

Research Paper

Satellite Image-Based Land Surface Change Detection Using Image Processing

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Project Domain: Image Processing / Remote Sensing

Abstract

Satellite imagery provides an effective way to observe and monitor changes occurring on the Earth's surface over time. Images of the same geographical area captured at different time periods can be compared to identify changes such as construction, land-cover modification, vegetation loss, water-body variation, and other visible surface changes. Remote-sensing change detection has traditionally included pixel-based and image-comparison techniques [1], [5], while recent research has increasingly focused on machine learning and deep learning approaches [3], [4]. This research proposes a lightweight and explainable satellite image change-detection system based primarily on classical image-processing techniques. The proposed system accepts two satellite images representing the same geographical area at different points in time. The images are preprocessed and aligned before a difference image is generated. Thresholding is then applied to distinguish significant differences from minor variations [6], followed by morphological processing to reduce noise and refine the detected regions. The system highlights changed regions and calculates a change percentage and severity indication. The proposed implementation uses Python, OpenCV, NumPy, Pillow and Matplotlib, with Streamlit for the user interface and Flask for backend processing. Unlike approaches that depend primarily on deep learning models, the proposed system focuses on a transparent processing pipeline in which each stage can be understood and evaluated independently. The system will be evaluated using known test cases and appropriate metrics such as accuracy, precision, recall and F1-score. The research also discusses limitations caused by image misalignment, noise, illumination differences, clouds, shadows and seasonal variations.

Keywords: Satellite Image, Change Detection, Remote Sensing, Image Processing, OpenCV, Image Differencing, Thresholding, Morphological Processing, Land Surface Change

Table of Contents

1. Introduction	
2. Motivation	
3. Problem Statement	
4. Objectives	
5. Related Work	
6. Research Gap	
7. Proposed System	
8. Methodology	
9. Proposed Features	
10. Technology Stack	
11. System Workflow	
12. Evaluation	
13. Expected Results	
14. Limitations	
15. Ethical Considerations	
16. Discussion	
17. Future Work	
18. Conclusion	
References	

1. Introduction

The Earth's surface continuously changes due to both natural and human activities. Urban expansion, construction, deforestation, agricultural changes, water-body variation, disasters and other environmental processes can alter the appearance of a geographical area over time. Satellite imagery provides repeated observations of Earth's surface and therefore offers an important source of information for monitoring such changes. Remote-sensing image change detection is generally concerned with identifying differences between images of the same geographical area acquired at different times, with applications in urban development, land-use monitoring, environmental monitoring, disaster assessment and other areas.

Traditional change-detection approaches have included pixel-based techniques, image differencing, image ratioing, change-vector analysis, transformation methods and post-classification comparison — a taxonomy established in Singh's foundational 1989 review of

digital change-detection techniques [5] and refined further by Hussain et al.'s later review of the progression from pixel-based to object-based methods [1]. Reviews of the field show that traditional approaches remain important because they can provide relatively direct and interpretable ways of identifying differences between images [1], [2]. At the same time, recent research has increasingly explored machine learning and deep learning techniques for improving change detection, particularly for complex scenes [3], [4]. However, these approaches can require larger datasets, computational resources and more complex model development. Recent reviews also note challenges such as image noise, registration errors, illumination changes, spatial heterogeneity and complex landscapes [3]. This research therefore focuses on developing a lightweight satellite-image change-detection system using classical image-processing techniques. The objective is not to replace advanced research methods, but to develop a transparent and practically implementable system suitable for a final-year BCA project.

2. Motivation

Manual comparison of two satellite images can be difficult when the images contain large geographical areas or many small changes. A user may visually inspect an image and notice obvious differences, but identifying and quantifying all significant changes can be time-consuming. The motivation for the proposed system is to provide an automated method that can compare two satellite images of the same geographical area, identify regions with significant visual differences, highlight the detected regions, estimate the percentage of the analysed area that has changed, provide an indication of severity, and present the results in an understandable visual form.

3. Problem Statement

Satellite images of the same geographical area may show different surface conditions when captured at different times. Manually identifying these changes is difficult, particularly when the images contain large areas or numerous small variations. The problem addressed in this research is: **How can two satellite images of the same geographical area captured at different times be automatically compared using image-processing techniques to detect, highlight and quantify significant land-surface changes?** The proposed solution focuses on classical image processing rather than deep-learning-based change detection.

4. Objectives

1. To accept two satellite images of the same geographical area captured at different times.
2. To preprocess and align the input images so that corresponding regions can be compared.
3. To generate a difference representation between the two images.

