Landslide Hazard and Monitoring

A. Jayakumar, T. Arulalan, Robert Neal, and A. K. Mitra

Abstract Landslides are a widespread geological event with nearly 12% of India's land area being prone to this natural hazard. The development of a reliable regional landslide early warning system is an immediate requirement for the country in the perspective of proper disaster management. This chapter begins by describing the most common morphological, geological, meteorological, and anthropogenic factors that may influence slope stability. It then explores the potential future use of Numerical Weather Prediction (NWP) forecast products for the assessment of landslide risk and early warning issuance. Related to this, a major discussion is about an objectively derived set of 30 daily weather patterns for India, which provide a historical classification allowing us to relate large-scale circulation at the country level to observed rainfall and landslide occurrence at a particular location—therefore providing us with a set of high-risk weather patterns which are susceptible to landslide occurrence. From a medium-range forecast perspective (out to two weeks), this chapter then describes how ensemble members from ensemble prediction systems (such as those run by the Indian National Centre for Medium-Range Weather Forecasting (NCMRWF)) can be objectively assigned to the closest matching weather pattern in order to produce probabilistic forecasts highlighting when the large-scale circulation may be susceptible to landslide occurrences. In addition, this chapter conducts a review of the local rainfall thresholds liable for triggering landslides, covering both intensity and antecedent thresholds. Nilgiri is used as a case study location, for determining the quantitative temporal probability of landslide initiation, which is essential for utilizing short-range forecasts from NWP models in a more efficient way.

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1 General Introduction

Landslides are the downslope movement of earth's material under the influence of gravity. Landslides are classified generally based on the type of movements (slide, fall, topple, spread, and flow) and the material in the slope (rock, earth, and debris) as well as other factors contributing the slope failures. The major classification of the landslides in terms of the material type and type of movement is originally devised by Varnes [\(1978\)](#page-14-0), for example, rock fall, rock slide, earth flow, etc. (Fig. [1](#page-2-0)). Slide materials are moved along a roughly planar surface in the translational slide whereas a coherent movement in a single unit is displayed in the block slide. Falls and topples are the abrupt movements of slope materials which are influenced by gravity, mechanical weathering, pore water pressure, etc. Lateral spreads are even occurring in flat terrain mainly caused by sand liquefaction (transformation from a solid into a liquefied state). Debris flows indicate the mobilization of soil or rock caused by intense surface-water flow, due to heavy precipitation or rapid snowmelt. A detailed review of the landslide classification is by Cruden and Varnes [\(1996](#page-13-0)) and further modifications to this categorization could be found in Hungr et al.([2013\)](#page-13-1).

Among all the natural hazards, landslides affect nearly 12% of India's land mass hence the development of an advanced landslide forecasting system is a thrust area needing focus from the perspective of natural disaster management in India.

Morphological, geological, meteorological, and anthropogenic factors all influence slope stability and the resulting landslide risk for a particular area. Morphological factors included the tectonic uplift, glacial rebound, and erosion of the hill slope. Causes of landslides from a geological perspective include factors such as slope, soil thickness, relative relief, drainage, material contrasts, permeability contrasts, and sheared, jointed, or fissured materials. Meteorological factors, such as the weather conditions over the previous days as well as on the day of any landslide also significantly influence the stability of slopes, particularly when significant rainfall or rapid thawing of lying snow is involved. Soil texture and structure greatly influence water infiltration, permeability, and water-holding capacity. The water-holding capacity of a landmass could be reduced through rapid infiltration (volume flux of water entering into the soil by rainfall/snowfall) through the pore space within rocks/soils. The infiltration rate is higher for coarse-textured soils than for fine-textured soils. The factor of safety, F_s , the ratio of shear strength to shear stress in a slope is also dependent on the cohesive nature of the soil, parent material (rock type), soil texture, etc. Moreover, the soil moisture retention capacity is dependent on the adhesive nature of the soil, which in turn relates to the stability of the hill slope (Kannan [2014](#page-13-2)). Even low soil moisture presence in non-cohesive soil would make it vulnerable to landslides. On the other hand, the anthropogenic factors such as the construction of roads, infrastructure, blockage of drainage systems deforestation are the major cause of landslides.

