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Spatio-Temporal Estimation of Glacier Dynamics Under Climate Change Scenarios Using Machine Learning Techniques

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Glaciers of the Upper Indus Basin (UIB) play a vital role in providing water resources, hydropower generation, and livelihood, but they are very vulnerable and sensitive to continuous climate change impacts. This research presents a novel approach for accurate mapping of glacier extent, clean ice, debris cover, seasonal snow, and glacier melt across the Hunza Basin. We have used Grey Level Co-occurrence Matrix (GLCM), Machine Learning (ML) techniques of Random Forest (RF), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) to conduct the purposeful research. ML models were trained on multispectral (Landsat, Sentinel-1 & 2, MODIS, and SPOT-5 from the last 35 years) and textural datasets. Overall, 6628 samples for training and 988 samples for testing were used to maintain a 70/ 30 ratio to evaluate overall accuracy (OA) and kappa coefficient ($\hat{k}$). RF ensured the best results (OA = 95.4 %, $\hat{k}$ = 0.965) in comparison of ANN (OA = 94%, $\hat{k}$ = 0.92) and SVM (OA = 92 %, $\hat{k}$ = 0.89). The accuracy of clean ice and seasonal snow remained consistent (producer accuracy and user accuracy >93%) compared to that of debris cover and glacier melt. Glacier retreat, increased ablation, formation of clean ice loss, and frequency of supraglacial melt due to expansion of debris cover up to 23.31% were witnessed spatially in the basin. Proposed approaches prove that ML techniques are very useful for the estimation of risk assessment in the climate-prone mountain basins and offer a robust way forward for hydrological modelling, glacier change monitoring, and water resource management.

Keywords: Glacier Dynamics; ML (machine learning); RF (random forest); ANN (artificial neural network); SVM (support vector machine)

Introduction:

The Hindukush-Karakoram-Himalayan (HKH) region encompasses 3500 km (located in the northern parts of Pakistan), surrounded by eight countries, and is an abode of more than 150 million people[1]. It is the world's highest and most densely populated mountain region, characterized by immense biodiversity of flora and fauna. However, it remains highly vulnerable, with climate change posing severe threats to its fragile mountain ecosystems. Geologically, the HKH region is the youngest mountain range, prompting natural hazards[2]. Temperature and precipitation variations are increasing day by day, resulting in glacier retreat and newly emerging intensified glacial lake outburst floods (GLOFs)[3]. Although mountain environments are generally associated with clean air, atmospheric winds can transport pollutants from other regions, leading to significant air quality challenges. Variation in the climatic conditions, cryosphere, air pollution, as well as hydrology of this region poses a potential threat to the population's livelihood alongside water flow in the shape of water availability, management and energy.

The rivers of the HKH are primarily fed by the lofty, snow-covered mountains of the Upper Indus Basin (UIB)[4], which contain most of Pakistan's snow-clad and glaciated areas. Snow and glaciers are significant hydrological processes that contribute >70% of annual streamflow in the UIB[5],[6]. The Hunza River, a highly glacierized basin, serves as a major contributor of meltwater to the Indus River[7]. Glacier retreat/ surge in Hunza resulted in the creation of numerous glacial lakes and such glacial lakes cause devastating flash floods and breaching of local accumulated water and dams with changing temperature and precipitation patterns, an effect on the hydrological processes is expected, which would affect water supply for domestic and industrial use, agricultural productivity, flora, fauna, wildlife ecosystems, and power generation[7],[8]. Substantial evidence confirms that the Earth's climate has warmed considerably in recent decades[9], with the degree of warming differing across regions. Understanding the impacts of climate change is essential for developing and planning effective adaptation strategies, as it underpins future predictions and decision-making[10],[11]. Various researchers have used remote sensing (RS) data to study hydrological processes in glacier-melted-water basins[12], [13],[14],[15]. MODIS-derived snow cover (SC) products, available on daily, 8-day, and monthly scales since 2000, have been extensively applied in snow cover assessments. Their proven efficiency has led researchers to widely recommend MODIS products for estimating snow cover area (SCA)[16],[17]. These snow cover products can be integrated with snowmelt models to simulate future water availability. Several snowmelt runoff forecasting models (such as SSARR, HEC-1, NWSRFS, PRMS, SRM, SWAT, and GWSER) are available[18],[19]. Energy-based models are very realistic for snowmelt simulation but require a lot of data, which is a constraint in the rugged terrain with data scarcity[20],[21]. Therefore, simple temperature indexed degree-day models are preferred in regions where data scarcity is a major issue.

The impacts of climate change on hydrology differ across river basins. In the Upper Indus Basin (UIB) and its surrounding region, these effects are particularly severe compared to other Asian basins, as they support a large population that relies heavily on snow and glacier melt for water resources and agricultural production, thereby directly influencing food security[22]. Glaciers are considered the best indicator of climate change as they are climate-sensitive but poorly gauged in high-altitude regions[23]. If the projected warming in the UIB continues, there will be severe social and economic consequences. Small glaciers may disappear sooner than expected, which will change the hydrology of the Indus River and affect Pakistan's water supply and distribution. Another consequence of this warming is the formation of glacial lakes.

In the HKH region, a total of 3,044 glacial lake outburst floods (GLOFs) have been recorded, with 52 recognized as posing potentially severe threats[24]. Over the past three decades, nearly 120 potential GLOF events have been reported in the Hunza and Shayok basins[25]. While glaciers are retreating worldwide, a few in the Central Karakoram remain stable or are advancing—a phenomenon known as the "Karakoram Anomaly"[26]. This behavior contrasts sharply with the neighboring Himalayan, Hindukush, and Tianshan ranges, where glaciers consistently exhibit negative mass balances[27]. Various factors can be attributed to the anomalous behavior of these glaciers: decrease in summer temperatures, increase in precipitation trends, elevation effects, and the augmented snowfall [28]. However, these glaciers are inclined to current climate change, and their magnitude is still unknown[29],[30]. In the Karakoram, the interactions between climate, the cryosphere, and the hydrosphere remain poorly understood, despite their critical role in ensuring sustainable water supplies. Progress in this area is hindered by limited field investigations, largely due to inadequate equipment and a lack of local expertise. Therefore, multispectral data, ML and GIS techniques are vastly famous to monitor glacier dynamics (on a large scale), elevation changes and mass balance[31].

Increasing temperature is a big issue that brings about a serious cause of global warming and accelerates melting processes. Atmospheric pollutants deposited on the surface reduce the albedo and accelerate the melt processes of the glaciers[32]. The primary sources of temperature increase in the region are pollution, burning fossil fuels, and biomass, which are sources of black carbon[33]. There has been a dire need to investigate the cryosphere changes time to time, climate change, and atmospheric pollution in an integrated and coupled framework[34].

ML algorithms are essential in finding solutions to glacier dynamics under various climate change scenarios, snow runoff modelling, and small hydropower potential. Their melting behavior, water resource in context to snow and glacier surfaces under current and future projections, to study their impacts on melting rates.

Glaciers are very significant as they provide us with fresh water and feed our rivers for agricultural activities. Moreover, the melting of glaciers gives birth to many GLOFs, which hamper the life of the people of the regions adversely. In this way, the GLOF-2 programmed of the Government of Pakistan in our glacier regions has become significant for safeguarding our interests and population. The research is also significant because environmental and climatic variability conditions are aggravating day by day, giving rise to snowmelt runoff. This research will not only benefit local and international researchers, but it will also help the administrators and planning department of Pakistan in tackling risk-prone areas at glaciers and the sub-glacial regions of UIB in Pakistan.

Long-term field monitoring of snow and glacier dynamics and climatic variables in the Hunza basin is often hampered due to inaccessibility at high altitudes and the complex climatology of the area. An in-depth scientific analysis and understanding of snow and glacier dynamics, interaction with climate change, and atmospheric variability are also missing. Keeping this in mind, the proposed research may facilitate understanding atmosphere–cryosphere interactions, water availability, and their future impacts.

Objectives of the Research:

The research aims to estimate the glacier dynamics for surface runoff modelling under climate change scenarios. Key objectives of this study are:

To evaluate the best methods of ML for monitoring and mapping glacier extent

To indicate snow cover extent by automating ML algorithms

To map glacier debris, clean ice, and stable terrain using RS and ML techniques for the Hunza Basin

Many researchers have enabled themselves to explore new trends in various research so that they can benefit from the novel and valuable information in the field of glacier dynamics. So, this research finds the best answers to the following questions?

What are algorithms used for estimating glacier dynamics?
Is ML useful for glacier dynamics?
Which methods of ML are accurate for glacier mapping?
How is climate change affecting the glaciers?
Is glacier mapping helpful for the decision maker to mitigate future disasters in the UIB to save the people?

Novelty Statement:

In this paper, a novel approach is presented for mapping glacier dynamics in the Hunza Basin. This approach is integrated with GLCM-based textural features and ML classifiers with a multispectral satellite dataset. We can relate ineffably that work on clean ice, debris cover, seasonal snow, ice loss, and glacier melt over the last 35 years is very much different from the previous studies. Because many researchers have worked on glacier extent only. We offer the first high-resolution multi-dataset driven analysis on the above-mentioned classes. Not only does this advancement make it easier to map glacier dynamics where such data is inaccessible, but the novel methods also fulfil the critical data gap to assess the impact of climate change on conducting hydrological modelling in the Hunza Basin.

