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REGION CLASSIFICATION AND CHANGE DETECTION USING LANSAT-8 IMAGES

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ABSTRACT

The change detection in remote sensing images remains an important and open problem for damage assessment. A new change detection method for LANSAT-8 images based on homogeneous pixel transformation (HPT) is proposed. Homogeneous Pixel Transformation transfers one image from its original feature space (e.g., gray space) to another feature space (e.g., spectral space) in pixel-level to make the pre-event images and post-event images to be represented in a common space or projection space for the convenience of change detection. HPT consists of two operations, i.e., forward transformation and backward transformation. In the forward transformation, each pixel of pre-event image in the first feature space is taken and will estimate its mapping pixel in the second space corresponding to post-event image based on the known unchanged pixels. A multi-value estimation method with the noise tolerance is produced to determine the mapping pixel using K-nearest neighbours technique. Once the mapping pixels of pre-event image are identified, the difference values between the mapping image and the post-event image can be directly generated. Then the similar work is done for backward transformation to combine the post-event image with the first space, and one more difference value for each pixel will be generated. Then, the two difference values are taken and combined to improve the robustness of detection with respect to the noise and heterogeneousness of images. (FRFCM) Fast and Robust Fuzzy C-means clustering algorithm is employed to divide the integrated difference values into two clusters- changed pixels and unchanged pixels. This detection results may contain few noisy regions as small error detections, and a spatial-neighbor based noise filter is developed to reduce the false alarms and missing detections. The experiments for change detection with real images of LANSAT-8 in Tuticorin between 2013-2019 are given to validate the percentage of the changed regions in the proposed method.

KEYWORDS

Change detection, remote sensing, heterogeneous images, mapping image.

1. INTRODUCTION

The change detection of remote sensing images plays an important role in the landcover and water bodies' changes over a time period. The remote sensing images before (pre) and after (post) the event may be obtained by heterogeneous sensors. To obtain the knowledge about changes, there is necessary to identify the change detection among the two datasets of heterogeneous remote sensing images before and after the time period. Heterogeneous images may reflect the different characteristics of the object and they are usually obtained by different types of sensors.[1] HPT can be broadly divided into three levels: pixel level, feature level and object level. For the detection methods in feature level, the features such as texture, edge, statistic measure are extracted from the original pixel information for comparison between pre-event and post-event images.[21]-[28] The deep neural networks are recently employed for the unsupervised feature learning to obtain the relationships of the pair of images in change detection. In object level, the image contents are classified using unsupervised or supervised methods, and the classification results of different images are compared and combined to detect the changes. The image segmentation is often involved with object-level change detection to extract and separate the objects in the image. A number of image segmentation methods have been used, such as region based methods (e.g. fuzzy clustering, region growing), edge or boundary based method.

The change detection methods in feature level and object level are often used for dealing with the images in different modalities. An interesting similarity measurement between heterogeneous images is identified and it takes the physical properties of sensor, the associated measurement noise models and local joint distributions. The LANSAT 8 image is used to detect the changes in the Soil, Water, Vegetation and buildings. The signature of building in the post-event and is predicated according to the 3-D parameters derived from the pre-event optical image and the acquisition parameters of the post-event data.[35] Then the changes are detected by comparing the actual post-event image with the predicted image. An unsupervised nonparametric method is developed for detecting changes among the multi-temporal LANSAT 8 images. This method relies on an interesting feature which captures the structural change between two LANSAT 8 images. A Bayesian network is introduced for the fusion of remote sensing data, i.e. multi-temporal LANSAT 8 images, with the ancillary information (e.g. geomorphic and other ground information) for area detection.[2]-[3] This method can effectively reduce the false alarms and well recognize the changed areas in the complex land cover ground conditions.

