Change Detection Method of High Resolution Remote Sensing Image Based on D-S Evidence Theory Feature Fusion

JIXIANG ZHAO, SHANWEI LIU, JIANHUA WAN, MUHAMMAD YASIR, AND HUAYU LI

1 College of Oceanography and Space Informatics, China University of Petroleum Qingdao, Qingdao 266580, China
2 School of Geosciences, China University of Petroleum Qingdao, Qingdao 266580, China

Corresponding author: Jianhua Wan (wjh66310@163.com)

This work was supported in part by the National Key Research and Development Program under Grant 2017YFC145600, and in part by the National Natural Science Foundation of China under Grant 41776182.

ABSTRACT Using high-resolution satellite image to detect change has been a hotspot in the field of remote sensing for a long time series. The change detection method combining feature extraction and machine learning could extract the change information effectively, but the manual sample selection is a huge workload for a wide range remote sensing images, and it is also difficult to ensure the accuracy of the pre-detection sample using a single difference image. Therefore, in this paper, a new method for change detection has been put forward based on multi-feature fusion of D-S evidence theory. In this approach, the texture difference image has calculated by structural similarity, because the difference image based on structural similarity plays a great role in change detection, which was verified in experiments. The difference images based on texture features and traditional spectral features are fused by D-S evidence theory, and texture features and spectral features have been fully utilized. Setting rules to select samples with high confidence based on pixels, and SLIC super-pixel segmentation has applied in order to improve further the credibility of the sample. Finally, the samples selected by SLIC segmentation optimization are sent to the classifier training to obtain the final result. The experimental results show that texture features play a very important role in the change detection of high-resolution remote sensing images, and D-S evidence theory could effectively fuse spectral texture features to improve the accuracy of change detection. The proposed method has high accuracy and good performance in change detection.

INDEX TERMS Change detection, D-S evidence theory, structural similarity (SSIM), multi feature fusion, remote sensing, and high-resolution satellite image.

I. INTRODUCTION

With the intensification of human construction activities and the continuous change of natural ecological environment, it is of great significance to obtain real-time and accurate land surface change information for protecting ecological environment, managing natural resources, and researching on social development [1]–[3]. Remote sensing earth observation technology has the ability of large-scale, long-term, and periodic monitoring. Remote sensing change detection can extract change information by acquiring the remote sensing images of the same ground object or natural phenomenon at different times [4], [5], which is an important technology for monitoring land surface changes.

In the past decade, a series of high-resolution satellites have launched a new era of satellite remote sensing. The acquisition of high-resolution remote sensing images is more convenient, with high spatial resolution and rich detailed information of ground features, which has important and far-reaching significance for the monitoring of land-use change [6]–[8], building change [9], [10], vegetation ecological monitoring [11]–[13], disaster monitoring and evaluation [14], [15], and coastline change [16]. A series of classical remote sensing change detection methods developed in the past few decades have also been applied in the change detection of high-resolution images. According to whether
there is prior information, these methods divided into two types: unsupervised and supervised [17], [18].

The unsupervised method for change detection is mainly through image difference [5], change vector analysis (CVA) [19], [20], multivariate alteration detection (MAD) [21], [22], spectral angle mapper (SAM) [23], spectral gradient differencing (SGD) [24], image transformation [25], [26], etc. Based on the image difference, image segmentation is carried out by using threshold [18], [27]–[29], clustering, or random field [30]–[33] to extract change information. This method is easy to operate and does not require prior knowledge. However, unsupervised change detection based on different images is often interfered with by various factors, such as the difficulty to determine the threshold value when segmenting the difference image, and different difference images highlight different change information. The application of a single difference image may cause seriously missed detection and false detection [34]–[36].

With the progress and development of machine learning theory, various machine learning techniques such as support vector machine (SVM) [37]–[41] and random forest (RF) [42]–[46] have been applied for change detection. In recent years, with the rapid development of big data and artificial intelligence technology, deep learning methods such as deep belief networks, convolutional neural network and twin network [47]–[52] has been applied to change detection, which improves the accuracy of change detection greatly. There are two types of change detection by supervision. One is post-classification change detection [53], [54], the results has obtained from the classification of two temporal remote sensing images, and the different classification results has compared directly under the two temporal phases. This method obtains the information of different change types, but the workload of classification in different phases is heavy, and the accuracy of change detection is difficult to guarantee [55] because of the different performance of classifiers. Another method of supervised change detection is to select the change-unchanged samples on the multitemporal images, and to train the binary classification model to predict and classify the whole image in order to get the change detection map [39], [41]. This method is a hot spot in the field of remote sensing change detection, which also has high accuracy. However, this method requires prior information to be used for sample selection [41], [56], [57], which will greatly increase the workload for large-scale remote sensing change detection in the actual change detection work. To solve the above problems, we propose a new change detection method for large-scale and high-resolution remote sensing images. The proposed method has the following three main characteristics:

- In order to solve the problem that a large number of training samples need to be marked manually in the supervised change detection, the D-S evidence theory has been used to fuse a variety of different images, and super-pixel segmentation has combined to realize the selection of changed and unchanged samples to reduce manual intervention.
- In view of the limited spectral band and insufficient spectral information of high spatial resolution remote sensing images, texture features has extracted as the supplement of spectral information, and structural similarity has used to generate the texture difference images.
- Support vector machine (SVM), random forest (RF) and deep neural networks (DNN) are used to train the model, and finally, the change information is extracted.

II. PROPOSED METHODOLOGY

In our proposed method, first calculated the spectral difference images, and the texture difference images. The texture difference image has calculated by structural similarity and the spectral difference has calculated from the original spectral characteristics, direction, intensity, and shape, where the theory as shown in subsections A and B. Next, D-S evidence theory has used to fuse multiple features of the above-mentioned different images as is shown in subsections C, and the change probability value of each pixel has obtained. In order to get the changed and unchanged pixels with high confidence as samples, SLIC super-pixel the segmentation method is used to remove the sample noise and further improve the sample reliability, as is shown in sub sections D. Finally, the overall change detection results graph is obtained by SVM, RF and DNN classifiers.

The steps of process used in the study are visualized in figure 1.

A. DIFFERENCE IMAGE BASED ON STRUCTURAL SIMILARITY

Wang Zhou and bovik put forward the concept of structural image quality evaluation, and combined with the relevant theory of human visual system (HVS), they defined structural similarity (SSIM) [58], which is mainly used to evaluate image quality, that is, to measure the similarity between the reference image and the image to be evaluated figure 2.

