Landslides
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ML-CASCADE: A machine learning and cloud computing-based tool for rapid and automated mapping of landslides using earth observation data

Abstract Landslides pose a significant threat to humans as well as the environment. Rapid and precise mapping of landslide extent is necessary for understanding their spatial distribution, assessing susceptibility, and developing early warning systems. Traditional landslide mapping methods rely on labor-intensive field studies and manual mapping using high-resolution imagery, which are both costly and time-consuming. While existing machine learning-based automated mapping methods exist, they have limited transferability due to low availability of training data and the inability to handle out-of-distribution scenarios. This study introduces ML-CASCADE, a user-friendly open-source tool designed for real-time landslide mapping. It is a semi-automated tool that requires the user to create landslide and non-landslide samples using pre- and post-landslide Sentinel-2 imagery to train a machine learning model. The model training features include Sentinel-2 data, terrain data, vegetation indices, and bare soil index. ML-CASCADE is developed as an easy-to-use application on top of Google Earth Engine and supports both pixel and object-based classification methods. We validate the landslide extent developed using ML-CASCADE with independent expert-developed inventories. ML-CASCADE is not only able to identify the landslide extent accurately but can also map a complex cluster of landslides within 5 min and a simple landslide within 2 min. Due to its ease of use, speed, and accuracy, ML-CASCADE will serve as a critical operational asset for landslide risk management.

Keywords Machine learning · Landslide extent mapping · Sentinel-2 · Cloud computing · Google earth engine

Introduction

Landslides are among the most damaging natural hazards, causing acute loss of life and property. According to the United Nations Disaster Risk Reduction, landslides have constituted 5.4% of climate-related disasters over the last two decades (*Economic Losses, Poverty & Disasters*, 2018). Due to their geographical location and limited resources low and middle-income countries are often the most affected by landslides. For instance India has 4.75% area highly susceptible to landslides and is responsible for 8% of global landslide fatalities (Ram & Gupta 2022; Sharma et al. 2024). Landslides are a sudden failure and are associated with fast-moving debris, which not only causes immediate damage to people's lives and infrastructure but also cause destruction of critical public infrastructure like roads, railways, and electric poles, thereby impacting nearby areas (Huggins et al. 2020). Additionally, landslides also have multiple long-term environmental consequences. Landslides trigger substantial erosion, significantly altering the landscape and degrading the water quality by depositing the eroded material (García-Ruiz et al. 2013). The efforts to understand and mitigate landslides are severely hindered by lack of spatial and temporal data of landslides (Novellino et al. 2024). Given the large number of landslides and their impact, it is essential to develop methods for rapid measurement of landslide extent.

Landslides are caused by a complex interplay between geotechnical, hydrological, and anthropological factors, making them difficult to understand and manage (Li et al. 2016a, b). Landslide modeling is based on the theory that future landslides will occur in conditions similar to past landslides (Guzzetti et al. 2012). Therefore, to understand the spatial distribution of landslides, the causal factors behind landslides, and reduce the damage caused by landslides, it is essential to monitor and create a database of spatiotemporal information about landslides, called landslide inventory (Casagli et al. 2016; Li et al. 2016a, b). Historically, landslide inventories were developed using field surveys, interviews, and geological data collection (Guzzetti et al. 2012; Sharma & Saharia 2023). Yet, these approaches have significant drawbacks since they are costly, time-consuming, require domain experts, and cannot be applied to large and remote areas. Consequently, a significant number of landslides are unreported and excluded from the inventory. Recent advancements in satellite remote sensing technology, characterized by their synoptic view, high spatiotemporal resolution, and large areal coverage, have generated significant interest in satellite data-based landslide mapping (Meena et al. 2022; Zhong et al. 2020). Most of the landslide mapping relies on multispectral data from high-resolution commercial satellite data like Worldview due to their high spatial resolution and ability to identify small landslides (Fiorucci et al. 2019; König et al. 2019). However, using commercial high-resolution imagery is not viable, especially in low and middle-income countries. Recently, medium high-resolution satellites like Sentinel-2 and Landsat have gained prominence since they are open source and contain multiple shortwave infrared and near-infrared bands in conjunction with visible bands (Lu et al. 2021; Shahabi et al. 2021). Nevertheless, an easy-to-use framework catering to developing landslide extent using medium resolution satellite data is missing.

In this study, we develop a semi-automatic method that combines the strength of satellite data, terrain data, vegetation indices and machine learning to produce landslide extent as accurately as manual mapping in a fraction of the time using cloud computing.

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To further the use of our method, we develop a web-based open-source application called ML-CASCADE. ML-CASCADE requires samples of landslide and non-landslide regions and uses a combination of pre- and post-event Sentinel-2 images and terrain factors to classify the image into landslides and non-landslides. Using GEE's cloud computing infrastructure, the landslide extents are produced instantaneously, which can be downloaded in a tiff format. Given ML-CASCADE's open-source nature, coupled with its speed, user-friendliness, and global adaptability, it will cater to a widespread audience, especially in developing countries.

Existing methods of landslide mapping

Landslide mapping using multispectral data relies on detecting significant changes on a hillslope occurring within a brief timeframe as a proxy for landslides (Sharma et al. 2024). This is achieved using a change detection approach by comparing two or more images acquired before and after a landslide event. Presently around 40% of landslide studies rely on manual mapping using change detection (Novellino et al. 2024), which although is less labor-intensive than field surveys but is still a time-consuming process. With the increasing volume of earth observation data, automated or semi-automated landslide detection, has gained significant attention (Chen et al. 2017; Fang et al. 2021). These approaches can be divided into index-based methods and Artificial intelligence (AI) based methods. The index based methods focus on identifying a sudden change in vegetation or topography as a proxy for landslides and account for around 9% of the total landslide studies (Novellino et al. 2024). Recently AI-based approaches are increasingly adopted due to their ability to model complex processes using data without explicitly modeling interactions between causal variables. Moreover, AI models can integrate multiple datasets and automatically identify relevant patterns in data, often achieving higher accuracy than rule-based systems. Due to these benefits of AI based approaches account for 16% of the recently published literature (Novellino et al. 2024).

Developing landslide extent from earth observation data using AI is a binary segmentation problem, which can be accomplished using either unsupervised or supervised classification techniques. Unsupervised classification techniques are based on grouping pixels with similar characteristics into the same cluster, which are further segregated into landslide and non-landslide clusters (Shahabi et al. 2021). Since the clusters are based on pixel similarity, unsupervised techniques don't require labeled data. However, unsupervised techniques are challenging to use due to spatial heterogeneity and complexity associated with landslides (Lei et al. 2019). On the other hand, supervised classification techniques use labeled data to learn the relation between input data and landslide extent. Although supervised methods require labeled data, they offer higher accuracy and precision than unsupervised methods. Supervised ML for landslide extent has been based on pixel- or object-based methods. Pixel-based methods treat every pixel as an individual data point. In contrast, object-based methods first create meaningful segments within the image that represent real-world objects, which are then classified based on the characteristics of the segment (Blaschke 2010). The pixel-based methods only rely on radiometric properties for classification, whereas object-based methods consider the textural, contextual, hierarchical, and morphological properties in addition to radiometric properties (Blaschke 2010; Ghorbanzadeh et al. 2022). Also, since pixel-based classification treats every pixel as independent, the classified image has a salt-and-pepper look, whereas object-based classified images do not exhibit this effect (Mei et al. 2019). Both pixel-based and object-based methods have been extensively used for landslide identification from earth observation data. For instance, Prakash et al., (2020) compared the predictability of pixel-based and object-based machine learning models and deep learning models for landslide identification. (Keyport et al. 2018) compared landslide identification accuracy of pixel-based and object-based methods using k-means clustering.

