

SEGMENTATION BASED CLOUD AND CLOUD SHADOW DETECTION IN SATELLITE IMAGERY

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ABSTRACT

One of the main source of noises in remote sensing satellite imagery is regional clouds and shadows of these clouds caused by atmospheric conditions. In many studies, these clouds and shadows are masked with multi-temporal imagery taken from the same area to decrease effects of misclassification and deficiency in different image processing techniques, such as change detection and NDVI (Normalized Difference Vegetation Index). This problem is surpassed in many studies by mosaicking with different images obtained from different acquisition dates of the same region. The main step of all studies that cover cloud cloning or cloud detection is the detection of clouds from a satellite image. In this study, clouds and shadow patches are classified by using a spectral feature based rule set created after segmentation process of Landsat 8 image. Not only spectral characteristics but also structural parameters like pattern, area and dimension are used to detect clouds and shadows. Rule set of classification is developed within a transferable approach to reach a scene independent method. Results are tested with different satellite imageries from different areas to test transferability and compared with other state-of art methods in the literature.

Keywords: Multi-temporal satellite imagery, cloud detection, cloud cloning, segmentation, threshold, ruleset.

UYDU GÖRÜNTÜLERİNDE BÖLÜTLEME TABANLI BULUT VE GÖLGE BELİRLEME

ÖZET

Uzaktan algılama uydu görüntülerinde atmosfer etkilerinden kaynaklı olarak ortaya çıkan bölgesel bulutlar ve bu bulutların gölgeleri, yapılan çalışmalarda problem oluşturan temel gürültü kaynaklarından biridir. Değişiklik analizi, Normalize Edilmiş Fark Bitki Örtüsü İndeksi (NDVI: Normalized Difference Vegetation Index) hesaplama gibi önemli dijital işlemlerde bulut ve gölge bölgeleri, genel olarak yanıltıcı sonuçlar veren bölgeler olduğundan çoğu zaman maskelenerek işlemler gerçekleştirilmektedir. Bu problem, birçok çalışmada, aynı bölgeden elde edilmiş çok zamanlı uydu görüntüleri ile mozaikleme yapılarak aşılmaktadır. Tüm bulut belirleme, gölge belirleme ve klonlama yöntemlerinin ortak adımı, görüntüdeki bulut ve gölge bölgelerinin belirlenmesi işlemidir. Bu çalışmada Landsat 8 görüntüleri kullanılarak, bulut ve gölge bölgeleri, görüntü bölütlemesinin ardından spektral özelliklerinin bir kural dizisi oluşturularak belirlenmiştir. Bulut ve gölge belirlemede, görüntülerin spektral özelliklerinin yanı sıra, doku ve alan gibi yapısal özellikleri de kullanılmıştır. Oluşturulan kural dizisi, birçok bölgede çalışması amaçlanarak transfer edilebilir bir yapıda oluşturulmuş, test görüntülerinde transfer edilebilirliği test edilmiş ve literatürdeki diğer yöntemlere olan üstünlükleri ve eksiklikleri gösterilmiştir.

Anahtar Kelimeler: Çok zamanlı uydu görüntüleri, bulut belirleme, bulut klonlama, bölütleme, eşik değeri, kural dizisi.

1. INTRODUCTION

One of the important problems of optical remote sensing is clouds and shadows which occur in data acquisition time because of atmospheric conditions. Annual cloud cover is 68% according to International Satellite Cloud Climatology Project-Flux (ISCCP-FD) data [1]. Shadows and bright features caused by clouds are affecting data analysis processes. These effects are; rising NDVI values, misclassification results and atmospheric correction difficulties [2]. In remotely sensed image, clouds and shadows are vital part of noise and detection of these features are important for further digital image processing analysis. [3-4]. When there is no opportunity to acquire multi-temporal images, clouds are becoming important problem for classification and image interpretation processes [5].

