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Landslides in the Northern Darjeeling District, India: Investigating dataset choice, international partnerships, and the use of global scale forecasting models for medium range prediction.

MPhil Environmental Science

School of Archaeology, Geography and Environmental Science

Siobhan Dolan

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Declaration: I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Siobhan Dolan

Abstract

This thesis explores landslide hazards within the framework of Disaster Risk Reduction (DRR) and the United Nations' initiatives, "Warnings for All" and "Information for All," aligned with the Sustainable Development Goals (SDGs).

Research Chapter I investigates the integration of global-scale landslide inventories (LSIs) to address data gaps and limitations in the Global South. LSIs are critical for hazard analysis, yet their availability and accessibility are limited. Using geospatial techniques and data integration methods, this chapter combines global LSIs to improve spatial and temporal coverage. The results demonstrate an increase in the number of recorded landslide events and provide a foundation for analysing global landslide trends and identifying vulnerable regions. However, the findings reveal significant limitations in applying global LSIs at the local scale. In the Darjeeling district of the Northeastern Indian Himalayas, gaps in spatial and temporal coverage highlight the inadequacy of current freely available datasets for localised hazard assessment. Recommendations emphasise collaborative and equiTable approaches to recording, maintaining, and sharing global landslide inventories to support DRR strategies.

Research Chapter II focuses on identifying historical landslides in the data-scarce Darjeeling district using ECMWF Re-Analysis 5th Generation (ERA5) total precipitation data and predefined intensity-duration (ID) thresholds. Combining findings from Chapter I with ERA5 data, this explores the potential of integrating meteorological datasets for landslide early warning systems. The analysis identifies "wet day" events and evaluates conditions preceding historical landslides recorded in the combined LSI. However, the approach is hindered by the lack of comprehensive landslide records, which limits the skill of the ID threshold method. The study underscores the need for improved landslide monitoring to enhance predictive capabilities.

In conclusion, this thesis highlights the importance of integrating datasets to advance global and local landslide understanding. By aligning with the UN's agenda, this research advocates for more inclusive and equiTable DRR practices.

Acknowledgements

I would like to thank so many people who have put up with me (or not!) in the past 6 years or so of this research project. The journey has been long and sometimes extremely difficult and if I didn't have some of the most wonderful support from those I'm about to thank, I don't think I would even be here today, never mind finishing a project that has had many ups, downs, meanders and unexpected bumps.

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Secondly, I would like to thank my family, the Dolan Clan; my mum Yvonne Dolan, my brother Timothy Dolan and most of all my dad Thomas Dolan who has given me the lifelong gift of enjoyment in attaining knowledge and drive to understand more about the world around me.

Thirdly, I would like to thank my wife, Camille Charles. She absolutely believes in me and has given me the space to work on my research this past year – something that I didn't really foresee happening. Without her unwavering commitment to me and our future together I think I would have never found the willingness to return to my research.

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From the bottom of my heart and from the future I now treasure – thank you.

Siobhan Dolan January 2025.

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List of Abbreviations

AUC	Area Under Curve
COOLR	Cooperative Open Online Landslide Repository
DFID	Department for International Development
DRR	Disaster Risk Reduction
DSIDT	Dikshit & Satyam Intensity Duration Threshold
ECMWF	European Centre for Medium Range Weather Forecasts
EDA	Environmental Data Service
EM-DAT	International Disaster Database
EPS	Ensemble Prediction System
ERA5	Fifth Generation ECMWF Atmospheric Reanalysis
EWS	Early Warning System
FPR	False Positive Rate
FWN	Far Western Nepal
GCRF	Global Challenges Research Fund
GFLD	Global Fatal Landslide Database
GIDT	Guzzetti Intensity Duration Threshold
GLC	Global Landslide Catalogue
GloFAS	Global Flood Awareness System
GPCP	Global Precipitation Climatology Project (NOAA)
ID	Intensity Duration
IMDAA	Indian Monsoon Data Assimilation and Analysis
LEWS	Landslide Early Warning System
LSI	Landslide Inventory

NASA	National Aeronautics Space Agency
ROC	Relative Operating Curve
SDG	Sustainable Development Goals
TPR	Total Positive Rate
UAV	Unmanned Aerial Vehicle
UNISDR	United Nations Office for Disaster Risk Reduction
WMO WIS	WMO Information System
WMO	World Meteorological Organisation

Chapter 1: Introduction

1.1 Background and Motivation

Disaster risk reduction is a discipline that aims at preventing ongoing, new and existing disaster risk. It also manages residual risk. This contributes to strengthening international and national resilience. These events are usually natural hazard events like flooding, heatwaves and landslides but can also be anthropogenic events like famine and war (UNDRR, 2017).

Research into the Disaster Risk Reduction (DRR) discipline and in particular landslide studies are critical for a number of reasons. Landslides pose significant risks for impact to human life, either through indirect impact damaging infrastructure or direct impact with fatalities. Understanding landslides in terms of their mechanisms and triggers helps in developing landslide early warning systems (LEWS) which can reduce loss of life and economic losses (Glade et al., 2000). The impact to the environment is also apparent, as landslides contribute to soil movement through direct movement, soil erosion and sediment transport which has impacts on water quality and flora and fauna habitats (Guzzetti et al., 2007).

1.2 Scope and aim of this study

The main aim of this study is to evaluate the current practice in the DRR discipline regarding accessibility in regard to the UN's Initiative on 'Warnings for All' and the Sustainable Development Goals (SDG) on 'Information for All', by using landslides as a focal point for this investigation. The thesis aims to do this by looking at two distinct sides: (i) current practice around 'data', and (ii) to create a freely available and useful tool for historical landslide identification in the Darjeeling district, India. By evaluating the datasets freely available and the people who work within the DRR discipline the thesis aims to show that the current practice at this moment in time is inaccessible and so goes against the UN's Warnings For All initiative (WMO, 2022) and against the 'information for all' SDG (UN, 2025) **See Thesis Section 2.2 Disaster Risk Reduction (DRR)**, which leads to poorer scientific enquiry and research. The thesis recommends that by striving to be more accessible, current practice moves closer towards best practice, and this leads to more accurate and skilful scientific research in the DRR discipline.

Objectives:

1. Combine freely available global LSIs and disaster databases to evaluate local representability. This process will investigate if current practice allows researchers who have little technological or monetary resource to obtain useful data in their locality.
2. The second objective aims to use the current practices as they are to create an easy-to-use historical landslide identification tool and evaluate the potential skill and useability of this new tool in the Darjeeling district, India. This simple method of using what's available without spending money and using a single laptop, allows for a potential addition to LEWS globally, no matter what the research conditions are in terms of funding and capacity.

1.3 Thesis layout and structure

To achieve these objectives, there are two major research chapters, 5.0 and 6.0 that constitute the main body of this thesis. Figure 1.1 shows the overall thesis structure.

I have considered the prose of the thesis and have decided to keep the style of writing quite personal as I find that not only will this encourage the readers to express themselves as human individuals who are also working within this DRR discipline and to keep the sense of personal identity of the researcher at the forefront of the work being presented.

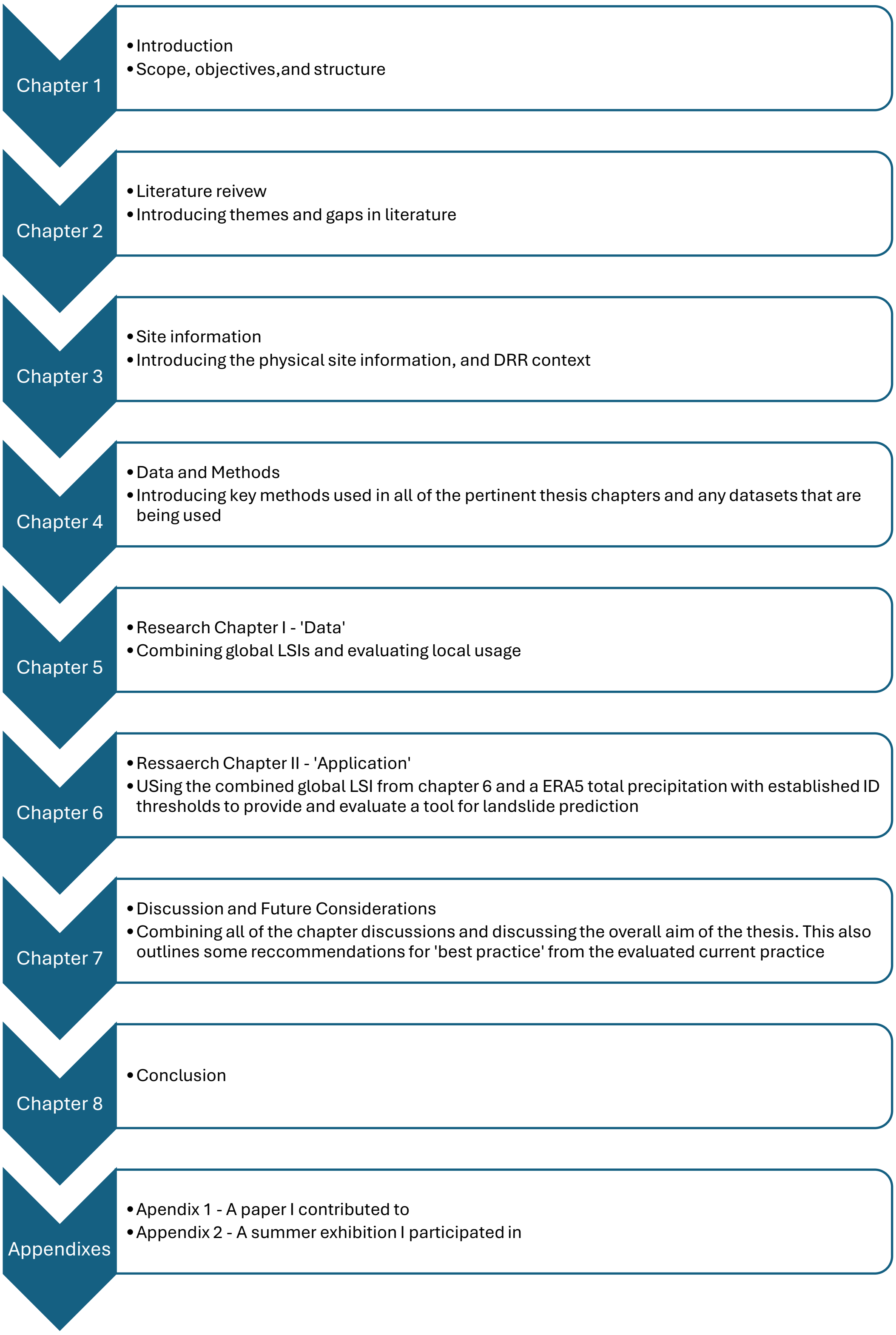


Figure 1.1: The complete thesis structure and simple descriptions of each chapter and section.

Chapter 2: Literature Review

2.0 Introduction

This literature review begins with a clear introduction to landslide hazards, disaster risk reduction (DRR), precipitation modelling and how precipitation and landslides can be combined to make landslide prediction models, including Intensity Duration Thresholds which will be used within this thesis. There will be a section at the end specifically aimed at the research questions that have been highlighted from this review, and that will be challenged within the thesis research chapters, data and application.

2.1 Landslide Hazard

Landslides are part of a group of natural hazards (other examples include earthquakes, floods and forest fires) that can change the organisation of ecosystems and cause devastation to society. The quantification of landslide deaths, injuries and damage is vastly underestimated, and the data is often incomplete (Haque et al., 2016). This could be due to the remote nature of landslides and the lack of correct classification of landslides. Additionally, when a landslide occurs bodies can be buried within the disturbed sediment which are unrecoverable because of the often large volume and the compact consolidation of their sediments. The World Bank Report (2005) stated that 3.7x106 km2 of the land surface is prone to landslides worldwide. This is an area bigger than the land surface area of India, Nepal and Bangladesh combined. This places nearly 300 million people in areas of potential landslide risk (Dilley et al., 2005). Landslides are very different in terms of size, types, distributions, patterns and triggering mechanisms (Malamud, 2003). Landslide susceptibility was usually thought to be time-independent (Roberts et al., 2021; Sania et al., 2017; Varnes, 1978), however recent 2015 papers by Marc et al. and Parker et al have challenged this assumption, stating that time-dependant controls, for example large magnitude earthquakes (M_w >6.0) have controls on landsliding. This means that the 7.8M_w April 2015 Gorkha earthquake which happened in Nepal killing 6,962 people and injuring 21,952 could have far reaching repercussions for controlling landsliding in and around the area (Roberts et al., 2021). Kargel et al., (2016) investigated the impact of this earthquake on the geological controls of the area effected and produced a catalog of triggered debris flows. A later study by Roback et al. (2028) found that there were over 25,000 landslides triggered by that earthquake event alone. The study area is within an area prone to earthquakes and would have felt some of the effects of this 2015 Gorkha Earthquake, and so any data in 2015 should be looked at critically, in case of an increase in landslide size or occurrence. This is because the Gorkha 2015 earthquake was responsible for shifting monsoon triggered landslide patterns in 2015 – making the landslides appear in higher slopes and reliefs (Jones et al., 2021).

A 2021 paper from Roberts et al. studies the idea that 'path-dependency' can happen not only in Italy, but in other geomorphic situations globally, and looks to prove this in the Himalayas. Path-dependency is the idea that landslides occur again (reactivates) on paths of failure from previous landslides or previous landslide events. So, for example, this effect means that it is a legacy effect, new landslides will spatially overlap pre-existing landslides more than those that do not overlap pre-existing landslides. This paper did observe both overlapping and non-overlapping landslides but noted that the landslides were geometrically different in this case (Roberts et al., 2021).

