A framework to detect digital changes in the mangrove forests

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Abstract

Despite the particular importance in marine ecosystems and food chain, mangrove forests are subject to destruction due to rapid population growth, poor planning, and inconsistent economic development. Identifying changes in these ecosystems is the first step in their sustainable management. Therefore, in this study, we have tried to determine the appropriate method for determining the changes in mangrove forests using satellite data and for identifying appropriate thresholds for revealing these changes. Based on the surveying of temporal variation of these forests, the tidal conditions are the first problem in determining the digital change of these forests. Accordingly, in order to determine the appropriate digital change detection method, OLI images in 2015 and ETM + images for 2001 were obtained in the same tidal conditions. The preprocessing operations included geometric, and radiometeric correction was done on these data. Then, to enhance spatial resolution, the fusion is done in a way that does not affect the output histogram. In the next step, first the images were enhanced by applying the spectral indexes, then the hybrid classification was applied to the images to extract the mangrove forest. At this stage, the changes in these forests were determined by post-classification comparison. In the next step, by combining the mangrove forest area at both time intervals, the total forest mask was obtained. Then, the NDVI spectral index was appropriately considered by analyzing the coefficients of variation of the spectral vegetation indices. Then, in the mask area of the mangrove forest, the NDVI was used to perform algebra change detection methods including image difference, image ratio, regression. Also, to determine the appropriate thresholds for algebra operations, the thresholds were applied based on deviation from the mean for all methods, then accordingly the changes were detected. Finally, by 120 sampling points, areas with the decrease, increase, and no change trends were visited and then overall accuracy and kappa coefficients were determined .Based on the results, the post-classification comparison has the highest accuracy in detecting changes. It was also found that the threshold of twice standard deviation showed the best accuracy in outputs.

Subjects: Remote Sensing
Keywords: Digital change detection, Image Algebra, Determination of thresholds, Post-classification comparison.

INTRODUCTION

Mangrove forests, with a daily production of 2.5 grams of carbon per square meter, are one of the most proliferating ecosystems on Earth. High-yielding products, along with shallow water, make these ecosystems ideal for supporting various components of the food network in a variety of aquatic environments and providing many services to communities. Services including providing essential habitats for birds and fish, preserving water quality, reducing coastal erosion, preventing floods, regulating the climate and supporting

economic activities such as hunting, fishing, and outing can be mentioned (Simard, Rivera-Monroy, Mancera-Pineda, Castañeda-Moya, & Twilley, 2008). However, these forests are at high risk due to rapid population growth, poor planning, and inconsistent economic development. The increasing problems of mangrove forests around the world are a severe problem in coastal ecosystems. Unfortunately, these forests are affected by human settlements, pollution, storms and sea waves (Vaiphasa, Skidmore, & de Boer, 2006). Up to now, about 35% of mangrove forests have been destroyed, and it is expected that by 2030 this destruction will reach about 60%. Reducing biodiversity, destroying freshwater resources, depositing on coral reefs and acidifying coastal soils, reducing the stability of the coastline, releasing more carbon in the atmosphere and reducing commercial fish are among the most critical effects of degradation and the disappearance of mangrove forests (Simard et al., 2008). These problems have led to an increase in demand for the production of detailed maps of mangrove forests at the species level and their diversity for monitoring the ecosystems of these forests. As international and governmental organizations have sought to develop plans for measuring the extent of these ecosystems (Vaiphasa et al., 2006).

Today, it is essential for effective resource management to know the extent and location of resources and how they change over time (Congalton & Green, 2008). Thus, ecological studies currently require biophysical and habitat data during the time for specific areas, which can easily be measured by remote sensing (Kerr & Ostrovsky, 2003). Remote sensing provides an extensive view of the terrain that is available over time, making it an essential tool in monitoring and managing resources (Kennedy et al., 2009). Among the remote sensing programs, the change detection plays a decisive role in this regard (Afify, 2011; Bahraminejad, Rayegani, Jahani, & Nezami, 2018; Barati, Rayegani, Saati, Sharifi, & Nasri, 2011; Fung & LeDrew, 1988; Gandhi, Parthiban, Thummalu, & Christy, 2015; Jahari, Khairunniza-Bejo, Shariff, & Shafri, 2011; Kennedy et al., 2009; Lu, Batistella, & Moran, 2008; Muchoney & Haack, 1994) . The change detection is the process of extracting, analyzing and defining information of the changes from satellite imagery (Xiaolu & Bo, 2011) . The digital change detection can provide an appropriate tool for monitoring the vast mangroves that are often hard to reach (Carney, Gillespie, & Rosomoff, 2014; Chen et al., 2013; Giri, Pengra, Zhu, Singh, & Tieszen, 2007; Giri et al., 2008; Jahari et al., 2011; Kuenzer, Bluemel, Gebhardt, Quoc, & Dech, 2011; Lee & Yeh, 2009; Liu, Li, Shi, & Wang, 2008; Pham & Yoshino, 2015; Rayegani, 2016; Vaiphasa et al., 2006). The digital change detection readily reveals shrinkage and degradation changes (Al-Fares, 2013; Carney et al., 2014; Jahari et al., 2011; Pham & Yoshino, 2015). Due to the importance of mangrove forests and the non-standardization of the remotely sensed studies on their resources in Iran, in this research, we have attempted to frame the mechanism for determining the digital change detection in mangroves based on field surveys.