Cloud detection algorithms are mainly grouped into two categories; classification based algorithms and rule-set based algorithms [6]. Classification based methods use training sets to classify cloud features [7-8]. Rule-set based algorithms need pre-defined cloud specific features for implementation. Automatization of these processes is quite difficult to implement because of difficulties in characterization of cloud features. ACCA (Automated Cloud Cover Assessment) method which is developed by Irish in 2006 is an example as an automatic cloud cover detection algorithm for Landsat 7 satellite imagery [9]. ACCA method is considered as a fundamental method for classification of cloud features in Landsat imagery [4][10]. The aim of this algorithm is detection of cloud ratio in the scene and appending this information to image metadata as "cloud cover". ACCA algorithm uses different spectral filters and thermal infrared channels for detection of clouds. Nevertheless, cloud and shadow boundaries are not precisely determined for automated analysis of multi-temporal Landsat imagery in this algorithm [2]. ACCA fails to be precise about determination of warm cirrus clouds and detects snow and ice as clouds in high-latitude regions. [4][10]. Another most-known and used cloud and shadow detection algorithm is Fmask method. Fmask is an object-based cloud and cloud shadow detection method for Landsat imagery [10]. Fmask uses Landsat Top of Atmosphere (TOA) reflectance and Brightness Temperature (BT) to find potential cloud pixels and clear sky pixels, then uses object-based cloud and cloud shadow matching process to find cloud shadows precisely.

Beyond understanding cloud detection algorithms, visual characterizations of clouds are important to solve this problem. Clouds in satellite imagery are visually categorized into two groups; opaque clouds and semi-transparent clouds. Determining of opaque clouds are easier to identify because of their high

brightness features in visible channels. Since, their signal covers both clouds and surface underneath cloud features, identification of semi-transparent clouds is difficult [11-13]. Cloud and shadow detection seems as a state-of-art task according to characteristics of clouds' bright behaviour and dark features of their shadows. In contrary, other possibilities can occur in different images such as clouds which are not bright and cold and shadow which are not dark. Also, shadows of clouds can occur in many different types over land. Based on these anomalies, shadow detection process is quite harder than cloud detection. Mostly, cloud region detection studies are completed by spectral tests. Spectral test can detect shadows in some conditions, but shadows caused by topography, wet areas, dark surfaces, and shadows which don't cause sufficient amount of darkness cannot be detected only by spectral methods [10][14]. Recently geometry based cloud shadow detection methods have been studied and shown to be more successful. Cloud shadows and clouds are matched by each other in object matching method which is well-known and tested method in geometry based methods. [15][16-18].

In the light of all information given above, cloud and shadow detection procedure is not a standardized process and ongoing work in remote sensing. In this study, a new method is proposed which is inspired by all methods mentioned in this paper about cloud and cloud shadows detection. Our proposed method detects cloud and cloud shadows from Landsat 8 imagery by using both spectral and geometrical properties after a super-pixel segmentation process. Beside spectral and geometric properties, discrimination of cold surface (snow, ice) and cloud-shadow is strengthened by using thermal infrared channels of Landsat. Neighbourhood relations are used to improve detection accuracy of cloud shadow regions around cloud areas. This method is tested with four different Landsat images taken from different study areas at different acquisition dates. This study can be regarded as a simplified, modified, automated and segmentation based version of ACCA and Fmask methods [2][10].

2. METHODOLOGY

Our cloud detection algorithm is based on usage of OLI (Operational Land Imager) and thermal bands. OLI bands are calibrated to ToA: Top of Atmosphere Reflectance and thermal bands are converted to brightness temperature to use in this algorithm. Cloud areas are identified using rule-set based classification applied on reflectance calibrated images by following super-pixel segmentation of satellite image. Following classification of cloud areas, cloud shadows are classified by evaluating spectral test and neighbourhood relations with cloud regions.

Developed method is a simplified version of ACCA and Fmask algorithms. Cloud and shadow masks obtained by Fmask and results obtained by our method are compared, and results are evaluated. General workflow chart of all steps concluded in study is given in Figure 1.

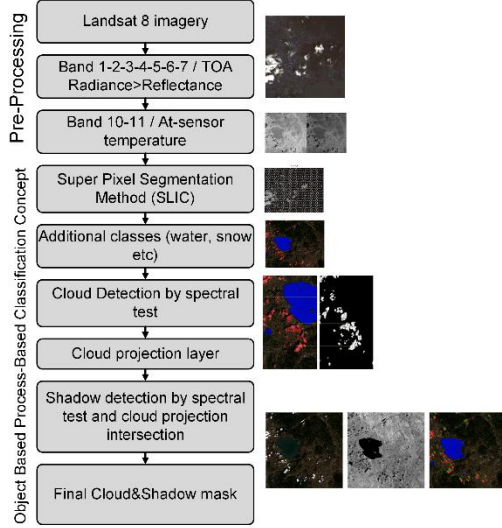


Figure 1. General workflow chart of study

2.1. Data Used and Study Area

Four different Landsat 8 images are selected as study area which have different land use characteristics and cloud covers between 10% and 30%. Evaluating results of the algorithm in different regions which have different surface characteristics is important to test transferability. Figure 2 shows the geographical distribution of selected images.

