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**MÉTODOS NÃO SUPERVISIONADOS DE DETECÇÃO DE MUDANÇA
APLICADOS AO MAPEAMENTO DE DESLIZAMENTO DE MASSA:
ESTUDO DE CASO EM SÃO SEBASTIÃO, BRASIL**

**São José dos Campos
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Trabalho de Conclusão de Curso apresentado como requisito parcial para a obtenção do título de Bacharel em Engenharia Ambiental pela Universidade Estadual Paulista “Júlio de Mesquita Filho”.

Orientador: Prof. Dr. Rogério Galante Negri

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São José dos Campos, 25 de Maio de 2023.

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RESUMO

O deslizamento de terra é um dos riscos geológicos potenciais que representam uma ameaça significativa para a população. Com as mudanças climáticas globais e o aumento na intensidade das chuvas em determinadas regiões, a frequência da ocorrência de deslizamentos de terra tem aumentado. Consequentemente, os danos e perdas associados a eventos dessa natureza também têm se agravado. Portanto, o estudo dos impactos causados por deslizamentos de terra é fundamental para avaliar as consequências desses eventos e desenvolver ações de auxílio e planejamento adequadas. A aplicação de métodos não supervisionados de detecção de mudanças em dados de sensoriamento remoto surge como uma ferramenta potencial no mapeamento automatizado de áreas atingidas por deslizamentos de terra. Isso permite uma resposta mais rápida e eficiente em situações de desastre e ajuda na identificação de áreas críticas que precisam de intervenção imediata. Neste contexto, este estudo se concentra na análise de diferentes técnicas não supervisionadas de detecção de mudanças entre imagens. Utilizando dados multiespectrais obtidas pelo sensor MultiSpectral Instrument, a bordo do satélite Sentinel-2, o estudo mapeia os deslizamentos de terra ocorridos em São Sebastião, Brasil, em fevereiro de 2023. Os resultados destacam a importância da escolha cuidadosa dos dados e dos parâmetros associados aos métodos adotados. A precisão na detecção de deslizamentos de terra está diretamente relacionada à qualidade e à resolução das imagens, bem como aos algoritmos e parâmetros escolhidos. Além disso, os resultados indicam que, entre as várias técnicas analisadas, as abordagens baseadas em conceitos de Aprendizado de Máquina apresentam os maiores índices de acurácia, com F1-Score e coeficiente kappa iguais ou superiores a 0.96 e 0.92, respectivamente. Isso demonstra a eficácia desses métodos na detecção de mudanças em imagens de sensoriamento remoto e na identificação de áreas afetadas por deslizamentos de terra.

Palavras-chave: Detecção de mudanças entre imagens, métodos não supervisionados, deslizamentos de terra, dados multiespectrais, Sentinel-2.

ABSTRACT

Landslides are one of the potential geological hazards that pose a significant threat to the population. With global climate change and an increase in rainfall intensity in certain regions, the frequency of landslides has increased. Consequently, the damage and losses associated with events of this nature have also worsened. Therefore, studying the impacts caused by landslides is essential to assess the consequences of these events and develop appropriate assistance and planning actions. The application of unsupervised change detection methods to remote sensing data emerges as a potential tool in the automated mapping of areas affected by landslides. This allows for a faster and more efficient response in disaster situations and helps identify critical areas that need immediate intervention. In this context, this study focuses on the analysis of different unsupervised change detection techniques between images. Using multispectral images obtained by the MultiSpectral Instrument sensor, on board the Sentinel-2 satellite, the study maps the landslides that occurred in São Sebastião, Brazil, in February 2023. The results highlight the importance of careful choice of data and parameters associated with the methods adopted. Accuracy in landslide detection is directly related to the quality and resolution of the images, as well as the algorithms and parameters chosen. Furthermore, the results indicate that, among the various techniques analyzed, approaches based on Machine Learning concepts present the highest accuracy rates, with F1-Score and kappa coefficient equal to or greater than 0.96 and 0.92, respectively. This demonstrates the effectiveness of these methods in detecting changes in remote sensing images and identifying areas affected by landslides..

Keywords: Change detection between images, unsupervised methods, landslides, multispectral data, Sentinel-2.

SUMÁRIO

1 – INTRODUÇÃO	14
2 – ARTIGO SUBMETIDO	18
3 – CONSIDERAÇÕES FINAIS	50
Referências	51
ANEXO A – Comprovante de Submissão	55

1 INTRODUÇÃO

As mudanças climáticas representam uma ameaça global crescente que está diretamente ligada a eventos naturais potencialmente desastrosos (STERN, 2006). Esse fenômeno é particularmente preocupante quando as condições climáticas extremas afetam diretamente o ambiente local, ou quando as atividades humanas contribuem para a intensificação desses impactos (ADGER; KELLY; NINH, 2012). Nesse contexto, as análises ambientais têm emergido como um tópico central, como apontado por Ahmed e Long (2013), unindo cientistas físicos e sociais na exploração dos impactos dos desastres relacionados à meteorologia, hidrologia e clima.

Desastres naturais, como ciclones, tornados, inundações e tsunamis, não apenas causam danos materiais significativos, mas também resultam em grandes deslocamentos e perdas humanas (KHAN et al., 2015; FITZPATRICK, 2010; WISNER, 2004). Entre os desastres, os deslizamentos de terra se destacam como uma preocupação crítica para as autoridades responsáveis pelo planejamento de infraestrutura e proteção ambiental (DAHALL et al., 2008). Os perigos associados a deslizamentos de terra são complexos e multifacetados, influenciados por uma série de variáveis intrínsecas e fatores externos. Entre as variáveis intrínsecas, a topografia desempenha um papel crucial, tornando áreas montanhosas e inclinadas mais suscetíveis a esse tipo de desastre. Além disso, fatores externos, como chuvas intensas, terremotos e atividades vulcânicas, podem desencadear deslizamentos de terra devido à instabilidade do solo (SIDDLER; JONES; PAYNE, 1991; WU; SIDLER, 1995; ATKINSON; MASSARI, 1998; DAI et al., 2001; CEVIK; TOPAL, 2003). Portanto, a combinação desses fatores com questões sociais, como a ocupação de áreas impróprias devido à desigualdade social, intensifica a vulnerabilidade dessas regiões, aumentando as chances de ocorrência de desastres (DIAS; HÖLBLING; GROHMANN, 2021). Portanto, a compreensão e o monitoramento cuidadoso desses elementos são fundamentais para a prevenção e mitigação de desastres naturais (AHMED; LONG, 2013).

Os deslizamentos de terra causados por chuvas na América do Sul têm uma concentração notável no Brasil, o que é destacado por Froude e Petley (2018), que apontam que o Brasil representa 37% dos eventos fatais relacionados a deslizamentos no continente. No contexto brasileiro, os desastres naturais são uma ocorrência recorrente, e os deslizamentos de terra emergem um risco de alta incidência no país, como observado em estudos anteriores (COELHO-NETTO; AVELAR; LACERDA, 2009; VIEIRA; GRAMANI, 2015; ESTATÍSTICA, 2019). Esses deslizamentos têm causado perdas econômicas e sociais praticamente todos os anos, resultando em impactos significativos na vida das comunidades afetadas (ESTATÍSTICA, 2019; FROUDE; PETLEY, 2018).

A alta incidência de deslizamentos de terra no Brasil pode ser atribuída a uma combinação de fatores. Primeiramente, as características geológicas e geomorfológicas do país, que incluem áreas montanhosas e declives íngremes, criam um ambiente propício para esses

eventos. Eventos pluviométricos intensos e prolongados, como chuvas torrenciais, são outra causa significativa, já que podem saturar o solo e desencadear movimentos de massa (DIAS; HÖLBLING; GROHMANN, 2021; TOMINAGA; SANTORO; AMARAL, 2009). Além disso, a desigualdade social no país, aliada ao crescimento desordenado das cidades, sem planejamento adequado do uso do solo, impulsiona a ocupação de encostas e morros, aumentando o risco de desastres, principalmente para aqueles que não têm poder aquisitivo para se adaptarem a tais circunstâncias, como observado por Dias, Hölbling e Grohmann (2021) e Tominaga, Santoro e Amaral (2009). Portanto, a compreensão aprofundada desses fatores e a implementação de estratégias de prevenção e mitigação são essenciais para reduzir a frequência e a gravidade dos deslizamentos de terra no Brasil.