Fig. 1 Schematic illustration of major types of landslide movements. Image courtesy is USGS fact sheet 2004–3072([https://pubs.usgs.gov/fs/2004/3072/\)](https://pubs.usgs.gov/fs/2004/3072/)

Though the landslide susceptible areas have been identified by the Geological Survey of India (GSI), the factors deforestation, urbanization as well as encroachments often change the susceptibility conditions. With advancements in computational and numerical modeling capabilities, the Indian Meteorological Department (IMD) is able to provide reliable meteorological input to localized regions from a high-resolution numerical weather prediction (NWP) model. One use of this forecast output is to provide guidance for forecaster-issued warnings of severe weather, such

as thunderstorms, strong winds, heavy snowfall, and heat waves. However, opportunities still exist to exploit this forecast information further in applications of weather impacts. In this context, a recent international research collaboration between Indian, Italian, and UK research institutes has been working on designing a new framework for the better use of forecast products within forecasts of rainfall-induced landslides. This monitoring system may help in the Early warning of landslides especially debris flows, shallow slides, etc.

The major discussion of this chapter is about the potential future use of meteorological data or forecast products for landslide forecasts. The chapter is arranged with the following major sections: A discussion of how large-scale weather patterns over India can be related to the occurrence of meteorological-induced hazards such as landslides; Review of the local rainfall thresholds for triggering landslides, specifically focusing on Nilgiri, where the Western and Eastern Ghat meet. The final section discusses a methodological way of using NWP models from the National Centre for Medium-Range Weather Forecasts (NCMRWF) within future landslide warnings.

2 Relating Weather Patterns to an Increased Likelihood of Landslide Occurrences

A weather pattern can be described as one of many circulation types over a defined region (e.g. the Indian subcontinent), which differs in its characteristics from other weather patterns over the same region and varies on a daily basis. The term 'weather regimes' can also be used to describe a defined circulation type. Weather regimes are typically larger in scale, fewer in number, and persist for more days than weather patterns. However, to a certain extent, the two terms can be used interchangeably. This section describes recent research led by the UK Met Office and with support from the NCMWRF among others (as part of the international collaboration described in Sect. [1\)](#page-1-0) to objectively define large-scale circulation patterns over India, which can be used in forecasting applications for weather impacts. Examples from the UK include relating weather patterns to coastal flooding (Neal et al. [2018](#page-14-1)), meteorological drought (Richardson et al. [2018\)](#page-14-2), flooding (Richardson et al. [2020](#page-14-3)), temperaturerelated excess mortality (Huang et al. [2020](#page-13-3)) and landslide occurrences (Robbins et al. [2018](#page-14-4)). The weather pattern for landslides will also be one of the first forecasting applications is being used in India, where recent research investigated the ability of weather pattern forecasts to identify periods more susceptible to landslide occurrences.

The weather over the Indian subcontinent is highly modulated by the transition of the prevailing easterly trade winds in winter to the westerly trade winds during the summer monsoon. It is possible to identify circulation pattern variability within this seasonality as the weather in India is highly influenced by the Himalayas in the north, the Bay of Bengal to the East, and the Arabian Sea to the west. In addition, along with the variability of the low-level jet of oceanic origin, a mid-latitude origin

western disturbance is a major factor controlling both the summer and winter seasons over India.

Research led by the UK Met Office has developed an objectively derived weather pattern classification for India using long historical meteorological data, providing a set of plausible weather pattern definitions throughout the year, with a catalog of observed patterns available over the last 40+ years (Neal et al. [2020\)](#page-14-5). These pattern definitions were generated using cluster analysis. Specifically, a non-hierarchical k-means clustering algorithm was applied to daily gridded reanalysis fields from ERA-Interim (Dee et al. [2011\)](#page-13-4) covering the period from 1979 to 2016. Other studies to generate circulation patterns using cluster analysis include Fereday et al. [\(2008\)](#page-13-5) who generated a set of 10 weather regimes for each two-month period throughout the year over Europe, Ferranti et al. [\(2015\)](#page-13-6) who generated a set of four large-scale weather regimes over Europe and Neal et al. [\(2016](#page-14-6)) who generated a set of 30 weather patterns over the UK and surrounding European area. Few similar studies exist over India—at least for weather patterns relevant for the whole of India and representative of circulation variability over the full year.

