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Robust Monitoring of Environmental Changes through Unsupervised Change Detection in Satellite Images

by

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CERTIFICATE OF APPROVAL

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Abstract

Environmental change monitoring is essential for understanding land-cover dynamics and supporting sustainable environmental management. Remote sensing provides an effective means of observing such changes using multi-temporal optical satellite imagery; however, reliable change detection remains challenging due to noise, nonlinear spectral variations, mixed pixels, and the limited availability of labelled reference data. This thesis proposes a block-based unsupervised change detection framework that integrates Kernel Principal Component Analysis (KPCA) with Fuzzy C-Means (FCM) clustering to improve the robustness and consistency of binary change detection. To evaluate the contribution of nonlinear feature extraction and clustering strategies, four framework variants are analysed: PCA with K-Means, PCA with FCM, KPCA with K-Means, and KPCA with FCM. The methodology begins with a difference-based change representation derived from co-registered bi-temporal images, followed by block-based spatial feature extraction to incorporate local context and reduce noise. Dimensionality reduction is performed using PCA and KPCA, where KPCA is implemented using a Nyström approximation to reduce computational cost, and unsupervised clustering is then applied to generate binary change maps. Experimental evaluation on a publicly available benchmark dataset using qualitative visual analysis and quantitative metrics demonstrates that PCA-based methods show limited performance in complex environments, while fuzzy clustering improves stability. The results confirm that the proposed KPCA–FCM framework provides the most consistent and reliable performance, offering an effective and practical solution for unsupervised environmental change detection using optical satellite imagery.

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Abbreviations

CD	Change Detection
FCM	Fuzzy C-Means
GEE	Google Earth Engine
K-Means	K-Means Clustering
KPCA	Kernel Principal Component Analysis
LULC	Land Use and Land Cover
MSI	Multispectral Image
NDVI	Normalized Difference Vegetation Index
PCA	Principal Component Analysis
RBF	Radial Basis Function
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SDG	Sustainable Development Goals
VHR	Very High Resolution
WHO	World Health Organization

Symbols

b	Number of spectral bands
c	Number of clusters
$\mathbf{C}$	Covariance matrix
$C(i, j)$	Change label at pixel location (i, j)
d	Block-based feature dimensionality ($d = h^2 \times b$)
h	Block (neighborhood) size
J_{FCM}	Objective function of Fuzzy C-Means
J_{KM}	Objective function of K-Means
k	Number of retained principal components
$k(\cdot, \cdot)$	Kernel function
$\mathbf{K}$	Kernel matrix
λ_i	i-th eigenvalue
m	Fuzzifier parameter in FCM
m, n	Spatial dimensions of the image
M	Number of Nyström landmark samples
$\boldsymbol{\mu}$	Mean vector
$\boldsymbol{\mu}_c$	Centroid of cluster c (K-Means)
n	Total number of pixels
N	Total number of feature samples ($N = m \times n$)
p	Number of spectral bands
r_{ic}	Hard assignment of pixel i to cluster c
σ	Kernel bandwidth parameter
Σ	Covariance matrix in PCA

u_{ic}	Membership degree of pixel i in cluster c (FCM)
$\mathbf{v}_i$	i-th eigenvector
$\mathbf{X}$	Feature matrix
$\mathbf{X}_1$	Pre-change image feature matrix (time T_1)
$\mathbf{X}_2$	Post-change image feature matrix (time T_2)
$\mathbf{y}_i$	Feature vector of the i-th pixel
$\mathbf{Y}_{KPCA}$	KPCA-transformed feature matrix
$\mathbf{Y}_{PCA}$	PCA-transformed feature matrix
$\phi(\cdot)$	Nonlinear feature mapping

Chapter 1

Introduction

1.1 Overview of Environmental Changes

Environmental change refers to fluctuations in the Earth's surface and natural systems caused by both natural processes and human activities. These changes have intensified over the past decades due to growing urbanization, deforestation, industrial expansion, and intensive agricultural activities. Such processes alter land-cover patterns and disrupt natural ecosystems at local, regional, and global scales. These changes lead to biodiversity loss, environmental degradation, and increasing climatic variability, which directly impact environmental sustainability and socio-economic resilience [4, 11, 13]. Figure 1.1 presents the main anthropogenic forces behind significant shifts in land cover and ecosystem deterioration, highlighting the need for satellite-based monitoring systems.

Most environmental changes occur gradually but often span vast geographical areas. This makes them difficult to detect using field-based monitoring, particularly in remote or inaccessible regions. Consequently, continuous environmental monitoring has become essential for understanding change patterns, identifying areas at risk, and supporting timely decision-making for mitigation and adaptation [12]. Traditional surveillance methods are often costly, time-consuming, and spatially limited, highlighting the need for reliable large-scale monitoring approaches.

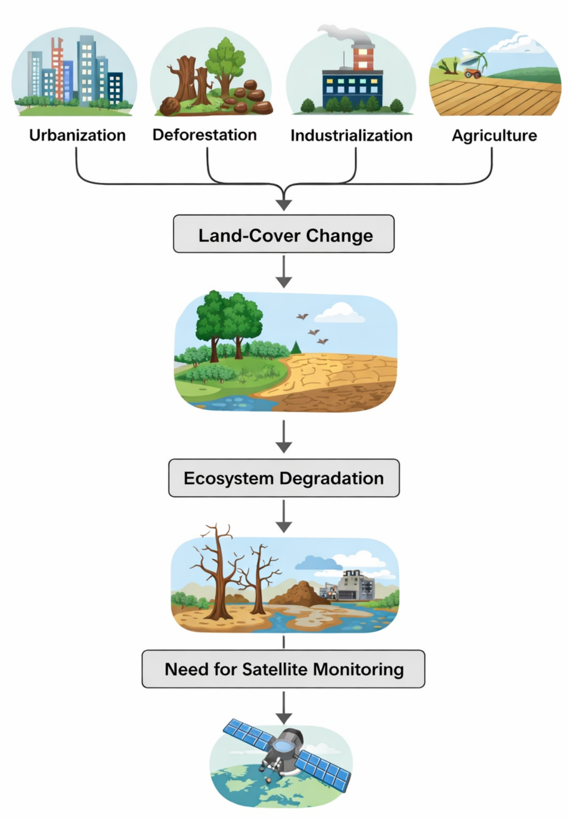

FIGURE 1.1: Human activities driving environmental change and the need for satellite-based monitoring

Remote sensing has emerged as an effective solution to overcome these limitations. Satellite-based Earth observation provides repetitive and consistent records of the same locations over time, enabling the analysis of land-cover dynamics, environmental change assessment, and long-term monitoring at broader scales. As a result, satellite data form the foundation of automated and unsupervised change detection frameworks used in modern environmental monitoring. Such frameworks also support sustainability assessment by providing repeatable indicators aligned with Sustainable Development Goals (SDGs) [14].

1.2 Environmental Hazards and Global Impacts

Global warming and increasing human pressure on the environment have led to a rise in environmental hazards worldwide. Variations in rainfall, temperature, and hydrological cycles are associated with an increased frequency of floods, droughts, wildfires, and related risks. These hazards cause not only ecological damage but also significant socio-economic impacts, particularly in vulnerable regions. Therefore, large-scale hazard monitoring is essential for understanding environmental threats and supporting effective management strategies. Figure 1.2 summarizes the relationship between climate change, major environmental hazards, and their impacts on human, economic, and ecological systems.

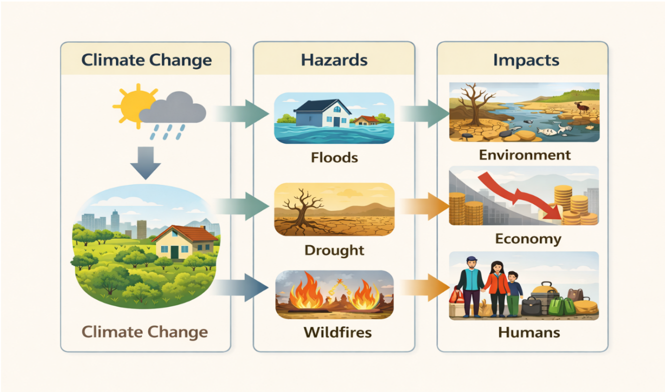

FIGURE 1.2: Impacts of environmental hazards

1.2.1 Climate Change and Hazard Intensification

Climate change has intensified environmental hazards such as floods, prolonged droughts, forest fires, and glacier melting [8, 9]. Rising global temperatures and disrupted rainfall patterns introduce uncertainty in water availability and ecosystem stability. Extreme weather events are becoming more frequent, emphasizing the importance of real-time monitoring systems. Effective monitoring supports hazard assessment, early warning, preparedness, and adaptation planning, helping communities build resilience to climate-related threats [14].

1.2.2 Statistics of Environmental Losses

Global health and vulnerability statistics highlight the severity of climate change impacts. According to the World Health Organization (WHO), a large portion of the global population resides in climate-risk-prone areas. Climate change is projected to increase mortality rates between 2030 and 2050 due to malnutrition, malaria, diarrheal diseases, and heat stress [21]. These statistics demonstrate that environmental risks pose significant threats to human health and safety.

1.2.3 Human and Ecological Consequences

Environmental degradation affects both ecological and human systems. Deforestation reduces vegetation cover and land stability, leading to soil erosion, altered hydrology, and increased flood risk [11]. Unplanned urban growth increases impervious surfaces, reducing groundwater infiltration and increasing surface runoff, which heightens flood and heatwave risks.

Ecologically, habitat fragmentation and deforestation reduce biodiversity and ecosystem resilience. These processes disrupt ecosystem services such as carbon storage, soil conservation, and water regulation, leading to long-term environmental imbalance [13]. Consequently, timely monitoring and analysis of land-cover change are essential for sustainable environmental planning and development.

1.3 Remote Sensing for Environmental Change Detection

Remote sensing plays a crucial role in environmental monitoring by providing consistent and repeatable observations of the Earth's surface. The analysis of multi-temporal satellite imagery enables the detection and quantification of changes in land cover, vegetation, water bodies, and built-up areas[23]. Due to its large spatial coverage and regular revisit cycles, satellite data have become a reliable source for automated and unsupervised change detection frameworks [2, 3].

1.3.1 Advantages of Satellite-Based Monitoring

Satellite remote sensing offers comprehensive spatial coverage and temporal consistency that are difficult to achieve through field-based surveys. Multi-temporal observations facilitate the detection of seasonal variations, gradual changes, and abrupt disturbances. Advances in Earth observation technology have improved spectral, spatial, and temporal resolution, while standardized datasets such as Harmonized Landsat and Sentinel-2 surface reflectance products enable multi-sensor analysis [1].

1.3.2 Commonly Used Satellite Missions

The Landsat mission provides a long-term, consistent archive useful for monitoring historical land-cover changes such as deforestation and land-use transitions [5]. Sentinel-2 offers higher spatial resolution and shorter revisit times, making it suitable for detailed and frequent environmental monitoring [2]. The combined use of Landsat and Sentinel-2 supports both long-term trend analysis and high-resolution mapping [6].

1.3.3 Applications in Floods, Deforestation and Urban Expansion

Satellite imagery is widely used for flood mapping, deforestation monitoring, and urban expansion analysis. Flood detection assists emergency response by identifying inundated areas in near real time [7]. Long-term satellite archives support deforestation assessment and disturbance monitoring [3, 11]. Urban expansion monitoring enables mapping of built-up growth and land conversion patterns, supporting urban planning and management [10].

1.4 Change Detection Concepts and Techniques

Change detection identifies differences in land surface conditions across time, supporting land-cover analysis, hazard assessment, and environmental management

[15]. Accurate change detection remains challenging in heterogeneous environments and in the absence of ground truth data [17, 18].

1.4.1 Supervised vs. Unsupervised Approaches

The change detection methods are generally divided into supervised and unsupervised approaches depending on whether labelled data is available or not. The Supervised techniques require training samples and reference maps that are already labelled. These methods can achieve high accuracy because the model learns from known examples. However, preparing reliable ground truth data is not easy. It requires significant time, effort, and cost, especially when working with large satellite images or wide geographical areas.

On the other hand the unsupervised methods do not rely on labelled data. They analyse spectral and statistical differences between multi-temporal images to separate changed and unchanged areas. Because unsupervised approaches are more practical for large-scale environmental monitoring where labelled samples are usually not available [27, 28]. In many studies the binary change detection using unsupervised clustering has shown dependable results, particularly in urban areas when using optical remote sensing data.

1.4.2 Satellite-Based Change Detection Workflow

Figure 1.3 illustrates the general workflow of satellite-based change detection, including data acquisition, feature extraction, clustering, and binary change map generation. Clustering methods such as K-Means and Fuzzy C-Means are widely used due to their efficiency in unsupervised settings [2, 4, 5].