Significant progress in machine learning models and earth observation have led to a rapid surge in the volume of data, which requires large storage and computational power, making it infeasible to develop models locally. This is especially true for change detection studies like landslide identification requiring time series of data. Planetary-scale geospatial analysis platforms like Google Earth Engine (GEE) host multi-petabytes of analysis ready data, allowing us to access and analyze a vast amount of data (Gorelick et al. 2017). GEE also provides access to powerful image processing and machine learning algorithms, which can be parallelized to produce results in real-time. Moreover, GEE provides a JavaScript based API for developers to create custom web applications which have been extensively used for land use mapping, surface water monitoring, and hazard detection (Calderón-Loor et al. 2023; Sharma & Saharia 2022). GEE based web applications have been developed for mapping landslides using changes in the Normalized Difference Vegetation Index (NDVI) (Milledge et al. 2022; Scheip & Wegmann 2021). Although NDVI based methods have been successful for landslides in vegetated areas, they suffer from multiple limitations. Firstly, they require calibration of NDVI thresholds, secondly, these methods don't include terrain information and, therefore, might consist of deforestation and crop removal as landslides. Lastly, they struggle to identify the extent of landslides in areas with sparse or no vegetation cover. ML based methods can overcome the drawbacks of index based methods and integrate multiple diverse datasets to provide high accuracy. However, ML models require expertise in feature development, model training and deployment, and large data storage coupled with computation power, which makes them inaccessible to non-expert users. In this study we develop a cloud computing based easy to use application with the capabilities of machine learning without the complexities associated with data and model development.

Datasets

This study uses open-source multispectral Sentinel-2 data, vegetation and soil indices developed from Sentinel-2 data, and terrain information. Since ML-CASCADE uses machine learning, relevant feature selection is of utmost importance (Ghorbanzadeh et al. 2021). Based on historical research, we identify a total of 19 features representative of hydrogeomorphic features of landslides, which are explained below:

Sentinel-2 bands

Launched by the European Space Agency (ESA), Sentinel-2 is a constellation of two polar-orbiting satellites capturing multispectral data across the visible, near-infrared, and shortwave infrared spectra with a temporal resolution of 5 days. Sentinel-2 has played a crucial role in disaster management, especially floods, droughts, volcanoes, and forest fires (Konapala et al. 2021; Kowalski et al. 2023). Due to the small footprint of landslides, landslide identification is still dominated by commercial high spatial resolution satellites, however, recently many studies have used Sentinel-2 for landslide identification. Sentinel-2 has 13 bands with spatial resolutions varying from 10 to 60 m. In this study, we use 6 Sentinel-2 bands (B2, B3, B4, B8, B11, B12) for pre and post landslide images resulting in a total of 12 bands. The bands B2, B3, and B4 are at 10 m resolution and are usually used to develop natural color composites. The near-infrared band B8 is commonly used for vegetation identification. Bands B11 and B12 are shortwave infrared bands useful for soil mineral identification. All these bands, directly or indirectly, can help identify the change in landscape for landslide mapping. GEE provides two levels of Sentinel-2 data; the level 1C data is top of atmosphere data provided by ESA and does not contain atmospheric and cirrus corrections. The level 2A data is the bottom-of-atmosphere (BOA) reflectance values developed by correcting for atmospheric disturbances from Sentinel-1C data using sen2cor processor ("Harmonized Sentinel-2 MSI, n.d."). Although level 2A data is better suited for landslide mapping, its coverage is not global. Since ML-CASCADE is built for global landslide mapping, we use Sentinel-2 level 1C data.

Vegetation index

Since landslides are the downward movement of debris along a slope, in a vegetated area, landslides cause loss of vegetation, exposing the bare surface. This loss of vegetation and subsequent exposure of fresh rock is a crucial criterion for mapping landslides using satellite data especially in vegetated slopes. NDVI is developed using the normalized difference of red and near-infrared reflectance from satellite data and is used as a proxy for vegetation. Many studies have used the change in NDVI as a proxy for mapping the extent of landslides (Milledge et al. 2022; Scheip & Wegmann 2021). To incorporate the impact of vegetation, we use pre-event vegetation, post-event vegetation, and change in vegetation as inputs to our machine learning model.

Bare soil index

Unlike indices like NDVI that primarily focus on healthy vegetation, the Bare Soil Index (BSI) is designed to identify areas with minimal or no vegetation cover. BSI combines spectral data from blue, red, near-infrared, and shortwave infrared bands to capture soil variations and detect soil movement (Phakdimek et al. 2023). The BSI developed from Sentinel 2 bands is shown in (1).

$$BSI = ((B11 + B4) - (B8 + B2))/((B11 + B4) - (B8 + B2)) \quad (1)$$

We use differential BSI, which uses the change between before and after landslide images to map landslides. Since differential BSI can identify areas that can show fresh landslide scarps, it has been extensively used as a variable for landslide identification (Ariza et al. 2021; Tehrani et al. 2021).

Terrain data

Since landslides occur on a slope, including terrain information helps improve the accuracy of landslides (Ghorbanzadeh et al. 2022). The Digital Elevation Model (DEM) contains the elevation of a place in gridded format and plays a crucial role in identifying landslide borders, which is challenging using only optical data (Ghorbanzadeh et al. 2022). We use NASA DEM, a global DEM at a spatial resolution of one arc second developed by reprocessing and void filling of Shuttle Radar Topography Mission (SRTM) data (Crippen et al. 2016; NASA JPL 2020). NASA DEM is also used to develop additional terrain variables, namely slope and aspect. The slope determines the shear stress and is the most critical driver of landslides, with steeper slopes posing higher risks of landslides (Sharma et al. 2024). Similarly, the aspect shows the direction of the slope and is responsible for governing the amounts of sunlight and soil moisture.

Methodology

Most GIS-based remote sensing data analyses consist of fetching data and processing using local machines. This type of analysis is challenging in the case of change detection studies such as landslides, where multiple pre-event and post-event images must be analyzed (Scheip & Wegmann 2021). The limitations are significantly exacerbated in developing and underdeveloped countries where researchers cannot afford large computing power, storage, and data downloads.

Furthermore, most landslides are still manually mapped, where a polygon is used to draw over raster data, as shown in Fig. 1. This process is not only time-consuming- but also adds subjectivity. For spatial modeling purposes, these polygons are converted into a raster format where if more than half of the pixel lies inside a polygon, it is assumed to be a landslide pixel. This whole process adds complexity and causes overestimation or underestimation of the extent based on the expert. On the other hand, machine learning methods are developed on raster data, considering each object/pixel independent and free from conversion error.

