# Change Detection Algorithm for Vegetation Mapping using Multispectral Image Processing

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**Abstract.** Agriculture is an important sector of the world. Agriculture's contribution to the nation's prosperity cannot be overlooked, despite the industry's significant role in the global economy. Agriculture in any geographic area is constantly changing. Changes are detected to build a knowledge base in order to ensure the preservation of these agricultural characteristics in particular location. The process of identifying differences in two different places or the state of an object or phenomenon by observing it at different times is known as change detection. This method is typically used to change the earth's surface two or more times. Here the primary source of data is geographic which is taken from Google Earth Engine(GEE) and is typically in digital (e.g., satellite imagery)can be used. The history of change detection begins with the history of remote sensing

**Keywords:** Change detection, quantum geographic information system, google earth engine, remote sensing images, google colab, multispectral Images

## 1 Introduction

In recent decades, remote sensing data have been employed widely as primary resource for change detection. Understanding the connections and interactions between human and natural events is crucial for better decision-making, and for this accurate change detection of Earth's surface features is necessary. The method of finding differences between scenes of the same location taken at several periods is known as remote sensing change detection (RSCD). Change detection is a method that assesses how a certain area's characteristics have evolved over the course of two or more time periods. Aerial or satellite images of the area obtained at various dates are frequently compared in order to discover changes. Recognizing the type and location of changes, quantifying changes, and evaluating the accuracy of change detection results are the general goals of change detection in remote sensing. The change detection techniques are divided into seven categories for ease of reference: (1) algebra; (2) transformation; (3) classification; (4) advanced models; (5) approaches using Geographical Information Systems (GIS); (6) visual analysis; and (7) other approaches. Absolute and relative change detection are the two types of change detection. Absolute change detection draws attention to the specific changes, such as the transition from forest to grassland. Although something has changed, relative change detection does not identify what that change is.

Utilizing several temporal data sets, change detection entails quantifying temporal impacts. Satellite data is frequently employed when someone is interested in tracking changes over vast areas and at frequent intervals. Executing checks against two states—the new state and the current state—is the main change detection technique. One of these states must be rendered if it diverges from the other, indicating that something has changed. Change detection is of two different forms. The first is supervised change detection, and the second is unsupervised change detection. The outcomes of the GIS study demonstrate the use of change detection information in crop insurance by assisting in the assessment of field damage. In order to conserve crops and reduce yield losses, farm management decisions can ultimately benefit from the GIS information gathered.

Due to its ability to quantitatively analyse the geographical dispersion of the target population, change detection is a crucial procedure in the management and monitoring of natural resources and urban growth. Assessment of deforestation, monitoring shifting cultivation, study of changes in vegetation phenology, seasonal variations in pasture production, damage assessment, and crop monitoring are just a few of the many areas where change detection is helpful.

### 1.1 Applications of Remote Sensing

In order to identify, measure, and analyse specific items, areas, or phenomena properties without coming into contact with them directly, remote sensing is the science and technology that enables this. Land use mapping, weather forecasting, environmental research, studying natural hazards, and resource exploration are some of the uses for remote sensing. The electromagnetic radiations that an object emits or reflects serve as the source of remote sensing data, which is subsequently used to identify and categorize the object. Its data can be used to track changes over time and receive the most recent land use patterns over broad areas at any one time. It can be used to update wetland delineation, asphalt conditions, and road maps. Regional planners and administrators utilise this data to frame policy decisions for the region's overall development.

## 2 Related Work

Land Cover Clustering for Change Detection using Deep Belief Network(2022) [1]:

Authors uses Clustering for unlabeled data, Deep brief network(deep learning model) for change detection. It complicates the entire clustering process, and as a result, the accuracy of change detection sometimes suffers.

Optical Satellite Image Change Detection Via Transformer-Based Siamese Network(2022) [2]:

Convolutional neural networks(CNN),Natural language processing(NLP), vision Transformer(ViT) are used. Siamese extensions of ViT networks that outperform in tests on two open change detection datasets. The effectiveness and superiority are demonstrated by experimental results on real datasets.

Using Hyperspectral Reconstruction for Multispectral Images Change Detection(2022) [3]:

The original multispectral data is used to generate hyperspectral data with richer spectral information, which is then used to detect changes. They uses reconstruction algorithms for image reconstruction. The results of the experiments show that the hyperspectral reconstruction method improves the accuracy of multispectral images.