Review of Literature:

In the HKH region, glacier melt and associated snow serve as the primary sources of water for the Upper Indus Basin (UIB). The hydrological behavior of snow- and glacier-fed rivers is largely governed by the extent and melting of the available snow cover area (SCA). On the other hand, the HKH region's SCA is under the influence of global warming. Therefore, it is important to estimate these catchments of snowmelt runoff and spatio-temporal changes in the snow-covered areas for better water resource management. Many methods for glacier dynamics and glacier monitoring are adopted for near-real-time estimation by ML and DL (Deep Learning) techniques emerging rapidly in geography and geospatial fields of science[35]. Where the authors have discussed ML, DL, and AI (Artificial Intelligence). These methods are very accurate in interpreting imagery of various types, as a human being thinks and physically incorporates sensibly.

A study conducted by[13] explained glacier dynamics related to snow cover using MODIS data and calculated the area of the UIB as 206,000 sq km, with the identification of perennial snow-covered areas as well as perennial streams. Snow-covered glaciers in the region contribute to the formation of glacial lakes, which can trigger glacial lake outburst floods (GLOFs) with potentially catastrophic impacts on local communities and small agricultural lands. At the same time, this vast glaciated landscape serves as a vital water source for Pakistan's agriculture and underpins the hydropower potential of the Indus River. In the research,[36] discussed the influence of climate variability on glaciers at the global level and expressed that almost 335 ± 144 Gt of mass of ice degraded per year from 2006 to 2016.[37] had suggested in their study about the ways of monitoring world glaciers periodically, as most of the world's regions are expected to face seasonal climate changes for future water accessibility to arid and semi-arid areas.

The authors in[38] believe that ML techniques are found to be very suitable for finding extensive changes in rock glaciers and their mass ice balance. They acknowledged angular debris cover with extensive sediments in arid and semi-arid mountainous regions of their study area with the help of band ratio techniques. As demonstrated in the study by[39], the authors introduced novel CNN- and OBIA-based methods for analyzing glacier dynamics, successfully mapping 120 rock glaciers out of 180 glaciers in the Chilean glacier regions. The technique used in the research was a fixed window of a 2x2 kernel algorithm.

A considerable amount of water is accumulated as snow and glaciers in catchments situated in high-altitude areas. These frozen snow and glacier reservoirs are the sources of several lakes, springs, streams, and rivers in this area. The world's current assessment of the glaciated area is approximately 14,900,000 sq km, making 10 percent of the earth's land area[40]. The study by[41] highlights the advantages of integrating various processes into GIS-based hydrologic models. It emphasizes that such models require comprehensive and up-to-date data on land use, soil characteristics, and climatic conditions. These requirements are from the key limitations of hydro-modelling.

In[42], researchers have described that GIS and remote sensing were considered the modern best techniques for estimating hydropower potential. Various software for a geographic information system (like ArcGIS, QGIS, ArcView, and WebGIS) and remote sensing (like ENVI, ERDAS Imagine, R, and e-cognition) are freely available for the analysis of DEM (Digital Elevation Model). Different analyses, like stream network exploration, basin detection, land use study, and terrain evaluation, can be performed by anyone, even those who are not experts [43].

In the research of[44], the authors have applied GIS and remote sensing techniques for hydropower potential estimations in terms of sustainable energy in Bangladesh. In[45], scholars have suggested a GIS-based method for the selection of hydro sites for small hydropower plants in the hilly areas of India. They developed an algorithm (using Visual Basic) for IRS-ID, LISS-3 with satellite imagery, with false composite colors for detection and calculations of hydro resources in hilly and plain regions.

Material and Methods:

Study Area:

An area located in the western Karakoram region of northern Pakistan, Hunza Basin is a part of the UIB that covers almost 13733 Km^2, where 3417 Km^2 (more than 25%) of the area is under glaciers[46]. Geographically, the study area lies between 35°80'N to 37°05'N latitude and 74°02'E to 75°48'E longitude, as illustrated in Figure 1.

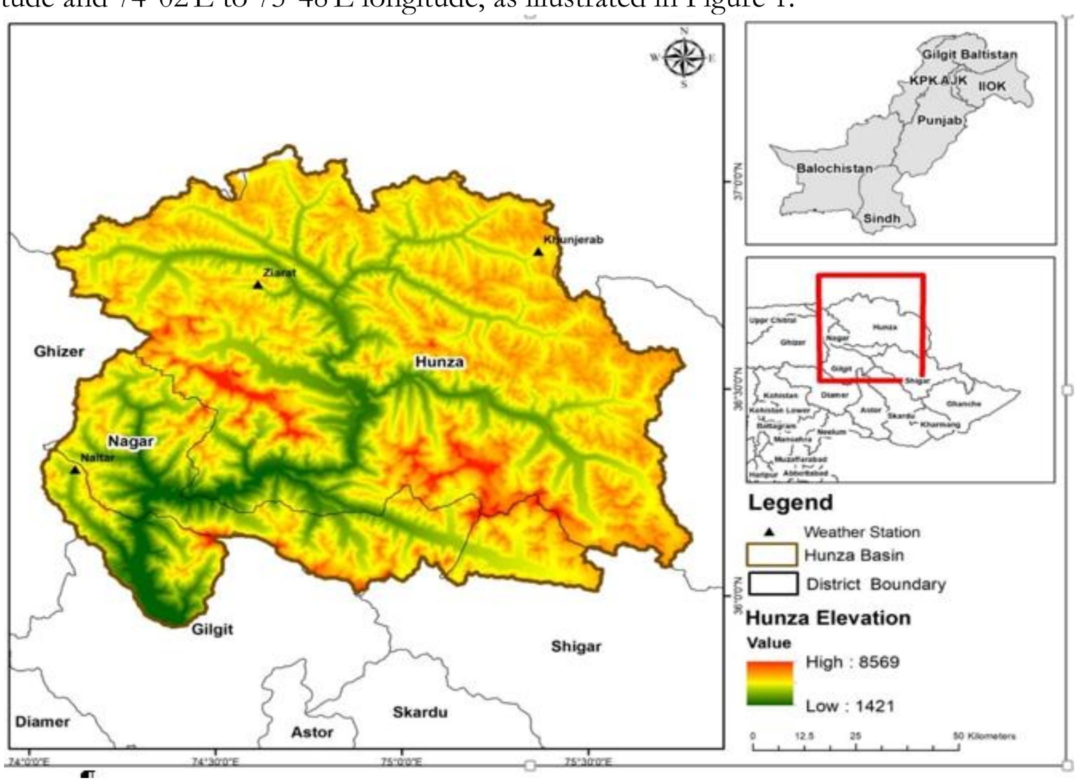

Figure 1. Study Area (Hunza Basin (UIB))

The region is 1395 to 7831 meters high above sea level and categorized into various elevation zones as shown in Figure 2 [24]. This study area has glaciers over 33% of its total area, which covers roughly 3600 Km^2[13]. Glaciers of this basin are normally bounded by debris cover, which brings about a cause of possible GLOFs that create a successive threat to the local people. These glaciers devastate property, infrastructure, and damage all sorts of road networks in the valley.

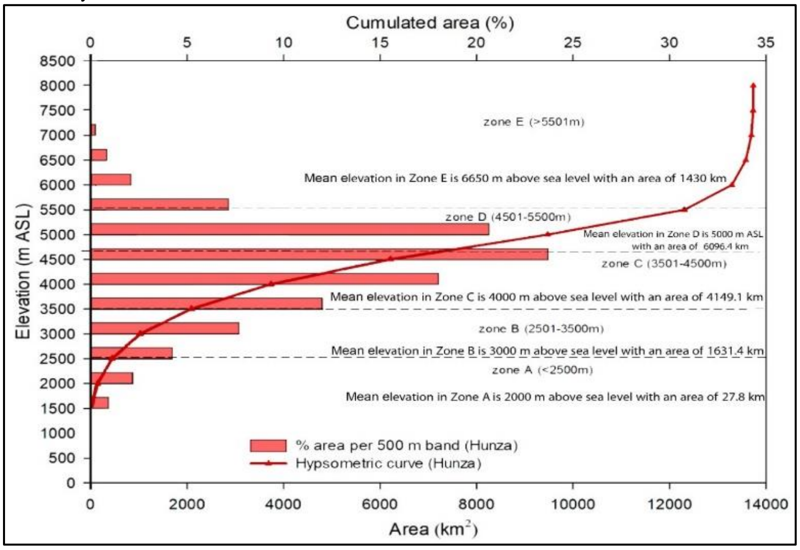

Figure 2. Elevation Curve of Hunza Basin[47]

Hypsometric curve and elevation area distribution of the Hunza Basin provide a complete picture of its geomorphology and topography. The surface area is represented in square kilometers on the lower horizontal axis, while with an increase in elevation, the upper axis reflects the cumulative percent of the total area of the basin. The height of the ocean above sea level is given on the vertical line that varies from 1000 m to more than 8000 m. Horizontal bars represent the proportions of land area across 500-m elevation bands, while the red curve depicts the cumulative distribution. The features point towards the spatial variability in terrain and dominance of the elevation zone[48]. The basin is classified into five elevation zones. Zone A (< 2500 m) has an average height of 2000 m, with only 27.8 km² proclaiming the limited nature of valley floors[49]. Zone B has a mean elevation of approximately 3,000 m and covers an area of 1,631.4 km². Its environmental conditions are comparable to those of the lower mountain slopes. Zone C (meaning 3,501 to 4,500 m) accounts for 4,149.1 km² with a mean altitude of 4000 m, which is substantially a mid-elevation scenario[15]. The largest extent is in Zone D (4501 - 5500 m), which is 6096.4 km² with a mean elevation of 5,000 m, with an elevation of mainly high altitude. Finally, Zone E, with an area of 1430 km^2 and an average elevation of 6650 m (above mean sea level), comprises the highest peaks of the basin and glacial accumulation zones. Nearly 80% of the basin's total area lies between elevations of 3,500 m and 5,500 m. Therefore, these elevation ranges play a critical role in shaping the region's hydrology[50]. Recent hydrological modeling highlights these dynamics further. An elevation-distributed hydro-climatic assessment using the Distance-Distributed Dynamics (DDD) model indicates that, in the Hunza Basin, glacier melt contributes about 45%–48% of total runoff, snowmelt accounts for 30%–34%, and rainfall runoff comprises 21%–23%.

