SENSITIVITY OF CHANGE VECTOR ANALYSIS

TO DETECT WATER-BODY CHANGES

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Abstract:

Qualitative and quantitative information is provided in Change Vector Analysis (CVA) in the context of change detection procedure. In this study, the Change Vector Analysis technique was implemented on multi-temporal multispectral remotely sensed data to monitor the dynamics of environmental change in wetland. Magnitudes of changes are determined based on any possible spectral band combination in the 2-dimentional Euclidian plane. And change magnitude is presented meaningful in the bands one, four, and seven. Categories of wetland changes are discriminated by means of the Tasseled cap (Kauth-Thomas Transformation) as biophysical indicator while, it reduces data redundancy and, representing the basic types of land cover – vegetation, soil and water. When inside the study area there is a probable reservoir caused by recently built dam, the images are then transformed into Kauth-Thomas features representing brightness, greenness, and wetness to enhance landscape features and optimize the data viewing capabilities. The results are shown the sensitivity of expected changes in different bands is distinctive to change magnitude discrimination. Furthermore, Greenness and Brightness are selected as an optimum choice for water-body change categorization.

1-Introduction

Remotely sensed data and GIS to land cover, land use monitoring and studying its change is a key to many diverse applications such as Hydrology, Geology, urbanization, agricultural development, forest land management, ice forecasting, etc. Natural Resource Management, Planning and Monitoring programs depend on accurate information about the land cover highlight the role of ascertaining the changes of specific area of interest within a certain time interval. Using multi-date satellite remotely sensed data to study land-cover change goes back to the early 1970s (Singh, 1989). Many remote sensing change-detection methods have been evaluated (Tin-Seong, 1995, Ridd and Liu, 1998, Sohl, 1999). The most commonly used change-detection methods are either spectrally based (image-to-image) or classification-based (map-to-map) method (Yang and Lo, 2002, Loveland et al., 2002).

Most of currently used change detection approaches are performed based on identifying the changes via applying threshold to ignore uninteresting change information. Four change detection techniques, image subtraction, image ratio method, image regression and change vector analysis CVA are used widely in the context of remote sensing. Change vector analysis CVA is a radiometric technique, the primary utility of ,which is the detection of all changes present in the input multispectral data (Malila, 1980). For each scene pair, these bands comprise the axes of an n-dimensional space. Although CVA is the most computationally intensive and time-consuming technique, including, atmospheric and radiometric normalization, it is the most accurate one for capturing and identifying changes using bands three and four of Landsat TM imagery (Berberoglu and Akin, 2009). It is also capable of utilizing any number of bands in change detection. The magnitude of change is determined by constructing a vector in the multispectral feature space (Almutairi and Warner, 2010). The direction images facilitate the discrimination of the change types (Siwe and Koch, 2008). This paper reviews the implementation of the change vector analysis by computing distance and angle are calculated in the Euclidian plane in any different possible two by two spectral bands combination. And results indicate the sensitivity of change information in the presence of the any possible spectral bands combination. And proper 2-dimential spectral bands for wetlands are determined in order to reduce the amount of redundant computation. Furthermore, changes are explored within land cover classes as well as changes from one land cover category to another.

2-Methods

2-1- Study area

This study area is located in East-Azarbaijan province and one district of the city of Varzegan. This site is selected in order to evaluate the performance of CVA approach especially in the presence of water body. Because of latest constructed dam, tremendous land-cover changes have taken place. Considerable recently occurred water-body is expected.

2-2- Remote sensing data

2-2-1- Landsat TM image

Most land-cover/land-use change studies utilized Landsat data due to the suitability of the data set as the long-term digital archive with a medium spatial resolution and relatively consistent spectral and radiometric resolution (Yang et al., 2003). The spectral information for the study case was acquired by the Landsat ETM+ and TM sensors covering the whole study area (path/row: 168/33). The imagery was provided as a data set in GeoTIFF format with UTM projection (UTM 32N), WGS-84 datum, and 31.5 m, 28.5 m pixel sizes. Remotely sensed images were acquired in 1989 as date-1 and 2001 as date-2. The six bands representing the visible and infrared spectrum (bands 1–5 and 7) were used in the study.