Precipitation is one the most common triggers for landslide events (USGS, 2025). The landslide occurrence over a temporal scale is largely controlled by rainfall patters with different types of resolution and can be analysed using statistical techniques (Asch & Van Beek, 1999). When there is good historical data on precipitation and landslide events then thresholds for critical daily rainfall and antecedent rainfall can be assessed. The skill of this threshold can obtain good results if the area in which the data is given is over a relatively homogeneous area, with one type of landslide with one size (Asch & Van Beek, 1999). A paper by Finlay et al. (1997) studied the probability of landslide occurrence and rainfall, and their results indicated that a rainfall duration of 1-12h is important in predicting the number of landslides and the antecedent rainfall also has some influence.

This is because waterlogged soils increase in weight, and this effects slope stability (Crozier, 2010) (Walker et al., 2013) (Blonska et al., 2016). This can increase the likelihood of shallow landslides, which can happen in all climates. Due to the water balance on shallow soils which is controlled by infiltration of rainwater, unsaturated percolation and a response to the rise of groundwater during storm events (Asch & Van Beek, 1999). This means that in extreme weather prone areas, for example South Asia where the monsoon seasons have intense rainfall, or tropical cyclones can occur (storms) there is a greater likelihood of landslides to happen. Variations in the strength of the monsoon control the impact and likelihood of landslides in the Himalayan chain in Nepal (Peatley et al., 2007).

As rainfall is the most common triggering factor of landslide occurrence, many government civil protection agencies use warning systems for landslides that are based on this interaction between landslides and rainfall (Martelloni et al., 2012). Rainfall and climate variations are used in literature for the definition of rainfall thresholds for the instigation of landslides (Segoni et al 2018). However, this paper argues that these empirical-statistical approaches ignore the physical relationships between rainfall and the mechanisms of landslides, they neglect the local antecedent conditions and the role of the hydrological processes happening in the slopes at the time of hazard occurrence (Canli et al., 2018).

Data-driven methods of landslide early warning systems evaluate the statistical relationships between the locations of landslides occurred in the past and landslide inducing factors – and then quantitative predictions are made for landslide free areas with similar conditions (Chae et al., 2017). Rainfall is the most important threshold in landslide early warning but has its difficulty in being used. This is due to the difficulty in assessing the effect of rainfall in the location as the failure depends on several factors, including the major one - heterogeneity of the soils. When thinking about using these thresholds it is necessary to analyse the relationships between soil properties and landslide triggering based on the physical and mechanical thresholds of each case (Chae et al., 2017).

Within this review, there is a logical framework for the 'SANF Early Warning System' for rainfall induced landslides in Italy (Chae et al., 2017) (Rossi et al., 2012). This is a system that is based of rainfall thresholds, for forecasting possible rainfall induced landslides in Italy. More on this system in another section around landslide prediction systems. The rainfall threshold method of landslide early warning is well described in this paper and it does look ahead into the applications of thresholds in the future of prediction systems.

Landslide Inventories

Landslide inventories have been collected nationally and internationally for several years. Landslide inventories are systematically collected records that provide a comprehensive record of landslide events – and can be collected at the meso (global) or micro (local) scale for different timeframes. Landslide inventories are constructed to provide basic information about landslide incidences to be used in tools for modelling landslide susceptibility, hazard, and risk of an area (van Western et al., 2006; Ghosh et al., 2020). Landslide inventories usually contain these basic things;

1. Location and Extent – crucial for understanding spatial distribution (Malamud et al., 2004)

2. Type and Size – These characteristics are useful when analysing landslide dynamics (Galli et al., 2008)

3. Temporal Information – helps with understanding triggering factors (Harp et al., 2011)

4. Triggering Factors – Aids with the correlation of landslides to triggering events or cascading hazards (Kreuzer & Damm, 2020)

5. Consequences and Impacts – property damage and lives lost are important to consider with vulnerability and DRR management (Guzzetti et al., 2012)

It is important to collect this information within landslide inventories as it helps with many applications and models within landslide research and management. These include;

1. Risk assessment and management – Identifying areas prone to landslide events (Tanyas et al., 2020)

2. Land use planning and decision making – planning and policy decisions to mitigate risks in landslide prone areas (Trigila et al., 2010)

3. Scientific research and knowledge building – understanding of landslide processes leads to the advancement of science in geosciences (Kirchbaum et al., 2015)

4. Emergency response and recovery – providing detailed information about the area in the aftermath of events(Marc & Hovius, 2014)

5. Public awareness and education – raising public awareness about the landslide hazards.

Landslide Inventories are very hard to create, and Petley et al (2005; 2006) investigated this through investigations in Nepal. By beginning to investigate global risk of landslides by creating a global LSI, the researchers found that LSIs were increasing poor, underfunded and undermanaged (Petley et al., 2005) (Petley et al., 2006).

The largest international landslide inventory is the Cooperative Open Online Landslide Repository (COOLR) landslide inventory created by the National Aeronautics and Space Agency (NASA) in the United States (Kirchbaum et al., 2012). This was previously known as Landslide Reporter and the Global Landslide Catalogue (GLC). Other global inventories include large disaster databases like DesInventar, EM-DAT and other collected global events, such as the Global Fatal Landslide Catalogue (GFLC) from the University of Durham (Froude & Petley, 2018). National landslide inventories are available in almost all countries that experience landslide events, with a few of the poorer Global

South countries either having them, but not available for public download, or created and managed in the Global North.

Landslide inventories are usually created or downloaded before the start of a research piece so that they can be used in conjunction with another dataset to infer a conclusion or create a tool. This research is looking at the available global inventories and what information is needed for them to be useful in the prediction of landslides. The current literature on global landslide inventories does not contain a standardisation of best practices on which information to record, how to record it and how to disseminate it. This has led to many different global landslide databases being produced, with gaps, missing information, and different coverages.

When considering the future of landslide inventories, it is important to look at the current literature. The current literature when comparing the global inventories show a difference in coverage and information gathering (Dandridge, 2023). A paper by Gomez, Garcia & Aristizabal (2023) combined all four of the largest global landslide inventories to create the Unified Global Landslide Database (UGLD), which increased the global coverage, the landslide points, the data collected and other key factors. The four databases differed in many different aspects, however together they created a complementary harmony when combined (Gomez, Garcia & Aristizabal, 2023). This paper concluded that there was a need for continued work by many different institutions to provide a global landslide database, but due to a limitation around the culture of landslide data collection and other factors this was not currently a plan for the future (Gomez, Garcia & Aristizabal, 2023).

Indian Landslide Hazards

The Himalayan Mountain chain has had an increase in landslide events in recent decades. Some studies have suggested that there has been an increase in rainfall due to a warming climate, while others have suggested a more anthropogenic cause such as an increase in infrastructure like roads. A paper by Muñoz-Torrero Manchado et al., (2021) used remote sensing techniques to try to answer the question, due to the lack of sufficiently high-resolution regional landslide inventories. By creating a local landslide inventory using remote sensing, the team made an inventory of 26, 350 landslides between 1992-2018, and statistically analysed the results. The results showed that there was a strong correlation between the annual number of shallow landslides and the accumulated monsoon precipitation (Muñoz-Torrero Manchado et al., 2021).

India has the most fatal landslides in the world (Froude and Petley, 2018) (Martha et al., 2021). India's large size and high population density makes the location highly vulnerable to landslides that have the most effect on the population. The monsoon driven seasonal system makes the possibility of rainfall triggered landslides more probable (Martha et al., 2021) and makes it hard to mitigate and manage the risks of landslides. The northeast Himalayas has the second most landslide occurrences in the entire Indian peninsula (Martha et al., 2021). South Asia is a global hotspot for landslide fatalities. There must be a focus on developing more reliable and comprehensive landslide inventories (Findan et al., 2024). Global landslide inventories show potential for use with historical databases to forecast precipitation-based Landsliding in Darjeeling District, India. The effectiveness of these systems depends on regional calibration, local geographical and meteorological considerations, and integration of high-resolution data. This has been seen through various studies on this topic. Khan et al. (2022) built a system for landslide hazard assessment, which used satellite-based systems for estimating landslide hazard, Teja et al. (2019) used an algorithm-based model for identifying precipitation conditions for landslides, and Segoni et al. (2021) used regional-scale landslide forecasting models which was calibrated by historical landslide data.

Kirchbaum et al. (2009) evaluated global landslide inventories, and this research highlighted the limitations of global inventories when used in application for predicting landslides. The paper stated that the global inventory was good for general information and location metrics but lacked adequate performance and sensitivity when observing the triggers around paring this with satellite precipitation products (Kirchbaum et al., 2009).

The 2024 paper by Chen et al. is investigating the recurrent and persistent landslides in the Himalaya Mountain chain for the past 30 years. The findings show that large-scale understanding of landslide dynamics is lacking for risk mitigation, 86% of landslides are persistent and recurrent and 22% of landslide areas had at least 3 or more instances of landsliding over this 30-year period (Chen et al., 2024). There were several factors for these landslide occurrences, including anthropogenic, climate and seismic. Chen et al. (2024) used a remote sensing-based methodology, using satellite images, daytime/nighttime imaging, topography and some reference data to train a machine learning model to map landslides in the mountains. It was then tested for accuracy using reported and manually mapped landslide datasets (Chen et al., 2024). The researchers then looked at different time series analysis of the dataset, looking at how long vegetation took to grow back (persistence) and how many times the landslide moved (recurrence). The results concluded that there was a significant correlation between temporal variation of the South Asian Monsoon Index and new landslide areas in July and August. 55-86% of the landslide areas mapped were classed as persistent and 3-24% as reactivated (Chen et al., 2024). The model managed to identify not only areas that have increased landslide persistence and reactivation, but also decreases due to changes in policy, afforestation efforts and law changes (Chen et al., 2024). The East Indian Himalayas has just over 50% of the first occurrence of landslides recorded before 1999, with the rest after that period. In this area persistence on average was below 5 years, and recurrence on average at 1 (Chen et al., 2024).

Overall, this technique in using machine learning to map and analyse persistence and reactivation is a new and novel technique which has been made due to the need for a landslide inventory in this scale. The technique has identified 265,000 landslides across the mountain range and over the 30-year period, something which has never been available (Chen et al., 2024).

2.2 DRR and Landslide Early Warning

2.2.1 DRR

Disaster risk reduction is a discipline that looks at the disaster cycle usually surrounding an event that has created a risk to infrastructure, livelihoods or populations. These events are usually natural hazard events like flooding, heatwaves and landslides but can also be anthropogenic events like famine and war (UNDRR, 2017).

DRR Cycle

Disaster risk reduction requires ways to look at risks and hazards in a holistic way (UN, 2015). It is important to consider a multi-hazard approach to disaster risk reduction as events of multiple hazards triggering other types of hazards happen in a clustering way, and this can be within proximity, spatially and temporally which decreases a community’s response and recovery phase (Liu et al., 2016). Disaster risk reduction has a management cycle schematic which shows the entire process from the mitigation phase to the recovery stage after the event occurs (Figure 2.1).

Figure 2.1: The Disaster Management Cycle showing the phases (coloured quarters) and the events (within the arrow) that can be used to break down the 'disasters' process so that the different stages can be managed effectively (UNISDR, 2015).

Early warning systems (EWS) can be one of the ways in which this information can be collated and used in management strategies for the mitigation and resilience of communities at risk. From Figure 2.1, the EWS can be included in the mitigation and preparation stages of the DRR Management Cycle. For an EWS to work efficiently however, the science behind the forecasts and predictions needs to be skilful and understood by policy makers and politicians in charge to make the decisions once a warning has been issued or not.

When conducting research into the usability of early warning systems there can be different skills tested using historical datasets. This type of testing is conducted within all early warning systems, predictions, and disaster risk management strategies where warnings based on predictions are issued. Contingency Tables can be used where there is a simple 2x2 matrix that can help visualise the performance of a system. An example of a contingency Table can be seen in Table 2.1.

Table 2.1: An example contingency Table

	Forecasts	
Observations	*Warning*	*No Warning*
Event	Hit	Miss
Non-Event	False Alarm	Correct Rejections

The contingency table can be used to count instances of hits (true positives), misses (false negatives), false alarms (false positives) and false negatives (correct rejections). Within the context of landslide prediction using the I-D thresholds (**See Thesis Section 4.5.2 Methods)** and the ERA5 precipitation hydrometeorological modelling **(See Thesis Section 2.3 Precipitation Modelling)** for prediction verification using historical landslide events the assumptions would be;

- Hits (True Positives): Instances where the system correctly predicts a landslide (the ERA5 I-D pushes the rainfall event above the I-D threshold and a historical landslide occurred).

- Misses (False Negatives): Instances where the system fails to predict an actual landslide (the ERA5 I-D rainfall event was not above the threshold but a historical landslide occurred).

- False Alarms (False Positives): Occurrences where the system predicts a landslide, but none occurs (where the ERA5 I-D rainfall even is above the threshold but a historical landslide was not reported).

- Correct Rejections (True Negatives): Occurrences where the system correctly predicts the non-occurrence of a landslide (the ERA5 I-D rainfall event was not above the threshold and there was not a historical landslide reported).

Hits and misses are critical metrics when assessing an EWS and predictions, they can be seen as the successful elements of an EWS. The false alarms and correct rejections represent the error aspects of predictions, where they can represent the 'trust' that the practitioners and community have on the system. An accurate prediction is needed for mitigation of risk in any successful DRR management system. There is a balance which is achieved between the number of false alarms and the misses that needs to happen. This leads to established 'accepTable' rates of each of these in disaster risk reduction as the EWS needs to be both reliable and credible.

