



Article

Global Landslide Finder: Detecting the Time and Place of Landslides with Dense Earth Observation Time Series

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Abstract: This paper presents a remote sensing approach for rapidly and automatically generating maps of surface disturbances caused by landslides on the global scale. Our approach not only identifies the locations of these disturbances but also pinpoints the estimated time of their occurrence. Using the Continuous Change Detection and Classification (CCDC) algorithm within the Google Earth Engine (GEE) platform, we analyzed two decades of Landsat 5, 7, and 8 surface reflectance data. We tested this approach in five landslide-prone regions: Iburi (Japan), Kashmir (Pakistan), Karnataka (India), Porgera (Papua New Guinea), and Pasang Lhamu (Nepal). The results were promising, with R^2 values ranging up to 0.85, indicating a robust correlation between detected disturbances and actual landslide events compared to manually made inventories. The accuracy metrics further validated our method, with a producer's accuracy of 75%, a user's accuracy of 73%, and an F1 score of 75%. Furthermore, the method proved well transferable across different locations. These findings demonstrate the method's potential as a valuable tool for near real-time and historical analysis of landslide activity, thereby contributing to global disaster management and mitigation efforts.

Keywords: landslide; CCDC; Landsat; NDVI; Google Earth Engine; time series



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1. Introduction

The ability to swiftly identify the time and location of landslide occurrences is crucial for enhancing global disaster management and mitigation efforts. Landslides, as rapid and often unexpected natural events, pose serious threats to both the landscape and human populations in affected areas [1,2]. In this paper, we introduce the Global Landslide Finder, an approach designed to exploit dense time series satellite data for the automated and rapid detection of landslides globally. This approach systematically processes two decades of earth observation datasets to generate maps that not only pinpoint landslide locations but also approximate the timing of these events. This methodology represents a novel approach to monitor and analyze landscape changes due to landslides across various geographical settings without the constraints of traditional data collection methods.

Traditional methods for detecting and assessing landslides often suffers from limitations in the aftermath of large-scale landslides. Accessibility to affected areas can be restricted, time constraints can hinder an evaluation, and danger zones may pose risks to field personnel. Remote sensing can provide timely, extensive, and detailed spatial data that can overcome the limitations of on-ground assessments [3]. Numerous studies have demonstrated the efficacy of remote sensing in mapping landslides, with several highlighting the potential of optical remote sensing for (semi-)automated mapping. These studies typically employ either mono-temporal techniques to identify landslides from a single image captured after a triggering event [4–6] or bi-temporal (change detection) techniques to detect surface change by comparing images before and after the event [7–9]. These studies often focused on precise spatial delineation of landslides; there has been limited focus on analyzing landslide activity over time. Satellite data acquired over longer time

intervals require methods for consistent and comprehensive mapping of landslides over large areas. By studying a series of satellite images covering a specific time frame, we can gain insight into landscape changes, which can indicate landslide dynamics and provide time-specific information of these changes. Only a few studies investigated landslide detection using multi-temporal remote sensing approaches [10–12]. Behling et al. [13] developed multi-temporal landslide inventories for a 2500 km² area in Southern Kyrgyzstan. They generated multiple bi-temporal images from multi-sensor time series data and applied various threshold-based analyses against the Normalized Difference Vegetation Index (NDVI). This approach relies heavily on conventional data management techniques for the collection and processing of multi-temporal sensor data, which makes it a time-consuming process, posing challenges for rapid landslide analyses across diverse areas and hindering the method's transferability. Nevertheless, this stance remains valid even when considering the adoption of advanced data management through geospatial cloud computing platforms. Kushanav et al. [14] used deep learning for mapping landslides using Planet Lab data. While innovative, the accessibility of Planet Lab data is commercially restricted, which sets a significant barrier to widespread application. In addition, the transferability and performance of deep learning models in diverse geographic settings remains a question of concern [15]. More daily temporal-resolution Planet Lab data could enhance the detection of landslides. However, excessive data can also complicate the training process of deep learning models, potentially leading to overfitting or increased computational demands, especially when distinguishing relevant features amidst variable cloud cover conditions [16]. The balance between data volume and quality, therefore, is crucial in optimizing the efficacy of deep learning applications in remote sensing for landslide detection [17]. The combination of having to deal with massive datasets, have different sources, and the availability of data to detect landslides has so far been a limiting factor in the continuous global detection of landslides.

To overcome this, we propose to use the Continuous Change Detection and Classification (CCDC) algorithm [18] for mapping the locations and timing of landslide occurrences. CCDC automates the processing of large datasets, which significantly enhances the speed and scalability of analysis across diverse geographic areas [19,20]. Furthermore, CCDC requires minimal customization to yield accurate results across different settings [19,21], addressing the limited transferability. CCDC has demonstrated effectiveness in minimizing the impact of cloud cover on satellite imagery analysis [18]. We implemented CCDC in Google Earth Engine (GEE), a cloud-based geospatial platform [22]. A key advantage of GEE is the close connection between the data and the algorithms, both of which can be accessed through an application programming interface (API, [19]). Our integration of the GEE platform with the CCDC algorithm [19,20] aims to overcome the limitations of data management, processing efficiency, and transferability previously identified in multi-temporal landslide mapping efforts. The overall objective is automated and rapid detection of landslide locations and timing across the whole globe.

2. Methods and Datasets

2.1. CCDC and Landslide Criteria

CCDC is a breakpoint-finding algorithm that uses dynamic thresholds to detect breaks in time series data. Details of the inner workings of CCDC can be found in Zhu and Woodcock [18]. We implemented the CCDC algorithm within the GEE platform to detect surface disturbances at the pixel level. The breakpoints obtained by temporal segmentation indicate specific moments in time when the landscape undergoes significant changes or disturbances. Such changes may result from a variety of events, including the formation of bare patches of land arising from various natural events, such as earthquakes, hydro-meteorological events [23,24], and anthropogenic events [25]. The core of the breakpoint definition is encapsulated in the use of so-called 'breakpoint bands'. These are not the conventional physical bands typically observed in multispectral imagery (e.g., red, green, blue, near-infrared) but rather conceptual indices adept at detecting notable shifts in

spectral signatures, signaling a change. We used the Normalized Difference Vegetation Index (NDVI) as our breakpoint band to detect changes, particularly in vegetation. NDVI has proven to be highly effective in identifying areas where vegetation has been removed or significantly reduced [26,27], thus indicating the presence of bare patches associated with landslide activity [4,5,28].

The temporal segmentation starts by applying a harmonic regression to the breakpoint band of the time series' initial segment. A change is detected when each measurement within a minimum number of consecutive observations exceeds a chi-squared probability threshold. The chi-squared probability threshold controls the sensitivity of the algorithm to detect change [18,19]. Assuming the time series still has enough observations, a new model is trained for the next segment. This process is repeated until the end of the time series. We varied the chi-squared probability threshold by using thresholds of 0.80, 0.85, 0.90, and 0.99 to examine the sensitivity of the detection algorithm. We set a minimum of 3 consecutive observations to flag change, as CCDC needs at least 3 consecutive observations [21]. After confirming changes for each pixel, CCDC generates a disturbance map. After generating the disturbance map, we filtered the map for areas that were unlikely to have landslides, such as water bodies and slopes of 10 degrees or less. The latter was grounded in a well-established correlation between steep slopes and the likelihood of landslide occurrence [1,29,30].

2.2. Datasets

We used Landsat 5, 7, and 8 Tier-1 surface reflectance (SR) data from 1 January 2000 to 1 January 2020, with a spatial resolution of 30 m $\times$ 30 m. The Tier-1-level SR data of this collection had precise geolocations and were inter-calibrated between the different Landsat instruments [31]. Each image underwent a pre-processing procedure, including the masking of pixels flagged by the Pixel Quality Assessment (QA) band, for cloud cover, shadow, and snow cover. We used data from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM) and the Joint Research Centre (JRC) Global Surface Water dataset [32] to derive slope and water body filters, respectively.