ML-based image classification can be done using either pixel-wise methods or object-based methods. Pixel-based methods treat each pixel as an independent entity independent of the characteristics or context of nearby pixels. The pixel-based methods suffer from salt and pepper noise, wherein a random pixel can be classified as a landslide. On the other hand, the object-based techniques first divide the image into meaningful segments based on the input datasets, which are then classified using machine learning methods. Although the object-based methods don't suffer from salt and pepper noise, they may cause overestimation. In ML-CASCADE, we provide the user with the flexibility to use pixel-wise methods or object-based methods. The object-based methods are implemented using Simple Non-Iterative Clustering (SNIC). SNIC is a non-iterative object creation approach that performs the clustering process in a single step without iteratively updating cluster centroids (Achanta & Susstrunk 2017). SNIC explicitly enforces connectivity, is computationally efficient and uses less memory. SNIC requires compactness factor, connectivity, and neighborhood size to develop optimum segments. The Compactness factor influences the shape of the cluster, with larger values leading to compact clusters. The connectivity defines the contiguity, whereas the neighborhood size

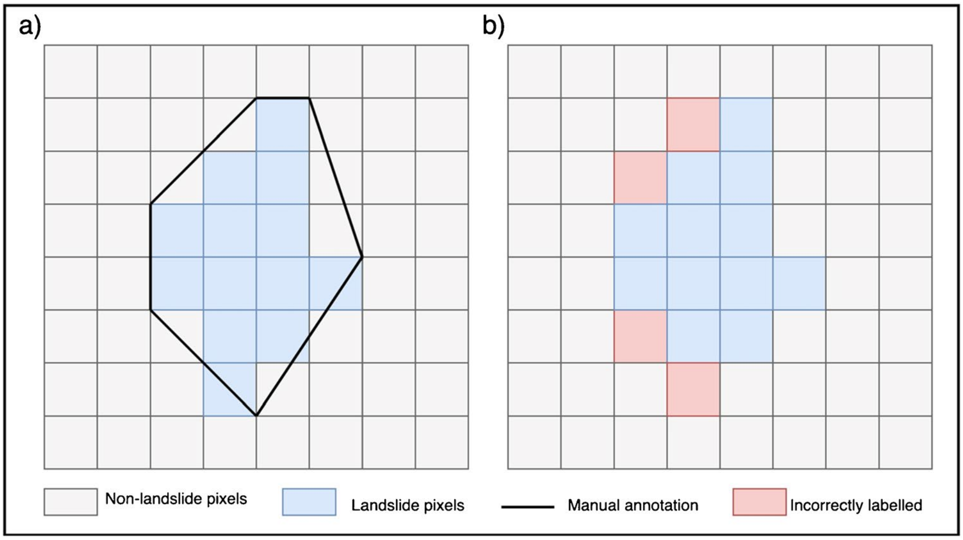

Fig. 1 Comparison of vector over a raster landslide mapping **a**) shows the manual mapping of landslide by an expert using a polygon **b**) shows rasterization of the manual extent

is defined to avoid tile boundary artifacts (Shafizadeh-Moghadam et al. 2021).

After selecting object-based or pixel-based classification, the classification is done using a vanilla Random Forest (RF) classifier. RF classifier is based on an ensemble of multiple decision trees where every decision tree is trained on a subset of training data (Breiman 2001). By training on diverse subsets of data and features, RF classifiers are less prone to overfitting, and by using a combination of decision trees, the RF models are more robust (Breiman 2001). Moreover, since all the RF trees are independent, RF classifiers can be parallelized and scaled to handle large amounts of data, especially in a cloud computing environment like GEE.

Despite the multiple benefits of the RF model, it yields limited performance when encountered with a novel input, which is not seen during training, also known as out of distribution data. To overcome this problem, ML-CASCADE is developed semi-automated, where the user provides samples of landslides and non-landslide points based on which the RF model gets retrained every time. Using the semi-automated approach, the user can increase the number of samples where the landslide extent was incorrect to produce better output, which is not possible in the case of a pre-trained model. Based on input data, the trained RF model provides the probability that a pixel/object belongs to the landslide class. This probability is converted into a binary image using a thresholding approach, finally providing the landslide extent.

The overall methodology is shown in Fig. 2.

Web application

ML-CASCADE is hosted on GEE and can be accessed from https://hydrosense.users.earthengine.app/view/ml-cascade. As shown in Fig. 3, the homepage contains one control panel and two map panels. The control panel contains buttons and widgets for the user to interact with the app and maps. The two map panels are linked, implying a process done on one map is automatically shown on the second map (e.g., Zooming on one map automatically zooms in the other map).

There are some practical considerations that must be kept in mind while using the ML-CASCADE web app. ML-CASCADE app can be used without a GEE account; however, it uses the get-downloadurl function, which supports a maximum request size of 32 MB and grid size of 10000. To process large images without size restrictions, the user can run the app inside the GEE console, which requires a GEE account. The steps to map the extent of landslides in real-time are explained in Fig. 4.

a. The primary requirement before mapping the extent of the landslide using ML-CASCADE is the knowledge of the approximate location and date of the landslide, which can be acquired from news or social media. The user starts by entering the coordinates and the date of the landslide event. Based on user inputs, the algorithm filters all Sentinel-2 images containing the landslide location for one year before and after the landslide date with a cloud pixel percentage of less than 30%. The algorithms also mask the areas identified as clouds by GEE bitmask. The cloud masking algorithm cannot capture many light clouds; therefore, on visual inspection, the landslide area might be covered with clouds. Also, since our algorithm filters all images where the landslide point is present, a case can arise when the landslide point is present on the edge of the image where the landslide is not visible. To overcome this problem, we define before and after image dropdowns. The default value for the after-image dropdown is set to 0, which loads the nearest available Sentinel-2 images in the natural color composite. Similarly, the before image number is set at -1, which loads the closest available image before the landslide in the natural color composite. The user can change the slider and click the Show Before and After Image buttons to render images in real-time and select an image where the landslide can be seen clearly. It is advised to change the selectors one step at a time since a larger