The system separates the task of similarity measurement into three comparisons: luminance, contrast, and structure. Suppose x and y are two non-negative image signals, which have been aligned with each other (e.g., spatial patches extracted from each image) Eq. (1) was used for measuring SSIM.

\[
SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\mu_x^2 + \mu_y^2 + C_1(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{1}
\]

where

- \(N\) is the number of pixels in the image block, \(\mu_x\) and \(\mu_y\) are the average gray value in the image block, \(\sigma_x\) and \(\sigma_y\) are the standard deviation in the image block, \(C_1\) and \(C_2\) are
constants defined to avoid instability when either \( \mu_x^2 + \mu_y^2 \) or \( \sigma_x^2 + \sigma_y^2 \) is very close to zero.

The remote sensing images of different time phases in the same area regarded as reference images and images to be evaluate. Detecting their changes can also be regarded as comparing the similarities between the two images. The higher the degree of similarity is, the less likely the change is, and the greater the reverse. SSIM algorithm is more in line with the definition of the human visual system, considering the biological characteristics of human eyes, and more in line with the mode of human perception of objective scene changes than the traditional formula simply defined by mathematics, and has application potential in the field of remote sensing change detection [59], [60]. Because the original SSIM is used to evaluate the overall image similarity, there is a large error in the local similarity comparison, and the high-resolution image has high spatial resolution and significant noise, which will greatly interfere with the comparison of local windows. Therefore, in the experiment, the filter is carried out in the local window firstly, and then Eq (2, 3, 4) was used for measuring SSIM.

\[
\bar{\mu}_x = \frac{1}{N} \sum_{i=1}^{N} \tilde{x}_i
\]
\[
\bar{\sigma}_x = \left( \frac{1}{N-1} \sum_{i=1}^{N} (\tilde{x}_i - \bar{\mu}_x)^2 \right)^{1/2}
\]
\[
\bar{\sigma}_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (\tilde{x}_i - \bar{\mu}_x) (\tilde{y}_i - \bar{\mu}_y)
\]  

where \( \tilde{x}_i \) and \( \tilde{y}_i \) is the gray value of the image after filtering, \( \bar{\mu}_x \) is the average gray value in the image block after filtering and \( \bar{\mu}_y \) is calculated in the same way as \( \bar{\mu}_x \), \( \bar{\sigma}_x \) is the standard deviation in the image block after filtering and \( \bar{\sigma}_y \) is calculated in the same way as \( \bar{\sigma}_x \).
When Gaussian filter has been used in the local window, the Similarity calculation Eq (5) is as follows:

$$GUASS - SSIM(x,y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$  \hspace{1cm} (5)

When average filter has been used in the local window, the Similarity calculation Eq (6) is as follows:

$$AVE - SSIM(x,y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$  \hspace{1cm} (6)

The spatial texture feature is a visual feature that reflects the homogeneity of images. It is widely used in image processing, computer vision, pattern recognition and other fields as well. Gray level co-occurrence matrix (GLCM) is a method based on the estimation of the second-order combination conditional probability density of an image. Due to the large dimension of gray level co-occurrence matrix, texture information has usually extracted based on its construction statistics. [61] it is pointed out that four kinds of statistics are independent of each other, namely Contrast (CON), Entropy (ENT), Angular second moment (ASM) and Correlation (COR) Eq (7, 8, 9,10):

$$CON = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} (i-j)^2 p(i,j)$$  \hspace{1cm} (7)

$$ENT = -\sum_{i=1}^{N} p(i,j) \log_2 p(i,j)$$  \hspace{1cm} (8)

$$ASM = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} p(i,j)^2$$  \hspace{1cm} (9)

$$COR = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{i=1}^{N} \sum_{j=1}^{N} (ij)P_{i,j} - \mu_x \mu_y}{\sigma_x \sigma_y}$$  \hspace{1cm} (10)

where $N$ is the number of gray levels of the image, $i$ and $j$ are the row and column elements of the matrix elements respectively. $P(i,j)$ is the element of GLCM, among which $\mu_x$ and $\mu_y$ are the mean value, $\sigma_x$ and $\sigma_y$ are the standard deviations.

In this paper, $5 \times 5$ window is choose to extract GLCM texture features because too large window leads to poor texture feature extraction effect while too small window has a large amount of calculation. Eq (5 and 6) calculates the difference images for four kinds of texture features.

B. DIFFERENCE IMAGE BASED ON SPECTRAL CHARACTERISTICS

A series of classical differential image generation methods has mostly been based on spectral features, such as image difference, image ratio, change vector analysis (CVA) [5], spectral correlation mapper (SCM) [23], and spectral gradient difference (SGD) [24]. Change vector analysis is an extension of image difference. By calculating the difference between all bands, the change vector is constructed. The length and direction of the change vector represent the intensity of change and different types of surface feature change respectively. It is also the most widely used method at present. Spectral correlation mapper describes the difference between multispectral images from direction and angle. Spectral gradient difference describes the spectral shape quantitatively and uses spectral gradient differences to represent the shape change between spectral curves [36]. Seven types of surface feature change has summarized from three aspects of spectral intensity, direction and shape. Through the analysis and comparison, it pointed out that if one of the three-change information has ignored, some change categories will be omitted. Based on the above judgment, this paper constructs spectral difference image data set from three aspects of spectral intensity, direction and shape.

Two remote sensing images ($X_1, X_2$) with the size of $I \times J$ were collected on the same ground at two different time $T_1$ and $T_2$. They were composed of $B$ spectral bands ($B > 1$), $X_i^{b}$ was $b$th band of $X_i$, $i = 1, 2, b = 1, 2, \ldots, B$:

The spectral intensity difference image calculated according to CVA algorithm Eq (11).

$$CVA = \sqrt{\sum_{b=1}^{B} (X_2^b - X_1^b)^2}$$  \hspace{1cm} (11)

where $X_2^b$ and $X_1^b$ are the $b$th band of $X_2$ and $X_1$, respectively.

The spectral directivity difference image calculated according to SCM Eq (12).

$$SCM = \sqrt{\sum_{b=1}^{B} (X_2^b - \bar{X}_2) \cdot (X_1^b - \bar{X}_1)}$$  \hspace{1cm} (12)

where $X_2^b$ and $X_1^b$ are the $b$th band of $X_2$ and $X_1$, $\bar{X}_2$ and $\bar{X}_1$ represents the average value of the spectral band.

