

Snow/Glacier Dynamics of Himalayan Ranges and Associated Hazards

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by

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Under the supervision of

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***Dedicated to the almighty, parents, teachers and my late
grandfather:***

Shri Mathan Chandra Mandal

I owe it all to you.

Many thanks for the endless love, support and encouragement!



भारतीय प्रौद्योगिकी संस्थान गुवाहाटी
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Declaration

I certify that

- The work contained in this thesis is original and has been done by myself and under the general supervision of my supervisor.
- The work reported herein has not been submitted to any other institute for any degree or diploma.
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Date: 12-05-2023

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CERTIFICATE

This is to certify that this thesis entitled “**Snow/glacier Dynamics of Himalayan Ranges and Associated Hazards**” submitted by **Sandeep Kumar Mondal (Roll No. 186104101)**, in the partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy, to the Indian Institute of Technology Guwahati, Assam, India, is a record of the bonafide research work carried out by him under my guidance and supervision at the Department of Civil Engineering, Indian Institute of Technology Guwahati, Assam, India. To the best of my knowledge, no part of the work reported in this thesis has been presented for the award of any degree at any other institution.

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SANDEEP KUMAR MONDAL



Abstract

The Himalayan cryosphere, also termed “the Third Pole,” acts as a natural storehouse to several mega river systems, such as the Ganges, Indus, and Brahmaputra, serving billions of people with fresh water. However, the high mountain ranges of the Himalayas are also susceptible to various categories of hazards, such as snow/rock-ice avalanches, landslides, earthquakes, and glacial lake outburst floods (GLOFs). The present study attempts to perform a series of investigations to understand better the dynamics of snow/glaciers in the Himalayan region and their contribution to perennial river streams. It also includes studying the major types of Himalayan hazards that have occurred in the recent past.

Satellite remote sensing has been used to study the spatio-temporal variations in the snow cover of the Sikkim Himalayas. An integrated approach of multivariate statistics and band ratio between 1989 and 2019 at an interval of 2-4 years helped capture the effective snow coverage. The intra-annual effective snow cover change has been observed to correlate inversely with the Extended Reconstructed Sea Surface Temperature (ERSST.v5) in Niño 3.4 region. The snow line altitude (SLA) has been observed to have a two-fold periodicity in the last 30 years.

Studying the composition of stable isotopes ($\delta^{18}\text{O}$ and δD) within the primary sources of the Teesta and Rathong river systems helped in understanding the spatio-temporal variability in the isotopic composition of water and moisture sources. A deterministic Monte Carlo-based three-endmember $\delta^{18}\text{O}$ -d-excess mixing model helped quantify the source endmembers' contribution to the river streams and waterfalls. Another Monte Carlo-based four-endmember strontium (Sr) model helped segregate the contribution of dissolved Sr flux from different lithologies. Moreover, an investigation of two natural thermal springs at North Sikkim showed arsenic contamination in one of the thermal spring samples indicating an isolated geothermal aquifer with an arsenic source near the Changme glacier.

An investigation conducted for the Shisper glacial lake outburst on 7th May 2022 revealed various factors such as glacial mass balance, reduced snow cover, and abnormal hike in the land surface temperature resulting in rapid glacial melt and breach of an ice-dammed glacial lake. The after-effects of the event were studied in terms of changing water quality and land cover along the stream using optical and SAR datasets. Another investigation conducted to capture the impacts of the MW5.7 earthquake on 20th March 2020 around Lake Dingmu in

Tibet showed reduced co-seismic coherence around the lake periphery through Sentinel-1 Radar datasets corroborating with the increased soil moisture captured through temporal difference liquefaction index (TDLI). An extensive study was conducted over glacial lakes in the Sikkim Himalaya using remote sensing, analytical methods, field-and lab-based analysis. The analytical hierarchy process (AHP) based assessment showed 7 lakes in Sikkim, 3 lakes in Nepal, and 3 in China as highly vulnerable to future outburst floods. Moreover, three backpropagation multilayer perceptron neural network (BPMLPNN) models showed good prediction accuracies with AHP-based target scores. Further, field-based geophysical techniques such as multichannel analysis of surface waves (MASW) and ground penetrating radar (GPR) were performed to understand the subsurface properties of soil and glaciofluvial deposits in the high-altitude Sikkim Himalayas. This was followed by the geotechnical and mineralogical analysis of glacial moraine and lacustrine deposits near the snout of Changme and Rathong glaciers in North and West Sikkim, respectively.

In the process of investigating episodes of Himalayan avalanches, the Chamoli disaster of 7th Feb 2021 was investigated for the triggering mechanism where prolonged glacial mobility was seen as a possible factor behind the formation of a prismatic wedge structure over the north-eastern slope of the Trisul mountain resulting in devastation along the Rishiganga-Dhauliganga valley, Uttarakhand. Kinematic analysis and numerical modeling explained the failure as stress-controlled. Another attempt was made to identify the activation zones of snow avalanches that occurred on 17th Jan 2020 around some of the major peaks of the Annapurna mountain range using C-band Sentinel 1 synthetic aperture radar (SAR) datasets and ALOS PALSAR digital elevation model (DEM).

Where the Himalayan region experiences frequent earthquakes, the remotely located glaciers remain isolated in terms of studying seismic impacts. Therefore, it was attempted to understand the impact of earthquakes on and around Himalayan glaciers using C band SAR datasets of Sentinel 1. Eight earthquake events of various magnitudes and hypocenter depths having their source in the vicinity of Himalayan glacial bodies were analyzed using Sentinel-1 datasets which showed vertical deformation within and around glacial bodies along with changes in the glacial moraine deposits as captured through a reduction in co-seismic coherence responses.

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List of Symbols

<u>Symbols</u>	<u>Description</u>
g	Acceleration due to gravity
O_m	ANN Output
V_{annual}	Annual glacial mobility
w	Atmospheric water vapour
σ^0	Backscatter intensity
σ	Boltzmann constant
C_v	Coefficient of variation
$\gamma_{complex}$	Complex coherence
b^*	Complex conjugate
A	Creep coefficient
ψ	Decorrelation/coherence
ρ	Density
Q_{cal}	Digital number
ζ	Effective parameters to minimize error function in BR-BPMLPNN model
ε	Emissivity
e	Epoch
z	Error vector
$D_{euclidean}$	Euclidean displacement
X	Expectation operator
V_b	Glacial velocity at the base
n	Glen's flow law exponent
H_{ij}	Hidden layer
IR	Influence radius of earthquake
δ	Isotopic composition value in per mil
J	Jacobi matrix
η	Learning parameter
ζ	Learning rate in GDX-BPMLPNN model
$\bar{c}$	Mean phase velocity
M_w	Moment Magnitude of earthquake
Ω	Momentum Coefficient in GDX-BPMLPNN model
μ	Momentum parameter
V_s	NEHRP shear wave velocity
$\tilde{o}$	Network output
γ_i	Performance weighted ratio
h	Planck's constant
α, β	Regularization parameters
λ_{SAR}	SAR wavelength
f	Shape factor
$V_{s(30)}$	Shear wave velocity at 30m depth
s_c	Standard deviation
ρ_{Band}	Surface reflectance
Θ	Surface slope

K	Thermal constant
L_λ	TOA spectral radiance
$\phi_{unwrapped}$	Unwrapped phase
c	Velocity of electromagnetic radiation
$z_{vertical}$	Vertical displacement
λ	Wavelength
w_{ij}^n	Weight assigned to neuron (n)
k	Weight vector
a, b	Zero mean circular Gaussian variables



List of Abbreviations

<u>Abbreviation</u>	<u>Description</u>
AAR	Accumulation Area Ratio
AGC	Automatic Gain Control
AHP	Analytical Hierarchy Process
ALOS	Advanced Land Observing Satellite
AMSR-E	Advanced Microwave Scanning Radiometer – Earth Observing System
AOT	Aerosol Optical Thickness
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BH	Bounce Height
BoB	Bay of Bengal
BPMLPNN	Backpropagation Multilayer Perceptron Neural Network
BR	Bayesian Regularization
BSP	Bishop Simplified Method
BT	Brightness Temperature
CCD	Charged Couple Device
CFSIRMS	Continuous-Flow Stable Isotope-Ratio Mass Spectrometer
CIF	Central Instrument Facility
CL	Changme Lacustrine
CM	Changme moraine
CoV	Coefficients of Variation
CPT	Cone Penetration Test
CR	Consistency Ratio
DAS	Data Acquisition System
DEM	Digital Elevation Model
DHSVM	Distributed Hydrology Soil and Vegetation Model
DIIRMS	Dual Inlet Stable Isotope-Ratio Mass Spectrometer
DInSAR	Differential SAR Interferometry
DN	Digital Number
DST	Direct Shear Test
EB	Energy Balance
EBM	Energy Balance Model
EC	Electrical Conductivity
EDX	Energy Dispersive X-ray
ELA	Equilibrium Line Altitude
EM	Electromagnetic
ENSO	El Niño/Southern Oscillation
ESA	European Space Agency
ESD	Enhanced Spectral Diversity
FCC	False Color Composite
FEM	Finite Element Method
FESEM	Field Emission Scanning Electron Microscopy
FFT	Fast Fourier Transformation
FIR	Finite Impulse Response

FOS	Factor Of Safety
FVC	Fractional Vegetation Cover
GACOS	Generic Atmospheric Correction Online Service
GCM	General Circulation Model
GCP	Ground Control Point
GDX	Gradient Descent Algorithm
GLOF	Glacial Lake Outburst Flood
GMWL	Global Meteoric Water Line
GNIP	Global Network of Isotopes in Precipitation
GNIR	Global Network of Isotopes in Rivers
GPR	Ground Penetrating Radar
GRD	Ground Range Detection
GSD	Ground Sampling Distance
GSSI	Geophysical Survey System instruments
HDPE	High-Density Polyethylene
HFT	Himalayan Frontal Thrust
HS	Hot Spring
IAEA	International Atomic Energy Agency
ICA	Independent Component Analysis
ICDD	International Center for Diffraction Data
ICIMOD	International Centre for Integrated Mountain Development
ICP-MS	Inductively Coupled Plasma Mass Spectrometry
IDW	Inverse Distance Weighted
IIR	Infinite Impulse Response
IPCC	Intergovernmental Panel on Climate Change
IRS	Indian Remote Sensing Satellite
IS	Indian Standard
ISM	Indian summer monsoon
ITCZ	Intertropical Convergence Zone
ITD	Iterative Tropospheric Decomposition
IUAC	Inter-University Accelerator Centre
IW	Interferometric Wide
LEM	Limit Equilibrium Method
LL	liquid limit
LM	Levenberg-Marquardt
LPA	Long-Period Average
LSE	Land Surface Emissivity
LST	Land Surface Temperature
LSU	Linear Spectral Unmixing
MASW	Multichannel Analysis of Surface Waves
MBT	Main Boundary Thrust
MCT	Main Central Thrust
MDD	Maximum Dry Density
MDM	Minimum Distance to Mean
ML	Maximum Likelihood
MODIS	Moderate Resolution Imaging Spectroradiometer
MSE	Mean-Square of Error

MSI	Multispectral Instrument
MSL	Mean Sea Level
MTMF	Mixed Tuned Matched Filtering
Mw	Moment Magnitude
NDCI	Normalized Difference Chlorophyll Index
NDFS	Normalized Difference Forest Snow Index
NDPCSI	Normalized Difference Principal Component Snow Index
NDSI	Normalized Difference Snow Index
NDTI	Normalized Difference Turbidity Index
NDVI	Normalised Difference Vegetation Index
NDWI	Normalized Difference Water Index
NED	National Elevation Dataset
NEHRP	National Earthquake Hazards Reduction Program
NIR	Near-infrared
NMAT	Nighttime Marine Air Temperature
OBIA	Object-Based Image Analysis
OLI	Operational Land Imager
OMC	Optimum Moisture Content
PALSAR	Phased Array type L-band Synthetic Aperture Radar
PCA	Principal Component Analysis
PCM	Pairwise Comparison Matrix
PDGL	Potentially Dangerous Glacial Lake
PEM	Point Estimate Method
PF	Probability of Failure
PL	Plastic Limit
POD	Precise Orbit Determination
RDTC	Range Doppler Terrain Correction
RGB	Red, Green, Blue
RGI	Randolph Glacial Inventory
RL	Rathong Lacustrine
RM	Rathong Moraine
RMESMA	Relative Multiple Endmember Spectral Mixture Analysis
RMSA	Relative Spectral Mixture Analysis
SAM	Spectral Angle Mapper
SAR	Synthetic Aperture Radar
SCA	Snow Cover Area
SCF	Snow Cover Fraction
SFF	Spectral Feature Fitting
SL	Shrinkage Limit
SLC	Single Look Complex
SNAP	Sentinel Application Platform
SNAPHU	Statistical-cost, Network-flow Algorithm for Phase Unwrapping
SNR	Signal-to-Noise Ratio
SP	Poorly Graded Sand
SPT	Standard Penetration Test
SRF	Strength Reduction Factor
SRM	Snowmelt Runoff estimation Model

SRTM	Shuttle Radar Topography Mission
SSM/I	Special Sensor Microwave/Image
SSR	Shear Strength Reduction
SST	Sea Surface Temperature
STD	South Tibetan Detachment
SW	Split-Window
SWIR	Shortwave-infrared
TDLI	Temporal Difference Liquefaction Index
TIM	Temperature Index Model
TIROS	Television and Infrared Observation Satellite
TIRS	Thermal Infrared Sensor
TKE	Total Kinetic Energy
TL	Trans-boundary Lake
TM	Thematic Mapper
TNR	Thermal Noise Removal
TOA	Top of the Atmosphere
TOPS	Terrain Observations with Progressive Scans
TV	Translational Velocity
UCT	Uniaxial Compressive Test
UEB	Utah Energy Balance
USGS	United States Geological Survey
VIRR	Visible and Infrared Radiometer
VSMOW	Vienna standard mean ocean water
VST	Vane Shear Test
VT	Vaikrita Thrust
WHO	World Health Organization
XRD	X-ray Powder Diffraction
ZTD	Zenith Total Delay

1.1 Background

Mountains are considered sensitive ecosystems to anthropogenic disturbances and environmental perturbations (Negi et al., 2019; Shrestha et al., 2013, 2019). Among various mountain ranges around the globe, the Himalayan ranges are identified as Asia's most populated, highest, and largest mountain systems (Sharma et al., 2017; Rawal et al., 2021). The mega river systems such as the Brahmaputra, Ganges, and Indus gain their runoff regime from the Himalayan glaciers (Immerzeel et al., 2010). Evidence gathered from enormous past studies revealed that the Himalayan ranges come under the category of very few regions where the effects of the changing climate are quite evident (Negi et al., 2022; Shrestha and Shrestha, 2019). Between 1906 and 2005, a hike in the global temperature has been observed by 0.74°C, more than half of which has occurred in the past three decades (IPCC, 2007; Negi et al., 2022). This directly or indirectly impacts the high-altitude glacial bodies (Adler et al., 2019; Drenkhan et al., 2019). Glaciers and their contribution to the perennial river systems affect the lives of 1.9 billion people downstream (Zemp et al., 2019). However, this also makes the Himalayan landscape highly susceptible to anthropogenic disturbances (Devkota et al., 2017; Mayewski et al., 2020). Another threat is the changing climate that substantially impacts the melting scenarios of snow and glacier, thus influencing their contribution to river flow. Several researches have reported enhanced receding rates of Himalayan glaciers that exceed the world average (Farinotti et al., 2019). The enhanced melting of snow and glaciers not only impacts water availability in lowlands but also introduces the risk of glacial hazards.

Researchers around the globe paid more attention to the Himalayan glaciers after a small typographic error in the 4th assessment report of the Intergovernmental Panel on Climate Change (IPCC) indicated an alarming loss of glaciers in this area by 2035 (Cogley et al., 2010). However, this was later retracted for corrections by IPCC (Vaughan et al., 2013), and an extensive review presented the knowledge and research gaps in the Himalaya-Karakoram glaciology (Bolch et al., 2012). Weather station data implies that Karakoram has experienced less warming in recent years than other parts of the Himalayan Range (Shekhar et al., 2010).

Also, the famous ‘Karakoram Anomaly’ (Hewitt, 2005; Kääb et al., 2012) explains the presence of advancing or stable glaciers mainly around the western Kunlun Shan region (Kääb et al., 2015) as compared to other receding glaciers worldwide (Zemp et al., 2015).

1.2 Motivation

Glaciers are the major component of the cryosphere, defined as huge chunks of metamorphosed ice and firn. They are often called “rivers of ice” due to their dynamic nature of slow, steady movement over the land surface. In the 1950s, several researchers attempted to study the glacial dynamics and the law behind the flow of glaciers (Glen, 1952; Steinemann, 1958). One such law is Glen’s flow law (Glen, 1952), a generalized Newtonian model associated with power-law viscosity. This law is widely used in modeling glacial flow at any temporal and spatial scale. However, the capability of Glen’s law is restricted to predicting a stationary stress vs strain rate relation at a minimal creep rate. On the other hand, numerous studies (Jellinek and Brill, 1956; Jacka, 1994) reveal the non-stationary creep of ice through lab experiments. Researchers attempted to justify the transition creep observed in the lab experiments on polycrystalline ice using viscoelastic constitutive relations and relating stress, strain, strain rates, and time in multiple ways (Sinha, 1978; Le Gac and Duval, 1980). Sinha (1978) used time-dependent non-linear constitutive equations to explain the creep behavior of ice when a constant compression load is applied. Morland and Spring (1981) described the viscoelastic behavior of polycrystalline ice using constitutive equations relating stress/stress rates to strain rates and accelerations. Szyszkowski and Glockner (1985) proposed a viscoelastic (based on dash-pot and spring elements) non-linear and uniaxial model describing three different creep stages (primary, secondary and tertiary) of ice. McTigue et al. (1985) used an incompressible fluid (grade-II) model for the first time in the field of ice mechanics and creep experiments which was later modified using power law viscosity by Man and Sun (1987). Azizi (1989) described polycrystalline ice's non-linear power law behavior during the primary creep stage. Shyam-Sunder and Wu (1990) used a differential flow model, comparing it with the models proposed by Sinha (1978) and Le Gac and Duval (1980). Meyssonier and Goubert (1994) provided a rheological model based on the viscoelastic strain of polycrystalline ice and proposed modifications to the models of Le Gac and Duval (1980) as well as Shyam-Sunder and Wu (1989).

Glacial dynamics and its mechanism depend on several factors, including local meteorology, seasonal variations, topography, drainage, melting, etc. Reeh et al. (2003) used

viscoelastic beam theory to propose the ice creep and tidal deflection of the Nioghalvfjærdsfjorden glacier in Greenland. Sugiyama et al. (2008) observed a reversal of flow and displacement direction of the Gornergletscher glacier in Switzerland. The retrograde glacial mobility was anticipated to be due to the redistribution of stress due to the rapid drainage of a supraglacial lake, thus leading to the viscoelastic recovery of ice. Later, Riesen et al. (2010) proposed a constitutive model for predicting instantaneous (elastic) deformation and recoverable transient strain when glacial ice is subjected to (lake formation) as well as removal (drainage from lake) of external load.

Glacial hazards can be defined as specific processes related to glaciers that impart adverse effects directly or indirectly on human lives and activities (Qin, 2018). These include avalanches, glacial surges, glacial lake outburst floods (GLOFs), glacial collapse, and debris flow (Richardson and Reynolds, 2000). Glacial recession in the Himalayan terrain led to forming several glacial lakes with high prospective risk due to GLOF (Nie et al., 2013). Himalayas have evidenced GLOF events of varying degrees of severity once every three to ten years (Bajracharya et al., 2007). Especially the Hindu Kush-Karakoram-Himalayan region has witnessed numerous outbursts/flash floods in recent decades (Wester et al., 2019). Out of these unfortunate incidents, most of the GLOFs occurred in the Gilgit-Baltistan region of Karakoram especially due to severe rainfall, abrupt hike in temperature, and heatwaves (Ashraf et al., 2021). Some of the recent incidents include the 2007 and 2008 GLOF on Passu glacier (Ashraf et al., 2014), the 2013 GLOF in Reshun valley (Riaz et al., 2014), and GLOF events between 2008 and 2017 due to the sudden breach of the supraglacial lake on Ghulkin glacier and many more. The Hassanabad basin is another region highly susceptible to outburst floods attributed to the active movement of the Shisper and Muchowar glaciers (Khan et al., 2021). The Hassanabad ravine witnessed five minor GLOF events between 1890 and 1905 (Hewitt and Liu, 2010). Three major GLOF events were recorded in 2019 and 2020 (Muhammad et al., 2021), and the most recent one was on 7th May 2022, respectively. The advantage of remote sensing lies in assessing the impact of a natural disaster such as outburst floods where field-based investigation becomes dangerous. Satellite remote sensing, both optical and microwave, offers a great alternative to extract information about the degradation in water quality. Ritchie et al. (2003) presented the importance of satellite remote sensing in monitoring the spatio-temporal alterations in water quality that are not readily or easily available from in-situ records. The integrated use of optical and SAR datasets proves to be an effective approach to assessing water quality after a major flood event such as the 2021 Chamoli disaster (Meena et al., 2021).

1.3 Aim and Objectives of the Study

Based on the above discussion and considering the research needs with an emphasis on developing an understanding of the Himalayan cryosphere, the aim of this research is outlined as- **Snow/Glacier Dynamics of Himalayan Ranges and Associated Hazards** with the following objectives:

1. To study the snow/glacier dynamics of Sikkim Himalayas.
2. To investigate the hydrological, lithological, and geothermal sources of the Teesta river system, Sikkim Himalayas.
3. To perform a vulnerability assessment of glacial lakes to breach and outburst in and around Sikkim Himalayas.
4. To study the devastating episodes of rock/ice/snow avalanches in the Great Himalayas.
5. To investigate the impact of earthquakes on and around remotely located high-altitude glaciated regions of the Himalayas.

1.4 Organization of the Thesis

The thesis contains eight chapters.

- **Chapter 1** contains a brief overview of the Himalayan cryosphere incorporating the impacts of climate change, glacial dynamics, and natural hazards. The objectives of the study are also mentioned in this chapter.
- **Chapter 2** focuses on understanding relevant literatures on satellite remote sensing-based monitoring and mapping snow/glacier and glacial lakes, estimation of glacial melt to perennial river systems, and a broad spectrum of natural hazards in the high-altitude mountainous regions. Subsequent chapters are equipped with objective-specific literatures.
- **Chapter 3** describes the effective snow cover mapping of the Sikkim Himalayas on spatio-temporal basis.
- **Chapter 4** deals with estimating hydrological and lithological endmembers to the Teesta River system of Sikkim and investigating high-altitude geothermal aquifers.
- **Chapter 5** presents an investigation of glacial lakes and an assessment of the vulnerability of lakes in the trans-boundary Sikkim Himalayas.
- **Chapter 6** describes the field investigations and various field- and laboratory-based analyses of high-altitude glacial deposits.

- **Chapter 7** presents a detailed investigation of cascading avalanche episodes in the Himalayan ranges using satellite remote sensing as a potential tool.
- **Chapter 8** describes the impact of earthquakes on the glacial bodies and other glacial deposits in different parts of the Himalayan cryosphere.
- **Overall Conclusion** summarizes the objective-wise significant findings and the study's overall conclusion. The recommendations for future work have also been presented in this section.



Review of the Literature

2.1 Monitoring Glaciers and Glacial Lakes

Glacial studies began long ago. In 1830, the movement of glacial ice was confirmed in the Alps for the first time. It was also mentioned that the movement varied from place to place. Gravity has been recognized as the driving force for the movement of glacial mass (Cuffey and Paterson, 2010). Glacial mobility is not only due to ice sliding over its bed but also due to the self-initiative flowing tendency of ice. Cuffey and Paterson (2010) introduced several terminologies to demarcate boundaries for the freshly accumulated snow and melted ice. For this, the longitudinal profile of a typical valley glacier was divided into two zones: the accumulation zone and the zone of ablation. The accumulation zone is defined as where snow/ice accumulates due to precipitation of snow, hail, drifting snow, snow avalanche, and glaze. The ablation zone is the zone of ice loss from the glacier due to melting, evaporation, calving, deflation, etc. An equilibrium line separates these two zones. This line is marked as per the glacial mass balance. A positive mass balance keeps the position of the equilibrium line (EL) down on the glacier surface, and a negative mass balance positions the equilibrium line upwards. EL is very useful in demarcating the ablation and accumulation zones on satellite images.

Mapping is considered a first-hand approach toward snow/glacial study. Remote Sensing is used widely today to monitor the inaccessible and isolated snow fields where regular human invasion for scientific studies becomes problematic in terms of climate and topography. The theory behind glacial mapping lies in different spectral signatures of snow and ice due to large offset in the reflectance of ice and snow in the visible, near-infrared (NIR), and shortwave-infrared (SWIR) portions of the spectrum, which makes them distinguishable from other materials. However, some limitations exist due to mixed responses from a debris glacier and contaminated ice. Optical Remote Sensing has been used for snow cover area (SCA) mapping for many years (Hall et al., 2002; Zhou et al., 2005), but the attempt to map SCA with the help of microwave remote sensing helped in developing long-time series (since 1978). Combining these two products can be beneficial as optical imagery can offer a high spatial

resolution, whereas microwave imagery can help in cloud penetration. There is continuous emittance of microwave radiations from the Earth's surface that can be monitored from space with the help of passive microwave remote sensing. There are several passive sensors of such kind like the Special Sensor Microwave/Image (SSM/I), Scanning Multichannel Microwave Radiometer (SMMR), and the Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) providing global scale time series continuously. Active microwave sensors can distinguish snow from other surface features in all weather conditions. Shi et al. (1994) tried to examine the advantage of Synthetic Aperture Radar for snow/glacial mapping. The use of active microwave remote sensing to map snow has a limitation: dry snow cannot be reliably recognized (Wang et al., 2008). Under dry conditions, the underlying ground surface forms a significant source of backscattering signals. Water in liquid form over the surface of the snowpack reduces the penetration depth (Rott and Nagler, 1994). However, active microwave datasets have higher spatial resolution than passive sensors.

Normalized Difference Snow Index (NDSI) is an effective and convenient method for snow cover mapping (Hall et al., 1995; Kulkarni et al., 2002). Sibandze et al. (2014) applied NDSI to create a glacial inventory in the South African context. However, there are some drawbacks to using NDSI for mapping snow, particularly in snow-covered forested regions. Wang et al. (2015) used a revised band ratio named the Normalized Difference Forest Snow Index (NDFSFI) and distinguished snow-covered evergreen coniferous forests from snow-free evergreen coniferous forests. To gain an increment in the accuracy of the results so obtained, a new approach was implemented called Principal Component Analysis (PCA) in association with the Normalized Difference Snow Index (NDSI). This combination was referred to as the Normalized Difference Principal Component Snow Index (NDPCSI) and helped to reduce the data dimensionality. This method was implemented on both Landsat 8 as well as Moderate Resolution Imaging Spectroradiometer (MODIS) data and concluded to have good accuracy. Apart from band ratioing, many supervised and unsupervised classification approaches can be used to map snow cover in a satellite image. Albert (2002) implemented 16 different methods on Landsat 5 thematic mapper (TM) imagery and ranked them based on their efficiencies. Methods involving hand digitization, supervised/unsupervised classification techniques, fuzzy classification algorithms, threshold techniques, and band math algorithms. Classification involved the use of Maximum Likelihood (ML), Minimum Distance to Mean (MDM), Parallelopiped, and Spectral Angle Mapper (SAM). The fuzzy classification technique included Mixed Tuned Matched Filtering (MTMF), Linear Spectral Unmixing (LSU), and

Spectral Feature Fitting (SFF). However, the highest accuracy could be obtained by manually digitized and supervised techniques followed by SAM and NDSI.

Understanding of reflectance characteristics of snow, good spatial resolution satellite imagery, periodic data acquisition, snow-cloud discrimination, and snow under mountain shadow affects the interpretation of snow cover mapping. Aggarwal et al. (2016) used Landsat 8 and Indian Remote Sensing (IRS) satellite imagery to identify clear snow-covered glaciers in the Teesta river basin, situated in the Sikkim state of India. Sharda et al. (2018) used Object-Based Image Analysis (OBIA) for mapping glacial/snow and glacial lakes at Siachen using Landsat datasets. To map the glacial lakes, several supervised and unsupervised classification methods, namely Maximum Likelihood (ML), k-means clustering, etc., and Normalized Difference Water Index (NDWI), have been used. But using such techniques could not eliminate the problem of shadow misclassification and thus result in lake exaggeration. For a typical lake surface, the NDWI value ranges from -0.60 to -0.85 (Huggel et al., 2002). The significant disadvantages of using NDWI are listed as follows:

- a) Lakes that are covered by ice are not reported.
- b) Meltwater on glaciers is mapped as the water surface.
- c) Water-rich soils mapped as lakes
- d) Shadow classification as lakes because of Rayleigh scattering in the blue band.

2.2 Snow/glacier Melt Estimation

The flow of a river originating from glaciers is affected by intra-annual variations in rainfall, energy availability, and changes in glacial water storage in the long run. An appreciable amount of specific discharge contributed from snow/glacial ice melting often affects the flow for considerable distances downstream. An increase or decrease in the melting process of the glaciers can trigger an increment or decrement in the flow discharge of the river respectively. Therefore, snow melt models are important for predicting melt that can come from a particular glacier at a specific time in the year. Singh et al. (1997) tried to estimate the average runoff input of snow and glacier melt in the annual stream flow of the Chenab River at Akhnoor using a water balance approach. The total water budget of the basin was assessed for 10 years (October 1982-September 1992). Rainfall data from 25 well-distributed stations were utilized to calculate the total rainfall input to the watershed. The total flow volume was calculated using discharge data at the Akhnoor gauging station. Evapotranspiration losses were computed only

for the snow-devoid areas neglecting the evaporation loss due to rainfall over the snow-covered area. The annual contribution of snow and glacier melt to the annual discharge of the Chenab river was estimated to be around 49%.

Several snowmelt models are introduced to quantify snowmelt in a specific time domain. In general, models that are used to determine snowmelt are categorized into two categories: Energy Balance Models (EBM) and Temperature Index Models (TIM) (Debele et al., 2010). Kraus (1975) made use of an EBM to give a better physical understanding of complex phenomena, snow ablation dependence on special meteorological situations, and the ablation forecasts possibility based on the laws of micrometeorology in mountainous areas. Kondo and Yamazaki (1990) developed a model in which snow melt and other properties, such as snow surface temperature and freezing depth, can also be estimated. This was a Heat Balance Model, and parameters like maximum liquid water content, albedo, and thermal conductivity were given as input. It was analyzed that thermal conductivity or an increase in liquid water content increased the snow melt value. Hock (2005) compared various melt models. It concluded that the relative accuracy of modeling incoming radiation in mountain terrain is quite satisfactory. Still, there are some major uncertainties in modeling turbulent fluxes and temporal/spatial variability in albedo in current energy balance melt models and therefore require further research for higher spatial and temporal resolution. Singh et al. (2009) used the water balance approach to determine the average contribution of snow/glacier melt in the annual flows of the Sutlej river at Bhakra dam. Jost et al. (2009) used the Distributed Hydrology Soil and Vegetation Model (DHSVM) to detect hydrological changes as an alternative to paired catchment studies and determine the hydrologic sensitivity of a catchment to assist in forest management decisions. Jost et al. (2012) compared the basic temperature-index model with three extended temperature-index-based models and the physically based snow model in the DHSVM for forested catchments. You et al. (2014) worked with the Utah Energy Balance (UEB) snowmelt model to derive snow energy content, surface temperature, snowmelt outflow, and snow water equivalent. Aggarwal et al. (2014) studied snowmelt runoff using a temperature index-based snowmelt runoff estimation Model (SRM).

Stable isotope traces ($\delta^{18}\text{O}$, $\delta^2\text{H}$) are known to be conservative, and changes in concentration can be seen with hillslopes due to mixing processes. For the last few decades, studies have been conducted, and it has been established that ratios of stable oxygen and hydrogen isotopes can be used as a valuable means to study streamflow (Dincer and Payne, 1971). These stable isotopes in the flow of rivers have been used successfully to study the

characteristics of the river (Ramesh and Sarin, 1992; Rai et al., 2009). Isotope hydrograph separation is a method that is based on the assumption that specific water sources adding to the runoff of the river at a location are known and can be distinguished by statistically different values of specific properties and that stream water is a mix of individual water sources (Dincer et al., 1970). Cooper et al. (1991) studied stable isotopes of oxygen and natural and fallout radionuclides and their use for identifying water sources and quantifying watershed fluxes of precipitation-borne solutes and particles that come in contact with tundra vegetation at Imnavait Creek, Alaska. Even though numerous studies have implemented isotopic traces, using isotopes to measure the contribution of base flow, rain, and snow/glacial to the Himalayan glacier-fed rivers has gained little attention. Maurya et al. (2011) tried to quantify the contribution of glacial meltwater by separating River Ganga's hydrograph into three components: surface runoff, glacial ice melt, and groundwater discharge. A three-component isotope mixing model was used along with river water's electrical conductivity (EC) to estimate the time-varying relative fraction of each component. Ohlanders et al. (2013) first attempted to estimate the water balance of the Central Andean watershed in Chile using stable isotopes of water in streamflow and its sources. Ahluwalia et al. (2016) went for two methods: isotope analysis and hydraulic modeling, to measure the snow/glacial melt contribution to the Beas river originating from Beas Kund Glacier. Varay et al. (2017) also attempted to study 194 samples of river, tributary, and groundwater of pre- and post-monsoon seasons in the Sutlej and the Yamuna river basins for stable isotopes. The trend of $\delta^{18}\text{O}$ and EC along the stream gave a qualitative idea of the influence of headwaters in the watershed downstream, thereby allowing inference on melt contribution.

2.3 Natural hazards in Snow/glacial Regions

Snow/glaciers are a major component of the Earth's system as they control the regulation of net solar insolation captured by the Earth's surface and maintain the perennial nature of the major river systems. The Himalayan snow/glaciers act as a lifeline to some of the major river systems of the Indian subcontinent, namely the Ganga, Indus, and Brahmaputra. Associated with these mega processes is the potential risk of hazards. Snow/glacier or glacier-related processes or features posing adverse effects on human lives and property, directly or indirectly, can be considered snow/glacial hazards (Reynolds, 1992; Richardson and Reynolds, 2000). This includes slope failures, landslides, avalanches, earthquakes, and earthquake-induced hazards to glacial surging and catastrophic outburst floods due to breaches of naturally dammed glacial lakes.

In the Himalayas, snow and ice avalanches have left significant environmental traces. Ladakh, Jammu and Kashmir, Uttarakhand, Himachal Pradesh, and Sikkim are the Indian states affected by avalanches. Avalanches often cause loss to humans, infrastructure, and property and block transport corridors (Ganju and Dimri, 2004; Singh et al., 2005). Avalanches are spontaneous and controlled by several factors, such as snow variability, topography and weather condition (McClung, 2006). Other catastrophic hazards are landslides. Froude and Petley (2018) prepared a database of 5318 non-seismic landslides between 2004 and 2017, of which 3285 events were rainfall-induced. Within the Himalayan region, 580 landslides occurred, of which 477 were rainfall-induced. This makes up ~15% of global landslide events. Himalayan terrain is vulnerable to landslides due to its complex geological setting, steep slopes, high topographic roughness, and fragile topography. A major portion of the Himalayas is seismically active and subjected to extreme precipitation episodes and enhanced anthropogenic activities. Some major landslides have occurred in the Uttarakhand Himalayas, especially in the Mandakini valley, Chamoli, and Rudraprayag (Naithani et al., 2002; Martha et al., 2013, 2015). Another major landslide-prone region is Himachal Pradesh which includes Pawari, Luggarbhati, and Dharla (Roy et al., 2018; Kumar et al., 2018; Pradhan et al., 2019). In the north-eastern Himalayan region, Sikkim and Darjeeling have been the most reported areas for landslides (Anbarasu et al., 2010; Mondal and Mandal, 2019; Bera et al., 2019). To identify landslides, it is required to understand the area's mechanism, triggering factors, geology, and topography.

The convergence rate of the Indian plate to the Eurasian plate is fundamental to defining the recurrence interval of seismicity in the Himalayan ranges. However, due to effectively rigid strata up to a few millimeters, the collisional velocity is slowed down due to the absorption of the major fraction of convergence as internal distortion within Asia. While seismic activities are almost absent from the Indian plate's interior, they are ubiquitous on the Tibetan Plateau and surround its margins. Most earthquakes in the Himalayas occur with shallow hypocentres (<30 Km). Deeper earthquakes point toward the subsiding Indian plate into the mantle (Bilham, 2019). Earthquakes having hypocentre depth >40 Km are rare episodes in the case of continent-continent collision, as in the case of the Himalayas. This indicates the absence of the Wadati-Benioff seismic zone. The convergence between southern Tibet and the Indian plate is important in studying Himalayan seismicity as it provides the highest possible anticipated rate of seismic productivity. The Main Himalayan Thrust (~100 Km wide and 2000 Km long) has a mean convergence rate of 17 mm/yr, accumulating seismic moment of 10^{20} Nm/yr. This is

equivalent to the seismic moment released by a M_w 7.3 earthquake. This way, considering no other earthquakes for the last 350 years, an M_w 9.0 earthquake event would release an accumulated 4m of convergence with ~2000 Km long rupture (Bilham, 2019). Some major earthquakes, especially having $M_w > 7$, such as the 1950 Assam earthquake ($M_w = 8.6$) and the 2015 Gorkha earthquake ($M_w = 7.8$) ruptured the orogenic belt. However, earthquakes with $M_w > 5$ show substantial deformations to the surficial features in close proximity, and the effect fades away with the distance from the epicenter. Satellite Remote Sensing was first used in the 1970s in seismic study. Formations due to long-term processes, such as faults, were identified using satellite imagery (Trifonov, 1984). However, there had been a lack of scope in studying short-term and immediate deformations due to seismic events. With the advancement in satellite remote sensing techniques, post-seismic phenomena such as surface deformations, change in surficial thermal response, and alteration in humidity, aerosol and gaseous contents of the atmosphere can now be studied. Earthquake impact assessment is a crucial task that must be conducted after seismic events. The most common approach for determining earthquake magnitude and aftereffects is the analysis of ground-based seismometer datasets. However, due to their limited deployment in high-altitude glaciated regions, it is difficult to study certain earthquake events that occur close to those glacial bodies. Therefore, a number of geophysicists and seismologists have supplemented such ground-based methods with geodetic and satellite remote sensing-based approaches (Li et al., 2021). Space-borne sensors operational in the infrared spectrum help study the anomaly in thermal emission of the Earth's surface after an earthquake (Saraf and Choudhury, 2005; Mondal and Bharti, 2021). The method of interferometric study using synthetic aperture radar (InSAR) effectively studies small-scale deformations associated with earthquakes in centimeters/millimeters with confidence. In 1993, satellite interferometry was used for the first time to study the Landers earthquake that occurred on 28th June 1992 ($M_w = 7.3$) (Massonnet et al., 1993).

Himalayas have evidenced GLOF events of varying severity once every three to ten years (Bajracharya et al., 2007). Especially the Hindu Kush-Karakoram-Himalayan region has witnessed numerous outbursts/flash floods in recent decades (Ashraf et al., 2017; Wester et al., 2019). Out of these unfortunate incidents, most of the GLOFs occurred in Karakoram's Gilgit-Baltistan region, mainly due to severe rainfall, abrupt hike in temperature, and heatwaves (Din et al., 2014; Ashraf et al., 2021). Some of the recent incidents include the 2007 and 2008 GLOF on Passu glacier (Ashraf et al., 2014), the 2013 GLOF in Reshun valley (Riaz et al., 2014), and GLOF events between 2008 and 2017 due to the sudden breach of a supraglacial lake on

Ghulkin glacier and many more. The Hassanabad basin is another region that is highly susceptible to outburst floods attributed to the active movement of the Shisper and Muchowar glaciers (Khan et al., 2021). The Hassanabad ravine witnessed five minor GLOF events between 1890 and 1905 (Hewitt and Liu, 2010). Recently, three major GLOF events were recorded in 2019 and 2020 (Muhammad et al., 2021), and the most recent one was on 7th May 2022, respectively.

The first and foremost step in studying GLOFs is the identification of susceptible glacial lakes. In this regard, satellite remote sensing serves as the most effective tool for detecting and monitoring glacial lakes and their parent glaciers (Wang et al., 2015; Patel et al., 2019). According to a report shared by the International Centre for Integrated Mountain Development (ICIMOD), the Himalayan region is adorned with 15000 glacial bodies and 9000 glacial lakes (Mool et al., 2005). Only within the Hindu-Kush region, 8790 glacial lakes have been identified by Ives et al. (2010), out of which 203 lakes were identified as potentially dangerous in terms of future GLOFs. In fact, numerous naturally formed isolated lakes are located far from the glacial bodies devoid of any glacial origin. Some of these lakes situated above 3500m a.s.l are seen to be the remnants of those glacial lakes left due to glacial retreat (Campbell, 2005). In the past few years, the retreat of glaciers has not only affected the hydrological processes but also led to the volumetric expansion of glacial lakes (Yao et al., 2010). Watanabe et al. (1994) observed the increase in the volume of glacial lakes in Khumbu Himalaya and used it to assess the potential of GLOF. Lichtenegger et al. (2008) employed microwave remote sensing to detect the variations of Imja glacial lake. Molnia (2009) used TERRA-Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery to monitor the formation of glacial lakes in the Afghanistan glacial region. However, there are certain limitations in using optical remote sensing for mapping glacial lakes, including obscuring cloud cover, shadow effect from mountains, seasonal snow, degree of turbidity of lake water, and frozen lake surfaces (Wangchuk and Bolch, 2020). The use of synthetic aperture radar (SAR) data is considered robust for identifying glacial lakes that are partially frozen. However, noise removal relies on manual corrections and auxiliary datasets (Wangchuk et al., 2019).

2.4 Conclusion from the Literature Review

The Himalayan cryosphere is a topic of immense importance and interest to researchers around the globe. Where the complex tectonism of the Himalayas attract seismologist, the mega catchments and large river systems have been a field of great interest to hydrologists and other

researchers. It can be understood through previous literature that the Himalayas' dynamicity is too complex. Especially the remotely located glaciers and glacial features that lack field-based investigations due to inaccessibility, harsh weather conditions, and risk of natural hazards. In the past few decades, technological advancements, especially satellite remote sensing, have profoundly helped in the easy, fast, and efficient investigation of remotely located glacial bodies.

Literature review revealed that many studies had been carried out in different locations of the Himalayan ranges, highlighting the impact of climate change, receding and advancing glaciers, natural calamities, and many more. However, most of these studies focus on the Western and Central Himalayas. As the Eastern Himalayas are comparatively less explored in terms of snow/glacial dynamics and cascading natural hazards and/or their occurrence possibilities, it becomes imperative to develop a better understanding of the Eastern Himalayan cryosphere and its components. Considering this as a broad research gap, the notion has been further magnified and attempted for investigation in this thesis. An attempt has been made to investigate the Sikkim Himalayas, a significant part of the Eastern Himalayas for its snow/glacial dynamicity, glacial lakes, hydrological and lithological feeds to the major river systems. The thesis also addresses major cascading hazards in the Himalayan ranges in the recent past and investigate them in terms of their triggering mechanism, plausible factors behind trigger, and impacts.

Snow/Glacier Dynamics of the Sikkim Himalayas

3.1 Introduction

3.1.1 General

The cryosphere is one of the major parts of the Earth's System. Glaciers and firn, seasonal snow coverage, sea/river/lake ice, ice sheets, permafrost, and seasonally frozen grounds are important components of the cryosphere. The latitudinal positioning of these components along with low temperature and high altitude supports our planet's major storage of fresh water. Numerous glacial/snowmelt-fed river systems originate from these high-altitude mountainous regions. Major Himalayan glacier-fed rivers such as the Ganges, Indus, and Brahmaputra serve billions of people with fresh water. Any considerable change in this frozen component of the ecosystem can be indicative of the changing climate (Karl et al., 1996; Brown et al., 2000). In addition, snow-covered areas are also susceptible to hazards such as snow avalanches, landslides, and Glacial Lake Outburst Floods (GLOFs). Conventional techniques such as field surveys, sampling, and data acquisition are hazardous and challenging due to extremely low temperatures, rugged/steep topography, and high altitudes. Moreover, most glaciers are situated in remote and almost inaccessible locations. Hence, spaceborne/airborne remote sensing is a powerful tool for monitoring changes in the cryospheric components. Remote sensing can help in Spatio-temporal monitoring and determining several physical parameters of snow like wetness, density, grain size, snow water equivalent, albedo, snow depth, rate of accumulation, and ablation (Thakur et al., 2017), etc. The cryosphere also plays a pivotal role in managing the heat regimes, thus controlling the radiation balance of the planet on a local, regional as well as global scale (Bonan, 2015). At the local level, where snow cover influences different parameters of soil such as hydraulic conductivity, moisture, and temperature of the soil strata, it also affects carbon sequestration and microbial colonization (Isard et al., 2007; Monson et al., 2006). On the other hand, snow coverage controls the discharge of snowmelt-fed perennial rivers, availability of water, and groundwater recharge (Jain et al., 2008) and also governs the flora (type, density, and community structure), thus indirectly controlling the fauna at the regional scale (Löffler, 2005). Therefore, it can be said that snow and its properties such as albedo and thermal insulation together influence the geological and biochemical processes.

In the Himalayan regions, where several dams are constructed over different rivers to harness hydroelectricity, snowmelt contribution to discharge plays a vital role in hydel power generation and supply. Thus, snow cover monitoring is important in various sectors such as the management of water resources (Foster et al., 2005), snowmelt runoff modeling (Butt and Bilal 2011,), growth of vegetation cover in snow-covered areas (Peng et al., 2010), risk management for natural hazards, etc.

Different portions of the electromagnetic (EM) spectrum are differently responsive to surficial features. This can be utilized for studying various aspects of surficial snow coverage and its properties. Optical remote sensing which uses the reflective domain of the EM spectrum in the visible (0.4-0.7 μm) and infrared (0.7-2.5 μm) regions can be employed to map snow cover and glacial ice (Kulkarni et al. 2010). However, optical remote sensing is ineffective in the case of Himalayan studies as the region is adorned by obscuring cloud cover most of the time in a year. Moreover, it is restricted to only studying the surface properties of snow/glaciers. Microwave remote sensing, on the other hand, can help overcome such issues to an extent. It was in 1960 that the first attempt was made to map snow coverage using Television and Infrared Observation Satellite (TIROS-I) datasets (Dietz et al., 2012). Since then, a chronological advancement can be seen in the methods of snow mapping using space-borne datasets with different Spatio-temporal resolutions and spectral bands. The theory behind glacial mapping lies in different spectral signatures of ice and snow due to large offsets in the reflectance in visible and shortwave infrared regions of the EM spectrum, which makes them distinguishable from other surficial features. One of the most widely used and convenient methods of mapping snow cover is the Normalized Difference Snow Index (NDSI) (Hall et al. 1995). However, there are some drawbacks of using NDSI, particularly in forested snow-covered regions. To overcome this hindrance, Wang et al. (2015) used the Normalized Difference Forest Snow Index (NDFSIS) that helped in differentiating evergreen coniferous forests in terms of snow-covered and non-snow-covered areas. Apart from band ratio techniques, there can be many supervised and unsupervised classification approaches to map snow cover using satellite data. Albert (2002) implemented 16 different methods on LANDSAT 5 TM images and ranked them based on their efficiency. Methods involved hand digitization, NDSI, supervised and unsupervised classification techniques along with fuzzy classification algorithms such as Spectral Feature Fitting (SFF), Mixed Tuned Matched Filtering (MTMF), and Linear Spectral Unmixing. However, the highest accuracy could be obtained by using hand digitized supervised techniques and NDSI. Sibandze et al. (2014) tried

to improve the accuracy of NDSI mapped results using Principal Component Analysis (PCA) that reduced data dimensionality. This combination referred to as Normalized Difference Principal Component Snow Index (NDPCSI) concluded to have good accuracy.

Crosta et al. (1989) used Feature-Oriented Principal Component Analysis (FPCA), also known as the “Crosta technique”, for geological mapping of a region in south-east Spain. Minerals have characteristic absorption features in specific wavelength regions. The statistical interpretation of loadings of selected TM bands in different PCs helped to generate a color composite image (Crosta image) for the identification of different minerals. Kulkarni (2004) tried to locate glaciers in the Baspa basin situated in Himachal Pradesh, India using Indian Remote Sensing Satellite (IRS-1C) stereo images that were digitally processed to generate orthoimage. The position of the glacier was determined by viewing images under stereo perception and was confirmed by field investigation. The temporal comparison of its position showed retreat. Several studies conducted over other small and large glaciers in the western Himalayas concluded that the retreat was more in the case of small glaciers, confirming more sensitivity towards climatic variations than the large glaciers. Optical Remote Sensing is used for snow cover area (SCA) mapping for many years (Zhou et al., 2005) but an attempt to map SCA with the help of active microwave remote sensing benefited in resolving some drawbacks of optical remote sensing. Because of its cloud-penetrating capacity, microwave remote sensing is more effective in snow/glacial studies where cloud cover obscures the surficial features. Wet/dry snow can be effectively mapped through microwave remote sensing such as dual-polarimetric Synthetic Aperture Radar (SAR) datasets (Wang et al., 2008; Varade et al., 2019). In the case of dry snow, it is the underlying surface that becomes the dominant source of backscattered signals. Shi et al. (1994) tried to examine the effectiveness of SAR for snow/glacial mapping. It was found that L-band (Singh et al., 2013) and C-band polarimetric SAR datasets (Muhuri et al., 2017) could be processed to distinguish between snow-free and snow-covered areas. However, it was challenging to distinguish glacial ice from snow and rock.

Even though NDSI is a widely used method for snow mapping, its reliability is compromised in the presence of certain surficial features such as reflective water bodies and shiny surfaces of a rock outcrop (Hall et al., 2002). This resulted in the requirement of a better technique with improved snow mapping accuracies. One such method is the use of multivariate statistics such as Principal Component Analysis (PCA) or Independent Component Analysis (ICA). PCA helps in transforming a number of spectral channels into some specific principal components leaving behind the original spectral band imageries containing most of the

variance (Singh, 1989). Another advantage of using PCA is the decorrelation of highly correlated spectral bands that are redundant for mapping surficial features into some less correlated images based on eigenvectors (Muchoney and Haack, 1994; Patel et al., 2019). However, implementing PCA over satellite imageries turn original surficial features into PCs that need to be more interpretable and are needed to be studied in conjunction with the eigenvector/correlation matrix. One cannot run PCA for every feature as visualization, and the algorithm's performance is compromised. Moreover, PCs cover the maximum amount of variance among the surficial features; thus selecting an inappropriate PC might lead to loss of information. Another computational and statistical technique is ICA. ICA transformation is an unsupervised method of feature extraction that works on an assumption that each spectral band is a linear combination of ICs. The major difference between PCA and ICA is that in IC transformation the assumption of Gaussian distribution unnecessary (Hyvarinen, 1999).

Blanford (1884) proposed the first hypothesis that the accumulation of snow in the Himalaya during winter adorns a negative correlation with the summertime monsoon over the western region of India. Since then, several studies have been conducted to monitor the effects of Himalayan snow cover over the changing climate of the globe (Yamagata and Masumoto, 1989). Shaman and Tziperman (2005) studied the El Niño/Southern Oscillation (ENSO) associated anomalies of sea surface temperature (SST) in the tropical Pacific responsible for exciting Rossby waves affecting the snowfall and winter storms over the plateau. Thus, snow mapping is not just useful in monitoring the temporal areal fluctuations of snow/glacial abundances but also helps in quantifying the annual ablation-accumulation of snow cover which can be inferred as effect of climate change over snow/glacial built-up.

3.1.2 Glacial Dynamics

Glaciers are the perennial storehouse of freshwater in high altitudes/low latitudes. Glaciers behave differently in different seasons due to which glacier dynamics (flow velocity) vary seasonally due to enhanced melting rate in the ablation period and decreased melting in the accumulation period (Zwally et al., 2002; Joughin et al., 2008; Scherler and Strecker, 2012; Satyabala, 2016). Furthermore, glacial sensitivity is very complex and heterogeneous involving several meteorological (Scherler and Strecker, 2012), hydrological (Singh et al., 2006) and topographic (Hooke, 2005) parameters. Glacial dynamics also includes surface mobility, glacial facies, changes in the areal extent and elevation profile that can be extensively studied by spaceborne/airborne remote sensing techniques (Berthier et al., 2005; Kumar et al., 2011; Bhambri et al., 2012; Bhardwaj et al., 2015; Thakur et al., 2016, 2017). Glaciological

investigations conducted from field-based and satellite driven study have shown that the Himalayan glaciers behave in synchronization with various meteorological parameters such as temperature and precipitation resulting in retreat and negative mass balance (Wagnon et al., 2007; Dobhal et al., 2008; Bhambri and Bolch, 2011; Azam et al., 2014; Pratap et al., 2016). Thus, extensive monitoring in high temporal and spatial resolution is very much required for analyzing flow velocity patterns of glaciers in the Himalayas, which may be more challenging and redundant from optical remote sensing techniques. Radar technology, due to its cloud penetrating capacity, is very advantageous in all-weather glaciological monitoring and proves to be more suited for studying the rugged and valley-adorned terrain of mountainous regions such as the Himalayas (Goldstein et al., 1993; Strozzi et al., 2002).

The mobility of glacial surface is a major component of glacial dynamics. It plays a significant role in energy redistribution thus manipulating the distribution of the temperature profile of the glacial body. It helps in evaluating the mass, ice flux (Sattar et al., 2019), and thickness (Hooke, 2005; Cuffey and Paterson, 2010; Gantayat et al., 2014). In the western Himalayas, decreased annual surface velocity of glaciers is reported in the Hindu-Kush region (Bajracharya and Shrestha, 2011; Haritashya et al., 2015). Between 1982 and 2009, approximately 70% reduction in mobility was reported for the Yala glacier situated in the Nepal Himalayas (Sugiyama et al., 2013). Between 2000 and 2010, around 43% downfall in flow velocity is observed in Pamir (Heid and Kääb, 2012). On the other hand, glaciers lying in the Karakoram region show accelerated flow velocity (Rankl et al., 2014; Dehecq et al., 2019). In case of the Zemu glacier, one of the largest glacial bodies of the eastern Himalayas, glacial retreat at the rate of 9.1m/yr is observed that has increased substantially to 20m/yr between 2014 and 2018 (Rashid and Majeed, 2020). As glaciers are spread over a large area with varying slope and topography, large variations in velocity profile can be observed in different parts of a glacier. Around Himalayan main ridge, flow velocity of about 0-37m/yr is reported in southern part (Quincey et al., 2009) whereas in the northern side, flow velocity ranging between 100-200m/yr is reported (Kääb, 2005).

Correlation of an optical pair to determine surface displacements can be performed through various methods such as least square matching (Kaufmann and Ladstädter, 2003), orientation correlation (Haug et al., 2010), phase correlation (Avouac et al., 2006), normalized cross-correlation (Berthier et al., 2003) and cross-correlation in Fourier domain (Rolstad et al., 1997). However, phase and orientation correlation prove to be more robust for monitoring glacial surface velocities (Heid and Kääb, 2012). The frequency correlation for tracking

temporal surface deformations is recommended due to good quality outputs and more sensitivity to noise (Ayoub et al., 2009). The accuracy of the algorithm depends directly on the co-registration of input images. Inaccurate orthorectification and geometric corrections can lead to signals of linear ramp in the surface deformation field. However, if the temporal span between image pairs is high (around one year), signals of linear ramps are nearly absent. Errors due to sensor noise, line/column stripping, shadows and clouds lead to deteriorating effects on the displacement outputs (Scherler et al., 2008).

There are various techniques in microwave remote sensing to measure glacial surface velocity such as SAR-Interferometry (Kumar et al., 2011), Multiple Aperture Interferometric (MAI) technique (Gourmelen et al., 2011) and offset tracking (Strozzi et al., 2002). The approach of measuring surface deformations with the help of SAR can be divided into amplitude-based and phase-based methods. In order to achieve this, L-band and C-band radar can be used. The pros and cons of using either of these microwave bands derive from the sensor (wavelength). The shorter the wavelength, the better the spatial resolution, whereas the longer the wavelength, the better the surface penetration (Howell et al., 2018; Jelenek and Kopačková-Strnadová, 2021). Where L-band SAR can be useful in large-scale studies such as soil moisture, geomorphological and tectonic studies (Chaparro et al., 2018; Fernandez-Carrillo et al., 2019), and X-band systems help in tracking landslides and lava flows to a finer scale (Kubanek et al., 2017), C-band SAR systems act as a compromise for both the utilizations (Atzori et al., 2013; Wang et al., 2018; Howell et al., 2018).

Where intensity and coherence tracking measures 2-dimensional displacement in azimuth and slant range direction, the interferometric technique using SAR estimates displacement in slant range direction only (Strozzi et al., 2002). For tracking glacial surface displacement on temporal basis, differential SAR interferometry (DInSAR) serves as an important technique provided, there exists a minimum temporal (1-3 days) and geometrical baseline (Mondal and Bharti, 2022). This technique had its form from InSAR using sets of differential interferograms in order to derive temporal variations over deformation (Berardino et al., 2002). Gabriel et al. (1989) used DInSAR for the first time. Soon after, it became a very effective method for analyzing surface deformations due to subsidence, landslides, earthquake triggered slope failures, glacial velocity etc. (Peltzer and Rosen, 1995; Massonnet et al., 1995; Mouginot et al., 2012; Samsonov et al., 2020; Devaraj and Yarrakula, 2020; Crosetto et al., 2020)

In this chapter, an attempt has been made to incorporate multivariate statistical techniques in conjunction with band ratio for effective mapping of snow coverage of the Teesta river basin with improved accuracy as compared to the individual algorithms. The outputs of these techniques have been integrated into a digital logic gate operation (AND gate) for an effective snow cover product of the catchment. Further, the periodicity of SLA has been checked from 1989 till 2019 and the intra-annual changes in the snow cover have been compared with the changing SST over the Niño 3.4 region of the Pacific Ocean. Also, the Zemu glacial body within the Teesta watershed has been analyzed for its surficial velocity, debris coverage and land surface temperature (LST) to investigate the glacial dynamics.

3.2 Study Area

3.2.1 Teesta Watershed

The selected Teesta basin is the part of the NE landscape of the Indian terrestrial boundary lying between 27°00'46"N to 28°07'48"N latitudes and 88°00'58"E to 88°55'25"E longitudes (Figure 3.1). The total geographical area is about 7096 Km² of which about 883 Km² is acquired by only glaciers accounting for about 12%. Sikkim, a part of the north-eastern Himalayan mountain ranges has more than 43% of areas with steep slopes and rugged terrain. The elevation ranges between 213m (at the outlet of Teesta river in the south) and 8586m (at the summit of Mt. Khangchendzonga) from the mean sea level (MSL). Due to this large elevation gradation, several climatic diversities can be seen, ranging from the subtropical type in the south to the high alpine type with tundra vegetation in the north and west. The average annual rainfall is around 2500 mm with heavy rain and snowfall in the mountains. Snow coverage plays a crucial role in the formation of glaciers. The ablation and accumulation pattern of snow is affected by precipitation patterns and long-period average (LPA) temperature. In Sikkim, the monthly distribution of snow cover shows appreciable changes from October till April. The mean snowline of Sikkim glaciers was measured to be ~6000 m above MSL in 1990 (Basnett et al., 2013; Shukla et al., 2018). The mean annual air temperature increased by 1.03°C from 1987 to 2011 (Basnett et al., 2013). The region receives heavy snowfall due to western disturbances during February than the north-eastern retreating monsoon.

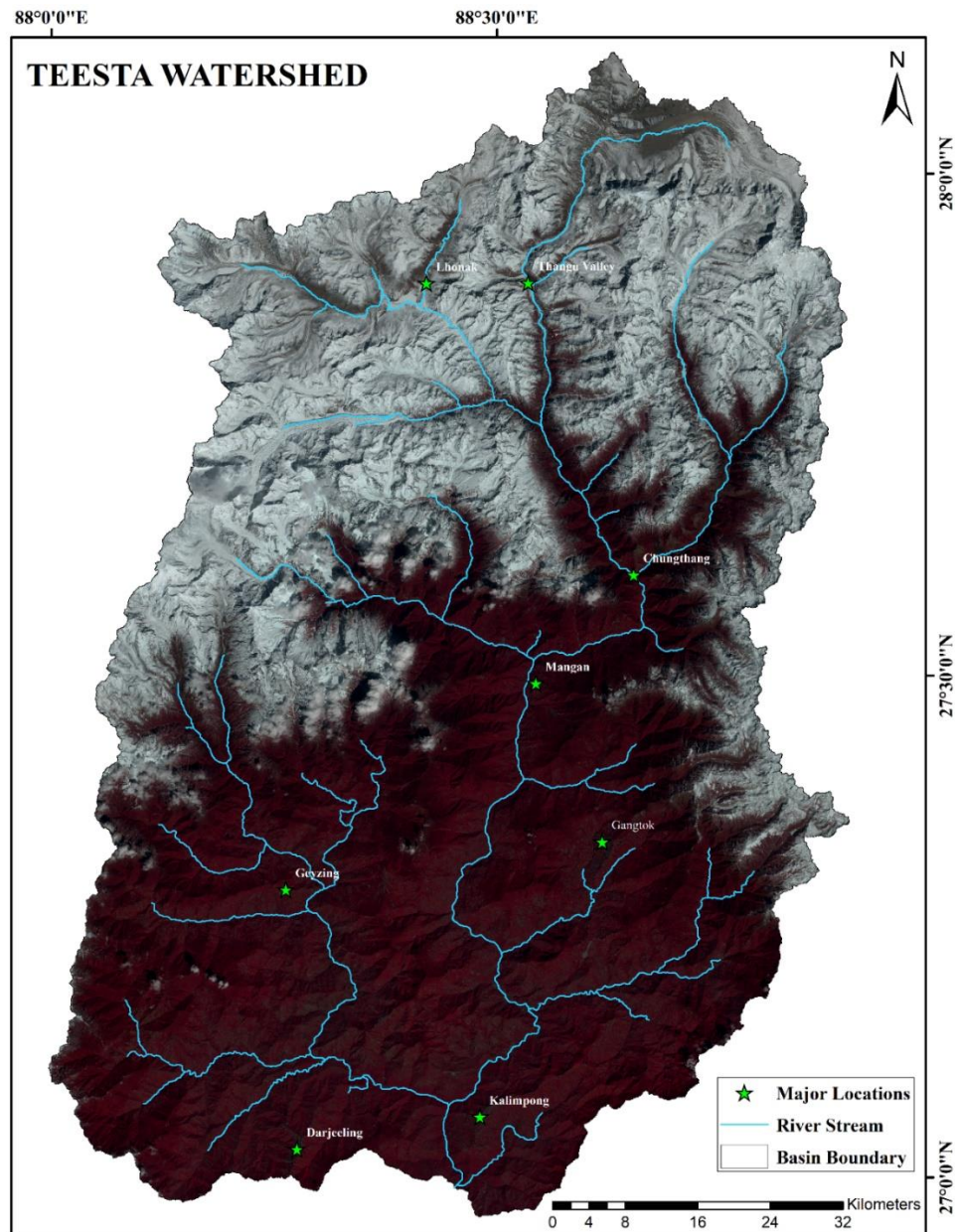


Figure 3.1: Standard False Color Composite (FCC) map of the study area: Sentinel 2 MSI (29th Feb 2020)

3.2.2 Zemu Glacier

Zemu is a debris-covered valley glacier situated in the Sikkim Himalayas. This glacier does not show any significant retreat in the last couple of decades due to the heavy dominance of debris near the snout and at the terminus (Basnett et al., 2016). In terms of litho-stratigraphical characterization, the region belongs to a deeply faulted area. Rock benches are possibly formed above the valley due to neo-tectonic upliftment (Samanta et al., 2019). The major geomorphological features marked in and around the Zemu glacier have been represented in Figure 3.2.

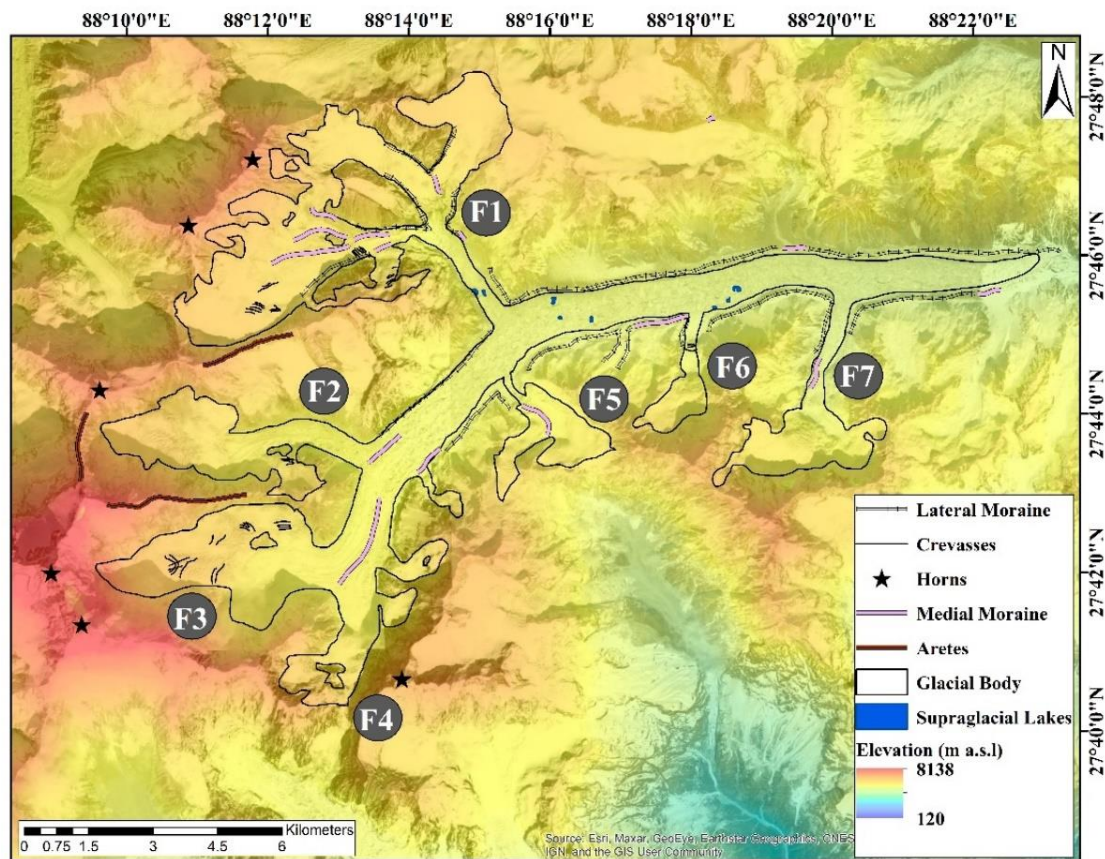


Figure 3.2: Map showing the geomorphological units of Zemu glacier

The glacial body can be divided into a main trunk and seven spreading arms or flanges (F1 to F7) from both sides of the glacial trunk. Other glacial bodies around the Zemu glacier are separated by an arete, a thin jagged crest that appears as a serrated knife. The low points of the surface thus separated are cols. Horns can be observed in certain locations around the glacial body. These features are formed when the glacier erodes multiple aretes forming a sharp-edged triangular peak. The glaciers in the Sikkim Himalayas are mainly adorned by moraine. As a glacier scrapes along, it scours rock fragments and soil from either side, leading to the formation of a lateral moraine along the sides of a glacier. The lateral moraine is deposited on the glacial top devoid of postglacial erosion. This helps in the paleo-investigation of the glacial evolution as the lateral moraines are preserved in the form of high ridges despite glacial melt. Terminal/end moraines are ridges of loose and unconsolidated debris at the snout of a glacier. The end moraine's size depends on whether the glacier is retreating or advancing or is in equilibrium. However, as a glacier retreats, postglacial erosion may eventually destroy the end moraine. Another important geomorphological feature of Zemu glacier is supraglacial lakes which can be termed as ephemeral ponds of water lying on top of the glacial body.

3.3 Datasets Used

Landsat 8 OLI (Operational Land Imager) and Sentinel 2 MSI (Multispectral Instrument) datasets have been used respectively. The Landsat 8 (L-8) raster dataset contains eleven spectral channels including one panchromatic (0.50-0.68 μm), one coastal aerosol detection (0.43-0.45 μm) and one cirrus (1.36-1.38 μm) band whereas Sentinel 2 (S-2) data contains thirteen spectral bands including one coastal aerosol detection (0.42-0.46 μm); one water vapor (0.93-0.96 μm) and one cirrus (1.33-1.41 μm) band as shown in Table 3.1. Compared to L-8 OLI, S-2 MSI has a better spatial resolution but is devoid of thermal bands. The aerosol detection band of both datasets was not included in the analysis. As this is a spectral channel of lower wavelength, it is more informative to Aerosol Optical Thickness (AOT) determination and comparatively less sensitive to surface reflectance. Moreover, the NIR bands were also not considered as these bands are informative to vegetation as well as snow due to which it becomes difficult to obtain a principal component that is informative to only snow-covered areas. Accordingly, Landsat 5 TM (Thematic Mapper) and Landsat 8 OLI datasets for the past 30 years were selected at an interval of 2-4 years with low cloud coverage for ablation (October-December) as well as accumulation period (February-April). MODIS/Terra 8-day L3 Global 500m composite products (MOD10A2) dated between 27th February 2019 and 13th March 2019 were used for the accuracy assessment of the results obtained. MOD10A2 is a filtered derived product of MOD10A1 data as it maximizes the Snow Cover Fraction (SCF) and reduces the cloud cover. This is because a pixel in MOD10A2 data is marked cloud adorned only when it is cloudy for 8 days. But, if a pixel is identified as snow for at least a single day within the 8-day domain of data acquisition, it is classified as snow. Moreover, if a pixel is not snowed for 8 days, it is classified as land cover. A pair of S-2 datasets at a temporal offset of 365 days were used to derive the surface velocity of the Zemu glacier as shown in Table 3.1. L-8 dataset of 10th March 2019 was used to compute the LST and debris cover within the glacier. High-resolution terrain corrected advanced land observing satellite (ALOS) phased array type L-band synthetic aperture radar (PALSAR) 12.5m digital elevation model (DEM) of 12th September 2009 was used to derive SLA as well as modelled thickness of the glacial body. PALSAR is an active microwave payload that acquires terrestrial observation data devoid of cloud interferences (JAXA, 2020). The datasets are geometrically corrected with the help of existing DEM, and radiometric adjustment is made in the layover and foreshortening regions (Laurencelle et al., 2015). After corrections, final products generated using high-resolution National Elevation Dataset (NED-13) DEM are available in 12.5m ground resolution whereas

products developed using moderate resolution DEMs such as SRTM 1 arcsec, NED-1 and NED-2 are available in 30m resolution. The NED dataset is generated by the U.S. Geological Survey (USGS) with the help of digital photogrammetry, or LiDAR, adjusted to a common vertical unit and coordinate system. Distributed per the North American Datum (NAD) 1983, NED is considered the best available elevation data in the raster form for Hawaii, Alaska, and some territorial islands of the U.S. The accuracy of NED depends on the source DEM quality, not being poorer than 2.5m (Gruber et al. 2012). The 3 months running average ERSST.v5 datasets of fluctuations in sea surface temperature recorded over the Niño 3.4 location of the Pacific Ocean for the year of effective snow mapping were used to compare fluctuations with effective snow coverage of the past 30 years. The ERSST as compared to the other SST analyses such as the Hadley center SST (HadSST), Optimum Interpolation SST (OISST), Centennial Observation Based Estimates of SSTs (COBE-SST), and Kaplan SST have been adjusted with the help of Nighttime Marine Air Temperature (NMAT) data (Huang et al., 2015). The first-guess (FG) data from ERSST.v3b were bias-corrected and used in the assessment of the quality of ERSST.v4 datasets. Any observations exceeding the FG by 4.5 times the standard deviation of SST were not considered. However, selecting bias-corrected FG resulted in considering more warm SSTs as the observations were cold-biased before 1940s (Huang et al., 2015). This has been improved in ERSST.v5 (Huang et al., 2016). The boundary of the Zemu glacial body has been adopted from the Randolph Glacial Inventory, RGI 6.0 (RGI Consortium, 2017).

Table 3.1: Datasets used for analysis and accuracy assessment of the results

<i>Effective Snow Cover, LST and Debris Mapping</i>						
<i>Satellite</i>	<i>Data Type</i>	<i>Date</i>	<i>Wavelength Range (No. of Spectral bands)</i>	<i>Spectral Bands Used</i>	<i>Bands</i>	<i>Spatial Resolution</i>
<i>Landsat 8</i>	OLI & TIRS	10 th March 2019	0.43-0.67 μm (4); 0.85-0.88 μm (1); 1.57-2.29 μm (2); 10.60-12.51 μm (2)	0.45-0.67 μm (3); 1.57-2.29 μm (2)		30m (Visible, NIR); 100m (Thermal)
<i>Sentinel 2</i>	MSI	1 st March 2019	0.42-0.79 μm (7); 0.79-0.96 μm (3); 1.36-2.28 μm (2)	0.42-0.79 μm (6); 1.36-2.28 μm (2)		10m (Visible, NIR); 20m (SWIR)
<i>MODIS/Terra</i>	MOD10A2	27 th February and 13 th March 2019		Derived product		500m
<i>Sub-pixel Correlation using COSI-Corr (Sentinel 2)</i>						
<i>Master</i>	<i>Slave</i>	<i>Time Gap</i>	<i>Spectral Channel Used</i>	<i>Pixel Size</i>	<i>Pixel Depth</i>	
1 st March 2019	29 th February 2020	365 Days	Band 4 (Red; 0.65-0.68 μm)	10 m	16 bit	

3.4 Methodology

3.4.1 Multivariate Statistical Techniques

The process started with the conversion of the brightness values to Top of the Atmosphere (TOA) reflectance values (Smith et al., 2013). This was followed by the Gaussian stretching

on all the selected bands for normalizing the standard deviation and spectral mean values. This resulted in equal dominance of selected spectral channels in the output. The next step was Principal Component Analysis (PCA).

In satellite remote sensing, especially when dealing with multi-/hyper-spectral datasets, different types of statistical methods can be employed for image enhancement and extracting surficial features (Garcia-Haro et al., 2001). A multivariate statistical approach such as PCA/Hotelling transformation (Singh and Harrison, 1985) deals with the reduction in data dimensionality. PCA transformation is homologous to the Karhunen-Loeve transformation which is based on the principle of operating over the covariance matrix of multi-/hyper-spectral image spectral channels pertaining to eigenvalue decomposition (Gonzalez and Woods, 1993; Schowengerdt, 1997; Rodarmel and Shan, 2002). This operation generates a first component that contains the largest proportion of input data variance and the subsequent components with lesser proportions of data variances (Fung and LeDrew, 1987). With this concept, PCA over satellite imagery helps in generating new images in which variance associated with unchanged surficial features are represented in the first component whereas the changed features are registered in subsequent components (Koutsias et al., 2009). In this study, forward PCA transformation was applied to the selected spectral channels. Thus, principal components were derived along with their eigenvector loadings (weights) and eigenvalues, correlation, and covariance matrices for the selected bands. Statistical analysis of these eigenvector loadings and eigenvalues helped in selecting the specific principal component further analyzed for their effectiveness in snow/glacial mapping.

In the next step, Independent Component Analysis (ICA) transformation was performed. Similar to PCA, ICA (Comon, 1994) is also a linear transformation approach that can be implemented over satellite datasets to derive mutually independent components from a set of correlated spectral bands. The significant difference between PCA and ICA is that PCA is more of studying covariance matrix with a Gaussian assumption whereas the assumption of independent sources for an ICA transformation is non-Gaussian.

With the help of ICA, correlated channels can be separated without having prior information about the source statistics (Hyvarinen et al., 2001). The ICA model operates with the assumption that a given set of correlated RVs (random variables) are formed from independent components that are linearly mixed. One major advantage of ICA is that it can differentiate surficial features in the sub-pixel scale (Chen and Zhang, 1999). This study

applied a forward IC transformation for the spectral bands to derive distinct independent components along with their eigenvalues and eigenvector weights in different bands, correlation, and covariance matrices. Statistical analysis of the components helped in identifying the useful IC for mapping snow coverage over the study area.

3.4.2 Band Ratio and Logic Gate Operator

The next technique that was employed to derive snow coverage was NDSI. Initially devised for Landsat TM bands, this band ratio technique was adopted because it has comparatively better classification accuracy. Other algorithms for the identification of snow such as RMESMA (Relative Multiple Endmember Spectral Mixture Analysis), RMSA (Relative Spectral Mixture Analysis), etc. have much-compromising accuracy than NDSI (Shreve et al., 2009). However, its accuracy is compromised in forested catchments and the presence of reflective water surfaces. This was done by ratioing the difference in reflectance obtained from the green band and SWIR band on the numerator and the sum of the reflectance obtained from the same bands on the denominator as shown in equation 3.1. As per the recommendation (Kulkarni et al., 2006; Hall et al., 1995), the NDSI threshold of 0.4 was used for the characterization of surficial snow (Hao et al., 2008). Finally, useful outputs of PCA, ICA, and NDSI were used as input to digital logic gate operation (AND-gate) to derive an effective snow cover map. As the AND-gate operation gives an affirmative output if all the inputs are high, the resultant map shows the area under snow only when the same area is snow-covered in all three inputs.

$$NDSI = \frac{\rho_{band\ 3} - \rho_{band\ 6}}{\rho_{band\ 3} + \rho_{band\ 6}} \quad (3.1)$$

where $\rho_{band\ 3}$ & $\rho_{band\ 6}$ is the surface reflectance in green and SWIR₁ bands of Landsat 8 OLI sensor respectively.

3.4.3 Sub-pixel Correlation and Modeling of Glacial Depth

In this section, Fast Fourier Transformation (FFT) correlation in COSI-Corr has been adopted which is capable of tracking sub-pixel shifts up to 1/50th of the pixel (Avouac et al., 2006). The red band (band 4) of Sentinel 2 MSI (master and slave imagery) acquiring surface reflectance information in the wavelength range of 0.65-0.68 μ m and spatial resolution of 10 m has been processed. The sliding window 32×32 pixels and step window size of 2×2 pixels have been used resulting in 20 m square pixels in the output. Theoretically, the size of the sliding kernel is determined on the basis of ground-based knowledge of glacial displacement and should be

at least twice the surface displacements (Das, 2021). Due to the inaccessibility of Zemu glacier and lack of ground-based knowledge, previous studies (Remya et al., 2019; Rashid et al., 2020) and multiple experimental attempts helped in determining the sliding kernel of 32×32 pixels and step kernel of 2×2 pixels to provide promising results. In order to minimize the dominance of high-frequency noise on the correlation outputs, the robustness iteration and frequency mask threshold has been chosen as 4 and 0.9 respectively.

The COSI-Corr algorithm gives three different outputs. The first two outputs provide displacements in the east-west (east positive) and north-south (south positive) directions respectively. The net ground displacement at various locations throughout the glacial body is determined as the Euclidean displacement ($D_{euclidean}$) as shown in equation 3.2. The annual surface mobility (V_{annual}) of the Zemu glacier has been calculated using equation 3.3.

$$D_{euclidean} = \sqrt{D_{EW}^2 + D_{NS}^2} \quad (3.2)$$

$$V_{annual} = (Daily\ Average\ Velocity) \times 365 = \frac{D_{Euclidean}}{T} \times 365 \quad (3.3)$$

where ' D_{EW} ' and ' D_{NS} ' represents displacement components in the east-west and north-south directions respectively. ' T ' represents the period (days) between the acquisition of satellite images used for correlation. The estimated depth of the Zemu glacier has been modelled using the laminar flow equation (Cuffey and Paterson, 2010; Maanya et al., 2016) as shown in equation 3.4.

$$V_s = V_b + \frac{2A}{n+1} \tau_b^n H \quad (3.4)$$

where V_b and V_s are the glacial velocity at the base (interface between ground and glacial bottom) and surface (interface between the atmosphere and glacial top) respectively. Since, it is difficult to measure the basal velocity of the glacier, it has been to be 1/4th of V_s (Gantayat et al., 2014). A represents the creep coefficient (varies with the grain size, temperature and impurity content) assigned a value of $32.4 \times 10^{-23} \text{ Pa}^{-3} \text{ s}^{-1}$ (Cuffey and Paterson, 2010). Glen's flow law exponent (n) has been assumed as 3. The basal stress (Remya et al., 2019) has been modelled with the help of equation 3.5.

$$\tau_b = f \rho g H \sin \theta \quad (3.5)$$

where f , ρ and g represent shape factor (0.8), metamorphosed ice density (900 kg m^{-3}) and acceleration due to gravity (9.8 m s^{-2}) respectively. θ represents the surface slope estimated using ALOS-PALSAR DEM over 100 m interval elevation contours (Linsbauer et al., 2012).

Substituting basal stress shown in equation 3.5 to equation 3.4 gives the modelled glacial depth as

$$H = \sqrt[4]{\frac{1.5V_s}{A(f\rho g \sin \theta)^3}} \quad (3.6)$$

Low pass filter has been applied to eliminate ambiguous depth pixels from the modelled depth result. To estimate the spatial distribution of modelled glacial thickness, discretized thin-plate spline interpolation technique has been used. The uncertainties associated with modeling the depth of the Zemu glacial body has been determined using the expression shown in equation 3.7 (Remya et al., 2019).

$$\frac{dH}{H} = \sqrt{\left(\frac{1}{4} \frac{dV_s}{V_s}\right)^2 + \left(\frac{3}{4} \frac{df}{f}\right)^2 + \left(\frac{3}{4} \frac{d\rho}{\rho}\right)^2 + \left(\frac{1}{4} \frac{d\sin\theta}{\sin\theta}\right)^2} \quad (3.7)$$

In the cross correlation of optical satellite datasets, sources of errors in the velocity field includes wavelength orbital error, noise due to temporal decorrelation, attitude jitter distortions, satellite and topography dependent artifacts (Ding et al., 2016). A common problem with a push-broom scanner is misaligned arrays of Charged Couple Device (CCD) resulting in stripe artifacts in the displacement outputs which can be eliminated through general orthorectification (Leprince et al., 2008; Ding et al., 2016). Moreover, variations in altitude of the satellite results in cyclical distortions along the flight direction. These types of systematic distortions can be excluded using destripe (Ayoub et al., 2009) which depends on the fraction of stable ground with no surface movement in the satellite scene. In fact, higher the fraction of stable ground, better is the removal of attitude effects. Sikkim lies near main central thrust (MCT) and its glacial bodies are covered with moraine and highly rugged terrain. As a result, it is challenging to apply destripe on the satellite scene used for correlation.

3.4.4 Land Surface Temperature (LST)

To understand the physics behind different processes over the land surface, LST can be considered as a significant parameter. Various algorithms have been devised for estimating LST such as single-channel, multi-channel, multi-angle algorithms respectively (Sòria and Sobrino, 2007). Out of these, split-window (SW) algorithm (Becker and Li, 1990) is considered as very effective multi-channel algorithm as it gives the added advantage of eradicating the effect due to the atmospheric profile between the surface and satellite sensor. The algorithm is employable over various instruments such as Moderate resolution Imaging Spectro-radiometer (MODIS) on board Terra and Aqua, Visible and Infrared Radiometer (VIRR) on board

Fengyun 3 satellites etc. Technically, Landsat 8 Thermal Infrared Sensor (TIRS) is very suitable for deriving LST using a split-window algorithm (Jin et al., 2005).

The SW algorithm was proposed by McMillin et al. (1975) who observed two infrared bands for atmospheric absorbance in order to derive sea surface temperature (SST). However, deriving LST using this algorithm requires an added component of land surface emissivity (LSE) (Price, 1984). There is significant difference in emissivity of land as compared to that of the ocean. This is because of vast heterogeneity due to surface roughness, soil moisture content, overlying vegetation cover, and viewing angle. Therefore, estimating LST for every pixel becomes mandatory as substantial change can be registered over short distances. Qin et al. (2001) proposed SW algorithm for AVHRR that incorporated two essential parameters i.e. atmospheric transmittance and LSE. The results showed an improved accuracy of 1.75 °C. Thus, the algorithm proposed by Qin et al. (2001) was adopted for Landsat 8 TIRS bands as it was tested and more accurate. In case of satellites datasets having wide swath, it is necessary to perform view angle correction on transmittance through the atmosphere. Whereas, for Landsat 8 TIRS, revolving at a height of 705 Km tracing swath of 185 Km, the zenith view angle varies upto 7.5°. At this angle, the influence of atmospheric transmittance on TIRS bands is almost negligible. Moreover, as transmittance through the atmospheric profile is different for various constituents, it depends on the wavelength of the spectral channel and therefore different for both the TIRS bands. Atmospheric gases such as carbon dioxide, nitrogen dioxide, ozone etc. are homogenous whereas spatial variability can be observed in case of water vapour. Therefore, the effect due to gaseous composition of the atmosphere can be assumed to be constant whereas the characteristic absorption of water vapour between 10.5-12.5 µm is considered in the SW algorithm (Coll et al., 1994).