2-3- Image Pre-processing

2-3-1- Geometric Registration and Radiometric Normalization

The images were geometrically corrected and geocoded to the Universal Transverse Mercator (UTM) coordinate system by using a reference image. Images acquired at different times usually have different amounts of haze and dust in the atmosphere, these differences leads to mask real changes or make similar land cover appears to have changed (Berberoglu and Akin, 2009) that called uninteresting changes. As consequence of the multi-temporal character of this study, all satellite images were radiometrically corrected, in order to normalize the reflectance values of each pixel to those pixel values of the reference image. This process included the conversion of digital values to reflectance values, using the relationships proposed by (Markham and Barker, 1987) and the radiometric rectification according to a methodology proposed by (Hall et al., 1991).
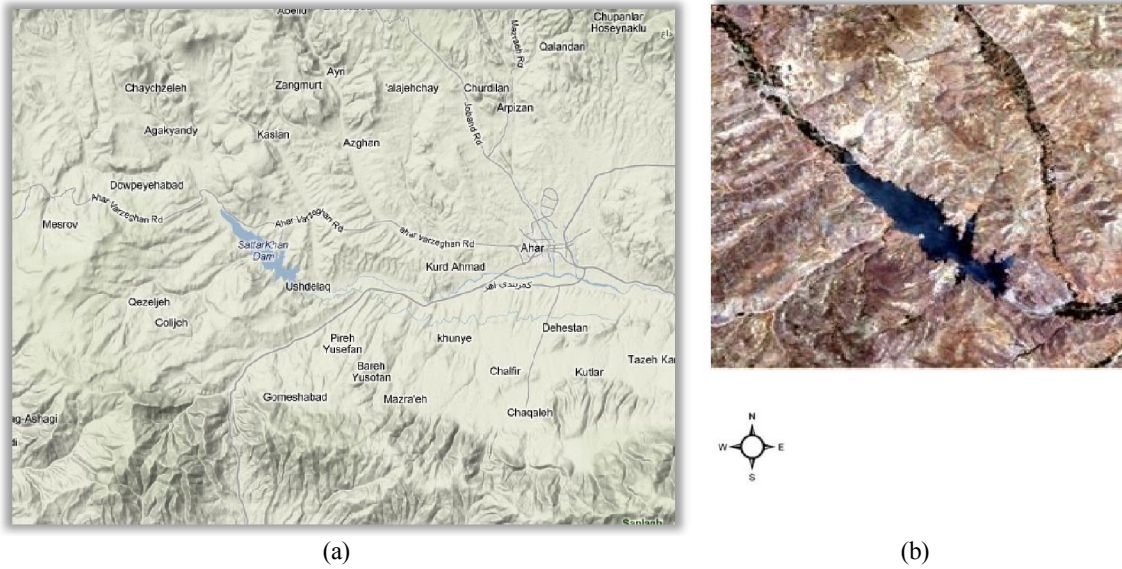
| (a) | (b) |

Figure 1. Area under study a) Location of study area, Google Map b) The image is false color composites of Landsat ETM+ bands 1- 5 and 7 for 2001.

2-4- Change/No-Change Pixel Detection

2-4-1-Modified Change Vector Analysis

Malia gave a general idea of change vector analysis in 1980. While change detection is estimated by Tasseled Cap (Collins and Woodcock, 1996, Lu et al., 2004, Chen et al., 2003, Singh, 1989) and image blob (Singh, 1989, Stringa, 2000), this study is performed based on purely radiometric bands related changes extraction and Tasseled Cap. Change Vector Analysis uses spectral properties to map both the: 1) magnitude of change and, 2) the direction of change between the n-dimensional (spectral) input for each date. Change magnitude is measured as the Euclidean distance or length of the change vector from a pixel measurement at date-1 to the corresponding pixel measurement at date-2 (Kuzera et al., 2005). The magnitude of change is a scalar variable representing the length of the vector, and is assumed to be related to the degree of physical change on the ground (Almutairi and Warner, 2010).

