Development of a landslide early warning system incorporating hydrometeorological variables and InSAR data

Abstract

A landslide is defined as a movement of rock, earth or debris along a slope under the influence of gravity. Landslides occur when shear stress on a slope is more than the shear strength of the soil. Landslides are mostly triggered by rainfall and earthquakes and cause considerable loss of human life and infrastructure.

Site-specific landslide studies can be done using geotechnical methods. However, to study landslides at a regional or national scale, we need to understand the landslide conditioning factors at large-scale using model simulations or remote sensing data. In recent years there has been an exponential increase in open-source satellite data and computational power. With these developments coupled with improved algorithms, we now have the capability to monitor landslides remotely and accurately.

In this project, the aim is to advance our understanding of landslides with the following research goals and associated tasks

1. To assess how pre-event hydrological and meteorological conditions impact landslide occurrence. We will generate accurate high-resolution hydrometeorological variables by assimilating satellite soil moisture in land surface models.
2. To identify the starting of the movement of the landslide we will create an automated framework to develop regular InSAR-based ground displacement from Sentinel 1 data.
3. Develop a machine learning-based regional experimental early warning system with real-time nowcast rainfall data, hydrometeorological data, InSAR, and other ancillary datasets

In this study, we aim to develop an experimental early warning by identifying the landslide governing factors, developing accurate and high-resolution datasets for these factors, and incorporating them into a machine learning-based landslide early warning system.

Introduction

Predicting landslides is a complex task that is of both scientific interest and societal relevance. The slope failure mechanism is difficult to capture because the stress on the soil at the scale of the landslide is difficult to measure. Also, since multiple interactions take place simultaneously at the hillslope scale, the soil failure mechanism is still not fully understood.

The factors impacting landslides are divided into antecedent and triggering conditions. Antecedent conditions are the pre-existing conditions that affect the landslides but are not the causative factors, e.g., geology and geomorphology of the area, soil types, tectonics, local terrain, and land use land cover. The triggers are the external stimulus that causes a near-immediate response in form of a landslide. The main triggering conditions are precipitation, earthquakes, and snowmelt with precipitation accounting for the greatest number of landslides. There has been a recent increase in the number of landslides. Some studies have attributed the recent increase in landslides to heavy rainfall under climate change, while others have pointed out the increase of human interference in slope stability (Gariano & Guzzetti, 2016).

A global analysis of precipitation estimates indicates that although rainfall is a trigger, the landslide behavior is not well explained by rainfall alone (Jia et al., 2020). Earlier landslide models are limited as they do not consider the impact of time-varying factors such as soil moisture, and runoff leading to inaccurate models. For site-specific studies, the geotechnical models and physical dynamic models can reasonably be parameterized, but at a larger scale, we require data-driven models which can be used to identify general patterns. This is especially true for geologically diverse and data-poor regions such as India (Sujatha & Sridhar, 2021).

Previous studies mostly develop a landslide susceptibility map and use rainfall thresholds to ascertain the location of the landslide (Hidayat et al., 2019; Lagomarsino et al., 2013). These studies are simplistic and mostly ignore other predisposing hydrometeorological factors which are crucial for triggering scenarios. The requirement for high-resolution datasets has hindered landslide studies. Nevertheless, with the combination of land surface models and remote sensing, hydrometeorological information is becoming increasingly available at high resolution and on a large scale (Palazzolo et al., 2021). With the increasingly available data, we can develop efficient machine learning and deep learning models, which can be used to identify general patterns in data and provide early warning for landslides.

Objective 1. Developing High-Resolution Hydrometeorological variables

For the same rainfall conditions, the landslides triggered at one place might not be triggered at another location, showcasing the importance of antecedent conditions. The meteorological and hydrological antecedent conditions and their impact is documented as shown in Table 1.

Table 1: Antecedent hydrological and meteorological variables and their impact on landslides

Variable	Impact on landslides	Reason
Precipitation	Increasing	Major trigger of landslides. Increases weight of soil, decreases cohesion
Air temperature	Varying	Higher temperature leads to higher evapotranspiration as well as snowmelt having converse effects
Wind speed	Varying	Leads to drying of soil, but also increases the snowmelt which have opposite effects
Soil Moisture	Increasing	Decreases cohesion and increases weight of soil
Evapotranspiration	Decreasing	Decreases water from the land surface
Snow Depth	Increasing	Melting Snow adds extra water to the slope
Surface Runoff	Increasing	Excessive runoff may initiate debris flows or undercut stream banks