DRR Governance

The DRR discipline is governed internationally and nationally. There are many different organisations related to DRR, including large international organisations like the United Nations Office for Disaster Risk Reduction (UNDRR) which chaired and created the Sendai Framework for Disaster Risk Reduction 2015-2030. This framework looked at 4 priorities in these 15 years;

1. Understanding disaster risk
2. Strengthening disaster risk governance to manage disaster risk
3. Investing in disaster risk reduction for resilience
4. Enhancing disaster preparedness for effective response and to "build back better" in recovery, rehabilitation and reconstruction.0

The United Nations also investigates global sustainable development and in 2015 released a blueprint for peace and prosperity for all people and the planet. This blueprint has 17 goals at the heart of its structure, and these are called the Sustainable Development Goals (SDG). These goals are;

1. No poverty
2. Zero hunger
3. Good health and well-being
4. Quality education
5. Gender equality
6. Clean water and sanitation
7. Affordable and clean energy
8. Decent work and economic growth
9. Industry, innovation and infrastructure

10. Reduced Inequalities

11. Sustainable cities and communities

12. Responsible consumption and production

13. Climate action

14. Life below water

15. Life on land

16. Peace, justice and strong institutions

17. Partnerships for the goals

These SDGs and the DRR discipline are highly interconnected. The Goal targets of 1, 2, 11 and 13 are in direct link to the discipline, with contributions from the discipline contributing to resilient infrastructure, fostering more effective institutions and more. There is a systemic risk to communities and the sustainability of these communities, and so DRR must be integrated into policies and programs to reduce risk to other systems. SDG Target 11.5 clearly states that by 2030 there will be a significant reduction in the number of deaths caused by disasters (UNDRR, 2015).

This Sendai Agreement along with the UN's Sustainable Development Goals frame the national governance frameworks for many countries.

CRED – Centre for Research on the Epidemiology of Disasters.

CRED is an organisation from the Universite Catholique de Louvain that looks at Natural Hazards and the consequential Disasters which happen after the hazard. It is an organisation that is a reference organisation in the field of disaster and emergency. CRED manages the EM-DAT database, which is used to quantify the many different natural hazards and technological disasters. The two main publications from CRED which have applicability to this research is the 2015 'Human cost of weather-related disasters 1995-2015', and 'The human cost of disaster: and overview of the last 20 years (2000-2019)' published in 2020. These two reports discuss the trends of disasters over a long period of time (10 years or 20 years) and make recommendations about how the future of DRR management could be to combat the impact of these disasters by the community (UNDRR, 2015; UNDRR, 2020). The findings from these reports discussed that over 90% of the disasters have been weather related (floods, storms, heatwaves) worldwide, with an increasing exposure of people and economic assets leading to higher economic losses (UNDRR, 2015). The reports agree that better management and use of EWS could save lives and economic loss, leading to fewer disasters being registered on the EM-DAT database.

The CRED reports show that India is one of the 'hotspot' countries for climato-meterological disasters, with only China and the USA being within the same category. The hazards themselves are divided into categories with (wet) landslides grouped in with hydrological hazards. Landslides overall come in as the 5th most occurring natural disaster (UNDRR, 2015). Landslides were attributed to killing some of 20,000 people over the period of 1995-2015, with 8 million people affected over this period too (UNDRR, 2015). In India 62,325 deaths (3 per million inhabitants) were recorded over the 20-year period too, making it the second highest death toll recorded on EM-DAT.

How does this relate to my work?

Weather related disasters are the majority of disasters as shown by the reports by CRED. These disasters are set to increase due to climate change and the increase in extreme weather. This means examining rainfall triggered landslides for landslide prediction is in the best interest for mitigating landslide triggered disasters, loss of life and costs. However, using CRED data and reports to discuss landslide events is problematic, due to the criteria for CRED (UNDRR, 2020) and thus EM-DAT to record them is;

- 10 or more people killed
- 100 or more people affected
- Declaration of a state of emergency
- Or a call for international assistance.

Despite this, EM-DAT and CRED reports are a valuable resource for understanding the overall trends of natural hazards and disasters, and we can infer that if extreme weather and weather related disasters are increasing, then weather triggered natural hazard events are increasing too, including rainfall-triggered landslides. India has been highlighted as one of the top 3 countries for disasters, and second highest death toll, and so working within this site makes sense to try and reduce the number of disasters overall.

National Governance

Looking at the way national startergies are used within these remits under DRR management strategies is a useful way of understanding how these are utilised in a practical way.

UK Foresight Review

The UK Foresight Review is part of the UK Government's Office for Science and has an objective of advising the government on policies surrounding the uncertainty of future decisions. It is led by the Government Chief Scientific Adviser who reports directly to the Prime Minister and the Cabinet Secretary (Foresight, 2012). The UK Foresight Review is a summary of Foresight's programme of work for 12/13 and includes completed and current projects for the timeline, the Horizon scanning programme and the future of food and farming. There is also a section of the report designed to evaluate the impact of past projects and their impact on coastal and flash flooding. This report is a direct output of an objective to provide understanding of the development of effective strategies, policies and priorities at a national and international level (Foresight, 2012). The other objectives of the project is to build a comprehensive evidence base for major issues looking 10-80 years into the future, provide shorter projects to fill gaps in current policy and the Horizon Scanning Centre which provides training, toolkits and networks to strengthen capacity and best practice (Foresight, 2012).

Within this Foresight review and programme, there is an entire section on reducing risks of future disasters. This is due to the uncertainty surrounding the changing climate, growing natural hazards and man-made disasters. The report states that the impact of these disasters, even if felt predominantly in the Global South, will have repercussions for global trade, commodity prices and security (Foresight, 2012). The project concluded that disaster and death should not be the ineviTable consequences of natural hazards and instead it is possible to stabilise disaster impacts if science can be used more effectively. The report states that it will require a new approach and culture to reduce these risks (Foresight, 2012). The new approach should include;

- Improved forecasting of natural hazards
- Improved information about vulnerability to hazards
- And improved evidence on what actions are effective in reducing disaster risk.

As part of this report, there was also a section on migration and global environmental change. This area of the report highlighted changes in environmental conditions that contributed to rising natural hazard incidences. This led to another project looking at flood and coastal defence – something which is very important to the UK government as flooding is the primary natural hazard in this country.

How does this relate to my work?

The importance of this report on my work is that governments are already looking at how disaster risk reduction management can be implemented to reduce impact on the global population. This includes highlighting the importance of creating a next generation of complex infrastructure like satellites and supercomputers to run forecasting models. Large scale reports like this confirm that researching prediction and forecasting technologies is important for the future of DRR and reducing impact to global communities (UNDRR, 2007.).

Early Warnings 4 All

Established in 2022, the UN's initiative called 'Early Warnings for All' (EW4ALL) has a goal to ensure that every citizen on the globe has access to early warning systems to be protected from hazardous weather, water or climate events (UN, 2023). This vision has been laid out in an 'executive action plan' which looks at the period of 2023-2027. This has been indicated as an issue of importance as the UN states that 1 in 3 of the global population (mostly from the Global South) has inadequate access to multi-hazard early warning systems. The UN Secretary General has endorsed EWS to save lives and provide preventative financial support to the globe. This initiative aligns with the Paris agreement, supports targets form the Sendai Framework for Disaster Risk Reduction and contributes to the 2030 Agenda for Sustainable Development. The initiative is built on four pillars:

- Disaster risk knowledge and management
- Detection, observation, monitoring, analysis and forecasting
- Warning dissemination and communication
- And Preparedness and response capabilities.

These four pillars encompass things like the data and tools needed to generate EWS products, capacity building for impact-based warnings, ensuring that countries have national hydrometeorological plans, have access to innovative forecasting and prediction applications, the creation of preparedness action plans and risk mapping, and the development of standard operational procedures that are people centred (UN, 2023). The pillars are managed by organisations such as the UNDRR, the WMO and the IFRC.

Since the development of this initiative, the 2023 Global Status of Multi-hazard Early Warning Systems report revealed that 101 countries reported having an EWS, which means that this Figure has doubled since 2015.

There have been some critical insights from literature on this initiative. The initiative requires that there are the tools, knowledge and capability for creating and distributing the warnings, however the focus if the aim is early warnings *for all* then the people who receive these warnings should be at the forefront of the research. Early warning systems call this step the ‘last mile’ of the process, but it has been criticised that this ‘last mile’ should be the ‘first mile’ (Kelman & Mercer, 2023) (Kelman & Fearnley, 2024). The warnings and tools that are being developed need to have inference from the people they are designed for, otherwise it is unknown what the need and use is for. For example, if the message is a warning for a lahar, but the word lahar is unknown by those receiving the message, how are the users going to prepare for this? Can the users stockpile supplies if they’re living in poverty? These questions are raised when the EWS are meant for ‘all’ of society. Inclusivity in EWS has been discussed by Fearnley (2023) who discussed this as 5 elements;

- integration of inclusivity from the first mile
- building capacity development and outreach
- expanding inclusivity by raising awareness
- building a local and national system
- and practical action for the future

These elements are designed to include and involve everyone in the design of warnings and draws elements from the ‘Designing Inclusive and Accessible Warning Systems: Good Practices and Entry Points’ report by the UCL Warning Research Centre (Yore et al., 2023).

The current way of thinking about EWSs as an end-to-end linear process is flawed and instead should be thought of as a multi-point, multi-pathway feedback loop (Kelman & Fearnley, 2024). All aspects of the hazardous conditions should be considered when warning a population – and this should affect the advice given, and the lead time of each advice given. Flash flooding, and tornadoes for example have different lead-times, different advice and different needs for the population, but if they happen simultaneously what advice should be followed, and can the population follow the advice if they're disabled, poor, or a minority persecuted? (Kelman & Fearnley, 2024).

Overall, the initiative is a fantastic idea and has a clear objective of what is ideal, however when catering for a vast variety of different people, with different needs and knowledge more careful thought and consideration needs to be made.

How does this relate to my work?

When considering landslide prediction systems, we must decide if they're needed by society, and where they would fit in the overall DRR and EWS landscape. Currently there are no global landslide prediction systems, and no operational local landslide prediction systems available for this to available for EWS in areas at risk of landslides. Even if they were available, would they be used and needed by the people affected? I think that for there to be warnings for all, there has to be a comprehensive tool base for making warnings and impact-based decisions. Thinking about the 'last mile' first, I can see that having a system that is based on predictive events could increase lead time, which can then create opportunities for society to create action plans relevant for the society. Increasing the lead time on landslide events, especially those like fatal rainfall-triggered landslide events, is something that would have a direct link to saving lives.

2.3 Precipitation Modelling

Use of ECMWF global products in other hazard EWSs

In Vitolo, et al. the authors are trying to contribute to the goal of creating a Multi-Hazard Early Warning System (MH-EWS) platform (2019). This 2019 paper proposes four information layers for this MH-EWS platform that will help responders and decision makers concisely and quickly highlight the possibility of upcoming concurrent natural hazards. These four information layers were created with the use of medium-range (3-15 days) forecasts from the European Centre of Medium-range Weather Forecasts (ECMWF). These layers considered hazard indices and datasets that included: weather forcing, wildfire danger and heat stress. There was also a three-step modelling workflow process that was: 1. calculating the daily climatology, 2. mapping of multi-hazard hotspots for past and future dates using reanalysis and medium-range forecasts and 3. mapping of the probability of occurrence of future simultaneous hazards using ensemble forecasts (Vitolo et al., 2019). The creating of hotspot maps is from analysing different maps and the spatial overlay of the forecasted hazards indices and the relevant climatology on the given date of creation. This was done with a methodology that includes creating binary maps where cells generated a 0 or 1 value depending on if the forecasted value of the hazard was above a threshold (Vitolo et al., 2019). These binary maps are then summed up as pairs and the cells are given different values depending on if they have no hazards present (0), only fire hazard (1), only heat stress hazard (2) or both hazards are present (3). The 2016 paper by Coughlan de Perez et al. develops a system that defines a forecast probability that can be used by decision makers to trigger humanitarian action. It uses global tools such as ECMWF's GloFAS river discharge data to trigger the warnings. Another interesting aspect of this journal is that the study area in Uganda only has one reporting point and so is considered data scarce. This is similar to this project's study sites in India and Nepal. The triggering forecast used by Coughlan de Perez et al. is given a constraint of acting in vain for less than 50% of the time. This project will be using contingency Tables and hit/miss ratios and so this paper shows how that information can be used in a practical application for research.

There are positives to take from these papers and their research. Their methods show that the spatial comparison and grouping of two hazards can be done for a multi-hazard warning system, and that medium-range forecasting can give the needed datasets for this work to be completed. These conclusions mean that the project on Flash Flooding and Landslides using global tools to evaluate and create a warning system tool for decision makers can be done and could be potentially used in disaster risk reduction management by decision makers, making it a valuable tool for operational levels. There are limits within these two papers that also relate to the project. These are the use of archived reports for the validation of past hazard events. Vitolo et al. uses news reports to validate the past hazard events with the hotspot and mapping products they create for the European Summer 2017 (2019). The 2016 paper by Coughlan de Perez et al. also uses media as part of their analysis, and the authors used a data mining technique that looked to sort the newspaper reports into current, past, mixed and unrelated flood hazards. 15% of these news articles were false positives. This meant that the news text was describing something which was not actually a flood (Coughlan de Perez et al., 2016). There are other limits to using media archives for creating a dataset used in scientific research that has been detailed in other journals. Some of these limits include: Language barriers, false negatives, cost of time for manual verification of events, loss of information through lack of public engagement with certain platforms that differ for each country and truth of sources (Velev & Zlateva, 2012) (Middleton et al., 2014) (Albuquerque et al., 2015). This project is also using archived data. This is primarily used for the landslide occurrence dates because there is a significant problem within landslide inventories where they do not hold this type of information.

Using this methodology to acquire this information will help to verify the use of global tools for future prediction of hazards in the study area.

