A new land-cover match-based change detection for hyperspectral imagery

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ABSTRACT

The presence of phenomena such as earthquakes, floods and artificial human activities causes changes on the Earth’s surface. Change detection (CD) is an essential tool for the monitoring and managing of resources on local and global scales. Hyperspectral imagery can provide more detailed results for detecting changes in land-cover types. The main objective of this paper is to present a new, supervised CD method by combining similarity-based and distance-based methods to increase the efficiency of already existing CD approaches. The proposed method applies in two phases and uses three different algorithms, including image differencing, modified Z-score analysis and spectral angle mapper. The efficiency of the proposed method is evaluated using Hyperion multi-temporal hyperspectral imagery. The receiver-operating characteristic curve index is used for assessing and comparing the results. The results clearly demonstrate the superiority of the proposed method for the detection and production of more accurate change maps. Furthermore, the proposed method is also able to detect changes with an accuracy of more than 96%, a false alarm rate lower than 0.03 and an area under the curve of about 0.986 in overall comparison to other conventional CD techniques. In addition, this method achieved an optimal threshold value with more rapid convergence.

Introduction

Many organizations have reported that several types of environmental changes have occurred especially in recent years that cause many problems for wide areas of the Earth’s surface. Monitoring these changes has proven costly and time consuming. Direct access to most of the affected regions is hindered by various difficulties, but remote-sensing technology has solved many of these issues (X. C. Chen, Kumar, & Faghmous, 2015). With the advent of remote-sensing science, continuous data collection from the Earth’s surface at minimum cost and with wide coverage provides a valuable source of information for change detection (CD) purposes (K. Wu, Yi, Niu, & Wei, 2015). Thanks to the improvement of temporal resolution (S. Liu, Bruzzzone, Bovolo, & Du, 2016), and new existing types of sensors such as the Airborne Visible Infrared Imaging Spectrometer (AVIRIS), POLSAR, Landsat-8 and Sentinel-2, which acquire images in various ranges of wavelengths on the electromagnetic spectrum, there is great interest in extracting information from multi-temporal datasets. The most important ongoing problem with conventional CD approaches is using multispectral (MS) datasets with a limited spectral resolution, which results in the extraction of major changes only (S. Liu, 2015; C. Wu, Du, & Zhang, 2013).

Nowadays, with the development of technologies for airborne systems and space-borne remote-sensing sensors, the ability to obtain data in both high spatial and high spectral resolution is increasingly feasible (Scheffler & Karrasch, 2013). This leads to the use of remote-sensing satellites in various areas of Earth science studies, including object detection (Cheng & Han, 2016; Cheng, Zhou, & Han, 2016), image classification (Cheng, Han, Zhou, & Guo, 2014; Cheng et al., 2015; Hassanzadeh & Karami, 2016; Raczkö & Zagajewski, 2017), anomaly detection (AD) (L. Zhang & Zhao, 2017) and CD (Shah-Hosseini, Homayouni, & Safari, 2015; K. Wu et al., 2015).

The field of CD in particular has had several kinds of recent research efforts (K. Wu et al., 2015; Yang & Sun, 2015). The most important criteria in CD are the real-time and accurate detection of land-cover changes. CD is a process which measures the differences between objects in the same place at different times (Singh, 1989). Example applications of CD include creating an accurate and on-time change map that can prevent tragedies, updating land-cover change maps, optimal management of recourse and study of variation in human activities (Q. Du & Yang, 2008; C. Wu et al., 2013; K. Wu et al., 2015).

Hyperspectral sensors are generally mounted on two platforms: airborne (e.g. AVIRIS and HYDICE) and...
spaceborne (e.g. Hyperion, CHRIS and IASI). A new series of spaceborne sensors (e.g. EnMAP, PRISMA and HyspIRI) is scheduled to launch in the near future, which will further increase the availability of hyperspectral imagery with improved data quality (S. Liu, 2015). Hyperspectral sensors operate at continuous wavelengths, with a bandwidth of approximately 10 nm (S. Liu, 2015; Smith, 2012). Traditional MS sensors collect data in a single pass, using specific wavelengths throughout a select few spectral bands of the electromagnetic spectrum (Ferrato & Forsythe, 2012; S. Liu, 2015). This small window of spectral bands is one of the primary disadvantages of MS sensors, because some of the observed objects show the same spectral behavior as other, different objects when using the coarse bandwidths of current MS sensors (Govender, Chetty, Naiken, & Bulcock, 2008; S. Liu, 2015; Omo-Irabor, 2016). This in turn affects the ability to identify and distinguish objects accurately, lowering overall accuracy (OA) and making the spectral information offered by MS data less elaborate. Hyperspectral imagery, on the other hand, operates at much finer spectral resolutions. It offers more abundant and more detailed information and can distinguish objects that would otherwise appear similar. Aside from providing increased identification power, the higher resolution further increases accuracy by providing more details, thus promoting efficiency in most applications, especially in CD analysis (S. Liu, 2015; Omo-Irabor, 2016; Smith, 2012; C. Wu et al., 2013).

When carrying out CD procedures on hyperspectral images, some problems appear that affect the results, such as the presence of noise in the images, and different atmospheric conditions, all of which lead to more computational complexity and an increase in execution time (S. Liu, 2015; Shah-Hosseini et al., 2015). Our proposed CD algorithm, however, can help reduce the aforementioned problems in the processing of hyperspectral images.

