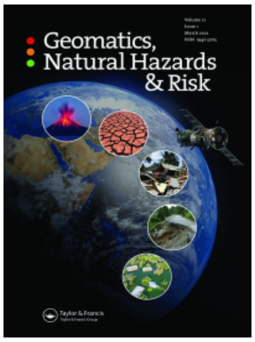

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Detecting small-scale landslides along electrical lines using robust satellite-based techniques

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ABSTRACT

Robust Satellite Technique (RST) was applied to detect small-scale landslides along electrical lines in Sicily, Italy. To this end, electrical poles were selected as targets within the study area. The methodology, implemented in Google Earth Engine (GEE) environment, exploits the Copernicus Sentinel-2 platform to identify anomalous land cover variation, in terms of Normalized Difference Vegetation Index (NDVI), possibly related to small displacements affecting electric poles. Since the applied methodology is based on land cover change, dense vegetation plays an important role in detecting small-scale landslides. Therefore, we targeted months with the highest vegetation density, such as February, March, and April from 2016–2023. The results obtained reveal that out of the five targeted electrical poles, four of them exhibited anomalies > 2-sigma indicating significant changes in land cover possibly related to local ground movement as confirmed by aerial photos collected in the period 2015–2023. Our findings reveal anomalies of −2.17 and −2.36 on 7/17/2017 and 9/05/2017 for pole 1. For pole 2, the results show an anomaly of −2.02 on 8/11/2018. The results also indicate anomalies of −4.40 and −2.99 on 7/09/2021 and 9/27/2022 for pole 3. For pole 4, the findings show an anomaly of −3.10 on 1/18/2019.

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1. Introduction

Landslide disasters rank among the most prevalent and severe natural calamities globally (Guzzetti et al. 2005). A landslide occurs when rock and soil masses on slopes deform and fail, primarily shifting horizontally along a particular surface due to gravity or other forces such as seismic activity or water pressure (Guzzetti et al. 2006; Guzzetti et al. 2012). The consequences of landslides can be diverse and profound, impacting multiple facets of human existence and the natural environment. In this

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context, landslides have the potential to inflict substantial harm on human infrastructure, disrupting everyday routines, economic operations, and emergency response endeavors (Miao and Wang 2023; Yin et al. 2023). Human infrastructure encompasses the constructed frameworks and amenities that facilitate human endeavors and communities, including buildings, roadways, bridges, utilities (such as water, electricity, and telecommunications), and transportation grids (Zhang et al. 2020a). In this regard, electrical infrastructures are one of vital parts of human life. Landslides present a significant hazard to electrical infrastructure and other utilities (Helderop and Grubesic 2019). When a landslide occurs, it can dislodge trees, displace rocks, and carry debris downhill, potentially causing damage or complete destruction to electrical poles, transformers, and power lines along its path. This can lead to power outages affecting communities and industries reliant on those lines (Zhong et al. 2018; Zhang et al. 2020b). The destruction of electrical infrastructure can have far-reaching consequences, including disruptions to power supply, impacts on communication networks, safety risks, economic losses, and challenges in restoration efforts (López et al. 2017). In regions prone to landslides, utility companies often implement measures to mitigate risks to electrical infrastructure. These measures may include reinforcing poles, burying lines underground where feasible, and conducting regular inspections and maintenance (Perera et al. 2018; Spegel and Ek 2022; Kazemi Garajeh et al. 2024). Furthermore, the implementation of early warning systems and emergency response plans can help reduce the costs for the inspection of electrical infrastructure and facilitate a swift recovery process (Ponziani et al. 2023).

Remote sensing technologies play a vital role in the monitoring, assessment, and early warning systems for landslides (Chang et al. 2023). These advanced tools enable researchers and authorities to observe and analyze large land areas in a remote way, furnishing crucial data for landslide detection and management (Casagli et al. 2023). Microwave and optical techniques have both been implemented in studying landslide (Tong and Schmidt 2016; Squarzoni et al. 2020; Xie et al. 2020; Hou et al. 2022; Fang et al. 2023; Ponziani et al. 2023; Fang et al. 2024; Li et al. 2024). Along with advances in satellite data, learning-based approaches such as machine learning and deep learning have been developed and utilized for large-scale landslide detection (Azarafza et al. 2021; Wang et al. 2021; Ghorbanzadeh et al. 2022; Jiang et al. 2022; Sreelakshmi et al. 2022). However, the performance and reliability of learning-based models can be influenced by variations in geological, environmental, and socio-economic factors across different contexts. Additionally, some learning-based algorithms, especially complex models like deep learning, demand substantial computational resources for training and inference, which may pose challenges for researchers and organizations with limited access to high-performance computing resources (Albanwan et al. 2024). Synthetic Aperture Radar (SAR) stands out for its ability to penetrate through clouds and dense vegetation, making it invaluable for monitoring landslides in regions prone to frequent cloud cover or dense foliage. SAR can detect subtle ground movements, providing valuable insights into slope stability and potential landslide activity (Liu et al. 2024). Apart from a study done by Tzouvaras et al. (2020), no other studies have used SAR for small-scale landslide detection to the best of our knowledge. SAR systems are susceptible to interference from vegetation cover, particularly in densely vegetated regions (Kyriou and Nikolakopoulos 2020; Lv et al. 2023). Concerning optical techniques for landslide investigation, the traditional ones typically rely on fixed thresholds to distinguish changes in land cover associated with such events for instance applying indexes like Normalized Difference Vegetation Index (NDVI) or Normalized Difference Water Index (NDWI, Niraj et al. 2023; Chen et al. 2024). However, these techniques often lack automation and are challenging to apply to areas with characteristics different from those where they were initially calibrated or validated. Moreover, like all methods reliant on fixed thresholds, they may suffer from sensitivity accuracy issues and false alarm proliferation (Yang et al. 2019; Ghorbanzadeh et al. 2020).

In the domain of landslides, transitions in land cover types (e.g. from vegetation to bare soil) frequently occur following this phenomenon. Such changes can provide a good opportunity to map and detect areas affected by landslides (Satriano et al. 2023; Niu et al. 2024). There are several indices used to highlight vegetation-covered areas in remote sensing imagery. NDVI is one of the most common and widely utilized (Khan et al. 2022). It is an important vegetation index, frequently applied in research on global environmental and climatic changes. NDVI is calculated as the ratio of the difference between the reflectance measurements in the red and near-infrared bands (Bhandari et al. 2012; Xu et al. 2016). In this regard, using learning-based approaches such as the Robust Satellite Technique (RST) can help to solve the aforementioned problems. To monitor small-scale landslides, the first requirement of the RST is the characterization of signal behavior under *normal* (i.e. unperturbed) conditions. No signal can inherently be interpreted as *anomalous*; it can only be identified as such through comparison with a predefined *normal* behavior. The second step in the RST process is to establish change detection criteria. These criteria should be specified for each phenomenon under consideration, the chosen technology, and the time and location of observation. It is important to note that the same signal, which is typically observed at a specific time and place, might appear anomalous when considered in a different context. Lastly, criteria for detecting space/time anomalies must also account for the natural variability of the signal unrelated to the phenomenon being studied (Tramutoli 1998; 2007). The RST technique is also capable of identifying at a pixel level statistically significant variations (with different confidence levels) of the investigated signal, thus overcoming the limitations of fixed threshold approaches (Di Polito et al. 2016; Filizzola et al. 2022). The RST approach (Tramutoli 2007) is based on a multi-temporal analysis of historical satellite observations acquired under similar observational conditions (e.g. the same month of the year, the same hour of the day, the same sensor, and so on), which would not be available in other methods like machine learning-based approaches. Freely available satellite images, such as Sentinel-2, make the use of multi-temporal images for small-scale landslide monitoring easier, as RST relies on the analysis of historical datasets. Cloud cover is considered one of the main limitations when using optical datasets. However, the temporal frequency of Sentinel-2 (every 5 days) has partly compensated for this issue (Tarrio et al. 2020; Shahabi et al. 2021).

