Extraction of water body, cloud shadow and cloud detection using object-based classification

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(Received: Jan 26, 2019; in final form: June 12, 2019)

Abstract: Shadow plays a crucial role in Satellite Image Interpretation. Shadow may sometimes obscure ground features. In Optical Imagery, the Spectral Signature (DN value) of Water Body and Cloud Shadow are similar. Features which lie within shadow, reflect less energy and are difficult to identify. This results in difficulties in digital classification, which depends completely on reflectance value (DN value). The object based classification approach utilizes spectral value as well as Shape, Texture and Context information. Such additional attributes are helpful for the detection of the shadow and water body separately. In this study, LISS-3 data of part of Rajkot district, Gujarat was used for detection of cloud shadow, cloud and water bodies. The three parameters such as average DN, reliability and threshold values were used for the shadow and cloud detection. Reliability is a criterion for providing priority to desired class in case of class mixing. Clouds were separated by keeping value of minimum threshold as 185. The water body is differentiated from the shadow by providing reliability of 0.4 as compared to providing reliability of 0.3 in case of the shadow. The results clearly showthat in optical satellite images, cloud shadows can be separated from the water body and the cloud can be detected using Object-Based techniques.

Keywords: Reliability, Shadow, Classification, Cloud

1. Introduction

Accuracy of the classified image depends upon the classification technique. Digital classification of satellite data, which uses spectral signature (DN value) of the individual pixel (Willhauck, 2000), works well when the classes are spectrally separable. These can be carried out using supervised classification, unsupervised classification or combination of these (Enderle and Weih, 2005). In case of spectral mixing, these techniques fail and importance of the neighboring pixels (Spatial and Contextual information) may also be neglected.

In contrast, object-based image analysis incorporates not only spectral value, but also shape, texture and context information (Flanders et al., 2003) for classification. Image is divided into groups of homogeneous pixels, which are called objects-created from the segmentation process. On applying proper rules, the objects are classified to ground cover features. Basic entity is group of pixels rather than the single pixel. Object-based image analysis of satellite data has been utilized for decades (Ryherd and Woodcock, 1996; Flanders et al., 2003), but in recent years it has been utilized in different areas such as vegetation monitoring (Yu et al., 2006), forest cover analysis (Heyman et al., 2003), water body extraction (He et al., 2016).

In satellite image interpretation, shadows play very crucial role. It aids in interpretation as well as creates difficulty. Features can be identified as their association with shadow, such as, shadow and water body appear similar, but identified separately due to shadow association with the cloud and hills. Features which lie within shadow, reflects less energy and are difficult to identify. In optical imagery, the spectral signature (DN value) of water body, cloud shadow and hill shadow are similar. Individual identification of these are difficult using digital classification methods which solely depends upon spectral value. Object-based approach incorporates not only spectral value, but also shape, texture and context information. Using object-based approach, classes which are spectrally similar can be separated out.

In present study, separation of cloud shadow from the water body and cloud detection using Object-Based approach has been attempted. The data used was LISS-3 (Optical) data of part of Rajkot district, Gujarat. This analysis makes use of DN, reliability and threshold value using open source Software - Inter IMAGE for the desired objective. Using reliability value, priority will be given to the class where there is mixing between two classes. The results show that cloud shadow can be separated from the water body and cloud can be detected using Object-Based technique.

2. Study Area and data used

The Study Area was part of Rajkot district located in Gujarat State associated with ground cover features water body, cloud, cloud shadow, settlement and vegetation. The data used was Indian Remote Sensing-P6 (IRS-P6) Satellite, LISS-3 acquired on 27-09-2016 with the resolution of 23.5 m. Wetland boundary of year 2016 (Wetland inventory of India, 2016) was utilized as reference data for the accuracy assessment. Both the data sets are shown in figure 1.