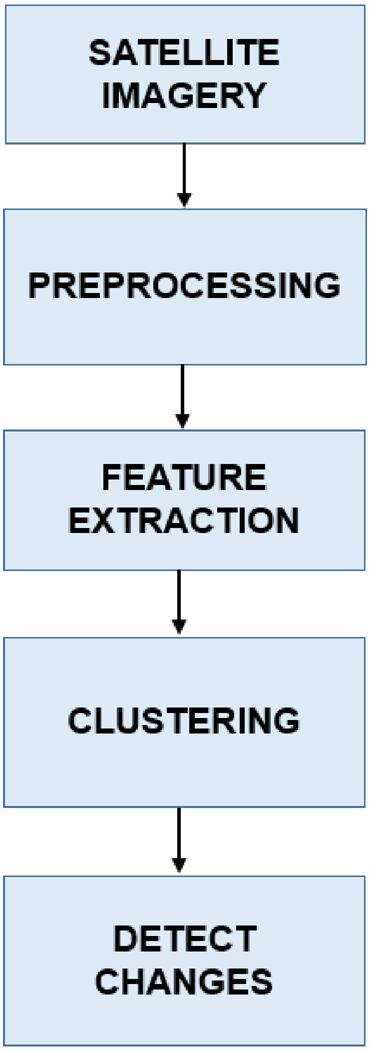

FIGURE 1.3: Satellite-based change detection workflow

1.5 Clustering Algorithms in Unsupervised Change Detection

The clustering plays a central role in unsupervised change detection as it allows multi-temporal satellite image pixels to be grouped into changed and unchanged classes without the use of labelled training samples.This is especially important and is particularly valuable in remote sensing applications where the availability of reliable ground truth data is often limited, expensive to acquire, or completely absent across large spatial extents. In multispectral satellite imagery effective clustering methods need to handle challenges such as spectral variability, noise, mixed pixels and the gradual land cover transitions that commonly occur in real world environments. Among the various unsupervised clustering approaches KMeans and Fuzzy C-Means have been widely used due to their simplicity, computational efficiency and adaptability to high-dimensional remote sensing data [1–3, 5]. These techniques have been extensively employed in classical unsupervised change detection studies and therefore are selected in this research as representative clustering strategies for comparative analysis.

1.5.1 K-Means Clustering

K-Means is hard dissimilarity algorithm where every pixel belongs to just a single cluster. It is implemented by reducing within-cluster variance by means of centroid updates. The algorithm is computationally easy and rapid and thus fits well with large satellite data. Nevertheless, K-Means presupposes that clusters are well-defined and makes hard assignments, this is why it cannot be applied to transitional areas and mixed pixels. It is also prone to centroid starting, which yields changeable clustering conclusions in intricate settings [5].

1.5.2 Fuzzy C-Means Clustering

Fuzzy C-Means (FCM) is a soft clustering algorithm in which each pixel can belong to more than one cluster with a membership value ranging between 0 and 1. This characteristic allows FCM to better represent mixed pixels and gradual land-cover transitions compared to hard clustering methods. Since environmental changes in satellite imagery often occur smoothly rather than abruptly, FCM is well suited for analysing heterogeneous landscapes and uncertainty-prone boundary regions [20].

Unlike KMeans that forces each pixel into a single cluster. FCM provides partial membership to multiple clusters by allowing it to model uncertainty in boundary regions more effectively. This makes FCM particularly useful in complex environments such as urban rural interfaces, forest edges and agricultural regions. where land-cover classes overlap and change gradually.

Despite these advantages the Fuzzy C-Means has several limitations. The algorithm is sensitive to noise and can be computationally expensive due to repeated updates of membership values and cluster centers. Its performance also depends on proper initialization and parameter selection particularly the choice of the number of clusters which can significantly affect convergence and stability in unsupervised change detection applications[20].

1.5.3 Limitations of Conventional Clustering Methods

Traditional clustering methods often misclassify boundary regions and are sensitive to noise and illumination variations. These limitations highlight the importance of robust feature representation prior to clustering.

1.6 Motivation for Kernel-Based Unsupervised Change Detection Frameworks

The reliable change detection depends not only on the clustering method but also on how well the image features represent actual changes on the ground.The PCA is commonly used for feature extraction in remote sensing because it is simple and helps reduce noise by removing repeated spectral information [19]. PCA also reduces data dimensionality that makes the clustering faster and easier.The recent studies have shown that classical PCA is highly sensitive to noise, sparse disturbances and mixed pixels commonly present in optical satellite imagery.Although robust PCA variants incorporating sparse deviation modelling and uncertainty handling have been proposed to improve stability. So the such methods remain limited to linear subspace representations and may still fail to capture complex nonlinear spectral behaviour.

In optical satellite imagery the environmental changes are often influenced by mixed land cover, gradual transitions, seasonal effects and atmospheric conditions. These factors introduce nonlinear behaviour in spectral values that cannot always be represented properly using linear methods. As a result some important change information may be lost or weakened when PCA is applied leading to less effective clustering and inaccurate change maps.

1.6.1 Limitations of Linear Feature Representation

The environmental changes often behave in a nonlinear way due to land cover diversity, surface atmosphere interactions, seasonal variation and sensor differences.The PCA mainly captures directions of maximum variance that may be dominated by illumination variation, noise or outliers rather than actual land cover change.This is the reason why the limitation reduces the robustness of heterogeneous environments and has motivated the development of robust PCA that explicitly represents sparse deviations and uncertainty in image data [19].This can reduce the separation between changed and unchanged areas in the feature space and make clustering results less reliable [15, 17].

In addition to that the PCA assumes that major changes can be described using linear combinations of spectral bands. In practice this assumption does not always hold particularly in complex environments such as urban areas, forests or flood affected regions. As a result the PCA based change detection methods may fail to detect subtle or gradual changes and may produce unstable or noisy results.

1.6.2 Role of Kernel Principal Component Analysis

Kernel Principal Component Analysis extends conventional PCA by enabling nonlinear feature extraction through the use of kernel functions. Instead of operating directly in the original data space. The KPCA maps the data into a higher-dimensional feature space where nonlinear relationships among spectral features can be more effectively identified [22]. This nonlinear transformation improves the separation between changed and unchanged regions particularly in complex environmental settings. As a result the KPCA provides more meaningful feature representations for clustering-based change detection and helps improve the overall robustness and stability of unsupervised change detection methods.

1.6.3 Framework-Based Evaluation Strategy

A framework based evaluation strategy is used to compare PCA and KPCA fairly. PCA based frameworks are treated as baseline methods. While KPCA replaces PCA under the same preprocessing and clustering conditions. This approach ensures that any differences in performance are due to the feature extraction method rather than other factors.

The main objective of this evaluation strategy is to examine how nonlinear feature extraction affects the robustness, stability and reliability of unsupervised change detection. By comparing linear and nonlinear feature extraction within the same framework.This study aims to identify a more suitable approach for environmental change detection using multi-temporal optical satellite imagery.

1.7 Problem Statement

Despite the wide availability of multi-temporal satellite imagery, achieving reliable unsupervised change detection remains challenging. Uncertainty and instability in clustering-based change detection methods are commonly caused by sensor noise, atmospheric effects, mixed pixels, and nonlinear spectral behaviour [15, 18]. Traditional linear feature extraction methods and classical clustering techniques often produce inconsistent change maps, distorted boundaries, and reduced robustness under complex environmental conditions. These limitations restrict their practical applicability, highlighting the need for a systematic evaluation framework to identify robust and stable unsupervised change detection configurations for reliable environmental monitoring.

1.8 Research Objectives

1.8.1 General Objective

The primary goal of this study is to compare and identify a robust unsupervised change detection framework for environmental monitoring using multi-temporal optical satellite imagery. Specifically, this study contrasts linear feature extraction using Principal Component Analysis (PCA) with nonlinear feature extraction using Kernel Principal Component Analysis (KPCA) in combination with clustering algorithms in order to determine which framework yields the most stable, consistent, and reliable change detection results under real-world environmental conditions.

1.8.2 Specific Objectives

The specific objectives of this study are as follows:

i. To develop an unsupervised change detection approach for robust environmental monitoring using multi-temporal optical satellite imagery.

ii. To implement and compare feature extraction methods (PCA and KPCA) and clustering techniques (K-Means and FCM) within the proposed approach to determine the most effective combination for change detection.

iii. To evaluate the robustness and performance of the proposed approach across diverse land-cover categories.

1.9 Research Questions

This study examines the impact of different feature extraction and clustering techniques on the robustness and reliability of unsupervised environmental change detection using multi-temporal optical satellite imagery. By comparing linear (PCA-based) and nonlinear (KPCA-based) feature representations in combination with different clustering algorithms, the study aims to determine which framework produces more stable and consistent change detection results under real-world environmental conditions.

The research questions of this study are as follows:

i. To what extent does Kernel Principal Component Analysis (KPCA) improve the robustness of unsupervised change detection compared with linear PCA-based feature extraction?

ii. How does nonlinear feature representation affect the stability and consistency of unsupervised change detection results in noisy and heterogeneous land-cover environments?

iii. How effectively do different combinations of feature extraction (PCA/KPCA) and clustering methods (K-Means/FCM) contribute to reliable and interpretable change detection performance?

1.10 Significance and Limitations of the Study

1.10.1 Contributions to Knowledge

This study contributes to the field of remote sensing-based environmental monitoring by providing a structured and systematic evaluation of unsupervised change detection frameworks. It examines the influence of feature representation on detection robustness by comparing linear feature extraction using Principal Component Analysis (PCA) with nonlinear feature extraction using Kernel Principal Component Analysis (KPCA). By integrating these feature extraction methods with K-Means and Fuzzy C-Means (FCM) clustering algorithms, the study highlights the role of nonlinear modelling in improving the stability and consistency of change detection outputs. The controlled comparative framework adopted in this research enhances methodological understanding and supports reproducible evaluation in unsupervised change detection studies.

1.10.2 Practical Implications

From a practical perspective, this research supports more reliable environmental and hazard monitoring by improving confidence in satellite-derived change maps. Accurate detection of land-cover changes, such as deforestation, flood impacts, and urban expansion, is essential for informed decision-making in disaster risk reduction, environmental management, and sustainable land-use planning. The findings of this study can assist researchers and decision-makers by providing a stable and consistent unsupervised change detection framework, particularly in scenarios where ground truth data are limited or unavailable.

1.10.3 Target Audience

The outcomes of this research are relevant to researchers, students, and practitioners working in remote sensing, environmental monitoring, and geospatial data analysis. In addition, government agencies and environmental organisations involved in land management, hazard assessment, and climate-related monitoring may benefit from the findings, as these applications often require large-scale and repeated change detection analyses.

1.10.4 Scope of the Study

This study focuses on unsupervised environmental change detection using multi-temporal optical satellite imagery. Landsat and Sentinel-2 data are considered due to their widespread use, global coverage, and free accessibility. The study evaluates feature extraction techniques, including PCA and KPCA, in combination with K-Means and Fuzzy C-Means clustering algorithms to generate binary change maps that distinguish between changed and unchanged regions. Emphasis is placed on assessing robustness, stability, and consistency of detected changes under realistic environmental conditions.

1.10.5 Limitations

Despite its contributions, this study has several limitations. First, it is restricted to optical multispectral satellite imagery, which is susceptible to cloud cover, atmospheric effects, shadows, and illumination variations. Second, KPCA introduces higher computational complexity compared to PCA, as it requires the construction and eigen-decomposition of an $N \times N$ kernel matrix, where N denotes the number of samples, which can be computationally demanding for large datasets. Third, the unsupervised nature of the framework means that some detected changes may correspond to seasonal or phenological variations rather than permanent land-cover changes. Finally, quantitative evaluation depends on the availability of reference data or visual interpretation, which may introduce uncertainty in accuracy assessment.

1.11 Thesis Organization

This thesis is organised into five chapters. Chapter One introduces the background and motivation of the study, highlighting the importance of environmental monitoring, the role of remote sensing, and the need for robust unsupervised change detection techniques. It also presents the problem statement, research objectives, research questions, significance, scope, and limitations of the study. Chapter Two reviews related literature on environmental change detection, remote sensing applications, feature extraction techniques, and clustering-based unsupervised methods, and identifies existing research gaps. Chapter Three describes the proposed methodology, including the selected satellite datasets, preprocessing steps, and the implementation of PCA- and KPCA-based feature extraction combined with K-Means and Fuzzy C-Means clustering. Chapter Four presents the experimental results and analysis, including qualitative and quantitative evaluation of the proposed approach in terms of robustness, stability, and accuracy. Finally, Chapter Five summarises the main findings, discusses the contributions of the study, and provides recommendations for future research.

1.12 Conclusion

This chapter emphasised the importance of environmental monitoring and demonstrated the effectiveness of satellite remote sensing for detecting land-cover changes over time. It discussed key environmental challenges and the increasing need for reliable and stable monitoring approaches. The chapter also reviewed fundamental concepts of supervised and unsupervised change detection, along with commonly used clustering techniques. The limitations of linear feature representations and conventional clustering methods motivated the exploration of kernel-based feature extraction, particularly Kernel Principal Component Analysis (KPCA). Finally, the research problem, objectives, research questions, and scope were presented to provide a clear foundation for the subsequent chapters of this thesis.

Chapter 2

Literature Review

2.1 Introduction and Background

Remote sensing change detection is used to study how the Earth's surface changes with time by comparing satellite images of different dates. It is mostly used for environmental monitoring, land-use and land-cover mapping, checking urban growth, and also for disaster impact studies. Since multi-temporal satellite images are now available in huge quantity, it has become important to use methods that can automatically detect changes from large datasets in a reliable way [23].