Durante os dias 18 e 19 de fevereiro de 2023, a cidade de São Sebastião, localizada no estado de São Paulo, Brasil, testemunhou uma série de deslizamentos de terra. Estes eventos foram desencadeados por chuvas extraordinárias, que atingiram um acumulado de 683 milímetros em apenas 24 horas. As condições climáticas extremas, combinadas com a ocupação de áreas de risco pela população, resultaram não apenas em deslizamentos de terra, mas também em alagamentos. Lamentavelmente, esses incidentes resultaram na perda de sessenta e cinco vidas e deixaram muitas famílias desabrigadas. (COSTA, 2023; CHARTER, 2023).

Nos últimos vinte anos, houve uma notável adoção de tecnologias digitais no contexto da pesquisa e gestão de riscos relacionados a deslizamentos de terra (BAO et al., 2022). Essas tecnologias desempenham um papel fundamental na prevenção e mitigação desses eventos. Elas podem ser categorizadas em quatro grupos principais: detecção, comunicação, processamento e ação, como observado em estudos anteriores, incluindo Aceto, Persico e Pescapé (2018) e Lember, Brandsen e Tönurist (2019).

A tecnologia de detecção é particularmente crucial para a gestão de riscos de deslizamentos de terra. Ela envolve a coleta de informações relacionadas a deslizamentos de terra por meio de uma variedade de sensores. Isso inclui a medição de dados como precipitação, deformação das montanhas e pressões no solo (CHAI; LV; XIAO, 2019; HERMLE et al., 2021; QI et al., 2021). Sensores subterrâneos, como extensômetros, piezômetros, medidores de inclinação e acelerômetros, são usados para monitorar deformações e pressões no subsolo. Por outro lado, os sensores remotos desempenham um papel fundamental no monitoramento de deslizamentos de terra. Isso inclui sensoriamento multiespectral (óptico), radares de abertura sintética (SAR) e sensores LiDAR. Esses sensores possibilitam a detecção a longa distância sem a necessidade de contato direto com a área de risco e oferecem a vantagem de cobrir grandes áreas a um custo relativamente baixo, tornando-os ideais para monitoramento em larga escala (BAO et al., 2022; ZHAO; LU, 2018).

O sensoriamento remoto é uma ferramenta valiosa na detecção de deslizamentos de terra, oferecendo várias vantagens significativas que contribuem para a eficácia desse processo. Como destacado por Meneses e Almeida (2012), o sensoriamento remoto permite a coleta repetitiva de dados em intervalos curtos, fornecendo imagens de alta qualidade com resolução espacial e temporal variável. Essas características, juntamente com a capacidade de oferecer uma

visão global de áreas de interesse, tornam o sensoriamento remoto uma fonte rica de informações para a detecção de deslizamentos de terra (CHEN et al., 2018).

Essa tecnologia tem sido amplamente empregada na detecção de deslizamentos de terra, utilizando uma variedade de métodos baseados em características, aprendizado de máquina e detecção de mudanças (HUANG et al., 2020). Essa diversidade de abordagens pode levar a uma economia de recursos humanos e à automação do processo de detecção. Como resultado, os dados de sensoriamento remoto se tornaram a principal fonte de informações em várias aplicações de detecção de mudanças.

Para realizar a detecção de mudanças (Change Detection - CD) usando dados de sensoriamento remoto, é essencial comparar a representação espacial de duas imagens em momentos distintos e controlar todas as variações causadas por diferenças em variáveis não relevantes. O objetivo é medir as alterações ocasionadas pelas diferenças nas variáveis de interesse, conforme explicado por Green, Kempka e Lackey (1994). Uma suposição fundamental nesse processo é que as alterações nos objetos de interesse resultarão em modificações nos valores de reflectância ou nas texturas locais das imagens, e essas mudanças podem ser distinguidas de outras variações, como aquelas causadas por condições atmosféricas, iluminação, ângulos de visão e umidade do solo (DEER, 1995). Como resultado, várias técnicas foram desenvolvidas ao longo do tempo para a detecção de mudanças em imagens de sensoriamento remoto, abrangendo métodos como análise multitemporal, segmentação de imagens, classificação de padrões, entre outros (SINGH, 1989; MOUAT; LANCASTER, 1993; DEER, 1995; COPPIN; BAUER, 1996; JENSEN et al., 1997; YUAN; ELVIDGE, 1998; SERPICO; BRUZONE, 1999; JENSEN, 2005).

Essas técnicas desempenham um papel fundamental na detecção de mudanças, permitindo a identificação de áreas suscetíveis a deslizamentos de terra com base em alterações nas características do terreno ao longo do tempo (CHEN et al., 2018). Isso não apenas contribui para a prevenção e mitigação de desastres naturais, como também auxilia na tomada de decisões informadas em relação à gestão de riscos em áreas vulneráveis.

Os métodos de detecção de mudanças se dividem em duas categorias principais: supervisionados e não supervisionados. Os métodos supervisionados requerem amostras reais e informações detalhadas sobre as transições na cobertura do solo, enquanto os métodos não supervisionados empregam técnicas automáticas para gerar mapas binários indicando a presença ou ausência de mudanças (SINGH, 1989; BRUZZONE; PRIETO, 2000; VOLPI et al., 2012).

Dentre os métodos não supervisionados, existem várias abordagens notáveis. O método de Análise de Vetor de Mudanças (CVA) (MALILA, 1980) utiliza limiarização e comparação de vetores de pixels para detectar mudanças. Outro método, conhecido como PCA-KM (CELIK, 2009), combina a Análise de Componentes Principais (PCA) com o algoritmo K-Means para reduzir a dimensionalidade e agrupar dados em clusters, o que é útil para a detecção de mudanças. O Gustafson-Kessel Clustering (GKC) (GUSTAFSON; KESSEL, 1979) emprega o algoritmo Simulated Annealing (KIRKPATRICK; GELATT; VECCHI,) de agrupamento para detectar mudanças. O Unsupervised Slow Feature Analysis (USFA) (WU; DU; ZHANG, 2014) foca em características de baixa frequência. O Alternating Sequential Filtering (ASF) (MURA et

al., 2008) aplica filtros sequenciais para destacar padrões de mudança. O método Floating References (FR) (NEGRI; FRERY, 2019) utiliza referências flutuantes para identificar alterações na cena. Por fim, o Homogeneous Block Single-class Classification (HBSC) (NEGRI et al., 2021) concentra-se na detecção de anomalias, identificando regiões que não seguem o padrão homogêneo da cena.

Neste contexto, o objetivo deste estudo é analisar diferentes métodos não supervisionados para a detecção de mudanças a partir de imagens multiespectrais, aplicados à identificação de deslizamentos de terra. A região de São Sebastião, localizada no estado de São Paulo, Brasil, foi escolhida como estudo de caso devido a múltiplos eventos de deslizamentos de terra ocorridos recentemente. Para esta análise, serão utilizadas imagens obtidas pelo sensor Sentinel-2 MSI e atributos extraídos dessas imagens. Para avaliar os resultados, dados de referência provenientes do projeto Charter (INPE, 2023) serão adotados.

Essa pesquisa tem o potencial de contribuir significativamente para identificar áreas em que deslizamentos de terra ocorreram e auxiliar na gestão de riscos em áreas suscetíveis a esse tipo de desastre. A combinação de métodos não supervisionados com tecnologias de sensoriamento remoto pode oferecer uma abordagem eficaz e escalável para monitorar e prevenir deslizamentos de terra, proporcionando maior segurança às comunidades afetadas.