It is particularly important to note that glacier melt is greatest at mid-elevations (approx. 3218 to 3755 m; Figure 2), suggesting that these areas significantly contribute to basin discharge, and they are also the zones in which most land area is located. The hypsometric and elevation–area distribution plot illustrates that the Hunza Basin is largely situated between 3,500 m and 5,500 m, while also emphasizing the critical interconnections between terrain, cryosphere processes, and hydrology. The topography is relatively steep and geologically young, due to which the presence of higher glacial cover and the dynamic melt contribution retain the hydrological resources for the Upper Indus Basin.

Data Collection:

Multisource satellite data were collected for the study area. Snow-covered distribution is fundamental for hydrological and meteorological applications. Different operational snow products will be derived from satellite sensors with different initial times and resolutions, depending on cloud cover. A snow cover area product with a resolution higher than 1 km and traced back to 1990 to 2025 of snow extent from MODIS, Landsat, Sentinel 1 & 2, and SPOT-5 imagery is incorporated to identify snow-covered trends in the study area from 1990 to 2025. Thus, this region's most extended snow cover data (almost 35years) has generated a trend. The snow-covered products were further validated with the available station snow measurements of the Automatic Weather Station (AWS) installed by a Chinese collaborator of SUPARCO on the Batura glacier. Field observations were confirmed during this research in the basin, and the snow product was validated from the Chinese Fengyun satellite MERSI sensor.

Table1. Satellite Information for Data Source

Satellite / Sensor	Data Used period	Spatial Resolution	Revisit (Days)	Applications for Glacier Dynamics	Reference
Landsat 5 TM	1990 - 99	30 m	16	Glacier area & retreat monitoring	[51]
Landsat 7 ETM+	1999 - 2012	30 m, 15 m (pan)	16	Glacier mapping & debris detection	[52]
Landsat 8 OLI/TIRS	2013 - 15	31 m, 15 m (pan)	16	Glacier extent	[53]
SPOT-5	2002 - 12	2.5 - 10 m	26	Glacier outlines, DEMs	[54]
SPOT-6	2012 - 25	1.5 - 6 m	26	High-resolution glacier monitoring	[55]
Sentinel-1 SAR (C-band)	2014 - 25	10 m (IW mode)	6 to 12	Glacier velocity & flow	[56]
Sentinel-2 MSI	2015 - 25	10 - 20 m	5	Glacier mapping & debris cover	[57]
MODIS (Terra & Aqua)	2000 - 25	250 m - 1 km	Daily	Snow cover, albedo	[58]

Limited research has been conducted on the mass balance status of glaciers and glacier area changes in the study region, partly due to the high cost of commercial satellite data. DEM is taken from available satellite optical stereo pairs of images (ASTER) from recent years for glaciers.

Glacier mass change was estimated by differencing DEM and altimetry data, which were cross-validated with available datasets. These products were then used to assess glacier mass variations within the basin. There are few in situ measured velocity data on glaciers in the region, and the data from remote sensing are only found on some surging glaciers for a limited period. In this research, offset tracking and interferometry algorithms to Synthetic Aperture Radar (SAR) data and feature tracking algorithms to multi-spectral sensors are also applied on board satellites with open data, i.e., Landsat TM/ETM+/OLI, Sentinel-1 & 2, MODIS, and SPOT-5. Because these satellites operate on different repeat cycles, their data were integrated to estimate the seasonal and annual velocity fields of selected benchmark glaciers in the absence of direct measurements. Spatio-temporal changes in snow, glaciers, and glacial lakes were analyzed, complemented by in situ observations on snowpacks and glaciers to assess snow cover depth, glacier mass balance, velocities, and glacial lake dynamics. Activities involved the use of Ground Penetrating Radar (GPR) sounding, differential GPS (dGPS) surveys, snow pit analyses, and profile observations on monitored glaciers to collect primary data on snow and ice thickness, glacier surface elevation and velocity, snout variation, as well as snow physical properties such as density and water content. Field observations and visits were managed to measure the location of these three times a year; however, a local technician was hired on a self-help basis to take their measurement once a month. These measurements enabled the estimation of glacier advance/retreat and surface thickness changes. Furthermore, the in-situ data will be compared with satellite datasets for validation, ensuring that the validated imagery can be reliably applied to glaciers across the entire Hunza Basin.

Metrological Data:

Meteorological data, including temperature and precipitation records, were utilized in this research. However, hydro-meteorological data remain scarce in the Hunza Basin, particularly at high-altitude locations, due to rugged terrain and limited accessibility. Thus, an acute shortage of in situ ground data was felt to ascertain the realistic position of the situation of glaciers in the area and address the HKH anomalies. However, there were a few stations (Khunjerab, Ziarat, Naltar) installed by WAPDA in Hunza valley with a shorter data period starting from 1995, and PMD records weather data from Gilgit, Aliabad, and Karimabad for Hunza since 1961[59]. Hydro-meteorological data were obtained from ERA5 and Chinese gauging stations installed in the studied region at high altitudes. Data recorded by ERA5 at Khunjerab (Hunza basin) was taken for this research. Trends in these meteorological variables were detected using a statistical tool with the latest libraries of the R language. These trends were correlated with snow and glacier variations to identify the factor that is causing rapid melting.

Glacier Dynamics:

Glacier dynamics are usually known as snow cover, glaciers with debris cover, clean ice, stable terrain, and identification of GLOFs. ML tools were employed to extract features using the Gray-Level Co-occurrence Matrix (GLCM) method. These methods were very useful for mixed and complex types of imagery. There are 11 techniques for GLCM. However, a few were used to extract glacier dynamics and their mapping. In the equations, p = value, I row, j columns.

ASM (Angular Second Moment):

It creates uniformity in pixel pair repetition for the image analysis and feature extraction. ASM detects disorder in the textures of the features where the energy level reaches a maximum level, but does not increase the value by one.

$$\text{ASM} = \sum_i \sum_j p_{ij}^2 \text{ and Energy} = \sqrt{ASM} \tag{1}$$

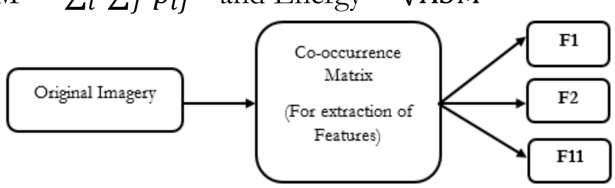

Figure 3. GLCM- Features on Co-occurrence Matrices

Entropy:

Entropy quantifies the level of disorder and complexity in an image. It is higher in non-uniform or heterogeneous areas, reflecting greater textural complexity, and lower in homogeneous regions. Entropy is inversely related to energy, making it a significant indicator of texture variation within imagery. In homogeneous image areas, entropy values are low, while in heterogeneous regions they are higher, reflecting greater textural variability. Thus, entropy serves as a key indicator of non-uniformity in image texture.

$$\text{Entropy (ent)} = \sum_i \sum_j p_{ij}\, log_2\, p_{ij} \qquad (2)$$

Contrast:

The spatial frequency and difference of GLCM within an image are both measured by this function. It catalogues changes inside the image in terms of values (both low and high values) and the layout of pixels.

$$\text{Contrast (con)} = \sum_i \sum_j (i-j)^2 p_{ij} \qquad (3)$$

Homogeneity:

It is called an inverse difference moment. It makes more significant assumptions for pairs of items with smaller grey tone variances. If contrast reduces, energy remains stable; thus, homogeneity rises in this way.

$$\text{Homogeneity (hom)} = \sum_i \sum_j \frac{1}{1+(i-j)^2}\, p_{ij} \qquad (4)$$

Variance:

Variance increases when grey level values differ from the mean values.

$$\text{Variance (Var)} = \sum_i \sum_j (i-\mu)^2 p_{ij} \qquad (5)$$

Dissimilarity:

In dissimilarity, instead of weight increasing exponentially (like 0,1,4,9 etc.), the values move diagonally as contrast acts and weights of dissimilarity increase linearly (like 0,1,2,3,4 etc.)

$$\text{Dissimilarity} = \sum_i \sum_j |i-j| p_{ij} \qquad (6)$$

ML Algorithm Selection:

RF, ANN, and SVM classifiers for the imagery classification technique were used in experiments. Utilizing RF and SVM hyperplane structures in high-dimensional space depicts excellent pattern classification[60]. GLCM with RF and SVM gave complete contrast between the grey level pair at a certain distance that was calculated for single variable likelihood co-occurrence, as shown in Figures 3 and 4. To enhance classification accuracy and feature extraction, all models were applied to achieve higher-order feature representation based on their statistical measures.