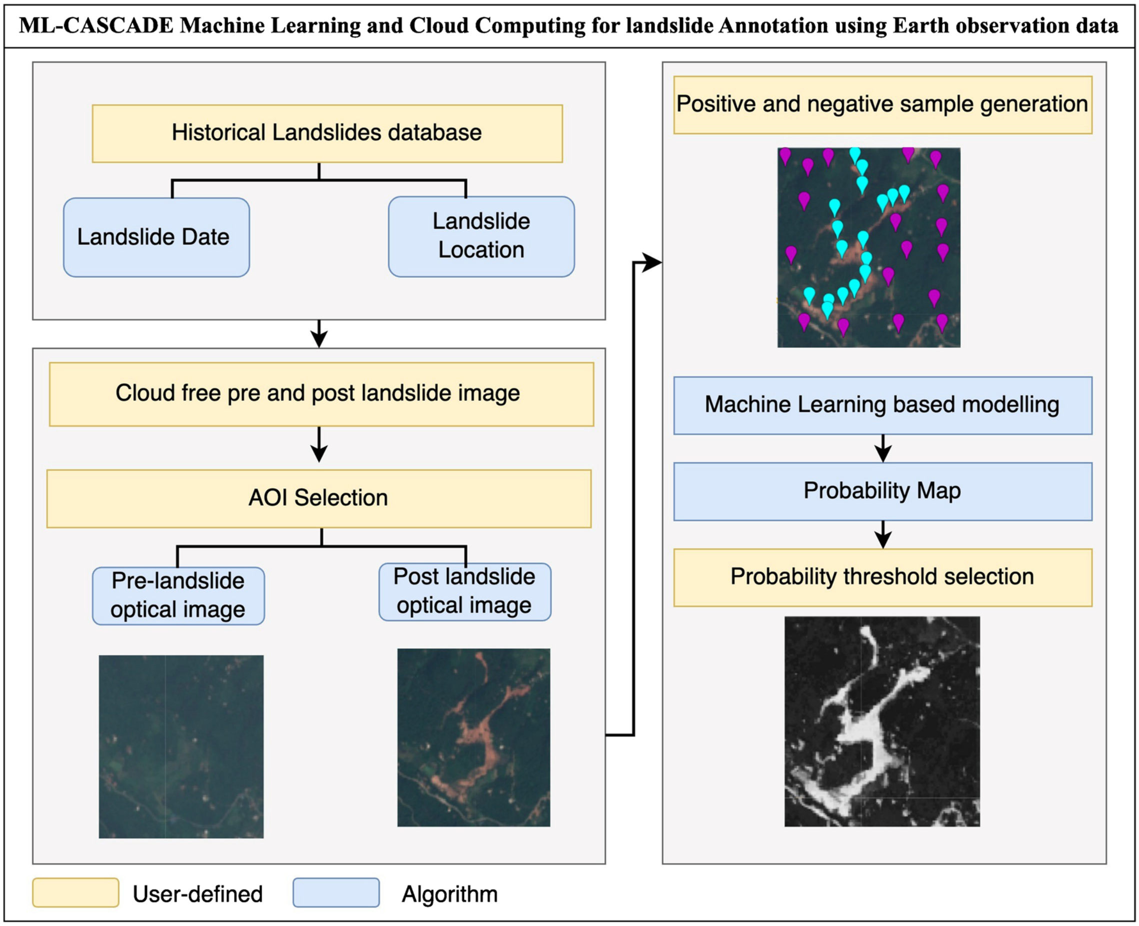

Fig. 2 Overall methodology of ML-CASCADE

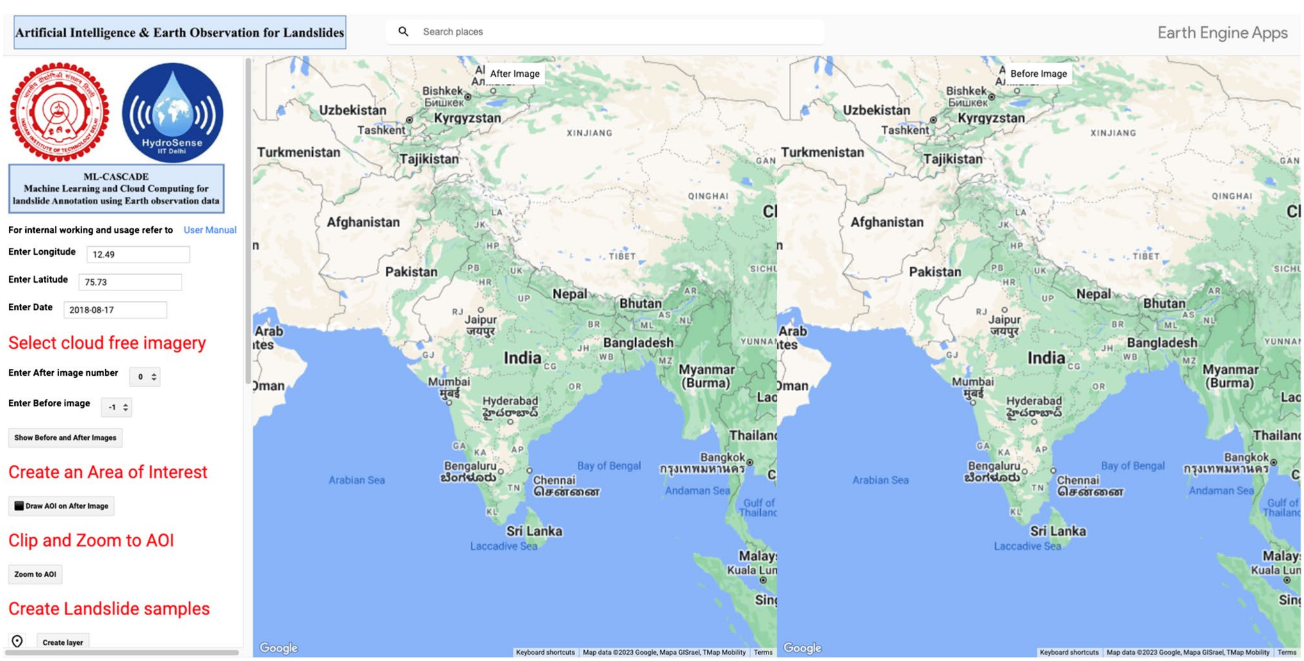

Fig. 3 Homepage of ML-CASCADE hosted on Google Earth Engine

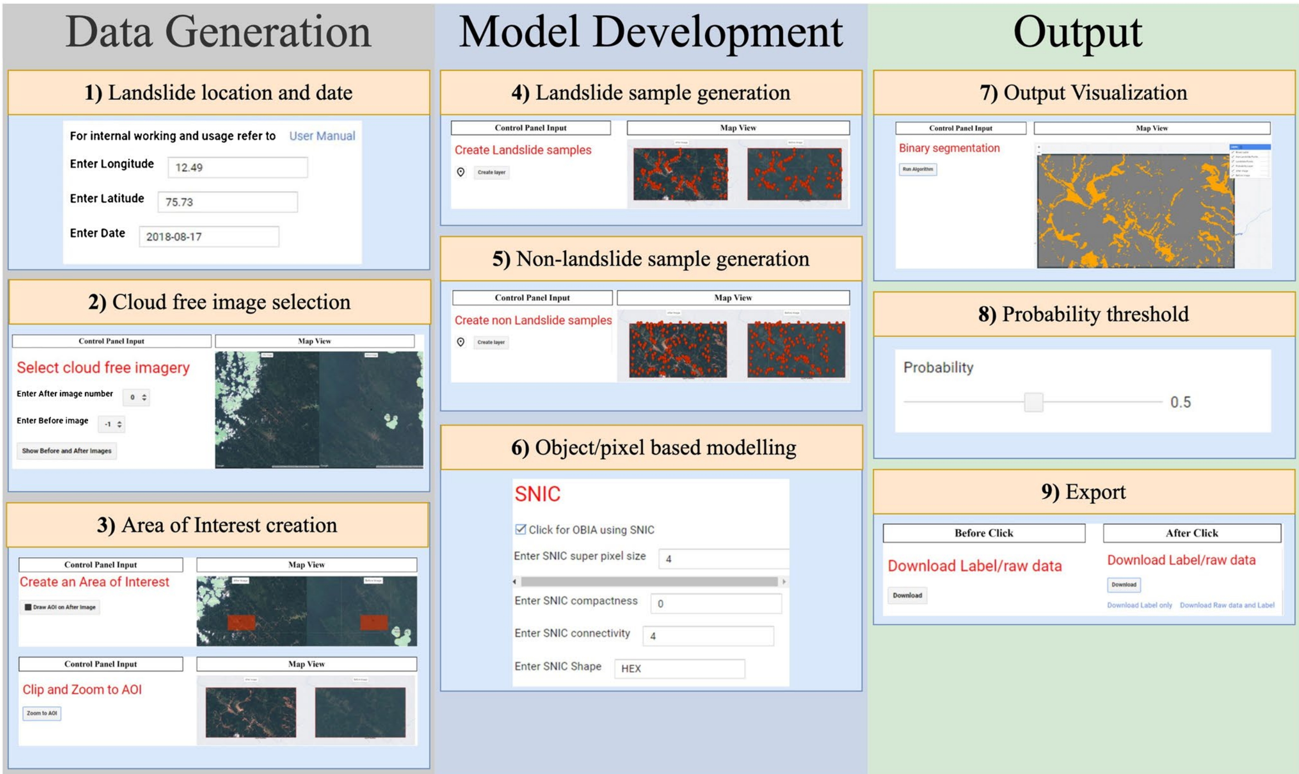

Fig. 4 Steps to map the extent of landslides using ML-CASCADE

value means the image is temporally far from the landslide date.