2 ARTIGO SUBMETIDO

Moço, G. A. ; Negri, R. G. Unsupervised change detection methods applied to landslide mapping: case study in São Sebastião, Brazil.

Artigo elaborado de acordo com as diretrizes do periódico “Journal of Applied Remote Sensing” (ISSN 1931-3195), submetido em 8 de novembro de 2023. O comprovante de submissão do referido artigo é apresentado no Anexo [A](#).

Unsupervised change detection methods applied to landslide mapping: case study in São Sebastião, Brazil

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Abstract. Landslides constitute a significant geological risk for populations globally. The increased frequency of landslides due to global climate change and intensified rainfall in specific regions has led to more substantial losses and damages associated with such events. Consequently, the study of landslide impacts assumes critical importance for assessing the effects and devising measures for assistance and planning. The application of unsupervised change detection methods to remote sensing data emerges as a potential tool for automating the mapping of landslide-affected areas. In this context, the study encompasses an analysis of various unsupervised change detection techniques. As a case study, the landslides that occurred in São Sebastião, Brazil, in February 2023, were mapped using multispectral images acquired by the MultiSpectral Instrument sensor aboard the Sentinel-2 satellite. The results underscore the imperative nature of a careful selection of data and parameters associated with the chosen methods. Moreover, among all the alternative techniques examined, those founded on Machine Learning concepts consistently yielded the highest levels of accuracy. These methods demonstrated F1-Score and kappa coefficients equal to or greater than 0.96 and 0.92, respectively. These findings highlight the utility of Machine Learning-based techniques for landslide mapping and addressing geological risks.

Keywords: Unsupervised, change detection, landslide, multispectral, Sentinel-2.

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1 Introduction

Climate change represents an escalating global threat and is intricately linked to natural events that can potentially turn catastrophic.¹ These threats are exacerbated when local environments are affected by environmental changes and human activities.² In this context, environmental analysis has garnered increasing attention within the academic community.³ Physical and social scientists have directed their efforts towards understanding the causes and consequences stemming from meteorological and climatological events, such as cyclones, tornadoes, floods, tsunamis, and more, which, in turn, result in substantial material and human losses.^{4–6}

Among various types of disasters, landslides emerge as a paramount concern for authorities responsible for infrastructure planning and environmental protection.⁷ The risks associated with

these landslides are influenced by a multitude of intrinsic variables and external factors, ranging from topography to intense rainfall, earthquakes, and volcanic activities.^{8–12}

In South America, landslides are typically induced by heavy rainfall. Brazil, in particular, experiences recurring landslides, making them the most frequent type of disaster in the country,^{13–16} leading to substantial economic and social losses virtually every year. The heightened prevalence of landslides in Brazil can be attributed to a convergence of geological and geomorphological features, prolonged and intense rainfall episodes, and urban development in unsuitable areas.^{17,18}

Over the past two decades, there has been widespread adoption of digital technologies in the field of landslide-related risk research and management.¹⁹ These technologies can be broadly classified into four primary categories: detection, communication, processing, and action.^{20,21} Detection technology involves the collection of information about landslides through sensors, encompassing data such as precipitation, mountain deformation, and pressures.^{22–24} Sensors employed in landslide risk management include underground sensors, such as strain gauges, piezometers, tilt meters, and accelerometers, which monitor subsurface deformations and pressures, and remote sensors, which enable long-distance detection without direct contact. These remote sensors include multispectral sensing (optical), synthetic aperture radars (SAR), and LiDAR sensors.²⁵ It is important to note that remote sensors offer the advantage of large-scale monitoring at a lower cost. In contrast, underground sensors provide higher accuracy and real-time measurements but apply to more limited areas.¹⁹

Among the previously mentioned alternatives, Remote Sensing is a valuable tool for landslide detection. It offers several key advantages, including repetitive data collection at short intervals, high-quality images with variable spatial and temporal resolution, a global perspective, and data presented in a digital format suitable for computational analysis.²⁶ Through feature-based methods,

Machine Learning techniques, change detection algorithms, and Remote Sensing have empowered the automated mapping of landslide-affected areas with minimal reliance on human resources.^{27,28} These characteristics collectively establish Remote Sensing as the primary information source for landslide detection and analysis.

Within the spectrum of techniques utilized in analyzing the impacts induced by landslides, change detection methods hold a significant position. These methods are designed to compare the spatial configuration of a particular region across two or more time instances and to quantify or map the alterations that have occurred.²⁹ The underlying principle behind utilizing remote sensing data for change detection revolves around the assumption that modifications to the objects of interest will result in changes in reflectance values or local textures. These alterations are distinguished from changes caused by other factors, such as variations in atmospheric conditions, lighting, viewing angles, and soil humidity.³⁰ Based on this fundamental assumption, a range of change detection techniques has been developed.^{30–37}

Change detection methods can be categorized into two main groups: supervised and unsupervised techniques. Supervised methods demand actual samples and comprehensive information regarding land cover transitions, while unsupervised methods employ automated techniques to generate maps indicating the presence or absence of changes.^{31,38,39}

Among unsupervised techniques, several noteworthy methods have been developed for change detection. The CVA (Change Vector Analysis) method⁴⁰ relies on applying a threshold to the amplitude of differences in comparisons between time instances. Another prominent approach is the PCA-KM method.⁴¹ This technique combines Principal Component Analysis (PCA) with the K-Means (KM) algorithm to extract local features and discern between cases with and without changes. Another effective method is the GKC+SA (Gustafson-Kessel Clustering combined with

Simulated Annealing).⁴² It utilizes the Gustafson-Kessel Clustering algorithm⁴³ parameterized by Simulated Annealing⁴⁴ to identify clusters representing instances of change or stability. The USFA (Unsupervised Slow Feature Analysis) technique⁴⁵ employs data transformation to distinguish between high-frequency cases indicative of change and low-frequency cases signifying the absence of change. The Alternating Sequential Filtering (ASF) method⁴⁶ utilizes morphological filters to accentuate change patterns. The Floating References (FR) method⁴⁷ innovatively leverages the concept of non-fixed references to statistically model spatio-temporal changes. Lastly, the HBSC (Homogeneous Block Single-class Classification) technique⁴⁸ concentrates on anomaly detection to compare different images and map associated changes.

In light of the motivations and discussions presented, this study aims to analyze various unsupervised methods for detecting changes in remotely sensed images, with a particular focus on the identification of landslides. As a case study, we will examine the region of São Sebastião, state of São Paulo, Brazil. This region experienced multiple landslide events between February 18 and 19, 2023.⁴⁹ The study will utilize images acquired by the Multispectral Instrument (MSI) sensor onboard the Sentinel-2 satellite. To assess the accuracy of the mapping process, we will rely on reference data provided by established databases.

This article is structured as follows: Section 2 introduces the theoretical principles underlying a range of unsupervised change detection methods, along with discussions on attribute extraction from remote sensing images. In Section 3, we provide insights into the study area, the images employed, and the reference data used for result evaluation. Section 4 encompasses the analysis and discussion of the obtained results, followed by our conclusions in Section 5.