The spectral shape difference image calculated according to SGD algorithm Eq (13, 14).

$$g_{lb} = \frac{X_i^{b+1} - X_i^b}{\xi_{b+1} - \xi_b}, \quad l = 1, 2, b = 1, 2, \ldots, B - 1$$  \hspace{1cm} (13)

$$SGD = \left( \sum_{b=1}^{B-1} (g_{2b} - g_{1b})^2 \right)^{1/2}$$  \hspace{1cm} (14)

where $\xi_b$ Is the wavelength of band b.

C. MULTI FEATURE FUSION OF D-S EVIDENCE THEORY

D-S evidence theory is dealing with uncertain information, which can fuse uncertain information [62]. It is an important extension of traditional Bayesian theory, D-S evidence theory can deal with both single hypothesis and compound hypothesis, and has a wide range of applications in image processing, risk evaluation, fault diagnosis and so on [63].
For a non-empty set $U$, it is called discernment framework, which consists of a series of mutually exclusive and exhaustive elements $A$. Any proposition in the problem domain should belong to power set $2^U$. Define BPAF: $m: 2^U \rightarrow [0, 1]$ in $2^U$, and let

\[
\begin{align*}
  m(\emptyset) &= 0 \\
  \sum_{A \subseteq U} m(A) &= 1
\end{align*}
\]

(15)

where

$m(A)$ represents a trust measure for a subset of evidence pairs. The meaning of is $m(A)$ as follows: (1) if $A \subseteq U$, then it means the certain trust degree of to $A$; (2) if $A = U$, then it means that the number does not know how to allocate; (3) if $A \subseteq U$ and $m(A) > 0$, $A$ is called a focal element of $m$. D-S evidence theory adopts orthogonal and combined evidence sources.

Let $m_1, m_2, \ldots, m_n$ be $n$ BPAFs in $2^U$, their orthogonal sum is denoted as:

\[ m = m_1 \oplus m_2 \oplus \ldots \oplus m_n \]

(16)

Defined as:

\[
\begin{align*}
  m(\emptyset) &= 0 \\
  m(A) &= \frac{\sum_{A_i=\emptyset; 1 \leq j \leq n} m_j(A_i)}{1 - K} \quad (\forall A \subseteq U)
\end{align*}
\]

(17)

where

\[
K = \sum_{\cap A_j = \emptyset; 1 \leq j \leq n} m_j(A_i)
\]

(18)

$K$ is the conflict degree of evidence. Eq. (17) called the Dempster’s combination rule.

In this paper, the pixel of image is taken as the basic unit, and the framework of evidence theory is defined as $U = \{Y, N\}$. Where $Y$ represents the changed pixel and $N$ represents the unchanged pixel, so the non-empty subset is $\{Y\}$, $\{N\}$, $\{Y, N\}$. Then BPAFs constructed according to the spectral feature difference images and texture structure similarity:

\[
\begin{align*}
  m_i(\{Y\}) &= (1.0 - S_i) \times \alpha_i \\
  m_i(\{N\}) &= S_i \times \alpha_i \\
  m_i(\{Y, N\}) &= 1.0 - \alpha_i, \quad i = 1, 2, 3, 4
\end{align*}
\]

(19)

where $\alpha_i$ is the trust degree of evidence to the discernment frame, $S_i$ is the change probability value of difference image, which is constructed by the sigmoid function in this paper Eq (20):

\[
f(x) = \frac{1}{1 + e^{-(x-C)}}
\]

(20)

where $x$ is the gray value of the difference image, $C$ is a constant and calculated by OTUs method in this paper, which has also considered as the best segmentation threshold of difference image. The red arrow, the pixel change probability increases when $x$ is greater than $C$ and increases gradually. On the contrary, the pixel change probability gradually decrease as shown by the green arrow in the figure 3.

Finally, we implement evidence fusion with Eq. (17). Setting appropriate BPAF thresholds for changed and unchanged classes, we can get the changed image areas. In addition, the conditions of pixel change set as follows Eq (21):

\[
\begin{align*}
  &\text{changed, } m(Y) - m(N) > 0.5 \\
  &\text{unchanged, } m(N) - m(Y) > 0.5 \\
  &\text{unknown, otherwise}
\end{align*}
\]

(21)

where $m(Y)$ is the probability of pixel changed after D-S evidence theory fusion, while $m(N)$ is the probability of pixel unchanged.

### D. SAMPLE OPTIMIZATION FOR SUPER PIXEL SEGMENTATION

In this paper, simple linear iterative clustering (SLIC) has used for super-pixel segmentation [65]. It is a simple and easy to implement algorithm proposed in 2010, which could generate compact and nearly uniform super-pixels. With a high comprehensive evaluation in terms of operation speed, object contour maintenance and super-pixel shape, it is more in line with the expected segmentation effect. The algorithm steps are as follows:

- Transform the color image into CIELab color space $[I_k, a_k, b_k]$ and XY coordinates $[x_k, y_k]$ to form a 5-dimensional feature vector as $c_k$ ($c_k = [I_k, a_k, b_k, x_k, y_k]$)

(22)

- According to the set number of super-pixels, the seed points has evenly distributed in the image. Assuming that there are $N$-pixels in the image and the pre segmentation has divided into $K$ super-pixels of the same size,
then the size of each super-pixel is $N/K$, then the distance (step size) of adjacent seed points is $S = \sqrt{N/K}$ approximately.

- In the neighborhood of the seed point, the seed point is reselected (generally $n = 3$), the gradient value of all pixels in the neighborhood is calculated, and the seed point is moved to the place with the minimum gradient in the neighborhood. In order to accelerate the convergence of the algorithm, the search range is limited to $2S \times 2S$.
- A distance metric has constructed for 5-Dimensional eigenvectors as follows Eq (23).

$$
\begin{cases}
    d_{lab} = \sqrt{(l_i - l_j)^2 + (a_i - a_j)^2 + (b_i - b_j)^2} \\
    d_{x,y} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \\
    D = \sqrt{(\frac{d_{lab}}{m})^2 + (\frac{d_{x,y}}{S})^2}
\end{cases}
$$

where $m$ is the equilibrium constant, generally 10.
- The above steps has iterated continuously. In practice, it has found that 10 iterations can achieve ideal results for most of the images, so the general number of iterations is 10.