The RST approach has been already successfully applied to study different natural and anthropic hazards (Mazzeo et al. 2007; Faruolo et al. 2010; Eleftheriou et al. 2016; Lacava et al. 2017; Marchese et al. 2017; Satriano et al. 2019; Filizzola et al. 2022), including large-scale landslides (Satriano et al. 2023). The aims of this study are to: (1) extend the applicability of RST to small-scale landslides, and (2) assess the effects of small-scale landslides on electrical poles. To achieve these objectives, Sentinel-2 satellite images with a spatial resolution of 10 meters were used to analyze the study area in southern Italy's Sicily region from 2016 to 2023. Land cover change, detected using the NDVI, plays a crucial role in landslide detection in this study. Aerial photos of the studied poles from 2015 to 2023 were used to validate the accuracy of the results.

2. Location of study area

Figure 1 shows the Sicily region in Italy where electrical poles analyzed in this study are located. Sicily is connected to the Italian mainland grid *via* submarine power cables. These connections ensure a reliable power supply to the island and allow for the import and export of electricity as needed. High-voltage transmission lines

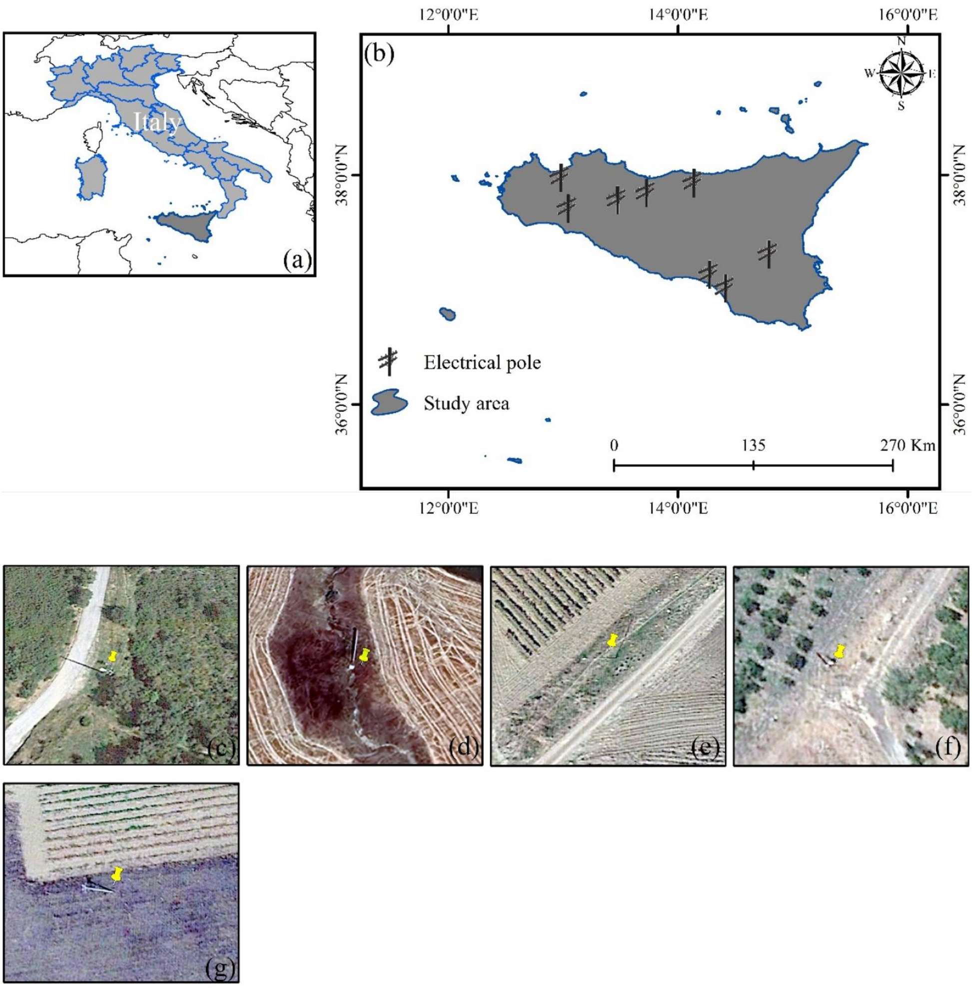

Figure 1. Location of the study area in (a) Italy, (b) Sicily, and (c–g) locations of electrical poles 1–5 on Google Earth.

crisscross the island, transmitting electricity from power plants to distribution centers and substations (Favuzza et al. 2015; Heggarty et al. 2020). These lines are essential for ensuring the efficient transfer of electricity across the island. Sicily's electrical distribution network delivers electricity from transmission substations to homes, businesses, and industrial facilities. This network includes transformers, distribution lines, and other infrastructure to ensure that electricity reaches consumers reliably. Despite its relatively modern infrastructure, Sicily faces challenges common to many regions, including aging infrastructure, occasional blackouts or power outages due to extreme weather events, environmental hazards, and system failures, and the need for continued investment to modernize and expand the grid (Ippolito et al. 2018; Adu et al. 2022).

Sicily is located on the Pelagian promontory of the African plate and is composed of the Iblean foreland, the Gela foredeep, the thick Sicilian orogen, and the thick-skinned Calabrian–Peloritani wedge. Its fold-and-thrust belt formed as a result of the complex rollback of the African–Pelagian slab, which was initially associated with the counterclockwise rotation of Corsica and Sardinia, followed by the clockwise rotation of the Calabria–Peloritani–Kabylian units during the late Neogene period. Sicily's geology is varied, encompassing sedimentary, volcanic, and metamorphic rocks. The island's stratigraphy includes limestone, marl, clay, and volcanic deposits, each with distinct stability traits that affect landslide risk. Situated near the collision zone between the African and Eurasian tectonic plates, Sicily experiences significant tectonic activity. This results in a complex network of faults and geological weaknesses that increase the likelihood of landslides (Broquet 2016). From an environmental perspective, Sicily is one of the most significant biodiversity hotspots in the Mediterranean basin with mediterranean climate. It offers a wide variety of habitats—including marine, coastal, inland, and high-mountain environments. Sicily is the largest region in Italy and the largest island in the Mediterranean Sea, encompassing 14 smaller inhabited islands and three active volcanoes (Incarbona et al. 2010).

