

Evaluation of snow coverage detecting techniques utilizing satellite imagery (A case study: Urmia Lake Basin, Iran)

Marzieh Alizadeh ^a, Behzad Hessari ^{b*}, Mir-hasan Mir-yaghoubzadeh ^c, Maryam Mohammadpour ^d

^a M.Sc in Water Resources, Urmia University, Urmia, Iran

^b Associate Professor, Department of Water Engineering, Urmia University, Urmia, Iran

^c Associate Professor, Department of Natural Resources, Urmia University, Urmia, Iran

^d PhD in Water Resources Engineering, East Azarbijan regional water company, Urmia, Iran

ABSTRACT

Snow cover is a critical component of the hydrological cycle in broad mountainous regions, performing as a crucial reservoir for drinkable and agricultural water. Precisely evaluating the extent of snow cover within watersheds is a fundamental aspect of snow hydrology, significantly impacting water resource management and climate research. This assessment is crucial for forecasting water availability, comprehending climatic trends, and ensuring a sustainable water supply for these areas. In this study, we estimate the snow cover levels of the Urmia Lake basin in Iran using MODIS imagery. Initially, snow cover variations were examined through depth and the number of snow days at nine synoptic stations over a 20-year period (1999-2019). To extract snow cover and snow line levels from MOD10A1 and MOD02H satellite images on a monthly and daily basis, unsupervised algorithms, supervised classification, and the Normalized Snow Index (NDSI) were employed. The year 2016 was identified as a typical meteorological year concerning basin rainfall and temperature variations. The efficacy of the selected algorithms was assessed by applying them in the normal year of 2016. The results were analyzed using the Kappa coefficient index and overall accuracy. The Kappa coefficients for the three detection algorithms ranged from 0.94 to 0.98. While the Maximum Likelihood method exhibited higher Kappa coefficients, no significant differences were noted among these classification methods. These maps facilitate basin hydrological modelling, runoff estimations, actual evapotranspiration, water balance, and snow water equivalent in mountainous regions.

©2025 Urmia University

Keywords:
Snow Cover
MODIS
NDSI
Urmia Lake Basin

1. Introduction

Snow is a globally significant factor in climate change, and it plays a fundamental role in mountainous areas. The snow-covered area (SCA) is a crucial parameter for many applications, such as climatology, meteorology, and hydrology, due to its impact on water availability and the Earth's radiation budget. Moreover, as snow extent is introduced as a state variable in hydrological models, SCA data can be used to predict the water phase and provide information on risk phenomena such as flooding (Stillinger

et al., 2023; Richiardi et al., 2021). For these reasons, the study and monitoring of snow cover have relevant concepts in the study of risk management, socioeconomic models, and basin-scale hydrological modeling (Hedrick et al., 2018; Niittynen et al., 2018). Snow cover has also been identified by the Global Observing System for Climate as one of the 50 Essential Climate Variables because it is an important variable in monitoring climate change (Bojinski et al., 2014; Richiardi et al., 2021; Yin et al., 2024).

* Corresponding authors.

E-mail address: b.hessari@urmia.ac.ir

<https://doi.org/10.30466/jwec.2025.121597>

Received: 06 September 2024

Accepted: 12 January 2025

On-site observations are not sufficient to characterize the properties and distribution of snow spatially in mountainous areas. However, satellite observations can provide information on the different properties of snow and its distribution with high temporal and spatial continuity (Hall et al., 2002; Li et al., 2020). Snow detection with optical sensors pertains to the reflection and absorption characteristics of snow. Satellite remote sensing is the best tool for measuring snow cover and snow albedo at regional to global scales (Molotch et al., 2004; Bair et al., 2019; Stillinger et al., 2023). The capability to map the snow cover from space was achieved in the early era of spaceborne remote sensing (Dozier et al., 1981; Warren, 1982). Now, spaceborne multispectral instruments are used to monitor many snow surface properties such as the fractional snow-covered area, snow albedo, snow grain size, reduction in albedo from light-absorbing particles, estimate persistent ice cover, analyze the impacts of wildfire on snowmelt, evaluate continental climate models, force regional climate models, partition snow and glacier melt, reconstruct snow water equivalent, quantify anthropogenic LAP impacts on snowmelt timing, and forecast streamflow (Stillinger et al., 2023). As satellite sensors play a significant role in monitoring snow cover extent, various authors have demonstrated that SCA maps from optical satellite sensors can derive significant parameters such as the snow cover duration, snow cover start, and snow cover melt, and improve hydrological model prediction (Notarnicola et al., 2013). SCA maps are derived from optical satellite images with high spatio-temporal resolution (AVHRR, MODIS) to ensure daily availability with high ground resolution. MODIS, with multispectral capabilities and medium spatial resolution, repeats daily information by two satellites, Terra and Aqua, and it succeeds at both regional and global scales (Notarnicola et al., 2013; Hall et al., 2002; Wang et al., 2003). Despite the availability and general performance of the MODIS snow product, obvious limitations affect the monitoring of local-scale details to map snow cover with the highest possible amount of spatial details. However, the estimation of fractional snow cover is of interest because it represents an improvement of resolution with respect to 500 m of MODIS standard products (Notarnicola et al., 2013). Most optical sensor snow detection algorithms have been built using the normalized-difference snow index (NDSI). The NDSI index, formulated by Dozier (1989), utilizes the spectral signature of snow to differentiate it from other land-use classes and clouds. Recently, numerous algorithms have been created based on this index to extract various snow parameters, including the snow cover binary product, snow depth, snow

water equivalent, and fractional snow cover (Richiardi et al., 2021).

Based on MODIS snow cover products released globally, many studies have been conducted on recovering snow cover under clouds, mostly including temporal/spatial filtering, multi-sensor synthesis, and the SNOWL (snow line) algorithm using the digital elevation model (DEM) (Parajka et al., 2008 & 2010; Gao et al., 2011; Hori et al., 2017; Deng et al., 2021; Bousbaa et al., 2022 and so on). The temporal-filtering method utilizes the short-term dynamic change in cloud layers to recover snow cover beneath the clouds, but it usually requires very high temporal resolution satellite images, such as revisiting cycles of more than two times in a day. The spatial filtering method typically uses adjacent cloud-free pixel information, but it ignores rapid changes in snow cover and is not suitable for mountainous regions with significant spatial heterogeneity (Dong and Menzel, 2016). The multi-sensor synthesis method integrates optical satellite images with microwave satellite images or ground observation data to enhance the recognition capability of snow cover under clouds (Bousbaa et al., 2022; Shen et al., 2016). Zhang et al., (2024) reconstructed snow cover under clouds and cloud shadows in a mountainous region in Babao river basin of the Qilian mountains in China. this study introduced two main innovations to reconstruct snow cover: (1) combining S2 and L8 images and choosing different CCS detection methods, and (2) improving the cloud shadow detection algorithm by considering land cover types, thus further improving the mountainous-snow-monitoring ability. According to the time-series analysis of three hydrological years, it was found that there was a marked difference in the spatial distribution of snow cover in different hydrological years within the basin, with fluctuations observed overall. Yin et al., (2024) studied a new retrieval algorithm of fractional snow. this study selected the Qinghai-Tibet Plateau as the experimental area, utilizing AVHRR-CDR surface reflectance data (AVH09C1) and calibrating with the MODIS snow product MOD10A1, with a simulated Normalized Difference Snow Index (NDSI) model. Also, in order to detect the effects of land-cover type and topography on snow inversion, they tested the accuracy of the algorithm with and without these influences, respectively (vanilla algorithm and improved algorithm). The results indicate that the logic model based on NDSI has the best fitting effect, with R-square and RMSE values of 0.83 and 0.10, respectively. Meanwhile, the accuracy was improved after taking into account the effects of land-cover type and topography. The model is validated using MOD10A1 snow-covered areas, showing snow cover area differences of less than 4% across 6 temporal phases. The validation results

demonstrate that the AVHRR snow cover percentage remote sensing product proposed in this study exhibits high accuracy in the Tibetan Plateau region, also demonstrating that land-cover type and topographic factors are important to the algorithm. Patra et al. (2015) used rough set theory to compute individual spectral band relevance and significance. Tan et al. (2013) proposed an unsupervised framework for selecting and combining spectral and spatial information for Support Vector Machine classification. In principle, the classification of multispectral image data should be straightforward and achieve high acceptable accuracy. However, more often, a judicious combination of the two will be necessary to attain optimal results. A hybrid supervised/unsupervised strategy is therefore also presented (Richards and Jia, 2006).