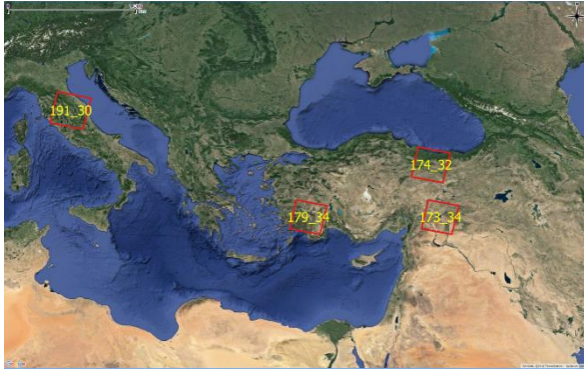


Figure 2. Study area and distribution of selected images

2.2. Pre-processing

Landsat 8 data is provided as raw DN (Digital Number) numbers. Data can be rescaled to the Top of Atmosphere (TOA) reflectance and radiance using radiometric rescaling coefficients stored in the product metadata file (MTL file). By this conversion, image data becomes physically meaningful units. Metadata file also contains the thermal constants needed to

convert TIRS data to the at-satellite brightness temperature.

Conversion to TOA Reflectance

OLI and TIRS band data can be converted to TOA spectral radiance using the radiance rescaling factors stored in the metadata file (Equation 1):

$$L_{\lambda} = M_L Q_{cal} + A_L \quad (1)$$

L_{λ} = TOA spectral radiance (Watts/(m² * srad * μm))
 M_L = Band-specific multiplicative rescaling factor from the metadata
 A_L = Band-specific additive rescaling factor from the metadata
 Q_{cal} = Quantized and calibrated standard product pixel values (DN)

OLI band data can be converted to TOA planetary reflectance after radiance conversion using reflectance rescaling coefficients given in the product metadata file (MTL file). Equation 2 is used to convert DN values to TOA reflectance for OLI data [19].

$$\rho_{\lambda'} = M_p Q_{cal} + A_p \quad (2)$$

$\rho_{\lambda'}$ = TOA planetary reflectance, without correction for solar angle. Note that $\rho_{\lambda'}$ does not contain a correction for the sun angle.
 M_p = Band-specific multiplicative rescaling factor from the metadata
 A_p = Band-specific additive rescaling factor from the metadata
 Q_{cal} = Quantized and calibrated standard product pixel values (DN)

Also, sun angle correction is applied to ToA reflectance values by using Equation (3)

$$\rho_{\lambda} = \frac{\rho_{\lambda'}}{\cos(\theta_{SZ})} = \frac{\rho_{\lambda'}}{\sin(\theta_{SZ})} \quad (3)$$

ρ_{λ} = TOA planetary reflectance
 θ_{SE} = Local sun elevation angle. The scene center sun elevation angle in degrees is provided in the metadata
 θ_{SZ} = Local solar zenith angle; $\theta_{SZ} = 90^{\circ} - \theta_{SE}$

After all of these conversions, all processed are applied to reflectance images.

Conversion to At-Satellite Brightness Temperature

TIRS band data can be converted from spectral radiance to brightness temperature by using the thermal constants presented in the metadata file by using Equation (4) [19].

$$T = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \quad (4)$$

T = At-satellite brightness temperature (K)
 L_λ = TOA spectral radiance (Watts/(m2 * srad * μ m))
 K_1 = Band-specific thermal conversion constant from the metadata
 K_2 = Band-specific thermal conversion constant from the metadata

Brightness temperature information is used in cloud detection algorithm which shows lower temperature values in cloud regions compared to other regions. TIR2 channel which is indicating better cloud discrimination is used for cloud and shadow detection (Figure 3).

