



Expert Systems with Applications

Volume 224, 15 August 2023, 120072

Spectral unmixing based random forest classifier for detecting surface water changes in multitemporal pansharpened Landsat image

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Received 12 May 2022, Revised 27 February 2023, Accepted 6 April 2023, Available online 7 April 2023, Version of Record 19 April 2023.

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<https://doi.org/10.1016/j.eswa.2023.120072> 

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Abstract

The gradual depletion of surface water in major lakes and their impact in the sustainable development of local water resources has been a great challenge. Monitoring surface water

and detecting changes in the lake are the main objectives of this study. Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper (ETM+) and Landsat Operational Land Imager (OLI) of 2010, 2000 and 2018 Lake Urmia images acquired from US Geological Survey were used for detecting the changes. Surface water changes are usually identified by extracting the water features from individual time series multispectral images. In this study, a novel change detection framework has been proposed involving pixel level fusion and classification. The spatial frequency based undecimated wavelet transform fusion (UDWT – SF) effectively extracted the spectral information from MS image and spatial information from PAN image of the same scene captured at different time periods. The endmembers of the fused images were selected using pixel purity index endmember extraction algorithm and the abundance estimation by the application of fully constrained least square spectral unmixing algorithm. An efficient sub-pixel classification process is designed by employing the spectral signatures, Normalized Difference Water Index (NDWI) and the abundance estimation generated from the pansharpened image in a random forest classifier. Experimental results indicate that the proposed classifier attained 99.9945% user's accuracy for water area and 99.9675% producer's accuracy for changed area. Similarly, the producer's accuracy of water and changed area are 99.9866% and 99.9868% respectively. The kappa coefficient and the overall accuracy of the proposed sub-pixel random forest classification on multitemporal multispectral image is 0.97 and 99.89% respectively. The lake surface area is computed and it is found that an area of 1369 Sq km has been decreased from the year 2000 to 2010 and 310 Sq km decreased from 2010 to 2018 as per the assessment based on the proposed random forest classifier. Spectral unmixing based random forest classifier (RF-SP) on fused image yields better results in terms of accuracy compared to other classifiers and it is more appropriate for detecting the multitemporal surface water changes.

Introduction

Change detection in the Geographical Information System (GIS) is a process of identifying how an area has changed between two or more-time intervals. It is helpful in many remote sensing applications such as Land use changes, Rate of deforestation, Surface water changes, Crop monitoring, Flood monitoring, Urban sprawl and other environmental changes (Byun et al., 2015, Coppin et al., 2004, Kaliraj et al., 2017). Surface water is one of the fundamental resources for the survival of humans and for a better ecosystem. Accurate data on the spatial distribution of surface water is required for assessing the water resources for future, suitable vegetation, watershed, and also for environmental monitoring. Extracting surface water and detecting changes were possible with the help of satellite remote sensing at different spatial, spectral and temporal resolutions. The fundamental reason behind using

the satellite data for detecting changes is due to the fact that the changes in surface results in remarkable changes in radiance values rather than the changes caused due to the atmospheric condition and differences in sun angle. Thus, the change detection in surface water involves selecting the geographical location, assessing the nature and accuracy of changes detected from multitemporal multispectral Landsat images. Changes occurred in the geographic area can be found from remote sensing images of the target taken over different time periods. In recent decades, data provided by satellite sensors such as Landsat, NOAA, Aqua, ADEOS, Spot, IKONOS, etc., were used. The data captured by the Landsat sensors involves varied characteristics that can be used for ecological studies. The National Aeronautics and Space Administration (NASA) launched the first Landsat satellite successfully in July 1972 followed by many more satellites with enhanced features. From Landsat-1 to 8, the Landsat program has been a combined initiative of NASA and US Geological Survey (USGS).

Sensor, solar, atmospheric and topographic effects cause distortion in images acquired by Landsat sensors. Before employing different change detection algorithms on multitemporal Landsat images, there is a necessity to execute a sequence of preprocessing procedures. Preprocessing involves calibration, atmospheric correction, mosaicking, coregistration, resampling and clipping. Image preprocessing would minimize distortion effects and there are software packages with numerous addons, which can be used to process these Landsat images.