b. Once the before and after images are finalized, the user needs to create an area of interest (AOI) on the after map. Clicking on Draw AOI on After image button will change the cursor to a + sign and allow the user to draw a rectangular AOI on the after image panel. Upon creation, the AOI will be shown on both before and after image panels. In case an inaccurate AOI is created, the user can create another AOI, although the app will only save the most recent AOI. Once the AOI is finalized, the user clicks on Zoom to AOI, which clips both before and after images and zooms to the area selected on both before and after images.

c. Once the AOI images are visible on the map, the user needs to create landslide and non-landslide samples. The user must start the point tool from the control panel to start creating landslide samples. Once an appropriate number of sample points for landslides have been created, the user must click the Create layer button, which stops the point tool and saves the samples. The same process has to be repeated to develop non-landslide samples. For optimum extent estimation, the user must make sure that areas that can be confused with landslides but are non-landslides should especially be marked (e.g., playgrounds and rural roads). User must also make sure to consider the edge cases. To use the object-based segmentation, the user must check the SNIC box and supply the SNIC parameters, as explained in "Datasets" section.

d. To run Random Forest and create a classification layer based on landslide and non-landslide samples, the user needs to click Run Algorithm. The map will go from a linked map to a single map with multiple layers containing the before-landslide image, the after-landslide image, the landslide points provided by the user in red, and the non-landslide points in green. Based on the model run, two new layers will be generated: the probability layer and the binary landslide layer.

e. The RF model in the app is set in probability mode, and the landslide binary layer is a threshold on the probability layer. This approach allows for managing areas where the model shows uncertainty or cases of potential underestimation or overestimation. By utilizing the probability layer slider, the user can visualize the dynamically updated classification layer. Once all the results are satisfactory, the user can download the data offline for further use, and the app can be reset for other extent mapping.

Since we are using a data-driven approach, the mapping accuracy depends on the quality of the landslide and non-landslide samples the user provides. Therefore, some precautions must be taken while developing landslide and non-landslide samples. Firstly, the number of landslides and non-landslide samples should be equal and cover all the areas of interest for a better classification. Secondly, areas with a similar spectral signature to landslides but not landslides, e.g., Rocks, sediments, or unpaved roads, may be incorrectly classified as landslides. To remove such discrepancy, an increased number of samples should be provided in complex areas, which will enable the model to learn better features and achieve more accurate classification.

Results

The most susceptible areas to landslides in India are the Himalayas and the Western Ghats (Sharma et al. 2024). We demonstrate the applicability of ML-CASCADE to two most devastating landslides in India—one in Western Ghats (Kodagu landslide) and one in the Himalayas (Kotrupi landslide).

Kodagu landslide in western ghats, India

In August 2018, the Western Ghats of India experienced unusually heavy rainfall, leading to significant cluster landslides in the Kodagu district of state of Karnataka, India. Prior to the nineteenth century, a significant portion of Kodagu was covered with rainforest; however, there has been an extreme change in land use, triggering a severe change in the hydrology and ecology of the area (Putty et al. 2021). Changes in land use, especially deforestation, have been viewed as one of the causal reasons for these landslides (Putty et al. 2021). Following the landslides, the National Remote Sensing Centre (NRSC) used multiple high and medium-resolution optical satellite datasets for rapid mapping of these landslides using semi-automatic object-based methods, this data has been acquired from Bhuvan (https://bhuvan-app1.nrsc.gov.in/disaster/disaster.php#).

For developing the landslide extent using ML-CASCADE, we set the latitude and longitude values to 12.49 and 75.73, respectively, and the date to 17/08/2018. Based on visual inspection, we set the after image at 4 and the before image at -5, we identified the Area of Interest lying between longitude 75.61° to 75.80 ° and latitude 12.40 ° to 12.51 °. As explained in "Datasets" section we provide 98 landslide samples and 98 non-landslide samples to ML-CASCADE and use the default probability threshold of 0.5. To create an objective comparison between landslides identified by NRSC and ML-CASCADE, we manually identify the extent of over 100 landslides in Google Earth Pro using the time-lapse feature. It is to be noted that the landslide polygons developed using Google Earth Pro are not complete since the high-resolution images are not available for certain places after the landslides happened. Figure 5 shows the landslide inventories developed by ML-CASCADE, NRSC, and Google Earth Pro.

To gain an idea of the strengths and weaknesses of each method, we present a qualitative comparison of these inventories:

a) Landslide extent:

To objectively compare the extent mapped by NRSC and ML-CASCADE, we present a large landslide with a complex shape that has been successfully mapped using all three methods. As seen in Fig. 6, ML-CASCADE is closer to the manual extent, whereas NRSC-mapped landslides seem to overestimate the extent of the landslide. Since NRSC uses object-based identification which classifies by creating larger objects, it is plausible that landslides mapped by NRSC overestimate the extent. When using object-based identification using SNIC, we see a similar pattern. Hence, we don't recommend

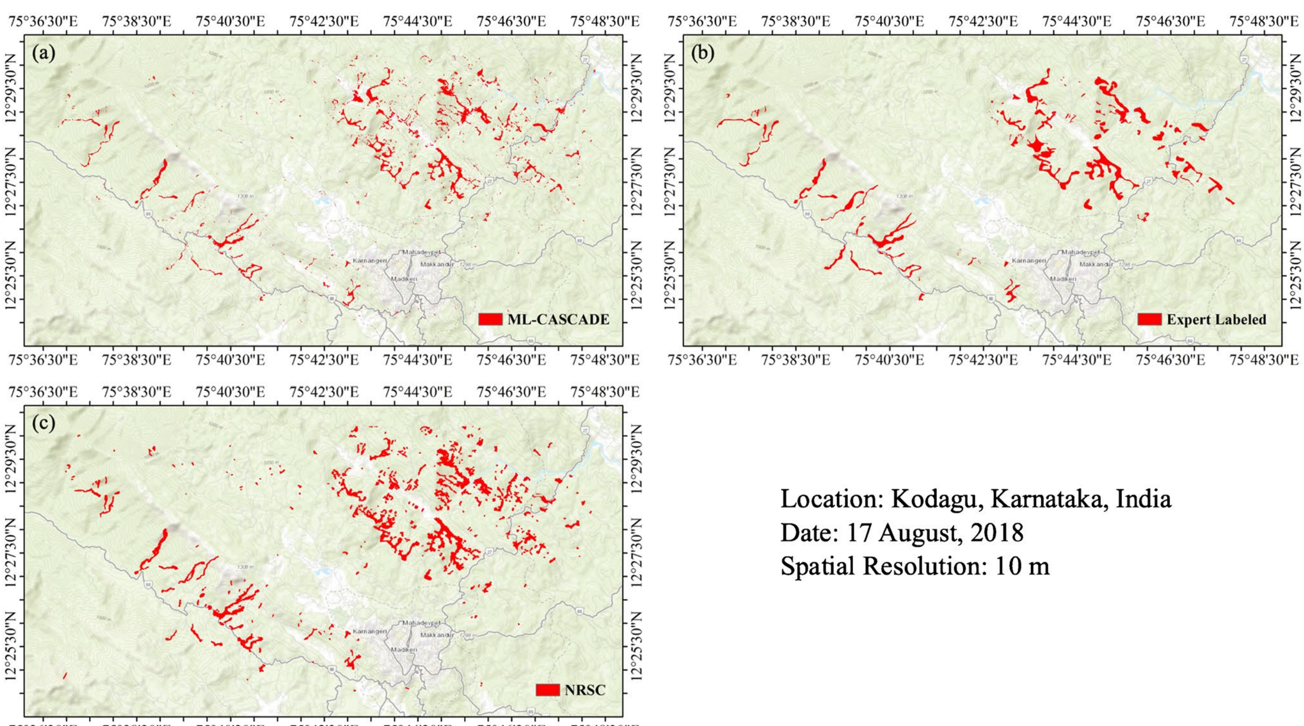

Fig. 5 Landslides extent mapped in Kodagu using various methods **a**) Landslides extent mapped using ML-CASCADE **b**) Landslides by the expert **c**) Landslide extent mapped by NRSC using object-based methods