In recent years, much research has been done on detecting changes in hyperspectral datasets. These methods include four major groups. The first group is a post-classification-based procedure. In that method, classification approaches are applied to date 1 and date 2, and then the two classified maps are compared on a pixel-by-pixel basis in order to produce the final change map (Ahlqvist, 2008; Hazel, 2001; Serra, Pons, & Sauri, 2003; Singh, 1989; Song, Woodcock, Seto, Lenney, & Macomber, 2001; Walter, 2004). Zhou, Troy and Grove (2008) used an object-based land-cover classification for extracting changes. First, they extracted objects of the data and then applied rule-based classification to classify each object in the image. The extracted change map (Almutairi & Warner, 2010) utilized maximum likelihood classification for CD of multi-temporal datasets. They manually created training data to produce the change map. In addition, the effect of radiometric normalization errors on the accuracy of change analysis is compared. Woo and Do (2015) performed an AdaBoost classifier for segmenting multi-temporal data. First, they extracted 2D co-occurrence features and used a digital elevation model (DEM) to extract 3D co-occurrence features. In the second step, an AdaBoost classifier was applied to extract the change map. However, these methods provide “from-to” change information, and atmospheric conditions do not affect the CD result; they suffer from a number of disadvantages, including a dependence of the result’s efficiency on the accuracy of the classification, getting impressed by noise and problems with the supervised algorithms which require training data (which contains no-changes). It should be noted that collecting training sets for most of the multi-temporal datasets is a considerable effort (C. Wu et al., 2013). Also, the class labeling and dimensional reduction is another critical issue in supervised classification methods (Feng, Li, Du, & Zhang, 2017; Marpu, Gamba, & Benediktsson, 2011a; Shah-Hosseini et al., 2015).

The second group is a transformation-based procedure that uses a transformation technique in order to map data from image space to feature space. Nielsena and Müllerb (2003) applied a multivariate alternative detection (MAD) technique which is based on canonical correlation analysis. The purpose of this method is to find the linear combination of two datasets that causes the highest variance. Some researchers (Marpu, Gamba, & Benediktsson, 2011b; Nielsen & Canty, 2005) improved the MAD approach and suggested a new model, iteratively reweighted MAD (IR-MAD); this method tries to extract the changed pixels in a repetitive reweighted procedure. Rivera in Rivera (2005) used the principal component analysis (PCA) process for CD. The main purpose of PCA is to transform input data space into a new set of linearly uncorrelated variables, and also a number of components equal to the number of variables in the original space. Eismann, Meola and Hardie (2008) used covariance equalization (CE) and chronochrome (CC) algorithms as predictors for CD. Their approach began by segmenting the datasets; then CE and CC were considered as predictors. Then, Reed–Xiaoli (RX) and global AD algorithms were used for extracting the final change map. Although these techniques could efficiently process high-dimensional data, finding the change component among the various numbers of components is a big challenge. These methods generally do not consider the continuous spectral signatures from hyperspectral datasets. In addition, these algorithms increase both the computational complexity and the running time (S. Liu et al., 2016; Shah-Hosseini et al., 2015).

The third group is a direct multi-date classification procedure. These methods only use one classifier to classify multi-date datasets, based on the fact that the
Statistics of the changed pixels are significantly varied from the no-changed pixels (Hussain, Chen, Cheng, Wei, & Stanley, 2013). Mas in Mas (1999) used an unsupervised classification algorithm (ISODATA classifier) for CD and the extraction of change information. The advantages of these methods are easy implementation and less computational time requirement. The most important disadvantages of these techniques, however, are several issues regarding labeling of the changed pixels and providing too little information about the change matrix; in supervised methods, there is also a need for dimensionality reduction (Almutairi & Warner, 2010; Yuan, Lv, & Lu, 2015). The fourth group is a matched-based (MB) procedure. These methods are further divided into two more groups: similarity based (SB) and distance based (DB) (Choi, Cha, & Tappert, 2010). These methods aim at measuring the difference between data in all bands using a math operator (Adar, Shkolnisky, & Dor, 2012). These CD methods are simple, fast and less sensitive to atmospheric conditions (Hussain et al., 2013).

Based on the above analysis of the current CD methods, it is necessary to use CD algorithms that mainly focus on key points, including (1) sensitivity to subtle changes with high accuracy and low false alarm rates; (2) simple and easy implementation; (3) low computational cost and the ability to process high-dimensional data; (4) use of low training sets; (5) utilizing continuous spectral signatures, one of the great advantages of incorporating hyperspectral imagery that promotes efficiency in most applications, especially in CD analysis; and (6) suffering less impact from atmospheric and noise conditions.

The main goal of this paper is to propose a new SB–DB method for CD of hyperspectral images that could be used to minimize the mentioned problems. The proposed method successfully takes into account both correlation-based and DB techniques. Two real hyperspectral images from different locations have been used as a case study. Image differencing (ID), the modified Z-score (MZ) algorithm and the spectral angle mapper (SAM) algorithm were all utilized in the presented SB–DB procedure (SAMZID)\(^3\). The performance of the CD results will, therefore, be increased, and the final change maps indicate that the capability of this algorithm to detect changes is noticeably more efficient.