Large-scale weather regimes over India follow a relatively predictable evolution throughout the course of the year, driven predominantly by the onset and retreat of the Asian summer monsoon (Rao et al. [2005\)](#page-14-7). However, the objectively derived weather pattern definitions derived by the UK Met Office open up opportunities for future research and forecasting applications over India. Firstly, the new weather pattern definitions may help understand the synoptic-scale driving forces behind the occurrence of high-impact weather (e.g. intense thunderstorms) or the occurrence of specific meteorologically driven hazards (e.g. landslides). Secondly, they could be used within the probabilistic medium- to long-range weather pattern forecasting tools, where daily weather pattern forecast probabilities are derived by assigning multiple forecast scenarios (ensemble members) from global ensemble prediction systems (such as the one run by the NCMWRF) to the closest matching weather pattern definition. This application is similar to what is already done operationally in Europe; e.g., Ferranti and Corti [\(2011](#page-13-7)) and Neal et al. ([2016](#page-14-6)).

Results from the recent research led by the UK Met Office suggest that 30 weather patterns are enough to sufficiently represent variability within different phases of the Indian climate (Neal et al. [2020\)](#page-14-5), where weather patterns are generated by clustering daily wind fields around 1.5 km above sea level. Each of the 30 weather patterns can be categorized into one of seven broad-scale regimes, called (1) winter dry period, (2) western disturbances, (3) pre/post-summer monsoon, (4) monsoon onset, (5) active monsoon (Fig. [2](#page-5-0) left image), (6) break monsoon and (7) retreating monsoon (Fig. [2](#page-5-0) right image). The dominant precipitation patterns can be shown to vary between these seven regimes as well as between the sub-patterns within each regime. This is important for identifying the most prone landslide periods within a large-scale regime.

Once the weather patterns have been defined, the daily historical weather pattern catalog introduced earlier in this section can then be used to relate observed weather patterns to past occurrences of landslides. This helps build up a picture of the

Fig. 2 An example of two contrasting Indian weather patterns. Left: An example of an active monsoon weather pattern (under south-west monsoon period) showing the prevailing westerly winds and heavy rain across western, central and north-eastern parts of India. Right: An example of a retreating monsoon (under north-east monsoon period) weather pattern, showing the prevailing north-easterly winds and rainfall affecting the southern tip on India

overall synoptic-scale driving mechanisms behind meteorologically induced landslides. Then, a high confidence forecast for a particular weather pattern allows climatological assumptions to be made about where in India may see an increased likelihood of landslides. This approach should work best for medium to long-range forecast periods (one week onwards) when high-resolution NWP forecasts of rainfall have less skill.

3 Rainfall Thresholds for Landslide Occurrences

A landslide rainfall threshold is defined as the minimum intensity or duration of rainfall needed to trigger a landslide (Varnes [1978](#page-14-0)) and a similar threshold value is estimated for other meteorological and hydrological parameters such as soil moisture, pore pressure, etc. The paper by Kanungo and Sharma ([2014\)](#page-14-8) documents the thresholds analyzed for landslide occurrences. Both empirical and physical models are used as a methodology for landslide occurrence using antecedent and triggering rainfall. Xiaohui et al. ([2018\)](#page-14-9) used both empirical and physical models, in that the former is based on the type of rainfall measurements (e.g., intensity and duration of the rainfall event), whereas the latter one is making a relationship between safety