A CNN-Transformer Network With Multiscale Context Aggregation for Fine-Grained Cropland Change Detection(2022) [4]:

Authors uses CNN-transformer network ,Multiscale context aggregation (MSCANet) as the feature extractor. MSCANet demonstrates its space and computation complexity advantages. All of the results fully demonstrated the MSCANet's capability in efficient and effective cropland Change detection.

Style Transformation-Based Spatial–Spectral Feature Learning for Unsupervised Change Detection(2022) [5]:

Style transformation-based change detection algorithm with spatial-spectral feature learning (STFL-CD),Detection Network With Attention Mechanism, and Convolutional neural networks(CNN) are used by authors. They tried to remove the influence of "same object with different spectra" and had some shortcomings. Further research will be conducted in nonlinear ST methods in the future to deal with the multitemporal HSI change detection task more effectively.

A Survey on Deep Learning-Based Change Detection from High-Resolution Remote Sensing Images(2022) [6]:

Deep learning-based change detection using high-resolution images. It discusses the most popular feature extraction deep neural networks as well as the mechanisms for building them. Describes the change detection framework at first. After that, the methods are classified based on the deep network architectures used.

Detection of Urban Built-Up Area Change From Sentinel-2 Images Using Multiband Temporal Texture and One-Class Random Forest(2021) [7]:

The proposed multitemporal image classification method based on one-class Random forest (iOCRF) focuses on the  built-up area change. It is suitable for including multiband temporal texture, and is data dimensionality insensitive. More research is needed to assess the performance of the proposed method in other study areas and changes of interest.

Image based Land Cover Classification for Remote Sensing Applications(2021) [8]:

They deals with Convolution neural network (CNN) in deep learning, supervised and un-supervised classification methods. Here the accuracy of land cover classification is heavily dependent on the time and location of the image capture.

Land Use and Land Cover Classification using Recurrent Neural Networks with Shared Layered Architecture(2021) [9]:

Authors uses Recurrent Neural Network (RNN) and Shared Layer Recurrent neural networks(SLRNN). SLRNN outperforms others in terms of accuracy. Not all pixels considered by SLRNN were correctly classified, but some were incorrectly classified.

Deep Learning Approaches to Earth Observation Change Detection(2021) [10]:

Two distinct approaches to detecting change (semantic segmentation and classification). Both use convolutional neural networks to address these specific requirements. Further developed and applied in post-processing workflows for a wide range of applications

Recent Applications of Landsat 8/OLI and Sentinel-2/MSI for Land Use and Land Cover Mapping: A Systematic Review(2020) [11]:

Advising the scientific community on how to use L8/OLI and S2/MSI data to gain a thorough understanding of land use land cover (LULC) mapping. Change detection in various landscapes, particularly agricultural and natural vegetation scenarios. When using representative samples, classification models tend to achieve higher accuracies.

A Land Cover Change Detection Method Combing Spectral Values and Class Probabilities(2020) [12]:

Here spectral-based direct comparison (SDC) method and class probability-based direct comparison (CPDC) methods are used. To obtain class probability information, the supervised change detection method requires manual selection of training samples.

Deep Learning for change detection in Remote Sensing Images (2020) [13]:

Learn complex features of remote sensing images automatically using a large number of hierarchical layers. Among all classifiers, the Random Forest Classifier has the highest accuracy. The Artificial Neural Network (ANN) predicted soil fertility, crop yield, and crop yield with the highest accuracy.

Deep Learning for Land Cover Change Detection(2020) [14]:

The presented Long short term memory (LSTM) approaches are adaptable to a variable number of image sequences. The chosen pre-processing improves the water classification while avoiding effectively reducing the dataset.

A Deep Learning Architecture for Visual Change Detection(2018) [15]:

This paper proposes a parallel deep convolutional neural network (CNN) architecture for localising and identifying differences between image pairs. Change-Net is a deep architecture for detecting differences between pairs of images. Change-Net outperforms the competition.

# 3 Proposed Work

## 3.1 Datasets

We have used Google Earth Engine (GEE) for taking the input satellite images. Google Earth Engine enables users to visualize and analyze satellite images of our planet. It is a platform for geospatial analysis in the cloud that allows users to see and examine satellite photos of our world.

**Fig. 1.** Images of Switzerland from Google Earth Engine(2012)

**Fig. 2.** Images of Switzerland from Google Earth Engine(2015)

### 3.2 System Architecture

Deep Active Learning is supported in the implementation of the Siamese U-Net model with the pre-trained ResNet34 architecture as an encoder for the Change Detection task on the Remote Sensing dataset.