This paper is organized as follows: in “Methodology” section, details of hyperspectral CD methods are presented. “Study area and dataset” section details the type of threshold selections used. “Implementation” section introduces study areas and hyperspectral datasets. In “Experiments and result” section, the evaluation results are presented, and finally, “Conclusion” section includes the conclusion on the experiment results.

**Methodology**

The proposed methods consist of two phases. The first phase is the predictor phase, and the second is the learning phase. Both phases will be explained in detail in the following sections.

**Predictor phase**

The predictor phase is used to predict the change area using MB methods. Such a procedure will yield a changing area that contains more difference value when compared to the no-changes area. The predictor phase is applied in accordance with the proposed method. Spectral MB methods are divided into two groups, including the SB and DB methods. Both groups are widely used in CD, as well as research and relevant studies (S. Liu, Bruzzone, Bovolo, & Du, 2015; C. Wu et al., 2013; Xu, Zhang, He, & Guo, 2009). We propose a new method by combining the SB–DB metrics to detect changes in multi-temporal hyperspectral imagery. Figure 1 shows an overview of the utilized SAMZID algorithm. The proposed framework includes three main steps: (a) preprocessing of each dataset; this process has many sub-steps that will be explained in “Dataset preprocessing” section; (b) applying the SAMZID technique in order to extract the initial change map; for more details, see the next subsections and, finally, (c) selecting an appropriate threshold value based on the highest accuracy to map out the final change map. Consequently, the output of this procedure is a binary change map.

**Similarity-based (SB)**

SB methods are used in the fields of machine learning, artificial intelligence and pattern recognition, all of which are widely employed in classification applications (Y. Chen, Garcia, Gupta, Rahimi, & Cazzanti, 2009; Duch, 2000). This approach can detect various types of phenomena based on spectral properties and spectral signatures (Y. Du et al., 2004). Measuring the spectral properties between two different vectors using these SB indices is incorporated into many applications, especially in remote sensing. Examples include image classification (Hosseini, Homayouni, & Safari, 2012; Padma & Sanjeevi, 2014), image registration (Ren, Song, Zhang, & Cai, 2016), target detection (Chang, 2003; J. Zhang, Cao, Zhuo, Wang, & Zhou, 2015), dimensional reduction (Q. Du & Yang, 2008; Keshava, 2004; Hasanlou, Samadzadegan, & Homayouni, 2015; J. Zhang et al., 2015; Nahr, 2016).

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\(^3\)Spectral Angle Mapper Z-score Image Differencing.
Pahlavani, & Hasanlou, 2014) and CD (Ahlqvist, 2008; Inglada & Mercier, 2007; S. Liu et al., 2015).

**Image differencing**

ID is one of the most common methods in CD and is widely used in land-cover CD (Equation (1)). The ID algorithm is applied to the geo-referenced images in order to produce the change map (Xu et al., 2009).

\[
D^K_{X} = X^K_{ij}(t_2) - X^K_{ij}(t_1)
\]  

where \(X^K_{ij}(t_1)\) and \(X^K_{ij}(t_2)\) are the date 1 and date 2 pixel digital number (DN) values in row \(i\) and column \(j\), in band \(K\).

**Z-score analysis**

The Z-score is a method for standardizing a set of values (Dever, 2006). The mean deviation of the magnitude and direction in this method shows the distribution in a unit of standard deviation (Equation (2)) (Cheadle, Cho-Chung, Becker, & Vawter, 2002). In this paper, we have squared the common Z-score value. In other words, thanks to the use of only positive values (as a result squaring the Z-score), discrimination will be increased especially among values which are very close to each other (Equation (3)). By incorporating the modified version of Z-score (Equation (3)), we can easily achieve better discrimination of change pixels from no-change pixels, especially in CD applications.

\[
Z_{\text{score}}(x_i) = \frac{x_i - \mu}{\delta}
\]  

\[
\text{Modified}_{\text{Z-score}}(x_i) = \text{normalized} \left( \sum_{j=1}^{\text{Number of bands}} \left( \frac{x_i - \mu}{\delta} \right)^2 \right)
\]

where in Equations (2) and (3), \(\delta\) is standard deviations of values, \(\mu\) is the mean value of a dataset and \(x_i\) is the input data value.

**Spectral angle mapper**

The SAM algorithm measures the spectral angle between the reference map and target vectors in \(n\)-dimensional space. This algorithm is insensitive to sunlight because the spectral angle between two vectors is independent of vector length (Adar, Shkolnisky, & Ben Dor, 2014; Moughal & Yu, 2014; Wen & Yang, 2009). The SAM algorithm can be calculated as follows (Equation (4)).
\[
\text{SAM}_\alpha = \cos^{-1}\left(\frac{|x \cdot y|}{|x| \cdot |y|}\right)
\]  
(4)

where \(\text{SAM}_\alpha\) is the spectral angle, \(x\) and \(y\) represent the target and reference spectra, respectively.

**Fusion of ID, MZ and SAM metrics**

We have developed a new algorithm that combines ID, MZ and the SAM approach. Recently, many researchers have begun to successfully use combinations of SB and DB techniques in their research, particularly in classification applications such as spectral information divergence (SID) and its integration with the SAM algorithm (Chang, 2000; Y. Du et al., 2004), Jeffries–Matusita (JM) (Padma & Sanjeevi, 2014) and SAM combinations (Padma & Sanjeevi, 2014) and correlation-based methods (Im, Jensen, & Tullis, 2008).