MATERIAL AND METHOD

Study area

Hormozgan province has four protected areas with a forest cover of mangrove (knowns as Hara in Iran). Among them, the Protected Area of Hara is located between the north of Qeshm Island and Khamyr port which is considered as the best mangrove forest in terms of quality. Therefore, destruction of the forests of this area will be very effective in changing the ecosystem of the area. These forests are located in a subtropical climate zone with rainfall of 100-300 mm/year, and altitude of the sea level, or up to 6 meters above sea level. Based on the latest proposed frontier of the Office of Department of Environment in Hormozgan Province, this wetland has an area of more than 100 thousand hectares (Rayegani, 2016). Figure 1 shows the position of the Protected Area of Hara against the province of Hormozgan and Qeshm Island.
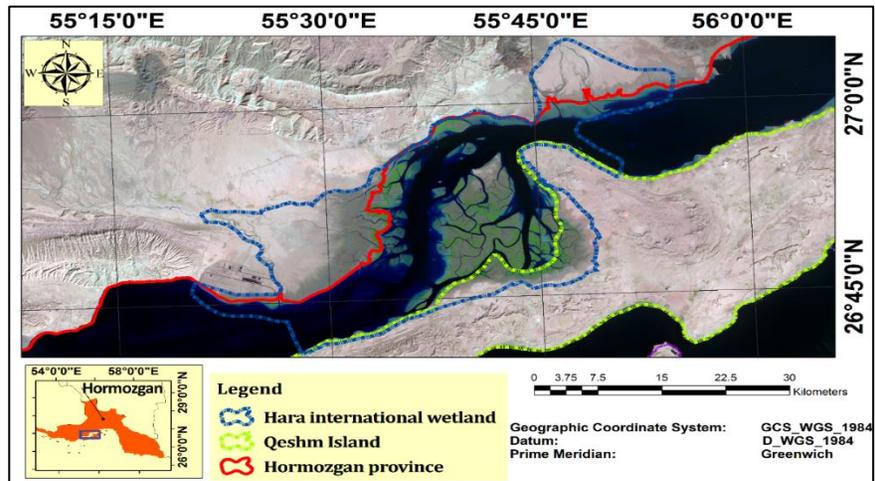
Figure 1. Study Area, province of Hormozgan and Qeshm Island