In order to determine the LST of Zemu glacier (Figure 3.3), brightness temperature (BT) has been derived using the Top of Atmospheric (TOA) spectral radiance (L_λ) multiplying the multiplicative rescaling factor (0.0003342) with corresponding TIR bands and adding additive rescaling factor (0.1) for band 10 and 11 respectively following equation 3.8 as given below (Mondal and Bharti, 2021):

$$L_\lambda = A \times Q_{cal} + B \quad (3.8)$$

In the equation, L_λ denotes TOA spectral radiance ($\text{watt m}^{-2} \text{srad}^{-1} \mu\text{m}^{-1}$), A and B are the band specific multiplicative and additive rescaling factors respectively and Q_{cal} represents band 10/11 digital number (DN) value. Brightness Temperature (BT) is microwave radiation radiance

propagating upward from the top of the atmosphere of the Earth. It has been deduced adopting the following formula (equation 3.9):

$$BT = \frac{K2}{[\ln \frac{K1}{L_\lambda} + 1]} - 273.15 \quad (3.9)$$

Here, $K1$ (774.8853, 480.8883) and $K2$ (1321.0789, 1201.1442) are the thermal constants for band 10 and 11 respectively. Band-4/5 are used to calculate the Normalised Difference Vegetation Index (NDVI). The resultant value of NDVI range between -1 to +1. The NDVI result has been reclassified further into soil and vegetation using threshold of 0.2 and 0.574185 respectively to find out Fractional Vegetation Cover (FVC). FVC is calculated by using the equation 3.10 given below:

$$FVC = \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \quad (3.10)$$

Land Surface Emissivity (LSE) acts as an important parameter for deriving LST using SW algorithm. LSE for band 10/11 has been estimated using NDVI threshold method (equation 3.11).

$$LSE = \epsilon_s(1 - FVC) + \epsilon_v \times FVC \quad (3.11)$$

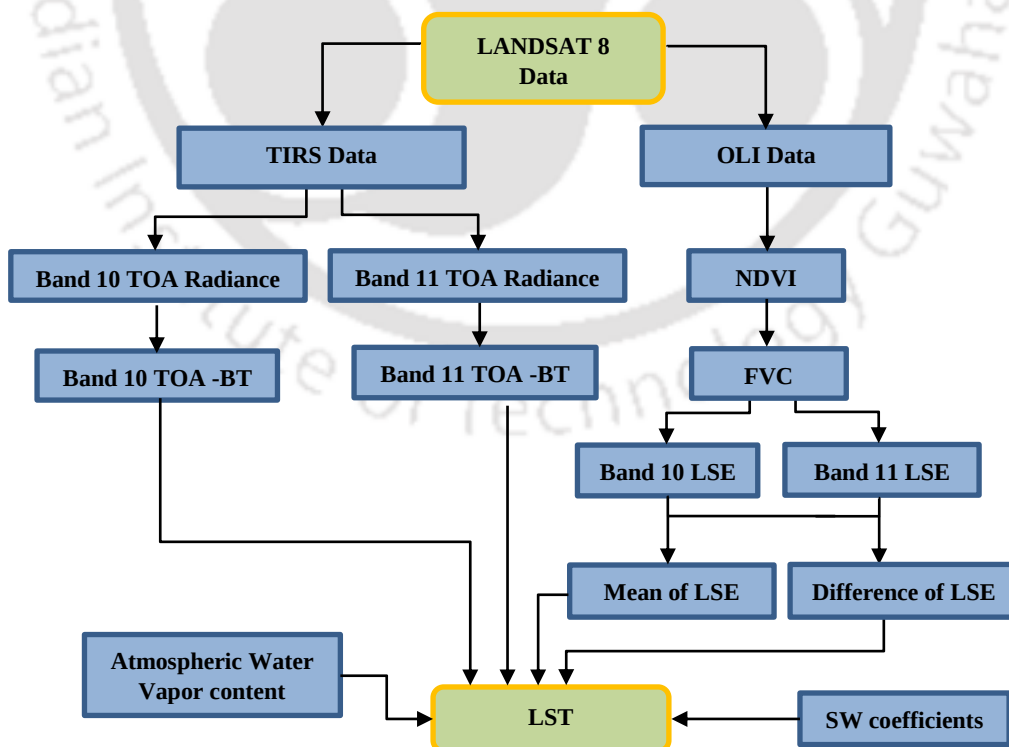


Figure 3.3: Flowchart of LST estimation using the split-window algorithm

In the equation mentioned above, ε_s (0.971, 0.977) and ε_v (0.987, 0.989) represent soil and vegetative emissivity values for bands 10 and 11, respectively. After generating LSE for both the bands of TIR, the mean and difference in LSE are derived as,

$$LSE_{mean} = \frac{LSE_{B10} + LSE_{B11}}{2} \quad (3.12)$$

$$LSE_{difference} = LSE_{B10} - LSE_{B11} \quad (3.13)$$

Finally, the LST has been calculated by applying a structured mathematical algorithm i.e. Split-Window (SW) algorithm. The formulation is given below as equation 3.14:

$$LST = BT_{B10} + C_1(BT_{B10} - BT_{B11}) + C_2(BT_{B10} - BT_{B11})^2 + C_0 + (C_3 + C_4w)(1 - LSE_{mean}) + (C_5 + C_6w)LSE_{difference} \quad (3.14)$$

In this equation, C_0 to C_6 are the SW coefficient values as mentioned in Table 3.2 (Sobrino et al., 1996; Zhao et al., 2009) and w is the atmospheric water vapour content of the area during data acquisition.

Table 3.2: Coefficients of split-window algorithm

Split-window coefficients	Value
C_0	-0.268
C_1	1.378
C_2	0.183
C_3	54.300
C_4	-2.238
C_5	-129.200
C_6	16.400

3.4.5 Debris Index

Glaciers are composed of varying amount of debris especially the Himalayan Glaciers (Fushimi et al., 1980; Bolch et al., 2008; Hewitt, 2009). Debris-covered glaciers, also called moraine-covered or debris-mantled glaciers act as an effective agent of sediment transport (Kirkbride, 1995). This transport of sediments can be either on its surface (supraglacial) or within the ice mass (subglacial) or even below the glacier (subglacial). As glacial ice/snow is different from debris in terms of albedo and thermal inertia, changes in the exposed debris cover of a glacial body could disturb the radiative balance (amount of solar irradiance absorbed) of a glacial body thus enhancing the surface temperature and melt rate respectively. One of the widely used automated algorithms to distinguish debris-covered ice from clean snow/ice is the band ratio technique as shown in equation 3.15 (Racoviteanu et al., 2009; Pfeffer et al., 2014):

$$Debris\ Cover = \frac{\rho_{Band\ 4}}{\rho_{Band\ 11}} \quad (3.15)$$

where $\rho_{Band\ 11}$ is the reflectance in SWIR (1.565-1.655 μm) band for Sentinel 2 MSI datasets used. The threshold of 1.8 is considered to distinguish clean ice glacier areas from debris-covered areas.

3.4.6 Accuracy Assessment

This involved resampling the MOD10A2 products to L-8 and S-2 ground resolution. In the Himalayan region, the MODIS product has data voids. Therefore, the random sampling approach was adopted to generate the error matrices in which 1368 sample points (n) were used. This was done so that none of the points used in the accuracy assessment lie over the void adorned region of MOD10A2. The error matrices helped in depicting correspondence between classified (PCA, ICA, NDSI, and AND-operator) class labels and reference (MOD10A2) class labels, representing overall accuracies of snow mapping as well as kappa coefficient and conditional kappa coefficient of the snow class. Knowing the fact that the error matrices portray only an estimate of the accuracy of classification, the McNemar test was also conducted to check statistically significant differences within the snow maps thus produced. Based on χ^2 test, McNemar test is implemented with the continuity correlation accounting the fact that χ^2 distribution is continuous while the statistic is discrete (Dietterich 1998). It is a non-parametric test that monitors the binary distinction between incorrect and correct class allocations of two outputs. The McNemar test computes the z score:

$$z - score = \frac{f_{12} - f_{21}}{\sqrt{f_{12} + f_{21}}} \quad (3.16)$$

where f_{12} is the total aggregate of correct paired class allocations in snow map-1 but incorrect in snow map-2 and f_{21} is vice versa. $z_c \geq 3.84$ shows statistically significant differences between two snow maps at a 95% confidence level and confirms the null hypothesis be rejected if $z > z_c$.

3.5 Results and Discussion

3.5.1 Effective Snow Cover Mapping

After the pre-processing of selected L-8 and S-2 bands which involved reflectance normalization and Gaussian stretching, PCA and ICA transformations were executed. Table 3.3(a, b, and c) represents the eigenvector loadings of all the PCs as well as ICs along with their corresponding variance. For PC1, the variance is very high accounting for more than 90% along with almost equal loadings from all the bands. Such high variance represents a high correlation between spectral bands. Other than PC1, all the components have low variance

because of their sensitivity towards different surficial features responsive to spectral signatures in different wavelength regions. For PC2, very high eigenvector loading with positive sign can be seen for band 6 and 11 (SWIR-I) as well as band 7 and 12 (SWIR-II) of L-8 and S-2 respectively whereas the rest of the bands have lower values of loadings with the opposite sign (Crosta et al. 1989).

Table 3.3(a): Eigenvector loadings of different PCs and ICs for Landsat 8 OLI dataset of 10th March 2019

PRINCIPAL COMPONENTS	PC1	PC2	PC3	PC4	PC5	IC1	IC2	IC3	IC4	IC5
SPECTRAL BANDS										
B2	0.451	-0.387	0.625	-0.448	0.236	0.548	-0.201	0.656	0.331	0.345
B3	0.454	-0.352	-0.132	0.161	-0.791	0.545	-0.185	-0.050	-0.066	-0.814
B4	0.455	-0.329	-0.477	0.373	0.563	0.546	-0.172	-0.603	-0.300	0.467
B6	0.434	0.601	0.425	0.520	0.016	0.238	0.735	0.299	-0.560	0.019
B7	0.442	0.507	-0.428	-0.604	-0.024	0.218	0.596	-0.337	-0.695	-0.025
TOTAL VARIANCE (%)	93.00	6.79	0.15	0.05	0.01	88.83	10.94	0.18	0.04	0.01

Table 3.3(b): Eigenvector loadings of different PCs for Sentinel 2 MSI dataset of 1st March 2019

PRINCIPAL COMPONENTS	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
SPECTRAL BANDS								
B2	0.402	-0.319	0.402	0.538	-0.377	-0.377	-0.012	0.002
B3	0.376	-0.214	0.134	-0.042	-0.196	0.865	-0.084	0.010
B4	0.388	-0.219	0.323	-0.660	0.284	-0.272	-0.328	-0.004
B5	0.359	-0.120	-0.150	-0.194	0.089	-0.068	0.880	0.099
B6	0.342	-0.052	-0.536	0.072	0.017	-0.077	-0.146	-0.749
B7	0.339	-0.028	-0.586	0.114	0.026	-0.089	-0.299	0.655
B11	0.273	0.742	0.065	-0.253	-0.548	-0.082	-0.007	0.001
B12	0.333	0.485	0.242	0.391	0.656	0.106	0.002	-0.014
TOTAL VARIANCE (%)	89.22	8.58	1.26	0.35	0.29	0.15	0.12	0.03

Table 3.3(c): Eigenvector loadings of different ICs for Sentinel 2 MSI dataset of 1st March 2019

INDEPENDENT COMPONENTS	IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8
SPECTRAL BANDS								
B2	-0.351	-0.216	0.450	0.101	0.594	0.080	0.297	0.413
B3	-0.352	-0.203	0.358	0.202	0.046	-0.084	-0.131	-0.800
B4	-0.352	-0.259	0.308	0.117	-0.735	0.004	-0.155	0.370
B5	-0.350	-0.246	-0.186	-0.813	-0.078	0.153	0.270	-0.136
B6	-0.348	-0.183	-0.461	0.096	0.135	-0.759	-0.115	0.124
B7	-0.348	-0.147	0.552	0.378	0.085	0.616	-0.151	0.004
B11	-0.363	0.627	-0.066	0.207	-0.212	-0.062	0.610	-0.082
B12	-0.365	0.580	0.136	-0.282	0.169	0.509	-0.624	0.109
TOTAL VARIANCE (%)	99.70	0.27	9.4×10^{-3}	7.33×10^{-4}	3.25×10^{-5}	1.22×10^{-6}	1.10×10^{-6}	7.2×10^{-7}

Therefore, PC2 has been considered useful for snow mapping as snow exhibits spectral signatures in the SWIR region of the EM spectrum. In Independent Component transformation, IC1 shows positive eigenvector loadings from all the bands accounting for more than 88% of the total variance. Except for the SWIR channels, IC1 is composed of almost equal loadings

from all the bands. However, in IC2, very high eigenvector loadings with positive signs can be seen for the SWIR bands whereas other bands account for loadings with an opposite sign. This arrangement can highlight surficial features exhibiting spectral signature in SWIR bands and IC2 can be useful in mapping snow cover. NDSI has been employed to delineate snow from other land covers in the watershed. A threshold of 0.4 has been used that helped in distinguishing snow from clouds and reflective water bodies. In the PC2 image, snow is mapped along with some fluvial channels. This problem is compromised with the ICA transformation where IC2 mapped snow coverage devoid of fluvial features but obscuring clouds are also mapped along with the snow. NDSI helped in mapping snow cover that is free from cloud interferences. To check the effective snow coverage in the region, PC2, IC2, and NDSI are used as an input to digital logic gate operation (AND-gate) for effective snow cover maps from L-8 (Figure 3.4) and S-2 (Figure 3.5) datasets.

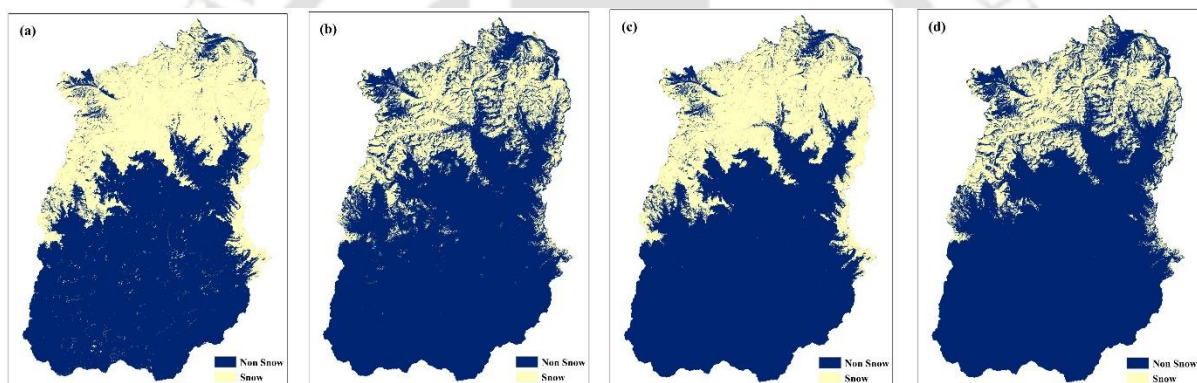


Figure 3.4: Binary products (snow cover in yellow) derived from Landsat 8 OLI dataset of 10th March 2019, representing percent snow cover: (a) **PC2** (37.13%), (b) **IC2** (23.39%), (c) **NDSI** (33.77%), (d) **AND-operated** (22.87%)

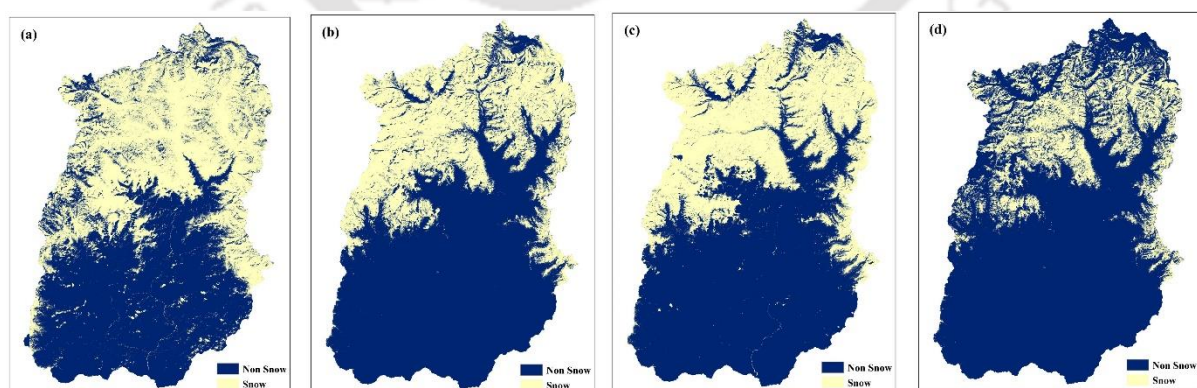


Figure 3.5: Binary products (snow cover in yellow) derived from Sentinel 2 MSI dataset of 1st March 2019, representing percent snow cover: (a) **PC2** (46.90%), (b) **IC2** (44.84%), (c) **NDSI** (41.74%), (d) **AND-operated** (34.48%)

The effective snow maps derived from AND operator have shown improved accuracy of mapping in terms of overall accuracy, kappa, and conditional kappa as shown in Table 3.4.

The misclassifications of every individual algorithm are removed through the AND-operated snow cover map. Only those pixels marked as snow in all the input algorithms are marked as snow in the output. Else, if a pixel is marked as snow by one algorithm but marked as non-snow by another algorithm is considered as non-snow in the output. Accepting the fact that the accuracy assessment values do not differ drastically, the AND-operated map does not include fluvial features, obscuring cloud cover, and reflective water bodies as snow cover in PC2, IC2, and NDSI respectively. Finally, the McNemar z-scores calculated for each set of AND-operated results and input snow maps have confirmed that statistically significant differences do not exist between the AND-operated maps and the other products at a 95% confidence level. The accuracies for PCA is almost similar from both Landsat 8 and Sentinel 2. However, the overall accuracy, kappa, and conditional kappa for ICA is slightly more for Landsat-8 but the McNemar score is higher for Sentinel 2. Whereas, in case of NDSI, the overall accuracy and kappa is greater for Landsat 8 but the conditional kappa and McNemar score is slightly higher for Sentinel 2. There is a mixed accuracy response of multivariate statistical techniques and band ratio over Landsat 8 and Sentinel 2 datasets as shown in Table 3.4. After deriving the effective snow cover maps using AND-gate operator, the accuracies are better for Landsat 8 than Sentinel 2 MSI. One possible reason behind this slightly improved accuracy of Landsat 8 can be its spatial resolution (30m) as compared to Sentinel 2 (10/20m) as MOD10A2 product is a 500m derived product which is slightly less coherent as a base product for Sentinel 2 due to its finer ground resolution as compared to Landsat 8. Thus, the implementation of a final AND-gate operation to a set of algorithm-derived products for effective mapping of snow cover is advantageous if misclassification of a specific feature is a distinct property of a particular algorithm. If all the methods result in a common error, the digital AND-gate operation fails. Moreover, a field visit was conducted between 17th January and 28th January 2021 (Figure 3.6). Since, the northern district of Sikkim experiences snowfall, locations lying in two different routes of Lachen and Lachung respectively were checked for snow coverage on 24th January 2021 which were used as field validation points to the effective snow mapping done using Landsat 8 OLI data of the same date as shown in Figure 3.7.

Table 3.4: Datasets for effective snow cover mapping and accuracy assessment of the results

<i>Algorithm</i>	<i>Overall Accuracy</i>		<i>Kappa</i>		<i>Conditional Kappa</i>		<i>McNemar z-score</i>	
	L-8	S-2	L-8	S-2	L-8	S-2	L-8	S-2
PCA	80.63	80.47	0.61	0.61	0.51	0.52	0.35	0.36
ICA	84.94	82.37	0.70	0.65	0.78	0.70	0.29	0.33
NDSI	84.58	81.66	0.69	0.63	0.65	0.70	0.30	0.35
AND-operated	85.53	84.14	0.71	0.68	0.82	0.74		

(a)

Right to left: Sandeep Kr. Mondal, Antony J. Moothedan, Dr. Rishikesh Bharti, Prof. Subashisa Dutta, Chitesh Sharma, Vatsal D. Patel, Late Dr. Avilash Sahoo, Soumya Guchhait



(b)

Yumthang Valley: 3277m a.s.l



Figure 3.6: Pictures from the Sikkim field investigation between 17th and 28th January 2022 showing (a) the team members and (b) snow cover at Yumthang valley

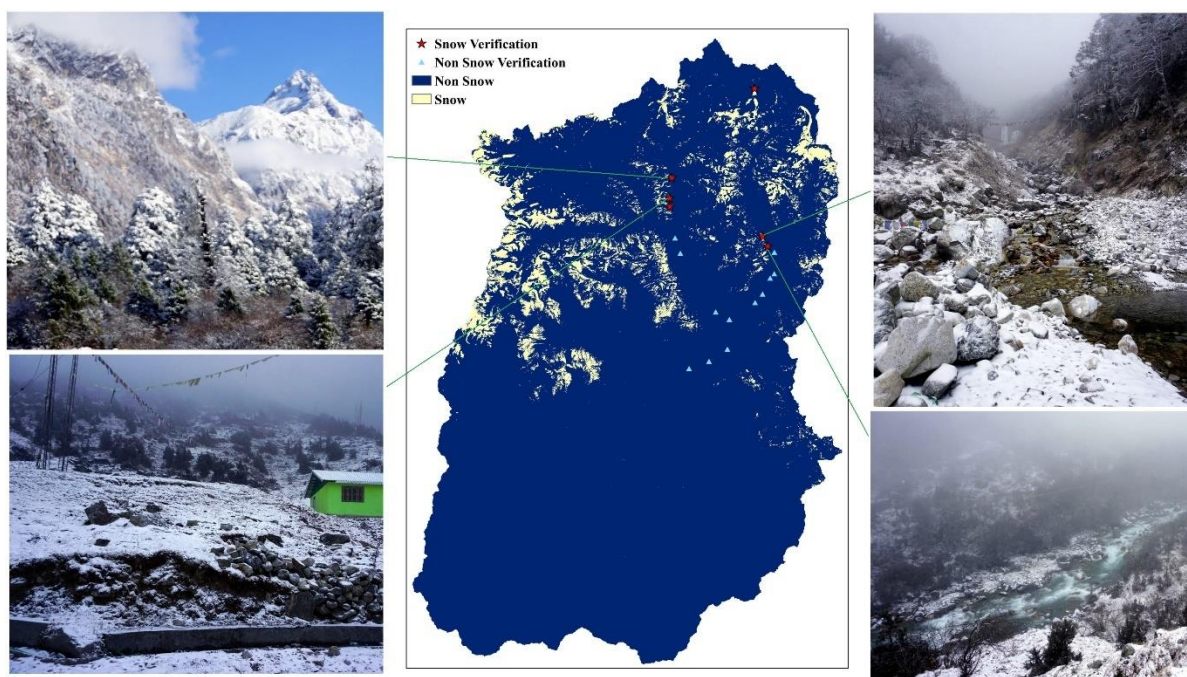
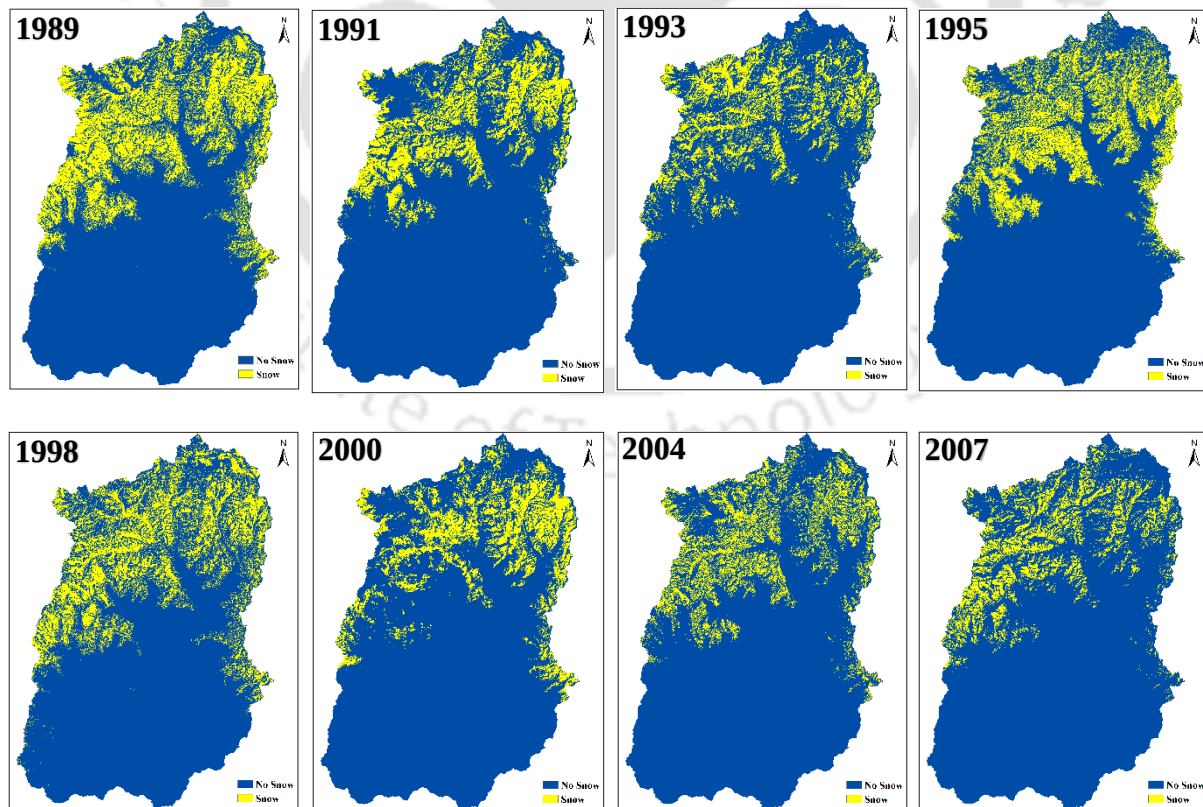


Figure 3.7: Effective snow cover map derived from Sentinel 2 MSI dataset of 24th January 2021 with the locations of selected field observations

The AND-operated effective snow cover maps of Sikkim between 1989 and 2016 for both accumulation and ablation periods are shown in Figure 3.8 and 3.9 respectively. The 3-month average SST fluctuation is represented with the past 30 years' intra-annual snow cover in Figures 3.10a and 3.10b. Where SST recorded over the Niño 3.4 region of the Pacific Ocean as shown in Table 3.5 represents a periodicity during both ablation and accumulation period, an inverse correlation is observed between the ablation period SST and intra-annual snow cover between 1989 and 2019. An increase in the SST (consecutive 3 months average) during the ablation period (October-December) shows a decrease in the intra-annual snow coverage of the basin during the same year and vice versa. This can be seen as an interesting synchronization of the cryosphere with other spheres of the earth system governing a change in the SST at a place (Niño 3.4 region) far away from the north-eastern Himalaya. Looking at the effective snow cover of the Teesta basin for the last 30 years between 1989 and 2019, it can be clearly stated that the Himalayan cryosphere is a very dynamic component of the earth system where the fluctuations in the pattern of snow cover might seem haphazard in shorter span (on seasonal/annual basis) but follows a periodic path in longer span of time (on a decadal basis). A possible reason behind this captured phenomenon of negative correlation between Niño 3.4 region SST and intra-annual snow coverage of Teesta basin can be explained with the first hypothesis of Blanford (1884) and the study conducted by Shaman and Tziperman (2005). Accumulation of snow leads to less absorption of incoming solar radiation due to its high

albedo leading to lowering of ground temperature not just during wintertime but also subsequent spring and summer. Further, this anomalous reduction in summertime ground temperature results in fluctuation in the thermal gradient of land and sea. The SLA is calculated for the accumulation period and it shows a two-fold periodicity in the last 30 years as shown in Figure 3.10c. It represents a declining trend between 1989 and 1998 with a steep fall between 1995 and 1998. After 1998, the SLA starts rising till 2010 with a steep rise from 2007. Between 2010 and 2019, the trend of SLA is again decreasing. Thus, a periodicity in SLA can be observed every 9-12 years for the Sikkim Himalaya. A decrease in the SLA means more snow coverage as snowfall starts from lesser elevation covering more area in the catchment. SLA reaches its minimum limit of 2379m in 1998 and maximum limit of 2971m in 2010 when the accumulation period snow coverage is 1636 and 1147 Km² respectively. The average SLA for the Sikkim Himalaya during the accumulation period is calculated as 2680m for the last 30 years between 1989 and 2019. Even though the trend of SLA fluctuation and intra-annual snow coverage between 1989 and 2019 are periodic, their periodicity is not in synchronization with one another. Here, SLA is calculated for the accumulation period especially during peak snowfall (between January and March). However, the intra-annual snow cover considers surficial snow cover during both accumulation and ablation periods.



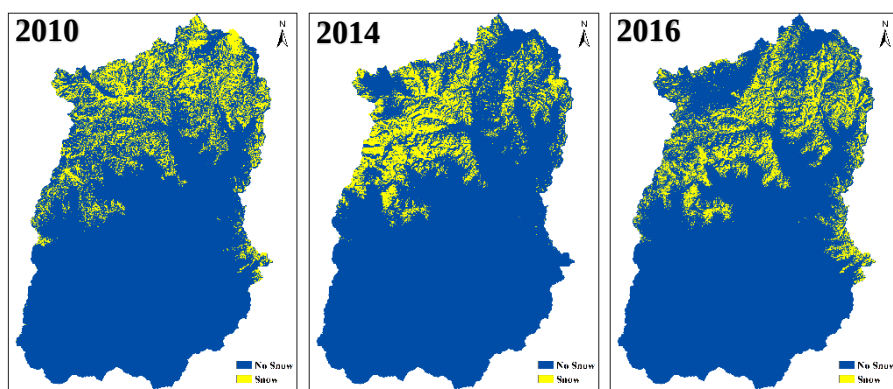


Figure 3.8: Maps showing AND-operated effective snow coverage (in yellow) during accumulation period of Sikkim since 1989

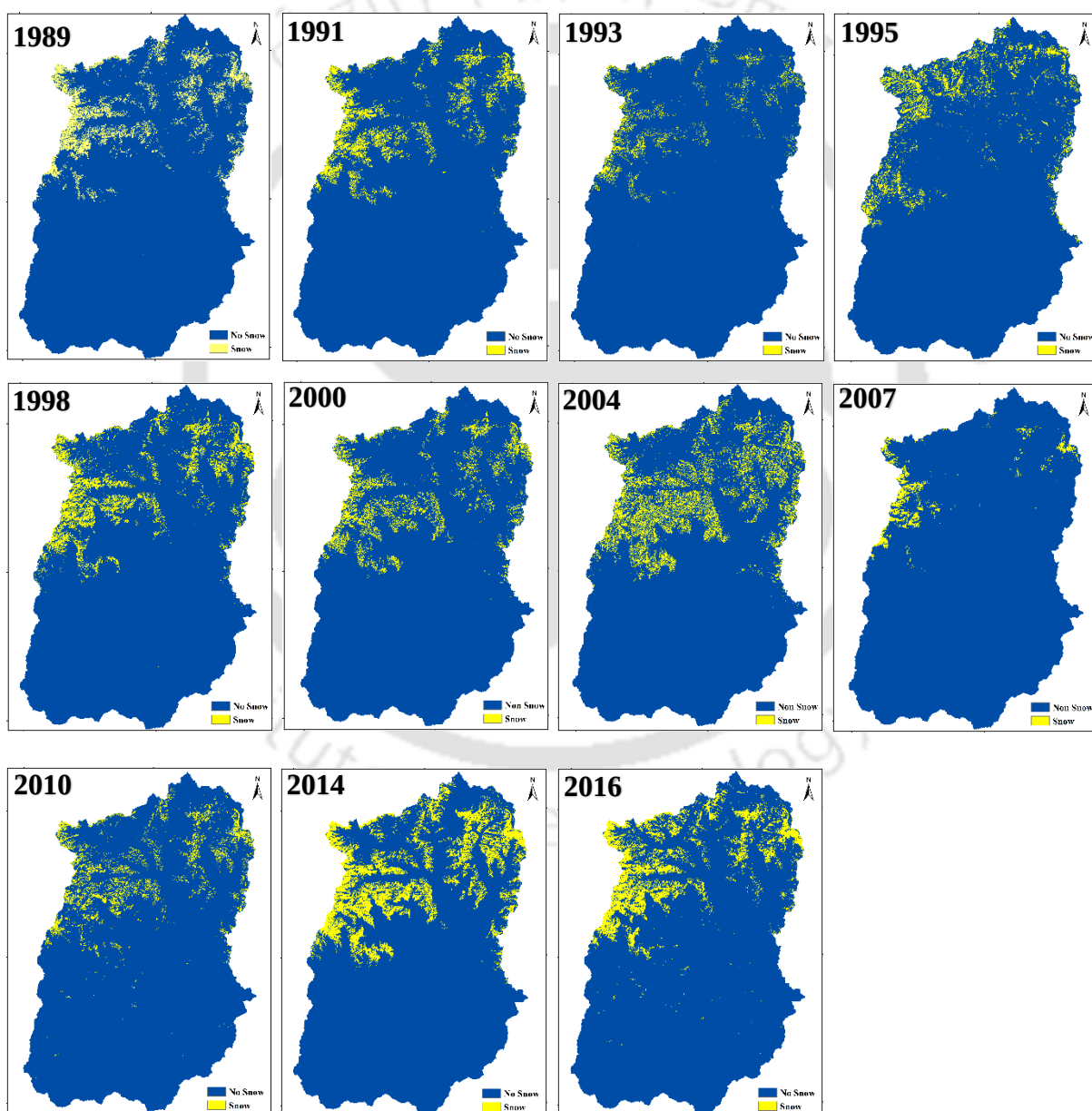


Figure 3.9: Maps showing AND-operated effective snow coverage (in yellow) during ablation period of Sikkim since 1989

Table 3.5: Values representing the spatio-temporal changes in the snow cover area with corresponding Niño 3.4 region SST and SLA

Sl. No.	Satellite	Date of acquisition [Effective Snow Cover in Km ²]		Intra-Annual Change in Km ²	ERSST.v5 consecutive 3 months average SST data in degrees		Snow Line Altitude (m)
		Accumulation Period	Ablation Period		Accumulation Period	Ablation Period	
1.	Landsat 5 (TM)	23-03-1989 [1904]	25-10-1989 [552]	1352	-1.1	-0.2	2754
2.		09-02-1991 [1284]	08-11-1991 [494]	790	0.3	1.2	2660
3.		02-03-1993 [1073]	28-10-1993 [225]	848	0.5	0.1	2629
4.		09-04-1995 [1554]	19-11-1995 [423]	1131	0.3	-1	2619
5.		01-04-1998 [1636]	29-12-1998 [569]	1067	1	-1.6	2379
6.		21-03-2000 [1160]	16-11-2000 [481]	679	-1.1	-0.7	2543
7.		13-02-2004 [1079]	29-12-2004 [817]	262	0.3	0.7	2666
8.	Landsat 8 (OLI)	21-02-2007 [932]	03-10-2007 [165]	767	0.2	-1.3	2726
9.		13-02-2010 [1147]	14-12-2010 [424]	723	1.2	-1.6	2971
10.		24-02-2014 [1018]	07-11-2014 [1005]	13	-0.5	0.6	2779
11.		17-03-2016 [1099]	30-12-2016 [859]	240	1.6	-0.6	2741
12.		01-03-2019 [1632]	21-11-2019 [733]	899	0.7	0.5	2695

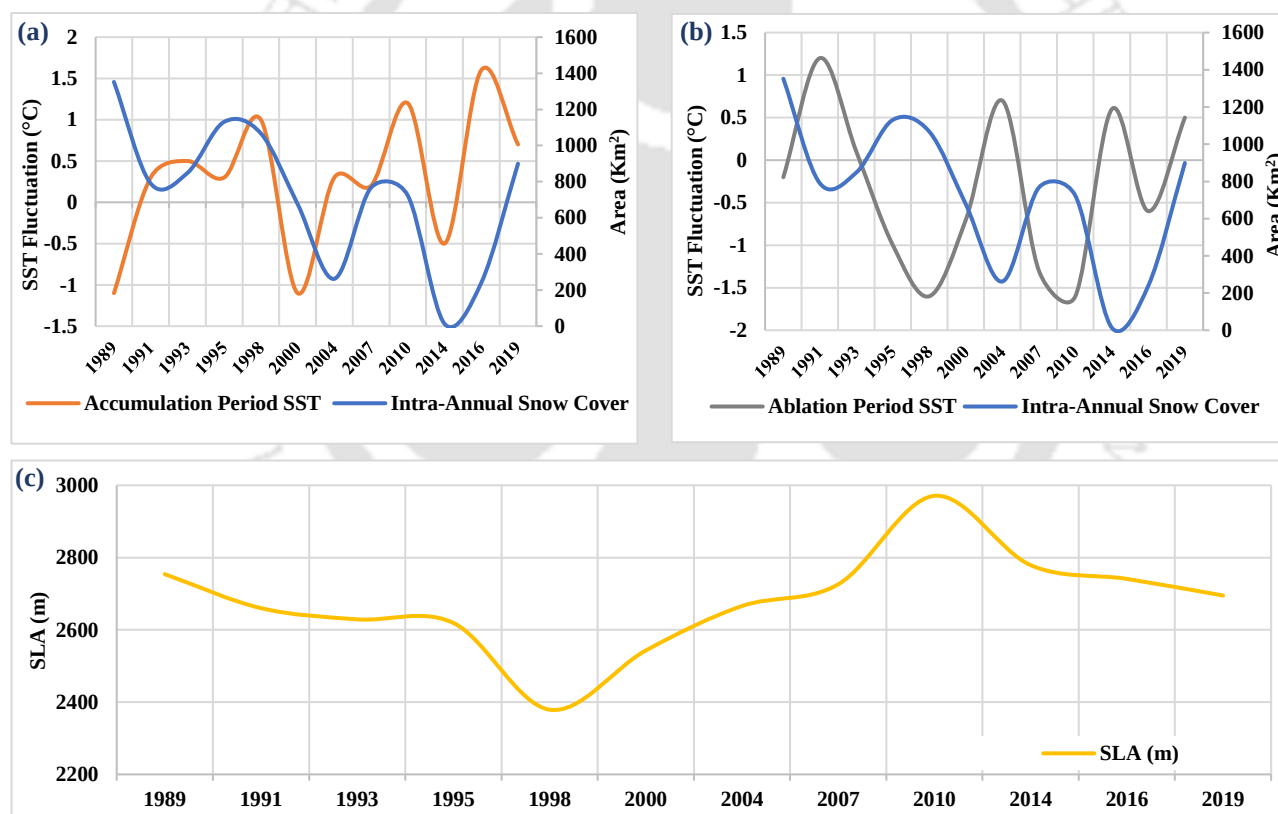


Figure 3.10: The graphical representation of intra-annual snow cover variation for the Sikkim Himalayas with average SST (ERSST.v5 consecutive 3-month) fluctuation for the accumulation (a) and ablation (b) periods. The changes in the accumulation period Snow Line Altitude (c) is represented for the period of 1989 to 2019

3.5.2 Glacial Velocity and Modelled Depth

The surficial velocity of the Zemu glacier between 2019 and 2020 (Figure 3.11a) shows that the glacier behaves differently in the bifurcating arms/flanges than the main trunk. The annual surface mobility is comparably higher in the flanges with the maximum tracked velocity of 16.8 m/yr. The mean velocity of the glacial body is 2.2 m/yr. The velocity of the main trunk varies between 1-12 m/yr. The velocity is minimum at the boundary of the glacial body which rises away from the periphery. Such a large variation in surface mobility of different zones within the glacial body explains that Zemu glacier is devoid of a generalized glacial dynamics. The modelled glacial thickness (Figure 3.11b) shows that the glacier has maximum depth of 329 ± 46 m and a mean depth of 78 ± 11 m. The main trunk is comparatively thick as compared to the flanges. There are distributed patches throughout the glacial body showing higher values of glacial depth. These patches are not eliminated by the low pass filter applied over the glacial thickness output and possibly indicate overdeepenings as well as supraglacial lakes (Rashid et al., 2020).

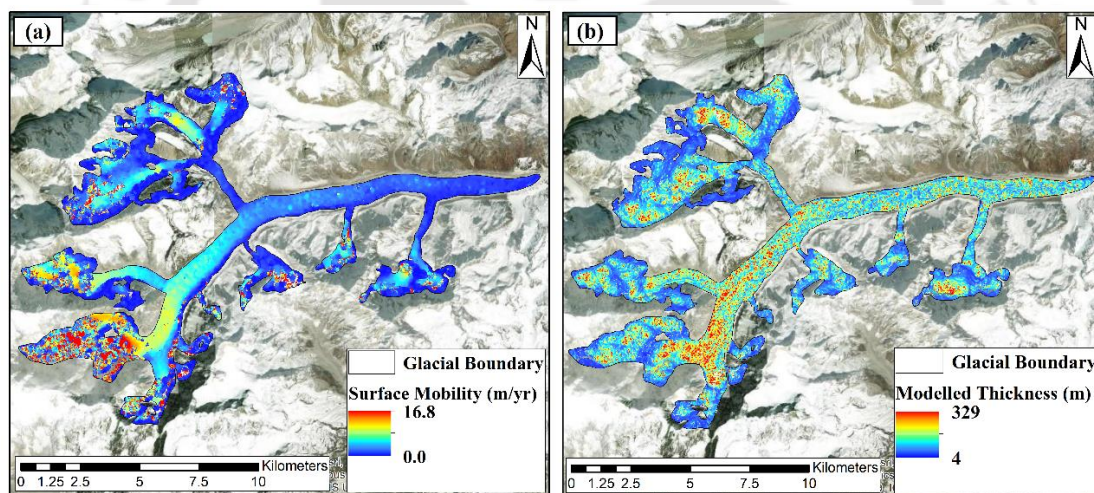


Figure 3.11: Map showing (a) annual surface velocity and (b) modelled glacial thickness of the Zemu glacier

The modelled depth of Zemu glacier has been estimated using equation 3.6 and the uncertainties associated with the adopted method and datasets have been calculated using equation 3.7. The mean velocity of stable ground surface through correlation of Sentinel 2 MSI datasets has been estimated as 1 m/yr. Since, displacement of stable ground should be zero (Saraswat et al., 2013), the movement captured by COSI-Corr method has been considered as an error. In addition, COSI-Corr correlation accuracy (Leprince et al., 2007) as well as co-registration of Sentinel 2 MSI datasets (Komura and Sugimoto, 2021) can introduce errors in the mobility which has been considered as 0.5 m ($\sim 1/20$ th of pixel) and 3 m respectively. The error associated with the influence of drag along the flow lines is reflected in the shape factor.

Considering fluctuations in the shape factor between 0.9 during accumulation and 0.7 during ablation period, the error percentage has been considered as $\pm 12.5\%$ in the present study (Linsbauer et al., 2012; Gantayat et al., 2014). In the Himalayan glaciers, the density of metamorphosed ice varies between 830 and 923 Kg m^{-3} (Bhambri et al., 2015). Considering this typical variation, 10% uncertainty has been adopted. The error in slope ($\sin \theta$) arises due to vertical error in the DEM used which has been considered as 8.34% (Kumar et al., 2020). Thus, the uncertainty associated with the modelled depth of Zemu glacier has been estimated as 14%.

3.5.3 Debris Cover and LST

The Zemu glacier can be considered a debris-covered glacier as a majority of the glacial area (60.7 Km^2 accounting for 88.47%) is covered with debris as shown in Figure 3.12a. Where the glacial trunk is almost associated with debris, some of the portions within the glacial flanges are clean ice regions. These regions are mainly localized towards the periphery of the glacial boundary. The LST derived using Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) of 10th March 2019 shows that the surface temperature within the glacial body fluctuates between -20.7°C and 6.7°C (Figure 3.12b). The mean LST of Zemu glacier is -7.08°C which is below the melting point (0°C). The distribution of LST within the glacial body follows the observations from debris mapping and surface mobility. The lowest LST has been captured within the flanges where maximum glacial mobility and the presence of clean glacial ice have been observed. As moving towards the main trunk, the LST increases and exceeds the melting point. Such observations can be indicative of the main trunk as a potential melting zone of the glacier where the LST lies above 0°C even in the month of March which is the winter period. However, thickness of the obscuring debris within a glacial body plays a vital role in governing glacial melt. Where debris cover of few inches result in increased absorption of solar radiations resulting in enhanced glacial melt, a much thicker debris above metamorphosed ice may result in reduced melting as well.

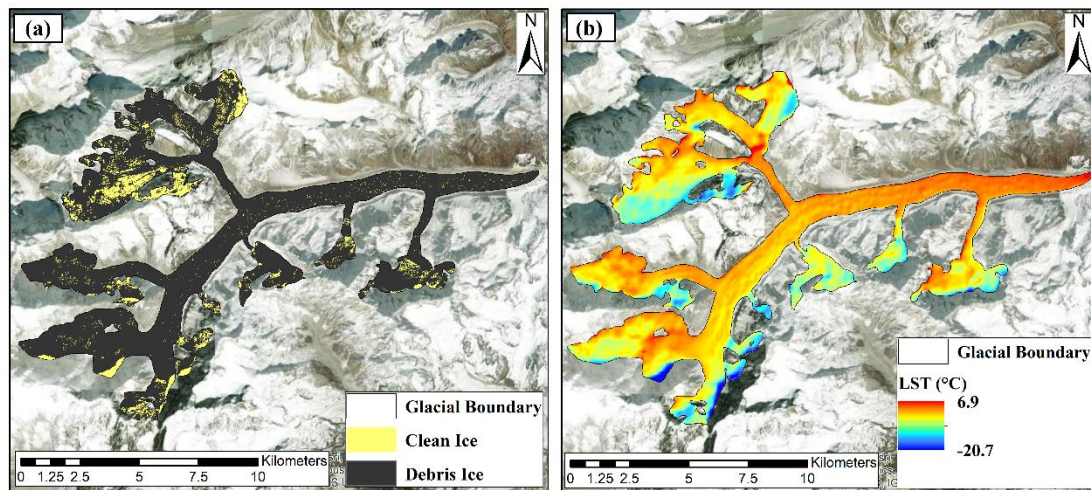


Figure 3.12: Map showing (a) debris coverage (88.47%) and (b) LST with the Zemu glacial body

3.6 Conclusion

It is evident from the results that the combined technique of multivariate statistics and band ratio can help in better estimation of snow cover area of the Teesta basin. NDSI is an effective method of snow cover mapping. However, its accuracy is compromised in the presence of reflective water surfaces. PCA is a widely used statistical transformation algorithm but mapping with the help of PCA compromises the ability to discriminate fluvial water from snow. ICA on the other hand proves to be better in mapping snow cover but the effects of cloud coverage remain a matter of concern. Applying digital logic AND-gate operation helped in generating effective snow cover maps of the Teesta basin for the last 30 years which are free from fluvial channels, cloud cover, and reflective water bodies misclassified as snow in PC2, IC2, and NDSI snow maps respectively. The final results have been justified with an accuracy assessment which showed an improved overall accuracy of 84.14% - 85.53%, kappa of 0.68 – 0.71, and conditional kappa of 0.74 - 0.82 for L-8 and S-2 respectively. Moreover, the McNemar test z-scores do not show statistically significant differences between the final AND-operated output and inputs. An inverse correlation has been observed in the last 30 years between ablation period SST over the Niño 3.4 region of the Pacific Ocean and intra-annual snow cover. The SLA also shows a two-fold periodicity in every 9-12 years for the Sikkim Himalaya since 1989.

The annual surface mobility of the glacial body between 2019 and 2020 shows that a large valley glacier such as Zemu is devoid of a generalized glacial dynamics. The surface velocity is maximum in the flanges than the main trunk. The modelled glacial depth shows the maximum depth of 329 m with the flanges being comparatively thinner than the main trunk. Major portion of the glacial body (88.47%) is covered by debris and shows large variations in

LST between -20.7°C at the periphery of flanges where clean glacial ice is observed and 6.9°C within the main trunk which is dominated by debris. Such findings can be indicative of the glacial trunk as a potential melting zone of the glacier.



Hydrological, Lithological, and Geothermal Sources of the Teesta River System, Sikkim Himalayas

4.1 Introduction

4.1.1 General

Understanding the sources of perennial river systems is essential to understanding the impact of changing climate. Especially the Himalayan rivers such as the Ganges, the Indus, the Brahmaputra, the Mekong, the Yangtze, the Salween, and the Teesta originate from non-renewable sources called glaciers. It is critically important to understand the governing mechanism of river systems in terms of their source and intermediate processes. Especially the glacier-fed rivers where fluctuations in glacial melt influence the flow. Over the past few decades, researchers claim the shrinking behavior of Himalayan glaciers (Bolch et al., 2012a; Shrestha et al., 2015). This raises questions about the perennial access to fresh water for millions of people in Southeast Asia, accounting for 8.58% of the world's population.

Freshwater is essential in maintaining biodiversity in the terrestrial environment (Wanjui, 2013). This becomes much more crucial for the Indian subcontinent, which is densely populated ($1/8^{\text{th}}$ of the world population), coupled with extensive agrarian practices (Singh, 2004; Malhan and Rao, 2017). Snow/glacial melt and rainfall are the major components of freshwater for agriculture. The south-west monsoon, also known as the Indian summer monsoon (ISM), is the major contributor to yearly precipitation in India, accounting for ~80% (Annamalai et al., 2007; Chevuturi, 2019). The rest of the ~20% precipitation is due to the north-east monsoon during winter and the mid-latitude westerlies (Kripalani and Kumar, 2004; Dimri et al., 2013). The winter precipitation occurs between December and February in the form of snowfall that provides melt contribution to the north Indian rivers later in the early summer (Dai, 1990; Dimri et al., 2016). Studies suggest that the overall contribution of the winter monsoon is quite significant and requires attention. With the increase in the population within the subcontinent, there is an exponential increment in the demand for freshwater supply (Okello et al., 2015; Liu et al., 2017).

Monsoon can be defined as an atmospheric phenomenon, an amalgamation of various atmospheric circulations on a regional scale governed by land-air-sea interactions and solar radiative cycle resulting in alterations in seasonal pressure systems, therefore, defining the climate of a region (Zhisheng et al., 2015). Over the past centuries, its domain has shifted from a regional/sub-continental scale to a global scale that assimilates subtropics/tropics vertically up to the stratosphere (Wang and Ding, 2008; Chang et al., 2011). In the context of the Indian subcontinent, variations in heat capacities of ocean and land, especially the Thar desert and the Tibetan Plateau, create a low-pressure zone that governs the migration of the equatorial convergence zone, also known as the intertropical convergence zone (ITCZ). This leads to the reversal of seasonal winds delivering rainfall to different subcontinent regions (Charney, 1968; Chao and Chen, 2001).

The ~1500 mi long Himalayan stretch is pivotal in the precipitation pattern over the Indian landmass. On the one hand, where it hinders the icy winds from the north; on the other hand, it blocks the departure of moisture-laden summer monsoon towards the north. Between October and February, icy winds from Central Asia result in snowfall in the Himalayan ranges, which helps maintain the perennial flow of some major river systems (Benn and Owen, 1998). However, the contribution of the winter monsoon decreases as moving away from the east (Benn and Owen, 1998; Ali et al., 2019).

4.1.2 Hydrological Sources

Fluctuating climate conditions have led to a significant alteration in the ice mass of Himalayan glaciers, impacting the regional hydrology and climate cycle (Bolch et al., 2011; Guruprasad et al., 2022). Although chronological and regional heterogeneity exists, a general agreement prevails that glacial mass recession has amplified in the past few decades (Lee et al., 2021). Glacial mass balance studies originated in Sweden in 1945 using conventional techniques such as snow pits, probing, and snow stakes (Holmlund et al., 2005). However, such techniques demand trained labor and need more coverage and temporal monitoring. In recent times, mass balance studies have been conducted using various methods such as the glaciological, hydrological, altimetry, gravitational, and accumulation area ratio (AAR) (Racoviteanu et al., 2008). As periodical investigation helps in developing a better understanding of the characteristics of glaciers, methodologies adopting satellite remote sensing are preferred over techniques that involve complex and time-consuming fieldwork (Kulkarni et al., 2021; Majeed et al., 2021).

Researchers monitor snow cover (Mondal and Bharti, 2022; Patel et al., 2019) and quantify glacial mass loss on an annual basis where remote sensing is associated with melt-modeling techniques such as the Ice, Cloud, and land Elevation Satellite (ICESat) (Gardner et al., 2013), space gravimetry data from the Gravity Recovery and Climate Experiment (GRACE), satellite/airborne laser altimetry (Kääb et al., 2012; Jacob et al., 2012), digital elevation models (DEMs) (Gardelle et al., 2013) and meteorological datasets. Accepting the fact that these techniques provide significant insight into the process of glacial recession and accumulation, there exist possibilities of considerable disagreement (Boral and Sen, 2020). Remote sensing techniques consider both accumulation (mass gain) and ablation (mass loss) over a balance year for estimating the glacial mass loss, which cannot provide volumetric loss that flows into the perennial rivers as melt contributions. Such as glacial melt during summer if equal accumulation during winter indicates zero net mass loss; however, the glacial body might have delivered a substantial amount of melt contribution to its river network. Researchers have also developed cryospheric-hydrological models (Lutz et al., 2014) to quantify snow- and ice-meltwater contributions to Himalayan river systems. However, such modeling-derived melt-water contribution shows considerable disagreement in the case of Himalayan rivers. Also, it becomes difficult to validate the results from other studies as consideration of source end-members lack homogeneity (Boral and Sen, 2020). This necessitates new techniques to quantify various source endmembers to surface water flows. It can help in developing a better understanding of the perennial river systems of the Himalayan region and their dependence on the glacial melt. Moreover, this would help improve our understanding of the regional scale basin hydrology of the Himalayas.

Therefore, to understand the complicated mechanism of Himalayan hydrology, processes such as evapotranspiration, mixing, recycling and the origin of moisture sources (snow melt, glacial melt, rainfall, and/or groundwater), it is crucial to investigate the isotopic characterization of meteoric precipitation, which also explains the phase-transition during the transportation of moisture (Henderson-Sellers et al., 2004; Jasechko et al., 2014; Ali et al., 2020). Even though the global network for isotopes in precipitation (GNIP) provides detailed long-term variations in δD and $\delta^{18}O$ of a region, studies in the Himalayan region still face some challenges. Due to unfavorable weather and rugged topography, data collection is minimal, resulting in serious challenges in the quantitative study of surface water for its moisture source (Ali et al., 2020). Moreover, isotopic composition of river waters can be influenced due to several hydrologic processes such as isotopic fractionation (Taylor et al., 2002), in-stream

evaporation, or catchment evapotranspiration leading to heavier isotope enrichment (Simpson and Herczeg, 1991), and fractional contribution of surface and sub-surface sources into the discharge of river streams (Buttle, 1994). Even though these processes result in spatio-temporal variations in the isotopic composition of river streams, the seasonally varying isotopic composition reflects the continental and regional isotopic variance of meteoric water sources (Rozanski et al., 1982). This helps understand the dynamics of seasonal water vapor within a watershed (Laskar et al., 2014) and further conduct a paleoclimate study over the riverine sediment deposits.

4.1.3 Lithological Sources

Riverine transport of sediments from continental lithology to oceans acts as a pathway regulating the process of geochemical cycling of elements (Das et al., 2022). This influences the composition of river waters, which can be traced through their solute chemistry. Himalayan rivers such as the Indus, Ganga, and the Brahmaputra deliver immense amounts of sediments (dissolved as well as particulate matter) to the Arabian sea and the Bay of Bengal (Milliman and Meade, 1983). The Ganga-Brahmaputra system (G-B) holds the fourth position in the transport of sediments to the world oceans (Galy and France-Lanord, 2001). Himalayan rivers have a relatively higher concentration of Strontium (Sr) and radiogenic $^{87}\text{Sr}/^{86}\text{Sr}$ (Krishnaswami et al., 1992). This plays a pivotal role in regulating Sr isotope budgets in the oceans (Palmer and Edmond 1989). Studies reveal that there has been a monotonic rise in the marine $^{87}\text{Sr}/^{86}\text{Sr}$ values in the past ~40 Ma (Veizer et al., 1999). This indicates increased fluxes of continental weathering to oceans. This leads to a hypothesis that the enhanced weathering of silicate rocks has resulted in this increased radiogenic Sr supply to the oceans, especially during the late Cenozoic period (Raymo and Ruddiman, 1992).

4.1.4 Geothermal Sources

The Indian subcontinent hosts around 340 natural thermal springs located in various parts of the country (Chandrasekharam, 2000). In the Sikkim Himalayas, several thermal springs exist in the Yumthang, Borong, Rishi, Polot, and Yumesamdong regions (Panda et al., 2016), with their surface temperature lying in the range of 38-59°C (Bhatia, 2014). These springs indicate their geotectonic history of evolution, including flood basalt volcanism, continental collision, orogeny, transform faults, and supercontinental breakup (Valdiya, 2015). Thermal springs are located near the region of crustal movements, geothermal systems, and magmatic activities of recent times (Pandey and Negi, 1995). Especially in the Himalayan region, such springs are clustered between the Central Himalayan axis and the Main Central Thrust (MCT) (Tiwari et

al., 2016). Besides their religious significance and therapeutic values (Kalota, 1978), Indian thermal springs also possess the potential for geothermal power generation (Chandrasekharam, 2001). Moreover, the extraction of heavy metals is another valuable aspect.

This necessitates a comprehensive study of the Teesta watershed in terms of hydrological, lithological and geothermal sources as performed. This includes

1. Isotopic composition of different water sources, moisture sources and quantifying the percentage composition of endmembers in the headwaters of the Teesta River basin.
2. A state-of-the-art Strontium model to quantitatively segregate Sr fluxes from various lithologies within the Teesta watershed.
3. Isotopic composition of natural thermal springs and elemental analysis.

4.2 Study Area

Sikkim is a north-eastern state of India that encompasses the eastern Himalayas sharing its geographical boundary with Bhutan, Tibet, and Nepal in the east, north, and west, respectively (Dubey et al., 2019). The state's northern region is acquired by several glacial bodies accounting for 12% (~883 Km²) of the state area (Aggarwal et al., 2017), with the Zemu glacier being the largest. The transboundary catchment of the Teesta river covers a total area of 12,159 Km², of which 10,155 Km² lies within India and the rest in Bangladesh (Khan and Ali, 2019). The Teesta basin experiences significant spatial variation in the mean annual rainfall that varies from 200 mm in the high-altitude cold and arid regions to 5000 mm in the lower reaches of dense vegetation cover. The river basin receives 80.2% of the annual precipitation during monsoon and the remaining 19.8% in other seasons (13.6% in summer, 5.5% in post-monsoon, and 0.7% in winter) (Ranade et al., 2007). Steep topography associated with heavy rainfall leads to higher surface runoff. This results in soil erosion, failure of channel walls, and landslide episodes. The average winter temperature of the watershed is 25°C which recedes to 3°C during winters, provided the high-altitude glaciated regions remain below freezing (Ali et al., 2020). The relative humidity remains above the margin of 70% throughout the annual hydrological cycle.

The Teesta river gained its origination from the glacial bodies in the North Sikkim district, such as the Zemu, Chamgme, Pahunri, Kangchengyao, and Khangse glaciers (Meetei et al., 2007; Goyal and Goswami, 2018; Ali et al., 2020). Two primary glacier-fed streams, namely the Lachen Chu and Lachung Chu, converge in the Chungthang region of North

Sikkim, forming the Teesta river after that (Figure 4.1). Other tributaries such as the Rangpo Chu, Talung Chu, Rongni Chu and Rangeet join the Teesta river at Rangpo, Singhik, Singtam, and the border between Sikkim and West Bengal, respectively (Ali et al., 2020). Due to the topographical profile of the region and the contribution of various water sources to the discharge of the streams, The Teesta river has turbulent flow throughout Sikkim, carrying sediments and boulders along. The continuous process of deposition and denudation results in newly formed landforms from existing land exhibiting large geographical variability (N.D.M.A., 2013). Rock glaciers, relict lake sediments, glacial moraine deposits, gravel terraces, and talus fans characterize landforms in the upper reaches. Whereas the middle and lower reaches of the watershed can be characterized by subdued relief and comparatively less steep terrain (Ali et al., 2018). Vegetation cover within the catchment varies from alpine type in the northern higher elevation to tropical deciduous type in the southern lower elevations.

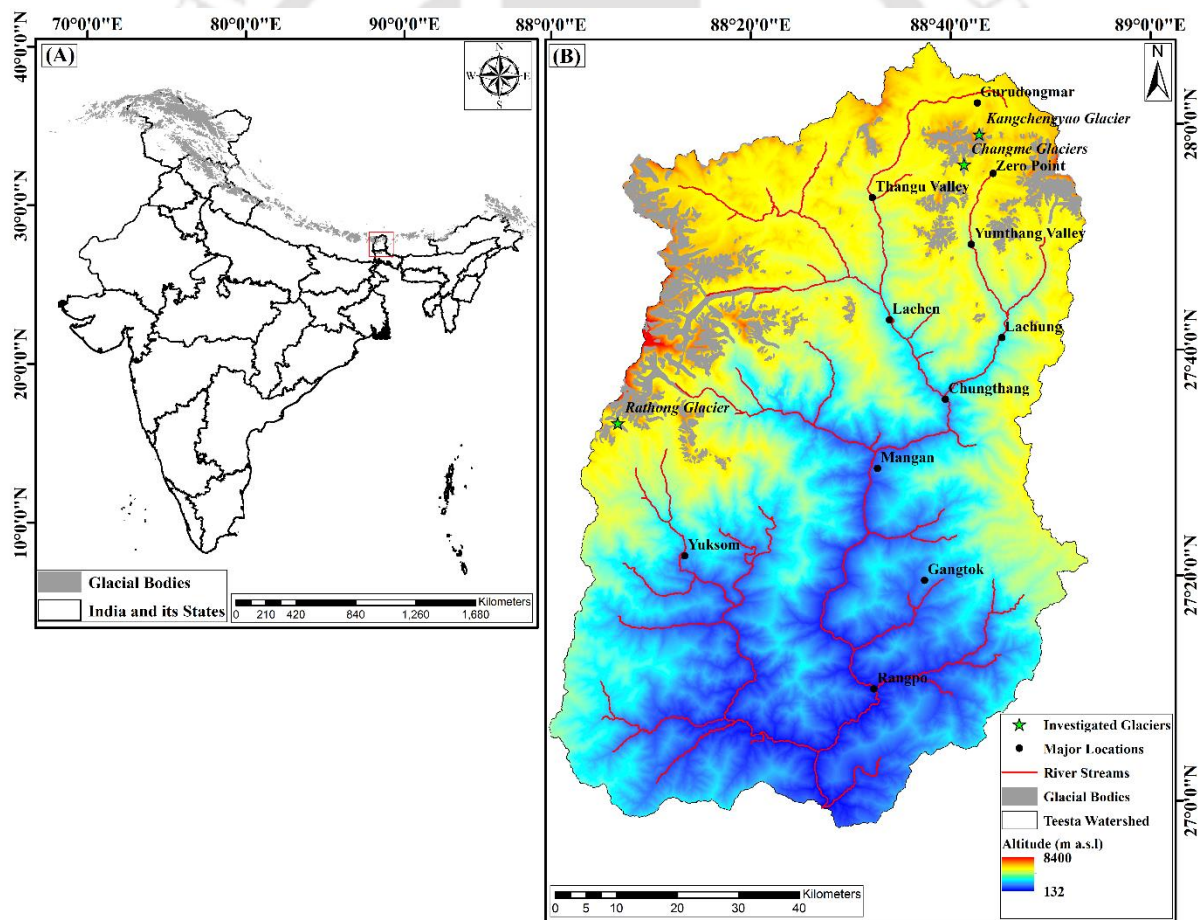


Figure 4.1: Study area map showing (A) Indian landmass and Himalayan glaciers, (B) Teesta watershed with major locations, glacial bodies and river streams

4.3 Isotopic Study of the Headwaters of the Teesta Basin

4.3.1 Water Samples Collection and Analysis

Seasonal analysis of water samples for stable isotopes in the north-eastern Himalayan region is critically important to understand the contribution of non-renewable sources (glacial melt) into the perennial streams. The heavy runoff season culminates within the monsoon season, after which the perennial river streams return to their base flow condition (Ali et al., 2020). This investigation is focused on collecting water samples from various sources contributing to the discharge of the primary river streams of the Teesta river, namely, the Lachen Chu and Lachung Chu of North Sikkim. The Teesta watershed because of its altitudinal variations and geographic location experiences temperate, tropical and alpine climatic scenarios. The major seasons in a year are winter (January-March), summer (March-April) and monsoon (April-December). The Monsoon period can be further subdivided into beginning monsoon (April-May), incessant monsoon (May-September) and end monsoon (September-December). The water samples were collected in three different periods between 18th-23rd Jan 2021 (Winter), 3rd-7th Aug 2021 (Incessant Monsoon), and 15th-24th Oct 2021 (End Monsoon) as shown in Figure 4.2. Also, a separate field investigation was dedicated to collecting water samples in West Sikkim between 7th-10th April 2022 (Summer) to study the Rathong river originating from the Rathong glacier (Figure 4.3).

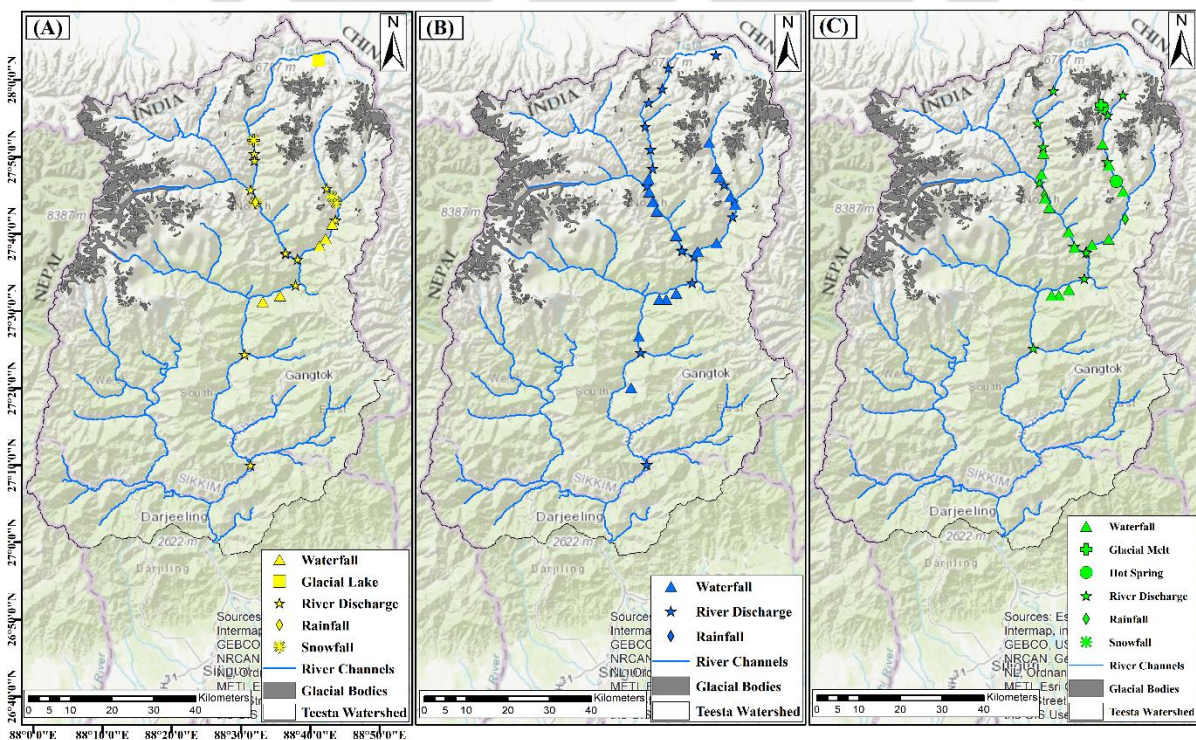


Figure 4.2: Map showing the sampling locations of water sources during (A) winter (Jan-2021), (B) peak-monsoon (Aug-2021) and (C) end-monsoon (Oct-2021) along Teesta and its tributaries, Lachen Chu and Lachung Chu rivers

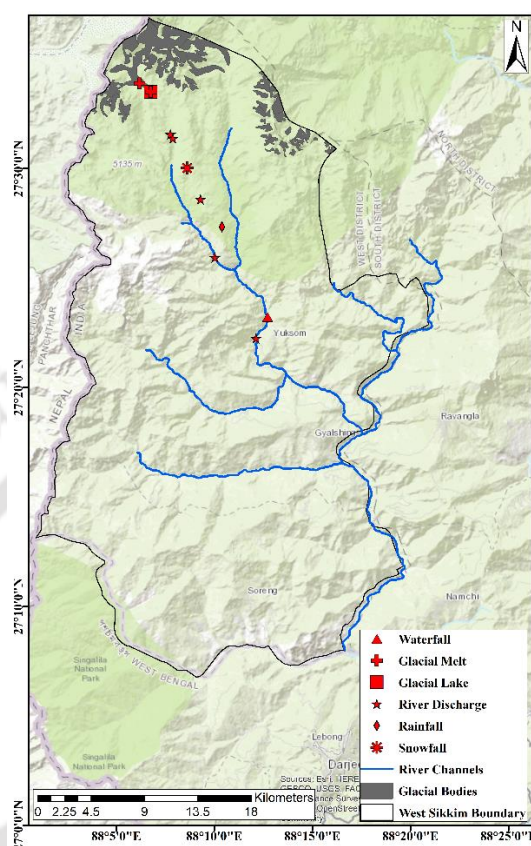


Figure 4.3: Map showing the sampling locations of water sources during **summer** (April-2022) along Rathong river in west Sikkim

Various water sources such as snowfall, rainfall, glacial melt, natural waterfalls, river streams, and glacial lakes were collected on a spatio-temporal basis (Figure 4.4). A total of 102 water samples which includes forty-one samples from streams (main and tributaries) of Teesta river, five from Rathong river, eight snow melt and six rainfall samples, thirty-seven waterfall samples, one glacial lake samples, and four glacial ice-melt have been collected from various locations and different periods (Table 4.1). **Special precautions were taken during the collection of snow and glacial samples. As melt water from a glacial body can be a mixture of both snowmelt and melting metamorphosed glacial ice, glacial outcrops and calving zones were identified, personally visited and samples were collected with utmost carefulness.**



Figure 4.4: Field photographs during spatio-temporal collection of samples for the study of stable isotopes

The water samples were collected in 30 ml pre-cleaned high-density polyethylene (HDPE) bottles to measure stable isotopes ($\delta^{18}\text{O}$ and δD). Before collection, the bottles were rinsed thoroughly multiple times with sample water at the acquisition site. The water samples were filled to the brim of the respective HDPE bottles and capped tightly to avoid exchanging with atmospheric moisture and evaporation. Later, the samples were transferred to the nuclear hydrology laboratory (National Institute of Hydrology) for isotope analysis. A dual inlet stable isotope-ratio mass spectrometer (DISIRMS) was used to quantify δD . a continuous-flow stable

isotope-ratio mass spectrometer (CFSIRMS) was used to measure the $\delta^{18}\text{O}$ values of each sample. The samples were equilibrated with H_2 and CO_2 for the quantification of stable isotopes proportion with a precision range of $\pm 0.1\text{‰}$ and $\pm 1.0\text{‰}$ for $\delta^{18}\text{O}$ and δD , respectively, by analyzing the International Atomic Energy Agency (IAEA) standards (Behera et al., 2019).

$$\delta (\text{‰}) = \left(\frac{R_{\text{sample}} - R_{\text{standard}}}{R_{\text{standard}}} \right) \times 10^3 \quad (4.1)$$

here, R_{sample} and R_{standard} define the ratio of $^2\text{H}/^1\text{H}$ and $^{18}\text{O}/^{16}\text{O}$ isotopes for water samples collected from the field and standard water sample, respectively. The results are expressed in per mil (‰) relative to the Vienna standard mean ocean water (VSMOW) and expressed with ‘ δ ’ as represented in equation 4.1.

Table 4.1: Isotopic composition ($\delta^{18}\text{O}$, δD and d-excess) of water samples from various sources in different timelines (seasons) within the Teesta watershed

S. No.	Sample ID	Date of collection	Source	Location (District)	Altitude (m)	Longitude	Latitude	$\delta^{18}\text{O}$ (‰)	δD (‰)	d-excess (‰)
1	Mn'La'-F-01	18-01-2021 (Monday)	Waterfall	North Sikkim	1421	88°33.890'E	27°30.889'N	-8.3	-50.1	16.41
2	Mn'La'-F-02	18-01-2021 (Monday)	Waterfall		1461	88°36.405'E	27°31.620'N	-9.1	-57.4	15.37
3	Mn'La'-Rd-03	18-01-2021 (Monday)	River Discharge		1308	88°38.703'E	27°32.994'N	-11.5	-74.7	17.49
4	Mn'La'-Rd-04	18-01-2021 (Monday)	River Discharge		1773	88°37.300'E	27°37.070'N	-10.2	-65.3	16.15
5	Mn'La'-Rd-05	18-01-2021 (Monday)	River Discharge		1763	88°37.313'E	27°37.176'N	-12.8	-86.6	15.51
6	La'Gd'-Sn-06	19-01-2021 (Tuesday)	Snowfall		3702	88°33.028'E	27°43.806'N	-3.7	-10.6	19.40
7	La'Gd'-Sn-07	19-01-2021 (Tuesday)	Snowfall		3684	88°32.845'E	27°51.841'N	-3.6	-12.0	17.12
8	La'Gd'-Rd-08	19-01-2021 (Tuesday)	River Discharge		3487	88°32.940'E	27°50.103'N	-13.9	-96.2	14.86
9	La'Gd'-Rd-09	19-01-2021 (Tuesday)	River Discharge		3379	88°32.955'E	27°49.226'N	-10.7	-69.9	15.84
10	La'Gd'-Rd-10	19-01-2021 (Tuesday)	River Discharge		2738	88°32.335'E	27°45.420'N	-14.5	-100.3	15.60
11	La'Gd'-Rf-11	19-01-2021 (Tuesday)	Rainfall		2677	88°33.008'E	27°43.787'N	-5.9	-26.7	20.64
12	La'Lu'-F-12	20-01-2021 (Wednesday)	Waterfall		2172	88°42.258'E	27°38.063'N	-8.8	-53.5	17.15
13	La'Lu'-F-13	20-01-2021 (Wednesday)	Waterfall		2328	88°43.180'E	27°38.965'N	-8.7	-54.1	15.55
14	La'Lu'-Rd-14	20-01-2021 (Wednesday)	River Discharge		2599	88°44.652'E	27°41.337'N	-11.8	-77.3	17.47
15	Lu'Yu'-Sn-15	21-01-2021 (Thursday)	Snowfall		3068	88°44.779'E	27°43.609'N	-5.4	-22.7	20.76
16	Lu'Yu'-Sn-16	21-01-2021 (Thursday)	Snowfall		3277	88°44.192'E	27°44.388'N	-5.3	-23.6	19.00
17	Lu'Yu'-Rd-17	21-01-2021 (Thursday)	River Discharge		3374	88°43.448'E	27°45.497'N	-12.5	-83.8	16.53
18	Lu'Mn'-F-18	22-01-2021 (Friday)	Waterfall		1818	88°44.157'E	27°40.826'N	-8.6	-52.5	16.03
19	Lu'Mn'-Rd-19	22-01-2021 (Friday)	River Discharge		1615	88°39.039'E	27°36.353'N	-11.0	-71.9	16.15
20	Lu'Mn'-G-20	22-01-2021 (Friday)	Glacier		5160	88°42.532'E	28°02.084'N	-12.8	-89.2	13.26
21	Lu'Mn'-Rd-21	22-01-2021 (Friday)	River Discharge		1626	88°39.042'E	27°36.354'N	-12.2	-80.6	17.19

22	Mn'Si'- Rd-22	23-01-2021 (Saturday)	River Discharge	South Sikkim	605	88°31.171'E	27°24.083'N	-11.4	-74.2	16.71
23	Mn'Si'- Rd-23	23-01-2021 (Saturday)	River Discharge		250	88°31.798'E	27°09.706'N	-9.5	-60.9	15.05
24	La-Gd F-01	03-08-2021 (Tuesday)	Waterfall		2793	88°32.650'E	27°44.700'N	-10.84	-69.61	17.12
25	La-Gd Rd-02	03-08-2021 (Tuesday)	River Discharge		2712	88°32.333'E	27°45.417'N	-15.08	-107.36	13.26
26	La-Gd F-03	03-08-2021 (Tuesday)	Waterfall		3117	88°32.600'E	27°46.333'N	-9.50	-60.54	15.45
27	La-Gd Rd-04	03-08-2021 (Tuesday)	River Discharge		3164	88°33.200'E	27°47.683'N	-13.21	-89.46	16.18
28	La-Gd Rd-05	03-08-2021 (Tuesday)	River Discharge		3481	88°32.933'E	27°50.133'N	-13.52	-93.36	14.78
29	La-Gd Rd-06	03-08-2021 (Tuesday)	River Discharge		3813	88°32.217'E	27°53.117'N	-14.16	-100.18	13.11
30	La-Gd Rd-07	03-08-2021 (Tuesday)	River Discharge		4289	88°32.767'E	27°56.150'N	-14.86	-106.69	12.15
31	La-Gd Rd-08	03-08-2021 (Tuesday)	River Discharge		4472	88°34.733'E	27°57.900'N	-14.20	-99.73	13.88
32	La-Gd Rd-09	03-08-2021 (Tuesday)	River Discharge		4715	88°35.683'E	28°00.550'N	-15.33	-112.03	10.58
33	La-Gd Rd-10	03-08-2021 (Tuesday)	River Discharge		5158	88°42.567'E	28°02.117'N	-14.77	-107.07	11.07
34	La-Lu F-11	05-08-2021 (Thursday)	Waterfall		2650	88°33.117'E	27°43.400'N	-10.30	-65.70	16.69
35	La-Lu F-12	05-08-2021 (Thursday)	Waterfall		2417	88°33.733'E	27°42.217'N	-10.07	-63.09	17.48
36	La-Lu F-13	05-08-2021 (Thursday)	Waterfall		1928	88°36.450'E	27°39.050'N	-7.62	-45.33	15.59
37	La-Lu Rd-14	05-08-2021 (Thursday)	River Discharge		1751	88°37.267'E	27°37.167'N	-13.61	-92.62	16.27
38	La-Lu Rd-15	05-08-2021 (Thursday)	River Discharge		1758	88°37.300'E	27°37.067'N	-9.75	-62.99	14.99
39	La-Lu F-16	05-08-2021 (Thursday)	Waterfall		1790	88°39.533'E	27°36.950'N	-8.06	-48.64	15.83
40	La-Lu F-17	05-08-2021 (Thursday)	Waterfall		2174	88°42.283'E	27°38.033'N	-9.97	-64.36	15.36
41	La-Yu Rf-18	06-08-2021 (Friday)	Rainfall	North Sikkim	2978	88°44.900'E	27°43.017'N	-6.49	-39.64	12.31
42	La-Yu F-19	06-08-2021 (Friday)	Waterfall		2883	88°45.050'E	27°42.933'N	-10.51	-69.24	14.86
43	La-Yu F-20	06-08-2021 (Friday)	Waterfall		3207	88°44.383'E	27°43.933'N	-11.72	-77.85	15.94
44	La-Yu Rd-21	06-08-2021 (Friday)	River Discharge		3367	88°43.500'E	27°45.483'N	-12.85	-87.88	14.95
45	La-Yu F-22	06-08-2021 (Friday)	Waterfall		3494	88°42.883'E	27°46.450'N	-12.93	-88.56	14.86
46	La-Yu F-23	06-08-2021 (Friday)	Waterfall		3595	88°42.433'E	27°47.583'N	-10.46	-68.29	15.35
47	La-Yu F-24	06-08-2021 (Friday)	Waterfall		3930	88°41.417'E	27°50.917'N	-13.22	-89.30	16.49
48	La-Yu Rd-25	06-08-2021 (Friday)	River Discharge		2616	88°44.650'E	27°41.333'N	-12.45	-84.70	14.87
49	Ch-Mn Rd-26	07-08-2021 (Saturday)	River Discharge		1584	88°39.067'E	27°36.333'N	-11.82	-78.77	15.79
50	Ch-Mn Rd-27	07-08-2021 (Saturday)	River Discharge		1320	88°38.683'E	27°32.950'N	-11.92	-77.30	18.02
51	Ch-Mn F-28	07-08-2021 (Saturday)	Waterfall		1414	88°36.383'E	27°31.633'N	-7.56	-44.28	16.19
52	Ch-Mn F-29	07-08-2021 (Saturday)	Waterfall		1422	88°34.917'E	27°30.867'N	-8.32	-51.56	14.97
53	Ch-Mn F-30	07-08-2021 (Saturday)	Waterfall		1378	88°33.900'E	27°30.883'N	-7.78	-47.26	14.98
54	Mn-Si F-31	07-08-2021 (Saturday)	Waterfall		760	88°30.917'E	27°26.167'N	-6.03	-34.61	13.65
55	Mn-Si Rd-32	07-08-2021 (Saturday)	River Discharge	South Sikkim	576	88°31.150'E	27°24.067'N	-10.99	-73.26	14.63
56	Mn-Si F-33	07-08-2021 (Saturday)	Waterfall		820	88°29.700'E	27°19.583'N	-7.11	-45.41	11.49
57	Mn-Si Rd-34	07-08-2021 (Saturday)	River Discharge		274	88°31.817'E	27°09.683'N	-10.74	-71.99	13.91

58	Lu-Yu Rd-1	15-10-2021 (Friday)	River Discharge	North Sikkim	3606	88°42'14" E	27°48'02" N	-13.64	-90.84	18.30
59	Lu-Yu F-02	15-10-2021 (Friday)	Waterfall		3595	88°42'28" E	27°47'36" N	-10.70	-67.68	17.93
60	Lu-Yu Rd-04	15-10-2021 (Friday)	River Discharge		3367	88°43'30" E	27°45'29" N	-13.52	-89.26	18.90
61	Lu-Yu F-05	15-10-2021 (Friday)	Waterfall		3218	88°44'27" E	27°44'11" N	-11.13	-70.36	18.68
62	Lu-Yu Rd-06	16-10-2021 (Saturday)	River Discharge		4674	88°41'37.7" E	27°55'6.7" N	-15.22	-103.90	17.89
63	Lu-Yu G-08	17-10-2021 (Sunday)	Glacier		4699	88°41'28" E	27°55'23" N	-15.78	-106.86	19.37
64	Yu-Zp F-09	18-10-2021 (Monday)	Waterfall		3814	88°41'34" E	27°50'21" N	-12.97	-84.41	19.36
65	Yu-Zp Rd-10	18-10-2021 (Monday)	River Discharge		4534	88°42'24" E	27°54'04" N	-15.14	-103.96	17.18
66	Yu-Zp Rd-11	18-10-2021 (Monday)	River Discharge		4943	88°44'39" E	27°56'38" N	-13.90	-96.36	14.84
67	Yu-Zp Sn-12	18-10-2021 (Monday)	Snowfall		4985	88°44'53" E	27°56'45" N	-23.05	-161.50	22.91
68	Yu-Zp Rf-13	18-10-2021 (Monday)	Rainfall		2693	88°44'43" E	27°40'35" N	-18.78	-132.66	17.55
69	Yu-Ch F-14	19-10-2021 (Tuesday)	Waterfall		2166	88°42'16" E	27°38'02" N	-14.90	-101.23	17.93
70	Yu-Ch F-15	19-10-2021 (Tuesday)	Waterfall		1965	88°39'51" E	27°37'21" N	-12.61	-85.81	15.07
71	Yu-Ch Rf-16	19-10-2021 (Tuesday)	Rainfall		1582	88°39'01" E	27°36'22.3" N	-25.05	-187.52	12.86
72	Yu-Ch Rd-17	19-10-2021 (Tuesday)	River Discharge		1582	88°39'01" E	27°36'22.3" N	-14.44	-98.11	17.44
73	La-Gd Sn-18	21-10-2021 (Thursday)	Snowfall		3902	88°32'16" E	27°53'43" N	-29.69	-213.82	23.70
74	La-Gd Rd-19	21-10-2021 (Thursday)	River Discharge		3812	88°32'12" E	27°53'07" N	-15.79	-111.64	14.68
75	La-Gd Rd-20	21-10-2021 (Thursday)	River Discharge		3476	88°32'56" E	27°50'03" N	-15.21	-105.06	16.64
76	La-Gd F-21	21-10-2021 (Thursday)	Waterfall		3379	88°32'58" E	27°49'14" N	-13.06	-87.00	17.50
77	La-Gd F-22	21-10-2021 (Thursday)	Waterfall		3143	88°32'39" E	27°46'35" N	-16.63	-115.92	17.12
78	La-Gd Rd-23	22-10-2021 (Friday)	River Discharge		4427	88°34'32" E	27°57'18" N	-16.25	-116.99	13.04
79	La-Gd Sn-24	22-10-2021 (Friday)	Snowfall		4427	88°34'32" E	27°57'18" N	-29.21	-213.83	19.81
80	La-Gd Rd-25	22-10-2021 (Friday)	River Discharge		2712	88°32'20" E	27°45'25" N	-15.57	-107.81	16.72
81	La-Ch Rf-26	24-10-2021 (Sunday)	Rainfall		2683	88°33'02" E	27°43'48" N	-11.83	-81.62	12.99
82	La-Ch F-27	24-10-2021 (Sunday)	Waterfall		2656	88°33'06" E	27°43'24" N	-11.08	-72.12	16.51
83	La-Ch F-28	24-10-2021 (Sunday)	Waterfall		2414	88°33'44" E	27°42'14" N	-10.91	-70.02	17.23
84	La-Ch F-29	24-10-2021 (Sunday)	Waterfall		1928	88°36'27" E	27°39'03" N	-8.13	-47.13	17.94
85	La-Ch Rd-30	24-10-2021 (Sunday)	River Discharge		1751	88°37'16" E	27°37'10" N	-13.85	-94.65	16.18
86	La-Ch F-31	24-10-2021 (Sunday)	Waterfall		1761	88°37'18" E	27°37'04" N	-12.56	-84.15	16.31
87	La-Ch Rd-32	24-10-2021 (Sunday)	River Discharge		1308	88°38'41" E	27°32'59" N	-11.91	-79.19	16.10
88	Ch-Mn F-33	24-10-2021 (Sunday)	Waterfall		1448	88°36'24" E	27°31'37" N	-10.95	-71.06	16.50
89	Ch-Mn F-34	24-10-2021 (Sunday)	Waterfall		1412	88°34'56" E	27°30'52" N	-10.63	-69.56	15.47
90	Ch-Mn F-35	24-10-2021 (Sunday)	Waterfall		1398	88°33'54" E	27°30'53" N	-9.08	-57.82	14.81
91	Ch-Mn Rd-36	24-10-2021 (Sunday)	River Discharge		577	88°31'09" E	27°24'04" N	-12.32	-80.66	17.87
92	G-01	07-04-2022 (Thursday)	Glacier		4665	88°07'4.98" E	27°33'27.24" N	-19.62	-140.17	16.79
93	L-02	07-04-2022 (Thursday)	Lake		4620	88°07'4.98" E	27°33'27.24" N	-15.85	-116.34	10.46

94	G-03	07-04-2022 (Thursday)	Glacier	West Sikkim	4667	88°06'30.81" E	27°33'51.06" N	-19.43	-137.25	18.19
95	NC-04	08-04-2022 (Thursday)	River Discharge		4069	88°08'04.49" E	27°31'30.74" N	-14.1	-98.11	14.69
96	Rd-05	08-04-2022 (Thursday)	River Discharge		4004	88°08'11.67" E	27°31'19.9" N	-15.37	-106.66	16.30
97	Sn-06	08-04-2022 (Thursday)	Snowfall		4361	88°08'55.43" E	27°29'58.19" N	-3.54	-7.01	21.31
98	Rd-07	08-04-2022 (Thursday)	River Discharge		3964	88°09'35.44" E	27°28'31.64" N	-13.12	-89.22	15.74
99	Rf-08	09-04-2022 (Friday)	Rainfall		3645	88°10'40.47" E	27°27'15.57" N	-0.15	22.05	23.25
100	Rd-09	10-04-2022 (Saturday)	River Discharge		2496	88°10'17.87" E	27°25'51.87" N	-10.2	-65.15	16.45
101	Wf-10	10-04-2022 (Saturday)	Waterfall		1540	88°12'57.87" E	27°23'06.96" N	-10.08	-61.96	18.68
102	Rd-11	10-04-2022 (Saturday)	River Discharge		1286	88°12'21.63" E	27°22'09.40" N	-9.62	-59.93	17.03

4.3.2 Isotope Mixing Model

The contributions of endmember sources such as glacial melt, groundwater, rainfall, and snowfall to the river streams are considered fingerprints or excellent tracers to water sources in rivers as they are fractionated through natural hydrological processes (Klaus and McDonnell, 2013). In the present study, an attempt is made to quantify the percentage composition of glacial melt, snow melt, and rainfall in the headwaters of Lachen Chu, Lachung Chu, and Rathong river streams using a season and basin-specific three-endmember isotope mixing model. The model is developed using the $\delta^{18}\text{O}$ and the deuterium excess (d-excess) composition of water samples from various sources, as shown in the equation below (Dansgaard, 1964):

$$d\text{-excess} = \delta D - 8 \times \delta^{18}\text{O} \quad (4.2)$$

The model considers glacial melt, snow melt, and rainfall as the major contributors to the headwaters of river streams. The intrusion of water from the hyporheic zone/underground and minor water sources such as atmospheric depositions are assumed to be negligible. Another reason for excluding groundwater from the model lies behind the lack of possible groundwater sources for sampling in the Lachen and Lachung region above Chungthang. The data of stable isotopes ($\delta^{18}\text{O}$ and δD) from the Global Network of Isotopes in Precipitation (GNIP) and the Global Network of Isotopes in Rivers (GNIR) follows the Global Meteoric Water Line (GMWL) (Halder et al., 2015) so as our datasets as well (Figure 4.5). Therefore, insignificant alteration in isotopic composition of river streams due to evaporation can be considered.