The hydro-climatological regime of the Urmia Lake basin is characterized by both snowfall and rainfall. All renewable surface and groundwater resources in this area are highly dependent on snow coverage and the timing of snowmelt. Water resource planning systems, agricultural water consumption management, and the restoration efforts for Urmia Lake are all significantly influenced by the fluctuations of snow coverage in mountainous areas. Climate change has a profound impact on these snow coverage patterns and the timing of snowmelt. In this study, we employed three distinct algorithms, with an emphasis on the use of multispectral imagery, to map snow cover in the Urmia Lake basin in Iran. The goal was to better understand and predict the effects of these climatic factors on the region's water resources.

This study innovatively leverages the high temporal and spatial resolution of MODIS sensor satellite image products, specifically MOD10A1 and MOD02H, to accurately detect and analyze snow cover changes in the Urmia Lake basin in Iran. By employing image analysis, this research applies a comprehensive suite of algorithms—including the Normalized Difference Snow Index (NDSI), supervised classification (support vector machine, maximum likelihood, and minimum distance), and unsupervised classification (K-means). The utilization of these advanced remote sensing techniques, combined with rigorous statistical validation using the Kappa coefficient, enables a more precise assessment of snow cover trends and hydrological dynamics. This approach not only enhances our understanding of snow hydrology in mountainous regions but also provides a robust framework for water resource management and climate adaptation strategies in arid and semi-arid areas, where traditional field measurements may be challenging.

2. Materials and Methods

2.1. Case Study Area and Data

The Urmia Lake basin, located in northeast Iran (Fig. 1), has a land area of 51,876 km², with Urmia Lake occupying 10% of its total area. In this basin, 17 permanent rivers and 12 seasonal rivers flow into Urmia Lake. It is characterized by a semi-arid and dry-cold climate with a mean annual rainfall of 359.1 mm, a minimum temperature of 4.3 °C, a maximum temperature of 17.7 °C, and an average streamflow of 18.2 m³/s (Narimani et al., 2023).

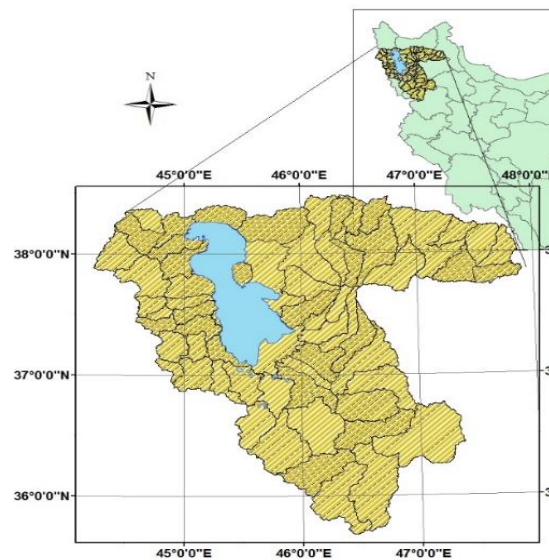


Fig1- Location of Urmia Lake basin in Iran

To determine the normal meteorological year, daily temperature and precipitation data were collected from 60 climatological stations in the Urmia Lake basin over a 54-year statistical period (1966–2020). However, data were only used over 20 years (1999–2019) at nine stations to ensure data continuity and validity. For regional analysis, the data were distributed to the basin by creating Thiessen polygons in ArcGIS software. The data were dimensionless, and a normal hydrological year was obtained for the research period (Table 1 and Figure 2). In this study, snow cover maps were created from observations collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Terra satellite (modis.gsfc.nasa.gov). The proposed MODIS snow algorithm was designed and developed to monitor snow coverage over the Urmia Lake basin. MODIS is a key instrument aboard the Terra (EOS AM) and Aqua (EOS PM) satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. Terra MODIS and Aqua MODIS view the entire Earth's surface every one to two days, acquiring data in 36 spectral bands

(<http://modis.gsfc.nasa.gov/about/>) (Notarnicola et al., 2013). The following MODIS products were used to produce the SCA maps at 500 m resolution:

MOD02H product: Atmospherically corrected surface reflectance product for MODIS spectral bands 1–7 at 250–500 m resolution for extracting reflectance values to determine SCA and snow classification from images.

MOD10A1 product: MOD10A1 is a tile of daily snow cover L3 at a spatial resolution of 500 m. The daily observations selected from multiple observations in MOD10A1 contain snow cover, snow albedo, fractional snow cover, and quality assessment (QA) data.

Table 2 illustrates the characteristics of the downloaded images in the snowy months of the meteorological year in the study area. Topographic information was obtained from the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) (90 m resolution) (Fig. 2).

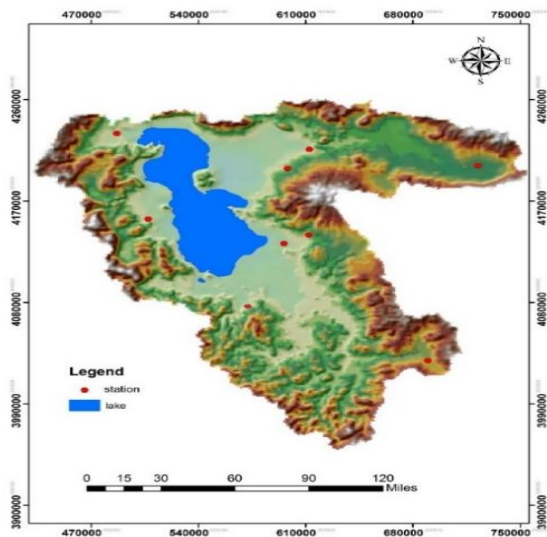


Fig 2- 3D-DEM map and location of selected stations

Table 1- Selected Synoptic stations info of the study area

sea Altitude (m)	latitude	Longitude	Station name
1312	37 ⁰ 32	45 ⁰ 52	Urmia
1290	37 ⁰ 20	46 ⁰ 04	Bonab
1364	38 ⁰ 08	46 ⁰ 17	Tabriz
1817	36 ⁰ 24	47 ⁰ 06	Tekab
1682	37 ⁰ 56	47 ⁰ 23	Sarab
1379	44 ⁰ 55	38 ⁰ 13	Salmas
1648	37 ⁰ 56	46 ⁰ 07	Sahand
1477	37 ⁰ 24	46 ⁰ 16	Maragheh
1351	37 ⁰ 26	46 ⁰ 2	Mahabad

Table 2- Characteristics of the used images

Month	Image	Date
Nov	A2015308 (First week)	2015.11.4
	A2015319 (Second week)	2015.11.15
	A2015326 (Third week)	2015.11.22
	A2015333 (Forth week)	2015.11.29
Dec	A2015342 (First week)	2015.12.8
	A2015356 (Third week)	2015.12.22
	A2015363 (Forth week)	2015.12.29
Jan	A2016004 (First week)	2016.1.4
	A2016030 (Forth week)	2016.1.30
Feb	A2016034 (First week)	2016.2.3
	A2016041 (Second week)	2016.2.10
Mar	A2016062 (First week)	2016.3.3
	A2016069 (Second week)	2016.3.10
	A2016078 (Third week)	2016.3.19

2.2. Snow cover mapping technology

At the beginning of the twentieth century, Hall and Martinec (1985) began to map snow cover areas because of the importance of studying snow areas in applications such as hydrology. Snow cover mapping has been widely used in research into snow hydrology, climatology, and snow-related disasters. These studies and the development of the technology used in them can be summarized as follows:

1. Use of snow line height to calculate snow-covered area.
2. Use of photographs from land surveys to map snow cover.
3. Use of aerial photographs to map snow cover.
4. Use of different images from remote sensor satellites to produce snow cover maps.

Satellite remote sensing systems are now the most widely used technology in snow cover mapping and have broadened from case studies to the whole globe (Hall et al., 1995; Dozier, 1989).