SLIC algorithm has used to segment the two temporal images respectively, and then the vector super position has carried out to construct the super-pixel block figure 4.

![Figure 4. Sketch map of vector merging.](image)

In each super-pixel region, statistical changes, unchanged and unknown pixels. All pixels in the region will regarded as the category when a category accounts for more than 50%, in order to remove broken patches and scattered points.

### III. EXPERIMENT AND ANALYSIS

In the current research work, the pre-processing steps has performed in the ENVI 5.3 software and the ground truth for reference has completed manually in the ArcGIS 10.2 software. The difference images and accuracy index is calculated by MATLAB 2018. The final machine learning training is carried out in PyCharm 2020.1, with machine learning library named Sklearn. And the DNN model was trained based on Caffe framework.

The confusion matrix has calculated in order to evaluate the results of change detection accuracy. Furthermore, the overall accuracy (OA), false alarm rate (FA), missed detection rate (MA) and Kappa coefficient (KC) were calculated by the confusion matrix, which are the commonly used evaluation indexes for the change detection accuracy [32], [36], [66]. The MA indicates the proportion of the unmeasured area in the real change area to the real change area, which reflects the degree of missed detection of the change detection. The FA indicates the proportion of unchanged region detected as the changed region in the real unchanged region. The OA could reflect the detection error as a whole because it represents the proportion of the change region and unchanged region that has correctly detected in the real change region and unchanged region. KC has reported to be more cogent than OA because more detailed classification information is involved [32].

The calculation formula of each evaluation index is as follows:

$$
FA = \frac{FP}{FP + TN}
$$

$$
MA = \frac{FN}{FN + TP}
$$

$$
OA = \frac{TP + TN}{TP + TN + FP + FN}
$$

where $TP$ represents the number of pixels that actually change and the change is detected, $TN$ represents the actual number of pixels that have not changed and have been detected unchanged, $FP$ represents the actual number of pixels that have not changed but detected changes, $FN$ represents the number of pixels that have actually changed but not detected.

It should note that traversal method has used to determine the best threshold according to kappa to ensure get the best results. In this case, the fairness of the different method comparison could be shown.

### A. DATA INTRODUCTION AND PREPROCESSING

In this paper, three sets of GF-2 satellite images from Weifang City, Shandong Province, China, has used for the change detection analysis. The spatial resolution of the three sets of data is 1 m, and the necessary geometric registration and relative radiometric correction has carried out. The histogram matching method has used to make the gray scale distribution of the image in one phase close to that of the other phase, to reduce the interference of color differences in change detection.

The first set of data (Figure 5) and the second set of data (Figure 6) have a small coverage and a small number of pixels, which has used to verify the effectiveness of SSIM to generate differential images. The third set of data (Figure 7)
FIGURE 5. The first test dataset of size 287 × 340 pixels. (a) Remote sensing image in 2019; (b) Remote sensing image in 2020; (c) Ground truth for reference.

FIGURE 6. The second test dataset of size 350 × 350 pixels. (a) Remote sensing image in 2019; (b) Remote sensing image in 2020; (c) Ground truth for reference.

has a large coverage and a large number of pixels, which has used to verify the overall change detection process.

B. RESULTS AND ANALYSIS
The GAUSS-SSIM and AVE-SSIM difference image were calculated and threshold segmentation was carried out to get the change detection result for the first and second sets of data. Figure 8 and 9 are the change detection results of the two groups of experiments, respectively. In this experiment, three traditional methods of different images generating were carried out, including CVA, IR-MAD, and PCA. Besides, the difference image generating has also performed by SSIM. The results of CVA are close to the ground truth for reference in three traditional methods, while the result of IR-MAD and PCA have a large number of missing and false detection. As for the GAUSS-SSIM and AVE-SSIM, their results are better than the results of IR-MAD, PCA, and SSIM.

In order to compare the experimental results more intuitively, the quantitative analysis results of the two groups of experiments as shown in Table 1 and 2 respectively. In addition, AUC curves has developed to measure the performance of different methods for change detection figure 10. From the above results, it the SSIM can be used as an effective difference image generation method, but its performance is not stable. There are obvious missing detection and more noise in the two data. After Gaussian filtering and mean filtering in the local window, the detection performance of the difference image change detection based on SSIM are significantly improved. KC of GAUSS-SSIM and AVE-SSIM has maintained at more than 70%, which is better than the other methods. In addition, AVE_SSIM shows the best performance in both datasets. The same result is also evident that the GAUSS-SSIM and AVE-SSIM are better than the others in figure 10 are where their AUC curve is closer to the top left. All the above experiments show that the AVE-SSIM is an effective way to generate a differential image, and AVE-SSIM has used to calculate the difference images of the texture features for the third dataset.

After extracting features from the third set of experimental data, D-S evidence theory fusion were carried out firstly figure 11. In order to verify the effectiveness of D-S evidence theory fusion, this paper selects a certain number of samples for the different images generated by CVA, AVE-SSIM, IR-MAD and PCA respectively, and compares them with the selected samples after D-S evidence theory fusion. In order to ensure the fairness of comparison, samples automatically selected and evaluated according to the confidence level from high to low under the premise of a fixed number (figures 12). Specifically, in the difference images obtained by various methods, the higher the gray value is, the greater the probability of change will be. The number of samples will be fixed, and the samples will be selected in the order of gray value from high to low to further evaluate the accuracy of the samples.

The number of samples is between 5000 and 40000, and the interval is 5000. It can be seen that the accuracy of samples by CAV is the highest among the traditional methods of generating different images, which is more than 80%, but the

| Table 1. Evaluation of change detection of the first dataset. |
|-----------------|--------------|-------------|---------|--------|
| Method          | FA (%)       | MA (%)      | OA (%)  | KC (%) |
| CVA             | 37.19%       | 5.26%       | 86.82%  | 61.95% |
| IR-MAD          | 24.09%       | 21.50%      | 77.86%  | 47.82% |
| PCA             | 46.40%       | 13.63%      | 78.22%  | 40.62% |
| SSIM            | 24.14%       | 4.88%       | 90.34%  | 75.27% |
| GAUSS-SSIM      | 13.68%       | 8.99%       | 89.85%  | 73.97% |
| AVE-SSIM        | 14.95%       | 7.35%       | 90.76%  | 75.83% |