Precipitation Modelling in Landslide Science

Precipitation modelling is being increasingly used within landslide science (Gariano & Guzzetti, 2016) (Segoni et al., 2018). Landslide science extensively leverages precipitation modelling to predict and mitigate landslide risks (Segoni et al., 2018). Intense or prolonged rainfall is a primary trigger for landslides, as it increases soil moisture, reduces cohesion, and destabilizes slopes **(See Thesis Section 2.1 Landslide Hazard).** By integrating precipitation forecasts with geotechnical models, scientists can identify areas prone to landslides and issue early warnings (Borga et al., 2011). Precipitation models simulate rainfall patterns and intensity, crucial for estimating the saturation levels of soils in susceptible areas. Advanced tools like Weather Research and Forecasting (WRF) models and machine learning techniques enhance the spatial and temporal resolution of these predictions. These models are often integrated with Geographic Information Systems (GIS) to overlay rainfall data on topographical maps, highlighting critical risk zones (Reder & Rianna, 2021). Furthermore, coupling hydrological models with real-time precipitation data enables dynamic monitoring of landslide risks, especially in regions experiencing extreme weather events linked to climate changing.

The use of reanalysis datasets such as ERA5 from the ECMWF, MERRA-2 from NASA, and the CFSR from the US National Centres for Environmental Prediction, for landslide prediction has shown promise but also significant limitations. Studies utilizing ERA5-Land data have demonstrated its ability to improve statistical correlations between rainfall and landslide events, yet its coarse spatial resolution often fails to capture localized precipitation extremes critical for triggering landslides (Botto et al., 2025). Similarly, MERRA-2 has been employed for hydrological estimations of landslides, but its daily rainfall estimates may not sufficiently capture short-duration, high-intensity rainfall events that are key to landslide initiation (Palazzolo, 2023). While ERA5 precipitation data has been useful in reconstructing rainfall histories, its applicability is constrained by the lack of comprehensive landslide inventories, limiting predictive accuracy (Reder & Rianna, 2021). The reliance on retrospective datasets means that real-time early warning applications remain challenging.

ERA5, the reanalysis dataset by the European Centre for Medium-Range Weather Forecasts (ECMWF), is widely used in landslide-related projects. It provides global, high-resolution data on precipitation, temperature, and soil moisture, essential for understanding landslide triggers. Projects like the Copernicus Emergency Management Service and the Landslide Hazard Assessment for Situational Awareness (LHASA) model rely on ERA5 to analyse past events and improve hazard forecasts. Its historical data supports identifying trends and correlations between rainfall and landslides.

ERA5 is the ECMWF's reanalysis product released in 2020 for public use and includes the data from the dates of 1950 to the present. It provides hourly estimates of different climate, earth and ocean variables. The variables are created by combining historical observations into global estimates using data assimilation and advanced modelling techniques. Some of the observations come from satellite data (e.g. satellite radiances from infrared and microwave, or satellite altimeter data) and in-situ data provided by the WMO WIS (e.g. drifting buoys, ground-based radar and wind profilers) (Hersbach, 2020). More detailed information about the data assimilation and advanced modelling techniques can be found in the ERA5 documentation on ECMWFs Confluence system (ECMWF, 2025).

The resolution of the ERA5 reanalysis dataset creates limitations at simulating the frequency of daily precipitation intensities in mountain areas due to ERA5's variations of the diurnal cycle. ERA5 is relatively good at simulating the intensity of the rainfall but does not show the exact location of this(Lavers et al., 2022; Paranunzio & Marra, 2024).

ERA5 total precipitation measurement has a known issue called 'the drizzle effect' in the modelling community. This effect is the tendency of climate models to model excessively frequent and weak precipitation events (Gutowski et al., 2003; Adinolfi, 2023). The adoption of a 1mm threshold is usually considered to be best practice when discriminating between dry and wet days when mitigating this issue (Adinolfi, 2023). This issue is especially noticeable in areas that suffer from high precipitation and is noticed among many different climate models, and not just ERA5 (Light et al., 2022). This effect is eclipsed by the improvements seen in ERA5 from ERA-Interim and so the adoption of the 1mm threshold discussed before is seen as a small inconvenience for such large increases in skill (Hersbach, 2020). ERA5 performs well against other more recent modelling products like the Indian Monsoon Data Assimilation and Analysis (IMDAA) produced by the IMD and the UK Met Office in terms of capturing monsoon onset and withdrawal dates and correlation to monsoon rainfall in general, however in finer details and extreme events it can be outperformed (Rani et al., 2021; Singh et al., 2021).

ERA5 data has been applied in several landslide-related projects. For example, it was used in developing hydrometeorological thresholds for landslide prediction (Melillo et al., 2018). The ERA5-Land dataset, with high-resolution soil moisture and rainfall data, aids in identifying critical rainfall-triggering conditions by reconstructing precipitation events leading to slope failures. This supports tools like the CTRL-T (Calculation of Thresholds for Rainfall-Induced Landslides) model, which integrates soil moisture data at multiple depths to assess landslide risks dynamically (Melillo et al., 2018)

Using ERA5 as a way of historically mapping landslide triggers is useful for making a prediction system. Using ERA5 and seeing how it performs can identify regions with frequent landslide-triggering rainfall, can establish a precipitation threshold for landslides. This can eventually be used for imputing historical triggers into prediction systems, or basically training the system, which can then use real-time or forecasted weather data to issue landslide warnings. Over a long historical period, using datasets like ERA5 could also look at the landslide trends in a climate change context, perhaps being able to create scenario-based modelling to evaluate future risks based on historical triggers. The use of ERA5 for calibrating and validating models that predict landslide occurrences based on the rainfall thresholds from the historical analysis. This type of analysis has been done for different projects. For example, the GloFAS system combines ERA5 data with hydrological modelling to monitor and predict global flooding (Copernicus.eu, 2024) and has been used to study the intensity and frequency of heatwave (Brimicombe, 2023), helping to identify trends and assess risks under changing climate conditions. However, ERA5 is not perfect. ERA5 suffers from a precipitation bias, especially in areas with complex topography. For example, in Poyang, China ERA5 had a significant overestimation of precipitation (Yan et al., 2024). ERA5 is also spatially coarse, which means in areas that have variability within these grid squares (like the study area) it can be quite insufficient (Harrigan et al., 2020). ERA5 has a dependence on atmospheric data assimilation too, which can create challenges with surface level variables accuracy (Tarek et al., 2020).

2.4 Intensity Duration Thresholds

Landslide intensity-duration (I-D) thresholds are crucial for understanding and predicting landslide events. Specifically shallow precipitation triggered landslides like those described in **Thesis Section 2.1 Landslide Hazards.** This is also specifically important for this research, as the research site is predominantly shallow monsoon (precipitation) based landslide hazards **(See Thesis Section 3.0 Site 3.4 Landslide hazards and landslide triggers).** I-D thresholds define the minimum rainfall intensity and duration necessary to initiate landslides. Rainfall intensity refers to the rate at which rain falls during a period of precipitation and is typically measured in millimetres per hour (mm/h). Duration is the period over which the rainfall occurs and is usually measured in hours or days (Iverson, 2000; Guzzetti et al., 2008). I-D thresholds are therefore a combination of these two factors, forming a critical boundary: below the boundary, the probability of landslide event is low, and above the boundary the likelihood of landslide even significantly increases. Empirical methods have been used to establish these thresholds. These involve analysing historical data of landslide and precipitation records to identify the minimum intensity and duration values associated with the landslide events. These I-D thresholds vary across different geographical locations due to the other factors that influence landslide susceptibility like geology, land use, topography, soil properties and local climate. There have been many different studies on I-D thresholds conducted globally (Guzzetti, Peruccacci, Rossi, & Stark, 2008) and locally, including locations like Nepal (Dahal & Hasegawa, 2008), Belgium (Van de Vyver, 2015), Italy (Guzzetti et al, 2007), South Korea (Kim, Chun, Kim, Catani, Choi, & Seo, 2020), India (Dikshit et al., 2019), Taiwan and Colombia (Marín, 2021). I-D thresholds in India have also started to be researched as numerical-model derived I-D thresholds, with a case study conducted in a Northwestern Himalayan catchment area by Dixit et al., (2023) Understanding I-D thresholds can help researchers predict, manage, and mitigate landslide risks within a management plan and early warning system.

Indian I-D thresholds have been calculated by researchers, and span the geologic conditions of the country that experience many landslides, like the lower mountainous Kerela region (Naidu et al., 2018), the Northwestern Himalayas in Uttarakhand (Saha & Bera, 2024), and in the study area of this thesis, the North Eastern Himalayas regions of Darjeeling, Kalimpong and Sikkim (Dikshit et al., 2020).

Combining I-D thresholds with modelled precipitation databases like ECMWF's ERA5 have only limited conducted experimentation. A paper by Bezak et al., (2019) presented a methodology for predicting precipitation triggered landslides based on a conceptual hydrological model, which demonstrated an approach that could be potentially adapted for use with ERA5. The paper looks at landslide incidences in Slovenia, where they use 20 landslides to calibrate and evaluate the methodology they propose. They use three different I-D thresholds in their verification; local, regional and global I-D thresholds.

The idea of combining hydrological models to I-D thresholds has been considered within some papers, however. Bogaard & Greco (2017) discuss the importance of hydrological information in addition to precipitation characteristics in landslide early warning systems. Wu et al., (2015) made a simplistic physical model which uses the Mohr-Coulomb law and Darcy's Law, which could be applied with integration of models like ERA5. Guzzeti et al., (2008) in their global database of I-D thresholds and relationships discuss that the database they have complied could be useful when used in conjunction with hydrological models.

Bogaard & Greco (2017) and Guzzeti et al., (2008) do point out some systematic errors that could occur when using hydrological models, such as lack of constraints on rainfall event durations. This is discussed in the next section based on ERA5 and its applicability in conjunction with I-D thresholds.

I-D thresholds have been calculated in Kalimpong (Dikshit & Satyam, 2018; Teja, Dikshit & Satyam, 2019) and Sikkim (Sengupta, Gupta & Anbarasu, 2009; Harilal et al., 2019). These I-D thresholds are; $I=3.52D^{-0.41}$ in Kalimpong (Dikshit & Satyam, 2018) or $E = (4.2 +/- 1.3)\ D^{(0.56 +/- 0.05)}$ (Teja, Dikshit & Satyam, 2019) and $I= 100\ D^{-0.92}$ or $I=43.26\ D^{-0.78}$ for Sikkim.

The difference between the I-D thresholds in Kalimpong and Sikkim are very different. Darjeeling is closer to Kalimpong than Sikkim, and so the Kalimpong threshold will be used in this study. The global I-D threshold is much higher and flatter than both Sikkim and Kalimpong I-D thresholds. The different thresholds including this global threshold can be seen in the Figure 2.10 below.

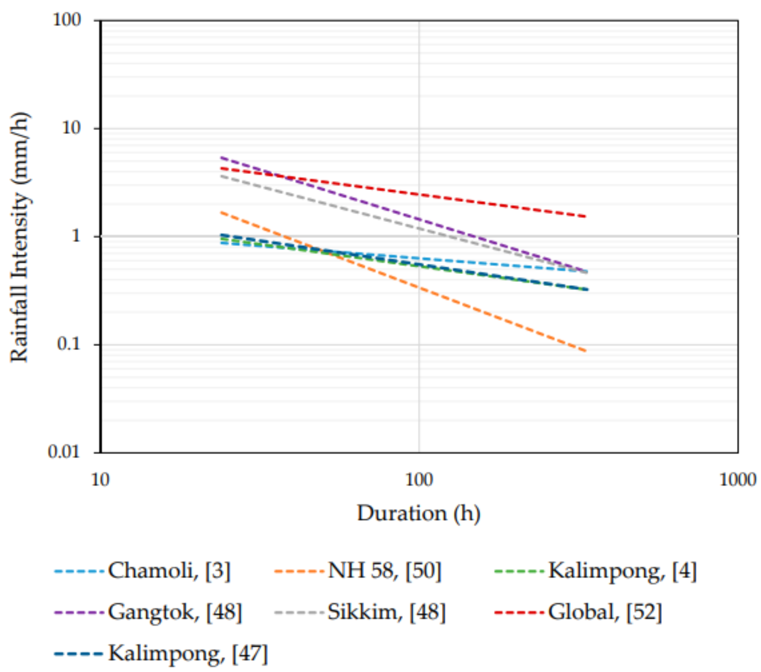


Figure 2.2: Comparison of different ID thresholds in the Himalayas with the Global ID threshold from Caine, 1980 (Dikshit et al., 2020).

2.5 Landslide Prediction Systems

The current literature surrounding the prediction of precipitation triggered landslides in Darjeeling District India is sparse, and prediction of these types of landslides with intensity-duration thresholds in conjunction with ERA5 in this district non-existent in this area and has only recently started to be attempted in Italy as a first for the globe (Palazzolo et al., 2023). There have been some studies using ERA5 within some forms of landslide prediction, for example in the US for identifying initiation thresholds (Mirus, et al., 2018), or in Italy using the ERA5 Soil Moisture data to improve the established shallow landslide forecasting (Marino et al., 2020).

Landslide prediction and the rates for performance evaluation has been discussed in some papers. Intrieri & Gigli (2016) discussed landslide forecasting and the factors that influence predictability. In this paper they presented a methodology for increasing the confidence of landslide prediction and addressed the challenges in balancing accurate predictions with the consequences of false/missed alarms. They proposed a 'predictability index' where they evaluated the methods they proposed, where points were awarded for the variance of prediction points around the time of failure (Intrieri & Gigli, 2016). There are other papers that look at the contingency Table and subsequent rates for evaluation. For example, a paper by Ho & Lee (2017) did a performance evaluation of a physically based model for shallow landslide prediction where they achieved a probability of detection rate of 1.00 and a false alarm rate lower then 0.25, which made it a promising application for shallow landslide early warning.