factors, F_s , of the slope with the rainfall depth (in terms of the daily or hourly rainfall amount). A detailed description of one of the physical models can be found in Montrasio and Valentino ([2008\)](#page-14-10). A process-based model is a model combining both meteorological and geotechnical parameters by incorporating a link between the slope stability condition to the rainfall pattern and infiltration (e.g. Iverson [2000](#page-13-8)). Empirical rainfall thresholds are broadly classified based on the following rainfall measurements; (a) rainfall events, (b) antecedent conditions, and (c) hydrological conditions (Reichenbach et al. [1998](#page-14-11)). Furthermore, threshold analysis based on the rainfall events is segregated into intensity–duration thresholds, thresholds based on the total event rainfall, rainfall event–duration thresholds, and rainfall event–intensity thresholds (Guzzetti et al. [2007](#page-13-9)). Area-specific threshold analysis is broadly subdivided into global, regional, or local thresholds depending on the geographical extent and scale effect of meteorological and hydrological conditions.

Antecedent thresholds are based on the amount of the antecedent rainfall prior to the slope failure or landslides. Accumulated rainfall controls soil saturation level and infiltration through the rock and increases the pore-water pressure. The different criteria under the period of consideration for the antecedent threshold analysis in the Himalayan region are reviewed in the paper by Kaungo and Sharma ([2014\)](#page-14-8). The result from their study shows a minimum 10-day antecedent rainfall of 55 mm and a 20-day antecedent rainfall of 185 mm are required for the initiation of landslides over the Chamoli-Joshimath region of the Garhwal Himalayas. Dikshit and Satyam ([2018\)](#page-13-10) introduced a two-dimensional probabilistic thresholds by applying a statistical method of Bayesian analysis using a combination of intensity, duration, and event rainfall. The use of a probabilistic approach over deterministic methods is a better approach to employing an early warning system for landslide-affected areas and can be used as the first line of action.

There are many studies documented about the rainfall triggering analysis over the Himalayan region, but a systematic study is lagging at the rainfall threshold analysis over Nilgiri and Tamil Nadu, which are locations prone to massive landslides during the north-east monsoon period. Sujatha and Suribabu ([2017\)](#page-14-12) discussed that the landslides at Coonoor may be triggered by high pore-water pressures generated during the prolonged and intense rainfall. They report that the landslides over this location may happen when a heavy rainfall spell is followed by a period of continuous rainfall.

Under the FSP projects on the development of a landslide early warning system in Nilgiris, GSI provided data on landslide dates, latitude, and longitude and observed daily rainfall from 24 rain gauges in the Nilgiri district of Tamil Nadu State. Nilgiri receives maximum rainfall during retreating monsoon periods and withdrawal periods of the summer monsoon (Sujatha and Suribabu [2017\)](#page-14-12). Hence this section is more focused on establishing the relationship between the intensity of rainfall versus antecedent rainfall prior to landslide events in Nilgiri, whereas the seasonality in the rainfall measured among two monsoon periods is not considered here. Figure [3](#page-7-0) shows the location map of observed rain gauges and landslide incidents reported by GSI. Both landslide catalog and rainfall measurement data are available from 1987 to 2017. The rain gauges and observed landslides are located between

 $11^{\circ}14'$ and $11^{\circ}26'$ North latitude and between $76^{\circ}40'$ and $76^{\circ}53'$ East longitude. The 24 rain gauges are located at places like valleys, tea estates, and villages in the Nilgiri district, namely Adderley, Benhope, Burliyar, Carolina, Coonoor, Glendale, Hillgrove, Indco, Kairabetta, Kallar, Kattabettu, Katteri, Ketty, Singara (lower, upper divisions), Moutere, Mullur, Ooty, Runnymede, Selvaganpathy, Simspark, Tigerhill, Tuttapallam, and Upasi, and their locations are marked in Fig. [3](#page-7-0). There are three hill stations in the Nilgiri district, namely Ooty, Coonoor, and Kotagiri.