2.3. Study Areas

We selected five regions (Figure 1) that are known for their susceptibility to landslides and which had a known triggering event in the years 2000 to 2020. Iburi (Japan) is in the southern part of Hokkaido Island. Iburi experienced an earthquake of Mw 6.6 at a depth of 37 km on 6 September 2018, which triggered approximately 6000 landslides over an area of 46 km² [33,34]. Kashmir, a region in Pakistan, is situated in a seismically active region of the Himalayas. Kashmir was affected by a 7.8 Mw earthquake on 8 October 2005, which triggered thousands of landslides over an area of 7500 km² [35,36]. Karnataka is located in the Western Ghats in India. Karnataka experienced extreme rainfall in August 2018, resulting in floods and 771 landslides covering an area of 7.1 km² [37]. Porgera, Papua New Guinea, is situated in a complex zone of collision between the Australian and Pacific Plates. A 7.5 Mw earthquake on 25 February 2018, followed by four powerful aftershocks, triggered approximately 11,500 landslides over an area of 185 km² [25]. Pasang Lhamu is located in the Rasuwa district in Central Nepal. Part of the tectonically active Himalayan belt, Pasang Lhamu is prone to earthquake-triggered landslides and rockfalls due to high precipitation, complex topography, and anthropogenic activity [4,38,39].

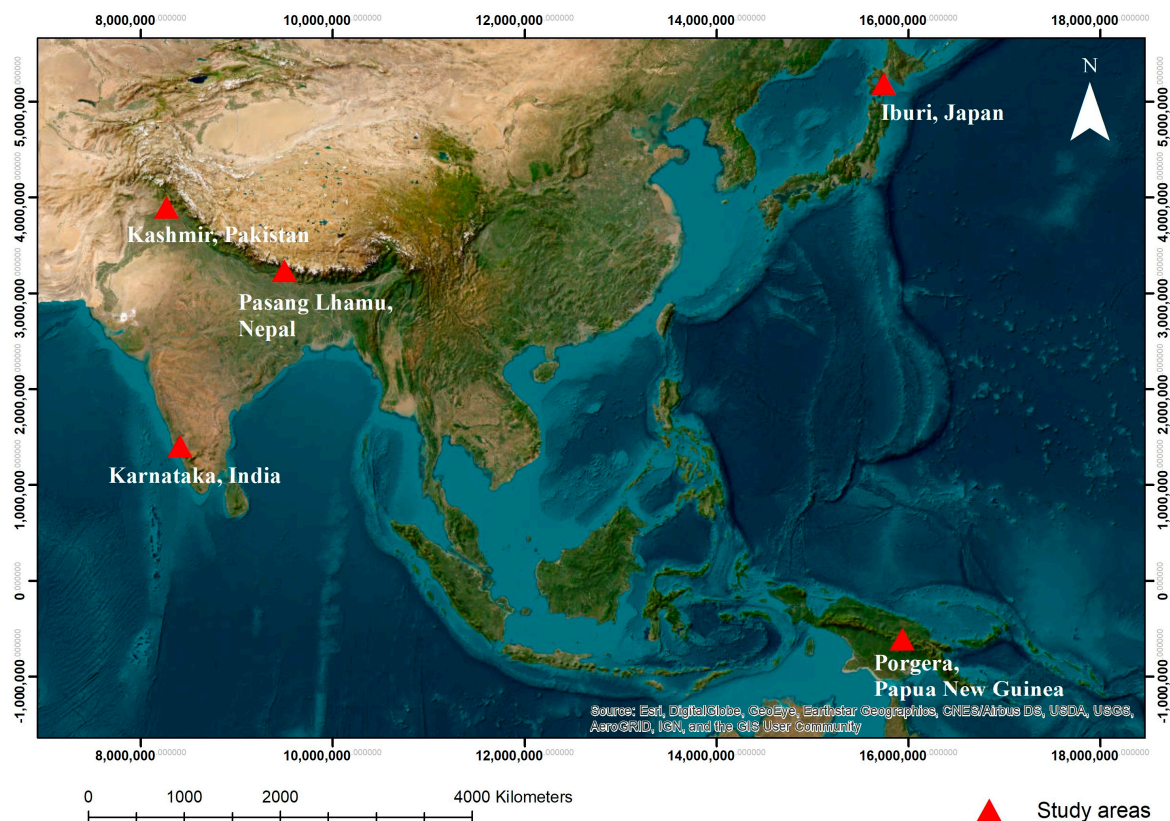


Figure 1. Locations of five study areas prone to landslides with historical landslide events from 2000 to 2020. This map highlights Iburi (Japan), Kashmir (Pakistan), Karnataka (India), Porgera (Papua New Guinea), and Pasang Lhamu (Nepal). (The base map is from Esri World Imagery).

2.4. Validation

Our method can detect landslides at the resolution of the NDVI breakpoint band originating from Landsat, which is $30\text{ m} \times 30\text{ m}$. By contrast, most landslide inventories we used as references were created with images of 1-to-3 m resolution, making a direct pixel-to-pixel or polygon-based validation an ill comparison. We therefore performed comparisons in slope units (SUs) [4]. By using SUs, we addressed the issue of discontinuity in landslide detection. Aggregating occurrences within these units rather than comparing at the pixel level allowed us to overcome the limitations of varying resolutions between our method and the reference inventories. This approach ensured a more coherent and comprehensive assessment of landslide susceptibility, reflecting the continuous nature of landscape processes more accurately. SUs subdivide the terrain into units that reflect the natural landscape's processes and conditions, which is deemed apt for landslide susceptibility modeling and zonation [40–43]. The slope units were generated from a SRTM DEM using *r.slopeunits* software v1.0 [43].

To validate our study, we used five separate reference landslide inventories, each specific to a different region within our study area. These reference inventories were obtained from various sources: high-resolution aerial photos and satellite imageries (PlanetScope and RapidEye), and ground observations. Furthermore, several methods were employed to outline the shapes of the landslides, including manual delineation, semi-automatic detection, and the application of deep learning techniques. Detailed information about these inventories is provided in Table 1.

Table 1. Detailed list of landslide inventories used in the study areas.

Regions	Temporal	Type of Inventory	Source
Iburi	Event-based inventory 2018	Polygon	Manual delineation from aerial photographs and ground observations [33]
Kashmir	Event-based inventory 2005	Polygon	Satellite-based interpretation [44]
Karnataka	Event-based inventory 2018	Polygon	Deep learning delineation from PlanetScope imagery [6]
Porgera	Event-based inventory 2018	Polygon	Manual delineation from PlanetScope imagery [25]
Pasang Lhamu	Multi-temporal inventories 2009–2018	Points (initiation points)	Semi-automatic detection from RapidEye imagery [45]

Following Amatya et al. [4], we compared our mapping results with the reference inventories by making landslide density maps, overlaying our mapping results and the reference landslide polygons onto the SUs (Appendix A, Figure A1). We then compared the SUs with landslides obtained from our method against those found in reference inventories and only included data from the year of the landslide event in the reference inventories that were created. We also used the multi-temporal reference inventories from Table 1 for validation and employed accuracy metrics, such as producer’s accuracy (omission error) to measure the proportion of actual landslide occurrences that were correctly identified by the algorithm, user’s accuracy (commission error) to measure the proportion of predicted landslide occurrence that was correctly identified, and the F1 score to measure the test’s accuracy, considering both the user’s accuracy and the producer’s accuracy.

3. Results

3.1. CCDC Temporal Segmentation

The NDVI time series, as a breakpoint band, and the time segments detected by the CCDC algorithm for three selected pixels with different land covers in Iburi are shown in Figure 2. The first chart highlights two segments caused by a deviation from the typical NDVI trajectory toward the end of 2018. The second chart highlights a single segment, showing a stable NDVI without significant disturbances. Finally, the third chart highlights three segments, indicating deviations from the expected NDVI trajectory, with disturbances corresponding to the periods around 2006 and 2010. Each pixel on the disturbance map is color-coded based on when the change was detected, providing a visual representation of where and when the land surface was altered (Figure 3).

