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Machine Learning-Based Snow Cover Mapping in Uttarkashi, Chamoli and Pithoragarh Using Cloud-Based Remote Sensing Tool

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ABSTRACT

Snow cover monitoring is essential for hydrological modelling, climate change analysis, and water resource management, especially in the Himalayan cryosphere. The most cutting-edge global open-source platform for sophisticated geospatial big data analysis is Google Earth Engine (GEE). This study leverages Google Earth Engine (GEE) and data sets available, that is, Harmonized Sentinel-2 imagery, VIIRS, and Digital Elevation to delineate annual snow cover in Uttarkashi, Chamoli, and Pithoragarh districts of Uttarakhand. This paper aims to (i) Land Use Land Cover (LULC) Mapping. (ii) Detection of Snow cover in the Himalayan region districts of Uttarkashi, Chamoli, and Pithoragarh, Uttarakhand, India, using the annual composite median of Sentinel-2 imagery. (iii) To compare the performance of various machine learning models, that is, Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART) for 5 classes. (iv) To calculate the area of 5 classes for the years 2019 and 2024. (v) To build classified maps using the algorithm that results in the best overall accuracy. Here, three machine Learning approaches, Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART), are trained using input parameters such as bands, spectral indices (NDVI, NDBI, NDSI, BSI), and topographic parameters (elevation, slope) derived from ALOS DEM. Cloud-masking techniques refine the dataset, ensuring high-quality spectral inputs. The result demonstrated the successful mapping of LULC's five land cover classes: bare soil, snow, vegetation, built-up areas, and water bodies. The study demonstrated high classification accuracy in 2019 for RF, SVM, and CART across all districts, achieving 95.7%, 93.2%, and 90.7% in Chamoli, 96.5%, 97.3%, and 95.6% in Pithoragarh, and 88.6%, 90.0%, and 87.3% in Uttarkashi. In 2024, the accuracy rates improved to 96.2%, 93.9%, and 94.6% for Chamoli, 95.8%, 92.5%, and 91.6% for Pithoragarh, and showed significant gains reaching 95.4%, 95.4%, and 96.1% for Uttarkashi. Results indicated that estimated In Chamoli, RF consistently performed better, demonstrating an 8.3% increase in snow from 2,206 km^2 to 2,388 km^2, while Pithoragarh experienced a 25% loss from SVM to RF (from 2,099 km^2 to 1,573 km^2). Snowfall in Uttarkashi increased by 10.8% from SVM to CART: from 1,804 km^2 to 1,998 km^2, with CART doing exceptionally well in 2024.RF proved most reliable overall, but regional variability suggests a need for adaptive model selection.

INTRODUCTION

The mapping of Land Use Land Cover (LULC) using a variety of remotely sensed datasets, such as optical, Synthetic Aperture Radar (SAR), Unmanned Aerial Vehicle (UAV), and others, is the primary application of remote sensing technologies (Lu & Weng 2007, Goswami & Ashok 2024a). Numerous practical uses, such as flood mapping, disaster management, future disaster preparedness, rehabilitation and reconstruction prioritization, effective land-use planning, and natural resource management, benefit from the classification and identification of different land cover types (Sushil 2018, Tsai et al. 2019, Khanduri 2021, Rawat et al. 2022, Siddique et al. 2022, Saini & Rawat 2023). Unlike a conventional plain area, the Himalayan region has a unique geography, with many rivers, glaciers, and high mountain ranges (Sushil 2018). Understanding a range of natural and human systems requires constant monitoring of the quantity of snow cover, which can be accomplished practically via remote sensing.

The higher Himalayan region is susceptible to several natural hazards because of factors like freeze-thaw cycles, thrusts and faults, earthquakes, high relief, few valleys, steep slopes, intense rainfall, and temperature fluctuations. Finding places that are more vulnerable to these types of natural disasters and creating mitigation plans can both be facilitated by an understanding of the region's LULC trends. Also, classifying land use and land cover, or LULC, is essential for controlling resource depletion in emerging areas and lessening the effects of population increase. Effective LULC classification aids in mitigating the negative effects of urbanization's rapid expansion on global energy resources, facilitating resource management, sustainable planning, and environmental preservation (Avtar et al. 2019). According to (Qu & Long 2018, Stehfest et al. 2019)Accurate LULC maps of a region can assist in classifying the land into major classes to provide an overview of the resources, their use, and their influence on the socioeconomic development of the area. Additionally, it can assist researchers in examining a range of environmental challenges at different scales. Another important indicator of climate change is the alteration in LULC (Li et al. 2022). Furthermore, the water balance of that specific area is always disrupted by changes in the climate (Sridhar et al. 2013, 2019), geomorphology, and LULC patterns (Duda & Hart 1974). A thorough LULC map is therefore necessary as a dynamic element for the monitoring of water quantity and quality (Tariq et al. 2021, 2023), land management (Asif et al. 2023, Zheng et al. 2023), hazards, and risk assessment (Goswami & Ashok 2024a). In order to manage the land use in the area, high-resolution data processed using creative and sophisticated geospatial techniques (Dou et al. 2021) are crucial. The region frequently experiences hazards like avalanches, rockfalls, debris flows, and cloudbursts, and as a result of altered weather patterns, their frequency and intensity have increased (Bhatt et al. 2014). In addition to playing a major role in a nation's economic development, natural resources like forests are crucial for preserving a region's biodiversity, climate, ecological balance, and water conservation. One of the most important indicators of the general health of the biological system in the area is the state of the forests. Natural catastrophes can happen at any time and are growing more frequent (Siddique et al. 2022). Understanding climate, ecology, and water cycles requires regular monitoring of snow cover (Nijhawan et al. 2019).

Abdi (2020) evaluated the performance of four different machine learning algorithms in classifying land cover using Sentinel-2 satellite data in a complex mixed-use area in south-central Sweden. Four methods were investigated in this study: deep learning, Extreme Gradient Boosting (XGBoost), Random Forests (RF), and Support Vector Machines (SVM). The study found that SVM, with an overall accuracy score of 75.80%, was closely followed by the Xgboost classifier. The study also discovered that Sentinel-2 bands in the red edge and shortwave infrared regions of the spectrum were crucial to the classification process. Using Sentinel-2 data(Saini and Ghosh, 2018b) also classified crops using RF and SVM classifiers. The results indicated that while SVM reported an overall accuracy of 81.85%, RF (84.22%) achieved the best classification accuracy. Additionally, their study demonstrated how beneficial Sentinel-2 data is for mapping vegetation. In a different study, the authors used supervised learning for LULC mapping and used hybrid, optical, and microwave datasets (Sentinel-2, Sentinel-1, respectively) (Chachondhia et al. 2021).

Every dataset was assessed using the RF and SVM machine learning (ML) algorithms. In terms of classification outcomes, the optical and hybrid datasets performed better than the microwave dataset (Noi & Kappas 2017) conducted another LULC investigation using Sentinel-2 satellite data, and they evaluated the effectiveness of k Nearest Neighbour (KNN), RF, and SVM classifiers. According to this comparative analysis, SVM (95.32%) achieved somewhat better accuracies than KNN (94.59%) and RF (94.70%). Using Sentinel-2 satellite images from 2022, machine learning algorithms such as CART (Oliveira et al. 2012), SVM (Oliveira et al. 2012), and random forest (RF) (Choubin et al. 2019) can produce accurate and educational LULC maps. Key land cover features in the study area, such as vegetation, built-up areas, barren land, and water bodies, can be identified using a variety of satellite indices, including the Normalized Difference Vegetation Index (NDVI) (Defries & Townshend 1994), Modified Normalized Difference Water Index, and Normalized Difference Built Index (NDBI) (Shen et al. 2019).