Data collection

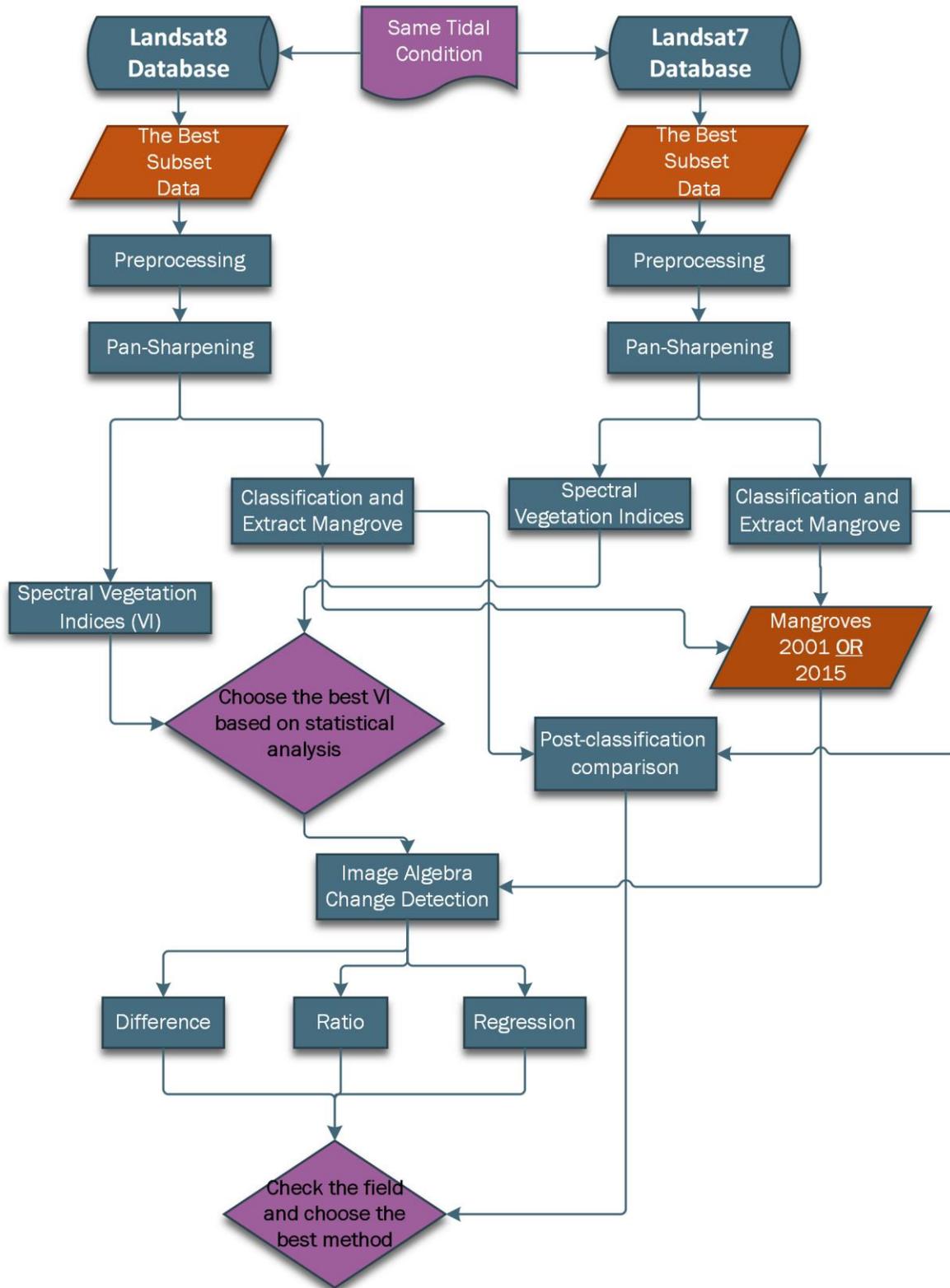Figure 2 shows the overall method of this study. Each section of the research will be described below.

Figure 2. Paradigm of methodology

The tidal condition at the time of receiving satellite images is one of the problems and limitations of any research in the field of mangrove forests. The tidal conditions affect estimated areas of mangrove cover, and all research that has been carried out on mangrove forests has encountered this limiting factor (Carney et al., 2014; Giri et al., 2008; Jahari et al., 2011; Lee & Yeh, 2009; Nguyen, McAlpine, Pullar, Johansen, & Duke, 2013; Pham & Yoshino, 2015). In this study, the satellite images used in 2015 and 2001 were chosen to be as close as the time of the year, and both were in the same situation in terms of the tidal conditions.

Also, preliminary analyzes on the images showed that by combining the images for one year in the form of maximum, minimum and median values, the error of the digital change detection would increase due to differences in tidal conditions. Accordngly, we tried to use the images in the final analysis which not only have a low tide condition but also mangroves are at the peak of phenological power (Jensen, 2005). Regarding the temperature, tidal conditions, and visual examination of Landsat images, the best time to compare was winter (around February & March). Therefore, images of winter with low tide condition have been prepared for the study area. Accordingly, the OLI sensor data for the date of 14/02/2015 and the ETM + sensor for 3/3/2001 date were collected.