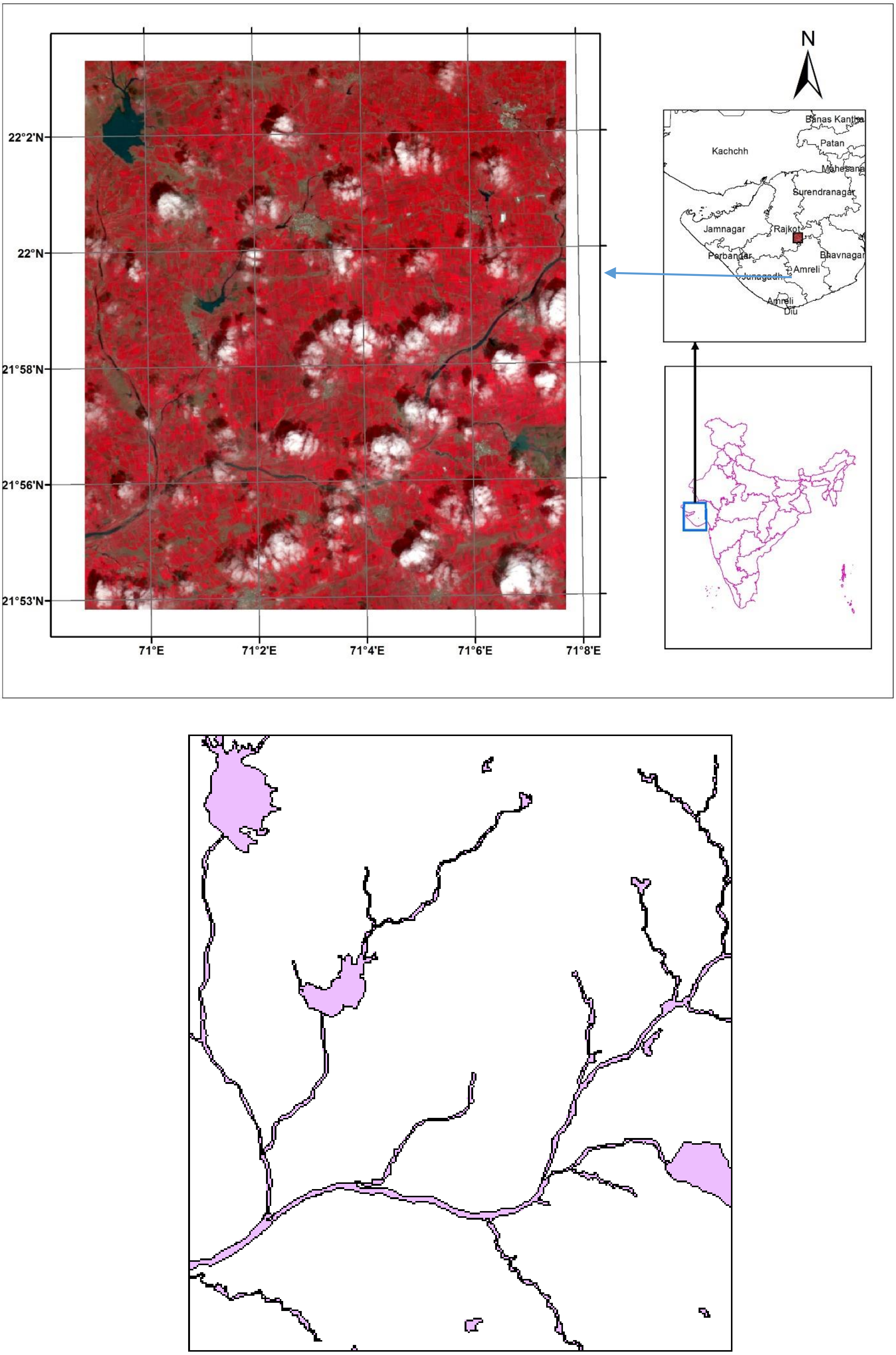

Figure 1: LISS-3 data and wetland boundary of part of Rajkot district, Gujarat.

3. Objective

Objective of this study was detection and separation of water body-cloud Shadow and identification of Cloud using Object-Based classification.

4. Methodology

The objective of study was achieved using object-based classification technique which utilized spectral (DN value) as well as shape, texture and contextual information. For the classification, Inter IMAGE- an open source software was utilized. The image was classified into 4 classes viz. water, cloud shadow, non-shadow and cloud. Objects are created from the multiresolution segmentation approach (Baatz and Schape 2010) using scale parameter 30, compactness weight 0.5 and color weight 0.8. Heterogeneity and closeness of pixels between the objects are governed by scale and compactness respectively. Further, the objects are classified into various classes by applying different rules. Rules which are ratios and averages of DN values in different spectral bands (Green, Red, NIR and SWIR) were incorporated for the achievement of objective. These rules were combined with two additional parameters, reliability and threshold value. Reliability gives the higher weightage of class in the case of class mixing. Priority will be given with higher reliability value to the class where geographic overlay exists between two classes. Different threshold value had been checked for the classification of cloud and shadow.

Initially, image was divided into water and non-water with the rule WBI (Water Body Index) associated with water class. WBI is the ratio of reflectance (DN) value associated with green and near infra-red wavelength bands (Green-NIR)/ (Green + NIR) (McFeeters, 1996). Positive value of WBI indicates water bodies. Non-water class is divided into cloud and non-cloud with the rule average DN values of all bands associated with non-cloud class and threshold value 185. Finally, non-cloud class was divided into non-shadow and shadow with the same rule as non-cloud but decreased threshold value (100) associated with shadow class. Threshold value 185 and 100 gave the best possible result for the cloud and shadow identification. Rules which have been incorporated for the classification are summarized in the following table 1.