4. To use thresholding to distinguish significant differences from small variations.
5. To apply morphological processing to reduce unwanted noise and refine detected regions.
6. To highlight the detected changed regions on the satellite image.
7. To calculate the percentage of the analysed area identified as changed.
8. To provide a simple severity or anomaly indication based on the amount of detected change.
9. To display before-and-after images and the resulting change map.
10. To evaluate the detection performance using suitable reference data and metrics such as accuracy, precision, recall and F1-score.

5. Related Work

5.1 Traditional Remote-Sensing Change Detection

Remote-sensing change detection has been studied for several decades. Traditional approaches commonly compare information obtained from images acquired at different times. Major reviews classify traditional approaches into pixel-based and object-based methods [1]: pixel-based methods use individual pixels as fundamental analysis units, while object-based methods operate on groups of pixels or image objects.

5.2 Image Differencing

Image differencing is one of the straightforward approaches to change detection, and is among the earliest techniques catalogued in Singh's foundational taxonomy of change-detection methods [5]. In this method, corresponding pixels or image values from two dates are compared to produce a difference image. Large differences can indicate possible changes, while small differences may correspond to unchanged regions or minor variations. The advantage is simplicity and interpretability, although performance can be affected by noise, illumination differences and registration errors [2].

5.3 Threshold-Based Change Detection

After generating a difference image, a threshold can be used to separate significant differences from insignificant ones. Conceptually, a difference below the threshold is treated as unchanged, while a difference at or above the threshold is treated as changed, producing a binary change map. This project's thresholding stage draws on the well-established automatic threshold-selection method introduced by Otsu, which selects a threshold by minimizing intra-class variance in a grayscale histogram [6] — a technique originally developed for general image segmentation but widely reused in change-detection pipelines for exactly this step.

5.4 Modern Machine Learning and Deep Learning

Recent research increasingly applies machine learning and deep learning to remote-sensing change detection. These methods can learn complex image representations, especially for difficult scenes [3], [4]. However, they can require training datasets, model development and greater computational resources. The proposed project therefore focuses on classical image processing as its main detection method. A basic machine-learning algorithm may be considered later only if it provides a meaningful improvement.

6. Research Gap

The literature demonstrates a progression from traditional image-comparison techniques toward machine-learning and deep-learning approaches [1], [2], [3], [4]. Traditional approaches are relatively simple and interpretable but may be sensitive to noise, image quality, registration errors and complex scenes. Advanced learning-based methods can address some of these challenges but introduce additional computational and implementation complexity. Therefore, this project focuses on a middle ground: a lightweight, modular and explainable change-detection system that uses classical image processing to automatically identify and quantify significant changes between two temporal satellite images. The contribution is not the invention of a new change-detection theory. Instead, it is the design and implementation of a clearly structured system that combines established image-processing operations into an accessible final-year project with measurable outputs.

7. Proposed System

The proposed system accepts two satellite images of the same geographical area captured at different times and processes them through a sequence of modules: **Image Input** → **Preprocessing** → **Image Alignment** → **Difference Calculation** → **Thresholding** → **Morphological Processing** → **Changed Region Extraction** → **Change Percentage** → **Severity Indication** → **Visualization/Report**. The system is designed to be modular so that individual processing stages can be tested independently. A full component-level breakdown is provided in the companion Architecture Paper.

8. Methodology

8.1 Input Images. The system requires two satellite images representing the same geographical area but captured at different times. The images should preferably have compatible spatial coverage and resolution.

8.2 Image Preprocessing. The images are prepared for analysis through operations such as resizing to a common dimension, converting to an appropriate representation, reducing unwanted noise and normalizing image information when required.

8.3 Image Alignment. The corresponding geographical regions in the two images should be aligned as accurately as possible. If images are not aligned, stationary objects may appear at different pixel positions and be incorrectly detected as changes.

8.4 Difference Image. After preprocessing and alignment, corresponding image information is compared using image differencing, the classical technique described in Section 5.2 [5]. A conceptual operation is $D(x,y) = |I_2(x,y) - I_1(x,y)|$, where I_1 represents the earlier image, I_2 represents the later image and D represents the difference magnitude.

8.5 Thresholding. A threshold separates significant differences from smaller variations, following the automatic thresholding approach described in Section 5.3 [6]. Difference values below the threshold can be treated as unchanged and values at or above the threshold as possible changes, producing a binary change mask.

8.6 Morphological Processing. Thresholding may leave small unwanted regions or gaps. Morphological operations can refine the binary change mask. Opening can help remove small isolated noise, while closing can help fill small gaps and connect nearby regions.

8.7 Changed Region Extraction. After thresholding and morphological refinement, the system identifies connected or significant changed regions and creates a highlighted output image.