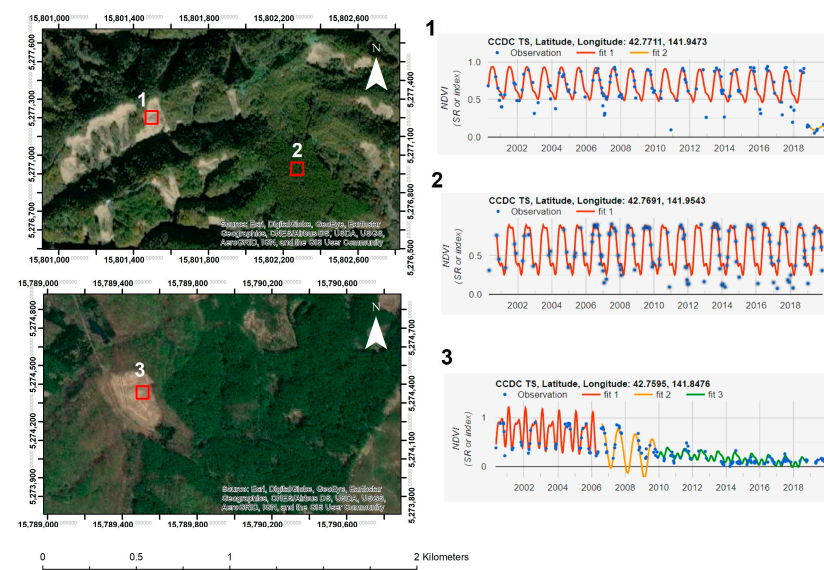


Figure 2. NDVI time series of selected pixels in the Iburi region, Japan. The first chart shows a deviation from the typical NDVI pattern toward the end of 2018. The second chart shows a stable

NDVI without significant disturbances. The third chart reveals deviations from the expected NDVI trajectory, corresponding to disturbances occurring around 2006 and 2010 (The base map is from Esri World Imagery).

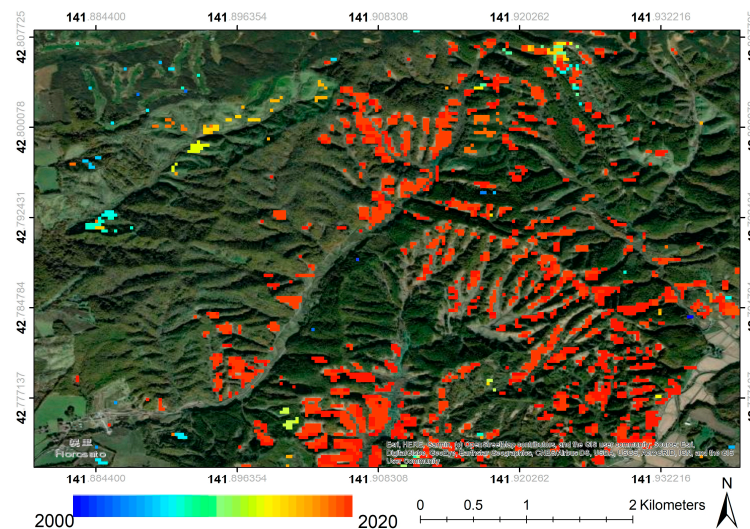


Figure 3. The cumulative map of land disturbances from 1 January 2000 to 1 January 2020, in the Iburi region, with the color gradient representing the timing of disturbances. (The base map is from Esri World Imagery).

3.2. Landslide Validation

We compared the SUs in four regions: Iburi, Kashmir, Karnataka, and Papua New Guinea (Figure 4a–d). For the Pasang Lhamu region, a direct comparison of landslide areas was not possible because the inventory provided only point data, lacking specific area information. Therefore, for Pasang Lhamu, we evaluated the CCDC algorithm's accuracy by categorizing the results into True Positive (TP), False Negative (FN), and False Positive (FP). We used multi-temporal reference points from Table 1 as the ground truth to make these classifications. The spatial distribution of landslide area coverage showed there were correlation between the proposed method and the reference inventories across the four regions, as illustrated in the scatter plots in Figure 5. For Iburi (Figure 5a), the scatter plot showed an R^2 value of 0.81. Most data points clustered near the lower end of both axes, suggesting that smaller landslides were more common in this region. The dense clustering of points near the origin meant that both the proposed method and the reference inventory consistently identified small landslide areas. In Kashmir (Figure 5b), the scatter plot showed an R^2 value of 0.85, the highest among the four regions. Similar to Iburi, the data points were densely packed at the lower end of the axes, indicating that smaller landslides were frequently detected. The scatter plot for Karnataka (Figure 5c) presented an R^2 value of 0.62. Here, the data points were more widely spread along both axes, reflecting a wider range of landslide sizes. This spread suggested greater variability in the landslide areas identified by both methods, with some larger landslides being present. In Papua New Guinea (Figure 5d), the scatter plot showed an R^2 value of 0.56, the lowest among the four regions. Similar to Karnataka, the data points were dispersed across a wider range, suggesting variability in landslide sizes. The broader spread of data points indicated that the proposed method and the reference inventory identified a wide range of landslide areas, including some large ones. For Pasang Lhamu, the algorithm achieved a producer's accuracy of 75% and a user's accuracy of 73%, corresponding to omission and commission errors of 25% and 27%, respectively, with an F1 score of 75%.

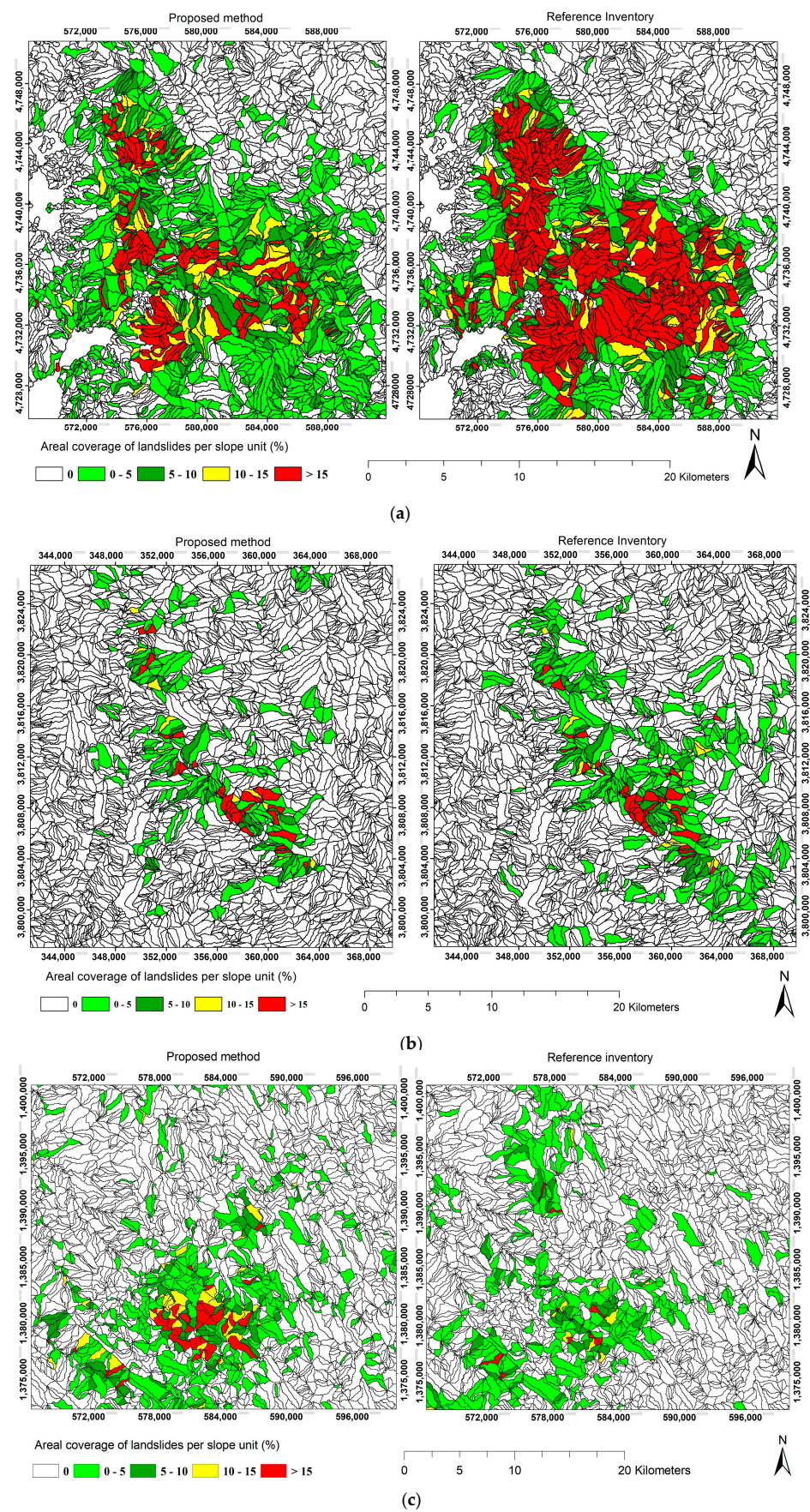


Figure 4. Cont.