A change detection method for heterogeneous images is presented based on the change measure, which is defined by the local statistics estimated according to the dependence of the pair of images before and after the events. [18]It transfers the multi-source remote sensing data represented in low-dimension observation spaces into a high-dimension feature space and an iterative coupled dictionary learning (CDL) model is generated for unsupervised change detection from multi-source images in the high-dimension feature space.[14]-[19] A Bayesian model coupled with a Markov random field is generated for detecting changes from homogeneous or heterogeneous remote sensing images, and this method mainly consists of two steps, i.e. the image segmentation by region based approach and building a similarity measure between the images based on the joint statistical properties of the objects. A dynamic evidential reasoning (DER) fusion method for change detection of heterogeneous images is used. Each image is classified first, and then DER is used to combine the classification results of different images taking into account with available prior knowledge.

DER is able to deal with multi-temporal (more than two) images. DER has been further extended to a more general framework called multi-dimensional evidential reasoning (MDER) to handle the images acquired by different sensors. In the feature and object levels, different images are compared using the features or target classification results that are derived according to the pixel values. Some original pixel information may be lost during the process of feature selection and classification. In the pixel level methods,[24] the normalized pixel values in different LANSAT 8 images can be compared for change detection between the homogeneous images, and the pixel information can be fully utilized to produce good results.
The contents of heterogeneous images reflect the different characteristics of the object, and they are generally described in distinct feature spaces like the LANSAT 8 image. Thus, the change detection cannot be carried out by directly comparing heterogeneous images. In this work, we consider the change detection between MAY 2013 and MAY 2018 LANSAT 8 images. A new method is proposed to transfer one image from its original feature space where gray space with one dimension to another space and the spectral space with three even more dimensions assuming it is not affected by the event, and the transferred image is named mapping image. The pre-event image and post-event image are represented in a common feature space so that their pixels values can be easily compared for change detection. The process is called homogeneous pixel transformation (HPT) consisting of forward and backward transformations. The expected value to find the sufficient pixel information from HPT for pursuing as good as possible for identifying detection performance. The image transformation between different feature spaces and some unchanged regions in the pair of images will be selected as the prior knowledge for estimating the

mapping image. Because of the noisy influence and the heterogeneousness of images,[29] some pixels are very close and their values in one feature space may have more or less different values in another space even if they are not affected by the event. Such uncertainty often causes false alarms, and this is a big challenge in the actual estimation of mapping image.

The proposed method uses a multi-value estimation strategy using the *K*-nearest neighbors (K-NN) technique to manage with this problem. In the forward transformation, for each pixel mention **x** in pre-event image, their K-NN are selected from the given unchanged data according to their pixel values, and then *K* corresponding pixels in the post event image are considered as the possible estimations values for mapping of **x**. So the mapping pixels are calculated by the weighted average of the *K* corresponding pixels in the post-event image based on the new weight determination rule.[37] After the mapping pixel is obtained, it is now directly compared with the actual pixel in the post-event image to get a difference value by using that pixel. Then simultaneously do the backward transformation to associate the post-event image with the feature space of the pre-event image, and calculate another difference value. Thus the two difference values are obtained and are combined to further improve the robustness of detection with respect to noise and modality difference of the images.[22]-[30] The multivalue estimation strategy joint is the combination of forward and backward pixel transformation and is able to efficiently reduce false alarms in change detection of heterogeneous images.

Fuzzy c-means (FCM) clustering method is generated to divide the integrated difference values that is the sum of the two difference values of all pixels into two clusters which is 1) The changed pixels and 2) The unchanged pixels. In the detection results, it may contain some noisy regions, for example very small regions of false alarms and missing detections. A new noise filter is employed to still improve the detection performance based on belief functions theory, it is good at representing and combining the uncertain and ignorant information. [15] It is considered that the pixels are located together which is close to each other in the space location and generally have the similar changed or non-changed pixels.[36] So the change detection knowledge about the spatial neighbors around one pixel will be taken into account to improve the detection result of the pixel using Dempster's combination rule theory with a proper discounting technique. Two pairs of real images (e.g. LANSAT 8 images) from MAY 2013 to MAY 2018 are used to evaluate the performance of the proposed change detection method.