Landslide Prediction Systems (Using Rainfall Thresholds)

Italian SFER

The Italian SFER (Stochastic Finite-Element Response) system is an advanced computational tool for landslide prediction, combining geotechnical engineering and probabilistic analysis. SFER models the response of slopes under various stress conditions, accounting for complex interactions between soil and water. It uses stochastic simulations to incorporate uncertainties in material properties and environmental factors, enhancing its predictive accuracy. Applied in real-world cases such as the Vajont Valley disaster of 1963 (Petley, 2013) and the Campania landslides (Catani et al., 2005), SFER has been instrumental in early warnings, reducing loss of life and property. By integrating monitoring data with simulations, it supports decision-makers in risk assessment and disaster mitigation planning.

In the Indian Himalayas, prone to frequent landslides due to monsoons, earthquakes, and deforestation (Kumar et al., 2020), a system like the SFER system could be adopted revolutionize risk management. By adapting its models to local geotechnical conditions, it could provide early warnings for vulnerable areas. Integration with community-based monitoring and local infrastructure projects would ensure tailored, actionable insights, potentially saving lives and reducing economic losses.

Slovenian MASPREM

Slovenia is susceptible to shallow rainfall triggered landslides and since 2011 have been trying to create a landslide early warning system that is predictive in nature. This system is based on susceptibility maps, landslide triggering rainfall thresholds and a precipitation forecasting model. These are at a national scale (1:250,000) and a regional scale (1:25,000). The landslides in this model are overpredicted and do not correspond to the landslide inventory, however the system captures crucial factors when determining landslide location (Jemec Auflič et al., 2016). A conceptual model of this system can be seen in Figure 2.3.

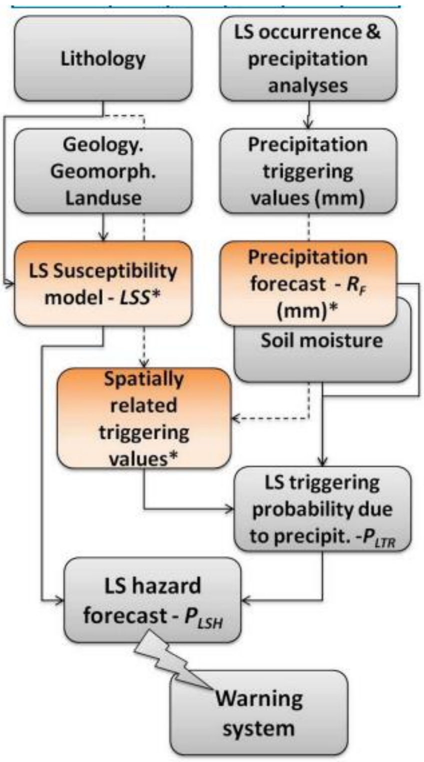


Figure 2.3: Conceptual Model for modelling the Slovenian landslide hazard forecasting system (Jemec Auflič et al., 2016).

The forecasting system uses rain thresholds that are based on the lithostratigraphic unit within Slovenia and gets its rainfall forecasts from ALADIN/SI over a 72hr period. The uncertainty with using this model comes from the landslide susceptibility model (lowest uncertainty), the rainfall triggering values (medium uncertainty) and the precipitation forecast data (highest uncertainty) (Komac, Šinigoj & Jemec Auflič, 2014).

How does this relate to my work?

This relates to my work as I am looking at using historical landslide data and reanalysis datasets to investigate if ECMWF products could potentially be skilful for future rainfall prediction systems to predict landslides in India. I'm starting out by using reanalysis and not the EPS but it will show if ECMWFs global system can identify historical rainfall triggered landslide events.

2.6 Future of Landslide Science

There is no doubt that international cooperation and efforts within the DRR discipline creates more opportunity for impactful work and positive effects. Landslide science has lots of promising scientific communities coming together to try and answer some of the big landslide questions moving forward, including around landslide prediction. One of these collaborative efforts is LandAware. This association is an initiative to collaborate and share experiences, needs and innovations in landslide early warning through 8 different working groups.

- Glossary & Catalog of LEWS (WG01)
- Communication-Networking (WG02)
- Communication with stakeholders (WG03)
- eLearning (WG04)
- Innovations (WG05)
- LEWS Data (WG06)
- Operational LEWS (WG07)
- And IoT-based methods and analyses (WG08)

LandAware have started this endeavour with a glossary and catalogue of LEWS, with the hope that by creating the glossary LEWS practitioners can all begin to use the same terminology when describing their technologies, their innovations and their experiences with each other. This glossary includes terms like ‘advisory’ ‘alert’ and ‘disaster’. An example of the glossary can be seen in Table 2.2.

Table 2.2: Snapshot of the LandAWARE glossary (LandAWARE, 2024)

Term	Definition	Abbreviation	Synonym	Reference (the first defining the term...)	EWS Element
Accuracy	Degree of conformity of a measure to a standard or true value; in other words, how close a predicted or measured value is to the true value.			NOAA, 2022	
Advisory	Highlights special weather conditions that are less serious than a warning. They are for events that may cause significant inconvenience, and if caution is not exercised, it could lead to situations that may threaten life and/or property.	ADVY		NOAA, 2022	
Advisory	All stages or levels considered by the LEWSs, and the related messages.			Guzzetti et al., 2020	Warning dissemination and communication
Alarm level	A loud noise or a signal that warns people of danger or of a problem.			Oxford Learner's Dictionary	
Alarm level	Pre-designated level of a device system, over which the device provides an audio/visual signal to call intensive attention for the users. When used in LEWS, alarm levels are set as a threshold (cutoff) in the device system, generally in local LEWS. Some countries use it interchangeably with such terms as alert level			Madhusudhan et al., 2018	
Alarm system	Is a system that detects process parameters of ongoing hazard events to initiate an alarm automatically, e.g., in the form of red flashing lights accompanied by sirens.			Stähli et al., 2015	Detection, monitoring, analysis and forecasting
Alert	A warning of danger or of a problem.		Warning	Oxford Learner's Dictionary	Warning dissemination and communication
Alert parameters	The parameters monitored used in the adopted warning model.			Proposed by LandAware from Pecoraro et al., 2019	
Attention level	Attention (to something/somebody) the act of listening to, looking at or thinking about something/somebody carefully; interest that people show in somebody/something.			Oxford Learner's Dictionary	

2.7 Research Questions

The research questions that this thesis will be investigating are:

1. What freely available global and national landslide inventories are available for researchers when researching Darjeeling, India?

a. Are the landslide inventories identified fit for use when validating historical reforecasting of precipitation triggered landslides in Darjeeling, India?

2. Can historical precipitation triggered landslides in Darjeeling, India be identified with the global scale reanalysis precipitation dataset ERA5, and established Intensity Duration Thresholds?

a. Is there statistical significance in the skill of identifying historical landslides in Darjeeling, India using ERA5?

b. Will this mean that global models can be used in areas that are data poor?

c. What are the future considerations when using models in this way in the future?

These research questions have been identified from gaps in the literature. Research question 1 is tackled in Thesis Section Research Chapter I: ‘Data’ and research question 2 is tackled in Thesis Section Research Chapter II: ‘Application’.

Chapter 3: The Study Area

This section introduces the physical characteristics of the selected study area and provides background context of the history of the region and the geopolitical significance of the region to current geopolitical affairs. The site information has been introduced this way because I think that it is important to include not only a technical site evaluation and investigation but also include the historical and geopolitical significance of the country and area that is of particular interest. This is due to the relationships, partnerships and project partnerships that are formed within international projects, and the interaction that researchers can have with stakeholders when interacting with them either home or away. Having a broad understanding of this especially in post-colonial countries is an important aspect of the research for any researcher crossing the Global North-Global South divide and has far reaching consequences around the project. My overall hope is that with a background relating to both disciplines it will become apparent that when researchers consider both sides of the coin, then they can work with consideration, care and equipped with knowledge needed to work within post-colonial organisations.

For more information on this outlook see **Thesis Section 1.2 Introduction: Scope and Aim of this Study.**

3.1 South Asia

Introduction to South Asia

South Asia is a diverse geopolitical, geological and geographic area of the world, and the uniqueness of the study area makes researching DRR and landslides a very interesting prospect. To introduce the area for any readers that are unfamiliar with the area, a brief introduction to the location, geology, climate conditions and the study area in general will be presented before showing the importance of the study area to rainfall triggered landslides.

South Asia's global positioning is due to tectonic movements that occurred after the breakup of Pangea the supercontinent over 200 million years ago. Around 50 million years ago two tectonic landmasses, the Eurasian plate and the Indian Plate collided. Both plates have a similar plate density and so subduction could not occur. The pressure of the plates led to mountain building processes, creating the large mountain range called the Himalayan Mountains. Movement in the Himalayas still occurs today, with the mountain range increasing in height 1cm every year (BGS, 2025).

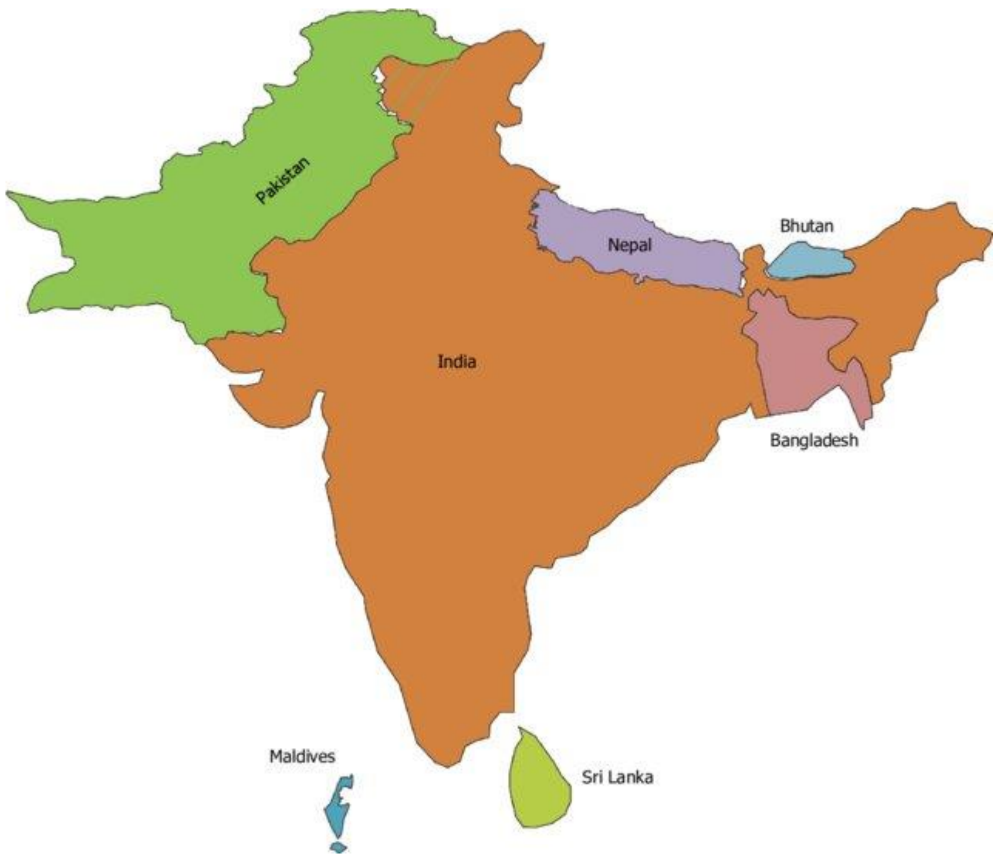


Figure 3.1 : A geopolitical view of South Asia (Hosain et al., 2022)

Geopolitically, South Asia consists of 8 countries: Afghanistan, Pakistan, India, Nepal, Bangladesh, Sri Lanka, Bhutan, and the Maldives (Figure 3.1). The South Asian Association for Regional Cooperation (SAARC) was established in 1985 to help the countries stay united in economic cooperation. India has the largest population of these countries, with Pakistan second, and Bangladesh third (United Nations, 2022).

The geology of South Asia is diverse and has a long geological history of their formation. Due to the uplift of the plates at the Himalayas, layers that would have been lost due to subduction or kept underground can be seen and studied.

Figure 3.9 is a geological map of the study area and shows some of the diversity that is contained even within a small locality. The terrain within the Himalayas is prone to geological hazards as it is tectonically active and has variable topographic characteristics. Landslides dominate the natural hazards which occur in the Himalayas, which cause a vast variety of loss; economic loss, loss of life, livelihood loss, infrastructure loss and biodiversity loss (Mathew et al., 2013). South Asia has a history of strong and powerful earthquakes, leading to large loss of life. In 2004, there was a 9.1M earthquake, and in 2005 a M7.6 earthquake that resulted in the greatest number of casualties in South Asia relating to earthquake events (IDMC, 2012). Not only geological types of natural hazards happen in South Asia, but other natural hazards occur here too. These include; cyclones (Hossain & Mullick, 2020), floods (Azeem, 2023), drought (Kafle et al., 2023) and avalanches (Acharya et al., 2022).

India

The Indian subcontinent is dominated by a monsoonal climatology (Faluga & Wang, 2022). This monsoon period is usually defined as occurring between the months of June and September due to the consistent pattern of rainfall observed historically and is an important phase of the year for India as it has a critical impact on the region’s climate, agriculture and economy. This is because the region receives around 75-80% of its annual rainfall within these four months of the monsoon season (Saha, 2023). The monsoon when it begins, is called the ‘onset’ and usually begins in early June, at the southern end of the Indian subcontinent beginning with the South state of Kerala and gradually progresses northwards.