2.3. Preprocessing of MODIS Satellite Images

Images taken from satellites cannot be used as maps due to many geometric distortions. These distortions are caused by several factors, such as the rotation and curvature of the Earth, errors in image band position, the complex arrangement of image sensors, errors in satellite position and attitude, and surface altitude variations. Therefore, they need to be geometrically corrected before processing satellite images (Kim et al., 2018). Geometric correction attempts to correct for positional errors and transform the original image into a new image with the geometric characteristics of a map (Fagan & DeFries, 2024). Geometric correction is performed in two steps: 1) Georeferencing of satellite images using ground control points. 2) Resampling to produce a geocoded image as a raster file. For these steps, a mathematical transformation function is developed to calculate the geographic coordinates

for each image (Toutin and Carbonneau, 1992). In the first step of implementing algorithms, data were pre-processed. In this study, Environment Visualizing Image (ENVI) software was used for preprocessing and geometric correction of imageries. This software release from ITT Visual Information Solutions has a high ability to perform spectral analysis with a very high processing speed. In addition, it is a complete image-processing system that includes spectral tools, geometric correction, terrain analysis, and radar analysis, while also incorporating strong GIS functionality for working with both raster and vector data. This software incorporates benefits due to its ability to work with atmospheric tools (FLAASH) and Digital Elevation Module (DEM) extraction (Thurston, 2008). ArcGIS software was used to prepare the outputs and convert the coordinates of MODIS images. Furthermore, the radiometric error of images was determined using the Fast Line of Sight Atmospheric Analysis of Hypercube (FLAASH) method. FLAASH is a software tool that corrects visible and near-IR spectral imagery for the effects of the atmosphere using a first principles, physics-based approach. The result is a spectral reflectance image that can be further analyzed for surface classification, material detection and characterization, and other applications. FLAASH was developed collaboratively by Spectral Sciences, Inc. and AFRL, with additional support from NIMA, NASA, and the SITAC. FLAASH is based on radiation transport modeling using the industry-standard MODTRAN code, which was also developed by the Spectral Sciences/AFRL team. In Phases 2 and 3 of the AFRL SBIR program, Spectral Sciences, Inc. and Research Systems, Inc. developed a commercial version of FLAASH as a plug-in to the popular ENVI image processing software package. ENVI FLAASH, currently available from Exelis Visual Information Solutions, has enjoyed widespread use in the hyperspectral community since its introduction in December 2001 (Spectral Sciences, 2024).

2.4. Snow MAP Algorithm based on Satellite Imagery

Snow cover mapping is required to distinguish snow pixels from non-snow pixels. Identifying snow pixels can be performed using satellite data in several ways: 1) Subjective visual inspection. 2) Multispectral image classification. 3) Pixel statistics. 4) Reflectance ratio. 5) Microwave remote sensing (Wang & Li, 2003).

For these purposes, various algorithms to map snow cover have been developed using satellite imagery; these algorithms are based on optical sensors, passive microwave sensors, or the integration of both (Riggs et al., 2021). In this study, the datasets were obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS). For all products with a spectral range of 0.4–2.4 μm , four methods have often been used to map snow cover: Normalized Difference Snow Index (NDSI), supervised classification, unsupervised classification, and

digital number (DN) statistics (Wang & Li, 2003). In this case, three algorithms were implemented: 1) NDSI, 2) Supervised Classification, and 3) Unsupervised Classification in northwestern Iran. To apply these algorithms, selected indices justified on pixels of the MOD10A1 and MOD02H products of the MODIS sensor for snowy months in normal meteorological years were used. Then, the results were compared with each other and evaluated. In this research, pixels of 0–100 related to the snow area in MODIS images. These images were diagonal because of the sensor location in the study area. Finally, snow-covered areas were obtained from monthly images of those products for the 2015–2016 meteorological year.

2.5. Normalized Difference Snow Index (NDSI)

The Normalized Difference Snow Index (NDSI), developed by Hall et al. (1995), is an important snow-related variable used to identify snow in MODIS images with 500-m resolution. NDSI has been widely used to understand the presence of snow in pixels. NDSI is based on the spectral characteristics of snow, reflecting its very high visible reflectance and very low reflectance in the shortwave infrared (SWIR). Snow ranges are theoretically possible for pixels with NDSI values between 0 and 1 (Hall et al., 1995; Nolin and Liang, 2000). Typically, an NDSI over 0.4 has been widely used as a threshold in cases where obvious snow-covered pixels need to be captured (Lee & Choi, 2022; Zhang et al., 2020).

The spectral curve of snow indicates the high reflectance of snow in the visible range and its low reflectance in the near-infrared range (Fig. 3), which is the basis of the definition of NASA's global snow cover index (Hall et al., 1995; Riggs et al., 2021). Figure 2 displays a subset of the snow and non-snow unmembered spectral libraries in the MODIS bands. Importantly, the spectral reflectivity of snow can vary depending on snowpack properties such as snow depth, grain size, liquid water content, and dust content, and thus can vary both in time and space (Xiao et al., 2022). NDSI is an integral part of the SNOMAP algorithm for the identification of snow (Hall et al., 2002).

$$\begin{aligned} \text{NDSI} &= (\text{band4} - \text{band6}) / (\text{band4} + \text{band6}) \\ \text{NDSI} &= (\text{Green}_{0.53} - \text{SWIR}_{1.65}) / (\text{Green}_{0.5368} + \text{SWIR}_{1.65}) \end{aligned} \quad (1)$$

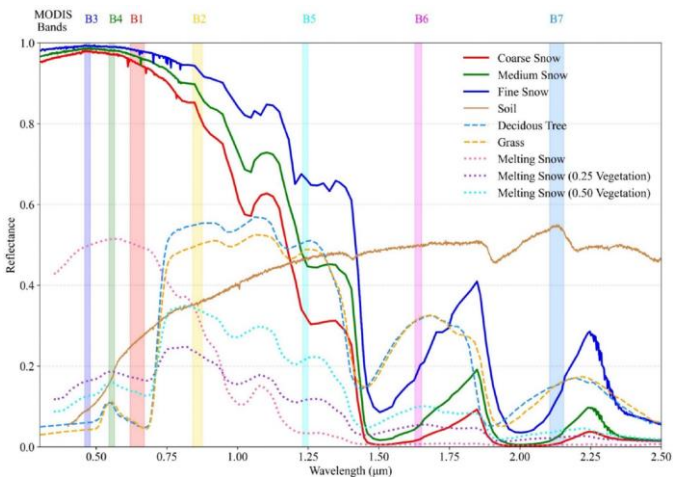


Fig 3- Examples of spectral reflectance of the snow and non-snow endmembers from the JPL spectral library and a subset of the snow endmembers modeled through SNICAR for different effective snow grain (Xiao et al., 2020)). The shadow wide indicates the spectral bandwidths of MODIS bands 1–7. The reflectance of snow within fine grain size (24 μm), medium grain size (82 μm), and coarse grain size (178 μm) generated by the SNICAR radiative transfer model are also shown.

2.6. Supervised Classification Algorithm

The Supervised Classification Algorithm (SCA) is also used to assist in the determination and/or identification of the snow cover area. Supervised Classification based on sampling at a training site, produces a statistical character for the reflectance information of a certain surface feature. By checking the emission value of every pixel, images can be classified and their spectral characteristics determined. For more accurate sampling, a false-color image was prepared. Then, a color image is created by combining the three color composite (RGB) and assigning each color. The false colour composite are attributed to the infrared, red, and green bands, respectively. The purpose of choosing the right bands is to minimize the low-value data and to use the useful information as much as possible. Minimum distance and maximum likelihood classifiers are among the most commonly used classification methods. To ensure that classifications are accurate, field surveys should also be conducted as often as possible (Richards and Jia, 2006; Wang & Li, 2003). In this research the false color composite and NDSI index was performed and Maximum Likelihood Classification method was used to snow cover mapping.

2.7. Unsupervised classification Algorithm

A useful tool for mapping snow cover areas over the Earth’s surface is the accessibility of satellite remotely sensed images. However, this requires accurate techniques that allow snow-cover classes to be distinguished among other land covers. This goal can be achieved using supervised classification. The supervised classification method requires training data to be

available for all considered classes. However, in situ measurements are difficult in some areas. Indeed, land-truth data for snow-cover mapping are usually limited. To overcome this problem, an unsupervised approach was proposed by scientists (Macchiavello et al., 2009). Unsupervised classification generates clusters based on similar spectral characteristics inherent in the image. Then, you classify each cluster without providing training samples. The snow cover is also placed in one or more clusters based on the brightness of the pixels; the brightness of the pixels depends on the depth of the snow cover (Richards and Jia, 2006).

2.8. Accuracy assessment

In this study, the accuracy of classification in SNOMAP is evaluated using the Kappa coefficient. The Kappa Statistic or Cohen’s Kappa (1999) is a statistical measure of inter-rater reliability for categorical variables. In fact, it is almost synonymous with inter-rater reliability. Kappa is used when two raters apply a criterion based on a tool to assess whether or not some conditions occur. If the two raters can reliably use the criterion to make the same assessment on the same targets, then their agreement will be very high and provide evidence that we have reliable ratings. If they cannot, then either the criterion tool is not useful or the raters are not sufficiently trained. It is calculated on the basis of the observational and prediction matrix (Table 3):

Table 3- Observational and forecasting matrix (Belvasi, 2013):

	Positive	Negative
Positive	A	B
Negative	c	d

where:

- A: The number of snow observation points and snow forecast points
- B: number of snow observation points and non-snow forecast
- C: The number of non-snow observation points and snow forecast
- D: Number of non-snow observation points and non-snow forecast

$$\text{Kappa} \quad (2)$$

$$= \frac{\text{Observational agreement} - \text{Prediction agreement}}{1 - \text{Prediction agreement}}$$

$$\text{Observational agreement} = \frac{a + b}{a + b + c + d} \quad (3)$$

$$\text{Prediction agreement} \quad (4)$$

$$= \left(\frac{a + c}{N} * \frac{a - b}{N} \right) + \left(\frac{b + d}{N} * \frac{c + d}{N} \right)$$

There is no agreement between the observation and prediction points. If the Kappa coefficient is between 20% and 40%, the agreement is insignificant, and if the Kappa coefficient is between 40% and 60%, the agreement is moderate. If the Kappa coefficient is between 60% and 80%, the agreement is good, and if the Kappa coefficient is between 80% and 100%, the agreement between observation points and prediction points will be excellent (Balvasi, 2015). In this study, the Kappa coefficient was calculated using ENVI software.