| Table 2. Evaluation of change detection of the second dataset. |
|-----------------|--------------|-------------|---------|--------|
| Method          | FA (%)       | MA (%)      | OA (%)  | KC (%) |
| CVA             | 41.16%       | 3.32%       | 93.80%  | 57.73% |
| IR-MAD          | 57.84%       | 8.73%       | 86.74%  | 29.72% |
| PCA             | 78.61%       | 2.73%       | 90.25%  | 24.33% |
| SSIM            | 40.48%       | 7.01%       | 89.99%  | 46.57% |
| GAUSS-SSIM      | 24.99%       | 2.57%       | 95.45%  | 72.98% |
| AVE-SSIM        | 26.33%       | 1.55%       | 96.16%  | 75.90% |
accuracy rate of samples cannot exceed 90%. After the fusion of D-S evidence theory, the accuracy rate of selected samples is above 95%, which is obviously better than other methods. However, the number of samples cannot be determined according to the accuracy in actual change detection. In addition, samples has selected by Eq (21) figure 13(a). In order to remove the interference noise and improve the credibility of sample selection, the samples has further selected based on the part D of Section II, which as shown in figure 13(b). After the segmentation optimization, the isolated sample points has significantly reduced, and the sample integrity is improved. Compared with the samples before segmentation optimization, the accuracy of the later samples increases from 93% to 98%, which shows the effectiveness of segmentation optimization.

The classifier used to train and predict according to the automatically selected samples. In this research, MASSIM algorithm [60] and DSFA algorithm [26] are performed in addition to the three traditional methods, which are CVA, IR-MAD and PCA.

In the experiment, SVM parameter, RF parameter and DNN parameter setting are as follows:
RF: the number of trees is set to 50, and the maximum depth of decision tree is set to 10.
SVM: penalty coefficient is set to 1, kernel function adopts RBF, kernel function coefficient is set to 'auto'.
DNN: there are 5 layers of input layer and hidden layer, 20 neurons in each layer and output layer. Sigmoid function is used as activation function and cross entropy error is used as loss function.

The figure 14 shows the detection results of different method, and three smaller regions, A, B and C, were selected for more detailed analysis.

Change detection results of area A as shown in figure 15. The phenomenon of missing detection and false detection of several traditional methods is more serious figure 15 (a), (b) and (c), and the same situation also appears in the MASSIM and DSFA figure 15 (d) and (e). After the fusion of spectral features and texture features, the threshold segmentation method is used for change detection, and the result is quite different from the real ground interpretation value, as shown in figure 15 (f – h). After the spectral features are classified by machine learning, the results are shown in figure 15 (i – k). After the texture features are classified, the results are shown in figure 15 (l – n). In comparison, the machine learning change detection based on texture features is obviously better than the change detection method based on spectral features. After combining the spectral and texture features, the machine learning classification results are shown in figure 15 (o – q). As can be seen from the result graph, the change detection effect based on RF classification is better comparing with the other two classification methods. As a whole, the machine learning classification change detection based on texture features in the region is closer to the ground interpretation, mainly due to the existence of spectral pseudo changes in this region, the use of spectral features for change detection in this region will be greatly affected.

Change detection results of area B as shown in figure 16. The traditional detection method and the detection results based on spectral different image fusion have serious false detection figure 16 (a – f, i – k). The main reason is that this area is a dense area of buildings, and different imaging angles and sunlight of satellites will cause serious spectral differences. Therefore, detection methods based on the spectral will detect the differences that are not the real changes of the ground conditions and it causes serious false detection. Relatively speaking, the detection effect based on texture features is better, as shown in figure 16 (g, l – n). The detection results based on spectral and texture fusion also successfully avoid more noise interference, as shown in figure 16 (h). After combining spectral and texture features, the detection based on SVM, RF and DNN classifiers has noise interference, as shown in figure 16 (o – q), which is the main disadvantage of pixel based classification. The noise interference could be removed by post-processing operations such as filtering and morphological operation, but the detection result of DNN classifier is very noisy as shown in figure 16 (q).

| Method                  | FA (%) | MA (%) | OA (%) | KC (%) |
|-------------------------|--------|--------|--------|--------|
| CVA                     | 38.18% | 4.55%  | 92.43% | 55.43% |
| IR-MAD                  | 42.40% | 6.79%  | 89.99% | 45.49% |
| PCA                     | 24.42% | 8.15%  | 90.36% | 53.36% |
| MASSIM                  | 24.34% | 4.12%  | 94.07% | 66.54% |
| DSFA                    | 65.25% | 10.88% | 84.21% | 19.90% |
| Fusion of spectrum      | 47.43% | 6.55%  | 89.76% | 42.47% |
| Fusion of texture       | 29.13% | 1.66%  | 95.86% | 73.29% |
| Fusion of spectrum and  |        |        |        |        |
| texture                 | 25.92% | 1.41%  | 96.56% | 78.09% |
| SVM-spectrum            | 43.34% | 2.88%  | 93.47% | 57.51% |
| RF-spectrum             | 42.26% | 3.02%  | 93.44% | 57.82% |
| DNN-spectrum            | 66.06% | 1.19%  | 92.95% | 43.31% |
| SVM-texture             | 19.99% | 1.74%  | 96.70% | 80.30% |
| RF-texture              | 23.51% | 1.61%  | 96.50% | 78.69% |
| DNN-texture             | 21.65% | 1.74%  | 95.60% | 80.22% |
| SVM-spectrum and texture| 18.93% | 1.89%  | 96.57% | 79.14% |
| RF-spectrum and texture | 25.72% | 0.71%  | 97.21% | 81.67% |
| DNN-spectrum and texture| 25.43% | 1.53%  | 96.29% | 77.66% |
Change detection results of area C as shown in figure 17. It shows poor change detection results in the figure 17 (a - f), due to the spectral difference caused by the sensor, imaging in different time periods is not the change of real objects. In contrast, the detection results based on texture difference image are relatively fragmented and lack of integrity as figure 17 (g). The detection results of fusion spectrum and texture can detect the change better, however, there is a serious omission from the figure 17(h). The results of machine learning change detection based on texture features in figure 17 (i – n) are obviously better than those based on spectral features, as shown in figure 17 (i – k), but there are some missing detection phenomena. After combining spectral and texture features, the detection results based on SVM and RF classifier are obviously better than other methods. In addition, the detection result based on RF classifier has less noise, which is consistent with the actual ground interpretation data, as shown in figure 17 (p).

