Comparing the Performance of Fuzzy Operators in the Object-based Image Analysis and Support Vector Machine Kernel Functions for the Snow Cover Estimation in Alvand Mountain

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Abstract

Snow cover is a significant driver in many ecological, climatic, and hydrological processes regarding the mountainous regions and high-latitude areas. Researchers believe that remote-sensing data can provide better estimates of snow cover ranges in comparison with the traditional surveying methods. Therefore, the present study was conducted using Sentinel-2B satellite images to compare the performance of the support vector machine (SVM) kernel functions and object-oriented fuzzy operators in estimating the amount of snow cover in the Alvand Mountain. In this research, the data consists of four Sentinel-2B satellite bands at 10 m spatial resolution (B2, 3, 4 & 8), launched on March 6, 2020. In this research study, the linear, polynomial, radial, and sigmoid SVM kernel functions, as well as the object-oriented fuzzy operators (AND, OR, MGE, MAR, MGWE, and ALP) have been employed. The results indicated that among these algorithms, AND algorithm, which represents the logical commonality, included the lowest return fuzzy value of 98%; therefore, this algorithm seems to provide the overall highest accuracy. Based on these findings, in the digital image classification, the object-oriented processing method can make it possible to achieve the highest accuracy compared to the SVM kernel functions. The reason is that a wide range of information, such as texture, shape, position, content, and bandwidth is associated with the objects in this classification method.

1. Introduction

Snow is an important water resource. In the mountainous regions, particularly the arid ones, snowmelt water is the primary source of many rivers. Moreover, the global radiant energy balance is highly affected by the albedo and low thermal conductivity of snow cover (Liu, C et al 2020). Also, in such high-latitude areas, the snow cover is a significant driver in many ecological, climatic and hydrological processes (Gascoin, S et al 2019). Since snow can be considered as the water storage with a short delay during the seasonal run-off, it constitutes a crucial component of the hydrological cycle (Muhammad, S. and Thapa, A 2020). Thus, the seasonal snowpack has considerable control over the hydrology and economy in many mountainous and cold regions globally. Similarly, the snow variability affects various ecological procedures, such as the species composition, distribution, and phenology (Alonso-González, E et al 2018). Therefore, achieving a deeper understanding of the present and future climate, water cycle, and ecological changes requires an accurate assessment of the seasonal snow cover. The climatological, hydrological, and ecological significance of snow cover is linked to its energy storage, high reflectance, good insulating properties, remarkable thermal capacity, being a substantial water storage resource, with the eventual release during the melting season (Czyzowska-Wisniewski, E et al 2015).

Monitoring the snow cover is an important means of studying its spatial and temporal changes, as well as the distribution analysis of the regional precipitation. This climatic phenomenon can be assessed using the measuring stations, modeling, remote sensing technology, and applied programs. Although accurate information regarding the measurement location can be provided through the ground stations, these stations are still limited in terms of the spatial scale; that is because providing sufficient information to produce long-term data about snow (on a spatial scale) is not achievable in many parts of

the world when the information is obtained through a scattered network of meteorological stations. Nevertheless, the spatial and temporal characteristics of snow can still be monitored through modeling. Yet, the accuracy of such modeling results has been proven to be low due to the lack of information regarding the initial conditions (Azizi, G et al 2017). Moreover, due to the limited number of meteorological stations and the pointwise measurements thereof, these stations are not suitable alternatives for studying snow as a continuous phenomenon. Also, the snowfield measurement and sampling are timely procedures and not cost efficient. Alternatively, using remote sensing technology not only makes it possible to access high-altitude sites, but also it is generally less expensive than the formerly mentioned methods. Furthermore, satellites are proper imagery tools for measuring snow cover due to the snow reflectance and the visible contrast between snowfields and most surfaces (Raispour, K 2016). Remote sensing data can provide better estimates of snow cover ranges compared to the traditional surveying methods. Thus, nowadays, the use of remote sensing data with more accurate information on snow cover is an operational method of efficient water resource management (Mirmousavi, S. H. and Saboor, L 2014).