With Kappa coefficients and overall accuracy metrics acting as important performance indicators, the effectiveness of the three machine learning models (CART, SVM, and RF) may be assessed through validation and accuracy evaluations. According to the study (Abdi 2020), GEE can interpret Sentinel-2 satellite images effectively enough to generate LULC maps for the four land cover classes that are defined with accuracy and dependability. With an emphasis on model performance, feature recognition, accuracy evaluations, and the effectiveness of GEE in processing satellite images, this study tackles a number of issues pertaining to the application of machine learning techniques (Pushpalatha et al. 2024) within Google Earth Engine for LULC mapping. The results demonstrate the ability of GEE and three machine learning models (CART, RF, and SVM) for generating trustworthy LULC maps, particularly when applied to land-use and environmental research. Improved accuracy and robustness are made possible by combining geospatial methods for LULC analysis with three machine learning models—RF, SVM, and CART(Chachondhia et al. 2021). We can obtain more accurate and thorough LULC classification results by combining the advantages of these models and utilizing geospatial data, which will capture the intricate spatial relationships and patterns inherent in land use dynamics. In a recent work, Boonpook et al. (2023) evaluated the ability of a deep learning model named LoopNet to autonomously categorize land use using Landsat-8 images (Nijhawan et al. 2018). The results show that LoopNet performed better than SVM and RF (overall accuracy = 89.84%). Sentinel satellites, both optical and radar, were used by Billah et al. (2023) to track floods and evaluate damage in northeastern Bangladesh. With a 90% accuracy rate for mapping land cover, the RF classifier was shown to be more efficient than other Machine Learning Classifiers. Sentinel-2 data and the RF method were utilized to analyse LULC change in Vietnam. For time series datasets, the approach produced high accuracy (for both the 2019 (90.7%) and 2020 (91.1%) datasets). India is especially susceptible to natural disasters due to its diversified geology, climate, geomorphology, vegetation, geography, and sizable population. The Himalayan region's seismic-tectonic instability makes it particularly vulnerable to different mass wasting events. While prompt planning and action can greatly lessen the effects of natural disasters and return things to normal, they can also be prevented to a large degree. To address each disaster planning issue, a thorough evaluation of LULC in the area may be quite helpful. By applying three machine learning techniques, RF, SVM, and CART, for classification in the Chamoli, Pithoragarh, and Uttarkashi districts of Uttarakhand, India, this work aims to create useful snow cover maps and land use land cover (Saini & Singh 2024). The viability of employing satellite Sentinel-2 imagery for this purpose will also be examined.

MATERIALS AND METHODS

The study utilizes the following datasets:

Sentinel-2 Surface Reflectance (S2_SR_HARMONIZED) (Claverie et al. 2018)**:** Optical imagery for vegetation, water, and built-up land classification.

- **ALOS AW3D30 DEM** (Tadono et al. 2014): Elevation and slope data for terrain analysis.
- **VIIRS Stray Light Corrected Nighttime Day/Night Band** (Mills et al. 2013)**:** enhances low-light imagery accuracy by removing stray light interference, enabling precise detection of nighttime emissions (e.g., urban lights, wildfires, auroras).
- **JRC/GSW1_4/Global Surface Water** (Pekel et al. 2016)**:** The dataset helps distinguish between water bodies and snow/urban regions by mapping global water dynamics (1984–2021). Its incorporation with Sentinel-2 and DEM data may improve the precision of glacier lake, flood, and snowmelt monitoring.

The Northern Indian state of Uttarakhand is home to several breathtaking sights. However, it is particularly susceptible to a variety of natural disasters because of its unique climate, ecology, tectonic activity, and socioeconomic landscape. Earthquakes, landslides, avalanches, hailstorms, cloudbursts, flash floods, forest fires, and lightning strikes are among the many natural disasters that occur in the area. The establishment of hydroelectric power plants, riverbed mining, and the building of local roads and structures have all significantly altered the landscape, land use, and natural eco-geological systems. The study focuses on a specific region defined using the geometry variable in GEE. The northern Indian Himalayan state of Uttarakhand covers a variety of latitudes (28°43′ N to 31°27′ N) and lengths (77°34′ E to 81°02′ E). Its varied geography includes snow-covered Tibetan borders and the fertile Terai plains. Three districts, Uttarkashi, Chamoli, and Pithoragarh, are at its centre; they are distinguished by their distinct geographic locations, cultural diversity, and ecological importance.

The study examines the snow cover in three Uttarakhand Himalayan districts: Uttarkashi, Chamoli, and Pithoragarh. These districts are vital to the state's ecology, with the Ganges fed by glaciers in Uttarkashi, Chamoli blending biodiversity and spirituality, and Pithoragarh bordering Nepal and Tibet. The study reveals five critical LULC classes in these districts: built-up, snow, vegetation, water, and bare lands, highlighting the need for close monitoring of their delicate ecosystems. The research regions in Uttarakhand, India, are depicted in the Fig. 1 along with their elevation. A map of India is displayed in image (a), with the state of Uttarakhand highlighted to denote the study area. Detailed elevation maps of the districts of Uttarkashi, Chamoli, and Pithoragarh are shown in images (b), (c), and (d), respectively.

Elevation ranges are represented on these maps using color-coded gradients, where red/brown denotes higher altitudes, and blue denotes lower elevations. ≤1379 m (blue), 1379–2758 m (green), 2758–4137 m (yellow), 4137–5516 m (red), and >5516 m (brown) are the height zones of Uttarkashi. With comparable colour schemes, Chamoli and Pithoragarh range from ≤1395 m to >5578 m and ≤1380 m to >5520 m, respectively. Understanding topography and

