NW Himalaya, India. *Int. J. Disaster Risk Reduct.* **2019**, *35*, 101094. [\[CrossRef\]](#)
74. Swarnkar, S.; Mujumdar, P.; Sinha, R. Modified hydrologic regime of upper Ganga Basin induced by natural and anthropogenic stressors. *Sci. Rep.* **2021**, *11*, 19827. [\[CrossRef\]](#)
75. Gurnell, A.M.; Edwards, P.J.; Petts, G.E.; Ward, J.V. A conceptual model for alpine proglacial river channel evolution under changing climatic conditions. *Catena* **1999**, *38*, 223–242. [\[CrossRef\]](#)
76. Ye, Q.; Wang, Y.; Liu, L.; Guo, L.; Zhang, X.; Dai, L.; Zhai, L.; Hu, Y.; Ali, N.; Ji, X.; et al. Remote sensing and modeling of the cryosphere in High Mountain Asia: A multidisciplinary review. *Remote Sens.* **2024**, *16*, 1709. [\[CrossRef\]](#)
77. Kääb, A.; Huggel, C.; Fischer, L.; Guex, S.; Paul, F.; Roer, I.; Salzmann, N.; Schläefli, S.; Schmutz, K.; Schneider, D.; et al. Remote sensing of glacier- and permafrost-related hazards in high mountains: An overview. *Nat. Hazards Earth Syst. Sci.* **2005**, *5*, 527–554. [\[CrossRef\]](#)

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