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Evaluation of Object-oriented and Pixel-Based Techniques for Extracting Snow Cover Surface Using Landsat 8 Satellite Images (Case Study: Damavand Mountain Range)

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Highlights

- Evaluation of snow cover extraction methods in mountainous regions using Landsat8 imagery.
- Comparison between object-oriented and pixel-based techniques for accuracy.
- Utilization of SAM classification and NDSI, NDVI, and LST algorithms for image processing.
- Object-oriented method outperforms pixel-based method with a general accuracy of 92%.
- Demonstration of the effectiveness of remote sensing in overcoming challenges in snow cover assessment in inaccessible mountainous areas.

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Abstract

Accurate snow cover extraction is crucial in water resources management, particularly in regions where snowfall contributes to atmospheric precipitation. However, it poses challenges in mountainous areas due to limited accessibility, diverse topographic and physiographic features, and insufficient meteorological stations. To overcome these limitations, remote sensing, which offers multiple advantages like providing information at different scales, extensive coverage, and cost-effectiveness, is employed to assess various snow cover extraction methods in mountainous regions. This study aimed to assess the effectiveness of object-oriented and pixel-based techniques in extracting snow cover using Landsat8 satellite imagery. The pixel-based method relies on classifying numerical values of images, while the novel object-oriented approach takes into account not only numerical images but also background information, texture, and content for classification. The SAM classification method, a pixel-based technique, and object-oriented classification methods, along with NDSI, NDVI, and LST algorithms, were utilized to process the images. Thematic maps were derived from each classification, and their overall accuracy was evaluated in the post-processing stage. The results revealed that the object-oriented classification method exhibited a general accuracy of 92%, outperforming the pixel-based method, which achieved a general accuracy of 81.6%. This demonstrates that the object-oriented method is more precise in extracting snow cover in the mountainous area of Damavand.

Nomenclature

Indices		***Variables***	
OLI	*Operational Land Imager*	b_6	*Minus reflectanceratio of the visible band*
TIRS	*Thermal Infrared Sensor*	b_2	*Middle infrared band*
OO	*Object-Orientated*	M_L	*Multi-band radiance*
SD	*System Dynamics*	Q_{cal}	*Raw image*
SAM	*Spectral Angle Surveying*	A_L	*Add band raddiance*
LST	*Land Surface Temprature*	***Parameters***	
NDSI	*Normalized Snow Cover Index*	L_λ	*Spectral radiation*

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NDVI	*The vegetation Index*	*T*	*Ground surface temperature in degrees kelvin*

1. Introduction

Iran is characterized by low precipitation levels, making it one of the regions with the lowest precipitation. The water sources in Iran primarily comprise superficial and subsurface waters, with the main water supply dependent on precipitation[1]. Snow is a crucial form of precipitation in the hydrological cycle of mountainous regions, serving a vital role in supplying drinking and agricultural water resources through delayed flows during high-water seasons and minimal flows during low-water seasons. Additionally, it plays a significant role in energy production[2]. Despite mountainous areas covering only a small portion of the Earth's surface, they profoundly impact the hydrological landscape of catchments. In numerous regions, snow cover in the mountains plays a crucial role in acting as the primary surface and groundwater supply, thanks to its delayed release of water[3], [4]. Snow serves as a natural reservoir, storing water during winter and releasing it in spring, making it a significant energy source for hydroelectric power during the low-pressure season.

Moreover, this stored water provides essential resources for agriculture and contributes to biodiversity at both local and regional scales[5]. Predicting and estimating runoff resulting from snowfall, along with a quantitative understanding of its diverse production processes, are fundamental challenges in hydrological knowledge. Consequently, achieving a comprehensive and systematic understanding of snow's quantity and quality is of great importance, as it serves as the foundation for studying and implementing development projects in various fields related to water resources, water structures, and environmental aspects in catchment areas[6]. An essential parameter for modeling snow runoff involves estimating the snow cover surface in snow-covered regions. The precise extraction of snow cover surface is regarded as a critical and fundamental operation in water resources management, particularly in areas where snowfall significantly contributes to overall precipitation[7]. The majority of snow-covered areas are situated at high altitudes in mountainous regions. However, accurately measuring snow in these areas is challenging due to limited accessibility, diverse topographical and physiographic characteristics, and insufficient meteorological stations. As a result, the current state of snow measurement in these regions is not satisfactory.

As a result, the accumulation and melting of snow in these areas are not precisely and comprehensively measured. Hence, indirect methods, such as remote sensing, are employed for accurately estimating the snow cover surface in high-altitude areas. Remote measurement is a valuable approach in addressing these challenges[8]. Remote sensing has proven to be a versatile and invaluable tool with numerous advantages, encompassing providing information at different scales globally, nationally, and regionally. Its wide coverage capabilities, cost-effectiveness, ability to generate multi-time information, and diverse applications have found extensive utilization across various fields[9], [10]. One of the applications of remote sensing is the creation of cover maps, such as snow cover maps. A comprehensive set of observations is necessary to accurately analyze snow-related issues, which can be obtained using snow gauges. The Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) sensors offer numerous advantages, including an appropriate number of bands, sufficient spatial resolution, and consecutive time series data, making them suitable tools for this purpose[11], [12]. Damavand, the tallest mountain in Iran and the Middle East and the highest volcanic peak in Asia, features a steep gorge that accumulates a significant amount of snow during the rainy season[13], [14]. Therefore, Damavand's snow-capped heights are among the largest sources of numerous rivers with continued urban, rural, and nomadic life. Therefore, it seems necessary to determine the snow cover surface in this area for research by natural sciences experts, geographers, and water engineers.

The classification of digital satellite imagery is recognized as one of the most crucial methods for extracting practical information, such as the extraction of snow surface data[15]. Currently, the classification of digital satellite images is done by two general methods, which are: (a) classification method based on numerical values of visual or pixel elements (pixel base) and (b) classification method based on visual objects (object-oriented). In conventional pixel-based methods, classification is based on the numerical value of each pixel, which results in the reflection of the corresponding effects on the ground[16]. However, spectral information is merged with spatial information in the object-oriented classification method, and pixels are segmented based on shape, texture, and gray tone at the image surface with a specific scale, where image classification is done based on these segments[17].