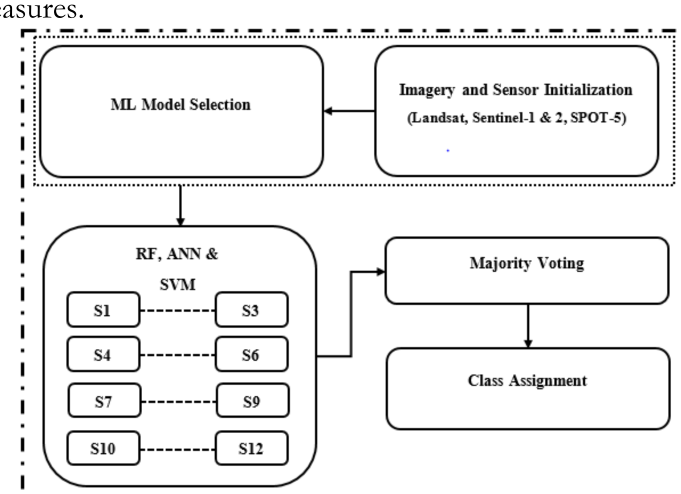

Figure 4. Framework, R Classes are initialized as Glacier Dynamics

Training Data Set:

There were thousands of images and their segmentations from which 70% of the data was trained, and the remaining 30% was tested for the requisite results.

Accuracy Assessment:

Accuracy assessment of the extracted features from the imagery was computed through Kappa Coefficient Analysis and with the measurements[60]. The validation for ML features extraction to analyze the overall validation and accuracy.

Accuracy

Sensitivity

Specificity

Positive Predictive Value (PPV)

$$\hat{k} = \frac{N \sum_{r=1}^{r} X_{ii} - \sum_{r=l}^{r} (x_{i+} \times x_{x+i})}{N^2 - \sum_{r=l}^{r} (x_{i+} \times x_{x+i})} \quad (7)$$

$$\hat{k} = \frac{(Total \times Sum\ correct) - Sum(row - column)}{Total\ Squared - Sum\ (row - column)} \quad (8)$$

To derive actual values and quantities, the following equations were applied as part of detailed accuracy assessment methods for validation. Moreover, the Dice coefficient was employed to quantify and distinguish overlapping or merged spatially aligned areas between traditional segmentation methods and the segmentation of the target region of interest (ROI) at higher elevations. Extraction of imbalance classes was ensured even using intersection-over-union (IoU) by computation of the average over class recognition.

Accuracy : $$\frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

Sensitivity : $$\frac{TP}{TP + FN} \quad (10)$$

Specificity : $$\frac{TN}{TN + FP} \quad (11)$$

Dice : $$\frac{2 \times TP}{(FP + TP) \times (TP + FN)} \quad (12)$$

TP = True Positive, which presents positive results in the specific class extraction.

TN = True Negative, which removes negative abnormal results in the course of feature extraction

FP = False Positive, absence of abnormality with positive results of classification

FN = False Negative, which means that there would be mixtures of classes with negative results.

Results and Discussions:

This study demonstrates the effectiveness of machine learning in analyzing glacier dynamics in the Indus Basin. The integration of satellite data with machine learning models has enhanced the ability to monitor and predict glacier changes. Future work may focus on incorporating higher-resolution datasets and developing real-time monitoring systems for better disaster preparedness.

Climate Variability Trends:

Figure 5 shows the results of temperature variations from 1990 to 2025. There is a glaring change in temperature in the monthly temperature anomalies of the Hunza Basin, and this increasing trend has been accelerated since 2025, which is very noticeable, and the warming has been accelerating since 2005.

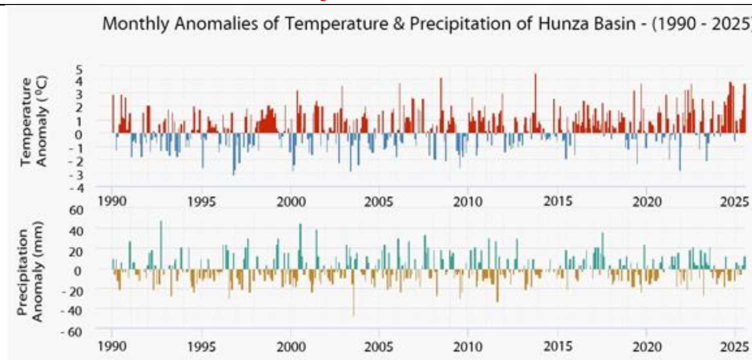

Figure 5. Monthly Trends on Temperature vs Precipitation in Hunza Basin (1990 - 2025) [13]

The 1990s witnessed a balanced variability both in positive and negative. However, from the early 2000s onward—and more prominently after 2010—positive temperature anomalies exceeding +4 °C have been observed on a monthly scale, indicating a clear temporal trend toward warmer conditions. This pattern is consistent with regional studies that have documented rising temperatures across the Hunza Basin.

Precipitation Trends and Hydrological Implications:

Precipitation varies greatly from one season to another, from one year to the next. Sometimes, there are great fluctuations that occur in the upper region of the basin, especially near Khunjerab (over +40 mm), but dry spells show no change and depict a noticeable rising tendency over time.

High mountain basins such as Hunza rely heavily on accurate predictions of annual precipitation and snowfall accumulation and storage, given the abrupt and variable nature of these phenomena[61]. Thus, the combination of intermittent rainfall and rapidly rising temperatures creates severe challenges for hydrological management in the Hunza Basin. Over short periods, rising temperatures accelerate snow and glacier melt, leading to higher river flows during the season. During extreme weather events such as floods and droughts, the likelihood of future GLOFs increases due to persistently rising temperatures and irregular rainfall patterns, which accelerate glacier retreat and alter runoff dynamics. Irrigation, farming, hydropower, and the livelihoods of people downstream in the Hunza Basin[62]. The Hunza Basin is extensively glaciated, with glaciers contributing to its highest total annual flow[22]. Inter-annual increasing positive temperature anomalies have been accumulating since 2010, indicating a significant glacier melt. Rising summer temperatures accelerate ablation, while reduced and unpredictable snowfall limits glacier mass restoration at higher altitudes. As a result, many glaciers across the basin exhibit a persistent negative mass balance. In the short term, this increases downstream runoff; however, continued glacier retreat makes the basin progressively more vulnerable to reduced water availability during dry periods. In addition to potential GLOFs and flash floods, increasing meltwater and severe local rainfall putting regional infrastructure and lives at risk.

These processes render the Hunza basin's glaciers particularly sensitive to ongoing climate change, adding independent weight to the call for adaptive water management in the Indus basin. Key findings from the graphs were: -

Rising Temperatures. The temperature had been increased in positive anomalies prevailing post-2010 (+4 to 5 °C extremes, Figure 6).

Inconsistent Rainfall. There was no consistent increasing trend in precipitation anomalies over the long term, ranging from 40 mm above to 40 mm below average precipitation circumstances.

Glacier Melt Intensification. Warmer summer conditions and declining snowfall were the driving negative glacier mass balance, promoting glacier melt and runoff shift.

Hydrological Risks. The interaction of warming and irregular precipitation increases floods, droughts, and GLOFs, which already endanger water security and local people.

Future Consumption. It also means available water is likely to be higher in the short term as more melt, but the long-term sustainability of glaciers and dry-season flows is at risk.

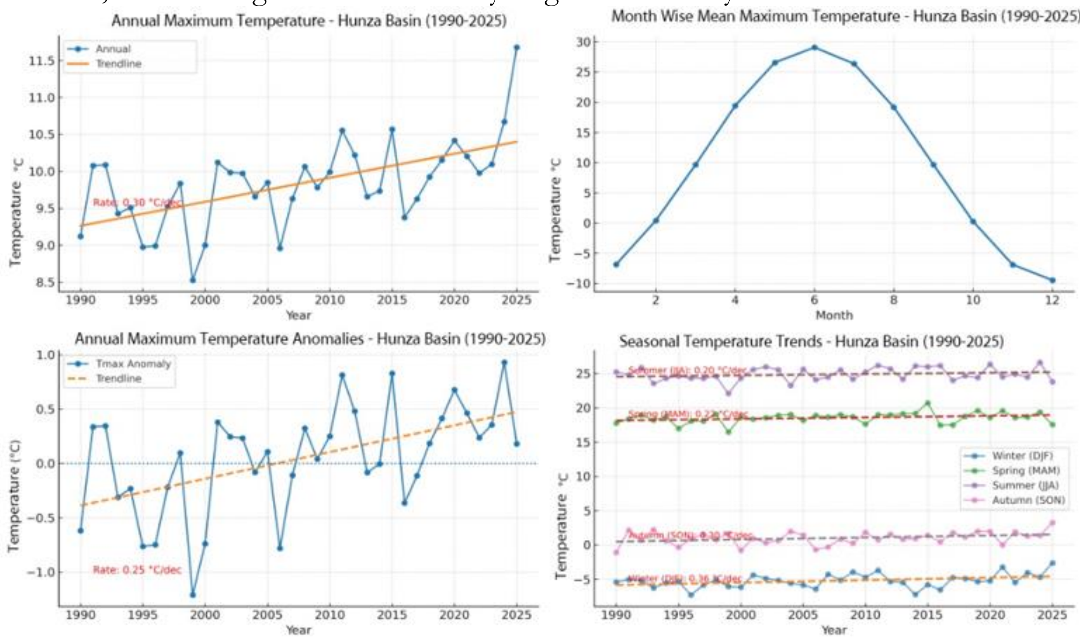

Figure 6. Temperature Trends (PMD Data) in Hunza Basin (1990 - 2025)