3. Materials and methodology

3.1. Materials

To detect the effects of landslides on electrical poles, different types of data have been exploited in this study. Sentinel-2 Multi Spectral Instrument (MSI) Level 1 data has been used to implement the methodology here presented. This study utilized a total of 2437 Sentinel-2 images for detecting landslide occurrence from 2016 to 2023 for February, March, and April as shown in Table 1. Electrical poles in displacement to

Table 1. Sentinel-2 dataset and relative information for each test-case poles.

Pole	Sentinel-2 historical datasets	Number of images	Targeted aerial photo
1	February 2016–2023	425	2/23/2023
2	February 2016–2023	219	2/18/2023
3	March 2016–2023	281	3/18/2023
4	March 2016–2023	221	3/22/2023
5	February 2016–2023	427	2/14/2023
6	April 2016–2023	317	4/19/2023
7	February 2016–2023	260	2/20/2023
8	March 2016–2023	287	3/23/2023

be used as test-cases have been preventively identified and located using aerial photos (from 2015 to 2023) and relative additional information kindly provided by Geocart SPA (https://www.geocartspa.it/english/) (Figure 2). Further aerial photos (again courtesy of Geocart SPA), acquired at different times and relative to the test-cases chosen, have been then used to identify and define poles 'normal condition', i.e. a time in which those poles were not damaged yet.

3.2. Methodology

3.2.1. Normalized difference vegetation index (NDVI)

As mentioned, land cover changes can be a good sign of mass movement and the NDVI index is the principal indicator used to detect this changes on optical satellite

Figure 2. Aerial photos of electrical poles identified as test-cases. Date of acquisition: pole (1) 2/18/2023, pole (2) 3/22/2023, pole (3) 2/14/2023, pole (4) 4/19/2023, and pole (5) 2/13/2023.

images. The NDVI is in general exploited as a valuable indicator of vegetation growth and density patterns, being particularly sensitive to the abundance and vitality of green vegetation (Mondini et al. 2011; Kazemi Garajeh et al. 2022). In this study we implemented NDVI to Sentinel-2 images, using near infrared - NIR (0.8 μm) and RED (0.4 μm) bands at 10 meters of spatial resolution and 5 days of a temporal resolution. Equation 1 represents the formula for NDVI (originally named Band Ratio Parameter by Rouse et al. 1974)

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{1}$$

NDVI values range from −1 to 1, where, values higher than 0.3 usually indicate vegetated areas (more dense/healthy, more high), values close to 0 indicate cloud, and values less than 0 may represent water bodies (Filizzola et al. 2017).

3.2.2. Robust satellite technique (RST)

The RST approach has been already successfully applied to detect and map large landslides (Satriano et al. 2019), in this study we tested and validated its applicability to small scale displacement.

RST (Figure 3) is an automated method for detecting changes, relying on the comprehensive analysis of historical satellite data series to characterize signals in terms of spectral, spatial, and temporal dimensions (Tramutoli 2007). This process is followed by an anomaly detection phase utilizing locally generated self-adaptive thresholds, specific to the time and location of observation. For landslides application, the aim is to detect potential alterations in land cover, using as indicator the NDVI index. The method is applied here to assess various instances of landslides affecting electrical poles and follow the process described in Satriano et al. 2019 completely implemented in GEE. In detail: Sentinel-2 L1C images from 2016 to 2023 have been collected for the study area and a cloud mask have been implemented using the specific QA60 band (provided as additional band within each image) and the Cloud Probability collection where the QA60 was not available. The NDVI index has been then computed for each one of the non-cloudy images. Starting from this NDVI images collection, the relative temporal mean (μ) and its standard deviation (σ) have been calculated on monthly base at pixel level, thus obtaining two values for each month of the year. The description and number of the exploited Sentinel-2 images are reported in the following Table 1 for each test-case pole.

After this statistical signal characterization, the RST methodology incorporates the implementation of a change detection phase, useful to weigh any deviation of the measured NDVI value from its expected one, described by the temporal mean and standard deviation. This is carried-out through the implementation of the Absolutely Local Index of Change of Environment (ALICE), as outlined below:

$$\otimes_{NDVI}(x, y, t) = \frac{NDVI(x, y, t) - \mu_{NDVI}(x, y)}{\sigma_{NDVI}(x, y)} \tag{2}$$

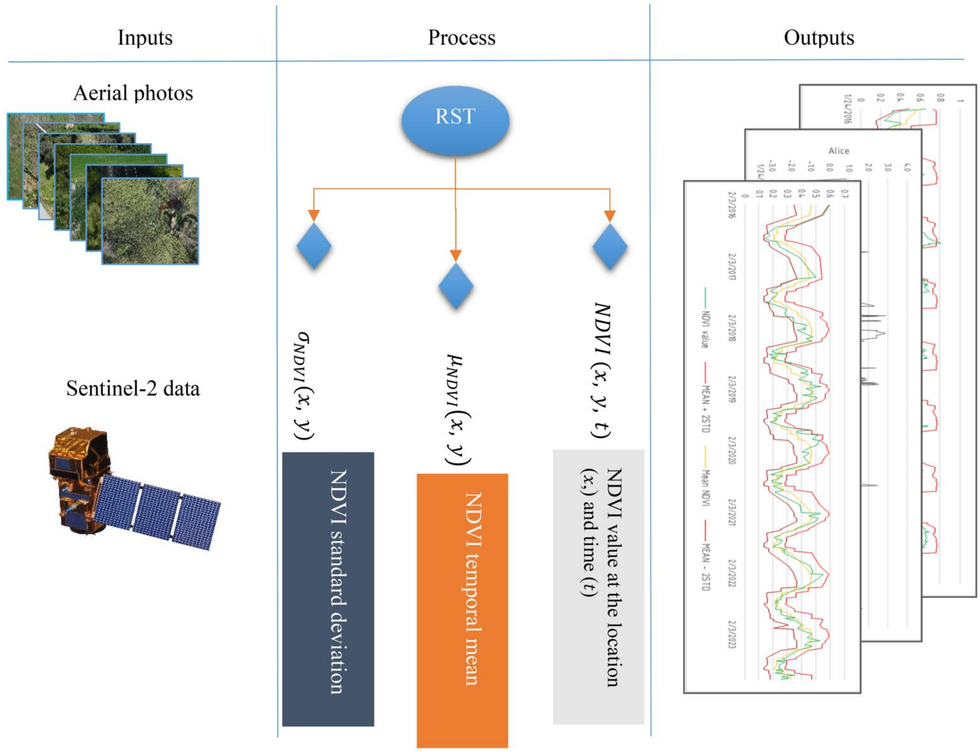

Figure 3. An overview of the applied methodology for detecting small-scale landslides along electrical lines.