Numerous studies have been conducted to compare the capabilities of object-oriented and pixel-based techniques for extracting various applications, some of which are discussed here. One such study employed an object-oriented design approach to illustrate watershed-scale hydrologic processes. This method employed the concepts of 'inheritance' to define individual objects at multiple levels and 'aggregation' to represent the interactions between objects. The result was the development of a novel watershed-based hydrological model known as OBJTOP, which stands for an object-oriented and topographic-based model. The top-level object in this model represented the watershed, encompassing sub-objects such as precipitation, evapotranspiration, vegetation, soil, and channel. The OBJTOP method provided a concise and straightforward demonstration of hydrologic processes. Its model organization offers advantages in model coding, preservation, and future improvements, making the program design strategies appealing to other program designers[18]. Remote sensing methodology has matured importantly during the past decade.

Operational satellites offer reliable and regular coverage for global areas. The data obtained from these satellites is provided in a digital format, which enhances the flexibility of hydrological modeling. In a research paper, object-oriented programming methods were explored to develop dynamic hydrological models. It explored their capacity for receiving actual and near real-time data from remote sensors to make it better.

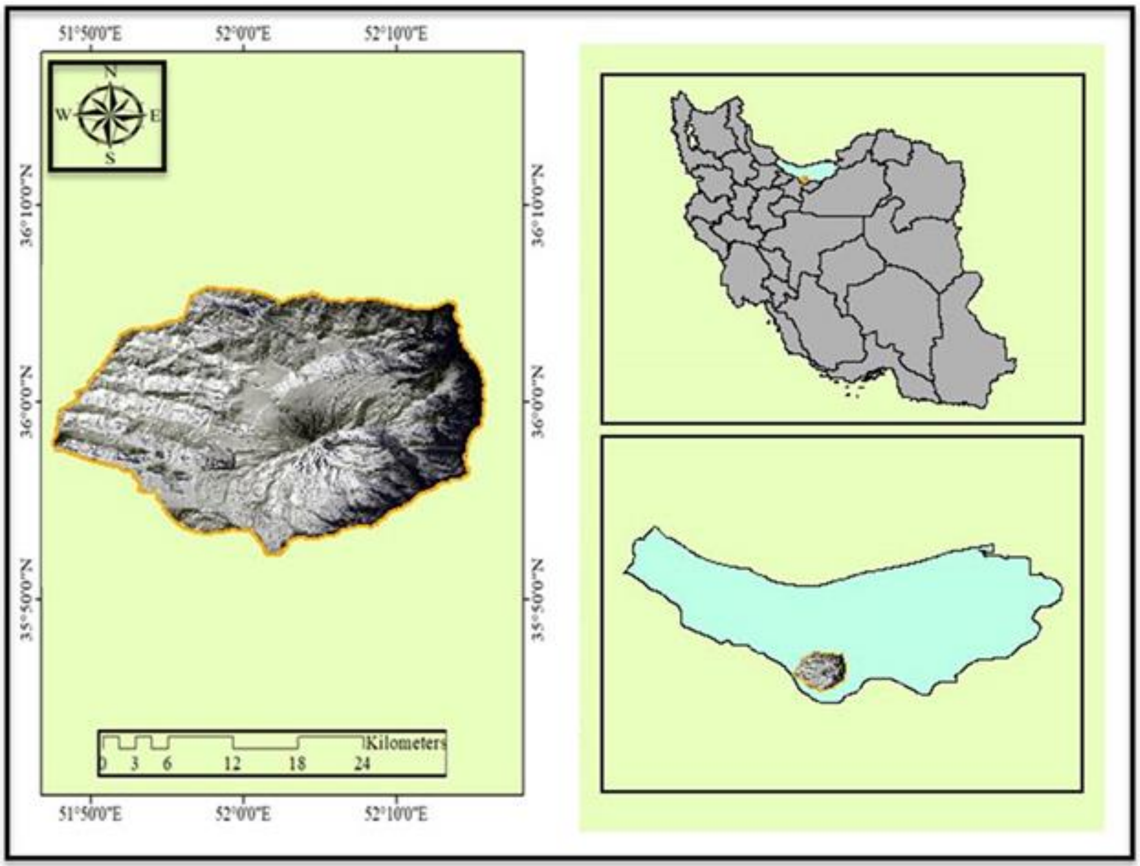

Fig. 1. Location of the study area

Hydrological predictions. The streamflow synthesis and reservoir regulation model were provided to indicate how a developed hydrological model might be adapted for creating a dynamic object model[19]. Another research paper aimed to employ an Object-Oriented (OO) method based on System Dynamics (SD) concepts to analyze the dynamics of a hydrological system at a watershed scale. The application of this approach was demonstrated using an Iranian watershed as a case study. The model underwent validation and verification tests, and the outcomes revealed that the developed model effectively simulated monthly runoff[20]. A study was organized to evaluate the accuracy of different data in snow cover mapping under Himalayan conditions. The results were compared with a ground-based approximation of snow cover. A suitable correlation

resulted between satellite-based estimations and ground-based ones[21].

The present study aimed to assess the accuracy of snow cover surface calculations in the Damavand Mountain area using two processing methods: object-oriented and pixel-based. Due to the high cost, limited accuracy, and infrequent readings from snow metering stations, Landsat8 satellite imagery data was utilized for snow cover extraction. The Landsat8 satellite imagery, with sensors offering a spatial resolution of 30 meters for OLI and 90 meters for TIRS, was chosen due to its high spatial resolution. Hence, this study aimed to evaluate the capability of the object-oriented and pixel-based methods using OLI and TIRS sensors for extracting the snow cover surface in the Damavand Mountain range.