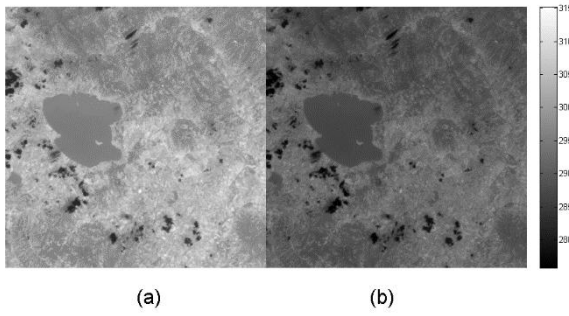


Figure 3. Landsat-8 image converted brightness temperature (a) TIR1 (b) TIR2

2.3. Cloud and shadow detection

Segmentation

Super pixels are used to combine pixels into meaningful groups to create pixel groups. Merging pixels which have similar information is speeding up image processing tasks. SLIC (simple linear iterative clustering) algorithm is an efficient method for segmentation of image which is based on spatially localized version of K-means clustering method. Fundamental specifications and advantages of SLIC method are evaluated in [20].

SLIC starts by dividing image domain into a regular grid with $M \times N$ tiles. M and N values are given as an input, where (5)

$$M = \frac{\text{imageWidth}}{\text{regionSize}} \quad N = \frac{\text{imageHeight}}{\text{regionSize}} \quad (5)$$

A region (super pixel or k-means cluster) is initialized from each grid center (6)

$$x_i = \text{round}_i \frac{\text{imageWidth}}{\text{regionSize}} \quad (6)$$

$$y_i = \text{round}_j \frac{\text{imageWidth}}{\text{regionSize}}$$

Following this step, regions are obtained by running k-means clustering, started from the centers (7).

$$C = \{\Psi(x_i, y_i), i=0, 1, \dots, M-1 \quad j=0, 1, \dots, N-1\} \quad (7)$$

K-means uses the standard Lloyd algorithm alternating by assigning pixels to the closest centers [21]. The only difference compared to standard k-means is that each pixel can be assigned only to the center originated from the neighbour tiles. After creation of super pixels, each super pixel is taken into account to check if area is less than minimum region size value which is taken as an input from user [22]. Results of SLIC algorithm which is applied to cloud image are shown in Figure 4.

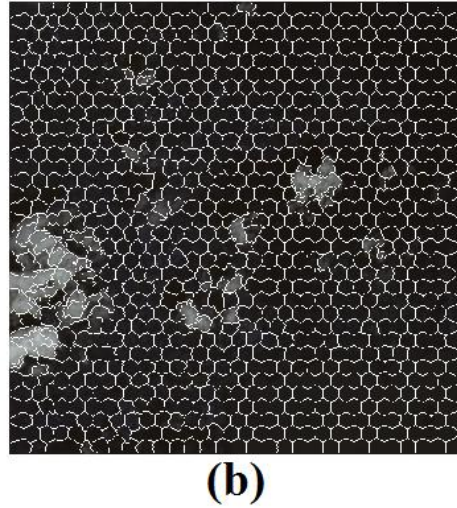
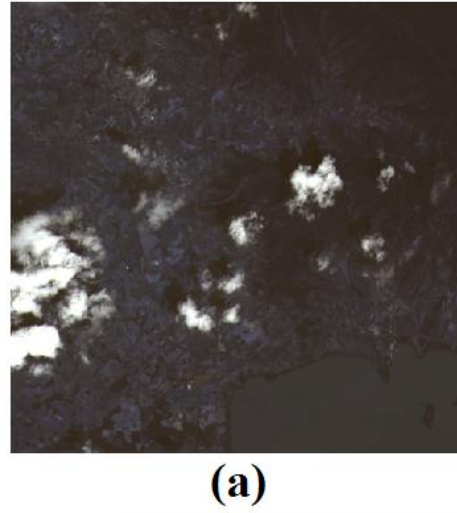


Figure 4. Results of SLIC algorithm applied to cloud image (a) Original image (b) SLIC superpixel segmentation result

Cloud Detection

Detection of cloud features from Landsat image is started by identification of spectral characteristics of clouds. Spectral signatures collected from image are

shown on Figure 5. Algorithm is developed on the basis of these signatures.