3. Results and discussion

The use of remote sensing and satellite imagery in the field of snow cover studies can provide better assessments of snow cover extents than traditional methods. Given that a significant portion of snow cover occurs in mountainous and hard-to-reach areas, studying and monitoring all snow-covered surfaces by traditional methods and direct access to snow measurement stations is almost impossible. Therefore, employing remote sensing methods to obtain more accurate information about snow cover surfaces yields better results, which is crucial for water resource management discussions, climate change assessments, snow studies, and watershed hydrology studies. This study analyzed snow cover changes using satellite images and the Google Earth Engine system in the Urmia Lake basin in Iran. This basin is critical for water resource management and the revival of Lake Urmia. This issue has amplified the importance of this research several times. To achieve this, first, by examining weather data over a 20-year statistical period at nine weather stations in the region, the hydrological year 2015–2016 (1395 Iranian water year) was selected as the normal meteorological year. Figure 3 illustrates the dimensionless changes in the meteorological parameters (precipitation and temperature) used to determine the normal meteorological year. Subsequently, using MODIS sensor products, including MOD10A1 and MOD02H, and snow separation indices such as NDSI, supervised classification, and unsupervised classification within the selected statistical period and the normal year, snow cover changes were investigated. The preprocessing stages of the images included radiometric and geometric corrections and classification of the images into snow-covered and non-snow-covered areas using ENVI and ARC GIS software. Figure 4 shows the primary image view based on satellite positioning. In the next step, the snowmelt

chart, equivalent snow height, and map of the first snowfall related to the normal year were extracted and examined for homogeneous areas within the basin. Finally, by evaluating and comparing the snow separation indices, the results obtained from these algorithms were assessed using the Kappa Coefficient.

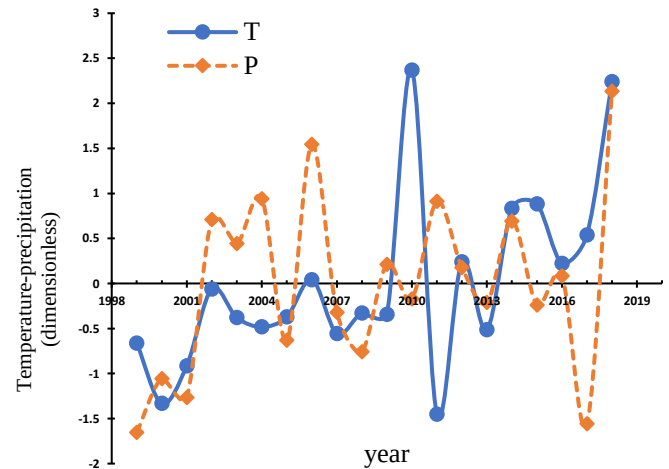


Fig 4- Determining of the normal meteorological year in Urmia Lake basin

3.1. Map of contour lines and the first snow cover

Satellite imagery analysis revealed that the first snowfall in the Urmia Lake basin occurred on November 3rd, 2015, during the normal year. The blue-colored areas in Figures 5 and 6, with pixel values ranging from 0 to 100, represent the snow cover in this region. The first snow cover was observed in the western and northwestern parts of the basin at an elevation of 2350 to 2450 meters, in the northern parts at 2450 to 2550 meters, and in the eastern parts at 2350 to 2650 meters. Therefore, the approximate snow line in this basin is located at an elevation of 2350 to 2450 meters. The daily average temperature of the basin was 9.3°C. However, most stations were located below 1500 meters, while the first snow line was observed at 2350–2450 meters, indicating that the existing stations could not record the snowfall. Additionally, the average air temperature on November 3rd, 2015, was 6.3°C and 7.4°C in the eastern and western parts of the basin, respectively, based on data from nearby synoptic stations (Tabriz, Sahand, Sarab, Maragheh, Bonab, Urmia, Mahabad, Salmas, and Takab). As a result, the daily average temperature of the basin was 9.3°C. However, most synoptic stations were located at an elevation of less than 1500 meters, while the first snow line was observed at 2350 to 2450 meters. This means that the existing stations could not record it. Additionally, the calculated area of snow cover on November 3rd, 2015, was 1539 km².

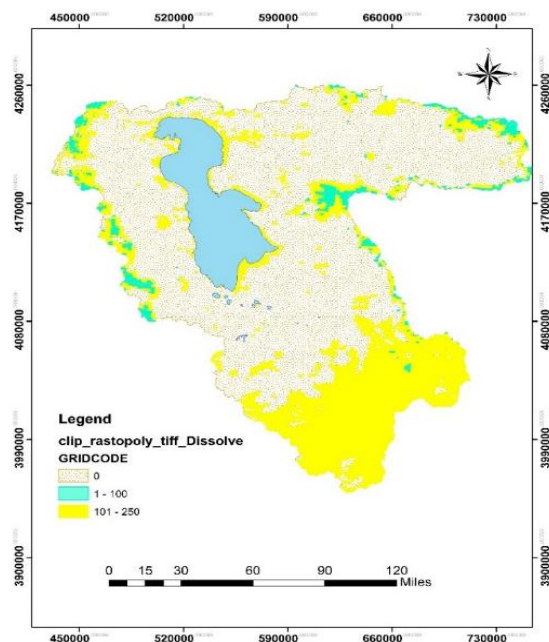


Fig 6- Map of the first snowfall of the normal metrological year at the basin

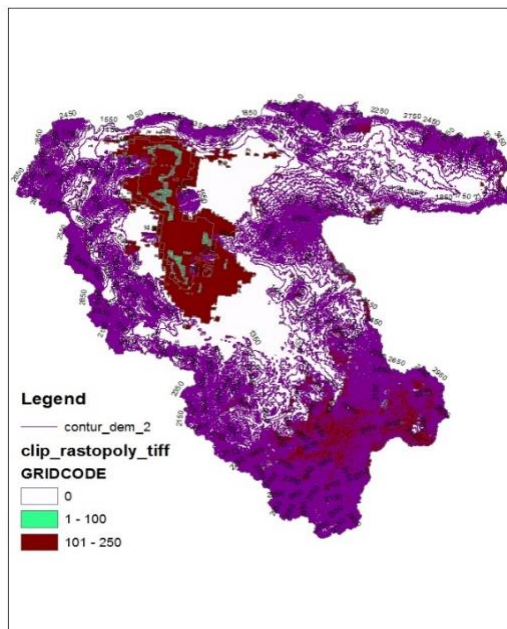


Fig 5- Map of elevation lines and height of the first snow cover in Urmia Lake basin

3.2. Map of the Snow Cover and Equivalent Snow Heights in the Urmia Lake Basin

Figure 7 and Table 4 depict the monthly changes in snow cover and snow cover levels in the Urmia Lake basin extracted from

monthly MODIS (MOD10A1) images in ENVI and GIS software. As shown in Table 4 and Figure 7, in normal years, with the onset of the rainy season, snow accumulates at higher elevations during the winter. As the weather warms up in spring, the snow cover recedes, with snow patches observed at elevations above 2500 m in the northern and northeastern slopes. The pixels ranging from 0 to 100, indicated by blue on the map, represent the snow in the area. However, water production is dependent on the presence of a rainy and snowy regime, and recent climate change has disrupted this natural process, leading to significant changes in both snow levels and temperature variations.

Table 4 - Area of snow levels in the months of a normal year and their equivalent heights

month	A(km ²)	h(m)	Date
1	3210.7	2200	2015.04.15
2	724.4	2800	2015.05.08
3	32.6	3225	2015.06.03
4	0	3800	2015.07.28
5	0	3800	2015.08.19
6	0	3800	2015.09.03
7	24.5	3000	2015.10.16
8	1539.5	2350	2015.11.03
9	11271.6	1800	2015.12.07
10	23607.3	1400	2016.01.30
11	24363.6	1650	2016.02.04
12	15037.6	1750	2016.03.20

3.3. The snow separation indicators result

The results of all three algorithms for snow separation were obtained using MOD02H images of MODIS sensor, separately.