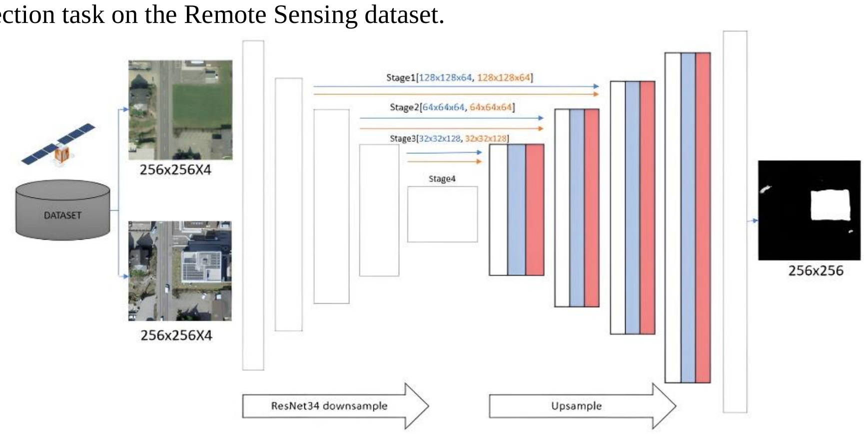


**Fig. 3.** Architecture diagram of Siamese Neural Network

A Siamese neural network uses ResNet34 as an encoder. The images are cropped to the correct size. The multispectral image is sent into the convolutional layers of the neural network to produce a feature vector. A feature vector holds all of the features of a picture. Time stamp T1's image X1 generates the feature vector f(X1) that corresponds to image X1. The picture X2 of timestamp T2 similarly generates the feature vector f(X2) corresponding to image X2. The identical Convolution layers receive both X1 and X2 simultaneously. The sent Convolution layers have the same parameters. The feature vector is a 128-bit encoded vector. Our Siamese neural network's output is a difference vector of both the feature vectors.

## 4 Algorithm and its Description:

A sort of artificial neural network is the siamese neural network that employs the same weights to compute equivalent output vectors from two separate input vectors while operating in parallel. A precomputed version of one of the output vectors frequently serves as a benchmark for comparison with the other output vector. These networks compare the feature vectors of the inputs to determine how similar they are. We conduct verification, identification, or recognition tasks using Siamese networks; the most well-known applications are face recognition and signature verification.

A siamese network consists of two comparable neural networks that each take one of the two input images. The contrastive loss function uses the final layers from both networks to determine how similar the two images are. The Siamese architecture seeks to distinguish between input images rather than categorise them.

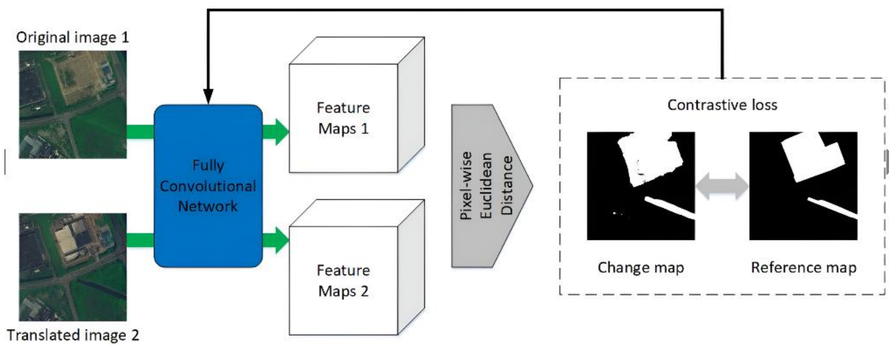


**Fig. 4.** Dataflow diagram of the Siamese detector, the changed pixels are white while the unchanged are black.

There are two sister networks that are identical neural networks with the same weights. One of these networks receives a feed of each image in the image pair. It optimises the networks using a contrastive loss function.

The contrastive loss function is given as follows:
$$(1\text{-}Y)1/2(D_w)^2 + (Y)1/2\{\max(0, m\text{-}D_w)\}^2 \quad (1)$$

where Dw is referred to as the Euclidean distance between the sibling Siamese networks' outputs.

Mathematically the Euclidean distance is:

$$(\{G_w (X_1) – G_w (X_2)\})^{1/2} \quad (2)$$

where Gw is one of the sister networks' outputs. The data pair for input is X1 and X2.