Preprocessing

The remote sensing systems do not work perfectly. Also, the atmosphere, land, water, and soil are the composites that do not allow remote sensing instruments to record them correctly, with spectral, spatial, temporal and radiometric limitations . As a result, in the process of receiving data, there are errors that can reduce the quality of data collected by the sensor. Radiometric and geometric are two common errors in remote sensing data. In the radiometric correction, we try to improve the accuracy of the reflectance, emission, or scattering recorded by the remote sensing system. In a geometric correction, the aim of location correction is to measure reflection, diffusion, or distribution of their location with other geographic information or spatial decision-making systems. In a geometric correction, we try to fix the location of measurements. By doing so, the location measurement fits with other spatial information (Jensen, 2005; Koch & Mather, 2013). In this study, according to the multi-temporal study, absolute atmospheric correction and extraction of reflectance values using the ATCOR plugin (Al-Fares, 2013; Campbell & Wynne, 2011; Jensen, 2005; Liang, Li, & Wang, 2012)in ERDAS IMAGINE 2014 software, was performed. In order to correct geometric data, the OLI sensor data was geometrically corrected with the help of ground control points (Jensen, 2005; Koch & Mather, 2013), and then the ETM + sensor data was registered to it (Jensen, 2005).

Enhancement & Remote Sensing Processing

Pan Sharpening

In this study, ETM + and OLI sensor data are used, which have a spatial resolution of 30 m. In these sensors, there is a 15m spatial resolution panchromatic band that can be used to improve the spatial resolution of other bands. This spatial enhancement is usually known as the Resolution Merge, Pan-Sharpening or Fusion (Jensen, 2005). There are many ways to improve spatial resolution by the panchromatic band. In this study, several images were investigated using different fusion methods and finally, the Brovey Resolution Merge method (Jensen, 2005; Jong & Meer, 2004; Li, Chen, & Baltsavias, 2008; Liang et al., 2012) was selected. To choose the fusion method, we tried to look at the histogram of the output image, because one of the methods for determining the variation in this study was the Image Algebra Change Detection in which the histogram is very important (Jensen, 2005). Finally, regarding to ETM + and OLI data, in order to better detect mangroves from

other complications, the panchromatic band was used with multispectral bands.

Spectral Vegetation Indices (SVIs)

In remote sensing, the interpretation and detection of various materials is based on their spectral behaviors (Lyon, Yuan, Lunetta, & Elvidge, 1998). Therefore, the exact recognition of these behaviors is necessary. Plants show special behaviors in different bands because of having a series of specific materials in their leaves that help to differentiate them from other materials (Rogan, Franklin, & Roberts, 2002). One can even use these characteristics to distinguish plants from each other and determine their species because each species has its own spectral properties in a more precise look. In this research, in order to enhance the images, various spectral vegetation indices that are common in vegetation studies (Bahraminejad et al., 2018; Barati et al., 2011; Giri et al., 2007; Lee & Yeh, 2009; Liu et al., 2008) such as NDVI, PVI, MTVI1, MTVI2, and MCARI have been used. After examining the appearance of mangrove forests and extracting the statistical parameter of the coefficient of variation in enhanced images, their performance in unsupervised classification, among different spectral indices, NDVI and then MTVI1 showed better performance than other indices. Accordingly, the NDVI index which was proved to be effective in similar studies (Giri et al., 2007; Lee & Yeh, 2009; Liu et al., 2008; Lyon et al., 1998) was used further in the analysis.

Digital change detection of mangrove forest

Digital change detection of mangrove forest in this study was done in two ways: Post-Classification Comparison and Image Algebra Change Detection (Ilsever & Unsalan, 2012; Jensen, 2005; Li et al., 2008). Initially, the mangrove forests were extracted by the hybrid method (Jensen, 2005) (combination of two methods of supervised and unsupervised classification) based on the cognition of the study area in each study period. Accordingly, the post-classification comparison method was carried out after the classification.

Then from the class of the mangroves in both periods, a total mask of the mangroves was obtained by the "OR" Boolean logic. Due to the effect of water in the process of change detection by the algebraic method, this mask was used to extract statistical parameters so that the histogram of the algebra function is normalized. Three, image difference, image ratio, regression methods were used to detect changes (Jensen, 2005). In the NDVI image difference method, the NDVI image of the first date (ETM+) was subtracted from the NDVI image of the second date (OLI) (Eastman, 2012; Jensen, 2005; Lu, Mausel, Brondizio, & Moran, 2004; Lyon et al., 1998). Then the mask of mangrove was applied to it so that from the histogram, the mean values and standard deviation would be extracted only from the mangrove cover. In order to distinguish the actual changes from natural variation (Eastman, 2012; Jensen, 2005), three common thresholds were considered ($\mu \pm 2\sigma; \mu \pm 3\sigma; \mu \pm 1.5\sigma$) to select the best threshold based on field surveys in the future.

In the image ratioing method, the second image (OLI) was divided by the first image (ETM+), but the result is not linear. To correct it, natural logarithm was applied to the result for the linearization of the data (Eastman, 2012). As in the first method, statistical values were obtained based on the application of the mangrove mask. In this method, three thresholds for detection of real change were also considered.