Changes are not easily identified in any single band or spectral feature. The CVA is applicable to any number of spectral bands, whether original scaled radiance, calibrated radiance or transformed variables (Phua et al., 2000). In this paper changes are studied based on both magnitude and direction of every possible 2-dimentional combination of radiometric bands and Tasseled Cap. In the absence of uninteresting change information, resulted maps have the potential to illustrate the changed areas.

So, Euclidian distance among any 2-dimensional spectral bands in pixel level is calculated (Figure 2). In addition, the summation value of aforementioned values is calculated as the other criterion of change detection, to determine the total magnitude of changes. The n-space Euclidean distance between pixels p and q in the presence of spectral bands is the length of the line segment connecting them (1). If a pixel's gray values in two images on date-1 and date-2 are shown by **Q**= (q1, q2, q3, q4,…, qn) and **P**=(p1,p2,p3,p4,…,pn) , and n presents the number of bands, respectively (1).

$$d(p, q) = d(q, p) = \sqrt{(p1 - q1)^2 + (p2 - q2)^2 + \cdots + (pn - qn)^2} \tag{1}$$

While equation (1) is applicable for n-dimensional Euclidian space, for this study case 2-dimentional magnitude of change vector in Euclidian plane can be calculated as

$$d(p, q) = \sqrt{(p1 - q1)^2 + (p2 - q2)^2} \qquad (2)$$

Bands 1, 2, 3, 4, 5 and 7 of the TM 1989 image and ETM+ 2001 image are used in CVA analysis. According to Equation (2) change magnitudes between 1989 and 2001 images for each pair of spectral bands are calculated and with respect to the spectral bands 28 numbers of maps are resulted. And total change amount is calculated by using equation (1) just for correspondent bands.

Moreover, changes are analyzed based on direction of any possible spectral bands on the 2-dimentional plane. Change direction is measured as the angle of the change vector from pixel measurement at date-1 to the corresponding pixel measurement at date-2 (Siwe and Koch, 2008) (Figure 3). Furthermore, in order to change magnitude estimation corresponding angles are calculated as (3)

$$\qquad (3)$$

Optimum thresholds were assigned in order to ignore uninteresting change information. Conventionally, the corresponding magnitude change vector threshold is determined empirically. The intensity of change that acquired is assigned arbitrary based on statics and histogram as low change (56-104), medium (104-148), and high (148-199). Outliers with respect to standard deviation from the mean and considering changed features based on prior knowledge are assumed for values below 56 and above 199.

2-5- Change type categorization

Type of change pixels can be discriminated by means of CVA. The tasseled cap transformation defines a new coordinates system in which characteristics of the remotely sensed data can be more meaningfully viewed (Crist and Cicone, 1984). Tasseled Cap transformation is performed on Landsat bands 1-5 and 7 in order to highlight the Wetness, Brightness, and Greenness qualities of the environment (Kauth and Thomas, 1976). These transformations produced new image features representing wetness, Greenness, and brightness based on new axes associated with biophysical properties of the scene (Lorena et al., 2002). Values of brightness highlight variations in soil reflectance throughout the study area.