2 Theoretical Framework

2.1 Unsupervised change detection methods

Change detection involves the process of identifying disparities in the state of an object or phenomenon by comparing observations made at different points in time.³¹ These techniques typically entail the comparison of a pair of images, denoted as $\mathcal{I}^{(1)}$ and $\mathcal{I}^{(2)}$, which were captured at distinct time intervals but pertain to the same spatial domain $\mathcal{S} \in \mathbb{N}^2$. The aim is to generate a third image that highlights the alterations occurring between the two-time instances.⁴⁷

Formally, we denote by $\mathbf{x}_i^{(j)} = \mathcal{I}^{(j)}(s_i)$ the attribute vector associated with the position $s_i \in \mathcal{S}$, where $\mathbf{x}_i^{(j)}$ is an element of the attribute space $\mathcal{X}$. These attribute vectors $\mathbf{x}_i^{(j)}$ capture measurements acquired by the image sensor at specific locations on the Earth's surface. Following this notation, the changes occurring between $\mathcal{I}^{(1)}$ and $\mathcal{I}^{(2)}$ at position s_i can be represented by the scalar z_i . Consequently, $\mathcal{Z}$ is the resulting image that represents the changes over $\mathcal{S}$. In a straightforward approach, $\mathcal{Z}(s_i) = \left\| x_i^{(1)} - x_i^{(2)} \right\|_2$ denotes the amplitude of the temporal difference at s_i .⁴⁷

Change identification techniques are rooted in the principles of Pattern Recognition and Digital Image Processing. Chen Wu et al.⁵⁰ categorize these techniques into five primary groups: (i) algebraic operations between images; (ii) image transformation; (iii) attribute extraction; (iv) image classification; and (v) other methods. In a broader perspective, Michele Volpi et al.³⁹ classify change detection methods into supervised and unsupervised categories. Supervised methods rely on labeled data to train a classifier, whereas the unsupervised approach relies on processes based on thresholds and data clustering. Notably, unsupervised methods are distinguished by their independence from prior knowledge, which renders them particularly appealing when compared to supervised methods.⁴⁷

The subsequent sections provide concise discussions on various unsupervised change detection methods, all of which are subsequently delineated in the experiment design and analyses, as presented in Sections 3.3 and 4, respectively.

2.1.1 CVA

Introduced by Malila (1980),⁴⁰ the CVA method is widely recognized and is distinguished by its three primary steps: (i) determination of the change vector; (ii) computation of the amplitude of differences; and (iii) application of amplitude thresholding.

In the initial stage, images corresponding to the same geographical area but captured at different times are compared and produced an “image of differences” in which a change vector represents each pixel. Subsequently, the magnitude of each change vector is computed, giving rise to a one-dimensional image. Finally, the magnitude image undergoes a thresholding process to create a map that distinguishes temporal changes.^{51,52} Commonly employed algorithms, such as Otsu (1979)⁵³ or Kittler-Illingworth (1986),⁵⁴ are typically applied in the thresholding step.

2.1.2 PCA-KM

Introduced by Celik (2009),⁴¹ the PCA-KM method combines Principal Component Analysis (PCA)^{31,55} with the K-Means algorithm.⁵⁶ The process begins by segmenting the amplitude image of temporal differences into non-overlapping blocks of dimension $h \times h$, which serve as the basis for vectors containing the corresponding observed values. These vectors are subsequently projected into a space defined by the PCA transformation, retaining only the first s components of this projection, with $s \leq h$. Finally, the projected data undergoes clustering using the K-Means algorithm, aggregating them into two groups, with the one closest to the origin of the projected

space being associated with the absence of changes.

2.1.3 GKC+SA

Gustafson and Kessel (1979)⁴³ introduced an adaptive distance norm that incorporates a fuzzy covariance matrix to gauge the distance between groups and observations. This innovation forms the basis of the Gustafson-Kessel Clustering (GKC) method, where each group is characterized by an adaptive matrix that is dynamically adjusted to represent the data distribution.

Similar to the PCA-KM method, Gustafson and Kessel (1979)⁴³ advocates the application of the GKC algorithm to distinguish between two groups, the regions of change and non-change. This differentiation is based on the amplitudes of differences and contextual information derived from the application of moving spatial averages to these amplitudes. The parameterization of the GKC algorithm is achieved through the use of the Simulated Annealing (SA) strategy,⁴⁴ employing the Xie-Beni measure⁵⁷ as the objective function.

2.1.4 USFA

Wu et al. (2014)⁴⁵ introduced the USFA algorithm, which is designed to extract from input data the invariant features, often referred to as “slow” variables or components. In the context of change detection, pixels that exhibit no alterations correspond to the slowly variable component, while pixels that have changed exhibit rapid variations. Within the space of invariant features transformed by the Slow Feature Analysis (SFA) technique, it is presumed that unchanged pixels are effectively suppressed, leading to improved separability among pixels that have experienced changes.

In these conditions, the input data transforms and is mapped to a new attribute space, simplifying the identification of regions with changes and regions without changes. To achieve this,

thresholding techniques can be applied, such as the Otsu (1979)⁵³ or Kittler-Illingworth (1986) algorithms,⁵⁴ which are computed based on the frequency distribution of the transformed data after discretization using classical rules, for example, those defined by Scott (1979)⁵⁸ or Freedman-Diaconis (1981).⁵⁹

2.1.5 ASF

Dalla Mura et al. (2008)⁴⁶ present an approach based on the iterative application of morphological filters. Commencing with the amplitude difference image, this method involves iterative applications of opening operations (i.e., erosion followed by dilation) and closing operations (i.e., dilation followed by erosion), with a gradual increase in the dimensions of the structuring element. The number of iterations serves as a parameter for the method. The primary objective of this described process is to streamline amplitude differences while retaining the geometrical attributes of the targets.

Lastly, the Kittler-Illingworth algorithm⁵⁴ is utilized to threshold the outcome of the preceding process, categorizing pixels with values below and above the threshold as “no change” and “change”, respectively.

2.1.6 FR

Negri and Frery (2021)⁴⁸ introduced the FR method, which discriminates between areas of change and non-change by examining deviations in behavior among similar objects. A notable feature of this method is its utilization of floating references, which are identified through clustering. This approach renders the method independent of prerequisites like radiometric normalization and other pre-processing steps.

The process starts with the spatial smoothing of the initial instant, denoted as $\mathcal{I}^{(1)}$, where the attributes' average values within a specified neighborhood are employed. Subsequently, a divisive hierarchical grouping is executed with the goal of partitioning the initial instant into subsets of a predefined minimum size. Finally, trend references are established for the deviations' amplitudes between $\mathcal{I}^{(1)}$ and $\mathcal{I}^{(2)}$. Values that significantly deviate from these references are considered indicative of relevant changes.

2.1.7 HBSC

Negri et al. (2021)⁴⁸ introduce the HBSC method, a comprehensive approach that consists of four distinct steps. Initially, a difference image is computed for each attribute in a pair of images. Subsequently, homogeneous blocks are identified on this difference image, which are regarded as regions representing “no change”. Finally, using the non-change examples and the difference image, modeling and the application of the One-class Support Vector Machine method were carried out. This methodology enables the extrapolation of “non-change” occurrences, thus facilitating the detection of changes across the entire spatial domain.

An essential characteristic of the HBSC method is its consideration of both the statistical data behavior and the geospatial distribution. This comprehensive approach enables more informed and robust decisions regarding the homogeneity of regions classified as “no change”.

2.2 Attribute extraction

In image processing, the extraction of texture attributes is a standard pre-processing step, as it facilitates the creation of alternative representations that harness inherent spatial information. Texture, in this context, pertains to patterns of intensity variations within an image, encompassing spatial

information. This spatial information is crucial for characterizing identified objects or regions of interest in the image.⁶⁰

Haralick (1973) introduced a widely adopted method for computing texture features from the Gray Level Co-occurrence Matrix (GLCM).⁶¹ The GLCM provides the foundation for calculating various texture characteristics, including second angular momentum, contrast, correlation, entropy, variance, inverse difference moment, difference mean, difference variance, difference entropy, sum mean, variance of sum, and sum entropy.

Furthermore, in addition to its various applications, PCA can be employed with images to extract attributes. As described by Jensen (2015),⁶² the transformation of original data through PCA facilitates the condensation of redundant data into a smaller number of bands or attributes. This not only aids in reducing dimensionality but also yields uncorrelated representations with enhanced descriptive capacity.