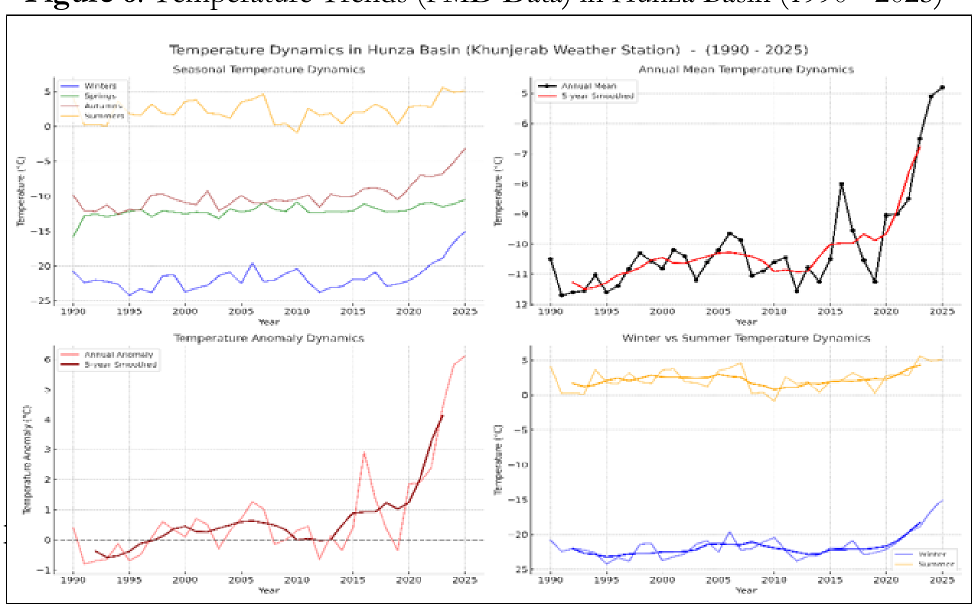

Figure 7. Temperature Trends (ERA5 Data) in Hunza Basin (1990 - 2025)

Lapse Rate Context:

Figure 6 displays temperature interpretation in graphical perspectives using PMD metrological data. Temperature increases after 2010 on both maximum and minimum sides. Higher maximum temperature (0.30 °C per decade) increases the glacier ablation and increases the minimum temperature, shortens the freezing period, and reduces the seasonal snowfall. Using the standard lapse rate of 6.5 °C per kilometer means that temperature decreases by approximately 6.5 °C for every 1,000 meters of elevation gain. Figure 7 demonstrates the weather conditions of the Khunjerab weather station, which is located at 4,730 m a.s.l. Applying the standard lapse rate, a temperature of 0 °C at this station would correspond to approximately +6.5 °C at 3,700 m and about –6.5 °C at 5,700 m. As glaciers in the Hunza Basin extend from around 2,500 m to over 7,000 m, even modest warming observed at the station scale carries amplified implications across the basin's hypsometric range. When summer temperatures at the Khunjerab station remain at or above 0°C, the lapse rate indicates that mid-elevation glaciers between 3,500 and 4,000 m surpass the melting threshold. This results in accelerated ablation and subsequent glacier retreat with elevation.

Winter Warming:

Winters at Khunjerab remained extremely cold (–20 °C or below), but with a warming trend of approximately +1 °C per decade, the cold season is becoming shorter and more intense. Along with lapse rates, there was snowfall closer to even above 0°C that was normally much colder at 3000 to 3500m, and it had potential for minimizing accumulation.

Seasonal Contrast:

The summer is getting warmer compared to winter, and the melt zone goes up more quickly than the accumulation zone. This imbalance causes the glacier to melt and have a negative mass balance. Based on lapse rates, the observed warming at the station (> +1 °C per decade) corresponds to an upslope shift of the melt threshold by approximately 100–200 m per decade.

Anomalies:

Figure 6 denotes anomalies of 0.25 °C per decade, and after 2010, this increase. The shift to positive temperature anomalies after 2005 indicates that the equilibrium line altitude (ELA) has risen, consistent with the effects of the lapse rate. Due to the lapse rate, even a modest rise in temperature (1–2 °C) at higher elevations in Hunza could raise the equilibrium line altitude (ELA) by 150–300 m, reducing the net accumulation that feeds glaciers. The annual mean temperature in the Hunza Basin shows an increasing trend of +1.06 °C per decade with 95% confidence limits between +0.65 and +1.48 °C from 1990 to 2025. ELA rising by 100 to 175 m every ten years and sometimes over 225 m with normal lapse rates (6 to 7 °C/km). This implies that in areas with limited snow accumulation, the melt zones expand, leading to a more negative mass balance. Consequently, snow melts earlier, resulting in increased runoff into the Hunza Basin.

Glaciers Spatial Dynamics:

Table 2 and Figure 8 present the results of glacier dynamics, showing that glacier extent decreased from approximately 3,900 km² in 1990 to around 3,400 km², reflecting the impacts of climate change. This numerical data differs very much from the previous published studies, estimating 2565 to 2600 km², as the author has only applied it to 21 big glaciers[63],[64]. The difference displayed in the mapping and extraordinarily higher numerical values due to the inclusion of seasonal snow cover at a large scale; therefore, debris cover was undermined by debris-covered ice. Using late-summer composites and more stringent NDSI thresholds, we refined glacier outlines, resulting in updated sustainable glacier areas of 2,550–2,600 km². Clean ice accounts for 73% of the glacier area, while debris cover represents 27%, consistent with Karakoram-wide estimates. The basin's hydrology is strongly influenced by seasonal snow, which varies in extent between 9,000 and 12,000 km² depending on the year and season. Glacier dynamics in the Hunza Basin from 1990 to 2025 reveal an overall retreat, with notable variations in the mass balance of clean ice, debris-covered ice, and seasonal snow. The total glacier area reduced from 3956 km² in 1990 to 3424.47 km² in 2025, accounting for a loss of up to 13.4% over the last 35 years. This loss was not uniform over time, remaining largely stable until 2015, consistent with observations for the Upper Indus Basin (UIB). However, from 2015 to 2020, a sudden change was witnessed during which clean ice loss more than 350 km² (11.3%). By 2025, the area of clean ice is estimated at 2,577.47 km², representing a reduction of approximately 750 km² compared to the 1990 baseline.

The composition of ice surfaces also changed as the area covered by debris increased from 635 km² (16% of the glacierized area) in 1990 to 847 km² (26%) in 2025. This gradual increase indicates that surface insolation has gone up and glaciers have gone to thinner under relatively balanced mass budgets (as has also been observed across the Hunza with an expansion of debris-covered areas). The area of clean ice declined significantly, with the reduction accelerating after 2015. Extreme variations in seasonal snowfall, ranging from 9,500 to 12,000 km², further influence annual glacier melt due to temperature fluctuations. A noteworthy glacier melt was witnessed during the research period from 1990 to 2025. In 1995, the calculated area was 84.23 km², reaching a minimum of 11.46 km² in 2000. Overall, a total melt of 243.19 km² was projected by 2025. As a consequence of global climate change, glacier runoff was shown to increase significantly across different parts of the Hunza Basin, as illustrated in Figure 8. Most of these results were largely consistent with previous studies. For instance,[65] reported glacier changes from 2,565 to 2,590 km² between 1990 and 2018, reflecting a net decline of only about 1%. In contrast, the RGI v6.0 data indicate slightly higher glacier melt in the Himalayan regions of the Karakoram[52],[63]. Our results and dataset indicated higher absolute magnitudes, primarily due to differences in methodology, the use of machine learning algorithms, and the incorporation of the latest temperature data from PMD. Nevertheless, the stable behavior in the early years of 2010 and subsequent retreat of glaciers was consistent with geodetic mass balance observation as already available in the relevant studies[65],[66]. Regional increase of debris covers and hydrological drift muddled by[56] and[67] are consistent with the growing debris fractions and rapid glacier melt. As a result, the derived spatio-temporal trends provided robust estimates that align with the known behavior of Hunza Basin glaciers, despite differences in magnitude.