Brightness is defined in the direction of soil reflectance variation, obtained from a weighted sum of all bands. Wetness presents information concerning the moisture status of the environment, obtained from the contrast of the sum of visible and near-infrared with the sum of longer-infrared bands. Values of greenness respond to the combination of high absorption in the visible bands and high reflectance in the near-infrared which is characteristic of green vegetation (Crist and Cicone, 1984). The combinations of these new transformed bands are concerned as an input for change vector analysis. Brightness, wetness, and greenness are practiced in 2-dimensional space to determine the optimum change characteristics. The magnitude and direction of the difference images were calculated for brightness and greenness (Siwe and Koch, 2008) as (4)

$$|\Delta G| = \sqrt{(\text{brightness dif.}^2) + (\text{greenness dif.}^2)} \qquad (4)$$

The direction of a vector can be described by a series of cosine function in a multi-dimensional space (Land-Use/Land-Cover Change Detection Using Improved Change-Vector Analysis) which is called direction cosines (Hoffmann, 1975). The sample directions are determined as in Equations 5 and 6 since direction cosines are calculated to the Wetness/Greenness and Wetness/Brightness as well as Greenness/Brightness:

$$\cos \alpha = \text{brightness}/\Delta G \qquad (5)$$

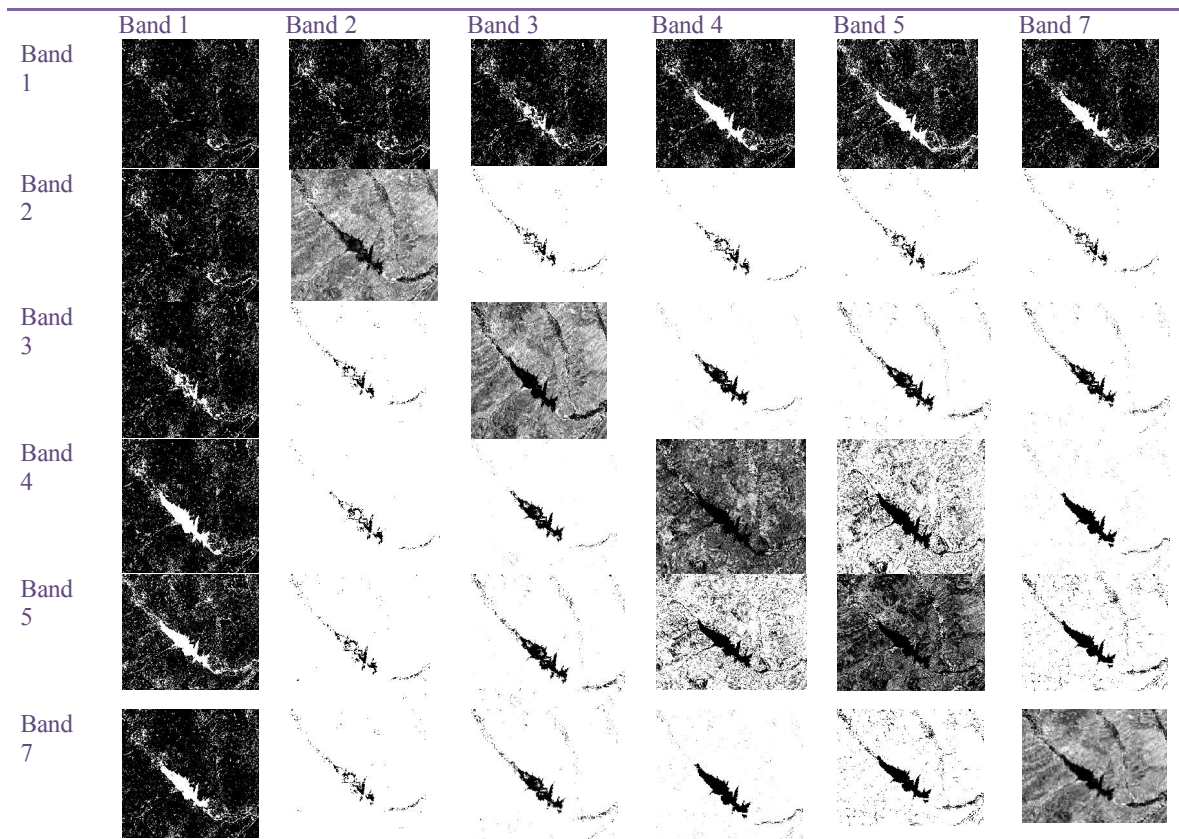$$\cos \beta = \text{greenness}/\Delta G \qquad (6)$$