**Algorithm: Siamese Neural Network**

Input: High-Resolution satellite images

Output: Change map

1. Begin

2. Assume that Q = (cQ, tQ) and R = are the two input images (cR, tR)

3. Calculate the Euclidean distance between the matrix representations of the two matrices as follows: $D\phi(Q,\ R)$=‖$\{\phi(CQ)\ \oplus\ \phi(tQ)\}\ -\ \{\phi(CR\ )\ \oplus\ \phi(tR\ )\}$‖2, to determine how semantically linked the two matrices are.

The caption representations for the query and the candidate matrix are (cQ) and (cR), respectively, and the matrix representations are (tQ) and (tR), respectively.

4. To ensure that D(Q, R) is modest, contrastive loss is specified as a quadratic function of table pair distances (close to zero)

5. If margin m is equal to or more than zero else and table R is comparable to table Q.

$$L(y,\phi,\ Q,\ R) = 1\ 2\ (1 - y)D\phi\ 2\ (Q,\ R) + 1\ 2\ y\ \{\max\ (0,\ m - D\phi(Q,\ R))\}^2 \quad (3)$$

6. The pair's genuine label is y.

7. Pairs with distance scores below this threshold are considered similar, whereas pairs with greater distance scores are judged dissimilar. Labels for a binary classification are obtained by thresholding the distance at half of the margin, m/2.

8. Output is the Images' Difference Label. L (Q, R) (Q, R)

As everything evolves through time, it can be quite beneficial to comprehend and measure this change. For instance, examining the infrastructural development of a city or town over time can be used to estimate its level of economic success. Every model has to be having the ability to recognise the changes in which we are interested while being able to ignore those that are not relevant to our use case. To detect changes in structures over time, it may be necessary to ignore changes in things like roads, trees, and water bodies. This is more of a data normalisation issue because images taken over time would have variations that would be difficult to constantly account for. When capturing facial photos with a smartphone, the lighting and orientation settings will never be the same. Photos acquired by satellites may be affected by changes in cloud cover, sunlight reflection, and the azimuthal and elevational angles of the satellite itself.

The simplest and most direct way to measure change, using a pixel difference between elements, is no longer an option. There are more clever ways to do this, but the results are still quite subpar. Two photos (taken at two separate timestamps) are fed into a Siamese neural network, which uses a series of convolutional layers to create higher-order feature vectors for each image. The magnitude of change is then determined by comparing the feature vectors using the Euclidean norm. According to the hypothesis, comparing two images when there has been no obvious change would lead to similar vectors in the feature vector's dimensional space.

A Contrastive Loss function is used to train Siamese networks. It attempts to reduce the distance between the two feature vectors if there is no change and vice versa. The illustration that follows makes an attempt to illustrate it using a scenario involving two classes. If neither of the two photographs showed the modifications we were practising for, the real label would be 1.

The strengths of this algorithm are Well Paired With the Best Classifier, Learning from Semantic Similarity, More Resistant to Class Inequality. Weakness of this method are requires longer training than typical networks, Avoid Producing Probabilities.

## 5 Result Analysis and Observations

From the Google Earth Engine, satellite pictures are downloaded. It provides us with multispectral images of Switzerland. Images with twodifferent time stamps were acquired in order to identify the changes that have taken place over the past few years. The output of Remote Sensing Change Detection (RSCD)is a binary image that clearly identifies the locations of Land Use and Land Cover (LULC) changes.

The following images show the satellite image at time stamp T1 i.e., (a), the satellite image at time stamp T2 i.e.,(b), and the third image is the change map we obtained i.e.,(c)

(a) (b) (c)

**Fig 5**. The changes occurred in the agricultural land due to urbanization

(a) (b) (c)

**Fig 6**. The changes occurred in agricultural land due to construction of building

The Siamese neural network generates accurate results. The Confusion Matrix is created via the suggested approach. A table that shows how many predictions a model got right and wrong is called a confusion matrix. It is used to assess the efficacy of a categorization model. When the expected value and the actual value are both positive, TP takes place. When the actual and projected values are both negative, TN happens. When an optimistic prediction is made but the actual is adverse referred to as the Type 1 error as well. FN is the outcome when both the fact and the prediction are true referred to as the Type 2 error as well.