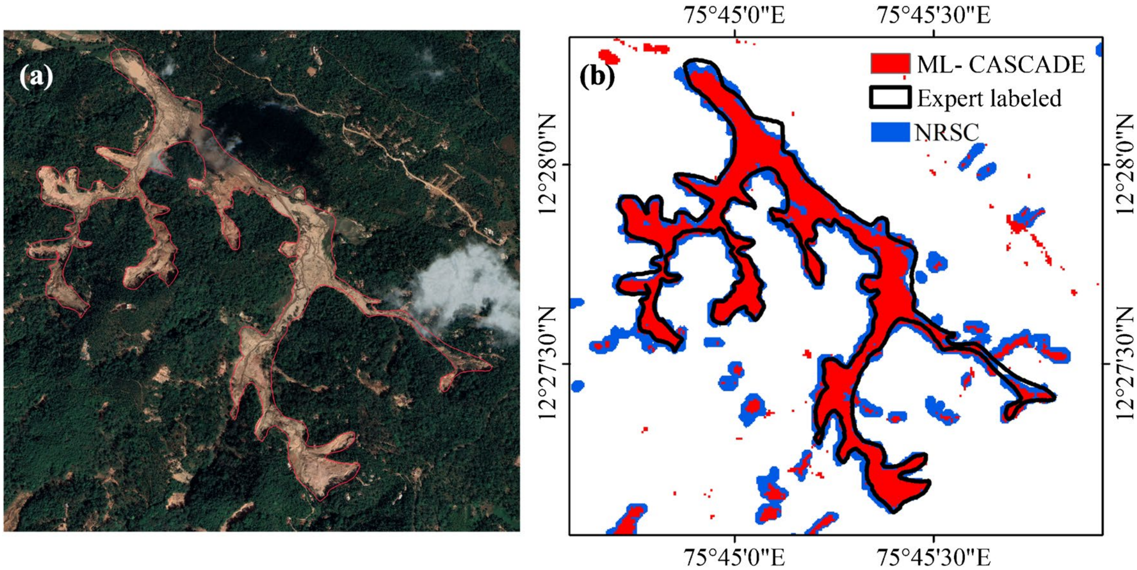

Fig. 6 Comparison of extent estimation **a**) landslide extent developed by the expert **b**) Extent comparison between ML-CASCADE, NRSC, and expert labeled extent

using SNIC on small landslides where creating large objects can cause an overestimation of the extent. We use an Intersection Over Union (IOU) metric (2) to compare the landslide extent developed by NRSC and ML-CASCADE for this particular landslide.

$$\mathrm{IOU}(\mathrm{image1},\ \mathrm{image2}) = (\mathrm{Overlap})/(\mathrm{L}_{\mathrm{image1}} + \mathrm{L}_{\mathrm{image2}} - \mathrm{Overlap} \tag{2}$$

where,

Overlap = Landslide pixels identified in both image1 and image2
$\mathrm{L}_{\mathrm{image1}}$ = Landslide pixels identified in image1
$\mathrm{L}_{\mathrm{image2}}$ = Landslide pixels identified in image2

The IOU between landslide mapped by expert and NRSC is 0.645. In contrast, the IOU between landslide mapped by expert and ML-CASCADE is 0.720, validating that ML-CASCADE can better map the extent of landslides.

b) Missing landslides:

Although due to the non-availability of imagery, we could not map all landslides using Google Earth Pro, there are still many instances of landslides that are identified by ML-CASCADE and Google Earth Pro but absent in NRSC data. Figure 7 shows one instance of a landslide identified by ML-CASCADE and Google Earth Pro but is missing in the NRSC database.

b) Salt and pepper noise:

In this study, we use a pixel-based machine learning method, which is susceptible to salt and paper noise. As seen in Fig. 5c, random pixels have been incorrectly identified as landslides. Since

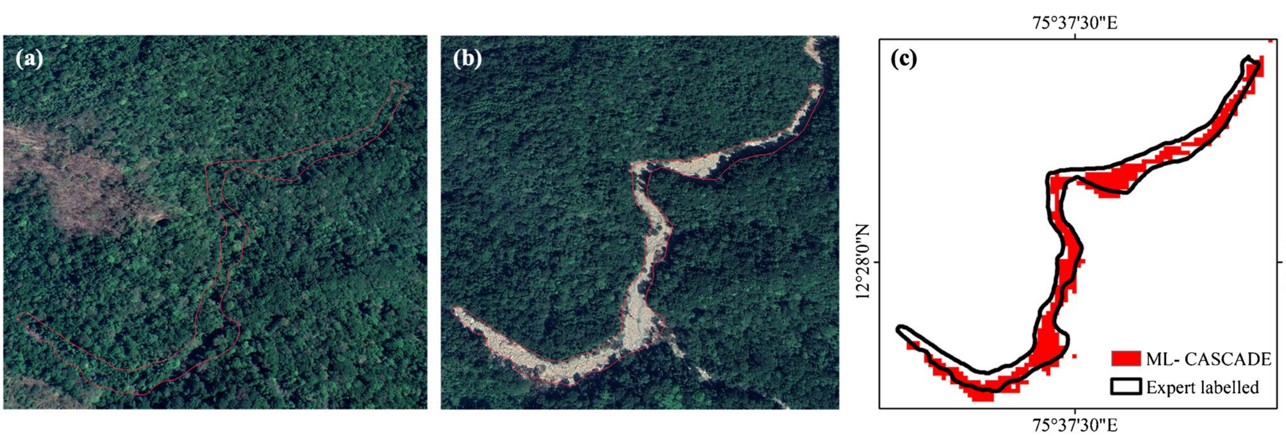

Fig. 7 Missing landslide in NRSC database **a**) Pre-event Google Earth Pro image (01/2018) **b**) Post-event Google Earth Pro image (10/2018) **c**) Landslide identified by ML-CASCADE

NRSC uses object-based mapping, such noise is absent in landslides mapped by NRSC.

c) Extent near rivers:

As seen in Fig. 5, ML-CASCADE overestimates landslides, especially around the rivers. During monsoons, rivers accumulate substantial sediment along the bank of the river. Since ML-CASCADE uses change detection, it identifies those sediments as landslides. Although this can be avoided by increasing the number of samples along the bank of the river, however mapping extent becomes very complex when a landslide occurs along the river, especially with medium-resolution data like Sentinel-2.