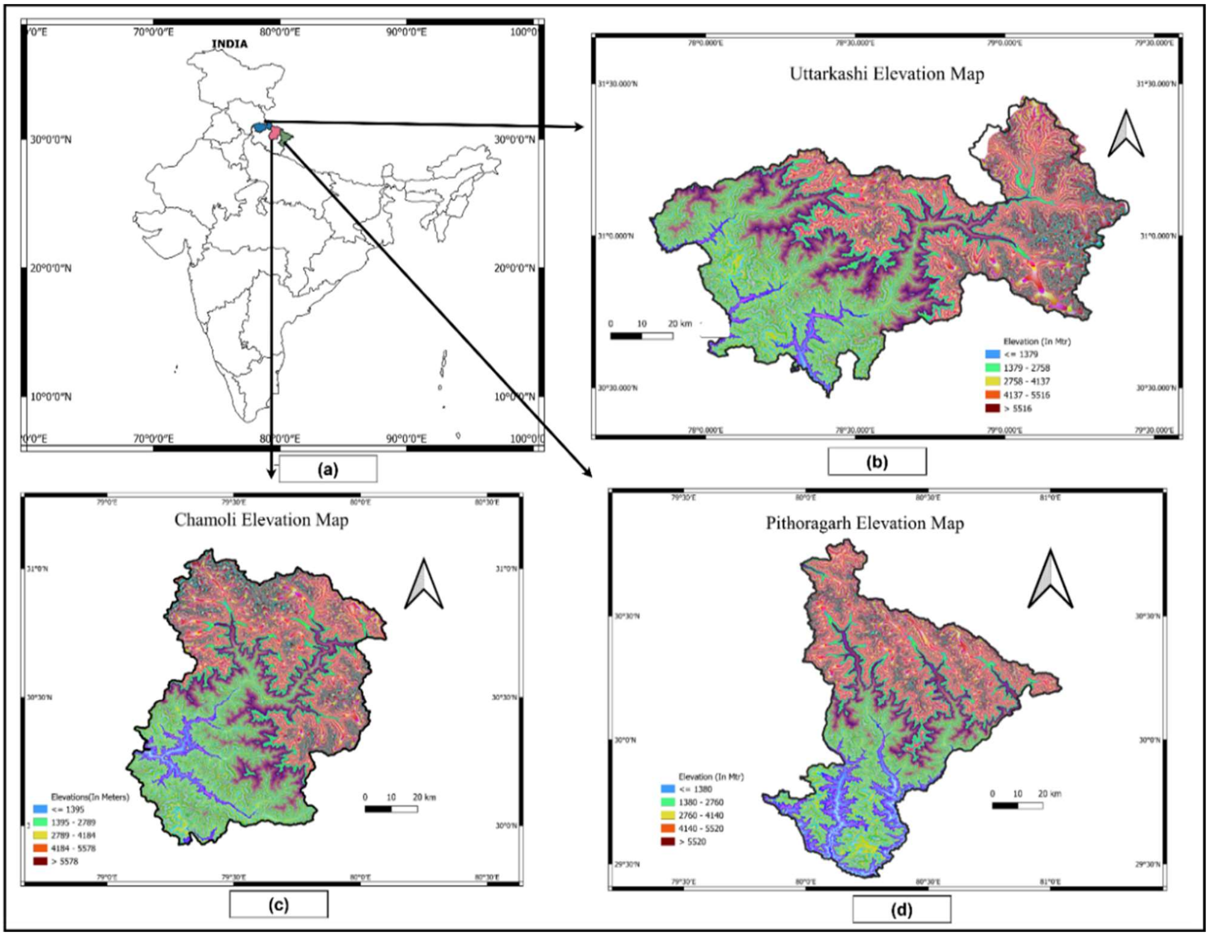

Fig. 1: Location of study area, a. Map of India, i.e, location of study area in Uttarakhand state, b. Uttarkashi District, c. Chamoli District, d. Pithoragarh District.

hydrological patterns is aided by the display of rivers and contour variations.

Methodology

The proposed methodology for Land Use Land Cover (Kadavi & Lee 2018) Classification Snow cover mapping is depicted in the proposed method, which begins with an annual Harmonized Sentinel-2 MSI, VIIRS Stray light corrected Nighttime Day/Night Band, Digital Elevation Model (ALOS DSM: Global 30m v3.2) and WWF HydroSHEDS satellite imageries acquisition process for the years 2019 and 2024, followed by data preparation. We employed Google Earth Engine's pre-processed Sentinel-2 Surface Reflectance (SR) dataset, which includes applied atmospheric and radiometric corrections, eliminating the need for additional processing. For our comparative analysis between 2019 and 2024, we acquired all available scenes with less than 20% cloud cover from two annual periods: January-December 2019 and January-December 2024. All selected images were at the native 10-meter spatial resolution. Using modal compositing to minimize cloud and aerosol effects, we generated multispectral image tiles for each year by stacking the Blue (B2: 490 nm), Green (B3: 560 nm), and Red (B4: 665 nm) spectral bands. The study area boundary was delineated using a shapefile obtained from the Survey of India (https://www.surveyofindia.gov.in/). Training data points were generated through a combination of spectral indices derived from Harmonized Sentinel-2 MSI, VIIRS Stray light corrected Nighttime Day/Night Band, Digital Elevation Model (ALOS DSM: Global 30m v3.2), and WWF HydroSHEDS datasets, visual interpretation of Sentinel-2 imagery, and validation using high-resolution Google Earth basemaps. When machine learning classifiers are trained on the dataset, the data analysis process starts. Two parts of the reference dataset are separated, one for testing and one for training, with a 70%:30% split, respectively. After that, the testing dataset is used to evaluate the classifiers' performance.

For classification utilizing remotely sensed data, machine learning methods such as RF, SVM (Kadavi & Lee 2018), and CART are frequently employed (Qu & Long 2018, Saini & Ghosh 2018b, 2018a, Nijhawan et al. 2019, Chachondhia et al. 2021, Dou et al. 2021, Tariq et al. 2021, Billah et al. 2023). This study utilized three supervised machine learning approaches: RF, SVM, and CART, with ensemble learning involving decision trees to obtain useful LULC maps and snow cover (Breiman 2001). It can tolerate noisy, correlated characteristics and does well with multidimensional data. The remote sensing community regularly uses this classifier because it can successfully and efficiently handle a wide range of issues. Support Vector Machine (SVM) is a potent method designed especially to tackle regression and non-linear classification problems (Cortes & Vapnik, 1995). SVM divides high-dimensional feature spaces using hyperplanes, handling intricate datasets with high accuracy. However, careful selection of regularization parameters and kernel functions can be computationally costly. Classification and Regression Tree (CART) is a non-parametric, tree-based classifier that uses feature thresholds to partition data, minimizing impurity and generating interpretable decision rules for classification or regression tasks. (Breiman et al. 2017) The CART algorithm, a rule-based classification and regression tool, can handle classification and regression tasks but is susceptible to overfitting, instability, and difficulty in identifying complex relationships in non-linear or unbalanced datasets. After training machine learning models, five LULC classes, i.e., Bare, Snow, Vegetation, Built-up, Water, are predicted using the testing dataset. For the evaluation process, a confusion matrix is produced by each classifier using the testing dataset.

Technical Workflow of the Proposed Methodology

Fig. 2 explains the technical workflow of the proposed methology which tells about the data sources, Pre-processing,

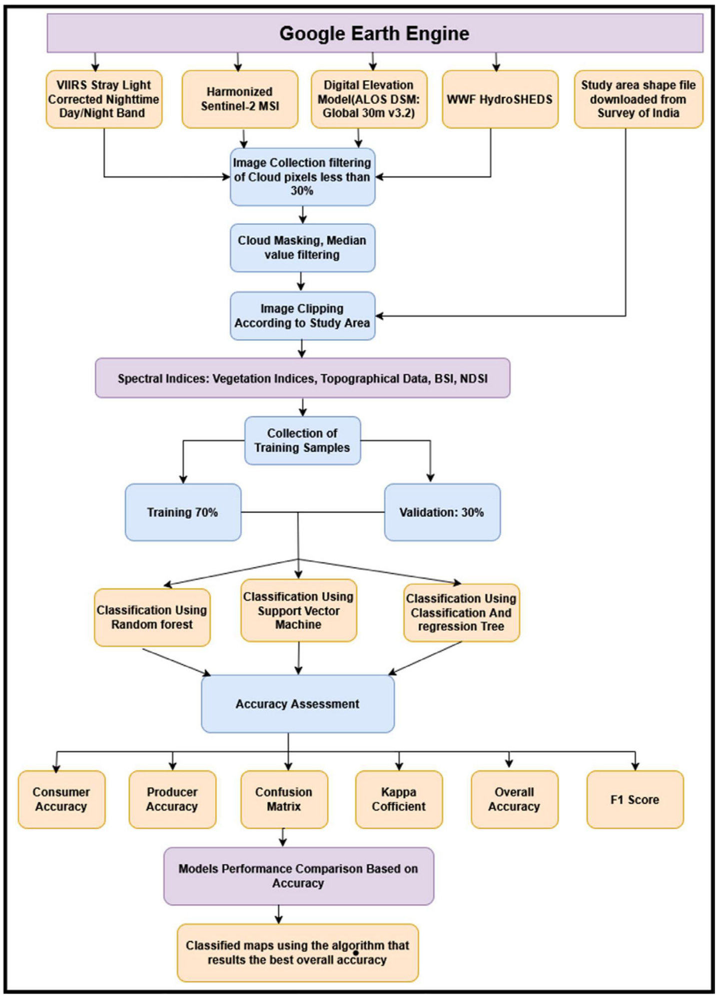

Fig. 2: Workflow of the proposed methodology.

methodology, feature extraction, training and validation, classification algorithm, accuracy assessment, and model comparison.