Where, the $NDVI$ represents the index values at the pixel (x, y) level at the time (t). μ_{NDVI} is the temporal mean of $NDVI$, and σ_{NDVI} is the standard deviation of $NDVI$ estimated from historical datasets for the same pixel.

The formula (2), in case of a Gaussian distribution of the variable, describes a standardized variable following a normal (Gaussian) distribution with a zero mean (μ) and a variance (σ) of 1. Increasing ALICE absolute values can be associated with statistically anomalous events (Satriano et al. 2019). $\otimes_{NDVI}(x, y, t)$ values lower than -2, -3, and -5 indicate a decreasing occurrence probability equal to 2.27%, 0.15%, and 2.8×10^{-5}%, respectively. Lower $\otimes_{NDVI}(x, y, t)$ absolute values are associated with even lower occurrence probabilities. In our case (signal distribution is quasi-Gaussian, e.g. Lacava et al. 2011) ALICE values and probability of occurrence of NDVI anomalies in the hypothesis of a Gaussian distribution, are employed just as an indication of their significance (i.e. how rare they are in the considered time series).

4. Results

This study applied the RST methodology just described for detecting small-scale landslides to monitor their effects on the electrical poles.

The methodology has been implemented to 5 test-case poles reported in Figure s 1 and 2, and the relative results will be presented and discussed in the next. For the first analyzed Pole 1, in Figure 4d is reported an aerial photo taken on the year 2022 where the pole appears clearly in displacement, while in Figure 4c there is another photo acquired some years before, in 2015, in which is possible to see that pole in 'normal condition' still not damaged. Implementing the RST methodology to this test-case we expect to be able to observe negative statistically significant change in land cover (i.e. NDVI index) at the time in which the displacement occurred, within the temporal range defined by the previous photos (i.e. 2015–2022). To this aim the historical NDVI trend (green line) for the Pole 1 pixel, retrieved from Sentinel 2 L1C images, has been reported in Figure 4a together with its temporal mean (yellow line)

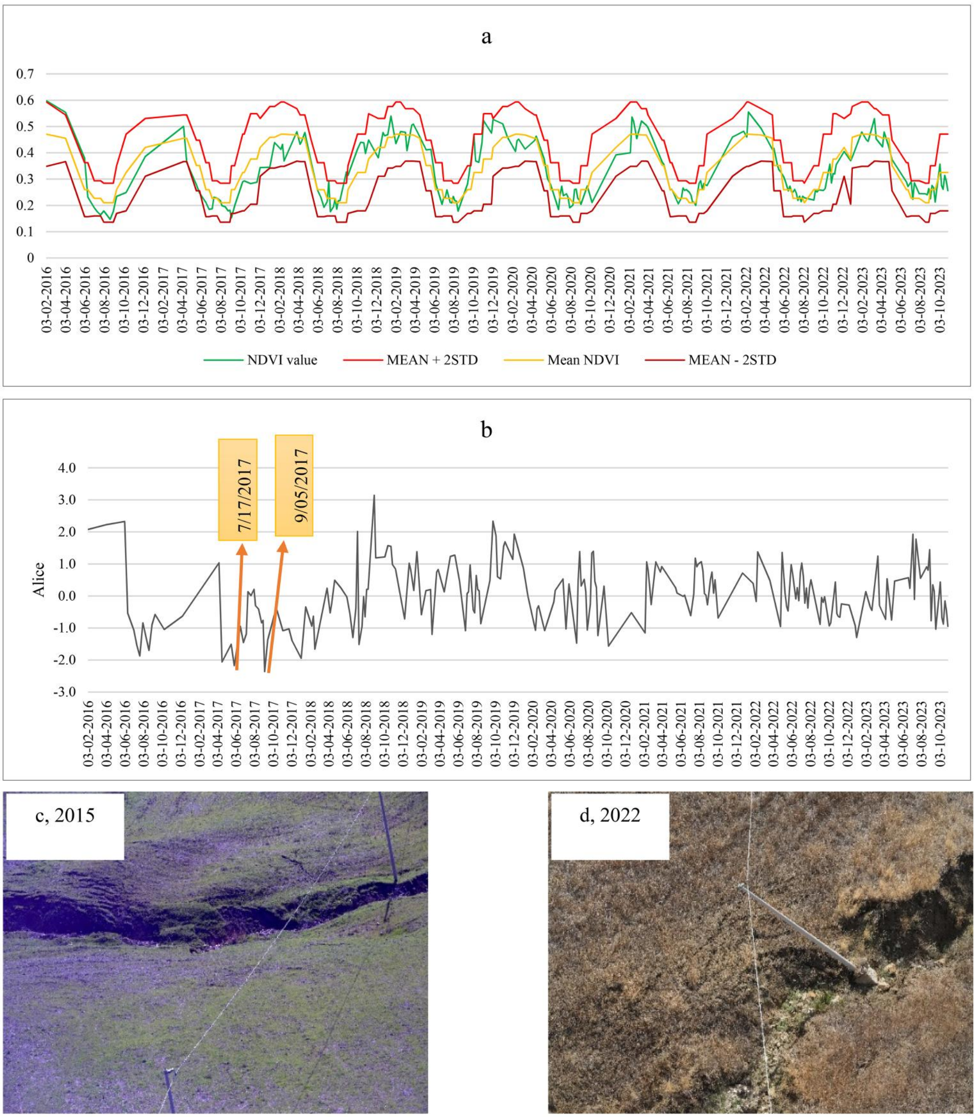

Figure 4. Variation in various factors of the RST from 2016 to 2023 for pole 1; (a) NDVI (green line), mean + 2STD (red line), mean NDVI (orange line), and mean-2STD (dark red), (b) ALICE trend, (c and d) aerial photos before and after the events.

and standard deviation (red lines). Looking at this graph is possible to recognize two NDVI values recorded both in 7/17/2017 and 9/05/2017 lower than the mean value and outside of the range defined by deviation standard. This is clearer looking at the graph in Figure 4b, where the same trend is reported in terms of ALICE: ALICE index < -2 are visible for the dates identified in Figure 4b. This behavior highlights that some significant changes in land cover happened in 2017, between the pre- (2015) and post- (2022) images showed in Figure 4c and 4d, it is therefore possible to suppose that this is the moment in which the landslide began. It is worth noting that no other anomalous values have been observed along the NDVI historical trend, i.e. no other significant land cover changes arise from the analysis carried out, this corroborates what was hypothesized and suggests that after the landslide occurrence new vegetation was born on the area, bringing the conditions observed by satellite back to normal.

