environmental sciences proceedings

MDPI

Proceeding Paper

Change Detection from Landsat-8 Images Using a Multi-Scale Convolutional Neural Network (Case Study: Sahand City) †

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† Presented at the 5th International Electronic Conference on Remote Sensing, 7–21 November 2023; Available online: https://ecrs2023.sciforum.net/.

Abstract: Identifying changes in Earth's phenomena is vital for understanding and mitigating the impacts of environmental issues. Monitoring Earth's surface phenomena can be done effectively using satellite images acquired at different times. In addition to spectral features, spatial features play a significant role in detecting precise changes. However, classical change detection (CD) methods rarely consider spatial information and fail to account for scale variations within images. The present introduces a novel deep learning-based CD method that hierarchically extracts spatial-spectral features in various scales to address these issues. The proposed deep neural network generates a binary change map by employing a multi-scale approach that integrates the information of patches of varied sizes at the decision level. We conducted experiments using Landsat-8 images from Sahand City, East Azarbaijan, Iran, because of their remarkable capacity to represent Earth's surface details. Tabriz's population growth has led to rapid development in Sahand city to accommodate citizens. Studying these changes can offer valuable insights into urban planning. The performance of the proposed deep model is evaluated in comparison to two classical methods, including the Change Vector Analysis (CVA) method and a random forest (RF) algorithm. Based on the change detection results, the proposed deep learning network demonstrates a significant improvement in the kappa coefficient (K.C.) compared to the RF and CVA methods, with an increase of approximately 11.86% and 29.36%, respectively. Furthermore, in terms of overall accuracy (O.A.), the proposed network outperforms both the RF and CVA methods by approximately 17.08% and 29.16%, respectively. The proposed multi-scale deep network performs better in detecting changes across all metrics. As a result, CVA fails to identify changes with sufficient accuracy.

Keywords: multi-scale deep network; random forest; change vector analysis; change detection; multispectral remote sensing

Citation: To be added by editorial staff during production.

Academic Editor: Firstname Lastname

Published: date

1. Introduction

With the expanding human population, human interventions have intensified in nature to fulfill diverse needs. Consequently, it becomes crucial to monitor environmental changes to preserve wildlife and effectively manage human activities [1]. Field-based surveys are acknowledged as a primary method for detecting changes but are burdened with various drawbacks. They are time-consuming, require significant human resources for fieldwork, and have limitations in terms of geographic coverage. These factors present challenges in monitoring changes using solely field-based techniques [2]. On the other hand, multi-temporal remote sensing images provide a cost-effective and efficient approach for monitoring changes in the Earth's surface [3].

Change detection (CD) methods can be categorized into supervised and unsupervised approaches. Unsupervised methods directly detect changes without needing training samples, while supervised methods utilize training samples to identify changes [4]. Mishra et al. [5] studied land use and land cover changes in a Himalayan watershed using the maximum likelihood algorithm on Landsat-5 and Sentinel-2 images. Christaki et al. [6] applied Artificial Neural Networks to detect changes in UAV images after a catastrophic earthquake, explicitly focusing on the textural features. While Classical algorithms primarily rely on spectral information, which may yield less accurate outcomes, they can incorporate spatial features to improve identification accuracy. However, manual extraction of spatial features is scene-specific and requires careful selection of appropriate features from a range of options [7].

In contrast to classical feature extraction methods, deep learning networks can automatically extract high-level spectral-spatial information. As a result, the user's involvement in determining and identifying suitable features is reduced. Furthermore, the extracted features will no longer depend on the image scene. Roy et al. [8] introduced a new framework based on convolutional neural networks (CNN), where deep spatial features extracted by 2-D CNN were used as inputs for 3-D CNN. Aghdami-nia et al. [9] developed a modified version of the standard U-Net model called the automatic coastline extraction framework to enhance sea-land segmentation. Previous methods have primarily focused on utilizing single-scale CNNs, which limits their ability to capture the intricate multiscale spatial patterns inherent in images. Additionally, selecting the appropriate input patch size around each pixel requires precise user input.

The primary motivation behind our research is to improve the accuracy and comprehensiveness of change detection by automating the extraction of high-level information and surpassing the limitations of traditional CD methods. This study introduces a novel CNN-based CD method that considers the multiscale spectral-spatial features. The performance of the proposed model is evaluated against conventional techniques such as Change Vector Analysis (CVA) and Random Forest (RF). Comparative analyses demonstrate the superiority of our CNN-based CD method and provide valuable insights into its reliability and accuracy. The findings of this study have the potential to enhance wildlife conservation efforts, facilitate effective management of human activities, and help broaden the effectiveness of remote sensing in environmental monitoring.