Data sources:

- **Google Earth Engine**: The platform used for processing and analysing geospatial data.
- **VIIRS Stray Light Corrected Nighttime Day/Night Band**: Provides nighttime light data, useful for urban and human activity analysis.
- **Digital Elevation Model (ALOS DSM: Global 30m v3.2)**: Provides topographic data.
- **WWF HydroSHEDS**: Offers hydrological data like river networks and watersheds.
- **Study Area Shapefile**: Defines the geographic boundary for analysis, downloaded from the Survey of India.
- **MOD10A1.061 Terra Snow Cover Daily Global 500m:** Snow Cover Daily Global 500m product contains snow cover, snow albedo, fractional snow cover, and quality assessment (QA) data

Preprocessing:

- **Image Collection Filtering**: Filters out images with more than 30% cloud cover to ensure data quality.
- **Cloud Masking**: Removes cloud-contaminated pixels from the images.

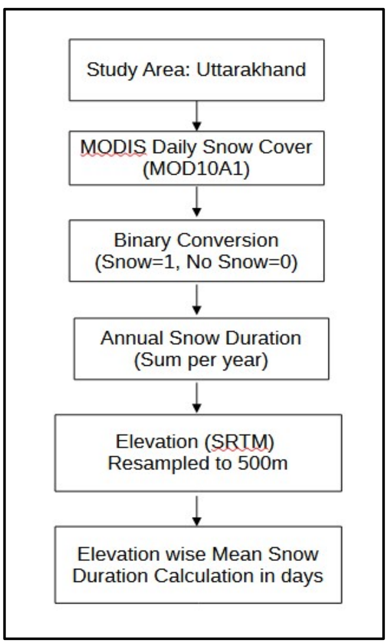

Fig. 3: Workflow to calculate snow cover duration analysis for the period of the year (2000–2023).

- **Median Value Filtering**: Reduces noise by using median pixel values over a time series (Goswami & Ashok 2024b).
- **Image Clipping**: Crops the images to the study area boundary.

Feature extraction:

- **Spectral Indices**: Calculates indices like Vegetation Indices (e.g., NDVI), Bare Soil Index (BSI), Normalized Difference Snow Index (NDSI), and incorporates topographic data for enhanced classification. Error! Reference source not found.Shows the formulas of varies indices.

Training and validation:

- **Collection of Training Samples**: Gathers labelled data for supervised classification.
- **Data Splitting**: Divides the data into 70% for training and 30% for validation.

Classification algorithms:

- **Random Forest**: An ensemble learning method for classification.
- **Support Vector Machine (SVM):** A kernel-based method for classification.
- **Classification and Regression Tree (CART):** A decision tree-based approach.

Accuracy assessment:

- **Precision**: Measures how often the classifier correctly predicts a class.
- **Recall**: Measures how well the classifier represents relevant positive cases out of all actual positives.
- **Confusion Matrix**: A table showing true vs. predicted classifications.
- **Kappa Coefficient**: Evaluates classifier agreement beyond chance.
- **Overall Accuracy**: The total percentage of correctly classified pixels.
- **F1 Score**: Balances precision and recall for class-specific accuracy.

Model comparison and output:

- **Models Performance Comparison**: Compares the accuracy of Random Forest, SVM, and CART to select the best-performing algorithm.
- **Classified Maps**: The final output is a land cover map generated using the algorithm with the highest overall accuracy.

Table 1: Spectral indices formulas.

Index	Formula	Purpose
NDVI	(B8-B4)/(B8+B4)	Vegetation Health
NDBI	(B11-B8)/(B11+B8)	Built-up Areas
MNDWI	(B3-B11)/(B3+B11)	Water Bodies
BSI	((B6+B4) -(B2+B11))/((B6+B4) +(B2+B11))	Bare Soil Detection
NDSI	(B3-B11)/(B3+B11)	Snow

For each ML classifier (RF, SVM, and CART), a variety of evaluation parameters are generated from the confusion matrix, including overall accuracy, precision, recall, F-score, and kappa coefficient. The following is a definition of the utilized parameters:

(i) **TP**: True Positive, which stands for the total number of samples that were correctly classified.

(ii) **TN**: the sum of all samples for which the negative class is properly predicted by the model.

(iii) **FP**: False Positive, which stands for the total number of incorrectly classified samples that belong to several classes but were wrongly assigned to a specific class.

(iv) **FN**: False Negative is a classification error that occurs when a sample of a given class is mistakenly categorized as not belonging to that class.

Another often-used parameter for remote sensing classification applications is the Kappa Coefficient, which ranges from 0 to 1. It illustrates the discrepancy between the actual and improbable(expected) agreements. A Kappa score of 0 indicates that there is no agreement between the reference image and the classified image. On the other hand, a kappa value of 1 indicates that the reference image and the classified image are identical. Therefore, the more precise the classification, the greater the kappa value (ka). Equations 1, 2, 3, 4, and 5 are used, successively, to produce a variety of metrics, including accuracy, precision, recall, F1-score, and kappa values.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Negative} + \text{False Positive}} \quad \ldots(1)$$

$$\text{Precision} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Negative} + \text{False Positive}} \quad \ldots(2)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad \ldots(3)$$

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \ldots(4)$$

$$\text{kappa} = \frac{\text{Observed accuracy} - \text{Chance agreement}}{1 - \text{Chance agreement}} \quad \ldots(5)$$

RESULTS AND DISCUSSION

The VIIRS Stray Light Corrected Nighttime Day/Night Band, Harmonized Sentinel-2 MSI, Digital Elevation Model (ALOS DSM: Global 30m v3.2), and WWF HydroSHEDS satellite datasets are used in this study to classify LULC and map snow cover in the Himalaya region using RF, SVM, and CART classifiers. One of the most biologically varied areas of the globe, the Himalayas are home to a variety of habitats, including subtropical forests, alpine meadows, and glaciers. The area's forests and snow are vital parts of its ecology, offering a number of significant advantages that are vital to the environment and its inhabitants. Some of the world's biggest and most significant rivers, such as the Ganges, Brahmaputra, and Indus, are found in the Himalayan region. The snow and ice that build up on the area's mountains and glaciers feed these rivers. The rivers wouldn't have enough water to support the local ecosystems and population without this snow and ice. Thus, snow cover mapping and LULC classification are essential data for decision-making and the research area's sustainable development.

The reference dataset was gathered using Google Earth Engine, and Training data points were generated through a combination of spectral indices derived from the Harmonized Sentinel-2 MSI, VIIRS Stray light corrected Nighttime Day/Night Band, Digital Elevation Model (ALOS DSM: Global 30m v3.2) and WWF HydroSHEDS datasets, visual interpretation of Sentinel-2 imagery, and validation using high-resolution Google Earth basemaps. It was then split into 70:30 ratios, with 30% of the samples being used for testing and 70% of the reference samples being utilized for training. Each land cover class has its own exclusive partitioning of the reference data pixels, to put into practice the RF, SVM, and CART machine learning techniques. Higher statistical accuracy in remote sensing is a sign of more precise maps of snow cover and LULC.

In this study, the F1-score, Precision, and Recall were employed to determine class-specific accuracy, while the confusion matrix was used to compute the overall accuracy and the kappa coefficient. The effectiveness of the RF, SVM, and CART algorithms for classification was assessed using a suitable sampling dataset. Estimates of the producer's (recall) and user's (precision) accuracy for each spatial cover class, as well as the F1-score, overall accuracy, and kappa coefficient as a general measure of the classification findings' efficacy, were calculated using the confusion matrices of these algorithms.

Table 2: Classifier overall accuracy and kappa coefficient obtained by RF, SVM, and CART.