Figure 5d shows an aerial photo taken in 2022, where the pole is clearly displaced. In contrast, Figure 5c presents a photo from 2015, where the pole appears undamaged and in normal condition. By applying the RST methodology to this case, we aim to detect significant negative changes in land cover (indicated by the NDVI index) during the period between the two photos (2015–2022). To achieve this, we analyzed the historical NDVI trend for the pixel corresponding to Pole 2, derived from Sentinel 2 L1C images, as illustrated in Figure 5a. This figure also displays the temporal mean (yellow line) and standard deviation (red lines) of the NDVI values. Notably, the NDVI value recorded on 8/11/2018 is lower than the mean and falls outside the standard deviation range. This anomaly is further clarified in Figure 5b, which shows the same trend in terms of the ALICE index, with ALICE index < -2 visible for the dates identified in Figure 5b. This pattern indicates significant land cover changes in 2018, suggesting that the landslide likely began between the 2015 and 2022 images shown in Figure 5c and 5d. Additionally, no other anomalous values were observed in the NDVI historical trend, indicating no other significant land cover changes. This supports the hypothesis and suggests that new vegetation growth after the landslide restored the area's conditions to normal as observed by satellite.

For the third analyzed Pole 3, in Figure 6d is reported an aerial photo taken on the year 2023 where the pole appears clearly in displacement, while in Figure 6c there is another photo acquired some years before, in 2016, in which is possible to see that pole in 'normal condition' still not damaged. Implementing the RST methodology to this test-case we expect to be able to observe negative statistically significant change in land cover (i.e. NDVI index) at the time in which the displacement occurred, within the temporal range defined by the previous photos (i.e. 2016–2023). To this aim the historical NDVI trend (green line) for the Pole 3 pixel, retrieved from Sentinel 2 L1C images, has been reported in Figure 6a together with its temporal mean (yellow line) and standard deviation (red lines). Looking at this graph is possible to recognize two NDVI values recorded both in 7/09/2021 and 9/27/2022 lower than the mean value and outside of the range defined by deviation standard. This is clearer looking at the graph in Figure 6b, where the same trend is reported in terms of ALICE: ALICE index < -2 are visible for the dates identified

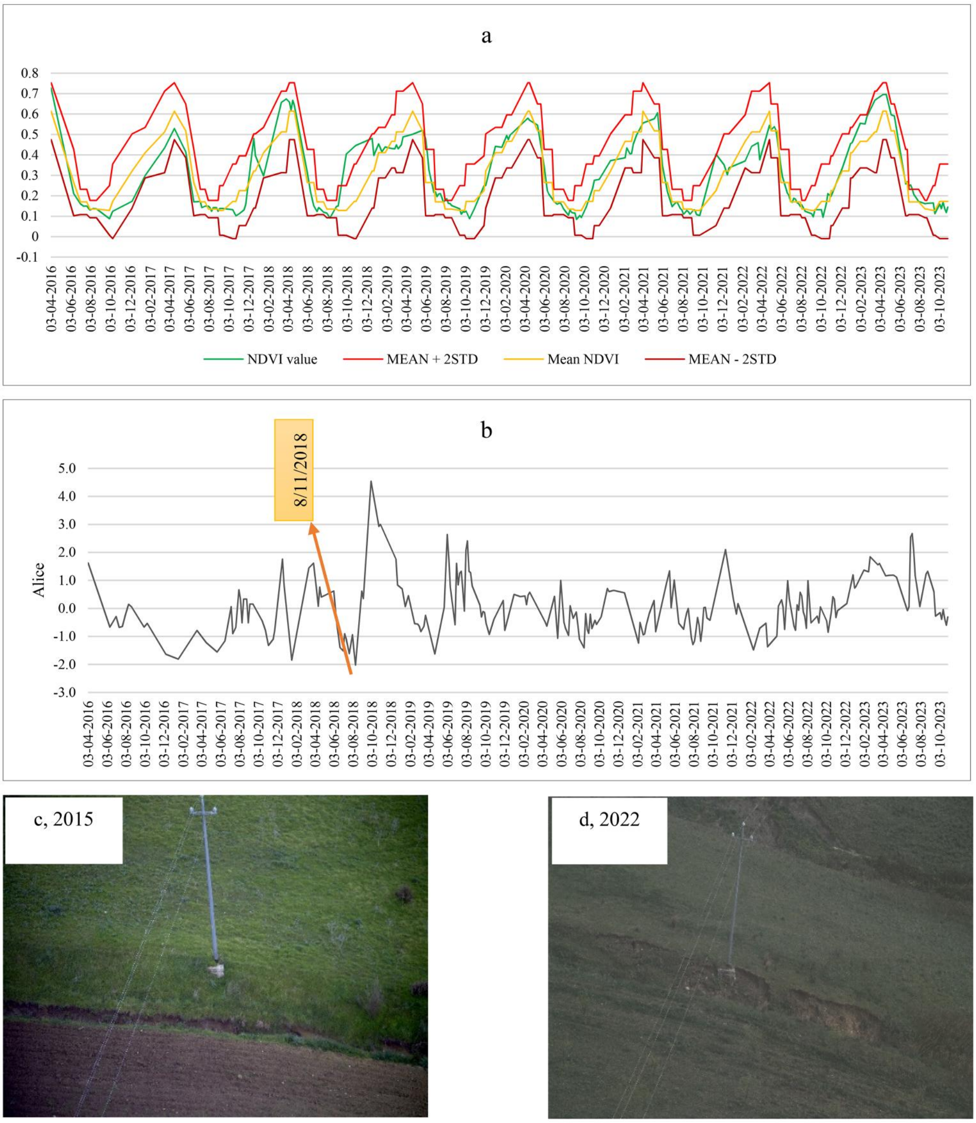

Figure 5. Variation in various factors of the RST from 2016 to 2023 for pole 2; (a) NDVI (green line), mean + 2STD (red line), mean NDVI (orange line), and mean-2STD (dark red), (b) ALICE trend, (c and d) aerial photos before and after the event.

in Figure 6b. This behavior highlights that some significant changes in land cover happened in 2021 and 2022, between the pre- (2016) and post- (2023) images showed in Figure 6c and 6d (as in Figure 2 pole 3), it is therefore possible to suppose that these are the moments in which landslides occurred. It is worth noting that no other anomalous values have been observed along the NDVI historical trend, i.e. no other significant land cover changes arise from the analysis carried out, this corroborates what was hypothesized and suggests that after the landslide occurrence new vegetation was born on the area, bringing the conditions observed by satellite back to normal.