Our proposed method begins by applying the ID algorithm (Equation (1)) to a cube of two different times from hyperspectral datasets. The output of the first step is the input of the second step. In that second step, the MZ analysis is applied to the output of the first step (Equation (3)). Additionally, the hyperspectral data cube is processed by the SAM algorithm (Equation (4)) directly after the preprocessing step. The combination and fusion are applied on the output of the MZ analysis, and the output of the SAM algorithm in two ways: using the format of \(\text{SAMZID}_{\text{tan}}\) and \(\text{SAMZID}_{\text{sin}}\) (Equations (5) and (6)). This configuration is illustrated in Figure 1. By incorporating these metrics, the proposed fusion method reduces illumination effects of different dates of datasets on the one hand, while on the other hand, weight changes result in an enhancement of the performance of the CD result (Padma & Sanjeevi, 2014). As part of the combination and fusion step, and in order to assimilate the effects of the corresponding metrics, data were normalized to the interval \([0, 1]\).

As mentioned earlier, due to the different atmospheric condition of the multi-temporal hyperspectral image, multiplying the incorporated metrics (ID, MZ and SAM) will result in a sort of weighting of the change and no-change pixels. Also, this combination can increase metrics distance in the change area and no-change area which increases the CD method’s ability to detect more detailed changes using hyperspectral imagery.

For a better overview of the proposed method, see Figure 2. This figure represents three spectral signatures, including (a) an ideal target spectral signature, (b) a target spectral signature affected by atmospheric conditions and (c) a target spectral signature affected by noise. As mentioned before, the most important characterization of the SAM algorithm is insensitivity to sunlight. This key feature helps minimize atmospheric conditions, but due to the existence of noise, it may still have a negative effect on the results. This can be proved by Figure 2. Suppose the target spectral signature is a spectral vector in dataset time 1, and the target spectral signature affected by noise is the corresponding spectral vector in dataset time 2. The SAM algorithm responds to these two vectors with a high value and considers the result a change pixel, while the vectors are no-change vectors. Z-score analysis, on the other hand, considers two spectral vectors: a target spectral signature affected by atmospheric conditions, and a target spectral signature that this algorithm assigned a high value – but both these vectors are no-change pixels. But by combining both methods, the effect of both noise and atmospheric conditions can be minimized.

**Figure 2.** Different type of spectral signatures.
**Learning phase**

The learning phase specifies the change and no-change areas in a binary format based on threshold selection. After applying the predictor phase, it can be said that the pixel values in the initial output change map data have a low value for no-change and a high value for change pixels. In this step, the initial change map is only suitable for visual analysis and interpolation. In order to better distinguish the change and no-change pixels from each other, another step for optimum threshold selection is necessary. The output result of this step then converts the initial change map to a binary format, meaning “zero” for no-change and “one” for change pixels.

The threshold selection is a crucial part of our proposed approach. To improve the efficiency of the CD methods, various procedures can be used to determine the optimum threshold (Bruzzone & Prieto, 2000). In this paper, the optimal threshold value is selected using testing data as part of ground truth data. To that end, in the first step, we find the minimum and maximum in the output of the predictor phase, and the optimum threshold is selected in the range of 0.01×(maximum – minimum). In next step, we can calculate the related accuracy based on a currently selected threshold from testing data. By calculating different accuracies from different thresholds, we can then sort and select for both maximum accuracies and for the corresponding threshold.

**Other MB methods**

There are many MB methods that have been widely used in previous studies. In our research, we compared those MB techniques with our proposed method (the SB and DB integration approach). To that end, we evaluated the performance of each method separately. The various approaches can be divided into two groups. The first group includes DB methods such as Hellinger (HE), Canberra (CA), Euclid (EU), Dis–Taminoto (DT), Bray–Curtis (BC) and JM (Choi et al., 2010) techniques. These methods are presented in Table 1.

The second group consists of SB methods including Kulczynski (KU), Pearson Correlation Coefficient (PCC) and Taminoto (TA) indices (Choi et al., 2010). They are listed in Table 2.

For our research, we tested different MB techniques in different combinations of Tables 1 and 2. Listing all possible combinations would go beyond the scope of this article, however.

**Study area and dataset**

This section presents the study areas and the incorporated image datasets for detecting changes using hyperspectral imagery. These datasets are open accessible and can be downloaded from the Earth Explorer website.

**Study area**

We utilized two datasets to evaluate the performance of the proposed method. These datasets have been previously used in many hyperspectral CD papers such as S. Liu et al. (2015) and C. Wu et al. (2013), and they can be considered benchmark datasets. The first dataset is a farmland near the city of Yuncheng, Jiangsu Province, China. The data were acquired on 3 May 2006, and 23 April 2007, respectively. This scene is mainly a combination of soil, river, tree, building, road and agricultural fields. The second study area covers an irrigated agricultural field in Hermiston City, Umatilla County, Oregon, USA. These data

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### Table 1. Different type of DB methods.