The paper is organized as follows: Section 2 outlines the research methodology. Section 3 discusses the experimental results. Lastly, Section 4 provides a summary of the conclusions.

2. Methodology

As mentioned, this study compares the proposed MSCNN CD method with two classical CD methods, CVA and RF. The workflow of the study is depicted in Figure 1.

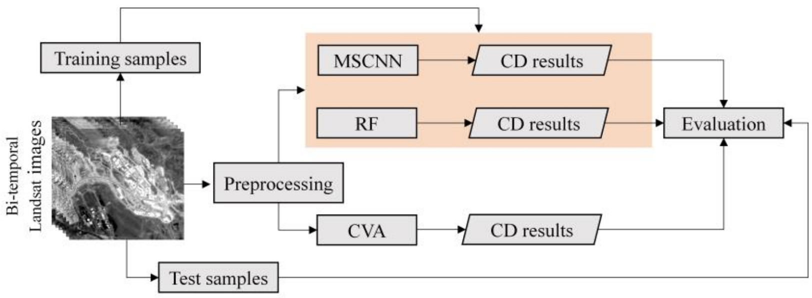


Figure 1. The workflow of the study.

Figure 1 illustrates the initial steps of the study, where the images undergo geometric and radiometric preprocessing. This step is essential for all the research conducted. Training and testing samples are collected from a manually generated ground truth image in the subsequent step. Following this, change maps are generated using the three CD methods. Finally, the change maps are evaluated and compared. The following sections provide a summarized description of each of the employed CD methods.

2.1. CVA

The CVA technique defines a change vector as the disparity vector between two n-dimensional vectors in a feature space, thus establishing it as an unsupervised method. These vectors represent two separate observations of the same pixel at different time points. The length of the change vector corresponds to the magnitude of the change event in the spectral feature space. The change magnitude (CM) can be quantified as follows:

$$CM = \sqrt{(DN_{11} - DN_{21})^2 + (DN_{12} - DN_{22})^2 + \cdots} \quad (1)$$

where DN_{ij} represents the digital number of band *j* for data *i* [10]. Then, the Otsu thresholding technique [11] is employed to obtain a binary change map.

2.2. RF

The RF is recognized as a classifier employing a Classification and Regression Trees ensemble for prediction purposes. The trees are generated using a bagging technique, where a subset of training samples is randomly selected with replacement. Consequently, certain samples may be drawn multiple times, while others may not be chosen at all [12]. The RF model is trained using the collected samples, and subsequently, predictive processing is applied to the stacked images to generate a change map.

2.3. Multiscale CNN

CNNs have been extensively used in various remote sensing applications. CNNs utilize shared connections kernel to extract high-level spatial features. These networks include multiple layers, including convolutional, activation function, batch normalization, pooling, and fully connected layers [13]. As previously mentioned, single-scale CNNs struggle to capture the multiscale information in remote sensing images. Determining the optimal patch size requires a time-consuming trial-and-error process [14]. This study introduces the MSCNN as a potential solution, incorporating a multiscale framework that eliminates the need to search for the optimal patch size and reduces reliance on a single value. The desired configuration is depicted in Figure 2, illustrating the network architecture.

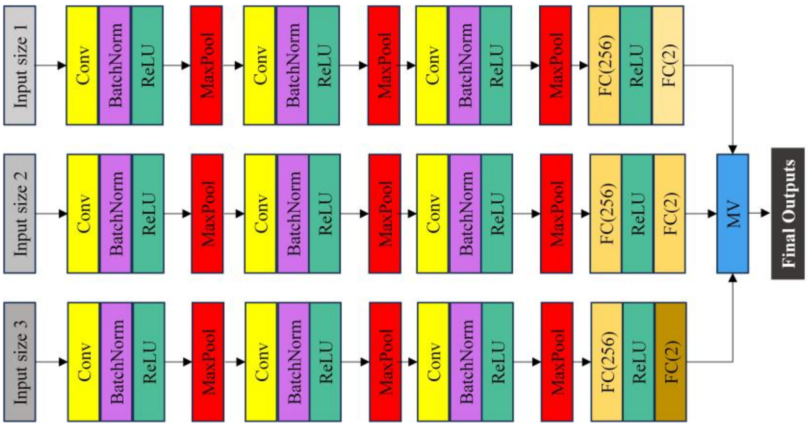


Figure 2. The proposed MSCNN architecture.