Figure 2. Change presentation of two by two spectral bands combination resulted by Euclidian distance
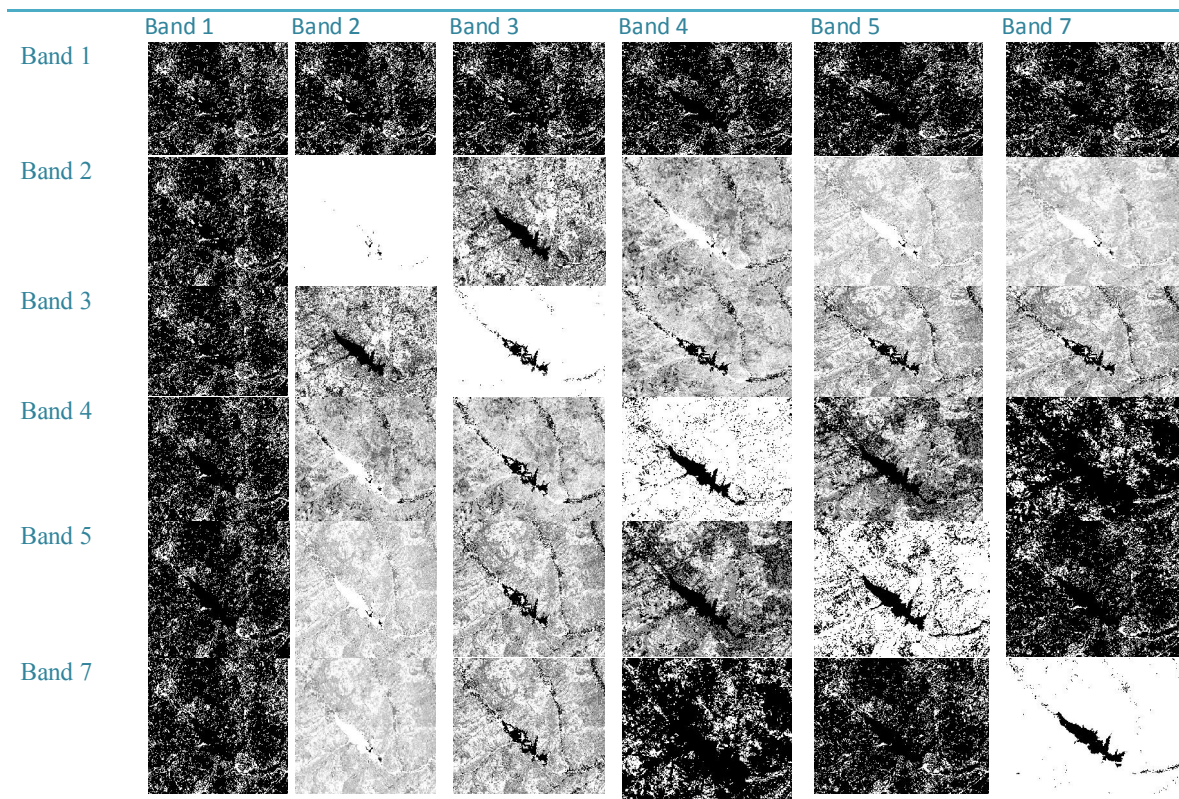

Figure 3. Change presentation of two by two spectral bands combination resulted by angle calculation

Change directions within pixels in the brightness and greenness bands are described by (Siwe and Koch, 2008):

1) Angles measured between 0 to 90 indicate increase in greenness and increase in brightness.
2) Angles measured between 90 and 180 indicate an increase in greenness and a decrease in brightness.
3) Angles measured between 180 to 270 indicate decrease in greenness and decrease in brightness.
4) Angles measured between 270 and 360 indicate a decrease in greenness and an increase in brightness.