| Distance based | Indices |
|----------------|---------|
| HE            | $\text{HE}(X, Y) = \sqrt{1 - \left( \frac{X \cdot Y}{\sqrt{\left( |X|^2 \cdot |Y|^2 - X \cdot Y \right)}} \right)}$ |
| BC            | $\text{BC}(X, Y) = \left( \sum_{n} \left( |x_i - y_i| \right) \right) / \left( \sum_{n} \left( |x_i + y_i| \right) \right)$ |
| EU            | $\text{EU}(X, Y) = \sqrt{\sum_{i,n} (x_i - y_i)^2}$ |
| CA            | $\text{CA}(X, Y) = \sum_{i,n} \left( |x_i - y_i| / (|x_i| + |y_i|) \right)$ |
| SID           | $\text{SID}(X, Y) = \sum_{i} x_i \log(x_i/y_i) + \sum_{i} y_i \log(y_i/x_i)$ |
| DT            | $\text{DT}(X, Y) = -\log_{10} \left( \frac{X \cdot Y}{|X|^2 \cdot |Y|^2 - X \cdot Y} \right)$ |
| JM            | $\text{JM}(X, Y) = \sqrt{\frac{X^2}{2} - \sqrt{\frac{Y^2}{2}}}$ |

### Table 2. Different types of SB methods.

| Similarity based | Indices |
|------------------|---------|
| KU               | $\text{KU}(X, Y) = \left( \frac{X \cdot Y}{\sum_{i=1}^{n} (x_i - y_i)^2} \right)$ |
| TA               | $\text{TA}(X, Y) = \left( \frac{X \cdot Y}{|X|^2 \cdot |Y|^2 - X \cdot Y} \right)$ |
| PCC              | $\text{PCC}(X, Y) = \left( \sum_{i=1}^{n} (x_i - \mu_x) \cdot (y_i - \mu_y) \right) / \left( \sum_{i=1}^{n} (x_i - \mu_x)^2 \right)^{0.5} \cdot \left( \sum_{i=1}^{n} (y_i - \mu_y)^2 \right)^{0.5}$ |

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2[https://earthexplorer.usgs.gov/](https://earthexplorer.usgs.gov/).
were acquired on 1 May 2004, and 8 May 2007. The land-cover types are soil, irrigated fields, river, buildings and types of cultivated land and grassland. Both datasets originate from the Hyperion sensor (Figure 3). Figure 3(c) shows the spectral profile of the types of change class for the China dataset: three main change classes that relate to changes in the land cover, as well as part of the river. Among the presented profiles, there is only one new profile, while the other profiles are shared between two datasets. The changed spectral profile for the USA dataset is presented in Figure 3(f) and contains five change classes. Based on the presented profiles, the main changes relate to an irrigated agricultural field, as well as the edge of the river. This dataset also shows two common profiles in the multi-temporal dataset.

**Hyperspectral datasets**

There are two main types of hyperspectral data acquisition: spaceborne and airborne. The Hyperion sensor is a space-borne system carried on the EO-1 satellite, and it is acquiring data continuously. The Hyperion sensor includes 242 spectral bands which cover wavelengths between 0.4 and 2.5 µm. The spectral range is divided into two intervals: the VNIR range, which includes 70 bands with wavelengths ranging from 356 to 1058 nm, and the SWIR range, which consists of 172 bands with wavelengths between 852 and 2577 nm. The spectral and spatial resolution of this sensor is about 10 nm and 30 m, respectively, over a 7.5-km strip. After reduction of water absorption and noisy bands, a resulting 154 spectral bands were used. Table 3 shows details for the incorporated datasets.

**Implementation**

**Accuracy assessment**

Accuracy assessment is a key part of any process in remote-sensing image analysis (Janssen & Vanderwel, 1994). There are various types of methods for evaluating the accuracy of processes like CD, classification, target detection etc. The most common criteria used in the assessment of CD methods are the receiver-operating characteristic (ROC) curve, OA, kappa coefficient and others (Foody, 2002; H. Liu & Zhou, 2004). The ROC curve is the most important index, and the criterion most frequently used for evaluating CD results. It uses graphical plots in order to demonstrate the performance of the binary classifier systems for all possible threshold values. In this study, the results of the proposed approach were evaluated using the area under the curve (AUC), false alarm rate and ROC curve accuracy (Alatorre, Sánchez-Andrés, Cirujano, Beguería, & Sánchez-Carrillo, 2011; Pontius & Schneider, 2001). The accuracy and false alarm rate formulas are presented in Equations (7) and (8), respectively.

![Figure 3. The (a) and (b) presented false color composite of the original hyperspectral images acquired in 2006 and 2007 of the China, respectively. The (c) presented change spectral profile for China dataset. The (d) and (e) false color composite of the original hyperspectral images acquired in 2004 and 2007 of the USA, respectively. The (f) presented type of change spectral profile for dataset USA.](image)
Accuracy \(= \frac{\sum \text{True negative} + \sum \text{True positive}}{\sum \text{Total of population}} \) 

\( (7) \)

False alarm rate \(= \frac{\sum \text{False negative} + \sum \text{False positive}}{\sum \text{Total of population}} \) 

\( (8) \)