The change identification process involves utilizing separate 2D CNN networks with various input dimensions to classify the stacked bi-temporal Landsat images, and the Majority Voting (MV) algorithm is employed to integrate the results. The [3×3, 7×7, and 9×9] patch sizes are used as the input. The sequencing of the filters is presented in the subsequent order: [64,128,256], accompanied by a kernel size of 3x3. Batch normalization layers are used to address overfitting in the convolutional layers. The learning rate and the optimizer are set to 0.0001 and Adam, respectively.

3. Experimental Result

3.1. Study Area and Dataset

This study utilizes Landsat-8 satellite images to evaluate the effectiveness of the proposed network in monitoring changes in the Sahand city area. Sahand City is situated in the East Azerbaijan province of Iran, with a longitude of 46°7'19.16" and a latitude of 37°56'18.41". In response to the population growth of Tabriz, this city was established in 2007 as a measure of population control and city management. Sahand city, located 20 kilometers southwest of Tabriz, has witnessed rapid development in recent decades, particularly after the construction of the Tabriz-Sahand highway, which has improved accessibility for residents of both cities. The Landsat images were obtained from the Google Earth Engine on July 10, 2013, and August 1, 2021. The geographic location of the studied area is depicted in Figure 3.

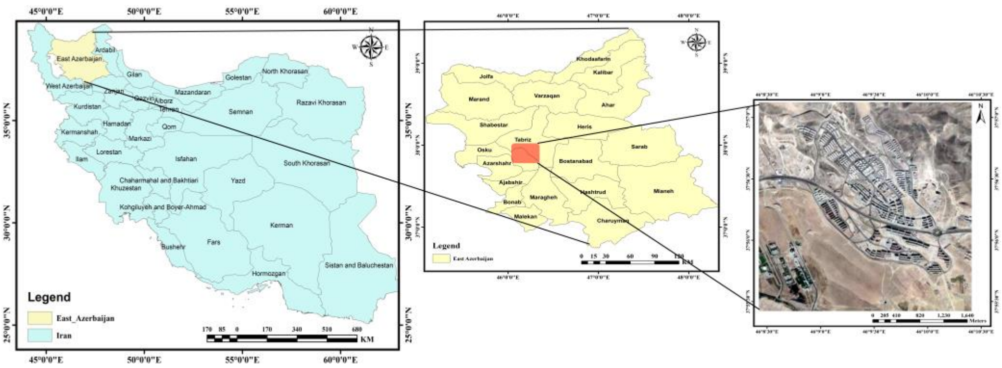
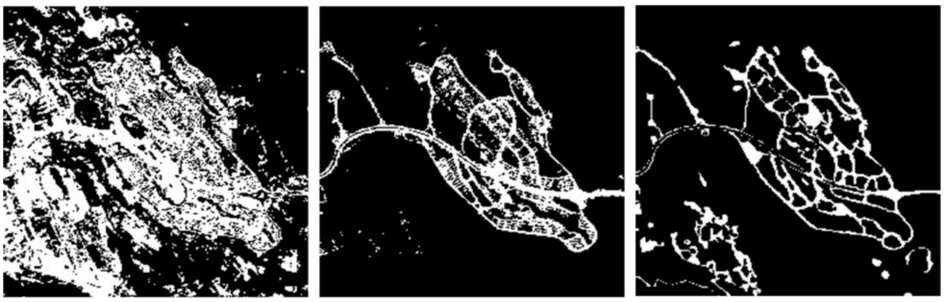


Figure 3. The location of Sahand city within the country's divisions (The image is from Google Earth).

3.2. Result Analysis

Figure 4 visually presents the obtained binary change maps generated by the CVA, RF, and MSCNN techniques. The findings indicate that CVA has incorrectly identified most areas as changes. In contrast, the RF and MSCNN techniques have demonstrated superior performance in detecting changes.



(a) (b) (c)

Figure 4. The generated binary change maps: (**a**) CVA, (**b**) RF, (**c**) MSCNN.

The CVA method solely relies on pixel-based information and often exhibits inadequate efficacy in change detection. Introducing sample data to the change detection algorithms, known as supervised methods, can significantly improve detection accuracy. To enhance result analysis, Figure 5 showcases the confusion matrices of the binary change maps, comparing them with the ground truth data. This presentation allows for a comprehensive evaluation. Based on the confusion matrices, it is evident that the CVA algorithm misclassified 190 pixels, while RF and MSCNN misclassified 132 and 50 pixels, respectively. These numbers provide valuable insights into the performance of each algorithm in terms of pixel classification accuracy.