2. Materials and methods

2.1. Location of the study area

Damavand is located in the central part of Alborz and the northern direction of Haraz valley of Mazandaran, in the Larijani section of Amol city, 62 km west of Amol, 26 km north of Damavand city, and 69 km northeast of Tehran. The area studied by Damavand in the present study is between longitudes ’59 ˚51 to ’16 ˚52 east longitude and ’49 ˚35 to ’05 ˚36 north latitude (Fig.1). With a height of 5671 meters, Damavand is the highest peak in Iran and is part of the Central Alborz Mountain range. Damavand mountainous area with mild summers and snowy winters is very heavy, and the amount of rainfall in this area is 540 mm per year, which Downpours at altitudes of more than 3,000 meters is mainly in the form of snow. Also, according to climate maps, the maximum precipitation at altitudes between 3000 and 4000 meters reaches 775 mm. The presence of large permanent glaciers is a feature of this mountainous region.

2.2. Applied Data

The present study evaluates the accuracy between pixel-based and object-oriented methods in extracting the snow cover surface of the study area from the images of OLI and TIRS sensors, Landsat8 satellite, dated 11/24/2015 (No. Passages and rows 35 - 164), have been used. The process of obtaining the required images involved sending a formal request to the US Geological Survey, and subsequently, the relevant images were acquired from the specified site (refer to Table 1 for the site details). The characteristics of the multispectral OLI sensors and the thermal bands of the TIRS are detailed in Table 2. Also, in this research, the capabilities of Envi, eCognition, and Arc Map software were used to perform pre-processing, processing, classification, and accuracy evaluation. Fig. 2 shows the general research process.

Table 1. Image specifications used in the research

	Sensors	Row	Transition	Date	Base	Correction level
Landsat8	OLI	35	164	02/13/2016	WGS84	LIT
Landsat8	TIRS	35	164	02/13/2016	WGS84	LIT

Table 2. Features of the multispectral OLI sensors and TIRS thermal bands

Sensors	Spectral Band	Wavelength (µm)	Pixel-size (m)	Swath width (km)
OLI	Band 1 - Coastal/Aerosol	0.0 – 433.453	30	185
	Band 2 – Blue	0.0 – 450.515	30	185
	Band 3 – Green	0.0 – 525.600	30	185
	Band 4 – Red	0.0 – 630.680	30	185
	Band 5 - Near-infrared	0.0 – 845.885	30	185
	Band 6 - Short wavelength infrared	1.1 – 560.660	30	185
	Band 7 - Short wavelength infrared	2.2 – 100.300	30	185
	Band 8 - Panchromatic	0.0 – 500.680	15	185
	Band 9 - Cirrus	1.1 – 360.390	30	185
TIRS	Band 10 - Thermal infrared	10.11 – 30.30	100	185
	Band 11- Thermal infrared	11.12 – 50.50	100	185

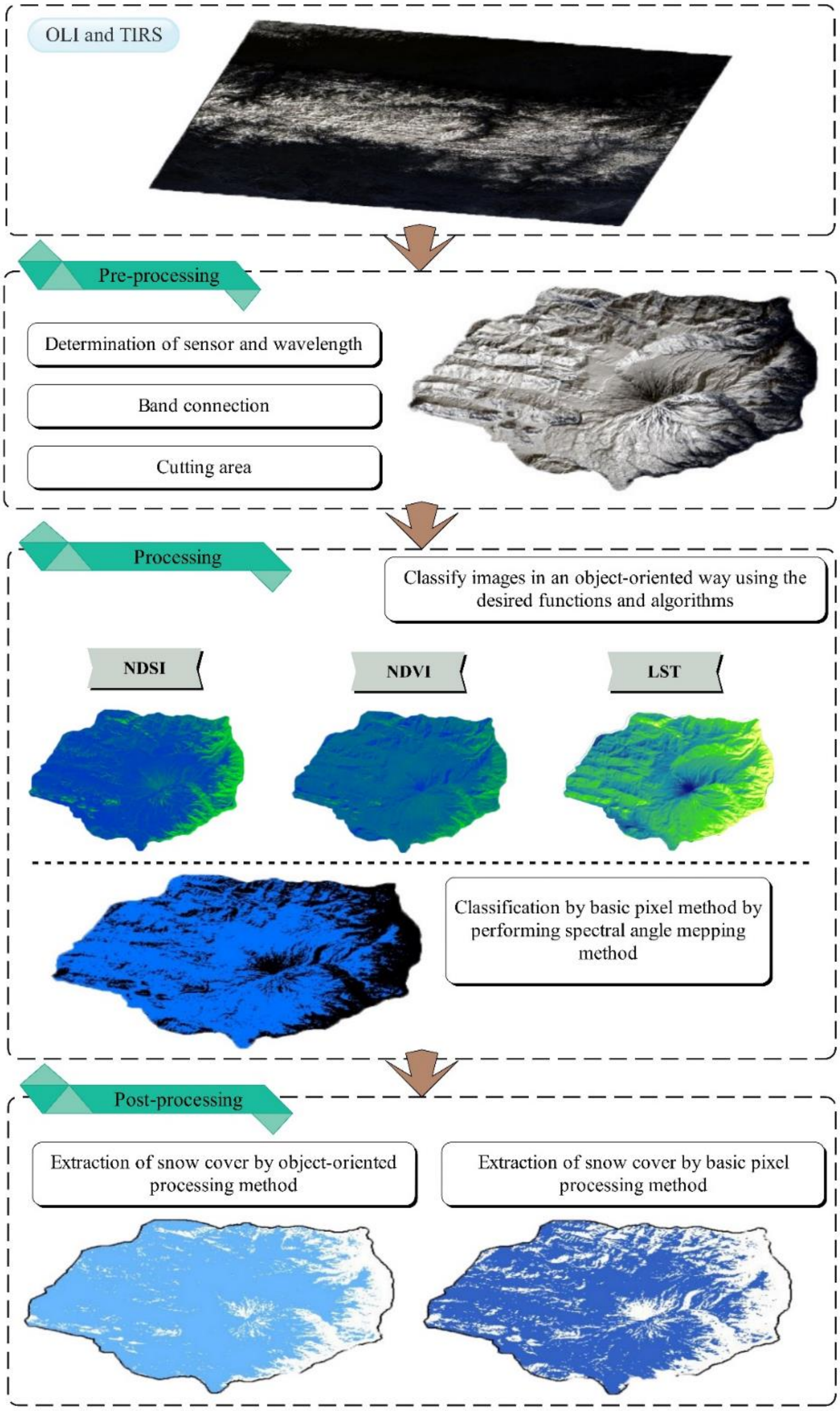

Fig. 2. Research general process

2.3. Checking the quality of images

The pre-processing operation, which in some cases is interpreted as the retrieval and restructuring of an image, is the execution of all actions while correcting all possible distortions and errors by extracting them from the basic information. This study examined the quality of images before any analysis and data processing for atmospheric and geometric error. Therefore, this study applied the flash method to the images for atmospheric correction. The classification process should be highly accurate by eliminating atmospheric effects. Also, applying this type of image can be normalized to compare.