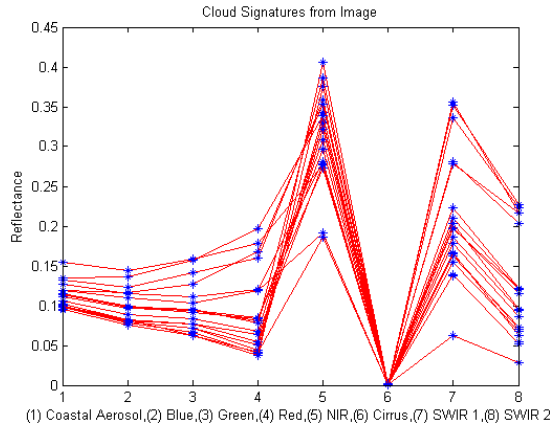


Figure 5. Cloud spectral signatures collected from image

As seen in Figure 5, cloud areas have high brightness values in NIR (Band 5), and SWIR (Band 7) which makes them easily distinguishable in those regions. In addition to this, information about characteristics of bright objects on the blue band is taken into account and values of these three bands are multiplied with each other. Cloud shadows are discriminated from other features by dividing thermal channel to the multiplication of three bands based on information of low-temperature characteristic of cloud features on thermal infrared bands (8). NDSI is a normalized difference of two bands (Green and SWIR1) to map snow. Beside the advantage of using the thermal infrared band, NDSI information is also added to the

procedure to cope with difficulties caused by snow-covered areas which have bright and cold temperature features (9). NDSI index is used for discrimination of clouds and snow cover [23]. Pixels which have NDSI values greater than 0.6 are classified as snow.

$$Index_{cloud} = \frac{Red * Near Infrared 2 * Blue}{Thermal 2} \quad (8)$$

$$NDSI = \frac{Green - SWIR 1}{Green + SWIR 2} \quad (9)$$

(Snow NDSI > 0.6)

Thermal band usage is also easing the process of opaque cloud classification. Band ratio of cloud pixels compared to other land cover types is resulting in high values in cloud regions which ease thresholding process for cloud detection. Cloud classification is developed within a multi-criteria structure shown in Table 1. Pixels have temperature less than 300K are classified as cloud candidate by using information provided by USGS (Figure 6).

Table 1. Cloud classification criteria

NDSI	Not snow (NDSI < 0.6)
Thermal Infrared	<300 Kelvin
Cloud Classification Index	The dynamic threshold which comes from brightest object cluster of the image.

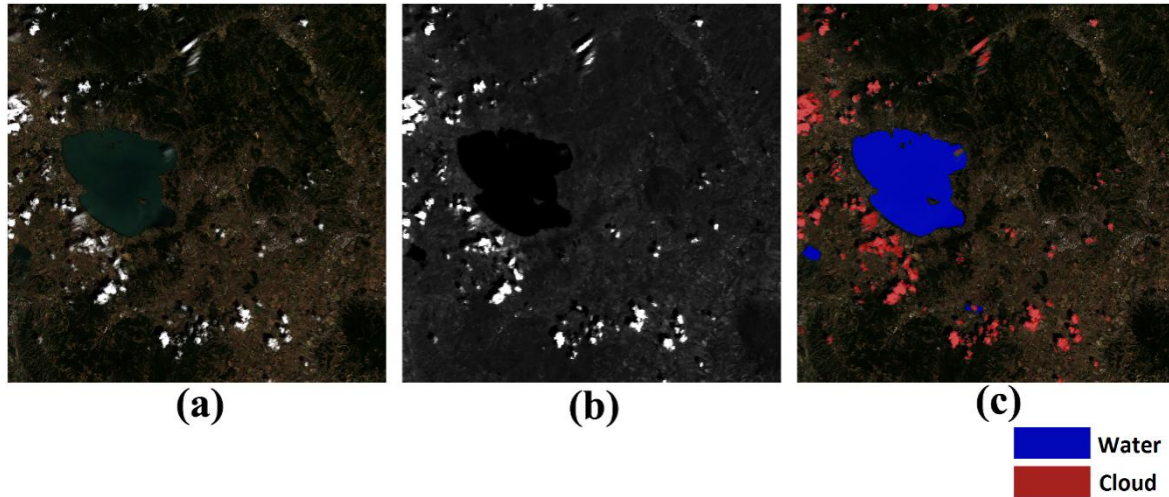


Figure 6. (a) Original image (b) Cloud detection index (c) Classified cloud areas

$$Index_{shadow} = \frac{NIR * SWIR 1}{Red} \quad (10)$$

Shadow Detection

Similar to cloud features, cloud shadow classification method is also developed based on interpretation of spectral signatures which are collected from cloud shadow areas (10). Cloud shadow areas are distinguished easily by using this index which eases dynamic thresholding for shadow detection.