The existing work is based on Remote sensing images is commonly used to monitor the earth surface evolution. This monitoring can be conducted by detecting changes between images acquired at different times. The iterative case is when an optical image of a given area is available and new image is acquired in an emergency situation resulting from a natural disaster for instance by a radar satellite.[3] In such a case, images with heterogeneous properties have to be compared for change detection. This proposed work states a new approach for similarity measurement between images acquired by heterogeneous sensors. The approach exploits the considered sensor physical properties and specially the associated measurement noise models and local joint distributions. These properties are inferred through manifold learning. The obtained similarity measure has been applied to detect changes between many kinds of images.

2.HOMOGENEOUS PIXEL TRANSFORMATION

A pair of heterogenous images before (pre-) and after (post-) an event which are denoted by **X** (1^{st} image) and **Y** (2^{nd} image) is used. Because the images **X** and **Y** reflect the different object characteristics which are represented in different feature spaces *X* and *Y*, it is almost impossible to directly compare their pixels values for change detection. In this we want to transfer the image **X** from the original feature space *X* to another space *Y* considering that it is not affected by any of the event. Then the transferred image $\hat{\mathbf{Y}}$ is called the mapping image and it will be described in the same feature space as the post-event image **Y**. So the images ˆ**Y** and **Y** are homogeneous, and they can be directly compared for the change detection process. In this determining the mapping of an image plays a crucial role in the change detection method. A new homogeneous pixel transformation (HPT) method is generated here to take out the estimation of mapping image. [11]-[13] Some unchanged regions in the pair of images **X** and **Y** are selected at first for the prior knowledge for HPT, and they are selected as unchanged pixel pairs and are denoted **by** $T = \{(X_n, Y_n), n = 1, \ldots, N\}$. It is denoted that the selected pixels are not affected by the event, but there is no idea for the content of each pixel. So they have weak prior knowledge about the pixel, and it cannot be further used for training the supervised classifier for the image classification. The unchanged regions easy to obtain, and it is convenient for their applications. The other pixels in the image can be transferred from one feature space to another space based on the selected unchanged pixel pairs. In HPT, the forward transformation to transfer the pre-event image **X** to the feature space ***Y*** in which the post-event image **Y** is represented, and do the backward transformation to associate the post-event image **Y** with the space ***X*** corresponding to the pre-event image **X** in the same way. Now consider the forward transformation first, and it is assumed that the image is with accurate registration. Each pixel $\mathbf{x}_i$ in the image **X**, and its actual respective pixel that are located at the same position as $\mathbf{x}_i$ in the post-event image **Y** is given by $\mathbf{y}_i$, and then the estimation of its mapping pixel are described in the space of *Y* is denoted by $\hat{\mathbf{y}}_i$.

In this proposed work, a multi-value estimation strategy using *K*-nearest neighbors (K-NN) technique is estimated to deal with uncertainty of pixel transformation. The K-NN of $\mathbf{x}_i$ from the prior knowledge of the unchanged pixels in the pre event image as $\dot{\mathbf{x}}_i$, $i = 1, \ldots, K$ with the corresponding pixels in the post-event image as $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$. Each of $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$ can be considered as a potential estimation of the mapping pixel $\hat{y}_i$. Thus, the *K* pixels $\dot{\mathbf{y}}_k$, $b_k = 1, \ldots, K$ provide multiple estimations (i.e. potential range) for $\hat{y}_i$. Hence, the value of mapping pixel $\hat{y}_i$ can be approximated by the weighted sum of $\dot{\mathbf{y}}_i$, $i = 1, \ldots, K$, and it is given by eq. **(1).**