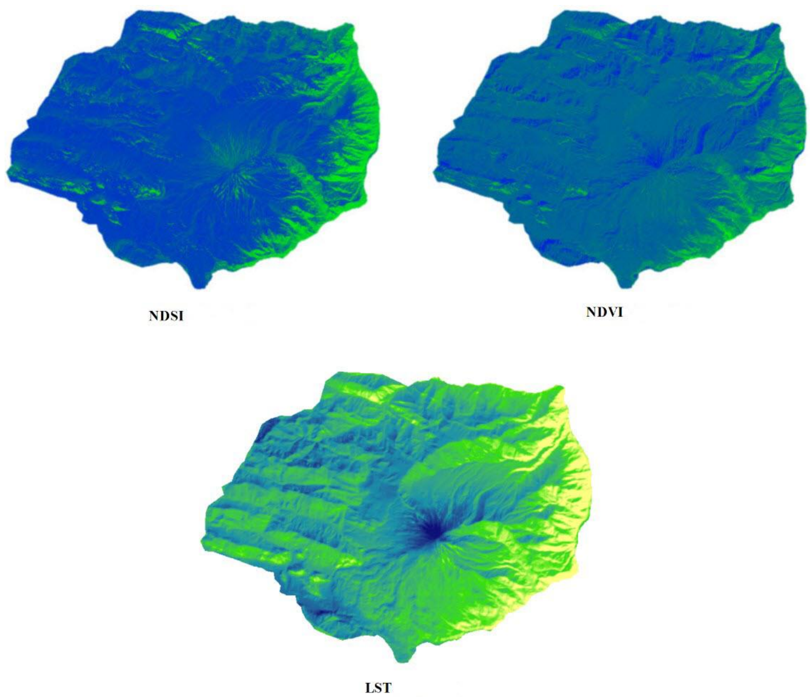

Fig. 3. Functions used in object-oriented image processing

Geometric errors also cause displacement, deformation, and alteration of the status of effects on the image, so these errors must be removed or reduced from the image. To check the geometric condition of the images and ensure the appropriateness of the geometry of the images, vector layers of roads and waterways were placed on the satellite images. By doing this method, the geometric accuracy of the images used was ensured.

2.4. Preparing images

After downloading the images related to the study area and ensuring the absence of common errors, Envi 5.3 software was used to determine the wavelength, type of sensor, and integration of the required images. After this step, the image integrated into the ArcMap10.4.1 software environment was cut according to the study area, saved in IMAGINE Image format, and entered into eCognition and Envi 5.3 software to Prepare for classification and extraction of snow cover surface.

2.5. Stage of satellite image processing for classification

Classification is one of the most important goals of satellite image processing processes. The final result is usually the creation of thematic maps of land cover with specific land-use features. In general, classification consists of two stages: The first step is identifying the categories or classes of real complications. In remote sensing, these categories can include, for example, forest areas, water, pastures, snow, and other types of cover, which geographically depend on the scale and nature of the study area. The second stage of classification is labeling the components that need to be classified. Classification methods are divided into supervised and unsupervised methods based on whether they also use non-visual information for image analysis or classify exclusively based on image data. In this research, pixel-based and object-oriented types of monitored classifications have been used.

2.5.1. Image classification based on pixel base

In the context of pixel-based classification, the process involves labeling images using statistical parameters associated with their pixel values. Besides the input images, this method relies on external information about the region and the classes involved. Human intervention becomes necessary in this approach, which is referred to as supervised classification. Supervised classifications typically seek resemblances with the known pixels of each class.

2.5.1.1. Spectral Angle Surveying (SAM) Classification Method

The present study uses the spectral angle mapping (SAM) method to extract the snow surface in the study area by a pixel-based method. This method is a physics-based spectral classifier and compares an N-dimensional angle from a reference spectrum with image pixels. This algorithm determines the spectral similarity by calculating the angle between the spectrum and the training pixels as vectors in the space of equal dimensions for several bands. The final spectral member used in the SAM method can be obtained through ASCII files, spectral library, or directly from an image (ROI); in this study, the final member was removed from the snow surface in the form of ROI.

2.5.2. Image classification based on object-oriented techniques

Object-oriented classification is a process that connects land cover classes to visual objects. After the classification process, each visual object is assigned to one (or none) class. This classification is based on fuzzy logic and converts the value of tolls to a fuzzy value (between zero and one) with a certain degree of membership for each class. In this process, the pixels are classified with different degrees of membership in more than one class. The classification is done according to the nearest neighbor algorithm based on each class's degree of membership.