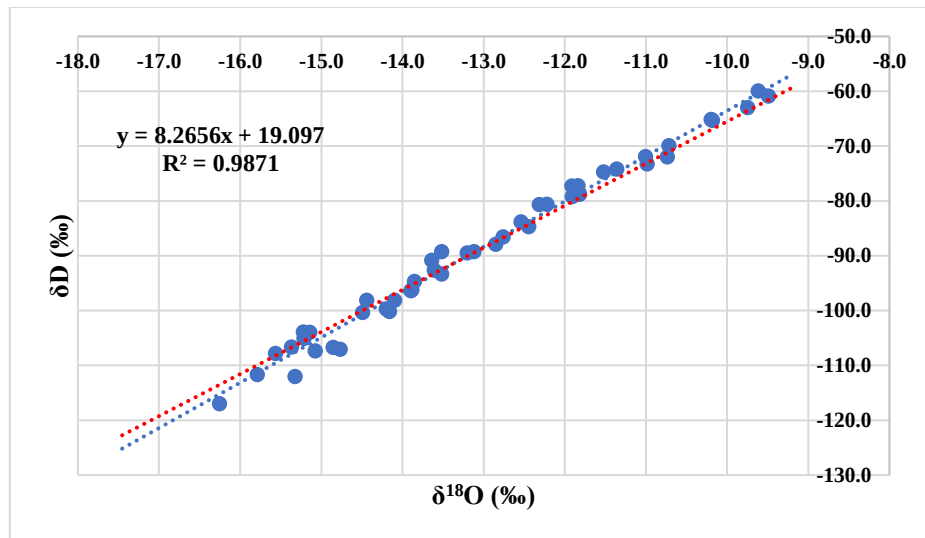


Figure 4.5: Isotopic composition of riverwater samples from the Teesta watershed along with the GMWL in red ($\delta D = 8.17 \times \delta^{18}O + 11.27$) (Rozanski et al., 1993) and RWL in blue ($\delta D = 8.2656 \times \delta^{18}O + 19.097$) through river water samples

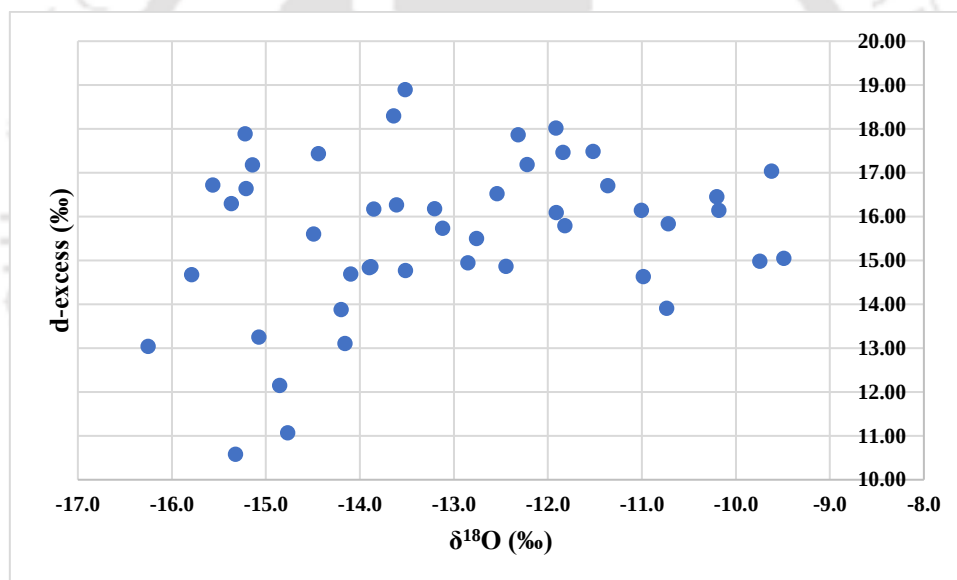


Figure 4.6: Cross plot between $\delta^{18}O$ and computed d-excess of river water samples

It is to be noted that the model treats rain and snow as independent endmembers. As rain samples were collected from comparatively lower elevation regions of north Sikkim compared to the snow samples, some differences exist in the isotopic compositions. Precipitation in the Himalayan region shows altitudinal and seasonal variability in terms of $\delta^{18}O$ and d-excess (Boral and Sen, 2020). The two primary sources (dual-source) of precipitation in the Himalayan regions are the western disturbances between December and March that find their origin in the Mediterranean Sea and the south-west monsoon between July and September that originates in the Bay of Bengal and the Arabian sea. Precipitation due

to western disturbances is characterized by greater d-excess ($\sim 20\text{‰}$) as compared to south-west monsoon ($\sim 10\text{‰}$) (Bershaw et al., 2012).

Sampling of end members has helped to capture the seasonal variations in the $\delta^{18}\text{O}$ and d-excess of snow and rainfall in the Teesta watershed (Table 4.1). This has helped quantify seasonal snowmelt and rainfall contribution to the river streams. This study uses season-specific variations in $\delta^{18}\text{O}$ and d-excess of rainfall and snow as the best possible proxy for defining the composition of dual-source precipitation components.

Even though stable isotopes of oxygen ($\delta^{18}\text{O}$) and hydrogen (δD) are widely used as effective tracers in hydrograph separation studies, they are strongly correlated (Figure 4.5). However, d-excess (equation 4.2) and $\delta^{18}\text{O}$ are truly independent of each other (Figure 4.6) and, therefore can be effectively used as independent tracers. The isotope mixing model is based on the following equations:

$$\delta^{18}\text{O}_{\text{snow}} \times f_{\text{snow}} + \delta^{18}\text{O}_{\text{rain}} \times f_{\text{rain}} + \delta^{18}\text{O}_{\text{glacier}} \times f_{\text{glacier}} = \delta^{18}\text{O}_{\text{river}} \quad (4.3)$$

$$d - \text{excess}_{\text{snow}} \times f_{\text{snow}} + d - \text{excess}_{\text{rain}} \times f_{\text{rain}} + d - \text{excess}_{\text{glacier}} \times f_{\text{glacier}} = d - \text{excess}_{\text{river}} \quad (4.4)$$

$$f_{\text{snow}} + f_{\text{rain}} + f_{\text{glacier}} = 1 \quad (4.5)$$

Here, $\delta^{18}\text{O}_{\text{snow}}$ and $d - \text{excess}_{\text{snow}}$ represent the composition of snow meltwater, $\delta^{18}\text{O}_{\text{rain}}$ and $d - \text{excess}_{\text{rain}}$ are the rainfall composition and $\delta^{18}\text{O}_{\text{glacier}}$ and $d - \text{excess}_{\text{glacier}}$ are the composition of glacial ice meltwater. Equation 4.5 is the mass balance equation where f_{snow} , f_{rain} and f_{glacier} represent the fractions of snowmelt, rain, and glacial melt contributing to the river stream, respectively. Therefore, the equations mentioned above can be written as equation 4.6 that can be solved to obtain the fractional contribution of snowmelt, rain, and glacial melt into the river streams.

$$\begin{pmatrix} \delta^{18}\text{O}_{\text{snow}} & \delta^{18}\text{O}_{\text{rain}} & \delta^{18}\text{O}_{\text{glacier}} \\ d - \text{excess}_{\text{snow}} & d - \text{excess}_{\text{rain}} & d - \text{excess}_{\text{glacier}} \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} f_{\text{snow}} \\ f_{\text{rain}} \\ f_{\text{glacier}} \end{pmatrix} = \begin{pmatrix} \delta^{18}\text{O}_{\text{river}} \\ d - \text{excess}_{\text{river}} \\ 1 \end{pmatrix} \quad (4.6)$$

4.3.3 Results and Discussion

4.3.3.1 Variations in Stable Isotopes

The composition of $\delta^{18}\text{O}$ and δD in the water samples from various sources of the Teesta watershed are shown in Table 4.1. The $\delta^{18}\text{O}$ values along river streams vary seasonally and deplete with altitude. The maximum and minimum $\delta^{18}\text{O}$ values on seasonal basis for the major river streams of North Sikkim and West Sikkim are shown in Table 4.2. Higher $\delta^{18}\text{O}$ values

are observed in the lower reaches (lower altitude) at the confluence of Lachen Chu and Lachung Chu near Chungthang during winter-2021 or within the main Teesta river at much lower elevations during monsoon. The lower $\delta^{18}\text{O}$ values are recorded in the upper reaches (higher altitude) closer to the river streams' source (glacial bodies) throughout the year. The Lachen Chu river has also been observed with minimum $\delta^{18}\text{O}$ values along the upper reaches throughout the year that increases along the downstream. Similar observations have been made in the Rathong river stream, where the minimum $\delta^{18}\text{O}$ values have been observed at upper reaches close to the glacial source that increases downstream of the river. In precipitation, maximum values of $\delta^{18}\text{O}$ have been recorded for snow and rainfall during end-monsoon (Oct-2021), whereas the least $\delta^{18}\text{O}$ values have been observed during peak-winter (Jan-2021) as shown in Table 4.3. Table 4.4 is informative to the $\delta^{18}\text{O}$ values of three different glacial bodies contributing to the discharge of its daughter streams that finally meet the Teesta river stream downstream. A variation in the $\delta^{18}\text{O}$ values can be observed in all three glacial melt samples collected from three different locations in Sikkim. These glacial bodies feed three major tributaries of the Teesta river originating from North and West Sikkim.

Table 4.2: Seasonal variations in the maximum and minimum values of $\delta^{18}\text{O}$ in river samples

Period	District	Minimum $\delta^{18}\text{O}$			Maximum $\delta^{18}\text{O}$		
		Sample-ID	Value (‰)	Altitude (m)	Sample-ID	Value (‰)	Altitude (m)
Jan-2021 (Winter)	North Sikkim	La'Gd'-Rd-10	-14.50	2738	Mn'Si'-Rd-23	-9.50	250
Aug-2021 (Incessant Monsoon)	North Sikkim	La-Gd Rd-09	-15.33	4715	La-Lu Rd-15	-9.75	1758
Oct-2021 (End Monsoon)	North Sikkim	La-Gd Rd-23	-16.25	4427	La-Ch Rd-32	-11.91	1308
April-2022 (Summer)	West Sikkim	Rd-05	-15.37	4004	Rd-11	-9.62	1286

Table 4.3: Seasonal variations in the maximum and minimum values of $\delta^{18}\text{O}$ in precipitation samples

Precipitation Source	Minimum $\delta^{18}\text{O}$			Maximum $\delta^{18}\text{O}$		
	Sample-ID	Value (‰)	Season	Sample-ID	Value (‰)	Season
Snow	La-Gd Sn-18	-29.69	End-Monsoon	La'Gd'-Sn-07	-3.60	Peak-Winter
Rain	Yu-Ch Rf-16	-25.05	End-Monsoon	La'Gd'-Rf-11	-5.90	Peak-Winter

Table 4.4: $\delta^{18}\text{O}$ composition of various glacial bodies feeding tributaries of Teesta river

Glacial Source	Sample ID	GLIMS ID	$\delta^{18}\text{O}$ Value (‰)	Altitude (m)	Daughter Stream
Kangchengyao	Lu'Mn'-G-20	G088710E27986N	-12.80	5160	Lachen Chu
Changme	Lu-Yu G-08	G088684E27960N	-15.78	4699	Lachung Chu
Rathong	G-03	G088109E27582N	-19.43	4667	Rathong

There exists a strong correlation between the behavioural pattern of oxygen and hydrogen isotopes in the Teesta watershed. The δD values of the Teesta river streams fluctuate between -60.9‰ and -100.3‰ during winter, -62.99‰ and -112.03‰ during peak monsoon and between -80.66‰ and -111.64‰ during end monsoon. For the Rathong river stream, this

range varies between -59.93‰ and -106.66‰ during winter. The varying trend of δD along the course of the river streams shows good agreement with $\delta^{18}O$. The d-excess values of the river streams lie between 10.58‰ and 18.90‰ throughout the year.

4.3.3.2 Tracing $\delta^{18}O$ and d-excess of Endmember Sources

There exists large intra-seasonal variability between d-excess and $\delta^{18}O$ of the river streams (Figure 4.6) as well as snow-melt (Figure 4.7) and rainfall (Figure 4.8). Variability of $\delta^{18}O$ and d-excess is also reflected with latitude, longitude, and altitude (Figure 4.10). Naturally, river water is a complex mixture of various source end members which undergo several processes during formation and contribution to the river streams. For instance, during the process of furnisation, precipitated snow gets recrystallized, which alters the composition of precipitated snow and is governed by various atmospheric parameters (Arnason,1981). Again, heavy rainfall episodes in the Himalayas result in more depletion of the isotopic compositions than the equilibrium rainfall events (Gat, 1996). The stable isotopic composition of rainfall is also affected due to intermittency, intensity, and evaporation of rainfall. This results in a complex relationship between stable isotopes of oxygen/hydrogen with lat/long and elevation.

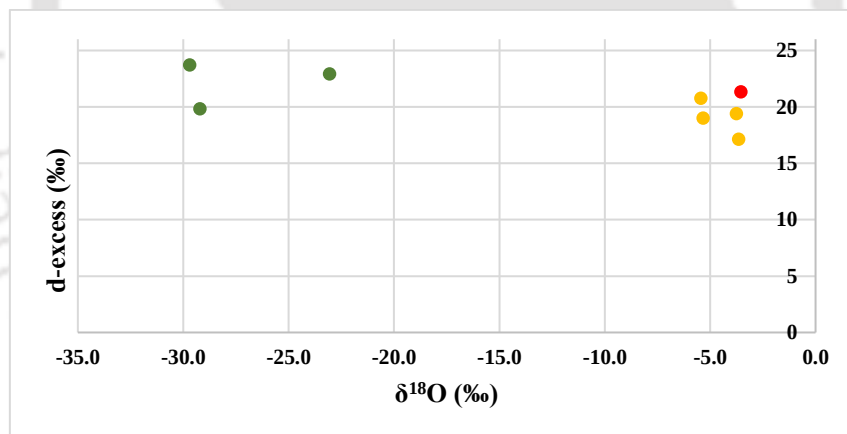


Figure 4.7: $\delta^{18}O$ vs d-excess for source endmember (snow melt) in which yellow and red dots indicate snow samples during winter of 2021 and summer of 2022 respectively and green dots indicate snow samples during end monsoon 2021

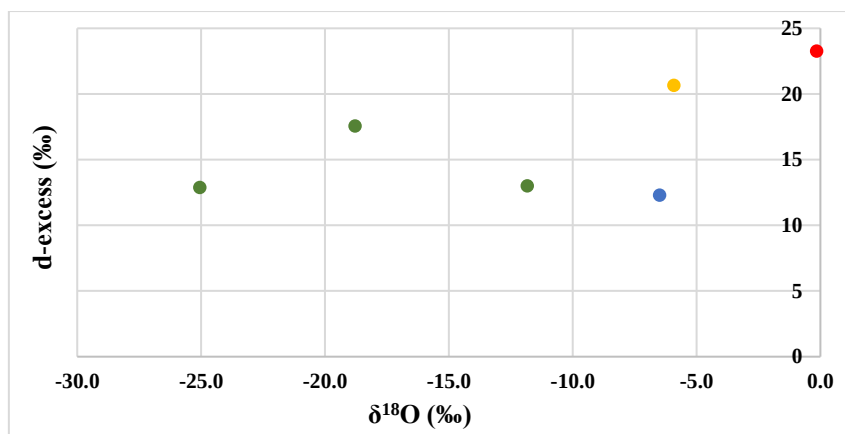


Figure 4.8: $\delta^{18}\text{O}$ vs d-excess for source endmember (rainfall) in which yellow and red dots indicate rain samples during winter of 2021 and summer of 2022 respectively whereas blue and green dots indicate rain samples during incessant (Aug-2021) and end monsoon (Oct-2021)

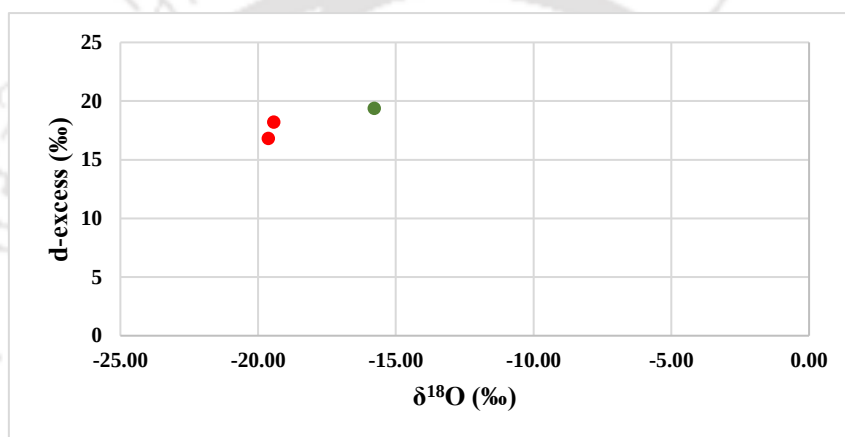


Figure 4.9: $\delta^{18}\text{O}$ vs d-excess for source endmember (glacial melt) in which red dots indicate glacial melt samples during summer of 2022 from Rathong glacier (West Sikkim) whereas green dot indicates glacial melt sample from Changme glacier during end monsoon (Oct-2021)

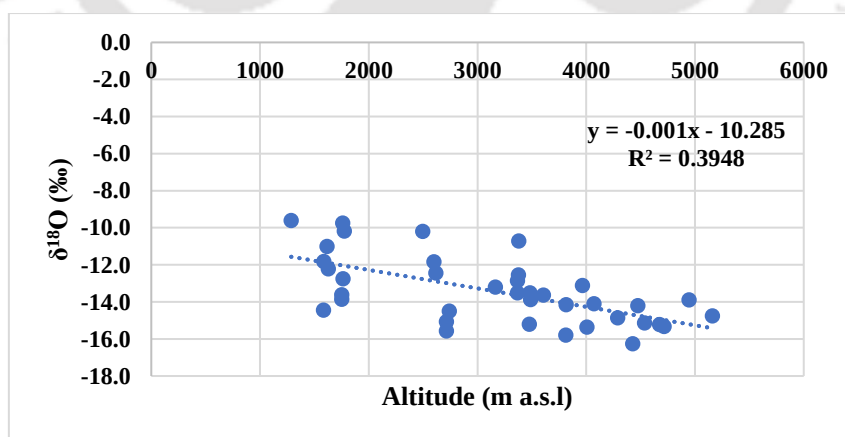


Figure 4.10: $\delta^{18}\text{O}$ vs altitude in the streams of Lachen Chu and Lachung Chu, Teesta and Rathong river within the Teesta watershed

4.3.3.3 Tracing Moisture Sources and Local Climatic Conditions

The Teesta watershed receives rainfall from the Bay of Bengal (BoB) branch of the ISM and is governed by the altitudinal gradient (south-north trajectory) of the watershed. The higher and trans-Himalayan region (northern region) experiences a steady decline in precipitation whereas the lesser-Himalayan region (foothills or southern region) remains humid (Dubey et al., 2018). The high-elevation northern region also receives precipitation during winters between December and March due to southern branches of mid-latitude westerlies (Wei and Gasse, 1999; Ali et al., 2019). Due to this reason, mixed signals from two different moisture sources are anticipated in the northern region of the watershed. Moreover, other processes such as local scale recycling of water, evaporation of ambient precipitation, and mixing of waters from different moisture sources occur along the Himalayan ranges (Hren et al., 2009). The westerlies move into the higher Himalayan region and the Qinghai-Tibetan plateau along the Brahmaputra river. This also applies to the Teesta watershed (Ali et al., 2020). During winter (Jan-2021), $\delta^{18}\text{O}$ value of -9.5‰ has been observed in the southern low-elevation region (250m a.s.l) along the main Teesta river. As moving toward the high-elevation northern region (towards the glacial source), there is a progressive decline in the $\delta^{18}\text{O}$ values to -13.9‰ (3487m a.s.l) and -12.5‰ (3374m a.s.l) towards upstream of Lachen Chu and Lachung Chu respectively. During **incessant monsoon** (Aug-2021), $\delta^{18}\text{O}$ values shift from -10.74‰ (274m a.s.l) to -14.77‰ (5158m a.s.l) and -12.85‰ (3367m a.s.l) towards Lachen Chu and Lachung Chu respectively. During end-monsoon (Oct-2021), the $\delta^{18}\text{O}$ values shift from -12.32‰ (577m a.s.l) to -16.25‰ (4427m a.s.l) and -13.90‰ (4943m a.s.l). Another interesting thing to note is the comparatively greater depletion of ^{18}O isotope as moving towards the glacial source of Lachen Chu river than the Lachung Chu river stream. This represents progressive depletion and distillation of ^{18}O isotope in the clouds as it propagates towards elevated northern region from the low-altitude southern region (orographic ascent) attributed to subsequent rainout and cooling (Hren et al., 2009). This effect of orographic ascent is greater for Teesta river's western tributary (Lachen Chu) above Chungthang than the eastern tributary (Lachung Chu). In the case of the Rathong river, similar observations have been made during winter (April-2022) with a greater $\delta^{18}\text{O}$ value (-9.62‰) at 1286m a.s.l that reduces to -14.1‰ at 4069m a.s.l. A glacial lake situated at the Rathong glacial snout at an elevation of 4620m a.s.l shows $\delta^{18}\text{O}$ value of -15.85‰.

The d-excess values are widely used to study the deviation of the regional-scale isotopic composition of water from the GMWL as well as infer the moisture sources (Craig, 1961; Lai and Ehleringer, 2011; Tian et al., 2018). Within the water samples, d-excess values are

primarily governed by humidity and air temperature. Greater d-excess values indicate lower relative humidity and vice versa (Dansgaard, 1964). Low-latitude ocean surface evaporation infers high relative humidity and low d-excess. Sub-cloud evaporation or local evapotranspiration leads to decreased d-excess values (Dansgaard, 1964). The d-excess values also help understand the atmospheric conditions and processes governing the Spatio-temporal transformation of water composition (Dalai et al., 2002). Researchers have found that d-excess can be used independently to calibrate atmospheric general circulation models (GCMs; Joussaume et al., 1984; Jouzel et al., 1987; Hoffmann et al., 1998). They can also be used to investigate the present as well as previous precipitation processes. The d-excess of water samples in the Teesta watershed varies between 10.58‰ and 23.70‰ with an average d-excess of 16.29‰. The d-excess of Teesta river tributaries ranges from 10.58‰ to 18.90‰ with a mean of 15.51‰. In the case of the Rathong river, d-excess fluctuates between 14.69‰ and 17.03‰ with an average of 16.04‰. The difference between the overall mean of water samples and the mean of river samples indicates the mixing of water from rain, snow, and glacial melt (Cooper, 1998). The seasonal mean d-excess of 16.14‰, 13.99‰ and 16.53‰ during winter, incessant and end monsoon lie close to the overall mean except for incessant monsoon period. The Teesta watershed lies in the trajectory of the BoB branch of ISM due to which the southern part of the watershed experiences heavy precipitation and humid climatic condition. With a steady decline of ISM, the northern region experiences winter precipitation contributed by the mid-latitude westerlies (Yihui and Zunya, 2008; Dubey et al., 2018). The long-term mean of d-excess for the ISM and mid-latitude westerlies are ~ 8 and 22 ± 6 , respectively (IAEA, 1992). The d-excess values presented in this study suggest the dominance of mid-latitude westerlies in the northern region of the Teesta watershed and tributaries such as Lachen Chu and Lachung Chu. The progressive decline of ^{18}O as moving toward the glacial source of the river streams agrees with other studies (Ali et al., 2020; Boral and Sen, 2020) that suggest mixing of moisture sources in the trans- and higher Himalayan catchments.

4.3.3.4 Quantification of Source Endmembers to River Streams and Waterfalls

Model Inputs and Execution

The input parameters of the isotope mixing model are the season-dependent source endmembers, $\delta^{18}\text{O}$, and d-excess of water samples from river streams. In order to determine the relationship between $\delta^{18}\text{O}$ and d-excess of the river samples, source $\delta^{18}\text{O}$ and computed d-excess are represented on a scatter plot, as shown in Figure 4.6. The scatter plot reveals large natural variability attributed to a lower degree of covariance, which makes them fit to be used

as independent tracers in the mixing model. Executing the model with the help of mean $\delta^{18}\text{O}$ and d-excess may unnecessarily deliver fractional estimates of endmembers sensitive to the adopted mean value (Khan et al., 2017). Therefore, the mean (μ) isotopic composition has been calculated for the source endmembers seasonally and assigned a range from previous researches on Himalayan regions (Kumar et al., 2010; Rai et al., 2016). The range defined for precipitation (snow and rain) are $\mu \pm 10\text{‰}$ for d-excess, and $\mu \pm 2.5\text{‰}$ for $\delta^{18}\text{O}$, whereas the range assigned for glacial ice melt-water are $\mu \pm 5\text{‰}$ for d-excess and $\mu \pm 2.5\text{‰}$ for $\delta^{18}\text{O}$. Since estimating the isotopic composition of glacial bodies in the Sikkim Himalayas has not been performed so far, the range has been assigned as per research conducted over other Himalayan glaciers (Ali et al., 2020; Boral and Sen, 2020). Thus, the source endmember ranges can be considered as the best possible estimates for seasonal apportionment of river streams in the Teesta watershed.

The fractional composition of snow (f_{snow}), rain (f_{rain}) and glacial melt (f_{glacier}) has been derived using equation 4.6 in which the obtained $\delta^{18}\text{O}$ and computed d-excess of the source endmembers have been randomly sampled from the defined ranges. The d-excess and $\delta^{18}\text{O}$ of the river samples have been acquired from the database shown in Table 4.5. As frequency distribution analyses, a random sampling of d-excess and $\delta^{18}\text{O}$ for the endmembers (snow, rain and glacial melt) has been performed. This shows that d-excess and $\delta^{18}\text{O}$ of endmembers are evenly distributed within the defined range, thus, equally probable. The season-specific isotope mixing model has been deterministically executed through a Monte Carlo framework. The model has been iterated 10^4 times for every river water sample. Retaining 10^4 iterations, mean and standard deviation of all the iterations has been considered the best possible result. Moreover, the 25th, 75th, and 95th percentile have also been calculated.

Model Outputs

The results from the deterministic Monte Carlo-based three endmember $\delta^{18}\text{O}$ -d-excess mixing model show large variability in source endmembers contributions to the river streams and waterfalls above the confluence of Lachen Chu and Lachung Chu at Chungthang and the Rathong river. The percentage contribution of snowmelt, rain, and glacial ice melt-water contributions to the headwaters of Lachen Chu, Lachung Chu, and Rathong river has been shown in Table 4.5. The average and standard deviation of snow, rain, and glacial-melt contribution to the river streams and waterfalls are shown in Table 4.6. Precipitation contribution shows varying proportions for snow and rainfall separately. During the incessant

monsoon period, precipitation accounts for 60% contribution to the river streams and waterfalls in the Teesta watershed. Results show a consistency in the glacial-melt contribution between 40 and 47% in all the seasons with some increment in the end-monsoon period. However, with the conventional understanding of glacial melt-water contributions to Himalayan rivers, it is expected to observe the highest glacial melt-water contribution during summer or pre-monsoon. Some anomalous observation has been made earlier in case of the Indus and the Ganges showing peak ice-melt contribution during monsoon. On the other hand, river systems such as the Brahmaputra and the Yangtze show enhanced ice-melt contribution during the pre-and peak-monsoon period (Boral and Sen, 2020). Several mechanisms bring an understanding towards such anomaly. Such as obscuring snow cover over glacial bodies during the pre-monsoon period might result in diminished glacial melting. Other possible reasons being time lag between glacial melt-water production and transport process, rain-induced glacial melting during monsoon, and volumetric effect between monsoon and pre-monsoon (Boral and Sen, 2020).

Table 4.5: Source endmember contributions (%) in the river stream and waterfall samples of Teesta watershed at mean, 25th, 75th, and 95th percentile of 104 iterations for each water sample

S. No.	Sample code/ ID	Altitude (m)	Mean			25 th Percentile			75 th Percentile			95 th Percentile		
			Snow (%)	Rain (%)	Glacial-melt (%)	Snow (%)	Rain (%)	Glacial-melt (%)	Snow (%)	Rain (%)	Glacial-melt (%)	Snow (%)	Rain (%)	Glacial-melt (%)
1	Mn'La'-F-01	1421 m	27	40	33	14	42	44	9	44	47	2	48	50
2	Mn'La'-F-02	1461 m	19	47	34	14	36	49	10	41	49	4	44	52
3	Mn'La'-Rd-04	1773 m	26	35	39	11	33	56	8	39	52	3	40	57
4	Mn'La'-Rd-05	1763 m	21	31	48	6	20	74	8	32	60	5	29	66
5	La'Gd'-Rd-08	3487 m	17	33	51	5	14	81	9	28	63	7	23	70
6	La'Gd'-Rd-09	3379 m	23	36	41	10	30	60	9	38	54	4	38	58
7	La'Gd'-Rd-10	2738 m	23	23	54	3	12	85	7	28	65	6	22	72
8	La'Lu'-F-12	2172 m	33	31	36	12	41	47	7	44	49	1	47	52
9	La'Lu'-F-13	2328 m	20	47	32	15	39	47	10	42	48	3	46	51
10	La'Lu'-Rd-14	2599 m	37	15	48	6	28	67	5	37	58	2	35	63
11	Lu'Yu'-Rd-17	3374 m	30	22	49	6	23	71	6	34	60	4	31	65
12	Lu'Mn'-Rd-19	1615 m	26	32	42	9	29	62	8	37	55	4	37	60
13	Lu'Mn'-Rd-21	1626 m	35	16	49	5	25	69	5	36	59	3	33	64
14	La-Gd-F-01	2793 m	29	26	44	43	25	33	23	67	10	47	26	27
15	La-Gd-Rd-02	2712 m	47	14	39	60	30	10	34	33	33	45	47	8
16	La-Gd-F-03	3117 m	30	32	38	35	31	34	20	67	14	41	32	27
17	La-Gd-Rd-04	3164 m	37	19	44	53	24	22	29	53	18	48	32	19

18	La-Gd Rd-05	3481 m	41	18	41	54	28	18	30	46	24	46	39	15
19	La-Gd Rd-06	3813 m	45	17	37	55	32	13	32	37	32	43	47	10
20	La-Gd Rd-07	4289 m	49	15	36	58	34	8	34	30	37	42	52	6
21	La-Gd Rd-08	4472 m	44	17	39	56	30	14	32	39	29	45	43	12
22	La-Gd Rd-09	4715 m	53	14	32	59	38	3	35	21	43	40	59	1
23	La-Gd Rd-10	5158 m	51	16	33	56	37	6	34	26	40	40	57	4
24	La-Lu F-11	2650 m	29	29	42	40	27	34	21	68	11	45	27	28
25	La-Lu F-12	2417 m	27	29	44	39	25	36	21	72	7	46	23	30
26	La-Lu F-13	1928 m	25	38	37	25	34	41	15	76	10	39	30	32
27	La-Lu Rd-14	1751 m	38	17	45	55	23	21	30	51	19	49	32	19
28	La-Lu Rd-15	1758 m	31	31	37	35	32	32	20	64	16	41	34	25
29	La-Lu F-16	1790 m	26	37	38	28	32	40	16	75	10	40	29	31
30	La-Lu F-17	2174 m	31	30	39	37	31	32	21	64	15	42	33	25
31	La-Yu F-19	2883 m	33	29	38	39	32	29	22	60	18	41	36	23
32	La-Yu F-20	3207 m	34	24	42	46	27	27	25	59	16	46	32	23
33	La-Yu Rd-21	3367 m	39	21	41	51	28	21	28	50	22	45	37	17
34	La-Yu F-22	3494 m	39	20	41	51	28	21	28	49	23	45	38	17
35	La-Yu F-23	3595 m	32	29	39	39	30	30	22	62	16	42	33	24
36	La-Yu F-24	3930 m	36	19	45	54	23	23	29	54	17	49	31	20
37	La-Yu Rd-25	2616 m	38	22	40	49	29	22	27	51	22	44	37	18
38	Ch-Mn Rd-26	1584 m	34	24	42	46	27	27	25	58	17	45	33	22
39	Lu-Yu Rd-1	3606 m	34	16	50	57	17	25	30	59	11	54	23	23
40	Lu-Yu F-02	3595 m	27	27	46	43	22	35	22	71	7	48	22	30
41	Lu-Yu Rd-04	3367 m	32	16	52	57	16	27	29	62	8	55	20	25
42	Lu-Yu F-05	3218 m	27	25	49	45	19	35	23	72	5	51	19	30
43	Lu-Yu Rd-06	4674 m	38	11	51	65	16	19	34	51	16	55	26	19
44	Yu-Zp F-09	3814 m	30	18	52	55	15	30	28	66	6	55	18	27
45	Yu-Zp Rd-10	4534 m	39	12	49	64	18	18	34	48	18	53	30	17
46	Yu-Zp Rd-11	4943 m	41	17	42	56	27	17	31	45	25	47	39	15
47	Yu-Ch F-14	2166 m	37	12	51	63	17	20	33	52	15	55	26	19
48	Yu-Ch F-15	1965 m	38	21	41	49	28	22	28	51	21	45	37	18
49	Yu-Ch Rd-17	1582 m	37	14	49	60	19	21	32	52	16	52	28	19
50	La-Gd Rd-19	3812 m	46	11	43	65	25	10	36	35	29	49	41	10
51	La-Gd Rd-20	3476 m	41	12	48	64	20	16	34	46	20	52	32	16
52	La-Gd F-21	3379 m	34	19	48	54	20	26	28	59	13	51	26	23
53	La-Gd F-22	3143 m	43	6	51	71	17	12	38	41	21	56	31	13

54	La-Gd Rd-23	4427 m	51	10	40	65	29	5	37	27	36	46	49	5
55	La-Gd Rd-25	2712 m	41	10	48	65	19	15	35	44	21	53	32	15
56	La-Ch F-27	2656 m	31	26	43	43	26	31	23	64	13	46	29	25
57	La-Ch F-28	2414 m	29	26	45	43	24	33	23	67	10	47	25	28
58	La-Ch F-29	1928 m	21	35	43	30	26	44	16	83	2	44	20	36
59	La-Ch Rd-30	1751 m	38	17	45	57	23	20	31	50	19	49	33	18
60	La-Ch F-31	1761 m	35	21	44	50	25	25	27	56	16	48	31	21
61	L-02	4620 m	28	21	51	31	1	68	13	47	41	16	10	74
62	NC-04	4069 m	23	31	46	21	20	59	20	43	37	28	5	67
63	Rd-05	4004 m	17	31	52	18	20	63	25	34	40	25	2	73
64	Rd-07	3964 m	23	35	42	19	27	54	21	44	34	33	3	64
65	Rd-09	2496 m	27	42	31	17	40	43	19	54	27	44	4	52
66	Wf-10	1540 m	23	46	31	12	47	41	24	49	27	48	1	52
67	Rd-11	1286 m	27	44	29	16	44	40	20	55	26	47	3	50

Table 4.6: Overall seasonal contribution (%) of source endmember in the river stream and waterfall samples of Teesta watershed

Season	Average (%)			Standard Deviation (%)		
	Snow	Rain	Glacial-melt	Snow	Rain	Glacial-melt
Winter 2021	26	31	43	±6.3	±10.3	±7.5
Incessant Monsoon 2021	36	24	40	±8.0	±7.1	±3.5
End Monsoon 2021	36	17	47	±6.8	±7.2	±3.8
Summer 2022	24	36	40	±3.9	±8.9	±10.0

Model Limitations

The three-endmember mixing model used in this study is a basin-specific model developed explicitly for the Teesta watershed. With certain assumptions such as negligible intrusion of underground water and hyporheic zone as well as atmospheric depositions, the selection of source endmembers may also introduce some bias in the obtained results. Since the model is based on $\delta^{18}\text{O}$ and d-excess tracer equations, the model is capable of segregating contributions from utmost three source endmembers. However, intra-annual (monthly basis) study of isotopic composition, incorporating new conservative tracers and contemporary datasets, might help minimize the model's uncertainty and biases.

4.3.4 Conclusion

Glaciated Himalayan region act as a storehouse of freshwater in its frozen state, feeding several river systems of the Indian subcontinent. This necessitates studying the Himalayan catchments and rivers for their moisture sources and the seasonal contribution of glaciers to the perennial streams. In this study, different water sources within the Teesta watershed have been

extensively studied for the stable isotopic composition ($\delta^{18}\text{O}$ and δD) that helped in the outcomes mentioned below:

- The Spatio-temporal analysis of stable isotopes on a seasonal basis reveals seasonally varying $\delta^{18}\text{O}$ values of the river streams, rain, and snow. Three glacial bodies in three different locations in the Teesta watershed show varying $\delta^{18}\text{O}$ compositions. These glaciers feed three major tributaries of the Teesta river system.
- A progressive decline in the $\delta^{18}\text{O}$ values as moving towards the non-renewable glacial source has been observed in the headwaters of two major tributaries, Lachen Chu and Lachung Chu. More significant depletion of $\delta^{18}\text{O}$ isotope has been observed in the case of the Lachen Chu river. This indicates progressive depletion and distillation of ^{18}O isotope in the clouds (orographic ascent) attributed to cooling and subsequent rainout. This is also observed in the Rathong river stream in West Sikkim.
- There is a difference between the mean d-excess of all the water samples (16.29‰) and river streams (15.51‰), indicating water mixing from precipitation and glacial melt. For the Rathong river, the d-excess (16.04‰) is comparatively close to the overall mean. The d-excess values suggest the dominance of mid-latitude westerlies over ISM in the high-altitude northern region of the Teesta watershed.
- The deterministic Monte Carlo-based three endmember $\delta^{18}\text{O}$ -d-excess mixing model shows consistent mean glacial-melt contribution in the Teesta river stream that ranges between 40% and 47% in different seasons with a maximum glacial-melt contribution in the end-monsoon period. Such behaviour disagrees with the conventional understanding of maximum glacial-melt during summer or pre-monsoon. Such anomalous behaviour has also been observed in several other Himalayan river systems.

4.4 Segregating Sr Fluxes from Various Lithologies within Teesta Watershed

4.4.1 Datasets Used

The datasets required for the quantification of Strontium sources to the stream flow of the Teesta river have been acquired from Das et al., 2022. The samples were collected in April 2018, the beginning of the Indian summer monsoon (ISM). The emphasis of this study is to perform effective segregation of Sr flux into the river streams of the Teesta river system so as to develop a better understanding of the lithological inputs.

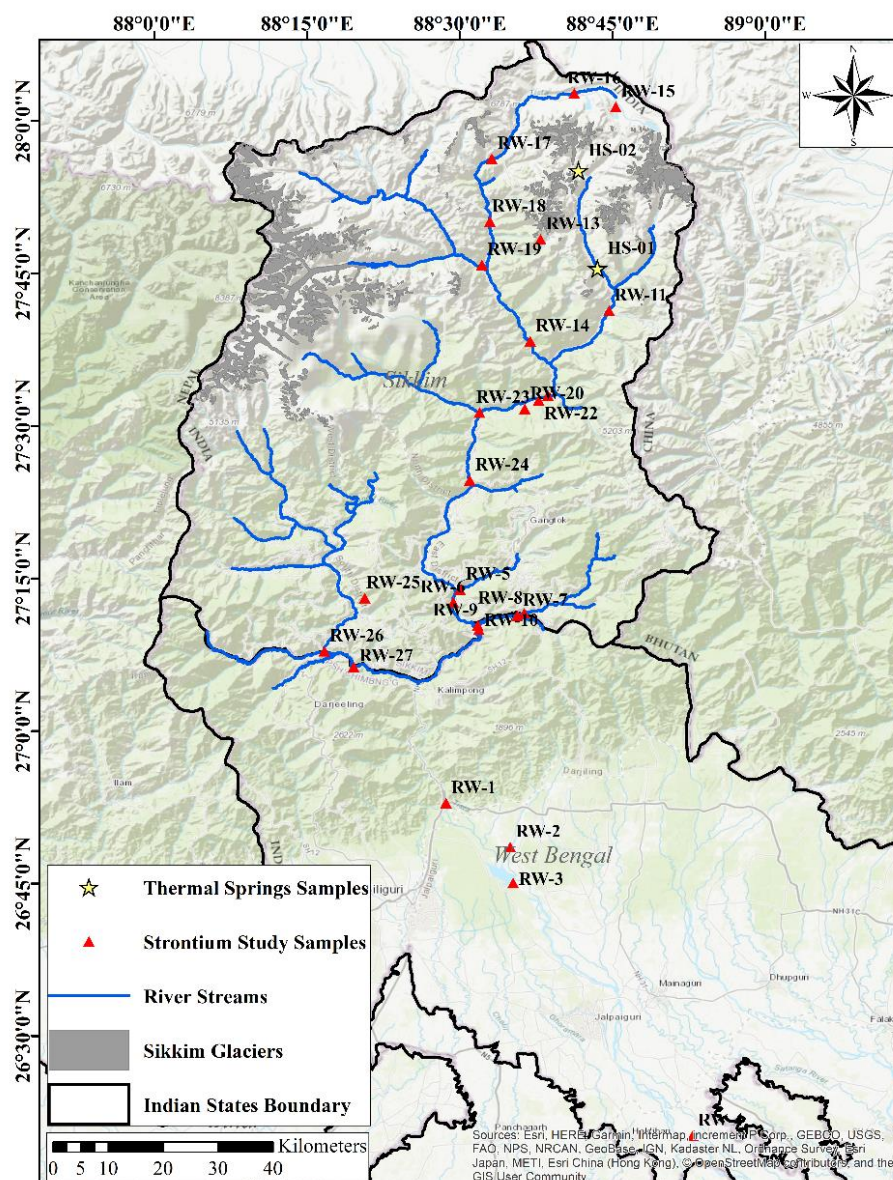


Figure 4.11: Study area map showing sampling locations of datasets used for the analysis

4.4.2 Four Endmember Strontium Mixing Model: Inputs and Execution

Apportionment of dissolved Sr in the river streams is essential in terms of identifying Sr flux and its contribution from various lithological sources. In this context, a state-of-the-art Strontium mixing model has been developed to segregate the Sr endmember contributions (silicates, carbonates, vein calcites and calc-silicates) to the river stream flux. The datasets used in the model has been acquired from Das et al., 2022. The water samples were collected during April, 2018 which is the beginning of Indian Summer Monsoon (ISM) in the study area. The sampling locations are represented in Figure 4.11. The relationships used in the Sr mixing model has been mentioned below:

$$Sr_s = Na^* \times (Sr/Na)_s \quad (4.7)$$

$$Sr_c = Ca_c \times (Sr/Ca)_c \quad (4.8)$$

$$Sr_{vc} = Ca_{vc} \times (Sr/Ca)_{vc} \quad (4.9)$$

$$Sr_{cs} = Ca_{cs} \times (Sr/Ca)_{cs} \quad (4.10)$$

$$Sr_T = Sr_s + Sr_c + Sr_{vc} + Sr_{cs} \quad (4.11)$$

Here, Na^* , Ca_c , Ca_{vc} and Ca_{cs} represents the sodium and calcium derived from silicates, carbonates, vein calcites and calc-silicates respectively. $(Sr/Na)_s$, $(Sr/Ca)_c$, $(Sr/Ca)_{vc}$ and $(Sr/Ca)_{cs}$ is the ratio of (Sr/Na) and (Sr/Ca) released from different lithologies. Sr_T , Sr_s , Sr_c , Sr_{vc} and Sr_{cs} represents the total dissolved strontium and strontium flux from various silicate and carbonate lithologies. Equation 4.7 to 4.10 can be written in the matrix form as follows:

$$\begin{pmatrix} (Sr/Na)_s & 0 & 0 & 0 \\ 0 & (Sr/Ca)_c & 0 & 0 \\ 0 & 0 & (Sr/Ca)_{vc} & 0 \\ 0 & 0 & 0 & (Sr/Ca)_{cs} \end{pmatrix} \times \begin{pmatrix} Na^* \\ Ca_c \\ Ca_{vc} \\ Ca_{cs} \end{pmatrix} = \begin{pmatrix} Sr_s \\ Sr_c \\ Sr_{vc} \\ Sr_{cs} \end{pmatrix} \quad (4.12)$$

It is to be noted that Sr flux from carbonate lithologies can have significant impact on the overall Sr budget and river water chemistry due to its higher solubility (Jacobson et al., 2002; Zhang et al., 2019). From the information provided in Das et al. (2022) as well as other researches conducted over Himalayan lithotypes (Singh et al., 1998; Bickle et al., 2001; Geological Survey of India, 2012), the input parameters of the Sr mixing model have been determined (Table 4.7 & 4.8). The Sr flux contributions (in nm) from various lithologies has been derived using equation 4.2 in which entities $((Sr/Na)_s, (Sr/Ca)_c, (Sr/Ca)_{vc}$ and $(Sr/Ca)_{cs})$ have been randomly sampled from the assigned ranges (Table 4.7). As frequency distribution analyses, random sampling of entities for the lithological Sr inputs has been performed. This shows that the entities are evenly distributed within the assigned range, thus, equally probable. The Sr mixing model has been deterministically executed through a Monte Carlo framework. The model has been iterated 10^4 times for each river water sample. Retaining 10^4 iterations, mean and standard deviation of all the iterations has been considered the best possible result.

Table 4.7: Ratio of strontium and anions from various lithologies

Entity	Mean		Standard Deviation	
	Teesta River	Headwaters (>2000m a.s.l)	Teesta River	Headwaters (>2000m a.s.l)
$(Sr/Na)_s$		1.30		± 0.30
$(Sr/Ca)_c$	0.20	0.50	± 0.15	± 0.04
$(Sr/Ca)_{vc}$	0.18	0.59	± 0.06	± 0.13
$(Sr/Ca)_{cs}$		0.60		± 0.20

Table 4.8: Assigned values for the anions in the Sr mixing model

Anions	Values
Na ⁺ (μm)	Available for each stream sample (Das et al., 2021)
Ca ²⁺ (μm)	Available for each stream sample (Das et al., 2021)
Ca _c (μm)	89% Ca ²⁺
Ca _{vc} (μm)	10% Ca ²⁺
Ca _{cs} (μm)	1% Ca ²⁺

4.4.3 Results and Discussion

The Monte-Carlo-based four-endmember Sr mixing model shows the contribution of Sr from different silicate and carbonate lithologies, as shown in the Table 4.9. Results show maximum contribution (in nm) of silicates with the average input of 177 ± 138.2 nm into the strontium load of the Teesta river system (Figure 4.12). Carbonates deliver the second maximum mean contribution of 72.7 ± 59.4 nm, whereas calc-silicates and vein calcites are the trace contributors with the mean load of 6.6 ± 6.2 nm and 1.4 ± 1.1 nm, respectively. Interestingly, the water samples (RW13/15/16/17/18) close to the high-altitude glaciated regions reveal maximum contribution (in nm) from carbonate lithologies. As already evidenced from previous studies (Das et al., 2022), carbonates (including vein calcites and calc-silicates) have higher solubility resulting in an enhanced rate of weathering. Thus, carbonate lithologies deliver a greater amount of leached Sr into the river streams than silicate lithologies. In the Teesta watershed, vein silicates are found only in the northernmost Lachi formation, with less abundance of calc-silicates (Geological Survey of India 2012). Also, altered/diagenetic carbonates are not found in the watershed (Das et al., 2022). With this assumption of calc-silicates and vein silicates as trace contributors of Sr in the river streams, the maximum amount of dissolved Sr load comes from the silicate and carbonate lithologies of the north-eastern Himalayas derived from the mixing model. Moreover, the dissolved Sr load from silicate and carbonate lithologies within the watershed are almost independent of altitude, as shown in Figure 4.13. The trendlines in the figure shows a decline in the silicate contributions to Sr flux with increase in elevation or moving towards the upstream whereas this trend is reversed for carbonates.

Table 4.9: Strontium mixing model-based segregation of lithologies (in nm) of the Teesta river at different locations

Sample	Altitude (m a.s.l)	Sil (nm)	Carb (nm)	CS (nm)	VC (nm)	Sr Modelled (nm)	Sr Tested (nm) (Das et al., 2022)	Error (nm)	Error%
Mainstream									
RW-15	5066	151.9	180.1	17.9	0.4	350.2	350	-0.2	0.05
RW-16	5017	69.8	182.3	17.8	3.8	273.7	273	-0.7	0.25

RW-17	4283	232.0	236.3	6.7	3.9	478.9	478	-0.9	0.19
RW-18	3450	100.3	118.8	26.8	0.9	246.8	243	-3.8	1.55
RW-14	1902	118.3	97.8	3.0	1.7	220.8	223	2.2	0.99
RW-21	1268	177.0	40.2	10.4	1.9	229.6	229	-0.6	0.27
RW-24	539	60.8	147.2	2.5	2.9	213.4	211	-2.4	1.15
RW-6	281	152.8	53.8	6.8	0.1	213.6	213	-0.6	0.29
RW-10	244	112.1	85.3	1.9	0.5	199.8	202	2.2	1.07
RW-1	135	277.0	26.2	5.7	3.0	311.9	315	3.1	0.99
RW-3	104	283.1	73.2	1.4	1.7	359.4	364	4.6	1.28
RW-4	67	350.0	104.6	4.9	0.7	460.2	459	-1.2	0.26
Tributaries									
RW-19	3129	283.0	25.5	5.0	3.2	316.7	316	-0.7	0.23
RW-13	5006	10.1	68.7	6.2	1.4	86.4	87	0.6	0.70
RW-11	2585	69.3	10.0	10.3	1.0	90.6	89	-1.6	1.83
RW-22	1319	40.3	15.5	1.1	0.1	56.9	52	-4.9	9.36
RW-20	1393	14.6	49.2	3.3	0.9	68.0	68	0.0	0.05
RW-23	759	52.3	88.8	0.9	0.9	142.9	145	2.1	1.43
RW-5	317	178.9	8.0	2.0	0.8	189.7	186	-3.7	1.98
RW-7	385	89.5	28.0	3.8	1.3	122.6	123	0.4	0.35
RW-8	410	49.8	58.9	8.2	1.6	118.4	123	4.6	3.76
RW-9	255	118.5	19.5	4.3	1.2	143.5	139	-4.5	3.22
RW-25	900	469.4	58.1	8.0	1.0	536.5	536	-0.5	0.09
RW-26	269	239.2	6.7	1.7	0.5	248.1	252	3.9	1.53
RW-27	228	398.9	43.5	10.9	1.5	454.8	454	-0.8	0.18
RW-2	127	502.7	63.2	0.9	0.6	567.4	568	0.6	0.11

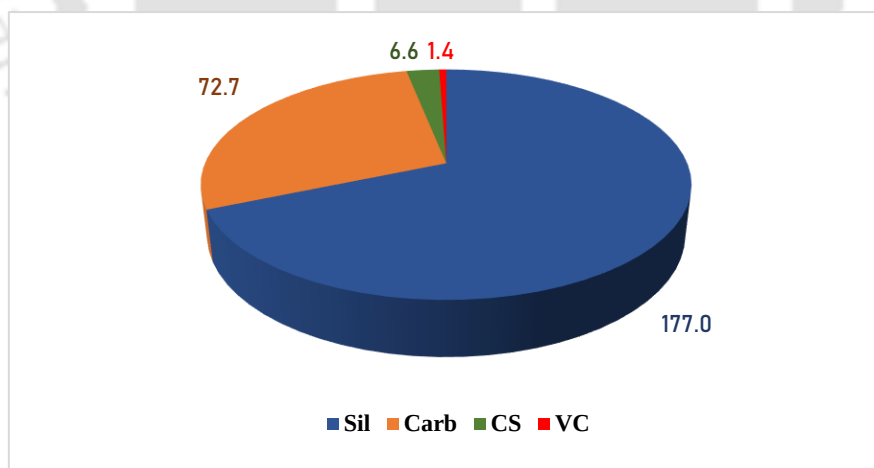


Figure 4.12: Pie chart showing Sr flux (in nm) from different lithologies

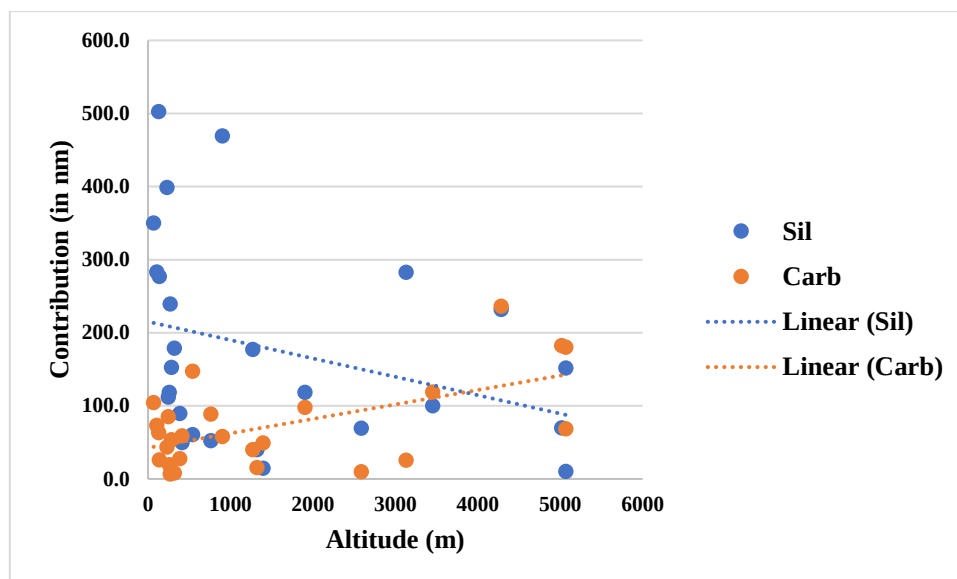


Figure 4.13: Plot of dissolved Strontium contribution from silicates and carbonates lithologies vs Altitude (m a.s.l)

4.4.4 Conclusion

A deterministic Monte Carlo-based Sr model shows maximum contribution of dissolved Sr flux from carbonate lithologies near the non-renewable glacial sources and overall maximum mean contribution from silicate lithologies (177 ± 138.2 nm). The contribution from carbonate lithologies increase with increase in the altitude of river streams (upstream) whereas contribution from silicate lithologies follow an opposite trend.

4.5 Isotopic Composition of Natural Thermal Springs and Elemental Analysis

4.5.1 Data Collection and Analysis

The thermal spring samples (HS-01 & HS-02) were collected during field investigation to North Sikkim on 15th and 16th August 2021, respectively at Changme glacial snout and Yumthang valley (Figure 4.11). The samples were collected in 30 ml high-density pre-cleaned polyethylene (HDPE) bottles to determine stable isotopes ($\delta^{18}\text{O}$ and δD). Prior to collection, the HDPE bottles were rinsed thoroughly several times with spring water during acquisition. The samples were filled and capped tightly to avoid evaporation and interaction with atmospheric moisture. The samples were sent to the nuclear hydrology laboratory (National Institute of Hydrology) for stable isotope analysis. A dual inlet stable isotope-ratio mass spectrometer (DIIRMS) was used to determine δD . The $\delta^{18}\text{O}$ values of each sample were measured using a continuous-flow stable isotope-ratio mass spectrometer (CFSIRMS). Further, the samples were equilibrated with CO_2 & H_2 to quantify the proportion of stable isotopes using

precision range of $\pm 0.1\%$ and $\pm 1.0\%$ for $\delta^{18}\text{O}$ and δD , respectively, by analyzing the International Atomic Energy Agency (IAEA) standards (Behera et al. 2019).

$$\delta(\text{‰}) = \left(\frac{R_s - R_{s'}}{R_{s'}} \right) \times 10^3 \quad (4.13)$$

Here, R_s and $R_{s'}$ define the ratio of $^2\text{H}/^1\text{H}$ and $^{18}\text{O}/^{16}\text{O}$ isotopes for thermal spring samples and standard water sample, respectively. The results are expressed in per mil (‰) relative to the Vienna standard mean ocean water (VSMOW) and expressed with 'δ' as represented in equation 4.13. The quantitative analysis of heavy metals (Ti, V, Cr, Mn, Fe, Co, Ni, Cu, Zn, As, Se, Mo, Ag, Cd, Sn, Sb and Pb) and radionuclide (^{238}U) have been performed with the use of inductively coupled plasma mass spectrometry (ICP-MS) at Inter-University Accelerator Centre (IUAC), New Delhi. The instrument (ICP-MS) was calibrated using standard solutions of 100, 50, 20 and 1 μgL^{-1} which were prepared from $10^3 \mu\text{gL}^{-1}$ multi-element stock solution through dilution process. Standards (AMH, JB-1a, MBH and DGH) were used for QA/QC, (Punia et al., 2021). In order to assess the accuracy and precision of the analysis, measurement of the elemental concentration in the standards and blank (Milli Q prepared from 18.2 $\text{M}\Omega\cdot\text{cm}$ Ultrapure, Sigma-Aldrich) were performed after every 10 samples. The detection limit fluctuates between 0.1 and 1000 μgL^{-1} for Mn, Fe and ^{238}U .

4.5.2 Results and Discussion

The composition of thermal spring samples in terms of their stable isotopic composition ($\delta^{18}\text{O}$ and δD) indicates the possible recharge source of the geothermal aquifer zone (Tiwari et al., 2016). The $\delta^{18}\text{O}$ value of the higher altitude thermal spring is less than that of the lower altitude thermal spring. The computed d-excess value recedes with elevation. Due to inadequate sampling (only two thermal springs), deducing the correlation between $\delta^{18}\text{O}$ and δD becomes immaterial. However, the deuterium excess ($\delta\text{D} - 8 \times \delta^{18}\text{O}$) is capable of defining the recharge mechanism. The d-excess values of 14.99‰ and 18.87‰ for the thermal springs (Table 4.10) indicate a strong affinity towards meteoric origin that matches with several other natural thermal springs of the Garhwal Himalayas and Ladakh region as investigated earlier (Dalai et al., 2002; Shivanna et al., 2008). The elemental analysis of the thermal spring samples shows significant differences with respect to each other (Table 4.11). Sample HS-02 collected from the geothermal source near the snout of Change glacier shows significantly high arsenic content (67.05 ppb), which is much higher than the permissible limit of 10 and 50 ppb as per the regulations set by the Indian standards and World Health Organization (WHO). As arsenic is highly toxic in its inorganic form, using arsenic doped water for irrigation and drinking can

lead to severe health hazards such as chronic arsenic poisoning, cardiovascular disorders, cancer, and skin lesions. As the locals and tourists extensively use thermal springs due to their medical and sociological importance, it is important to check arsenic doping to avoid health hazards to masses. The thermal sample shows a surprisingly higher concentration of tin (2095.35 ppb) as well as some amount of Uranium (2.52 ppb) that remains within the permissible limit (30 ppb) set by WHO. Both the thermal spring (HS-01 & HS-02) are located not too far from each other, and the heavy metal compositions of both springs vary substantially. Where HS-02 shows severe arsenic contamination with high tin concentration, the HS-01 sample collected near Yumthang valley seems safe regarding heavy metals content. Such findings infer these two thermal springs as isolated geothermal aquifers with a localized source of arsenic near the Changme glacial snout region that does not interfere with other geothermal reservoirs.

Table 4.10: Stable isotopic composition of natural thermal springs at north Sikkim

Sample code/ ID	Date of collection	Location	Altitude (m)	Longitude	Latitude	$\delta^{18}\text{O}$ (‰)	δD (‰)	d-excess (‰)
HS-01	15-10-2021 (Friday)	Yumthang Valley	3367 m	88°43'30" E	27°45'29" N	-16.74	-115.05	18.87
HS-02	16-10-2021 (Saturday)	Changme Glacier	4674 m	88°41'37.7" E	27°55'6.7" N	-18.29	-131.31	14.99

Table 4.11: Heavy metals composition of natural thermal springs (* denotes contamination)

Element	HS-01 (ppb)	HS-02 (ppb)	IS-Standards (Acceptable) (ppb)	IS-Standards (Permissible) (ppb)	Other Standards (ppb)	Reference
Ti	3.08	2.76	No Guideline	No Guideline	100	Dong et al., 1993
V	BDL	0.08	No Guideline	No Guideline	15	OEHHA
Cr	BDL	BDL	50.00	No Relaxation	50	WHO
Mn	BDL	BDL	100.00	300	500	IS 3025 (Part 59); WHO
Fe	0.74	BDL	300.00	No Relaxation	1000	IS 3025 (Part 53); Kumar and Puri, 2012
Co	BDL	BDL	No Guideline	No Guideline	4	MoWLAP
Ni	0.22	0.16	No Guideline	No Guideline	20	WHO
Cu	BDL	4.49	50.00	1500	2000	IS 3025 (Part 42); WHO
Zn	BDL	5.95	5000.00	15000	3000	IS 3025 (Part 49); WHO
As*	4.46	67.05	10.00	No Relaxation	50	BIS; WHO
Se	0.23	0.11	10.00	No Relaxation	10	IS 3025 (Part 56); WHO
Mo	6.75	7.47	70.00	No Relaxation	70	IS 3025 (Part 2)
Ag	2.27	2.27	100.00	No Relaxation	No Guideline	Annex J of IS 13428
Cd	0.00	0.01	3.00	No Relaxation	3	IS 3025 (Part 41); WHO
Sn	19.51	2095.35	No Guideline	No Guideline	NIL	NIL
Sb	0.32	1.02	No Guideline	No Guideline	5	WHO
Pb	BDL	BDL	10.00	No Relaxation	50, 15	IS 3025 (Part 47); WHO; US EPA
U	BDL	2.52	No Guideline	No Guideline	30	WHO

4.5.3 Conclusion

The Teesta watershed is rich in terms of its biodiversity and freshwater reserves. This necessitates a quantitative study of the hydrological and lithological feeds as well as investigating the natural thermal springs. The heavy metal analysis shows arsenic contamination (67.05 ppb) of thermal spring located near the Changme glacial snout but no such contamination for the Yumthang valley spring. This indicates isolated geothermal aquifers with a localized source of arsenic near the Changme glacial snout.



Glacial Lake Vulnerability: An Investigation from Himalayan Ranges

5.1 Introduction

The great Himalayan ranges are known to have a large number of glacial lakes (Maharjan et al., 2018). Each lake is unique in terms of its parent glacier, shape, topographic features, and volumetric capacity. Such glacial lakes either lie at a distance from the glacial body, behind the lateral moraines/glacial terminus (proglacial lakes) or directly on the glacial surface (supraglacial lakes) and are primarily fed by snow- and ice-melt (Salerno et al., 2012; Otto, 2019). These lakes are characterized by their formation, emergence, temporal expansion, lifespan, disappearance, dam structure, and impact upon outbursts (Nie et al., 2017; Mertes et al., 2017). Glacial lakes are dynamic Himalayan features and can be seen as an indirect indicator of glacial change (Gardelle et al., 2011) that may present hazards to the downstream areas (Costa and Schuster, 1988). A sporadic outburst of glacial lakes may transform into powerful floods with direct damage potential, which counts them in the category of catastrophic glacier-related hazards (Osti and Egashira, 2009; Mergili et al., 2011). Glacial lake outburst floods (GLOFs) get triggered either due to external influences such as overtopping waves or moraine-dam failure or self-destruction such as the settlement of ice-cores, extreme precipitation, rock/ice avalanche or seismic activities (Somos-Valenzuela et al., 2015; Carrivick and Tweed, 2016; Harrison et al., 2018). Some of the largest past events of glacial lake outburst floods (GLOFs) in the Himalayas have resulted in great loss of life and property (Vuichard and Zimmermann, 1987; Tashi, 1994; Bhargava, 1995). Some of them being the 1969 and 1970 Ayaco lake breach (Liu et al., 2014), the 1977 Nare lake breach (Buchroithner et al., 1982), the 1985 Dig Tsho outburst (Vuichard and Zimmermann, 1987), the 1998 Sabai Tsho GLOF (Osti and Egashira, 2009) and, the 2013 Chorabari cascade (Ghosh et al., 2019). Most of these cascading events have occurred due to the breach of moraine-dammed glacial lakes (Carrivick and Tweed, 2016; Veh et al., 2019; Khan et al., 2021). Nonetheless, risk assessment of GLOF is necessary for the Himalayas, where ~70% of the hydroelectric power plants are situated over potential tracks of outburst floods (Schwanghart et al., 2016).

The rapid expansion of the existing glacial lakes and the formation of new ones enhances the likelihood of GLOFs in the Himalayan ranges (Wang et al., 2015; Khadka et al., 2018). Mahalangur region of the central Himalayas has been reported with an accelerated areal augmentation of glacial lakes between 1987 and 2017 (Khadka et al., 2018). Several historic GLOF events have motivated the need to conduct a vulnerability assessment of glacial lakes, especially in the Hindu-Kush Himalayas (Ives et al., 2010; Emmer, 2018; Fujita et al., 2013; Schwanghart et al., 2016; King et al., 2017; Veh et al., 2019), including Tibet (Chen et al., 2007; Wang et al., 2011), Bhutan (Ukita et al., 2011) and Nepal (Somos-Valenzuela et al., 2015; Rounce et al., 2017). This starts with developing inventories of glacial lakes as it allows researchers quick identification of lakes which sought for detailed investigation (Allen et al., 2009). The International Centre for Integrated Mountain Development (ICIMOD) developed a comprehensive inventory of glacial lakes for the Hindu-Kush as well as Sikkim Himalayas (Campbell and Pradesh, 2005; Ives et al., 2010). Worni et al. (2013) developed an inventory of Himalayan glacial lakes integrated with an extensive risk assessment. Abdul Hakeem et al. (2018) identified enormous glacial lakes within the Teesta watershed using satellite remote sensing and investigated them for expansion on a temporal basis. A study conducted by ICIMOD in 2003 shows the existence of 266 glacial lakes covering an area of 20.2 Km² in the Sikkim Himalaya (Campbell and Pradesh, 2005). The study concluded that despite being a smaller watershed, the count of glacial lakes and potential for GLOF is very high in the Teesta River basin. An investigation by the Centre for Inter-Disciplinary Studies of Mountain & Hill Environment, University of Delhi, observed 313 glacial lakes (21.5 Km²) using LISS-III datasets of 2000 in the Teesta basin. Raj et al. (2013) identified 320 glacial lakes using LISS-III data of 2010. Aggarwal et al. (2016) observed 143 such lakes using LISS-III data of 2011. These studies reveal inconsistent observations of glacial lakes, especially in the Teesta watershed that could be attributed to ineffective interpretation, which involves visual, semi-automatic, and automatic techniques. Other possible reasons such as unavailability of cloud and snow-free data, hill shadow, terrain, and physical lake conditions (frozen).

An objective and accurate classification of potentially dangerous glacial lakes (PDGLs) is challenging but needs improvement. It is important to note that not every glacial lake is unstable or holds the possibility to breach catastrophically (Huggel et al., 2004). The probability of glacial lake outburst is a function of the external triggering factors and the susceptibility of natural dams to breach (Richardson and Reynolds, 2000). Moraine-dam stability depends on its structure, geometry, and material properties (Korup and Tweed, 2007;

Fujita et al., 2009). In fact, the stability of a moraine dam may improve or deteriorate over time (Clague and Evans, 2000; Worni et al., 2013). There are various methods to appraise the PDGLs across the Himalayan regions (Rounce et al., 2016; Prakash and Nagarajan, 2017), which were initially adopted from British Columbia (Mckillop and Clague, 2007), Swiss Alps (Huggel et al., 2004) and other places around the globe (Emmer and Vilímek, 2013; Wang et al., 2011). Rounce et al. (2016) developed a unified and robust evidence-based framework to assess GLOF hazard in the Nepal Himalayas, classifying glacial lakes with susceptibility to avalanches and steep moraine dams as highly hazardous. Allen et al. (2019) performed the GLOF assessment in the Tibetan region using an automated approach incorporating the mean slope of the moraine dam, rock/ice avalanche potential, upstream watershed of each lake, and lake area to rank each lake in terms of hazard. Wang et al. (2015) observed the PDGLs using the analytical hierarchy process (AHP) in the Chinese Himalayas. Prakash and Nagarajan (2017) considered eleven parameters to identify PDGLs in the western Himalayas. All the above-mentioned studies incorporate the lake area threshold of $<0.1 \text{ Km}^2$ to classify safe glacial lakes in terms of GLOFs. However, some recently reported GLOF events in the Indian and Nepal Himalayas have been reported from glacial lakes having an area $<0.1 \text{ Km}^2$ (Das et al., 2015; Byers et al., 2019; Rafiq et al., 2019).

In the present study, an attempt has been made to conduct a study of glacial lakes in the Himalayas using both satellite remote sensing-based and field-based investigations. This includes

4. GLOF due to the breach of Shisper glacial lake in the Karakoram Himalaya triggered on 7th May 2022.
5. Impact of Mw5.7 Tibet earthquake of 20th March 2020 around lake Dingmu.
6. Vulnerability assessment of transboundary Sikkim Himalayan lakes

5.2 Shisper Glacial Lake Breach

5.2.1 Event Description

It was on 7th May 2022 that a massive outburst flood occurred due to a breach of Shisper glacial lake. Experts stated that an anomalous increment in the melting rate of the parent glacier due to an abrupt rise in temperature by around 5°C (heat waves) resulted in more than 40% hike in the lake volume in the past 20 days thus resulting in a breach. The melt contribution from the parent glacier into the lake reached up to 5000 cusecs (1 cusec = 28.32 litres/sec) before the collapse. The International Centre for Integrated Mountain Development (ICIMOD) revealed

that the pre-breach size of Shisper lake had been 15% more than the recorded size in past three years (<https://www.icimod.org/increasing-risk-of-glacial-lake-outburst-floods-in-hunza-river-basin/>). The outburst flood led to loss of life and property along with the destruction of the Hassanabad bridge built on the Karakoram highway over the Hunza river.

5.2.2 Study Area

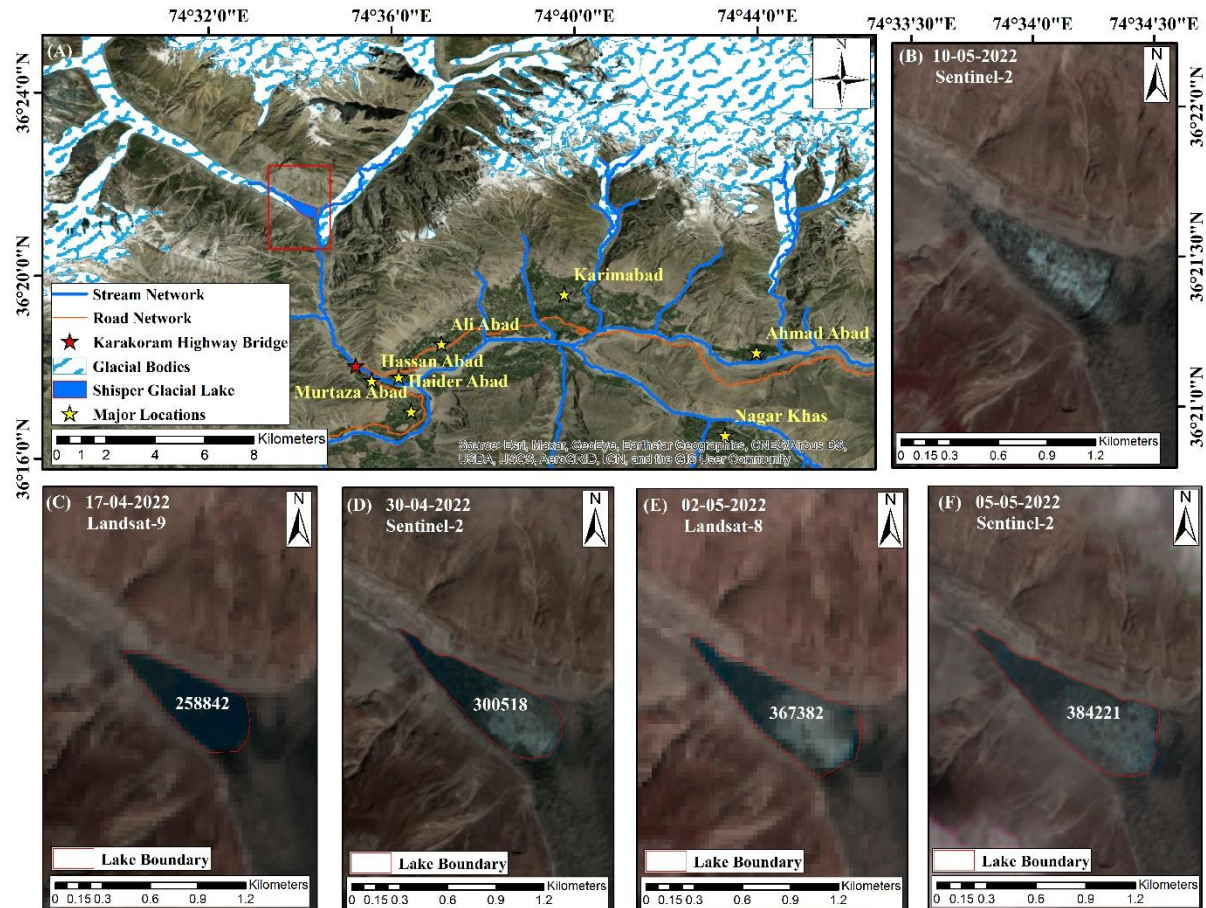


Figure 5.1: Study area map showing satellite view of the region and Shisper glacial lake: (A) Major locations, glacial bodies, road networks and lake (B) Lake after the breach of 7th May 2022, (C) Lake before the breach on 17th April 2022 (Lake area: 0.26 Km²), (D) 30th April 2022 (Lake area: 0.30 Km²), (E) 2nd May 2022 (Lake area: 0.37 Km²) and (F) 5th May 2022 (Lake area: 0.38 Km²)

Shisper glacier is the western component of the Hassanabad glacier with the Muchuwar glacier in the east (Muhammad et al., 2021). The glacier belongs to the group of Passu mountain glaciers that lies in the upper Indus basin within the western Karakoram belt of the Himalayan mountain range. Shisper and Muchuwar glaciers share a common tongue with an ice-dammed glacial lake at the snout of the Shisper glacier. Lying between 36° 15' to 36° 30' N latitudes and 74° 28' to 74° 39' E longitudes, the Shisper glacier acquires a total area of 54.7 Km². Similar to the other valley glaciers of Karakoram, Shisper and Muchuwar glacier has a main

trunk lying between the elevation range of 5267 and 7611 m a.s.l, the glacier delivers its melt contribution into the Hunza river as shown in Figure 5.1. The region receives 125 mm of annual precipitation with a mean average temperature of 11°C. However, the steady mobility of the glacier leads to blockage of the outlet from the Muchuwar glacial snout. The glacier being highly susceptible to surge and outburst floods, there had been several glacial lake outburst floods (GLOFs) in the past since 1890. Some of the recent GLOFs occurred in June 2019 and May 2020 affecting the downstream areas. Bhambri et al. (2020) tracked significant seasonal fluctuations in surface velocities during the glacial surge of 2018 reaching up to 18m/day in the month of June. Moreover, an increment in the Shisper lake volume reaching up to 16 million cubic meters in May, 2019 has also been identified.

5.2.3 Datasets Used

In the present study, an attempt has been made to utilize the reflective, emissive, and microwave domain of satellite remote sensing for the purpose of investigating the incident, the possible reason behind the triggering phenomenon, and the after-effects of the glacial lake breach. Landsat 8/9 Operational Land Imager (OLI) and Sentinel 2 Multi-Spectral Instrument (MSI) datasets have been used to capture the anomalies. Landsat 8/9 provides fair resolution (30 m) satellite imageries in eleven spectral channels between 0.43 μm and 12.51 μm , covering the visible, near-infrared (NIR), shortwave infrared (SWIR), and thermal infrared (NIR) region of the electromagnetic (EM) spectrum. Sentinel 2 provides information in thirteen spectral channels devoid of thermal bands between 0.43 μm and 2.28 μm capturing visible (10 m), NIR (20 m), and SWIR (60 m) regions of the EM spectrum. As Landsat 8 and Landsat 9 are identical twins in terms of their spectral, spatial, radiometric, and temporal resolution, utilizing both the datasets improves the time interval of data acquisition (<16 days) as shown in Table 5.1. This is advantageous in studying natural hazards such as floods as datasets can now be acquired in the close time domain around the event date. Sentinel 1 level-I ground range detection (GRD) and single look complex (SLC) datasets have been used to derive the surface mobility of glacial bodies and alterations along the Hunza river stream. Sentinel 1 mission is equipped with two satellites, namely Sentinel 1A/B revolving in near-polar orbits providing datasets within 12 and 6 days as an independent and pair satellites respectively. The satellites acquire C-band synthetic aperture radar (SAR) data in 5.405 GHz (center frequency) in single (HH, HV) as well as dual (VV+VH, HH+HV) polarization schemes (Filipponi 2019). Moreover, a high-resolution digital elevation model (DEM) in 12.5 m spatial resolution from Advanced Land Observing Satellite (ALOS) polarimetric Phased Array L-band Synthetic Aperture Radar (PALSAR) has been

utilized to derive the stream networks around the Hassanabad region of Hunza river valley. PALSAR is a microwave sensor operating in L-band and acquiring data in all weather conditions. The DEM derived using PALSAR is transformed from orthometric height to ellipsoidal height to match the elevation profile with other available DEMs. The area's glacial boundaries, including Shsisper and Muchuwar glacier, have been used from Randolph glacial inventory (RGI 6.0).

Table 5.1: Datasets used in the study (* denotes the polarization used in the study)

Sentinel 1 SLC & GRD Datasets				
Pre-GLOF Datasets	Post-GLOF Dataset	Beam Mode-Sub Swath/Path	Frame/Flight Direction	Polarization
4 th April 2022	10 th May 2022	IW-1/27	116/Ascending	*VV+VH
16 th April 2022				
28 th April 2022				
Landsat 8/9 OLI & TIRS Datasets				
Pre-GLOF Datasets	Post-GLOF Dataset	Spectral Channel Used	Pixel Size	Pixel Depth
17 th April 2022 (L-9)	10 th May 2022 (L-9)	Band 3 (Green; 0.53-0.59 μm)	30 m	16 bit
		Band 4 (Red; 0.64-0.67 μm)		
		Band 5 (NIR; 0.85-0.88 μm)		
		Band 6 (SWIR-I: 1.57-1.65 μm)		
2 nd May 2022 (L-8)		Band 10 (TIR-I; 10.6-11.19 μm)	100 m	
Sentinel 2 MSI Datasets				
Pre-GLOF Datasets	Post-GLOF Dataset	Spectral Channel Used	Pixel Size	Pixel Depth
11 th November 2017	10 th May 2022	Band 3 (Green; 0.543-0.578 μm)	10 m	16 bit
8 th September 2018		Band 4 (Red; 0.65-0.68 μm)		
13 th October 2019				
22 nd September 2020		Band 5 (Red Edge; 0.698-0.713 μm)	20 m	
27 th September 2021				
30 th April 2022				
5 th May 2022	Band 11 (SWIR-I; 1.565-1.655 μm)			
ALOS PALSAR DEM				
2 nd January 2009		Beam Mode/Path	Frame/Flight Direction	Polarization
		Fine Beam Single (FBS)/527	710/Ascending	HH

5.2.4 Methodology

The methodology presented has been adopted for carrying out two distinct stages of the investigation. The first stage is identifying the plausible factors behind the occurrence of the GLOF event. The second stage is to capture the after-effects of the event. Several parameters

have been derived from optical, thermal, and microwave remote sensing techniques as shown in Figure 5.2.