3.4. Normalized Difference Snow Index (NDSI)

The snow cover area was calculated in GIS software for cloudless images and selected normal years. Finally, the snow cover map was determined according to snow cover index and area of the region. Figures 8 and 11 indicate the snow cover maps and snow levels changing obtained from evaluation algorithms in the basin, respectively. In these images, code 1 (white area on the map) represents the snow heights in the region. As shown, during the cold months of the year from December to January, the snow cover is extended to the lower altitudes and towards the lake, and in the summer, it retreats to snow spots, mainly on the northern slopes.

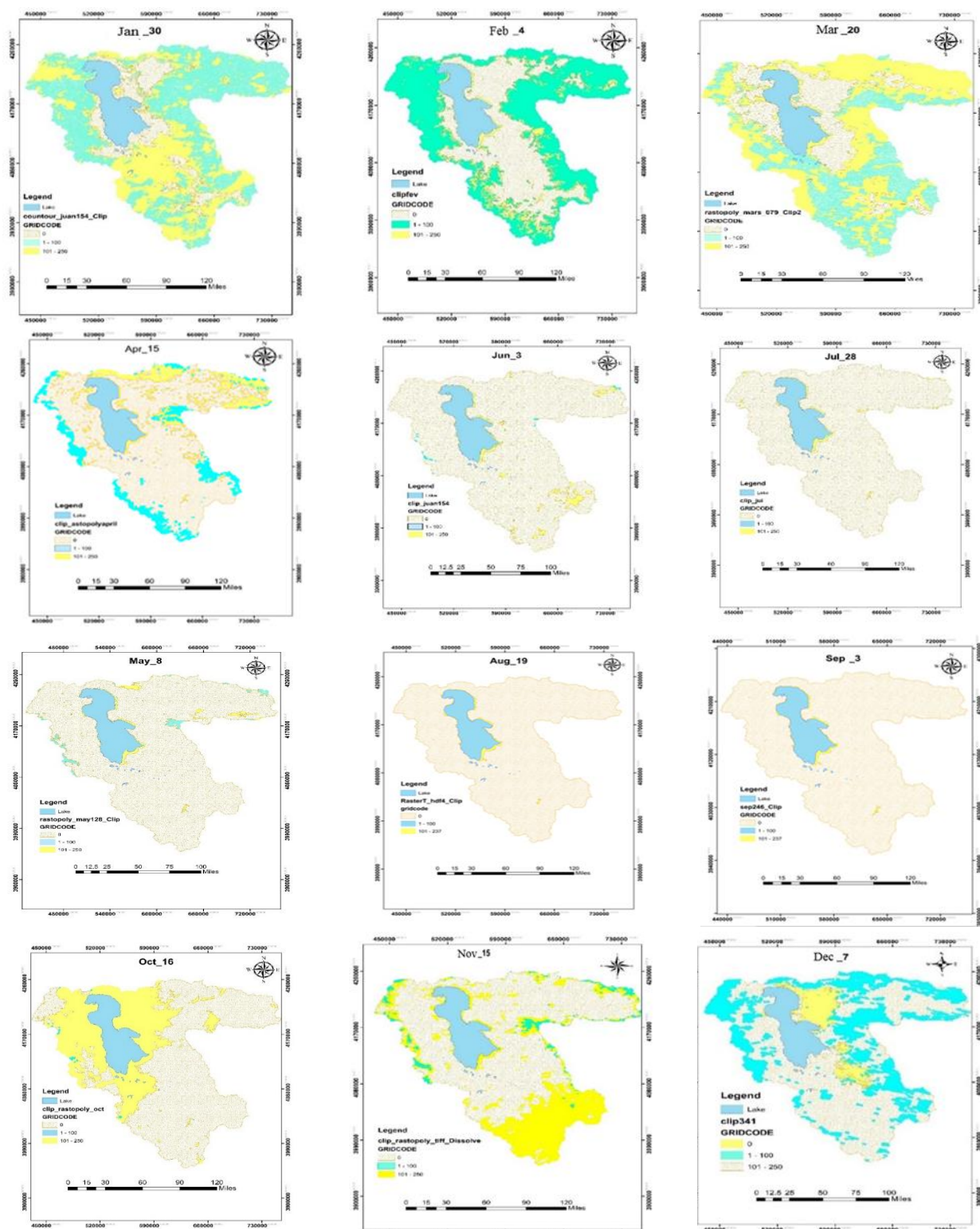


Figure 7 - Monthly maps of snow line subsidence during a normal year in the Urmia Lake Basin

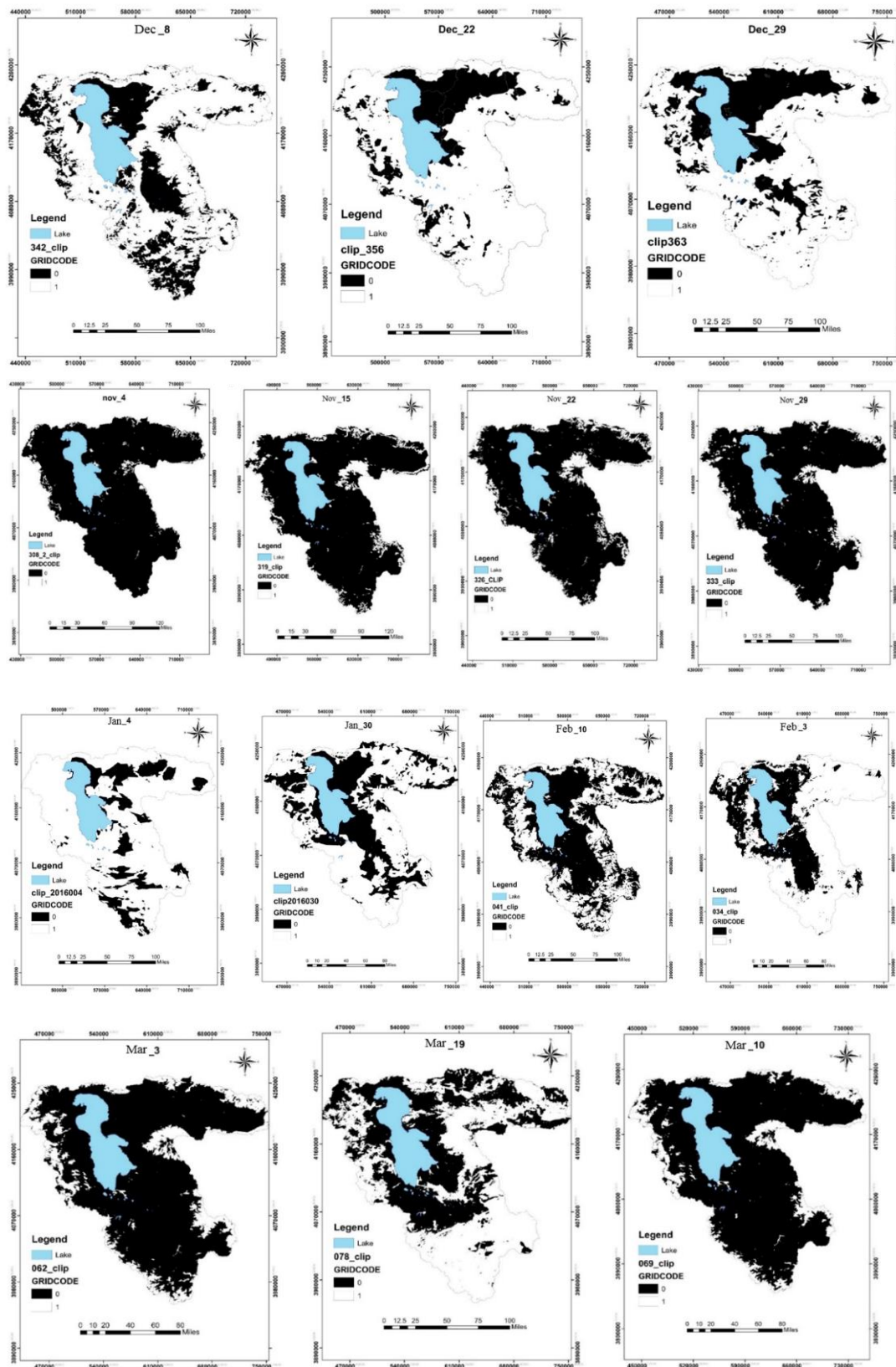


Fig 8- Snow-Covered Area Map based on NDSI Index, (1: Snow, 0: non-Snow).