2.5.2.1. Segmentation of images

Segmentation stands as the primary and crucial phase in micro image classification, dividing the images into distinct units for further analysis. In the context of image analysis, a segment refers to a cluster of neighboring pixels within an area, characterized by their significant shared attributes, such as texture similarity and numerical value. The whole image is segmented during the segmentation process, and the image objects are produced based on the homogeneity criterion in color and shape. Adjusting the scale parameter directly affects the average of the image object's size, and the large value allows large image objects to be created. Conversely, smaller segments are produced by selecting a small number as the scale. In addition to the scale parameter, the appropriate strip composition for classification is another effective parameter in segmentation quality. In an object-oriented analysis of images, in addition to the possibility of using the best strip composition for segmentation, the possibility of applying weight to each of the tapes is also available. In the present study, Multi-Resolution Segmentation and Spectral Difference Segmentation were used, and the RGB strip combination was used 2-5-7 for the images of the study area. For this purpose, by analyzing the results of the segmentation of images with different scale parameters and spatial separation of images, the scale parameter 60 was selected for segmentation. Due to the importance of bands 2-4-6 and land surface temperature (LST) for segmenting, the weights shown in Table 3 were applied. Also, the softness criterion was 0.4, and the compression coefficient was 0.6

Table 3. Selected weights for the selected strip composition in the image segmentation process

Picture bar	Applied weight
Band 2	20
Band 3	10
Band 4	20
Band 6	20
LST	30
Total	100

2.5.2.2. Object-oriented classification of images

Object-oriented classification is a process that links land cover classes to graphical objects. Each image object is assigned to one or none of the classes in this process. Each object's membership degree is determined by the interpreter for the classes and is classified based on the highest degree of membership in a given class. This type of classification is a recurring process in the eCoginition software environment. This means that the classification is done several times to achieve the highest membership degree for the classes. Each visual object was attributed to different classes based on their degree of membership during the object-oriented processing process. In eCognition software, defining the appropriate conditions for each class forms the basis of fuzzy classification. By determining the characteristics related to spectral information and geometric characteristics of classes during the image processing process, fuzzy logic operators, including Max, or operator with the maximum return value of fuzzy value, the arithmetic mean of fuzzy value, the geometric mean of fuzzy value, and the and operator, a recursive operation can be used as the result of multiplication of fuzzy value and define the appropriate conditions for classification[22]. In the present study, in addition to the fuzzy and algorithm (recursive operator as the product of the fuzzy value), NDSI, NDVI2, LST algorithms have been used to classify and extract the snow cover surface (Fig.3).

2.6. Normalized Different Snow Cover Index (NDSI)

Normalized Snow Cover Index (NDSI) is a spectral ratio obtained from the spectral difference between infrared and visible bands to detect changes in snow cover surface. This index uses the advantages of snow spectral reflection in the visible band with high reflectivity and infrared spectrum range that has low reflectivity to highlight the snow from the cloud and areas without snow cover. Like many ratio methods, Spectral capture reduces the effects of the atmosphere[23]. In Landsat8 images, this algorithm is obtained from the minus reflectance ratio of the visible band (band 2) and the middle infrared band (band 6) divided by the total reflectance in these two bands (Equation 1).

$$NDSI=\frac{b6-b2}{b6+b2} \qquad (1)$$

According to Equation 1, the NDSI algorithm was created in the eCognition software environment, and the threshold used to extract the snow cover was set to $NDSI \geq 0.4$. A commonly used approach is to set a threshold value to threshold the NDSI and determine whether a pixel represents snow. Pixels with NDSI values above this threshold are classified as snow, while those below the threshold are classified as non-snow. The optimal threshold value can vary depending on the specific satellite sensor, the snow conditions, and the study area. A typical threshold value for NDSI to identify snow is around 0.4 or 0.5, but it is crucial to adjust this value based on the characteristics of the data and the specific application. At a threshold greater than 0.4, the NDSI analysis successfully distinguished snow from other land cover types, according to[24]. This algorithm alone is not accurate enough to extract the snow surface, i.e., snow inside the valleys cannot be extracted through this algorithm. Therefore, NDVI and LST algorithms were used to extract snow surfaces accurately.

2.7. Normalized Different Vegetation Index (NDVI)

This index is one of the most famous, simplest, and practical indicators for separating snow from soil and vegetation.

Through this index, the land use that was mixed with snow cover was isolated. Also, during the implementation of the LST index, those surfaces that did not have snow cover but had a temperature equivalent to snow were separated using this algorithm. This algorithm was used as a filter on the LST algorithm to solve mixing snow with other users. This index was calculated through Equation 2.

$$NDVI=\frac{b5-b4}{b5+b4} \qquad (2)$$

In this equation, b4 and b5 are the red and infrared bands close to the OLI sensor.

In the eCognition software environment for snow extraction, the NDVI threshold > 0.4 was considered, and the result of this algorithm distinguished land users mixed with snow. The choice of the NDVI threshold depends on the analysis's specific objectives and the study area's characteristics. The NDVI > 0.4 is better for identifying areas with moderate vegetation cover, according to.

2.8. Ground surface temperature (LST)

In the last few decades, the estimation of ground surface temperature has improved significantly through satellite data. Since the ground surface temperature is one of the most applicable layers for extracting snow cover surface, this algorithm has been used in the present study to extract snow cover in the study area. Different algorithms have been proposed to estimate the ground surface temperature. In the present study, due to the high accuracy and suitability of band 10 compared to band 11, the single band algorithm of the TIRS sensor 10 band has been used to calculate the ground surface temperature. In order to calculate the ground surface temperature in Landsat8 images, the digital values of the image must be converted to spectral radiation (DN to Radiance conversion) related to band 10 using Equation

$$L_{\lambda}= (\ M_L * Q_{cal}\ )+ A_L \qquad (3)$$

L_{λ}: Spectral radiation.
M_L: Multi Bands Radiance.
Q_{CAL}: Raw image.
A_L: Add Band Radians

The "M_L" and "A_L" parameter numbers were obtained from the image reference file, which has different numbers in different images.

The ground surface temperature map was obtained after converting DN to Radiance through Equation 4 (Fig. 4).

$$T=\frac{K_1}{\text{In}\left(\frac{K_2}{L_{\lambda}}\right)+1} \qquad (4)$$

T: Ground surface temperature in degrees Kelvin.

Values K_1 and K_2 are available in the image reference.

Lλ: Band 10 radiance.

The threshold considered at this stage for ground surface temperature was higher than -1, and the vegetation index (NDVI) was lower than 0.2 (LST> -1 and NDVI <0.2).

In connection with the three algorithms proposed for snow surface extraction, it can be said that these algorithms complement snow surface extraction and provide better output and high accuracy. Then, using the expressed three algorithms, the snow cover surface was extracted, and the problem of mixing snow with cloud surfaces and other users was solved.