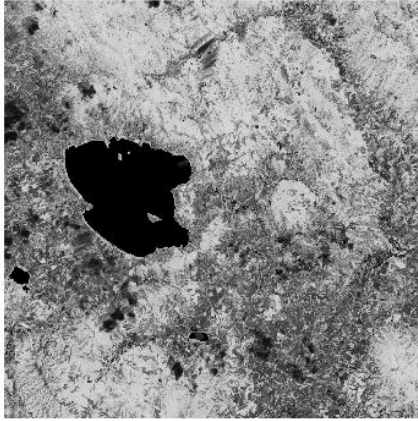
Not only clouds, but also higher buildings, hills and factors which cause height difference can also cause shadows according to sun azimuth. Shadows and water bodies are misclassified to each other because of their dark behaviour. In this study, NDWI (Normalized Difference Water Index) and cloud

projection methods are used to overcome these two misclassification problems mentioned above (11) [24].

NDWI values are calculated to prevent misclassification of water bodies and shadow areas to each other. The constant threshold is used to classify water bodies automatically (Equation 11)(Figure 7).

$$NDWI = \frac{NIR - Green}{NIR + Green} \quad (11)$$

(Water - NDWI < -0.2)



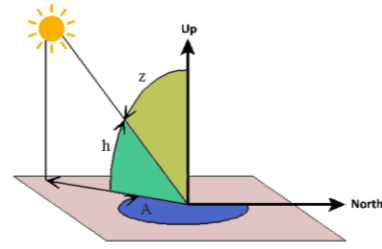
(a)



(b)

Figure 7. (a) NDWI image (b) Water classification

Secondly, the projection of cloud features to a specific distance is calculated according to sun azimuth angle which comes from image metadata. It is used to prevent conflict of cloud shadow features with other shadows. Sun azimuth angle is an angle which is measured clockwise from the north while image acquisition (Figure 8).



h: elevation angle, measured up from horizon
z: zenith angle, measured from vertical
A: azimuth angle, measured clockwise from North

Source: (<http://www.esrl.noaa.gov/gmd/grad/solcalc/szelem.gif>)

Figure 8. Sun elevation, sun azimuth and zenith angle

Cloud-shadow distance is designated as 20 pixels based on tests applied on the image. These projected areas are potential cloud shadow features. The intersection of areas from cloud shadow index and potential cloud shadow projections is used to identify final cloud shadow classification (Table 2)(Figure 9).

Table 2. Shadow classification rules

NDWI	Not water
Potential cloud projection	Intersection
Shadow detection index	The dynamic threshold which comes from darkest object cluster of the image.

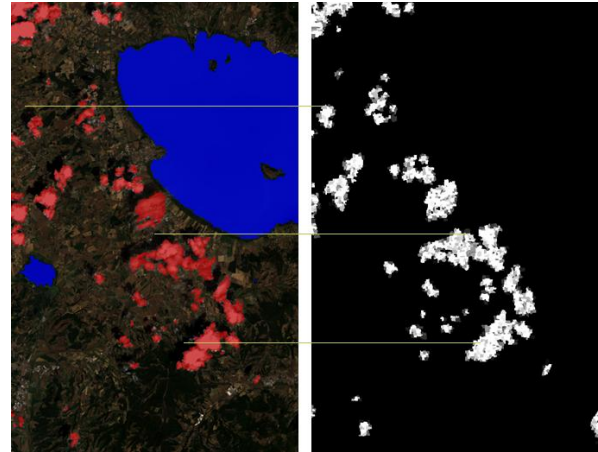


Figure 9. Relationship between clouds and cloud shadow projections

Neighbour edges of cloud and shadow classifications are added to these classified areas by region growing to complete all classification process (Figure 10).