This study has chosen the nearest rain gauge (within 1.5 km distance) from the landslide locations that gives a maximum rainfall intensity (filtered-out rain gauge with a lower rainfall intensity than 5 mm) on the day of each landslide event. Figure [4](#page-9-0) is representing the relationship between antecedent rainfall prior to the landslide (cumulative rainfall calculated from the past 1, 3, 7, 10, 15, 20, and 30 days before the landslide event date) and the intensity of rainfall observed on the day of the landslide event reported at Nilgiri. GSI has identified 509 landslide events which

Fig. 3 Location map of observed rain gauges and landslide incidents at Nilgiri district in the Tamil Nadu State, reported by GSI

were caused by 116 rainfall events. In Fig. [4,](#page-9-0) all panels (a–f) are divided into two halves by the diagonal line in order to distinguish between the scattering bias of rainfall intensity (y-axis) and antecedent rainfall (x-axis). The diagonal divider itself indicates that the daily rainfall on the day of the landslide and the antecedent rainfall prior to the landslide is the same.

As observed from Fig. [4](#page-9-0) a-f, the majority of landslide events are biased towards the antecedent rainfall prior to the landslide in comparison to the daily rainfall on landslides of different time durations (3, 7, 10, 15, 20, and 30 days). Figure [4a](#page-9-0) is illustrating the 3-day antecedent rainfall prior to a landslide event (x-axis) against the daily rainfall intensity on a landslide event (y-axis). From the scattered diagram, 48.1% of the total landslide events (i.e. 245 landslides out of a total of 509 were caused by 68 rainfall events) are biased towards the daily rainfall intensity and the rest of 51.9% of landslide events (i.e. rest of 264 landslides were caused by 48 rainfall events) are biased towards 3-day antecedent rainfall prior to landslide events. When it is analyzed for another cumulative period, the ratio of biases towards daily rainfall intensity and antecedent rainfall is estimated as 35.8:64.2, 16.9:83.1, 14.3:85.7, 12.4:87.6 and 4.7:95.3 for the case of 7-day, 10-day, 15-day, 20-day and 30-day antecedent rainfall respectively (Fig. [4](#page-9-0)b–f). Hence, it may be stated that a maximum of 95.3% of the landslide events (i.e. 485 landslides caused by 95 rainfall events) occurred under the influence of 30-day antecedent rainfall prior to landslide events, and the effect of increasing chances of landslide is dominated by cumulative rainfall over the intensity of rainfall on the day of landslide incidents when duration increases prior to the event.

The general conclusion on the basis of 3-day antecedent rainfall and intensity rainfall on the day of landslide events occurred at Nilgiri district is that both might be contributing equally, and Fig. [4a](#page-9-0) gives only the bias difference of 3.7% towards antecedent rainfall, whereas 7-day to 30-day antecedent rainfall are having more biased towards duration increments compared to the intensity of rainfall on the day of landslide events (Fig. [4b](#page-9-0)–f).

4 Meteorological Forecast Data Used for Early Warning

NCMRWF operates state-of-the-art numerical weather prediction (NWP) models– with both global and regional configurations with forecasts covering time scales from a few days to a few weeks in advance over India. Recent advances in this capability are in the use of the Unified Model, which is a collaborative model developed with the UK Met Office. The NCMWRF version is called the NCMRWF Unified model (NCUM). Different configurations of the NCUM are given in Table 2 by Rajagopal et al. [\(2019](#page-14-13)). This section of the chapter mainly focuses on the potential use of seamless forecast products in generating a framework for landslide predictions.

Fig. 4 Relationship between antecedent rainfall prior to failure (3, 7, 10, 15, 20 and 30 days shown at panels from a-f respectively) and daily rainfall at failure for 509 landslide occurrences caused by 116 rainfall events at Nilgiri district in Tamil Nadu

Fig. 5 A debris flow occurred on 14th June, 2018 at Chettiyampara colony in Kurumbilangod Village in Malappuram District of Kerala and is triggered by three days of antecedent rainfall. Image courtesy is GSI Field Season: 2018–19 (Item No.: M4SI/NC/SR/SU-KRL/2018/21108)