$$\hat{Y}_i = \sum_{k=1}^{k} w^k y^k \quad \textbf{(1)}$$

The determination of the weighting factors w_k , $k = 1, \ldots, K$ in **(1)** is a main key in the calculation of the mapping pixel $\hat{y}_i$. Where exists some related methods which are used to calculate the weighting factors w_k , $k = 1, \ldots, K$ in the field of pattern classification. In the incomplete pattern classification problem, the missing attributes values are given based on the known attribute values using the K-NN technique. This is considered that if their known attribute value from one pattern is quite close to another pattern that is training data and their missing part should be also very close to their corresponding part of their training pattern. So that the K-NN of the incomplete pattern are detected respective to their known attributes, and the missing attributes of their pattern will be filled by the weight average of their selected *K* neighbors. The weighted factors are usually calculated according to the distance between the pattern and their selected neighbors in the known attributes. The bigger distance in them leads to the smaller weighting factor. The change detection of heterogeneous images in the realistic situation is very complicated. Some pixels are found closer to $\mathbf{x}_i$ than other pixels in pre-event image, but their corresponding pixels are not so close to $\mathbf{y}_i$ as these other pixels in post-event image because of their noisy factor and their detection of heterogeneousness. A pair of real images LANSAT 8 from MAY 2013 and MAY 2018 are acquired for Tuticorin region and the changes for being detected for every regions.

(a) **(b)**

Figure 1**:** The LANSAT 8 images are given as input images and the comparison is done for images between may 2013 and may 2018.(a) may 2013, (b) may 2018

In the estimation of the mapping pixel value $\hat{y}_i$ by eq. (1), the exponential function often used in the weighted K-NN classifier is employed here to calculate the weighting factor of each selected pixel $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$.

$$W^K = e^{-\gamma \tilde{d}_k} \qquad \textbf{(2)}$$

where γ is a tuning parameter to control the distance influence in the calculation of weighting factor, and determination of the parameter will be explained later. For convenience of applications, $\tilde{d}_k$ is defined by the normalized distance measure.

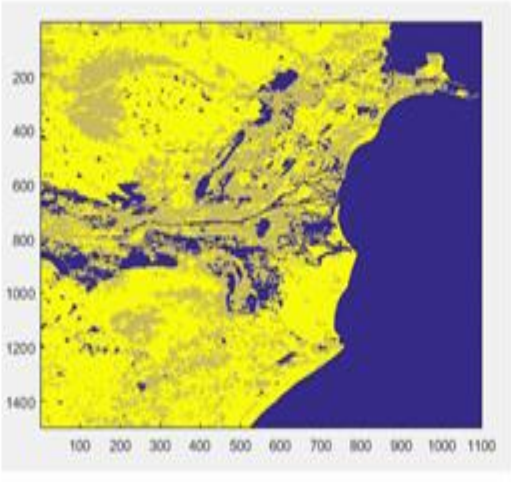
$$\tilde{d}_k = \frac{\|\mathbf{y}_i - \dot{\mathbf{y}}_k\|}{\max_k \|\mathbf{y}_i - \dot{\mathbf{y}}_k\|} \qquad \textbf{(3)}$$

where $\| \cdot \|$ represents the normal Euclidean distance. The estimated mapping pixel value $\hat{\mathbf{y}}_i$ will be found close to the selected pixels and thay are very near to $\mathbf{y}_i$. If the pixel $\mathbf{y}_i$ is seriously affected by the event, the actual pixel $\mathbf{y}_i$ generally will become far away from all the K selected pixels $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$. Because the mapping pixel $\hat{y}_i$ defined by the weighted sum of $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$ as eq. (1) and (2) always lies around these K selected pixels, the distance between $\hat{y}_i$ and $\mathbf{y}_i$ will be also very large.

For the remaining pixels in the pre event image, the difference values of the mapping pixels and the actual pixels in the post event image can be calculated. The difference image (DI) between $\hat{\mathbf{Y}}$and $\mathbf{Y}$ is obtained.

3.FAST AND ROBUST FUZZY C-MEANS CLUSTERING ALGORITHM

The homogeneous pixel transformation is used for separating the original image pixels into post event and pre event pixels. After the separation of respective pixels they are being represented in the projection plane based on their pixel value. Based on their pixel value in the projection plane the two LANSAT 8 images are compared and the changed regions are being detected for every regions.