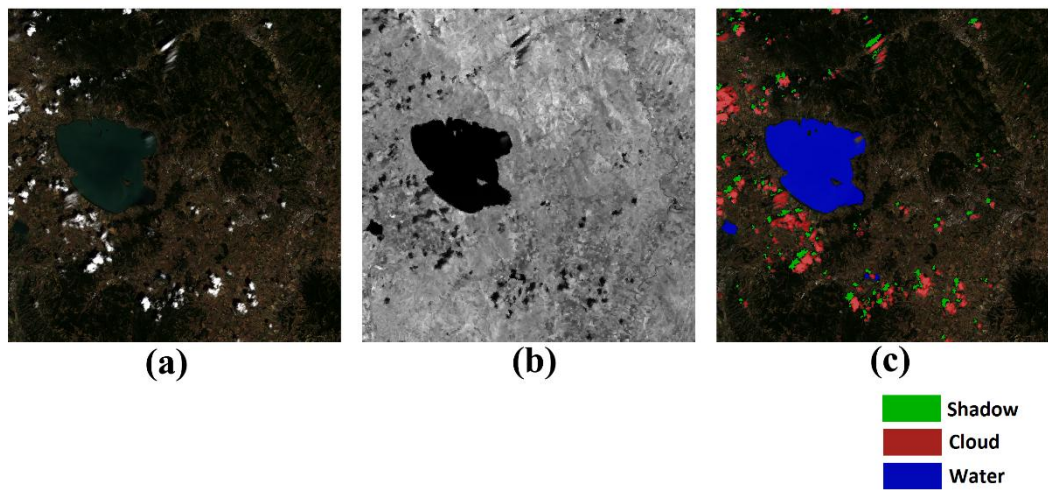


Figure 10. (a) Original image (b) Shadow detection index (c) Classified cloud shadow areas

Results from our study and Fmask are compared in Figure 11 for four different study areas.