a) Precipitation is the most important climatic variable for triggering landslides. Precipitation increases the moisture in the soil surface. Increased moisture increases the weight of the soil on the slope and decreases the cohesion leading to slope failure. Precipitation intensity leads to runoff and erosion further destabilizing the slope causing landslides.
b) Air temperature has a varying relationship with landslides according to location. Higher air temperature increases evapotranspiration and decreases the soil moisture leading to increased soil stability; on the other hand, for areas covered with snow high temperature leads to the melting of snow leading to runoff which infiltrates into soil reducing soil stability. Higher temperature also leads to freezing and thawing process causing rockfalls.
c) Wind speed also has a dual relationship with landslides. On one hand, wind reduces the moisture from the soil surface increasing stability; on the other hand, wind causes instability of trees and boulders which when removed decrease cohesion and increase instability.
d) Soil moisture increases the propensity of the slope to landslides by increasing the weight of the soil and decreasing cohesion.
e) Evapotranspiration is the loss of water for soil surface as well as vegetation. Increased evapotranspiration results in a decrease of soil moisture from the soil surface thus increasing the shear strength of soil and decreasing the gravity weight of soil.
f) Snow Depth is used to depict the thickness of the snow above the ground. The frozen snow increases the gravity weight of the slope leading to a higher landslide chance. Even when the

snow melts it leads to an increased runoff causing higher erosion as well as increased soil moisture.

g) Surface runoff is the excess part of precipitation water that could not infiltrate the soil. Surface runoff is associated with an increase in soil erosion. A high-velocity surface runoff erodes loose soil or small rock particles leading to debris flow. Overall, high surface runoff is associated with higher landslide probability.

As it is evident, landslides have a complex relationship with hydrometeorological variables based on location, hence high-resolution hydrometeorological variables are required to accurately identify the probability of landslides.

Earlier hydrometeorological variables identification at the resolution of landslides was difficult; therefore, the studies used methods such as recent rainfall threshold or antecedent wetness index which calculates the cumulative rainfall over a certain number of days preceding the landslide to describe water accumulation in the slope (Guzzetti et al., 2020; Mirus et al., 2018). The antecedent wetness method ignores the fact that slope wetness in some cases is poorly related to antecedent rainfall. Currently, with the ingestion of satellite data in land surface models, it is possible to generate high-resolution accurate soil moisture products

The knowledge of our physical understanding of the system is embodied in land surface models. Land Surface Models simulate the earth's systems using laws of physics. Land Surface models can sometimes be simple due to the absence of inputs or contain errors due to inaccurate measurement. The satellite data, on the other hand directly measures the required variables, but has its own bias due to instrument or calibration errors. When data from both sources are used synergistically, their combined strength can be used to minimize errors from individual sources. Therefore, we can use data assimilation to blend inaccurate model data with somewhat inaccurate satellite data to create an ensemble product with better accuracy.

Thus, we aim to develop high-resolution hydrometeorological variables ingesting SMAP satellite data into the CLSM land surface model which is forced using a combination of IMD forcings and MERRA2.

Objective 2. InSAR data development

InSAR is a geodetic method that uses the phase of two or more SAR images to develop surface deformation. InSAR can measure millimeter-scale deformations and is especially useful for natural hazard monitoring like earthquakes, volcanos, and landslides. Displacement monitoring is critical for risk associated with sudden slope failure. (Sharifi, Hendry, et al., 2022). SAR satellites carry sensors that provide phase information. This phase information is used to generate relative change in the distance between the sensor and the ground surface. Although many remote sensing tools (LiDAR, UAV), as well as in-place instruments (inclinometers), exist for deformation monitoring, Sentinel 1 InSAR provides regular, open-source, high-resolution deformation data at a large scale (Soltanieh & Macciotta, 2022). InSAR is especially useful for remote areas where in-place sensors cannot be used due to economic and technical viability. All these properties make InSAR a robust method for landslide displacement monitoring, especially in data-poor countries.

InSAR is not only useful to measure the displacement of slow-moving landslides but can also be used for sudden failures. Using InSAR data in conjunction with other landslide conditioning factors and hydrometeorological factors will help us understand landslide-triggering mechanisms (Huntley et al., 2021).

Objective 3. Landslide Early Warning Systems

An early warning system is used to disseminate timely and meaningful information to people threatened by hazards so that the impact of the threat can be minimized. Early warning systems have been consequential in the reduction of landslide hazards (Sharifi et al., 2022). The early warning system hereby referred to as EWS should incorporate all the features affecting the mass wasting process, must be accurate, and have less uncertainty.