**Table 1**. Confusion Matrix

| | Change | No Change |
|---|---|---|
| Change | 90 | 1 |
| No Change | 12 | 106 |

The Siamese neural network produces the metrics shown below. The basic metric for model evaluation is widely used to measure accuracy, which counts the percentage of accurate forecasts over all other predictions. Precision is measured by the frequency of correct positive forecasts (true positives). A measurement that combines recall and precision is the F1-Score.

**Table 2.** Metrics

| **METRICS** | **FORMULA** | **VALUES** |
|---|---|---|
| ACCURACY | (TP+TN)/(TOTAL) | 0.938 |
| PRECISION | (TP)/(TP+FP) | 0.989 |
| RECALL | (TP)/(TP+FN) | 0.882 |
| F1- SCORE | 2(PRECISION*RECALL)/ (PRECISION + RECALL) | 0.932 |

• F-Measure offers a single score that integrates precision and memory problems into a single value.

• It was noted that a binary image was generated, with the white portion corresponding to the change and the black portion corresponding to no change.

• It was found that the model had a 93.8% accuracy rate.

• Precision counts the number of positive class predictions that really fall into the positive class. The model's accuracy was found to be 98.9%.

• Recall quantifies the number of times the dataset's valid examples were used to make accurate class predictions. The model's accuracy was demonstrated to be 88.2%.

## 6 Conclusion

In this project, Switzerland was chosen as a specific place from Google Earth Engine, and we utilised two different timestamps to check for changes. These photos, which were taken using multispectral remote sensing technology, were used in our investigation. We used a Siamese neural network to achieve change detection of the input location.Through the Siamese neural network featured vectors of the two input images are calculated and the euclidean distance between the two featured vectors are computed. In the change map the white color denotes the change and the black color denotes there is no change. Several acquisition functions and methods for calculating prediction uncertainty have performed admirably in our tests. All qualified strategies significantly outperform a naive random baseline and accomplish the performance of a model that has been trained using only a small number of samples from the entire collection of available data.

# 7 Future Scope

The project's objective is to identify changes in agricultural areas using remote sensing photographs. Consequently, there is a chance for change in agricultural areas. Our future research will include calculating the percentage change and percentage change in water bodies, mountains, before and after natural disasters, and other characteristics.

# 8 References

[1] P. Coppin, I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin, “Digital change detection methods in ecosystem monitoring: A review,” Int J.Remote Sens., vol. 25,no. 9, pp. 1565-1596,2004.

[2] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, and B. A. Johnson, “Deep Learning in remote sensing applications: A meta-analysis and review,” ISPRS J. Photogramm. Re-mote Sens., vol. 152, pp. 166-177, Jun. 2019.

[3] L. Zhang, B. Du, “Deep learning for remote sesing data: A technicaltutorial on the state of the art,” IEEE Geosci. Remote Sens. Mag., vol.4, no. 2,pp. 22-40, Jun. 2016.

[4] K. L De Jong and A. S. Bosman, “Unsupervised change detection in satellite images using convolutional neural networks,” Dec 2018.

[5] N. Kadhim, M. Mourshed, and M. Bray, “Advances in remote sensing applications for urban sustainability,” Euro-Medit. J. Environ. Integr., vol. 1,no. 7, pp. 1-22, 2016.

[6] L. Wen, M. Matsuoka, B. Adriano, “Damage detection due to the typhoon Haiyan from high-resolution SAR images”, in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 3, no. 1, pp.123-133, May 2019, doi: 8.1207/MGRS. 2019.2931830.

[7] R. J. A Tough, D. Blacknell and S. Quegan, “A statistical description of polarimetric and interferometric synthetic aperture radar”, in IEEE Journal of

Selected Topics in Applied Earth Observations and Remote Sensing, vol.7, no.1, pp.67-93, April 2019, doi: 6.1107/MGRS. 2019.1431430.

[8] Kevin Louis de Jong, Anna Sergeevna Bosman, "Unsupervised Change Detection in Unlabeled Optical Remote Sensing using CNN", in IEEE Transactions on Geoscience and Remote Sensing, vol. 2, no. 1, pp.102-114, March 2019, doi: 6.1219/MGRS.2019.1214110.

[9] 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. 1, pp. 218-236, Jan.2007.

[10] L. Wen, M. Matsuoka, B. Adriano, "Damage detection due to the typhoon Haiyan from high-resolution SAR images", in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 3, no.1, pp.123-133, May 2019, DOI:8.1207/MGRS. 2019.2931830.