When data is transformed through PCA, a component number equal to the number of dimensions in the input data is generated. The first component (PC1) encompasses information shared among all original bands or attributes. The second principal component (PC2) captures the most salient spectral features within the dataset. Consequently, the final principal components tend to concentrate noise and are less informative.⁶³

Eigenvalues and eigenvectors play a fundamental role in defining the principal components. The significance of each principal component is directly related to the magnitude conveyed by its associated eigenvalue.^{26,64}

3 Materials and Methods

3.1 Study Area

In order to assess the effectiveness of unsupervised change detection techniques for mass landslide mapping, a specific area within the municipality of São Sebastião, state of São Paulo, Brazil, was selected as the study site (see Figure 1). This region recently experienced severe landslide events due to an exceptional rainfall event, with a recorded precipitation of 683 mm between February 18th and 19th, 2023. These events had devastating consequences, impacting not only the local population but also disrupting the region's infrastructure and logistics.^{49,65}

According to the Köppen climate classification, the study area falls under climate type Af, characterized by a Tropical Climate with the absence of a distinct dry season and consistent rainfall throughout the year.⁶⁶ The hot season in this region persists for approximately 5.6 months, extending from October 22th to April 8th, during which the average daily maximum temperature exceeds 32 °C.⁶⁷ Moreover, the study area encompasses slopes with varying altitudes, ranging from sea level to 320 meter, and is predominantly composed of cambisol soils. It is worth noting the presence of both metamorphic and sedimentary rocks in this region.^{68–71}

3.2 Data sets

To carry out this research, multispectral images acquired by the MSI (MultiSpectral Instrument) sensor on board the Sentinel-2B satellite were utilized. This sensor is capable of capturing the radiometric behavior of targets across a range of spectral bands from blue to shortwave infrared. The images under consideration were captured over the study area on February 15th and 25th, 2023, as illustrated in Figure 2(a-b). The section corresponding to the study area is comprised of 395×232 pixels and exhibits a spatial resolution of 10 m for the spectral bands, including blue

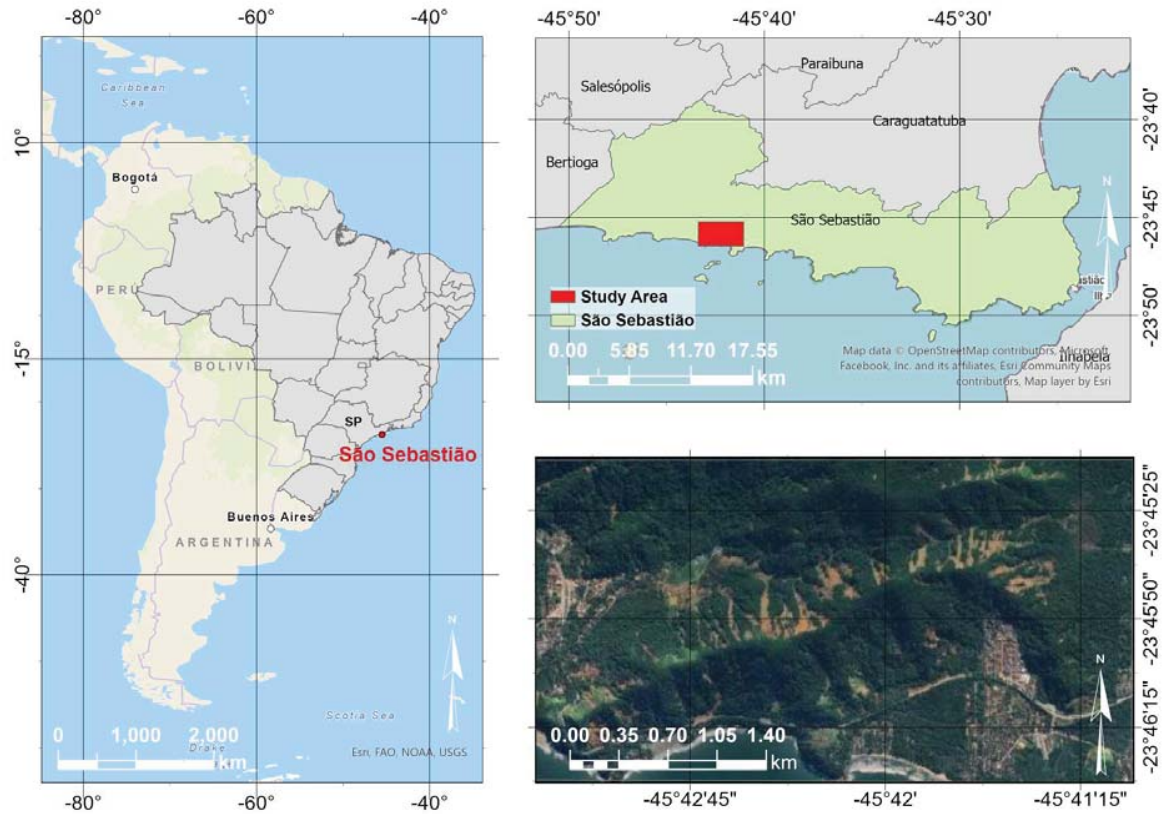


Fig 1 Geographic location of the study area

(band 2 ~ 490 nm), green (band 3 ~ 560 nm), red (band 4 ~ 665 nm), and near-infrared (band 8 ~ 842 nm).

In order to evaluate the outcomes, are employed reference data provided by the Disasters Character project (INPE, 2023).⁷² This project is a consortium involving various institutions and space agencies dedicated to supplying orbital data during global emergencies resulting from natural disasters. Figure 2(c)) depicts the reference data, encompassing samples collected from regions impacted by recent landslide events (“change”) and those that remained unaffected (“non-change”).

3.3 Experiment design

Figure 3 summarizes the experimental design considered in this study.

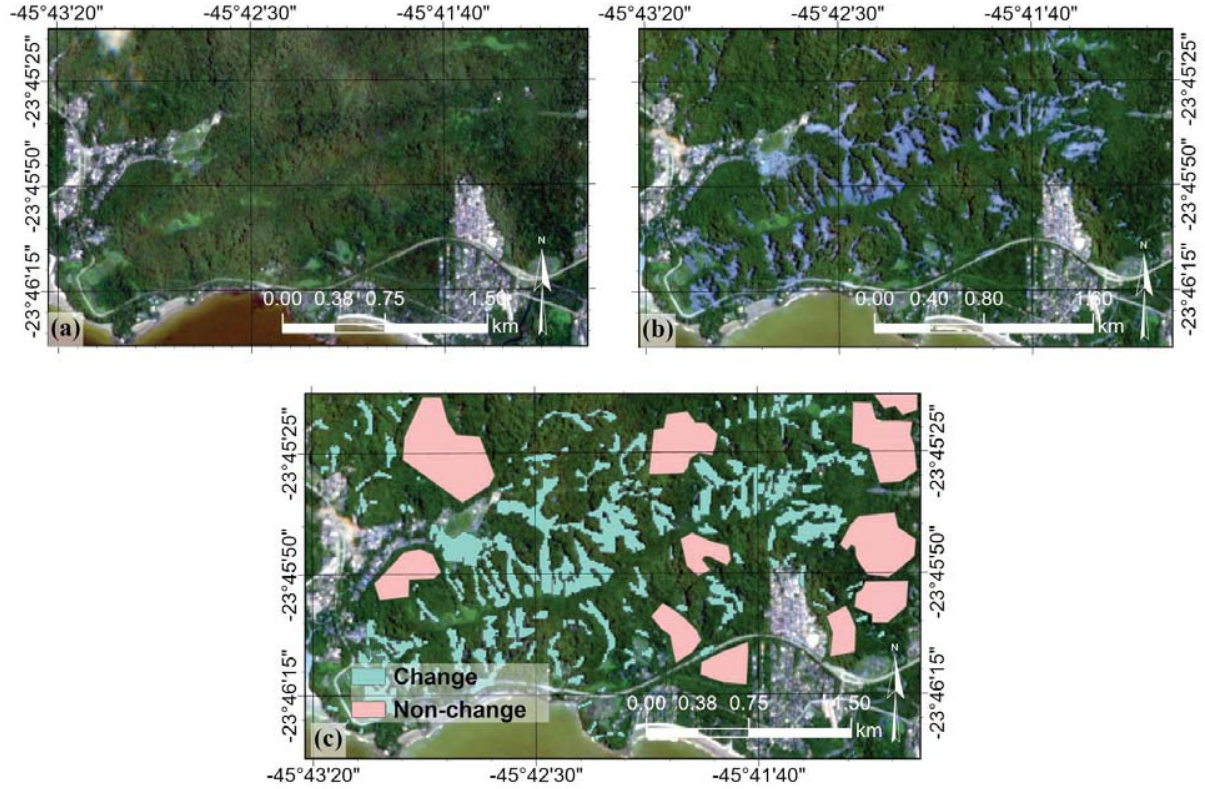


Fig 2 (a) Images of the study area before (February 15th, 2023) and (b) after (February 25th, 2023) the landslide events. (c) Representation of reference samples denoting areas affected (“change”) and unaffected (“non-change”) by recent landslide events. Representations in natural composite composition.