In order to compare the experimental results more intuitively, the quantitative analysis results of the experiment as shown in Table 3. From the Table 3, it concluded that: the OA of CVA, PCA and MASSIM detection results are more than 90%, but its detection performance is not outstanding through kappa evaluation. Among the traditional detection methods, DSFA has the worst effect, due to the method is mostly applied to the change detection of hyperspectral or multi band remote sensing image, and the change detection is carried out through the difference of many spectral characteristics. Compared with the traditional method, the OA of change detection based on spectral difference image fusion is 89.76%, while the kappa coefficient is 42.47%, and its performance is not outstanding. However, the
FIGURE 14. The change detection results of the third test dataset. (a) CVA. (b) IR-MAD. (c) PCA. (d) MASSIM. (e) DSFA. (f) Fusion of spectrum. (g) Fusion of texture. (h) Fusion of spectrum and texture. (i) SV-spectrum. (j) RF-spectrum. (k) DN-spectrum. (l) SV-texture. (m) R-texture. (n) DNN-texture. (o) SVM-spectrum and texture. (p) RF-spectrum and texture. (q) DNN-spectrum and texture. (r) Ground truth for reference.

FIGURE 15. Change detection results of region A of the third dataset. (a) CVA. (b) IR-MAD. (c) PCA. (d) MASSIM. (e) DSFA. (f) Fusion of spectrum. (g) Fusion of texture. (h) Fusion of spectrum and texture. (i) SV-spectrum. (j) RF-spectrum. (k) DN-spectrum. (l) SV-texture. (m) R-texture. (n) DNN-texture. (o) SVM-spectrum and texture. (p) RF-spectrum and texture. (q) DNN-spectrum and texture. (r) Ground truth for reference.

performance of image fusion based on texture difference is significantly improved, the OA has increased to 95.86%, and the kappa coefficient has increased by nearly 30%, showing that the role of spatial texture features is far greater than spectral features in the change detection of high-resolution optical images. The overall accuracy increased to 96.56%, and the kappa coefficient increased to 78.09%. It shows that spectral features can be used as a powerful supplement to texture features in the detection of high-resolution images.
FIGURE 16. Change detection results of region B of the third dataset. (a) CVA. (b) IR-MAD. (c) PCA. (d) MASSIM. (e) DSFA. (f) Fusion of spectrum. (g) Fusion of texture. (h) Fusion of spectrum and texture. (i) SV-spectrum. (j) RF-spectrum. (k) DN-spectrum. (l) SV-texture. (m) R-texture. (n) DNN-texture. (o) SVM-spectrum and texture. (p) RF-spectrum and texture. (q) DNN-spectrum and texture. (r) Ground truth for reference.

FIGURE 17. Change detection results of region C of the third dataset. (a) CVA. (b) IR-MAD. (c) PCA. (d) MASSIM. (e) DSFA. (f) Fusion of spectrum. (g) Fusion of texture. (h) Fusion of spectrum and texture. (i) SV-spectrum. (j) RF-spectrum. (k) DN-spectrum. (l) SV-texture. (m) R-texture. (n) DNN-texture. (o) SVM-spectrum and texture. (p) RF-spectrum and texture. (q) DNN-spectrum and texture. (r) Ground truth for reference.

Based on spectral and texture features, machine learning methods (SVM, RF and DNN) are used for change detection. The accuracy of the results is better than or equal to the accuracy of threshold segmentation after feature fusion. From the kappa coefficient, the performance of machine learning method is better than that of feature fusion method. On the whole, the SVM and RF classifier’s accuracy and kappa coefficient are better than the other methods, which shows that the ability of feature mining and classification detection of machine learning is still better than that of traditional methods.
methods, so machine learning still plays an irreplaceable role in change detection.

IV. CONCLUSION

The current research work proposed a new method for change detection based on multi feature fusion of D-S evidence theory. In this method, SSIM model is used to calculate the difference images of texture features and the fusion of spectral and texture features is achieved by the D-S evidence theory. The samples are selected automatically based on fusion image, and the samples will be trained in the classifier to get the final change detection results.

The effectiveness of this method was verified in the experiment, and the results demonstrate that the proposed method has a high detection accuracy. The experimental results also show that: the change detection results of threshold detection based on multi feature fusion are obviously better than other traditional methods, but the detection performance is poor compared with the method based on machine learning; at the same time, the experimental results show that the texture feature plays a major role in the change detection of high-resolution remote sensing images, which is obviously better than the spectral features, mainly due to the high-resolution image light. There are few spectral bands, insufficient spectral information, high spatial resolution and rich texture features.

It needs to be pointed out that the change detection process proposed in this paper is an open framework, which is open in feature extraction and classifier selection. Different feature combinations and classifiers can be selected for change detection. Therefore, in the future work, we will extract different features, optimize the combination of features, and select more advanced classifiers for change detection experiments.

CONFLICT OF INTEREST

The authors proclaim no conflict of interest concerning this paper.

REFERENCES

[1] K. K. Goldewijk, A. Beusen, and P. Janssen, “Long-term dynamic modeling of global population and built-up area in a spatially explicit way: HYDE 3.1,” Holocene, vol. 20, no. 4, pp. 565–573, Jun. 2010.

[2] M. A. Friedl, D. Sulla-Menashe, B. Tan, A. Schneider, N. Ramankutty, A. Sibley, and X. Huang, “MODIS collection 5 global land cover: Algorithm refinements and characterization of new datasets,” Remote Sens. Environ., vol. 114, no. 1, pp. 168–182, Jan. 2010.

[3] M. Jung et al., “Recent decline in the global land evapotranspiration trend due to limited moisture supply,” Nature, vol. 467, no. 7318, pp. 951–954, Oct. 2010.

[4] A. Singh, “Review article digital change detection techniques using remotely-sensed data,” Int. J. Remote Sens., vol. 10, no. 6, pp. 989–1003, Jun. 1989.

[5] D. Lu, P. Masek, E. Brondizio, and E. Moran, “Change detection techniques,” Int. J. Remote Sens., vol. 25, no. 12, pp. 2365–2407, 2004.

[6] G. J. Scott, M. R. Englund, W. A. Starns, R. A. Marcum, and C. H. Davis, “Training deep convolutional neural networks for land-cover classification of high-resolution imagery,” IEEE Geosci. Remote Sens. Lett., vol. 14, no. 4, pp. 549–553, Apr. 2017.