Region	Model	2019		2024	
	ML Classifiers	OA [%]	Kappa [%]	OA [%]	Kappa [%]
Chamoli	RF	95.7	95.7	96.2	96.2
	SVM	93.2	91.3	93.9	91.8
	CART	90.7	88.1	94.6	92.8
Pithoragarh	RF	96.5	95.5	95.8	94.5
	SVM	97.3	96.6	92.5	90.1
	CART	95.6	94.3	91.6	89.2
Uttarkashi	RF	88.6	85.6	95.4	94.2
	SVM	90	87.3	95.4	94.2
	CART	87.3	84	96.1	95.1

This study of comparative analysis evaluates three machine learning classifiers, RF, SVM, and CART, for land use/land cover classification across three Himalayan regions (Chamoli, Pithoragarh, and Uttarkashi) between 2019 and 2024, as shown in Table 2. The results demonstrate RF's superior consistency, maintaining high accuracy (OA >95.7%) and reliability (Kappa >94.5%) across all regions with minimal fluctuations (±0.7%). While SVM and CART showed remarkable improvements in Uttarkashi (CART: +8.8% OA, +11.1% Kappa, SVM: +5.4% OA, +6.9% Kappa), they exhibited significant declines in Pithoragarh (SVM: -4.8% OA, -6.5% Kappa, CART: -4.0% OA, -5.1% Kappa). Chamoli witnessed steady performance across all models, with CART showing the most improvement (+3.9% OA, +4.7% Kappa). The strong OA-Kappa correlation (differences <2%) confirms classification reliability, though SVM and CART's regional performance variations highlight their sensitivity to local conditions, contrasting with RF's robust generalization across diverse terrains and temporal changes. These findings suggest RF's suitability for regional-scale LULC mapping, while SVM and CART may require location-specific tuning for optimal performance.

For LULC classification, this work assesses RF, SVM, and CART classifiers in three Himalayan regions (2019–2024). The acronyms used before delving deeper into the confusion matrix and calculating accuracy measures for a particular LULC class are described in Table 3. RF proved to be the most dependable because of its remarkable stability (OA>95.7%, Kappa>94.5%) and low variations (±0.7%). Both SVM and CART had a dramatic reduction in Pithoragarh (SVM: -4.8% OA, CART: -4.0% OA), whereas they showed notable improvements in Uttarkashi (CART: +8.8% OA, SVM: +5.4% OA). Across models, Chamoli's performance remained consistent, with CART seeing noteworthy increases (+3.9% OA). The veracity of the results is confirmed by the significant OA-Kappa correlation (less than 2% difference). The results highlight the significance of context-aware model selection in LULC mapping by

Table 3: Abbreviations for various land use and land cover.

Abbreviation	Full Form	Description
RF	Random Forest	A machine learning classifier based on ensemble decision trees.
SVM	Support Vector Machine	A supervised learning model used for classification/regression.
CART	Classification and Regression Tree	A decision tree-based algorithm for classification or regression tasks.
OA	Overall Accuracy	Overall classification accuracy across all classes.
SC	Snow Cover	Land cover class representing snow-covered areas.
VC	Vegetation Cover	Land cover class representing vegetated areas (e.g., forests, crops).
BU	Built-up	Land cover class representing urban or constructed areas.
Kappa	Kappa Coefficient	Statistical measure of inter-rater agreement, adjusted for chance.
F1	F1-score	The F1 score is the harmonic mean of precision and recall, balancing both to assess classification model performance.
LULC	Land Use Land Cover	Land Use Land Cover shows land's use and surface type.
NDVI	Normalized Difference Vegetation Index	NDVI (Normalized Difference Vegetation Index) measures vegetation health using satellite reflectance of red and near-infrared light.

Table 4: Normalised Confusion Matrix Chamoli produced by RF in 2019.

	Classification (Predicted)						
	Actual\Predicted	Bare	Snow	Vegetation	Built-up	Water	Producer's Accuracy/Recall
Ground Truth (Actual)	Bare	0.96	0	0	0.04	0	0.96
	Snow	0.04	0.96	0	0	0	0.96
	Vegetation	0	0	0.95	0	0	1
	Built-up	0.05	0.05	0	0.9	0	0.9
	Water	0	0	0	0.08	0.92	0.92
	Consumer's Accuracy/Precision	0.92	0.95	1	0.9	1	Overall Accuracy = 95.7 %

Table 5: Normalised Confusion Matrix Chamoli produced by RF in 2024.

	Classification (Predicted)						
	Actual\Predicted	Bare	Snow	Vegetation	Built-up	Water	Producer's Accuracy/Recall
Ground Truth (Actual)	Bare	0.97	0	0	0.03	0	0.97
	Snow	0	1	0	0	0	1
	Vegetation	0.03	0	0.97	0	0	0.97
	Built-up	0.18	0	0	0.82	0	0.82
	Water	0	0	0	0.14	0.86	0.86
	Consumer's Accuracy/precision	0.93	1	1	0.82	1	Overall Accuracy = 96.2%

recommending RF for reliable regional applications and requiring location-specific tuning for SVM/CART because of their sensitivity to local variables.

This study provides the confusion matrices of the best classification outputs from RF, SVM, and CART, highlighting class-wise performance and patterns of misclassification in land use/land cover mapping. Excellent LULC maps were created by every ML classifier shown in Fig. 4.

This multi-class classifier RF for Chamoli for the year 2019, shown in Table 4, achieves 95.7% overall accuracy, with Vegetation (100% recall/precision) and Water (100% precision, 92% recall) performing best. Bare (96% recall, 92% precision) and Snow (96% recall, 4% Bare misclassification) show strong results, while Built-up (90% recall/precision) struggles with Bare/Snow overlap. NDWI/NDBI could improve Water-Built-up and spectral confusion. The model is reliable but refinable.

The Chamoli 2024 classifier RF is shown in Table 5, achieves 96.2% accuracy, excelling in Snow (100% recall/precision) and Vegetation (97% recall, 100% precision). Bare (97% recall, 93% precision) shows minor confusion with Built-up, which struggles (82% recall/precision, 18% misclassified as Bare). Water (100% precision, 86% recall) faces murky-water misclassification. Key challenges include Built-up ↔ Bare (urban expansion) and Water ↔ Built-up (spectral overlap). Improvements like GLCM texture analysis and NDBI/NDWI indices can enhance classification, though urbanization and climate change require adaptive refinements for Himalayan monitoring.

The Pithoragarh 2019 SVM classifier shown in Table 6 achieves 97.3% accuracy, with Snow and Built-up (100% recall/precision) performing flawlessly. Vegetation (97% recall/precision, 3% Bare misclassification) and Water (100% precision, 94% recall, 6% Bare confusion) show

Table 6: Normalised Confusion Matrix Pithoragarh produced by SVM in 2019.

	Classification (Predicted)						
	Actual\Predicted	Bare	Snow	Vegetation	Built-up	Water	Producer's Accuracy/Recall
Ground Truth (Actual)	Bare	0.94	0	0.06	0	0	0.94
	Snow	0	1	0	0	0	1
	Vegetation	0.03	0	0.97	0	0	0.97
	Built-up	0	0	0	1	0	1
	Water	0.06	0	0	0	0.94	0.94
	Consumer's Accuracy/precision	0.88	1	0.97	1	1	Overall Accuracy = 97.3 %

Table 7: Normalised Confusion Matrix Pithoragarh produced by RF in 2024.

	Classification (Predicted)						
	Actual\Predicted	Bare	Snow	Vegetation	Built-up	Water	Producer's Accuracy/Recall
Ground Truth (Actual)	Bare	0.97	0	0	0	0.03	0.97
	Snow	0.03	0.97	0	0	0	0.97
	Vegetation	0	0	0.96	0	0	1
	Built-up	0	0	0.12	0.88	0	0.88
	Water	0	0	0	0.11	0.89	0.89
	Consumer's Accuracy/ precision	0.97	1	0.93	0.93	0.89	Overall Accuracy = 95.8 %

Table 8: Normalised Confusion Matrix Uttarkashi produced by SVM for 2019.