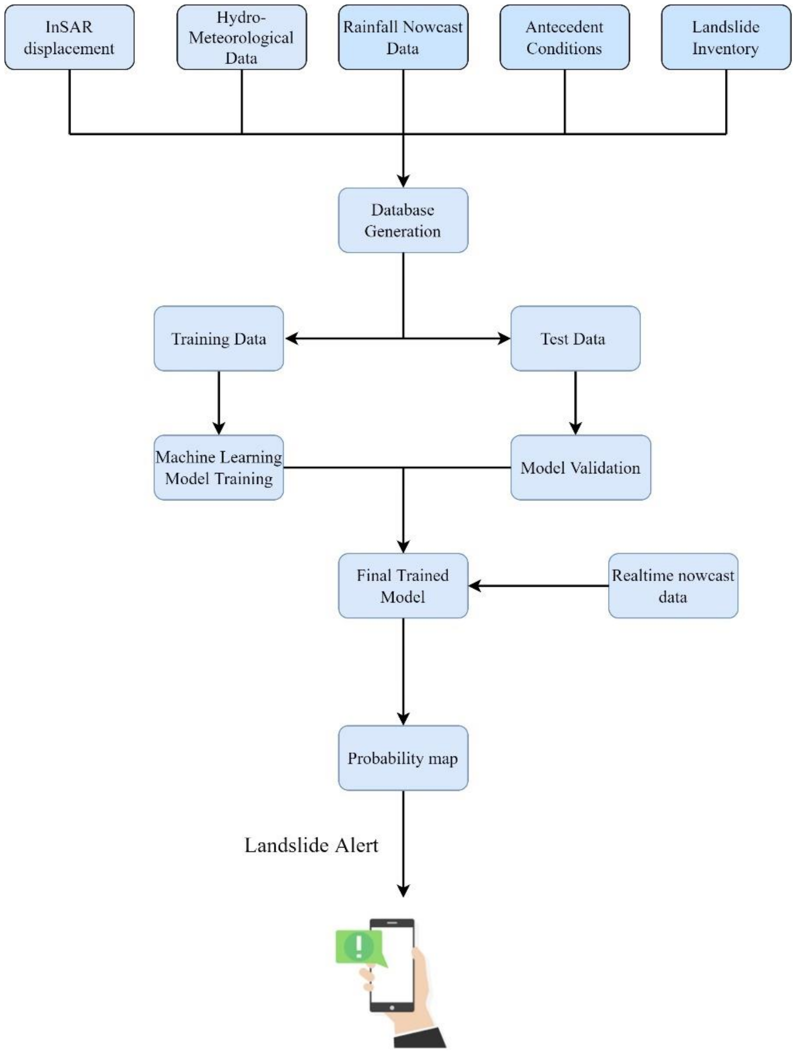
To develop a robust landslide EWS, we need a real-time system based on nowcasts that can identify the imminent landslide zones and an effective communications network that can inform the citizens of immediate threats. Many communication networks already exist in today's information age, and a landslide information system can easily be incorporated into one of those networks.

Most nowcasting landslide systems are based on the "rainfall threshold" which is defined as the minimum amount of rainfall for possible landslide occurrence in a period. Most EWS exploit rainfall thresholds over landslide susceptibility maps and ignore other parameters. An accurate early warning system for landslides must be based on various triggering factors and antecedent information coupled with a scientific framework. A recent study in Washington USA, which accounted for hydrologic measurements, soil moisture along with rainfall, proved to be more accurate than the old, rainfall-only thresholds for landslides (Mirus et al., 2018).

EWS is valuable to forecast landslides, and when operational, it can save lives and reduce infrastructure damage. Still, EWS is complex, and there is no set procedure to design, implement and verify them. Currently, the deployed landslide EWS are limited, and these cover a very small area of the landslide-affected regions, but these EWS have proven to be very effective.

The global landslide early warning named LHASA has been developed by NASA (D. Kirschbaum & Stanley, 2018). Still the LHASA model is based on rainfall thresholds and fills in where no regional EWS is present, but it has a probability of detection between 8% to 60%, which leaves immense space for improvement (D. Kirschbaum & Stanley, 2018).

We aim to develop an operation early warning system integrating hydrometeorological outputs from land surface models, deformation data from InSAR, and terrain information from high-resolution DEMs and other antecedent conditions. The model will be trained on historical data from GLFS and COOLR as well as other sources (Froude & Petley, 2018; D. B. Kirschbaum et al., 2010). We aim to use multiple machine learning models to learn the relationship between landslide conditioning variables and landslides. The proposed EWS will provide detailed probabilistic maps of the specific times, and locations of impending landslides at high resolution as well as provide opportunities to guide post-disaster assessments.



India Landslide Early Warning System Framework

Deliverables:

1) Under OVDF the aim is to develop an accurate simulation of hydrological variables using a combination of physics-based models with observations from satellite datasets. I have already developed low-resolution hydrometeorological products (Sharma et al., 2021). Currently, my aim is to improve the spatial resolution for the incorporation of hydrometeorological data into our landslide early warning system.
2) Further I will develop a machine learning-based early warning system incorporating hydrometeorological variables, InSAR, and satellite data.

The rationale behind choosing the University of Alberta:

The University of Alberta does cutting-edge research in the field of landslides and is a world-leading center for innovation in the geotechnical aspects of landslides. Under the leadership of Prof. Renato Macciota Pullisci the University of Alberta is also recognized as a ‘World Center of Excellence for Landslide Research’ by UNESCO and UNISDR.

India on the other hand has been working mostly on landslide susceptibility and structural measures for landslide mitigation. The landslide early warning systems in India are sensor-based, costly, and limited to important corridors. Under this project, I aim to develop a landslide early warning system incorporating the expertise of the University of Alberta in geotechnics and InSAR, and the expertise of Hydrosense lab- IIT-Delhi in machine learning and land surface modeling. The collaboration will help initiate the development on satellite-based early warning systems in India.

Timeline:

Month 1-3 Developing high-resolution hydrometeorological variables

Month 3-6 Development of an automated framework for SAR data

Month 6-12 Developing, testing, hyperparameter tuning, and deploying the landslide early warning system

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