9. Proposed Features

- **9.1 Before-and-After Comparison:** View both satellite images together.
- **9.2 Changed-Region Highlighting:** Highlight detected regions directly on the image.
- **9.3 Difference Map:** Provide a visual representation of detected differences.
- **9.4 Change Percentage:** Estimate the proportion of the analysed area identified as changed.
- **9.5 Severity Indication:** Categorize overall detected change into levels such as Low, Moderate and High using a clearly defined project rule.
- **9.6 Analysis Summary:** Present input images, change map, highlighted regions, change percentage, severity and processing information.

10. Technology Stack

Layer	Tool
Programming	Python

Layer	Tool
Image Processing	OpenCV
Numerical Processing	NumPy
Image Handling	Pillow
Visualization	Matplotlib
Frontend/UI	Streamlit
Backend	Flask
Development Environment	Visual Studio Code

11. System Workflow

1. Upload two satellite images.
2. Validate the input images.
3. Preprocess and prepare the images.
4. Align corresponding geographical regions.
5. Calculate image differences.
6. Apply thresholding to isolate significant differences.
7. Apply morphological processing to refine the change mask.
8. Extract changed regions.
9. Calculate change percentage.
10. Determine a simple severity indication.
11. Display the before image, after image, difference map, highlighted regions and summary.

12. Evaluation

A change-detection system should not be evaluated only by visual inspection. The proposed system will therefore be tested using prepared image pairs for which expected changed regions are known. The detected change map can be compared with a reference change map. Accuracy measures the overall proportion of correctly classified pixels or regions. Precision measures how many areas classified as changed are actually changed. Recall measures how much of the actual changed area was detected. F1-score combines precision and recall. **Actual metric values will only be reported after implementation and testing** — this paper reports no fabricated results.

13. Expected Results

The proposed system is expected to produce a clear comparison between two input satellite images, a difference map, a binary or refined change mask, highlighted changed regions, a calculated percentage of detected change, a simple severity indication and quantitative evaluation using appropriate reference data. The expected result is an automated image-based change-detection aid that provides both visual and numerical information while keeping the processing steps understandable.

14. Limitations

The system is not expected to identify every detected difference as a genuine geographical change. Possible sources of false detection include image misalignment, clouds, shadows, seasonal vegetation changes, differences in illumination, atmospheric effects, image noise and different image resolutions — challenges specifically noted as persistent, unresolved issues in recent comprehensive reviews of the field [3]. Therefore, the system should be described as an image-based change-detection aid rather than a system that guarantees every detected difference represents a real-world geographical change.

15. Ethical Considerations

The system should use legally obtained imagery and clearly identify dataset sources where required. Automated results should not be presented as absolute truth, and system limitations should be communicated clearly. Unsupported conclusions should not be made solely from detected visual differences.

16. Discussion

The proposed system combines established image-processing concepts into a single workflow for temporal satellite-image comparison. Its main advantage is simplicity and interpretability: preprocessing prepares the images, alignment improves correspondence, differencing identifies variations [5], thresholding separates significant differences [6], morphological processing cleans the detection mask, and subsequent calculations quantify the result. Traditional remote-sensing research demonstrates the use of pixel-based and image-comparison methods [1], [2], [5], while modern research increasingly uses machine-learning and deep-learning approaches [3], [4]. For a final-year implementation, classical image processing provides an opportunity to study the fundamentals of change detection without making the project dependent on a complex trained model. The project can also serve as a foundation for future comparison with machine-learning methods.

17. Future Work

Future versions may include support for multispectral satellite imagery, improved registration, automatic threshold selection, enhanced cloud and noise handling, object-level change analysis, additional satellite datasets, comparison with a basic machine-learning algorithm [4], semantic change classification, larger benchmark datasets and improved automated reporting. A basic machine-learning algorithm may be investigated as an optional enhancement rather than a mandatory component of the current system.

18. Conclusion

This research proposes a Python-based satellite image change-detection system for identifying significant land-surface changes between two images of the same geographical area captured at different times. The proposed system uses classical image-processing techniques including preprocessing, image alignment, image differencing [5], thresholding [6] and morphological processing. Detected regions are highlighted and quantified using change percentage and a simple severity indication. The project is intentionally designed as a lightweight and explainable system using Python, OpenCV, NumPy, Pillow, Matplotlib, Streamlit and Flask. Instead of relying on deep-learning models, it focuses on understanding and implementing fundamental image-processing operations involved in temporal change detection. The system will be validated using known test cases and appropriate evaluation metrics including accuracy, precision, recall and F1-score. Limitations caused by image quality, registration, illumination, clouds, shadows and seasonal variations will also be documented.

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All 6 references above were independently verified against publisher records (ScienceDirect/Elsevier, MDPI, Springer, IEEE Xplore) before inclusion. The original draft’s 4 references were confirmed exactly accurate; references [5] and [6] were added to directly ground the paper’s two core classical techniques — image differencing and thresholding — in their foundational literature, since the original draft correctly flagged these as still needed.