Aforementioned statements reported by (Siwe and Koch, 2008) about the brightness and greenness are extended to the both brightness-wetness and greenness-wetness approaches (Figure 5). Results indicate that a general trend about wetland categorization is: 1) Whilst increments in both types are observed, water or high moisture land is expected. 2) While any possible pair of the following variables is decreased, moisture reduction between dates is likely.

3- Results

The potential of the technique in categorizing wetlands could not be assessed fully in the absence of fieldwork. Correspondent change and non-changed thresholds are assigned empirically without any field measurement. Changes are studied in every possible combination of 2-dimentioanl spectral bands. And potentially useful bands for CVA technique to water-body and wetland categorization are introduced. Hence, for wetland change magnitude decision making, and even change categorization based on 2-dimentional Euclidian distance, bands one, four, and seven are seemed capable based on visual interpretation of (Figure 2) with respect to change magnitude map (Figure 4). Conventional CVA change detectors use Euclidian distance to estimate change magnitude since, in this study spectral bands direction are calculated and tested, results indicate potentially useful information both for magnitude and change type detection.

Further, Greenness/Brightness, Wetness/Greenness, and Wetness/Brightness are explored for water-body change categorization. Consequently, efficient choice for water-body change type discrimination is seemed to be Greenness/Brightness (Figure 6). Whereas it is assumed that because of specification of wetness Tasseled cap, it would be the one of the choices in 2-dimentional Tasseled Cap based change type discrimination; optimal results are not met in the presence of wetness. In this paper, initial land cover is not considered as an area of interest since changes that have occurred and lead to wetlands are studied. Including (Figure 6) presents the area where, land-cover type is changed to water-body and wetland.
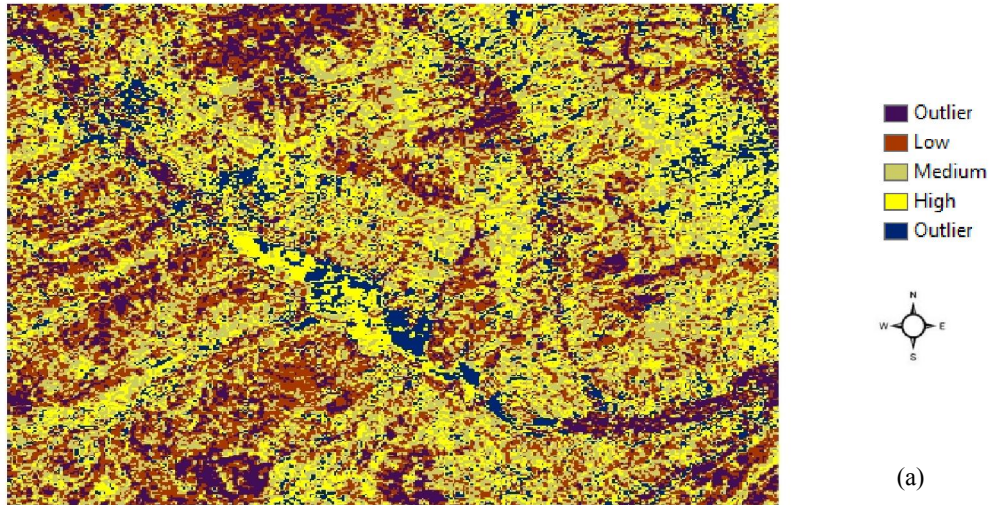
(a)
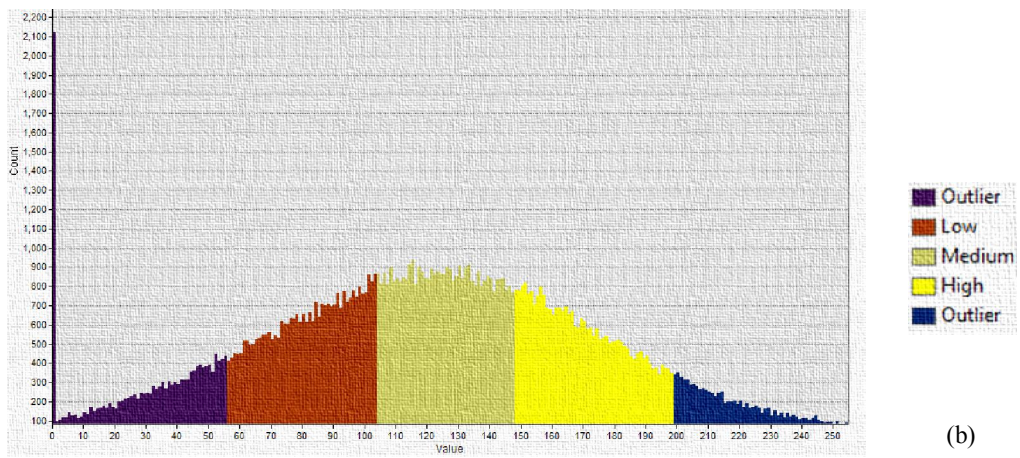
(b)