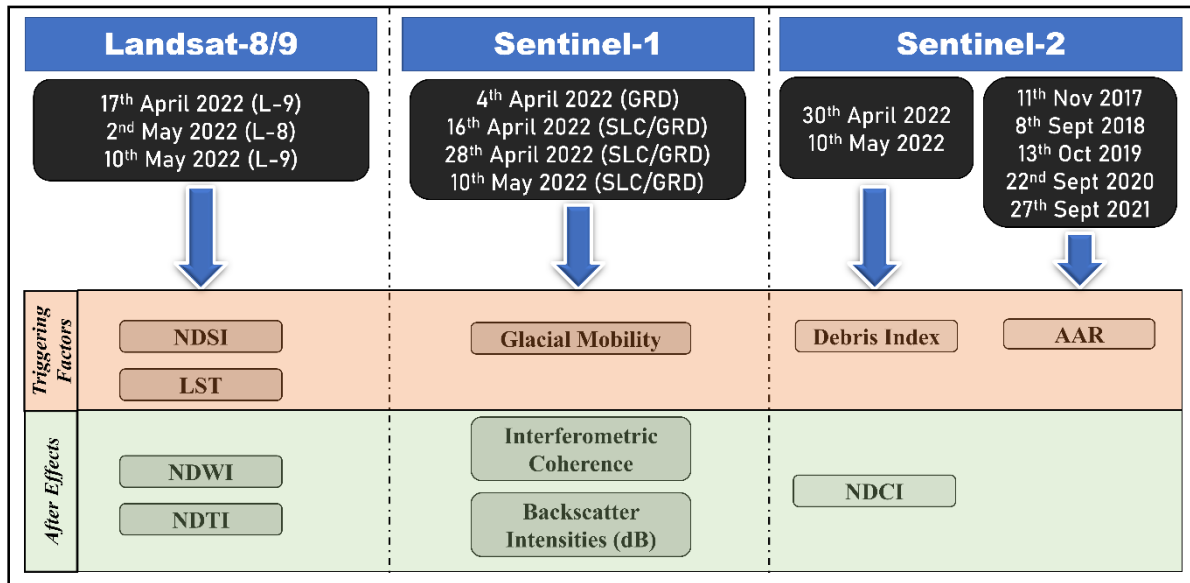


Figure 5.2: Flowchart of the optical (Landsat-8/9 & Sentinel-2) and SAR (Sentinel-1) datasets used and adopted methods to investigate the triggering factors and after effects of Shisper glacial lake breach

5.2.4.1 Accumulation Area Ratio (AAR)

The Himalayas consists of rugged terrain and harsh climatic conditions, making the ground-based mass balance monitoring limited to very few glaciers for a few years. Accumulation-Area-Ratio (AAR) method was established to compute the mass balance of Gara and Gor-Garang Glaciers in the Baspa basin, Western Himalayas through satellite-based observations (Kulkarni, 1992). The regression equation for Karakoram Himalayas is shown in equation 5.1.

$$\text{Specific Mass Balance (in cm w. e.)} = 243.01 \times \text{AAR} - 120.187 \quad (5.1)$$

To distinguish snow from rocky outcrops, bright soil, and clouds, Green (B3) and SWIR bands (B11) have been utilized as explained in equation 5.3. For a given hydrological year, the ELA (Equilibrium Line Altitude) of the glacier implies that the amount of accumulation and ablation is equal at that particular altitude. The ELA at the end of a hydrological year is used as a boundary to differentiate the Accumulation and Ablation zone of the glacier for the given year. NDSI (Normalized Difference Snow Index) threshold of 0.75 ~ 0.96 can be used for the extraction of the firm line for the given region (Zhao et al., 2020). By employing NDSI and firm line threshold, the accumulation area of the glacier can be extracted during the end of the ablation period, i.e., in the month of mid September to early November. The accumulation area ratio is given by equation 5.2.

$$AAR = (Accumulation\ Area) / (Total\ area\ of\ glacier) \quad (5.2)$$

5.2.4.2 Normalized Difference Snow Index (NDSI)

One of the major advantages of satellite remote sensing lies in monitoring changes over a large area on the Earth's surface. Hall et al. (1995) tried to utilize the spectral differences in snow-covered and snow-free areas as observed by Moderate Resolution Imaging Spectroradiometer (MODIS) to establish an automated approach to monitoring fluctuations in global snow cover on a daily basis. The same approach, termed NDSI works on the basic behavior of snow reflectance, which is high in the visible and low in the SWIR region of the electromagnetic spectrum (Nolin and Liang, 2000). NDSI can be defined as the difference in the captured reflectances in the visible (preferably green band) and SWIR (1.57-1.65 μm) band divided by the sum of reflectances in the two bands as represented by equation 5.3. NDSI helps in distinguishing snow from clouds and other non-snow areas. Moreover, this band ratio minimizes the influence of viewing geometry and atmospheric effects (Salomonson and Appel, 2004). A threshold of 0.4 has been considered to mask out surficial snow from other surface features (Hao et al., 2008)

$$NDSI = \frac{\rho_{Band\ 3} - \rho_{Band\ 6}}{\rho_{Band\ 3} + \rho_{Band\ 6}} \quad (5.3)$$

5.2.4.3 Normalized Difference Water Index (NDWI)

Similar to NDSI, this band ratio was first devised for MODIS for the detection of vegetation water content (Gao et al., 1996) and surface water features (McFeeters, 1996). NDWI is the difference of reflectance values in the green and NIR band ratioed by the sum of reflectances in the two bands, as shown in equation 5.4. NDWI greater than zero represents water bodies, and less than zero represents land surface and muddy water (Xu, 2006). In the case of floods, NDWI can be used as an index for assessing water quality as positive pixel values represent clear water in NDWI output that might shift towards negative values due to mud/debris contamination.

$$NDWI = \frac{\rho_{Band\ 3} - \rho_{Band\ 5}}{\rho_{Band\ 3} + \rho_{Band\ 5}} \quad (5.4)$$

5.2.4.4 Normalized Difference Turbidity Index (NDTI)

NDTI has been used as a supportive band ratio to the NDWI. Even though NDWI can distinguish between clean and muddy water after an outburst flood, NDTI uses the reflectance

response of green and red bands to detect turbid/muddy water in satellite imagery. The mathematical expression of NDTI is shown in equation 5.5:

$$NDTI = \frac{\rho_{Band\ 4} - \rho_{Band\ 3}}{\rho_{Band\ 4} + \rho_{Band\ 3}} \quad (5.5)$$

where $\rho_{Band\ 3}$ and $\rho_{Band\ 4}$ are the reflectance response in the green and red bands of Landsat-8/9 datasets, respectively. The reflectance of clean and sediment-free water is weak, small, and quasi-null in the green, red, and NIR spectral channels, respectively (Robin, 1995). Sediment-loaded water shows a similar reflectance response as that of bared soils (Guyot, 1989), where the green band shows lower reflectance than the red band. The positive values of this band ratio represents turbid water. Pixels showing NDTI values in the range of -0.03 and 0.03 indicate arable land cover with vegetation (Solovey, 2019).

5.2.4.5 Normalized Difference Chlorophyll Index (NDCI)

Accepting the fact that band ratios act as a powerful tool in delineating a specific surface feature considering its spectral response, it becomes difficult to quantitative analysis, especially in water quality. Over the past few years, several algorithms have been designed to quantify chlorophyll (Chl-a) concentration in turbid productive water bodies particularly using NIR bands (Mishra and Mishra, 2012). These algorithms can be broadly divided into three different classes of two-band empirical (Moses et al., 2009), three/four-band empirical (Le et al. 2009), and three-band semi-analytical (Gons et al., 1999) algorithms, respectively. Chl-a concentration in a water body depends on two factors, temperature and level of nutrients (Meena et al., 2022). The Chl-a concentration of river water gets altered soon after a flood event that can be easily detected using NDCI as shown in Eq. (6):

$$NDCI = \frac{\rho_{Band\ 5} - \rho_{Band\ 4}}{\rho_{Band\ 5} + \rho_{Band\ 4}} \quad (5.6)$$

where $\rho_{Band\ 5}$ and $\rho_{Band\ 4}$ are the reflectance in the red edge (0.698-0.713 μm) and red (0.65-0.68 μm) band for Sentinel-2 MSI datasets respectively. Once NDCI is derived, the Chl-a concentration ($\mu\text{g/L}$) can be derived using equation 5.7 (Mishra and Mishra, 2012).

$$Chl-a\ Concentration\ (\mu\text{g/L}) = 194.325 \times NDCI^2 + 86.115 \times NDCI + 14.039 \quad (5.7)$$

The higher the value of NDCI, the higher the Chl-a concentration; thus, the poorer the water quality (USEPA, 2008). NDCI value of 0.06 corresponds to a 20 $\mu\text{g/L}$ Chl-a concentration which is the lower contamination limit. A negative range of NDCI represents overflow conditions followed by lower Chl-a concentration.

5.2.4.6 Debris Index

One of the widely used automated algorithms to distinguish debris-covered ice from clean snow/ice is the band ratio technique, as mentioned in equation 5.8 (Racoviteanu et al., 2009; Pfeffer et al., 2014).

$$Debris\ Cover = \frac{\rho_{Band\ 4}}{\rho_{Band\ 11}} \quad (5.8)$$

where $\rho_{Band\ 11}$ is the reflectance in SWIR (1.565-1.655 μm) band for Sentinel 2 MSI datasets used. The threshold of 1.8 is considered to distinguish clean ice glacier areas from debris-covered areas.

5.2.4.7 Land Surface Temperature (LST)

In order to understand the impact of sudden hike in temperature (heat waves) resulting in enhanced melting of glacial bodies, it is crucial to analyze the surface temperature of the glaciers. The thermal infrared bands of Landsat 8/9 are widely used in deriving the LST of an area. The process followed is shown in Figure 5.3. The first step involves obtaining top of the atmosphere (TOA) spectral radiance (L_λ) in watt m^{-2} $srad^{-1}$ μm^{-1} of the TIR band (band 10) as shown in equation 5.9:

$$L_\lambda = M \times Q_{cal} + A \quad (5.9)$$

where M and A represent the multiplicative and additive rescaling factors for Landsat 8/9 datasets as mentioned in Table 5.2 and Q_{cal} represents band 10 digital number (DN) value. The next step involves determining the TOA brightness temperature (BT), which is the microwave radiation radiance from the top of the atmosphere, as shown in equation 5.10 (USGS, 2013; Mondal and Bharti, 2021).

$$BT\ (^{\circ}C) = \frac{K_2}{\left(\ln \frac{K_1}{L_\lambda} + 1\right)} - 273.15 \quad (5.10)$$

where K_1 and K_2 are the thermal constants for band 10 as shown in Table 5.2 below.

Table 5.2: Coefficients used in deriving LST from band 10 of Landsat 8/9

SATELLITE	M	A	K_1	K_2
Landsat-8	0.0003342	0.10	774.8853	1321.0789
Landsat-9	0.0003800	0.10	799.0284	1329.2405

This study adopted the normalized difference vegetation index (NDVI) threshold method to derive the emissivity (Avdan and Jovanovska, 2016). The importance of calculating NDVI

(equation 5.11)) is crucial in obtaining the proportion of vegetation (P_v) which has a relation to emissivity (ε).

$$NDVI = \frac{\rho_{Band\ 5} - \rho_{Band\ 4}}{\rho_{Band\ 5} + \rho_{Band\ 4}} \quad (5.11)$$

P_v is calculated using the $NDVI$ threshold for soil (0.5) and vegetation (0.2) as shown in equation 5.12, (Wang et al., 2015; Avdan and Jovanovska, 2016). Further, P_v is used to derive the emissivity equation 5.13). Finally, the emissivity-corrected LST is calculated as shown in equation 5.14, (Stathopoulou and Cartalis, 2007).

$$P_v = \left(\frac{NDVI - NDVI_S}{NDVI_V - NDVI_S} \right)^2 \quad (5.12)$$

$$\varepsilon = 0.004 \times P_v + 0.986 \quad (5.13)$$

$$LST (^{\circ}C) = \frac{BT (^{\circ}C)}{\left\{ 1 + \left[\left(\frac{\lambda \times BT (^{\circ}C)}{\rho} \right) \ln(\varepsilon) \right] \right\}} \quad (5.14)$$

where λ is taken as 10.895 which is the wavelength of emitted radiance for band 10 (Markham and Barker, 1985), and ρ is calculated as shown in equation 5.15:

$$\rho = h \frac{c}{\sigma} = 1.438 \times 10^{-2} \text{ mK} \quad (5.15)$$

where h is the Planck's constant (6.626×10^{-34} Js), c is the velocity of electromagnetic radiation ($2.998 \times 10^8 \text{ ms}^{-1}$), and σ is the Boltzmann constant ($1.38 \times 10^{-23} \text{ JK}^{-1}$) (Weng et al., 2004).

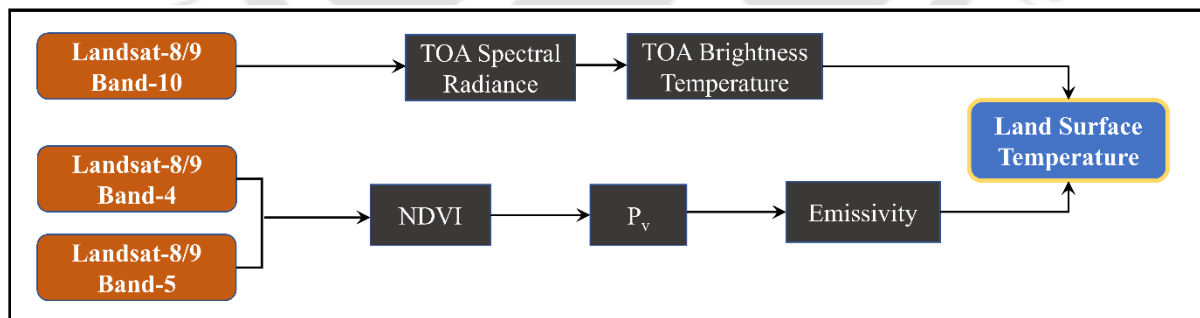


Figure 5.3: Process flowchart for deriving land surface temperature (LST) from Landsat 8/9 datasets

5.2.4.8 Intensity Offset Tracking

For the purpose of studying the cloud-prone Himalayan glaciers, active microwave remote sensing, such as all-weather spaceborne synthetic aperture radar (SAR) systems act as a potent tool. Especially for the estimation of glacial movements, sub-pixel offset tracking implemented over a pair of SAR scenes from almost identical orbital geometry is quite advantageous (Strozzi

et al., 2002; Pritchard et al., 2005). Another approach is SAR interferometry (InSAR). However, it fails until the temporal baseline lies between 1-3 days between the pair of data acquisitions with a minimum geometric baseline (Yellala et al., 2019). SAR intensity offset tracking works on matching intensity between two acquisitions and delivering sub-pixel level surficial velocity in 2-dimensions (azimuth and range directions) (Kumar et al., 2013). Moreover, as glaciers of the Himalayan landscape are covered with debris, offset tracking works more efficiently in deciphering the displacement components (Mondal and Bharti, 2022).

In the present study, SAR sub-pixel intensity offset tracking has been used. The method of cross-correlation optimization has been adopted for the GRD products of Sentinel 1 and processed in the Sentinel Application Platform (SNAP) designed by European Space Agency (ESA) as shown in Figure 5.4. The first step involves assigning the precise orbit vectors to the pair of SAR imagery. This is followed by thermal noise removal (TNR). Thermal noise disturbs the intensity of the SAR pairs. TNR reduces this disturbance in inter-sub-swath texture, thus normalizing the backscatter signal resulting in minimum discontinuities between the sub-swaths (Filipponi, 2019). The next step is radiometric calibration. This helps in acquiring radiometrically calibrated backscatter for the SAR imagery. The sub-pixel offset tracking has been applied over the radiometrically corrected pairs. The matching kernel (feature kernel) of 128×128 pixels (azimuth $\times$ range) and searching kernel of 10×10 pixels have been used. Oversampling factor and correlation coefficient threshold of 16 and 0.3 has been assigned, respectively. The cross-correlation threshold helps mask out unreliable offsets as a result of pixel distortions and sharp surface changes (Zhao et al., 2020). Finally, the derived velocity vectors are checked for the user-defined threshold of maximum velocity. From previous studies conducted over the western Himalayan glaciers, a 15m/day velocity threshold has been set (Fan et al., 2019; Amitrano et al., 2019). The Shisper glacier is a region of glacial surging; therefore, the maximum velocity threshold has been assigned to capture anomalous displacements if any, and prevent any underestimation of surface velocity. Finally, the obtained surface velocity outputs have been corrected for geometric distortions such as foreshortening and shadows due to topography through range doppler terrain correction (RDTC) using the Shuttle Radar Topography Mission (SRTM) 1arcsec DEM.

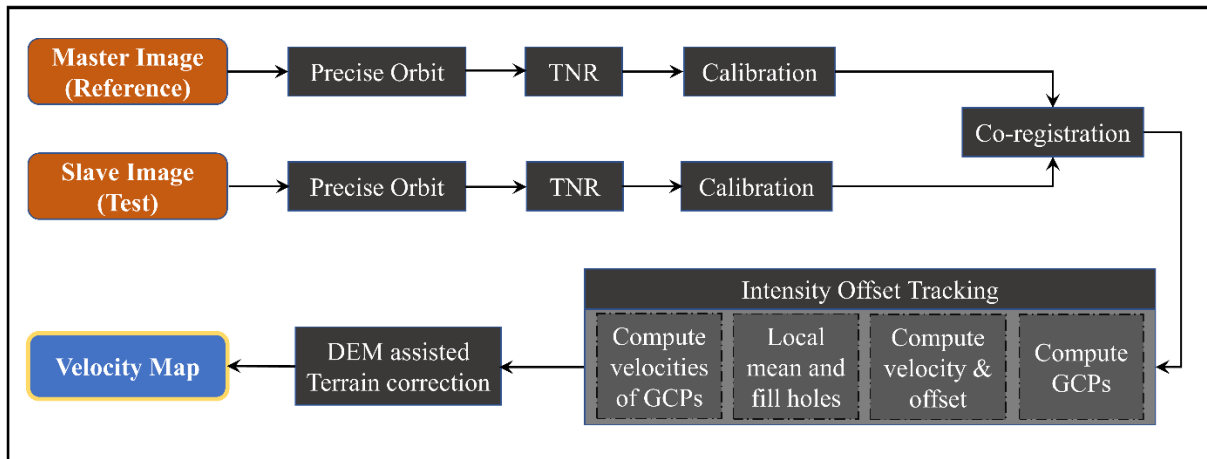


Figure 5.4: Sub-pixel intensity offset tracking flow diagram for surface velocity using Sentinel-1 IW GRD imagery

5.2.4.9 Interferometric Coherence

Interferometric coherence has applications in various types of natural hazards, such as earthquakes, landslides, and GLOFs for monitoring topographic changes (Zhang et al., 2020; Tzouvaras et al., 2020). However, coherence being a statistical value, the magnitude of ground displacements cannot be quantified (Closson and Milisavljevic, 2017). Coherence is produced using differential interferometry (DInSAR), as shown in Figure 5.5, and represents the quality of the produced interferogram. In other words, a coherence image depicts the similarity in reflected radar signals between a pair of SAR patches. Processing begins with considering an SLC pair where one image serves as a master/reference image (pre-date file) and the other image as a slave/test image (post-date file). This is followed by modifying the orbit state vector of both datasets using precise orbit ephemeris (<https://qc.sentinel1.eo.esa.int/>). One SLC file is composed of three sub-swaths. Therefore, in order to minimize the data bulk and computational time, interferometric wide swath sub-swath-1 (IW-1) has been extracted using TOPSAR split. Back geocoding has been performed through which the SAR coordinates are transferred to general cartesian coordinates with the help of SRTM 1arcsec DEM and very precise orbits. This is followed by enhanced spectral diversity (ESD), which rectifies the residual errors during co-registration. It uses the phase differences between SAR pair and derives azimuth errors in co-registration from differential phase. The next step is the formation of an interferogram by cross-multiplication of the reference image with the complex conjugate of the test image. This way, the phase and amplitude difference between SAR pair is generated. To emphasize phase signatures associated with surficial deformation, removing topographic phase contributions using DEM is necessary. The upcoming step is TOPSAR deburst which helps

merge the burst related to the region of interest. Further, multi-look helps eradicate speckle and improves the output quality (Cantalloube, 2014). The phase noise is further wrapped using Goldstein phase filter (5×5 kernel size). Finally, RDTC is executed to derive terrain-corrected interferometric coherence of the area.

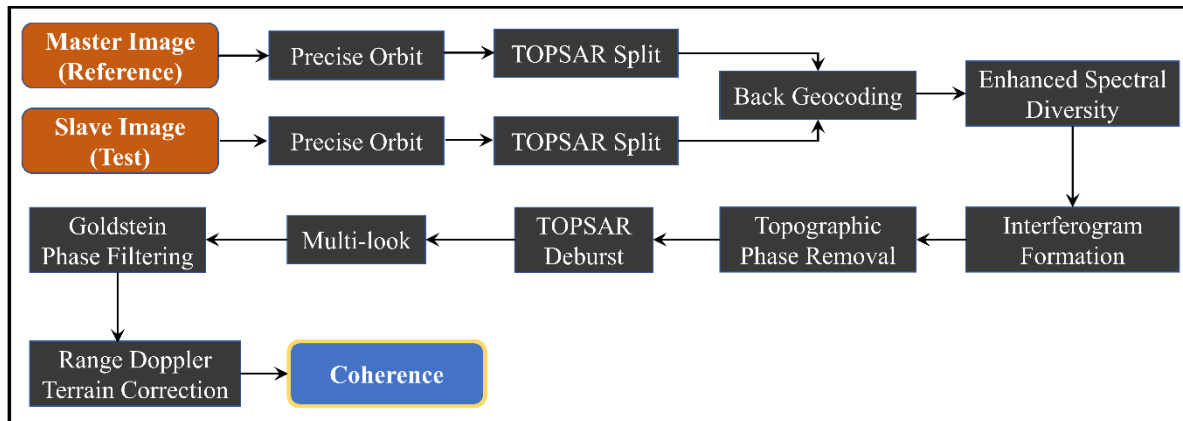


Figure 5.5: Process flowchart for coherence estimation from Sentinel-1 SLC data processing

5.2.4.10 Backscatter Coefficient (dB)

The backscatter coefficients derived from Sentinel 1 products indicate the reflective strength of the surface (Perrou et al., 2018). Stendardi et al. (2019) explained that the range of backscatter coefficients could be used to classify different surface features, as mentioned in Table 5.3. Once the SLC datasets are corrected for orbit and sub-swath (IW-1), it is extracted through TOPSAR split, as shown in Figure 5.6. The next step is radiometric calibration. This is followed by TOPSAR deburst and multi-look. The next step is Linear to dB scale conversion to derive backscatter intensity products. Finally, RDTC is done to obtain terrain-corrected backscatter coefficients in decibels.

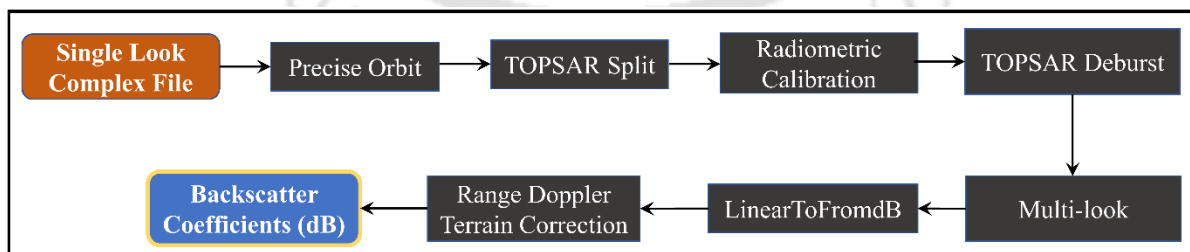


Figure 5.6: Process flowchart for estimation of backscattering from Sentinel 1 SLC data processing

Table 5.3: Classification of Sentinel 1 derived backscatter coefficient (Stendardi et al., 2019)

Range of Backscatter Coefficients (dB)	Surface Characterization
< -20 dB	Sand, Roads, Calm water and smooth surfaces

-20 to -10 dB	Agricultural crops, sparse vegetation and moderately rough surfaces
-10 to -5 dB	Forestry, Dense vegetation and rough surfaces
> -5 dB	Urban areas, Topographic gradient towards the radar and highly rough surfaces

5.2.5 Results and Discussion

5.2.5.1 Plausible Factors Triggering Breach

According to past records, the Shisper glacier and the proglacial lake located at its snout are highly vulnerable to surges and GLOF, respectively (Rashid et al., 2020). Recapitulating from the rock-ice composite avalanche incident that occurred on 7th May 2022 forming a temporary lake at the confluence of Rishiganga river and Ronti gad and sudden breach had a severe impact downstream (Shugar et al., 2021). It is clear that the western Himalayan cryosphere is very active in terms of natural hazards such as slope failures, rock and ice avalanches and outburst floods (Dobhal et al., 2013; Baig et al., 2020; Dikshit et al., 2020; Mondal and Bharti, 2022). Outburst floods triggered by a naturally consolidated moraine- as well as ice-dam breach confining an immense amount of water at higher altitudes with a steep topographic gradient can turn catastrophic downstream. Artificial confinement to the pathway of such floods, especially dams and bridges, adds more vulnerability.

In order to understand the mechanism that might have triggered the Shisper glacial lake breach, a series of methods have been adopted. Firstly, the region has been analyzed for the variation in the glacier accumulation area and AAR of the Shishper glacier. A decreasing accumulation trend can be seen in recent years, as shown in Figure 5.7. The highest mass gain (0.417 m w e) in 2017 and the lowest (0.172 m w e) in 2021 can be seen. A mean mass fluctuation of 0.308 ± 0.098 m w e was observed between 2017 and 2021 when two major GLOF events occurred (Muhammad et al. 2021). The specific mass balance decreased during the years 2019-2021. From the optical datasets of Landsat 8/9, NDSI results show a significant reduction in the snow coverage of the area since 17th April 2022 as shown in Figure 5.8. The threshold of 0.4 has been used to monitor the temporal changes in surficial snow. The NDSI output of 17th April shows 59.28% of the area under snow which reduces to 52.11% by 2nd May and further significantly reduces to 38.51% by 10th May 2022. Since the GLOF incident occurred during the month of May, the end of winter/accumulation period in the Karakoram Himalayas, NDSI results are insufficient to understand the phenomenon of the fast melting of Shisper glacial mass. However, a steady decrease in the NDSI value indicates a reduction in the surficial snow mainly due to melting.

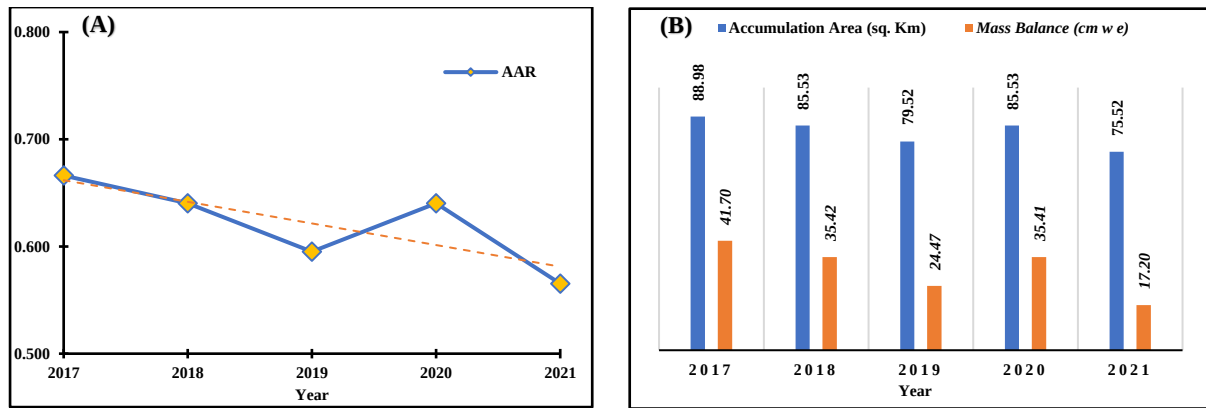


Figure 5.7: Temporal changes in the (A) AAR and fluctuations in the (B) mass balance of Shisper glacier

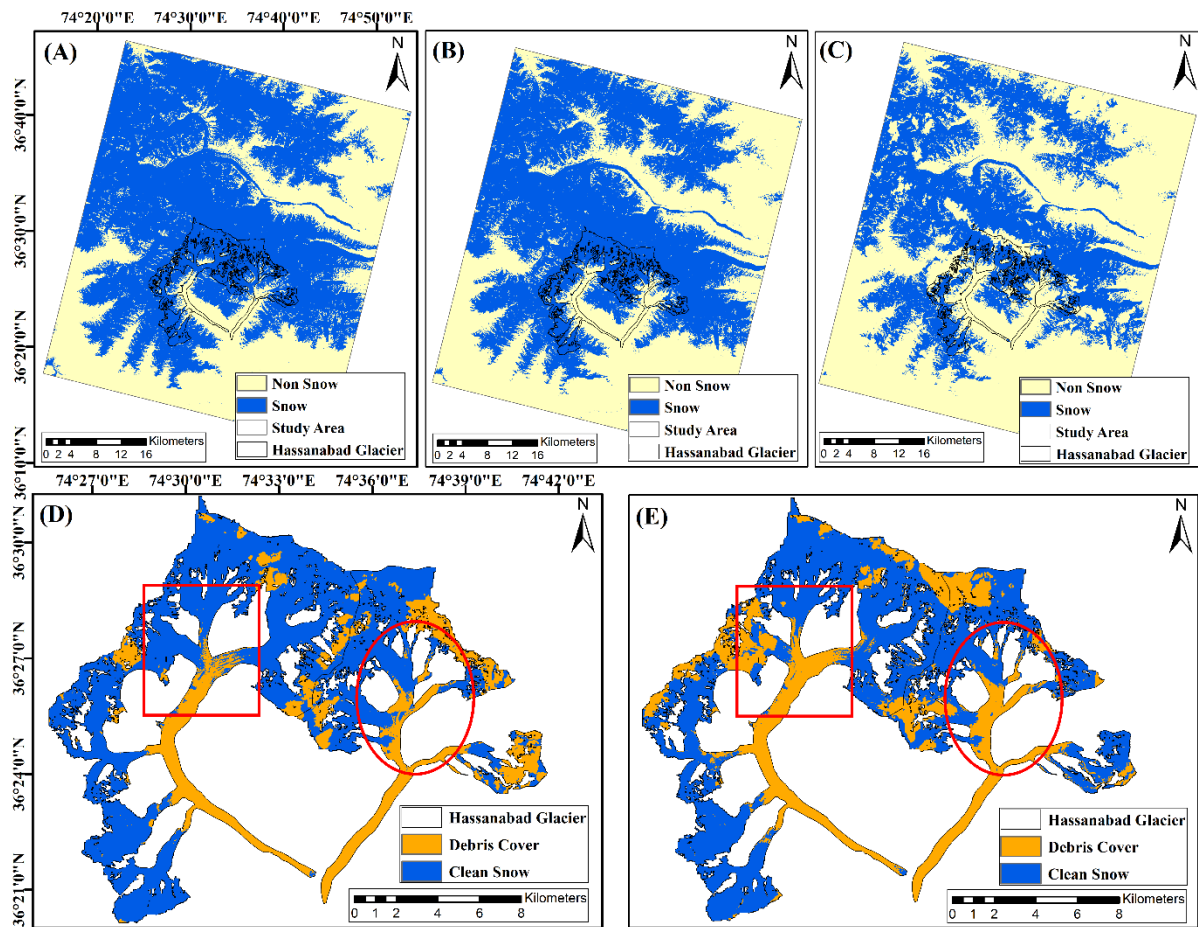


Figure 5.8: NDSI results showing snow coverages (A) 17th April 2022 (1523.4 Km²) (B) 2nd May 2022 (1339.1 Km²) (C) 10th May 2022 (989.6 Km²) as well as debris cover within the glacial body on (D) 30th April 2022 (36.3 Km² accounting for 27.2%) and (E) 10th May 2022 (43.1 Km² accounting for 32.3%)

Snow is a material having much higher albedo than firn/glacial ice (Winther, 1993). Moreover, radiative heat flux plays a significant role in snow/glacial melting contributing. Therefore, it is essential to understand the role of radiative heat flux in the fast-melting process of Shisper glacier. From the debris map derived from Sentinel 2 datasets, an increment in the debris

coverage within the Shisper (rectangular zone) and Muchowar (oval zone) glacial bodies can be observed (Figure 5.8D-E). The exposed debris coverage within the glacial body increases by 6.8 Km² between 30th April and 10th May 2022, accounting for 5.1%. Such increment in the debris coverage or decrement in the fresh/clean snow cover (total glacial area – debris cover) corroborates well with the snow cover decrease as observed from NDSI results. Also, debris/contaminated ice has much lower albedo as compared to fresh/clean snow. Thus, increment in the debris cover supports more absorption of solar radiation by the glacial body, thus increasing the temperature profile, leading to enhanced melting.

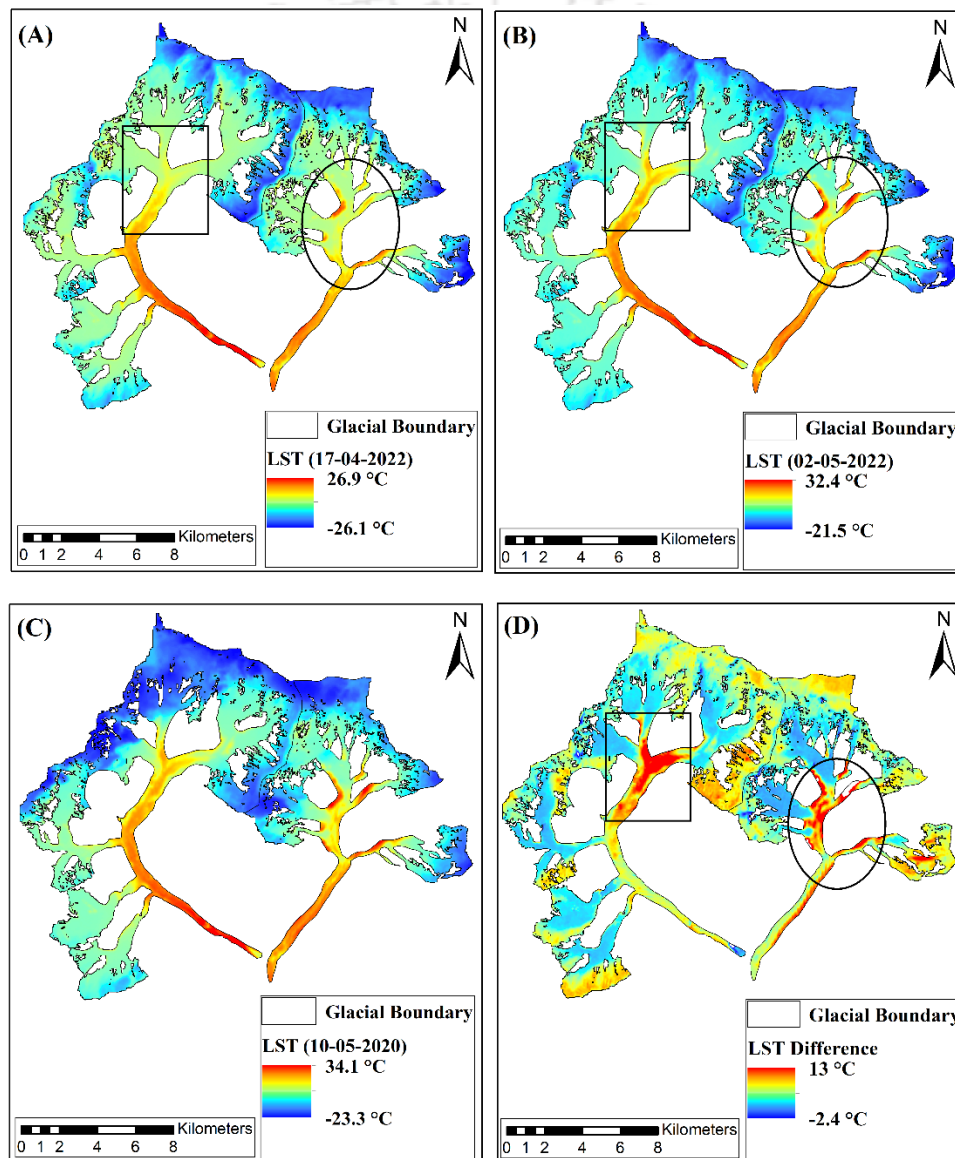


Figure 5.9: Map showing major fluctuations in the LST around main trunk of Shisper glacier (rectangle) and Muchowar glacier (oval) as mapped on (A) 17th April 2022 (B) 2nd May 2022 (C) 10th May 2022 and (D) LST difference between 2nd May and 17th April 2022

Snow/glacial melting is a complex phenomenon that occurs due to changes in a set of fluxes such as radiative heat flux, sensible heat flux, precipitation heat flux, and latent heat flux (Che et al., 2019). Significant changes in the temperature profile around a glaciated region are indicative of rapid melting. From the LST derived using TIR band 10 of Landsat 8/9, a sudden increment in the surface temperature can be clearly observed as shown in Figure 5.9. The minimum and maximum temperature within the glacial body lies in the range of -26.1°C and 26.9°C respectively on 17th April. This increases drastically to -21.5°C and 32.4°C on 2nd May, showing an increase in the surface temperature range by $> 5^{\circ}\text{C}$. Abrupt changes in the LST is indicative of rapid snow/glacial melting. Such changes occurred within 15 days between 17th April and 2nd May and reached 34.1°C , as shown in the LST map of 10th May 2022. From the LST difference map shown in Figure 5.9D, maximum increase in LST ($>12^{\circ}\text{C}$) can be observed within the rectangular and oval zone of Shisper and Muchowar glaciers, respectively. These zones are the glacial trunk's elevated regions that transfer the glacial melt discharge towards the snout where the glacial lake is located. An increase in debris cover has also been observed within these zones, as shown in Figure 5.8D-E. Since debris coverage has a much lower albedo than fresh snow cover, the overall absorption of solar radiation (watt/m^2) increases within the glacial body, leading to a localized increase in the surface temperature, resulting in the fast melting of glacial ice.

Figure 5.10 shows the changes in the pattern of short-term surface velocity ($\text{cm}/12$ days) of the glaciers. The surficial displacements of Shisper and Muchowar glaciers on pre-flood (Figure 10B and C) and post-flood (Figure 10D) timelines have been represented. The maximum surface velocity is observed around the glacial flanges bifurcating from the main trunk. Figure 5.10A shows the locations marked along the glacial trunks to capture the fluctuations in the glacial mobility as moving away from the proglacial glacial lake. From Figure 5.11A it can be clearly seen that the glacial mobility near the Shisper lake (Point-1) is around 5cm (4th April to 16th April 2022) that increases abruptly to 13cm in the next 12 days (16th April to 28th April 200) later restabilized to 7cm between 28th April and 10th May 2022. Even though surface velocity of a glacier is a complex phenomenon which depends on several parameters such as topographic slope, glacial thickness and season (Mondal and Bharti, 2022), a sudden incremental trend in the surface velocity of glacial snouts can be indicative of short-term changes in the glacial dynamics. Also, the abrupt hike in surface displacement is observed at point-6, 9 and 10 at Shisper glacier and Point-17 and 18 at Muchowar glacier (Figure 5.11B) where a maximum increase in LST ($>12^{\circ}\text{C}$) is captured.

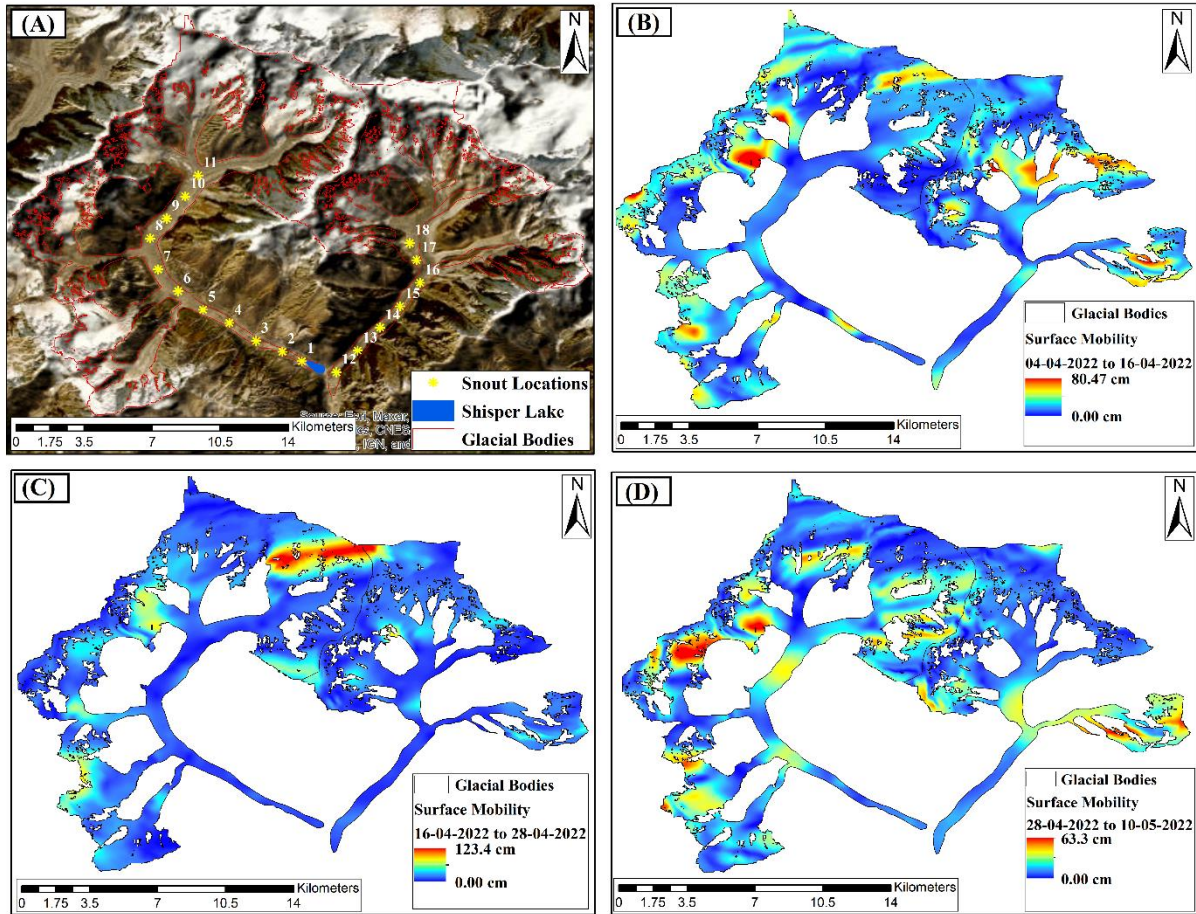


Figure 5.10: Map showing (A) the glacial boundary of Shisper and Muchowar glacier and locations considered along the main trunk and surface velocity between (B) 4th April and 16th April 2022 (C) 16th April and 28th April 2022 and (D) 28th April and 10th May 2022

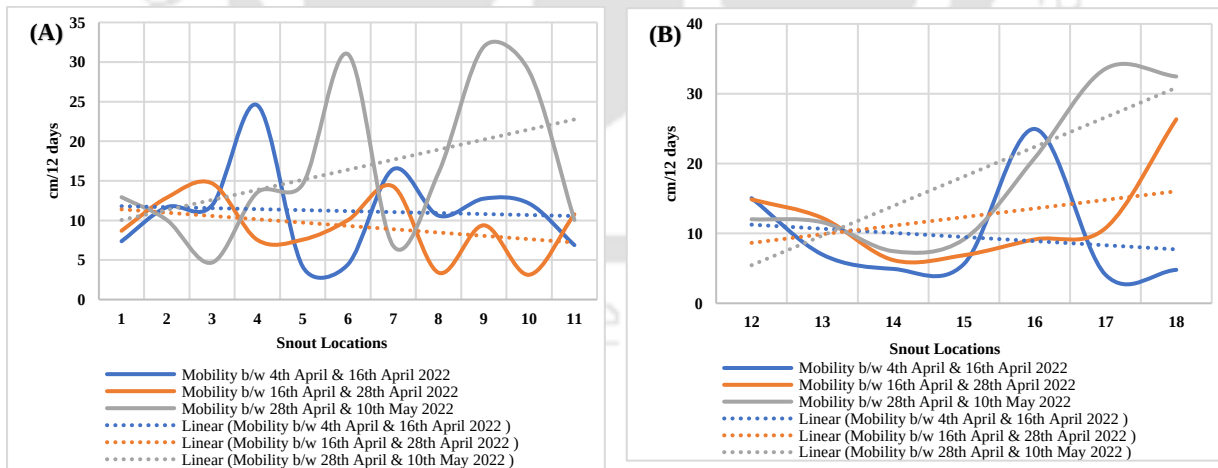


Figure 5.11: Indicating the velocity trend away from the snout for (A) Shisper glacial trunk and (B) Muchowar glacial trunk

5.2.5.2 After-effects

The after-effects of a flood event comprises several detectable alterations through satellite remote sensing such as changes in the water quality, flood plains, debris and sediment deposition, etc. Since, the proglacial lake lies close to the human settlements of Hassanabad region, it is essential to conduct a post-event analysis. The pre-and post-flood assessment of water quality has been done using optical and SAR datasets. Changes have been analyzed in five locations, as shown in Figure 5.12A. The first three locations have been considered before the Karakoram highway bridge that collapsed due to the outburst flood. One location has been considered just after the stream crosses the bridge. The last location has been marked at the meltwater stream point of convergence with the Hunza river stream.

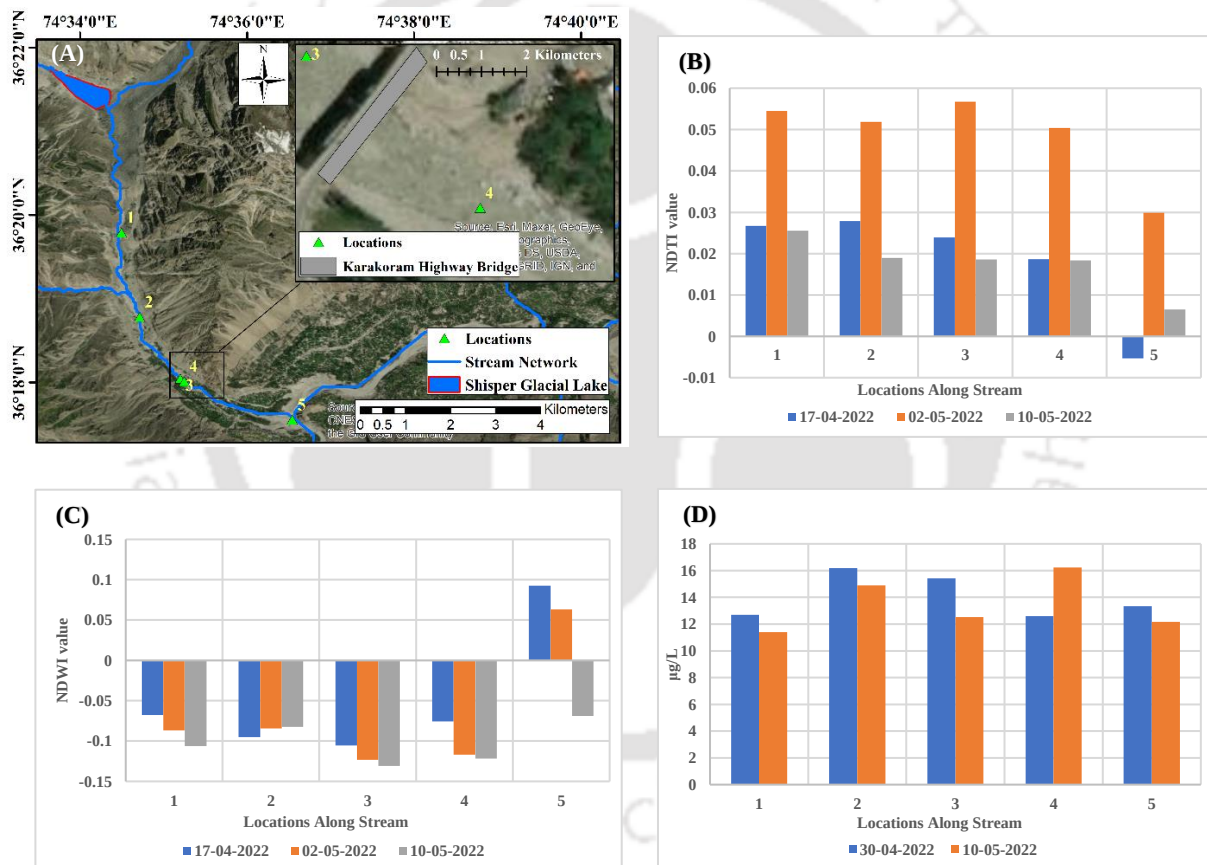


Figure 5.12: (A) Map showing locations considered for the assessment of after-effects of GLOF event and changes in (B) NDTI, (C) NDWI and (D) Chal-a concentration along the meltwater stream

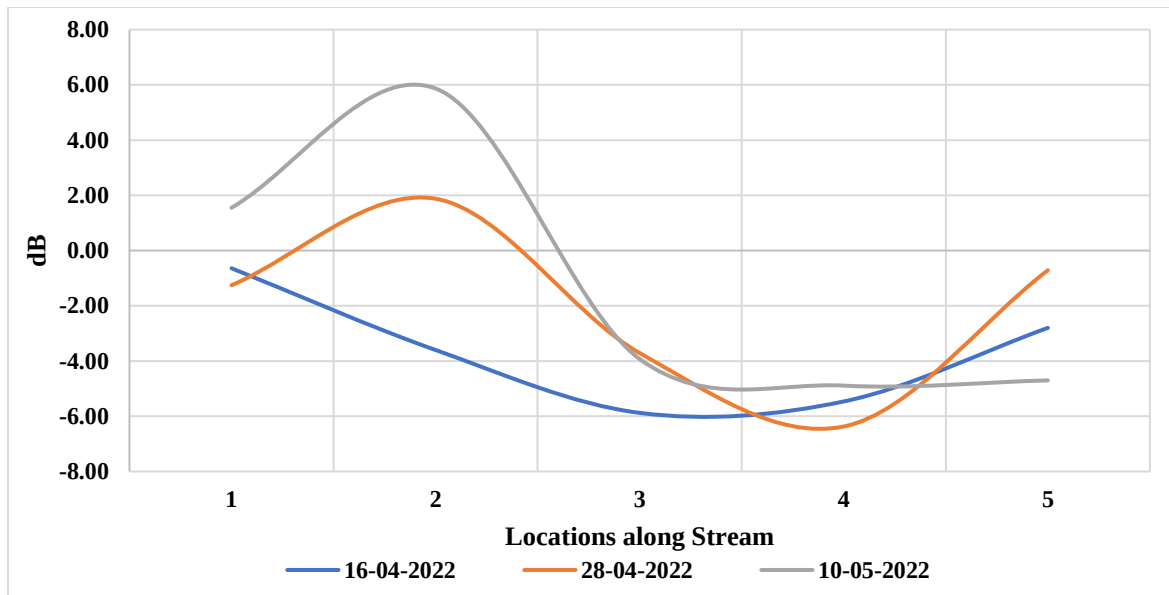


Figure 5.13: Changes in backscatter coefficient (dB) at different locations along the meltwater stream

The collapse of the Karakoram highway bridge due to a glacial lake outburst indicates a highly turbulent discharge that washed away the bridge along. Figure 5.12B represents the NDTI in various locations during pre-and post-flood. It can be clearly seen that the NDTI values along the stream lie below 0.03 that get disturbed due to outburst flood. Along the stream, NDTI is comparatively higher before the flood in all the locations. A peak in the NDTI is observed at location 3 prior to the flood, just before the water crosses the Karakoram bridge. However, the value gets stabilized at location 5, where the stream meets the Hunza river. Also, the increment in NDTI throughout the stream on 2nd May 2022 can be attributed to decreased water quality. A possible reason behind such anomalous rise in NDTI could be an increase in glacial melt contribution into the stream, leading to increased water activity in terms of discharge and turbulence, thus a hike in sediment load. Figure 5.12C shows the changes in NDWI values along the stream. The negative values of NDWI until point 4, just after the Karakoram bridge, represent muddy water that shifts towards positive at point 5 once the stream meets Hunza river. At locations 3 and 4, NDWI values further fall, symbolizing decreased water quality that corroborates well with NDTI's observations. At point 5 before the flood occurred, NDWI is positive, which indicates the presence of clean water. This later falls to negative after the flood indicating lowered water quality. The stream is checked for contamination using derived Chal-a concentration as shown in Figure 5.12D. The values are less than 20 µg/L and appear to be almost uniform throughout the stream. Such lesser values of Chal-a concentration indicate no contamination of water along the stream with a sufficiently

higher flow rate. Increased value of Chal-a concentration points towards contamination in water quality with a lowered flow rate which is not observed in this case.

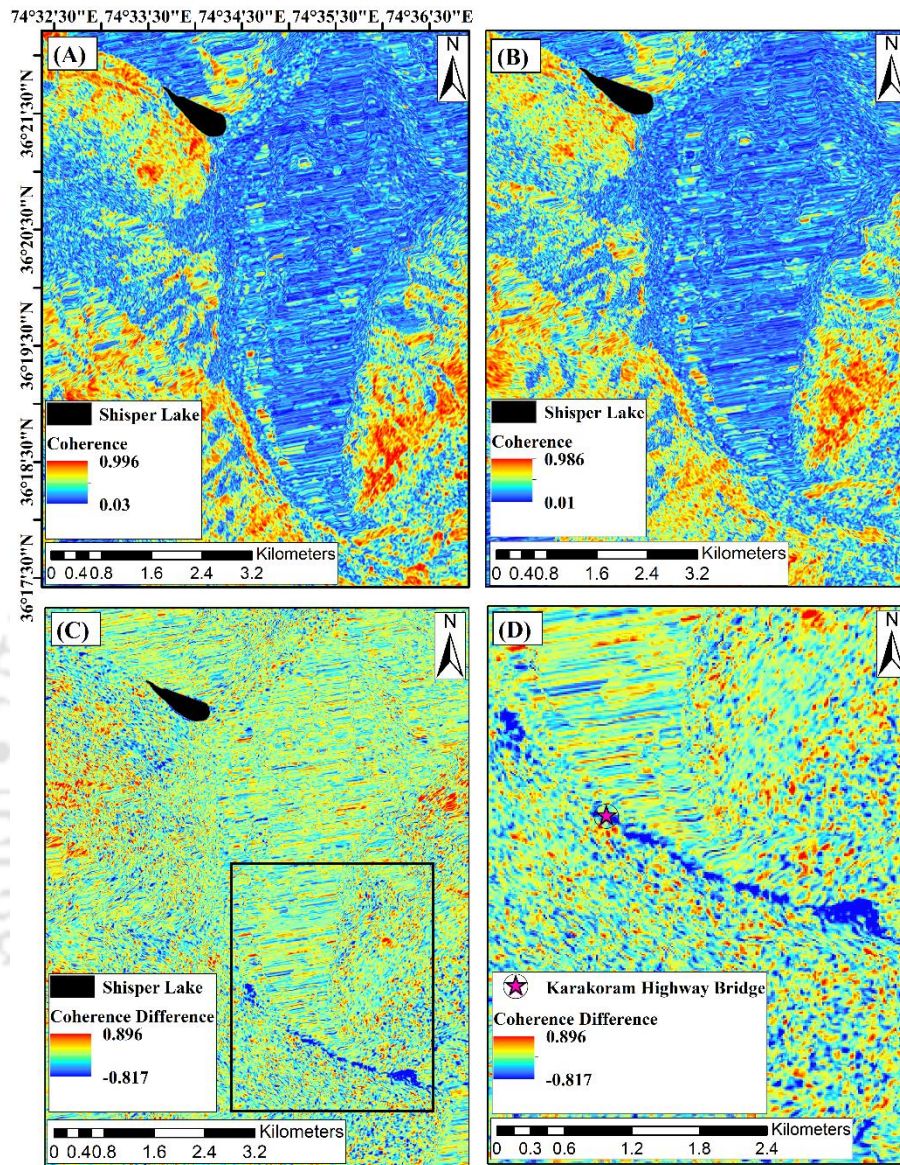


Figure 5.14: Map showing coherence derived between (A) 16th April and 28th April 2022 (B) 28th April and 10th May 2022 (C) Coherence difference between B and A and (D) Reduced coherence around Karakoram Highway Bridge (zoomed from C) and down the stream

The backscatter coefficient obtained from Sentinel 1 SAR datasets can capture alteration in the concentration of sediment load in water and various types of surfaces based on their roughness. The backscatter coefficient along the stream (Location-1 to 5) is shown in Figure 5.13. The values exceed -5dB which indicates highly rough topography. On 16th April, the backscatter coefficient is negative throughout the stream and shifts towards positive on 28th April at Location-2. Such a shift in the backscattering indicates the flow of increased discharge

into the stream that attributes to more waves in the stream. High backscatter coefficient at Location-1 and 2 on 10th May (post-flood) shows a further discharge increase. As location-1 and 2 lie close to the glacial lake, a continuous positive shift in the backscattering can be attributed to the rapid melting rate of the glacial bodies contributing a significant amount of meltwater discharge into the stream. The backscattering tends to get stabilized (reduced to <0 dB) after Location-2 as the stream approaches the Hunza river. Location-3, 4 and 5 does not show a contrasting shift in backscattering.

A GLOF event delivers land cover changes along the stream it propagates, which can be captured using the C-band SAR system of Sentinel 1. In the case of the presented Shisper glacial lake outburst flood, such changes have occurred in the form of bank erosions and the collapse of Hassanabad highway bridge. Figure 5.14 represents the pre-flood and co-flood coherence for ascending SLC data pairs. The warm color indicates a high correlation between SLC data pairs before and after the flood. The coherence values range between 0.996 and 0.03 for pre-flood (Figure 5.14A) and 0.986 and 0.01 for co-flood (Figure 5.14B), respectively as the study region has been masked from the used SLC scene. However, it is important to understand that the decorrelation captured pre- and co-flood comprises of three kinds of effects that need to be considered (Zebker and Villasenor, 1992).

$$\psi_{total} = \psi_{noise}\psi_{geo}\psi_{terrain} \quad (5.16)$$

$$\psi_{change} = \psi^{co-event} - \psi^{pre-event} = \psi_{noise}\psi_{geo} (\psi_{terrain}^{co-event} - \psi_{terrain}^{pre-event}) \quad (5.17)$$

Here, ψ_{noise} , ψ_{geo} and $\psi_{terrain}$ represents registered decorrelation due to sensor noise, geometric coherence attributed to perpendicular baseline component and correlation response due to changes in surface cover and/or vegetation respectively. Since, the SLC datasets have been obtained from the same satellite sensor (Sentinel 1), the effect of ψ_{noise} is good to be neglected. Moreover, considering Sentinel 1 observation over a flat surface and scatterers distributed uniformly within a pixel, the effect of ψ_{geo} obtained from the perpendicular baseline of the used SAR system remains almost identical and gets eliminated while computing the difference in coherence between two SLC pairs. Therefore, changes in $\psi_{terrain}$ can be attributed to only changes in the surface cover and/or vegetation. Figure 5.14C-D shows a significant reduction in the co-flood coherence along the stream as the discharge crosses the location of the Karakoram highway bridge and continues downstream. This indicates geometric deformation/collapse of man-made structures such as the Karakoram highway bridge and variation of land surfaces due to severe bank erosions.

5.2.6 Conclusion

The Karakoram Himalaya comprises numerous moraine- and ice-dammed glacial lakes with a high perspective risk of GLOF. This study extensively investigated the recently triggered Shisper glacial lake outburst flood of 7th May 2022 through satellite remote sensing. The study has been conducted in two stages, where the first stage deals with finding the plausible factors behind the cascade, and the next stage captures the after-effects. The salient points of the investigation are as follows:

- The accumulation area and the AAR of the Shishper glacier reflect a decreasing trend between 2017 and 2021. NDSI shows a significant reduction in the snow coverage of Hassanabad glaciated terrain between 17th April and 10th May 2022 followed by increased debris cover around the elevated regions of the glacial trunk between 30th April and 10th May 2022. A significant rise in LST is also observed within these elevated regions.
- The investigation of short-term surface velocity (cm/12 days) of glacial trunks shows hike in the surface mobility just before the outburst flood between 16th April and 28th April 2022. Moreover, an abrupt rise in surficial displacement is observed near the locations of increased debris cover and LST for both the glaciers.
- In analyzing the after-effects of the outburst flood, the water quality of the meltwater stream is checked using band ratio algorithms, namely NDTI, NDWI, and NDCI, respectively. Increments in the NDTI values are observed just before the flood in all the locations along the stream. This explains increased glacial melt contribution into the stream before flood, thus increased turbulence and sediment load. The results corroborate well with the reduction in NDWI values, particularly before and after the Karakoram Highway Bridge, indicating lowered water quality. The stream water seems to be devoid of Chal-a contamination ($<20 \mu\text{g/L}$) with a sufficiently higher flow rate along the stream before and after the flood event.
- The backscatter coefficient captured through the C-band Sentinel 1 SAR system shows a shift from negative on 16th April to positive on 28th April and 10th May 2022 along the stream close to the glacial lake. A possible reason behind such anomalous change in backscattering could be the enhanced melting rate of glacial bodies, thus increasing discharge into the meltwater stream resulting in more waves. However, this further gets stabilized ($<0 \text{ dB}$) as the stream water moves downstream towards the Hunza river.

- Reduction in the co-flood coherence is captured as the meltwater crosses the Karakoram highway bridge location. This can be attributed to the impact of the outburst flood in downstream, resulting in a bridge collapse and severe bank erosion episodes.

Therefore, from the presented investigation, it can be concluded that a significant reduction in the snow cover within a short span of time (within weeks) has led to increased exposure of debris within the glaciers that might have resulted in increased absorption of solar radiation by the glacial bodies. More absorption of solar radiation means increased surface temperature of glaciers, thus leading to enhanced melting. As the meltwater of the Shisper glacier feeds a proglacial lake located at its snout, a sudden increase in the meltwater contribution might have led to increased pressure over the ice-dammed structure confining the lake water and thus breaching.

5.3 Earthquake Impact around Lake Dingmu

5.3.1 Study Area

Lake Dingmu, also called Tingmo So ($28^{\circ}36'5.86''\text{N}$, $87^{\circ}32'32.82''\text{E}$), is a natural lake in Tibet. The lake is about 6 Km long and acquires an area of 11.5 Km^2 . The lake is situated at an elevation of 4157m above sea level (a.s.l) and is fed by streams of snow and glacial melt from the Himalayas. The lake is connected to the Pum Qu river, also called Bum Chu in Tibet and Arun in Nepal. The river receives its major contribution in discharge from the snow and glaciers near Shishapangma, the 14th highest mountain (8,027m). Human settlements with cultivation areas and some villages such as Qiangga, Yubia, and Peimalamu village can be seen on the north-western side of the lake.

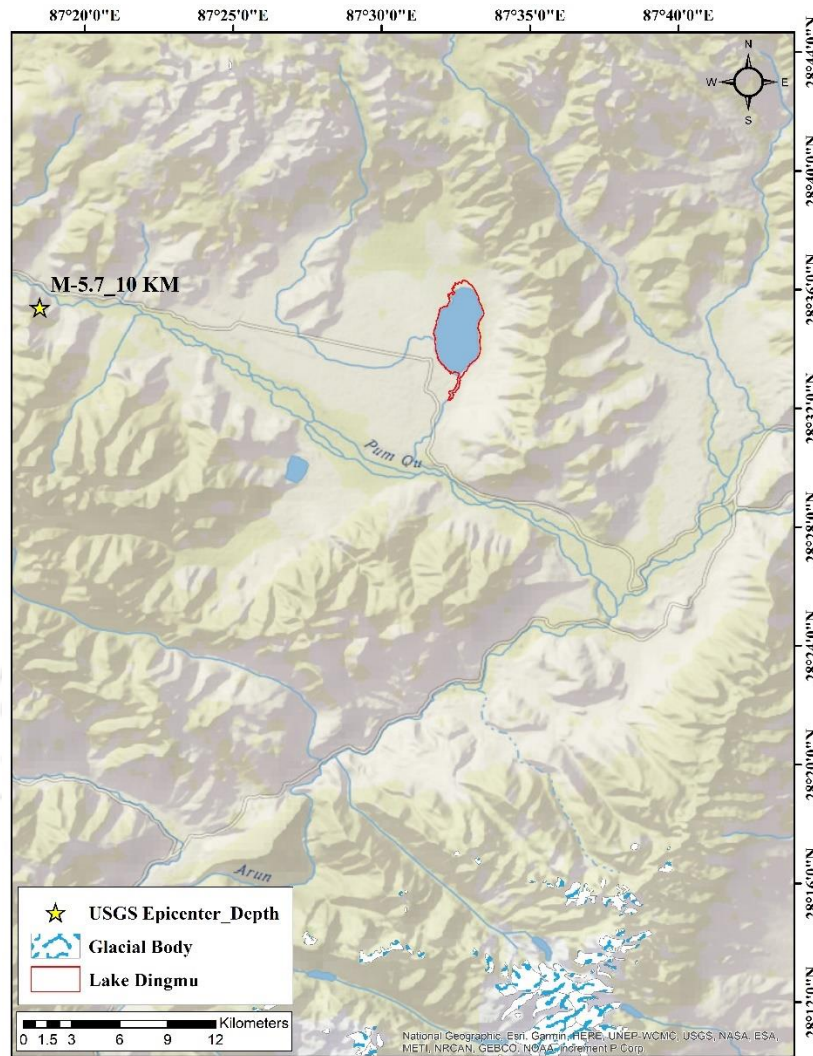


Figure 5.15: Study area map of lake Dingmu, Tibet

5.3.2 Datasets Used

The used Sentinel 1 C-band (centre frequency: 5.405 GHz) single look complex (SLC) datasets consist of two acquisitions taken on 4th and 16th March 2020 before the earthquake event and one after the event on 28th March 2020 along descending orbits. SLC datasets are level-1 products consisting of both phase and radar amplitude information and find their application in studying natural hazards. The sensor acquires data with Terrain Observations with Progressive Scans (TOPS) mode. This mode is specially designed for interferometric study with large special coverage (De Zan and Guarnieri, 2006). TOPS mode is burst-based; indeed, the antenna is flipped cyclically among various sub-swaths at the time of acquisition. This helps in significant improvement of range coverage with some detriment of azimuth resolution. The SAR datasets acquired through interferometric wide (IW) swath configuration covering about 250 Km are particularly useful in analyzing large area deformations due to a seismic event.

Landsat 8 Operational Land Imager (OLI) datasets of 19th March and 4th April 2020 have been used for pre- and post-seismic study respectively. The shortwave infra-red (SWIR-II) spectral channel (λ : 2.11–2.29 μ m) at a spatial resolution of 30m have been used.

The selection of dataset pairs (Sentinel 1 and Landsat 8) for this study has been carried out with few pre-defined conditions in mind. The first one is to keep minimum time period between pairs. In this case, the data acquisition gap between each pair of Sentinel 1 is 12 days along descending orbits and 15 days for Landsat 8 pair as shown in Table 5.4. The second condition is no cloud cover in the vicinity of the earthquake epicenter and lake. The third condition is enough areal coverage around the epicenter in order to capture the entire earthquake signal.

Table 5.4: Datasets used for capturing seismic impact

Earthquake Event (20 th March 2020)						
Time (UTC)		Location		Magnitude	Depth	
01:33:15		28.590°N 87.308°E		5.7	10 Km	
Sentinel 1 C-Band SLC Datasets						
Pre-Seismic Pair		Co-Seismic Pair		Beam mode/ Path	Frame	Polarization
Master	Slave	Master	Slave			
4 th March	16 th March	16 th March	28 th March	IW/121	496	VV+ VH
Landsat 8 OLI Datasets						
Pre-Seismic Data		Post-Seismic Data		Band Used/Spatial Resolution		
19 th March		4 th April		SWIR-II/30m		

5.3.3 Methodology

The processing begins with selecting master (pre-event) and slave (post-event) data for TOPSAR split that helps select the needful sub-swath. The next step is to employ modification to orbit state vector with the help of orbit ephemeris acquired from <https://qc.sentinel1.eo.esa.int/>. Back geocoding is performed to transfer the SAR coordinates to general cartesian coordinates using very precise orbits and 1-arcsec digital elevation model (DEM). The next step is enhanced spectral diversity used to rectify the residual errors in co-registration. It compares the phase differences of a pair of SAR images to derive the mis co-registration in azimuth from the differential phase. Interferogram is generated by cross multiplication of master data with complex conjugate of slave data. This helps in deriving the amplitude and phase difference between the pair of SAR imageries. The next step is deburst which is required to merge the burst related to the area of interest. This is followed by topographic phase removal providing differential interferogram. The next step is multi-look helpful in eliminating speckle, thus improving the quality of output (Cantalloube, 2014).

Finally, the phase noise is wrapped through Goldstein phase filter of 5×5 kernel. The steps followed is shown in Figure-5.16.

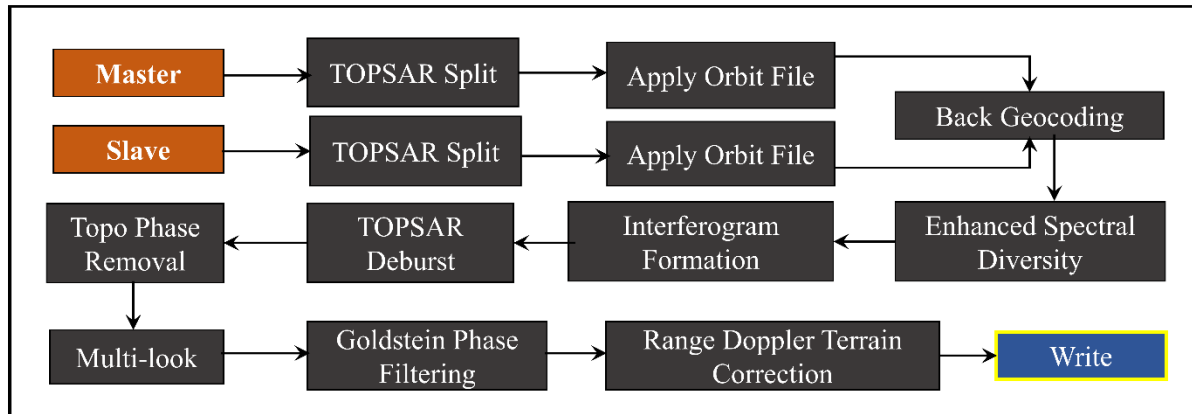


Figure 5.16: Flowchart of C-band SLC processing

The temporal difference liquefaction index (TDLI) has been used that utilizes SWIR-II bands of pre- and post-seismic data and detects changes in soil moisture content as shown in equation 5.18 [10]. The SWIR bands are effective in detecting changes in the moisture content in vegetation and soil. The SWIR-I (λ : 1.57–1.65 μm) of Landsat 8 OLI is sensitive to vegetation moisture content and thus widely used in normalized difference vegetation index (NDVI). On the other hand, SWIR-II is sensitive to soil moisture content. Positive values of TDLI symbolizes increase in soil water content whereas negative values indicate decrease in the soil moisture. Therefore, larger is the value of TDLI, larger is the possibility of liquefaction and vice versa.

$$TDLI = \frac{SWIR-II_{Pre-seismic} - SWIR-II_{Post-seismic}}{SWIR-II_{Pre-seismic} + SWIR-II_{Post-seismic}} \quad (5.18)$$

5.3.4 Results and Discussion

The determination of whether InSAR captures an earthquake epicenter is made by interpretation of wrapped and geocoded descending track interferogram. From Figure 5.17B, the formation of a lobate deformation pattern can be clearly seen as compared to Figure 5.17A. This is indicative of the unambiguous detection of an earthquake epicenter consisting of a series of deformation fringes (high fringe gradient). Five concentric fringes with around 10 Km wide series are identified, centered approximately 13.7 Km to the northeast of the USGS epicenter.

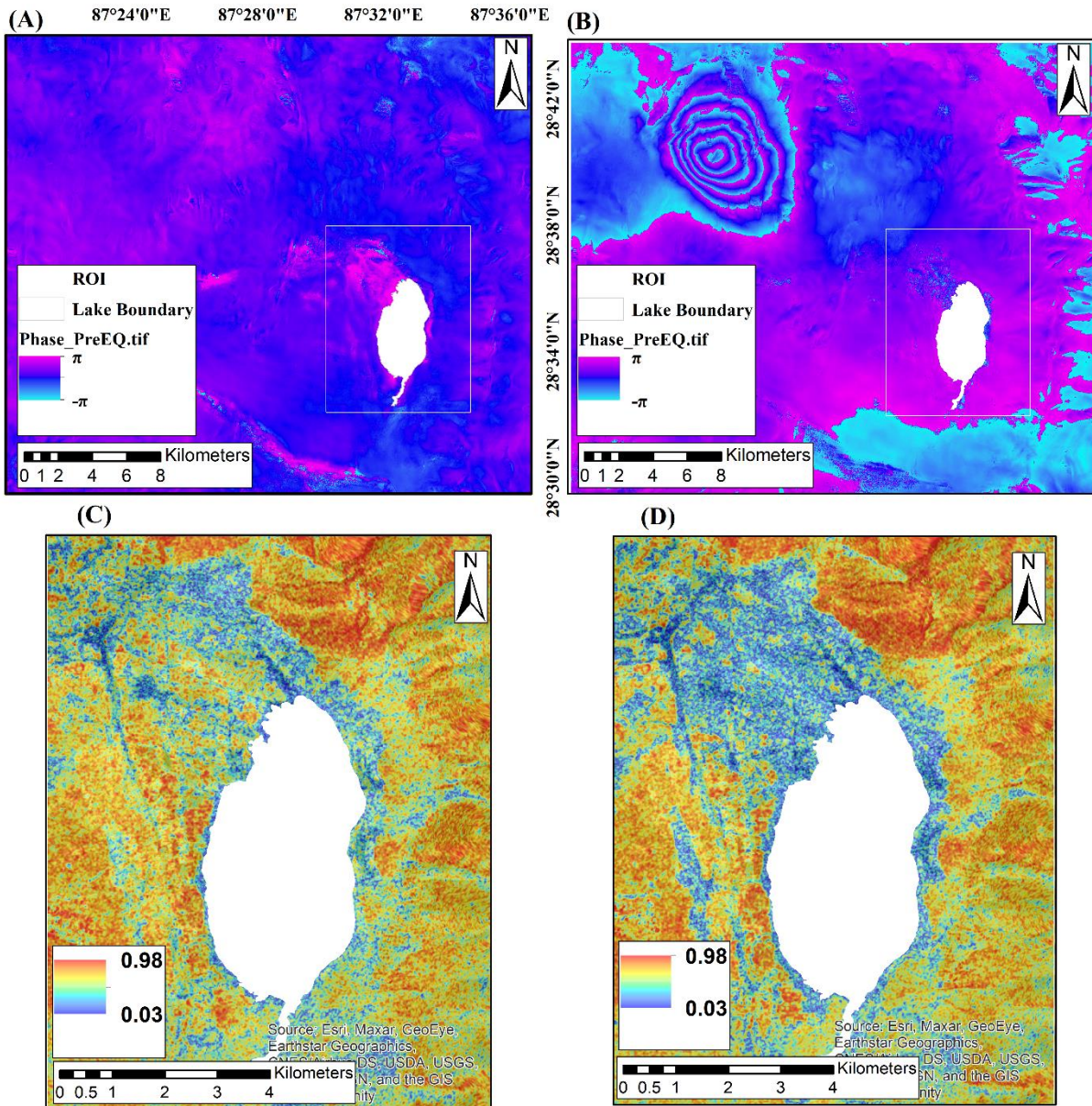


Figure 5.17: Results from Sentinel 1 SLC data showing (A) pre-seismic interferogram, (B) co-seismic interferogram, (C) pre-seismic coherence and (D) co-seismic coherence around lake Dingmu

Figure 5.17C and D represent the pre-seismic and co-seismic coherence for descending image pairs. Here, warm color is indicative of high correlation between the SLC pairs. The correlation values range between 0.98 and 0.03 as the results for the study area is masked from the results from the used SLC scene. A significant reduction in coherence has been registered from the pre-seismic to the co-seismic pair around the lake boundary and the north-western land cover from the lake. Human settlements, including roads, houses, and cultivation areas dominate the north-western land cover. Significant reduction in the coherence around this area can be indicative of high variation of land surface and/or geometric deformation of man-made constructions such as houses before and after the seismic event. Although surface deformations

are a source of decorrelation due to an earthquake, some other effects should also be considered (Zebker and Villasenor, 1992).

$$\Psi = \Psi_N \Psi_G \Psi_T \quad (5.19)$$

$$\Psi_{change} = \Psi^{Co} - \Psi^{Pre} = \Psi_N \Psi_G (\Psi_T^{Co} - \Psi_T^{Pre}) \quad (5.20)$$

In equation 5.19, Ψ_N , Ψ_G , and Ψ_T represent decorrelation registered due to noise within the radar system, geometric coherence due to the perpendicular component of baseline, and temporal changes in backscatter due to change in vegetation or surface cover, respectively. As soil liquefaction is registered due to Ψ_T , monitoring this component from the overall coherence is essential. This is done with the help of a coherence difference map prepared by subtracting the pre-seismic coherence from the co-seismic coherence, as shown in Figure 5.18A. In equation 5.20, Ψ^{Co} and Ψ^{Pre} are the co- and pre-seismic coherence, respectively. We assume that Ψ_N do not change before and during an earthquake, as the SLC datasets are obtained from the same sensor (Sentinel 1). Similarly, considering satellite observation over a flat area and uniform distribution of scatterers within a pixel, the effect of Ψ_G obtained from the critical and perpendicular baseline of Sentinel 1 remains almost identical. Thus, changes in Ψ_T can be attributed to changes due to soil liquefaction/cyclic mobility and/or vegetation and surface cover change. The periphery around Dingmu, a snow-melt fed lake can be characterized by deposition of sediments carried by the streams originating from the glaciers. Moreover, the study area lies within the sparse vegetation belt of Tibet. Therefore, there exists a possibility of liquefaction/cyclic mobility resulting in the observed decorrelation. Figure 5.18B shows the TDLI mapping results. Here, warm color indicates post-earthquake increment in moisture content within the lacustrine deposits around the periphery of Lake Dingmu. This supports the possibility of liquefaction/cyclic mobility phenomenon as explained by the coherence results. Table 5.5 shows the areal impact of the earthquake in terms of co-seismic coherence reduction and TDLI-based wetness difference. Moreover, the lake seems safe to breach and spill due to an earthquake event of MW5.7 or less. Even though lake Dingmu is situated at an elevation of 4157m a.s.l, the lake's local topography and periphery make it safe to breach.

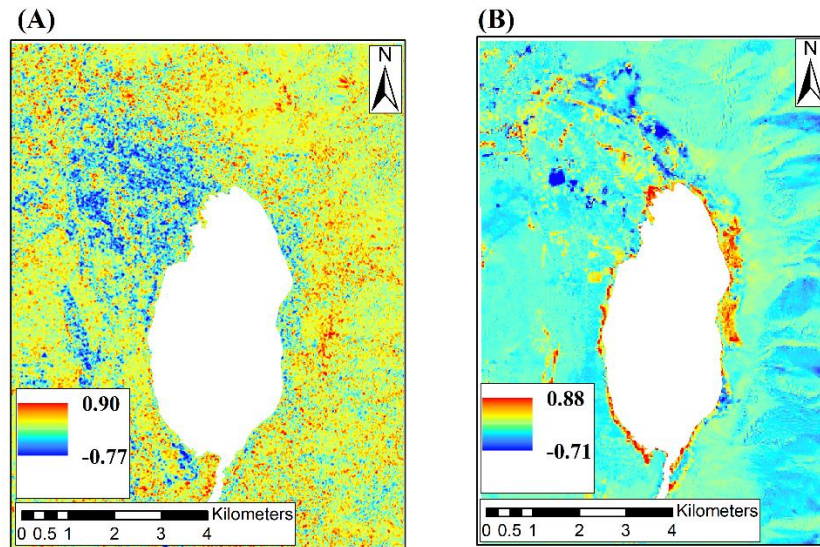


Figure 5.18: Maps showing (A) pre- and co-seismic coherence difference and (B) TDLI

Table 5.5: Quantification of area under liquefaction/cyclic mobility around lake Dingmu

Method (Threshold)	Area (sq. km)
Coherence difference (≤ -0.3)	4.43
TDLI (> 0)	4.12

5.3.5 Conclusion

Satellite remote sensing has great application for earthquake research around the globe, especially, in the Himalayan orogeny. An earthquake can put significant impact to naturally formed snow-melt fed lakes that are moraine-dammed or surrounded by lacustrine deposits. In this study, SLC datasets from Sentinel 1 helped capture an earthquake epicenter in proximity to the snow-melt fed lake Dingmu in Tibet. Analysis of coherence before and during the earthquake helped in understanding its impact over the deposits around the lake periphery arising the possibility of soil liquefaction/cyclic mobility. This is further supported by the results from TDLI that shows increment in soil moisture over the areas where coherence decreases after the seismic event. Significant changes in coherence registered over the north-western region indicate variation in buildings' land cover and/or geometric deformation. However, the seismic event and its impact over the lake periphery shows increased soil moisture, there is no evidence of water spilling out of the lake. A possible reason is the topography of the lake boundary that makes it safe to breach or spill due to an earthquake event.

5.4 Vulnerability Assessment of Lakes in Sikkim Himalaya

5.4.1 Study Area

The trans-boundary Sikkim Himalaya is a subset of the Eastern Himalayan region and share its geographical boundary with China in the north, Nepal and Bhutan in the west and east

respectively. Sikkim has a total area of 7096 Km² lying between 88°00'58" E & 88°55'25" E longitudes and 27°00'46" N & 28°07'48" N latitudes. The glacial bodies and glacial lakes are located in the high-altitude north and west districts of Sikkim. It shares some of its glacial bodies with Nepal. Moraine deposits and numerous glacial lakes surround the glacial bodies in this region. Such glacial lakes either form due to snow melt accumulation or lie at a distance from the glacial body, or behind the lateral moraines/glacial terminus (proglacial lakes) or directly on the glacial surface (supraglacial lakes) and are primarily fed by snow- and ice-melt. Figure 5.19 shows the map of trans-boundary Sikkim along with the glacial bodies and lakes.