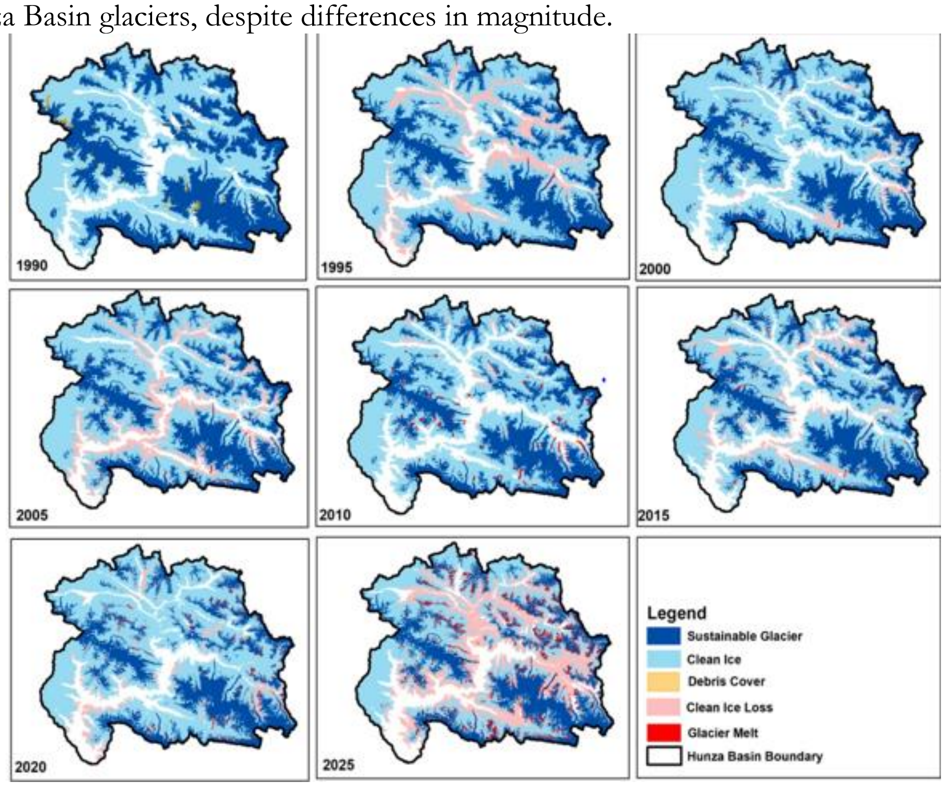

Figure 8. Spatio-temporal Glacier Dynamics of Hunza Basin

Figure 8 demonstrates how the spatio-temporal glacier dynamics of the entire Hunza Basin have been shifted from 1990 to 2025 with an interval of 5 years. In the maps, five classes with different colors were used to segregate the spatial pattern of the entire basin. These maps explain that the dark blue color represents sustainable glaciers that have steadily retreated, losing approximately 13.4% of their area over the past 35 years. The light blue color shows clean ice, the yellow colors display debris cover, the pink color indicates clean ice loss, and the red color indicates the glacier melt zone. The map panels show changes at eight major points, i.e., 1990, 1995, 2000, 2005, 2010, 2015, 2020, and 2025. The light blue areas (clean ice) are gradually shrinking toward the glacier boundaries, as shown in the panel. Glacier tongues and lower sections are more prominent, reflecting the combined effects of rising temperatures and debris cover (yellow). Over time, the loss of clean ice (pink) has led to increased debris cover and a reduction in overall glacier surface area. Areas highlighted in red on the maps indicate glacier melt. There was a slow retreat of glaciers during the time from 1990 to 2010, but it is more visible and noticeable in the lower ablation zones of the basin after 2015. It happened due to an increase in temperature. Glacier melt was accelerated commonly, and ultimately, debris cover was increased in 2015 and continued to increase in subsequent years. This growth is shown by the fact that the areas covered with rocks and gravel increased from 635 km2 (16%) in 1990 to 847 km2 (26%) in 2025. In 2020 and especially in 2025, the overall condition of the basin has significantly changed. Glaciers are shrinking, with only small amounts of clean ice remaining and ongoing melt dynamics. Reduced snow cover and lower albedo further influence the basin's hydrological patterns. Overall, the figures illustrate glacier retreat and confirm a shifting pattern, with relative stability observed during the 1990s and 2000s, reflecting implications for the hydrological and geological landscape of the Hunza Basin. Figure 9 displays graphical representations of the change scenarios of the maps of Figure 8 in the context of Table 2. It shows how things changed over time for each class. The extent of the sustainable glacier has been decreasing. The area of debris cover kept on increasing, and the amount of clean ice changed slightly till 2015, and the change was witnessed remarkably after 2015 onward.

Table 2. Class-wise Glacier Dynamics of Hunza Basin

Year	Glacier Extent	Debris Cover	Clean Ice	Seasonal Snow	Clean Ice Loss	Glacier Melt
1990	3956.11	635	3321	12175.12	-	-
1995	3871.88	667	3204.88	11067.35	116.4	84.23
2000	3860.42	699	3191.42	11855.63	13.46	11.46
2005	3840.78	721	3139.78	10841.33	51.64	19.64
2010	3816.07	762	3114	11279.54	25.75	24.71
2015	3792.42	794	3098.42	10765.93	15.58	23.65
2020	3667.66	820	2747	11468.83	351.42	124.76
2025	3424.47	847	2577.47	9485.57	169.53	243.19

The four panels in Figure 9 collectively illustrate how the Hunza Basin's cryosphere has been redistributed over the past 30 years. After 2015, glacier extent has continued to decrease steadily at a consistent rate. However, the panel depicting clean ice segments shows a disruption in 2015, followed by a gradual decline through 2025. In contrast to the debris cover panel, it depicts a monotonous increase from 1990 to 2025 and covers a large number of glacier-occupied areas, illustrating the glacier tongue. The last panel of Figure 9 illustrates the unstable and irregular decline of clean ice before 2015, followed by pronounced spikes of rapid decrease approaching 2020. Resultantly, it brings about a significant increase in glacier melt and runoff volumes. Collectively, these panels highlight a transition from relative stability to rapid change, as the basin's glacier snow balance is increasingly influenced by debris insulation and enhanced glacier melt runoff.

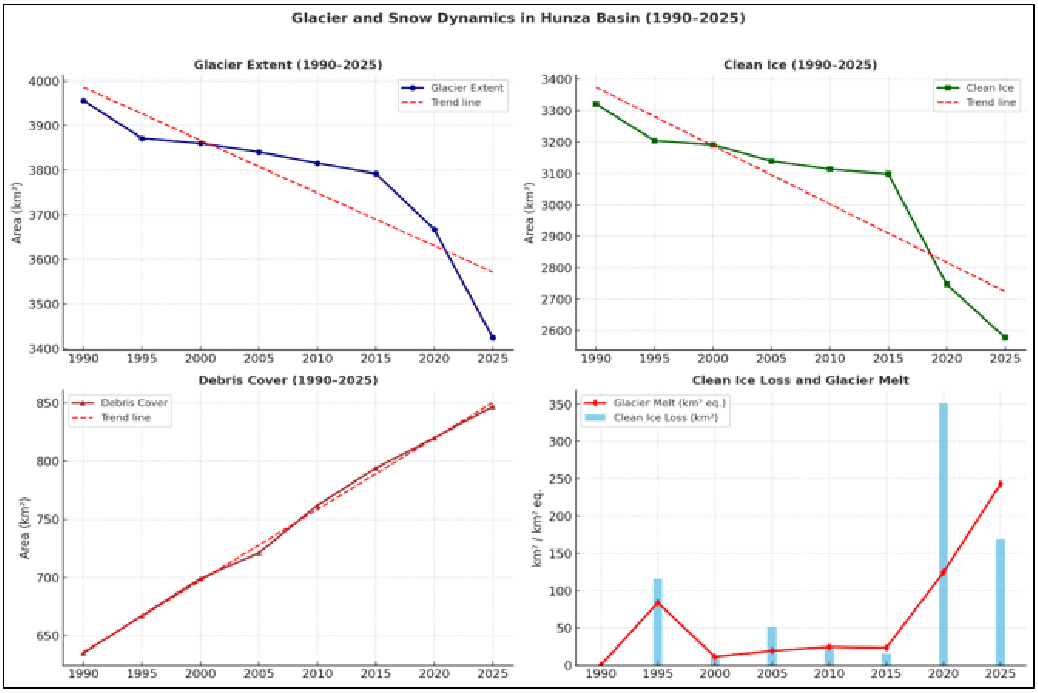

Figure 9. Class-Wise Graphical Illustration of Glacier Dynamics of Hunza Basin

The significant rise in clean ice loss is directly linked with the increasing temperature anomaly in the basin. It has resulted in months and months in recent years where temperature anomalies were more than $+4^0$ (as depicted in Figures 6 and 7). The warming has increased ELA (equilibrium line altitude) by 150m to 200m over the past ten years. This has happened due to a decrease in snow accumulation zones and an increase in glacier area that is subject to ablation. Seasonal changes in the snow cover make this response more prominent. When the snow melts faster, it reduces the intensity of the surface of the glacier's albedo, which causes the exposure of ice earlier due to absorption of heat inside, so it warms up faster, which triggers additional glacier melt. These combined fluctuations explain why clear ice has disappeared so rapidly, why debris cover has been spread, and why glacier melt has appeared more prominent over the last ten years.

Experimental Results of ML Classifications for Glacier Dynamics:

Tables 3, 4, 5, and 6 are experimental results of ML algorithms, which provide very good results for the estimation of glacier dynamics in this research. The following results are enumerated as depicted in the above-mentioned tables.