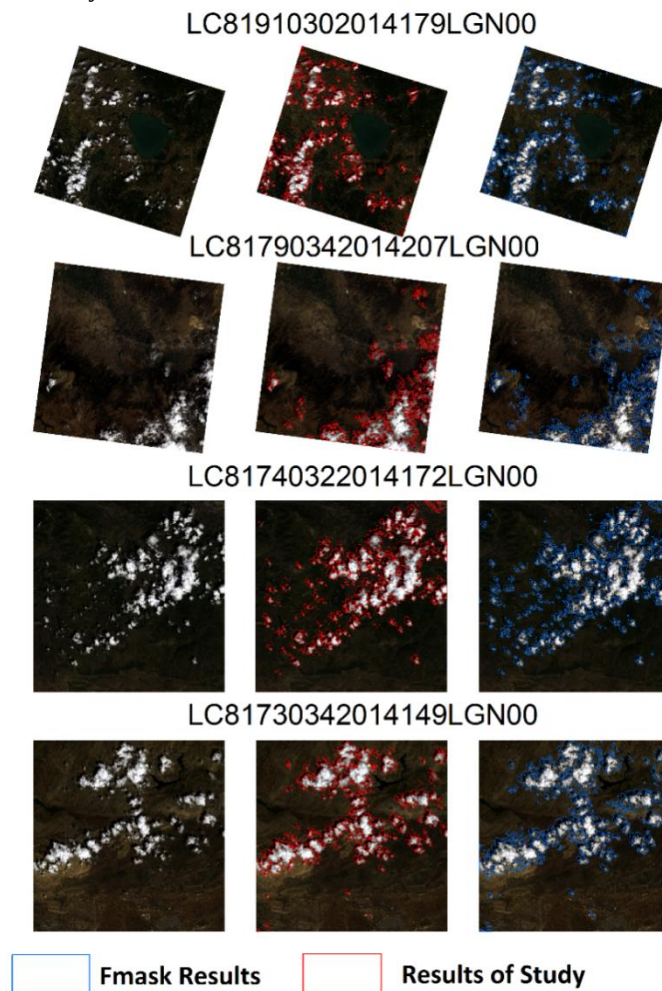


Figure 11. Results of our study compared with Fmask method

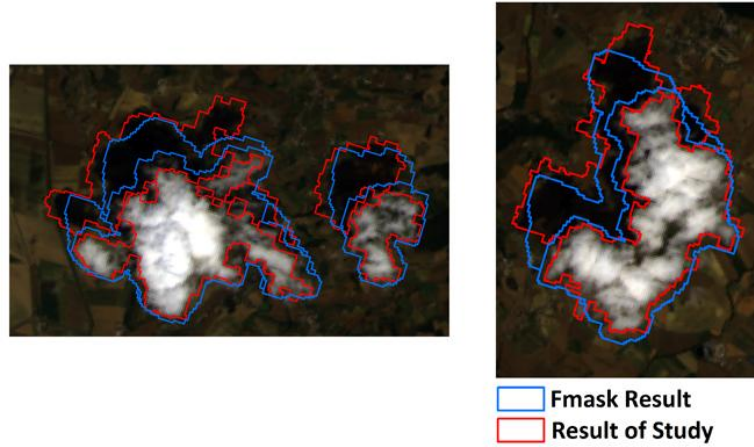


Figure 12. Detailed area from results

Zoom level is not sufficient to spot little details in Figure 11. Images taken from two different parts of the image are zoomed up in Figure 12 to show details and analyse them. Fmask and our method are both giving sufficient results for cloud and shadow detection. Ground truths of both cloud and shadow patches are manually digitized to calculate accuracy metrics for evaluation of results. Accuracy metrics of cloud and shadow detection results can be seen in Table 3.

Table 3. Accuracy metrics

(units: m2)	Cloud		Shadow	
	Our method	FMASK	Our method	FMASK
FN	49019439	10408916	18094272	34678429
FP	15113284	73504582	48253971	50534909
TP	207835135	246445658	86651967	54631517
Precision	0,93	0,77	0,64	0,52
Recall	0,81	0,96	0,83	0,61
F measure	0,87	0,85	0,72	0,56
Total Classified	222901200	319786200	144836100	95393700
Total GT	256854574	256854574	113219107	113219107
TP / TotalClassified	0,93	0,77	0,60	0,38

Precision and recall rates of our study are better than Fmask for four different test sites we used. Fmask method detects cloud with a bigger confidence interval which causes more classified areas. In this case, accuracy of two methods are also compared with a basic True Positive / Total Classified metric to understand classification accuracy. Fmeasure is also another metric which is commonly used for evaluation of target detection results. Results show that two methods show similar accuracy for cloud detection while our method shows more accuracy in shadow classification which uses cloud projection method to improve cloud&shadow relationships.

3. RESULTS AND DISCUSSION

Identification of cloud and shadow regions is a popular study area in remote sensing for a long time, and lots of methods have been developed. These methods provide sufficient accuracy in many cases. Nevertheless, they

don't provide enough accuracy for some specific cases. Beside pixel-based methods, segmentation based methods which groups pixels into super pixels is a new study area for detection of clouds and shadows. By separating the image into homogeneous pixel groups, not only computational workload can be decreased but also features can be obtained on the image effectively regarding geometrical characteristics by the help of object-based classification approach. Methods developed in this study is based on segmentation approach for cloud and shadow detection. Classification results is directly related to accuracy of super pixels created in the pre-processing step of classification. For this reason, region size is chosen as small as possible to decrease the size of super pixels to minimize feature loss while pixel grouping process. Spectral characteristics of features such as cloud and shadow in images are significant in terms of brightness and darkness. In the light of this information, cloud and shadow areas are grouped into super pixels by using SLIC segmentation algorithm. Clouds and shadows are detected from the image, by creating indexes developed within a spectral tests by adding different parameters such as; brightness temperature, sun azimuth, NDSI and NDWI to the multi-criteria rule set. Shadow classification accuracy is increased with the help of cloud-shadow projection approach as a new solution to this problem which uses the geometrical relation between cloud and shadow. As seen in Figure 12, our method gives more efficient results than Fmask regarding the geometrical accuracy of cloud and shadow structures because of its segmentation based approach. Segmentation based approach which uses both spectral and spatial information to group pixels provides more successful results compared to pixel based method in this study. Moreover, cloud projection method used in cloud shadow detection improved the accuracy of proposed method by using the spatial relationship between cloud and shadow features. Although, both methods have sufficient recall rate for cloud and shadow classification, region growing rate used by Fmask method to increase confidence interval

causes non-cloud and non-shadow areas classified as cloud and shadow on many regions. Table 4 summarizes accuracy metrics which is used to evaluate classification results. Our method shows more accuracy for both cloud and shadow detection. Fmask and ACCA methods are well known, well tested and successful cloud detection methods in literature. Beyond all tests we used in this article to evaluate accuracy of these results, much more images and ground truth from all over the world needs to be tested to better evaluate our method. Transferability of this method is tested with the same parameters by using different images from different study areas. In addition to algorithm like ACCA and Fmask, the usability and transferability of the algorithm developed here is proven in terms of simplification of processing steps and decreasing computational workload because of its super pixel based approach.

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