	Classification (Predicted)						
	Actual\Predicted	Bare	Snow	Vegetation	Built-up	Water	Producer's Accuracy/Recall
Ground Truth (Actual)	Bare	0.89	0.36	0	0.07	0	0.89
	Snow	0.37	0.96	0	0	0	0.96
	Vegetation	0.23	0	0.95	0.02	0	0.95
	Built-up	0.11	0	0	0.88	0	0.88
	Water	0	0	0	0.23	0.77	0.77
	Consumer's Accuracy/precision	0.83	0.96	1	0.72	1	Overall Accuracy = 90 %

strong results, while Bare (94% recall, 88% precision) faces minor misclassifications. Key challenges include spectral overlap in mixed pixels (Bare/Vegetation/Water)**.** Suggested improvements: textural features, NDVI (Vegetation), and NDWI (Water) for sharper class boundaries. Though reliable for Himalayan monitoring, the model needs refinement for urban planning and hydrology applications in complex terrain.

The Pithoragarh 2024 Random Forest classifier shown in Table 7 achieves 95.8% accuracy, with Bare and Snow performing best (97% recall/precision, F1=0.97–0.98). Vegetation shows 100% recall but 93% precision due to urban greenery confusion, while Built-up struggles (88% recall, 93% precision, F1=0.90) with green-roof misclassification. Water (89% recall/precision, F1=0.89) faces reflective-surface ambiguity. Key challenges include spectral overlaps (Built-up/Vegetation, Bare/Water). Improvements suggested: GLCM textures, NDBI (urban), and NDWI (water). Though effective for Himalayan monitoring, the model requires refinement for urban and water-body dynamics.

The Uttarkashi 2019 SVM model achieves 90% accuracy, as shown in Table 8 with Snow (96% recall/precision) and Vegetation (95% recall, 100% precision) performing best. Bare land (89% recall, 83% precision) shows minor confusion with Snow/Built-up, while Built-up (88% recall, 72% precision) struggles with false positives. Water has the lowest recall (77%, confused with Built-up). Key challenges include Water-Built-up reflectance and Bare-Snow spectral overlap. Recommendations: NDWI (Water), NDBI (Built-up), and texture features to improve classification. The model works well, but needs refinement for urban/water features in the Himalayan terrain.

The Uttarkashi 2024 CART model achieves 96.1% accuracy, shown in Table 9. Snow (100% recall/precision)

Table 9: Normalised Confusion Matrix Uttarkashi, produced by CART for 2024.

	Classification (Predicted)						
	Actual\Predicted	Bare	Snow	Vegetation	Built-up	Water	Producer's Accuracy/Recall
Ground Truth (Actual)	Bare	0.91	0	0.06	0.03	0	0.91
	Snow	0	0.96	0	0	0	1
	Vegetation	0	0	0.95	0	0	1
	Built-up	0	0	0	0.96	0.04	0.96
	Water	0	0	0	0.04	0.96	0.96
	Consumer's Accuracy/precision	1	1	0.93	0.93	0.93	Overall Accuracy = 96.1%

and Bare land (100% precision, 91% recall) performed strongly. Vegetation (100% recall, 93% precision) faces false positives, while Built-up (96% recall, 93% precision) shows minor confusion with Water. Water (96% recall, 93% precision) is rarely misclassified. Key challenges include spectral overlaps (Bare ↔ Vegetation/Built-up) and reflective surfaces (Built-up ↔ Water). Suggested improvements: NDVI (Vegetation), NDWI (Water), and GLCM texture analysis for urban areas. Though effective, the model requires refinement for Uttarkashi's rugged terrain. The analysis shows improved overall accuracy from 2019 to 2024 across all regions, with Uttarkashi achieving the most significant gains (+6.8% for RF). Random Forest consistently delivered the highest accuracy (≥95.4% OA in 2024), outperforming SVM and CART in most cases. All regions maintained strong classification performance in 2024, with OA scores remaining above 92.5% for all models.

The analysis of land cover categorization in Chamoli, Uttarkashi, and Pithoragarh shows distinct trends in classification accuracy for various types of terrain. The distinct spectral signature of snow cover allows for relatively Accurate classification (F1 scores 0.96-1.00); however, the most consistently accurate category is vegetation, which maintains a high accuracy (F1 0.95-1.00) because of its distinct spectral characteristics. Locations with varying reflectance and shadow effects still provide obstacles. The complex nature of urban characteristics in hilly terrain, where pixel intermixing and rocky topography severely impair classification precision, and spectral mixing with bare soil cause built-up regions to exhibit high variability (F1 0.72-0.94). Due to issues such as seasonal variations in water reflectance, shadow effects, and spectral similarities between fallow and bare ground, water bodies and bare land show mild performance swings (F1 0.77-0.97 and 0.83-0.97, respectively).

The most reliable classifier is Random Forest, which routinely outperforms SVM and CART, especially for troublesome classifications like built-up regions, where its ensemble method better manages spectral ambiguity. Although there have been noticeable increases in accuracy during the 2019–2024 era (such as Uttarkashi RF +6.8%), ongoing difficulties with built-up classification (particularly in Chamoli) and water body identification (in Pithoragarh) point to the need for methodological improvements. The main drawbacks are spectral misunderstanding between water and built-up surfaces and terrain-induced shadows that impact populated regions. In order to overcome these categorization difficulties in mountainous areas, future research should concentrate on combining terrain adjustment algorithms, higher-resolution data, and sophisticated spectral indices, especially for the most troublesome land cover classes.

Across the Himalayan terrains, Table 10 shows clear trends in classifier performance. Snow's distinct NIR reflectance qualities allow for near-perfect accuracy (1.00 F1 in Uttarkashi/Chamoli 2024) in classification; nonetheless, RF exhibits marginally better performance than SVM when handling shadow-affected pixels. SVM performs especially well in Chamoli's deep woods (1.00 F1 2019), and vegetation benefits from excellent NDVI separation, maintaining exceptional dependability (0.97-1.00 F1) across all regions and years.

Table 10: F1-Score Comparison (2019 vs 2024).

Region	Year	Best Classifier	Bare	Snow	Vegetation	Built-up	Water	Key Improvement
Uttarkashi	2019	RF	0.86	0.96	0.98	0.79	0.87	Baseline
	2024	RF	↑0.95	↑1.00	0.97	↑0.94	↑0.96	+15% Built-up
Chamoli	2019	SVM	0.94	0.96	1.00	0.90	0.96	Peak Vegetation
	2024	RF	↑0.95	↑1.00	0.98	↓0.82	0.92	+4% Bare
Pithoragarh	2019	SVM	0.91	1.00	0.97	1.00	0.97	Peak Snow
	2024	CART	↑0.97	0.98	0.97	↓0.90	↓0.89	+6% Bare

Table 11: Overall, Area calculated by best Performance Classifiers (Area in km^2).

Region	Year	Model	Bare	Snow	Vegetation	Built-up	Water	Classified Area	Total Area	Cloud Cover
Chamoli	2019	RF	1,774.54	2,205.64	2,358.23	592.78	49.57	6,980.75	7,814	833.25
	2024	RF	1,833.06	2,388.48	2,357.82	777.14	450.34	7,806.83	7,814	7.17
Pithoragarh	2019	SVM	1,616.92	2,098.53	1,910.71	825.37	101.62	6,553.13	7,226	672.87
	2024	RF	2,334.87	1,573.41	2,349.41	313.02	647.73	7,218.45	7,226	7.56
Uttarkashi	2019	SVM	3,218.46	1,803.58	1,836.01	229.17	13.62	7,100.83	7,989	888.17
	2024	CART	2,634.54	1,998.00	2,751.93	536.88	61.18	7,982.53	7,989	6.47

The most variable areas are built-up (0.79-1.00 F1), where RF's ensemble technique in Uttarkashi 2024 improved accuracy by 15% compared to 2019. This was due to improved handling of spectral mixing with bare soil. However, Chamoli's 8% decline (0.90→0.82) indicates that hilly urban morphology continues to provide difficulties, since SVM's kernel techniques outperformed CART's decision boundaries.