Performance of RF:

Table 4 shows that the RF model has achieved the highest performance among the ML algorithms, delivering an overall accuracy of 95.4% and a Kappa coefficient of 96.6%, demonstrating its effectiveness in producing reliable results. Therefore, these results were significantly perfect. Producer's accuracy (PA) was calculated as 96% and user's accuracy (UA) was calculated as 95% on clean ice, whereas PA was 94% to 96% on seasonal snow, with low performance known in omission error and commission errors. However, RF exhibited lower accuracies for glacier melt (PA = 90%, UA = 89%), a class prone to spectral confusion with both water bodies and ice, and for clean ice loss, which often overlaps with debris and melt zones (Table 4).

Performance of ANN:

The ANN model achieved an overall accuracy of 94.0% and a Kappa coefficient of 91.7%. Although slightly lower than RF, it still demonstrates strong classification reliability. ANN performed strongly for clean ice (PA = 97%, UA = 96%) and seasonal snow (PA ≈

95%) but struggled with debris cover (PA = 82%, UA = 82%). The high omission and commission errors for debris indicate the difficulty of the ANN model in accurately classifying spectrally mixed pixels along glacier margins. Likewise, the glacier melt class was detected as PA = 87% and UA = 88%. Moreover, the correctness of the class of clean ice loss was calculated as PA = 87% and 94% which is very sensitive to interim ice melt. Overall, ANN provided stable mapping but with larger variability across classes compared to RF (Table 5).

Performance of SVM:

SVM yielded the lowest overall accuracy (OA = 92.0% and Kappa = 89.0%), although still above the threshold of acceptable classification performance in hydrological mapping. It has classified clean ice well and gave results as (PA 95%, UA 95%). Its performance dropped for debris-covered (PA 79%, UA 77%) and for glacier-melt classes (PA 80%, UA 88%), indicating recurring confusion where classes have similar ranges. Seasonal snow was mapped with lower reliability (UA = 90.5%), likely because melting snow can appear similar to clean ice in the imagery (Table 6).

Comparative Reasoning of RF, ANN, and SVM:

For all three classifiers, clean ice consistently showed the highest mapping reliability, with both producers' and users' accuracy surpassing 94%. Debris cover in the study area remained very weak throughout the time period for which research was conducted. Besides this, glacier melt was also classified as a weaker class for which PA was calculated from 79 to 93% and UA was from 77 to 89% respectively. These results highlight the well-known challenges in detecting glacier meltwater structures, which exhibit mixed spectral signatures of ice and water. Moreover, debris covers were also very difficult to distinguish from the mixture of ice and debris. For this purpose, RF achieved remarkable results to segregate these segments, where the performance of RF was better than that of ANN and SVM. In terms of overall accuracy (OA) and Kappa (k), the RF model outperformed the others, providing a more balanced classification across all classes. Although SVM performed slightly better in terms of producer's accuracy (PA), it was less effective than ANN at identifying mixed pixels and signals in imbalanced classes, where ANN achieved a PA of 0.94. At high and alpine mountains, the situation is very different from the rest of the surroundings, so the choice of classifiers affects the robustness of thematic mapping issues. This was evident in the decline of Kappa (k) values, which steadily dropped from 96.6% to 91.7% and ultimately reached 89%.

Impact of Climate Change on Glacier Dynamics (Based on ML Results):

Results of all three incorporated models for classification offer trustworthy evidence for the impact of climate change on glacier dynamics in the study area. The reliability of the ML models for remote sensing is demonstrated by high overall accuracy (92 - 95%) and Kappa values (89 - 96%), as observed across all maps of glacier extents, snow cover, and glacier melt (Figure 8). Some of the mixed classes resulted in inaccuracies in estimating glacier dynamics and variations.

Glacier Extent and Clean Ice:

The accuracy of clean ice and glacier extent remains at a high level by PA/ UA of glacier extent, with > 93% and 95% clean ice, which indicates robust detection of different glaciers. The ongoing loss and degradation of clean ice indicate a continued trend of glacier recession. Increasing air temperatures (as observed over the UIB over the last few decades) accelerate surface melt, cause a decrease in ice accumulation, and lead to a zone of its wastage from areas with clean ice, which promotes direct ablation. This mechanism helps to explain the net negative mass balance observed in the basin.

Seasonal Snow: Glacier extent and clean ice accuracy loss were minor due to consistent PA/ UA (>93% for glacier extent >95%) for clean ice, showing robust differentiation of the glaciers. The repeated loss and progressive reduction of clean ice zones indicate ongoing glacier recession. At lower altitudes, higher temperature in winter seasons gives birth to more snowfall. Where hotter summer seasons bring about the cause of more snow/ glacier melt and rises to affect melt runoff volume, which is dully influenced under severe climate change scenarios. This phenomenon has a great impact on water availability for hydropower potential and common locality.

Debris Cover and Clean Ice Loss:

Debris cover showed lower classification accuracy, with producer's accuracy (PA) ranging from 79% to 93%. For clean ice, PA ranged from 85% to 92% and users' accuracy (UA) from 91% to 94%. These variations highlight significant challenges in classifying glacier surface conditions due to their heterogeneity and complex orientations. As and when the retreat of the glacier happens, then super-super glacial debris cover increases, and the surface of the glacier becomes more diversified. Thin debris cover accelerates melting by lowering albedo, and extensively thick debris cover warms the ice barrier in a non-linear response to climate change. Resultantly, the clean ice loss in the classification used can directly be interpreted as proof of current surface mass loss and glacier melt.

Glacier Melt:

Although PA and UA of all used classifiers were relatively simple (PA 80 - 90%, UA 88 - 89%), the relatively less reliable performance of all classifiers shows the complexity of the ice melting processes, characterized by the ice saturated and the continuous and occurring intermittently runoff of water. However, their presence highlights a growing spread of meltwater bodies and supraglacial lakes, both of which are strongly associated with a warming temperature and intensified surface energy. These melt features not only contribute to ice melt, but they also increase the potential for GLOF events to make them an unambiguous indicator of climate-driven glacier change. These findings support the relevance of other studies/ literature indicating glacier mass loss in the Hunza Basin and ongoing warming that led to the cryosphere affecting hydrology, flood hazards, and hydropower potential.

Discussion:

Table 3. Performance Analysis of RF, ANN, and SVM Classifiers

No	Classifier	Kappa Coefficient (k)	Overall Accuracy (OA)
1.	RF	96.57%	0.954
2.	ANN	91.7 %	0.94
3.	SVM	89%	0.919

Glancing critically at Table 3, we were able to know that the results of RF were outstanding for overall accuracy corresponding to the Kappa coefficient, i.e., 0.954 and 96.57. This is attributed to the quality of the dataset and the level of model training. The results of the ANN also outperformed SVM, as shown in the table and discussed in the following paragraph. The SVM classifier has performed; however, it was less effective (OA = 0.92, Kappa = 89%) due to challenges in managing large-scale, high-dimensional images, in contrast to ensemble approaches. In general, all three models provided satisfactory results; however, the performance of the RF ensemble structure was more accurate and generalizable for large-scale glacier monitoring and change detection.

Limited classes, such as debris cover, clean ice loss, and glacier melt, have similar types of spectral signatures. These signatures emit a similar reading, which is why these classifiers read likelihood misclassified, even though RF and ANN achieved the highest overall accuracies. The results from spectral resemblance between debris cover and glacial melted morainic material are very close to each other, with very little difference, so these classifiers offered less accuracy than that of the overall authenticity. Besides these, transitional characteristics of glacier melt, ice loss, and water-fed debris-covered layers are intermingled, thus the ultimate results reach lower accuracy. The existence of mixed pixels at the glacier boundaries also gives birth to less accurate classification. It happens due to a mixture of signals, inaccurate resolution of the sensors, and heavy cloud cover. Because of these challenges, on-site validation still needs to critically address the classification of different glacier surface dynamics, despite the high accuracy.

The increase of debris cover, glacier retreat due to its melt features, and clean ice loss in the Hunza basin are very much as the recent studies have estimated. This study has taken the whole basin, which is why the results are different; however, the trend is aligned with the relevant studies. [68] Conducted research on the Hunza Basin and narrated that glacier melt contributed its share of runoff from 45% to 48%, where snowmelt contribution was 30 to 34 %. Working on the effects of debris cover and mass balance of Batura Glacier, another group of researchers[69] highlighted that glacier melt had changed the surface energy balance due to the extensive spread of debris cover response. This research[61] was only on one glacier dynamics (Batura) for the last 20 years, whereas our research spanned over 35 years and encompassed the whole Hunza basin. Our findings are strengthening our stance to give depth that previous studies are in line with, as we had demonstrated the results on glacier retreat and snowmelt under climate change scenarios.

As summarized in Table 3, RF obtained the highest performance compared to that of ANN and SVM, signifying that our suggested method of ML was very accurate for the heterogeneous surface of high-dimensional glacier existence.