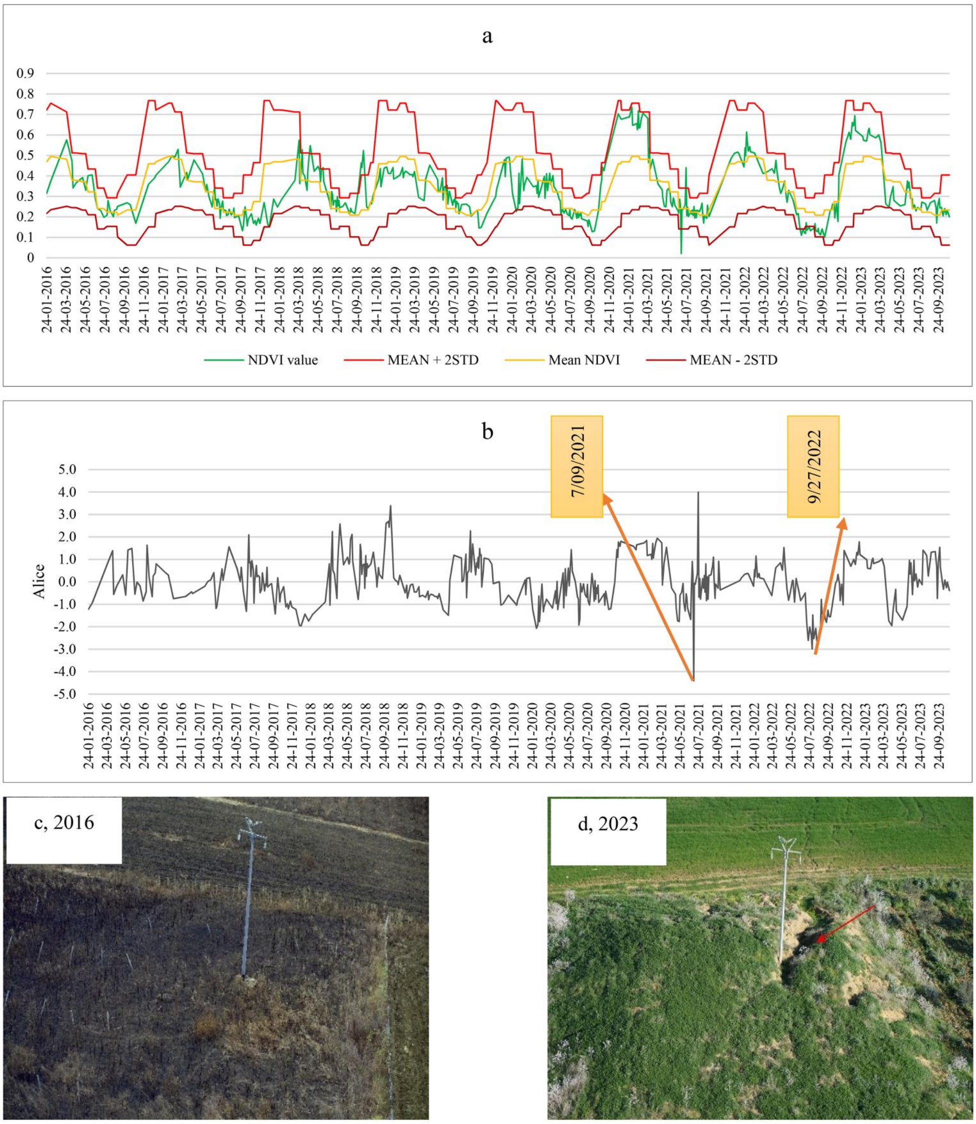

Figure 6. Variation in various factors of the RST from 2016 to 2023 for pole 3; (a) NDVI (green line), mean + 2STD (red line), mean NDVI (orange line), and mean-2STD (dark red), (b) ALICE trend, (c and d) aerial photos before and after the events.

Figure 7c presents a photo from 2017, where the pole appears undamaged and in normal condition. By applying the RST methodology to this case, we aim to detect significant negative changes in land cover (indicated by the NDVI index) during the period after photo (2017). This is because there is not any displacement before the acquired photo. To achieve this, we analyzed the historical NDVI trend for the pixel corresponding to Pole 4, derived from Sentinel 2 L1C images, as illustrated in Figure 7a. This figure also displays the temporal mean (yellow line) and standard deviation (red lines) of the NDVI values. Notably, the NDVI value recorded on 1/18/2019, is lower than the mean and falls outside the standard deviation range. This anomaly is

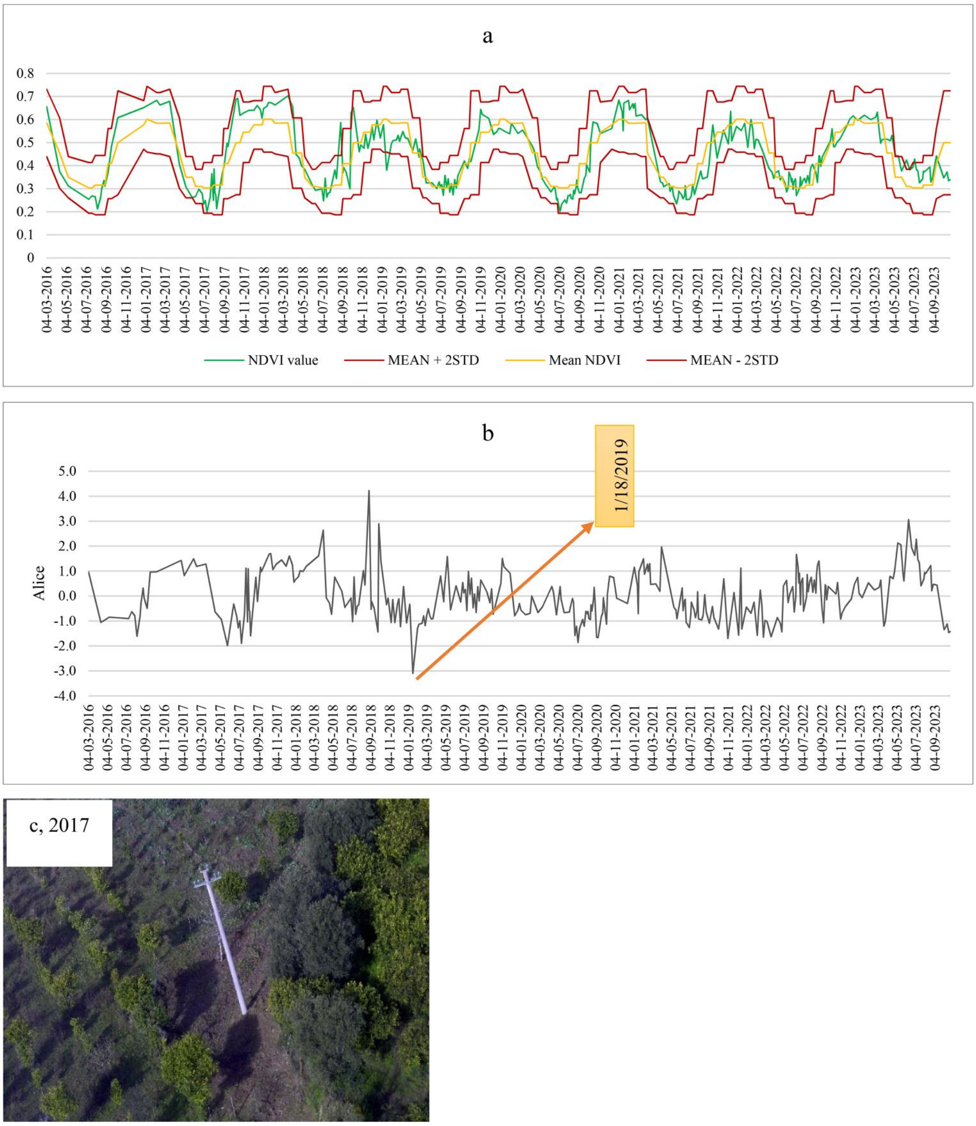

Figure 7. Variation in various factors of the RST from 2016 to 2023 for pole 4; (a) NDVI (green line), mean + 2STD (red line), mean NDVI (orange line), and mean-2STD (dark red), (b) ALICE trend, and (c) aerial photo before the event.

further clarified in Figure 7b, which shows the same trend in terms of the ALICE index, with ALICE index < -2 visible for the dates identified in Figure 7b. This pattern indicates significant land cover changes in 2019, suggesting that the landslide likely began after 2017, as shown in Figure 7c. Additionally, no other anomalous values were observed in the NDVI historical trend, indicating no other significant land cover changes. This supports the hypothesis and suggests that new vegetation growth after the landslide restored the area's conditions to normal as observed by satellite.