In earlier work, change detection techniques were mainly grouped into pixel-based, feature-based and object based methods. They were also divided into supervised and unsupervised approaches depending on whether labeled data is available or not [23].These studies not only explained that change detection is not just finding differences between two images. but it also tells us that there is a need to reduce unwanted effects like illumination variation, atmospheric changes, and sensor noise so that the detected changes are actually real. Because of this, feature extraction is considered an important step to improve the final results.

Si Salah et al. [24] later explained a common change detection workflow that includes image acquisition, preprocessing, feature extraction, change analysis and interpretation. In most studies optical satellite imagery is preferred because it provides good spectral information and it is available for many years, which is helpful for long-term monitoring [25]. But optical change detection still has some issues like radiometric differences between dates, seasonal changes and mixed pixels. Because of such problems unsupervised change detection methods are often preferred since they do not need labeled training samples and can be used for large areas more easily [17]. Therefore this research focuses on unsupervised change detection in optical satellite imagery by using feature extraction and clustering methods to generate change maps that are accurate and easy to understand.

2.2 Existing Contributions for Addressing Environmental Changes

Environmental changes like land-use change, deforestation, urban growth and ecosystem damage have been studied a lot using multitemporal optical satellite images. Optical remote sensing is useful for this work because it provides good spectral information, long-term data records and it is easily available for many areas.This helps researchers to monitor changes that happen slowly over time as well as sudden changes.

Many researchers have used medium-resolution optical satellite data for land-use and land-cover (LULC) mapping. In these studies automated methods are used to reduce manual work and also support monitoring for long time periods [15]. For urban environments high resolution optical imagery is important since it can capture fine scale changes. Because urban areas are usually messy and mixed. Thats why some researchers used multistage methods to better handle this and detect even small or slow changes more accurately [16].

Overall existing studies show that optical change detection plays an important role in environmental monitoring. However the issues such as radiometric differences, seasonal effects and mixed pixels can still reduce the accuracy of results across different landscapes. Because of this there is still a need for robust unsupervised change detection methods that can handle noise and complex spectral variations while remaining practical for large scale monitoring.

2.3 Existing Algorithms, Methods and Techniques

Satellite based environmental change detection has improved a lot over the years because of better remote sensing sensors and the development of unsupervised learning methods. Even though optical satellite images are widely used, they still face many problems such as radiometric differences, noise, mixed pixels and nonlinear spectral variations. Such problems can lower the accuracy and reliability of change detection results. Due to that many unsupervised change detection methods have been developed so that the changed and unchanged areas can be separated without the need of labelled training data.

In general the unsupervised change detection approaches can be grouped into four main categories: pixel based methods, transform based feature extraction techniques, clustering based approaches and hybrid or multistage frameworks. The next subsections explain these categories and discuss their main strengths and limitations.

2.3.1 Pixel-Based Change Detection Techniques

One of the oldest and least complicated approaches to detecting changes in multi-temporal satellite images is pixel-based change detection techniques. In this method we basically compare the pixel values from two dates and assume that if the difference is big, then some real change has happened on the ground. The most common pixel-based techniques are image differencing and image ratioing [23].

In image differencing we subtract the pixel values of one image from the other and the pixels with high difference are marked as changed. In image ratioing we divide the pixel values that can sometimes reduce the effect of lighting differences and highlight relative changes. These methods are easy to implement and also take less processing time, which is why they are still used as a baseline in many studies. However, the main issue is that pixel-based methods are very sensitive to noise, atmospheric conditions, radiometric differences and seasonal changes. Due to it they can wrongly detect changes in areas where actually nothing has changed, especially in complex or mixed land-cover regions. Also the results depend a lot on choosing the right threshold, so proper preprocessing is still important [23].

Overall, pixel-based techniques are good for basic comparison but for large-scale and reliable optical change detection. They are not always strong enough.

2.3.2 Transform-Based Feature Extraction Techniques

Transform based methods are used to make the change detection easier by converting the original image data into a different and usually smaller feature space. This helps in reducing redundant information and noise while highlighting the main features related to change. These methods are rarely applied before clustering so that changed and unchanged areas can be separated more clearly.

2.3.2.1 Principal Component Analysis

PCA is a very common linear method used to reduce the number of bands in multispectral satellite images.It basically converts the original spectral bands (which are usually linked with each other) into a new set of independent components, known as principal components.These components are arranged in such a way that the first ones contain the maximum information (highest variance), while the later ones carry less useful detail.

Let the image data matrix be denoted as

$$X \in \mathbb{R}^{n \times p}, \tag{2.1}$$

where:

- n is the total number of pixels,
- p is the number of spectral bands (or input features).

The covariance matrix is computed as

$$\Sigma = \frac{1}{n-1} X^T X, \tag{2.2}$$

Here X is mean centered meaning that each spectral band has zero mean.By applying Eigen decomposition to the covariance matrix Σ, we obtain:

$$\Sigma v_i = \lambda_i v_i, \tag{2.3}$$

Here v_i is the eigenvectors (principal components) and λ_i are the corresponding eigenvalues representing the variance captured by each component.

In multi-temporal satellite imagery, these dominant components often highlight significant land-cover changes while suppressing noise and redundant information. Çelik demonstrated that integrating PCA with K-Means clustering improves the separation between changed and unchanged regions and enhances robustness against noise in optical imagery [26] Subsequent studies have confirmed that PCA-based unsupervised change detection methods provide stable and reliable performance for environmental monitoring tasks [27, 28].

2.3.2.2 Kernel Principal Component Analysis

Kernel Principal Component Analysis (KPCA) extends conventional PCA by enabling the extraction of nonlinear features from multi-temporal satellite imagery. While PCA relies on linear projections, KPCA is capable of modelling complex nonlinear spectral relationships that commonly arise due to mixed land-cover types, seasonal variations, and sensor-related effects.

Suppose the input feature vectors extracted from the difference image be written as:

$$x_i \in \mathbb{R}^p, \quad i = 1, 2, \ldots, n. \tag{2.4}$$

KPCA applies a nonlinear mapping

$$\Phi : \mathbb{R}^p \to \mathcal{F}, \tag{2.5}$$

That projects the data into a high dimensional feature space $\mathcal{F}$. Instead of explicitly computing $\Phi(\cdot)$, KPCA employs a kernel function $k(\cdot, \cdot)$ defined as

$$k(x_i, x_j) = \langle \Phi(x_i), \Phi(x_j) \rangle. \tag{2.6}$$

A commonly used kernel in remote sensing applications is the Gaussian radial basis function (RBF) kernel, expressed as

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2} \right), \tag{2.7}$$

Here σ controls the kernel bandwidth and determines the degree of nonlinearity captured during the transformation.

The kernel matrix is centred and Eigen decomposition is performed to obtain the principal components in the kernel-induced feature space. By retaining the components corresponding to the largest eigenvalues, KPCA produces a compact nonlinear representation that enhances the separability between changed and unchanged pixels.

Previous studies have shown that kernel-based feature extraction improves unsupervised change detection performance by increasing class separability, particularly in heterogeneous environments where linear methods are insufficient [17, 18]. Although KPCA is computationally more demanding than PCA and sensitive to kernel parameter selection, it provides a powerful alternative for modelling complex spectral variations in optical satellite imagery. For this reason, KPCA is incorporated into the proposed unsupervised change detection framework.

2.3.3 Clustering-Based Approaches

Clustering is one of the main steps in unsupervised change detection. It groups pixels into changed and unchanged areas based on how similar their features are. After extracting the features and reducing the dimensions. Clustering methods are applied to split the pixels into different groups without using any labelled training data.

2.3.3.1 K-Means Clustering

K-Means is one of the most commonly used clustering methods in unsupervised change detection because it is simple and fast and it divides the feature vectors into k separate clusters by minimizing the variation within each cluster.

The objective function of K-Means is defined as

$$J = \sum_{i=1}^{N} \sum_{k=1}^{K} r_{ik} \left\| x_i - \mu_k \right\|^2, \tag{2.8}$$

where

- x_i denotes the feature vector of the ith pixel.
- μ_k represents the centroid of the k-th cluster.
- $r_{ik} \in \{0, 1\}$ is the binary assignment variable indicating whether x_i belongs to cluster k.
- N is the total number of pixels.

K-Means works step by step by updating the cluster centroids and pixel assignments repeatedly until it converges. Even though it is fast and scalable it uses hard clustering and can be sensitive to the initial starting points. Because of this its performance may drop when the data contains mixed pixels noise or gradual land-cover transitions which are quite common in optical satellite imagery [28].

2.3.3.2 Fuzzy C-Means Clustering

Fuzzy C-Means (FCM) is an improved version of K-Means because it allows a pixel to belong to more than one cluster with different membership values. This also renders it more appropriate in dealing with uncertainty and smooth transitions of land-cover in detecting environmental changes.

The objective function of FCM is given by

$$J = \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^{m} \|x_i - c_k\|^2, \tag{2.9}$$

where

- $u_{ik} \in [0, 1]$ denotes the membership degree of pixel i to cluster k.
- m is the fuzzifier parameter that controls the degree of fuzziness (typically $m = 2$).
- c_k represents the centre of the k-th fuzzy cluster.
- C is the number of clusters.

Unlike K-Means, FCM uses soft memberships, meaning a pixel is not forced to belong to only one cluster but can partially belong to multiple clusters at the same time. This property is particularly useful in satellite images where mixed pixels are common and land-cover changes are not always clearly defined, such as at urban–rural boundaries or in heterogeneous landscapes [20]. Studies have also shown that using PCA with FCM can improve the results by reducing spectral confusion in multispectral images [27]. However FCM can still be affected by noise, the initial starting values and parameter selection that may cause instability and increase computation time.

2.3.3.3 Multi-Stage and Spatially Aware Clustering

To overcome the issues of single-stage clustering, many researchers have suggested using multi-stage and spatially aware clustering methods for unsupervised change detection. In multistage methods a preliminary change map is created followed by an improvement of the results in a second step by re-clustering, feature transformation or adaptive thresholding. This extra refinement helps in reducing wrong classification caused by noise, mixed pixels and spectral confusion.

Spatially aware clustering methods focus more on improving the overall structure of the change map by using neighborhood information. This helps in reducing the salt-and-pepper effect and produces smoother and more connected change regions. Kondmann et al. [32]] reported that adding spatial context can improve both robustness and visual consistency especially in heterogeneous and high-resolution optical images. Similarly, Han et al. [33] proposed an unsupervised graph-based method that uses structured optimization to improve change detection performance especially in complex scenes.

Even though these methods often give better results. However these methods usually increase the computational cost and also require extra parameter tuning. That makes them less appropriate for large-scale monitoring. Overall, there is still a need for an efficient hybrid framework which can provide better accuracy by remaining easy to understand and practical to run.

2.3.4 Block-Based Change Detection Approaches

Block-based change detection approaches were introduced to address the limitations of pixel-wise methods by incorporating local spatial information into the analysis. Instead of analysing each pixel independently, these approaches consider a group of neighbouring pixels within a fixed-size block. By doing so, both spectral and spatial characteristics of the image are taken into account, which generally leads to more reliable and visually consistent change detection results.

In optical satellite imagery, individual pixels are often affected by noise, illumination variations, sensor inconsistencies, and mixed land-cover types. Pixel-based methods that ignore neighbourhood information therefore tend to produce noisy change maps with isolated and scattered detections. Block-based approaches help reduce this problem by exploiting the similarity between neighbouring pixels, resulting in smoother and more meaningful change regions.

A typical block-based change detection process begins with the generation of a difference image from two temporally separated satellite images. This difference image is then divided into overlapping or non-overlapping blocks of a predefined size. Features are extracted from each block to represent local spectral and spatial variations, and these features are later used as input to dimensionality reduction or clustering algorithms to classify regions as changed or unchanged.

Several studies have shown that block-based representations improve change detection accuracy, particularly in heterogeneous regions such as urban areas, forest edges, and agricultural landscapes. By incorporating neighbourhood context, these methods are more effective in identifying gradual land-cover transitions and spatially coherent changes that are often missed by pixel-based techniques. In addition, block-based approaches have demonstrated improved robustness to local noise and radiometric variations in multi-temporal optical imagery [26, 32].

The selection of block size is an important factor in block-based change detection. Smaller blocks may fail to capture sufficient spatial context, while larger blocks may smooth out local details and reduce spatial accuracy. Therefore, the block size is usually chosen carefully to achieve a balance between noise reduction and detail preservation.

Block-based methods are often combined with feature extraction and clustering techniques to form hybrid unsupervised frameworks. Integrating block-based representations with dimensionality reduction methods such as PCA or kernel-based techniques has been shown to further improve the separation between changed and unchanged regions. This combination allows spatial structure and spectral variation to be modelled more effectively, making block-based approaches suitable for unsupervised environmental change detection using optical satellite imagery.

Overall, block-based change detection provides a practical compromise between simple pixel-based analysis and more complex object-based methods. Its ability to incorporate spatial context while remaining computationally manageable makes it a suitable choice for large-scale unsupervised change detection and provides clear motivation for adopting a block-based strategy in the proposed framework.

2.3.5 Hybrid Change Detection Approaches

The hybrid change detection systems consist of feature extraction, dimensionality reduction, and clustering in one workflow. Every step in turn enhances the final outcome. Following the transformation of the features, there is the use of clustering to finalize the decision leading to better and easier detecting of change, particularly in unsupervised monitoring of the environment.