(a)

(b)

Figure 2: Images represented in Projection Plane (a) may 2013, (b) may 2018

FRFCM is used for dividing the pixel into two clusters whereas the changed pixel and the unchanged pixels according to their difference pixel values. The output pixel will be belonging to the each cluster. Fuzzy *c*-means (FCM) algorithms with spatial constraints (FCMS) have been used for effective image segmentation. They have the following disadvantages: (1) The introduction of local spatial information which is corresponding to the objective functions improves their insensitiveness to noise to some extent, where they still lack enough in robustness to noise and outliers in the absence of prior knowledge of the noise; (2) The objective functions, exists a crucial parameter $\boldsymbol{\alpha}$ used to balance between robustness to noise and effectiveness of preserving the details of the particular image and it is selected generally through experience (3) the time taken for segmenting an image is based on the size of the image, hence the larger the size of the image takes the more time in segmentation. Because of the complex variety of the heterogeneous images, the change detection results directly generated by FCM may still contain some noisy regions whereas small regions of false alarms and miss detections in the classification. The proper modification of the clustering results needs to improve the detection performance.

In the heterogeneous images, the noisy influence obtained and their difference of modalities in the images are large for some pixels in some case. Then the K selected pixels with close values to $\mathbf{x}_i$ in the pre-event image could be far away from $\mathbf{y}_i$ which is corresponding to $\mathbf{x}_i$ in the post-event image and if there is no change occurred. In such situation, it is important to make false detection based on the pixel transformation from one direction which is froward transformation. In this case if we do the opposite transformation which is backward transformation it is associated to $\mathbf{y}_i$ with the feature space X of the pre-event image and some pixels with close values to $\mathbf{y}_i$ in the post-event image may be also with their close values to the $\mathbf{x}_i$ in the pre-event image. Therefore, the fusion of forward and backward pixel transformation will improve the robustness of change detection. The change detected areas are represented by taking the common pixels from each image and clustered together.

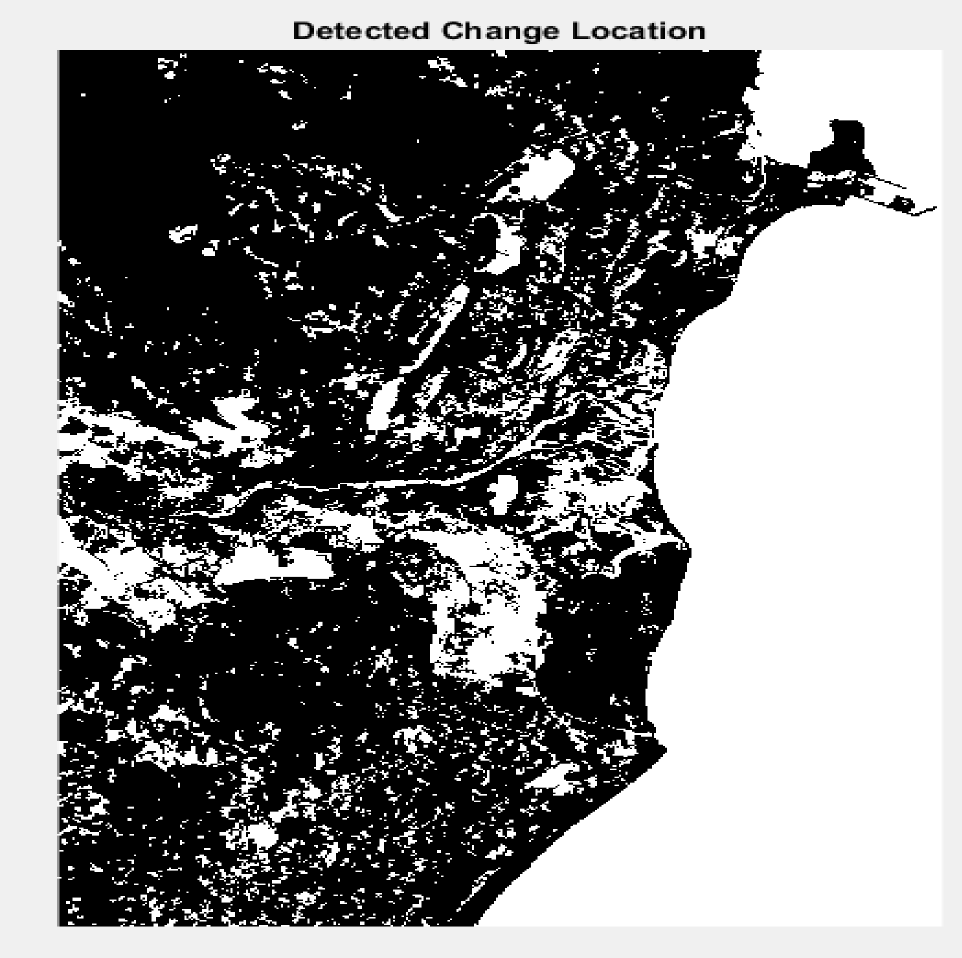
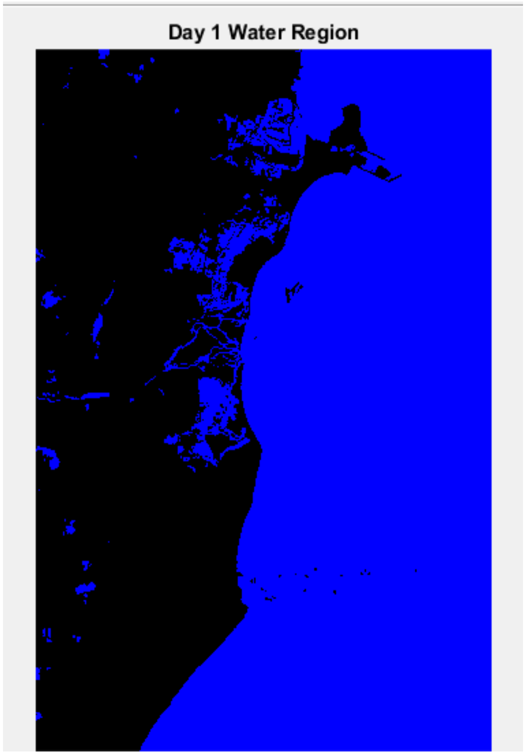