4.1. Confutation

In order to assess results obtained and just described, a confutation phase has been carried-out, going to apply the RST methodology to a test-case pole appropriately chosen because not in displacement. This phase is necessary to evaluate the robustness of the methodology implemented, which involves not reporting false identifications. In Figure 8d the aerial photo of the pole chosen, taken in 2022, in which no displacement is visible, in Figure 8c a photo before, relative to 2016, where the pole is in the same 'normal' conditions. Analyzing the relative NDVI historical trend

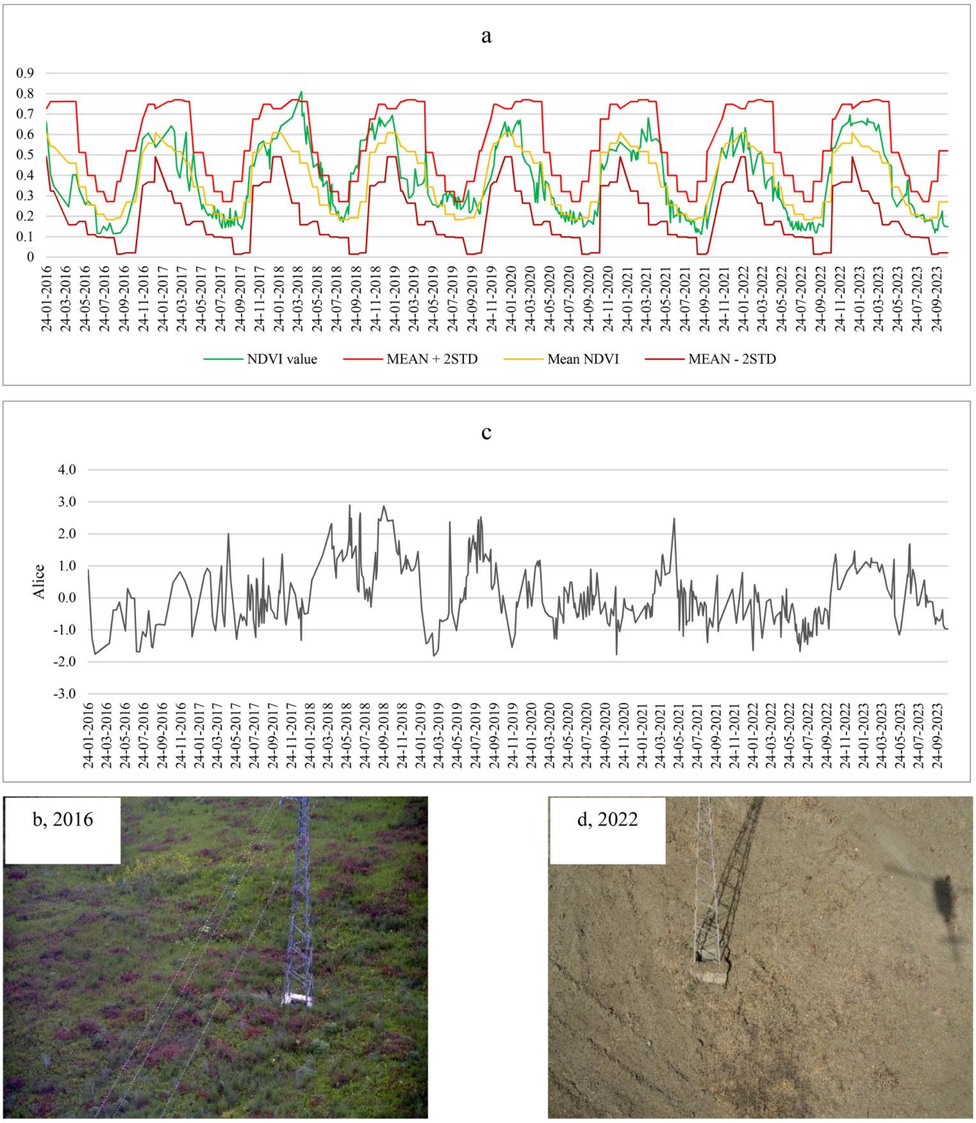

Figure 8. Variation in various factors of the RST from 2016 to 2023 for pole 5; (a) NDVI (green line), mean + 2STD (red line), mean NDVI (orange line), and mean-2STD (dark red), (b) ALICE trend, (c and d) aerial photos before and after the event.

(Figure 8a) (green line), always obtained from Sentinel-2 images, no values deviate from its expected value (temporal mean in yellow) and normal variability (deviation standard in red) can be identified. In the same way, no anomalous ALICE values can be detected in Figure 8b.

RST methodology demonstrates to be robust not returning false identifications in a case of clear absence of displacements and relative damages.

5. Discussion

Electrical poles play a pivotal role in ensuring the delivery of reliable electricity and communication services to communities. It's imperative to prioritize the proper installation, maintenance, and inspection of these poles to uphold the safety and efficiency of the utility infrastructure. In this regard, this study utilized an automated approach employing RST to detect poles affected by landslides. While previous research has focused on using remote sensing combined with learning-based techniques to detect large-scale landslides (Liao et al. 2022; Tiranti and Ronchi 2023; Wang et al. 2023; Yang et al. 2024), there has been less attention given to small-scale landslides, making their study necessary. Detecting small-scale landslides presents unique challenges due to the variability of land features on a smaller scale (Lu et al. 2019). However, the methodology applied in this study demonstrates the robust capabilities of RST. Previous applied techniques can detect events but are often prone to false positives when applied on a large scale, which limits their effectiveness and their ability to be fully automated (i.e. to identify previously unknown events). In contrast, the methodology presented here has demonstrated the ability to detect a landslide with no false positives and, due to its design, can be easily adapted for use in different locations and integrated into an unsupervised automatic detection system. In fact, all previous change detection methods based on fixed threshold tests require manual adjustment of these thresholds when applied to different locations or periods. In contrast, RST-based approaches, which rely solely on the processing of a homogeneous dataset of satellite images, can be considered fully transferable wherever the necessary satellite image dataset is available.