**Dataset preprocessing**

Data preprocessing is an important step before the main process. It can be divided into two categories: spectral correction and spatial correction. Preprocessing begins with spectral correction first, then spatial correction is applied after. The first step of preprocessing consists of removing data bands that contain no data. In our case study, a total of 44 bands (1-7, 58-76 and 225-242) were removed from our imagery (Scheffler & Karrasch, 2014). Two noisy bands among the total 198 bands, bands 77 and 78, were also removed (Datt, McVicar, Van Niel, Jupp, & Pearlman, 2003; Khurshid et al., 2006). In the second step, the pixels in sample 129 and all lines are shifted to sample 256 in SWIR spectral bands (Goodenough et al., 2003; Li, Zhang, Zhang, & Xu, 2008). The third step is de-striping and removing the zero-line by utilizing the global approach (Scheffler & Karrasch, 2013). The fourth preprocessing step is a radiometric correction. To achieve this, the DN values of pixels are converted into physical radiance. This step of preprocessing can be done using Equation (9) for bands 1-70, and Equation (10) for the remaining bands 71-242.

\[
\text{Radiance}_i = \frac{\text{DN}_i}{40.0} \quad 1 : 70 
\]

\[
\text{Radiance}_i = \frac{\text{DN}_i}{80.0} \quad 71 : 242 
\]

The next step of preprocessing is an atmospheric correction. This step is a very critical process, and we used the FLAASH model of ENVI software to achieve it. Then, band selection is applied as the result of the preprocessing. Totally, 154 bands were ultimately selected as input datasets for the proposed CD method. The final step of preprocessing the hyperspectral dataset is a spatial correction. For spatial or geometric correction, the ENVI image registration tool was used. Then, several GCP points were selected and a second-order polynomial was utilized for resampling, as well as the bilinear method for resampling gray values. The accuracy of the geometric correction (RMSE) is about 0.4 pixels.

**Experiments and results**

*Supervised threshold selection*

Based on the learning phase in previous part, the proposed method is now required to select suitable thresholds. The results show that by increasing the number of testing data from 10% to 100% of the ground truth, the accuracy of performance is negligible (close to 0.08%) and can be ignored. Selecting the optimum threshold is therefore independent of the number of testing data. We, therefore, extracted the ground truth data using visual analysis of the datasets and the ground truth map from previous papers and so obtained testing data for selecting the optimum threshold as illustrated in Table 4.

**Result of the CD**

The proposed method is applied to the multi-temporal hyperspectral datasets, and the results are compared with other methods. In order to assess the results quantitatively, a ground truth image is inevitably required. Outputs are presented in both visual and numerical schemes, and it should be noted that all output results are plotted based on the same colormap (gray level). Such a representation may be suitable for some forms of visual interpretation and assessment but may not be an efficient enough illustration for some other forms. For those cases, the assessment must be made based on quantity criteria, as mentioned in previous section, the results were scaled and normalized in the range [0,1]. The main advantage of scaling and normalization is avoiding the effect attributes with higher values have on those with lower values. Moreover, normalizing reduces numerical complexity during the CD procedure. Figure 4 illustrates the final CD maps of the SB and DB methods. According to Figure 4, a comparison of CD methods clearly shows that the best CD perfor-

**Table 3. Characterization of image datasets.**

| Datasets | Date acquisition | Time acquisition | Sun azimuth | Sun elevation angle (°) | Number of pixel | Number of used spectral bands |
|----------|------------------|------------------|-------------|------------------------|----------------|-------------------------------|
| USA      | 1/5/2004         | 18:33:12         | 145.007     | 54.9461                | 308 × 241      | 154                           |
|          | 8/5/2007         | 18:28:39         | 142.6289     | 60.7817                | 308 × 241      | 154                           |
| China    | 3/5/2006         | 02:10:26         | 121.3869     | 60.7817                | 420 × 140      | 154                           |
|          | 23/4/2007        | 02:14:56         | 126.9843     | 59.0155                | 420 × 140      | 154                           |

**Table 4. The number of testing pixels for selecting optimum threshold.**

| Dataset | Change pixel | No-change pixel |
|---------|--------------|-----------------|
| USA     | 169          | 574             |
| China   | 185          | 404             |
mance for the USA dataset is achieved by the SAMZID method (our proposed method). In addition, our proposed method also highlights the changed areas and separates them from the background clearly, while other methods mixed change and no-change areas. The false alarm rate is also very low in our proposed method. For example, in the USA dataset, there is a river which most CD methods extracted as a changed region, while our proposed method detected that this area is, in fact, a no-change area (Figure 4(a,o)).

Moreover, it was found that DB methods (Figure 4(c,j, n,i)) show better performance in comparison to SB techniques (Figure 4(d–f)). As was already discussed, the ROC curve is used for the quantitative evaluation of the detected results (Figure 4). Figure 5 shows the results obtained by our proposed methods and other MB methods when used on the USA dataset, based on the ROC curve. As is clear from Figure 5(a), the proposed methods and the EU method show good performance compared to other MB methods because the profiles related to these methods achieve the maximum value fast while having

Figure 4. The results of CD methods for USA dataset. (a) SAMZID, (b) BC, (c) EU, (d) HE, (e) CA, (f) KU, (g) JM, (h) DT, (i) SID, (j) Z-Score, (k) TA, (l) PCC, (m) SAM, (n) SAMZID\(_\text{Tan}\) and (o) ground truth.