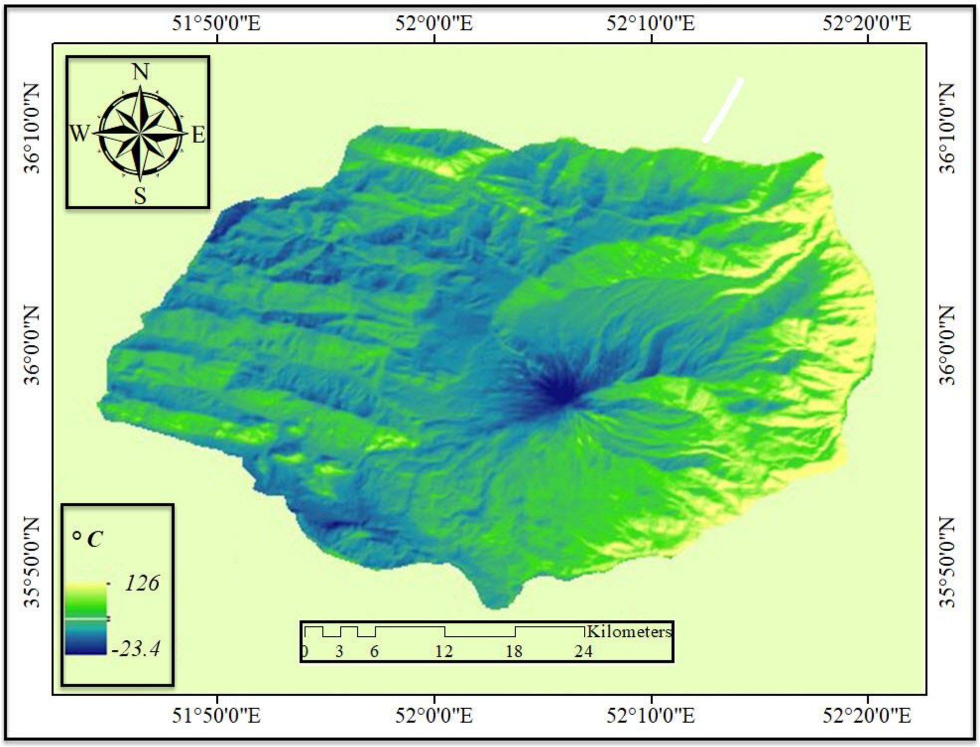

Fig. 4. Ground Surface temperature map

2.9. Assessing the accuracy of classification

It is necessary to use any local information to be aware of its accuracy. Therefore, no classification is complete until its accuracy has been assessed, and to ensure the accuracy ratio of the map extracted from satellite images, its accuracy must be evaluated. The accuracy of classification indicates the level of trust in the extracted map. General accuracy has been used to evaluate the classification accuracy performed by object-oriented and pixel-based methods. Overall accuracy is the average classification accuracy, which indicates the ratio of the correctly classified pixels to the sum of all specified pixels (Equation 5).

$$i=\frac{n_{ii}}{n_{i_+}}*100 \tag{5}$$

In the above equation, “i” to the user as a percentage, “n” _ “ii” is the number of segments correctly classified in each class, and “n” (“i” _” +”) is the total number of segments that are both correctly and incorrectly classified.

3. Results and Discussion

Object-oriented classification is a novel approach for extracting various land cover features. While the pixel-based method has traditionally been employed in recent research to extract snow cover, the object-oriented method offers a promising alternative for improved accuracy and efficiency in land cover classification. The present study has evaluated the capability of object-oriented and pixel-based techniques for snow surface extraction. In this study, the spectral angle mapping (SAM) method was used for classification based on the pixel-based method, shown in Fig. 5.

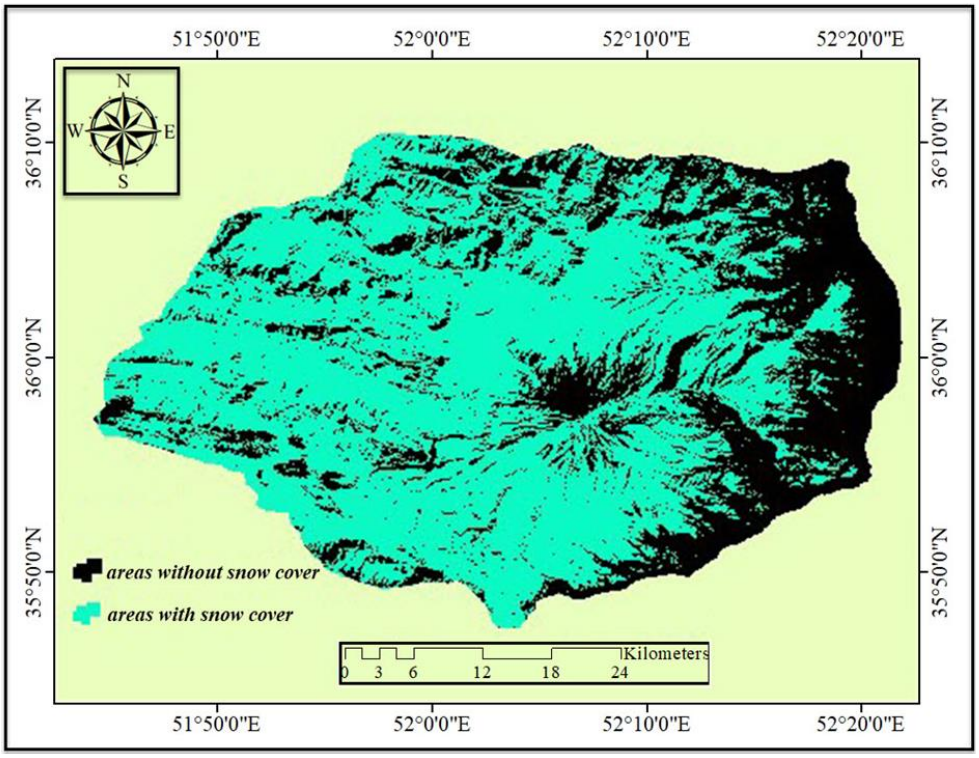

Fig. 5. Result of the snow cover surface extracted by pixel-based processing method

The pixel-based method was employed to extract the snow cover surface by analyzing image pixels and utilizing exclusively the designated training points. Visual interpretation of the snow cover extracted in Fig. 5 determined that the pixels were accurately classified. The areas identified as snow exhibit snow cover, while the remaining parts encompass other users. By lowering the accuracy of snow extraction, the possibility of extracting all snow surfaces is difficult. The overall accuracy of the extracted snow cover surface map for the study area was 81.6% (Table 4).