Table 1: Classification rules

Class	Rules
Water Body	(Green-NIR)/(Green + NIR)
Cloud and Shadow	(Green + Red + NIR + SWIR)/4

Extracted classes water body (Blue), cloud shadow (Black) and cloud (White) are shown in figure 2.

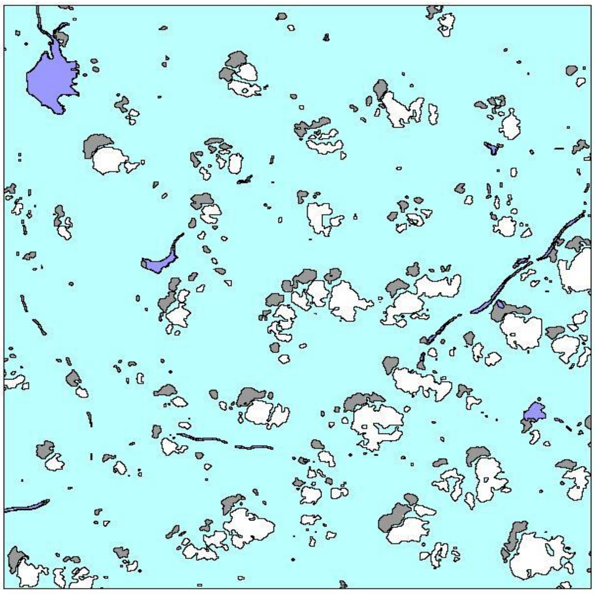

Figure 2: Classified water body (Blue), cloud shadow (Black) and cloud (White)

When the reliability of shadow class (0.3) is higher than the water class (0.2), there was mixing of water body and cloud shadow. Increased reliability of water class (0.4) as compared to shadow class (0.3) gives the separation of water body and cloud shadow (Figure 3).

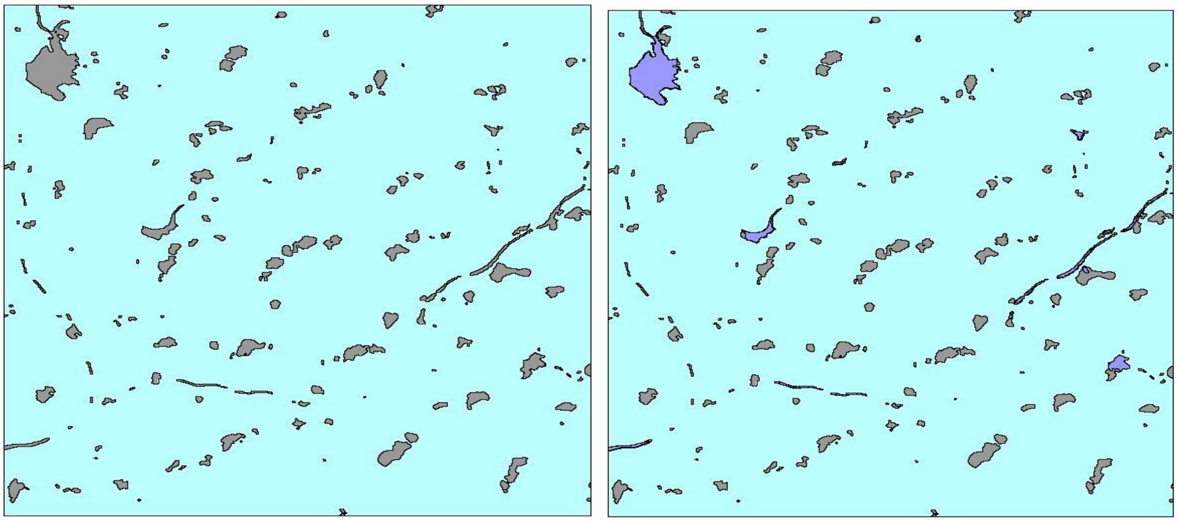

Figure 3: Mixed water body and cloud shadow and their separation

The sequence in which classes was extracted is shown in following flow-chart (Figure 4).