The image processing methods of remote sensing can be divided into two general categories. The first category with a single-pixel processing unit is called the pixel-based method. The processing units in the second category include image objects or a group of pixels; in other words, since a homogeneous group of pixels or the object image is the main processing unit, the image is processed in the object space and not in the pixel one; this makes it possible to define additional properties other than the spectral one, such as the shape, size, texture, and neighborhood (Momeni, M., Khosravi, I. and Mostaejran, B 2013). There are many research studies worldwide on measuring the snow cover level and the trend of its changes using remote sensing. For instance, Lopez et al. (2008), after monitoring the images from the period of 2000–2006 based on the NDSI index, examined the amount of snow cover and its changes in northern Patagonia. The results of this study marked the minimum snow cover with an area of 3600 km² in March 2007 and the maximum snow cover with an area of 11323 km² in August 2001. Boi (2009) presented a snow cover monitoring technique for Italy and the Alpine regions using visible, near infrared and infrared MSG data. Accordingly, the monthly and annual maps regarding the snow cover frequency has been estimated (Boi, P 2010). In another study, Mölg et al. (2010) examined and controlled the snow cover data of MODIS multi-temporal imagery at high altitudes of Italy. In this study, snow cover estimation in time-series images from 2002 to 2008 was conducted; the output maps were derived from combining Aqua and Terra snow cover maps, thereby reducing the cloudless and value-free pixels. Additionally, the snow cover maps, obtained from Landsat E.T.M. + satellite images, were utilized to validate the results. Moreover, this study confirmed the classification improvement by a combination of Aqua and Terra images. Finally, using the object-oriented fuzzy classification and Landsat satellite data, Farhan et al. (2018) estimated the changes in the seasonal snow cover level in the Astore River Basin (western Himalayan part of Pakistan). Subsequent to the segmentation of the satellite images, the degree of fuzzy membership was determined, and the area's snow cover level was estimated. As such, López-Moreno et al. (2020) considered the long-term trends of snow cover duration and depth from December to April of the years from 1958 to 2017 in the Pyrenees. The Mann–Kendall test illustrated that snow cover duration

and its average depth decreased during the research time scope; moreover, the persistent warming was proved to be a major factor for the snow cover decrease in the Pyrenees.

At last, the present study was performed to compare the performance of the support vector machine (SVM) kernel functions and object-oriented fuzzy operators in estimating the snow cover amount in Alvand Mountain (Hamadan Province, Iran) using Sentinel-2B satellite images.

2. The Study Area

Alvand Mountain is an individual mountain with an area of 1375 km², in the eastern branches of the central Zagros Mountains, located near the cities of Hamadan, Tuyserkan, Asadabad, and Bahar. It is connected to the Mounts Khodabandehlou and Chehel-Cheshmeh in the Kurdistan Province from the north-west and it stretches towards Rasvand altitudes and Mount Vafs in Arak from the south-east. The ridge of Alvand Mountain forms a natural boundary among Hamadan, Tuyserkan, and Alvand; moreover its highest peak with an altitude of 3584 meters is located 18 km to the south of Hamedan city. Geographically, this mountain divides the Hamadan Province into northern and southern parts while stretching from the north-west to south-east (Jafari, G. and Hosseini, S. A 2017). In Fig. 1 the location of the study area has been demonstrated.

3. Data And Method

The data used in this research consists of four Sentinel-2B satellite bands at 10 m spatial resolution (B2, 3, 4 & 8) that were launched on March 6, 2020. These bands were downloaded from the Sentinel Online technical website (sentinel.esa.int). The radiometric corrections were performed using the Sen2Cor plugin in the SNAP software. Subsequently, the bands were saved as an information layer with the TIFF extension. ENVI image analysis software was used to classify the SVM kernel functions and the calculation of accuracy. The Trimble eCognition Suite was utilized for the segmentation and classification of object-oriented fuzzy operators and the calculation of the accuracy. Finally, the most accurate algorithm was converted into a shape file using the ArcMap software and the area of snow cover was obtained. In Fig. 2 the research steps have been summarized.

4. Theoretical Foundation Of Research

4 – 1. Support vector machine

SVM is a machine learning method based on statistical learning theory (SLT). It can automatically discover the support vectors that draw great distinctions in classification; thereby it constructs a classifier that maximizes the class intervals, thus providing higher classification accuracy and better generalization (Wei, M et al 2019). Support vector machines (SVMs) are nonparametric statistical learning algorithms, originally aimed for binary classification by defining an optimal hyperplane with the maximum margin separating the two classes. In the case of nonlinear classification, to define the optimal hyperplane, SVMs

use various types of kernels that convert the nonlinear boundaries to linear ones in the high-dimensional space (Ustuner, M et al 2015). In machine learning, SVM analyzes the classification and regression analysis data. With training examples, the SVM algorithm develops a model that designates new instances to the suitable category (Goel, A. and Mahajan, S 2017). In other words, based on a set of input data and data training, the support vector machine could predict to which class any given data input belongs (Priyadharshini, S et al 2019). This algorithm is less sensitive to the phenomena related to multidimensional spaces. Therefore, it is a suitable method for classifying multispectral and hyperspectral data. Another advantage of this algorithm is that even with small training data, it can provide high accuracy in image classification (Daneshi, A et al 2016). In this algorithm, as described in Table 1, kernels are used to define how the separator hyperplane is placed.