Table 4. Pixel-based classification error matrix

Class	Snow cover	Other users	Total
Snow cover	6258	0	6258
Other users	0	1485	1485
Total	6258	1485	
Overall accuracy: 81/6			

The assigned Class method in the eCognition software environment was used to classify the images in an object-oriented way. Because in the object-oriented method, the pixels are divided according to the image surface's shape, texture, and gray tone. The issue of pixel fusion is effectively resolved by converting the pixels into image objects. This approach enables a more coherent representation of the data, enhancing the accuracy and quality of the results. Thus, the classification accuracy increases by assigning each object to a specific user. Also, the use of complementary algorithms such as LST, NDVI, and NDSI algorithm strengthens the accuracy of the results of the above method compared to basic pixel-based classification. The final result of the snow cover surface map by object-oriented method for the study area is shown in Fig.6, obtained with an overall accuracy of 92% (Table 5).

Table 5. Object-oriented classification error matrix

Class	Snow cover	Other users	Total
Snow cover	7040	0	7040
Other users	0	472	472
Total	7040	472	
Overall accuracy: 92			

Improvement: Integrating high spatial resolution data (Landsat 8) and the novel object-oriented image classification method has yielded remarkable outcomes. Apart from successfully extracting snow cover on various slopes of the study area, the algorithms demonstrated the ability to accurately detect snow cover within valleys, even under challenging conditions. The approach adopted has proven appropriate and acceptable in achieving these commendable results. By applying the LST algorithm within the object-oriented processing approach, it became feasible to differentiate and detect snow from clouds effectively, leading to favorable outcomes in snow surface analysis. The results in Fig.7 show a better understanding of the presented content.

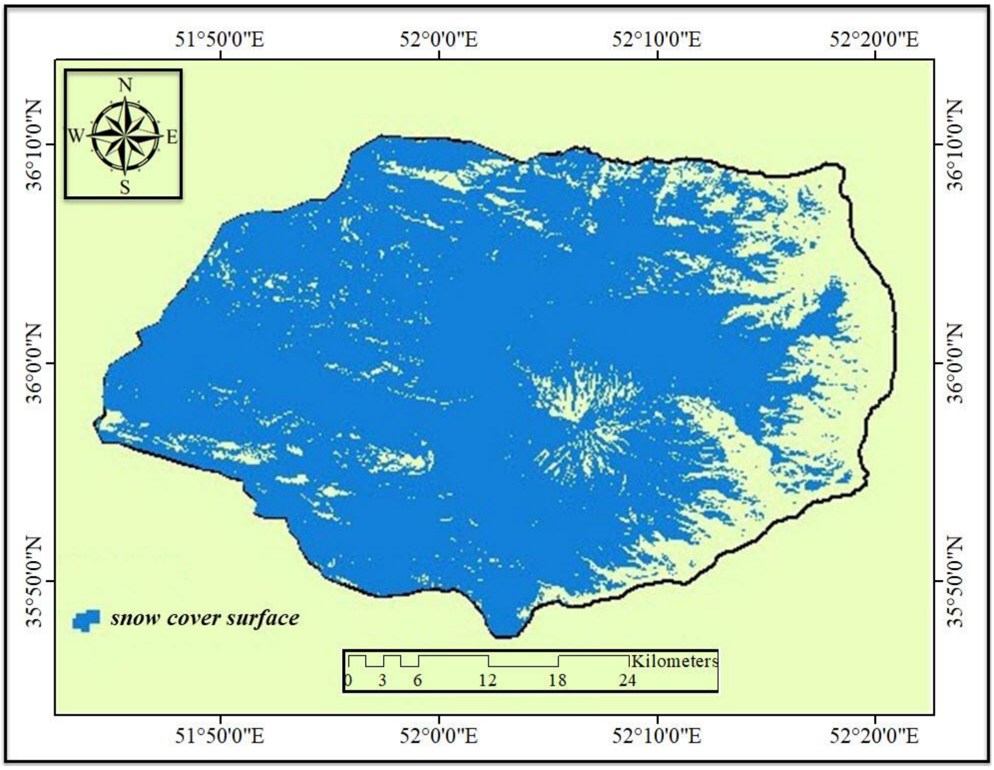

Fig. 6. Result of snow cover surface extracted by object-oriented processing method

Fig.8 shows the final result of the snow cover surface extracted from the study area in an object-oriented and pixel-based method. As can be seen in the research result, the snow cover surface has been estimated with very suitable accuracy by the object-oriented classification method. All the snow surfaces inside the valleys and slopes that cannot be extracted by the pixel classification method have been extracted. Also, the comparison of the result of the present study with recent research proves the accuracy of the object-oriented technique for classifying images to extract the surface of snow cover. Given the object-oriented classification method's superior accuracy compared to the pixel-based approach, the results obtained from this method hold great promise for effective water resource management in mountainous regions, where snow constitutes a significant portion of the precipitation. This method's reliable snow cover data can contribute substantially to informed decision-making and planning in critical areas.