The classification results of RF, ANN, and SVM provide novel insight into the glacier dynamics in the Hunza Basin and its variation through space and time. The consistently high overall accuracies (92 - 95%) and Kappa coefficients (0.89 - 0.97) demonstrate that ML algorithms, when combined with multispectral and GLCM-based texture features, are well-suited for mapping glaciers in complex high-mountain terrains. Temporally, the results emphasize distinct imprints of climate-induced glacier variations. Snow-free ice areas have decreased over recent decades, and snow-free ice loss and melt landforms have increased, indicating intensified ablation and ground thinning due to the warming trend. Seasonal snow cover exhibits substantial interannual variability, consistent with observed changes in precipitation patterns and rising summer temperatures documented in the Upper Indus Basin. These changes in time signify that the mass balance of glaciers of the Hunza Basin is changing gradually but significantly.

Meanwhile, results show significant spatial variability in glacier response. Debris cover increased predominantly in the lower ablation zones, where melting is most intense, whereas the retreat of clean ice was greatest on south-facing glacier tongues, which receive higher solar radiation. Seasonal snow changes were more pronounced in the mid-elevation band, and high alpine glaciers (>5000 m) are roughly stable. Though glaciers of the Hunza Basin exhibit retreating due to rising temperature, many glaciers in the center of the Karakorum regions are either stable or advancing, which is referred to as the 'Karakorum Anomaly.' This phenomenon of stability is frequently associated with precipitation of the winter season, comparatively fluctuating colder summer temperatures, and the existence of persistent accumulations of zones above 5000 m at high altitudes that reduce the melting of glaciers in response. Internal snow dynamics driving glacier surge behavior elucidate why certain glaciers are increasing in the face of local warming. But at the same time, glaciers at lower altitudes are characterized by shrinking with less accumulation of ice zones and increased susceptibility to summer temperatures and black carbon accumulation. These disparities demonstrate significant heterogeneity in the glacier's response throughout the Karakorum regions.

Recognizing these spatial patterns increases confidence in the classification results and emphasizes that site-specific monitoring should be favored instead of making basin-wide assumptions. The novel application of GLCM texture measures, methodologically, was helpful in the discrimination of spectrally similar land cover types, between debris-covered ice and transition zones of melting. Residual misclassifications, however, also have emphasized that the mapping of spectrally mixed surfaces, of areas in shadow, and of small-scale melt features remains a challenging issue. RF systematically performed better than ANN and SVM, which indicated that ensemble methods are more stable in dealing with the spectral variability of debris-covered glacier surfaces.

In terms of glacier changes and their modeling, recent studies have supported the hydrological implications. [70] Conducted research work on the simulation of future streamflow in the UIB using CORDEX by downscaling climate data, incorporating RCP4.5 and RCP8.5, where glacier melt was projected to be 86% and glacier melt was estimated to increase by 97%. Here, it is pertinent to mention that our study was very unique because we used more than three decades of multispectral remote sensing data and incorporated ML-based algorithms to derive reliable results on glacier dynamics. As a sequel to this, strong dependence for water resource estimation was achieved by combining ML models.

In total, this integrated spatiotemporal analysis supports the conclusion that climate change is responsible for the outcomes observed in the Hunza Basin, i.e., glacier retreat, loss in surface elevation, debris cover expansion, and an increase in glacier melt features. These changes in turn have potential consequences on hydrological regimes, flood hazards, and hydropower production in downstream areas. More fine-resolution optical images, SAR data, and deep learning models would be employed to increase the separability among classes, and the space and time characteristics of glacier change would be described more precisely with the change of climate in the future.

Our study shows that glaciers in the Hunza Basin are highly vulnerable to climate change and prone to major glacial changes. Continuous observations denote clear signs of glacier retreat, melting, and the progressive development of supraglacial features. These changes highlight an urgent need to formulate a strategy for glacier monitoring to track and understand the basin's growing vulnerability to climate change.

Conclusion:

This study highlights the rapid changes occurring in the Hunza Basin, where glaciers are experiencing significant clean ice loss, debris cover expansion, and large-scale melting. These trends point to a persistent decline in glacier mass balance driven by regional warming with serious downstream implications for hydrology, livelihoods, and water security. While short-term increases in meltwater may temporarily support hydropower generation and irrigation. Besides this, long-term instability threatens seasonal flow reliability and increases the risks of GLOFs. A key strength of this research lies in the use of ML methods. By integrating multi-sensor satellite data with GLCM-based texture analysis and RF, ANN, and SVM classifiers. We achieved highly accurate mapping of glacier and snow dynamics. These techniques are particularly valuable in data-restricted mountainous regions, where traditional approaches of GIS are difficult to implement. The incorporation of GLCM texture metrics with multi-sensor data improved class separability and provided strong evidence for persistent glacier retreat and destabilization under climate variability.

Machine learning models proved effective in analyzing complex remotely sensed imagery, offering precise, timely results that enhance understanding of glacier changes in the Hunza Basin. However, there remains room for improvement. Future studies should integrate high-resolution optical and SAR datasets with advanced hybrid deep learning models to improve the detection of debris-covered ice and spectrally mixed surfaces. Such advancements will strengthen glacier classification, improve hydrological modeling, and provide better estimates of meltwater runoff and hydropower potential. These improvements will enhance situational awareness and support climate change mitigation strategies in the UIB.

Author's Contributions:

Conceptualization: Malik Abid Hussain Khokhar; **Methodology:** Malik Abid Hussain Khokhar, supervised by Dr Isma Younes and Dr Adnan Ahmad Tahir; **Validation**: Malik Abid Hussain Khokhar and Dr Adnan Ahmad Tahir; **Investigation:** Malik Abid Hussain Khokhar, supervised by Dr Isma Younes and Dr Adnan Ahmad Tahir; **Data Collection:** Malik Abid Hussain Khokhar; **Writing Original Draft Preparation:** Malik Abid Hussain Khokhar; **Writing & Editing:** Malik Abid Hussain Khokhar; **Review:** Dr Isma Younes and Dr Adnan Ahmad Tahir; **Visualization:** Malik Abid Hussain Khokhar; **Supervision:** Dr Isma Younes and Dr Adnan Ahmad Tahir. All the authors have read and agreed to the published version of the manuscript.

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Conflict of Interest:

There is no conflict of interest among the authors for publishing this manuscript in this Journal. Moreover, we declare no conflict of interest and the funders have no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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Table 4. RF Classification Accuracy Assessment on Glacier Dynamics of Hunza Basin

Classes	Training Data/ Samples	Testing Data/ Samples	Glacier Extent	Debris Cover	Clean Ice	Seasonal Snow	Clean Ice Loss	Glacier Melt	Total Row	Producer Accuracy	User Accuracy	Omission Error	Commission Error
Glacier Extent	1225	525	421	28	0	0	0	0	449	95	94	5	6
Debris Cover	440	189	17	117	0	0	0	0	134	93	90	7	10
Clean Ice	2560	1097	0	0	900	20	6	0	926	96	95	4	5
Seasonal Snow	1580	667	8	0	10	535	0	0	553	94	95	6	5
Clean Ice Loss	573	246	0	2	0	2	103	0	107	92	91	8	9
Glacier Melt	250	107	0	0	11	0	0	92	103	90	89	10	11
Total (Column)			446	147	921	557	109	92	2272				
Overall Accuracy	0.954												
Kappa Coefficient	96.57%												

Table 5. ANN Classification Accuracy Assessment on Glacier Dynamics of Hunza Basin

Classes	Training Data/ Samples	Testing Data/ Samples	Glacier Extent	Debris Cover	Clean Ice	Seasonal Snow	Clean Ice Loss	Glacier Melt	Total Row	Producer Accuracy	User Accuracy	Omission Error	Commission Error
Glacier Extent	1225	525	426	23	0	0	0	2	451	94.45	94.45	5.55	5.55
Debris Cover	440	189	17	117	0	0	0	8	142	82.39	82.39	17.61	17.61
Clean Ice	2560	1097	0	0	900	20	6	0	926	97.19	95.95	2.81	4.05
Seasonal Snow	1580	667	8	0	20	525	0	0	553	94.94	94.26	5.06	5.74
Clean Ice Loss	573	246	0	2	0	12	93	0	107	86.92	93.94	13.08	6.06
Glacier Melt	250	107	0	0	18	0	0	75	93	86.65	88.24	19.35	11.76
Total (Column)			451	142	938	557	99	85	2272				
Overall Accuracy	0.94												
Kappa Coefficient	91.7%												

Table 6. SVM Classification Accuracy Assessment on Glacier Dynamics of Hunza Basin

Classes	Training Data/ Samples	Testing Data/ Samples	Glacier Extent	Debris Cover	Clean Ice	Seasonal Snow	Clean Ice Loss	Glacier Melt	Total Row	Producer Accuracy	User Accuracy	Omission Error	Commission Error
Glacier Extent	1225	525	418	31	0	0	0	2	451	92.68	93.30	7.32	6.70
Debris Cover	440	189	22	112	0	0	0	8	142	78.87	77.24	21.13	22.76
Clean Ice	2560	1097	0	0	880	40	6	0	926	95.03	94.73	4.97	5.27
Seasonal Snow	1580	667	8	0	30	515	0	0	553	93.13	90.51	6.87	9.49
Clean Ice Loss	573	246	0	2	0	14	91	0	107	85.05	93.81	14.95	6.19
Glacier Melt	250	107	0	0	19	0	0	74	93	79.57	88.10	20.43	11.90
Total (Column)			488	145	929	569	97	84	2272				
Overall Accuracy	0.9199												
Kappa Coefficient	89 %												

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