Table 1: Kernel functions used in SVM.

No	Algorithm	SVM kernel functions
1	Linear	$K(x_i, x_j) = x_i^T x_j$
2	Polynomial	$K(x_i, x_j) = (gx_i^T x_j + r)^d, g > 0$
3	Radial basis	$K(x_i, x_j) = \exp(-g\ x_i - x_j\ ^2), g > 0$
4	Sigmoid	$K(x_i, x_j) = \tanh(gx_i^T x_j + r)$

In this table, “ x_i, x_j ” is a training data set and “ g ” (gamma) represents a user-defined parameter as the kernel width; “ d ” shows the polynomial degree, “ r ” stands for the bias, and “ T ” is the unit matrix. In polynomial, radial, and sigmoid kernels, a penalty parameter would be used to improve the classification error; as it increases, the classification error is somewhat reduced. Similarly, bias is used in the polynomial and sigmoid kernels (Rezaei Moghaddam et al 2015).

4 – 2. Object-based image analysis (OBIA)

Although the high spatial resolution satellite images have advantages in observing the surface of the Earth in detail, there are challenges and limitations regarding the data processing, such as image classification. The former pixel-based analysis of remote sensing data resulted in imprecise identification of certain crops due to the pixel heterogeneity, mixed pixels, spectral similarity, and crop pattern variability. These problems can be alleviated through object-based image analysis (OBIA) techniques that incorporate new spectral, textural, and hierarchical features after the imagery segmentation. The object-based classification is conducted after the segmentation process of remote sensing imagery. Moreover, this method depends on the knowledge-based membership functions that clearly define rules to classify a feature; in other words, it essentially concerns employing a group of pixels and not applying a single-decision rule on a pixel-by-pixel basis (Esetlili, M. T et al 2018). Typically, image segmentation is the first

step in an OBIA workflow. It clusters relatively homogeneous pixels into objects. The most common image segmentation process in OBIA is the multi-resolution segmentation that serves the objective to derive these relatively homogeneous regions by a heuristic global optimization. This is a bottom-up algorithm that would merge the adjacent pixels with similar specifications to create initial image objects. It then merges similar objects to produce larger objects. This process continues until the internal heterogeneity related to the color, texture, and shape of these objects will not have exceeded the user-defined thresholds. Furthermore, usually, such multi-resolution segmentation procedures apply three parameters, scale, color, and shape. The scale parameter value is not equal to the sizes of the resulting objects but strongly influences their sizes. A high scale parameter value allows a high heterogeneity of image objects and leads to the production of larger segments; whereas, a low scale parameter value leads to high homogeneity of image objects and a smaller number of them (Najafi, P et al 2019).

4-2-1. Basic Fuzzy Concepts Used in OBIA

In mathematics, two general logics are distinguished, namely, binary and fuzzy. While binary is a two-valued logic that only considers {0, 1} for each object, fuzzy is a multi-valued logic that can specify [0, 1] for each member. The fuzzy set theory was introduced to investigate the uncertainty of linguistic terms instead of common numerical variables by Zadeh. As such, most OBIA studies use fuzzy rule-based classifications that either employ membership functions or use the nearest adjacent classifier (Najafi, P et al 2019). Fuzzy classification systems are well suited for handling sources of vagueness in information extraction using remote sensing data (Aksoy, B. and Ercanoglu, M 2012). However, in a fuzzy OBIA approach, the features related to each object can be described by a fuzzy proposition and may be treated as a fuzzy set characterized by a membership function. The membership degree for each object would be determined according to its attribute value. The class of each object is described by a fuzzy rule that expresses the relationship between the class and its described properties. The satisfaction degree of a class rule is also determined according to the membership degree of these properties (Feizizadeh, B et al 2017). The object-oriented fuzzy operators are shown in Table 2.

Table 2. Object-oriented fuzzy operators [25].

No	Operators	Abbreviations	Operation details
1	And (min)	AND	Logical intersection, including the minimum recursive value of fuzzy values
2	Or (max)	OR	Logical union, including the maximum recursive value of fuzzy values
3	Mean (geometric)	MGE	Geometric means of fuzzy values
4	Mean (arithmetic)	MAR	Arithmetic L-means of fuzzy values
5	Mean (geom. weighted)	MGWE	Weighted geometric means of fuzzy values
6	and (*)	ALP	Logical intersection and multiplication of fuzzy values

5. Results And Discussion

After preparing the satellite imagery, a radiometric correction process was applied to the image in the SNAP software environment using the Sen2Cor plugin. Also, a satellite image in TIFF format was called in ENVI software to prepare a classification map for the support vector machine kernel functions. Using the study area shapefile, the desired area was cropped. Subsequently, two classes regarding the snowy and non-snowy areas were created to collect training points. Moreover, the required training points for each class were determined based on the visual processing of images. Linear kernel, polynomial, radial base, and sigmoid functions were employed to classify the SVM algorithm. Furthermore, each classification map was separately generated. Eventually, the maps generated from the kernel functions of the SVM algorithm are illustrated in Fig. 3.