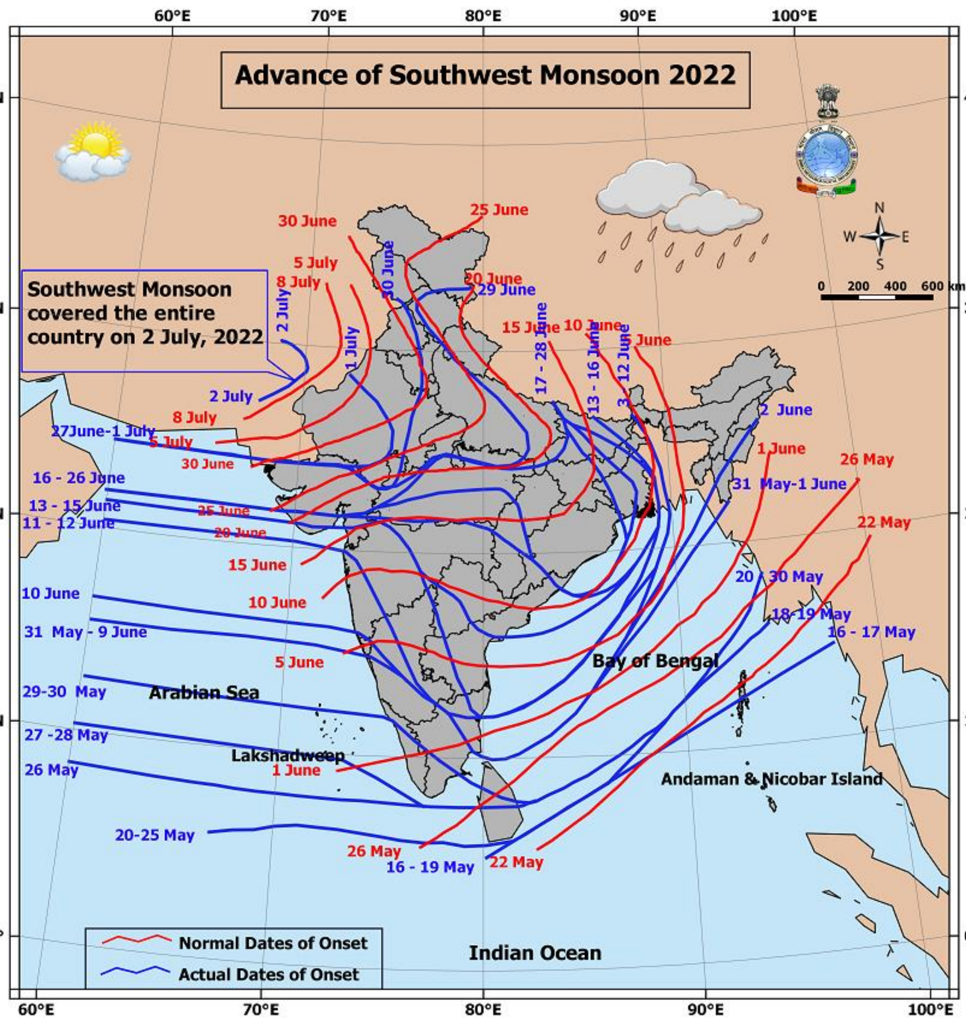


Figure 3.2: The advance of the 2022 monsoon season (IMD, 2022).

The 2022 monsoon onset calculated by the Indian Metrological Department (IMD) is shown in Figure 3.2. The IMD have shown the normal dates of the monsoon, as taken from the historical dates from previous onsets, and the actual date of the 2022 onsets. Not only is this a good illustration of how the monsoon advances throughout the Indian subcontinent, but it also shows how the onset has changed overtime due to climate change (Sandeep et al., 2023). The changes show that the onset is starting slightly earlier than normal, and advances to the northern areas earlier than in previous years. These dates are very important for the Indian population as the predictions for these dates are relied on by farmers for the economy and for food security and is important for government for the DRR management strategies and water management strategies in India (Datta et al., 2022). It is through this predicTable change in the climate that industries that rely on rainfall, such as agriculture can plan for future events and harvests. This predicTable nature of the monsoon also helps people to plan for impacts of the monsoon such as floods, drought and landslides (Nanditha & Mishra, 2021).

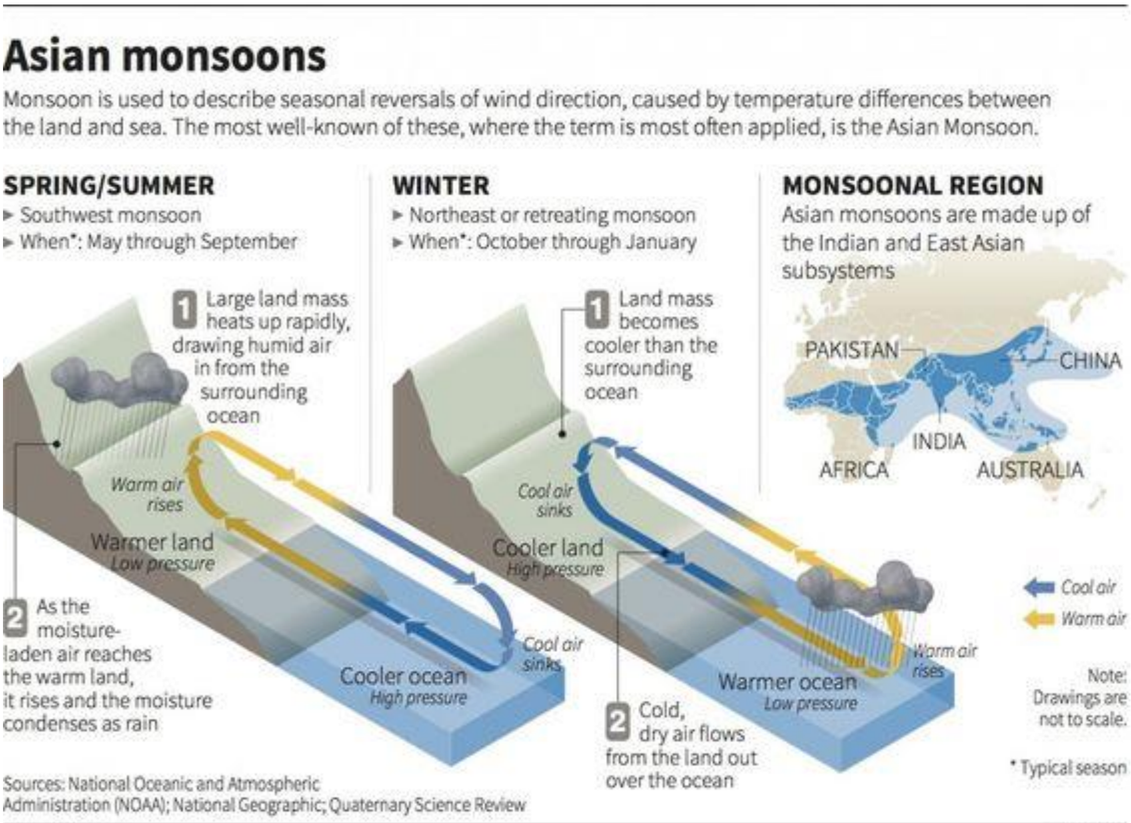


Figure 3.3: A Schematic of the warm and cool air relationships between the land and ocean driving the monsoon rains in the Indian Subcontinent (Foo, 2013)

The Indian monsoon is driven by a relationship between the atmosphere and the ocean, and the conditions during the year (Fryer, 2022). Some of these key factors include the differential heating of the land and sea, creating low pressure systems over the Indian subcontinent and a high-pressure system over the Indian Ocean. This pressure gradient pushes moisture in the air over the ocean into the land, resulting in heavy rainfall. The Tibetan Plateau in the North also plays a crucial role in heating the atmosphere, enhancing this monsoon circulation (Geen et al., 2020). There is year to year variations in the monsoon due to internal dynamics like the ocean/land pressure systems and external drivers like the Intertropical Convergence Zone (ITCZ) and global teleconnection events like El Nino Southern Oscillation (ENSO) (Geen et al., 2020).

The ITCZ is a band of low pressure around the Earth which lies next to the equator and is where the trade winds of the northern and southern hemispheres converge. This leads to an area that is often unsettled, with thunderstorms and heavy precipitation events (Hess et al., 1993; Yan, 2005).

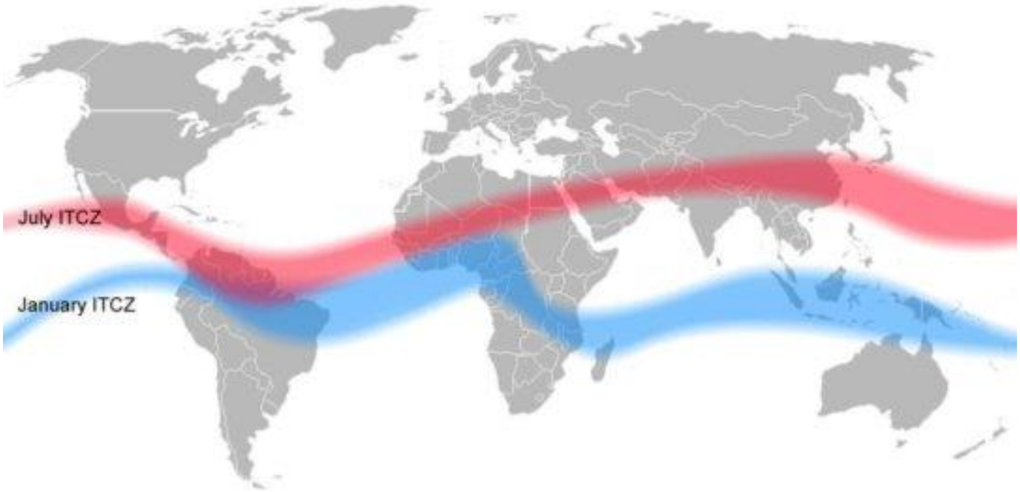


Figure 3.4: The ITCZ and its different positions during the year. The change between January and July is when the onset of the monsoon occurs over the Indian subcontinent and settles in the July position (Mats Halldin, 2018).

ENSO has a long historically proven influence on the monsoon period (Athira et al., 2023). The change from normal conditions to El Nino is dependant on the ocean's thermocline (the imagined line between the denser cold waters in the ocean and the less dense warmer waters in the ocean) being deeper than usual, changing the surface ocean temperatures and thus changing the rainfall patterns in the above atmosphere (Figure 3.5). Floods are more likely to occur in periods of La Nina and droughts are more likely to occur in periods of El Nino due to the changing of rainfall patterns driven by these ENSO processes (Athira et al., 2023).

Since the 1950's the monsoon has become more erratic (of lows and extreme events) and has weakened. Despite this floods and landslides have become more common (Lal et al., 2001; Lal,2003; Roxy & Chaithra, 2018; Seth et al., 2019)

Climate change is changing the monsoon climate in India through a number of different ways, including; increased intensity and extreme events (fryer et al., 2022), variability and erratic patterns (Sandeep et al., 2023), spatial redistribution of rainfall (Maharana et al., 2021), changes in low pressure systems (Fryer, 2022) and aerosol forcing and greenhouse gasses (Teschke, 2022). Those that affect precipitation triggered landslide events are the increased intensity, the variability of precipitation patterns and the redistribution of rainfall. With climate change, mean monsoon precipitation increases leading to more extreme precipitation events (Fryer et al., 2022, Sandeep et al. (2023) states that the monsoon season will be more erratic and unpredicTable, which will make it harder to manage natural hazard events, and the spatial changes that are predicted by Maharana et al. (2021) are thought to decrease precipitation in the Northeastern Indian Himalayas, which potentially could decrease rainfall triggered landslides. Climate predictions on the monsoon precipitation from various climate models show this variability and uncertainty in the future (Figure 3.6).

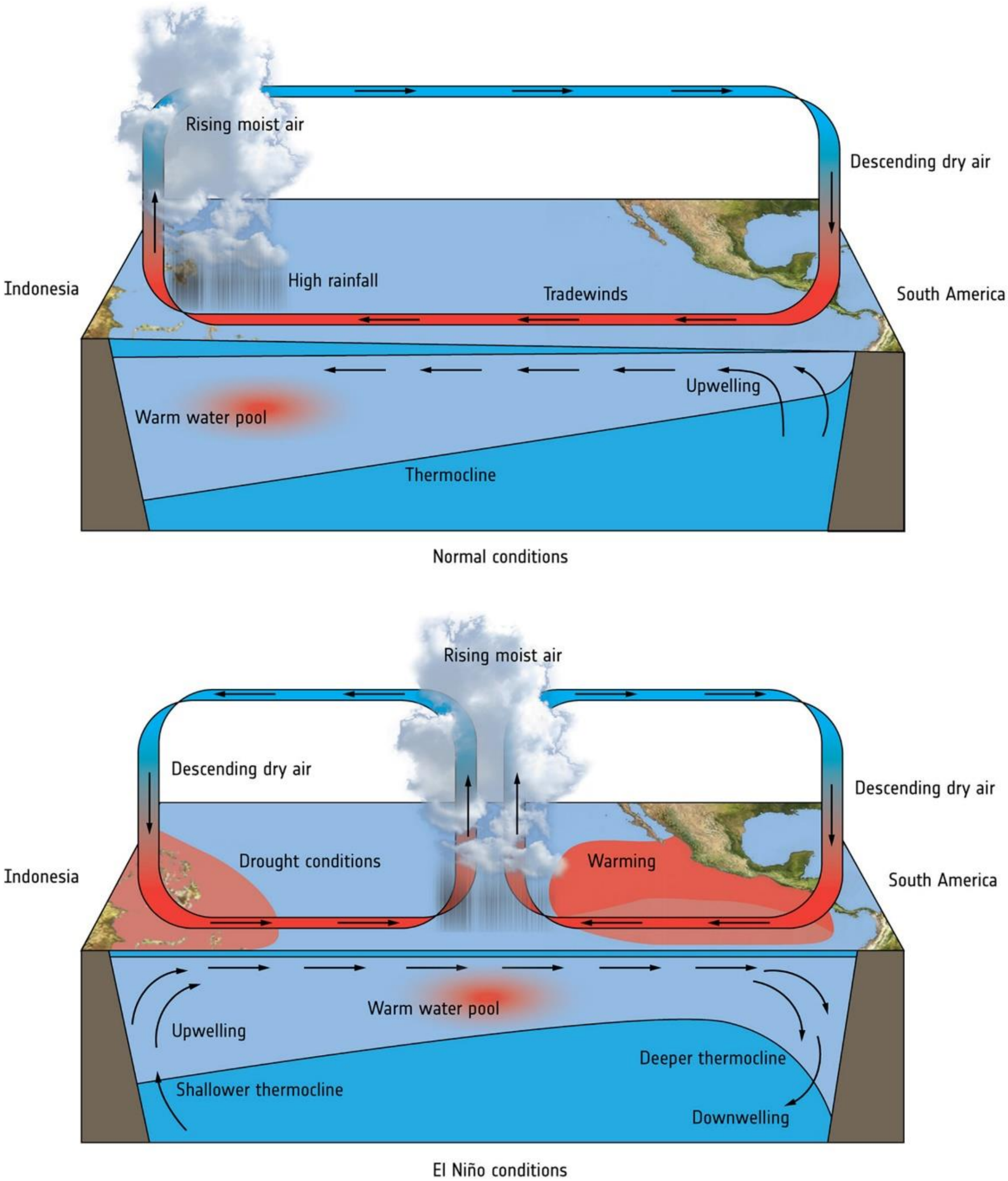


Figure 3.5: El Nino conditions in a schematic to show the relationship between the ocean and the atmosphere and how these changing thermal temperature changes the moisture of the air and drives pressure systems (ESA, 2018).