Landsat images with different spatial, spectral and temporal resolution are thus taken forward after sufficient preprocessing and enhancement for identifying and extracting the changes occurred over the last few decades. Water characteristics are mostly derived from multi-temporal satellite data individually and then analysed to identify changes. Image fusion is one of the promising methods for making remote sensed images, especially Landsat images, highly qualified for change detection analysis. There are several conventional methods to assist the change detection process, both with and without the fusion process (Coppin et al., 2004, Rokni et al., 2015, Singh, 1989). In general, Image fusion is the process of integrating multiple images into a single image, which is more informative than any of the individual images. The resultant fused image has more information when compared to any of the input images (Kalaivani and Phamila, 2016, Zhang et al., 2015). Several image fusion techniques were extensively used by the researchers in varied fields such as remote sensing, medical imaging, cyber security and so on (K. Kalaivani and Phamila, 2017, Zhang and Zhu, 2011).

Multispectral and panchromatic sensors are used to capture high spectral and spatial data from earth surface. The high spatial and high spectral resolution satellite images are merged to form a fused image which is rich in spatial and spectral information. Landsat images are prone to have mixed pixels, the presence of more than one category of land cover in a pixel (Liu, Trinder, & Turner, 2016). Pixel classification is less reliable in assessing the water resources for future management; hence a sub-pixel classification framework would pave the way for better classification accuracy (Myint et al., 2015, Trujillo-Pino et al., 2013, Wu and Du, 2017). Nevertheless, for surface water change detection, the robust pixel level image fusion combined with sub-pixel classification framework is designed and analysed in this study. In recent years, the frequency of Landsat time series used for change detection has risen exponentially. For the same location, 2 Landsat satellites offer utmost 45–46 images each year. A single satellite orbits the same location 16 days once, allowing for the processing of 22–23 images each year for a particular location (Zhu, 2017). The open access to Landsat data archive from 2008, has totally transformed how Landsat data is used, and has sparked plenty of new change detection algorithms based on time series satellite data. In remote sensing applications, researchers use existing satellite data in the form of spectral bands for identifying water features and detecting changes. To detect the water features, the thresholding method make use of range or break threshold in either a single reflectance band or derived spectral water indices. Several surface water mapping methods have been formulated to acquire the required water information from multispectral images. McFeeters used the reflectance bands such as Green (G) and Near InfraRed (NIR) of Landsat images to identify the water features (McFeeters, 1996). The middle infrared (MIR) and near infrared (NIR) bands were used by (Gao, 1996) to highlight the water features. A zero-threshold value was used by McFeeters to differentiate water with other features. Later (Xu, 2006) point out that zero threshold is not appropriate to separate water features from other land features and proposed to utilize the shortwave infrared (SWIR) reflectance instead of NIR. Still there were some issues with respect to shadow pixels and hence (Feyisa, Meilby, Fensholt, & Proud, 2014) proposed an index with NIR, SWIR 1 and SWIR 2 reflectance bands for differentiating water features in urban background.

Water pixels are identified using the water indexes mentioned above by using a simple threshold that is set for various images or classification priorities. Appropriate threshold for differentiating land–water was examined by trial and error and in comparing with reference maps produced using visual interpretation. Classification techniques are employed to the fused image to find and map the lake surface water changes. Supervised, unsupervised and ensemble methods are widely used for classification in remote sensing images (Romero, Gatta, Camps-valls, & Member, 2015). In general, supervised methods identifies an image or area based on a mixture of spectral characteristics, where each pixel

inside and beyond the training sets is analysed and allocated to a class to which it has the greatest probability of belonging (Sheikh, Sabir, & Bovik, 2006). Due to the deficit of ground truth images for supervised approaches, an unsupervised approach has been mandatory in most of the remote sensing applications. As a result, there is an emphasis on a number of methodologies that use an unsupervised approach to learn land cover classes and thereby classify them.

The spatial resolution of multispectral and hyperspectral sensors is large and they may have several distinct objects in a single pixel measured by the spectrum. The pure land cover components are called pure pixels or endmembers. The presence of more than one land cover component (endmember) within a pixel is common in Landsat images, which are referred to as mixed pixels. Number of linear and non-linear spectral unmixing algorithms for extracting the endmembers have evolved to unmix the pixels based on spectral reflectance (Dobigeon et al., 2016, Khatami et al., 2017, Quintano et al., 2012).