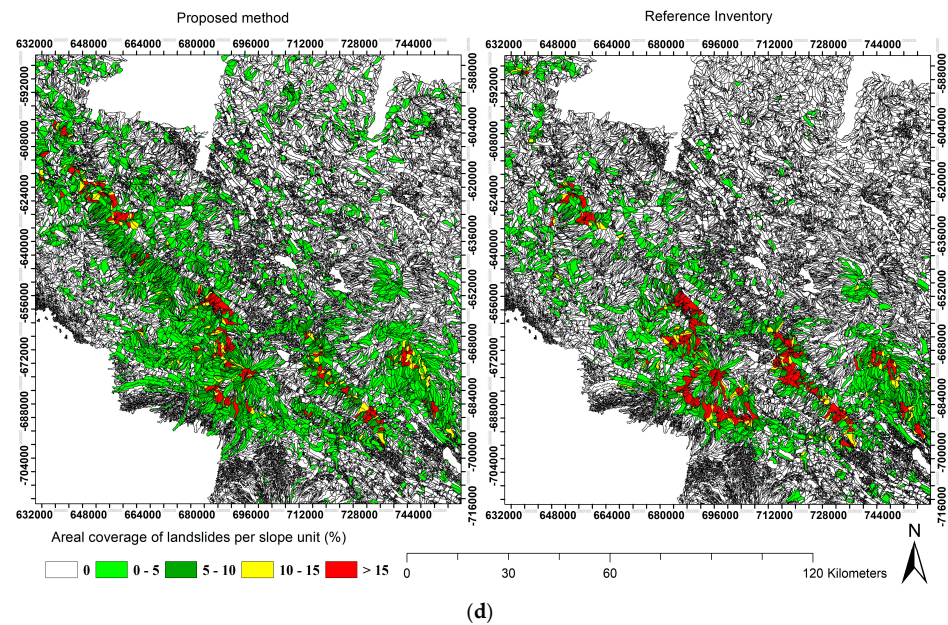


Figure 4. Comparison of areal coverage of landslides mapped per SU between the proposed method and reference inventory: (a) Iburi; (b) Kashmir; (c) Karnataka; (d) Papua New Guinea.

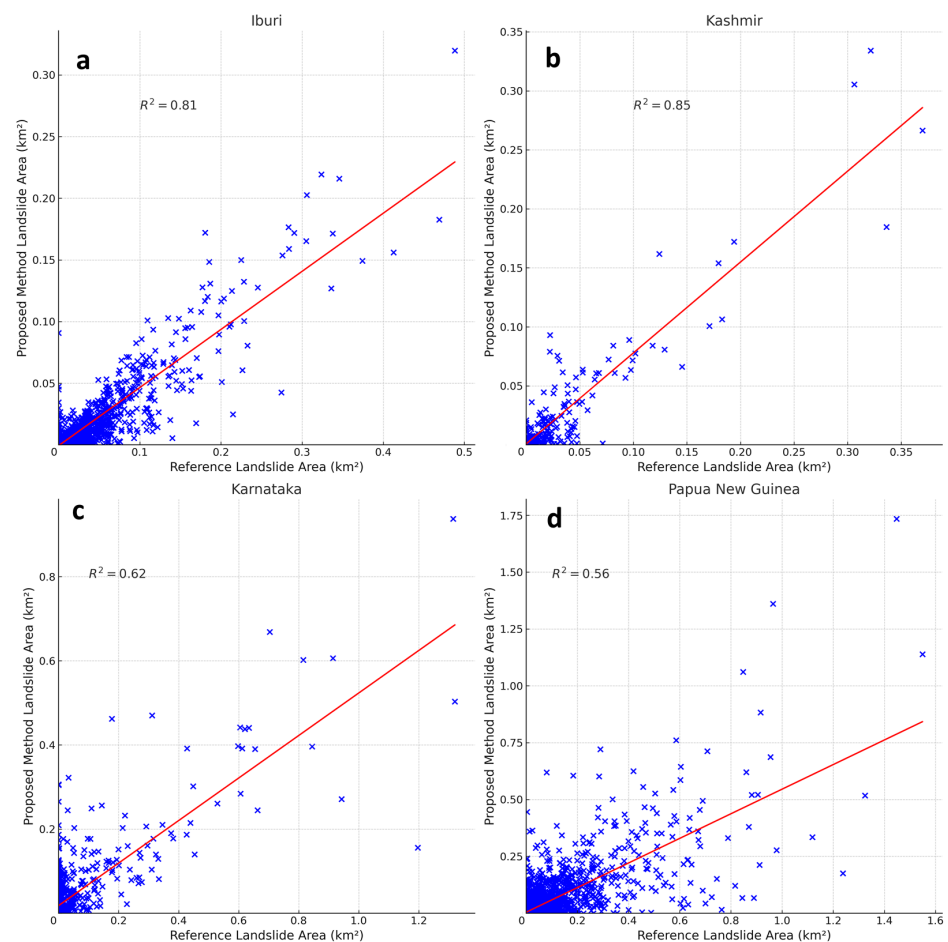


Figure 5. Scatter plot of landslide areas mapped for each SU between the proposed method and reference inventory: (a) Iburi; (b) Kashmir; (c) Karnataka; (d) Papua New Guinea.

3.3. Accumulated Disturbance Maps and Timing

The accumulated disturbance map for the landslide events listed in Table 1 is exemplified in Figure 6a, illustrating the Iburi region. Complementing this map is Figure 6b, which shows the count of pixels within the region that experienced changes over time. These results highlighted a significant increase in detected disturbances immediately following the landslide event. Specifically, in the Iburi region, a cluster of disturbances was observed following the 2018 Hokkaido Earthquake, offering a clear visual representation of the potential landslide's spatial extent. The corresponding number of changed pixels graph indicated a significant surge in disturbances immediately after the earthquake on 6 September 2018.