From the multispectral images ($\mathcal{I}^{(1)}$ and $\mathcal{I}^{(2)}$) used, as described in Section 3.2, and referred to herein as “Multi”, various texture attributes were extracted based on GLCM (Gray Level Co-occurrence Matrix). Additionally, the principal components were calculated using the PCA method.

Texture extraction was conducted using a neighborhood window of 9×9 pixels, with a displacement lag of 4 pixels in all directions. From each of the input multispectral images, a total of twelve texture attributes, as mentioned in Section 2.2, were generated. Following a qualitative assessment of the most pertinent texture attributes for representing the areas of interest, the attributes “dissimilarity”, “average”, “variance”, and “correlation” were selected. These attributes were computed from the band corresponding to the near-infrared. For subsequent discussions, the

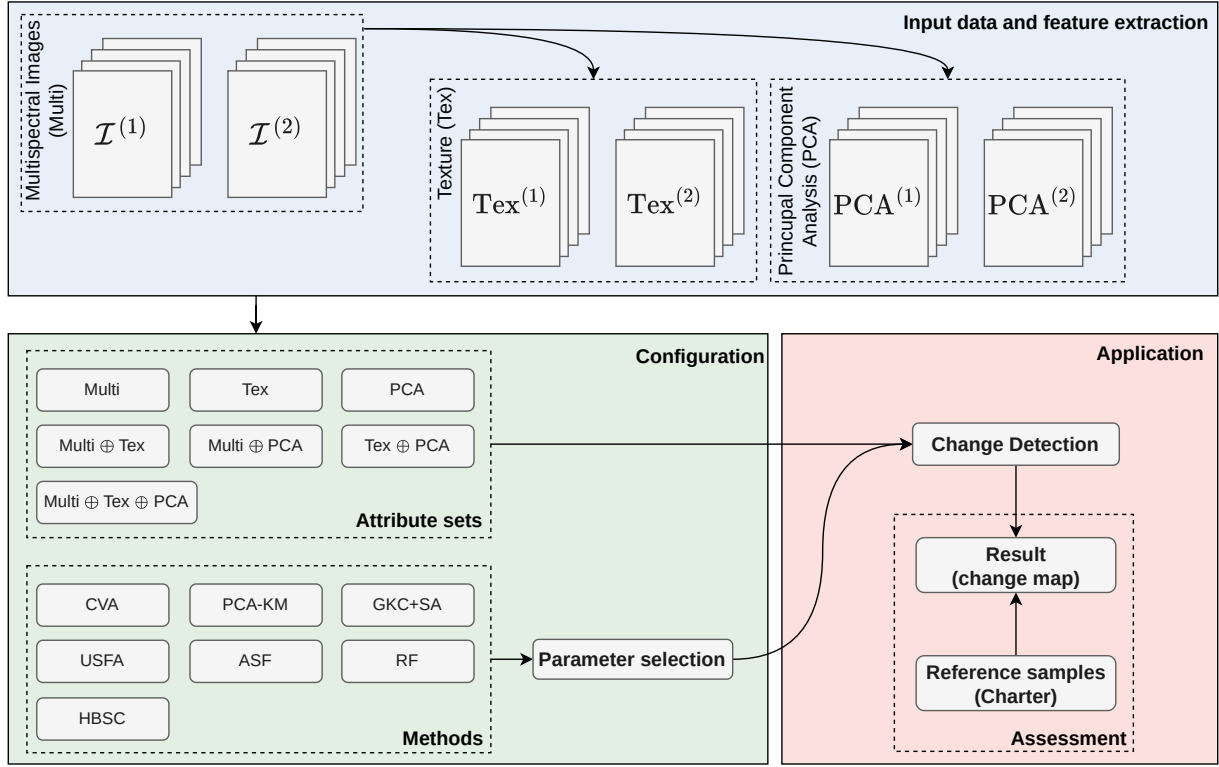


Fig 3 Experiment design workflow.

ensemble of extracted texture attributes will be denoted as “Text”.

In a similar vein, the PCA technique was applied to the original images, denoted as “Multi”. This procedure revealed that the first two principal components account for over 95% of the variance explained in the data, specifically 99.73% and 97.66% for the images dated February 15th and February 25th, respectively. Consequently, only the first two principal components will be considered in the following analysis. The attributes derived from this process will be referred to as “PCA12”.

After the above-described process, three pairs of images are defined, namely “Multi”, “Text”, and “PCA”. Based on these pairs, seven sets of attributes are established. Three sets correspond to the individual pairs: “Multi”, “Text”, and “PCA”. The remaining three sets result from pairwise combinations, i.e., “Multi+Text”, “Multi+PCA”, and “Text+PCA”. Additionally, there is a

combined set encompassing all attributes, denoted as “Multi+Text+PCA”. Each of these image pairs and attribute sets will undergo evaluation using the change detection methods discussed in Section 2 (i.e., CVA, PCA-KM, GCK+SA, USFA, ASF, FR, HBSC).

In addition to the different alternatives for data sets and change detection methods, different parameter settings for such methods were also tested. The CVA method was assessed based on two parameters: the thresholding method and the discretization rule. To threshold the difference image, both the Otsu⁵³ and Kittler-Illingworth⁵⁴ methods were considered. The Scott⁵⁸ and Freedman-Diaconis⁵⁹ rules were evaluated to discretize the histogram generated from the difference amplitude image.

In the evaluation of the PCA-KM method, two parameters were assessed: the block size for generating local representations of amplitude differences, designated as h (neighborhood size), and the number of principal components taken into account, denoted as s (subspace dimension). For h , two block sizes were considered: 3×3 and 5×5 . Regarding s , three values were scrutinized: 2, 3, and 5.

In concerns to the GKC method, it involves two key parameters: the convergence reference for the GKC method, represented as ϵ , and the “cooling factor” parameter utilized by the Simulated Annealing (SA) algorithm, denoted as α . The convergence reference was fixed at 0.0001, while the “cooling factor” parameter ranged from 0.8 to 0.9, with increments of 0.02.

For the USFA method, the same thresholding methods and discretization rules as those used in CVA were employed.

To assess the ASF method, the number of opening-closing iterations applied to the difference amplitude image was varied. We considered odd values of iterations, including 1, 3, 5, 7, and 9.

Regarding the FR method, two parameters are tuned: the neighborhood radius, which determines the range used in the spatial smoothing process, and the minimum cluster size, expressed as a percentage of the minimum size allowed for the clusters characterizing the initial instant. Initially, the neighborhood radius was set to 1, and we varied the minimum cluster size between 1%, 2%, and 3%. Then, the neighborhood radius was set to 0, and again, we varied the minimum cluster size between 1%, 2%, and 3%.

Finally, in the HBSC method, three parameters were considered: the significance adopted for the characterization of homogeneous blocks, denoted as α , the parameter associated with the SC-SVM method, denoted as ν , and the parameter associated with the radial basis function (RBF) kernel used in the SC-SVM method, denoted as γ . We set α to 0.6, ν to 0.001, and tested four different values for γ : 0.01, 0.05, 0.1 and 0.5.

For more details regarding the parameters required by each method, it is recommended to refer to the respective references cited in Section 2.