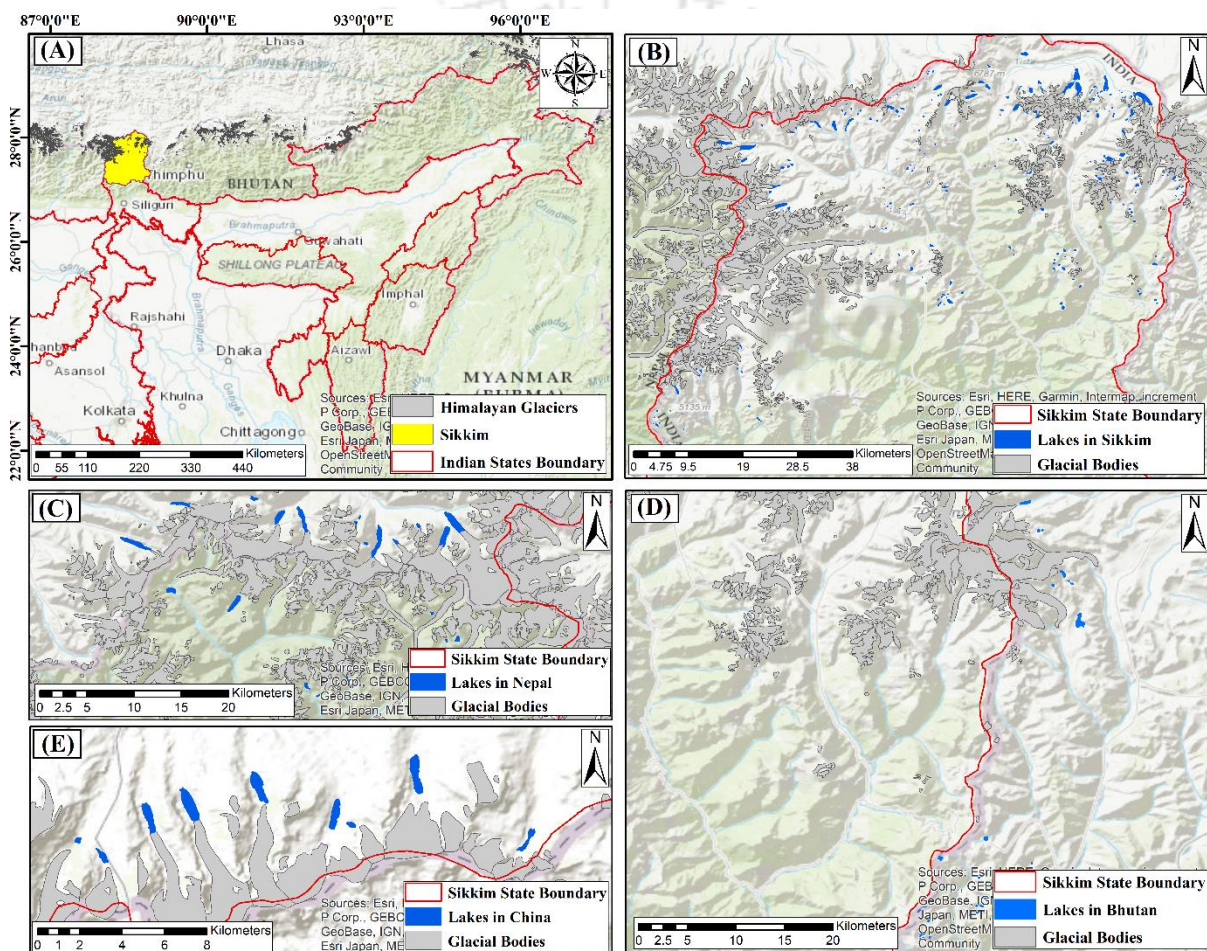


Figure 5.19: Study area map showing (A) Eastern Himalayan states, glaciers and lakes in and around (B) Sikkim, (C) Nepal, (D) Bhutan and (E) China

5.4.2 Data Preparation

In this study, Landsat 5 Thematic Mapper (TM) and Sentinel 2 Multispectral Instrument (MSI) datasets between 1989 and 2022 at an interval of 10-12 years have been used during the ablation period (October-December) with low obscuring cloud and snow cover to determine the temporal fluctuations in lake area as shown in Table 5.6. Lakes and other surficial water bodies,

including river streams have been identified using the Normalized Difference Water Index (NDWI) which utilizes the green and near-infrared (NIR) channels (Gardelle et al., 2011). Shadow zones and snow cover misclassified as water bodies have been eradicated with the help of hill shading (Huggel et al., 2002). High resolution (12.5m) terrain corrected ALOS PALSAR digital elevation model (DEM) of 11th February, 23rd February, and 12th June 2009 have been used for the Nepal, Bhutan, and Sikkim Himalaya, including China, respectively. The slope derived from filled DEM has been used to identify lakes with a threshold of $<4^\circ$. The lakes identified using moderate-resolution optical datasets and DEM have been verified with temporal imagery from Google Earth Pro (Cook et al., 2016; Aggarwal et al., 2016). Finally, manual delineation of lakes has been performed to develop an inventory of glacial lakes for better accuracy.

Table 5.6: Optical datasets used to capture temporal change in lake area between 1989 and 2022

Sl. No.	Satellite	Date of acquisition (Ablation period)	Spectral channels used [Ground resolution]
1.	Landsat 5 (TM)	25-10-1989	Band 2 (Green: 0.52-0.60 μm) [30m]
2.		16-11-2000	Band 4 (NIR: 0.76-0.90 μm) [30m]
3.		14-12-2010	
4.	Sentinel 2 (MSI)	25-11-2022	Band 3 (Green: 0.543-0.578 μm) [10m] Band 8 (NIR: 0.785-0.900 μm) [10m]

5.4.3 Methodology

5.4.3.1 Identification of Lakes

Lakes identified using an integrated approach of moderate-resolution optical satellite datasets, DEM, and Google Earth Pro imagery followed by manual corrections have been further classified on the basis of their quantitative characteristics, such as recent areal coverage in 2022, lake type, and position against parent glacier as shown in Table 5.7. Each lake has been assigned a lake ID along with other information such as position (latitude & longitude) and altitude (m a.s.l). Once the inventory has been prepared, which included 302 lakes within Sikkim and 97 lakes in Nepal, Bhutan, and China, the inventory has been updated with other characteristics such as empirical lake volume (Huggel et al., 2002), slope along lake upstream, connection to other glacial lakes, proximity to settlements, roads and past seismic clusters, and dam properties (freeboard and width/height ratio). Previous studies show that the most critical amongst glacial lakes are the proglacial lakes linked to the glacial snout (Aggarwal et al., 2016). Such lakes have been given special attention. Figure 5.20 shows pictures of some glacial lakes

investigated during field investigation in 2021-2022 in North Sikkim (Gurudongmar and Pragyan lake) and West Sikkim (Rathong supraglacial pool).

Table 5.7: Characteristics to describe lakes in the inventory

Lake Characteristics	Definition
Lake ID	Unique identification code provided to each lake (Sikkim lakes as L1 to L302 and trans-boundary lakes as LT1 to LT97)
Ground Position	Latitude and Longitude (WGS84) information
Altitudinal Position	Elevation of the water contained in the lake (m a.s.l)
Areal Coverage	Surface area as computed from optical satellite datasets and Google Earth Pro imagery
Lake Type	As analyzed from Google Earth Pro imagery -Snow-fed (SF) -Glacier-fed (GF) subcategorized as moraine-dammed (MDGF), ice-dammed (IDGF), combined moraine-ice-dammed (CDGF) and bedrock-dammed (BDGF)

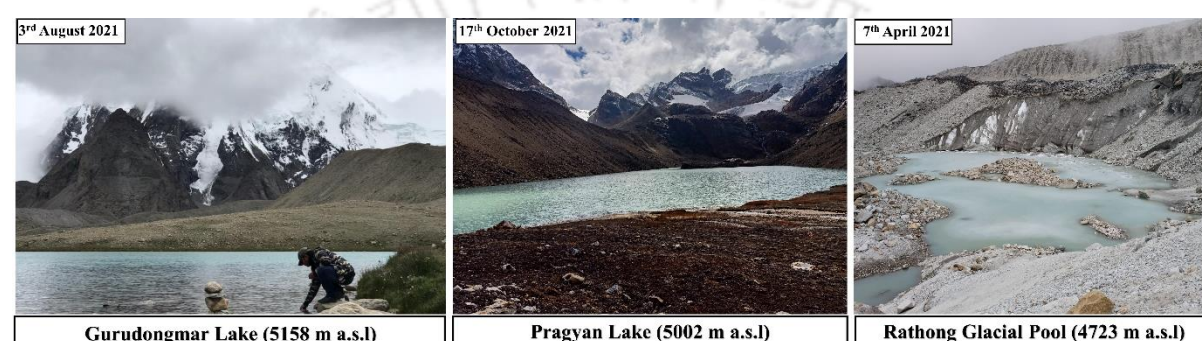


Figure 5.20: Glacial lakes investigated during field investigation in 2021-2022

5.4.3.2 Criteria for Vulnerability Assessment of lakes

With the aim to identify potential glacial lakes susceptible to future GLOF events, lakes with areal coverage of $>0.01 \text{ Km}^2$ have been considered for the vulnerability assessment. This way, 281 out of 399 lakes have been chosen. Various triggering and controlling parameters have been adopted as introduced by several researchers and shown in Table 5.7. Fifteen parameters have been considered for the GLOF susceptibility assessment of Sikkim and trans-boundary lakes (Table 5.8). Figure 5.21 shows some of the factors used in the vulnerability assessment of lakes.

Table 5.8: Parameters for GLOF susceptibility

Factors/ Parameters	Symbol	Details	Critical value	Classes	Class index value (i)	References
Lake area/ Empirical volume/ depth	LA	Lakes with an area (A) of $>0.02 \text{ Km}^2$ can store enough water to cause damage. Huggel's Volume: $0.14A^{1.42} \text{ m}^3$ Huggel's Depth: $0.14A^{0.42} \text{ m}$	$>0.01 \text{ Km}^2$	0.01-0.05 Km^2	0.20	ICIMOD, 2011; Huggel et al., 2002; Bolch et al., 2011; Aggarwal et al., 2017
				0.05-0.10 Km^2	0.40	
				0.10-0.50 Km^2	0.60	
				0.50-1.0 Km^2	0.80	
				$>1.0 \text{ Km}^2$	1.00	
Lake type	LT	Moraine- or ice- or combined dammed lakes are more critical to breach.		Snow-fed	0.25	ICIMOD, 2011
				Glacial melt-fed	0.50	
				Dammed Lake	1.00	
	LI	$>100\%$ since 2007		$<50\%$	0.25	

Increase in lake area				50-100%	0.50	Bolch et al., 2008; Bolch et al., 2011; Gardelle et al., 2011
				>100%	1.00	
Lake altitude	LE	Lakes at higher elevation have to cover longer and steeper path after breach due to which impact downstream increases due to more scouring and debris/sediment load.	>3500m a.s.l	<3500m a.s.l	0.50	ICIMOD, 2011
				≥3500m a.s.l	1.00	
Slope between glacier and lake	SO	Steep slope between lake and glacier increases the risk of rockfall or icefall into the lake	>12°	<12°	0.25	Wang et al., 2011; Prakash and Nagarajan, 2017
				12°-21°	0.50	
				>21°	1.00	
Discharge type	DT	Lakes with a perennial stream is comparatively safe than a closed lake.		Open	0.50	Huggel et al., 2002
				Closed	1.00	
Slope of moraine boundary	MS	Topographic gradient of inner boundary of the lake	>10°	<10°	0.50	Huggel et al., 2002
				>10°	1.00	
Parent glacier proximity	GP	Close to parent glacier means more input during peak melt period	Attached to glacier	>500m	0.25	Lü et al., 1999; Wang et al., 2011
				≤500m	0.50	
				Attached	1.00	
Connected Lakes	CL	Lakes connected to each other introduces more vulnerability as breach of the elevated lake increases the risk of breach for the lake at lower elevation.		Connected	0.50	
				Not Connected	1.00	
Proximity to road network	RP	Lakes close to road networks at higher altitudes increase the vulnerability.	<5 Km and sloping towards road	>5 Km	0.50	
				≤5 Km	1.00	
Settlement proximity	SP	Glacial lakes close to human settlement downstream increases vulnerability.	<50 Km	>50 Km	0.50	Bajracharya et al., 2007
				≤50 Km	1.00	
Freeboard offset	FO	Lesser the moraine freeboard level, more is the vulnerability.	<5 m	>5 m	0.25	Huggel et al., 2002 Emmer and Vilímek, 2013
				≤5 m	0.50	
				0 (surface drainage)	1.00	
Width/height ratio	WH	Lakes which are low and wide have higher longevity. Lesser width/height ratio indicates lesser stability of the dam.	<0.2	>0.5	0.25	Clague and Evans, 2000 Huggel et al., 2002 Emmer and Vilímek, 2013
				0.2-0.5	0.50	
				0.1-0.2	1.00	
Landslides	L	Lakes situated near landslide prone regions are more vulnerable.		>500 m	0.50	
				≤500 m	1.00	
Earthquakes and tectonic factors	E	Lakes close to past earthquake clusters and tectonic lineaments are considered more vulnerable.		Eastern Sikkim; Bhutan Lakes	0.50	Murty, 2004
				Nepal, West Sikkim, China; Western North Sikkim Lakes	1.00	

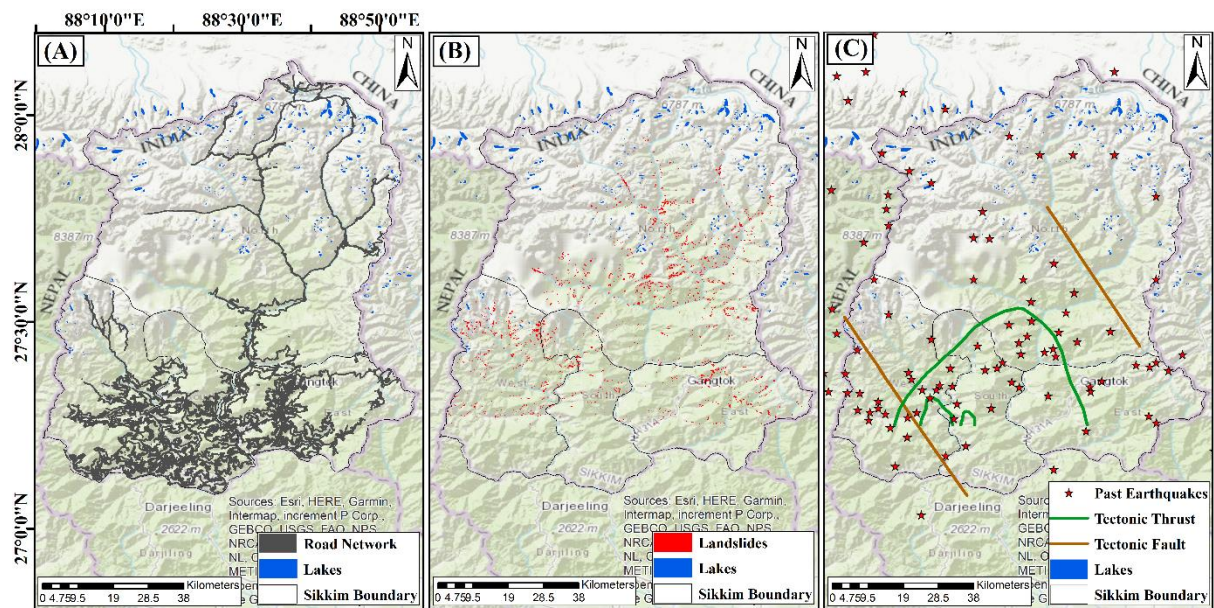


Figure 5.21: Glacial lakes investigated during field investigation

5.4.3.3 Analytical Hierarchy Process (AHP)

AHP is a form of multi-criteria decision-making technique to analyze complex problems with many criteria (Saaty, 1980). It facilitates obtaining the most suitable decision using multiple criteria. This is done by the mathematical estimation of relative preference of factors through expert judgment and pairwise comparison. A pairwise comparison matrix (PCM) allows one to compute the mathematical values of each factor and assess the significance of a factor compared to the rest of the factors. A PCM is prepared by assigning values in the scale of 1 to 9 to every pairwise comparison. In the matrix, 1 depicts equal importance of both the factors, 3 represents moderate importance, 5 shows strong importance, 7 as very strong importance and 9 represents that one factor is extremely important (Prakash and Nagarajan, 2017). The remaining values such as 2, 4, 6 and 8 depicts intermediate importance values. In order to evaluate the consistency of the decision, the consistency ratio (CR) can be evaluated using the factors' matrix. In general, $CR < 0.1$ is acceptable. CR greater than 0.1 indicates serious inconsistencies indicating that the AHP may not deliver meaningful judgments. From the previous studies on GLOF assessment (Aggarwal et al., 2017; Prakash and Nagarajan, 2017), a PCM has been developed assigning greater values to factors that are primarily associated with GLOF in the Himalayan region such as lake area, increase in the lake area, and moraine properties. Weights (ω) have been computed for each factor, and each class's final weight (W) has been calculated as a product of the class index value (i) and ω , as shown in Table 5.9.

Finally, the vulnerability score for the lakes has been calculated as a summation of the final weight (W) of every factor class.

Table 5.9: Pairwise comparison matrix with weight (ω) of factors

Factors↓→	LA	LT	LI	LE	SO	DT	MS	GP	CL	RP	SP	FO	WH	L	E
LA	1	1	1/5	4	8	5	6	3	4	8	8	1/3	1/3	4	4
LT	1	1	1/5	4	4	6	2	5	3	8	8	1	1	7	7
LI	5	5	1	6	7	4	4	3	8	9	9	2	2	8	8
LE	1/4	1/4	1/6	1	1/2	1/3	1/3	1/4	1/3	4	4	1/5	1/5	1	1
SO	1/8	1/4	1/7	2	1	1	1/5	1/4	1/4	3	3	1/6	1/6	3	3
DT	1/5	1/6	1/4	3	1	1	1	1/2	1	3	3	1/5	1/5	1/3	1/3
MS	1/6	1/2	1/4	3	5	1	1	1	1	3	4	1	1	1	1
GP	1/3	1/5	1/3	4	4	2	1	1	5	5	7	1	1	3	3
CL	1/4	1/3	1/8	3	4	1	1	1/5	1	5	6	1/5	1/7	2	2
RP	1/8	1/8	1/9	1/4	1/3	1/3	1/3	1/5	1/5	1	1	1/4	1/5	1/2	1/3
SP	1/8	1/8	1/9	1/4	1/3	1/3	1/4	1/7	1/6	1	1	1/4	1/5	1/3	1/3
FO	3	1	1/2	5	6	5	1	1	5	4	4	1	1/2	4	3
WH	3	1	1/2	5	6	5	1	1	7	5	5	2	1	3	2
L	1/4	1/7	1/8	1	1/3	3	1	1/3	1/2	2	3	1/4	1/3	1	1/2
E	1/4	1/7	1/8	1	1/3	3	1	1/3	1/2	3	3	1/3	1/2	2	1

5.4.3.4 Backpropagation Multilayer Perceptron Neural Network (BPMLPNN)

Artificial neural network has extensive implications in the field of optimization and classification. Backpropagation serves as a training algorithm for a multi-layer neural network. Backpropagation neural network (BPNN) can be considered a popular choice and key development for researchers around the globe (Sathyanarayanan et al., 1992; Zhang and Huang, 1995; Feng et al., 2002; Chen et al., 2010; Mondal et al., 2022). The ability to predict the dynamic nonlinearity of multiple responses proves BPNN an efficient choice for researches in various process modeling. Moreover, the neural network can be well-trained without considering prior distribution assumptions or the functional form (linear, exponential, quadratic, or higher-order polynomial) (Mukherjee and Routroy, 2012). Such inherent properties furnish BPNN with an added advantage over complex techniques of nonlinear regression (Basheer and Hajmeer, 2000). Some of the interesting features of BPNN are mentioned as follows:

- Adaptability and learning ability permits progressive modification of its internal structure according to the changing environment.
- Generalization ability.

- c) Capability to handle fuzzy information and imprecision.
- d) Noise insensitivity delivers accurate prediction in case of measurement errors and uncertainty in datasets (Bates and Watts, 1988).

In the backpropagation algorithm, weights are adjusted by considering the negative direction of the gradient from added squared errors with reference to the weight variables. Consider the input as a vector 'v', network output as 'o', desired output as 'δ', and weight vector as 'k'. The error vector 'z' can be represented as

$$z = o - \delta \quad (5.21)$$

In the backpropagation neural network (BPNN), weights are updated as

$$k_{i+1} = k_i - \eta \frac{\partial z^i z}{\partial x} \quad (5.22)$$

where η is learning parameter. In order to enhance the learning process, learning parameter can be substituted by momentum parameter μ where the weights are updated (Youssef and Pourghasemi, 2021).

$$k_{i+1} = k_i - \eta \frac{\partial z^i z}{\partial x} + \mu(k_i - k_{i-1}) \quad (5.23)$$

The general neural network architecture is shown in Figure 5.22. P^k denotes the number of independent parameters/variables given as input. These input parameters are associated with each of the neuron counts (H_{ij}) in a hidden layer (i and j represent the neuron group and element number, respectively) using weights (w_{ij}^n). With a specific number of neurons in the neural network, there are biases associated with them, as shown using grey balls in the hidden layer. The number of outputs are represented with blue balls as O_m with the weights from a hidden neuron as k_i . The weights are the solution of the differential equation that is needed to be solved.

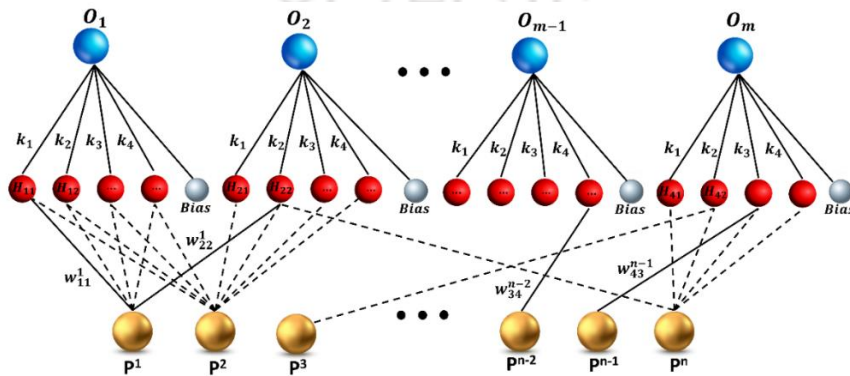


Figure 5.22: Architecture of artificial neural network (ANN)

The performance of different learning algorithm are measured using mean-square of error (MSE) which can be considered as a common performance measure as represented in equation 5.24.

$$MSE = \frac{1}{Nq} \sum_{m=1}^N \sum_{p=1}^q [(d_y^m)^2 - (O_y^m)^2] \quad (5.24)$$

where e is the number of completed training epoch. N represents the total number of training pattern. d_y^m and O_y^m represents the y^{th} actual and network predicted output of m^{th} training pattern, respectively.

Gradient Descent Algorithm-based Backpropagation with Momentum and Adaptive Learning Rate (GDX-BPMLPNN)

Backpropagation computes the derivative of the performance function w.r.t bias variable matrix (B_V) and weight. In the case of the gradient descent algorithm with momentum and adaptive learning rate (GDX), adjustment of each variable in matrix B_V is done as per equation 5.25.

$$dB_{ve} = \Omega dB_{ve-1} + \Omega \tau \frac{d(\text{Performance Function})}{dB_{ve}} \quad (5.25)$$

where e represents the number of epoch, Ω is the momentum coefficient, B_{ve-1} is the preceding change to the bias or weight, and τ is the learning rate. An assumption of the performance objective function is considered to be in quadratic form. The general error performance function for a BPNN design, as shown in equation 5.24 is slightly modified in the case of GDX. In order to prevent over-training/over-fitting and enhance the generalization of the final ANN architecture, a regularization approach is adopted which introduces a modified performance function termed as MSEREG (Mukherjee and Ray, 2008) and is expressed as

$$MSEREG(e) = \gamma_i \times [MSE(e)] + (1 - \gamma_i) \times [MSW(e)] \quad (5.26)$$

$$MSW(e) = \frac{1}{r} \sum_{ij=1}^r (w_{ij}^n)^2 \quad (5.27)$$

where γ_i and r represents the performance weighted ratio and sum total of interconnected weights respectively. Implementing such performance function results in smaller biases within the network, making the network response much smoother and less likely to over-train (Howard and Beale, 1998).

Momentum Coefficient (Ω)

Momentum coefficient (Hagan et al., 2002) is the fraction of weight change added to every subsequent weight change. Where high momentum cripples the network adaptability, low momentum may result in instability and weight oscillation. For a stable GDX-BPNN model, Ω should be adopted less than unity. Momentum factors close to one are required to smooth error oscillations. It is to be noted that smaller momentum factor is desirable in the middle of training whereas larger momentum factor is recommended during the end of the training.

Learning Rate (τ)

In a training cycle, the learning rate expands or limits the extent of weight adjustments. In case of a simple gradient descent BPNN model, learning rate is kept constant throughout the training phase (Hagan et al., 2002). However, too low learning rate results in substantial increase in the training time of the neural network, and too high learning rate affects the stability of the network, thus deteriorating the prediction ability (Howard and Beale, 1998). Until the weight adjustments start to approach plateau, high learning rate helps in accelerating learning. However, this increases the risk of the weight search jumping over a minimal error condition thus resulting in the backpropagation learning to approach global optima. This imperils the integrity of the neural network. Varying or adaptive learning rate ascertain better flexibility to cope with such redundancies, thus stabilizing the risk of failure and accelerating the training process. The adaptive learning rate increases the τ up to an extent such that the network learns but remains devoid of large errors (Mukherjee and Ray, 2008). It also reduces the τ as error decreases and phase of stable learning is attained. The optimal setting of τ depends on its application and is experiment-based. The learning rate can be gradually decreasing or time-varying as the algorithm approaches the optimal solution.

Number of Epochs (e)

On each epoch, training cases are reported to the neural network. This is followed by the comparison between the actual and target outputs, and the error performance is assessed. The measure of error along with the error surface gradient is used for the adjustment of weights. This process is iterated. With random selection of the initial neural network weight configuration, the learning stops as soon as the conditions mentioned below are achieved:

- a) The maximum number of predefined epoch is reached,
- b) Defined maximum iteration time is reached,

- c) Minimum error performance is reached,
- d) Performance gradient $\leq$ predefined minimum gradient.

Levenberg-Marquardt Algorithm-based Backpropagation (LM-BPMLPNN)

Levenberg-Marquardt (LM) algorithm is a modified form of Gauss-Newton method (Lippmann, 1994). The LM algorithm outperforms several simple and conjugate gradient descent methods (Ampazis and Perantonis, 2000; Nalbant et al., 2009). In Gauss-Newton approach, weights granted to the neural network are adjusted as represented:

$$k_{i+1} = k(i) - (J(i)^T J(i))^{-1} J(i)^T e(i) \quad (5.28)$$

where J represents the Jacobi matrix as defined:

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial k_1} & \frac{\partial e_1}{\partial k_2} & \dots & \frac{\partial e_1}{\partial k_m} \\ \frac{\partial e_2}{\partial k_1} & \frac{\partial e_2}{\partial k_2} & \dots & \frac{\partial e_2}{\partial k_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_n}{\partial k_1} & \frac{\partial e_n}{\partial k_2} & \dots & \frac{\partial e_n}{\partial k_m} \end{bmatrix} \quad (5.29)$$

Levenberg-Marquardt modification to equation 5.28 is

$$k_{i+1} = k(i) - (J(i)^T J(i) + \mu I)^{-1} J(i)^T e(i) \quad (5.30)$$

where μ is a parameter (Levenberg's damping factor) that ensures that the inversion of the matrix always produces result. The parameter is dependent on the evaluation of added squared errors. If error is reduced, μ is factored by some scalar Θ . If error is enhanced, μ is multiplied by scalar Θ (Reynaldi et al., 2012). As μ approaches zero, LM optimizer operates as a Gauss Newton method following approximate Hessian Matrix. On the other hand, as μ approaches larger values, it operates like a gradient descent method invoking a smaller step size. Pertaining to precise as well as faster response of Gauss Newton's method in the vicinity of least error, the optimizer works with the notion of attaining the state of Gauss Newton's operation as early as possible. Therefore, the reduction in μ with every iteration is followed by decrement in the error function. Increment in μ is a result of augmented error function due to an uncertain step. Thus, implementing such iterative process, the LM optimizer minimizes the error function for the purpose of attaining high performance of the network architecture.

Bayesian Regularization-based Backpropagation (BR-BPMLPNN)

The BR-BPMLPNN yields neural networks devoid of over-fitting and with consistent generalization (Kayri, 2016). The regularized objective function used for training can be expressed as shown in equation 5.31.

$$F = \alpha E_w + \beta E_D \quad (5.31)$$

where α and β denote regularization parameters, E_w and E_D represents sum of squared weights and sum of squared errors within the neural network respectively.

Consider input vector u and output vector d in the neural network model having training datasets D . Once each input is applied to the network, the output error (x_y^m) is computed which is the difference between d_y^m and O_y^m which is the target output and predicted output respectively. Furthermore, MSE is computed to minimize the mean of the added errors.

$$MSE = \frac{1}{Nq} \sum_{m=1}^N \sum_{p=1}^y (x_y^m)^2 = \frac{1}{Nq} \sum_{m=1}^N \sum_{p=1}^y [(d_y^m)^2 - (O_y^m)^2] \quad (5.32)$$

For a neural network model N_M , the posterior distribution ($P(w | D, \delta, \lambda, N_M)$) of weights vary according to the prior density ($P(w | \delta, N_M)$), likelihood function ($P(D | w, \lambda, N_M)$) and the normalization factor ($P(D | \delta, \lambda, N_M)$) following the Bayes' rule. The normalization factor ascertains the total probability to be unity.

$$Posterior = \frac{Prior\ density \times Likelihood\ function}{Normalization\ factor} \quad (5.33)$$

$$P(w | D, \delta, \lambda, N_M) = \frac{P(w | \delta, N_M) \times P(D | w, \lambda, N_M)}{P(D | \delta, \lambda, N_M)} \quad (5.34)$$

The posterior probability with network weights w as shown in equation 5.34 can be represented as (Kayri, 2016)

$$P(w | D, \delta, \lambda, N_M) = \frac{\exp(-(\delta E_w + \lambda E_D))}{Z_F(\delta, \lambda)} = \frac{\exp(-(F(w)))}{Z_F(\delta, \lambda)} \quad (5.35)$$

where δ and λ denotes the regularization parameters governing the complexity of the model and $Z_F(\delta, \lambda)$ shows the normalization factor. Therefore, for optimization Bayes' rule is applied again as represented:

$$P(\delta, \lambda | D, N_M) = \frac{P(D | \delta, \lambda, N_M) \times P(\delta, \lambda | N_M)}{P(D | N_M)} \quad (5.36)$$

Equation 5.36 shows the normalization factor of equation 5.34 where maximization of the likelihood function ($P(D | \delta, \lambda, N_M)$) results in the maximization of the posterior probability ($P(\delta, \lambda | D, N_M)$). Thus, the likelihood function can be evaluated as mentioned (Foresee and Hagan, 1997; Kayri, 2016; Narayan and Dwivedy, 2022):

$$P(D | \delta, \lambda, N_M) = \frac{Z_F(\delta, \lambda)}{Z_W(\delta)Z_D(\lambda)} \times \frac{\exp(-(\delta E_W + \lambda E_D))}{\exp(-F(w))} = \frac{Z_F(\delta, \lambda)}{Z_W(\delta)Z_D(\lambda)} \quad (5.37)$$

Where $Z_D(\delta) = (\pi/\delta)^{0.5K}$ and $Z_D(\lambda) = (\pi/\lambda)^{0.5S}$ shows the normalization factors and $Z_F(\delta, \lambda)$ can be evaluated by expanding equation 5.31 using the Taylor series around the minima of posterior distribution (ϖ) and considering a zero gradient as follows:

$$2\pi^{0.5K} \exp(-F(\varpi)) [\det(H(\varpi)^{-1})]^{0.5} = Z_F(\delta, \lambda) \quad (5.38)$$

Finally, estimation of the optimum values (δ^* , λ^*) of regularization parameters can be performed using equations 5.37 and 5.38:

$$\delta^* = \frac{\varsigma}{2E_W(\varpi)}; \lambda^* = \frac{S-\varsigma}{2E_D(\varpi)} \quad (5.39)$$

Where $\varsigma = K - \delta^* \text{trace}^{-1}(H^*)$, for $0 \leq \varsigma \leq K$. It denotes the effective parameters required for the minimization of the error function. K represents the total number of parameters. Computation of the Hessian matrix (H_M) at minima (ϖ) can be done with the help of Gauss-Newton approximation (Hagan and Menhaj, 1994).

5.4.4 Results and Discussion

Naturally formed high-altitude lakes in the Sikkim Himalayas as well as trans-boundary locations of Nepal, China, and Bhutan have been identified and classified into snowmelt-fed lakes, glacial lakes, and moraine-dammed glacial lakes. A total of 51 moraine-, ice-, combined-dammed glacial lakes, 26 glacial-melt-fed lakes, and remaining snowmelt-fed lakes have been identified. Interestingly, some of the lakes (especially moraine-dammed glacial lakes) have shown significant increase in their areal dominance since 1989 (Figure 5.23). However, the rate of increase in the areal coverage of glacial lakes is not consistent throughout trans-boundary catchments of the eastern Himalayas but more intense towards the western side of Sikkim, including Nepal.

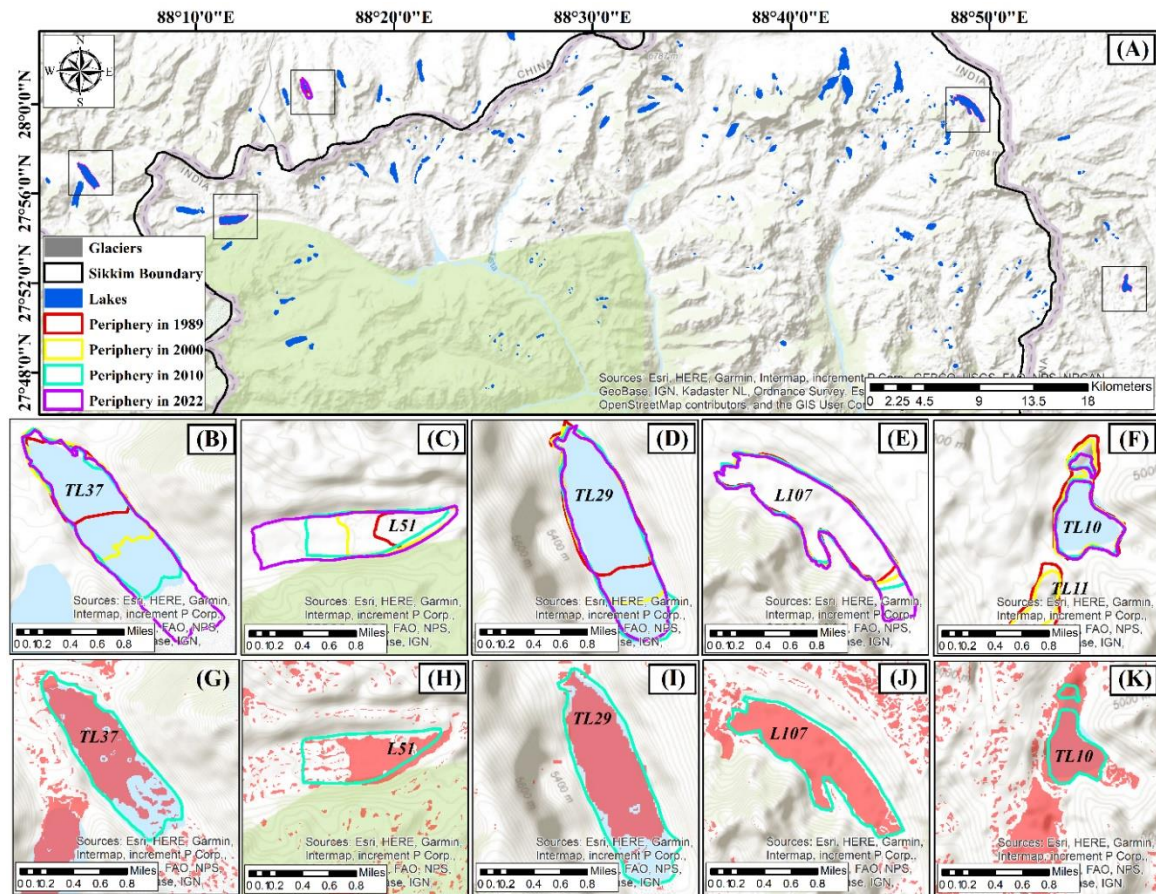


Figure 5.23: Map showing (A) inventory lakes, change in the lake area since 1989 for (B) TL37 in Nepal, (C) L51 (Lhonak lake) in Sikkim, (D) TL29 in China, (E) L107 in Sikkim, (F) TL10 and TL11 in Bhutan and DEM extracted lakes (<4°slope) for (G) TL37, (H) L51, (I) TL29, (J) L107 and (K) TL10 and TL11 respectively

The rate of lake area increment at an interval of every 10-12 years reduces as moving towards the eastern side of Sikkim towards Bhutan, as shown in Figure 5.24. Comparing two different proglacial glacial lakes, L51 and L107 are lying on the extremities of the Sikkim Himalaya. These lakes receive their melt input from the Lhonak glacier and Teesta Khangtse glaciers, respectively. Where L51 lies close to the western boundary of Sikkim, shows a substantial increase in the lake area in 2022 (1.73 Km²) which is 3.76 times the area in 1989 (0.64 Km²). L107 lies near the eastern boundary of Sikkim showing an areal increase from 1.63 Km² to 1.87 Km² between 1989 and 2022 that accounts for 1.15 times increment (Figure 5.24). Some of the glacial lakes in Bhutan such as TL10 and TL11 show reduced lake area since 1989. Moreover, TL11 almost vanishes since 2010. This unusual behaviour of reduction in the glacial lake area has not been observed in the western side of Sikkim Himalaya and Nepal. Since, lake area is an important parameter of glacial vulnerability, rapid increase in areal coverage of glacial lakes in Nepal and western Sikkim can be more alarming in terms of GLOF susceptibility than the eastern lakes and lakes within Bhutan.

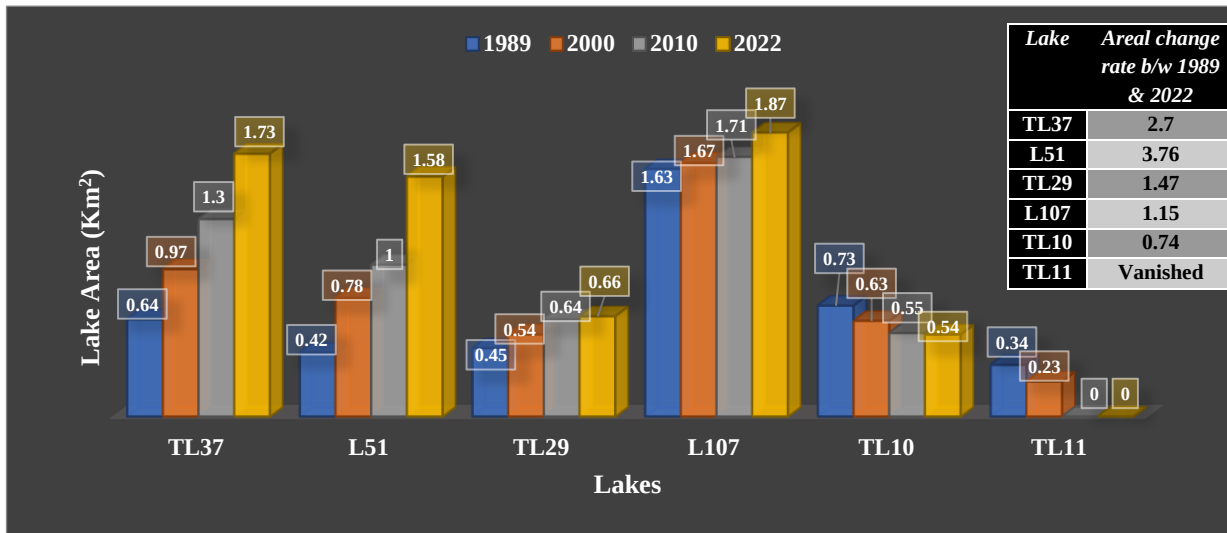


Figure 5.24: Temporal change in areal coverage (between 1989 and 2022) of lakes as moving from TL37 in Nepal to TL11 in Bhutan in the eastern direction

5.4.4.1 AHP-based Analysis

For the vulnerability assessment of lakes, weights for the fifteen factors/parameters have been calculated using the pairwise comparison matrix through six iterations on 105 comparisons using AHP, as shown in Table 5.10. The CR for comparisons is 0.098 (<0.1) implying a fair consistency in the pairwise comparison and judgements indicating the AHP to be acceptable. Therefore, the computed weights can be considered suitable for the assessment of GLOF susceptibility of moraine-dammed glacial lakes. The final weights for each parameter have been calculated by multiplying the class indices with each parameter's weight on the basis of the measurement of factors.

Table 5.10: Rank and weights of factors

Factors	Rank	Weight
Increase in lake area	1	0.216
Lake type	2	0.121
Width/height ratio	3	0.116
Lake area	4	0.113
Freeboard offset	5	0.104
Parent glacier proximity	6	0.074
Slope of moraine boundary	7	0.053
Connected Lakes	8	0.041
Earthquakes and tectonic factors	9	0.031
Stream order	10	0.029
Discharge type	11	0.028
Landslides	12	0.026
Lake altitude	13	0.023
Proximity to road network	14	0.013
Settlement proximity	15	0.012

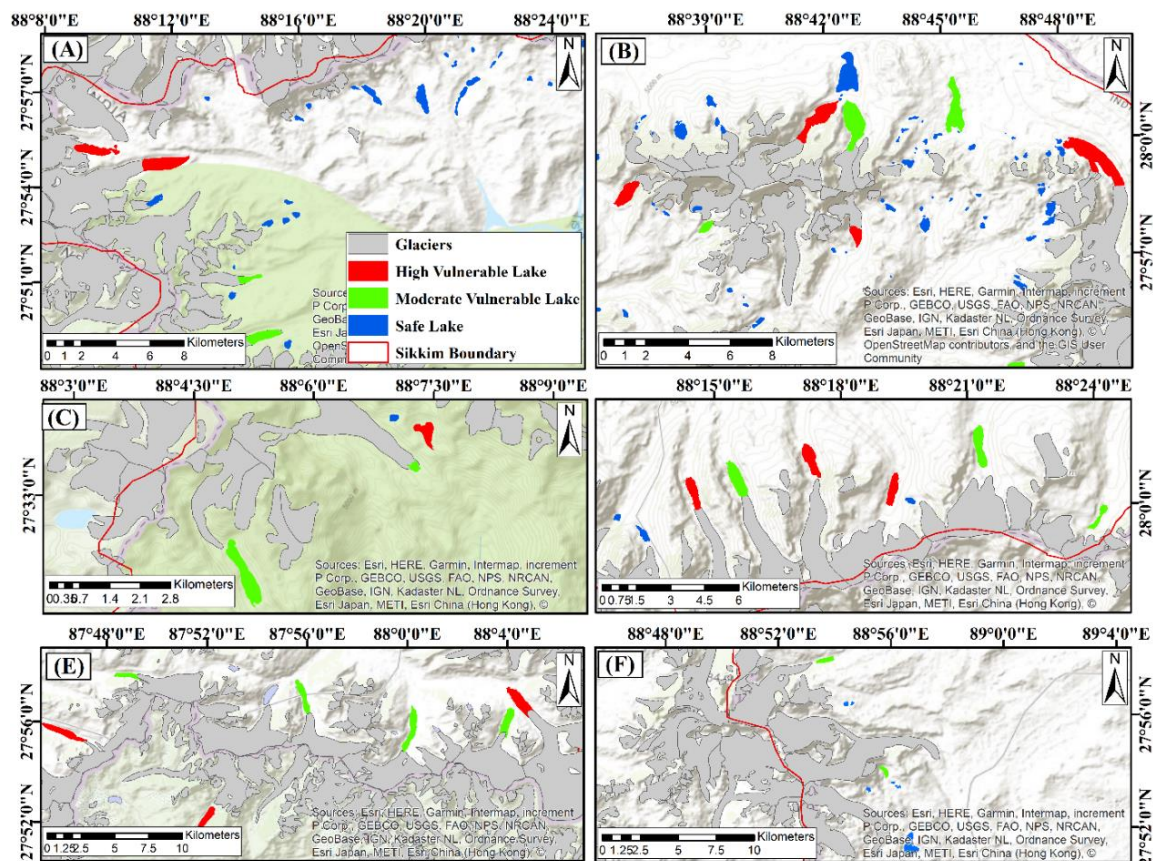


Figure 5.25: Map showing the AHP-based vulnerability assessment of lakes near (A) western boundary of North Sikkim, (B) eastern boundary of North Sikkim, (C) West Sikkim district, (D) China, (E) Nepal and (F) Bhutan

In order to prepare a database for feed into neural network models, 281 lakes have been ranked for susceptibility to outburst flood using AHP. In the earlier studies of GLOF susceptibility, ranking and classification are performed only for moraine-dammed glacial lakes (Prakash and Nagarajan, 2017; Aggarwal et al., 2017). To establish a reliable BPMLPNN model with sufficient number of datasets, every lake having an area of $>0.01 \text{ Km}^2$ has been ranked for vulnerability using AHP. Hence, the outburst vulnerability of lakes has been classified into three different classes (highly vulnerable, moderately vulnerable, and safe). From the AHP-based vulnerability assessment, 13 lakes have been categorized as highly vulnerable to outburst. All these lakes fall in the category of moraine-, ice- and combined-dammed lakes of which 7 lakes lie within Sikkim, 3 in Nepal, and 3 in China. No lakes in Bhutan lie in this category. 11 lakes in Sikkim, 4 in Nepal, 3 in China, and 2 in Bhutan lie in the category of moderately vulnerable lakes, as shown in Figure 5.25. The remaining 194 lakes within Sikkim and 54 lakes in the trans-boundary locations (mostly snowmelt-fed lakes) have been identified as safe in terms of outburst.

5.4.4.2 BPMLPNN-based Analysis

The BPMLPNN models used in this study have been analyzed with various neurons count for the input-output dataset for optimal structure. The mean square errors (MSEs) for the BPMLPNN models have been calculated with respect to the number of neurons in the hidden layer (H) as shown in Table 5.11. Varying the neuron count in the hidden layer for each algorithm and segregation, the model has been trained ten times for nullifying the chances of adopting arbitrary weights. This way, the mean value of MSE has been finalized for specific neuron counts (Table 5.11). The MSE decreases with an increase in the neuron count and reaches a specific count (n) at which the minimum value is gained and is termed as the optimal number of neurons for the BPMLPNN architecture (Figure 5.27). For the BR- and LM-BPMLPNN models, there has been a sharp decrease in the NMSE value with increase in neuron counts till 7 number of neurons after which the NMSE starts rising again. In the case of the GDX-BPMLPNN model, sharp fall in the NMSE initially is followed by flattening (marginally varying NMSE with an increase in neurons) till 11 neurons which is the optimal value. Afterwards, the NMSE starts increasing. The optimal architecture for the BR-BPMLPNN, LM-BPMLPNN, and GDX-BPMLPNN (15-11-1) as input parameter-optimal neurons-output is decided accordingly as shown in Figure 5.26.

Table 5.11: Segregation of lakes (%) and other parameters for the BPMLPNN models

Model	Data Segregation (%)			Optimal Neurons (n)	Performance MSE	Performance SSE
	Training	Testing	Validation			
BR-BPMLPNN	75	25	NIL	7	0.1412	29.6496
	80	20	NIL	7	0.1348	30.2002
LM-BPMLPNN	70	15	15	6	0.2364	56.2573
	80	10	10	7	0.2260	57.1764
GDX-BPMLPNN	70	15	15	11	0.4963	114.0617
	80	10	10	11	0.4937	117.4850

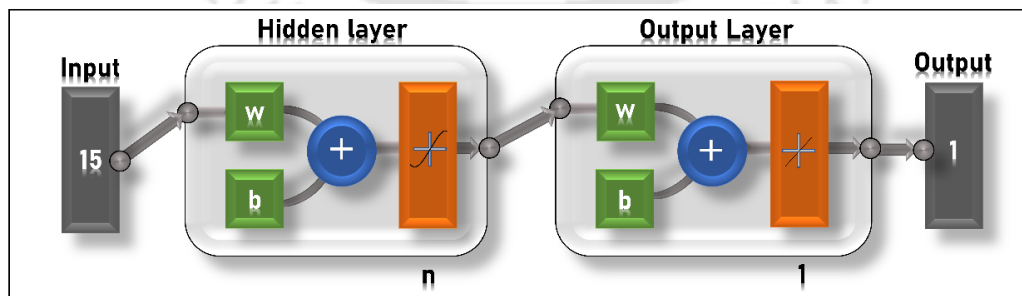


Figure 5.26: Layer architecture of BPMLPNN model (n: number of neurons) used in the study

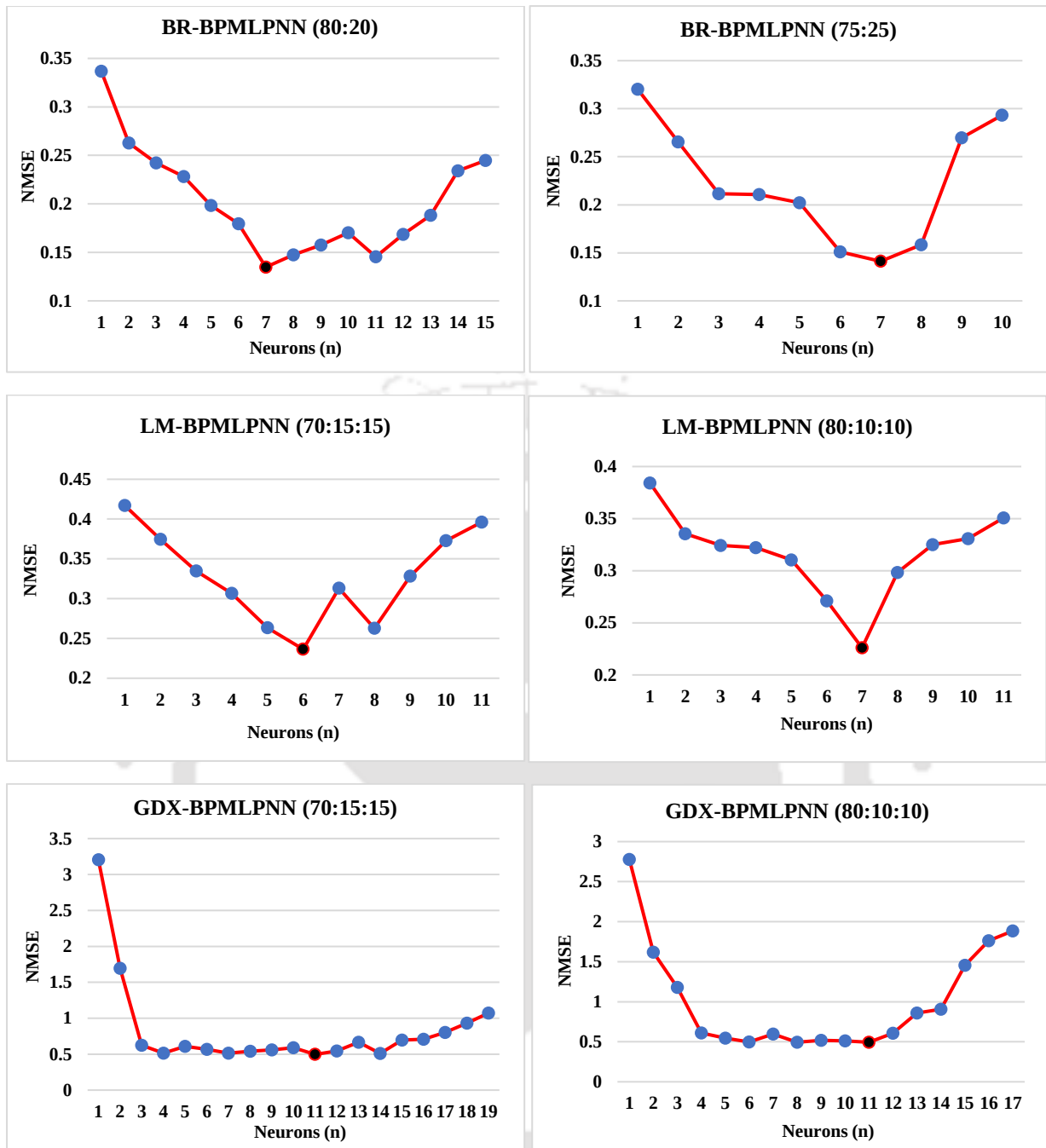


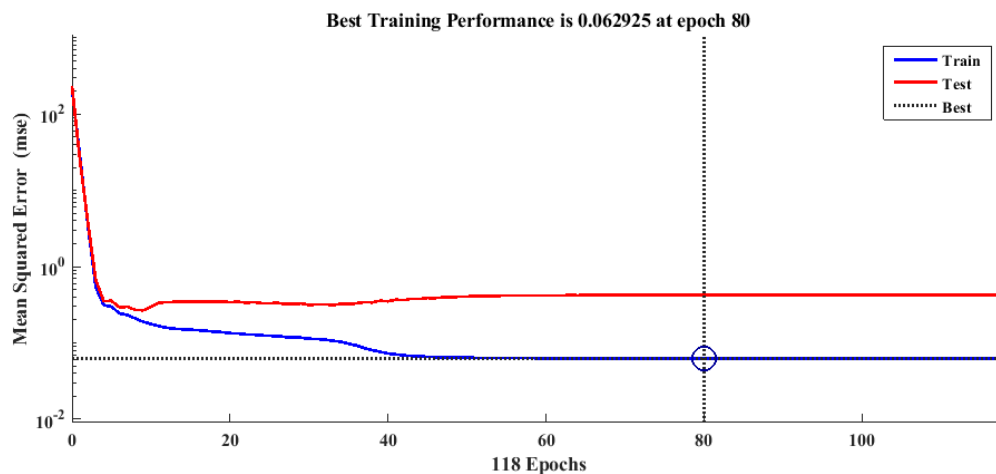
Figure 5.27: Normalized mean square error (NMSE) vs number of neurons in the hidden layer for various BPMLPNN models

The performance of BPMLPNN models has been analyzed for the estimation of GLOF vulnerability on the basis of scoring/ranking of each lake for every factor/parameter in the AHP-based assessment. Considering the optimal structure for BR-BPMLPNN models (15-7-1) for two different segregations of training:testing (75:25 & 80:20), training the models has been carried out for 2000 epochs with input-output datasets. Training parameters which include performance goal (G), minimum performance gradient (P_{g-min}), Levenberg's damping factor ($\mu_{initial}$ & μ_{final}), and maximum validation check (V_{max}), have been assigned as 0, 0.000001, 126

0.00001, 10, and 6 respectively. The training process is completed when any of the following conditions are attained: minimum possible MSE value reached, maximum epochs arrived, maximum validation achieved, and minimum error gradient crossed. The training of the BR-BPMLPNN model is completed at 80 and 517 epochs for the segregations (75:25 & 80:20) respectively with MSE values of 0.1412 and 0.1348, respectively (Figure 5.28 and 5.29). The other model parameters at the end of training process, such as training time, Levenberg's damping factor (μ), and error gradient have been mentioned in Table 5.12. The best validation performances of 0.0629 and 0.1088 have been achieved at epochs 80 and 517 for the two segregations as also illustrated in Figures 5.28 and 5.29, respectively. Finally, the correlation coefficient (R) between BR-BPMLPNN predicted outputs and AHP-based experimental targets for training and testing for two different segregations had been evaluated, as shown in Figures 5.28 and 5.29.

Table 5.12: Training parameters for the models

Model	Data Segregation (%)			Epochs	Training time	Levenberg's factor (μ)	Error Gradient	Validation check
	Training	Testing	Validation					
BR-BPMLPNN	75	25	NIL	80	00:01	10	0.0541	6
	80	20	NIL	517	00:01		0.0589	
LM-BPMLPNN	70	15	15	17	00:01		0.0758	
	80	10	10	9	00:01		0.0721	
GDX-BPMLPNN	70	15	15	101	00:03		0.1104	
BPMLPNN	80	10	10	104	00:03		0.1081	



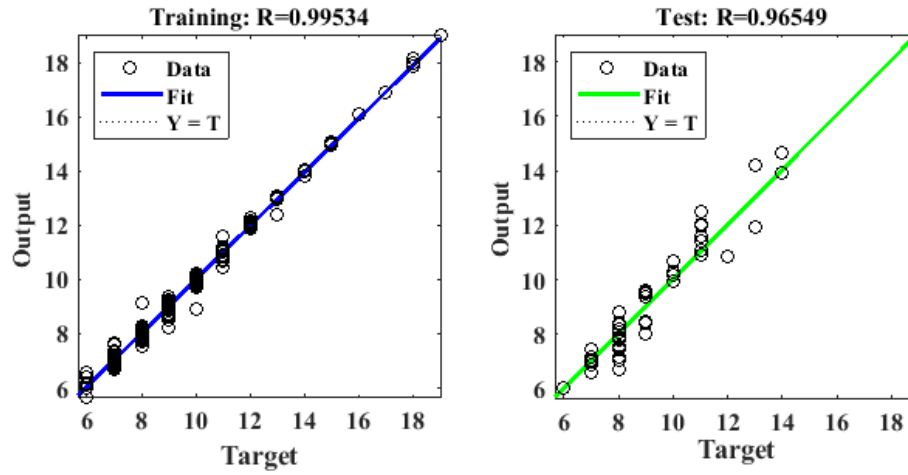


Figure 5.28: Best validation performance and correlation coefficient (R) for BR-based (75:25) BPMLPNN model training and testing respectively

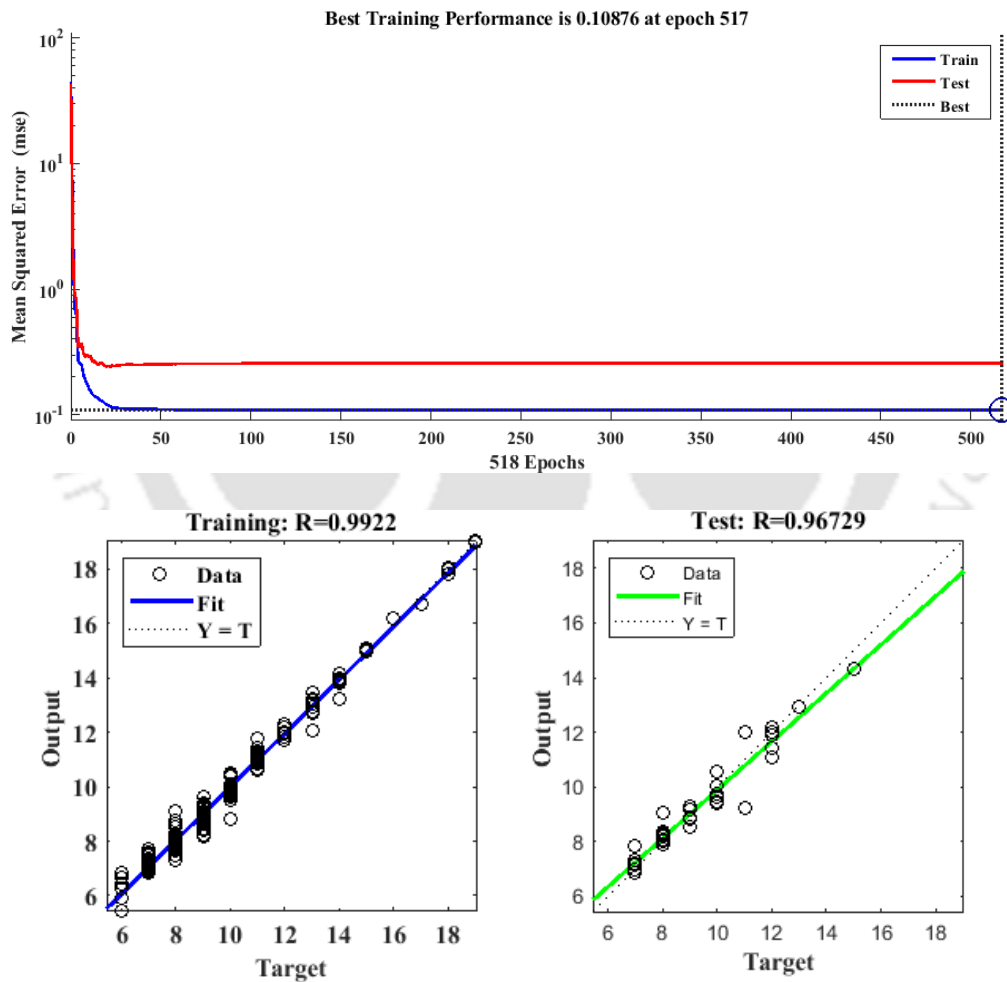


Figure 5.29: Best validation performance and correlation coefficient (R) for BR-based (80:20) BPMLPNN model training and testing respectively

In the case of the LM-based BPMLPNN models, the training procedure has been considered with optimal structure (15-6-1 & 15-7-1) for two segregations of

training:testing:validation (70:15:15 & 80:10:10) and compiled for 2000 epochs. Other training parameters such as G , P_{g-min} , $\mu_{initial}$, μ_{final} , and V_{max} have been set as 0, 0.000001, 0.00001, 10, and 6, respectively, as also consistently used for GDX-BPMLPNN model. The training is set to be terminated with the following conditions: maximum epochs reached, minimum NMSE attained, maximum validation reached as compared to previous decrement, and minimum error gradient crossed. Training the LM-based models have been accomplished at 17 and 9 epochs in 1 sec, obtaining MSE values of 0.2364 & 0.226 and best validation performances of 0.2588 and 0.3421 for segregations of 70:15:15 & 80:10:10, respectively. The correlation (R) between LM-based BPMLPNN predicted output and AHP-based experimental target had been represented in Figure 5.30 and 5.31 for two different segregations, respectively.

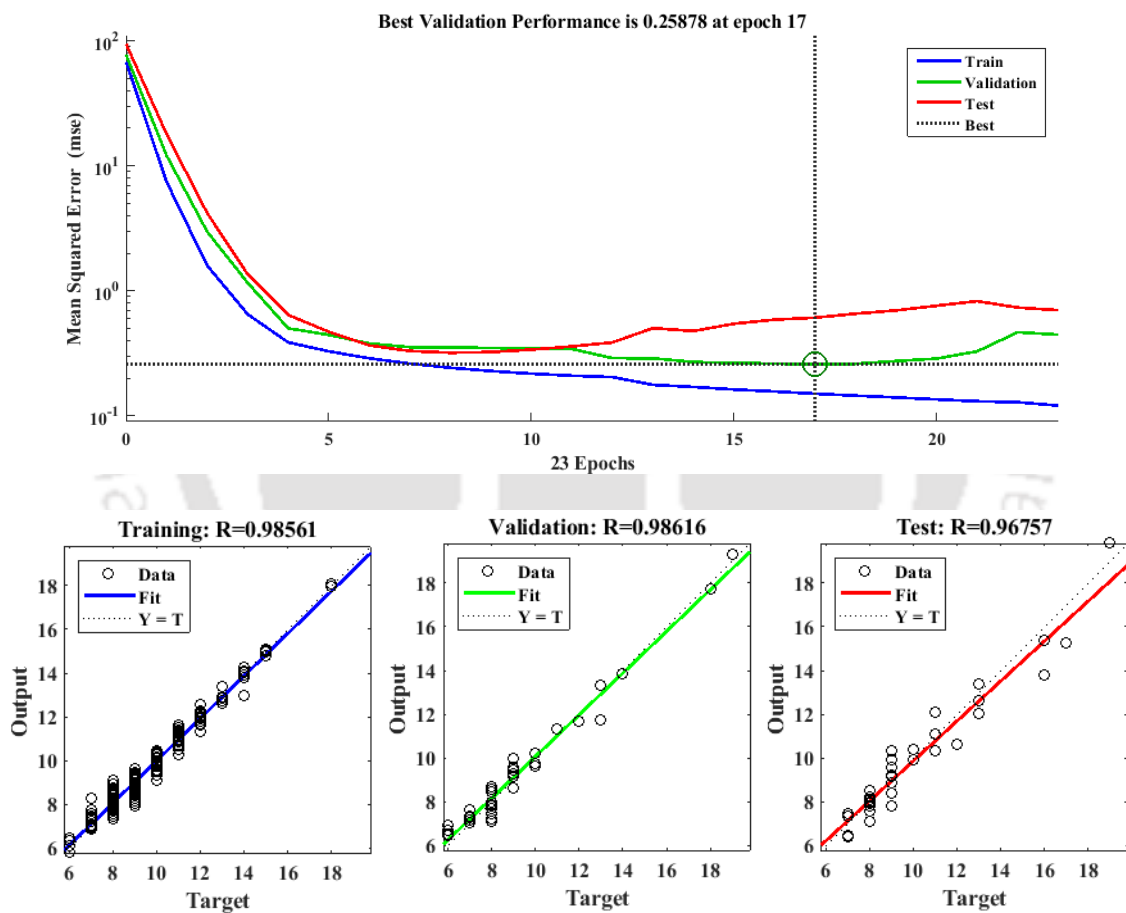


Figure 5.30: Best validation performance and correlation coefficient (R) for LM-based (70:15:15) BPMLPNN model training, validation, and testing respectively

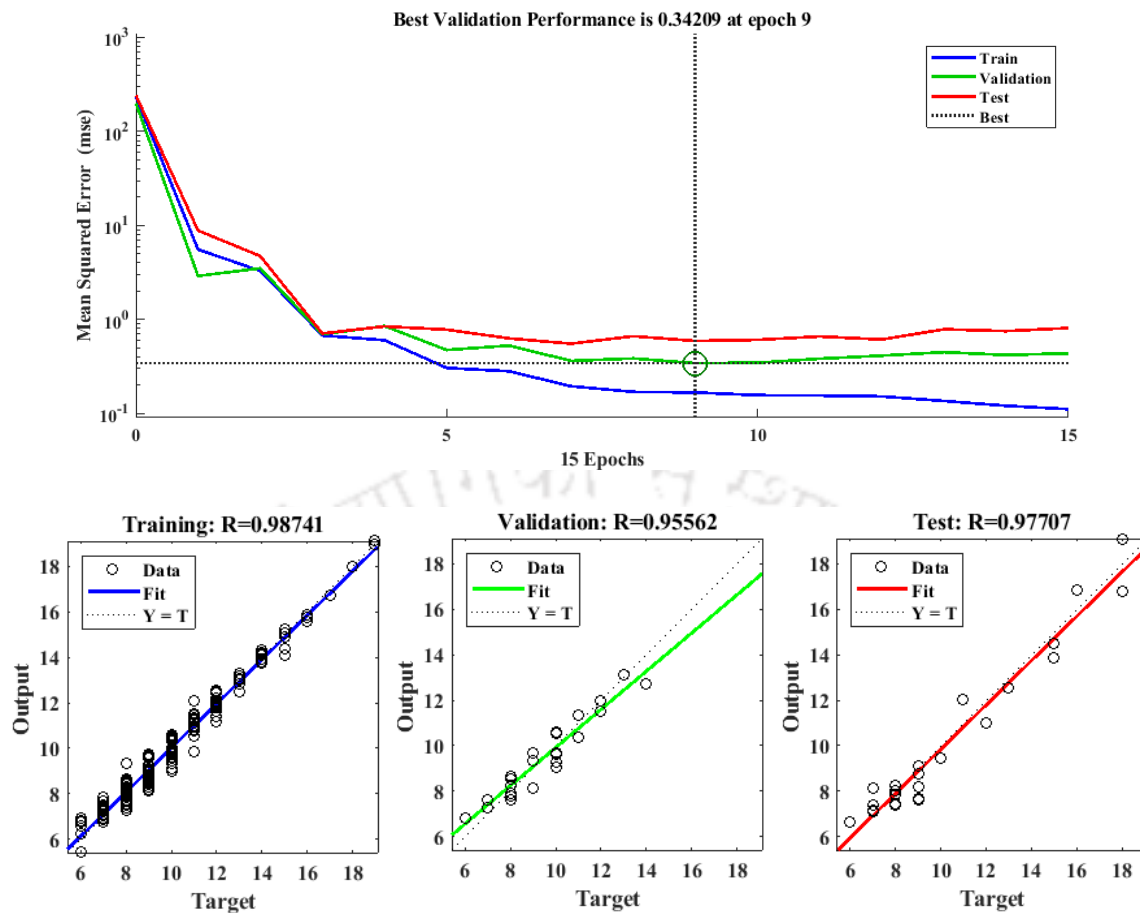


Figure 5.31: Best validation performance and correlation coefficient (R) for LM-based (80:10:10) BPMLPNN model training, validation, and testing respectively

Invoking optimal architecture (15-11-1) of GDX-based BPMLPNN models for two segregations of training:testing:validation (70:15:15 & 80:10:10), the training process is routed for 2000 epochs. The termination of model training relies on the following parameters: minimal NMSE attained, maximum epochs reached, minimum error gradient achieved, and highest validation failures verified. The training process was accomplished in 3 sec with the NMSE values of 0.4963 and 0.4967 and best validation performance of 0.7159 and 0.4495 for two segregations of 70:15:15 and 80:10:10, respectively. The correlation (R) between GDX-based BPMLPNN predicted output and AHP-based experimental target have been shown in Figure 5.32 and 5.33 for two different segregations, respectively. Owing to analysis based on the performance of the models in predicting vulnerability of lakes, it has been noticed that the order (based on correlation coefficient (R)) in which BPMLPNN models outperform each other as BR-BPMLPNN, LM-BPMLPNN, and GDX-BPMLPNN. However, there exists a very marginal difference between BR-BPMLPNN and LM-BPMLPNN models when other

performance parameters are compared, such as minimum epochs, training time and best validation performances.

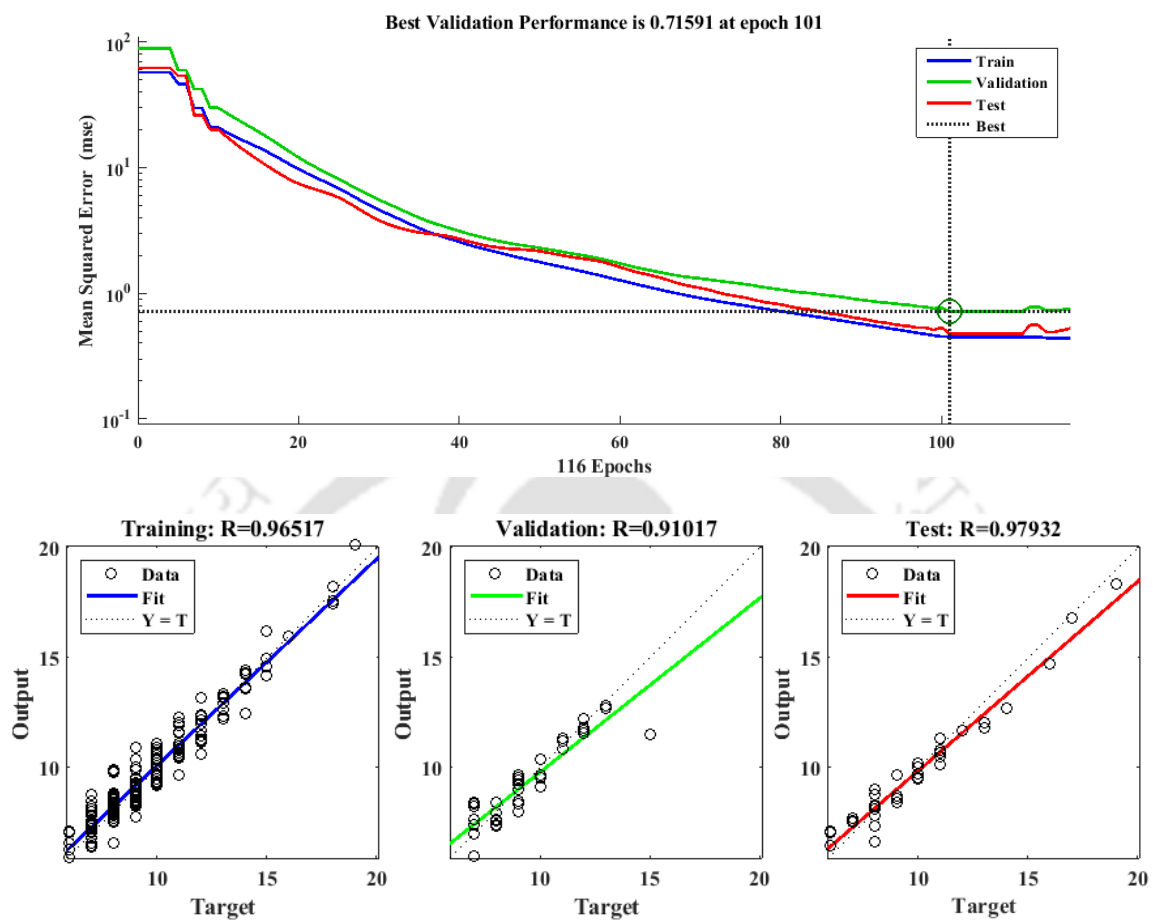
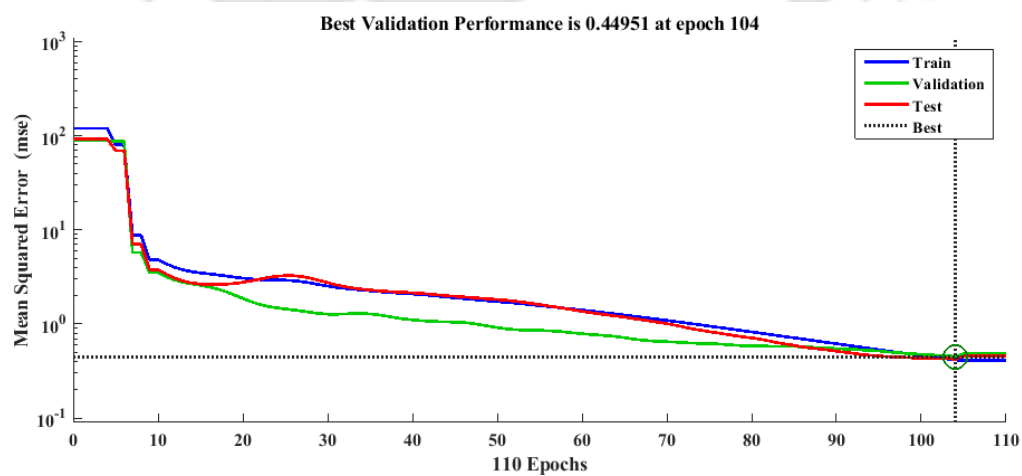


Figure 5.32: Best validation performance and correlation coefficient (R) for GDX-based (70:15:15) BPMLPNN model training, validation, and testing respectively



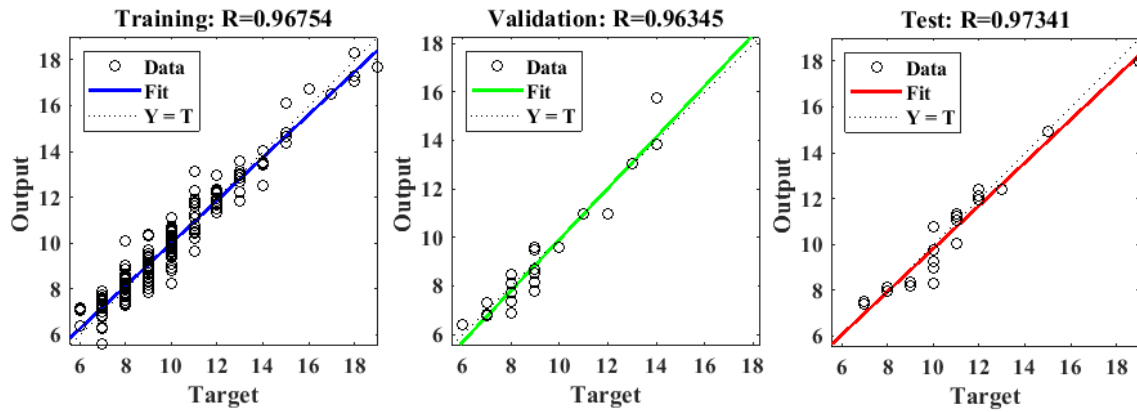


Figure 5.33: Best validation performance and correlation coefficient (R) for GDX-based (80:10:10) BPMLPNN model training, validation, and testing respectively

5.4.5 Conclusion

The present study has established an inventory of naturally formed high-altitude lakes within and around the trans-boundary Sikkim Himalayas. A total of 399 lakes were identified using an integrated approach of automated as well as manual identification, which were further filtered to 281 lakes based on the lake area threshold of $>0.01 \text{ Km}^2$. The vulnerability assessment has been carried out using fifteen parameters in an AHP-based assessment technique. The process helped in obtaining 7 lakes in Sikkim, 3 lakes in Nepal and 3 lakes in China as highly vulnerable to produce GLOF. Some of these lakes have shown large areal increment since 1989 all of them being moraine-dammed glacial lakes. Another 11 lakes in Sikkim, 4 in Nepal, 3 in China, and 2 lakes in Bhutan have come under the category of moderately vulnerable lakes. The remaining 194 lakes in Sikkim and 54 lakes in the trans-boundary locations have been identified as safe. Moreover, three backpropagation neural network models with BR-, LM-, and GDX- optimizers have been designed to determine their prediction accuracies with respect to the AHP target scores. This has been performed for different segregations of training and testing for BR-BPMLPNN and training, testing, and validation for LM- and GDX-BPMLPNN models. Invoking a comparison analysis of the training optimizers, BR-BPMLPNN model has been observed as the model with maximum performance but close similitude with LM-BPMLPNN model.

However, it cannot be neglected that estimation of the vulnerability of Himalayan lakes using remote sensing and analytical techniques has its own limitations. Therefore, it is required to conduct a field- and laboratory-based analysis of the moraine material that acts as an embankment to the glacial lakes in the Sikkim Himalayas. This can be helpful in understanding

the material and engineering properties of glacial moraines, which are important components of designing mitigation as well as moraine dam-breach modeling.



Characterization of Glacial Moraine and Lacustrine Deposits: An Investigation from Sikkim Himalayas

6.1 Introduction

Records of earthquakes (Mexico earthquake of 1985, Loma Pieta earthquake of 1989, Bhuj earthquake of 2001, etc.) and their extensive investigation prove that local site condition plays an influential role in the amplification of ground motions (Nath et al., 2018). The bedrock depth significantly alters the dynamics of the soil-subsurface system (Nath and Jakka, 2012). Therefore, it is crucial to understand the subsurface as accurately as possible because of its immense implication on the analysis of seismic impacts (Bard, 1995; Nath et al., 2015). The conventional techniques of subsurface geotechnical exploration have their challenges regarding extensive manpower and the cost involved. In this context, seismologists around the globe have begun to venture into some of the advanced geophysical techniques in exploring the subsurface and its geology. This results in easy and comparatively faster acquisition of data and processed information. Moreover, using geophysical techniques facilitates the investigation of a much larger area. Some of the areas where geophysical investigation finds wide application are exploration of fossil fuel, mineral exploration, detection of the subsurface water table, mapping permafrost, block field, sediment deposits underneath, internal structure, and depth of landslides (Hauck, 2001; Israil and Pachauri, 2003, Bicher et al., 2004; Sass, 2007). However, subsurface investigation through geophysical techniques demand experience and skill as factors such as dispersion and wave attenuation, mechanical properties of subsurface material, and various geological boundary conditions may introduce ambiguity to the data. Schrott and Saas (2007) recommend using two or multiple geophysical methods to deduce a strong conclusion from the investigation. Subsurface investigations through a combination of two or more geophysical techniques have been effectively accrued, especially for the Himalayan region (Pilecki et al., 2017; Nath et al., 2018). The Himalayan arc being tectonically active and seismically prone, has produced enormous catastrophic earthquakes such as the 1978 Assam earthquake, the 1905 Kangra earthquake 1934 Nepal earthquake, the 1991 Uttarkashi earthquake, the 1999 Chamoli earthquake, and many more (Nath and

Thingbaijam, 2012). Therefore, it is necessary to apprehend the local site conditions of Himalayan regions: qualitative and quantitative.

In the present chapter, an attempt has been made to investigate glacial moraine and lacustrine deposits around Changme and Rathong glacial snout in North Sikkim. This involves

1. Field-based geophysical investigation.
2. Laboratory-based geotechnical testing and micro-structural analysis.

6.2 Investigation of Glacial Moraine/soil Deposits

Sikkim Himalaya is characterized by a significant variation in altitude and topographic slope. The glacial bodies are located in high-altitude regions, which are also the source of major river systems such as Teesta and Rangeet, and enormous glacial lakes of various types and sizes also exist. Moraine deposits surround these glaciers and glacial lakes. Moraine deposits in the Himalayan region act as an embankment/dam material for naturally forming glacial lakes. Their strength and holding capacity control the stability of glacial lakes in terms of breach and outburst flood. Moreover, the region is seismically active, which adds an extra risk factor to the stability of glacial lakes in terms of future hazards. Therefore, conducting an extensive field- and laboratory-based analysis of moraine deposits around glacial bodies is necessary. In this section, moraine and lacustrine deposits around the Changme glacial snout (North Sikkim) and some other locations along the Lachung Chu and Lachen Chu tributaries of the Teesta river system have been investigated using geophysical techniques such as Multichannel Analysis of Surface Waves (MASW) and Ground Penetrating Radar (GPR). Moraine and Lacustrine deposits samples from Changme glacial snout (North Sikkim) and Rathong glacial snout (West Sikkim) have been collected (Figure 6.1) and brought to the Indian Institute of Technology (IIT) Guwahati campus to analyze them for their physical and engineering properties along with micro-structural analysis as shown in Figure 6.2.

Changme glacial moraine deposits
17th Oct 2021 (4698m a.s.l)



Rathong glacial moraine deposits
7th April 2022 (4667m a.s.l)



Rathong moraine sample collection
7th April 2022 (4667m a.s.l)



Rathong lacustrine sample collection
7th April 2022 (4667m a.s.l)



Figure 6.1: Photographs of glacial moraine and lacustrine deposits in Sikkim

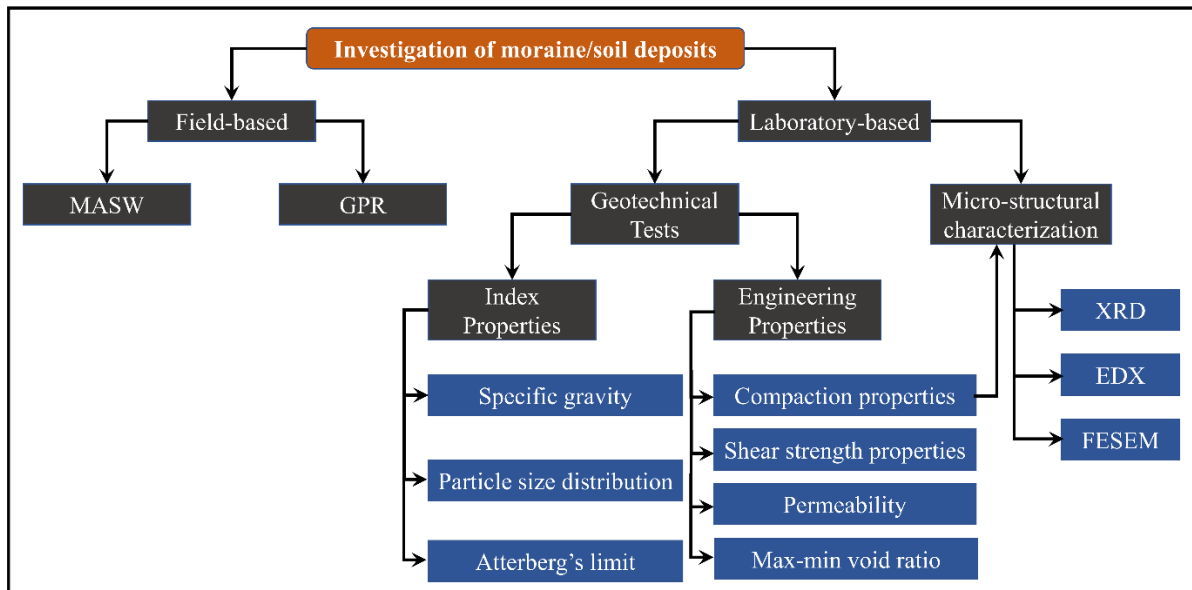


Figure 6.2: Tests and experiments for the geotechnical and geological investigation of moraine deposits in Sikkim Himalaya

6.2.1 Field-based Experiments

There are numerous geotechnical tests to understand the subsurface soil characteristics of a site. A standard penetration test (SPT) and cone penetration test (CPT) are the most commonly used field-based tests. Cyclic triaxial test, uniaxial compressive test (UCT), direct shear test (DST), and vane shear test (VST) are the most widely performed geotechnical tests in the laboratory. Both categories of tests have their advantages and disadvantages. Where the advantages of field-based experiments involve testing undisturbed samples in their natural environment and stratigraphic profiling, the disadvantages of such experiments include indirect and empirical measurement of engineering properties of soil, being labor-intensive, and involving colossal capital. Henceforth, engineers came up with the alternative of geophysical tests. A shock is created in geophysical methods like seismic reflection surveys or seismic refraction surveys. The reaction that the ground gives against the shockwave characterizes the subsurface soil properties.

The shear stiffness of soil is one of the most important properties engineers evaluate. The shear stiffness of soil can be interpreted with the response of ground to shear wave propagation, which is a body wave. Body waves have a very low signal-to-noise (SNR) ratio near the ground surface (Kramer, 1996). So, Rayleigh waves are used to characterize soil properties of the top 50 meters of the ground. Rayleigh waves typically have elliptical motions and high SNR because of their low frequency, low shear, and high amplitude (Park et al., 1999).

Moreover, Rayleigh waves have a velocity of nearly about 90 percent of that of the shear wave velocity. Multichannel Analysis of Surface Waves (MASW) is one of the most popular geophysical methods in practice these days. For imaging and describing the shallow subsurface, Rayleigh-type surface waves' frequency-dependent characteristics are used in this method for imaging and describing the shallow subsurface. In multichannel recordings, noise can be effectively identified and isolated based on unique trace-to-trace coherency in arrival time and amplitude (Park et al., 2007).