3.4. Supervised Classification Algorithm

After downloading the images, importing them into ENVI software, and correcting the geometric properties of the images, this probabilistic method requires external information about the area and the desired classes for classification. Various classification methods, such as Minimum Distance, Maximum Likelihood, Support Vector Machine, etc., exist for classification. In this study, the Minimum Distance method for one band combination and Maximum Likelihood Classification method for false color composite bands combination. was used.. Finally, the false-color image was imported into ArcGIS software, and the snow cover area was calculated. According to the legend of the map, white areas with code 1 correspond to snow cover (Figures 9 and 11).

3.5. Algorithm Unsupervised Classification

This type of classification is performed when our knowledge of the area is insufficient. After downloading and applying geometric correction to the images, the K-means method was used in this study for unsupervised classification to separate snow. The K-means method relies on the image's own information and works based on frequency and moving average, providing an initial estimate of the suitable area. This method performs classification based on the Euclidean distance. The area of snow cover resulting from this classification corresponds to the map legend in white in Figure 10 and is determined using ArcGIS software, as shown in Figure 11.

It is observed that the high values for Kappa and overall accuracy are anticipated due to the effective detection of snow from images and the substantial number of observations. Subsequently, these figures and values are utilized for the comparison of results.

3.6. Evaluation of Indices and Selection of the Best Index

To evaluate the indices and select the best one, the Kappa coefficient was used. The results showed that the Normalized Difference Snow Index (NDSI) method is more suitable than the other two methods, as it separates snow cover based on pixels related to snow, providing better delineation of snow boundaries compared to other factors in satellite images. Supervised classification is based on introduced samples, which are somewhat accurate and yield results closer to the

reality of the area. However, unsupervised classification has a high probability of error because there is no precise information about the area, and the results may contain inaccuracies. This method provides a general overview of classification, relying on the image's own information and acting based on the spectral behavior of phenomena. Therefore, because it only provides some initial information, this method is usually not suitable for evaluation. According to Table 5, and based on the overall accuracy and Kappa coefficient results, the NDSI index was better than other algorithms. The normalized difference snow index method is more accurate for snow delineation from images. Subsequently, snow separation indices including NDSI, supervised classification, and unsupervised classification algorithms were used to investigate changes in snow cover over a selected time period and in a normal year. Image preprocessing steps, including radiometric and geometric corrections, were performed, and image classification into snow-covered and non-snow-covered areas was carried out using ENVI and ArcGIS software. In the next step, the snowmelt curve, equivalent snow height, and map of the first snowfall in a normal year were extracted and analyzed for homogeneous regions in the basin. Finally, by examining and comparing the snow separation indices, the results obtained from the algorithms were evaluated using the Kappa coefficient.

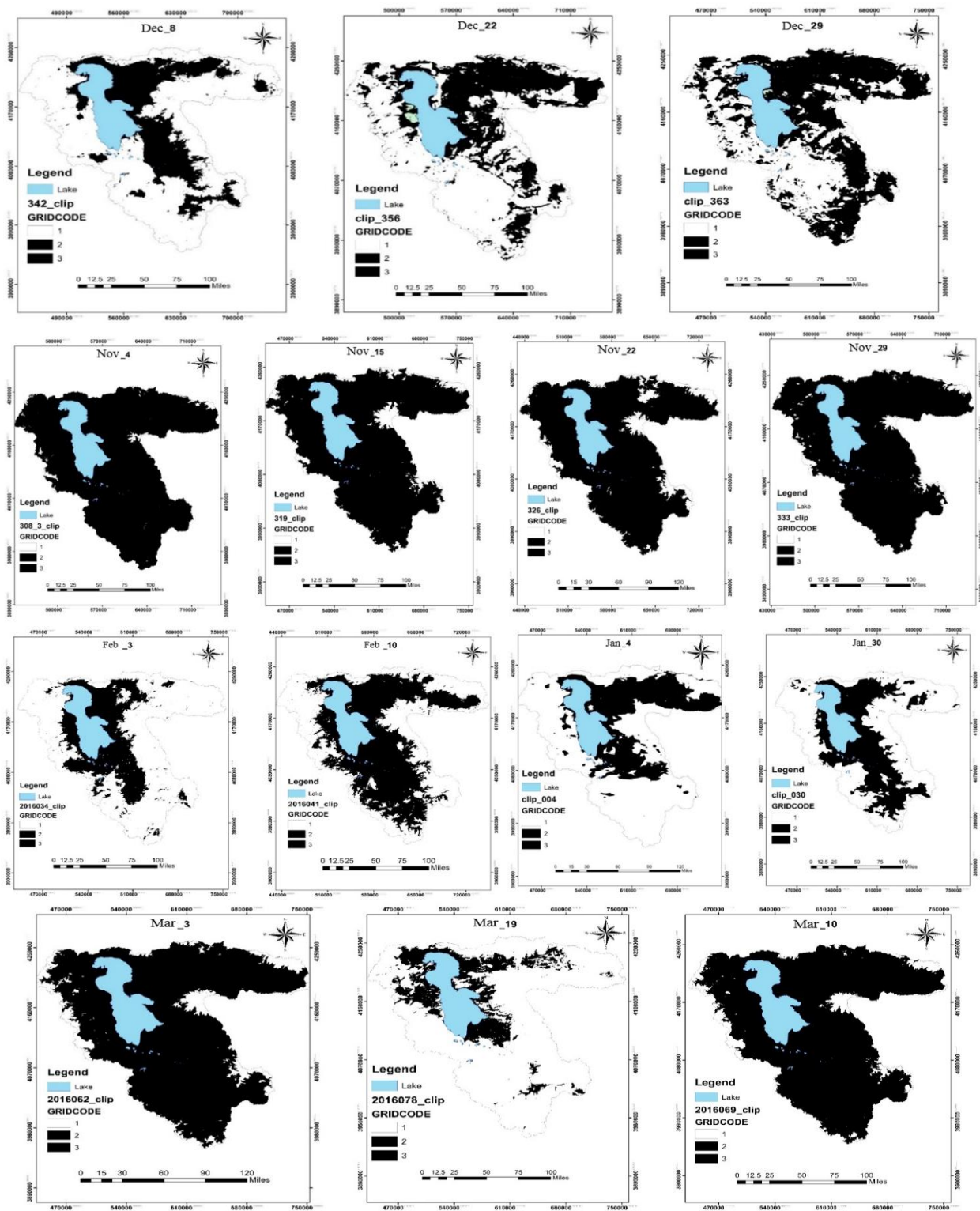


Fig 9- Snow-Covered Area Map by Supervised Classification Algorithm, (1: Snow, 2 & 3: non-Snow)