Figure 5. Different (a) ROC curve and (b) false alarm rate for the proposed method and other MB methods in USA dataset.
the greatest AUC. This performance is due to the excellent prediction of changes from no-change areas, as for each threshold, the change and no-change areas can be comfortably separated. As is clear from Figure 5(a), the highest accuracy is achieved using the proposed method. The false alarm rate curve is illustrated in Figure 5(b). Based on this figure, it is evident which methods achieved minimum fast while maintaining good performance. In both curves, the SAMZID<sub>Tan</sub> and SAMZID<sub>Sin</sub> methods indicate the highest performance for CD.

Although the accuracy of the EU metric is close to the presented method, it has a low convergence rate in identifying the optimal threshold (see Figure 5(b)). The numerical analysis of the results for the USA dataset is shown in Table 5. This table demonstrates the accuracy of the proposed method and the MB methods. Based on this table, the PCC, EU, SAMZID<sub>Tan</sub> and SAMZID<sub>Sin</sub> methods have good accuracy compared to other methods, while other MB methods show weak results on the USA dataset. However, the EU method has a higher accuracy than our proposed method, though the accuracy is lower and the false alarm rate is higher than in our proposed method. In this dataset, the SAMZID<sub>Sin</sub> has high accuracy and greater AUC than SAMZID<sub>Tan</sub>, with fewer false alarms.

As a second strategy, we also compared our proposed approach with several well-known conventional CD methods, such as MAD, PCA, IR-MAD, CC, CE, Fisher ratio (FR) (Kwon & Nasrabadi, 2005) and generalized likelihood ratio test (GLRT) (Boisgontier, Noblet, Heitz, Rumbach, & Armspach, 2009). The most prominent problem with these conventional approaches is that they suffer from a large number of components, which causes confusion for users when selecting informative components for detecting changes. Figure 6 shows visualized results for all algorithms used on the USA dataset.

As was mentioned before, the ROC curve was created to find out which component results in the highest accuracy. Figure 6 shows the potential of our proposed method when detecting detailed changes in comparison to other common methods. In addition, our proposed method shows the good prediction for separating change and no-change areas. More common CD methods have a tendency to mix change areas (foreground) with no-change areas. Figure 6(a) shows the performance of the FR algorithms, which predict part of the river as a changing area. Also, for IR-MAD and CC results in Figure 6(e,g), the stripping and noise influences are evident. Out of the common CD algorithms, three methods – CE, CC and PCA – show better performance on the USA dataset, while the FR method shows a weak performance.

Table 6 presents the accuracies of conventional methods as well as our proposed approach. Based on this table, both the proposed methods and some of the common methods provided an accuracy of more than 90%, while other methods have lower accuracy. The obtained ROC curve confirmed the accuracy of the results, as both show the same trends. As is obvious from Table 6 and Figure 7, the accuracies of the CC, CE and PCA methods are close to each other, while our proposed method clearly indicates the best performance. Our proposed method also shows the lowest false alarm rate out of all the compared methods, highlighting the importance of being able to distinguish change areas from no-change areas through predictor methods, which is of great relevance in CD.

In the next step, we applied our proposed method to the second dataset, located in China. For a better comparison, the MB and other methods are shown in Figure 8. As is clear from Figure 8, most MB methods show a good degree of consistency detecting all nearby changes in the China dataset. Also in Figure 8, the SAMZID<sub>Tan</sub> and SAMZID<sub>Sin</sub> methods represent changes with high severability and low false alarm compared to other methods.

As mentioned earlier, the ROC curve was used for numerical analysis (Figure 9(a,b)). This figure confirms the computed results for the USA dataset, as well as for the results computed from both datasets. It shows that our proposed method has the highest accuracy and the lowest false alarm rate. Additionally, the selected optimal threshold value shows the same performance in both utilized datasets, increasing the convergence speed. In

| Method          | Accuracy | AUC   | False alarm rate | Optimum threshold |
|-----------------|----------|-------|------------------|-------------------|
| EU              | 0.9559   | 0.9905| 0.04402          | 0.205             |
| PCC             | 0.8265   | 0.8090| 0.26524          | 0.445             |
| HE              | 0.73445  | 0.6827| 0.2654           | 0.891             |
| Z-score         | 0.95633  | 0.9773| 4.36627          | 0.23764           |
| BC              | 0.76235  | 0.7927| 0.23764          | 0.127             |
| CA              | 0.75930  | 0.7408| 0.24038          | 0.112             |
| JM              | 0.73445  | 0.6874| 0.26554          | 0.512             |
| TO              | 0.76765  | 0.7953| 0.23235          | 0.004             |
| DT              | 0.76767  | 0.7971| 0.23232          | 0.610             |
| SAM             | 0.86849  | 0.7519| 13.15002         | 0.690             |
| SID             | 0.76766  | 0.8147| 0.23233          | 0.780             |
| KU              | 0.76940  | 0.8288| 0.23054          | 0.768             |
| SAMZID<sub>Tan</sub> | 0.96170  | 0.9863| 0.03823          | 0.003             |
| SAMZID<sub>Sin</sub> | 0.96261  | 0.9869| 0.03738          | 0.005             |

The best performance value appears in bold.
the following, we have computed the ROC curves for different MB methods, which are shown in Figure 9.

It is worth noting that for the China dataset, all methods were able to detect most changes, with differences present only in some details. The visual analyses and the numerical results are shown in Figure 8, and the analysis in Figure 9, with Table 7 providing confirmation.