Kotrupi landslide in himachal pradesh, India

Our second case study delves into mapping the Kotrupi landslide, which occurred on August 13, 2017, in the Mandi district of Himachal Pradesh, India. The Kotrupi landslide occurred along National Highway 154, resulting in significant infrastructural damage and loss of 46 human lives (Roy et al. 2018). Due to its significant impacts, the Kotrupi landslide garnered substantial attention in the scientific community and has been thoroughly examined in multiple research articles (Pradhan et al. 2019; Roy et al. 2018; Singh et al. 2020). The earliest attempt to understand the kotrupi landslide was undertaken by NRSC which utilized data from Resourcesat-2, LISS-IV, and Cartosat-2S, acquired on August 15 and 16, to conduct a comprehensive mapping of the landslide (Roy et al. 2018). Their analysis revealed that the kotrupi landslide was a debris flow landslide with rotational failure plane with a runout length of 1155 m, width of 190 m and covered an area of 33,674 m^2 (Roy et al. 2018).

To map the Kotrupi landslide using ML-CASCADE we set the latitude to 31.91 and longitude to 76.88 and the landslide date to 13 August 2017. Based on visual inspection the cloud free imagery before image number was set as -2 and after image number was set as 1. The before and after image correspond to 12th June 2017 and the after image corresponds to 12th September 2017. We provide 20 landslide and 20 non landslide samples trying to cover all visible cases in the image. The overall landslide extent estimation process of Kotrupi landslide took less than 1 min. Since NRSC annotated the kotrupi landslide manually we consider the NRSC landslide extent as ground truth and only show the google earth imagery overlaying the landslide extent for visualization in Fig. 8. As can be seen in Fig. 8 although the shape of landslide extent mapped by ML-CASCADE and the NRSC is similar, the extent mapped by ML-CASCADE is shifted to the right by 1 pixel. This issue is unrelated to ML-CASCADE but pertains to the geolocation accuracy of Sentinel-2 data. Sentinel-2 Level 1C products are distributed as fixed geolocated tiles and have been observed to be misregistered by more than 1 pixel (10 m) (Yan et al. 2018). Although the recent updates to the processing software have reduced the misregistration error the older sentinel 2 data might suffer from geolocation problem. Since the kotrupi landslide was large ML-CASCADE was able to map the Kotrupi landslide with an IOU of 0.737 despite the geolocation error.

Using the pre-landslide imagery NRSC also discovered landslide scarps in the vicinity of kotrupi landslide showcasing that the slope was under stress and the area was prone to a major landslide (Roy et al. 2018). Similarly, the Salna landslide in Chamoli district, Uttarakhand, India, in 2007, the Sunkoshi landslide in the Sunkoshi river in Nepal in August 2014, and the Mantam landslide in Sikkim, India, in 2016, are examples of large damaging landslides that exhibited prior landslide scarps (Roy et al. 2018). This showcases the importance of mapping historical landslides and the role tools like ML-CASCADE can play in mapping landslides and mitigating landslide-related risks.

Discussion

Due to recent progress in computing power and satellite technology, various methods of mapping landslides using Earth Observation have been developed. As explained in "Existing methods of Landslide mapping" section landslide mapping methods from Earth observation can be subdivided into two sets. The first set of methods develop an index based approaches mostly using vegetation or bare soil change (Fayne et al. 2019; Notti et al. 2023; Scheip & Wegmann 2021). These methods are easy to implement, and some methods support cloud computing have an easy-to-use graphical user interface for visualization (Scheip & Wegmann 2021). Despite their ease of use and benefits these methods are simplistic and prone to errors. Another set of methods employ Artificial Intelligence (AI) based techniques and have been found to have a good landslide identification accuracy, however they are not straightforward to use (Dang et al. 2024; Ghorbanzadeh et al. 2021). Operational usage of AI based techniques requires large, annotated training data and knowledge of programming languages such as python. Moreover, the current AI based techniques don't provide an easy-to-use interface for non-expert users. Both index based and AI based methods produce fixed landslide maps and in case landslide annotation is incorrect, the incorrect segmentations have to be fixed manually. ML-CASCADE aims to bridge this gap by providing the power of machine learning and GUI along with cloud computing for speedy landslide annotation. Table 1 gives an overview of current landslide mapping methods on various parameters.

During our numerous experiments and extensive usage, we have found ML-CASCADE has multiple benefits over other landslide mapping techniques:

1) Ease of use: The ML-CASCADE interface is developed after taking inputs from non-GEE and GIS users. The interface is easy to use and offers flexibility in image selection, area of interest selection, pixel/object-based method selection, and thresholding. Moreover, ML-CASCADE is developed as an open-source app, allowing access to the codebase for future developments.
2) Accuracy: ML-CASCADE utilizes random forest, which is a robust machine learning model known for its ability to minimize overfitting and bias. ML-CASCADE can identify the landslide extent similar to the landslide mapped by expert from high-resolution Google Earth Pro imagery. Moreover, ML-CASCADE was able to map landslides missed by NRSC. However, ML-CASCADE is data-driven, and its accuracy depends on the quality of input data. Notably, it tends to overestimate landslides, particularly along river areas.
3) Speed: ML-CASCADE is developed using GEE cloud computing infrastructure and does not require data download. Moreover, by utilizing parallel processing of GEE, the model training and