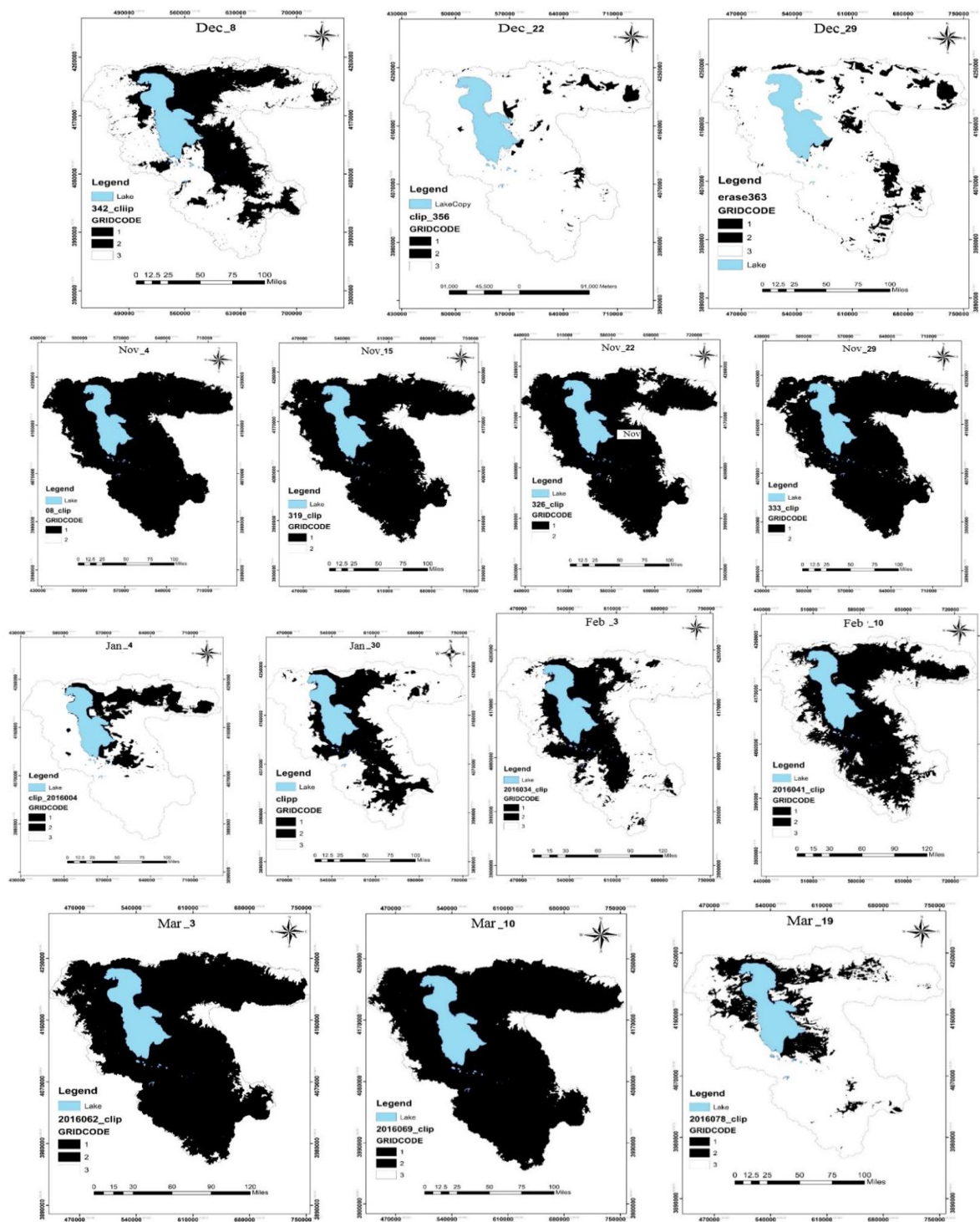


Fig. 10 - Snow-Covered Area Map by unsupervised classification Algorithm, (1 & 2: Snow, 3: non-Snow).

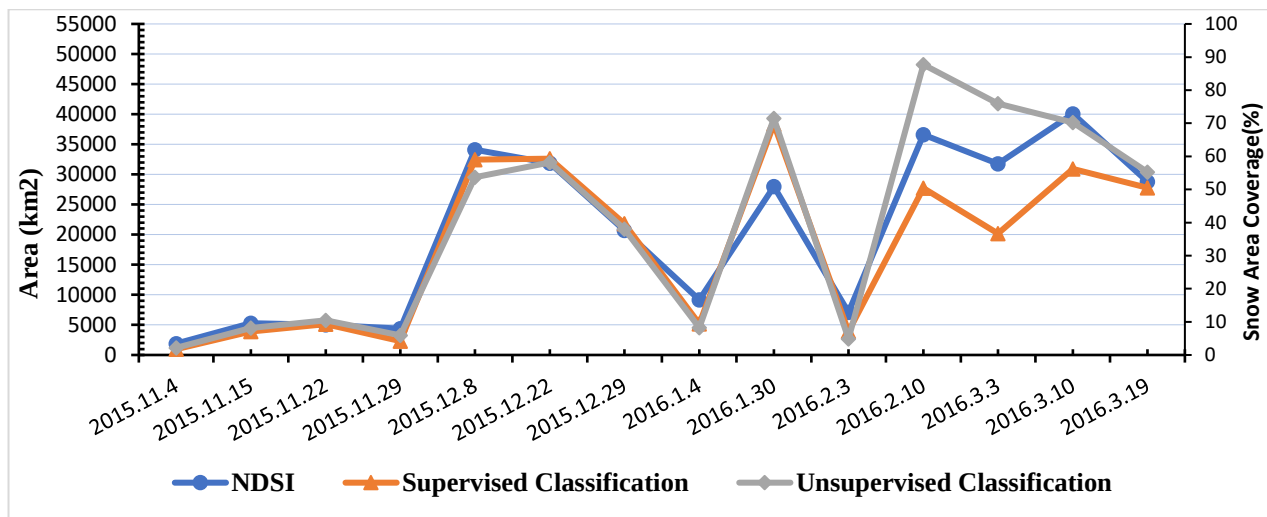


Figure 11. Comparison chart of snow levels obtained from three evaluation algorithms

Table 5- Kappa coefficient evaluation table

Image	Supervised classification						NDSI	
	(ML)				(SVM)		Kappa	Percentage of overall accuracy
	Kappa	Percentage of overall accuracy	kappa	Percentage of overall accuracy	kappa	Percentage of overall accuracy		
A2015308	0.9580	96.97	0.9465	95.2354	0.9787	98.3839	0.9887	98.6478
A2015342	0.9696	98.8776	0.9632	98.6857	0.9542	96.7458	0.9974	99.9457
A2016004	0.9972	99.8839	0.9765	97.3658	0.9852	98.2385	0.9888	98.6547
A2016041	0.9642	98.3652	0.9696	97.1253	0.9811	97.6854	0.9967	98.9857
A2016078	0.9854	97.6589	0.9974	99.8547	0.9658	96.3587	0.9996	99.9854

Conclusion

In this study, MODIS sensor satellite image products MOD10A1 and MOD02H were utilized to extract snow cover due to their high temporal and spatial resolution. The Google Earth Engine was employed for image analysis within the Lake Urmia basin in Iran. Initially, a 20-year statistical period was selected for the region, with the year 2015-2016 identified as a normal meteorological year based on data from nine weather stations in the Lake Urmia basin. Subsequently, the NDSI index, supervised classification, and unsupervised classification algorithms were applied to investigate changes in snow cover over the selected time interval and in a normal year. Image preprocessing steps, including radiometric and geometric corrections, were conducted, and image classification into snow-covered and non-snow-covered areas was performed using ENVI and ArcGIS software. The Kappa coefficient was employed to evaluate the results obtained from the identification algorithms. Support vector machine, maximum likelihood, and minimum distance methods were used to assess the supervised classification methods, while the K-means method was used to evaluate unsupervised

classification algorithms. Based on the results obtained from the Kappa coefficient, it was determined that the Normalized Difference Snow Index (NDSI) method is more suitable than other methods, as it effectively separates snow cover based on pixels related to snow. Finally, maps of snow cover levels in the study area were generated. In recent years, the Lake Urmia basin has experienced a decreasing trend in snowfall. Until field snow measurement data become available, the use of satellite image data and remote sensing systems will significantly aid in determining snow cover levels. The findings of this research can contribute to a better understanding and management planning of water resources, particularly in hydrological and agricultural contexts. The use of MODIS satellite image products can provide valuable information for snow cover monitoring and water resource management in arid and semi-arid regions.