Based on the results of Table 7, most methods provided an accuracy of over 96%. This rather uniform performance can be explained by the structure of the data that resulted in the detection of changes between two datasets. The SAMZID\textsubscript{Tan} methods show good performance compared to SAMZID\textsubscript{Sin}, but the difference is small. The HE method has shown the highest AUC, which is due to the
Figure 7. Different (a) ROC curve and (b) false alarm rate for the proposed method and other common CD methods in USA dataset.

Figure 8. The results of CD for China dataset. (a) SAMZID_{Sin}, (b) BC, (c) EU, (d) HE, (e) CA, (f) KU, (g) JM, (h) DT, (i) SID, (j) Z-Score, (k) TA, (l) PCC, (m) SAM, (n) SAMZID_{tan} and (o) ground truth.
suitability of this dataset for the prediction of change and no-change areas in all thresholds for this kind of land cover changes.

The same computations are done for the China dataset to evaluate the efficiency of our proposed method. Conventional CD methods were again used for comparison purposes (Figure 10). It seems evident that most of the conventional methods show good predictions for the change areas. The more common methods have different responses to the change area, and as can be seen in Figure 10(a,b,e,f), some mix-up between change areas and no-change areas occurs. Obtaining the optimum thresholds that cover all changes appears to be a big challenge for these methods. In both datasets, the final CD result of the IR-MAD method (Figures 6(e) and 10(e)) suffers from striping effects.

In order to evaluate the performance of the proposed method for the second dataset in ways similar to the previous dataset, we have again computed the ROC curve and false alarm rate. Figure 11 shows these characteristics for both the proposed method and other CD methods. Based on this figure, the proposed methods show good performance when detecting changes for each threshold. All utilized common methods show the same trend for detecting changes in both datasets, as is clear from Figures 7 and 11. Figure 11(b) presents a number of iterations and the false alarm rate, showing that the proposed method reached optimum threshold after about 30 iterations, while other methods needed more iterations to obtain the optimum threshold.

Table 8 presents a numerical analysis of the China datasets. Based on the results presented in this table, in addition to our proposed method, the IR-MAD, CC and CE methods show good performance and an accuracy of over 96%, with false alarm rates below 4%. But the proposed methods showed good performance and presented the best results.

The results show the highest accuracy for both datasets. In Table 5, the value of the AUC, the false alarm rate and the optimal threshold are better for the EU metric than they are for our proposed method; however, the accuracy is less than our proposed methods. It seems that the difference between the AUC of our proposed method and the EU metric is due to the presence of noise and inaccessibility to a reliable ground truth. In both Tables 5 and 7, the TA metric indicates the lowest optimum threshold value.

**Conclusion**

This paper presents a new method that integrates SAMZID$_{Sin}$ and SAMZID$_{Tan}$ approaches for CD based on MB indices (BC, SAM, Z-Score, EU, HE, CA, KU, JM, DT, SID, TA and PCC) to reduce existing challenges in CD of multi-temporal hyperspectral images. The proposed method is a mixed technique based on SB and DB
Figure 10. The results of change map detected by different common CD algorithm for China dataset. (a) FR, (b) GLRT, (c) PCA, (d) CE, (e) IR-MAD, (f) MAD, (g) CC, (h) SAMZID\textsubscript{Tau}, (i) SAMZID\textsubscript{Sim}, and (j) ground truth.

Figure 11. Different (a) ROC curves and (b) false alarm rates for the proposed method and other common CD methods for China dataset.
methods that increases the performance of CD results. The results related to our proposed method clearly show the following facts for our method: firstly, a more detailed CD of land-cover types; second, the lowest false alarm rate in comparison to other famous and commonly used CD methods like (FR, GLRT, PCA, CE, IR-MAD, MAD and CC); and third, easy implementation. Computations in both experimental datasets demonstrated that in the simple land-cover scenario (China dataset), all CD methods reached acceptable results but show differences in some detailed changes and achieved accuracy. In the more complex land-cover type (USA case study), all utilized CD methods show different performances in detecting changes, and as can be seen from the results presented in Table 6, our proposed method has the highest degree of consistency in producing the final change map when compared with other CD methods. Considering thresholds in both datasets, it seems that the procedure of convergence in the presented approach is faster with the SAMZID\textsubscript{tan} metric rather than SAMZID\textsubscript{Sinn} metric.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

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**Table 8.** Result of proposed CD method and different common CD methods in China dataset.

| Method  | Accuracy | AUC     | False alarm rate | Optimum threshold |
|---------|----------|---------|------------------|-------------------|
| PCA     | 0.88110  | 0.9246  | 0.11887          | 0.219             |
| CC      | 0.97037  | 0.9921  | 0.02962          | 0.403             |
| CE      | 0.97200  | 0.9942  | 0.02799          | 0.350             |
| IR-MAD  | 0.96210  | 0.9900  | 0.03790          | 0.365             |
| MAD     | 0.79086  | 0.7536  | 0.20913          | 0.456             |
| FR      | 0.71894  | 0.5704  | 0.28105          | 0.001             |
| GLRT    | 0.82568  | 0.8127  | 0.16918          | 0.246             |
| SAMZID\textsubscript{tan} | 0.98600  | 0.9952  | 0.01396          | 0.056             |
| SAMZID\textsubscript{Sinn} | 0.98590  | 0.9952  | 0.01409          | 0.055             |

The best performance value appears in bold.
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