2.3.5.1 PCA + K-Means Hybrid

Principal Component Analysis (PCA) used with K Means clustering is one of the first and most popular hybrid frameworks of unsupervised change detection. Celik [26] proposed this technique to address the drawbacks of the direct application of clustering algorithms to raw spectral bands, which can be highly correlated with each other and vulnerable to noise. Under this scheme, multi-temporal image properties are initially subjected to the PCA operation to downsize dimensionalities and eliminate redundant or noisy data, as well as to keep the dominant variance that changes with time. Subsequently, K-means clustering divides the transformed feature space into those that have changed as well as those that have not changed. The process can be summarized as:

$$X \xrightarrow{\text{PCA}} Y \xrightarrow{\text{K-Means}} C \tag{2.10}$$

where X represents the original multi-temporal image features.
Y denotes the PCA transformed components.
C corresponds to the final cluster labels.

Empirical results reported in the literature indicate that PCA enhances cluster separability by emphasizing dominant spectral variations related to land-cover change, thereby improving detection accuracy and reducing sensitivity to noise [26, 28]. However, the use of hard clustering in K-Means restricts its ability to model mixed pixels and gradual transitions, which are common in real-world environmental landscapes.

2.3.5.2 PCA + Fuzzy C-Means Hybrid

To overcome the issue of hard clustering, Kesikoğlu et al. [27] suggested a hybrid method that combines PCA with Fuzzy C-Means (FCM) for unsupervised change detection. Just like the PCA + K-Means approach. The PCA is used first to reduce the dimensionality and bring out the most important spectral features. After that FCM is applied to do soft clustering, where a pixel can partially belong to more than one cluster instead of being forced into only one class.

TThis hybrid framework can be expressed as:

$$X \xrightarrow{\text{PCA}} Y \xrightarrow{\text{FCM}} U \tag{2.11}$$

Here, U represents the fuzzy membership matrix, which shows how strongly each pixel belongs to each cluster.

The PCA + FCM hybrid framework is particularly effective in regions where changes occur gradually, such as urban–rural boundaries, wetlands, and agricultural landscapes. Because FCM supports partial membership and it can better model mixed pixels and reduce spectral confusion compared to K-Means [27]. Nevertheless, FCM remains sensitive to noise, initialization, and parameter settings, which may affect convergence behaviour and increase computational time.

The PCA + FCM hybrid approach works especially well in areas where land-cover changes happen gradually such as urban–rural boundaries, wetlands and agricultural regions. However FCM allows partial membership, it can handle mixed pixels and spectral confusion better than K-Means [27]. However, FCM can still be affected by noise and the initial parameter settings that may create issues with convergence and increase computational time.

Although Synthetic Aperture Radar (SAR) imagery is also widely used for change detection because it can capture images in all weather and both day and night, SAR data works differently from optical imagery. It is also heavily affected by speckle noise that normally requires extra preprocessing and specialized statistical modelling. For this reason this study focuses only on optical satellite imagery to maintain consistency and keep it directly aligned with the proposed feature extraction and clustering framework. The SAR-based change detection can be considered as a future extension of this work.

2.3.5.3 Kernel-Based Hybrid Change Detection Approaches

Apart from the linear hybrid methods, researchers have also looked into kernel-based hybrid approaches to improve change detection in complex and mixed environments. The main benefit of kernel methods is that they can capture nonlinear trends in data, but at the same time possess an unsupervised process model. Because of that, they can represent small and hidden spectral changes better than normal linear techniques.

Volpi et al. [17] showed that kernel-based unsupervised change detection improves separability by projecting multi-temporal remote sensing data into a higher-dimensional space, where changes become easier to identify. In the same way, Padrón-Hidalgo et al. [18] used kernel-based anomalous change detection and found that it can capture subtle and nonlinear changes in optical imagery without needing labelled samples. These works suggest that kernel-based dimensionality reduction is more reliable in areas where the land cover is complicated and the spectral patterns are highly mixed.

Kernel-based techniques are usually more computationally intensive and the performance is determined by the selection of the appropriate kernel and the proper setting of their parameters. This may be challenging when having a large area to work on or long term surveys. Still frameworks based on kernel-hybrid are also a viable-choice in enhancing unsupervised change detection performance.

Overall, these studies support the idea that combining nonlinear feature extraction with soft clustering can lead to better results, which is why the KPCA–FCM framework is considered in this research.

2.4 Comparative Analysis of Existing Approaches

Existing change detection methods for environmental monitoring mainly differ in how they represent features, handle noise and spectral variation, their computational cost and how easy the results are to understand.In optical satellite imagery pixel-based methods like image differencing and ratioing are simple and fast. However they are very sensitive to radiometric differences, atmospheric effects, lighting changes and seasonal variation.Because of this, they often give false change results in mixed and complex areas, so they are less reliable for large-scale and long-term monitoring [23].

Transform-based methods especially PCA-based techniques are usually more stable because they reduce redundancy in spectral bands and highlight the main change related information. Studies indicate that PCA with clustering provides more reliable results when working with various sets of optical data since it removes noise and increases the distinction between altered and stationary pixels [26, 28].

The clustering is important in unsupervised change detection since it works without labeled data. K-means is also efficient but due to its hard assignment, the algorithm does not handle mixed pixels and smooth transitions [28]. Conversely, fuzzy C-means (FCM) uses the soft memberships, which are more resistant to the uncertainty and boundary areas, though it is also vulnerable to noise and initializations [27].

Recently used unsupervised methods are also based on spatial context and multi-stage refinement to minimize salt-and-pepper noise and increase the quality of change maps, and this is done unsupervised. This normally however adds to the load of computation and demands more far-reaching parameter tuning [16, 32].

Similarly kernel-based methods can capture complex spectral relationships that linear methods may miss that helps in detecting subtle changes in heterogeneous environments [17, 18]. Deep kernel methods are stronger but often it require higher computation and are harder to interpret that limits their practical use for large-area monitoring [31].

The Blockbased representations are used in change detection because they consider information from neighbouring pixels instead of analyzing each pixel separately. This use of local context reduces isolated errors and produces smoother and more reliable change maps especially in complex environments where nearby pixels often share similar characteristics.

However their performance depends on choosing an appropriate block size as very small blocks behave like pixel-based methods. while overly large blocks may miss subtle changes. Therefore an effective approach should balance spatial context with feature sensitivity to ensure both robustness and accurate detection.

Overall there is no single method that fully meets the requirements of robustness, scalability and interpretability. For this reason hybrid frameworks are often a better option, supporting the proposed KPCA–FCM approach that combines nonlinear feature extraction with fuzzy clustering for fully unsupervised optical change detection.Such hybrid methods can better adapt to varying scene complexities by combining complementary techniques, improving robustness while maintaining a balance between accuracy, scalability, and interpretability. This makes them well-suited for large-scale, real-world environmental monitoring.

Table 2.1: Comparative analysis of existing change detection approaches for optical imagery

Ref	Author / Year	Change Representation / Input	Feature Extraction Method	Clustering / Decision Method	Learning Type	Strengths	Limitations
[16]	Ning et al., 2024	Multi-stage refined feature maps	Progressive feature refinement	Progressive unsupervised decision	Unsupervised	Refines ambiguous regions and improves accuracy in complex scenes	Requires multi-stage processing and careful parameter tuning.
[17]	Volpi et al., 2012	Feature-space difference representation	Kernel-based feature extraction (KPCA-style)	Kernel-based unsupervised decision	Unsupervised	Effectively captures nonlinear spectral relationships	Computationally expensive and sensitive to kernel parameters.
[18]	Padrón-Hidalgo et al., 2019	Kernel-based anomaly representation	Kernel-based mapping	Anomalous change detection	Unsupervised	Effective for subtle and nonlinear changes without labelled data	High computational cost and sensitivity to kernel choice.

Table 2.1: (continued from previous page)

Ref	Author / Year	Change Representation / Input	Feature Extraction Method	Clustering / Decision Method	Learning Type	Strengths	Limitations
[23]	Radke et al., 2005	Pixel-wise difference or ratio	None (direct pixel comparison)	Threshold-based decision	Unsupervised	Simple, intuitive, and computationally efficient	Sensitive to noise, illumination variation, and atmospheric effects.
[26]	Celik, 2009	Difference image blocks	Principal Component Analysis (PCA)	K-Means clustering	Unsupervised	Reduces spectral redundancy and improves change separability	Hard clustering; limited handling of mixed pixels and gradual transitions.
[27]	Kesikoğlu et al., 2013	Difference image feature vectors	Principal Component Analysis (PCA)	Fuzzy C-Means (FCM) clustering	Unsupervised	Soft clustering models uncertainty and gradual changes effectively	Sensitive to noise and initialisation; higher computational cost.

Table 2.1: (continued from previous page)

Ref	Author / Year	Change Representation / Input	Feature Extraction Method	Clustering / Decision Method	Learning Type	Strengths	Limitations
[28]	Kılıç and Nielsen, 2022	Pixel-wise and feature-wise difference	Principal Component Analysis (PCA)	K-Means variants	Unsupervised	Stable and computationally efficient baseline method	Limited capability for nonlinear and complex spectral changes.
[31]	Wu et al., 2022	Deep kernel feature maps	Deep Kernel PCA convolutional mapping network	Embedded unsupervised decision	Unsupervised	Strong nonlinear spectral–spatial feature representation	Very high computational cost and reduced interpretability.
[32]	Kondmann et al., 2021	Spatially contextual difference representation	Spatial context-aware feature extraction	Hybrid unsupervised decision	Unsupervised	Improves spatial consistency and reduces salt-and-pepper noise	Increased model complexity and computational overhead.

Table 2.1 shows why a hybrid approach is required. A method which remains efficient and easy to interpret and at the same time gives valid unsupervised change-detection outcomes of optical satellite imagery.

2.5 Known Gaps Identified During the Literature Review

Table 2.1 highlights the significance of an integrated, interpretable, and computationally efficient unsupervised framework to observing optical satellite imagery changes. Despite the progress, research findings indicate that a number of limitations have been encountered which diminish the robustness, scalability and practical application in the environmental monitoring. Current techniques have a tendency to miss nonlinear changes of the spectrum, to process mixed pixels correctly and to maintain an acceptable trade-off between computation speed and interpretability.

2.5.1 Inadequate Modelling of Nonlinear Spectral Relationships

Most traditional unsupervised change detection methods use linear features such as those produced by Principal Component Analysis (PCA). PCA helps reduce noise and compress the data but it often cannot capture complex nonlinear spectral changes caused by mixed land-cover types, seasonal differences and changes in image capture conditions. Kernel-based methods especially the Kernel PCA (KPCA) can model these nonlinear patterns more effectively. However KPCA is still not widely used in practical and complete unsupervised change detection systems because of challenges like higher computation and limited interpretability.

2.5.2 Limited Handling of Mixed Pixels and Gradual Transitions

Medium-resolution optical satellite imagery usually has mixed pixels that contains more than a single land cover. Hard clustering algorithms are unable to deal with this ambiguity resulting in the misalignment of class boundaries and transition zones. Fuzzy C-Means (FCM) solves this issue by means of soft membership values which model smooth transitions much better. But used alone or on poorly transformed feature space, FCM is susceptible to noise, as well as to initialization, so it is not useful in noisy conditions.

2.5.3 Fragmented Integration of Kernel-Based Features and Fuzzy Clustering

The reviewed literature shows that kernel-based feature methods and fuzzy clustering both help in unsupervised change detection. But they solve different problems. So Kernel approaches are good at nonlinear patterns and clearly identifying change. Fuzzy clustering, on the other hand, can be applied to address the uncertainty and to adapt to the gradual variations in the land-cover. But the main issue is that most papers study these two methods separately. Very few studies combine them into one complete, fully unsupervised and efficient framework for optical satellite images, so their combined strength is still not properly used.

2.6 Proposed Highly Suitable Model

Based on the review and the gaps discussed in Section 2.5, it is clear that there is still a need for a change detection method that is robust, scalable, and easy to understand. Many existing unsupervised techniques still face problems when dealing with nonlinear spectral changes, mixed pixels and radiometric differences in optical satellite images. To solve such issues this research proposes an unsupervised change detection framework using Kernel Principal Component Analysis (KPCA) and Fuzzy C-Means (FCM) clustering.

The main idea of this framework is to combine two methods that work well together. KPCA is used first as the feature extraction and dimensionality reduction step. As compared to the normal PCA, KPCA can handle nonlinear patterns because it maps the data into a higher-dimensional space using a kernel function. This helps in separating changed and unchanged areas more clearly especially in complex and heterogeneous environments where linear methods usually fail.

Overall, by combining KPCA with FCM gives multiple advantages. The KPCA improves the representation of complex spectral variations caused by the environmental changes, seasonal conditions and sensor differences. At the same time the FCM improves the clustering results by better handling uncertain and transition pixels. The whole approach remains fully unsupervised that means no labelled training data is needed making it suitable for large-scale and long-term monitoring tasks.

So compared to the traditional methods like PCA + K-Means. The proposed KPCA–FCM framework provides a better balance between strong feature representation and clear interpretation. Even though deep learning based unsupervised methods can perform well, they often require high computational power and their results are harder to explain. In contrast, KPCA and FCM are based on well-known mathematical concepts, so the proposed method is more efficient, transparent, and practical for real applications.