References

- 1- Bair, E. H., Rittger, K., Skiles, S. M., & Dozier, J. (2019). An examination of snow albedo estimates from MODIS and their impact on snow water equivalent reconstruction. *Water Resources Research*, 55(9), 7826-7842.
- 2- Balvasi, Imanali, Rezaei Moghadam, Nikjoo, Valizadeh Kamran, & Khalil. (2015). Comparison of Artificial Neural Network Model with Hierarchical Analysis Process in Landslide Hazard Assessment. *Environmental Risk Management*, 2(2), 225-250. Doi: [10.22059/JHSCI.2015.55063](https://doi.org/10.22059/JHSCI.2015.55063).
- 3- Bojinski, S., Verstraete, M., Peterson, T. C., Richter, C., Simmons, A., & Zemp, M. (2014). The concept of essential climate variables in support of climate research, applications, and policy. *Bulletin of the American Meteorological Society*, 95(9), 1431-1443.
- 4- Cohen, J., and Entekhabi, D. 1999. Eurasian snow cover variability and northern hemisphere climate predictability. *Geophysical research letters*, 26, 345 – 348.
- 5- Dozier, J. 1989. Spectral Signature of Alpine Snow Cover from the Landsat Thematic Mapper. *Remote Sens. Environ.* 42:57, 9–22.
- 6- Dozier, J., Schneider, S. R., and McGinnis, D.F. 1981. Effect of Grain-Size and Snowpack Water Equivalence on Visible and near-Infrared Satellite-Observations of Snow, *Water Resour Res*, 17, 1213-1221, DOI: [10.1029/WR017i004p01213](https://doi.org/10.1029/WR017i004p01213).
- 7- Hall, D. K., Riggs, G. A., & Salomonson, V. V. (2006). updated monthly. MODIS/Terra Snow Cover Monthly L3 Global 0.05 Deg CMG V005, [Dates used; January 2004 to December 2008]. Boulder, Colorado USA: National Snow and Ice Data Center. Digital Media.
- 8- Hall, D. K., Riggs, G. A., Salomonson, V. V. 1995. Development of the methods for mapping global snow cover using moderate resolution imaging spectroradiometer data. *Remote sensing of environment*. No. 54, 127-140pp.
- 9- Hall, D. K., Riggs, G. A., Samonson, V. V., Digirolmo, N. E., Bayr, K. J. 2002. MODIS snow-cover products. *Remote sensing of Environment*, 83, 181-194.
- 10- Hall, D.K., Riggs, G.A., Salomonson, V.V., 1995. Development of methods for mapping global snow cover using moderate resolution imaging spectroradiometer data. *Remote Sens. Environ.* 54 (2): 127–140.
- 11- Hedrick, A.R., Marks, D., Havens, S., Robertson, M., Johnson, M., Sandusky, M., Marshall, H.P., Kormos, P.R., Bormann, K.J., Painter, T.H. (2018). Direct Insertion of NASA Airborne Snow Observatory-Derived Snow Depth Time Series Into the iSnobal Energy Balance Snow Model. *Water Resour. Res.* 54, 8045–8063.
- 12- Tan, K., Li, E., Du, Q., Du, P. (2013). Hyperspectral image classification using band selection and morphological profiles. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 7(1), 40-48.
- 13- Kim, H. G., Son, J. H., Kim, T. (2018). Geometric correction for the geostationary ocean color imager from a combination of shoreline matching and frequency matching. *Sensors*, 18(11), 3599.
- 14- Lee, S., Choi, J. (2022). A snow cover mapping algorithm based on a multitemporal dataset for GK-2A imagery. *GIS Science & Remote Sensing*, 59(1), 1078-1102.
- 15- Li, M., Zhu, X., Li, N., Pan, Y. (2020). Gap-Filling of a MODIS normalized difference snow index product based on the similar pixel selecting algorithm: A case study on the Qinghai-Tibetan Plateau. *Remote Sens.* 12: 1077.
- 16- Macchiavello, G., Moser, G., Boni, G., & Serpico, S. B. (2009). Automatic unsupervised classification of snow-covered areas by decision-tree classification and minimum-error thresholding. In 2009 IEEE International Geoscience and Remote Sensing Symposium. 2, 11-1000.
- 17- Molotch, N. P., Painter, T. H., Bales, R. C., & Dozier, J. (2004). Incorporating remotely-sensed snow albedo into a spatially-distributed snowmelt model. *Geophysical Research Letters*, 31(3).
- 18- Narimani, R., Jun, C., Nezhad, S. M., Bateni, S. M., Lee, J., & Baik, J. (2023). The role of climate conditions and groundwater on baseflow separation in Urmia Lake Basin, Iran. *Journal of Hydrology: Regional Studies*, 47, 101383. <https://doi.org/10.1016/j.ejrh.2023.101383>.
- 19- Niittynen, P.; Heikkinen, R.K.; Luoto, M. (2018). Snow cover is a neglected driver of Arctic biodiversity loss. *Nat. Clim. Chang.* 8, 997–1001.
- 20- Nolin, A., Liang, S. 2000. Progress in bidirectional reflectance modeling and applications for surface particulate media: snow and soils. *Remote sensing reviews*, no. 14, 307-342.
- 21- Notarnicola, C., Duguay, M., Moelg, N., Schellenberger, T., Tetzlaff, A., Monsorno, R., Costa, A., Steurer, C., Zebisch, M. (2013). Snow cover maps from MODIS images at 250 m resolution, part 1: Algorithm description. *Remote Sens.* 5, 110–126.
- 22- Richards. J. A., Jia, X, 2006. *Remote sensing Digital Image Analysis, An Introduction*. Springer, Fourth. DOI: [10.1007/3-540-29711-1](https://doi.org/10.1007/3-540-29711-1)
- 23- Richiardi, C., Blonda, P., Rana, F.M., Santoro, M., Tarantino, C., Vicario, S. (2021). Adamo, M. A Revised Snow Cover Algorithm to Improve Discrimination between Snow and Clouds: A Case Study in Gran Paradiso National Park. *Remote Sens.* 13, 1957. <https://doi.org/10.3390/rs13101957>.
- 24- Riggs, G. A., Hall, D. K., Roman, M. O. (2021). NASA S-NPP VIIRS Snow Cover Products Collection 2 User Guide. NASA: Washington, DC, USA.
- 25- Patra, S. Modi, P. and Bruzzone, L. (2015). Hyperspectral Band Selection Based on Rough Set,” *IEEE Trans. Geosci. Remote Sensing*. 53(10): 5495–5503.
- 26- Spectral Sciences, 2024. <https://www.spectral.com/our-resources/case-studies/success-stories-flaash/>.
- 27- Stillinger, T., Rittger, K., Raleigh, M. S., Michell, A., Davis, R. E., & Bair, E. H. (2023). Landsat, MODIS, and VIIRS snow cover mapping algorithm performance as validated by airborne lidar datasets. *The Cryosphere*. 17(2):567-590.
- 28- Thurston, J., (2008). Review: ENVI 4.4. <https://sensorsandsystems.com/review-envi-44/>.
- 29- Toutin, T., & Carbonneau, Y. (1992). MOS and SEASAT image geometric corrections. *IEEE Transactions on Geoscience and Remote Sensing*, 30(3): 603-609.
- 30- Wang, J., W. Li, (2003). Comparison of methods of snow

- cover mapping by analysing the solar spectrum of satellite remote sensing data in China. *International Journal of Remote Sensing*, 24(21): 4129-4136.
- 31- Warren, S. G.: Optical-Properties of Snow, *Rev Geophys*, 20, 67-89, DOI 10.1029/RG020i001p00067, 1982.
- 32- Zhang, H., F. Zhang, T. Che, Wang, S. (2020). "Comparative Evaluation of VIIRS Daily Snow Cover Product with MODIS for Snow Detection in China Based on Ground Observations." *Science of the Total Environment* 724: 138156. doi:10.1016/j.scitotenv.138156.
- 33- Fagan, M. E., DeFries, R. S. (2024). Remote Sensing and Image Processing. *Encyclopedia of Biodiversity* (Third Edition). 5, 432-445.
- 34- Xiao, X., He, T., Liang, S., Liu, X., Ma, Y., Liang, S., Chen, X. (2022). Estimating fractional snow cover in vegetated environments using MODIS surface reflectance data. *International Journal of Applied Earth Observation and Geoformation*, 114, 103030.
- 35- Yin, H., Xu, L., Li, Y. (2024). A New Retrieval Algorithm of Fractional Snow over the Tibetan Plateau Derived from AVH09C1. *Remote Sensing*, 16(13), 2260. <https://doi.org/10.3390/rs16132260>.
- 36- Parajka, J., Blöschl, G. (2008). Spatio-temporal combination of MODIS images–potential for snow cover mapping. *Water Resour. Res.* 44, W03406.
- 37- Parajka, J., Pepe, M., Rampini, A., Rossi, S., Blöschl, G. A. (2010). regional snow-line method for estimating snow cover from MODIS during cloud cover. *J. Hydrol.* 381: 203–212.
- 38- Gao, Y., Lu, N., Yao, T. (2011). Evaluation of a cloud-gap-filled MODIS daily snow cover product over the Pacific Northwest USA. *J. Hydrol.* 404, 157–165.
- 39- Hori, M., Sugiura, K., Kobayashi, K., Aoki, T., Tanikawa, T., Kuchiki, K., Niwano, M., Enomoto, H. A (2017). 38-year (1978–2015) Northern Hemisphere daily snow cover extent product derived using consistent objective criteria from satellite-borne optical sensors. *Remote Sens. Environ.* 191, 402–418.
- 40- Deng, G., Tang, Z.G., Hu, G.J., Wang, J.W., Sang, G.Q., Li, J. (2021). Spatiotemporal dynamics of snowline altitude and their responses to climate change in the Tianshan Mountains, Central Asia, During 2001–2019. *Sustainability* 13, 39-92.
- 41- Bousbaa, M., Htitiou, A., Boudhar, A., Eljabiri, Y., Elyoussfi, H., Bouamri, H., Ouatiki, H., Chehbouni, A. (2022). High-Resolution Monitoring of the Snow Cover on the Moroccan Atlas through the Spatio-Temporal Fusion of Landsat and Sentinel-2 Images. *Remote Sens.* 14, 5814.
- 42- Dong, C., Menzel, L. (2016). Producing cloud-free MODIS snow cover products with conditional probability interpolation and meteorological data. *Remote Sens. Environ.* 186, 439–451.
- 43- Shen, H., Meng, X., Zhang, L. (2016). An integrated framework for the spatio-temporal-spectral fusion of remote sensing images. *IEEE Trans. Geosocial Remote Sensing.* 54, 7135–7148.
- 44- Zhang, Y., Ye, C., Yang, R., Li, K. (2024). Reconstructing Snow Cover under Clouds and Cloud Shadows by Combining Sentinel-2 and Landsat 8 Images in a Mountainous Region. *Remote Sensing*, 16(1):188. <https://doi.org/10.3390/rs16010188>.