6.2.1.1 Multichannel Analysis of Surface Waves (MASW)

Multi-Channel Surface Wave Analysis (MASW) is one of the most used geophysical methods to evaluate soil stiffness in the current practice. The non-invasive nature of the MASW method makes it the foremost choice for engineers to use for field exploration. The field instrument setup for this method consists of a hammer, a baseplate, multiple numbers of geophones, a triggering cable, control unit cables, a battery, and one data acquisition system, as shown in Figure 6.3 below. MASW survey can be done in both active and passive ways. In the field for active MASW survey, the base plate is placed at the start of the setup. One triggering geophone is placed just next to the baseplate. The triggering geophone is connected to a cable that bridges the Data Acquisition System (DAS) and the triggering geophone. Following the triggering geophone, multiple geophones are placed, connected through a cable to the DAS. This entire setup is shown in Figure 6.4 below. The base plate is struck with a hammer to generate seismic waves. These waves are then captured through the geophones. The ground stiffness is evaluated based on the arrival time of seismic waves to each geophone. The ground stiffness profile with respect to depth is obtained at the middle of the setup in a static linear array. This is called the 1-D MASW survey. In the 2-D survey, the array is shifted parallelly through a certain distance. Multiple shifts provide the complete 2-D profile of ground stiffness with respect to depth. In the 3-D survey, a parallel shift, and a perpendicular shift is performed to generate a 3-D profile. MASW survey is also done passively, where the seismic waves captured are not generated with the strike of the hammer. Instead, the waves produced from traffic, machine, blasting, etc., in the vicinity, are used. The raw data of MASW provides dispersion curves. This dispersion curve is the phase velocity-frequency graph. This graph is derived from the Fourier transformation of the group velocity-frequency of the seismic waves captured through geophones. An inversion analysis is done on the dispersion curve to evaluate the subsurface's final shear wave velocity profile.



Figure 6.3: MASW survey kit with all the components



Figure 6.4: Installation of MASW geophones for data acquisition

Records of the multichannel surface waves have been acquired during a field investigation conducted between 15th-24th Oct 2021 in the North Sikkim region. The datasets have been collected at different locations and altitudes along with the Changme glacial snout consisting of relatively homogenous glaciofluvial deposits, as shown in Figures 6.5 and 6.8.

The surface wave records have been collected using two different configurations of vertical geophones (12/24) arranged as a linear array with a 4.5 Hz natural frequency. Various combinations for measurement profiles and source offsets have been used, as shown in Table 6.1. For every combination, multiple surface wave records have been acquired, thus resulting in 167 records. The impact load has been created using a sledgehammer (10 Kg). The notion behind acquiring a large volume of datasets using multiple configurations of measurement profiles lies in the appropriate choice for the most informative results through the proposed methodology.

Table 6.1: MASW configurations (**bold** and underlined values are for the results presented)

Survey Code	Location	Configuration Orientation	Altitude (m a.s.l)	Number of Geophones	Offset (m)	Geophone Interval (m)	No. of Data
MASW1	Lachung Playground	NE-SW	2585	24	<u>3,4</u>	1	11
MASW2	Changme Glacial Snout	N-S	4698	24	<u>1,3</u>	1	14
MASW3	Yumthang Valley	N-S	3693	12	1,3	2	12
				24	<u>1,3</u>	1	13
MASW4	b/w Lachen & Thangu Valley	N-S	3268	12	1,3	2	14
				24	<u>1,3</u>	1	16
MASW5	b/w Lachen & Thangu Valley	N-S	3117	12	1,2,3,4	2	21
				24	<u>1,2,3,4</u>	1	23
		E-W		12	1,2,3,4	2	20
				24	<u>1,2,3,4</u>	1	23

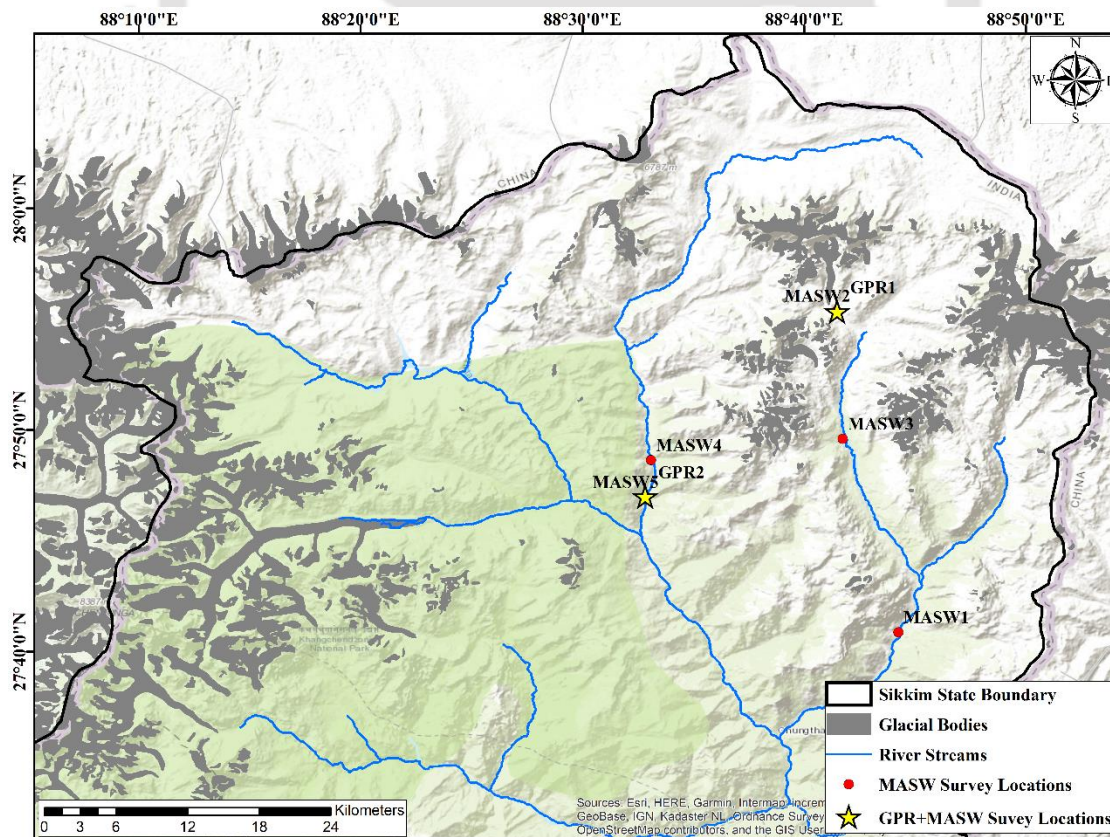


Figure 6.5: Map showing the locations of MASW and GPR survey in North Sikkim

6.2.1.2 Ground Penetrating Radar (GPR)

GPR is a non-destructive and non-invasive geophysical tool extensively used for subsurface investigations through imaging. Imaging the subsurface at shallow depths (≤ 10 m) can be performed at high resolution. For investigating much deeper depths, the resolution and accuracy get compromised. GPR operates according to the concept of dielectric constant. As moving vertically downwards on a ground surface, the properties of the soil layers change in terms of dielectric constants. The lower dielectric constant of soil indicates higher electromagnetic (EM) wave velocity and vice versa. The frequency of the antennas used in GPR range from 4 GHz to 10 MHz. The penetrating depth of the transmitted EM waves is a function of the antenna frequency. The instrument can be used in two different modes: transmission or frequency mode. The most commonly used method is the reflection profiling survey, performed using two antennae with a separate receiver and transmitter and is therefore also termed as bi-static mode. The antennas are positioned directly on the ground surface or near the ground. To enhance the speed of the survey and protect the equipment from damage, the antennas can be mounted on a wheeled platform or sled/trolley.

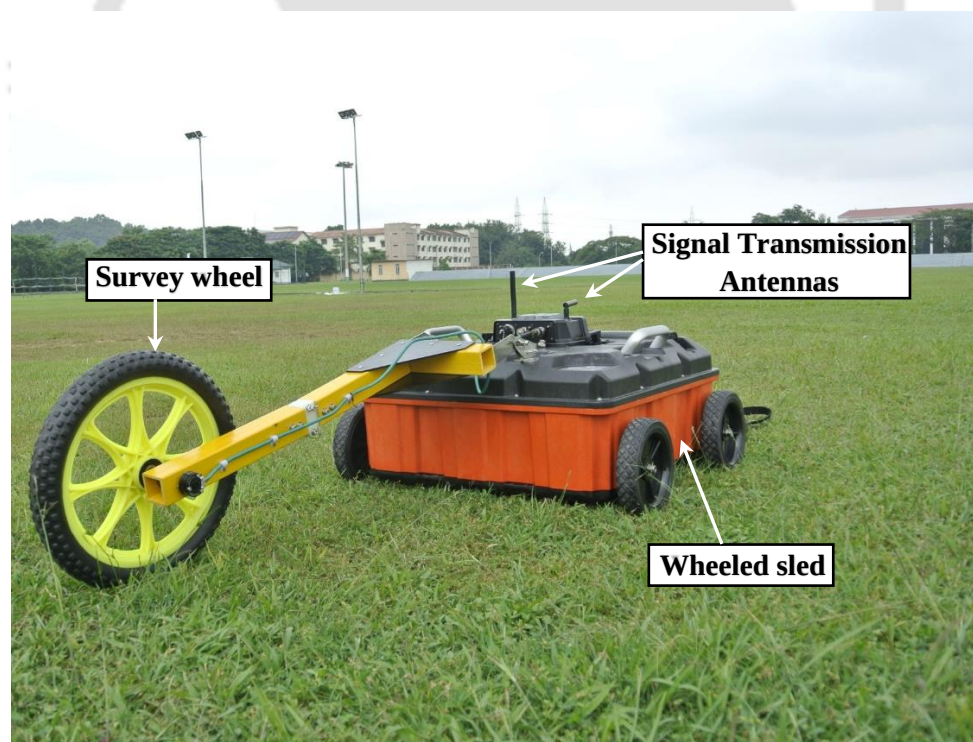


Figure 6.6: GPR and its components



Figure 6.7: Display and control unit of GPR

An investigation was conducted by Bristow and Jol. (2003) shows that the use of 100 MHz antennas results in the best trade-off between the resolution of data acquisition and the penetration depth. However, lower-frequency antennas (35 and 80 MHz) can be used to investigate bedrock at much deeper depths. Sass (2007) extensively measured the sediment thickness and depths of alpine talus slopes using GPR, seismic refraction and 2-D resistivity survey. It has been observed that utilizing two or multiple geophysical techniques improves the quality of data interpretation. GPR's resolution and range primarily depend on the antenna frequency and sediment mineralogy (Motoyuki, 2001). The major limitation of GPR is its incapability to determine the subsurface geology's mechanical or index properties. The moisture content of the subsurface layers profoundly influences the penetration depth of EM waves as soil's conductivity and electrical resistivity change. In the present study, a wheeled trolley-mounted GPR (200 MHz) has been used, having six major hardware components: (a) control unit, (b) transmitter, (c) receiver, (d) antennae, (e) survey wheel, (f) interface, display and data storage module (Figure 6.6 and 6.7). Automatic gain control (AGC) was applied while acquiring data (Neal, 2004). The datasets have been collected through point-to-point and time modes of the survey. Further, processing of the datasets has been performed using the GPR manual supplied by the Geophysical Survey System instruments (GSSI) in the RADAN (GSSI computer-based interface) software applying 2-D spatial fast Fourier transform, finite impulse response (FIR), and infinite impulse response (IIR) filters, gain control, de-convolution, surface normalization, hyperbola migration, and bandpass filtering.

6.2.2 Laboratory-based Experiments

Moraine and lacustrine samples collected from the Changme and Rathong glacial snouts were tested for their geotechnical properties in the geotechnical laboratory, Department of Civil Engineering, Indian Institute of Technology Guwahati. The samples were tested for relevant index and engineering properties as per the provisions of the Indian Standard (IS) codes (IS 2720 (Part III) – 1980; IS 2720 (Part IV) – 1985; IS 2720 (Part V) – 1985; IS 2720 (Part VI) – 1972; IS 2720 (Part XIII) – 1986; IS 2720 (Part XIV) – 1983; IS 2720 (Part XVII) – 1986. Moreover, to conduct the micro-structural characterization and understand the mineralogical composition of the samples, Field emission scanning electron microscopy (FESEM), X-ray powder diffraction (XRD) and energy dispersive X-ray analysis (EDX) was performed.

6.3 Results and Discussion

6.3.1 MASW Survey



Figure 6.8: MASW survey at a location (MASW5) between Lachen and Thangu valley (left) and (MASW2) Changme glacial snout (right)

6.3.1.1 Dispersion Analysis

The first step is dispersion analysis. The main objective behind dispersion analysis is identifying experimental dispersion curves based on the MASW records. For active-source surveys, the transform-based approach is most commonly used (Socco et al., 2010). This involves the phase shift method (Park et al., 1998), slowness-frequency transform (McMechan and Yedlin, 1981), and frequency-wave number transform (Yilmaz and Baysal, 2015), where the transformation of the multichannel time series is performed into a different domain from space-time domain. The phase shift method is comparatively more computationally efficient and robust, providing fundamental mode phase velocities more accurately even when the

datasets are acquired from a limited number of geophones. The phase shift method has three main steps: amplitude normalization and Fourier transformation, dispersion imaging, and extraction of dispersion curves. In the present study, the surface wave records have been analyzed using a phase shift approach in SURFSEIS 6.0 software, as shown in Figure 6.9.

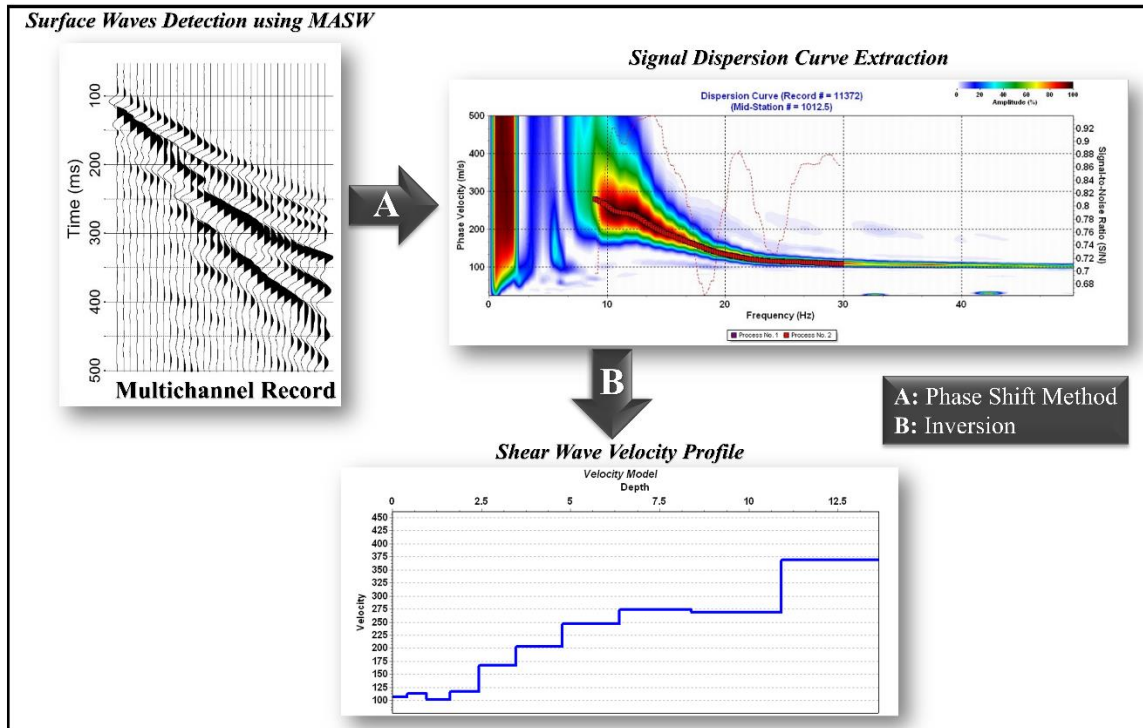


Figure 6.9: Flow diagram for MASW data processing

Every record has been processed separately using the phase shift approach. The variability associated with the identified elementary dispersion curves has been subsequently evaluated through the coefficient of variation (C_V) at each frequency among the values of estimated phase velocity (Equation 6.1), where s_c corresponds to the standard deviation and $\bar{c}$ is the mean phase velocity values at frequency f .

$$C_V = \frac{s_c}{\bar{c}} \quad (6.1)$$

The best-obtained records of dispersion images, along with the fundamental mode dispersion curves acquired for five locations in North Sikkim with the best-suited measurement profile configuration, have been shown in Figures 6.10 to 6.14. The estimates for the dispersion curve as obtained from diverse measurement profile configurations are reliable, characterized by the coefficient of variation (C_V) ranging between 1-8% at each frequency. The higher frequency components portray less variability than the lower frequency components.

The configuration adopted for the measurement profile i.e., the source offset and the receiver length spread, resulting in significant effects on the obtained dispersion imagery and, subsequently, on the dispersion curve frequency range. In general. The recorded time series obtained from the shortest receiver spread provided the most information on dispersion properties of higher frequency (shorter wavelength) wave components propagating through the uppermost soil layers. Increasing the length of receiver spread resulted in enhanced spectral resolution facilitating the identification of fundamental mode at the lower frequencies. Therefore, it has been observed that a longer receiver spread resulted in greater investigation depth as per the existing recommendations (Park et al., 2010).

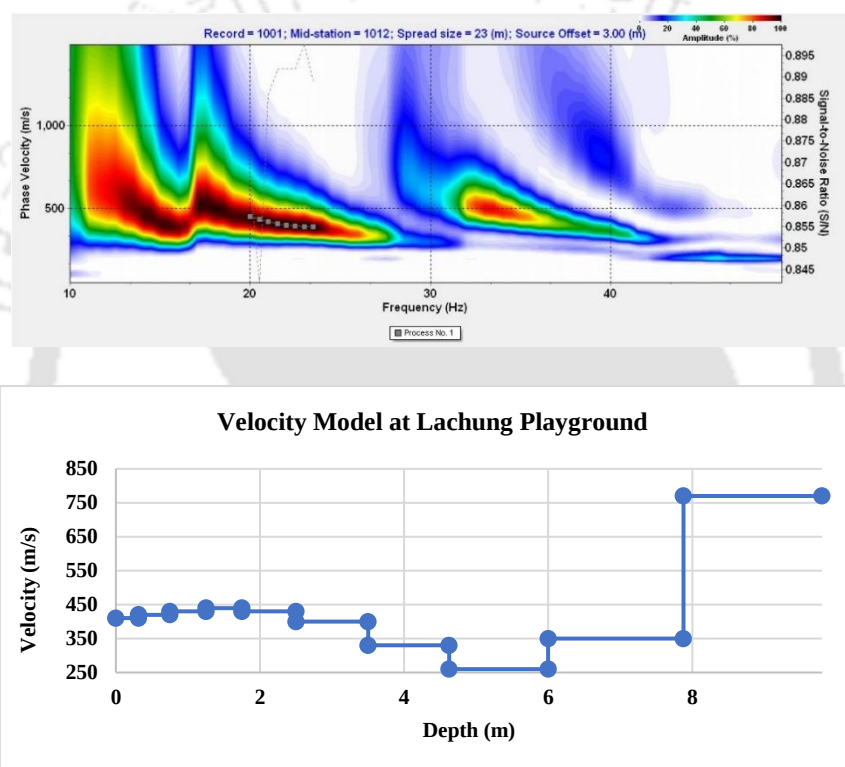
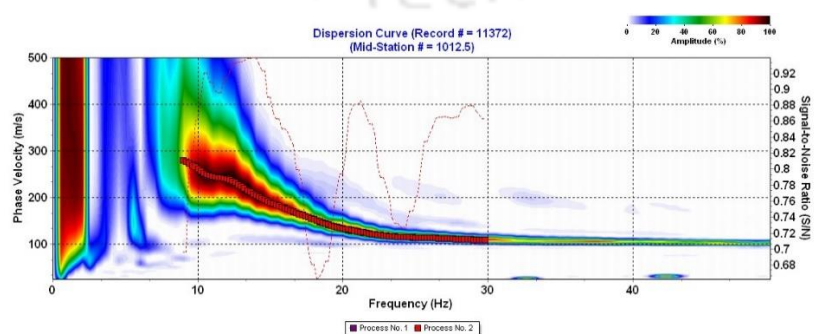


Figure 6.10: The fundamental-mode dispersion curve and shear wave velocity profile at Lachung playground (MASW1)



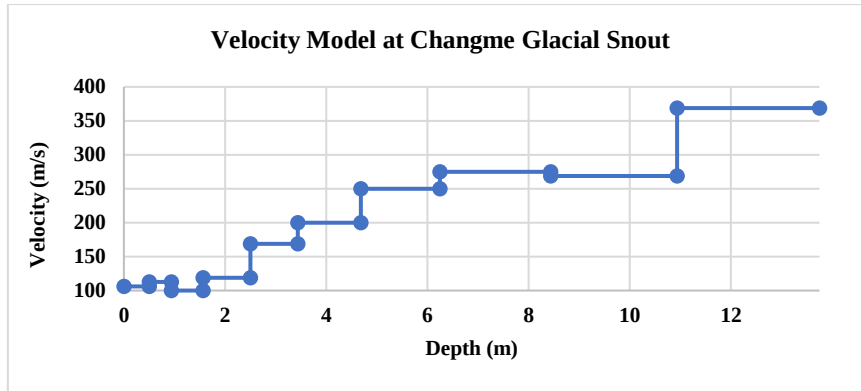


Figure 6.11: The fundamental-mode dispersion curve and shear wave velocity profile at Changme glacial snout (MASW2)

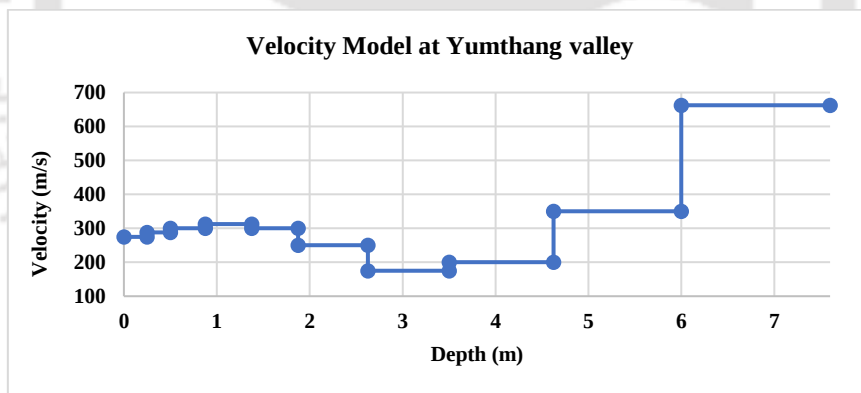
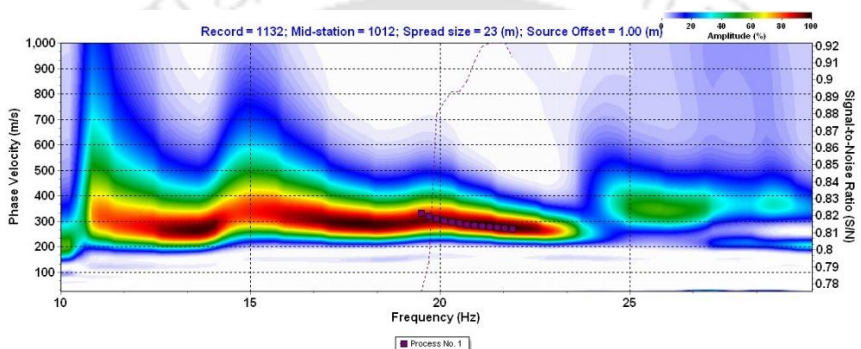
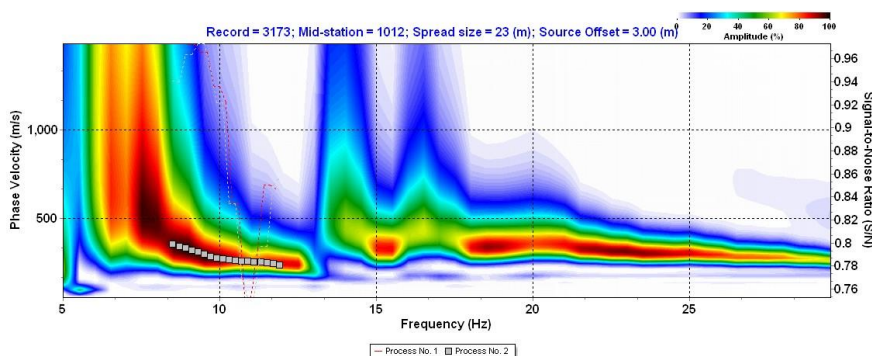


Figure 6.12: The fundamental-mode dispersion curve and shear wave velocity profile at Yumthang valley (MASW3)



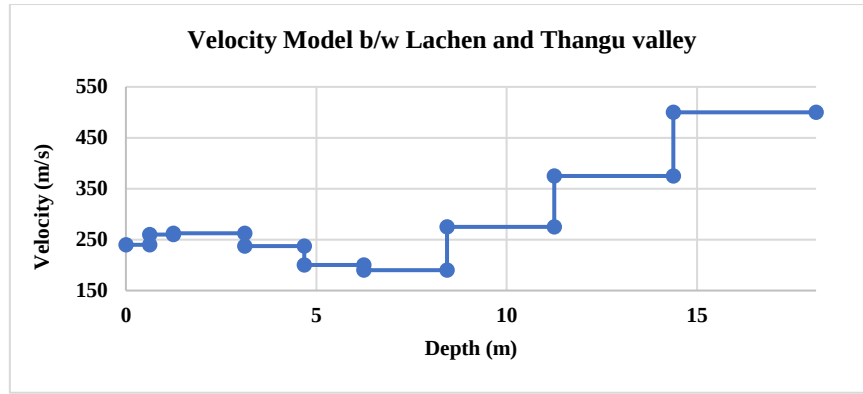


Figure 6.13: The fundamental-mode dispersion curve and shear wave velocity profile between Lachen and Thangu valley (MASW4)

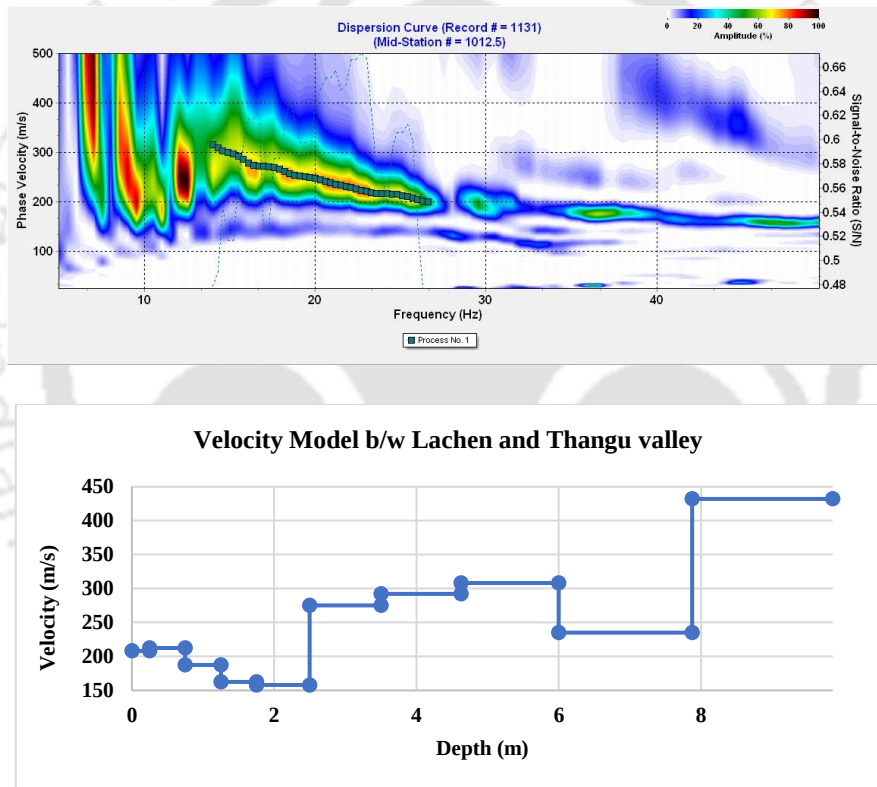


Figure 6.14: The fundamental-mode dispersion curve and shear wave velocity profile between Lachen and Thangu valley (MASW5)

Analyzing the dispersion curves obtained for various locations and at various altitudes in North Sikkim shows that in the case of Lachung playground at an elevation of 2585m a.s.l (MASW1), the frequency ranges between 8 Hz and 30 Hz as shown in Figure 6.10. Figure 6.11 shows the dispersion curve for Changme glacial snout (MASW2) at an elevation of 4698m a.s.l where the frequency lies in the range of 8 to 32 Hz. In Figure 6.12, the control points have a higher mode because of the modal jump in the dispersion curve between 18 to 23 Hz. Similarly,

in Figures 6.13 and 6.14, the dispersion curve control points range between 7 to 13 Hz and 13 to 27 Hz, respectively.

6.3.1.2 Shear Wave Characterization of Soil/moraine/glaciofluvial Deposits

Several types of research have been conducted, and numerous methods have been proposed for the classification of rocks and soils based on their site-dependent amplification properties (Joyner et al., 1981; Tinsley et al., 1985; Borchardt, 1994; Will et al., 2000). Joyner et al. (1981) proposed a way to characterize site conditions using average shear wave velocities up to a depth equal to 0.25 times the wavelength of the dominant frequency. However, this method did not find extensive application due to execution difficulties. Borchardt et al. (1991) developed a more simplified method using a correlation between the average shear wave velocity and amplification of ground motion up to 30m depth of rocks/sediments. This method has been incorporated into the National Earthquake Hazards Reduction Program (NEHRP). The NEHRP categorizes soils into different classes based on their thickness, vertical shear wave velocity profile, and liquefaction potential. According to NEHRP, the subsurface shear wave velocity (V_s) is estimated up to 30m. The subsurface NEHRP V_s at a particular site can be calculated using equation 6.2.

$$V_s = \frac{\sum_{i=1}^n D_i}{\sum_{i=1}^n \frac{D_i}{v_{si}}} \quad (6.2)$$

where V_s is the NEHRP shear wave velocity, D_i is the subsurface layer thickness (≤ 30 m) and v_{si} is the shear wave velocity at the subsurface layer in m/s. Table 6.2 shows the NEHRP classification system.

Table 6.2: Classification of site soil profile type for seismic amplification (N: SPT blow count; S_u : Undrained shear strength; PI: Plasticity Index and w: Water content)

NEHRP site class	General description	Average V_s to 30m (m/s)
A	Hard rock	> 1500
B	Rock	$760 < V_s \leq 1500$
C	Soft rock and very dense soil	$360 < V_s \leq 760$
D	Stiff soil ($50 \text{ kPa} \leq S_u \leq 100 \text{ kPa}$ or $15 \leq N \leq 50$)	$180 < V_s \leq 360$
E	Soil with more than 3m soft clay strata with $PI \geq 20$, $w \geq 40\%$, and $S_u < 25 \text{ kPa}$	≤ 180
F	Soils that need site-specific evaluations	

Analyzing the shear wave velocity (V_s) profiles for the five different locations in North Sikkim, the average V_s to 30m ($V_{s(30)}$) has been determined, as shown in Table 6.3. Maximum $V_{s(30)}$ has been observed at Lachung playground (MASW1), which is about 394 m/s. This site can be classified as site class C according to the NEHRP criteria. The Changme glacial snout

region lying close to the high-altitude glaciated regions has the lowest $V_{s(30)}$ value (209 m/s) and NEHRP site class D has been assigned. All the other locations come under the NEHRP site class D, as shown in Table 6.3. Figure 6.15 shows the $V_{s(30)}$ interpolation map of the region generated using the inverse distance weighted (IDW) interpolation method.

Table 6.3: NEHRP site classification for the locations investigated in North Sikkim

(Code) Location	$V_{s(30)}$ (m/s)	NEHRP site class
(MASW1) Lachung Playground	394	C
(MASW2) Changme Glacial Snout	209	D
(MASW3) Yumthang Valley	287	D
(MASW4) b/w Lachen & Thangu Valley	293	D
(MASW5) b/w Lachen & Thangu Valley	256	D

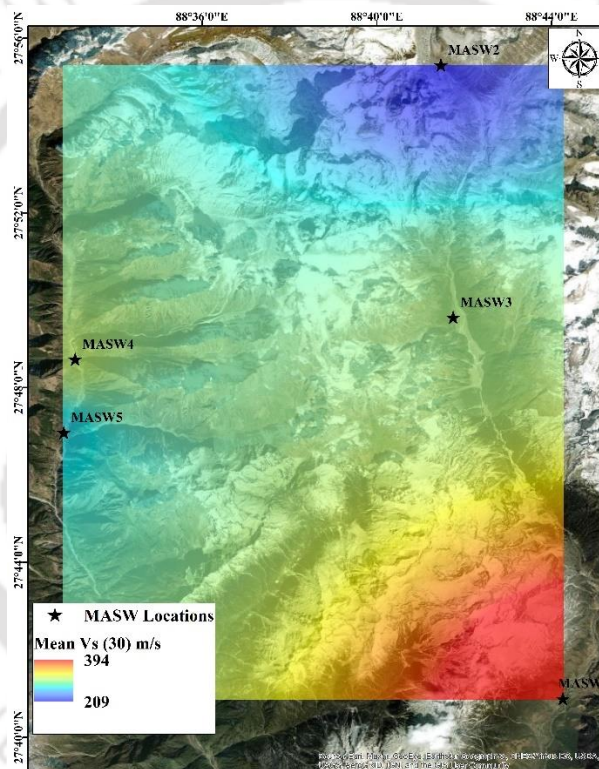


Figure 6.15: The $V_{s(30)}$ interpolation map of North Sikkim

6.3.2 GPR Survey

The GPR survey has been performed in two locations (MASW5 & MASW2) in North Sikkim where the MASW survey has also been conducted, as shown in Figure 6.16. The subsurface profiling for the GPR survey has been executed for the same orientation as the MASW survey. For the location between Lachen and Thangu valley (MASW5), the GPR survey provided subsurface information up to the depth of 20m with three distinct layers of varying thickness.

Demarcating the ground surface level at 0m, the initial layer extends up to 4m, followed by a second and third layer of about 4 and 12m thickness, respectively.



Figure 6.16: GPR survey at a location (MASW5) between Lachen and Thangu valley (left) and (MASW2) Changme glacial snout (right)

It is a well-understood fact that GPR imaging does not provide information regarding the subsurface's index and/or mechanical properties. Therefore, the layers demarcated in this section are based purely on visual inspection and interpretation of structural discontinuities underneath the ground surface. From 4 to 8m depth, observed parallel reflectors have been considered as the basis of layer segregation. Within the 2nd layer extending up to 8m deep, a gentle slope from 5 to 6m has been observed, as shown in Figure 6.17 (left). However, it must be considered that GPR's imaging performance is hampered in clay-rich/conductive environments due to larger signal attenuation (Nath et al., 2018). Therefore, there exists the possibility that the tail of a diffraction hyperbolae is misinterpreted as a sloping layer. This problem has been solved from interpretation using both GPR and MASW results. The V_s profile of the same location and orientation has been obtained using the MASW setup as shown in Figure 6.14. V_s can be defined as the velocity at which shear waves generated due to an earthquake event will propagate through the subsurface strata of soil/rock. V_s is directly proportional to the subsurface material's shear modulus ($\bar{G}$) which is a dynamic geotechnical property. Therefore, the estimation of V_s for a subsurface stratum can be considered the firsthand step in assessing the local site condition as it represents the stiffness of different subsurface layers. An attempt to comprehend the results from MASW and GPR simultaneously has helped gather some interesting observations in this case. The GPR-based subsurface

imaging indicates an inclined layer between 5 and 6m depths from the ground surface. The results obtained from the MASW survey reveal a fragile layer ($V_s \leq 300$ m/s) up to 8m deep from the ground surface. A sudden drop in V_s at 6m depth has been observed that can be attributed to the existence of layer inclination at this depth. Moreover, a sudden fall in the V_s has been observed between 6 and 8m depths followed by a sudden rise in the shear wave velocity. Increased V_s indicates increased stiffness of the subsurface layer and vice versa. This indicates a third layer with greater stiffness than the second layer from 8 to 20m depths.

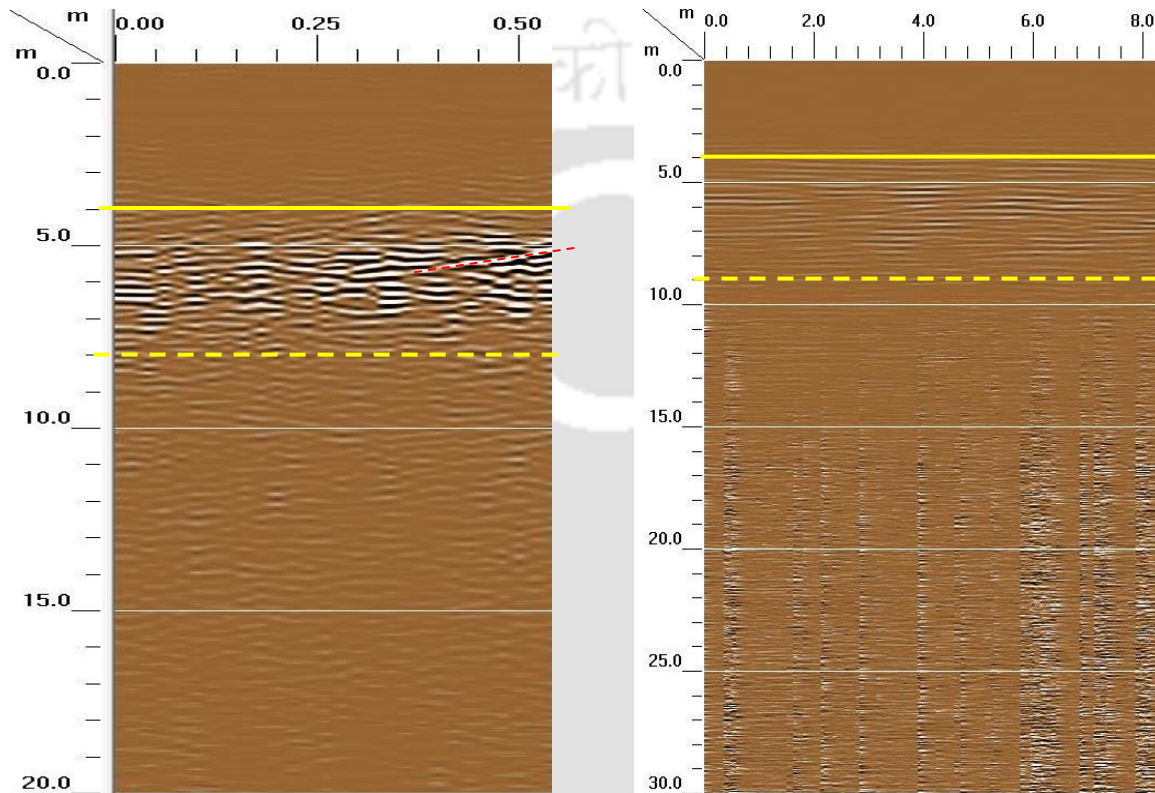


Figure 6.17: GPR results at two different locations (left: MASW5 & right: MASW2) in North Sikkim (continuous and dotted yellow lines denote the boundaries of the intermediate layer and dotted red line represents the inclined layer)

Figure 6.17 (right) shows the GPR survey at Changme glacial snout (MASW2). The results seem comparatively less informative than the MASW5 location. The first layer underneath the ground surface extends up to a depth of 4m, followed by a second layer of 5m thickness. Even though sets of parallel reflectors have been observed in the second layer, their visualization is less profound than the previous location (MASW5). The MASW survey shows a fragile layer up to 10.63m below the surface ($V_s \leq 300$ m/s), as shown in Figure 6.11. However, V_s has been observed with a sudden increase after 10.63m indicating a stiffer stratum underneath. Even though GPR profiling has helped in imaging the subsurface upto a depth of

30m, the information below 10m has been acquired with noise. This may be attributed to the dispersion and scattering of radio waves at that depth. As glaciofluvial deposits characterize the location, GPR may not be sufficient to investigate the subsurface to much deeper strata.

6.3.3 Laboratory-based Geotechnical Testing

Geotechnical testing has been performed for the Changme glacial moraine (CM) and lacustrine (CL) samples and Rathong glacial moraine (RM) and lacustrine (RL) samples. The index properties such as specific gravity, grain size distribution, and Atterberg's limits have been determined in accordance with the Indian Standard (IS) codal provisions mentioned in section 6.2.2 and Table 6.4. It has been observed that the specific gravity (G) of CM shows close similitude with RM. Similarly, not much differences in the specific gravity have also been observed between the CL and RL samples. In the case of Changme glacial deposits, CM has been observed with the dominance of non-plastic silt (~70%) with some fine and medium sand with no clay. The glaciofluvial sample (CL) from the same location has been identified with the major composition of fine sand (~77%) with an appreciable amount of silt (~21%) and a trace amount of medium sand but devoid of clayey particles. The liquid limit (LL) for both CM and CL samples has been determined as 25.23% and 35.9%, respectively (Table 6.4). However, the plastic (PL) and shrinkage limits (SL) could not be determined for either of the samples due to the presence of non-plastic silt. The moraine sample (RM) obtained from the Rathong glacial snout has been observed with a large proportion of gravel (~40%) (Figure 6.1) with a significant amount of sand (~60%). On the other hand, the RL sample has a dominance of fine and medium sand (~91%) with trace amounts of coarser sand particles and silt, as shown in Table 6.5. As also observed for CM and CL samples, the RM and RL samples are devoid of clay. The Atterberg's limits for the Rathong samples have not been determined because the samples are composed of coarse-grained particles in abundance, and finer particles such as silt and clay are either completely absent or present in negligible amounts. Thus, both the moraine and glaciofluvial samples from the Rathong region have been classified as poorly graded sand (SP) as per the provisions of the IS code.

Table 6.4: Index properties of deposits from Changme glacial snout

Properties	Value		Standard
	Moraine	Lacustrine	
Specific Gravity	2.55	2.61	IS 2720 (Part III) - 1980
Grain Size Distribution (%)			
Coarse Sand (4.75-2 mm)	0.00	0.00	
Medium Sand (2-0.425 mm)	10.00	2.15	
Fine Sand (0.425-0.075 mm)	19.98	77.21	IS 2720 (Part IV) - 1985
Silt (0.075-0.002 mm)	70.02	20.64	
Clay (<0.0002 mm)	0.00	0.00	

<i>Atterberg 's Limit (%)</i>			
Liquid Limit (LL)	25.23	35.90	IS 2720 (Part V) - 1985
Plastic Limit (PL)	NA	NA	
Shrinkage Limit (SL)	NA	NA	IS 2720 (Part IV) - 1972

Table 6.5: Index properties of deposits from Rathong glacial snout

Properties	Value	
	Moraine	Lacustrine
Specific Gravity	2.54	2.58
Grain Size Distribution (%)		
Gravel (>4.75 mm)	40.40	0.00
Coarse Sand (4.75-2 mm)	10.45	4.51
Medium Sand (2-0.425 mm)	29.62	31.21
Fine Sand (0.425-0.075 mm)	19.53	59.45
Silt (0.075-0.002 mm)	0.00	4.83
Clay (<0.0002 mm)	0.00	0.00
Atterberg 's Limit (%)		
Liquid Limit (LL)	NA	NA
Plastic Limit (PL)	NA	NA
Shrinkage Limit (SL)	NA	NA
Soil Classification (IS)	SP	SP

Considering the grain size distribution of the samples, compaction properties have been determined for CM and CL and not for RM and RL as optimum moisture content (OMC) and maximum dry density (MDD) are not preferred for coarse-grained soil. The OMC and MDD values for CM and CL samples have been mentioned in Table 6.6. A direct shear test has been performed to determine the shear strength properties (cohesion (c) and angle of internal friction (ϕ)) of the samples. Owing to the larger amount of silt in the CM sample, a much higher value of cohesion (22.3 kPa) has been observed as compared to RM as shown in Table 6.7. However, the ϕ value is higher for RM. In the case of CL and RL samples, the shear strength properties (c and ϕ) do not show much variations. The coefficient of permeability (k), obtained from the constant head permeability test, lie in the range of 10^{-4} to 10^{-3} and 10^{-6} to 10^{-5} for Rathong and Changme samples, respectively. The maximum and minimum void ratios for RM and RL samples, as obtained from the relative density test, are shown in Table 6.7.

Table 6.6: Engineering properties of deposits from Changme glacial snout

Properties	Value		Standard
	Moraine	Lacustrine	
Compaction Properties			
Optimum Moisture Content (%)	14	19	IS 2720 (Part VII) - 1980
Maximum Dry Density (g/cc)	1.80	1.65	
Shear Strength Properties			
Cohesion (kPa)	22.30	14.83	IS 2720 (Part XIII) - 1986
Angle of Internal Friction (°)	15.61	19.54	
Coefficient of Permeability (k in cm/s)	10^{-6} - 10^{-5}		IS 2720 (Part XVII) - 1986

Table 6.7: Engineering properties of deposits from Rathong glacial snout

Properties	Value		Standard
	Moraine	Lacustrine	
Shear Strength Properties			
Cohesion (kPa)	5.43	16.73	IS 2720 (Part XIII) - 1986

Angle of Internal Friction (°)	22.44	20.42	
Coefficient of Permeability (k in cm/s)	10 ⁻⁴ -10 ⁻³		IS 2720 (Part XVII) - 1986
Maximum void ratio (<i>e</i> _{max})	0.48	0.87	
Minimum void ratio (<i>e</i> _{min})	0.22	0.43	IS 2720 (Part XIV) - 1983

6.3.4 Physiochemical and Micro-structural Analysis

The physiochemical and micro-structural analysis of the moraine and lacustrine samples have been performed at the Central Instrument Facility (CIF), Indian Institute of Technology Guwahati. The morphological structure of the sediments has been examined with the help of field emission scanning electron microscopy (FESEM) (Zeiss, Gemini 300, Germany). Also, the mineralogical composition of the samples has been examined using X-ray Diffraction (XRD) (Rigaku, SmartLab9KW, Japan). The instrument is equipped with D/tex ultra 250 solid-state detectors working at $\lambda=1.54\text{\AA}$ and Cu- α X-ray source. The samples have been scanned at 3° to 80° diffraction angles, scan speed of 20° 2 θ /min, and 0.02 step size. The mineralogical composition thus obtained has been confirmed using available literature and the International Center for Diffraction Data (ICDD).

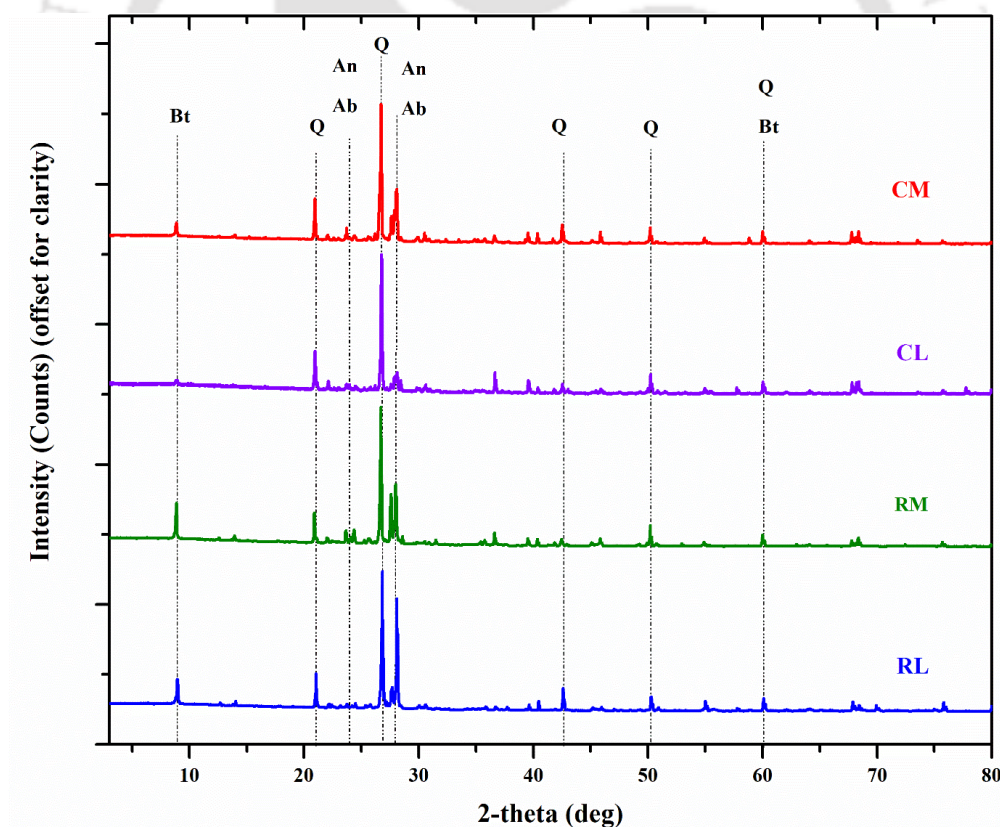
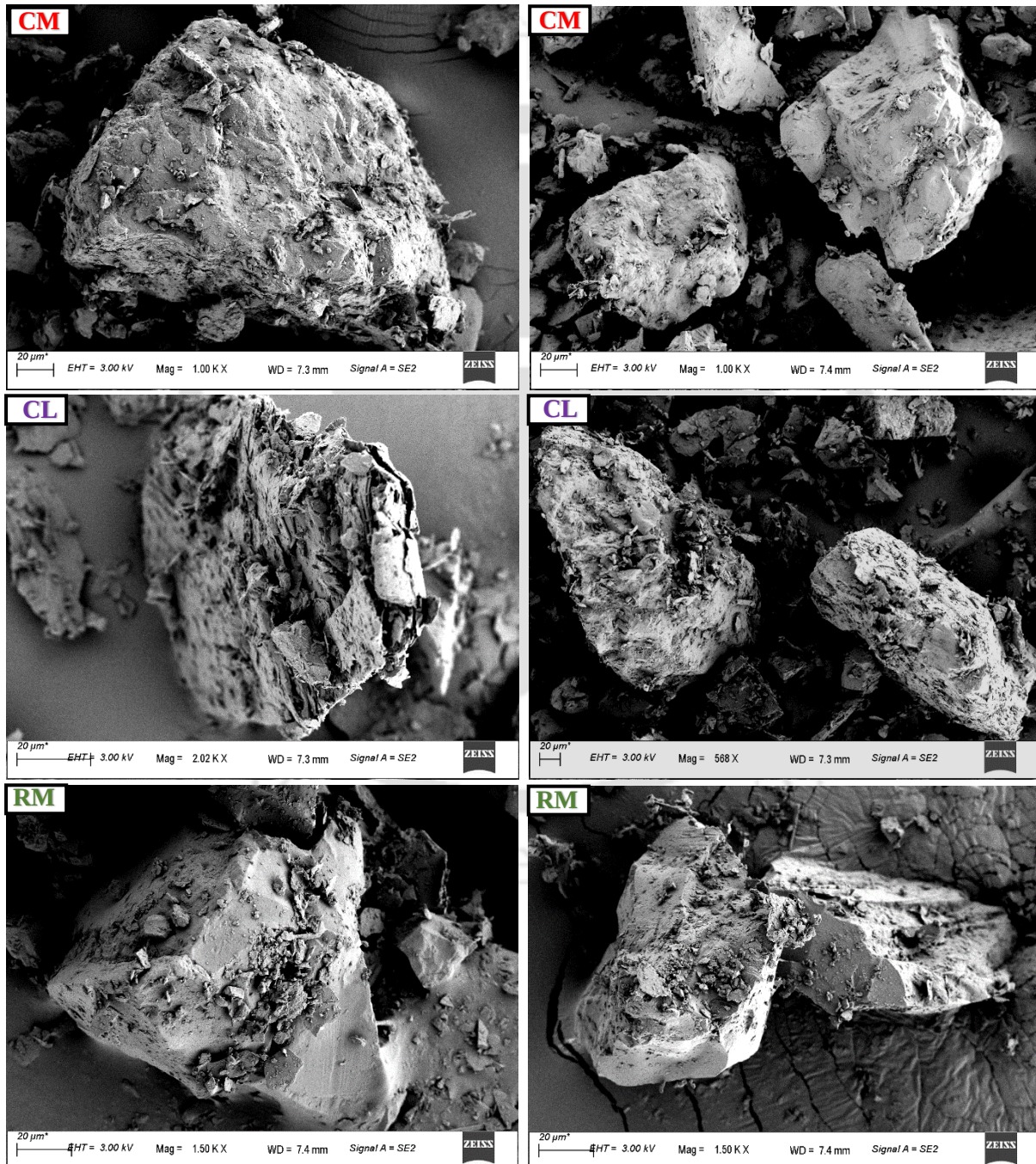


Figure 6.18: XRD pattern of moraine and lacustrine deposits from Changme and Rathong glacial snout (Bt: Biotite; Q: Quartz; Ab: Albite and An: Anorthite)

Figure 6.18 represents the XRD spectral analysis of the samples. Major minerals such as Quartz (Q: SiO₂), Biotite (Bt: K(Mg, Fe)₃AlSi₃O₁₀(F, OH)₂), Albite (Ab: NaAlSi₃O₈), and

Anorthite (An: $\text{CaAl}_2\text{Si}_2\text{O}_8$) have been identified from the XRD diffractogram. Silica (Si) and oxygen (O) have been found as the most abundant elements in all the moraine and glaciofluvial deposition samples using energy dispersive X-ray (EDX). Apart from these two major elements, aluminum (Al) and iron (Fe) have been identified along with some alkali metals such as sodium (Na) and potassium (K) and some alkali earth metals such as calcium (Ca) and magnesium (Mg). The surface morphology of the sediments obtained from the Changme and Rathong glacial environments, has been shown in Figure 6.19.



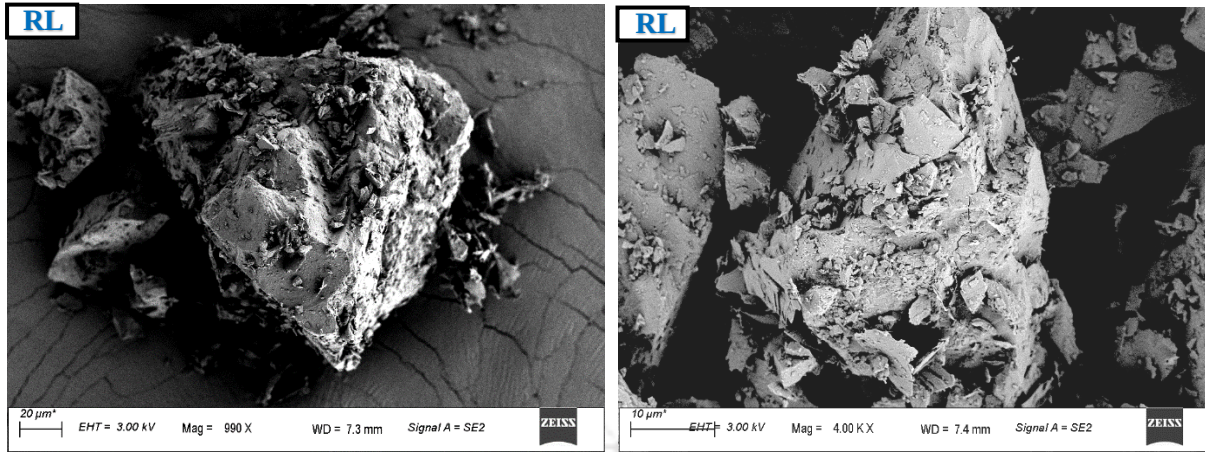


Figure 6.19: Surface morphology of Changme glacial moraine (CM), lacustrine deposits (CL), Rathong glacial moraine (RM) and lacustrine deposits (RL)

6.4 Conclusion

The integrated approach of field-based and laboratory-based investigation of moraine and lacustrine deposits from high-altitude Sikkim Himalayan regions helped in understanding various properties, which are mentioned as follows:

- Analyzing the shear wave velocity (V_s) profiles for various locations in North Sikkim helped in the site classification in terms of stiffness. Maximum $V_{s(30)}$ has been observed at Lachung playground and classified as site class C according to the NEHRP criteria, indicating very dense soil as a subsurface stratum. The Changme glacial snout region lying close to the high-altitude glaciated regions has the lowest $V_{s(30)}$ value, and NEHRP site class D has been assigned, indicating stiff soil.
- At Lachung playground, GPR indicates an inclined layer between 5 and 6m depths from the ground surface. A sudden drop in V_s at 6m depth has been observed from MASW that can be attributed to the existence of layer inclination at that depth. Moreover, a sudden fall in the V_s has been observed between 6 and 8m depths, followed by a sudden rise in V_s . Increased V_s indicates a third layer with greater stiffness than the second layer from 8m to 20m depths, as also observed using GPR imaging.
- GPR survey at Changme glacial snout seems comparatively less informative due to more noise attributed to the dispersion and scattering of radio pulses. The first subsurface layer extends up to 4m depth, followed by a second layer of 5m thickness. Sets of parallel reflectors have been observed in the second layer. The MASW survey shows a fragile layer up to 10.63m in depth. However, a sudden increase in V_s has been observed afterward, indicating a stiffer stratum underneath.

- The moraine samples obtained from Changme glacial snout have a large proportion of non-plastic silt with some sand but no clay. The lacustrine deposits from the same location show the major composition of sand with some silt but no clay. In the case of the Rathong glacial snout, the moraine sample has large proportion of coarse-grained particles and significantly less silt. The lacustrine deposits from the same location have been characterized by sand dominance. Due to the presence of silt, Changme glacial moraine has been observed with a greater cohesion value than Rathong moraine. The angle of internal friction is higher for the Rathong moraine sample. However, the shear strength properties do not show much variations for lacustrine samples from both locations.
- Minerals such as Quartz, Biotite, Albite, and Anorthite have been identified from the XRD diffractogram. Silica and oxygen have been found as the most abundant elements in the moraine and lacustrine samples with some proportion of alkali and alkali earth metals such as aluminum, iron, sodium, potassium, calcium, and magnesium as identified using energy dispersive X-ray (EDX).



Avalanche Studies from Himalayan Ranges

7.1 Introduction

Glacial hazards can be defined as certain processes related to glaciers that impart adverse effects directly or indirectly on human lives and activities (Reynolds, 1992; Qin, 2018). These include avalanches, glacial surges, glacial lake outburst floods (GLOFs), glacial collapse, and debris flow (Richardson and Reynolds, 2000). In the Himalayan landscape, slope instability and avalanches are associated with several threats, including loss of human life, livestock, property, and/or infrastructure. An avalanche can be defined as a mass sliding of snow, rock, or ice down a mountain slope due to temporally increased build-up (Park et al., 2010; Mondal and Bharti, 2022). In the Nepal Himalayas, the 2014 avalanche on the southern side of Mt. Everest had a catastrophic impact and was declared as the second deadliest disaster in the history of Himalayan hazards. The 2015 avalanche was triggered due to the Nepal earthquake of magnitude 7.8 that conquered the Everest base camp. Moreover, the earthquake triggered a series of avalanches that killed 23 people and left 61 injured (McClung, 2016). In 2014, a series of snowstorms and avalanches occurred in Nepal's Dhaulagiri and Annapurna region after about 1.8 m of snowfall in 12 hours due to the Hudhud cyclone (Hudhud, 2015). In 2020, avalanches in the Annapurna region close to the Annapurna base camp at an elevation of 3230 m left seven trekkers missing. There are enormous cases of avalanches, and several locations in the Himalayan region have been marked as avalanche-prone.

Over the past few decades, the western Himalayas have portrayed glacial expansion and mass gain (Copland et al., 2011; Bolch et al., 2012). Studies reveal that prolonged glacial expansion and mass gain episodes could be significant reasons behind surging (Quincey et al., 2011). Added to this, mass movement (Kargel et al., 2016), and slope instability (Panikkar and Subramanyam, 1997) frequently occur in the western Himalayan region due to neotectonic and structural activities along the zone of main boundary thrust (MBT) (Valdiya and Bartariya, 1989; Valdiya, 2003) and the presence of highly fragmented, sheared and crushed rocks (Kumar et al., 2017) as well as steep slopes (Paul and Mahajan, 1999). The Uttarakhand Himalayan region has witnessed more than 15 life-threatening hazards in the last 30 years,

especially due to slope instability (Bhambri et al., 2016). The 1998 Malpa rockfall (Pant and Luirei, 1999), the 2001 Phata Byung landslide (Naithani et al., 2002), the 2012 Asia Ganga landslide (Gupta et al., 2013), and many more have devastatingly affected the Uttarakhand Himalayas. On 7th February 2021, a hazard cascade was triggered because of a massive avalanche due to the detachment of a rock-ice composite wedge structure from the north-eastern slope of Trisul mountain. The incident caused the death of more than 200 people downstream of Rishiganga and Dhauliganga valley (Shugar et al., 2021; Rana et al., 2021; Rao et al., 2021). The region also witnessed colossal damage to infrastructure, including two hydel power projects in the valley (Shrestha et al., 2021).

In the process of understanding natural hazards triggered in the high-altitude Himalayan locations, field investigation is restricted due to challenging terrain and harsh weather conditions. Therefore, airborne and spaceborne-remote sensing datasets coupled with numerical modeling serve as an effective tool for analyzing and quantifying plausible factors behind a natural hazard (Ambrosi et al., 2018; Kääb et al., 2018). The advantage of remote sensing data and numerical modeling has been utilized to identify the significant factors responsible for the Kedarnath incident (Champati et al., 2016) and the Balia Nala landslide in Nainital, Uttarakhand (Kumar et al., 2017). The study reveals the neotectonic activity and discontinuities in the rockmass such as joints, shear zones, and faults affect the slope's stability. Kääb et al. (2018) studied glacial surges and avalanches in western Tibet in 2016 using a combined approach of satellite remote sensing, field investigation, and numerical modeling. The findings explain the role of weather- and climate-driven external forcing as a factor behind the substantial reduction of basal friction that acts as a resisting force and holds the glacial tongues frozen to the ground/bed. Using the analytical hierarchy process in conjunction with remote sensing helped in the effective demarcation of potential avalanche-prone areas in various locations of the western Himalayas (Snehmani et al., 2014; Sethya et al., 2018). Nath et al. (2021) used a combination of multivariate logistic regression protocol, machine learning, and analytical hierarchy process to understand the slope failure mechanism of Darjeeling-Sikkim Himalayas through remote sensing, geographical information system (GIS), geotechnical and geophysical investigations, and numerical modeling.

In this chapter, an attempt has been made to identify the activation zones of snow avalanches that occurred on 17th January 2020 around some of the major peaks of the Annapurna mountain range using space-borne C-band SAR datasets. Also, the composite rock-ice avalanche of 7th February 2021 along the north-eastern slope of Trisul mountain has been

investigated to identify the formation mechanism and plausible triggering mechanism of the detachment using SAR datasets, kinematic and probabilistic back analysis of the failed slope. In addition, rockfall simulation with probabilistic analysis of identified parameters has been conducted that has the potential to be used while planning mitigation measures in the near future.

7.2 Annapurna Snow Avalanche

7.2.1 Event Description

In 2020, avalanches in the Annapurna region close to the Annapurna base camp at an elevation of 3230 m left seven trekkers missing. The topography as well as climatic factors make the Annapurna region, one of the deadliest locations in terms of avalanches. The regions have a history of numerous avalanche events with catastrophic impact. In April, 2014, a series of avalanches on and around Dhaulagiri and Annapurna resulted in death of atleast 43 people including at least 21 trekkers (Thakuri et al., 2020). Table 7.1 shows the list of past avalanche records on and around Annapurna region of the Nepal Himalayas.

Table 7.1: Past records of avalanche near Annapurna region since 1970 (Thakuri et al., 2020)

<i>Year</i>	<i>Incident Location</i>	<i>Fatalities</i>
1970	Khumbu region (Ice-fall avalanche)	6
1978	Khumbu region (Ice-fall avalanche)	7
1982	Khumbu region (Ice-fall avalanche)	7
1984	Khumbu region (Ice-fall avalanche)	3
1992	Khumbu region (Ice-fall avalanche)	2
1995	Khumbu region (Snow-fall avalanche)	48
2006	Khumbu region (Snow-fall & ice-fall avalanche)	3
2009	Khumbu region (Ice-fall avalanche)	2
2014	Annapurna and Dhaulagiri (Snow avalanche)	59
2018	Dhaulagiri (snowstorm and landslides)	9
2019	Annapurna (snow-fall avalanche)	8
2020	Annapurna (snow-fall avalanche)	7

7.2.2 Study Area

The study area lies within the territory of Nepal Himalayas between latitudes of 28°21'29" to 28°59'56" north and longitudes of 83°54'14" to 84°37'8" east. Nepal has a parallel orientation with the Himalayas which is divided into various physiographical regions namely Siwalik Hills, Terai Plain, Middle Mountains, High Mountains, and the High Himalayas. The elevation of the middle mountains, also termed the Mahabharat Range lies between 1500 to 2700 m above sea level (a.s.l). It consists of the Inner Himalayan valleys and the Main Himalayas. The

High Mountains make the snow-covered Nepal Himalayas with elevations ranging between 4000 to 8849m a.s.l. The eight highest peaks on the planet are located in this area. The region has deep valleys, rugged topography, and steep slopes and is occupied chiefly by snow peaks, talus, undulating rocky slopes, glaciers, and colluvium deposits. Annapurna mountain range lies in the Gandaki Province of north-central Nepal. The major peaks lying in the Annapurna mountain range considered for study have been shown in Figure 7.1.

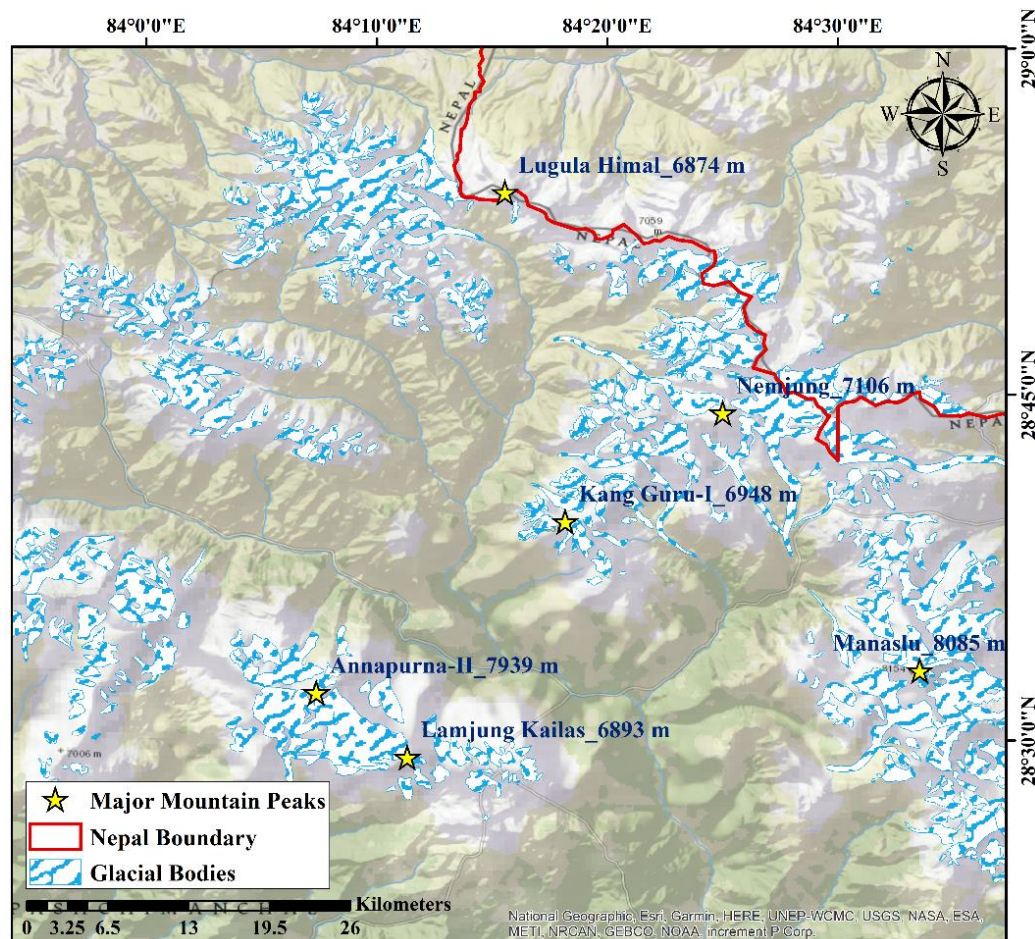


Figure 7.1: Study area map showing six major peaks of the Annapurna Himalayas

7.2.3 Datasets Used

The Sentinel 1 satellite has been designed for the Copernicus project for the Global environment and safety monitoring system. The present study involves acquiring descending pass Sentinel 1A single look complex (SLC) datasets before and after the avalanches of 17th January 2020 as summarized in Table 7.2.

Table 7.2: Summary of datasets used for Annapurna avalanche study

Sentinel 1A SLC Pair				
Pre-Avalanche Data	Post-Avalanche Data	Band/Sub-swath	Path/Frame	Polarization

13 th January 2021	25 th January 2021	C-Band/IW1	121/496	VV+ VH
DEM (ALOS-PALSAR)				
Data	Path/Frame	Absolute Orbit	Band/Polarization	
10 th March 2009	512/560	16653	L-Band/HH	

Sentinel 1 is a system of a pair of satellites, Sentinel 1A and 1B which alternately capture SLC data every six days from the same orbit with a ground resolution of 2.7m×22.5m (range×azimuth). The satellites capture information in the interferometric wide-swath (IW) mode covering an area of 250km×170km in a single scene. The high-resolution ALOS-PALSAR radiometrically terrain corrected digital elevation model (DEM) with 12.5m spatial resolution is used to derive the topographic slope of the area. PALSAR is an active microwave sensor that collects data in L-band frequency unaffected by weather obstacles. The DEM is processed to ellipsoidal height from orthometric height in order to match other available DEMs.

7.2.4 Methodology

The preprocessing of C-band (center frequency: 5.405 GHz) SLC datasets start with the TOPSAR split as shown in Figure 7.2. The SLC product is a union of three sub-swaths. In order to minimize the computational burden, the IW1 swath which covers the major location of Annapurna and other nearby peaks has been split. The next step is the orbit correction. This helps in updating the geometric position of the data with precise satellite position contained in the precise orbit determination (POD) restituted orbit file. This is followed by radiometric calibration which is important for the quantitative use of SLC data. This helps in the correction of radiometric bias, thus generating SAR pixel values that truly represent the surface's backscatter. Each sub-swath of an SLC product contains a series of bursts in azimuth. The next step is deburst which helps in including each individually focused burst data in azimuth-time order in the sub-swath image. Moreover, deburst also helps in eliminating black-fill demarcation through resampling and merging. The next step is multilook which helps transform the azimuth and range direction resolution to an output with nominal pixel size and suppresses speckle noise. This is followed by linear to dB scale conversion to generate backscatter intensity product in decibels.

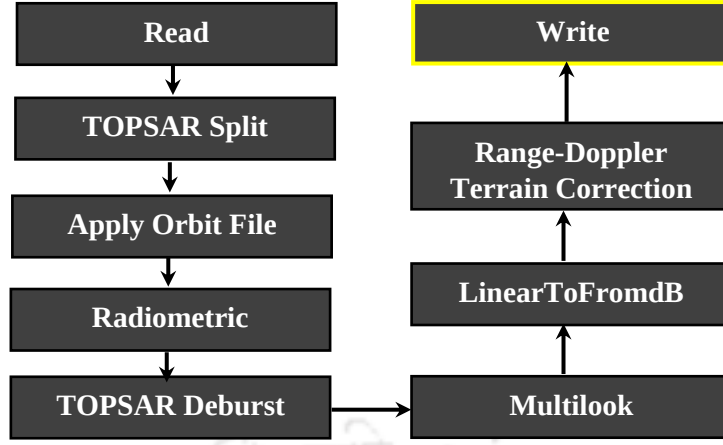


Figure 7.2: Flowchart of SLC data processing to derive backscatter intensities

7.2.5 Results and Discussion

A typical avalanche is characterized by the presence of different zones namely the release area which is the uppermost portion from where the avalanche initiates. Then there exists a transition zone below the release area with staunchwall and some deposition due to rough terrain. At the bottom, a tongue-shaped deposition zone with densely compacted snow-mass exists. The radar backscatter from different zones varies due to changes in the snow properties. From the first-order scattering physics, the net backscatter intensity (σ_{Net}^0) can be seen as an aggregate scattering from the snow volume (σ_v^0), snow surface (σ_s^0), ground surface underneath snow (σ_g^0), higher-order interactions between varying structures within the snowpack (σ_h^0) as shown in the equation 7.1 (Leinss et al., 2020; Mondal and Bharti, 2022b).

$$\sigma_{Net}^0(\theta) = \sigma_v^0(\theta) + \sigma_s^0(\theta) + \sigma_g^0(\theta) + \sigma_h^0(\theta) \quad (7.1)$$

Considering the general scattering physics from rough surfaces and bi-continuous media, scattering in snow-mass increases due to several factors which include increased interface roughness, decrease in incident angle (θ), etc. For dry snow of thickness in few meters, σ_g^0 usually dominates the net backscatter signal in the 1-10 GHz microwave domain. In this frequency domain, microwaves are poorly scattered at the surface and within the volume of snow, thus penetrating the snow to the ground underneath (Xu et al., 2012).

The Sentinel 1A SLC datasets used in this study are acquired from a C-band radar sensor that operates at a center frequency of 5.405 GHz. The backscatter intensities from the post-avalanche dataset represent sets of fringes (high gradient in backscatter intensities) in some of the locations near the peaks as shown in Figure 7.3. From the slope derived using ALOS-PALSAR DEM, the region dominated by these fringes lie above the topographic

gradient of 30° . A possible reason behind such patterns can be attributed to the backscatter response due to sloping mountain surface lying underneath the snowpack. As the topographic gradient of these regions are comparatively higher ($>30^\circ$), freshly precipitated dry snow can undergo easy sliding than the other areas. This leads to less deposition of dry snow giving dominance of backscatter response from the underlying ground surface. Thus, the areas where the fringes are formed in the backscatter image can be seen as an avalanche release area as the topographic slope creates suitable ground for the sliding of freshly precipitated dry snow.

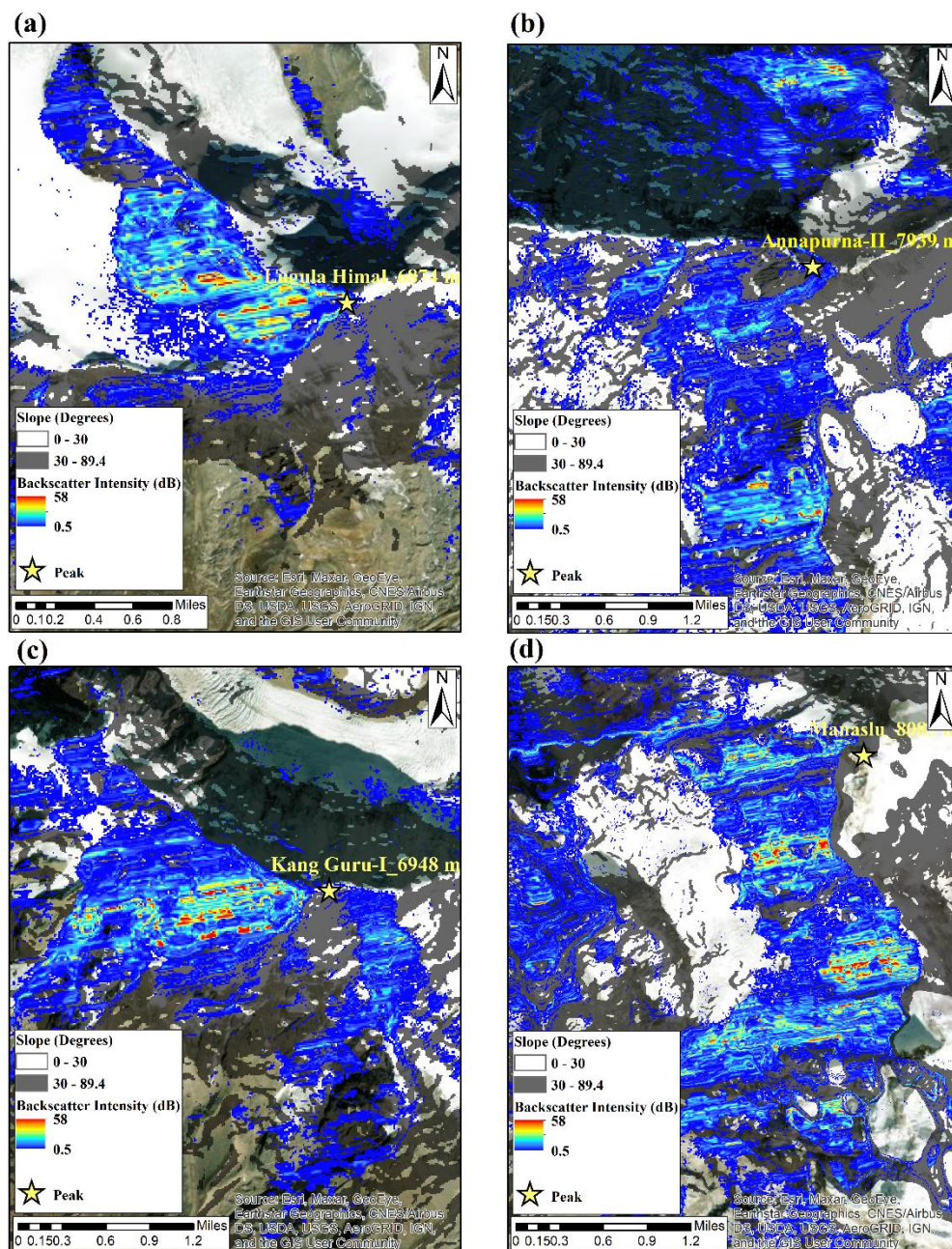


Figure 7.3: Map showing post-avalanche backscatter intensity (dB) image overlaid on the topographic slope of the area

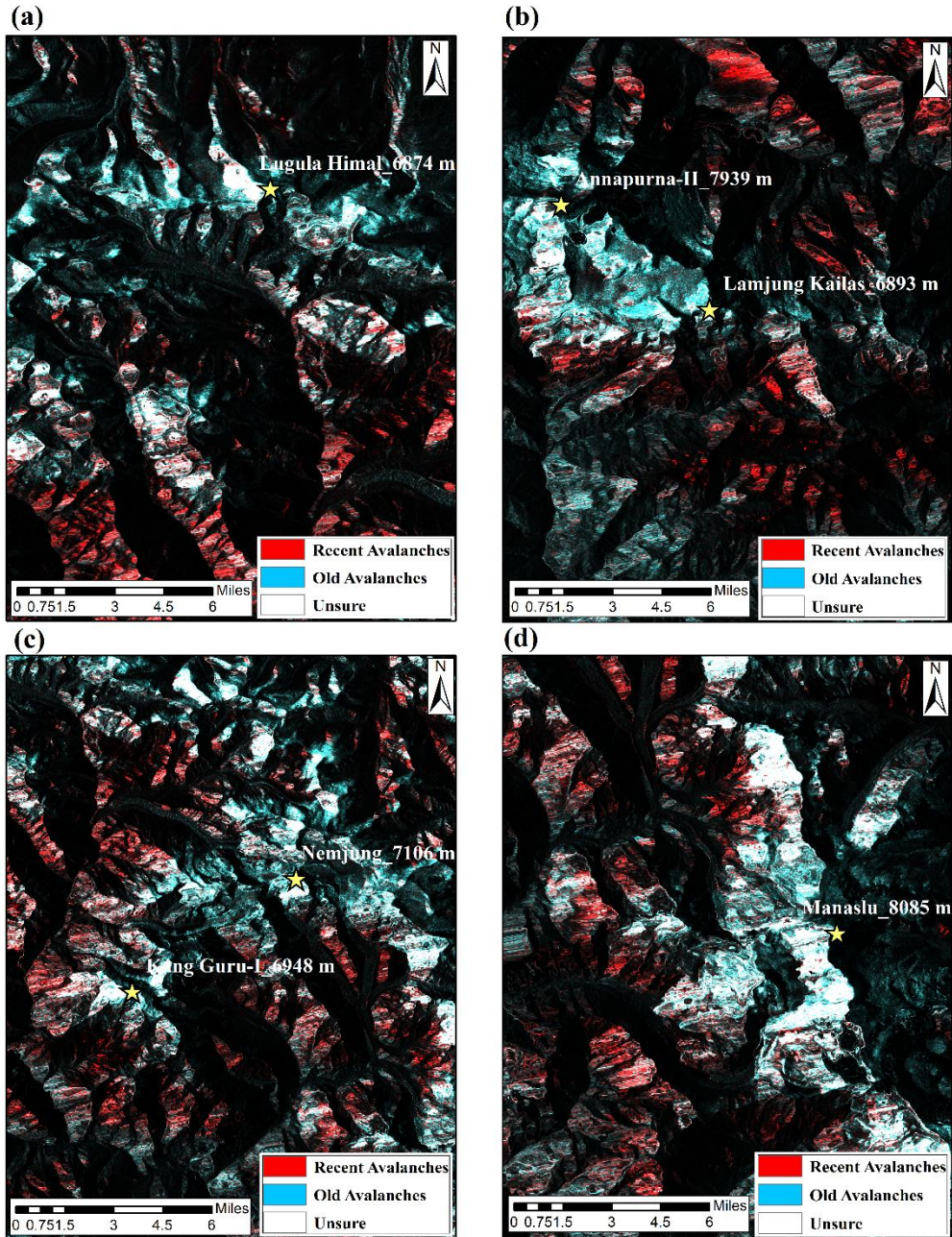


Figure 7.4: Color composite map showing the temporal classification of avalanches in the area

Although detecting avalanche sites is possible with a single post-avalanche backscatter intensity image, the visualization of pre-and post-avalanche backscatter intensities as a color composite image helps in temporal classification. The avalanches in the area can be classified into classes of recently occurred, old and unsure classes. In order to do this, backscatter intensities in dB have been normalized by clipping the upper and lower 1%. Then the pre-and post-event data have been stored in the RGB (Red, Green, Blue) channels as Img_{post} , Img_{pre} , Img_{pre} where Img_{post} and Img_{pre} represents imageries of post- and pre-avalanche backscatter intensities respectively (Leinss et al., 2020). In the color composite images, as shown in Figure

7.4, reddish portions represent recent avalanches due to increased backscattering. These portions are indicative of the avalanches that occurred between the pre-and post-event acquisitions i.e. between 13th and 25th January 2020. The region appearing blue represent older avalanches with decreased backscatter signal. These avalanches are assumed to have occurred before the pre-event acquisition i.e. before 13th January 2020. The portions of the images represented in bright/white portray features with unaltered backscatter intensity and therefore, do not fall in any of the two classes discussed above. Thus, it is impossible to classify these portions and, therefore, marked as an unsure class.

7.2.6 Conclusion

The Himalayan cryosphere and its associated natural hazards greatly impact the local civilization and its monitoring challenges to researchers around the globe. The Annapurna mountain range of the Nepal Himalayas region is highly prone to avalanches and snowstorms, which requires constant monitoring to minimize the associated risk. In the present study, Sentinel-1A radar datasets helped in detecting avalanches around the major peaks in the area. Analysis of the backscatter intensities helped in identifying the areas with fringes. Moreover, the topographic slope derived from ALOS-PALSAR DEM showed that the fringes are localized in the areas of slope > 30°. These areas are more likely to be the release area from where an avalanche initiates. The color composite image of pre-and post-avalanche backscatter intensities helped in temporal classification of the areas around the major peaks into recent and older avalanche classes. This can help understand the avalanche episodes and plausible triggering factors in the Nepal Himalayas.