The resulting change maps from each configuration, comprising the data, methods, and parameters, are evaluated using the F1-Score⁷³ and kappa coefficient,⁷⁴ computed based on reference samples from the Charter project (Section 3.2, Figure 2(c)). The most accurate outcomes will be selected for further analysis and discussion concerning the methods and changes in the study area.

The methods used in this study were applied using the M.I.C.E.⁷⁵ software. The ENVI 5.6 software⁷⁶ was employed to resize the images to the study area's portion and collect reference samples, while the QGIS 3⁷⁷ system was used to create cartographic representations.

4 Results and discussions

Following the experimental design described in Section 3.3, multiple change maps were generated for the study area (Figure 5). The ensuing discussions encompass both a quantitative analysis for assessing performance and comparing the various change detection methods under consideration, as well as a qualitative analysis of their capabilities in identifying patterns related to landslides.

In Figure 4, the values of the F1-Score and kappa coefficients are presented for each method, taking into account the various input attributes and tested parameters. The results suggest that the FR method achieved the highest performance, with an F1-Score of 0.972 and a kappa coefficient of 0.944. This method exhibited consistency across the tested attributes and parameters, except for the “Text” and “Multi+Text” attributes. The HBSC method showed results close to the FR when using “Multi” data, regardless of the tested parameters. However, its performance was less satisfactory when applied to other attributes.

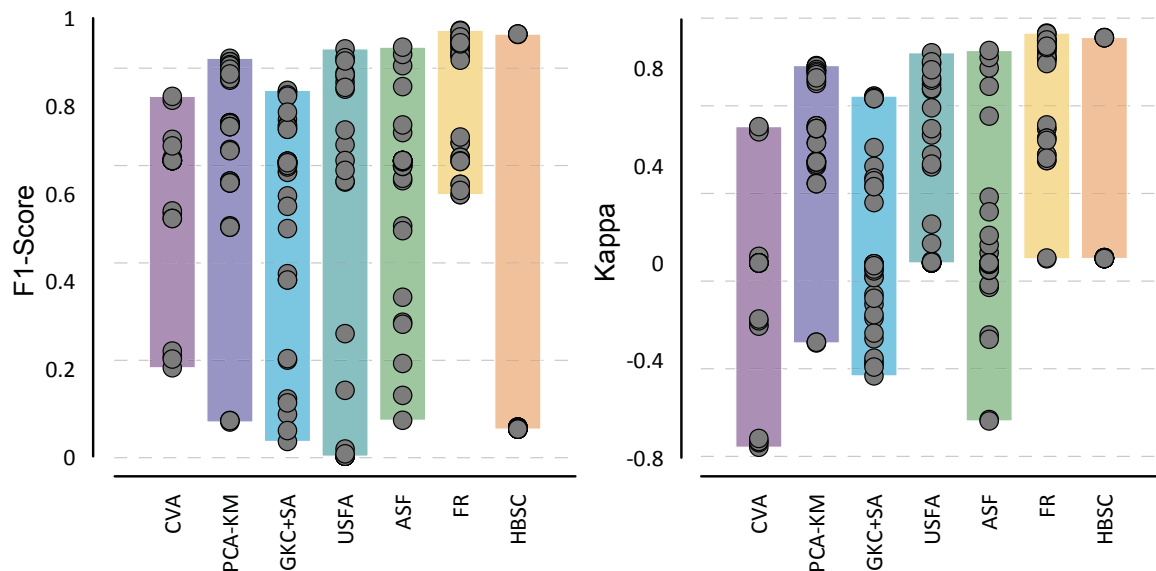


Fig 4 Values of the F1-Score and Kappa coefficients for each method analyzed, taking into account the different input attributes and tested parameters.

It is important to highlight the performance variation of the USFA method, which is notably

influenced by the choice of thresholding techniques. While the utilization of the Otsu algorithm resulted in subpar performance, as reflected in lower F1-Score and kappa coefficient values, employing the Kittler-Illingworth method yielded significantly improved results, with an F1-Score of 0.930 and a kappa coefficient of 0.863 when using the “Multi” dataset. Additionally, concerning the kappa coefficient, the CVA method with Kittler-Illingworth thresholding exhibited the weakest performance when applied to the “PCA12” attribute. These discrepancies emphasize the critical importance of systematically evaluating various parameter configurations to select the most suitable one, as this choice has a direct impact on the achieved results.

Table 1 presents the highest accuracy rates attained by each method with regard to the various attributes and parameters examined. These outcomes underscore the methods’ sensitivity to the input data. It is noteworthy that, for most methods, the utilization of the “Multi” attributes corresponds to superior results, except for the ASF method, which exhibits improved performance when applied to the “Multi+Text” attributes. Conversely, the “Text” and “Multi+Text” attributes yield the weakest performances. This observation can be attributed to the resemblance between the textures of vegetation and landslide areas, which hampers change detection. Additionally, since texture attribute calculation involves convolutional filters, the degradation of spatial resolution incurred by this process can affect the differentiation of objects of interest.

Figure 5 displays the most accurate change maps, as discussed earlier. In accordance with the quantitative analyses, the FR method produced the most reliable change map, with fewer false positives, particularly in urban areas, which is crucial for accurate change detection, especially in landslide-prone areas. Conversely, the qualitative analysis underscores CVA’s poor performance, as it exhibits frequent false positives across all regions. Once again, this observation corroborates the quantitative results. Regarding the ASF method, although it doesn’t rank as the worst

Table 1 The most suitable attributes obtained by the analyzed methods concerning the various parameters considered.

Methods	F1-Score	Kappa	Attribute	Parameters
CVA	0.822	0.560	“Multi”	Kittler-Ilingworth; Freedman-Diaconis’
PCA-KM	0.908	0.811	“Multi”	Neighborhood size: 3×3 ; Subspace dimension: 3
GKC-SA	0.835	0.685	“Multi”	ϵ (convergence): 0.0001; α (cooling factor): 0.84
USFA	0.930	0.863	“Multi”	Kittler-Ilingworth; Freedman-Diaconis’
ASF	0.934	0.873	“Multi+Text”	Iterations: 9
FR	0.972	0.944	“Multi”	Min. Clusters size: 1%; Neighborhood radius: 1
HBSC	0.964	0.926	“Multi”	α : 0.6; ν : 0.001; γ : 0.5

quantitatively, the qualitative analysis suggests low performance.

The results underscore the suitability of employing unsupervised change detection methods after making well-informed choices. This approach is particularly valuable in scenarios where supervision is difficult or impractical. However, the methods’ sensitivity to input settings, including parameters and attributes, emphasizes the need for a thoughtful selection process. The choice should consider the specific characteristics of the study area, the nature of the changes, and the detection requirements.

The results suggest that, for the type of application addressed in this study, the FR method using “Multi” images has shown promise. The utilization of floating references, identified through clustering, enabled the differentiation of areas of change and non-change based on behavioral variations observed in similar objects. On the other hand, the analysis demonstrates that the attributes extracted through the application of PCA and texture filters did not significantly contribute to the detection of changes in the context of the problem at hand. This underscores the importance of selecting attributes that are relevant to the characteristics of the changes one aims to detect, thereby