The steps of spectral unmixing from endmembers extracted using a convex geometric method are well defined and also the geometric view of spectral unmixing was discussed by (Kruse et al., 1993). N-FINDR algorithm was proposed to find a unique set of purest pixels in an image using geometry of convex sets (Winter, 1999). An integrated model combining the convex geometrics and statistical procedures was proposed to extract the endmembers from hyperspectral images (Berman et al., 2004). A detailed study on various endmember extraction algorithms was done and proved that linear spectral unmixing algorithms were more appropriate when the spatial and spectral information are concerned (Plaza, Martínez, Pérez, & Plaza, 2004). A simplex growing algorithm was proposed by (Chang, Wu, Liu, & Ouyang, 2006) to extract the endmembers based on the sequential approach with less computation. A review of various endmember extraction algorithms on hyperspectral images was done (Martínez et al., 2006). An integrated endmember extraction algorithm was proposed with a focus on reducing the correlation between the endmember spectra (Li & Zhang, 2011). Several algorithms have been developed for extracting the endmembers based on geometric and statistical procedures focusing on reduced computational complexity and high accuracy (Solankar et al., 2019, Wu and Du, 2017). Monitoring water and detecting changes has become inevitable to assess and avoid declining of surface water in lake. From the literature review, it is clear that an efficient sub-pixel classification framework need to be designed to address the mixed pixels and to calculate the area of surface water from a Landsat image. Therefore a sub-pixel classification methodology involving an optimal endmember selection and abundance estimation is proposed to further enhance the classification accuracy. A brief report on the study area is presented in the section 2 Image Acquisition. Image preprocessing, spectral distance estimation of land

cover classes, spectral unmixing were presented in the 3 Image preprocessing, 4 Spectral distance estimation of land cover classes, 5 Spectral unmixing respectively. The proposed spectral unmixing based classification methodology is explained in the Section 6 and the results were illustrated in Section 7.

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Section snippets

Image acquisition

The study area is Lake Urmia, which is located in the Northwest of Iran. It is one of the largest saline lakes and its depth is 16m and its length is 140km. Its total catchment area is 3.2 % of the total size of Iran, and the lake Urmia is approximately 7% of the country's surface water. About 60 rivers are observed in the lake catchment that flows across the industrial, urban and agricultural areas without proper facilities for treating the waste water. There is a constant decline in the...

Image preprocessing

Image preprocessing plays a vital role in remote sensing applications involving change detection, accuracy assessment and so on. Radiometric calibration and atmospheric correction was done to convert the satellite radiance to Top of Atmospheric (ToA) reflectance. The ToA spectral reflectance is changed to surface reflectance using Dark Object Subtraction method. Tiles of different path/row were mosaicked using B-Spline interpolation technique. The images are then co-registered with the lesser...

Spectral distance estimation of land cover classes

Supervised classification requires the training set to classify pixels based on land cover class. Land cover class refers the type of object/feature identified in the pixel of a multispectral image. There are number of classes in a multispectral image and each class must be assigned with multiple training areas/Regions of interest (ROI). Training areas are

polygons that are drawn over homogeneous regions of an image and overlay pixels that belong to the specific land cover class. The Region...

Spectral unmixing

Existence of more than one feature in a pixel is possible in most of the medium spatial resolution satellite images. A single pixel comprises a proportion of several ground cover spectral features known as *endmembers*, calculated by their fractional *abundances*. To make use of the multispectral data, there is a need to break down these mixed pixels into a set of endmember signatures and its respective proportions. The process of decomposing these mixed pixels is called *spectral unmixing*, which...

Normalized difference water index and spectral unmixing based random forest classifier

Most of the assessment in remote sensing applications were inaccurate due to the presence of mixed pixels in Landsat TM and ETM+. From the review of literature and results of various classifiers on pansharpened image, a sub-pixel classification framework was developed as shown in the Fig. 1, Fig. 2. Random forest classifier does not require any assumption on data distribution and this highly improves the performance on comparison with other classification methods such as maximum likelihood,...

Results and discussion

The fused images generated from the best component substitution and multiresolution algorithms were subjected to perform classification (Kalaivani & Phamila, 2020). Gram Schmidt (GS) transform is comparatively better among other component substitution algorithms, and Spatial Frequency based Undecimated Wavelet transform (UDWT – SF) fusion outperforms among the multiresolution algorithms. Hence the fused images generated from GS and the UDWT-SF was considered as source images for classification...

Conclusion

A robust spectral unmixing based sub pixel classification technique is proposed for identifying the surface water changes in a multitemporal pansharpened image. Multitemporal images acquired by the satellite sensors Landsat TM, ETM+ and OLI were exercised to assess the performance of existing and the proposed classification based

change detection framework. Initially, the Images were preprocessed with utmost accuracy. The multispectral and panchromatic images of two different time periods were ...

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper...

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