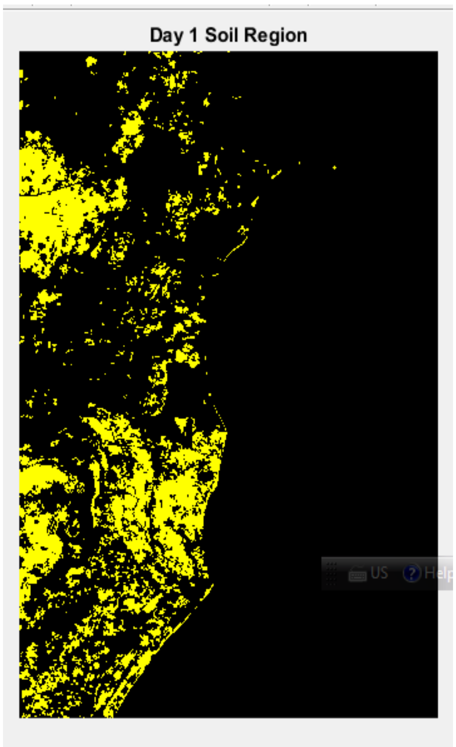
Figure 3: Change Detected Regions

4.EXPERIMENTAL RESULTS

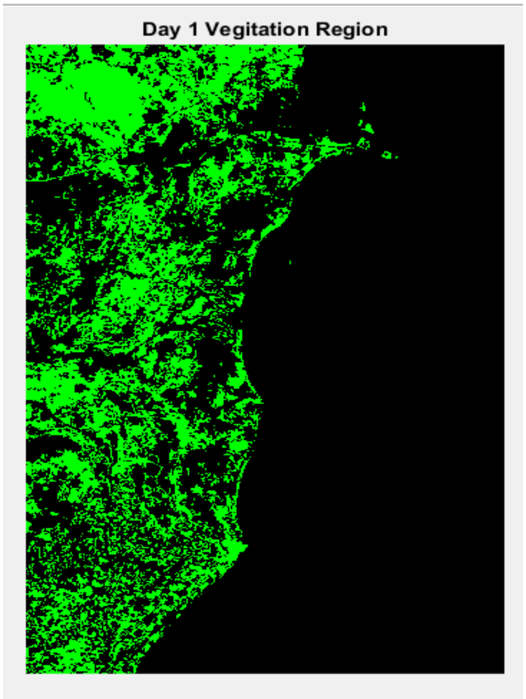
The proposed work uses Homogeneous Pixel Transformation technique for the purpose of Change detection and Region classification from this the Percentage for Change detected areas are being generated. The tool MATLAB 2016 is used to implement the proposed methodology. The training and testing were carried out in Windows 7 environment configured by Intel Pentium CPU 1.70GHz, 4GB RAM and 500GB storage. The LANSAT 8 images are given as input images and the comparison is done for images between May 2013 and May 2018. Based on the comparison results the percentages of change detected areas are calculated. The input images are represented in projection space and the pixel values are taken for detecting the changes in the input images. The common changes between two different time series are detected and represented in same image. The images are represented in separate regions as land, water, soil and vegetation based on their pixel value for May 2013 and May 2018 based on this the changes are detected separately for every region. After applying the Homogeneous Pixel Transformation technique and Fast Robust Fuzzy C-Means Clustering algorithm the changes are being detected for every region and are represented. The amount of change detected regions based on land, water, soil and vegetation are identified and they are compared with two time series images and their percentages are calculated.