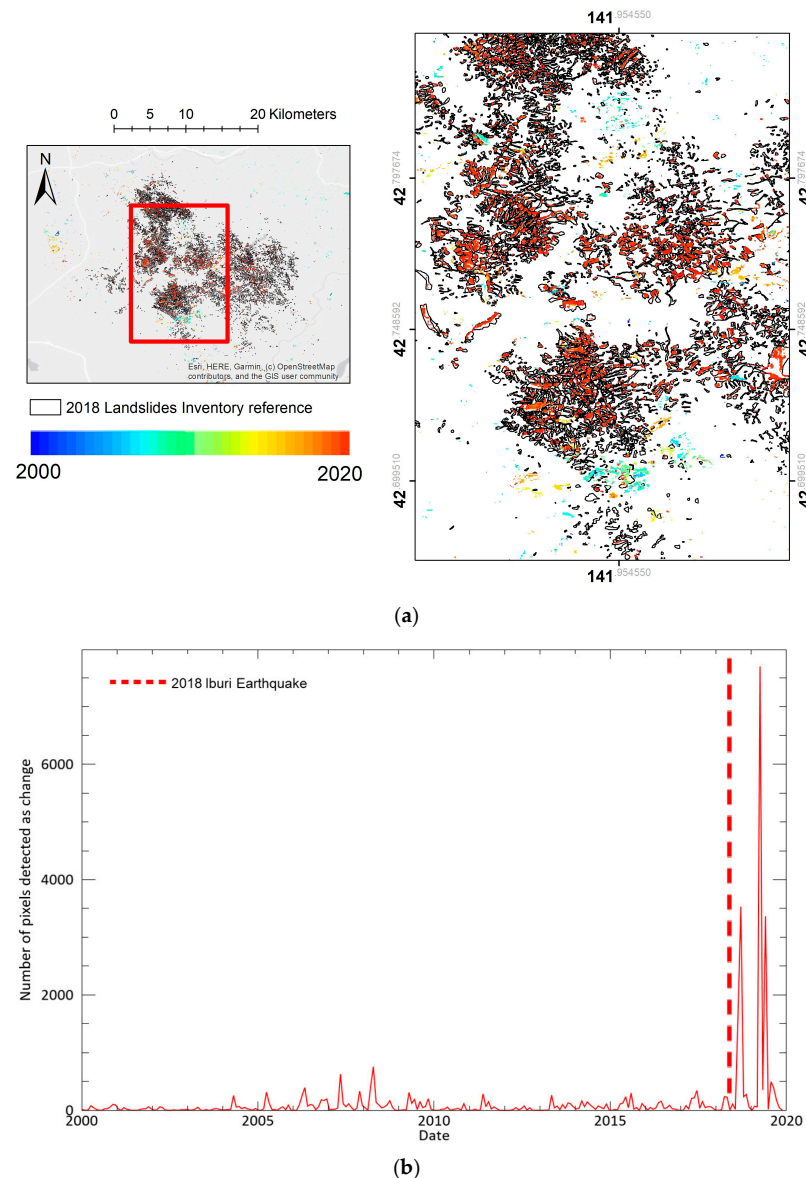


Figure 6. Panel (a) illustrates the cumulative map of land disturbances from 2000 to 1 January 2020, in the Iburi region, with the color gradient representing the timing of disturbances. Superimposed are polygons that outline the reference inventory of landslides that occurred in 2018, providing a spatial context for the disturbances depicted. Panel (b) depicts the time series of the number of changed pixels; notable spikes in the graph reflect increased detection of changes, the dashed line corresponds with a specific disturbance event. The number of changed pixels is calculated based on the entire area of the region in the **left panel** in Figure (a).

Other patterns were observed in other regions, as detailed in the Appendix B (Figures A2–A5). For instance, disturbances in the Kashmir region post the 2005 earthquake are captured in Figure A2a, and the number of changed pixels graph (Figure A2b) revealed a notable spike in changes immediately after the earthquake, demonstrating the earthquake's impact on surface disturbances. Additional significant changes were detected in the years 2006, 2009, and 2017. In the Karnataka region, the accumulated disturbance map (Figure A3a) showcases a distinct visual delineation of potential landslide areas, particularly from 15 to 17 August 2018. The number of changed pixels showed a substantial increase following this event (Figure A3b).

In Papua New Guinea, the spatial extent of accumulated disturbances was clearly highlighted within the timeframe of the 2018 Papua New Guinea earthquake, as shown in Figure A4a, with the number of changed pixels indicating a considerable change after the earthquake on 25 February 2018 (Figure A4b). These changes represented approximately 20,000 pixels undergoing change, marking it as one of the most significant single-event disturbances observed in the study areas. Finally, in the Pasang Lhamu Highway region, the accumulated disturbance map highlights the spatial extent of disturbances following multi-temporal landslide events (Figure A5a). The number of changed pixels showed a pronounced spike around the time of the 2015 Gorkha Earthquake (Figure A5b).

3.4. Chi-Square Threshold

We assessed the impact of the chi-square probability value (0.80, 0.90, 0.95, and 0.99) on the detection accuracy in comparisons against 1500 reference points from the multi-temporal inventories presented in Table 1. We observed that there was a clear relationship between the omission and commission errors as a function of the chi-square probability (Figure 7). With increasing chi-square probability, the omission error increased, while at the same time, the commission error decreased. An optimal value for landslide detection was obtained with a chi-square probability of 0.99, achieving a balance between an omission error of 26% and commission error of 25%.

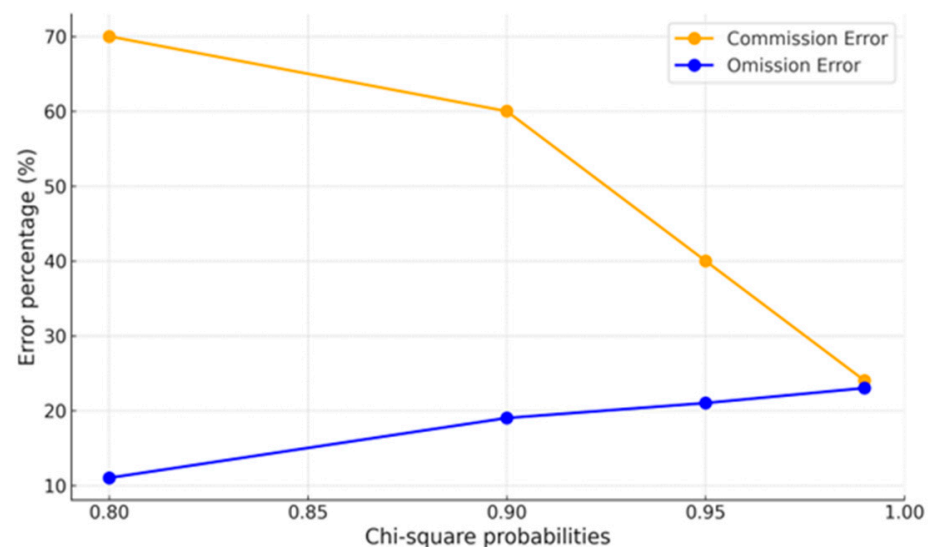


Figure 7. Omission and commission errors with the chi-square probability threshold changing from 0.80 to 0.99.

4. Discussion

4.1. Factors That Influence Detection

The use of dense Landsat time series and the CCDC algorithm provides the possibility of mapping surface disturbances that are related to landslide activity, both in time and location. Our approach led to the creation of accumulated disturbance maps that clearly delineated areas potentially affected by landslides (Figures A2a, A3a, A4a and A5a). Overall,

the spatial distributions of landslide area coverage across regions (Figure 4) were consistent, offering locations that correlated positively with the reference data, indicating that the method could identify landslide locations (Figure 5). While most observed changes were directly attributable to landslide activity, some were false positives. In the case of Pasang Lhamu, the primary sources of false positives were snow, glaciers, and debris flow within river catchments. Despite the implementation of cloud, shadow, and snow masking, the effects of glacier runoff, which carries debris and sediment that cause permanent changes to the landscape, are not addressed by masking, and were mistakenly detected as landslides. The region is known for its landscape dynamics, attributed to glacier outbursts and tectonic activity [39,46]. To accurately detect landslides in this area, more effective snow masking techniques are necessary, or alternatively, utilizing breakpoint bands other than NDVI that are sensitive to brightness changes.

The use of optical remote sensing data also can potentially lead to misclassifications due to clouds and cloud shadows. In Papua New Guinea, cloud cover and cloud shadows significantly hindered landslide detection: about 42% of the images had over 50% cloud cover. This region experiences frequent heavy cloud cover with high levels of precipitation. Despite preliminary efforts to mask clouds, some landslides were mistakenly identified as clouds and masked out. There is a trade-off between using aggressive versus simple cloud masking techniques: while aggressive cloud masking reduces cloud interference, it may also inadvertently eliminate pixels that could indicate potential landslides.

We analyzed the timing of landslides from the number of changed pixels. Several significant increases in the number of changed pixels immediately followed a triggering event, indicating a correlation between the observed changes and triggering events. However, not all observed significant changes were attributable to landslide activity. For example, in the Kashmir region, notable increases in detected changes during the years 2006, 2009, and 2017 (Figure A2b) were associated with extensive deforestation and the transformation of vegetated areas into urban space for the new city of Balakot.