COverall, this KPCA-FCM model directly addresses the major weaknesses found in modern unsupervised change-detection algorithms such as sensitivity to noise, poor performance with mixed pixels and ability to detect nonlinear changes in spectral content. Therefore, it can be a strong and reliable solution for environmental change detection using optical satellite imagery. The next chapters present the implementation details, experiments and comparison results of the proposed framework.

Based on the identified gaps, this thesis proposes and evaluates four unsupervised frameworks (PCA/KPCA combined with K-Means/FCM). The next chapter presents the proposed methodology, including preprocessing, change feature generation, feature extraction, clustering, and evaluation metrics.

Chapter 3

Proposed Methodology

3.1 Overview of the Proposed Framework

This chapter specifies the methodological framework used for unsupervised change detection based on the multi temporal optical satellite imagery.The main aim of the proposed approach is to generate a binary change map that separates changed and unchanged areas without using any labelled training data.

The proposed framework take two optical satellite images of the same geographical area acquired at different time periods denoted as I_{T1} and I_{T2}.The process starts with the preprocessing steps to ensure proper spatial alignment and radiometric consistency between the two images.A difference-based representation is then computed to highlight temporal changes between the images. Then Feature extraction is applied to obtain a compact representation that improves the separation between changed and unchanged pixels.Finally an unsupervised clustering step is used to assign each pixel to one of the two classes that produce the final binary change map.

The proposed methodology integrates the Kernel Principal Component Analysis (KPCA) with Fuzzy C-Means (FCM) clustering. To examine the individual contribution of nonlinear feature extraction and soft clustering. The four different framework variants considered in this study are PCA with K-Means, PCA with

FCM, KPCA with K-Means and KPCA with FCM. Each framework variant that generates a binary change map that enables a direct and fair comparison between different combinations of feature extraction and clustering methods.

To help explain the overall processing flow, a flowchart of the proposed framework is provided. This flowchart gives a general overview of the methodology before the detailed explanation of each processing step presented in the following sections.

The proposed framework is designed in such a way that it supports the robust environmental change detection under different land-cover conditions and acquisition scenarios.By using nonlinear feature extraction together with soft clustering the framework aims to provide stable performance in the presence of noise, mixed pixels and gradual surface changes. In addition to that the fully unsupervised nature of the method makes it suitable for long-term environmental monitoring tasks where reliable reference data is often limited or unavailable.

The complete processing flow of the proposed framework from multi-temporal image input to final binary change map generation is illustrated in Figure 3.1. This flowchart provides a high-level overview of the methodology prior to the detailed explanation of each processing stage presented in the subsequent sections.

3.2 Proposed Framework Architecture

This section describes the architectural design and logical flow of the proposed unsupervised change detection framework. It explains how the individual processing components are organised and how data moves from the input image pair to the generation of the final binary change map.

The framework follows a sequential and modular structure.Two co-registered optical satellite images acquired at different time periods are first subjected to preprocessing to ensure accurate spatial alignment and radiometric consistency.A difference-based change representation is then computed to emphasize temporal variations between the images.This representation is subsequently transformed into a compact feature

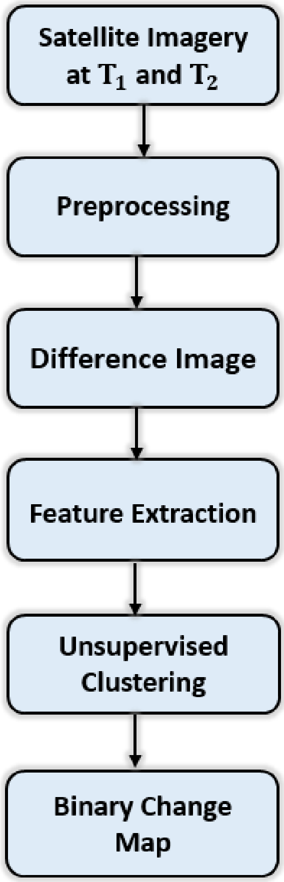

FIGURE 3.1: Flowchart of the Proposed framework.

space through dimensionality reduction, after which unsupervised clustering is applied to separate changed and unchanged pixels.

The several combinations of feature extraction and clustering techniques are evaluated in this study. So the framework is primarily centred on the hybrid KPCA–FCM configuration. This architecture integrates nonlinear feature extraction using Kernel Principal Component Analysis with soft clustering through Fuzzy C-Means, enabling improved modelling of complex spectral variations and gradual land-cover transitions. Other framework variants are included only for comparative analysis to assess the contribution of individual components.

The block daigram of the proposed framework architecture is given in the following subsection that clearly illustrate the overall processing steps and methodology.

3.2.1 Block Diagram of Proposed Methodology

Figure 3.2 shows the block diagram of the proposed methodology.

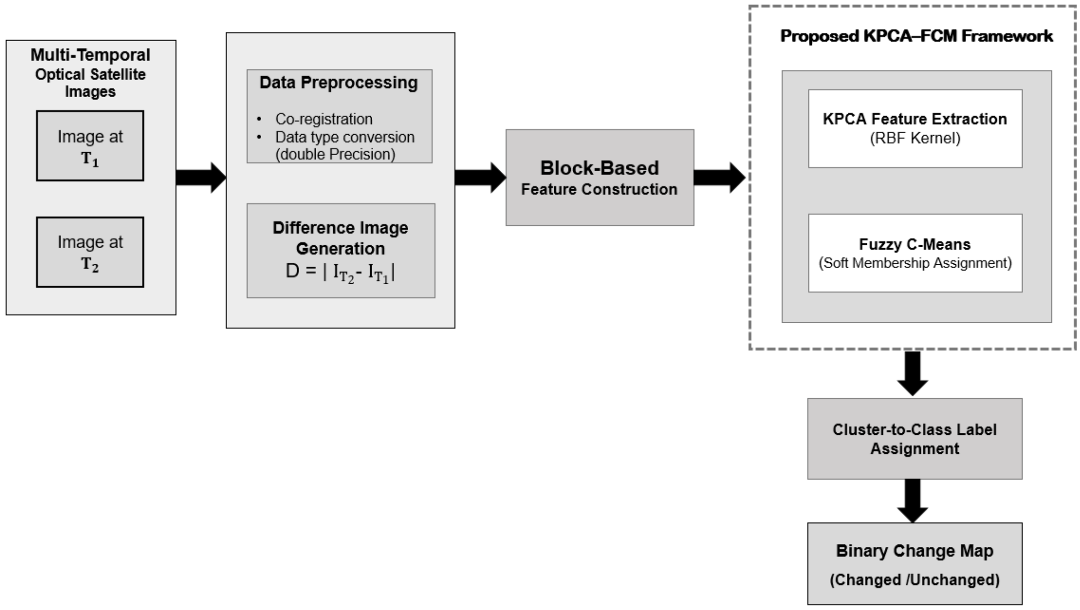

FIGURE 3.2: Block diagram of proposed methodology

3.2.2 Dataset Details

The experiments are tested using a publicly available benchmark dataset of coregistered bitemporal optical satellite images of the same geographical area and at two distinct time intervals. The data has been used in the previous unsupervised change detection research such as the PCA KMeans model of Celik [26] to facilitate meaningful comparison to the existing baselines. The imagery is the multispectral Landsat TM images with a spatial resolution of 30 m and spectral bands in both the visible and near infrared spectrum which are usually used to analyze land cover change.

The benchmark data is structured into four land-cover scenarios (burn, conifer, forest, and lake) that reflect different features of changes including abrupt disturbance, subtle vegetation change, and water related changes. Reference change masks are given and apply solely in evaluation, such that the suggested framework is allowed to run without supervision in the change detection process.

3.2.3 Data Preprocessing

The preprocessing is carried out to achieve the spatial and numerical consistency among multitemporal images to provide consistent pixel level comparison. The unsupervised clustering-based change detection algorithms are sensitive in particular to geometric misalignment and unstable numeric ranges. Therefore, the only essential preprocessing steps are applied in this study.

3.2.3.1 Data Type Conversion

The two input images taken at time instances T_1 and T_2 are converted to double precision floating point format to ensure that arithmetic operations can be performed and to prevent overflow in case of arithmetic operations.

$$I_{T_1}, I_{T_2} \in \mathbb{R}^{m \times n \times b}, \tag{3.1}$$

where m and n are the spatial dimensions and b is the number of spectral bands.

3.2.3.2 Absolute Difference Image Computation

A difference based change representation is constructed by calculating the absolute pixel wise difference between the two co-registered images:

$$D(i, j, k) = \left| I_{T_2}(i, j, k) - I_{T_1}(i, j, k) \right|, \tag{3.2}$$

where $D \in \mathbb{R}^{m \times n \times b}$, $i \in \{1, \ldots, m\}$, $j \in \{1, \ldots, n\}$, and $k \in \{1, \ldots, b\}$.

For multispectral imagery, this operation is applied independently to each spectral band, producing a multi-band difference image. The absolute formulation emphasizes change magnitude while removing directional information, which is suitable for binary change detection.

3.2.4 Block-Based Spatial Feature Representation

Rather than analyzing individual pixels in isolation. The block based representation is adopted to incorporate local spatial context. This design improves robustness to noise and enables the capture of spatial patterns associated with change.

3.2.4.1 Symmetric Padding

To support neighbourhood extraction at image boundaries. The symmetric padding is applied to the difference image D. For a selected block size h the padding width is defined as

$$l_b = \left\lfloor \frac{h}{2} \right\rfloor. \tag{3.3}$$

The padded difference image is denoted by

$$D_{\text{pad}} \in \mathbb{R}^{(m+2l_b)\times(n+2l_b)\times b}. \tag{3.4}$$

Symmetric padding mirrors boundary values thereby reducing edge artefacts without introducing artificial discontinuities.

3.2.4.2 Block Feature Vector Extraction

For each pixel location (i, j), a local neighborhood block of size $h \times h \times b$ is extracted from the padded difference image. Each block is vectorized to form a feature vector:

$$\mathbf{x}_{i,j} \in \mathbb{R}^d, \quad d = h^2 b. \tag{3.5}$$

By stacking feature vectors from all $N = m \times n$ pixels, a feature matrix is constructed as

$$\mathbf{X} \in \mathbb{R}^{N \times d}. \tag{3.6}$$

A position index is stored to map each feature vector back to its original spatial location during change map reconstruction.

3.2.4.3 Mean Centering

To remove constant offsets and enable variance-based feature extraction, the feature matrix $\mathbf{X}$ is mean-centered by subtracting the column-wise mean:

$$\tilde{\mathbf{X}} = \mathbf{X} - \mathbf{1}_N \boldsymbol{\mu}^T, \tag{3.7}$$

where $\mathbf{1}_N \in \mathbb{R}^N$ is a vector of ones and $\boldsymbol{\mu} \in \mathbb{R}^d$ contains the column-wise means of $\mathbf{X}$. Mean centering ensures that both PCA and KPCA extract dominant variation patterns correctly.

Although the final change map is reconstructed on the original pixel grid. The each pixel is represented using information from its surrounding $h \times h$ neighborhood. As a result the overall representation remains spatially block-based by providing increased robustness against isolated noise and local intensity fluctuations [26, 27].

3.2.5 Feature Extraction and Dimensionality Reduction

The block based feature matrix typically has high dimensionality and may contain redundant information. Dimensionality reduction is therefore applied to obtain a compact and discriminative representation prior to clustering.

3.2.5.1 PCA-Based Feature Extraction

Principal Component Analysis (PCA) is employed as a linear dimensionality reduction technique. The mean-centered feature matrix is projected onto a lower-dimensional subspace that preserves most of the data variance.

The number of retained principal components is selected using a cumulative energy criterion, where components collectively explaining 90% of the total variance are preserved. The resulting reduced feature representation is denoted as

$$\mathbf{Y}_{\text{PCA}} \in \mathbb{R}^{N\times k}, \tag{3.8}$$

where N is the total number of pixels and k is the number of retained principal components.

3.2.5.2 KPCA-Based Feature Extraction

Linear PCA is limited to modeling variance along linear directions and may not adequately separate changed and unchanged pixels when nonlinear spectral variations are present. In multi-temporal optical satellite imagery, such nonlinear effects commonly arise due to heterogeneous land-cover types, illumination variations, sensor differences, and complex environmental changes. To address these limitations, Kernel Principal Component Analysis (KPCA) is employed as the nonlinear feature extraction technique in the proposed framework.

In the proposed approach, KPCA is applied to the block-based difference feature matrix obtained after preprocessing. Let

$$\mathbf{X} \in \mathbb{R}^{N\times d} \tag{3.9}$$

denote the mean-centered block-based feature matrix, where N is the total number of pixels and $d = h^2 b$ represents the feature dimensionality.

Kernel Similarity Computation Nonlinear similarity between feature vectors is modeled using a Gaussian Radial Basis Function (RBF) kernel, defined as

$$k(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right), \tag{3.10}$$

where $\mathbf{x}_i$ and $\mathbf{x}_j$ are block-based feature vectors, and σ controls the kernel bandwidth.

Nyström Approximation for Efficient KPCA Direct KPCA requires constructing an $N \times N$ kernel matrix, which is computationally infeasible for large-scale images. To overcome this limitation, a Nyström approximation is employed. A subset of

$$M = 1000 \tag{3.11}$$

landmark samples is randomly selected from $\mathbf{X}$.