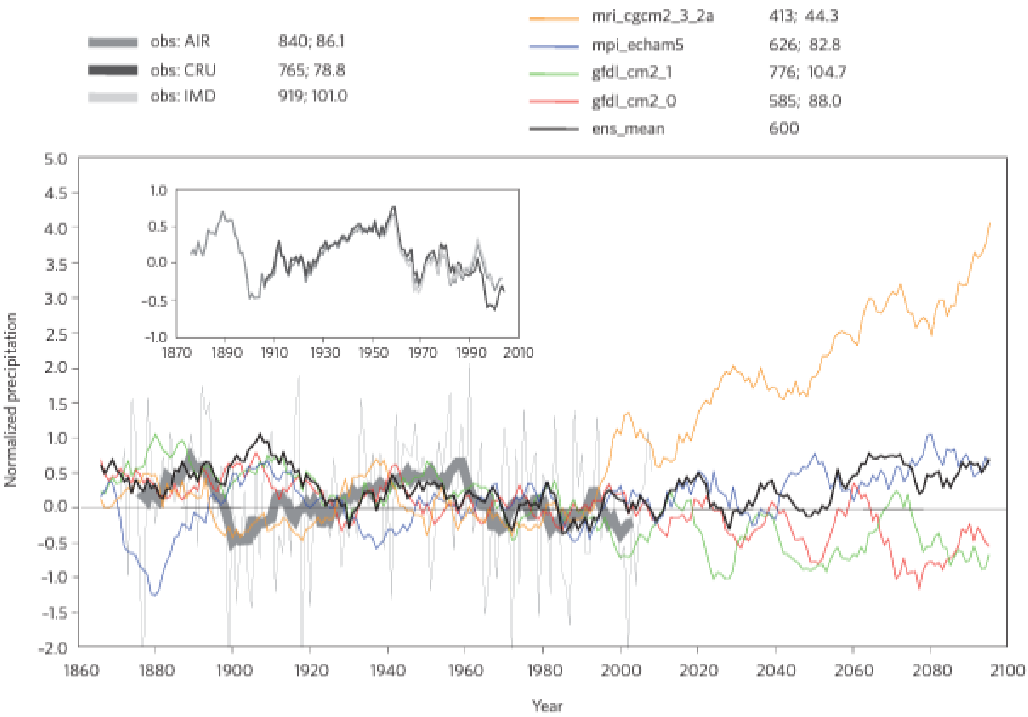


Figure 3.6: Historical and SRES A1B projection of South Asian Monsoon Rainfall: Taken from Turner & Annamalal, 2012.

3.2 Study Area

The study site is between 27.4 N and 26.8 S latitude and 88.0E and 88.8W latitude. The site is in the Darjeeling District of the Indian Himalayas and comprises of the towns Darjeeling and Kalimpong. The northern boundary reaches the Southern Sikkim cities of Singtam and Namchi, while the southern boundary reaches the town of Kurseong, still within the district of Darjeeling. The highest elevation in the site area is Tiger Hill, a mountain South of Darjeeling which is an elevation of 2590m. The study area spans over an area ~1730km^2. This area was chosen due to its mountainous terrain and large population sizes. Landslides are also common in these areas, with an impact to infrastructure, socioeconomics and livelihood. Figure 3.8a shows that the area is a mainly forested area with areas of built up urban towns, bare ground and rangeland. As the topography gets flatter towards the plains there are more instances of cropland. Figures 3.8b, 3.8c and 3.8d show the aspect, roughness and topography of the study area. From these maps it is apparent that the study area has a large amount of steep mountainous slopes, of a largely rough nature. This is an important feature of the area, and it is due to the nature of these slopes in the Himalayas that makes this study area good for testing landslide science, as landslide incidences are higher on rough, high angled slopes (Varnes, 1978 (Cellek, 2020).

Landslides in Northeastern India (Darjeeling Area – Study Area)

In this section, the nature of landsliding, the causes and triggers, recent earthquake events, landslide examples and landslide prediction are discussed for the study area.

Landslides are a recurring hazard in the Darjeeling region of the Northeastern Indian Himalayas, characterized by its steep slopes, fragile geology, and high rainfall (Sarkar et al., 2020). These events pose significant threats to human life, infrastructure, and the environment, making them a critical focus for disaster risk management and scientific inquiry (Dahal & Hasegawa, 2008).

The Darjeeling region's susceptibility to landslides stems from a combination of natural and anthropogenic factors. The region's geomorphology, dominated by young and tectonically active Himalayan ranges, comprises loosely consolidated rock formations and deeply weathered soils (Ghosh et al., 2020). These geological features are particularly vulnerable to destabilization, especially when combined with the intense rainfall characteristic of the Indian monsoon. The monsoon season, lasting from June to September, delivers torrential rains that saturate soils, reduce cohesion, and elevate pore water pressure, often triggering landslides (Sivakumar Babu & Srivastava, 2010). Notably, the region has experienced catastrophic landslide events linked to monsoonal activity, such as the 1968 landslides that resulted in extensive destruction and loss of life (Basu & De, 2003).

Several noTable landslide events have shaped the region's understanding of its vulnerability. The June 2015 landslides near Mirik were triggered by incessant monsoonal rains and caused significant damage to infrastructure, including road networks and tea plantations, which are vital to the local economy (SaveTheHills, 2015). Similarly, the Kalimpong landslide of 2007, driven by heavy rainfall, claimed numerous lives and highlighted the severe impact of poorly managed urban expansion on unsTable slopes (Chowdhury et al., 2010). These examples underscore the urgency of comprehensive mitigation strategies.

Seismic activity further exacerbates the landslide hazard in the Darjeeling region. The 2011 Sikkim earthquake, with a magnitude of 6.9, and the 2015 Nepal earthquake (magnitude 7.8) both triggered numerous landslides across the region (Meunier et al., 2008). These seismic events disrupt the delicate balance of forces on slopes, causing ground shaking that dislodges soil and rock. The cumulative effect of seismic shaking and pre-existing vulnerabilities created by intense rainfall heightens the risk of landslide initiation. Field investigations post these earthquake events revealed widespread slope failures, road blockages, and damage to settlements, underscoring the compounded risks posed by seismic activity in this geologically unsTable area (Gnyawali & Adhikari, 2017).

Anthropogenic activities, including unregulated construction, deforestation, and poorly planned road networks, have further destabilized slopes in the Darjeeling region. These human-induced factors exacerbate natural vulnerabilities by altering drainage patterns, reducing vegetation cover, and increasing surface runoff (Dahal et al., 2012). Urban expansion in landslide-prone areas without adequate engineering measures has magnified the scale and frequency of landslide occurrences (Basu & De, 2003).

Landslide prediction and early warning systems are crucial for minimizing risks in the Darjeeling region. Current efforts include the deployment of geotechnical monitoring tools, such as piezometers and inclinometers, to detect shifts in slope stability (Kumar et al., 2017). Satellite-based remote sensing and GIS mapping have become integral in identifying high-risk zones and assessing the likelihood of future landslides (Ghosh et al., 2020). Machine learning algorithms are increasingly employed to analyze historical data, rainfall patterns, and seismic activity to forecast potential landslide events (Sivakumar Babu & Srivastava, 2010). Collaborative initiatives between governmental agencies and local communities have also promoted the dissemination of early warnings, significantly enhancing preparedness (Dahal & Hasegawa, 2008).

Addressing the landslide hazard in the Darjeeling region requires a multifaceted approach. Improved land-use planning, afforestation programs, and community-based disaster preparedness can mitigate the impacts of landslides (Chowdhury et al., 2010). Advances in geotechnical monitoring, such as real-time landslide early warning systems, combined with seismic hazard assessment, are crucial for reducing vulnerability (Meunier et al., 2008). Moreover, integrating traditional knowledge with modern engineering practices offers sustainable solutions tailored to the region’s unique socio-environmental context (Gnyawali & Adhikari, 2017). By adopting these measures, the Darjeeling region can enhance its resilience against the dual challenges of natural and anthropogenic triggers of landslides.

Figure3.7: A OpenMap image of the study area, showing major towns, roads and water bodies, Darjeeling District, India.

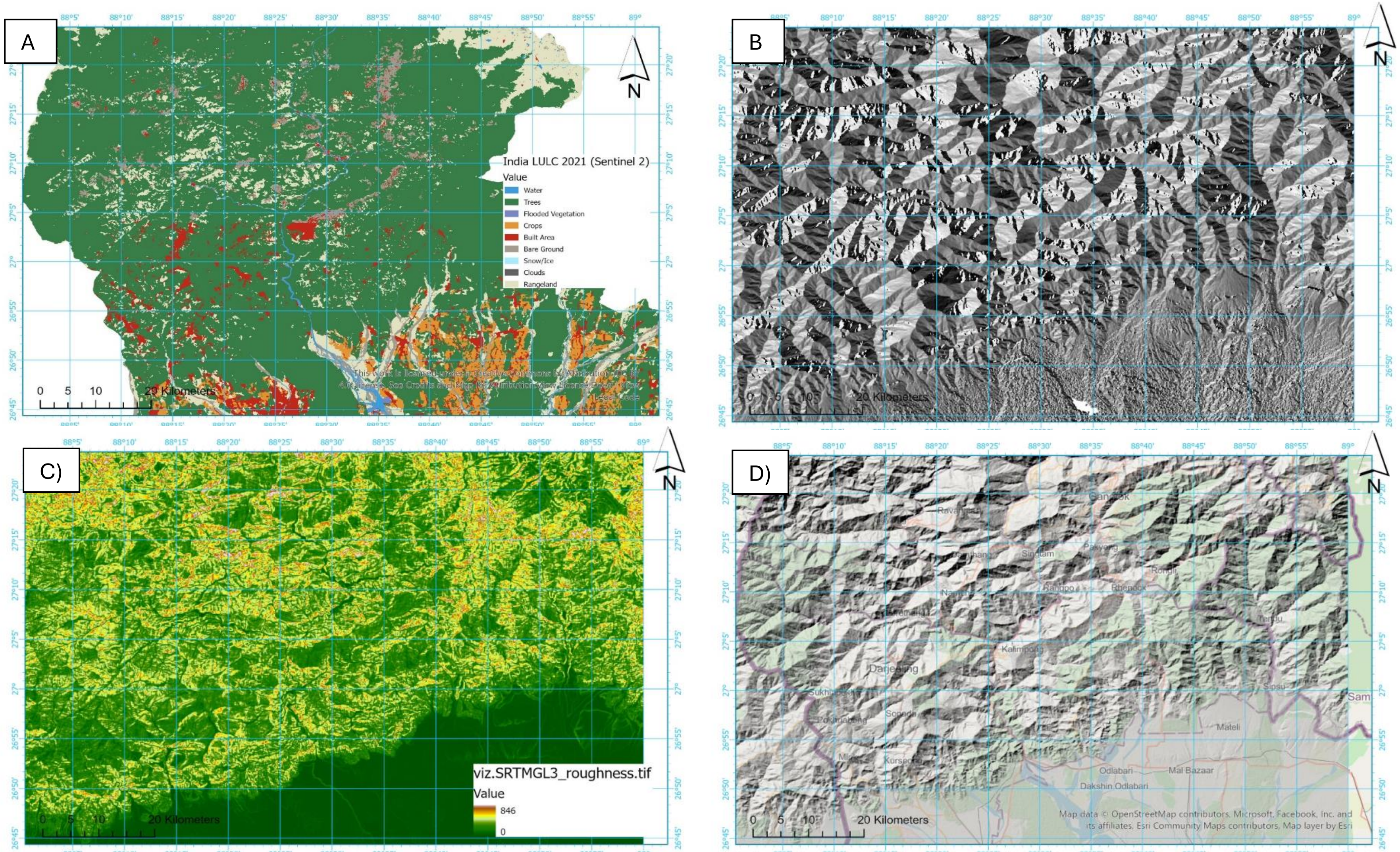


Figure 3.8.: The Study Area – these maps show the variability of the study site and show the common landslide characteristics that are used in modelling and understanding landslides in a study area (Sentinel 2, 2021). A) Land use map, B) Aspect map (STRM), C) Roughness map (STRM), and D) Hill Shade Map (STRM)

Geology of the Study Area

The geological environment of the Darjeeling and Sikkim Himalayas affects landslide occurrence. Geological factors affecting landslides include the regional geology and rock type and the structure of bedrocks, for example, faults and rock foliations (Rawat et al., 2015).