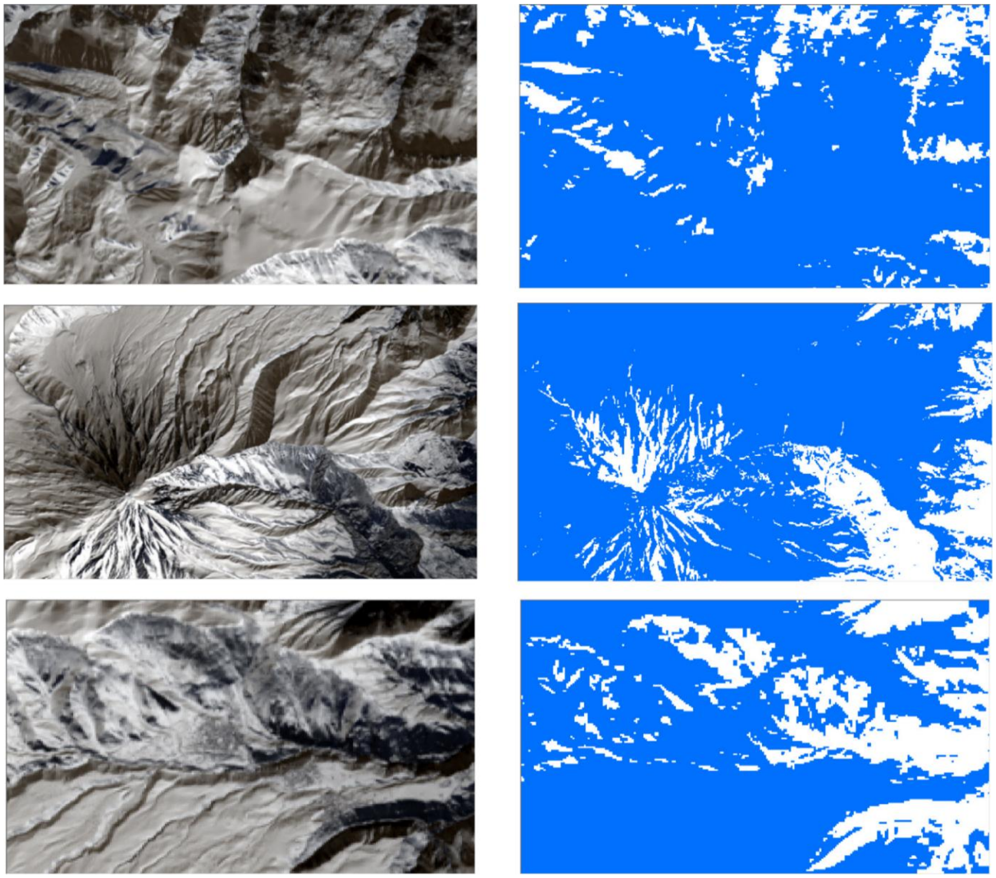

Fig. 7. Demonstration of the results obtained from the snow cover surface

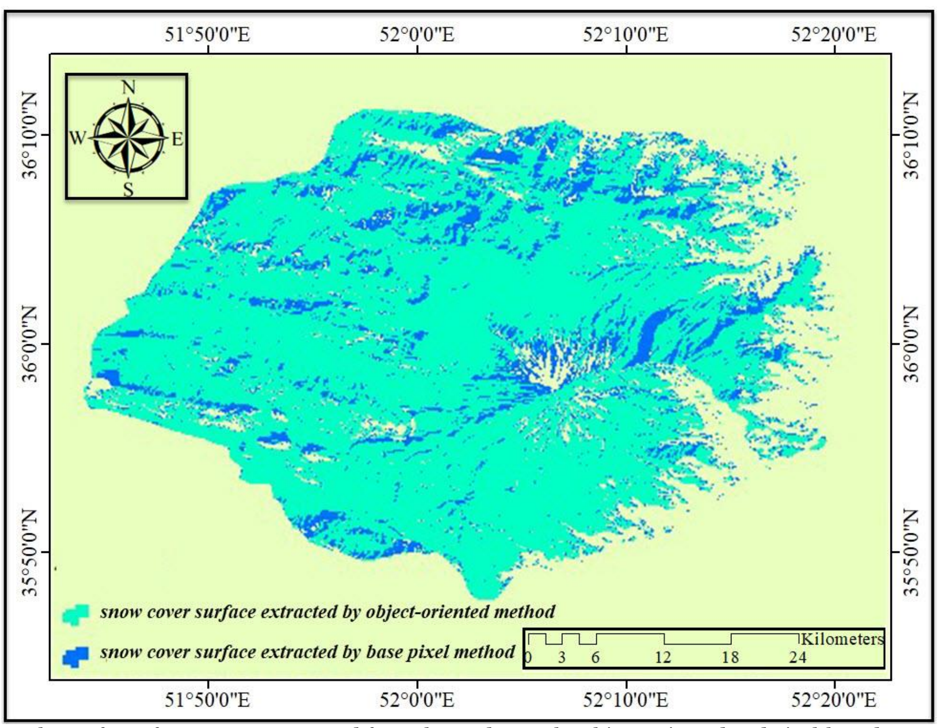

Fig. 8. The surface of snow cover extracted from the study area by object-oriented and pixel-based processing

4. Conclusion

This study aims to evaluate pixel-based and object-oriented methods in extracting snow cover surface in the

Damavand Mountain range from images of OLI and TIRS sensors of Landst8 satellite as well as SAM classification algorithms in pixel-based classification and Assign class was used in the object-oriented classification method. Pre-processing, processing, and post-processing steps with emphasis on training examples have been done in the Envi software environment (for implementation of classification by SAM method), eCognition (for implementation of object-oriented classification), and Arc Map (for preparing final and thematic maps), and finally, by calculating the overall accuracy for each classification method, it was concluded that the object-oriented method with an overall accuracy of 92% compared to the pixel-based method with an overall accuracy of

81.6 % has high accuracy. One of the reasons that made the object-oriented method more accurate than the pixel-based method is the classification of the object-oriented method based on image objects, which solved the problem of pixel fusion, as well as the use of this method by LST and NDVI algorithms as a supplement to the NDSI algorithm for accurate extraction of snow cover surface in the study area. As observed as a result of the research, the use of object-oriented processing methods and Landsat8 satellite images in the classification of images attain the required efficiency in extracting snow cover surfaces in mountainous regions. Due to the precise estimation of the snow surface and the cost-effectiveness of utilizing this satellite imagery type, the advantages of this type of image can be used with great confidence to check the surface of snow cover. The method presented in this research to estimate the snow surface can be a suitable guide for students and professors working in this field.

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