By leveraging historical datasets, which provide a comprehensive view of changes over an extended period, the RST can offer valuable insights into the variation of targeted features, such as land cover, over time. The RST is based on various statistical variables, including temporal mean, standard deviation, and NDVI mean from historical datasets. Temporal mean serves as a valuable tool for analyzing time series data, providing a concise summary of the average or typical value of a variable during a specific timeframe. Changes in the temporal mean can indicate significant events or disturbances in the system under study, such as a sudden decrease in vegetation indices indicating a possible landslide event. Standard deviation plays a crucial role in change detection studies, helping to weigh the significance of the anomaly. The results of this study demonstrate that, out of the five targeted electrical poles, anomalies were found in four. These findings were validated using aerial photos collected from the studied poles between 2016 and 2023. For one of the electrical poles, the results revealed no change in the land surface, which aligns with the aerial photos from the study area. The technique used is effective for detecting small-scale landslides in areas with dense vegetation. Generating historical datasets is crucial for utilizing RST in environmental feature modeling. With globally available satellite data such as Sentinel-2 and the Landsat series, employing RST becomes easier for studying environmental disasters like landslides on both local and global scales. This methodology is also suitable for developing early warning systems to monitor infrastructure, such as poles, in areas prone to environmental disasters. The methodology has been successfully tested in various parts of the world, including Greece, Mexico, Turkey, and the USA, achieving significant improvements in sensitivity and reduced false alarm rates. These results encourage its extension to other environmental emergencies and the use of different instrumental packages. This approach can also be easily applied to many other environmental processes, particularly those focused on detecting ongoing changes and evaluating their local impact. Additionally, the methodology can be adapted for landslide detection in regions with different geological characteristics. The availability of free remote sensing datasets, such as Sentinel-2, makes this technique easily accessible. As mentioned, we have constructed historical datasets of Sentinel-2 imagery for each pole to monitor the variation of land cover from 2016 to 2023. This study utilized a total of 2437 Sentinel-2 images for detecting landslide occurrence from 2016 to 2023. Recent advances in computer science have led to the use of learning-based approaches for landslide detection (Liao et al. 2022; Wang et al. 2023; Vegliante et al. 2024; Yang et al. 2024). However, they come with several disadvantages and challenges. Learning-based algorithms require large amounts of data to train effectively. However, landslide data might be limited, especially for certain regions or types of landslides. Additionally, the quality of available data can vary, with inconsistencies, inaccuracies, and biases that can affect the performance of the model. Models trained on data from one region or period may not generalize well to other regions or future events. Variations in geological, environmental, and socio-economic factors can affect the performance and reliability of the model in different contexts. Additionally, some learning-based algorithms, particularly complex models like deep learning, require significant computational resources for training and inference. This can be a barrier, especially for researchers and organizations with limited access to high-performance computing resources. Landslide detection models also need to be regularly updated to adapt to changing environmental conditions, land use patterns, and other factors that influence landslide occurrences. This requires ongoing data collection, model retraining, and validation efforts, which can be resource-intensive. Addressing these disadvantages requires a multidisciplinary approach involving collaboration between domain experts, data scientists, and stakeholders to develop robust, interpretable, and ethically sound landslide detection systems.

This study utilized the NDVI index to detect changes in land cover for small-scale landslide detection. In the applied methodology, changes in land cover are considered important indicators of alterations on the Earth's surface. In the context of using NDVI based on RST for small-scale landslide detection, vegetation is regarded as a vital factor. Since the study area is covered by various types of land cover, detecting landslides was not particularly challenging. However, using this technique in areas with sparse vegetation or bare soil would be challenging, highlighting an inherent limitation of all methods that rely solely on optical satellite data. Cloud cover is another challenge when using optical datasets, especially in regions or periods where cloudiness is frequent. Nevertheless, due to the temporal resolution of Sentinel-2 (providing at least five images per month), this issue primarily affects the timeliness of pole damage detection. The spatial resolution of the satellite data (Sentinel-2) used in this study is 10 meters, which can sometimes be insufficient for detecting very small-scale landslides.

Landslides pose significant risks to infrastructure, including electrical lines, as they can disrupt services, cause damage, and even lead to fatalities. Landslide detection and prediction help mitigate these risks by providing advance notice, allowing preventive measures to be taken. By detecting potential landslides early, the system can alert authorities and residents, giving them time to evacuate or take necessary safety precautions. This is particularly important for areas with high population densities or where infrastructure, such as electrical lines, is at risk. Electrical lines are often installed in areas prone to landslides due to geographical constraints or the need to serve remote regions. Landslide detection and prediction can help protect these critical infrastructure assets by providing alerts that trigger automatic shutdowns or proactive measures to reinforce or relocate vulnerable lines. Detecting landslides early can help minimize the financial impact of damage to electrical lines and other infrastructure. Repairing or replacing damaged infrastructure is often costly and time-consuming, so early warning systems can ultimately save money by preventing or minimizing these damages. In summary, the importance of an early warning system for landslide detection lies in its ability to reduce risks, enhance safety, protect infrastructure, save costs, preserve the environment, and maintain operational continuity, particularly for critical infrastructure like electrical lines.

6. Conclusion

Detecting and monitoring dynamic environmental hazards, such as landslides, has been challenging. With current remote sensing technology and methods, monitoring and simulating large-scale landslides has become possible. However, small-scale landslides and their effects remain a challenge. To address this, the study applied an automated satellite-based RST to detect the effects of small-scale landslides on electrical poles in southern Italy. The results reveal the high capability of automated RST in detecting small-scale landslides. Additionally, the findings show the effects of landslides on four of the five targeted electrical poles. This research highlights the efficiency of using GEE in combination with medium-spatial resolution Sentinel-2 data for monitoring mass movements, as it provides a vast amount of freely available remote sensing datasets. The efficiency of this method can assist researchers in risk management by improving their understanding of landslide mechanisms, enabling simulations of this phenomenon using long-term remote sensing datasets in landslide-susceptible regions. The results also demonstrate that frequent observation of electrical infrastructure can play a vital role in developing early warning systems to safeguard power lines and prevent further problems. In summary, the findings of this research are valuable for decision-makers and planners in the field of natural hazard management and for the power ministry in simulating and predicting mass movements in areas with electrical lines. The study establishes the high capability of this combined model for small-scale landslide mapping. The straightforward approach of the proposed model makes it a promising tool for future small-scale landslide mapping. Future research is recommended to use satellite data with high spatial resolution, as the landslides targeted in this study are on a small scale. Furthermore, densely vegetated areas are ideal for applying the RST for small-scale landslides.

Author's contributions

M. Kazemi Garajeh: Conceptualization, Methodology, Investigation, Writing- Original draft preparation; P. Paridad and V. Satriano: Methodology, Validation, Draft preparation, and Data curation; A. Guariglia, R. Santangelo, and V. Tramutoli: Supervision, Writing- Reviewing and Editing.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

Data availability statement

The datasets used and/or analyzed during the current study are available in the article/from the corresponding author on request.

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