[7] F. Song, Z. Yang, X. Gao, T. Dan, Y. Yang, W. Zhao, and R. Yu, “Multi-scale feature based land cover change detection in mountainous terrain using multi-temporal and multi-sensor remote sensing images,” IEEE Access, vol. 6, pp. 77494–77508, 2018.

[8] J. Useya, S. Chen, and M. Murefu, “Cropland mapping and change detection: Toward zimbabwean cropland inventory,” IEEE Access, vol. 7, pp. 53603–53620, 2019.

[9] Q. Peng, “Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends,” Remote Sens. Environ., vol. 117, pp. 34–49, Feb. 2012.

[10] Y. Y. Yu, L. Wu, Z. Xie, and Z. L. Chen, “Building extraction in very high resolution remote sensing imagery using deep learning and guided filters,” Remote Sens., vol. 10, no. 1, p. 18, Jan. 2018.

[11] S. Gairola, S. Proches, and D. Rocchini, “High-resolution satellite remote sensing: A new frontier for biodiversity exploration in indian himalayan forests,” Int. J. Remote Sens., vol. 34, no. 6, pp. 2006–2022, Mar. 2013.

[12] S. Liu, J. Tian, S. Wang, D. Wang, T. Chi, and Y. Zhang, “Crop drought area extraction based on remote sensing time series spatial-temporal fusion vegetation index,” in Proc. IEEE Int. Geosci. Remote Sens. Symp. IGARSS, Jul. 2019, pp. 6271–6274.

[13] J. Ji, S. Wang, Y. Zhou, W. Liu, and L. Wang, “Spatiotemporal change and landscape pattern variation of eco-environmental quality in Jing-Jin-Ji urban agglomeration from 2001 to 2015,” IEEE Access, vol. 8, pp. 125534–125548, 2020.

[14] A. Stumpf and N. Kerle, “Object-oriented mapping of landslides using random forests,” Remote Sens. Environ., vol. 115, no. 10, pp. 2564–2577, Oct. 2011.

[15] A. M. Youssef, H. R. Pourghasemi, Z. S. Pourtaghi, and M. M. Al-Katheeri, “Landslide susceptibility mapping using random forest, boosted regression tree, classification and regression tree, and general linear models and comparison of their performance at wadi Tayyab basin, Asir region, Saudi Arabia,” Landslides, vol. 13, no. 5, pp. 839–856, Oct. 2016.

[16] M. Yasir, H. Sheng, H. Fan, S. Nazir, A. J. Niang, “Automatic coastline extraction and changes analysis using remote sensing and GIS technology,” IEEE Access, vol. 8, pp. 180156–180170, 2020.

[17] N. Falco, P. R. Marpu, and J. A. Benediktsson, “A toolbox for unsupervised change detection analysis,” Int. J. Remote Sens., vol. 37, no. 7, pp. 1505–1526, Apr. 2016.

[18] L. Bruzzone and D. F. Prieto, “Automatic analysis of the difference image for unsupervised change detection,” IEEE Trans. Geosci. Remote Sens., vol. 38, no. 3, pp. 1171–1182, May 2000.

[19] J. Chen, X. Chen, X. Cui, and J. Chen, “Change vector analysis in posterior probability space: A new method for land cover change detection,” IEEE Geosci. Remote Sens. Lett., vol. 8, no. 2, pp. 317–321, Mar. 2011.

[20] F. Bovolo and L. Bruzzone, “A theoretical framework for unsupervised change detection based on change vector analysis in the polar domain,” IEEE Trans. Geosci. Remote Sens., vol. 45, no. 4, pp. 218–236, Jan. 2007.

[21] A. A. Nielsen, “The regularized iteratively reweighted MAD method for change detection in multi- and hyperspectral data,” IEEE Trans. Image Process., vol. 16, no. 2, pp. 463–478, Feb. 2007.

[22] M. J. Canty and A. A. Nielsen, “Visualization and unsupervised classification of changes in multispectral satellite imagery,” Int. J. Remote Sens., vol. 27, no. 18, pp. 3961–3975, Sep. 2006.

[23] O. A. C. Júnior, R. F. Guimaraes, A. R. Gillespie, N. C. Silva, and R. A. T. Gomes, “A new approach to change vector analysis using distance and similarity measures,” Remote Sens., vol. 3, no. 11, pp. 2473–2493, Nov. 2011.

[24] J. Chen, M. Lu, X. Chen, J. Chen, and L. Chen, “A spectral gradient difference based approach for land cover change detection,” ISPRS J. Photogramm. Remote Sens., vol. 85, pp. 1–12, Nov. 2013.

[25] J. S. Deng, K. Wang, Y. H. Deng, and G. J. Qi, “PCA-based land-use change detection and analysis using multi-temporal multsensor satellite data,” Int. J. Remote Sens., vol. 29, no. 16, pp. 4823–4838, Aug. 2008.

[26] B. Du, L. Lu, C. Wu, and L. Zhang, “Unsupervised deep slow feature analysis for change detection in multi-temporal remote sensing images,” IEEE Trans. Geosci. Remote Sens., vol. 57, no. 12, pp. 9976–9992, Dec. 2019.

[27] M. Zanetti, F. Bovolo, and L. Bruzzone, “Rayleigh-rice mixture parameter estimation via EM algorithm for change detection in multispectral images,” IEEE Trans. Image Process., vol. 24, no. 12, pp. 5004–5016, Dec. 2015.

[28] S. Patra, S. Ghosh, and A. Ghosh, “Histogram thresholding for unsupervised change detection of remote sensing images,” Int. J. Remote Sens., vol. 32, no. 21, pp. 6071–6089, Nov. 2011.

[29] Y. Bazi, L. Bruzzone, and F. Melgani, “An unsupervised approach based on the generalized Gaussian model to automatic change detection in multi-temporal SAR images,” IEEE Trans. Geosci. Remote Sens., vol. 43, no. 4, pp. 874–887, Apr. 2005.
W. Wiratama, J. Lee, and D. Sim, “Change detection using high resolution remote sensing images based on active learning and Markov random fields,” Remote Sens., vol. 9, no. 12, p. 1233, Nov. 2017.

W. Shi, P. Shao, M. Hao, P. He, and J. Wang, “Fuzzy topology-based method for unsupervised change detection,” Remote Sens. Lett., vol. 7, no. 1, pp. 81–90, Jan. 2016.