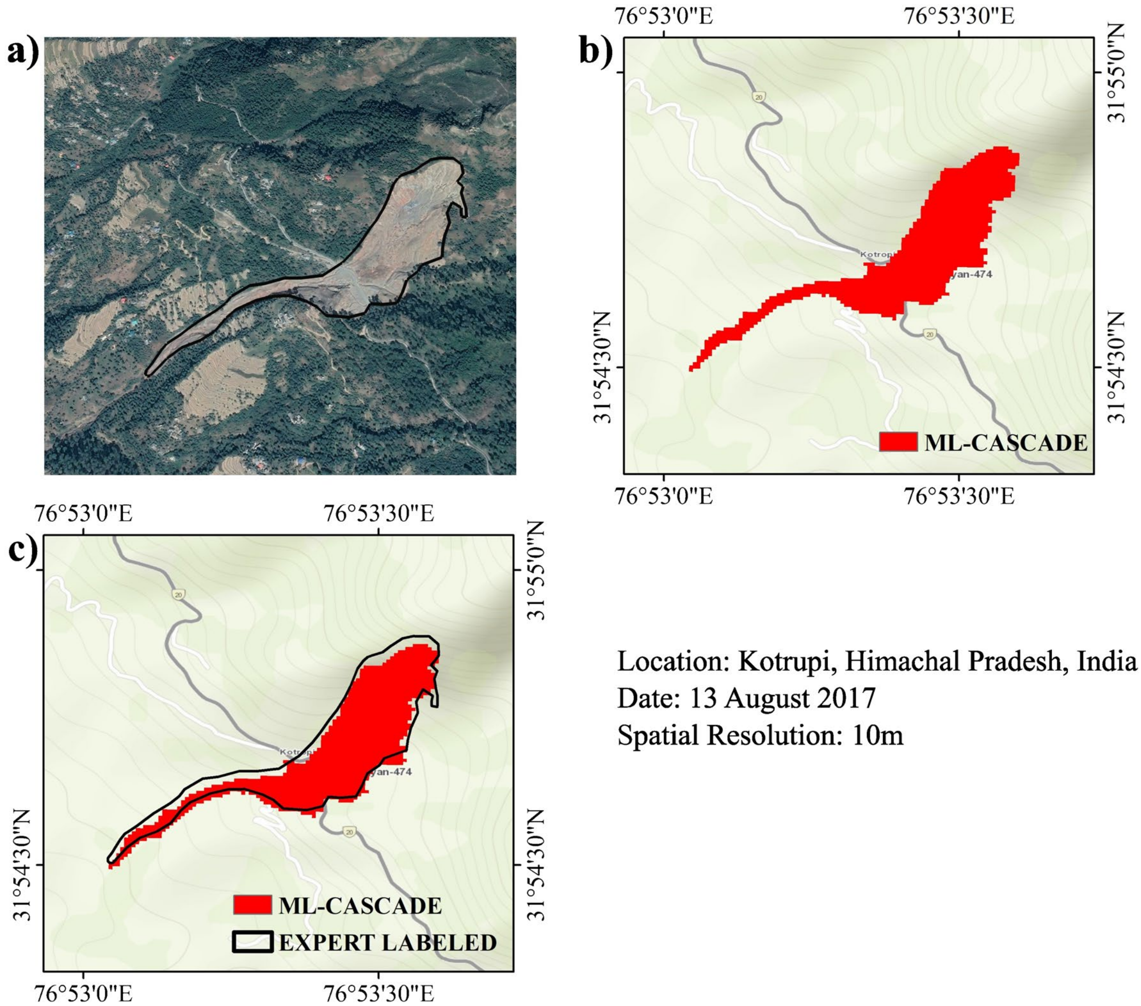

Fig. 8 Mapping of landslide extent of Kotrupi landslide, **a**) Google Earth Imagery (10th September 2017) overlaying the NRSC expert mapped polygon **b**) ML-CASCADE mapped landslide **c**) NRSC mapped landslide overlaying the ML-CASCADE mapped landslide

Table 1 Comparison of landslide extent mapping methods

Application	Data supported	Methodology	OBIA	Change detection	Automation	Cloud computing	Pre-trained Network	GUI
Hazmapper (Scheip & Wegmann 2021)	Landsat (30 m) and Sentinel-2 (10 m)	Index-based (NDVI change)	N.A	Yes	Automated	Yes	No	Yes
SaLAD (Amatya et al. 2021)	Rapid eye (5 m)	Random Forest	Yes	No	Automated	No	Yes	No
SLIP (Fayne et al. 2019)	Landsat (30 m)	Index based	N.A	Yes	Automated	No	No	No
Deep Learning (Ghorbanzadeh et al. 2022)	Sentinel-2 (10 m)	CNNs (Resnet)	N.A	No	Automated	No	Yes	No
ML-CASCADE (proposed)	Sentinel-2 (10 m)	Random Forest	Yes	Yes	Semi-Automated	Yes	No	Yes

outputs are produced in seconds, which would take hours on a local machine. For instance, mapping of landslide clusters using Google Earth Pro took more than 10 h of a skilled GIS user, whereas similar extent development using ML-CASCADE was done in 5 min.

4) Global Applicability: Machine learning models trained on a small dataset often lack transferability, limiting their applicability to other geographical locations. Even the models trained on large datasets generate spurious results when presented with out of domain data. ML-CASCADE overcomes this problem by being a semi-automated artificial intelligence based framework. For every new area of interest a new vanilla random forest model gets trained every times based on user generated samples. This allows for global applicability in diverse conditions, for instance, when mapping landslides in vegetated areas, the model will emphasizes on features like NDVI, NDVI change, and BSI. Conversely, when mapping in non-vegetated areas, the model will prioritize other spectral bands and slope characteristics. This adaptability is not feasible in pretrained models which have a fixed weights.
5) Comparison with deep learning methods: Recently automated deep learning methods like Convolutional Neural Networks (CNNs) and Vision Transformers(VITs) have achieved state of the art landslide segmentation accuracy (Dang et al. 2024; Ghorbanzadeh et al. 2022; Wu et al. 2024). Unlike pixel based methods CNNs and VITs consider both global and local context in an image which leads to better segmentation. However, all the deep learning models require large amount of annotated data which is labelled using manual techniques. Moreover, pretrained models have fixed parameters, and will produce erroneous results when presented with test examples significantly different from the training data (out of distribution). Once the pretrained models have produced incorrect results there is no mechanism to correct the results real-time and improve the model. ML-CASCADE aims to play an important role in developing the database for training deep learning based image segmentation models. Also, in case the deep learning models fail to capture the spatial extent of landslides ML-CASCADE can then develop correct segmentations which can be used to improve the deep learning model.

However, there are some limitations of the ML-CASCADE, which will form the basis for future improvement. ML-CASCADE is developed as an open-source app leveraging Sentinel-2 imagery, which is available at a spatial resolution of 10 m. Due to its medium spatial resolution, Sentinel-2 exhibits limited performance in landslide mapping compared to higher-resolution commercial sensors (Prakash et al. 2021). It's worth emphasizing that ML-CASCADE can map the large landslides accurately which are responsible for most of the damage and causalities. Additionally, the same framework and interface integrating vegetation and terrain data can be used to map small landslides using commercial imagery in GEE. Additionally, semi-automation, one of the biggest strengths of ML-CASCADE, is also a potential weakness since it introduces user bias. ML-CASCADE relies on samples provided by the user; therefore, an experienced user can develop a high-accuracy landslide extent with a lower number of high-quality samples than a non-experienced user. For instance, providing a large number of negative samples in the area affected by river sedimentation will lead to a higher accuracy than providing large samples in a vegetated area where no change has occurred. These drawbacks will form basis for future improvements.

Conclusion

Most landslides are unmapped since developing a comprehensive inventory requires significant domain expertise, time, and effort. With the changing climate and increasing anthropogenic activities on slope, there is a rising threat of landslide hazards. Mapping the extent of a landslide in real time is necessary to develop a comprehensive understanding of its causal factors and potential impacts. The idea behind ML-CASCADE is to develop an open-source app that can leverage the power of satellite imagery, cloud computing, and machine learning to map landslides in real-time. Since the application is semi-automated and requires samples for every new landslide mapping, it doesn't suffer from transferability and out-of-domain data issues like other ML models and can be used globally. ML-CASCADE is developed considering non-expert users in mind, however, it is still flexible enough to be tailored to users who understand machine learning, object-based identification, and GEE. ML-CASCADE is hosted as a GEE app with a user-friendly GIS interface that can be used without in-depth experience of GEE or GIS. We compare the inventory developed by ML-CASCADE with an object-based analysis inventory and a manual inventory. ML-CASCADE was not only able to identify the cluster of landslides but also able to map the extent accurately. Apart from developing landslide inventory, ML-CASCADE has multifaceted potential. Firstly, the mapped extent of the landslide can also be used for developing landslide geometry, yield estimation, and understanding the flux of materials. Secondly, ML-CASCADE is open source and allows modifying the existing code for other change detection tasks. Therefore, the GUI and codebase of ML-CASCADE can be adapted for other change detection studies like deforestation. Finally, using ML-CASCADE only requires an idea of the landslide location and the date of landslide and can be used to develop a large landslide inventory for training a fully automated convolutional neural network or transformer based models. Given its ease of use, speed, and mapping accuracy, ML-CASCADE can serve as an essential tool for hazard and risk assessment, especially in data deficient regions.

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Author contributions

Nirdesh Sharma: Conceptualization, Methodology, Software Development, Validation, Data Curation, Writing—Original Draft, Visualization.
Manabendra Saharia: Conceptualization, Writing—Review & Editing, Supervision, Funding acquisition.

Data availability

https://hydrosense.users.earthengine.app/view/ml-cascade

Declarations

Competing interest 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 paper.

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