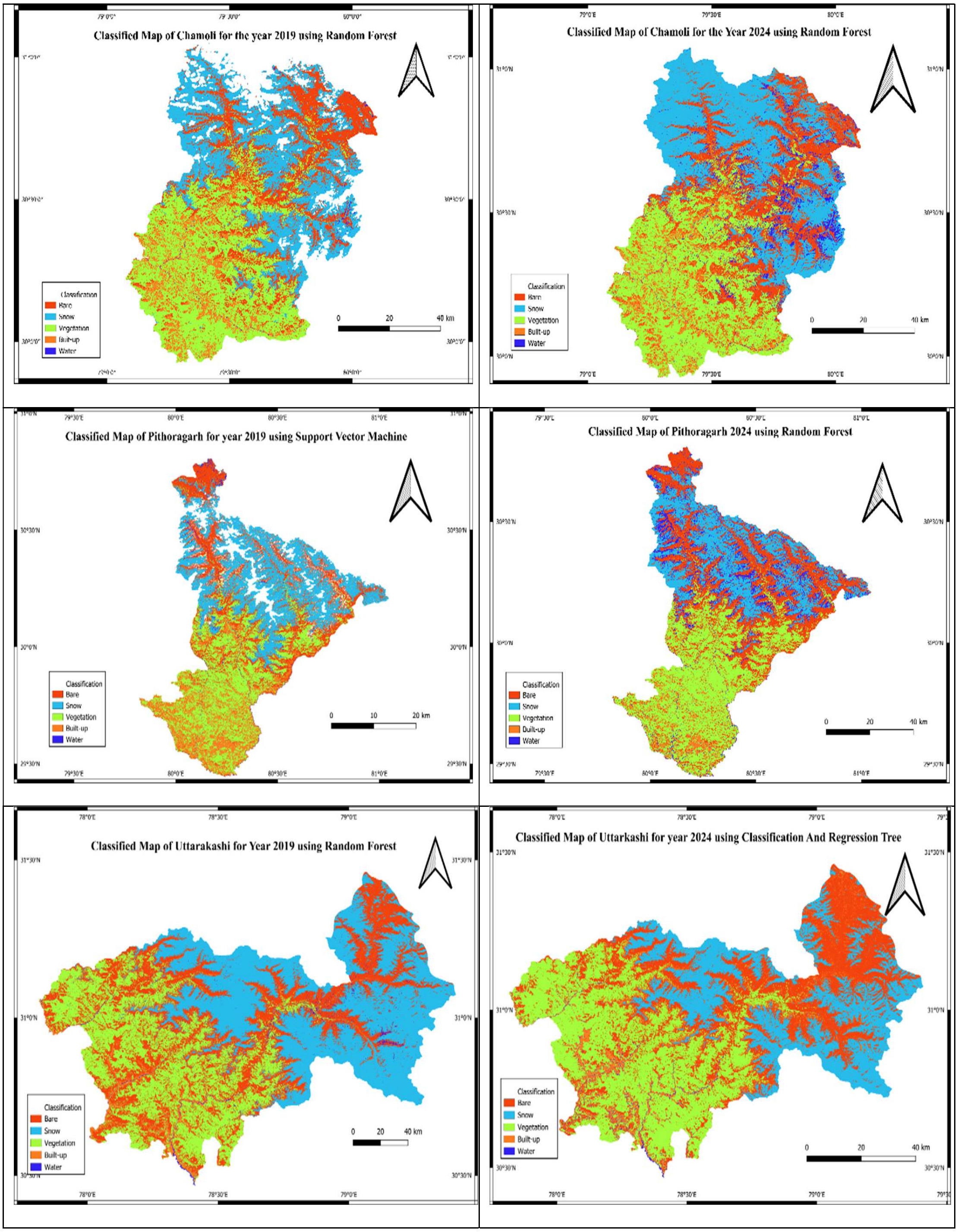

Fig. 4: The classified and LULC maps and Snow cover map of Chamoli, Pithoragarh, and Uttarkashi for 2019 and 2024 were created using an algorithm that achieved the highest overall accuracy.

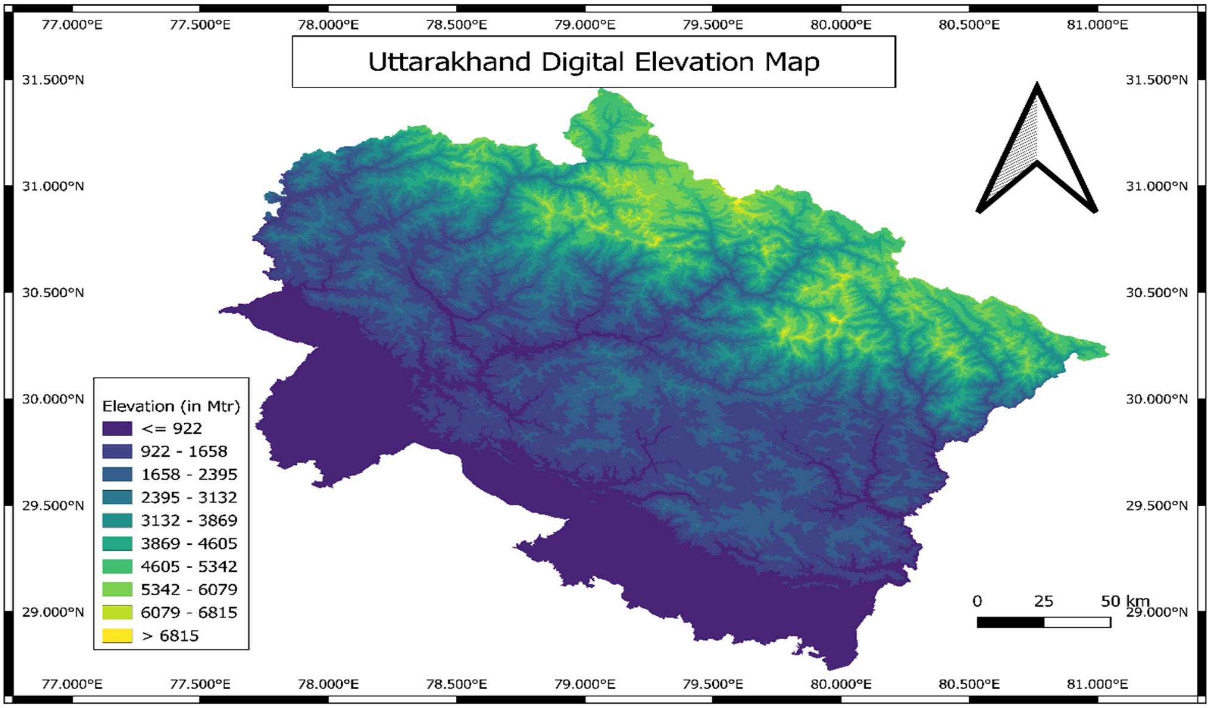

Fig. 5: Digital elevation map of Uttarakhand.