7.3 Trisul Mountain Rock-ice Composite Avalanche

7.3.1 Event Description

It was on 7th February 2021 that a massive avalanche got triggered due to the detachment of a rock-ice composite wedge structure from the north-eastern slope of Trisul mountain. Post-incident photographs captured from helicopter survey on 12th February 2021 helped in gathering first-hand information of the mountain slope and Ronti gad. Studies conducted using high-resolution satellite imageries and seismic signals from the local seismic networks confirm the collision of glacial block with the valley floor followed by another block (Meena et al., 2021a). Several factors such as the topography of the area, heavy precipitation before the incident, long term rise in air temperature and change in the local climatic conditions were anticipated to be responsible for the rock-ice avalanche (Thayyen et al., 2021; Shugar et al.,

2021). Investigations conducted using multiple satellite imageries of decade span and 3D geometrical model helped in understanding the progressive destabilization, top-corner cracks and bergschrund breaking (Mao et al., 2022). The time series analysis conducted using Persistent Scatterer Interferometry (PSI) SAR technique captured an increment in the ground deformation considered responsible for the expansion of cracks lying in the vicinity of Vaikrita Thrust (VT), thus failure (Kothyari et al., 2022). Pandey et al. (2021) observed an increment in the solar radiation and substantial changes in the temperature of the displaced material of the rockslide responsible for instability of glacial blocks causing the failure. Studies conducted for the impact of the disaster using optical and microwave datasets helped in capturing changes in the water quality of Rishiganga and the flood plains (Meena et al., 2021b; Meena et al., 2021c).

7.3.2 Study Area

Western Himalayas, also called the Punjab Himalayas, are spread around 350 miles from Sutlej in the southeast to the Indus river in the northwest. It comprises of the Dhaola Dhar, Karakoram, Pir Panjal, Ladakh, Zaskar and parts of the Shiwalik range. The terrain can be distinguished into two categories: the southern slopes are more steep and rugged, while the northern slopes are bare and gentle. Based on tectonic zonation, the western Himalayas are divided into Tethys, Trans, Lesser, Higher, and Outer Himalayas. In the western Himalayas, the Rishiganga catchment is composed of $\sim 690 \text{ Km}^2$ with several large valleys and hanging glaciers such as Changband, Hanuman, Trisul, Bethartoli, Ronti, and many more (Rana et al., 2021). The region falls in rugged topography with elevation ranging between $\sim 1200 \text{ m a.s.l}$ and $\sim 7800 \text{ m a.s.l}$. Eight peaks enclose the catchment, with Nanda Devi being the second highest peak rising to $\sim 7846 \text{ m a.s.l}$ (above sea level). The region is prone to avalanches due to hanging glaciers as slopes are sufficiently steep, leading to ice calving from the glacier's terminus (Pralong and Funk, 2006; Margreth et al., 2017). The region along the Rishiganga and Dhauliganga valley lies between the VT and the South Tibetan Detachment (STD), having weathered, pulverized, and fragmented rock strata (Rana et al., 2021). The formations of the area are mainly composed of muscovite-schist, Kyanite-biotite, leucogranite, and gneiss (Mukherjee et al., 2019). The geology of the area belongs to high-grade metamorphic rocks of the Vaikrita group.

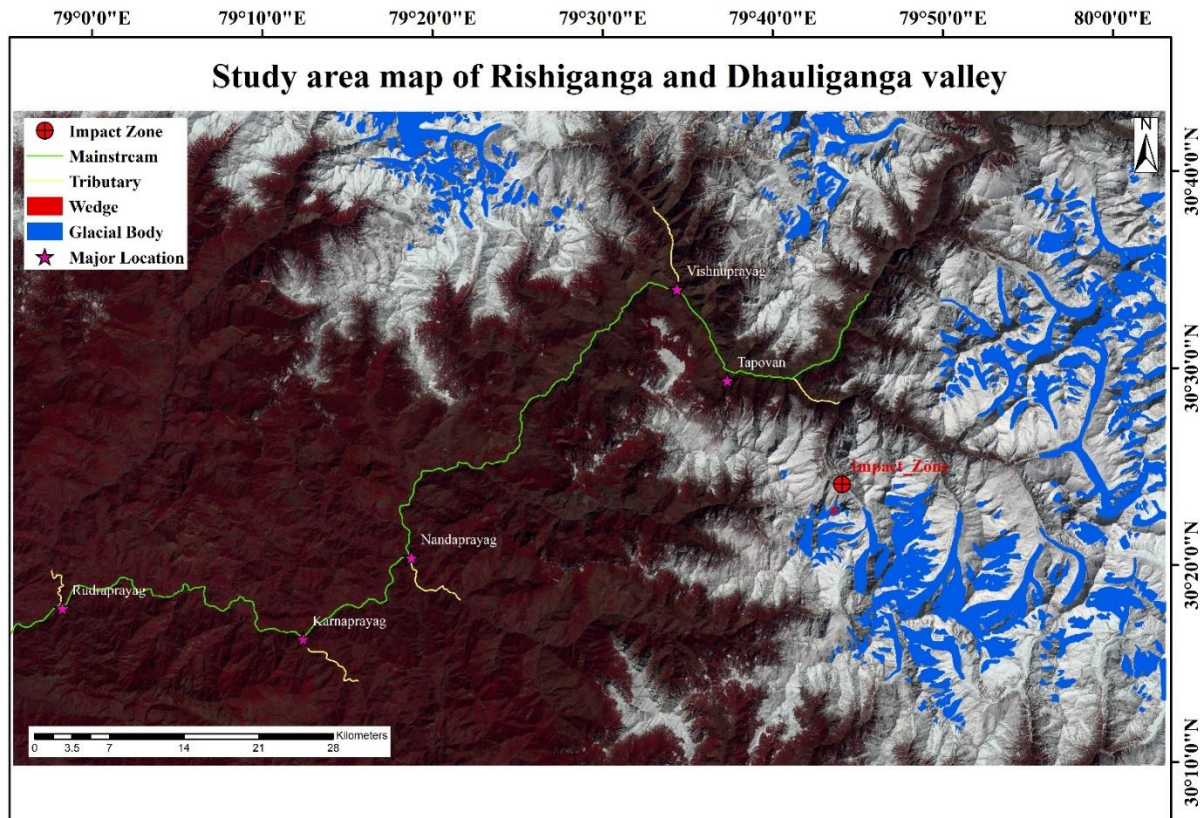


Figure 7.5: Standard False Color Composite (FCC) map of the study area highlighting impact location

Ronti glacier falls in the category of the hanging glacier that lies adjacent to Nanda Gunti (6390m a.s.l) to its east and Trisul (7120m a.s.l) to its west. It is a northward-flowing glacial body with the main trunk (~ 6 Km long) and three connecting flanges accounting for a total area of about 11.8 Km². The snout of the Ronti glacier lies at an elevation of ~4100m a.s.l, with its ablation zone characterized by crescentic crevasses, discernible traverse, fine-textured debris, and supraglacial lakes with an area of not more than 500 Km². Studies conducted using topographic maps, and satellite datasets have suggested that two different categories of moraine cover the glacier. One is vegetation-covered (conifer, juniper, birch, etc.) older moraine, mainly observed below ~3000m a.s.l and characterized by rolling crest. Another is non-vegetated or poorly vegetated fresh moraine, which is observed till the snout of the glacier and characterized by a sharp crest (Rana et al., 2021). Down the valley, where the older moraine culminates, the morphology of the valley is steeper, and the river flows through the gorge with large boulders. The study area falls within the Alaknanda catchment on the north-eastern slope of Trisul mountain, standing beside the valley of the Ronti glacier (Figure 7.5).

7.3.2.1 Rock-ice Wedge Failure

It was on 7th February 2021(10:21 IST) that a major rock-mass and glacial ice (79°43'53.61"E, 30°22'40.56"N; GLIMS ID: G079733E30381N) dissociated from the northern slope of Trisul mountain resulting in an avalanche with an average velocity ranging from 204 to 2016 kilometers per hour (Figure 7.6 and 7.7). The dimensional analysis of pre- and post-event using high-resolution satellite imageries and a digital elevation model (DEM) of the mountain slope revealed that a prismatic wedge (~74 m deep) with a triangular face (850m×550m) accounting for about 60 million metric tonnes (80% rock and 20% metamorphosed ice) of mass crashed over the Ronti gad valley floor [report from Glacier and Permafrost Hazards in Mountains (GAPHAZ, 2021)]. It had a tremendous amount of potential energy (~1.2 Petajoules) stored at an elevation of 5500 m asl and 1742 m above the valley floor. Failure of rock profile above the wedge top was detected in 2016 with the help of feature tracking. Steady displacement of rock block is observed in the subsequent years with magnified displacement in the summer season of 2017 as well as 2018 (Shugar et al., 2021). This phenomenon opened an 80m wide crevasse in the glacial ice and rock mass underneath above the topmost part of the wedge, confirming the instability and rockfall susceptibility of the north-eastern slope of Trisul mountain. Studies conducted using post-event satellite imageries explain that the structure was freely suspended from the slope face, and the avalanche may have been airborne initially for a short period as the lower segment of the eastern glacier seems intact. No sign of abrasion is registered due to the movement of composite mass avalanche over it. Once the free-falling avalanche hits the valley floor of Ronti gad, the next episode of splash deposits begins (Orwin et al., 2004; Mitchell et al., 2020).

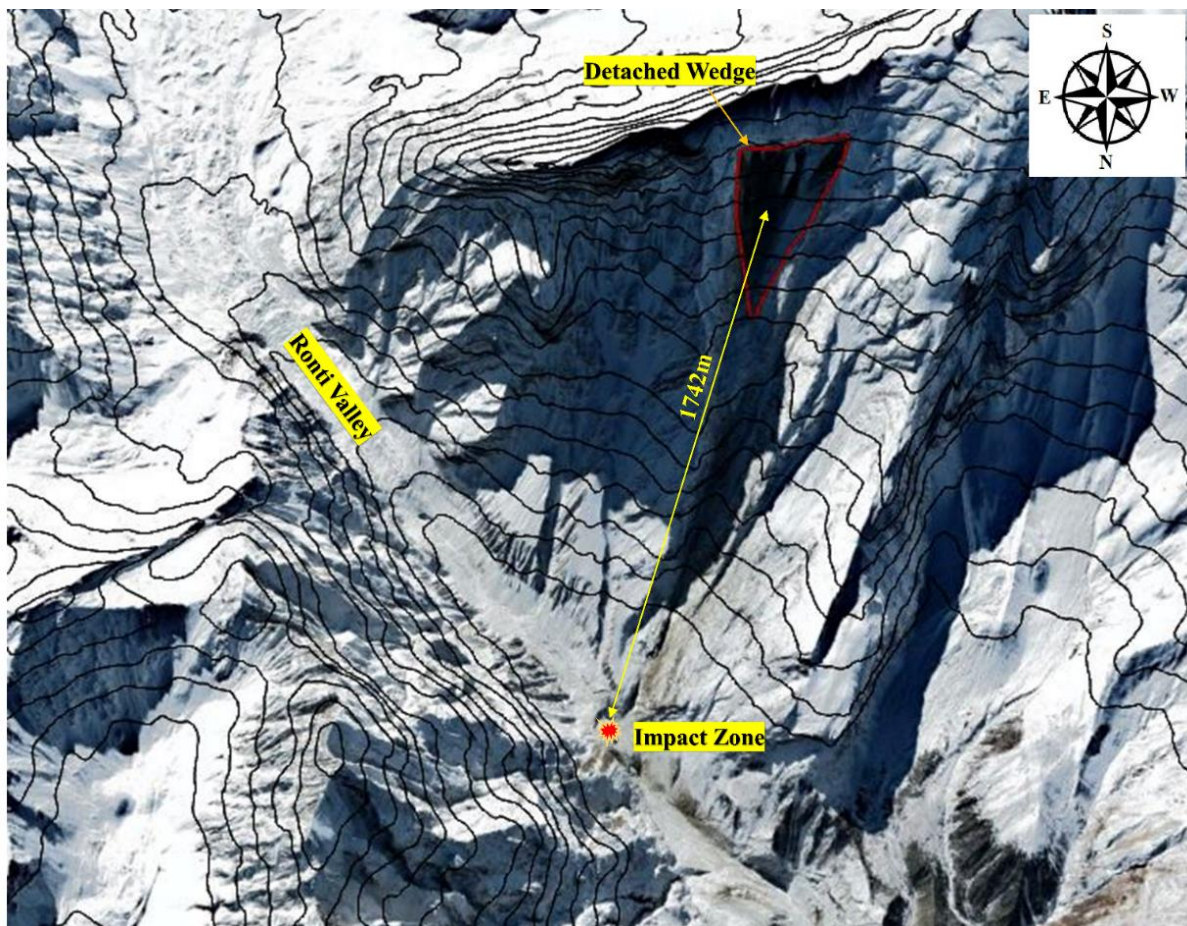


Figure 7.6: Image representing slope and impact location (Google Earth Pro image of 11th February 2021)

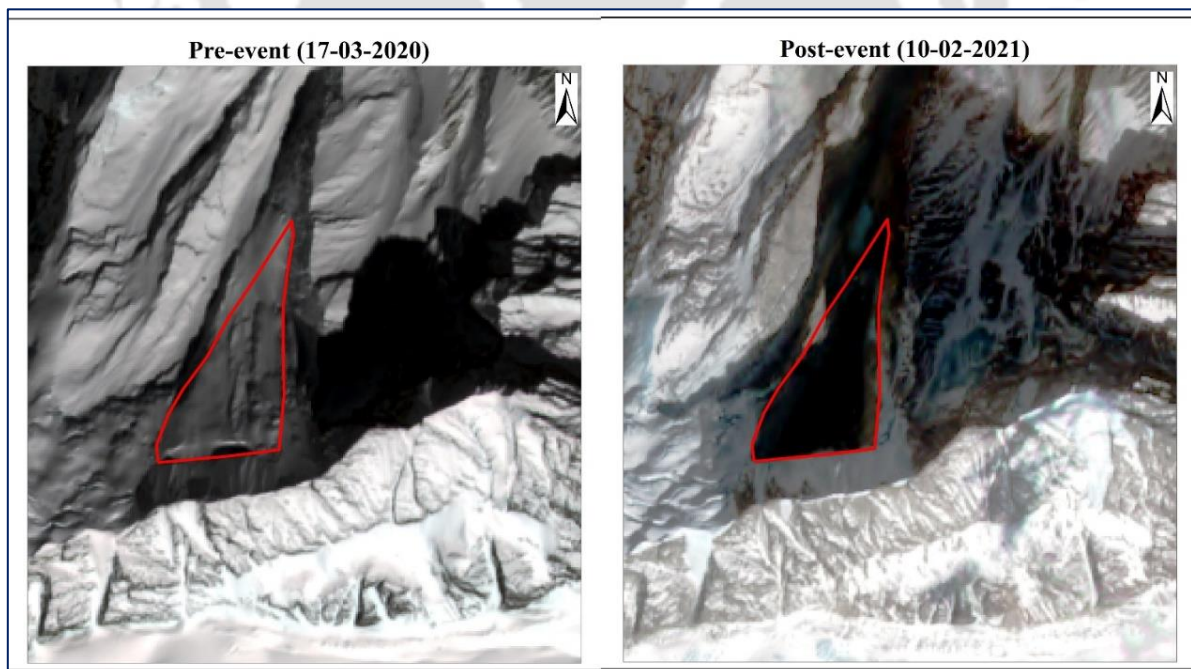


Figure 7.7: Wedge structure captured by Sentinel 2 MSI

High potential energy gained by the rock and ice avalanche soon gets converted into kinetic and thermal energy (frictional heating of ice), transforming it into very dynamic debris flow down the valley in the north-western direction (Shugar et al., 2021). The debris is mainly composed of boulders, ice blocks, meltwater, and sediments. These large boulders played a major role in forming a ~40m thick debris-dammed reservoir where Ronti gad confluences with the Rishiganga river. With time, a free-flowing river gets transformed into ~700m long lake in upstream of Rishiganga valley that soon fails. This results in a flash flood, thus vandalizing two hydel power projects in the Dhauliganga and Rishiganga valleys and loss of life and property (Pandey et al., 2022; Shugar et al., 2021).

7.3.3 Datasets Used

Sentinel 1 level-1 GRD (Ground Range Detected) datasets have been used to derive surficial mobility using Synthetic Aperture Radar (SAR) sub-pixel offset tracking on a seasonal and annual basis. The Sentinel 1 mission consists of a pair of near polar-orbiting satellites, Sentinel 1A/B acquiring data using a C-band SAR instrument in dual (HH+HV, VV+VH) and single (HH, HV) polarization, with a revisit time of 6 days (Filipponi, 2019). Sentinel 1 level-1 datasets are available in two different categories, namely GRD (Ground Range Detected) and SLC (Single Look Complex). The GRD product consists of focused SAR data being detected, multi-looked, and projected to ground range with the use of the Earth ellipsoid model (Sentinel 1 Team, 2013). Ellipsoid projection of the product is rectified using terrain height that is constant in range but varying with azimuth. Once multi-look is performed separately for each burst, a GRD image is produced by merging all bursts in all sub swaths. Because of the multi-look processing, GRD imagery consists of speckle reduced square pixels representing the sensor detected amplitude information, excluding the phase information. The high-resolution Google Earth pro imagery has been used to visualize the topographic features around the location of wedge failure. In addition, high-resolution terrain corrected advanced land observing satellite (ALOS) phased array type L-band synthetic aperture radar (PALSAR) DEM from Alaska Satellite Facility has been used to study the elevation profile of Trisul mountain range and Ronti valley. This high-resolution DEM is derived using PALSAR, a microwave sensor operating in L-band frequency which is processed and converted to ellipsoid height from orthometric height to match the elevation profile with other DEMs. The details about datasets used in this study are shown in Table 7.3. The boundaries for the glacial bodies present in the area are used from the Randolph Glacial Inventory (RGI 6.0) (RGI Consortium, 2017). Dips

v7.0 has been used for the kinematic analysis of the slope. Rockfall 6.0, Slide, and RS2 of Rocscience have been used to study the failure mechanism of the slope.

Table 7.3: Details of offset-tracking pairs from Sentinel 1A

Sentinel-1A Level-1 Datasets								
Timeline	Master Data	Slave Data	Microwave Band/ Frequency	Data Type	Beam Mode /Polarization	Spatial Resolution/ Width	Frame/Path/ Flight Direction	Temporal Baseline (Days)
Pre-Monsoon Monsoon Post-Monsoon Annual (2020-2021)	16 Mar 2020	2 July 2020	C-Band/ 5.405 GHz	GRD	IW/VV+VH	5m×20m/ 250 Km	92/129/ Ascending	108
	2 July 2020	18 Oct 2020						
	18 Oct 2020	3 Feb 2021						
	16 Mar 2020	3 Feb 2021						324
ALOS PALSAR Dataset								
Data	Date	Spatial Resolution	Microwave Band/ Frequency	Polarization		Beam Mode/Path	Frame/Flight Direction	Off-Nadir Angle
Hi-Res Terrain Corrected DEM	3 Sept 2007	12.5m	L-Band/ 1.27 GHz	HH+HV		FBD/520	590/ Ascending	34.3°

7.3.4 Methodology

The methodology adopted in this study has been presented in four distinct stages as represented in Figure 7.8. Stage one is for determining the surficial mobility of the Ronti glacier and triangular wedge over the north-eastern slope of Trisul mountain. The second stage is the kinematic analysis of the wedge structure to check for primary susceptibility of failure. Stage three is the probabilistic back analysis of the slope for failure. Finally, rockfall analysis followed by a probabilistic study of parameters as stage four of the study.

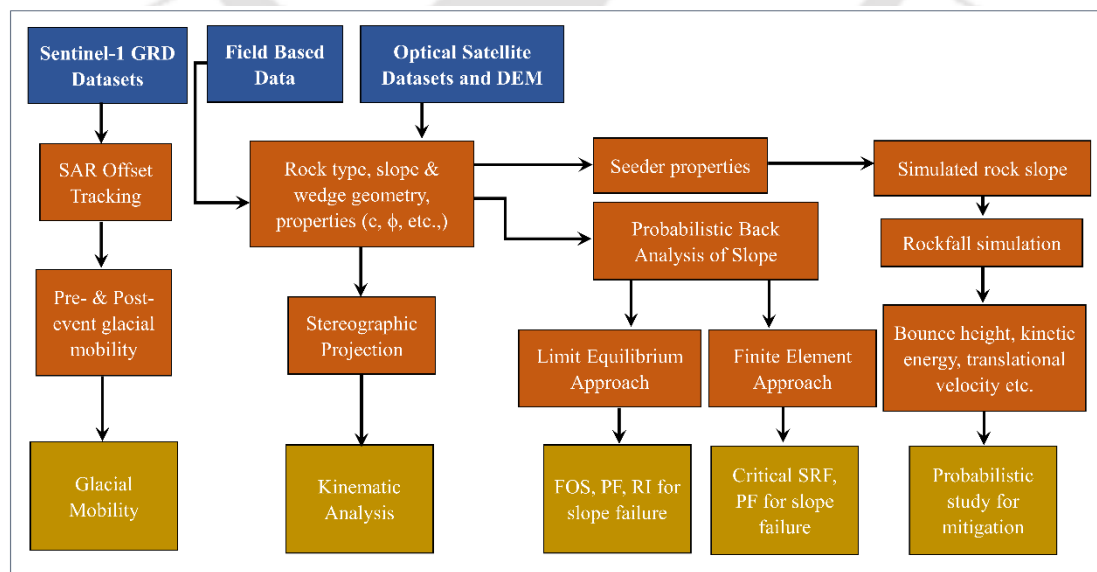


Figure 7.8: Flowchart showing the methodology adopted in the present study

7.3.4.1 Glacial Mobility using SAR Offset Tracking

For studying cloud-prone areas such as the Himalayas, microwave remote sensing, especially space-borne active synthetic aperture radar (SAR), is very useful. In order to study the glacial surface mobility using SAR, there are mainly two different approaches. The first one is subpixel scale offset tracking, and another one is interferometry (InSAR). Both the techniques require two different SAR scenes from the same orbital geometry acquired between two time periods (Strozzi et al., 2002; Pritchard et al., 2005; Kumar et al., 2013). InSAR method fails in the Himalayan glaciers unless the defined temporal baseline is at least 1-3 days and a minimum geometrical baseline exists between pairs of repeat pass datasets. However, if there is a high decorrelation between two repeat pass acquisitions, SAR amplitude or intensity offset tracking can be adopted. This method helps compute the two-dimensional (azimuth and range) velocity of the glacial surface to the sub-pixel level (Michel and Rignot, 1999; Kumar et al., 2013). As Himalayan glaciers are mostly debris-covered, deposition of debris over the glacial surface proves helpful in deciphering the components of displacement in both range and azimuth direction. This is because surficial undulations and distinctive patterns of debris can be traced from SAR intensity and amplitude datasets.

In this study, we have used SAR intensity offset tracking, which involves matching intensity between two temporally different but orbital geometry-wise similar images. Cross-correlation optimization of intensity pair has been used for offset tracking to sub-pixel level. GRD products of Sentinel 1 have been processed in Sentinel Application Platform (SNAP) developed by European Space Agency (ESA). A set of pre-processing steps have been carried out before executing the sub-pixel offset tracking (Figure 7.9). At first, the GRD pairs (slave and master images) have been co-registered with the help of precise orbit files containing the location information of the satellite at the time of data acquisition. This helped align pixels between the image pairs to within the range of thousandth and tenth of a pixel in azimuth and range direction, respectively. To reduce the processing time, subset/crop has been taken around the study area after co-registration. Offset tracking is then implemented which works on the computation of secondary ground control points (GCPs) corresponding to user-specified GCPs on a primary image using a normalized cross-correlation technique. The feature window (matching window) of 128×128 pixels (range×azimuth) and searching step of 10×10 pixels have been considered. The oversampling factor have been set to 16 while considering the correlation coefficient threshold of 0.3 to mask out the offsets which are unreliable due to sharp surface changes and serious pixel distortions (Guo et al., 2020; Zhu et al., 2021). The obtained

velocity vectors are compared with the user-defined maximum velocity threshold. The threshold value is considered depending on the type of feature to be monitored. From the previous studies on the glaciers of eastern Himalayas (Amitrano et al., 2019; Fan et al., 2019), a threshold of 15m/day has been considered so as to capture anomalous surficial movements if any and prevent underestimation of glacial velocity. Finally, the range doppler terrain correction has been done over the surface velocity output using SRTM 1arc-sec (30m) DEM. This is done for the correction of geometric distortions introduced by topography, such as shadows and foreshortening.

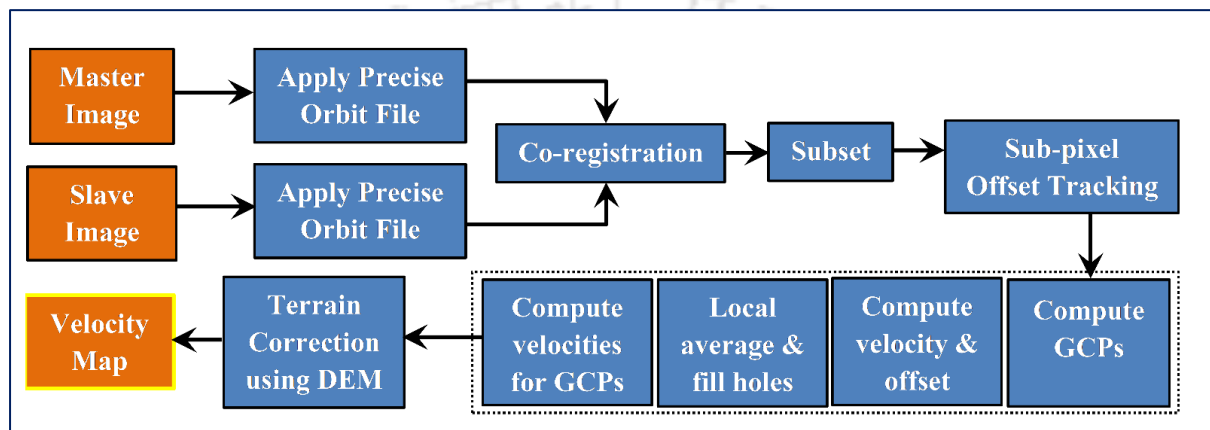


Figure 7.9: Sub-pixel offset tracking process flow for surficial displacement using Sentinel 1 GRD data

7.3.4.2 Kinematic Analysis

The Trisul Mountain slope lies close to VT and STD with weathered and fragmented rock strata. A physical model of the wedge structure is shown in Figure 7.10. The kinematic analysis is done using the friction method. This is conducted as preliminary slope stability check considering the joint sets and their dipping properties. While considering various failure mechanisms for the rock mass, there are two types of considerations: stress- and structurally-controlled. Some of the cases are a composite of these two and may also involve weathering. This study attempts to check for two types of failures, namely planar sliding and wedge sliding. For the kinematic admissibility of planar sliding, five necessary criteria must be met. First, the sliding plane must strike almost parallel to the slope face (in the range of $\pm 35^\circ$). Second, release surfaces providing negligible resistance to sliding must be present to define lateral slide boundaries. Third, the sliding face must daylight (the region around the poles belonging to the potentially unstable planes) in the slope face. Fourth, the friction angle must be smaller than the dip of the sliding plane. Fifth, the upper end of the sliding surface either terminates in a tension crack or intersects the upper surface (Wyllie and Mah, 2004). Similarly, for the

kinematic admissibility of wedge sliding, four essential criteria must be met. First, the dip of the line of intersection must not exceed the dip of the slope. Second, the intersection line must daylight the slope face. Third, the dip of the intersection line must be such that the strength of both planes is reached. Fourth, the upper end of the line of intersection either terminates in a tension crack or intersects the upper face.

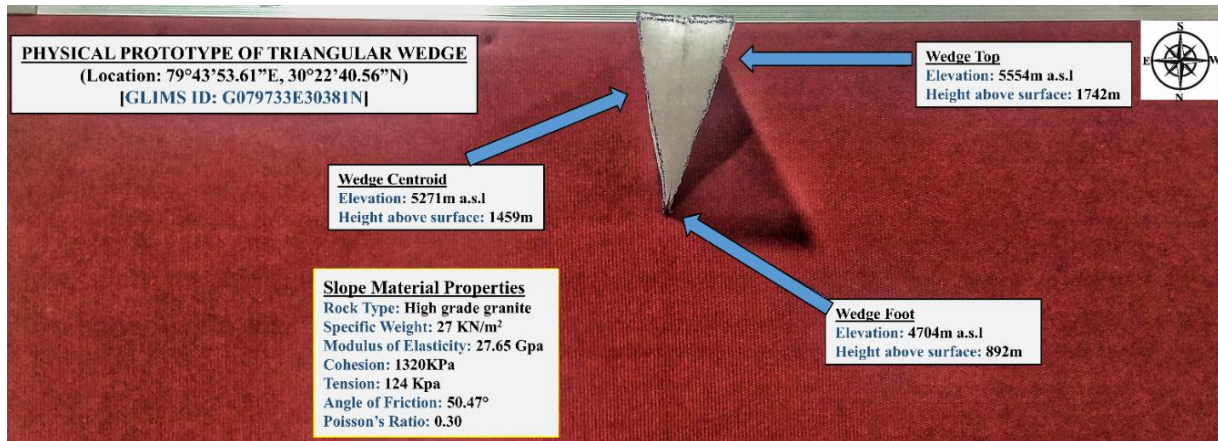


Figure 7.10: Generalized physical model of the wedge structure found in the study area

7.3.4.3 Numerical Modeling

Analysis of slope stability is performed in two different ways, namely forward analysis and back analysis. The forward analysis is used to assess a slope if it is performing safely as intended. Back analysis is used to determine slope conditions and mobilized shear strength at failure (Mandal et al., 2017). The mobilized shear strength can be obtained from laboratory tests on the collected samples from the field. However, there exists some discrepancy between the lab-based results and field observations which leads to uncertainties. In order to back analyze the stability of a failed slope, there are two distinct approaches, namely the deterministic and probabilistic approach (Duncan et al., 2014). In deterministic back analysis, all the input parameters that may cause the slope failure are assumed to be known. In the probabilistic back analysis, some or all the input parameters are treated as statistical distributions. This helps in considering the uncertainties associated with the parameters (Mandal et al., 2017). In this study, the probabilistic back analysis has been performed using the limit equilibrium method (LEM) and finite element method (FEM).

Table 7.4: Inputs to analysis of slope stability

Rock Properties (Intact)	
Specific weight:	0.027 MN/m ³
Modulus of Elasticity:	27.65 GPa
mi:	15.934
s:	1
a:	0.5
Poisson's Ratio:	0.30
Rock Mass Properties	
Geological Strength Index (GSI):	52
Modulus of Elasticity:	0.009 MN/m ³
Cohesion:	1320 KPa
Tension:	124.61 KPa
Angle of Friction:	50.47°
Poisson's Ratio:	0.30

Traditional LEM is one of the most widely used analytical methods for studying slope stability. The slope is analyzed using equivalent Mohr-Coulomb (MC) criteria for determining the shear strength along the failed surface, considering slope material to be homogenous. LEM works on the principle of static of equilibrium. The shear strength of the slope material is reduced by a factor of safety (FOS) to attain equilibrium against the shear stresses. This can be done in two ways. The first way is to consider the slope mass as a single free body. Another way is to treat the slope as slices where the net force acting on each slice should satisfy equilibrium. To conduct the probabilistic back analysis using LEM, the Slide module of the Rocscience software is used. Global minimum is considered for probabilistic analysis with the count of samples as 1000. Monte Carlo is chosen as the sampling method for three different coefficients of variation (CoV) values, i.e., 10%, 15%, and 20% (Falae et al., 2021). The Monte Carlo works on pseudo-random or random numbers to sample from probability distributions and generate a distribution for the final output (say FOS). Here, two parameters of rock mass, namely the angle of internal friction (ϕ) and cohesion (c), are chosen as random variables (RVs). The other parameters are considered deterministic input as they do not affect the critical failure surface's location and strength reduction factor (SRF). Initially, the deterministic analysis is conducted, taking the mean of input parameters. This is done to determine the critical failure surface. Then the probabilistic analysis is done for the critical surface, considering the generated samples of the parameters as RVs. Bishop Simplified Method (BSM) is used to establish a common platform to conduct a comparative study between LEM and FEM.

With the advancement in the analysis of slope stability, FEM has become a very effective method. The advantage of FEM over LEM lies in its flexibility. FEM has been very useful in studying slopes having complex configurations, progressive failures, and deformations at various stress levels. Using FEM, every failure mechanism can be modeled,

and it does not require any pre-defined assumption for the location or shape of the failure surface. FEM uses the shear strength reduction (SSR) technique for the analysis of slope stability. In this study, 2D stability analysis is conducted in the RS2 module based on the finite element. Discretization of the rock slope is done using a hexa-nodal triangular mesh element. The process of mesh convergence is repeated till the results remain unchanged. The roller boundary condition is assigned at the vertical end on the model's left side (Face AB) to restrict displacement in the horizontal axis. The fixed boundary condition is assigned at the base to restrict the displacement in both x- and y-axes. The other two slopes are kept free for displacement along the Cartesian plane. 0.1% energy tolerance is considered in the model as convergence criteria. Gaussian elimination is adopted to derive the solution of the FEM equation based on the principle of energy balance (EB). The in-situ stress generated in the vertical plane is considered twice the stress generated in the horizontal plane (Pain et al., 2014). Since the rock slope in this study lies in the vicinity of VT and STD consisting of weathered and fragmented rock strata (Pain et al., 2014; Rana et al., 2021), GSI equal to 52 is considered. The strength parameters considered in this study are mentioned in Table 7.4. FEM-SSR analysis is used together with Point Estimate Method (PEM). The principle of PEM is to conduct an iterative FEM-SSR for several estimation points and derive the failure probability from a statistical distribution based on output results. For each parameter chosen as RV, cohesion (c), and angle of internal friction (ϕ), two-point estimates are derived as shown in equation 7.2. FEM is performed for every possible combination of PEs generating 2^m solutions where m denotes the number of parameters chosen as RVs. As the count of samples is considered as 1000, the FEM-SSR analysis is run 4000 times for determining the FOS.

$$\text{Point estimates} = \text{mean} \pm \text{SD} \quad (7.2)$$

7.3.4.4 Rockfall Analysis

Rockfall comes in the category of geological hazard that mainly occurs over steep slopes of mountainous regions. Apart from the fragmentation of rock mass, this type of hazard may occur due to several factors that involve seismic tremors and heavy rainfall. Depending on slope characteristics, a rock/ice mass may undergo sliding, bounce, roll, or freefall. Understanding the risk and severity of rockfall requires understanding the potential/kinetic energy, translational velocity, bounce height, etc. In this study, Rockfall 6.0 is used to simulate the failure scenario using a deterministic approach. Numerical simulation is performed considering rock fragments as lumped mass and neglecting the slope roughness. Since the simulation is

conducted for a triangular wedge failure, rock and ice masses are assumed to be originated from the maximum height of the wedge. This is done to avoid any underestimation of results and adopt a pessimistic approach towards the hazard. As per previous investigation reports (GAPHAZ, 2021; Pandey et al., 2021), a composite wedge mass of about 25 million m³ detached from an elevation of 1742 m from a rock wall inclined at 35° from the vertical. In the rockfall simulation, 100 units of rocks/ice (seeder) are made to fall from the same height of modeled slope with a horizontal offset of a few meters to simulate the scenario. Considering non-seismic triggers, the initial horizontal, vertical, and rotational velocities of the falling rock masses are taken as 0.1m/s, 0m/s, and 0°/s respectively. Rock mass and the coefficient of restitution are stochastically modeled and served as an input in the simulation considering "truncated Gaussian distribution" with a 10% coefficient of variation (Chatterjee and Dey, 2019). The seeder properties and the stochastic parameters are listed below in Table 7.5 and Table 7.6, respectively.

Table 7.5: Inputs for numerical simulation of rock/ice fall

<i>Seeder Properties</i>	<i>Values (Rock)</i>	<i>Values (Ice)</i>
<i>Units</i>	100	100
<i>Mass (kg)</i>	550.6 million	45.85 million
<i>Density (kg/m³)</i>	2753	917
<i>Total Potential Energy (tera joules)</i>	1019	

Table 7.6: Stochastic parameters of rockfall

<i>Parameter</i>	<i>Horizontal velocity (rock/ice)</i>	<i>Coefficient of restitution</i>
<i>Standard deviation</i>	0.01 m/s	0.05
<i>Mean value</i>	0.10 m/s	0.5
<i>Relative max value</i>	0.11 m/s	0.55
<i>Relative min value</i>	0.09 m/s	0.45

7.3.5 Results and Discussion

The surface mobility of glacial bodies in the Rishiganga and Dhauliganga valley between 2020 and 2021 is shown in Figure 7.11. The mobility of the Ronti glacial body and triangular wedge along the north-eastern slope of Trisul mountain on both annual and seasonal (pre-monsoon, monsoon, and post-monsoon) basis is shown in Figure 7.12. The pre and post-monsoon seasons mainly cover the ablation and accumulation period for the glacial bodies in the western Himalayas, respectively. The annual velocity follows almost a fixed pattern throughout each glacial body.

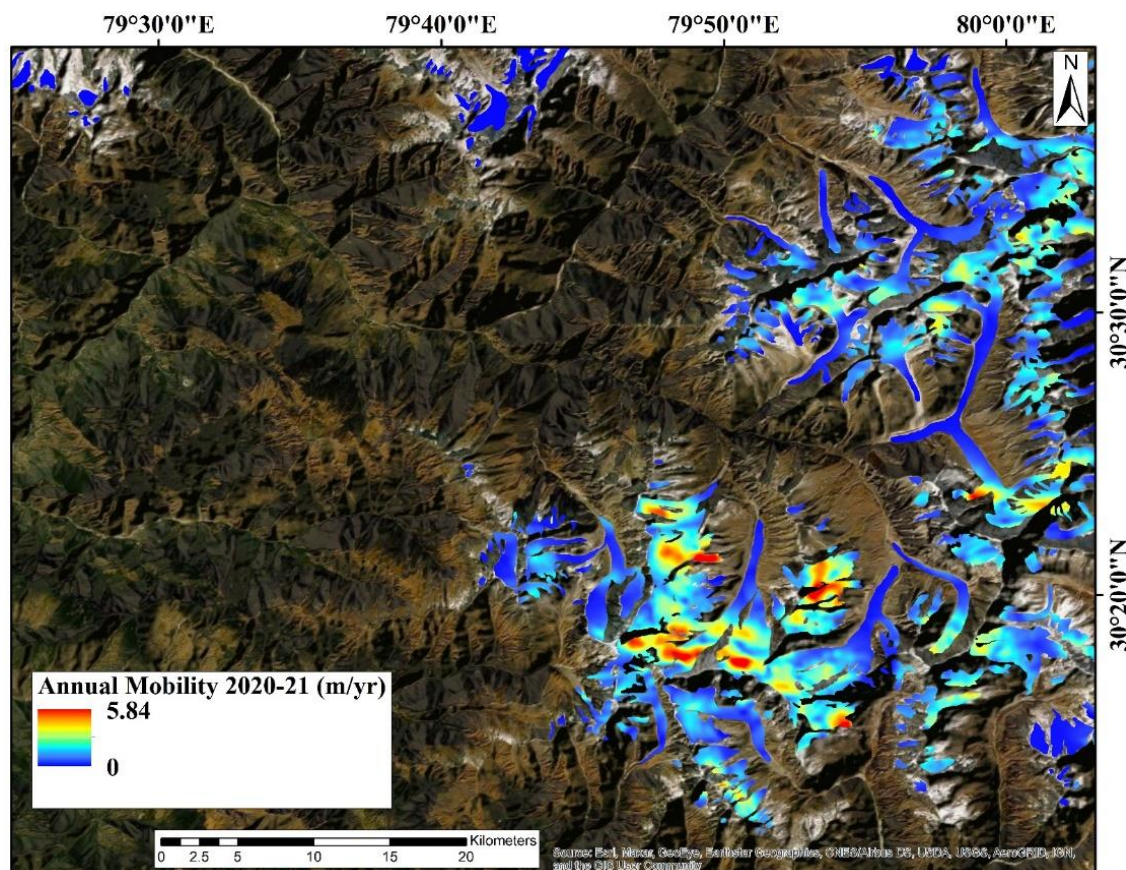


Figure 7.11: Map showing annual mobility of the glacial bodies in the Rishiganga and the Dhauliganga valley between 2020 and 2021

The highest velocity is observed in the order of $1.2\text{--}5.8\text{ m a}^{-1}$ at the upper trunk of the glaciers in the valley, which progressively recede to less than 0.2 m a^{-1} towards the snout of the glacier. The velocity profile of the Ronti glacier follows a similar trend. Maximum annual surficial displacement is detected towards the end of glacial flanges ranging between 150–185 cm, which reduces to less than 10 cm near the snout. It is to be noted that the surficial displacement of the Ronti glacial body is comparatively less than neighboring glacial bodies such as Trisul and Bethartoli glacier. The minimum surface displacement is in the post-monsoon period, and maximum displacement is observed in the pre-monsoon period. The snout of the Ronti glacier has maximum mobility in the range of 100 cm during ablation. The trend in displacement along the trunk and flanges of the glacier is similar for annual and pre-monsoon timelines, as shown in Figure 7.13. This indicates that the trend of glacial mobility during the ablation period governs the trend in annual mobility along a stretch of a glacier. It is to be noted that surficial displacement during the accumulation period is the least and therefore has less contribution in the annual mobility.

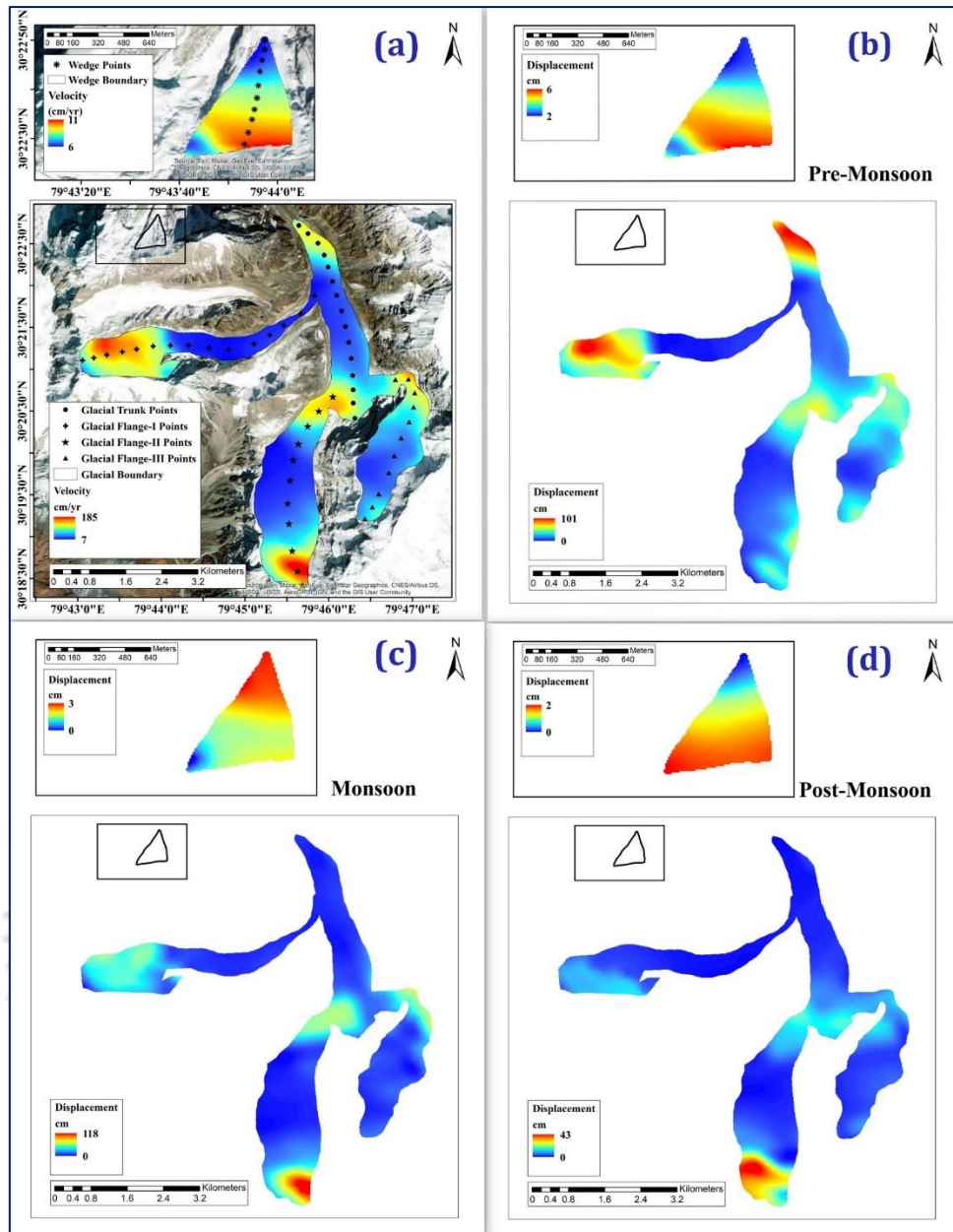
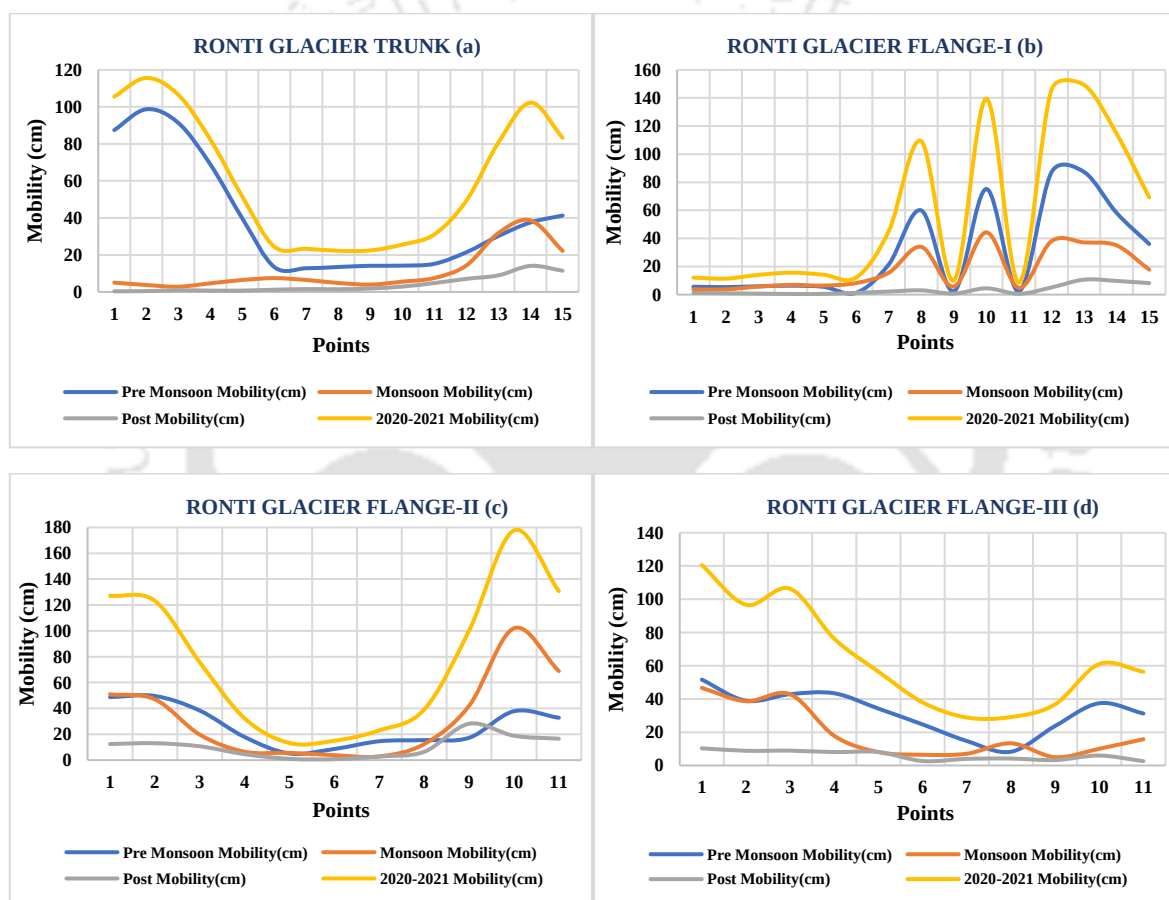


Figure 7.12: Map showing annual (a) and seasonal (pre-monsoon: (b); monsoon: (c); post-monsoon: (d)) mobility of the Ronti glacier and wedge between 2020 and 2021

For the triangular wedge, the rate of annual surface displacement is highest at the topmost edge with 11 cm a^{-1} and reduces progressively towards the foot to 6 cm a^{-1} . Seasonal analysis of mobility for the wedge suggests that the surface displacement decreases from the top of the edge to the foot during ablation and accumulation period except during monsoon when the displacement is almost constant at 3 cm. Since the seasonal and annual investigation of surface displacement for the wedge structure shows no anomaly, mobility has nothing to do with the activation of the avalanche that occurred on 7th February 2021. However, increasing surface displacement from the foot to the topmost edge can be considered a factor behind forming a triangular wedge over the mountain slope. Higher glacial velocity means a higher

displacement of the glacial surface at a location. With the resultant range of displacement along with the vertical profile of the wedge, it can be concluded that the slow but steady surface movement for a very long period can be a legitimate factor behind the formation of a prismatic wedge along a mountain slope. Also, the velocity of the glacier reduces with depth due to changes in the properties of the glacier as the glacier thickens. Ronti glacier falls in the category of hanging glaciers, and the standing wall of Trisul mountain exposes metamorphosed ice at the trench where a scenario of decreasing velocity can be observed. This can lead to the formation of the prismatic structure with greater displacement at the uppermost surface and lesser displacement with depth.



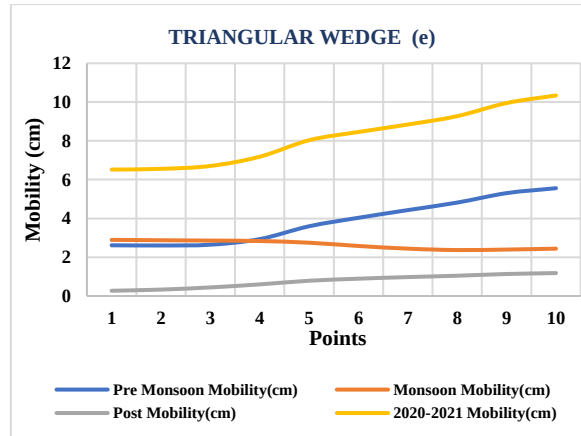


Figure 7.13: Indicating the mobility trend of (a) trunk, (b-d) flange-I/II/III of Ronti glacier and (e) wedge respectively

Table 7.7: Orientation of joint sets and rock slope

Joint Set	Joint-1	Joint-2	Slope
Dip Direction/Dip	N205° (SW) / 34°	N278° (SW) / 42°	N190° / 55°

The study area is a rocky wall on the north-eastern face of Trisul mountain with a steep valley by the side. Using the high-resolution imagery of Google Earth Pro and other investigation reports of the nearby areas (Pain et al., 2014; Jana et al., 2017), it has been found that the slope possesses mainly two joint sets dipping in different directions (Table 7.7). The presence of joint sets (density and orientation) plays a major role in rock slope failures. Kinematic analysis is carried out to figure out unstable joints within the rock mass responsible for structurally-controlled failure (planar or wedge). The difference between the dipping orientation of joint 1 and slope face is 15° ($<35^\circ$), due to which the possibility of slope failure due to planar sliding arises. However, the difference in dipping orientation between joint 2 and slope face is 88° which further rectifies the possibility of planar failure. From the equal-area stereographic representation of the lower hemisphere, the slope seems safe for both planar as well as wedge failure as the intersection of joints lie away from the critical zone (Figure 7.14). The plunge of the intersecting joints is less than that of the slope face. The intersection of the joints lie outside the daylight envelope. Therefore, none of the joint sets seem critical for planar or wedge sliding which defines the slope to be safe for structurally-controlled failure. It is not only the joint sets and their orientation that influences slope instability. Properties such as cohesion and friction angle are equally important to quantify stability. Thus, the slope has been checked for the possibility of stress-controlled failure using numerical modeling considering isotropic rock mass. The effect of discontinuities within the rock mass structure has been introduced based on previous investigations in the area (Table 7.7).

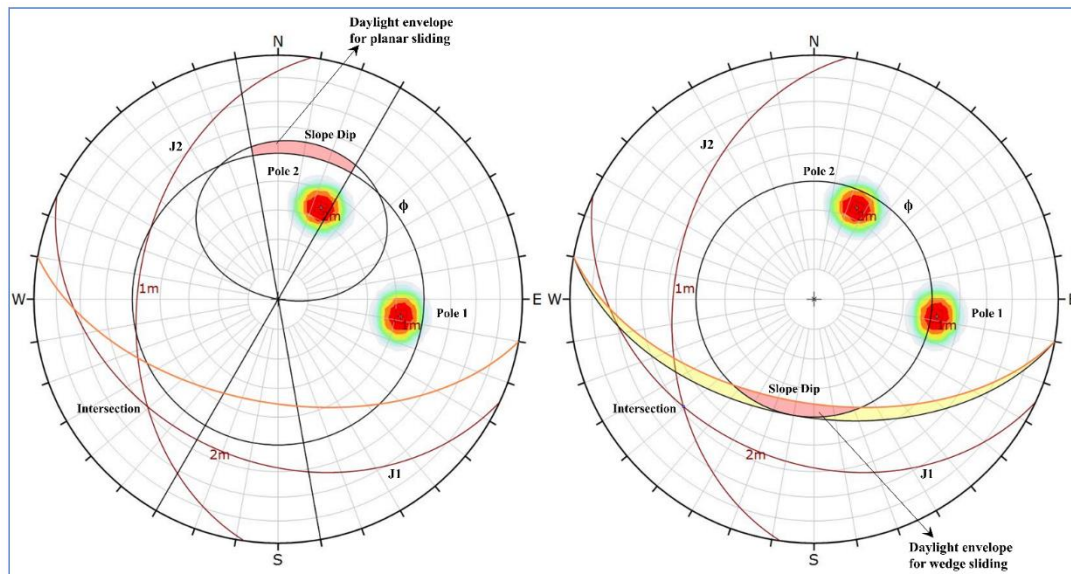


Figure 7.14: Kinematic analysis showing results for planar sliding (left) and wedge sliding (right) failure

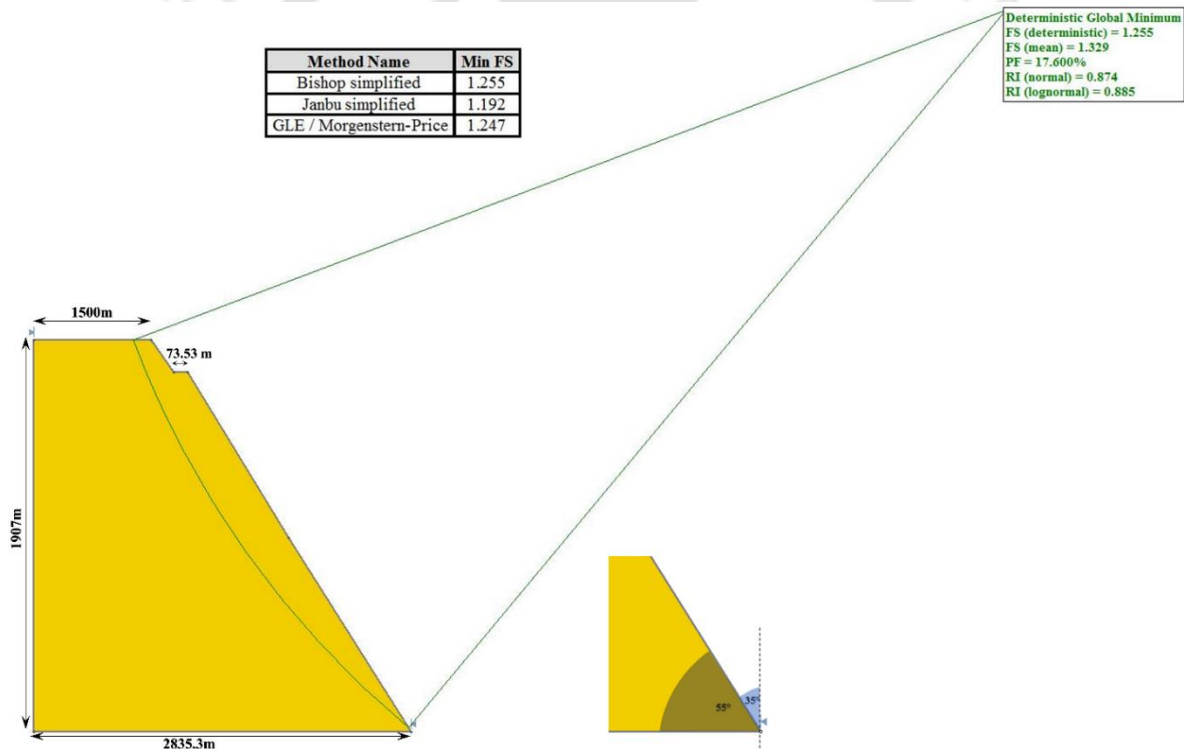


Figure 7.15: Result from limit equilibrium analysis of rock slope (at 20% CoV)

With the help of the equivalent continuum model considering gravity as the only driving force, the deduced critical failure surface is represented in Figure 7.15. The FOS from the deterministic back analysis is computed using three different methods namely, Bishop simplified, Janbu simplified, and GLE / Morgenstern-Price and the maximum FOS is calculated as 1.255 from the Bishop simplified method. The probabilistic back analysis delivers FOS as 1.273, 1.295, and 1.329 for 10%, 15% and 20% CoV respectively which is close to the

output from deterministic analysis. The probability of failure (PF) increases with the increment in CoV. The PF is found to be 17.6% at 20% CoV which means 176 samples have failed out of 1000 samples in the analysis. The reliability index (RI) falls with the increase in CoV with a maximum RI of 1.669 based on normal distribution and 1.823 based on lognormal distribution for 10% CoV respectively. This depicts the stress-controlled failure susceptibility of the slope as a slope is considered safe if the RI is ≥ 3 (Rocscience, 2012). The FOS obtained from probabilistic FEM-SSR is shown in Figure 7.16. There is no significant change in the FOS with changing CoV as shown in Table 7.8.

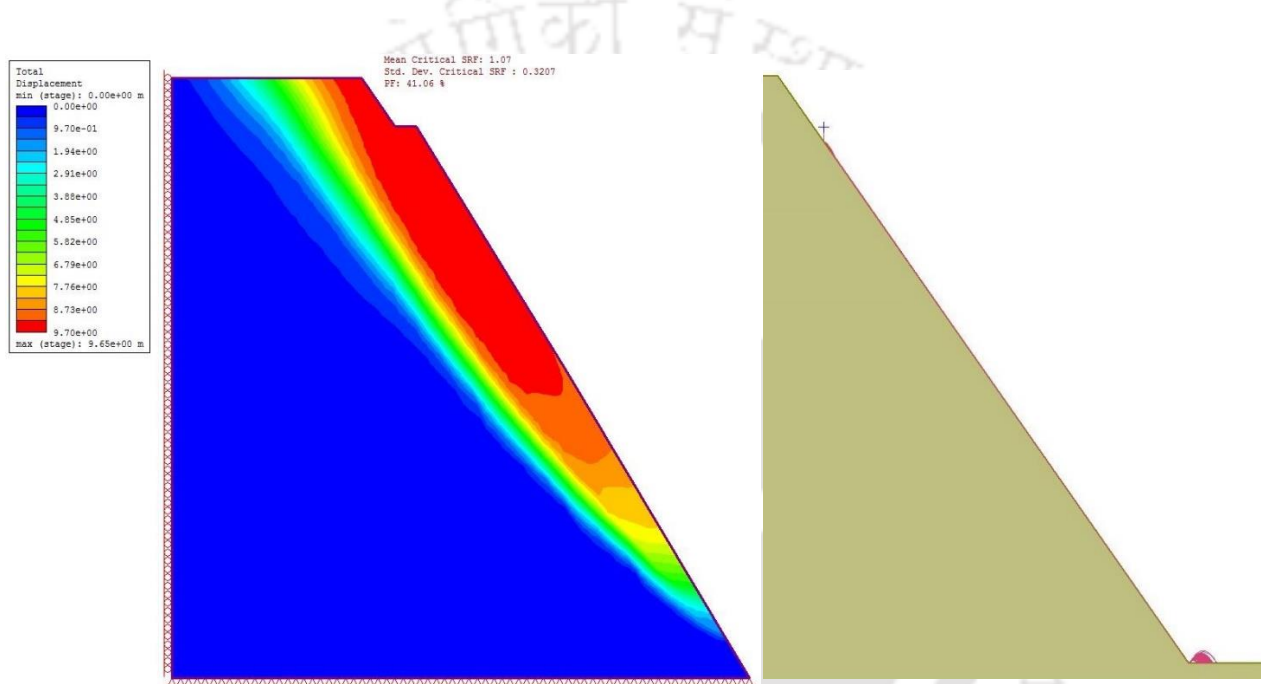


Figure 7.16: Result from Finite element SSR (left; at 20% CoV) and Rockfall analysis (right) of rock slope

Table 7.8: Probabilistic back analysis results (LEM and FEM-SSR)

Method		LEM (Slope)			FEM-SSR (RS^2)		
Coefficient of Variation (CoV)		10%	15%	20%	10%	15%	20%
Mean FOS	Bishop Simplified		1.255				
	Janbu Simplified		1.192		1.05	1.05	1.07
	GLE/Morgenstern-Price		1.247				
Standard Deviation FOS		0.168	0.258	0.377	0.140	0.223	0.321
Probability of Failure (PF)		3.6%	11%	17.6%	35.39%	41.56%	41.06%
Reliability Index (RI)	Normal	1.67	1.14	0.87			
	Lognormal	1.82	1.21	0.89			
At FOS = 1	Cohesion (kPa)	1294.19	1280.09	1305.86	1307.11	1308.09	1307.11
	Angle of Internal friction (°)	42.87	42.80	42.87	46.60	47.23	46.99

It is to be noted that changing CoV does not alter the failure mechanism as the critical failure surface remains the same. However, the PF shows an increase with increasing CoV with the maximum value of 42.4% at 20%CoV. This is because an increase in CoV results in an increment in the standard deviation, subsequently the variance. This results in an increase in the base of the plot of probability distribution function depicting an increased distance of

selected RVs from their mean. This ultimately leads to an increase in PF. The higher value of PF from FEM-SSR than LEM is because the mean FOS calculated by FEM is close to unity which is a critical demarcation of slope stability. Maximum shear strain of 9.2×10^{-2} is found along the surface of critical failure. The maximum vertical and horizontal displacement are seen as 1.58 m and 2.0 m, respectively. The maximum value of total displacement at the time of failure is found to be 2.6 m. Along the critical failure surface, the maximum volumetric strain is found as 1.11×10^{-2} near the toe of the wedge. The upper 800 m portion of the slope is dominated by tension elements responsible for tension cracks over the crest. This justifies the 80 m wide opening due to steady displacement of rock block as observed from feature tracking since 2016 (Shugar et al., 2021). The shear elements are located along the failure surface initiated from the tension zone and present till the toe of the wedge. This is indicative of the yield between the crest and the toe of the wedge.

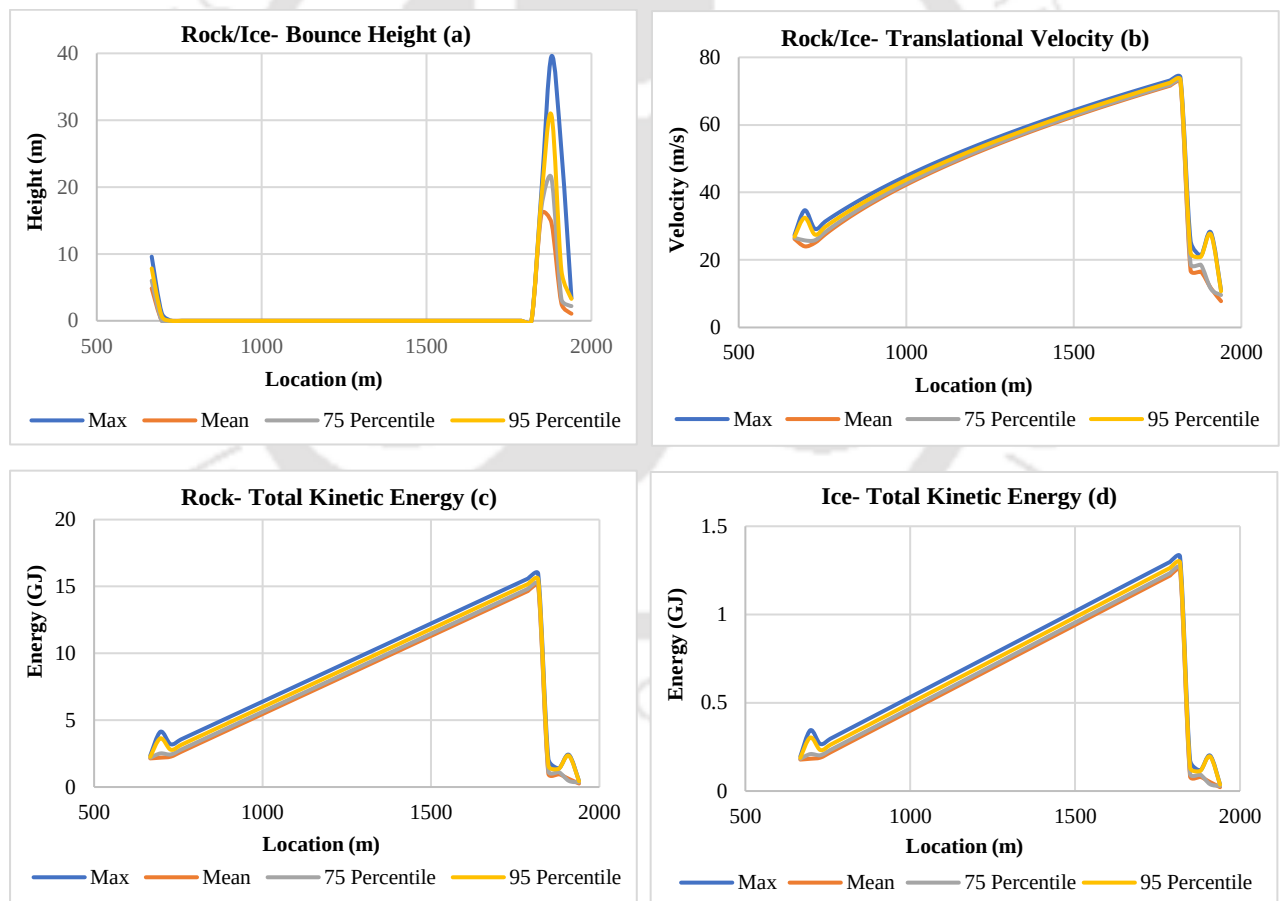


Figure 7.17: Illustration for (a) BH, (b) TV and (c-d) TKE of rock and ice fall at mean, maximum, 75 percentiles and 95 percentiles respectively

The rockfall simulation is performed following previous investigations considering 80% rock mass (20 million m^3) and 20% ice (5 million m^3). The seeder location is considered

the top of the prismatic wedge adopting a pessimistic approach while simulating rock-ice fall. Various parameters such as bounce height (BH), total kinetic energy (TKE), and translational velocity (TV) are obtained for both rocks as well as metamorphosed ice. This is done for a better understanding of the composite rock-ice failure scenario. The maximum BH, TKE/ TV locations for both rock and ice are marked at 39.56 m and 62.19 m, respectively, from the ground. The location remains unchanged with changing seeder properties from granite to metamorphosed dense ice. This shows that the parameters are dependent on the slope geometry and independent of the rockfall material. The parameters are obtained at their maximum, mean, 75, and 95 percentiles (Figure 7.17). This is performed as a probabilistic analysis to find out the parameters at every slope location at different risk levels. The slope had already undergone a wedge failure creating devastation downstream. The probabilistic analysis could help to look for a mitigation system or development of any infrastructure shortly. For instance, while designing a mitigation system for an infrastructural work of great importance that lies close to Rishiganga or Dhauliganga in proximity to the study area, the maximum or 95 percentiles of TKE, TV, and BH could be considered. On the other hand, for constructing an infrastructure of average to low importance, 75 percentile or mean of parameters could be considered while designing the mitigation system.

7.3.6 Conclusion

The Himalayan landscape is considered Asia's water tower. Several major river systems gain their origination from the Himalayan cryosphere. Hazards due to mass movements such as rock slides and glaciers burst in the proximity of these rivers impose catastrophic impacts over human lives and engineering structures. The rock-ice composite wedge structure on the north-eastern slope of Trisul mountain that collapsed on 7th February 2021 has been investigated. The salient points of the study are:

- The investigation of surface mobility of the Ronti glacier and the overhang wedge shows no anomaly and seem to move at a reasonable rate. Thus, it can be concluded that glacial mobility has not served as a factor behind the detachment of rock-ice composite structure. The resultant displacements along the vertical profile of the wedge show that the surface mobility is maximum near the topmost edge and recedes towards the foot. Such a trend of glacial mobility for a long period can be considered a possible causative factor in shaping the prismatic wedge structure.

- Kinematic analysis of the slope does not show susceptibility to structurally-controlled slope failure. The dipping properties of the two major joint sets and the slope illustrate that the rock formation is not vulnerable to planar or wedge sliding.
- The Probabilistic back analysis of the failed slope using LEM and FEM-SSR methods produces slope stability results at 10%, 15%, and 20% CoV, respectively, and are relatively close. Despite not having much difference in the mean FOS values, the PF obtained from LEM is relatively less than FEM-SSR. The RI from LEM analysis is less than 3 for both normal and lognormal distribution of RVs, which defines the slope as unsafe due to stress-controlled failure mechanism.
- Parameters from the numerical simulation of rock/ice fall from the mountain slope are obtained at the mean, maximum, 75 percentile, and 95 percentiles as a probabilistic analysis to understand the scenario of rockfall at a particular risk level. The analysis could be helpful while designing a mitigation system in the proximity of the hazard location.

Thus, integration of microwave remote sensing, numerical modeling and simulation provides an understanding about the formation as well as failure mechanism of the wedge structure from the Trisul mountain slope. Lying in the vicinity of VT and STD, the region requires continuous monitoring as well as detailed field-based geotechnical and geological investigation.

Seismic Impacts on Himalayan Glaciers

8.1 Introduction

Glaciers are the perennial storehouse of freshwater in high altitudes/low latitudes. Apart from the polar cryosphere, the Himalayan cryosphere has the largest glacial coverage accounting for an area of ~33,000 sq. km (Dyurgerov and Meier, 1997). Glaciers behave differently in different seasons and glacier dynamics (flow velocities) vary seasonally due to enhanced melting rates in the ablation period and reduced melting in the accumulation period (Zwally et al., 2002; Joughin et al., 2008; Scherler and Strecker, 2012; Satyabala, 2016). Glacial dynamics also includes surface mobility, glacial facies, changes in the areal extent and elevation profile that spaceborne/airborne remote sensing techniques have been studied extensively (Berthier et al., 2005; Kumar et al., 2011; Bhambri et al., 2012; Bhardwaj et al., 2015; Thakur et al., 2016, 2017). Glaciological investigations conducted from field-based and satellite-driven studies have shown that the Himalayan glaciers behave in synchronization with various meteorological parameters such as temperature and precipitation, resulting in retreat and negative mass balance (Wagnon et al., 2007; Dobhal et al., 2008; Bhambri et al., 2011; Azam et al., 2014; Pratap et al., 2016). These glaciers are located in the challenging, inaccessible, and seismically-prone areas of the eastern and western Himalayas. This makes earthquake impact assessment a crucial task that must be conducted after seismic events. The most common approach for determining earthquake magnitude and aftereffects is the analysis of ground-based seismometer datasets. However, due to their limited deployment in high-altitude glaciated regions, it is difficult to study certain earthquake events that occur close to those glacial bodies. Therefore, a number of geophysicists and seismologists have supplemented such ground-based methods with geodetic and satellite remote sensing-based approaches (Li et al., 2021).

Routine assessment of damage and continuous monitoring through the synoptic acquisition of data and analysis is essential to studying natural hazards. Especially earthquakes in the remote glaciated regions of Himalayan ranges, which are sudden and unpredictable and are capable of activating other hazards such as avalanches, glacial lake outburst floods and landslides. Therefore, extensive monitoring at high temporal and spatial resolution is essential

which may be more challenging from techniques such as differential global positioning system (DGPS), photogrammetry and optical remote sensing (Zhang et al., 2009). Radar technology, due to its cloud penetrating capacity, is advantageous for all-weather glaciological monitoring and proves to be more suited for studying the rugged and valley-adorned terrain of mountainous regions such as the Himalayas (Goldstein et al., 1993; Strozzi et al., 2002). Interferometry has served as an effective technique to study the Himalayan cryosphere and associated natural hazards such as avalanches (Leinss et al., 2020; Mondal and Bharti, 2022a), slope failures (Mondal and Bharti, 2022b), glacial lake outburst floods (Cochachin et al., 2017; Scapozza et al., 2019), landslides (Riedel et al., 2008; Zhang et al., 2018; Mondal et al., 2022) and earthquakes (Thomas, 2021; Li et al., 2021; Mondal and Bharti, 2022c). The approach to measuring surface deformations with the help of SAR can be divided into amplitude-based and phase-based methods using either L- or C-band radar. The pros and cons of these microwave bands derived from the sensor wavelength. The shorter the wavelength, the better the spatial resolution, whereas the longer the wavelength, the better the surface penetration (Howell et al., 2018; Jelenek and Kopačková-Strnadová, 2021). L-band SAR can be useful in large-scale studies such as soil moisture, geomorphological and tectonic studies (Chaparro et al., 2018; Zhang et al., 2019; Fernandez-Carrillo et al., 2019), X-band SAR systems help in tracking landslides and lava flows to a finer scale (Kubanek et al., 2017), and C-band SAR systems provide a compromise between both the utilizations (Atzori et al., 2013; Wang et al., 2018; Howell et al., 2018).

There are various techniques in microwave remote sensing to measure glacial surface velocity, such as SAR interferometry (Kumar et al., 2011), Multiple Aperture Interferometry (MAI) (Gourmelen et al., 2011), and offset tracking (Strozzi et al., 2002). Where intensity and coherence tracking measures two-dimensional displacement in azimuth and slant range direction, the interferometric technique only estimates displacement in slant range direction (Strozzi et al., 2002). For tracking glacial surface displacement on a temporal basis, DInSAR is an important technique, provided there exists a short temporal and geometrical baseline (Mondal and Bharti, 2022c). This technique employs a set of differential interferograms acquired for the same location over a period of time to derive a time series of temporal variations in deformation (Berardino et al., 2002). DInSAR is a very effective method for analyzing surface deformations due to subsidence, landslides, earthquake-triggered slope failures, and glacial velocity, among others (Peltzer and Rosen, 1995; Massonnet et al., 1995; Mouginit et al., 2012; Samsonov et al., 2020; Devaraj and Yarrakula, 2020; Crosetto et al.,

2020). For the Himalayan glaciers, offset tracking and DInSAR are the most common and widely used techniques (Kumar et al., 2009, 2013; Varugu et al., 2015; Thakur et al., 2018; Lal et al., 2018). In earthquake research, DInSAR has been used to estimate the co-seismic deformation field (Yang et al., 2019; Wang et al., 2018). In recent times, DInSAR has become a preferred technique for deriving precise surface deformation of glaciers on a temporal basis (Yasuda and Furuya, 2013; Milillo et al., 2017).

In this chapter, an attempt has been made to capture the impact of seismic events on and around glacial bodies situated in different parts of the Himalayan region using C-band radar interferometry.

8.2 Study Area

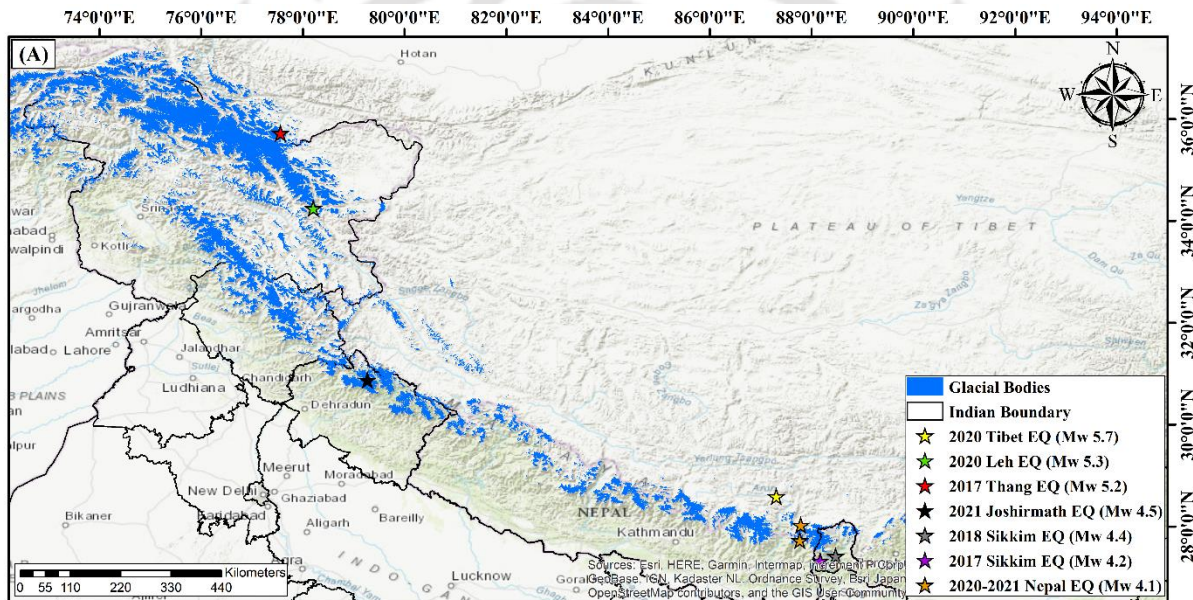


Figure 8.1: Study area map showing the Himalayan glaciers and selected earthquake epicenters

The collision between the Indian and Eurasian plates during the Cenozoic period resulted in the formation of two major orogenic features, the Tibetan plateau and the Himalaya-Hindu Kush mountains (Rajendran et al., 2017). The Himalayan orogeny falls under the category of an active orogenic belt with geological and geomorphic structures of the Quaternary-Holocene age (Thakur, 2013). Three principle thrusts, namely the main central thrust (MCT) (Hubbard and Harrison, 1989), main boundary thrust (MBT) (Meigs et al., 1995), and Himalayan frontal thrust (HFT) (Thakur et al., 2007), developed progressively in the early Miocene, late Miocene and Quaternary period respectively. The Himalayan arc and its contiguous emergent structures are seismically active and have resulted in very large earthquake events in the recent past, including devastating earthquakes such as the 1897 Shillong (Mw 8.1), the 1905 Kangra (Mw

7.8), the 1934 Bihar-Nepal (Mw 8.2), and the 1950 Assam (Mw 8.6) earthquakes. In the present study, eight earthquake events of different magnitudes, hypocenter depths, and epicenter locations that have occurred in the recent past and are close to the Himalayan glacial bodies were considered, as shown in Figure 8.1 and Table 8.1.

Table 8.1: Details of earthquake events in this study

Events	Date/ UTC Time	Epicentric Location	Seismic Magnitude (Mw)	Hypocentric Depth (Km)
Tibet Earthquake	20 th March 2020/ 01: 33: 15	28.590°N 87.308°E	5.7	10
Leh Earthquake	25 th Sept 2020/ 10: 57: 13	34.249°N 78.206°E	5.3	10
Thang Earthquake	6 th Dec 2017/ 23: 29: 03	35.724°N 77.562°E	5.2	74.3
Joshirmath Earthquake	23 rd May 2021/ 19:01:39	30.876°N 79.271°E	4.5	10
Sikkim Earthquake	17 th June 2018/ 15: 07: 37	27.420°N 88.474°E	4.4	49.8
Sikkim Earthquake	16 th May 2017/ 22: 13: 19	27.327°N 88.171°E	4.2	10
Nepal Earthquake	8 th Nov 2020/ 21: 44: 14	27.730°N 87.771°E	4.1	10
Nepal Earthquake	11 th Jan 2021/ 13: 59: 49	28.028°N 87.789°E	4.1	35

8.3 Datasets Used

Sentinel 1A/B SAR datasets were used in this study. Developed by the European Space Agency (ESA), Sentinel 1A/B is a dual satellite configuration that acquires data in the microwave C-band (λ : 5.6cm, f: 5.405 GHz) (Winsvold et al., 2018). Both the satellites lie on the same orbit plane with a combined temporal resolution of 6 days and individual temporal resolution of 12 days. Several data items are provided by Sentinel 1A/B, including Level-1 Ground Range Detection (GRD), Level-2 Ocean (OCN), and Level-0, Level-1 Single Look Complex (SLC). It also has various modes of operation, namely Wave (WV), Strip Map (SM), Extra Wide Swath (EW), and Interferometric Wide Swath (IW) modes. The IW captures data in a 250 Km swath having a spatial resolution of 5m×20m. IW mode acquires data in three sub-swaths with the help of Terrain Observation with Progressive Scans SAR (TOPSAR). Each sub-swath data is an aggregate of a series of bursts, and each burst is processed as a separate SLC file (ESA, 2016). In this paper, a state-of-the-art study has been conducted where pre- and co-seismic pairs of SLC datasets have been used, as shown in Table 8.2. Sentinel 2 Level 1C (L1C) multispectral instrument (MSI) data from the Nepal earthquake region of 17th January 2021 also was used. The L1C MSI product comprises orthorectified tiles covering an area of 100 sq. km (ESA, 2015). Radiometric measurements for the L1C products are available in Top of Atmosphere (TOA) reflectance, where the datasets have been resampled with constant Ground Sampling Distance (GSD) of 60, 20 and 10 m depending upon the native resolution of various spectral bands (ESA, 2015). Here, green (543-578 nm) and red (658-680 nm) bands at 10 m

and near-infrared (785-899 nm) band in 20 m resolution have been used to generate a False Color Composite (FCC) image of the zone of study. The boundary of the Himalayan glacial bodies has been adopted from the Randolph glacial inventory, RGI 6.0 (RGI Consortium, 2017).

Table 8.2: Sentinel 1A/B C-band SLC images used in this study

Sentinel 1 SLC Datasets							
Year-Earthquake	Pre-Earthquake Datasets		Co-Earthquake Datasets		Beam Mode-Sub-swath/Path	Frame/Flight Direction	Polarization
	Primary	Secondary	Primary	Secondary			
2020-Tibet Earthquake	04-03-2020	16-03-2020	16-03-2020	28-03-2020	IW-1/121	496/Descending	VV+VH
2020-Leh Earthquake	07-09-2020	19-09-2020	19-09-2020	01-10-2020	IW-1/136	476/Descending	VV+VH
2017-Thang Earthquake	15-11-2017	27-11-2017	27-11-2017	09-11-2017	IW-1,2/129	112/Ascending	VV+VH
2021-Joshirmath Earthquake	06-05-2021	18-05-2021	18-05-2021	30-05-2021	IW-1,2/63	487/Descending	VV+VH
2018-Sikkim Earthquake	30-05-2018	11-06-2018	11-06-2018	23-06-2018	IW-3/12	84/Ascending	VV+VH
2017-Sikkim Earthquake	02-05-2017	14-05-2017	14-05-2017	26-05-2017	IW-2/48	499/Descending	VV+VH
2020-Nepal Earthquake	25-10-2020	06-11-2020	06-11-2020	18-11-2020	IW-3/48	499/Descending	VV+VH
2021-Nepal Earthquake	24-12-2020	05-01-2021	05-01-2021	17-01-2021	IW-3/48	499/Descending	VV+VH

8.4 Methodology

8.4.1 Seismic Events and Interferometric Pairs Selection

The Himalayan region has experienced a large number of earthquakes of different magnitudes and hypocenter depths distributed from west to east. However, the primary goal of this study is to understand the impact of earthquake events in terms of glacial deformation. Therefore, earthquakes based on the magnitude range from Mw 5.7 to Mw 4.1 with varying hypocenter depths have been selected close to Himalayan glaciers at various locations.

DInSAR for seismic deformation studies relies on selecting SLC data pairs to obtain a good quality co-seismic deformation field. Since the study is based on understanding the seismic deformation of Himalayan glaciers, interferometric pairs have been selected based on the following criteria:

- The SLC products used should provide best possible areal coverage within the influence area of an earthquake
- Shortest possible temporal baseline
- Earliest post-seismic acquisition

- d) Maximum possible areal coverage around epicenter location to capture complete seismic signal

The influence area for each earthquake event has been determined using USGS shake maps (<https://earthquake.usgs.gov/data/shakemap/>). For the earthquake events devoid of shake maps, the influence area has been determined from the shake maps of other earthquakes with similar magnitude and hypocenter depth. These criteria helped minimize decoherence, as the shortest temporal baseline ensures high coherence, especially while investigating low-latitude regions, and minimizing the effect of ongoing glacial deformation after the earthquake.