The selection of the chi-square threshold also influences landslide detection. In our study, equal error rates between omission and commission indicated that the chosen chi-square probability threshold (0.99) was suitable for our analysis. Given these considerations, 0.99 appeared to be the optimal threshold for our applications. It achieved a reduction in commission error, dropping below 30%. The omission error remained around 20%, which is acceptable if maintaining a lower FP rate is crucial. In applications where missing a TP has severe consequences, a lower threshold might be preferable despite a higher commission error. Conversely, in situations where FPs are particularly costly or disruptive, pushing the threshold closer to 1.00 might be justified.

4.2. Advantage of the Method

The implementation of the CCDC algorithm on the GEE platform provides several advantages, such as the ability to process large datasets to automatically detect landslides over large areas and within 5 to 10 min, depending on the geographical area. For example, in Papua New Guinea, which covers an area of around 46,000 km², the approach takes the longest. This, however, contrasts sharply with the manual mapping efforts of Tanyas et al. [25], which required about a month for single-event analysis (personal communication). The efficiency of our method is also highlighted when compared to Amatya et al. [4], who utilized semi-automatic mapping techniques to generate a landslide inventory in Pasang Lhamu, which required up to one hour. By contrast, our approach delivers results in a matter of minutes, with extensive temporal coverage. This rapid automatic processing ensures timely landslide detection, which is critical for monitoring and immediate disaster response efforts.

4.3. Algorithm Transferability and Future Works

The algorithm's transferability to different areas is simple, with little need for localized adjustments, addressing limitations in previous multi-temporal landslide detection methods [13]. It is worth mentioning that the algorithm can create disturbance maps without training data. This uniform applicability is especially beneficial for global-scale monitoring, ensuring standardized and consistent detection. Lastly, the utilization of publicly available satellite data and cloud computing has benefits for natural disaster monitoring, such as landslides [47,48]. This approach offers promising potential for the development of a Global Landslide Finder. This innovative approach could be used to develop an automated landslide detection system by enabling the precise identification of landslide locations and timing on a global scale. Such a system would not only enhance our ability to monitor historically but also in near-real time. It also significantly contributes to the advancement of monitoring natural hazards, providing critical data for disaster management and mitigation strategies worldwide.

5. Conclusions

We developed the Global Landslide Finder, an automated and rapid multi-temporal landslide detection approach on the Google Earth Engine platform, leveraging 20 years of data from the Landsat archive. Applied to five landslide-prone areas, the CCDC algorithm detects locations of landslides and the time of the earliest detection. Our approach yielded quantitatively robust results, with R^2 values ranging from 0.59 to 0.85 when comparing landslide areas within specific slope units. Validation against multi-temporal reference landslide events further affirmed the method's accuracy, achieving a producer's accuracy of 75%, a user's accuracy of 73%, and an F1 score of 75%. These metrics underscore the method's reliability and precision in identifying landslide locations and their timing. In terms of processing speed and transferability to other areas, generating surface disturbance maps linked to landslides takes a matter of minutes. This makes this approach a practical solution for mapping landslides over large areas and has the potential for usage in immediate disaster response efforts. As such, it offers a valuable tool for both near real-time and historical landslide analysis, contributing to disaster management and mitigation strategies on a global scale. Future research should focus on developing a publicly accessible global landslide monitoring web application based on this approach. Such a web application would be invaluable for researchers, policymakers, and practitioners involved in land use planning, hazard assessment, and disaster risk reduction.

Author Contributions: M.A. created the concept and design, execution of building the script, and performed validation and analysis; H.v.d.W. and M.v.d.M. contributed to the concept, design, analysis, and review of the draft manuscript; A.E.J.B. reviewed the draft manuscript. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The underlying JavaScript code is available in Github (<https://github.com/aufaristama/CCDC-Landslide>, accessed on 19 August 2021). All data used in this research are open data.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

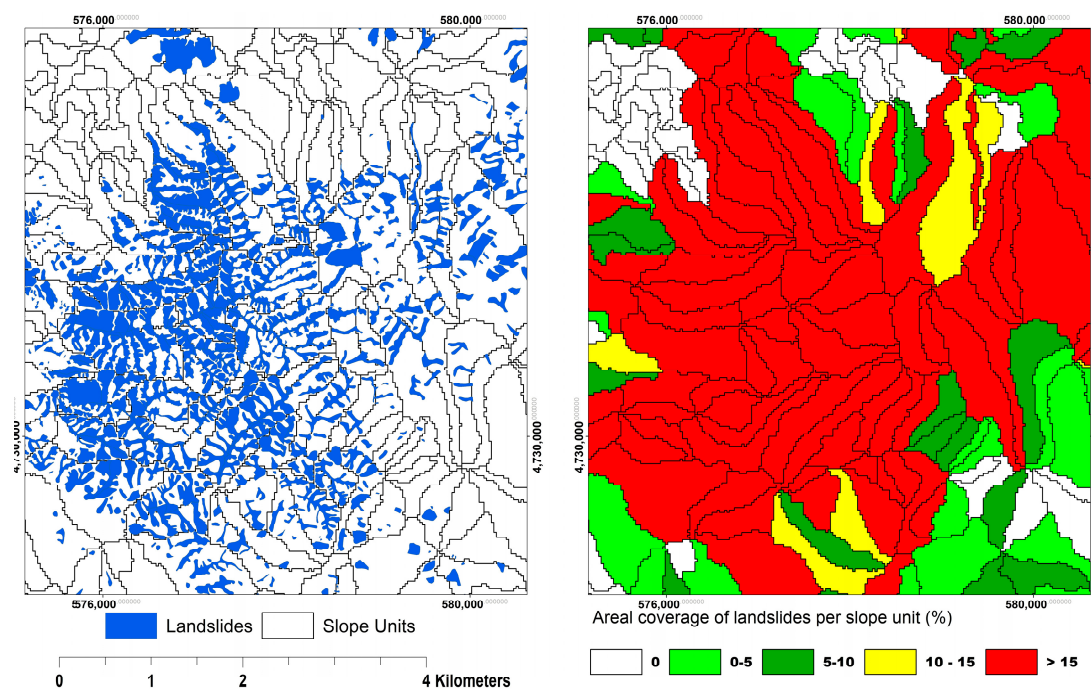


Figure A1. The process for intersecting the polygons of a landslide inventory with slope units to create a landslide density map. The density map shows, in percentage, the landslide coverage within each slope unit.