To prepare a classification map for the object-oriented fuzzy operators, the desired satellite image, pre-processed in the former stages, was called to the eCognition software as TIFF format. After defining a project, also two snow and non-snow classes were defined for the classification process. The necessary fuzzy operator was determined for each class. In addition, the segmentation was performed at different scales, with differing weight/compression coefficient to enhance the process. The 100-scale quantity, shape 0.6 and compression 0.8, provided a good segmentation. Figure 4 shows the segmentation of the satellite image.

The training points were determined for each class after the image segmentation (for snow and non-snow classes) based on the image visual processing. Figure 5 shows some training points for the snow class.

After preparing the snow cover map through the SVM kernel functions and object-oriented fuzzy operators, the classification accuracy of each used algorithm was calculated. Several ground reality control-points from snowy and non-snowy areas were selected using the ENVI software so that the accuracy of the SVM kernel functions could be calculated. Also, the overall accuracy, as well as the kappa coefficient, were both calculated for each desired function. Accordingly, to calculate the classification accuracy of the object-oriented model, ground reality control-points were selected using the eCognition software. The overall accuracy and kappa coefficient were calculated for the object-oriented model as well. In Table 3 the overall accuracy and kappa coefficient obtained in this study are demonstrated.

Table 3
The evaluation of classification accuracy results.

No	Algorithm	Total accuracy	Kappa coefficient
1	Linear	0.93	0.87
2	Polynomial	0.96	0.93
3	Radial basis	0.97	0.94
4	Sigmoid	0.89	0.69
5	AND	0.98	0.98
6	OR	0.96	0.93
7	MGE	0.96	0.94
8	MAR	0.95	0.91
9	MGWE	0.97	0.95
10	ALP	0.96	0.94

According to the results of this study, the higher accuracy of AND object-oriented fuzzy operator classification, the classification map of this operator was used to estimate the snow cover area. To obtain the snow cover area related to the satellite image in this research, the classification map, which was generated from the AND object-oriented fuzzy operator, was converted from raster format to vector and the shapefile related to the snowy areas was extracted in ArcMap software. To calculate the area in terms of square kilometers. The estimated value for the snow cover area in this study was 604 km².

6. Conclusion

In this study, the efficiency of object-oriented fuzzy actuators relative to the SVM kernel functions for extracting and estimating the snow cover level was evaluated using the Sentinel satellite 10 m bands. After pre-processing the satellite image, the classification maps of the SVM kernel functions and object-oriented fuzzy operators were generated so the accuracy of these functions could be calculated. In the present study, the linear, polynomial, radial base, and sigmoid SVM kernel functions, as well as the object-oriented fuzzy operators, including AND, OR, MGE, MAR, MGWE, and ALP have been used.

All in all, the results indicate that AND algorithm, representing the logical commonality and including the lowest return fuzzy value of 98% in used algorithms, provides higher accuracy overall; so, based on research results, with the use of object-oriented satellite image processing methods, not only higher accuracy can be achieved in the classification of digital satellite images when compared to the accuracy of the support vector machine kernel functions, they use a range of additional information related to the texture, shape, position, content, and bandwidths in classification. Therefore, due to their efficiency and

low cost, in estimating the level of snow cover, satellite images can be used to study and estimate the level of snow cover in mountainous areas. Furthermore, the application of ground surveys for studying snow cover is not only costly, but also they are not accurate enough due to the limited movability in these areas.

At last, the obtained results in this research can be used by the executive organizations to plan and manage water resources.

7. Abbreviations

support vector machine (SVM); statistical learning theory (SLT); object-based image analysis (OBIA)

8. Declarations

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Figures

Figure 1

Location of the study area.

Figure 2

Research implementation steps.

Figure 3

The maps produced by SVM kernel functions; (A) linear, (B) polynomial, (C) radial basis, (D) sigmoid.

Figure 4

Segmenting at scale 100, shape coefficient 0.6, compression coefficient 0.8

Figure 5

The maps produced by the classification of fuzzy operator functions; (A) AND, (B) OR, (C) MGE, (D) MAR, (E) MGWE, (F) ALP.