Figure 4. Change intensity illustration based on Change magnitude in the study area a) The change intensity map after threshold divided b) The relation between change intensity and change dimension
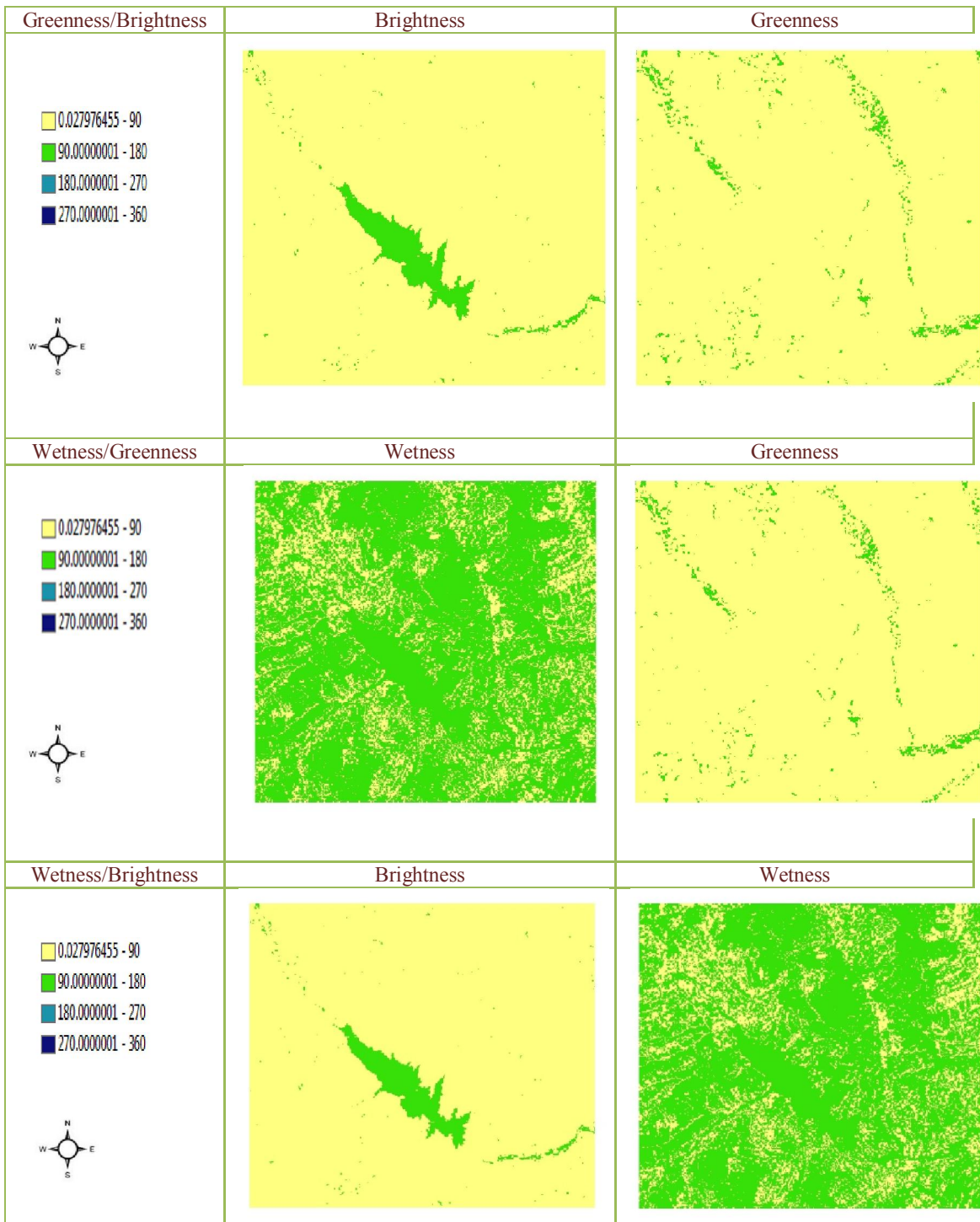
Greenness/Brightness	Brightness	Greenness
☐ 0.027976455 - 90 🟩 90.00000001 - 180 🟦 180.0000001 - 270 🟪 270.0000001 - 360		