Appendix B

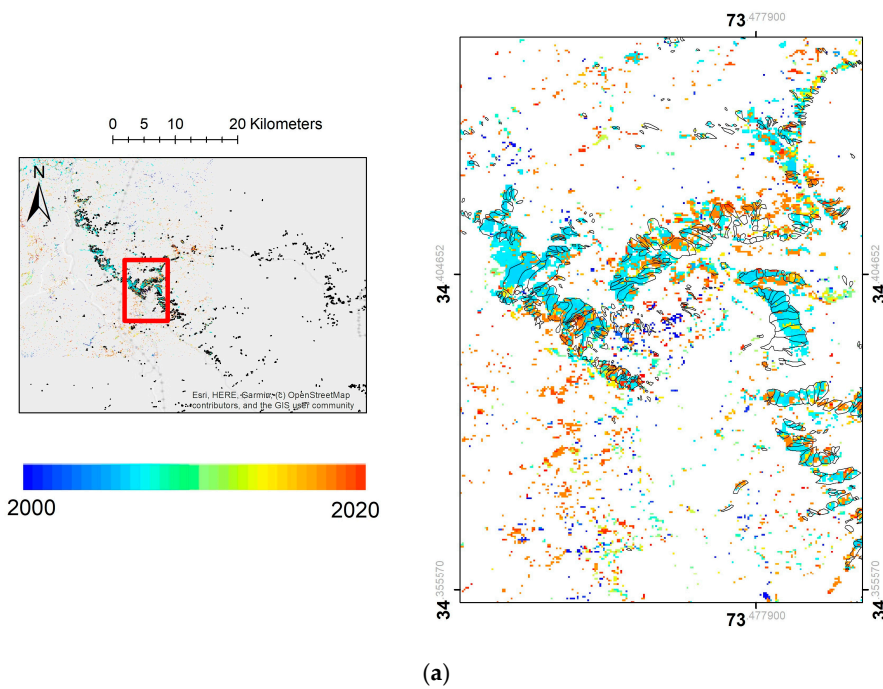


Figure A2. *Cont.*

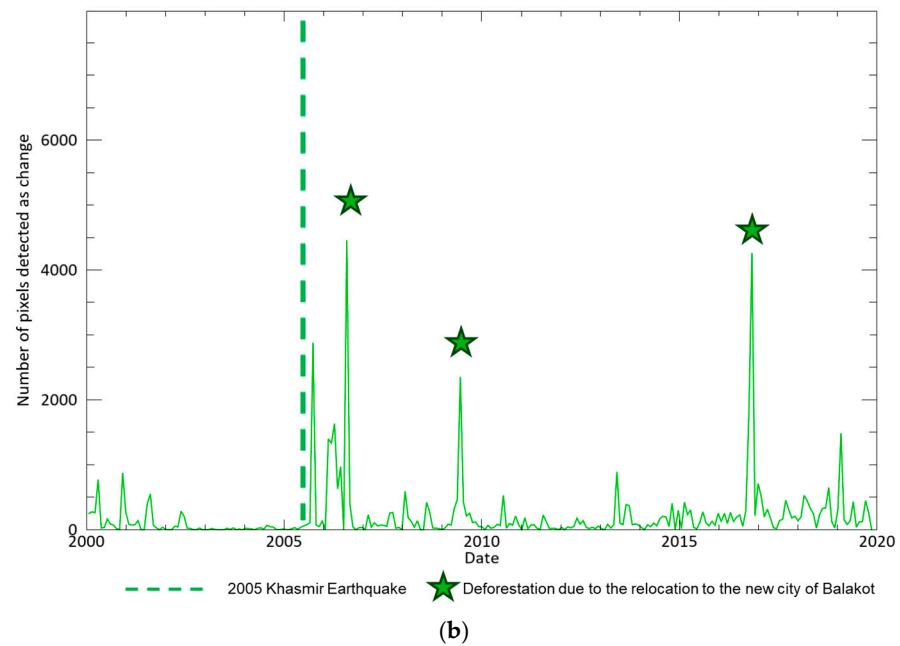


Figure A2. Panel (a) illustrates the cumulative map of land disturbances from 2000 to 1 January 2020, in the Kashmir region, with the color gradient representing the timing of each disturbance. Superimposed on this map are polygons that outline the reference inventory of landslides that occurred in 2005, providing a spatial context for the disturbances depicted. Panel (b) depicts the time series of the number of changed pixels; notable spikes in the graph reflect increased detection of changes, the dashed line corresponds with a specific disturbance event. Star symbols pinpoint activities that resulted in numbers of changed pixel spikes but are not associated with landslides. The number of changed pixels is calculated based on the entire area of the region in the **left panel** in Figure (a).

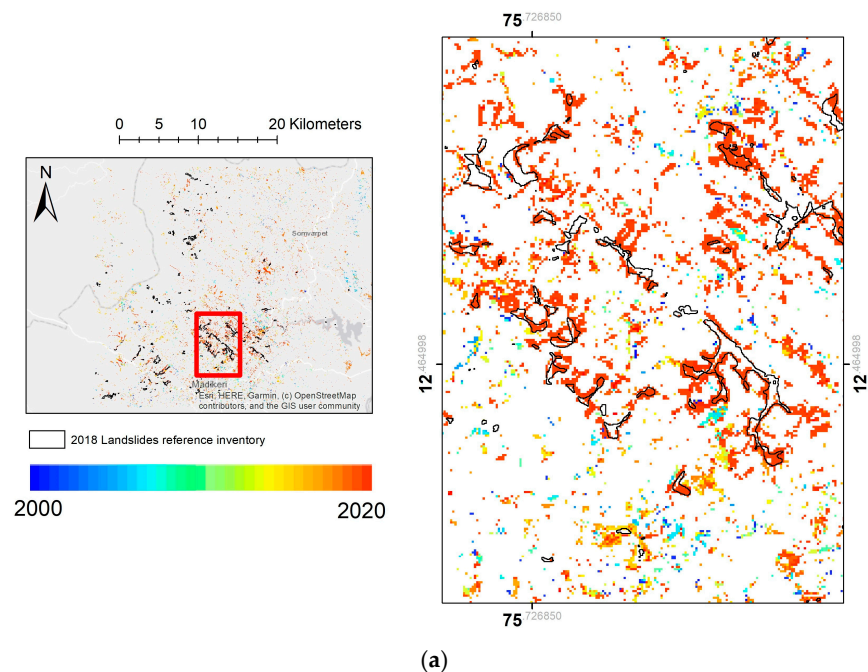


Figure A3. *Cont.*

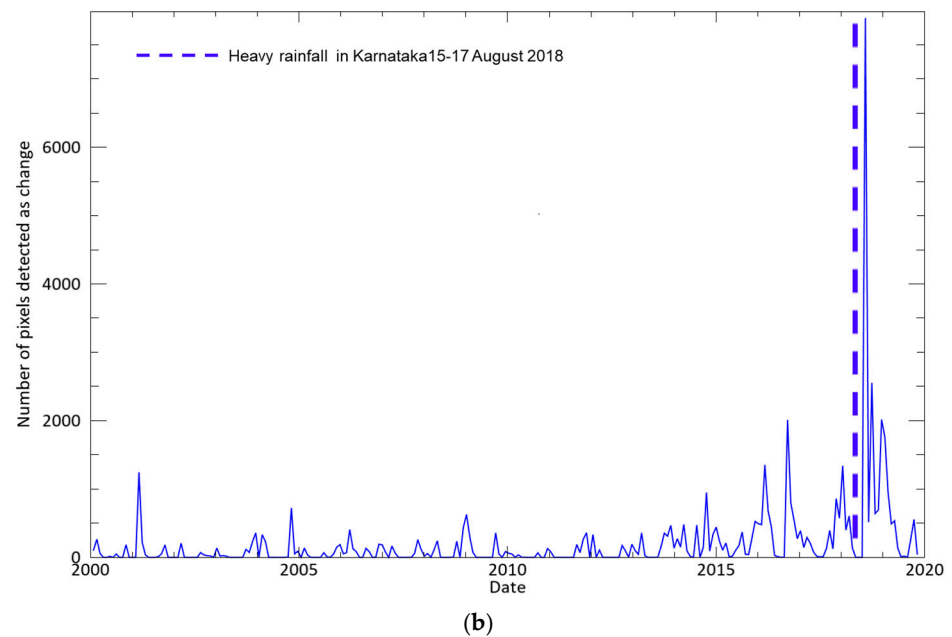


Figure A3. Panel (a) illustrates the cumulative map of land disturbances from 2000 to 1 January 2020, in the Karnataka region, with the color gradient representing the timing of each disturbance. Superimposed on this map are polygons that outline the reference inventory of landslides that occurred in 2018, providing a spatial context for the disturbances depicted. Panel (b) depicts the time series of the number of changed pixels; notable spikes in the graph reflect increased detection of changes, the dashed line corresponds with a specific disturbance event. The number of changed pixels is calculated based on the entire area of the region in the **left panel** in Figure (a).