8.4.2 Vertical Deformation

SAR systems such as Sentinel 1 are active radar systems operating in the microwave spectrum, transmitting and receiving pulses from the Earth's surface. These pulses or signals consist of phase and amplitude information. Therefore, in a SAR image, information from each pixel can be treated as a complex number where the real part represents the wave, and the imaginary part corresponds to phase and amplitude values (Moreira et al., 2013). The processing begins with identifying the primary and secondary data to execute DInSAR as shown in Figure 8.2. This involves obtaining the pre-seismic event SLC data as the primary file and the co-seismic data as the secondary file, respectively. The orbit state vectors were improved using precise orbit information for the SLC products. This is followed by the co-registration of primary and secondary images for the same sub-swath using one arcsec Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM). For co-registration, the constant range offset has been obtained by averaging the range offsets for every burst in the SLC split of IW mode (Varade et al., 2019). Enhanced Spectral Diversity (ESD) has been used to determine the constant azimuth offset. These offsets are required for applying azimuth and range corrections for each burst in the SLC split (Yagüe -Martinez et al., 2016).

flattened interferogram indicates the actual variation in altitude. Orthorectification (geocoding) of the unwrapped phase was performed using Range Doppler terrain correction (Hellwich and Ebner 2000). Finally, the vertical displacement from the unwrapped phase has been derived using equation 8.1 as follows:

$$Z_{vertical} = \frac{\phi_{unwrapped} \lambda_{SAR}}{-4\pi \cos \theta_{in}} \quad (8.1)$$

where $\phi_{unwrapped}$ represents the unwrapped phase interferogram, λ_{SAR} is the C-band wavelength of Sentinel 1 SAR instrument (57 mm) and θ_{in} is the incident angle (Walter, 2014). The cosine of the incidence angle converts the line-of-sight (LOS) displacement to vertical displacement. Sentinel 1 acquiring datasets at a wavelength of 5.6 cm are affected due to atmospheric delay, which can be eradicated using zenith total delay (ZTD) maps as obtained from generic atmospheric correction online service for InSAR (GACOS) (<http://www.gacos.net/>). GACOS makes use of the iterative tropospheric decomposition (ITD) model to segregate turbulent and stratified signals from tropospheric total delays (Yu et al., 2018; Li et al., 2018). This helps generate ZTD maps at high spatial resolution used to correct unwrapped interferograms as obtained through phase unwrapping. The difference in ZTD maps obtained for the primary and secondary datasets are deducted from the unwrapped phase to obtain an atmospherically corrected unwrapped phase further used to derive vertical displacement.

8.4.3 SAR Interferometric Coherence

To introduce a comparison between two SAR scenes and determine the coherence, the SAR pair needs to be precisely aligned, resampling the secondary scene to the primary scene. It is generally preferred that the baseline of imagery is low (<200 m) along with zero doppler SAR pair geometry (Olen and Bookhagen, 2018). Interferometry can be seen as the complex coherence between corresponding samples of SAR pair estimated from the absolute value of the correlation coefficient (Tamkuan and Nagai, 2017; Natsuaki et al., 2018). The complex coherence can be explained using equation 8.2.

$$\gamma_{complex} = \frac{X\{a, b^*\}}{\sqrt{X\{|a^2|\}.X\{|b^2|\}}}} \quad (8.2)$$

where X denotes the expectation operator, a and b are zero mean circular Gaussian variables, and $*$ represents the complex conjugate. The coherence value can be obtained from the complex coherence magnitude, as shown in equation 8.3.

$$\gamma = |\gamma_{complex}| = \frac{\frac{1}{n} \sum_1^n P.S^*}{\sqrt{\frac{1}{n} \sum_1^n P.S^*} \cdot \sqrt{\frac{1}{n} \sum_1^n P.S^*}} \quad (8.3)$$

where n denotes the kernel size of the sliding window. P and S are primary and secondary SAR scenes, respectively. In a coherence product, the value ranges between 0 to 1 where 1 stands for perfect coherence which is rarely observed in the nature. Coherence is sensitive to changing pixel information (phase or amplitude). Changes in the surface's backscatter properties, surface elevation or dielectric characteristics can result in the loss of coherence or de-correlation (Zebker et al., 1992). Thus, changing coherence can be helpful in the temporal and spatial estimate of when and where changes have occurred on the ground surface. However, the type or rate of change cannot be assessed (Olen and Bookhagen, 2018). The overall de-correlation captured from a pair of SAR scenes can be seen as a combination of different types of de-correlation (Strozzi et al., 2000) as shown in equation 8.4.

$$\gamma = \gamma_t \gamma_m \gamma_s \gamma_d \gamma_a \gamma_k \quad (8.4)$$

where γ_t represents thermal de-correlation as a result of uncorrelated noise within the radar sensor (Liu et al., 2014), γ_m is the de-correlation due to mis-registration of two SAR scenes (Franceschetti and Lanari, 2018), γ_s represents spatial de-correlation due to large baselines (Hoffmann, 2007). Due to large baselines, there exists a significant difference in the incident angle of SAR pair resulting in coherence reduction (Zebker and Villasenor, 1992). In addition, γ_s depends on the topography of the area under investigation. The slope facing the sensor shows significant de-correlation with an increase in slope angle due to the layover effect and foreshortening. On flat topography, the effect of γ_s can be corrected using common band filtering provided the range resolution is compromised (Hoffmann, 2007). Similar to γ_s , γ_d (doppler centroid de-correlation) occurs due to large variation in the squint angle between SAR-pair acquisitions. To avoid the effect of γ_d , antenna steering or range adaptive azimuth common band filtering can be adopted (Franceschetti and Lanari, 2018). γ_a occurs due to different water content in the atmosphere during both SAR acquisitions resulting in artifacts in the interferogram (Gens, 1996; Gupta, 2003). γ_k represents temporal de-correlation due to Earth's surface changes resulting from frost and dew cycles, snowfall, and melting around glaciated areas. In the areas covered by vegetation or forest, coherence loss occurs due to wind and plant growth (Wegmüller and Werner, 1995; Chen et al., 2002).

8.5 Results and Discussion

8.5.1 2020 Tibet Earthquake, Mw 5.7

For the purpose of detecting an earthquake event of sufficiently high magnitude ($M_w > 5$), DInSAR is an effective approach. There exists a strong correlation between the magnitude of an earthquake event and its detectability through SAR interferometry. Earthquake events with larger magnitude create significant surficial deformation that can be captured in the interferogram, and the deformation signal generated due to high-magnitude earthquake differs from other background processes (Li et al., 2021). Another critical factor is the hypocenter depth. The hypocenter depth governs whether an earthquake event generates surface deformation signals that are sufficient enough to be detected through DInSAR. As a general rule, the deeper the earthquake, the smaller the amplitude of the deformation at Earth's surface (Mellors et al., 2004). This makes shallow seismic events more detectable through co-seismic interferograms.

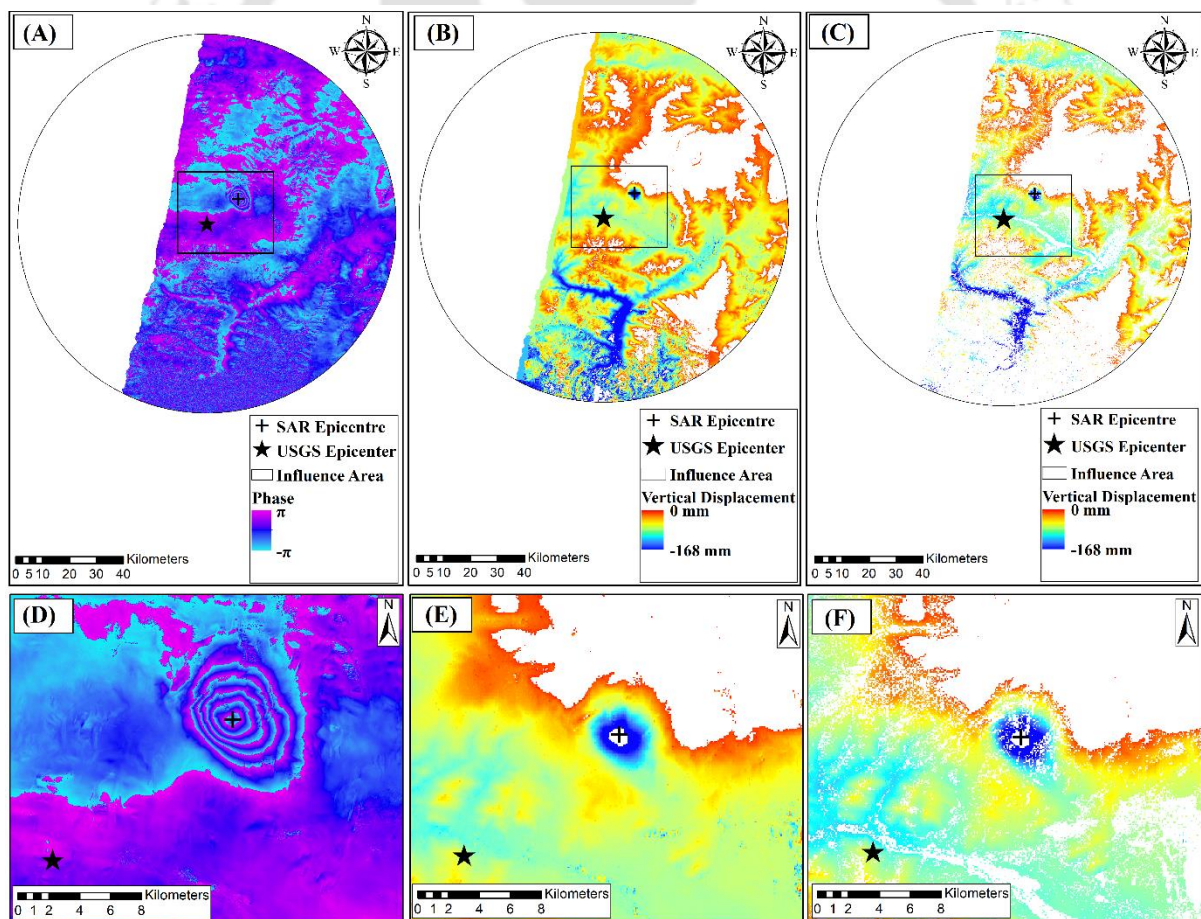


Figure 8.3: Map for 2020 Tibet earthquake (Mw 5.7) showing (A) orthorectified phase interferogram (B) vertical displacement (C) vertical displacement for coherence ≥ 0.6 , coseismic image (D) orthorectified phase interferogram at epicenter location (E) vertical displacement at epicenter location and (F) vertical displacement for coherence ≥ 0.6 , coseismic image

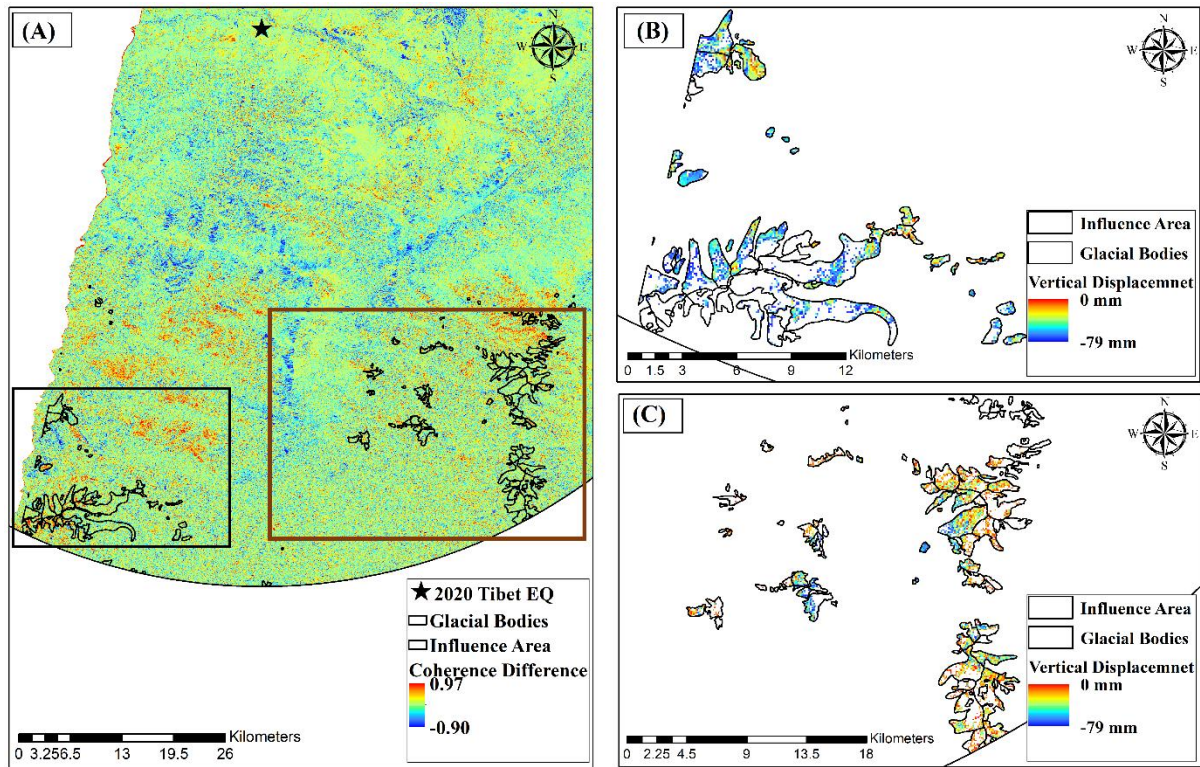


Figure 8.4: Map showing orthorectified layer of (A) difference between pre-and co-seismic coherence and (B) and (C) vertical displacement (mm) within glacial bodies derived from unwrapped phase interferogram for 2020 Tibet earthquake (Mw 5.7)

In the case of the 2020 Tibet earthquake with a hypocenter depth of 10 Km, lobate deformation with a 10 km wide series of concentric fringes can be seen in the phase image as shown in Figure 8.3A and D. The center of the concentric fringes represents the earthquake epicenter which lies approximately at a distance of 13.7 Km from the USGS epicenter. The vertical displacement around the epicenter lies between 0 and -168 mm. Negative displacement values indicate the subsidence at the surface, with maximum motion away from the epicenter at the DInSAR-derived epicenter location, as shown in Figure 8.3B, C, E, and F. In the case of DInSAR-based seismic deformation studies, the reliability and quality of results generated from unwrapped phase information depend on the co-seismic coherence (Thomas, 2021). The regions of high co-seismic coherence can be considered as the regions of more reliable surface displacement. To enhance the quality of the derived results, vertical displacement of the regions having high co-seismic coherence (≥ 0.6) has been masked out, as shown in Figure 8.3C and F. The influence area of the earthquake as defined from the isoseismal contours of the event shake map (<https://earthquake.usgs.gov/earthquakes/eventpage/us70008cld/shakemap/intensity>) and is considered as a circular area up to a distance of 69 Km from the USGS epicenter. The mean vertical displacement in the area is found to be -47.3 mm. We observe that there is only subsidence due to the 2020 Tibet earthquake (Mw 5.7). Li et al., 2022 detected the coseismic

deformation for the Tibet earthquake using ISCE (InSAR Scientific Computing Environment) (Rosen et al., 2012) with maximum deformation in the order of -126 and -157 mm through ascending and descending tracks, respectively. A seismogenic fault (dipping northeast) was detected with the main rupture zone of $\sim 5 \times 5 \text{ Km}^2$ and a maximum co-seismic quasi-vertical displacement of -164 mm. Figure 8.4B represents the vertical displacement of the glacial bodies with a mean displacement of -38.9 mm. To check for variations of surficial features such as glacial moraine deposits around the glacial bodies, the changes in coherence due to earthquakes were calculated, as shown in Figure 8.4A. A reduction in the coherence can be observed from pre-seismic to co-seismic SLC pair in some of the regions around the earthquake epicenter within the lacustrine deposits of natural lakes (Lake Dingmu) and human settlements (Mondal and Bharti, 2022c). Reduced coherence can be seen around some glacial bodies. However, such changes are not significant as the glacial bodies are situated close to the periphery of the influence area which is much away from the epicenter of the earthquake.

8.5.2 2020 Leh Earthquake, Mw 5.3 and 2017 Thang Earthquake, Mw 5.2

Figure 8.5. represents the vertical displacement captured due to the 2020 Leh earthquake (Mw 5.3). Within the influence radius of 61 Km, vertical displacement lies between 31 mm and -33 mm. Unlike the 2020 Tibet earthquake, where there is only subsidence, but no uplift of the surface after the earthquake, regions close to the epicenter location show positive vertical displacement for the 2020 Leh earthquake, with negative vertical displacements moving away from the epicenter. For the areas with coherence ≥ 0.6 , the mean vertical displacement is found to be -2.4 mm. Figure 8.6B represents the displacement of glacial bodies where the glaciers lying close to the epicenter show positive displacement or uplift. The glacial bodies far from the epicenter capture subsidence. The mean vertical displacement of the glaciers is found to be -2.5 mm. Figure 8.6A shows the coherence difference obtained by subtracting pre-seismic coherence values from the co-seismic coherence values. Reduction in coherence can be observed around the glacial bodies. Even though surficial deformations can act as a primary source of de-correlation, other factors such as de-correlation due to sensor noise from the radar system, geometric de-correlation due to perpendicular baseline component, and temporal de-correlation due to changes in surficial features and/or vegetation are important (Zebker et al., 1992; Mondal and Bharti, 2022c). Thus, temporal de-correlation before and during an earthquake event can be attributed to surficial changes and/or changes in vegetation cover. As Leh is characterized as a high-altitude dry-cold mountainous desert (Krishan, 1996), such reduced coherence due to an earthquake around glacial bodies can indicate

deformation/alteration of glacial moraine. However, because of the shape and size of the glacial bodies, it is difficult to unwrap the Figure 8.6B represents the displacement of glacial bodies where the glaciers lying close to the epicenter show positive displacement or uplift. The glacial bodies far from the epicenter capture subsidence. The mean vertical displacement of glaciers is found to be -2.5 mm. However, with an influence radius of 61 km, the region of investigation for seismic deformation is large and consists of ground surface and glacial bodies which are quite different from each other in terms of their material properties. Unwrapping the DInSAR phase information for the entire influence area of the earthquake may introduce unwrapping errors. Therefore, we investigated the vertical displacement due to seismic events glaciers and the surrounding ground surface separately, so as to avoid any unwrapping errors while considering a larger area. Considering small patches of glaciated regions and ground surface separately (Figure 8.7) at almost equal radial distance of 41 km shows that the glacial region experiences negative vertical displacements of up to -78 mm, which is much greater than the ground displacement, which lies in the range of 18 mm and -32 mm. The vertical ground displacement shown in the subregion of Figure 8.7C lies within the range of seismic displacement as shown in Figure 8.5B. Moreover, where the ground surface shows both uplift and subsidence, the glacial patch shows only subsidence. One possible reason behind the variation in the seismic deformation of glacial bodies and ground surface could be the differences in their material properties and dynamic response. Glaciers are huge masses of metamorphosed ice that behave as a Kelvin Voight (non-Newtonian) material with the ability to flow, which is different from the solid ground surface (Reeh et al., 2003). As a result, the impact of earthquakes on glacial bodies will be different from that of the ground surface.

Similarly, for the 2017 Thang earthquake (Mw 5.2), the vertical displacement ranges between 51 mm and -39 mm within the influence radius of 56 Km, with the mean displacement of 2.8 mm for regions masked with coherence ≥ 0.6 as shown in Figure 8.8B. For the glacial bodies within the influence area, the mean vertical displacement of 3.4 mm is observed (Figure 8.9B). From the coherence difference map (Figure 8.9A), reduced co-seismic coherence can be seen within and around the glacial bodies lying within the influence area. Alike Leh, Thang is also a dry-cold mountain desert devoid of vegetation around the glaciated regions. Reduced coherence due to an earthquake event within and around glacial bodies indicate possibility of surficial changes in glacial moraine deposits. Figure 8.10 shows the vertical displacement derived for glacial and ground patches separately. The glacial patches show very high vertical displacement due to the 2017 Thang earthquake that reaches up to -173 mm and -576 mm as

shown in Figures 8.10B and 8.10C respectively. Whereas, the seismic displacement of the solid earth patches does not exceed -39 mm as also is observed while considering the entire influence area for seismic displacement as shown in Figure 8.8. It also is interesting to observe that the glacial patch farther from the epicenter and surrounded by larger glacial bodies shows larger vertical displacement (Figure 8.10C) than the glacial patch close to the epicenter (Figure 8.10B). One possibility could be site-specific amplification of the seismic waves which is dependent on the material properties of glacial bodies, including shear modulus, damping coefficient, and thickness. However, better understanding of these effects would require extensive field- as well as lab-based studies of the behavior of glacial ice towards seismic loading.

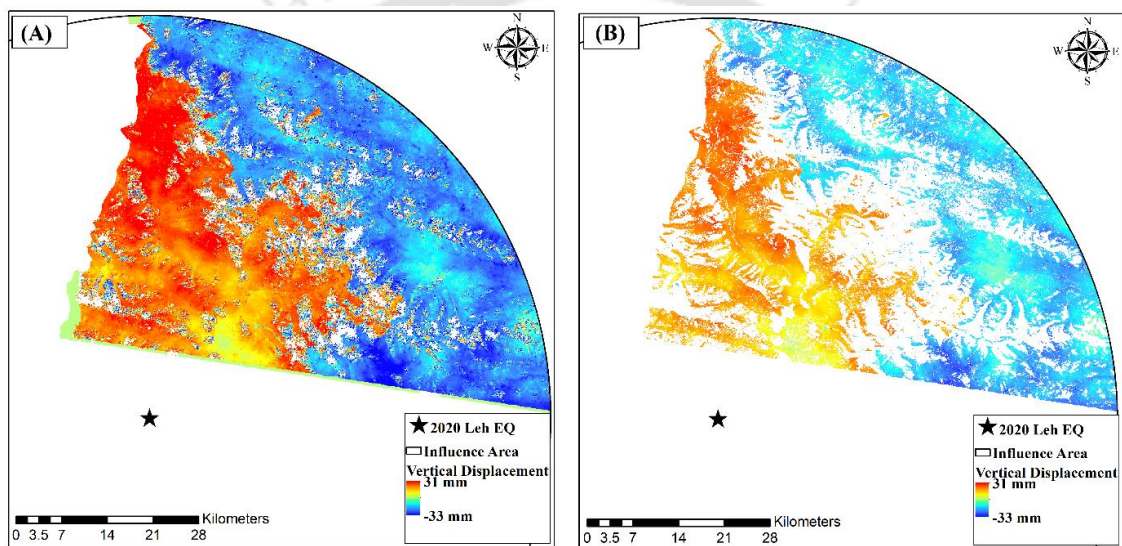


Figure 8.5: Map showing (A) orthorectified vertical displacement and (B) vertical displacement with co-seismic coherence ≥ 0.6 for 2020 Leh earthquake (Mw 5.3)

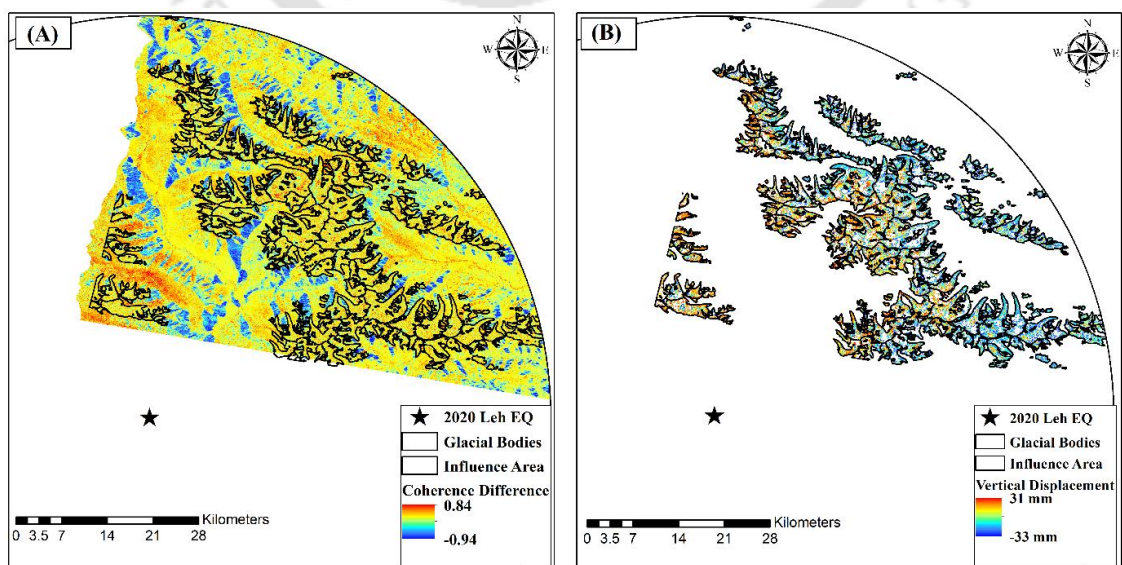


Figure 8.6: Map showing (A) difference between pre-and co-seismic coherence and (B) vertical displacement (mm) within glacial bodies derived from unwrapped phase interferogram for 2020 Leh earthquake (Mw 5.3)

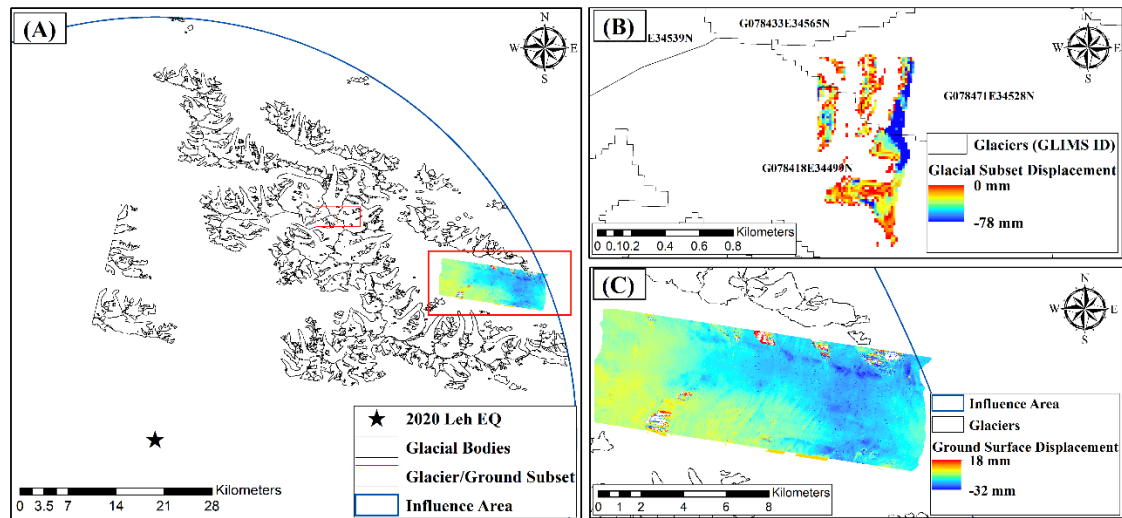


Figure 8.7: Map showing (A) glacial and ground subset regions, (B) vertical displacement (mm) within glacial subset and (C) vertical displacement (mm) within ground subset derived from unwrapped phase interferogram for 2020 Leh earthquake (Mw 5.3)

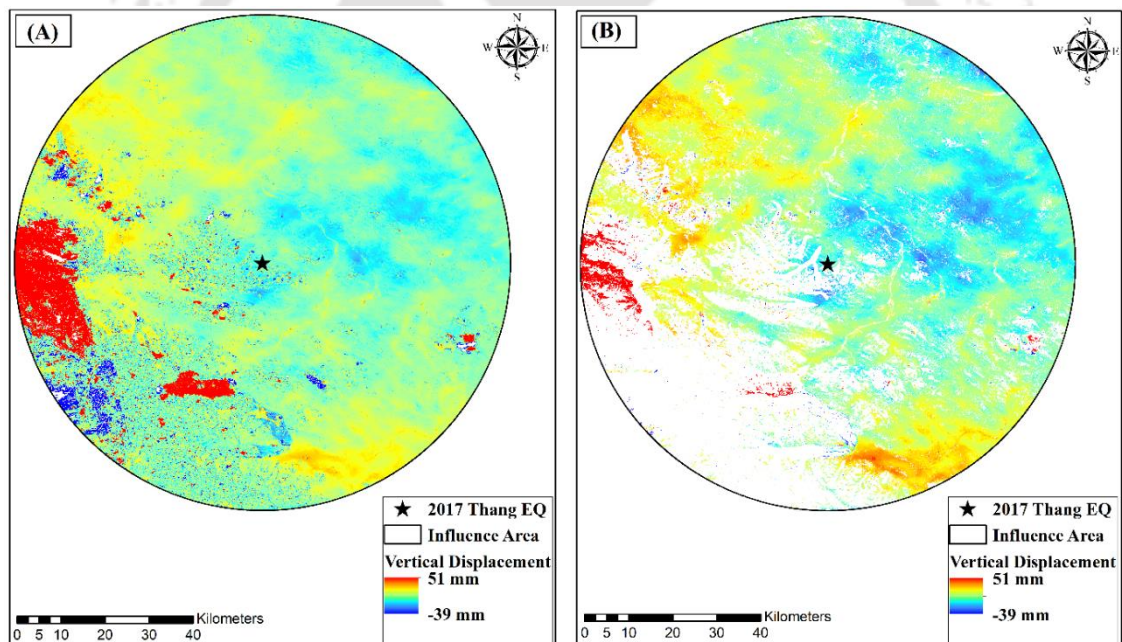


Figure 8.8: Map showing (A) orthorectified vertical displacement and (B) vertical displacement with co-seismic coherence ≥ 0.6 for 2017 Thang earthquake (Mw 5.2)

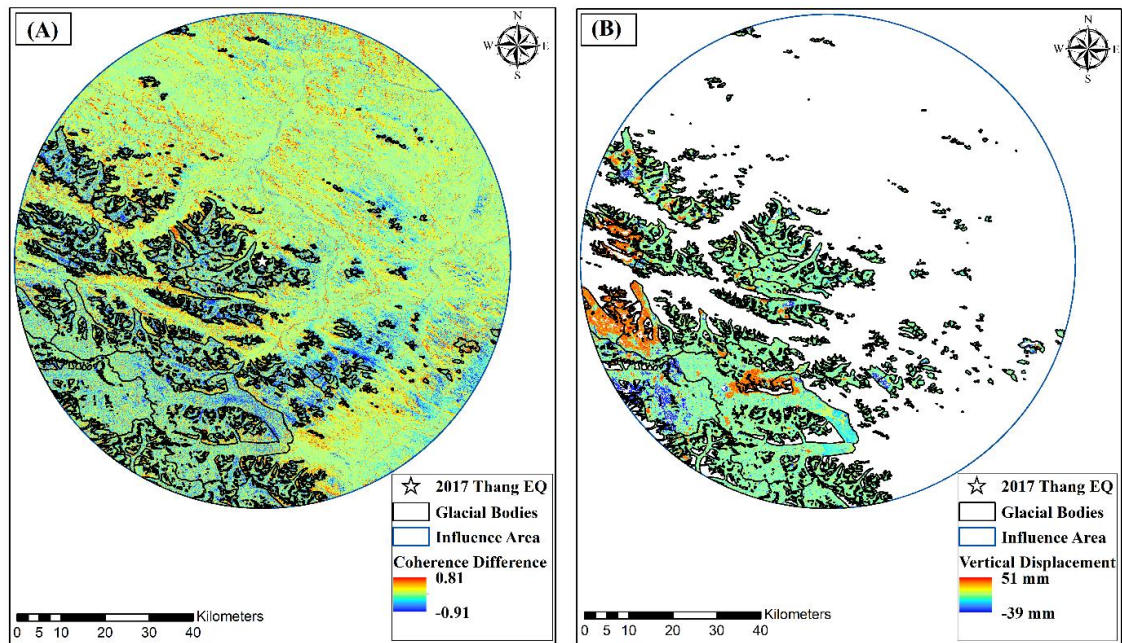


Figure 8.9: Map showing (A) the difference between pre-and co-seismic coherence and (B) vertical displacement (mm) within glacial bodies derived from unwrapped phase interferogram for the 2017 Thang earthquake (Mw 5.2)

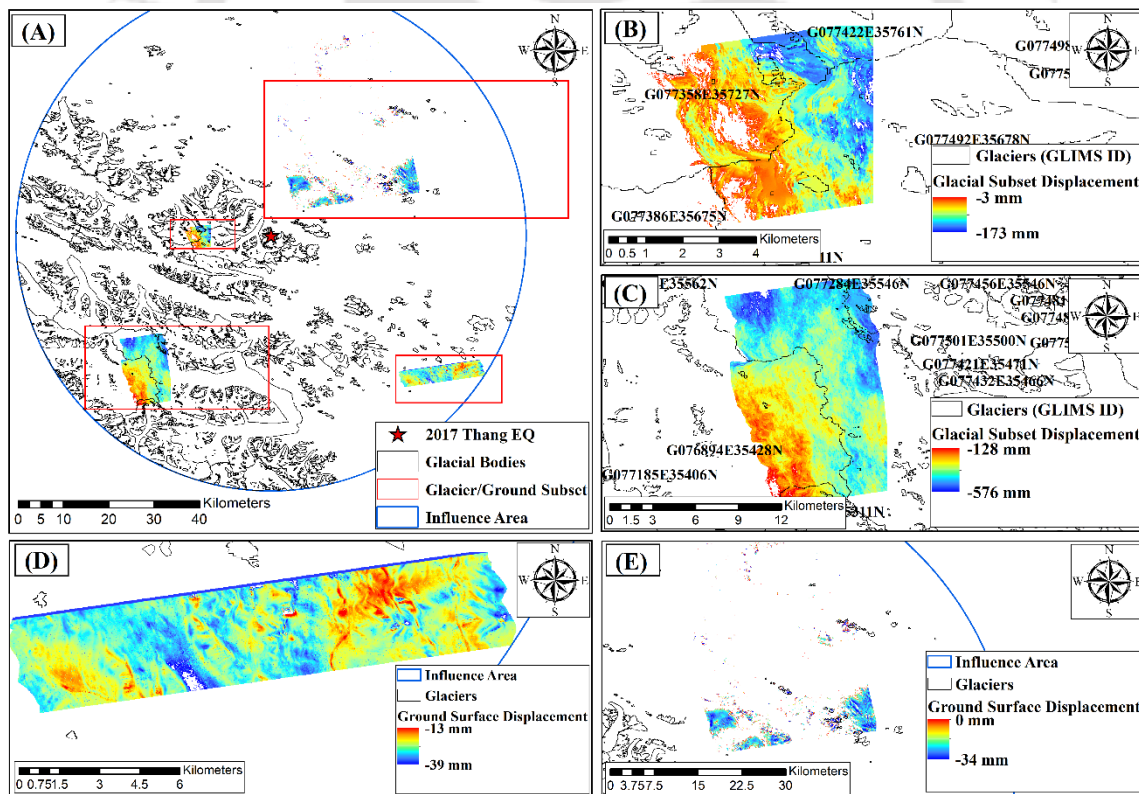


Figure 8.10: Map showing (A) glacial and ground subset regions, (B-C) vertical displacement (mm) within glacial subset and (D-E) vertical displacement (mm) within ground subset derived from unwrapped phase interferogram for 2017 Thang earthquake (Mw 5.2)

8.5.3 2021 Joshimath Earthquakes, Mw 4.5

The Joshimath earthquake (Mw 4.5) occurred on 23rd May 2021 at a hypocenter depth of 10 Km near the Gangotri glacier. Figure 8.11 shows the vertical deformation of the Earth's surface within the influence area (54 Km). The earthquake event resulted in both upliftment and subsidence, lying in the range of 45 mm and -52 mm respectively. However, the mean displacement of -1.7 mm is observed. Earthquake-induced vertical displacement for the regions with co-seismic coherence ≥ 0.6 shows the mean vertical shift in the order of 0.64 mm. For the glacial bodies, a mean vertical displacement of -2.2 mm is observed (Figure 8.12C and E). A major portion within the influence area shows negative vertical displacement except for some small patches and the north-eastern region of the influence area. The majority of glacial bodies are situated in the east-west region, and very few are in the northern side of the influence area. Therefore, the mean vertical displacement of the glacial bodies shows slightly greater subsidence as compared to the mean vertical displacement of the ground surface within the influence area. From the coherence difference map of the influence area, a reduction in the co-seismic coherence can be observed around the glaciated regions along the northern-eastern side of the influence area where earthquake-induced upliftment is observed. Figure 8.13 shows the seismic displacement of glacial and solid earth patches. As also was observed for the 2020 Leh earthquake and 2017 Thang earthquake, the glacial patch shows seismic displacement of up to -94 mm due to the 2021 Joshimath earthquake, which is much higher than the vertical displacement of ground patch, of as much as -51 mm.

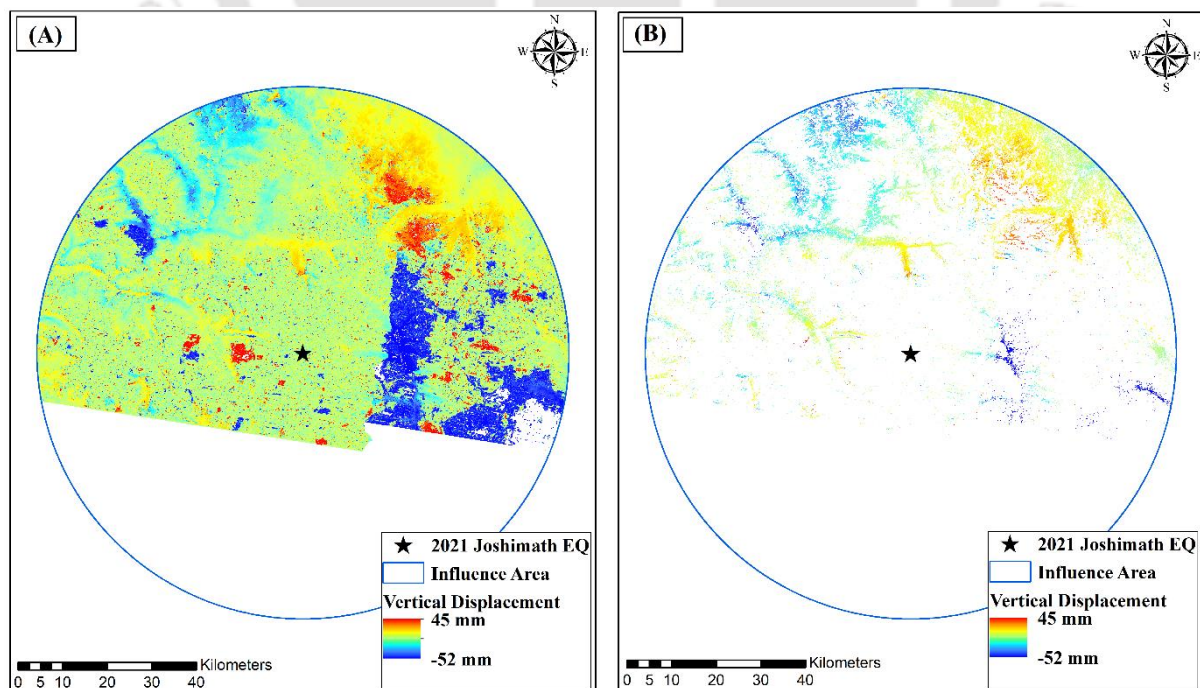


Figure 8.11: Map showing (A) orthorectified vertical displacement and (B) vertical displacement with co-seismic coherence ≥ 0.6 for 2021 Joshimath earthquake (Mw 4.5)

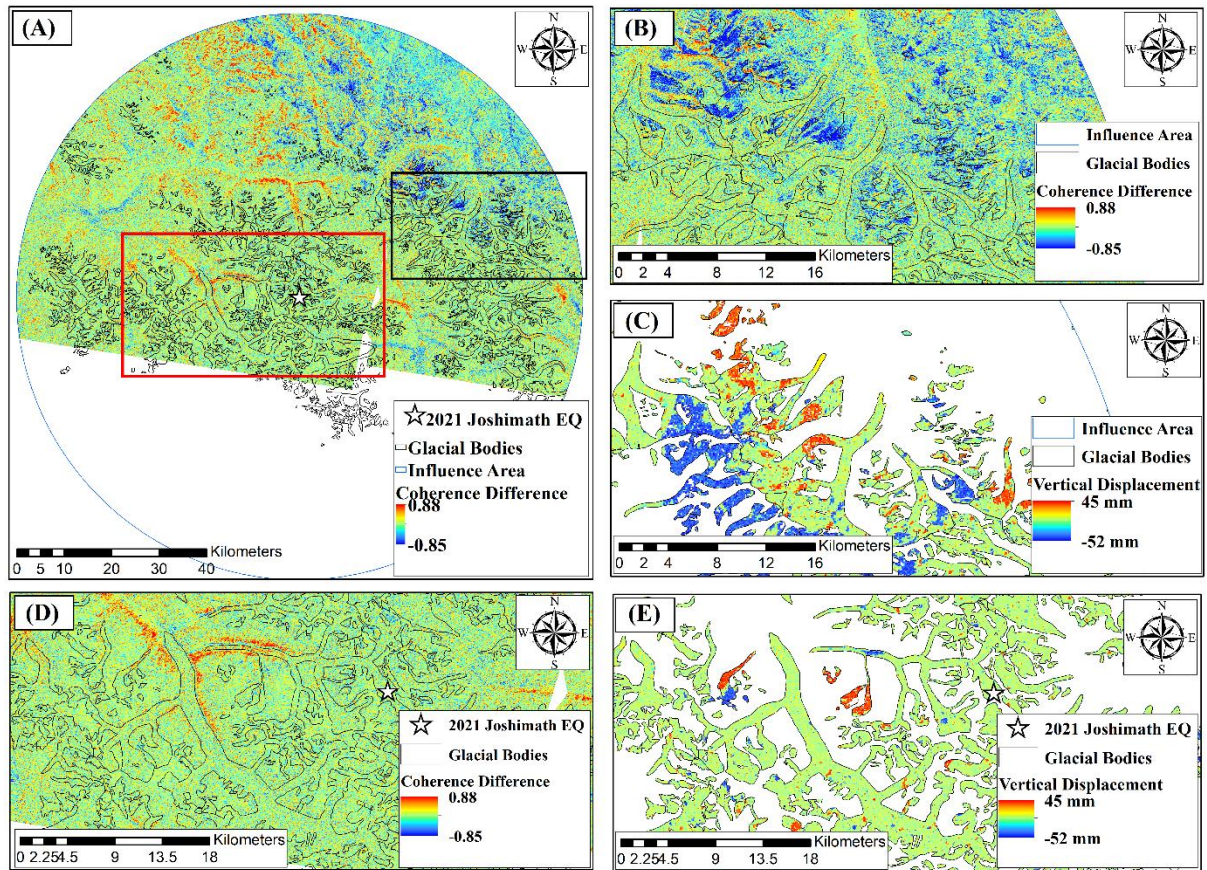


Figure 8.12: Map showing (A), (B), (D) difference between pre-and co-seismic coherence and (C), (E) vertical displacement (mm) within glaciers derived from unwrapped phase interferogram for 2021 Joshimath earthquake (Mw 4.5)

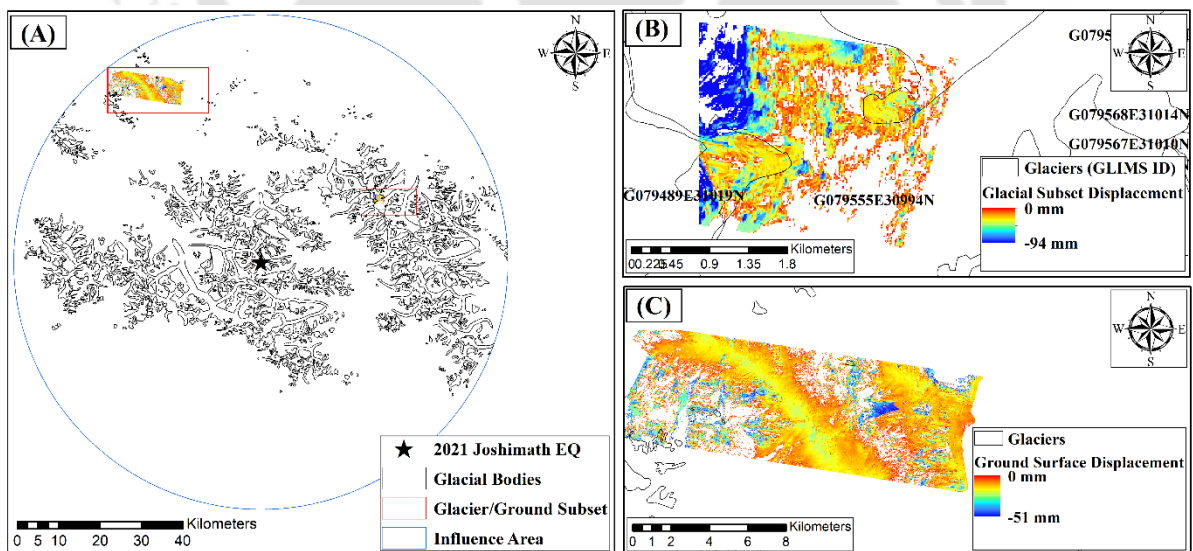


Figure 8.13: Map showing (A) glacial and ground subset regions, (B) vertical displacement (mm) within glacial subset and (C) vertical displacement (mm) within ground subset derived from unwrapped phase interferogram for 2021 Joshimath earthquake (Mw 4.5)

8.5.4 2018 Sikkim Earthquakes, Mw 4.4 and 2017 Sikkim Earthquake, Mw 4.2

Sikkim is a northeastern state of India that encompasses the eastern Himalayas and is situated in the high seismic hazard territory (Zone-IV) (IS1893, Bureau of Indian Standards, 2002). Sikkim generally has experienced moderate seismic impacts in the past. However, shake maps are not available for the earthquake events of $M_w < 4.5$ within the north-eastern Himalayan region. Thus, determining the influence radius of earthquakes is restricted for lower-magnitude earthquakes due to a lack of isoseismal contours.

As we know, the higher the magnitude (M_w), the greater the surface deformation that can be detected in an interferogram (Li et al., 2021). Also, the higher the hypocenter depth (D_H), the smaller the deformation amplitude at the surface (Mellors et al., 2004). This is well represented through isoseismal contours which govern the influence radius (IR) of an earthquake event in terms of surface deformations. Therefore, the relationship of M_w and D_H with IR can be represented as equation 8.5 and equation 8.6 respectively.

$$M_w \propto IR \quad (8.5)$$

$$D_H \propto \frac{1}{IR} \quad (8.6)$$

Detection of earthquake impacts on the Earth's surface depends on two major parameters: magnitude and hypocenter depth. The 2017 Sikkim earthquake is triggered at a hypocenter depth of 10 Km. In the previous sections, we investigated three other earthquake events of similar hypocenter depth but varying magnitudes, as shown in Table 8.3. The influence radius of these earthquakes differs linearly as shown in Figure 8.14A. Thus, the influence radius of the 2017 Sikkim earthquake is calculated as 46 Km. In the case of the 2018 Sikkim earthquake, the scenario is slightly different. The earthquake is triggered at a hypocenter depth of 49.8 Km. From past records, earthquakes at exactly the same hypocenter depth have not occurred in the Indian subcontinent. Thus, earthquakes of different magnitudes and hypocenter depths close to 49.8 Km have been considered, and their influence radii have been determined from USGS shake maps, as shown in Table 8.3. However, their relation (IR vs M_w) is not linear. Therefore, the normalized influence radius (IR_N) for these earthquake events at a hypocenter depth of 49.8 Km has been computed using Equation 8.7.

$$IR_N = \frac{D_H}{D_{H'}} \times IR \quad (8.7)$$

Here, D_H represents the hypocenter depth of 2018 Sikkim earthquake for which IR_N of each earthquake is calculated. This develops a linear relationship between IR and M_w as shown in Figure 8.14B. Thus, the normalized influence radius of the 2018 Sikkim earthquake is computed as 17 Km.

Table 8.3: Earthquakes and their respective magnitudes and influence radii

Earthquakes with Hypocenter depth of 10 Km			
Event/ Date	M _w	IR (Km)	
Tibet Earthquake/ 20 th March 2020	5.7	69	
Leh Earthquake/ 25 th Sept 2020	5.3	61	
Joshirmath Earthquake/ 23 rd May 2021	4.5	54	
Sikkim Earthquake/ 16 th May 2017	4.2	46	
Nepal Earthquake/ 8 th Nov 2020	4.1	39	
Earthquakes with varying Hypocenter depth close to 49.8 Km			
Event/ Date	M _w	D _H (Km)/ IR (Km)	D _H (Km)/ IR _N (Km)
Bhutan Earthquake/ 25 th March 2003	5.5	47.1/ 43	49.8/ 41
Jaisalmer Earthquake/ 9 th April 2009	5.1	44.3/ 40	49.8/ 34
Khangah Dogran Earthquake/ 19 th October 2000	4.9	47.7/ 26	49.8/ 25
Sikkim Earthquake/ 17 th June 2018	4.4	49.8/ NA	49.8/ 17

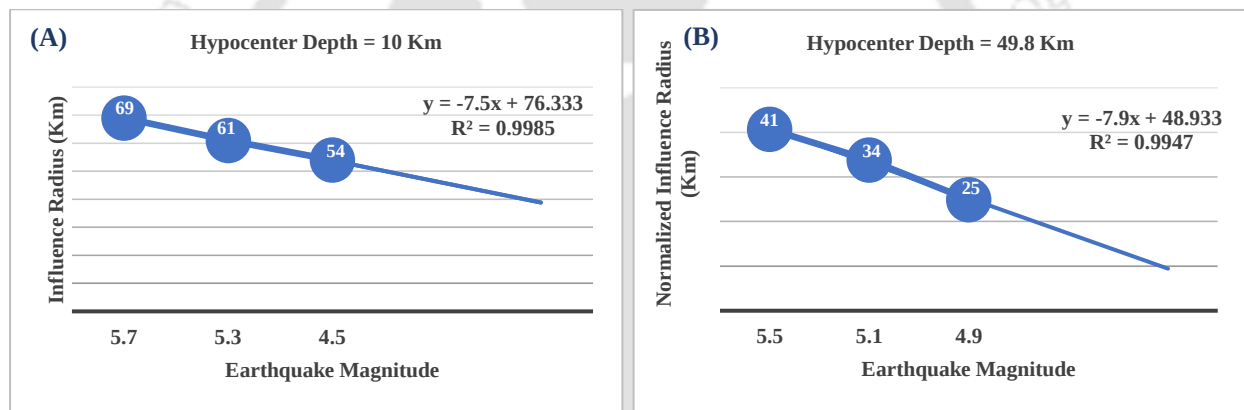


Figure 8.14: (A) Relation between IR and M_w of earthquakes triggered at hypocenter depth of 10 Km and (B) relation between IR_N and M_w of earthquakes triggered close to hypocenter depth of 49.8 Km

Figure 8.15A shows the impact of the 2017 Sikkim earthquake (M_w 4.2) with a hypocenter depth of 10 Km in terms of the coherence difference between pre-and co-seismic pairs. A significant reduction in co-seismic coherence has not been observed within the influence area (46 Km). However, this is expected as an earthquake event of a lower magnitude ($M_w < 4.5$) does not deliver a substantial impact on the Earth's surface (Lohman and Simons, 2005; Funning and Garcia, 2019). The vertical displacement lies in the range of 0 to -19 mm, indicating subsidence, much less than the earthquake events of higher magnitudes ($M_w \geq 4.5$) discussed in the previous sections. The earthquake-induced vertical displacements do not propagate till the glacial bodies which are clustered at the influence area's northern region.

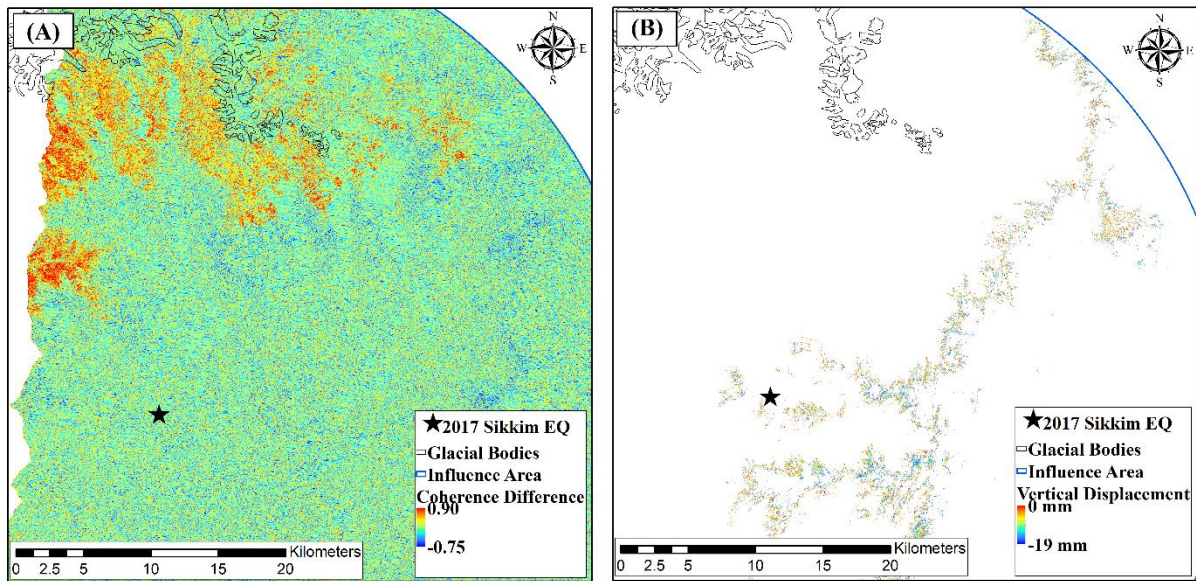


Figure 8.15: Map showing (A) difference between pre- and co-seismic coherence and (B) vertical displacement (mm) within influence area derived from unwrapped phase interferogram for 2017 Sikkim earthquake (Mw 4.2)

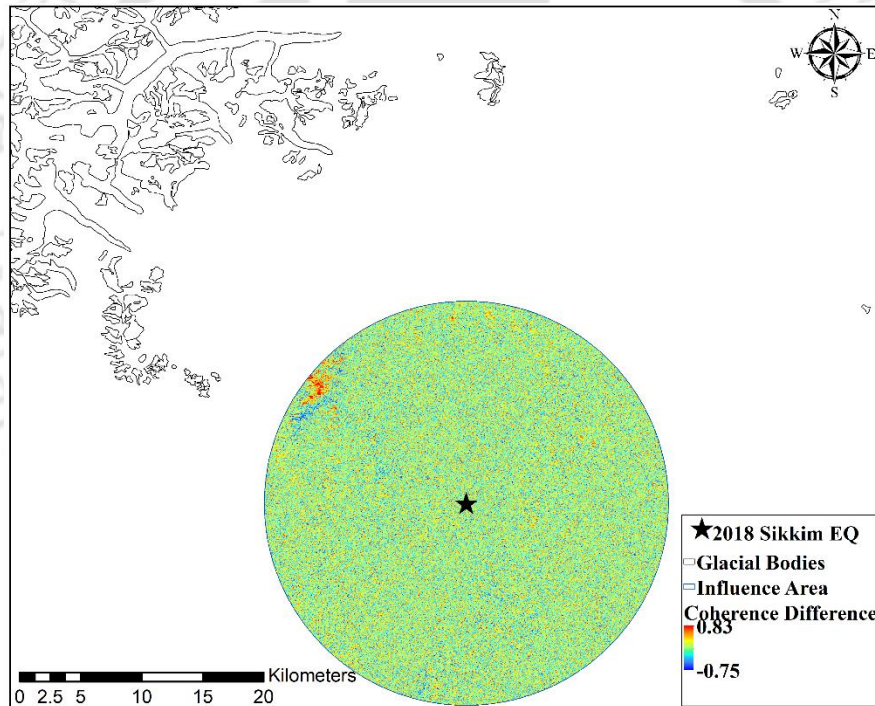


Figure 8.16: Map showing pre- and co-seismic coherence difference for the 2018 Sikkim earthquake (Mw 4.4)

Figure 8.16 shows the coherence difference map of the 2018 Sikkim earthquake (Mw 4.4) triggered at a hypocenter depth of 49.8 Km. The earthquake results in negligible impact within the influence area of 17 Km. Where the epicenter of both the earthquake events of 2017 and 2018 lie within Sikkim at a distance of 31.7 Km from each other, the 2017 earthquake (Mw 4.2) shows some subsidence, whereas vertical deformation has not been captured for the 2018 earthquake. The earthquake event that occurred in 2017 is comparatively shallow. InSAR-based detectable surficial displacement due to a deeper earthquake is smaller than a shallow

earthquake of the comparatively same magnitude. To better understand the impact of moderate earthquake events of the same magnitude but different hypocenter depths on glacial bodies, two different earthquake events in the Nepal region have been investigated in the next section.

8.5.5 2020 and 2021 Nepal Earthquakes, Mw 4.1

Comparative study on the impact of earthquakes on glacial bodies is a challenging task as no two earthquake events of similar magnitude get triggered at the same location. Even if two seismic events of similar magnitude occur in the proximity of glacial bodies, hypocenter depth and distance from the glacial bodies govern the magnitude of vertical deformation. This section attempts to understand the vertical displacement within glacial bodies due to two different earthquake events of Mw 4.1 triggered at an almost similar distance from the glacial bodies with different hypocenter depths. Despite having similar magnitudes, the influence radius of both earthquakes is different due to varying hypocenter depths. The influence radius of the 2020 Nepal earthquake triggered at a hypocenter depth of 10 Km is computed as 39 Km (Table 8.3). For the 2021 Nepal earthquake triggered at a hypocenter depth of 35 Km, previous records of earthquake events and their respective shake maps have been utilized to derive the normalized influence radius of 34 Km, as shown in Table 7.4. The linear relationship between the normalized influence radius of earthquakes and their magnitudes is represented in Figure 8.17.

Table 8.4: Earthquakes and their respective magnitudes and influence radii close to hypocenter depth of 35 Km

Earthquakes with varying Hypocenter depth close to 35 Km			
Event/ Date	M _w	D _H (Km)/ IR (Km)	D _H * (Km)/ IR _N (Km)
Dhekiajuli Earthquake/ 28 th April 2021	6.0	34/ 71	35/ 70
Haripur Earthquake/ 10 th October 2010	5.2	33.2/ 60	35/ 57
Bageshwar Earthquake/ 1 st May 2010	4.5	35.5/ 45	35/ 46
Nepal Earthquake/ 11 th January 2021	4.1	35/ NA	35/ 34

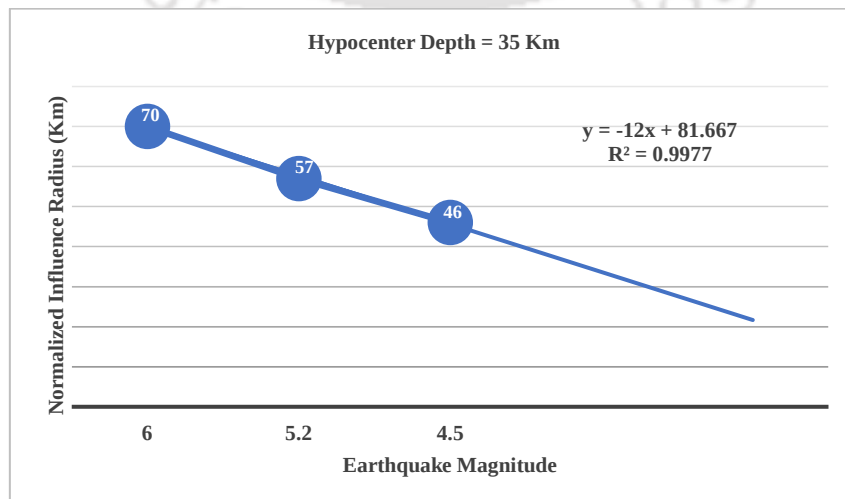


Figure 8.17: Relation between IR_N and M_w of earthquakes triggered close to hypocenter depth of 35 Km

The 2020 Nepal earthquake resulted in vertical displacement within the influence area from 0 to -16 mm, indicating surficial sinking (Figure 8.18B). The mean displacement is -10 mm. Within the glacial bodies, the mean vertical sinking is 7.7 mm. On the other hand, the 2021 earthquake resulted in a vertical displacement in the range of 0 to -12 mm with a mean displacement of -5.4 mm, as shown in Figures 8.19B, C and D. The earthquake events are triggered at a distance of 33 km from each in the winter of 2020-2021 (within 64 days). A common circular study zone considering the distance between the two event epicenters as the diameter is demarcated to capture vertical displacement to two earthquake events of the same magnitude but different hypocenter depths positioned at same distance from common glacial bodies. The 2020 earthquake at a comparatively shallow depth shows much more glacial region with sinking than the 2021 earthquake (Figure 8.20). As energy dissipation is more for an earthquake of greater hypocenter depth, shallow earthquakes deliver more impact on the surface, which can be clearly seen from the above scenario. Figure 8.18A and Figure 8.19A show the coherence difference map of the 2020 and 2021 earthquakes, respectively. Significant changes in coherence have not been observed in either case. Even though some locations show reduced co-seismic coherence values, this can be attributed to changes due to other factors. As vegetation cover surrounds the region, as shown in the False Color Composite (FCC) map (Figure 8.21), the coherence difference can be attributed to changes in vegetation cover and not certainly due to earthquakes.

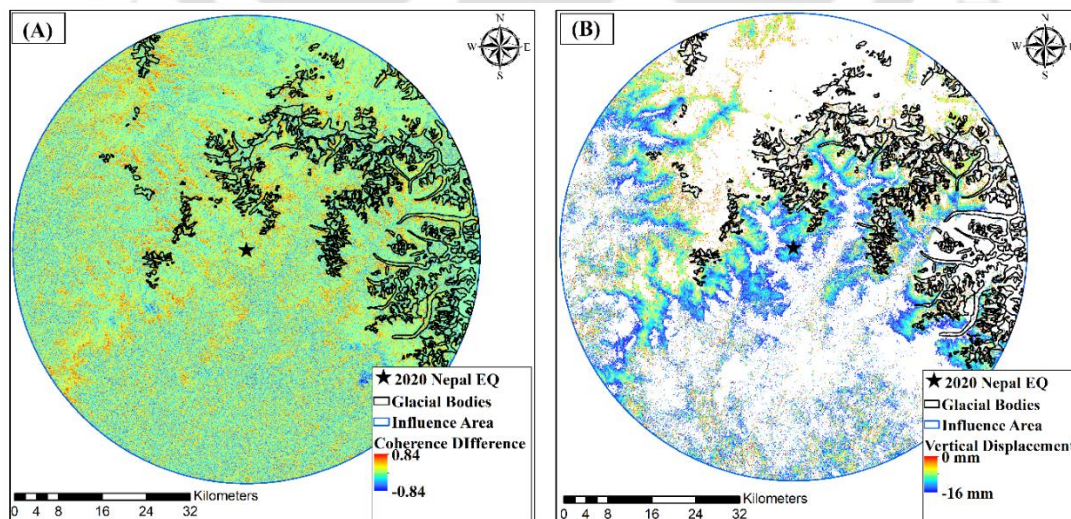


Figure 8.18: Map showing (A) difference between pre- and co-seismic coherence and (B) vertical displacement (mm) within influence area derived from unwrapped phase interferogram for 2020 Nepal earthquake (M_w 4.1)

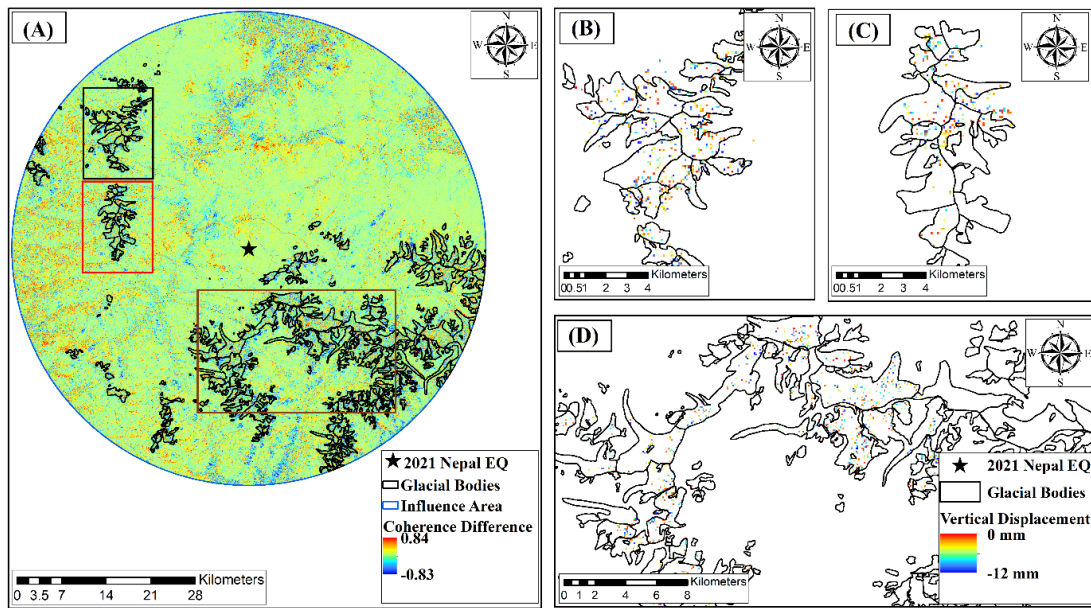


Figure 8.19: Map showing (A) difference between pre- and co-seismic coherence, (B), (C) and (D) vertical displacement (mm) within influence area derived from unwrapped phase interferogram for 2021 Nepal earthquake (Mw 4.1)

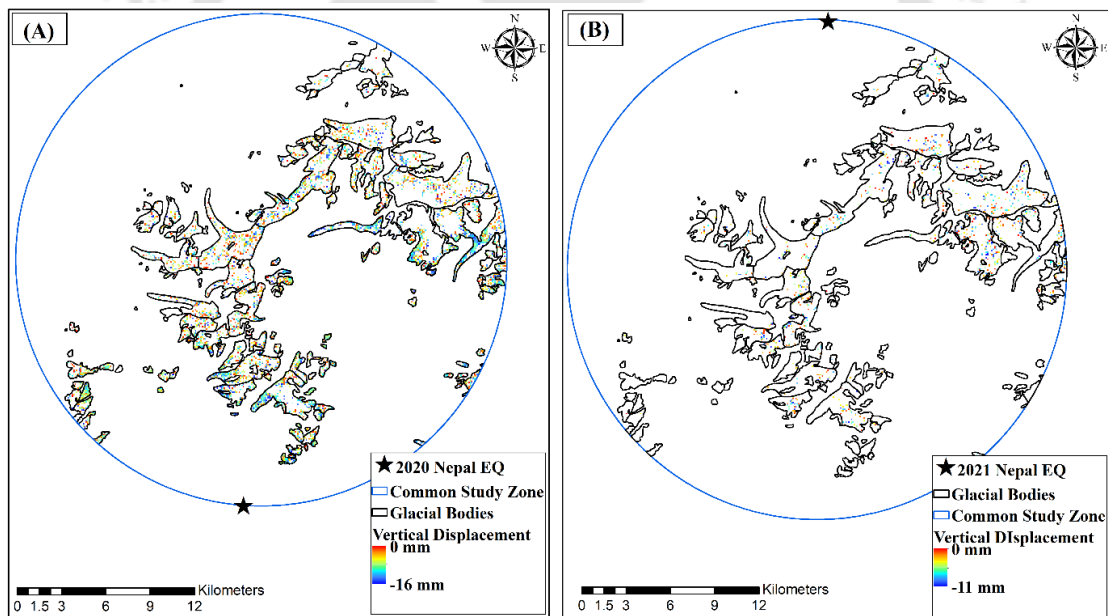


Figure 8.20: Map showing vertical displacement (mm) within glacial bodies of common study zone for (A) 2020 Nepal earthquake (Mw 4.1) and (B) 2021 Nepal earthquake (Mw 4.1)



Figure 8.21: False Color Composite (FCC) map of the common study zone in Nepal

After investigating several earthquake events in the glaciated regions of Himalayan ranges, it can be observed that InSAR acts as an effective tool in investigating earthquake impacts in areas where other conventional techniques are tough to implement. Where both magnitude and hypocenter depth play a paramount role in the detectability of an earthquake through C-band radar interferometry, this paper attempts to develop an understanding of seismic displacement of high-altitude Himalayan glaciated regions from western to the eastern ranges considering various categories of earthquakes. Where shake maps can be very useful in determining the influence radius of an earthquake of higher magnitudes ($M_w \geq 4.5$), normalized influence radii can be derived for lower magnitude earthquakes for which shake maps are unavailable. Moreover, every earthquake is unique in terms of its impact on the Earth's surface. Where some of the earthquake events such as the 2020 Tibet earthquake, the 2017 Sikkim earthquake, as well as the 2021 and 2021 Nepal earthquakes resulted in negative vertical displacement or subsidence, some of the seismic events such as the 2017 Thang earthquake, 2020 Leh earthquake and 2021 Joshirmath earthquake resulted in both uplift and subsidence.

As observed from multiple earthquake events, the seismic impact on solid earth regions and glacial bodies shows significant variation in terms of seismic displacements. The vertical displacement of a glacial mass is much higher than the solid earth for a particular earthquake, which suggests seismic amplification due to the presence of metamorphosed glacial ice over the ground surface. Moreover, increased vertical displacement of a glacial patch away from epicenter than the glacial patch close to the epicenter, in the case of the 2017 Thang earthquake, suggests that site-specific seismic amplification properties of glacial bodies plays a role in the

associated displacement. However, it is to be noted that glacial bodies are superimposed on top of the solid earth. Therefore, the vertical displacements identified via DInSAR may not be solely due to the glacial material alone but the composite displacement of both glacial body and the solid earth beneath. This cannot be segregated using satellite-based techniques.

8.6 Proposed Hypothesis

Considering the glacial bodies as dense and thick envelope of metamorphosed ice over the ground surface, there exist two different possibilities for the impact of earthquakes on glacial bodies in terms of vertical deformation:

- 1) Seismic waves resulting in the deformation of ground underneath glacial mass that propagates through the glacier and gets detected through InSAR. This reflects that glacial bodies being dense chunks of metamorphosed ice, remain unaffected due to seismic events in terms of vertical deformations and subduct or get uplifted in synchronization with the ground underneath.
- 2) Composite deformation of glacial mass and the ground underneath as detected through InSAR. This suggests that glaciers are different in terms of their composition and behavior compared to the ground surface, and therefore their response to seismic tremors is different. As glaciers flow due to their viscoelastic properties (Reeh et al., 2003), earthquakes may impact a glacial mass somehow differently than a solid bedrock or ground surface, which needs research attention.

This work highlights the necessity of investigating glaciers in terms of seismic impacts. Where DInSAR possesses the capabilities of detecting surface deformations, other InSAR techniques such as multi-track/multi-satellite techniques (minimum acceleration (MinA) combination approach) and GNSS-InSAR coupled ground deformation modeling can be effective in effectively capturing of earthquake-induced deformation fields in the glaciated regions.

8.7 Conclusion

DInSAR has recently emerged as a powerful tool for studying various natural hazards in the Himalayan region. Especially in the case of earthquakes, where every earthquake event is unique in terms of its source, magnitude, and impact. Therefore, we studied seismic events of varying magnitudes and hypocenter depths triggered in the proximity of different glaciated terrains of the Himalayan region using Sentinel-1A/B C-band DInSAR. The finding of this study are as follows:

- The 2020 Tibet earthquake (Mw 5.7) at a hypocenter depth of 10 km results in large vertical displacements within its influence area (69 km). A maximum subsidence of 168 mm is observed near the epicenter, with a mean displacement of -47.3 mm. The mean vertical displacement of glacial bodies is found to be -38.9 mm. Reduced co-seismic coherence is observed around some glaciers. However, such changes are insignificant as the glacial bodies are much away from the earthquake epicenter.
- In the case of the 2020 Leh earthquake (Mw 5.3), vertical displacement lies in the range of 31 mm and -33 mm, with a mean displacement of -2.4 mm within the influence area of 61 km. The glacial bodies lying close to the epicenter show positive displacement, or uplift, that shifts towards subsidence as we move away from the epicenter. The mean glacial displacement is found to be -2.5 mm. Comparison of glacial and solid earth patches separately, at equal radial distances of 41 km from the epicenter, reveals that the glacial region shows greater vertical displacement (up to -78 mm) than the solid earth.
- Similar to the 2020 Leh earthquake, the 2017 Thang earthquake (Mw 5.2) results in vertical surface displacement that varies from 51 mm to -39 mm, indicating both uplift and subsidence. The mean displacement of the Earth's surface and glacial bodies within the influence area (56 km) are -2.8 mm and -3.36 mm, respectively. Comparison of glacial and solid earth patches, unwrapped separately, followed by vertical displacement, shows much greater values of seismic displacement for glacial patches that varies up to -173 mm and -576 mm. This exceeds the range of displacements for the solid earth surface by a large offset, considering either small patches or the entire influence area of the earthquake. Moreover, glacial patch farther from the epicenter but surrounded by larger glacial bodies show larger values of vertical displacement than the glacial patch closer to the epicenter, indicating site-specific seismic amplification properties of glaciers.
- The 2021 Joshimath earthquake (Mw 4.5) leads to vertical displacement within its influence area of 54 km that ranges between 45 and -52 mm. The mean displacement of the ground surface and glacial bodies are 0.64 mm and -2.2 mm. From the coherence difference map of the area, a reduction in co-seismic coherence is found around the glacial bodies along the northeastern region of the influence area where surficial uplift is observed. Similar to the 2020 Leh and 2017 Thang earthquakes, glacial and ground

patches considered separately in case of 2021 Joshimath earthquake shows vertical displacement up to -94 mm and -51 mm respectively.

- The 2017 Sikkim earthquake (M_w 4.2), sourced at a depth of 10 km, shows displacement up to -19 mm within the influence radius of 46 km. Due to the lack of shake maps for earthquakes with $M_w \leq 4.5$, the influence area is computed using the linear relationship between influence radii and magnitudes of different earthquakes at a hypocenter depth of 10 km. The 2018 Sikkim earthquake (M_w 4.4) at a hypocenter depth of 49.8 km shows no vertical displacement within the normalized influence area of 17 km.
- The 2020 Nepal earthquake (M_w 4.1) shows vertical displacement between 0 and -16 mm with mean subsidence of 6.2 mm within the computed influence radius of 39 km. The mean subsidence of glacial bodies is derived as 7.7 mm. Whereas the 2021 Nepal earthquake (M_w 4.1) shows vertical displacement in the range of 0 to -12 mm, having a mean subsidence of 5.4 mm within the normalized influence radius of 34 km. Both earthquake events are triggered at a distance of 33 km from each other within 64 days. Studying two different earthquake events of similar magnitude located at almost the same distance from the glacial bodies but having different hypocenter depths show that a shallower earthquake has more impact on glacial bodies in terms of vertical displacement than a deeper one.

Thus, earthquake events around Himalayan glaciers can be well studied with the help of C-band SAR interferometry, where other geodetic and photogrammetric techniques are hard to implement. Moreover, the continuous data acquisition of orbiting radars at a certain temporal offset makes them effective in studying earthquakes which are very unpredictable in terms of their triggering location and magnitude.

Glacial bodies are a dense and thick envelope of metamorphosed ice that may not reproduce similar deformation as the solid earth surface and may result in site-specific amplification of seismicity. This suggests that because glaciers are different in terms of their composition and behavior, their response to seismic tremors is also different. As glaciers have viscoelastic properties, earthquakes, in terms of both the associated deformation and response to seismic waves, may impact a glacial mass differently than solid bedrock. Future research into the dynamics behind seismic deformation and amplification of glacial bodies should incorporate extensive modeling of that interaction.

As observed from analyzing multiple earthquake events, glacial mass studied separately using DInSAR reveal site-specific seismic amplification as compared to the solid earth surface. However, glacial bodies are thick chunks of metamorphosed ice lying over the ground underneath. Therefore, the vertical displacement of glacial bodies registered using DInSAR is likely the composite displacement of both glacier and the solid earth surface at the base of the glacier. To develop a better understanding of the impact of seismicity on glaciers, will require additional studies into the material and dynamic properties of glacial bodies.



The aim of the thesis entitled “**Snow/Glacier Dynamics of Himalayan Ranges and Associated Hazards**” is incorporating satellite remote sensing, analytical analysis, numerical modeling, artificial neural networks, geophysical techniques and laboratory-based analysis to investigate a broad spectrum of Himalayan cryosphere which includes snow/glacial dynamics, stable isotopes on intra-annual basis, source endmembers and lithological feeds to the discharge of perennial river systems, natural hazards covering avalanches, seismic impacts on glacial bodies, GLOF and vulnerability assessment of glacial lakes. The brief highlights and major conclusions of this study can be summarised as follows:

- The integrated use of multivariate techniques and band ratio on optical satellite imagery helped obtain effective snow coverage of Sikkim on an intra-annual basis between 1989 and 2019 that correlated inversely with the Extended Reconstructed Sea Surface Temperature (ERSST.v5) in Niño 3.4 region. The snow line altitude (SLA) shows a two-fold periodicity in the last 30 years in an interval of every 9-12 years.
- Studying the $\delta^{18}\text{O}$ values of the river streams, rain, and snow for the Teesta watershed shows seasonal variability and progressive decline as approaching the glacial source. This indicates rainout, which is more significant for one tributary (Lachung Chu) of the Teesta river than the other (Lachen Chu). The d-excess suggests the dominance of mid-latitude westerlies in the North Sikkim region.
- The glacial-melt contribution derived using the isotope mixing model shows glacial melt contribution in the 40-47% range, as also observed for other Himalayan rivers. The Monte Carlo-based Strontium mixing model shows carbonates as major contributors near glacial sources and overall maximum contribution from silicate lithologies. Analysis of natural thermal springs indicates an isolated geothermal aquifer with a localized source of arsenic near the Changme glacial snout.
- The vulnerability and risk of breaching for glacial lakes increase due to changing glacial properties, which depend on fluctuating weather conditions, as observed in the case of the Shisper glacial lake breach on 7th May 2022.
- Earthquake events of high magnitude close to the glacial lake may also hamper the strength of the lake embankment due to liquefaction/cyclic mobility, as investigated in the case of Lake Dingmu due to the 2020 Tibet earthquake (Mw 5.7).

- A vulnerability assessment performed for the trans-boundary Sikkim Himalayas using AHP shows 7 lakes in Sikkim, 3 lakes in Nepal, and 3 in China as highly vulnerable to future breaches. Designed BR-, LM-, and GDX-based BPMLPNN models show good prediction accuracies with AHP-based target scores.
- Integrated utilization of MASW and GPR show glaciofluvial depositions in North Sikkim under NEHRP site class D (stiff soil). Lab-based geotechnical testing show glacial moraine in the Sikkim Himalayas with an abundance of coarser material and non-plastic silt devoid of clay. The lacustrine deposits in North and West Sikkim belong to silty sand where clay is absent. Major mineral composition includes Quartz, Biotite, Albite and Anorthite.
- The use of SAR with high-resolution DEM can effectively identify avalanche activation zones, as investigated in the case of the Annapurna avalanche on 17th Jan 2020. Optical and microwave remote sensing, in conjunction with numerical modeling and simulation, can help investigate complex slope failures for plausible triggering mechanisms such as composite rock-ice avalanches of 7th Feb 2021, Western Himalayas.
- The high-altitude glaciated regions of the Himalayan ranges can be studied for earthquake impacts in terms of vertical deformations. In this context, C-band Sentinel 1 SAR datasets have been used to capture seismic deformation of glacial bodies due to eight different earthquake events of varying magnitude and hypocentre depth triggered around different glaciated regions of the Western, Central, and Eastern Himalayas **which is a novel contribution in the field of glaciology and seismology.**

Recommendations for Future Work

The future scope of the work is as follows:

- Estimating glacial-melt contribution to perennial river systems on seasonal basis for longer period of time (>15 years) using stable isotopes and energy balance models.
- Implementation of multiple geophysical techniques for determining properties of glacial deposits.
- Multi-track/multi-satellite techniques and GNSS-InSAR coupled modeling for high-altitude Himalayan deformations.

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A1 Field Investigations to Sikkim Himalayas

A1.1 Field Investigation-I [18th Jan 2021 – 23rd Jan 2021]

The field investigation was conducted by a team of professors and research scholars from the Department of Civil Engineering (CE) and Department of Mechanical Engineering (ME) Indian Institute of Technology Guwahati (IITG) and scientist from Defence Geoinformatics Research Establishment (DGRE), a wing of Defence Research Development Organisation (DRDO), Ministry of Defence, Government of India. The main objectives of the field investigation were to conduct a reconnaissance survey of North Sikkim during the winter season and gather ground-based control points of snow-covered and non-snow-covered locations to validate satellite remote sensing-based effective snow cover mapping as discussed in Chapter 3 of the thesis. Another objective was to collect samples of glacial-melt, snow, rainfall, river water, and waterfalls along the tributaries (Lachen Chu and Lachung Chu) and mainstream of Teesta river for isotopic study, as discussed in Chapter 4. Figures A1 and A2 represent the photographs captured during the field investigation. The locations of the water sample collection are mentioned in Table 4.1.

Between Rangpo and Chungthang



Figure A.1: Team of researchers for Field investigation-I to North Sikkim: from left to right, Soumya Gucchait (MTech-CE IITG), Late Dr. Avilash Sahoo (PhD-ME IITG), Vatsal D. Patel (Mtech-CE IITG), Chitesh Sharma (Scientist-C, DGRE), Prof. Subashisa Dutta (CE IITG), Dr. Rishikesh Bharti (CE IITG), Antony J. Moothedan (JRF-CE IITG) and Sandeep K. Mondal (PhD-CE IITG)

Between Lachen and Gurudongmar
19th Jan 2021 (3487m a.s.l)



Between Mangan and Lachen
18th Jan 2021 (1773m a.s.l)



Between Lachung and Mangan
22nd Jan 2021 (1818m a.s.l)



Between Lachen and Mangan
18th Jan 2021 (1461m a.s.l)



Between Lachung and Mangan
20th Jan 2021 (2599m a.s.l)



Between Mangan and Lachen
18th Jan 2021 (1308m a.s.l)





Figure A.2: Field investigation-I photographs of collecting river, snow and waterfall samples

A1.2 Field Investigation-II [3rd Aug 2021 – 7th Aug 2021]

The field investigation was conducted by a team of research scholars from the Department of Civil Engineering (CE) Indian Institute of Technology Guwahati (IITG) in North Sikkim. The main objective of this field visit was to collect water samples from various sources along the tributaries (Lachen Chu and Lachung Chu) and the mainstream of Teesta river during the monsoon period for the analysis of stable isotopes, as discussed in Chapter 4.





Figure A.3: Field investigation-II photographs of collecting river, snow, and waterfall samples

A1.3 Field Investigation-III [15th Oct 2021 – 24th Oct 2021]

A team of faculty and research scholars from the Department of Civil Engineering (CE) Indian Institute of Technology Guwahati (IITG) conducted this field investigation along with scientist and technical personnel from DGRE-DRDO to North Sikkim. This field visit's main objective was to visit various locations of North Sikkim, including Changme glacial snout, to conduct a field-based geophysical investigation (MASW & GPR) and collect moraine and glaciofluvial samples for further lab-based analysis as discussed in Chapter 6. Another notion was to collect water samples from various sources along the tributaries (Lachen Chu and Lachung Chu) and mainstream of Teesta river during the end of the ablation period to analyze stable isotopes.



Figure A.4: Field investigation-III photographs of collecting water and snow samples, GPR and MASW survey

A1.4 Field Investigation-IV [7th April 2022 – 10th April 2022]

This field investigation was conducted by a team of research scholars from the Department of Civil Engineering (CE) Indian Institute of Technology Guwahati (IITG) in West Sikkim. The main objective of this field visit was to reach up to Rathong glacial snout (4667m a.s.l.), and collect moraine and glaciofluvial samples for further lab-based analysis, as discussed in Chapter 6. Another aspect was to collect water samples from various sources during the accumulation period along the Rathong river stream, as discussed in Chapter 4.

Between Yuksom and Rathong
10th April 2022 (2496m a.s.l)



At Rathong Glacial Snout
7th April 2022 (4667m a.s.l)



At Rathong Glacial Snout
7th April 2022 (4667m a.s.l)



At Rathong Glacial Snout
7th April 2022 (4667m a.s.l)





Figure A.5: Field investigation-IV photographs of collecting water glacial, lake water samples for isotopic study, moraine and lacustrine samples for geotechnical and micro-structural properties.