The current NCMRWF global ensemble prediction system has among the highest horizontal resolution (-12 km) in the world. There are 23 ensemble members (22 perturbed and 1 control), among that 11 members and control members are initialized at 00UTC of the present day and the remaining 11 members are from 12 UTC of the previous day (Mamgain et al. [2018](#page-14-14)). This ensemble system provides up to 10-day global forecasts, whereby forecast scenarios (ensemble members) can

be objectively assigned to the closest matching weather pattern definition, such as those introduced in Sect. [2](#page-3-0). The probabilities for each weather pattern occurring at each forecast lead time from the ensemble members are evaluated based on the observed training parameters used in the clustered analysis. Statistics referred to in Neal et al. [\(2016\)](#page-14-6), such as the mean area weighted distance between members and their assigned weather patterns and the mean spatial correlation between members and their assigned weather patterns, can be used to match ensemble members to weather patterns. These probabilistic weather pattern forecasts provide useful guidance within the medium-to-long-range forecast periods (week one onwards).

For short-range forecasts and warnings of landslides, threshold analysis from the high-resolution model forecast based on the intensity and antecedent rainfall is used. The previous section discussed multiple rainfall parameters which can be used as a landslide-triggering threshold for the Nilgiri location in the Western Ghats. Power law distribution of the rainfall conditions such as rainfall duration and intensity resulting in landslides is written as the equation as $I = \alpha D^{\beta}$, where *I* is the rainfall intensity, *D* is the duration, α and β are the empirically derived parameters (e.g., Kanungo and Sharma [2014](#page-14-8)). Thresholds for the landslide occurrence with respect to rainfall intensity, and duration generated from power-law will be tested in the real-time for the selected pilot region from the model forecast. These combinations of parameters from the observed training sets will be compared with the regression values for the aforementioned parameters from the forecasted fields. We suggest that the power–law relationship between rainfall level and landslide occurrence can be used to estimate the probability of various levels of landslide activity during a rainfall event as a guide for making decisions related to emergency preparedness. This combination of parameters may be appropriate for shallow landslides but for complex failure types we may need a modified algorithm. For example, a Bayesian approach may be employed by combining observed rainfall data with the rainfall amount from the forecasted string to obtain antecedent rainfall.

For example, a landslide in Malappuram, Idukki, and Wayanad districts during June 14, 2018, lead to debris flow over a number of houses associated with a heavy spell of rain. Figure [5](#page-10-0) is an image of one of those sites located in Malappuram where the landslide caused severe impacts. The site was marked with heavy rainfall that lasted for three days preceding the event leading to the build-up of an excess pore water pressure. Figure [6](#page-12-0) (panel 3) shows the skill of the NCMRWF ensemble model in predicting antecedent high rainfall during the date of 9–13 June prior to slope failure in the Malappuram district on 14th June 2018 (Fig. [5\)](#page-10-0). Other panels are the surface atmospheric parameters modulating the safety factor of the slope location through soil saturation level and pore water pressure. Hence predicting most of these variables from the models in 10-day advance (that is current maximum lead time forecast available) will show the robustness of the model in picking the closest matching weather regimes and threshold analysis for initiating the landslide occurrence (e.g., Neal et al. [2022\)](#page-14-15).

Fig. 6 A 10 day forecast of surface temperature, surface humidity, 10-m wind, rain, and MSLP from NCMRWF ensemble forecast based on an initial condition of 00UTC 04 June 2018

Under the international collaboration project introduced in Sect. [1,](#page-1-0) an experimental prototype of a regional landslide early warning system (EWS) is being set up for two pilot regions:- by GSI over Darjeeling in West Bengal and Nilgiri in Tamil Nadu. Following this project, EWS for other landslide-prone areas is being taken up beginning with the Rudraprayag district, in Uttarakhand with a joint effort of GSI, National Remote Sensing Centre, Indian Space Research Organisation

(ISRO), Disaster Mitigation and Management Center (DMMC) and NCMRWF. Effective use of the new parameters such as pore pressure, soil type, and moisture holding capacity will be considered for the development of the EWS system. In future, the NWP model used in the landslide EWS will be upgraded to employ a 30 m resolution ISRO land use land cover (LuLc) over the Indian region along with Cartosat 30 m digital elevation map orography. ISRO LuLc provides recent and updated information about the vegetative and non-vegetative model tiles over the Indian region, where soil moisture/temperature forecasts play a critical role in the slope failure predictability within the landslide EW system.

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