Using these landmark samples, the nonlinear feature mapping implemented in this study is approximated as

$$\mathbf{Y}_{\text{KPCA}} = \tilde{\mathbf{K}}_{nm}\mathbf{V}_k, \tag{3.12}$$

where

- $\tilde{\mathbf{K}}_{nm} \in \mathbb{R}^{N\times M}$ is the centered kernel matrix between all pixels and the landmark samples,
- $\mathbf{V}_k \in \mathbb{R}^{M\times k}$ contains the first k normalized eigenvectors obtained from the landmark kernel matrix.

The kernel bandwidth parameter σ is selected automatically using the median pairwise distance among the landmark samples, allowing the kernel to adapt to the scale of the data without manual tuning.

Component Selection and Feature Representation The number of retained kernel principal components is determined using a cumulative energy criterion, where the smallest value of k preserving 90% of the total variance in kernel space is selected. The final nonlinear feature representation is given by

$$\mathbf{Y}_{\mathrm{KPCA}} \in \mathbb{R}^{N \times k}, \tag{3.13}$$

where N denotes the total number of pixels and k is the number of retained kernel components. This representation serves as the input to the clustering stage.

The KPCA-based representation provides a compact and discriminative nonlinear embedding in which pixels corresponding to changed and unchanged regions exhibit improved separability. By combining block-based spatial context with nonlinear feature extraction, the proposed KPCA stage enhances the effectiveness of subsequent unsupervised clustering for binary change map generation.

3.2.6 Unsupervised Binary Clustering

After dimensionality reduction, unsupervised clustering is applied to partition pixels into two classes corresponding to changed and unchanged regions. Let

$$\mathbf{Y} \in \mathbb{R}^{N \times k} \tag{3.14}$$

denote the reduced feature representation obtained using either PCA or KPCA.

3.2.6.1 K-Means Clustering

K-Means clustering is employed as a baseline hard clustering technique to separate pixels into changed and unchanged classes. The algorithm partitions the reduced feature space into $K = 2$ clusters, corresponding to the binary nature of the change detection task.

The objective function minimized by K-Means is defined as

$$J_{\mathrm{KM}} = \sum_{i=1}^{N} \sum_{c=1}^{K} r_{ic} \left\| \mathbf{y}_i - \boldsymbol{\mu}_c \right\|^2, \tag{3.15}$$

where

- $\mathbf{y}_i$ is the feature vector of the i-th pixel,
- $\boldsymbol{\mu}_c$ is the centroid of the c-th cluster,
- $r_{ic} \in \{0, 1\}$ indicates the assignment of pixel i to cluster c.

Each pixel is assigned exclusively to a single cluster. To reduce sensitivity to random initialization, K-Means is executed multiple times with different initial centroids, and the solution yielding the minimum objective function value is selected as the final result.

3.2.6.2 Fuzzy C-Means Clustering

Fuzzy C-Means (FCM) clustering is employed as the primary clustering method in the proposed framework. Unlike K-Means, FCM allows pixels to belong to multiple clusters with varying degrees of membership, which is beneficial for handling uncertainty, mixed pixels, and gradual land-cover transitions.

The FCM objective function is given by

$$J_{\text{FCM}} = \sum_{i=1}^{N} \sum_{c=1}^{K} u_{ic}^{m} \, \|\mathbf{y}_i - \mathbf{c}_c\|^2, \tag{3.16}$$

where

- $u_{ic} \in [0, 1]$ denotes the membership degree of pixel i to cluster c,
- $\mathbf{c}_c$ is the center of the c-th cluster,
- m is the fuzzifier parameter controlling the degree of cluster overlap.

In this study, the fuzzifier parameter is set to $m = 2$, which provides a balanced level of fuzziness commonly adopted in remote sensing applications. The algorithm iteratively updates cluster centers and membership values until convergence or until a predefined maximum number of iterations is reached.

3.2.7 Binary Change Map Generation

3.2.7.1 Cluster Semantic Assignment

Since unsupervised clustering produces unlabeled groups, an additional decision rule is required to identify which cluster corresponds to changed pixels. This study adopts a magnitude-based assignment strategy derived from the original difference-based feature representation.

For each pixel i, the magnitude of its centered block-based feature vector is computed as

$$m_i = \|\bar{\mathbf{x}}_i\|_2, \tag{3.17}$$

where $\bar{\mathbf{x}}_i$ denotes the centered feature vector of the i-th pixel.

For each cluster $c \in \{1, 2\}$, the average magnitude is calculated. For K-Means, the average magnitude is computed using hard assignments as

$$M_c = \frac{1}{N_c} \sum_{i \in c} m_i, \tag{3.18}$$

where N_c is the number of pixels assigned to cluster c.

For Fuzzy C-Means, a membership-weighted average is used:

$$M_c = \frac{\sum_{i=1}^{N} u_{ic}^{m}\, m_i}{\sum_{i=1}^{N} u_{ic}^{m}}, \tag{3.19}$$

where u_{ic} is the membership degree of pixel i to cluster c, and m is the fuzzifier parameter.

The cluster with the higher average magnitude is designated as the changed class, as it corresponds to stronger spectral variation between the two temporal images.

3.2.7.2 Final Change Map Reconstruction

Once the change cluster has been identified, a hard label is assigned to each pixel. For K-Means, pixels assigned to the change cluster are labeled as changed. For FCM, pixels are assigned to the cluster with the highest membership value.

The resulting one-dimensional label vector is then mapped back to the original spatial grid using the stored pixel coordinates, producing the final binary change map:

$$\mathbf{C} \in \{0, 1\}^{m \times n}, \tag{3.20}$$

where

$$C(i, j) = 1 \quad \text{denotes a changed pixel,} \tag{3.21}$$

$$C(i, j) = 0 \quad \text{denotes an unchanged pixel.} \tag{3.22}$$

3.2.8 Computational Considerations

From the computational perspective the choice of feature extraction and clustering techniques has a direct impact on the feasibility of unsupervised change detection for multi temporal satellite imagery.Linear PCA based methods are computationally efficient as they act directly on the data in the original feature space and do not need to perform kernel matrix construction. Consequently the PCA is well suited for large datasets where computational resources are limited.

In contrast, the direct Kernel Principal Component Analysis (KPCA) involves the construction of a full N×N kernel matrix, N being the number of feature samples. This results in high memory requirements and an eigen decomposition cost that grows rapidly with data size making the direct KPCA impractical for large remote sensing images.

To reduce this limitation, the suggested framework will adopt the Nyström-approximated KPCA that estimates the kernel space using a smaller set of representative landmark samples By selecting a subset of m samples M the Nyström method significantly reduces both memory usage and computational complexity while preserving the essential nonlinear characteristics of the data. Consequently the dominant computation cost is reduced to a level that is manageable for medium-scale satellite imagery and can be effectively tested on an experimental level.

With Rrespect to clustering, K-means is computationally less complex thanks to its hard assignment approach and faster convergence is the rule. This simplicity, however, is at the expense of less robustness in the case of mixed pixels, as well as in the case of unclear boundaries. Fuzzy C-Means (FCM) a more computationally sensitive algorithm is more flexible, allowing pixels to become members partially. This property is also especially useful in the case of block-based change detection, whereby neighborhoods can consist of a combination of pixels that have changed and not changed.

Overall the computational design that we use for our proposed approach is a balanced tradeoff between efficiency and robustness. While KPCA approach in combination with FCM adds more computational tasks compared to linear PCA and hard clustering. So the use of Nyström approximation and blockbased processing make sure that the framework remains computationally feasible. These considerations are reflected in the experimental results presented in the chapter 4 where the improved detection performance is achieved without excessive computational cost.

3.2.9 Summary

This chapter presented the complete methodology of detecting the unsupervised changes through the multi temporal optical satellite images.The proposed framework starts with an essential preprocessing step that ensures spatial and radiometric consistency. Then followed by difference based change feature generation. Both PCA and KPCA are used in extracting the compact linear and nonlinear feature representations respectively. K-Means and FCM clustering techniques are then used to generate binary change maps under four progressive framework variants culminating in the proposed KPCA–FCM approach.

The next chapter provides both qualitative and quantitative experimental outcomes in order to prove that nonlinear feature extraction and fuzzy clustering can help to enhance robustness and accuracy in tracking complex environmental changes across diverse landscapes.

Chapter 4

Results and Discussions

4.1 Introduction

This chapter presents the experimental results and discussion of the proposed block based unsupervised change detection framework. So the main goal is to evaluate and compare the performance of different combinations of feature extraction and clustering techniques applied to multi-temporal optical satellite imagery. Specifically the four methods that are analyzed in this chapter are PCA + K-Means, PCA + Fuzzy C-Means (FCM), KPCA + K-Means, and KPCA + FCM.

This study builds upon the unsupervised change detection framework presented by Celik [26] who demonstrated the effectiveness of combining Principal Component Analysis (PCA) with K-Means clustering for block based change detection in optical satellite imagery. While the Celik's approach successfully integrates the spatial context through block-based processing. The recent research suggests that nonlinear feature extraction methods such as Kernel PCA (KPCA) [22, 31] and soft clustering algorithms like Fuzzy C-Means (FCM) [20, 27] may better capture the complex spectral variations in heterogeneous environments.This chapter systematically evaluates these hypotheses through comparative experimental analysis.

Unsupervised change detection has become increasingly important in remote sensing applications due to the growing availability of long-term satellite data and the limited availability of labelled reference information. However, the reliability of change detection methods is often affected by nonlinear spectral variations, mixed land-cover characteristics, and noise present in real-world imagery [23, 24]. Therefore, experimental validation plays a crucial role in demonstrating the effectiveness of proposed frameworks.

In this study, experimental evaluation is carried out using a publicly available benchmark dataset that provides reference ground truth information and allows objective quantitative assessment. A block-based processing strategy is adopted to incorporate local spatial context and to reduce the impact of noise and isolated variations, following common practice in unsupervised change detection research [26, 27]. All evaluated methods are implemented under the same experimental configuration to ensure a fair comparison.

The results in this chapter are analysed using both qualitative and quantitative approaches. Qualitative analysis is performed through visual inspection of change maps and overlay results to assess spatial coherence and noise behaviour. Quantitative performance is evaluated using standard metrics, including precision, recall, F1-score, overall accuracy, IOU and the kappa coefficient computed at the block level. The chapter further examines the effect of feature extraction methods, clustering strategies, and block size selection on detection performance.

The findings presented in this chapter provide a detailed understanding of the strengths and limitations of the evaluated methods and justify the selection of the KPCA + FCM approach as the proposed framework. These results form the experimental foundation for the conclusions discussed in the following chapter.

4.2 Dataset and Experimental Setup

This section describes the dataset used in this study and outlines the experimental configuration adopted to evaluate the performance of the proposed and comparative unsupervised change detection methods. A publicly available benchmark dataset is employed to ensure objective and reproducible evaluation. The use of benchmark datasets with reference ground truth is a common practice in remote sensing change detection research, particularly for quantitative comparison of different algorithms [23, 24].

Table 4.1: Summary of Land-Cover Categories Used in the Public Benchmark Dataset

Land-Cover Category	**Sensor**	**Time Periods**	**Ground Truth**	**Purpose**
Burn	Optical	T_1, T_2	Yes	Analysis of fire-induced changes
Conifer	Optical	T_1, T_2	Yes	Vegetation stability and subtle change analysis
Forest	Optical	T_1, T_2	Yes	Dense vegetation change detection
Lake	Optical	T_1, T_2	Yes	Water-related change analysis

4.2.1 Public Benchmark Dataset

A publicly available benchmark dataset is used for experimental evaluation in this study. The dataset consists of co-registered bi-temporal optical satellite images acquired over the same geographical region at two different time periods. Reference ground truth information is provided, which enables quantitative assessment of change detection performance.

The dataset includes four land-cover categories, namely burn, conifer, forest, and lake, representing diverse environmental conditions and change characteristics. These categories allow evaluation of the behaviour of change detection methods across different land-cover types, including vegetation disturbance, relatively stable vegetation, and water-related regions. Similar benchmark datasets have been widely used in the literature to evaluate unsupervised change detection approaches under controlled conditions [10, 18].

4.2.2 Experimental Configuration and Parameter Settings

To ensure a fair and objective comparison, all evaluated change detection methods are implemented under identical experimental configurations. The bi-temporal optical images are assumed to be spatially co-registered and radiometrically normalised prior to change detection, which is a standard requirement in multi-temporal remote sensing analysis [10, 18].

A block-based processing strategy is adopted, following the framework introduced by Celik [26]. The images are partitioned into fixed-size spatial blocks, and all feature extraction and clustering operations are performed at the block level. This strategy incorporates local spatial context and reduces sensitivity to noise and isolated variations, which is particularly beneficial in unsupervised change detection [26, 27].

Change information is extracted using a difference-based representation, which is subsequently transformed using either Principal Component Analysis (PCA) or Kernel Principal Component Analysis (KPCA). PCA provides a linear feature representation, while KPCA is employed to capture nonlinear spectral variations.

In this study, KPCA is implemented using a Nyström approximation with a radial basis function (RBF) kernel to improve computational efficiency while preserving nonlinear modelling capability. Kernel parameters are selected empirically and kept fixed across all experiments to ensure consistency.