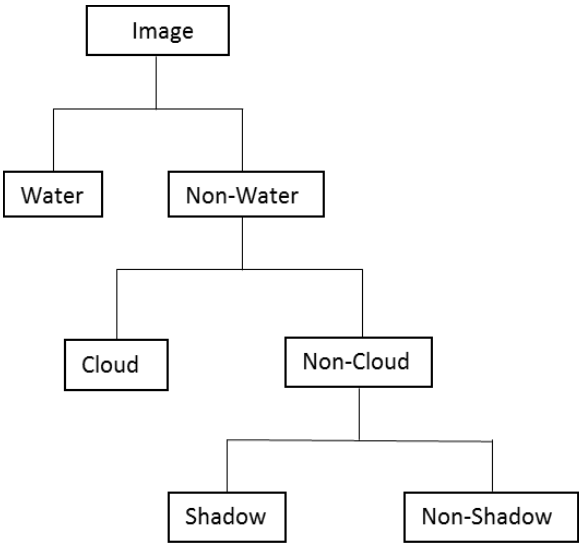

Figure 4: Flow-Chart: Extracted classes

For comparison of object and pixel based classification, pixel-based supervised classification was performed using ERDAS Imagine software. Supervised classification is shown in figure 5.

5. Accuracy Assessment

Accuracy assessment was performed visually. Classified water bodies, cloud shadows and clouds polygons were visually counted and compared to classes in data set taken as reference data for cloud shadow and cloud. For water body, wetland boundary of year 2016 was used as a reference data (Figure 1). Error matrix for the object-based and supervised classification are shown in tables 2 & 3 respectively.

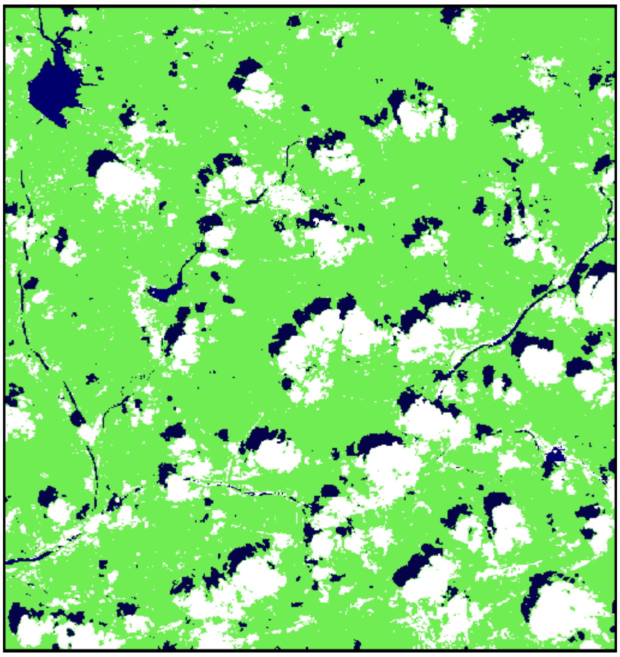

Figure 5: Supervised classification-water body (Blue), cloud shadow (Black) and cloud (White)

Producers accuracy, user's accuracy, overall accuracy and kappa coefficient of object-based and supervised classification are shown in tables 4 and 5 respectively.

Table 2: Error matrix of object-based classification

	Water Body	Cloud Shadow	Cloud	Others	Row Total
Water Body	**24**	4	0	0	28
Cloud Shadow	12	**60**	0	0	72
Cloud	0	0	**64**	0	64
Others	0	0	**0**	**0**	0
Column Total	36	64	64	0	**164**

Table 3: Error matrix of supervised classification

	Water Body	Cloud Shadow	Cloud	Others	Row Total
Water Body	**10**	14	0	0	24
Cloud Shadow	26	**50**	0	0	76
Cloud	0	0	**64**	16	80
Others	0	0	**0**	**0**	0
Column Total	36	64	64	16	**180**

Table 4: Result of object-based classification

	Producers Accuracy	Users Accuracy	Overall Accuracy	Kappa Coefficient
Water Body	66.67	85.71	**90.24**	**0.8473**
Cloud Shadow	93.75	83.33		
Cloud	100	100		

Table 5: Result of supervised classification

	Producers Accuracy	Users Accuracy	Overall Accuracy	Kappa Coefficient
Water Body	27.78	41.67	**68.89**	**0.5323**
Cloud Shadow	78.13	65.79		
Cloud	100	80		

6. Results and Discussions

Error matrix of object-based and pixel-based classification are shown in tables 2 and 3 respectively. From table 2, it had been observed that 12 polygons of water body were misclassified in cloud shadow and 4 polygons of cloud shadow was included in water body. However, from table 2, it had been observed that 26 polygons of water body were misclassified in cloud shadow and 14 polygons of cloud shadow was included in water body. 16 polygons of other classes were also included in cloud class.