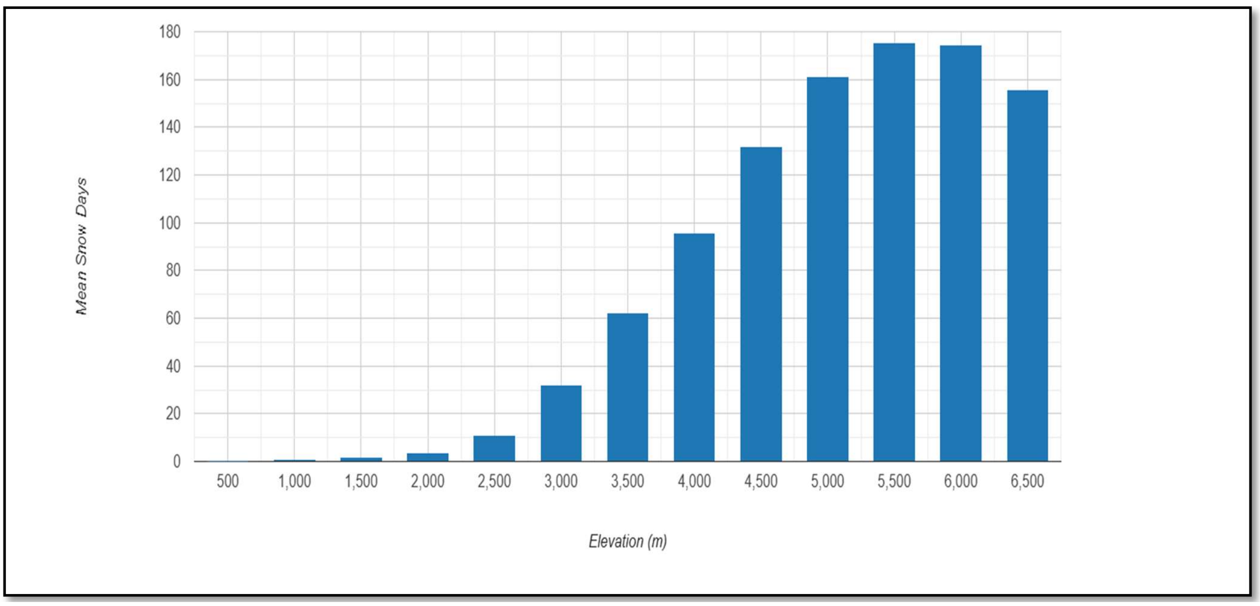

Fig. 6: Mean snow duration (in days) Vs elevation (in meters) for periods of year 2000-2023.

While CART in Pithoragarh 2024 struggled with the reflectance variability of glacial-fed water (-8% accuracy), RF's multi-temporal learning in Uttarkashi improved water detection by 9%. Water bodies exhibit modest fluctuations (0.87-0.97 F1). Although Chamoli's stable but sub-perfect scores show that there are still issues with fallow-land discrimination, bare land classification increased steadily (most notably by +9% in Uttarkashi RF).

The comparison between 2019 and 2024 shows how RF is superior, with its ensemble method and comprehensive feature selection providing 6-15% accuracy gains for difficult classes.

The land cover classification results (in km^2) for the three Himalayan areas (Chamoli, Pithoragarh, and Uttarkashi) for 2019 and 2024 are compared in Table 11 using the top-performing machine learning models (RF, SVM, and CART). Compared to Pithoragarh, which witnessed a 537% increase in water but a 25% loss in snow, Chamoli observed an 808% expansion of its water body (from 49.57 to 450.34 km2) and an 8% rise in snow cover. In Uttarkashi, the amount of vegetation recovered significantly, increasing by 50% to 2,751.93 km^2. Regional differences were evident in built-up areas, which decreased 62% in Pithoragarh and increased 31% in Chamoli. Significant technical advancements may be seen in the 2024 results, when 99.9% of all regions are identified, and cloud cover has decreased from 600–900 km^2 to less than 10 km^2. The most popular classifier in 2024 was Random Forest (RF), although CART did remarkably well for the vegetation of Uttarkashi. While some anomalies, such as the snow melting in Pithoragarh, need additional validation through spectral analysis and ground truthing, these discoveries also point to both real ecological changes (water expansion, vegetation regeneration) and sophisticated detection skills. Also, Fig. 5 shows the digital Elevation Map of Uttarakhand, and Fig. 6 shows Uttarakhand's average annual snow cover duration in days from 2000 to 2023 in relation to elevation.

CONCLUSIONS

This Research work was intended to accomplish the primary objectives, which are as follows: (i) Land Use Land Cover (LULC) Mapping. (ii) Detection of Snow cover in the Himalayan region districts of Uttarkashi, Chamoli, and Pithoragarh, Uttarakhand, India, using the annual composite median of Sentinel-2 imagery. (iii) To compare the performance of various machine learning models, that is, Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART) for 5 classes. (iv) To calculate the area of 5 classes for the years 2019 and 2024. (v) To build classified maps using the algorithm that results in the best overall accuracy. The study is loc ated the area where studying these LULC classes was made possible by the study area's location in a region with a variety of terrains and scenery. To encourage sustainable land use practices that benefit human communities and the environment, policymakers and planners can make better decisions by being aware of the distinctive features of each LULC. The following are the main points of the study: (i) The results of the implementation demonstrated that the RF classifier outperformed district Chamoli for the years 2019 and 2024, respectively, in terms of overall accuracy 95.7% and 96.2% and kappa value 95.7% and 96.2%., (ii) The results of the implementation demonstrated that the SVM classifier outperformed the district in 2019 with an overall accuracy of 97.3% and a kappa value of 96.6%, while RF classifier outperformed the district Pithoragarh in 2024 with an overall accuracy of 95.8% and a kappa value of 94.5%., (iii) The results of the implementation demonstrated that the RF classifier outperformed the district in 2019 with an overall accuracy of 95.5% and a kappa value of 94.4%, while RF classifier outperformed the district Pithoragarh in 2024 with an overall accuracy of 96.1% and a kappa value of 95.1%., (iv) The results indicated that most land cover classes achieved over 85% accuracy across all three classifiers (RF, SVM, and CART). The snow class showed particularly high classification accuracy (> 97%), whereas the water class had the lowest accuracy (> 88%), (v) All classifiers in the examination of snow categorization across the Himalayan areas showed good accuracy (96–100%), with RF consistently improving, especially in Chamoli (2024). In Uttarkashi (2024) and Pithoragarh (2019), SVM and CART both received Ideal performance; nonetheless, because of spectral similarities, all models consistently misidentified snow with water or sand. The most dependable performance across time and areas was shown by RF, while SVM and CART showed regional fluctuation. These results demonstrate the robustness of the classifiers' detection capabilities as well as the continuous difficulty of differentiating spectrally identical feature types in remote sensing. (vi) The study's findings showed that the study area's largest LULC class is vegetation and snow cover. Built-up and Water, on the other hand, is the smallest LULC class geographically. According to the findings, the estimated snow cover area is 2205.64 km^2 by RF for 2019 and 2388.48 km^2 by RF for 2024, additionally, the SVM estimates 2098.53 km^2 for 2019 and 1573.41 km^2 for 2024, additionally, the RF estimates 2924.72 km2 for 2019 and the CART estimates 1998 km2 for 2024., (vii) All three classifiers worked well overall and generated useful classification outcomes. Excellent LULC maps were created by every ML classifier. The study's findings showed that using a variety of satellite data, including the Harmonized Sentinel-2 MSI, VIIRS Stray Light Corrected Nighttime Day/Night Band, Digital Elevation Model (ALOS DSM: Global 30m v3.2), and WWF HydroSHEDS, is a practical way to map snow cover and LULC classes.

The study's future goals include employing remotely sensed datasets for time series analysis and enhanced LULC categorization. In the future, SAR data and Landsat, combined with deep learning algorithms, can enhance LULC classification for understanding snow cover dynamics and climate change response in global mountain ecosystems.

The digital elevation map of Uttarakhand, and Uttarakhand's average annual snow cover duration in days from 2000 to 2023 in relation to elevation. MODIS MOD10A1(Hall, 2015). Daily snow cover data were used to calculate the length of snow (in days/year). There is a noticeable upward trend, with longer and almost constant snow cover at higher elevations (>4000 m).

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