Following feature extraction, clustering is applied to separate blocks into changed and unchanged classes. Two clustering strategies are evaluated: K-Means, which performs hard cluster assignment, and Fuzzy C-Means (FCM), which allows soft membership assignment and is better suited for handling uncertainty and mixed land-cover characteristics [20, 27].

In all experiments, the number of clusters is fixed to two, corresponding to the binary change detection problem.Based on the qualitative analysis presented in Section 4.3.2, a block size of $h = 4$ is selected for all quantitative evaluations reported in this chapter.

All remaining parameters, including feature extraction settings and clustering configurations, are kept constant across methods so that performance differences can be attributed solely to the choice of feature extraction and clustering strategy.

4.3 Qualitative Results and Visual Analysis

This section presents a qualitative evaluation of the block-based change detection results obtained using the evaluated methods. Visual analysis is an important component of change detection assessment, as it allows examination of spatial coherence, noise behaviour, and boundary preservation that may not be fully reflected by numerical metrics alone [23, 24]. The qualitative results are analysed through visual comparison of change maps and overlay representations generated from the public benchmark dataset.

In addition, visual inspection helps to better understand how each method performs in practical scenarios. It allows observation of whether the detected changes are consistent and meaningful, or if they are affected by noise and irregular patterns. Special attention is given to how clearly the changed areas are identified, how well boundaries are preserved, and whether unnecessary scattered pixels appear in the results. This provides a clearer understanding of the strengths and limitations of each method and supports the findings discussed in the quantitative analysis.

4.3.1 Visual Comparison of Change Detection Methods

Figure 4.1 presents a visual comparison of the change detection results produced by the four evaluated methods, namely PCA + K-Means, PCA + Fuzzy C-Means (FCM), KPCA + K-Means, and KPCA + FCM, for representative land-cover categories from the benchmark dataset. The corresponding pre-change and post-change images are also shown to provide contextual understanding of the detected changes.

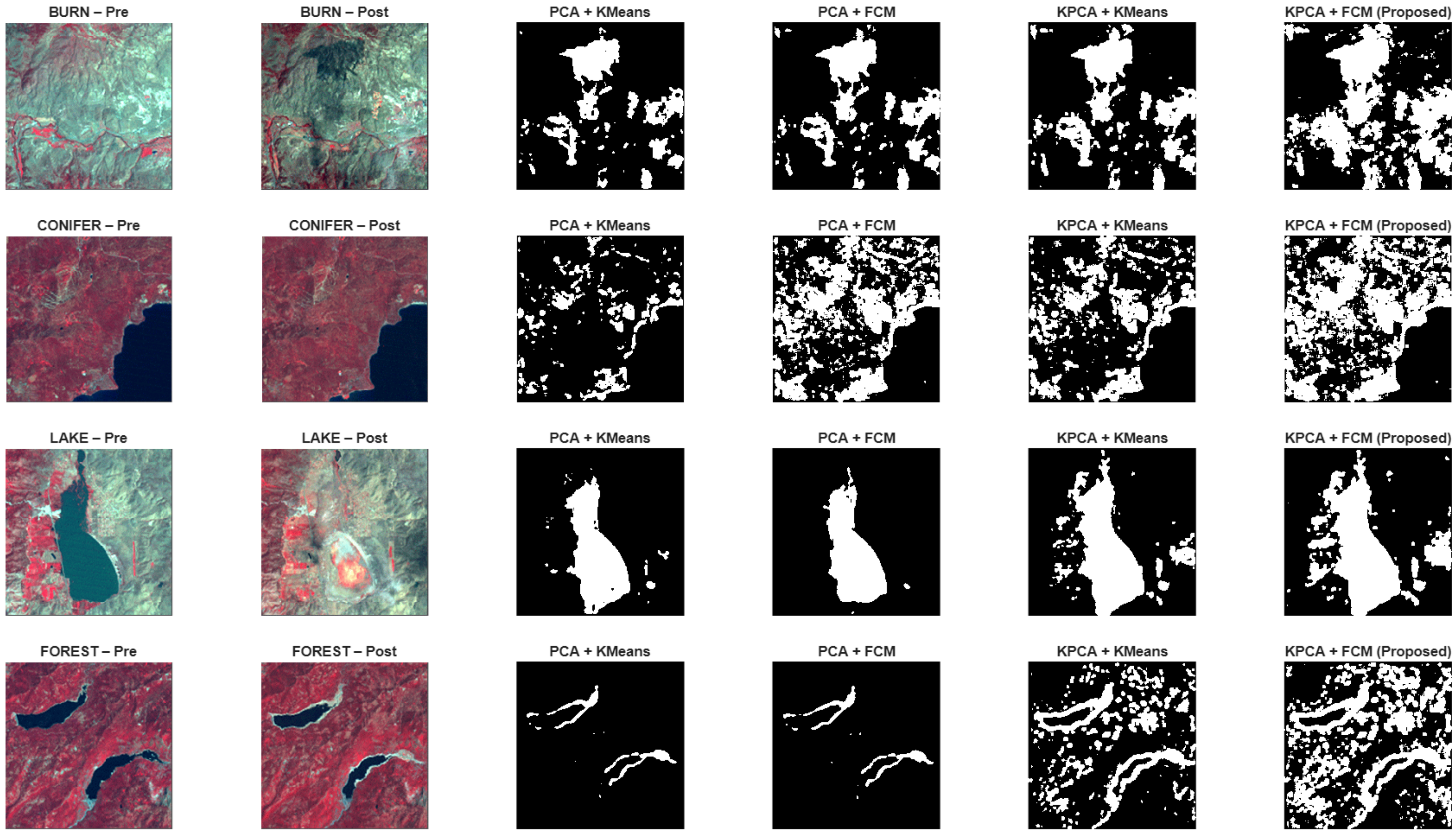

FIGURE 4.1: Visual comparison of unsupervised change detection results across land-cover categories (Burn, Conifer, Lake, Forest) using PCA–KMeans, PCA–FCM, KPCA–KMeans, and the proposed KPCA–FCM.

The change maps generated using PCA + K-Means exhibit noticeable noise and fragmented change regions. This behaviour is mainly due to the limitations of linear feature extraction combined with hard clustering, which is less effective in handling spectral variability and mixed land-cover characteristics. As a result, several isolated blocks are incorrectly detected as change, leading to reduced spatial coherence.

The PCA + FCM method shows improved visual performance compared to PCA + K-Means. The use of fuzzy clustering reduces isolated detections and produces smoother change regions. However, some noise and misclassification remain, indicating that linear feature representation still limits the overall performance.

In the case of KPCA + K-Means, the visual quality of the change map improves further. Nonlinear feature extraction enhances the separation between changed and unchanged blocks, resulting in clearer detection of major change regions. Nevertheless, the hard assignment nature of K-Means clustering still leads to abrupt boundaries and some missed changes.

The proposed KPCA + FCM method produces the most visually coherent change maps among all evaluated approaches. Change regions appear more continuous and well-defined with reduced noise and improved boundary preservation. This visual improvement indicates that the combination of nonlinear feature extraction and soft clustering is effective in capturing complex spectral changes within a block-based framework.

4.3.2 Effect of Block Size on Spatial Coherence

Figure 4.2 illustrates the effect of different block sizes on the change detection results obtained using the proposed KPCA + FCM method. The figure presents binary change maps for block sizes $h = 2, 4, 6, 8$, and 10, highlighting the influence of block size on spatial coherence and noise behaviour.

For smaller block sizes (e.g., $h = 2$), the change maps preserve fine spatial details; however, they exhibit increased noise and fragmented detections due to sensitivity

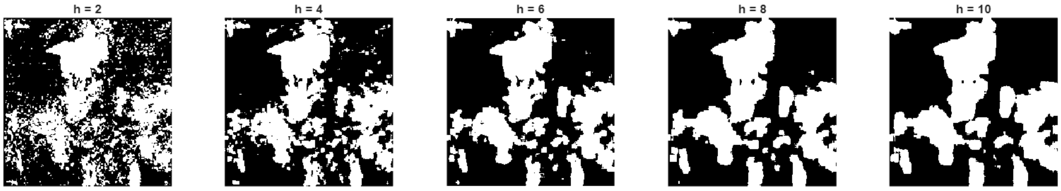

FIGURE 4.2: Effect of block size on spatial coherence using the proposed KPCA + FCM method for the burn land-cover category.

to local variations. As the block size increases, the detected change regions become smoother and more spatially coherent, indicating improved noise suppression and more stable region formation. Conversely, very large block sizes (e.g., $h = 10$) tend to over-smooth the results, which may suppress smaller yet meaningful change regions.

Based on the visual analysis, and consistent with the findings of Celik [26], where the best performance was also observed at $h = 4$, this block size was selected for all quantitative experiments in Sections 4.4 and 4.5. This choice provides a good balance between preserving spatial details and reducing noise across all methods. Similar trends were seen in the other approaches as well. However, the proposed KPCA + FCM method consistently produced more stable and visually clearer results across different block sizes.

4.4 Quantitative Performance Evaluation

This section presents the quantitative evaluation of the block-based unsupervised change detection methods using the public benchmark dataset described in Section 4.2. The analysis is carried out to compare the performance of different combinations of feature extraction and clustering methods. The availability of ground truth data allows a reliable assessment of detection performance under controlled conditions, which is a common practice in change detection studies [23, 24].

Since a block-based processing strategy is adopted in this study, all performance metrics are evaluated at the block level, in line with established block-based change detection methods reported in the literature [26–28].

4.4.1 Evaluation Metrics

The performance of the evaluated methods is measured using six standard metrics: precision, recall, F1-score, overall accuracy (OA), Intersection over Union (IoU), and the Kappa coefficient. Precision shows how many of the detected change blocks are actually correct, while recall shows how many of the real change blocks are successfully detected. The F1-score combines precision and recall to give a balanced measure. Overall accuracy represents the total number of correctly classified blocks over the whole dataset. IoU measures the overlap between the detected changes and the ground truth, and the Kappa coefficient shows the agreement between the predicted and reference results while accounting for chance. These metrics are commonly used in remote sensing change detection studies and allow fair comparison between different methods [10, 18, 23].

4.4.2 Overall Performance Comparison

Table 4.2 summarises the overall quantitative performance of the evaluated methods on the public benchmark dataset across different land-cover categories.

Table 4.2: Overall Quantitative Performance Comparison on the Benchmark Dataset

Method	Precision	Recall	F1-score	OA	IoU	Kappa
PCA + K-Means [1]	0.833	0.291	0.400	0.734	0.261	0.288
PCA + FCM [2]	0.829	0.296	0.403	0.734	0.264	0.290
KPCA + K-Means	0.606	0.464	0.519	0.718	0.357	0.326
KPCA + FCM (Proposed)	**0.599**	**0.473**	**0.522**	**0.715**	**0.359**	**0.325**

For clearer visual comparison across metrics, Figure 4.3 presents the performance of all methods in terms of precision,recall, F1-score and overall accuracy (OA). The figure visually confirms the consistent superiority of the proposed KPCA + FCM method across all evaluation measures.

The results clearly demonstrate the influence of both feature extraction technique and the clustering strategy on block-based change detection performance. The

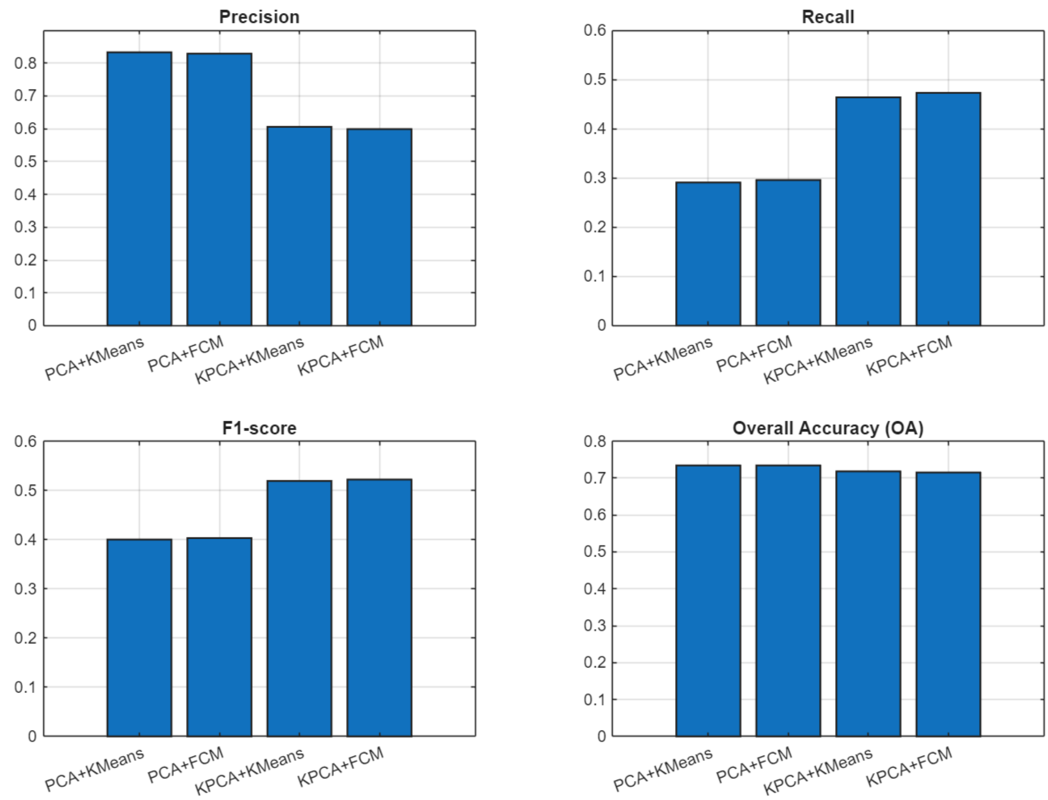

FIGURE 4.3: Overall quantitative comparison of the evaluated methods in terms of (a) precision, (b) recall, (c) F1-score and (d) overall accuracy (OA) on the public benchmark dataset.