From the object-based classification, separation of water body and cloud shadow and detection of cloud was achieved (Figure 2). Water can be extracted using water body index and shadow can be identified using average DN value of all bands. Reliability and threshold value plays a crucial role in this study. Higher reliability value of water as compared to shadow makes possible of the separation of these two (Figure 3) while higher threshold value of cloud as compared to shadow makes possible the identification of cloud (Figure 2). Cloud was classified with 100% accuracy and overall accuracy and kappa coefficient was quite good (Table 3). From pixel-based (Supervised) classification, water body and cloud shadow are mixed (Figure 5) because of same spectral signature associated of these two (Figure 6). Cloud was extracted but other (settlement) classes are also included in cloud class (Figure 5). Cloud was classified with 80% accuracy and overall accuracy and kappa coefficient was less (Table 5) as compared to object-based classification (Table 4).

It was observed that stream channel and water body extension was not fully detected (Figure 2).

7. Conclusion

In this study, separation of water body and cloud shadow and detection of cloud was achieved using object-based classification. Cloud shadow was separated from the water body and cloud was detected using three different parameters- DN value, reliability and threshold value with significant accuracy.

From visually assessed accuracy, it was found that classification for stream channel and extensions of water body were not fully achieved. Attempt is required to overcome this problem. This study was made over a specific area. Attempts are required to test this classification technique over a different area to see how the reliability and threshold value will affect the results.

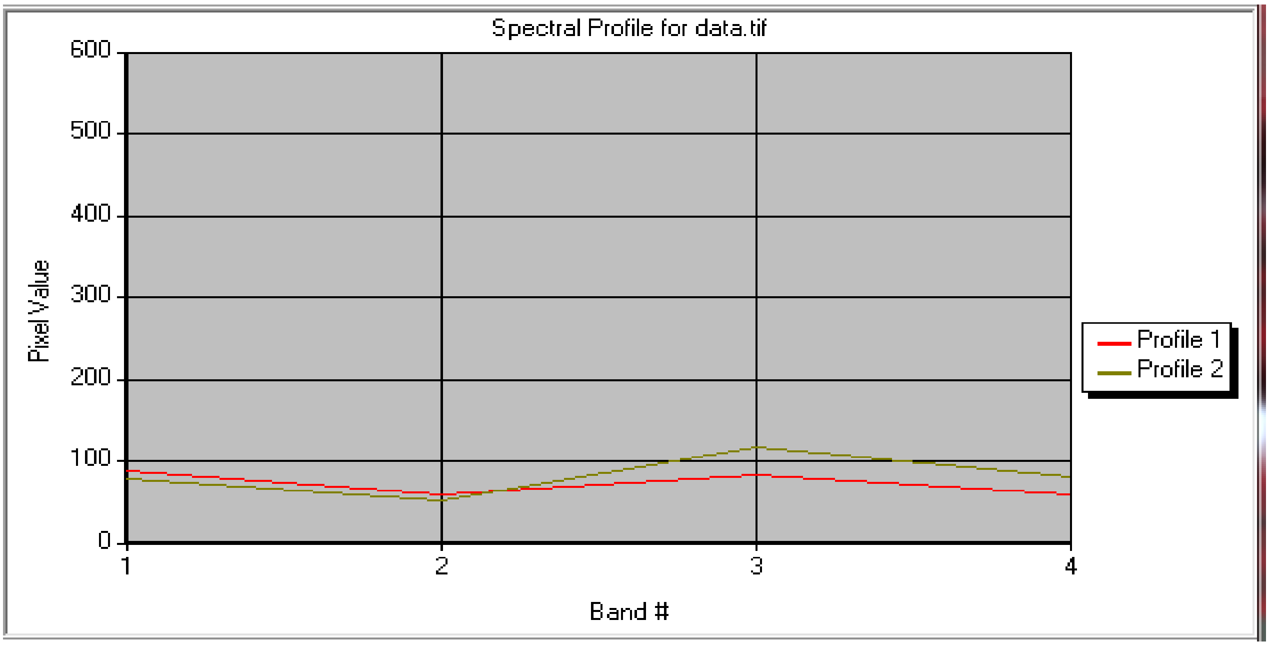

Figure 6: Spectral profile of water body and cloud shadow (Profile 1-water, Profile 2- Shadow)

Acknowledgements

Authors express their sincere gratitude to Sri D K Das, Director, Space Applications Centre (SAC) and Dr. Raj Kumar, Deputy Director, EPSA, SAC for their keen interest, guidance and encouragement. The authors wish to sincerely thank the reviewers for their critical comments and suggestions for improving the quality of the paper.

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