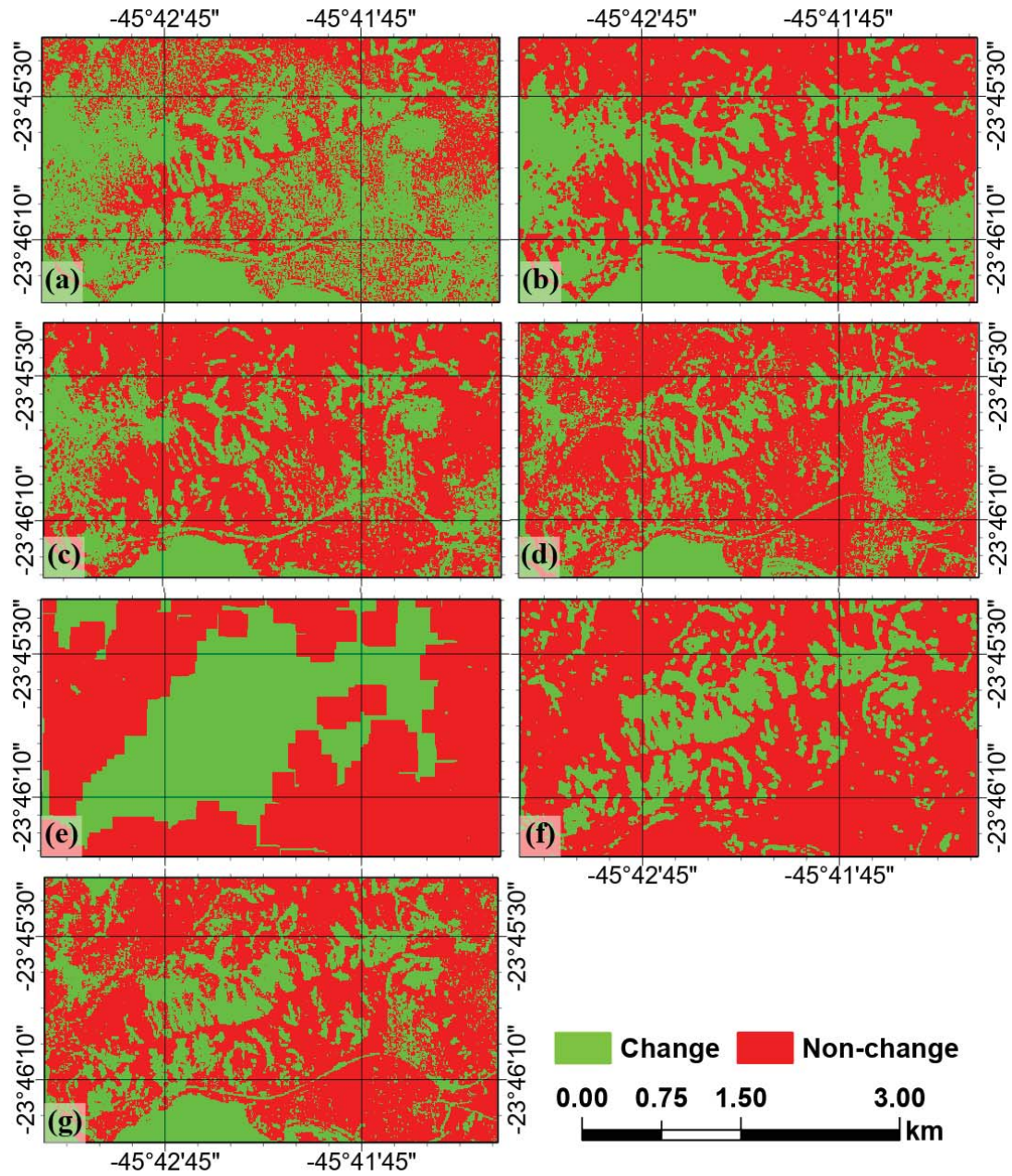


Fig 5 The top results attained by the analyzed methods: (a) CVA; (b) PCA-KM; (c) GKC-SA; (d) USFA; (e) ASF; (f) FR; (g) HBSC.

368 enhancing the accuracy and reliability of change maps.

5 Conclusions

The research conducted in this study assessed the efficiency of unsupervised methods in detecting changes for landslide identification in a study area located in São Sebastião, São Paulo, Brazil.

Among the various alternatives tested, the FR method consistently demonstrates high levels of accuracy, maintaining performance across different attributes and parameters. Additionally, the HBSC method yielded accurate results after proper data consideration. However, the other methods showed greater sensitivity to parameters and input data. Furthermore, the results emphasize the methods' sensitivity to input data, underscoring the sufficiency and superiority of multispectral data in comparison to other alternatives.

These findings underscore the significance of meticulously selecting suitable settings for each method to attain precise change detection outcomes. It's important to note that while the methods performed effectively in detecting changes in predominantly forested areas, additional challenges might arise when applying them in urban environments or different land use contexts. As a result, the results of this study not only aid in the effective identification of landslides but also provide a foundation for future research. Lastly, as a future perspective, it's recommended to explore these methods in different scenarios and assess various pre-processing techniques for attribute generation.

Disclosures

The authors declare that they have no conflict of interest.

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Data, Materials, and Code Availability

The main datasets generated during the current study were obtained from public repositories.

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List of Figures

- 1 Geographic location of the study area
- 2 (a) Images of the study area before (February 15th, 2023) and (b) after (February 25th, 2023) the landslide events. (c) Representation of reference samples denoting areas affected (“change”) and unaffected (“non-change”) by recent landslide events. Representations in natural composite composition.
- 3 Experiment design workflow.
- 4 Values of the F1-Score and Kappa coefficients for each method analyzed, taking into account the different input attributes and tested parameters.
- 5 The top results attained by the analyzed methods: (a) CVA; (b) PCA-KM; (c) GKC-SA; (d) USFA; (e) ASF; (f) FR; (g) HBSC.

List of Tables

- 1 The most suitable attributes obtained by the analyzed methods concerning the various parameters considered.

3 CONSIDERAÇÕES FINAIS

Este Trabalho de Graduação teve como objetivo a integração de conceitos fundamentais do curso de Engenharia Ambiental, com foco em sua aplicação em Geociências. Para alcançar esse propósito, foi abordado uma variedade de tópicos, incluindo Sensoriamento Remoto, Geo-processamento, Ciência da Computação, Estatística, Cálculo II e III, Geomorfologia e outras disciplinas afins. A combinação desses conhecimentos foi fundamental para o desenvolvimento da proposta.

Nos últimos anos, foi observado um notável aumento no uso de tecnologias de sensoriamento remoto para o monitoramento ambiental em diversas áreas de estudo. Essas tecnologias, aliadas a técnicas de detecção de mudanças ao longo de extensos períodos, são amplamente adotadas por instituições de prestígio, como o Instituto Nacional de Pesquisas Espaciais (INPE), em colaboração com o Programa Disasters Charter (Charter), que forneceu a base de dados de validação para este estudo. Esses avanços são essenciais para atingir os objetivos propostos neste artigo e para estabelecer conexões com os conceitos adquiridos durante a graduação.

Neste estudo, foi investigado vários métodos não supervisionados para a detecção de mudanças em imagens multiespectrais, aplicando-os à identificação de deslizamentos de terra ocorridos recentemente na região de São Sebastião, localizada no estado de São Paulo, Brasil. Foi utilizado imagens capturadas pelo sensor Sentinel-2 MSI e avaliado os atributos extraídos dessas imagens.

A análise dos resultados revelou a eficácia dos métodos não supervisionados na detecção de mudanças e na identificação de deslizamentos de terra na área estudada. Especificamente, os métodos FR e HBSC se destacaram devido aos altos níveis de acurácia alcançados. Além disso, os resultados destacaram a sensibilidade desses métodos em relação aos dados de entrada, como atributos e parâmetros, enfatizando a importância e superioridade dos dados multiespectrais em comparação com outras alternativas. No entanto, é importante notar que, embora esses métodos tenham demonstrado um desempenho satisfatório na detecção de mudanças em áreas predominantemente florestais, desafios adicionais podem surgir ao aplicá-los em ambientes urbanos ou em contextos de uso do solo distintos.

A pesquisa se configura como uma ferramenta essencial para facilitar a identificação de áreas com deslizamentos de terra. Ao catalogar essas ocorrências e realizar estudos sobre as variáveis potenciais relacionadas a esses eventos nessas áreas, ela se torna uma ferramenta valiosa para a prevenção e uma gestão mais eficiente desses incidentes.

Em relação às perspectivas futuras, é recomendado a exploração desses métodos em diferentes cenários e a avaliação de outras técnicas de pré-processamento para a geração de atributos.

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