Wetness/Greenness	Wetness	Greenness
☐ 0.027976455 - 90 🟩 90.00000001 - 180 🟦 180.0000001 - 270 🟪 270.0000001 - 360		

Wetness/Brightness	Brightness	Wetness
☐ 0.027976455 - 90 🟩 90.00000001 - 180 🟦 180.0000001 - 270 🟪 270.0000001 - 360		

Figure 5. Change type Illustration of Wetness, Brightness, and Greenness analysis in any possible the 2-dimentional pairs
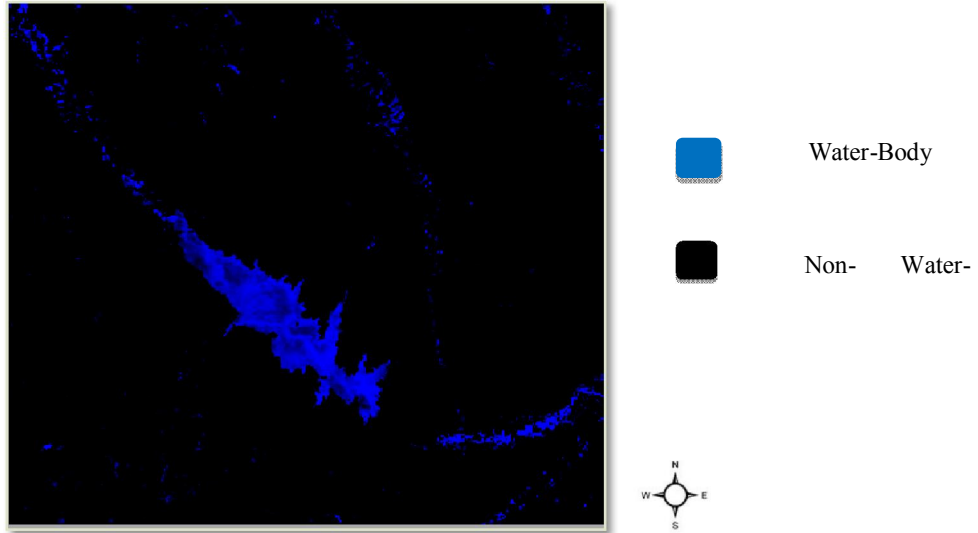
Figure 6. Water-body change type discrimination in the study area based on Greenness/Brightness Tasseled Cap

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