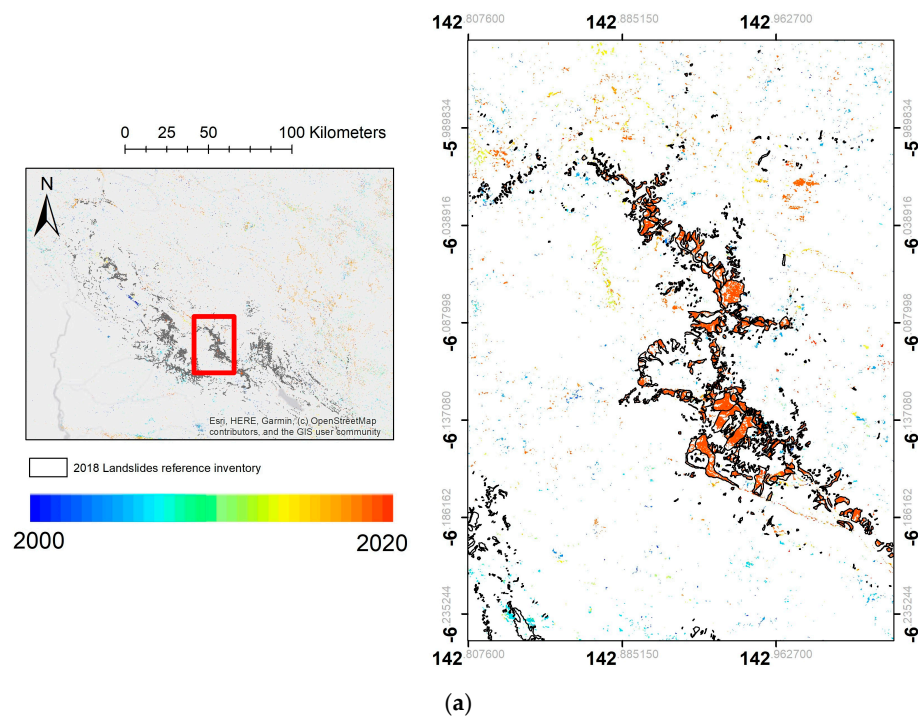


Figure A4. *Cont.*

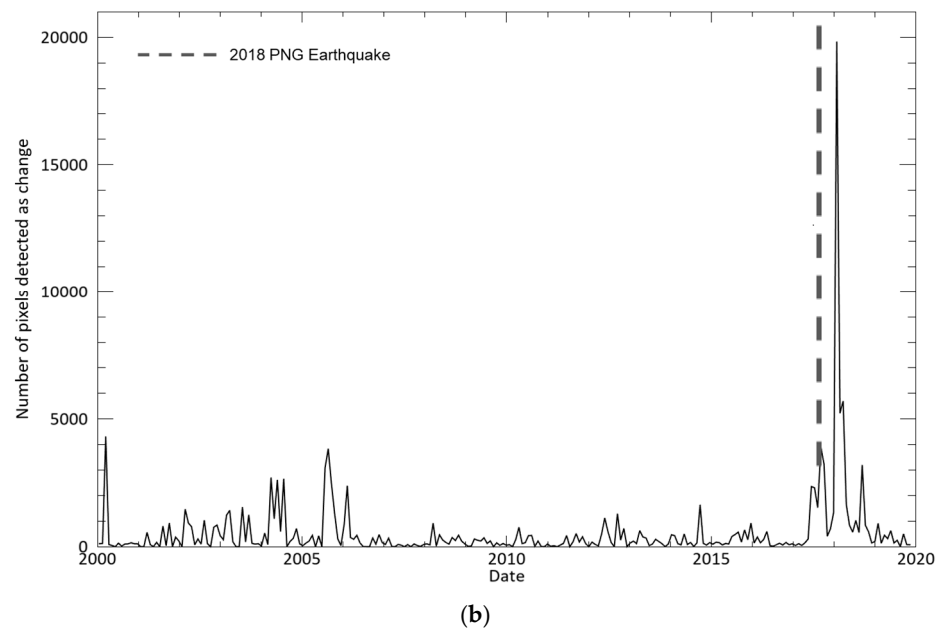


Figure A4. Panel (a) illustrates the cumulative map of land disturbances from 2000 to 1 January 2020, in the Papua New Guinea region, with the color gradient representing the timing of each disturbance. Superimposed on this map are polygons that outline the reference inventory of landslides that occurred in 2018, providing a spatial context for the disturbances depicted. Panel (b) depicts the time series of the number of changed pixels; notable spikes in the graph reflect increased detection of changes, the dashed line corresponds with a specific disturbance event. The number of changed pixels is calculated based on the entire area of the region in the **left panel** in Figure (a).

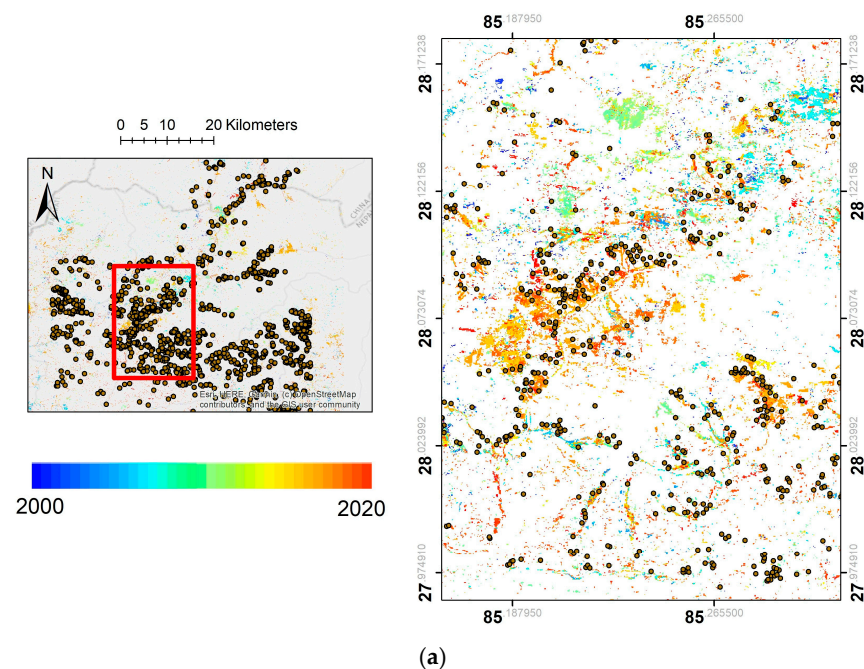


Figure A5. *Cont.*

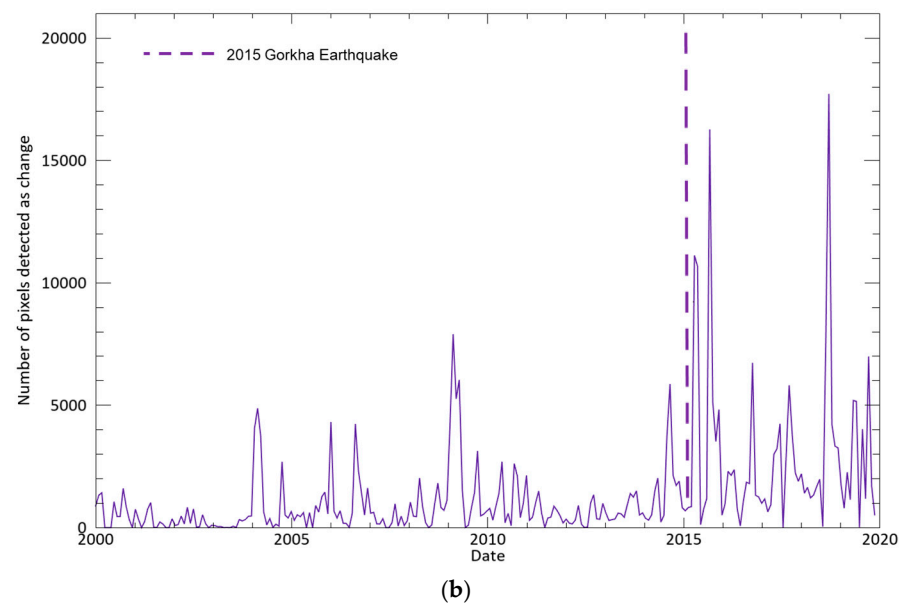


Figure A5. Panel (a) illustrates the cumulative map of land disturbances from 2000 to January 1, 2020, in the Karnataka region, with the color gradient representing the timing of each disturbance. Superimposed on this map are points that outline the reference initiation points of landslides that occurred between 2009 and 2018, providing a spatial context for the disturbances depicted. Panel (b) depicts the time series of the number of changed pixels; notable spikes in the graph reflect increased detection of changes, the dashed line corresponds with a specific disturbance event. The number of changed pixels is calculated based on the entire area of the region in the **left panel** in Figure (a).

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