M. Gong, L. Su, M. Jia, and W. Chen, “Fuzzy clustering with a modified MRF energy function for change detection in synthetic aperture radar images,” IEEE Trans. Fuzzy Syst., vol. 22, no. 1, pp. 98–109, Feb. 2014.

P. Chen, Y. Zhang, Z. Jia, J. Yang, and N. Kasabov, “Remote sensing image change detection based on NSCT-HMT model and its application,” Sensors, vol. 17, no. 6, p. 1295, Jun. 2017.

P. Du, S. Liu, P. Gamba, K. Tan, and J. Xia, “Fusion of difference images for change detection over urban areas,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 5, no. 4, pp. 1076–1086, Aug. 2012.

S. Le Hégarat-Mascle and R. Seltz, “Automatic change detection by evidential fusion of change indices,” Remote Sens. Environ., vol. 91, nos. 3–4, pp. 390–404, Jun. 2004.

P. Shao, W. Shi, and M. Hao, “Indicator-Kriging-Integrated evidence theory for unsupervised change detection in remotely sensed imagery,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 11, no. 12, pp. 4649–4663, Dec. 2018.

Y. Liu, D. Chen, A. Cheng, H. Wei, and D. Stanley, “Change detection of high resolution remote sensing image alteration based on multi-level mixed kernel SVM model,” Remote Sens. Land Resour., vol. 31, no. 1, pp. 16–21, Jan. 2019.

C.-H. Huang, H. Ren, and Y.-C. Tseng, “Comparison of change detection methods based on the spatial chaotic model for synthetic aperture radar imagery,” Terr. Atmos. Ocean. Sci., vol. 30, no. 4, pp. 481–492, 2019.

T. Bai, K. Sun, S. Deng, and Y. Chen, “Comparison of four machine learning methods for object-oriented change detection in high-resolution satellite imagery,” Proc. SPIE, vol. 10611, Mar. 2018, Art. no. 106110G.

L. Jia, J. Wang, J. Ai, and Y. Jiang, “A hierarchical spatial-temporal graph-kernel for high-resolution SAR image change detection,” Int. J. Remote Sens., vol. 41, no. 10, pp. 3866–3885, May 2020.

C. Pati, A. K. Panda, A. K. Tripathy, S. K. Pradhan, and S. Patnaik, “A novel hybrid machine learning approach for change detection in remote sensing images,” Eng. Sci. Technol., Int., vol. 23, no. 5, pp. 973–981, Oct. 2020.

A. Woodley, C. McLaughlin, H. Hutson, S. Geva, T. Chappell, W. Kelly, D. Perrin, W. Boles, and L. D. Vine, “High resolution change detection using planet mosaic,” in Proc. IEEE Int. Geosci. Remote Sens. Symp. IGARSS, Jul. 2019, pp. 6578–6581.

N. Zerrouki, F. Harrou, Y. Sun, and L. Hocini, “A machine learning-based approach for land cover change detection using remote sensing and radiometric measurements,” IEEE Sensors J., vol. 19, no. 14, pp. 5843–5850, Jul. 2019.

F. Harrou, N. Zerrouki, Y. Sun, and L. Hocini, “Monitoring land-cover changes by combining a detection step with a classification step,” in Proc. IEEE Symp. Ser. Comput. Intell. (SSCI), Nov. 2018, pp. 1651–1655.

V. Esavi and S. Homayouni, “Performance evaluation of random forest and support vector regressions in natural hazard change detection,” J. Appl. Remote Sens., vol. 10, no. 4, Dec. 2016, Art. no. 046030.

X. Liu and Y. Guo, “Remote sensing image change detection algorithm based on random forest,” Bull. Surveying Mapping, vol. 5, pp. 16–20, May 2020.

X. Zhang, X. Chen, F. Li, and T. Yang, “Change detection method for high resolution remote sensing images using deep learning,” Acta Geodetica et Cartographica Sinica, vol. 46, no. 8, pp. 999–1008, 2017.

H. Zhang and P. Zhang, “Deep difference representation learning for multispectral imagery change detection,” in Proc. 5th Int. Conf. Adv. Mater. Comput. Sci., 2016, p. 2016.

L. Khelifi and M. Mignotte, “Deep learning for change detection in remote sensing images: Comprehensive review and meta-analysis,” IEEE Access, vol. 8, pp. 126385–126400, 2020.

J. Zhao, M. Gong, J. Liu, and L. Jiao, “Deep learning to classify difference image for image change detection,” in Proc. UICNN, Beijing, China, Jul. 2014, pp. 397–403.

O. O. Karadag and O. Erdas, “Evaluation of the robustness of deep features on the change detection problem,” in Proc. 26th Signal Process. Commun. Appl. Conf. (SIU), May 2018, pp. 1–4.

W. Wiratama, J. Lee, and D. Sim, “Change detection on multispectral images based on feature-level U-Net,” IEEE Access, vol. 8, pp. 12279–12289, 2020.
JIANHUA WAN received the Ph.D. degree from Wuhan University, Wuhan, China, in 2001. He is currently a Professor with the College of Oceanography and Space Informatics, China University of Petroleum (East China), Qingdao, China. He has authored/coauthored more than 30 high-level articles. He is the inventor or co-inventor of five patents. His research interests include geographic information, ocean remote sensing, and smart city. He is also a member of the theory and method working committee of China Association for Geographic Information System Society, the Engineering Survey Special Committee of the Engineering Surveying Special Committee of CSGPC, the Oceanology and Limnology Information Technology Special Committee of Chinese Society for Oceanology and Limnology. He was a recipient of the National Science and Technology Award, the Provincial Science and Technology Award, and the National Natural Science Foundation. He is also the Director of the Chinese Society for Geodesy, Photogrammetry, and Cartography (CSGPC). He is also the Editor-in-Chief of Geomatics World and the Instructor of Huitiandi, a well-known WeChat platform in the field of surveying and mapping geographic information.

MUHAMMAD YASIR received the B.S. degree in geology from the University of Peshawar (UOP), Pakistan, in 2018. He is currently pursuing the master’s degree with the School of Geoscience, China University of Petroleum Qingdao, China. His research interests include coastline extraction, MATLAB programming, edge detection, image processing, remote sensing, GIS, spatial analysis, and application of GIS.

HUAYU LI received the B.S. degree from the College of Information Science and Engineering, Shandong Agricultural University, in 2019. She is currently pursuing the master’s degree with the College of Oceanography and Space Informatics, China University of Petroleum Qingdao. Her research interests include remote sensing image processing and change detection.