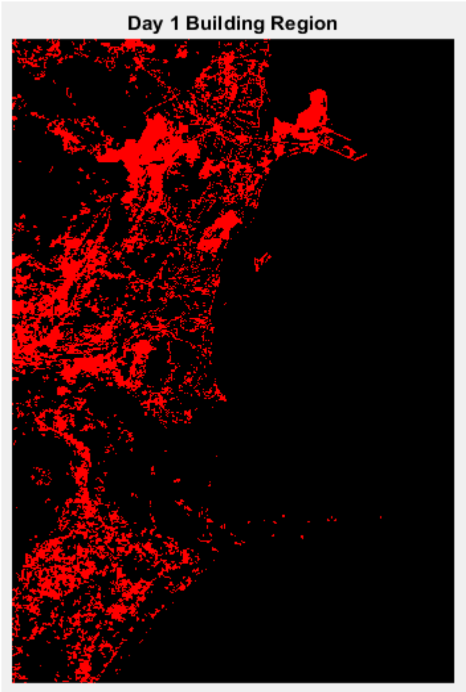
(a) Water region



(b) Soil region



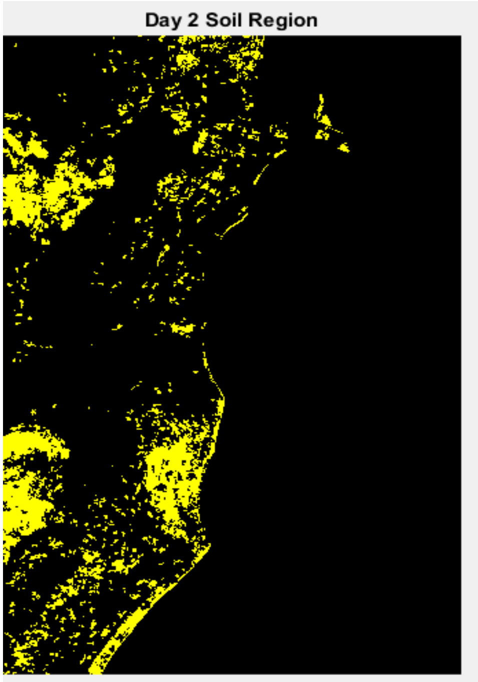
(c) Vegetation region



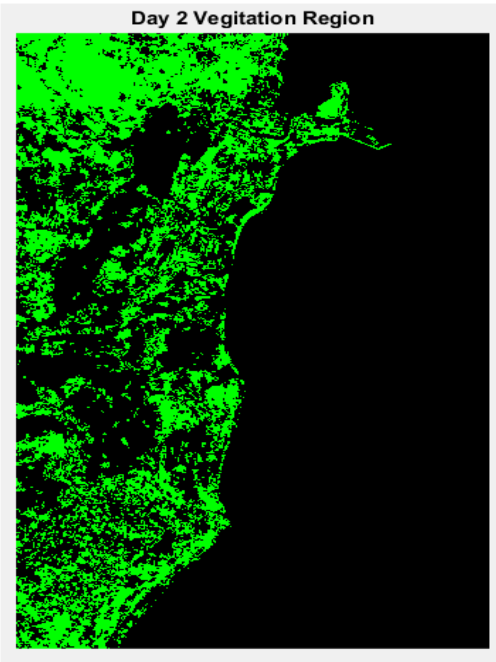
(d) Building region

Figure 4: Detected regions are separated based on their land area as (a) Water region (b) Soil region (c) Vegetation region (d) Building region on may 2013

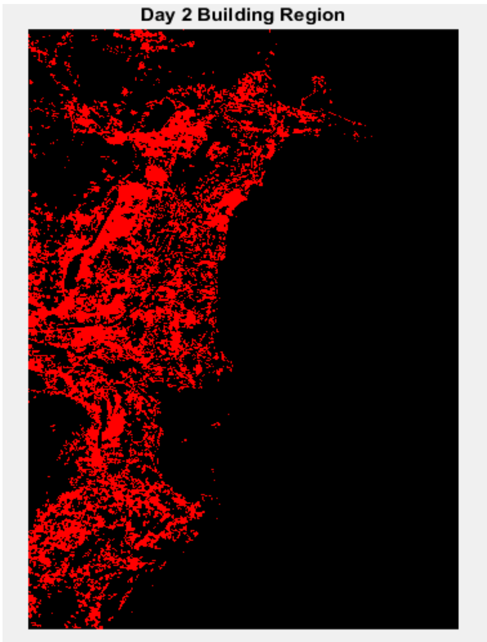
(a) Water region



(b) Soil region



(c) Vegetation region



(d) Building region

Figure 5: Detected regions are separated based on their land area as (a) Water region (b) Soil region (c) Vegetation region (d) Building region on may 2018

5.PERCENTAGE CALCULATION FOR EVERY REGION

Table 1: Percentage Calculation

REGION	CHANGED PERCENTAGE
WATER	7.3016
SOIL	57.3656
VEGETATION	56.0658
BUILDING	48.5636

The percentages are being calculated for every regions based on their changed pixel value. From this the Soil area is found with the 57.3656 percent of changes detected from May 2013-2018. This is found to be the highest change detected based on HPT. Then the Vegetation area is found with 56.0658 detected changes and Building is with 48.5636 and Water with 7.3016 percent respectively. These percent of change detected regions are generated accurately eliminating the noise factors to improve the performance levels.

6.CONCLUSION

A new change detection method for the heterogeneous remote sensing images has been proposed via homogeneous pixel transformation (HPT). HPT consisting of the forward and backward operations is to associate one image with the feature space of another image based on the prior known unchanged pixel pairs. By doing this, the pre-event and post event images are represented in a common feature space for the convenience of change detection. In heterogeneous images, the pixels with close values in one feature space may have more or less different values in another space due to noisy influence and modality difference, and such uncertainty often causes false detections. A new multi-value estimation method is introduced using K-nearest neighbors (K-NN) technique to Scope with the uncertainty in pixel transformation. The two difference values are combined in order to further improve the robustness of the detection method against noise and heterogeneousness of images. FCM algorithm is employed for clustering the integrated difference values of all pixels, and the changes are recognized by the clustering results. The experimental results show that HPT can efficiently improve the detection accuracy and reduce the false alarms with respect to other related methods. In the future work, we will extend the applications of HPT in more kinds of remote sensing images.

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