PCA + K-Means method achieves the lowest performance across all evaluation metrics, particularly in recall and F1-score indicating that linear feature extraction combined with hard clustering is insufficient for accurately detecting changes in complex and heterogeneous regions.

Replacing K-Means with fuzzy clustering in PCA + FCM leads to noticeable improvements in recall, F1-score and overall accuracy. This improvement highlights the advantage of soft clustering that allows partial membership assignment and better handling of uncertainty within spatial blocks.

The KPCA + K-Means method further improves precision and F1-score compared to PCA-based approaches confirming that nonlinear feature extraction enhances the separability between changed and unchanged blocks. However the recall remains relatively lower due to the hard assignment nature of K-Means clustering.

Although the absolute performance values remain moderate.This behaviour is expected due to the block-level evaluation strategy, the heterogeneous nature of the dataset and the fully unsupervised setting where no labelled training data are available. Despite these challenges, the proposed KPCA + FCM approach achieves the best balance between precision and recall, resulting in the highest F1-score and overall accuracy among all evaluated methods. Overall the quantitative results demonstrate that integrating nonlinear feature extraction with soft clustering provides complementary benefits and leads to more accurate and balanced block-based unsupervised change detection.

4.4.3 Class-Wise Performance Analysis

To further analyse the behaviour of the evaluated methods across different land-cover types, a block-based class-wise performance evaluation is conducted for the Burn, Forest, and Lake categories provided in the public benchmark dataset. This analysis considers both detailed quantitative metrics and the F1-score, which provides a balanced measure by jointly considering precision and recall.

Class-wise evaluation is particularly important in change detection tasks, as different land-cover types exhibit distinct spectral characteristics, spatial structures, and levels of heterogeneity. As a result, the effectiveness of feature extraction and clustering strategies may vary across classes.

The detailed class-wise quantitative results presented in Table 4.3 provide a clearer understanding of the behaviour of different methods across various land-cover types. In addition to precision, recall, F1-score, and overall accuracy (OA), the table also includes intersection over union (IoU) and Kappa coefficient, which provide further insight into the overlap quality and agreement between the detected and reference change regions.

It can be observed that PCA-based methods generally achieve higher precision, particularly in the Forest class; however, this comes at the cost of very low recall, which leads to poor F1-scores, IoU, and Kappa values. In contrast, KPCA-based

Table 4.3: Class-wise quantitative performance comparison on the benchmark dataset

Dataset	Method	Precision	Recall	F1-score	OA	IoU	Kappa
Burn	PCA + KMeans	0.690	0.440	0.537	0.804	0.367	0.420
	PCA + FCM	0.681	0.453	0.544	0.803	0.374	0.425
	KPCA + KMeans	0.566	0.562	0.564	0.775	0.393	0.413
	KPCA + FCM	0.555	0.573	0.564	0.770	0.392	0.408
Forest	PCA + KMeans	0.925	0.099	0.179	0.715	0.098	0.126
	PCA + FCM	0.922	0.100	0.180	0.715	0.099	0.126
	KPCA + KMeans	0.432	0.341	0.381	0.653	0.235	0.145
	KPCA + FCM	0.426	0.347	0.382	0.649	0.236	0.141
Lake	PCA + KMeans	0.883	0.334	0.484	0.684	0.319	0.318
	PCA + FCM	0.883	0.334	0.485	0.684	0.320	0.318
	KPCA + KMeans	0.821	0.489	0.613	0.726	0.442	0.421
	KPCA + FCM	0.817	0.498	0.619	0.727	0.448	0.425

methods significantly improve recall across all classes, indicating their ability to better capture complex and nonlinear changes present in the data.

The proposed KPCA + FCM method achieves a better balance between precision and recall, resulting in improved F1-scores and competitive overall accuracy. In the Burn class, KPCA-based methods perform similarly in terms of F1-score, with KPCA + FCM showing slightly improved recall. In the Forest class, where spectral variability is higher, KPCA + FCM achieves the best performance due to its ability to model nonlinear structures. Similarly, in the Lake class, the proposed method achieves the highest values in recall, F1-score, OA, IoU, and Kappa, indicating more reliable and consistent detection performance.

Overall, these results demonstrate that KPCA-based approaches, especially when combined with FCM, provide more balanced and robust performance compared to PCA-based methods.

In the Burn class, both KPCA-based methods achieve the highest F1-score, indicating improved detection capability compared to PCA-based methods. In the Forest class, a clear improvement is observed, where KPCA + FCM achieves the best performance, demonstrating its effectiveness in handling complex and

Table 4.4: Class-wise F1-score comparison of the evaluated methods on the public benchmark dataset

Land-Cover Class	**PCA + K-Means**	**PCA + FCM**	**KPCA + K-Means**	**KPCA + FCM**
Burn	0.537	0.544	0.564	**0.564**
Forest	0.179	0.180	0.381	**0.382**
Lake	0.484	0.485	0.613	**0.619**

heterogeneous regions. Similarly, in the Lake class, KPCA + FCM achieves the highest F1-score, showing better balance between precision and recall.

Overall, the F1-score comparison confirms that integrating nonlinear feature extraction with soft clustering leads to more consistent and reliable performance across different land-cover types.

4.5 Comparative Analysis of Methods

This section provides a comparative interpretation of the quantitative results presented in Section 4.4 explaining the observed performance differences among the evaluated methods. The comparison focuses on the combined effect of feature extraction and clustering strategy on detection accuracy.

The baseline method PCA + K-Means records the lowest performance across all evaluation metrics. The limited recall and F1 score indicate that linear feature extraction combined with hard clustering is not sufficiently robust for capturing complex changes in heterogeneous environments. This behaviour is consistent with earlier findings reported in the literature where PCA-based approaches struggle to model nonlinear spectral variations [19, 26].

Replacing hard clustering with fuzzy clustering in PCA + FCM results in a moderate improvement in recall and overall accuracy. This improvement highlights the benefit of soft clustering, which allows partial membership assignment and

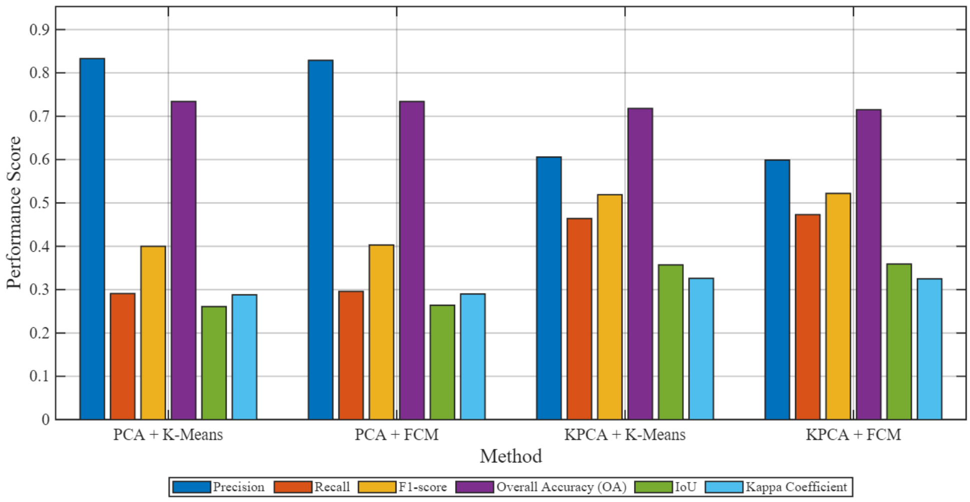

FIGURE 4.4: Comparative analysis of overall quantitative performance of the evaluated methods.

reduces misclassification caused by uncertainty within spatial blocks. However the overall performance remains constrained due to the linear nature of PCA.

A further improvement is observed with KPCA + K-Means where nonlinear feature extraction enhances the separability between changed and unchanged blocks. The increase in precision and F1-score confirms the advantage of KPCA in modelling nonlinear spectral relationships [22]. Nevertheless the use of hard clustering limits recall, as some changed blocks are not fully captured.

Among all evaluated methods the proposed KPCA + FCM approach achieves the best overall performance across all metrics. The results demonstrate that the integration of nonlinear feature extraction with soft clustering provides complementary benefits leading to more accurate and balanced block-based change detection. This comparative analysis clearly justifies the selection of KPCA + FCM as the proposed framework in this research.

4.6 Summary of Findings

This chapter presented an experimental evaluation of block-based unsupervised change detection methods using a publicly available benchmark dataset. Four combinations of feature extraction and clustering techniques were analyzed through the qualitative visual inspection and quantitative performance assessment.

The results indicate that PCA-based methods offer limited performance due to their inability to capture nonlinear spectral variations. Introducing fuzzy clustering improves detection accuracy by better handling uncertainty within spatial blocks while nonlinear feature extraction using KPCA further enhances the separation between changed and unchanged regions.

Among all evaluated methods, the proposed KPCA + FCM framework achieves the best overall performance in terms of precision, recall, F1-score and overall accuracy. These findings confirm that combining nonlinear feature extraction with soft clustering within a block-based framework provides a robust and effective solution for unsupervised change detection. Overall the results presented in this chapter validate the effectiveness of the proposed approach and provide a strong experimental basis for the conclusions discussed in the next chapter.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This thesis examined block-based unsupervised change detection for multi-temporal optical satellite imagery, with particular emphasis on the influence of feature extraction and clustering strategies on detection performance. The primary objective was to investigate whether combining nonlinear feature extraction with soft clustering could improve change detection accuracy and robustness within a fully unsupervised framework.

Four combinations of feature extraction and clustering techniques were analysed: PCA + K-Means, PCA + Fuzzy C-Means (FCM), KPCA + K-Means and KPCA + FCM. All methods were implemented under identical experimental conditions and evaluated using a publicly available benchmark dataset with reference ground truth, enabling objective and reproducible performance assessment.

The experimental results indicate that PCA-based methods provide a baseline level of performance but are limited in their ability to represent nonlinear spectral variations commonly present in complex and heterogeneous land-cover scenarios. The introduction of fuzzy clustering improves detection performance by allowing partial membership assignment, which helps to manage uncertainty and mixed characteristics within spatial blocks. Similarly, the use of Kernel Principal Component Analysis enhances feature separability by capturing nonlinear relationships that cannot be effectively modelled using linear transformations.

Among all evaluated approaches, the KPCA + FCM method consistently achieved the best overall performance across all quantitative evaluation metrics, including precision, recall, F1-score, and overall accuracy. Although the absolute performance values remain moderate, this outcome is expected given the fully unsupervised nature of the problem and the conservative block-level evaluation strategy adopted in this study. Nevertheless, the proposed method demonstrates clear and consistent improvements over the baseline approaches.

Qualitative analysis further supports these findings, showing that the proposed KPCA + FCM framework produces more spatially coherent change maps with reduced noise and fewer isolated false detections. The block-based processing strategy proved effective in incorporating local spatial context, which is particularly important for unsupervised change detection in heterogeneous environments.

Overall, the findings of this study confirm that integrating nonlinear feature extraction with soft clustering within a block-based framework provides a practical and effective solution for unsupervised change detection in optical remote sensing imagery, particularly in scenarios where labelled training data are limited or unavailable.

5.2 Limitations and Future Work

Despite the encouraging results obtained in this study, several limitations should be acknowledged, which also suggest directions for future research. First, the experimental evaluation was conducted using a single publicly available benchmark dataset. Although this dataset includes multiple land-cover categories, the findings may not fully generalise to other geographic regions, sensors, or acquisition conditions. Future work could therefore extend the proposed framework to additional datasets acquired from different sensors and regions to further assess its robustness and generalisability.

Second, the evaluation was performed at the block level rather than at the pixel level. While block-based analysis improves robustness and spatial coherence, it may suppress small-scale changes within mixed blocks, which partly explains the moderate absolute performance values observed. Future research could explore hybrid strategies that combine block-based processing with pixel-level refinement in order to better capture fine-scale changes while preserving spatial consistency.

Third, certain parameters, such as block size and kernel configuration, were selected empirically and kept fixed to ensure fair comparison among methods. Optimal parameter settings may vary across datasets and application scenarios. Adaptive parameter selection techniques, including data-driven block size selection or kernel parameter optimisation, could be investigated to improve flexibility and performance.

Finally, further improvements may be achieved by incorporating spatial regularisation or contextual constraints to enhance boundary consistency while maintaining the unsupervised nature of the framework. Comparative evaluation with more recent unsupervised or weakly supervised change detection methods could also provide additional insight into the strengths and limitations of the proposed approach.

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