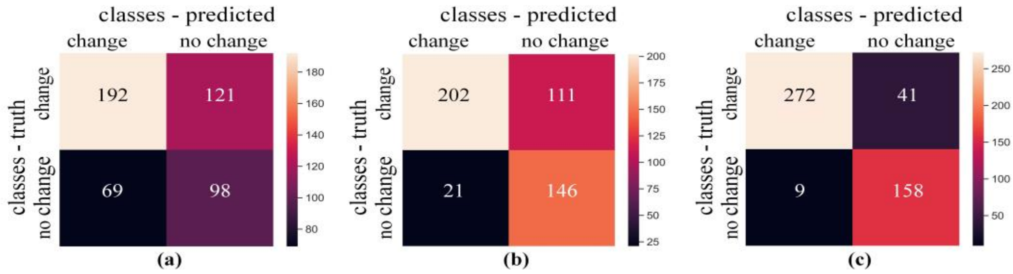


Figure 5. The confusion matrices: (**a**) CVA, (**b**) RF, (**c**) MSCNN.

Additional evaluation criteria, including precision, precision, recall, f1-score, Overall Accuracy (O.A), and Kappa Coefficient (K.C), are utilized to conduct a comprehensive and quantitative assessment of the results. Based on the assessment measures in Table 1, the proposed MSCNN approach demonstrates a precision of 89.58% in detecting changes, representing the highest precision among all methods. In contrast, CVA exhibits the lowest performance with a precision value of 60.42%. Similarly, when considering other criteria, it becomes evident that the proposed network outperforms both the RF and CVA algorithms regarding accuracy. These findings highlight the superior performance of the proposed network compared to the other two methods.

Sahand city has experienced notable transformations, particularly in converting barren lands into urban areas. Previously, this region was predominantly barren, providing an ideal location for urban development. The majority of changes observed in the area involve the construction of buildings and transportation routes.

Table 1. Accuracy assessment of three methods in CD.

Classes	**CVA**			**RF**			**MSCNN**		
	precision	**recall**	**f1-score**	**precision**	**recall**	**f1-score**	**precision**	**recall**	**f1-score**
Change	0.7356	0.6134	0.6690	0.9058	0.6454	0.7537	**0.9680**	**0.8690**	**0.9158**
No Change	0.4475	0.5868	0.5078	0.5681	0.8743	0.6887	**0.7940**	**0.9461**	**0.8634**
K.C (%)	48.66			66.16			**78.02**		
O.A (%)	60.42			72.50			**89.58**		

4. Conclusion

The progress in remote sensing methodologies has greatly improved the monitoring of environmental changes, including urban areas. This advancement has significantly enhanced our understanding and addressing of ecosystem modifications, which also have notable economic implications. However, classical methods cannot incorporate spatial information into their analyses, limiting their effectiveness in considering the spatial context of detected changes. On the other hand, deep learning-based techniques that extract spatial features offer high accuracy in change detection. Due to the rapid population growth of Tabriz, Sahand city has undergone significant development in a short period to accommodate citizens. Therefore, examining the changes in this city can provide valuable insights for better urban planning. For this aim, this study compared a new deep learning-based CD approach to classical CD methods, namely RF and CVA, to detect changes in Sahand City. Based on the evaluation of the results, the unsupervised CVA method had the lowest performance in CD. Employing supervised RF algorithms can enhance change detection accuracy, but utilizing the MSCNN network resulted in a remarkable 17% increase in the overall accuracy of the binary change map. The construction of buildings and new transportation infrastructure accounts for most of the changes in the area. This investigation challenges the widely held belief that simple algorithms can effectively detect changes. In contrast, the findings emphasize the importance and effectiveness of advanced deep learning techniques in substantially improving outcome accuracy.

Supplementary Materials: Not applicable.

Author Contributions: "Conceptualization, S.T. and BA.B.; methodology, S.T. and BA.B.; software, S.T. and BA.B.; validation, S.T. and BA.B.; formal analysis, S.T. and BA.B.; investigation, S.T. and BA.B.; resources, S.T. and BA.B.; data curation, S.T.; writing—original draft preparation, S.T.; writing—review and editing, S.T. and BA.B.; visualization, S.T.; supervision, M.M. "

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data is accessible at the https://earthengine.google.com.

Acknowledgments: We would like to thank the European Space Agency (ESA) for generously providing us with free access to the Landsat 8 imagery.

Conflicts of Interest: The authors declare no conflict of interest.

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