In the regression method, the NDVI image of the second (newer) image was simulated using the linear regression equation using the NDVI image of the first (older) date. Then the simulated image was subtracted from the original NDVI image of OLI sensor. Similar to the two methods of the simple differencing and ratio, the mangrove mask was used to determine the changes and three thresholds were considered. In all three methods, the lower part of the thresholds was considered as a degradation of the mangroves (for example $\mu - 2\sigma$)

Accuracy assessment using field surveying

In this study, 120 points were selected using random stratified sampling in the protected area of Hara (Congalton & Green, 2008). These points were analyzed based on the field surveying and for points that were not accessible with the visual interpretation of Landsat and Google satellite imagery (based on the experience gained from field observation), to obtain reference data to form an error matrix. Then, the error matrix was formed, and the total accuracy and kappa coefficient were obtained to determine the best method and to select the appropriate threshold for real change detection (Campbell & Wynne, 2011; Congalton & Green, 2008; Eastman, 2012; Jensen, 2005). Accordingly, the best method and threshold for detecting changes in mangrove forests was identified. After determining the rate of degradation in four regions, these regions were ranked in order to carry out reclamation and restoration projects.

RESULTS

Results and discussions

The results of the accuracy assessment showed that the difference method with a threshold of twice the standard deviation is more accurate than other methods of image algebra operation (kappa 0.76 and overall accuracy of 82%). By applying the mangrove mask, the output of the differential function showed a normal shape (Fig. 3), so the necessary condition for using this method was provided (Eastman, 2012; Jensen, 2005) And the accuracy of the assessment was also appropriate.

However, the post-classification comparison method with a total accuracy of more than 93% and a kappa of more than 0.9 showed the highest accuracy among the digital change detection methods.
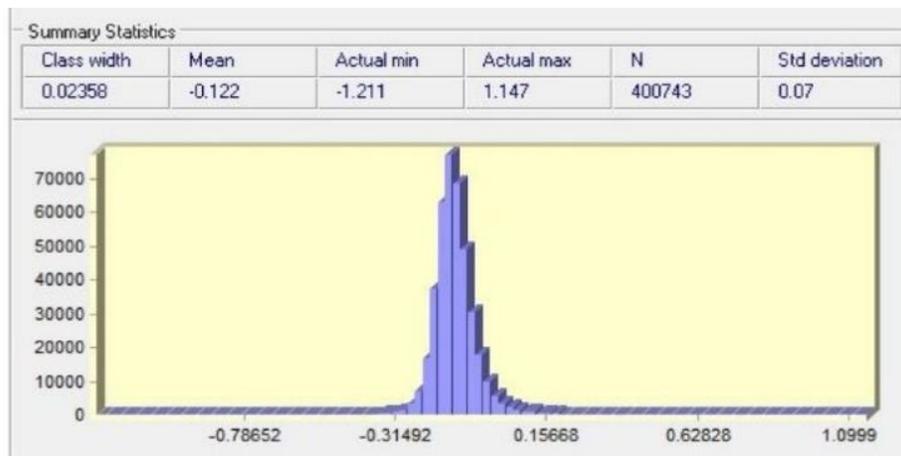

Summary Statistics					
Class width	Mean	Actual min	Actual max	N	Std deviation
0.02358	-0.122	-1.211	1.147	400743	0.07

Figure 3. Histogram of the NDVI in the simple differencing method

CONCLUSION

Given the higher precision of the post-classification comparison method in similar studies, the use of this method is proposed because in the image algebra methods it is necessary to define accurate thresholds that can be considered as a challenging process.

It is also suggested that in the stage of classification and extraction of mangrove forest while considering the tidal conditions of visualization, spectral vegetation indices be used as an auxiliary band. This can have a very positive impact on classification accuracy by reducing the environmental impacts (Jensen, 2005).

The results showed that the most significant error is observed in the water and forest boundary and it is necessary to use the spatial resolution enhancement by the panchromatic band to reduce the error.

In choosing the appropriate pan-sharpening method (fusion), the output histogram and its similarity to the histogram of the input image should be considered.

In the case of intelligent use of the capabilities of remote sensing, one can quickly identify the threatening factors of an ecosystem. In the case of mangroves, the only limiting factor is tidal conditions. It is therefore recommended that, as in this study, images are chosen to determine the changes that are in the same tidal state.

For future studies, it is also suggested that ; researchers consider time series data and trend analysis as in this analysis every single pixel is processed individually.

Acknowledgments

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