The geology of Darjeeling (featured in Figure 3.9) and the surrounding areas is very complex, due to its geological history of the broader tectonic formation of the Himalayas and subsequent evolution over millions of years. The region is however predominantly categorised by its metamorphic rock formations, created during the Himalayan orogeny. The Darjeeling Formation is one of the major geological features in this region, and it is compiled of high-grade gneissic rocks. Below this Darjeeling formation are the Darling groups, composed of phyllitic rocks which adds to the geological diversity of the region. The interactions between these formations have been extensively analysed by Banerjee et al. (2018) who studied unique structural features including an orogen-parallel top-to-E and top-to-W shear which is found particularly in the garnetiferous quartz mica gneiss of the Darjeeling Group . The diversity of the geological conditions here is also highlighted by different and abundant mineral deposits, which is significant for resource exploration and economic development of the region (Banerjee et al., 2018).

The geological environment and subsequent landslide occurrence are also affected by the hydrological action of river basins, and the Tista Basin is one of the largest in the Darjeeling Himalayas, with approximately five sub-basins situated in the Kalimpong region alone (Dikshit & Satyam, 2017), and is highly vulnerable to landslides. Land use, agricultural use and expansion of highways and anthropogenic engineering also interacts with landslides in this area.

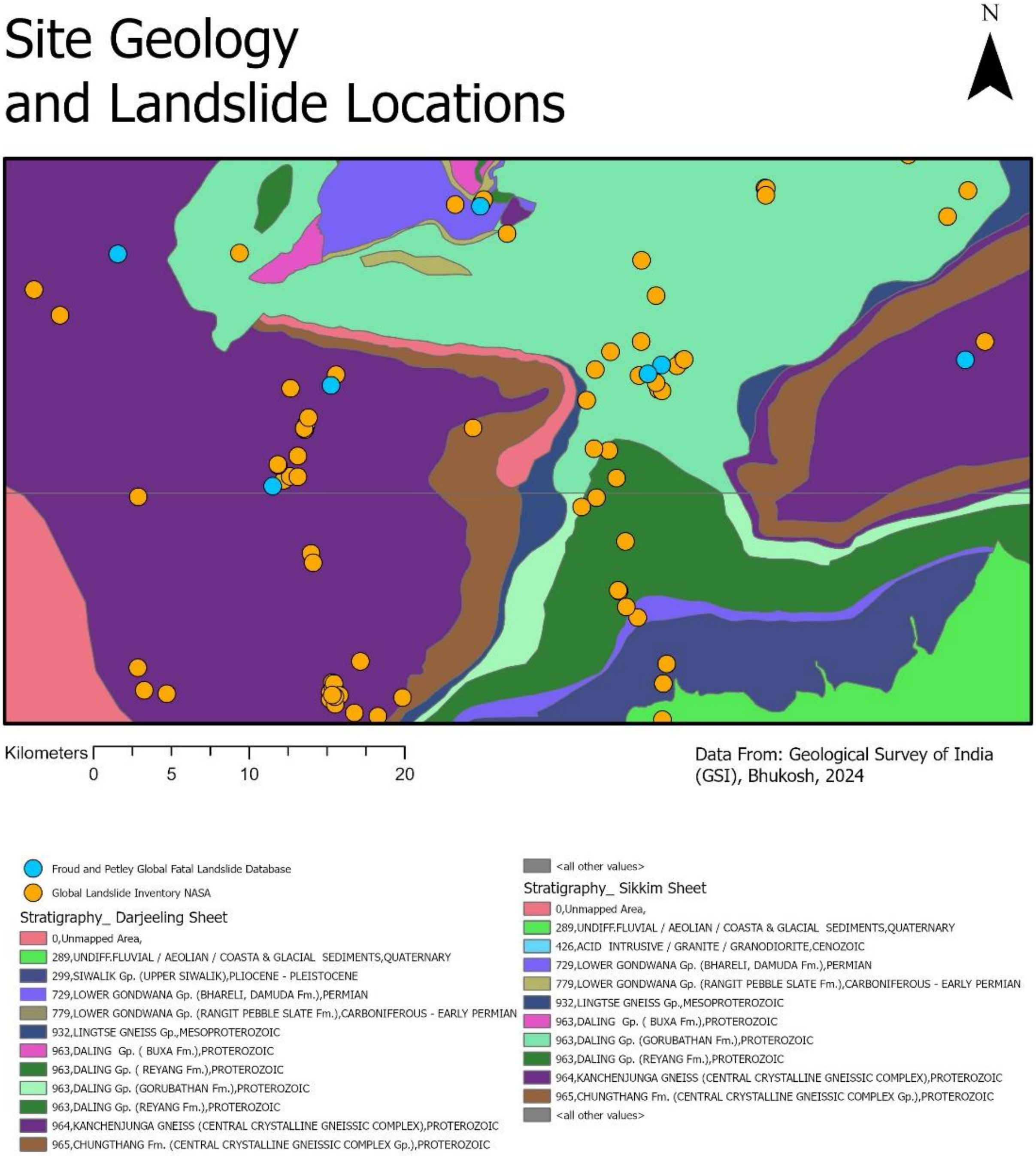
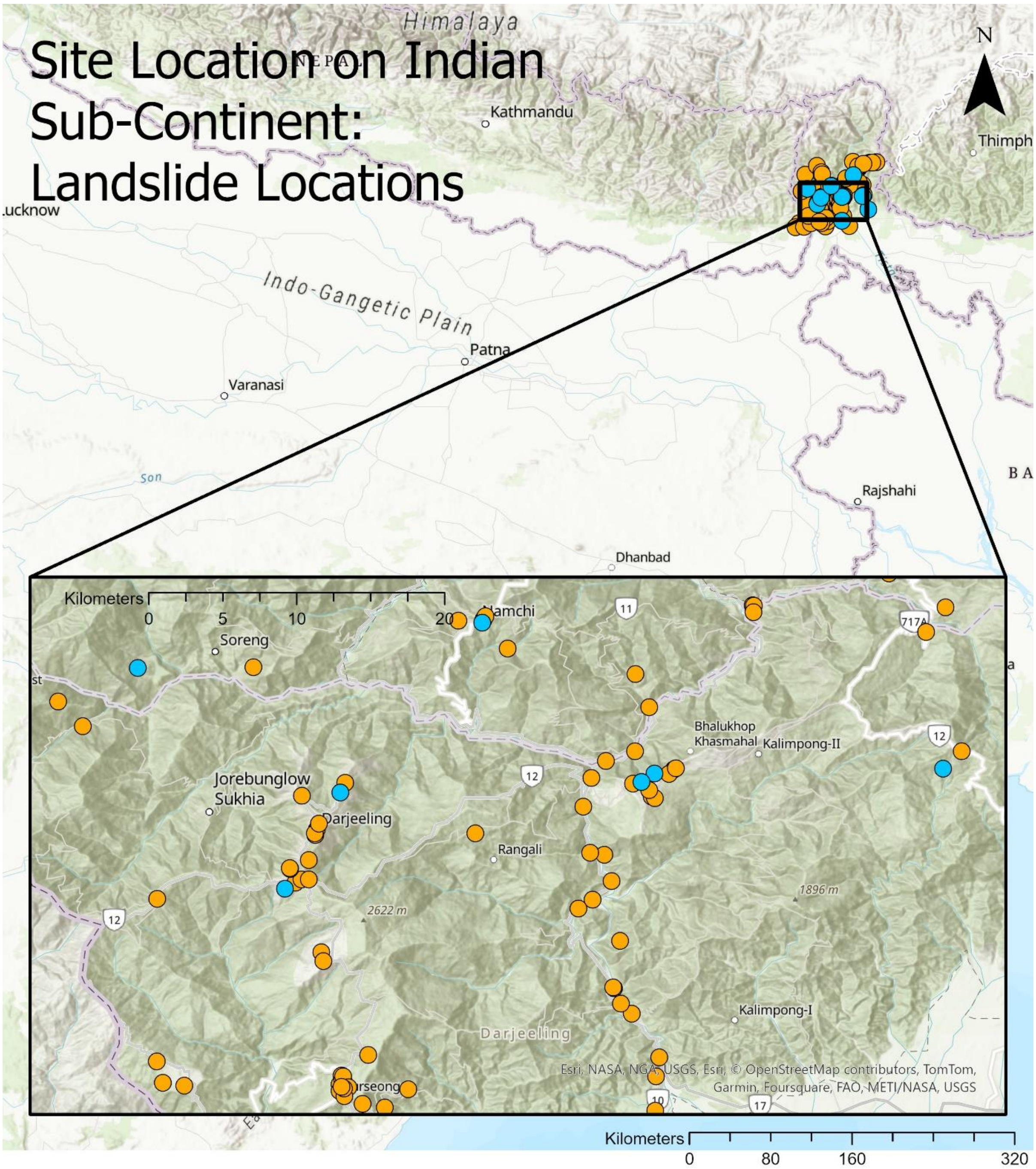


Figure 3.9: The geology of the study area



Froud and Petley Global Fatal Landslide Database

Global Landslide Inventory NASA

Figure 3.10: Landslide incidences from the GFLD and the GLC mapped onto the study area, with elevation apparent.

3.3 Indian Governance of DRR

In India, disaster risk reduction (DRR) is governed by a multi-tiered framework led by the National Disaster Management Authority (NDMA), established under the Disaster Management Act of 2005. The NDMA develops policies, plans, and guidelines for disaster preparedness and response. At the state level, State Disaster Management Authorities (SDMAs) and district authorities implement localized strategies. These institutions emphasize a shift from reactive relief measures to proactive risk reduction through early warning systems, capacity building, and community engagement. Integration with development planning, such as climate-resilient infrastructure, is prioritized. Collaboration among government agencies, non-governmental organizations, and the private sector enhances the overall governance of DRR. International frameworks like the Sendai Framework for Disaster Risk Reduction guide India's strategic goals.

Landslides represent a significant hazard within India's DRR framework, especially in mountainous regions like the Himalayas and the Western Ghats. The NDMA has specific guidelines for landslide risk management, focusing on early warning systems, landslide zonation mapping, and slope stabilization techniques. Geospatial tools and datasets such as satellite imagery and ERA5 data from ECMWF aid in identifying rainfall thresholds that trigger landslides. Local authorities collaborate with geological agencies to monitor vulnerable zones and implement community training on evacuation protocols. Integrating landslide risk management into urban planning and infrastructure projects, particularly in hill towns, is a priority to reduce disaster impacts.

In this specific study area within West Bengal, India the governance of DRR is a bit different. There seems to be a "hill-plains divide" within the Indian DRR policy. There is inadequate disaster management in the mountainous area of West Bengal, and the policies are aimed at plains regions neglecting mountain risks like landslides (McGowran, 2024). Landslides are often underrepresented in official DRR materials too, leading to many citizens looking at devolving DRR management to mountain regions, or creating a "ministry of mountains" (McGowran, 2024). Overall there is a need for making tailored DRR management strategies that consider regional vulnerabilities and the need for restructuring India's centralised DRR policies to integrate with lived experiences of the population.

Chapter 4: Datasets and Methodology

4.1 Research Design

The two main research questions as tools to answer the overall research problem will be tackled in 2 separate main research chapters (Chapters I & II, focusing on each of the research questions set out in **Thesis Section 1.3 Introduction: Thesis Structure**.

4.3 Data and Methods for 5.0 Research Chapter I 'Data'

This research chapter addresses a research gap highlighted in **Thesis Section 2.0 Literature Review** global landslide inventories are created by different agencies and do not have a single repository, or single best practice to make each of them within a standard format that can be used by landslide scientists around the globe. When landslide researchers use the inventories, they must be able to test the LSI for accuracy and usability within their study area. With some global inventories and disaster databases not covering certain areas, countries, or areas of the globe this opens a very important research question.

This first main research chapter is tackling the first research question:

- What global and national landslide inventories are available for researchers when researching Darjeeling, India?

To answer this question the data and methodology in the following sections has been selected.

4.3.1 Data

The datasets that are used in **Thesis Section 5.0 Research Chapter I** are two of the largest global landslide databases available at time of writing. These databases are called the Global Fatal Landslide Database (GFLD) (Froude and Petley, 2018) and Global Landslide Catalogue (GLC) (Kirchbaum et al., 2015).

These global scale LSIs provide a free of charge, broad coverage source of data that can be accessed by anyone. The global LSIs are compiled from a multitude of different resources and can provide a comprehensive view of landslides globally. Using these global LSI's have some limitations, however. There is a potential for data inconsistency and variability in data quality. The LSIs are not updated regularly or at all in the case of the GFLD. Global inventories are often unable to be applied at the local level due to specificity of characteristics and triggers.

An alternative to using global inventories would be to compile local landslide inventories for the study area, as this would be designed specifically for the study. It can also capture detailed information about the area, conditions, and practices in the locality. However, to gain the specificity and the accuracy of information, the disadvantage of compiling and using a more local dataset would be resource intensive – in both time and cost. To gain a detailed LSI for the study site, fieldwork, data-collection and validation of the data would need to be conducted.

Due to the financial restrictions on a MPhil project, coupled with the aims of the MPhil I have chosen to utilise the global scale LSIs. The aim of this project is to use the best current practice elements and conclude if they're able to create tools equitably by the researchers in the DRR field, and to do this I will be using the datasets that many researchers are using, and datasets that are continuing to be used in papers being published in this field **(See Thesis Section 2.7 Literature Review: Research Questions – 5.0 Research Chapter I)**. .

Global Landslide Catalogue (GLC)

The Global Landslide Catalogue (GLC) is the largest openly available inventory that has rainfall-induced landslides reported within it (NASA, 2024). The GLC is a report-based landslide inventory created and hosted by the National Aeronautics and Space Agency (NASA). It was created at the Goddard Space Flight Centre and contains around 11500 reports of landslides to date. The catalogue covers 1970-2019 from its last update in 2019. It is an earlier iteration of the Cooperative Open Online Landslide Reporter (COOLR) product which also includes another style of reporting - a citizen science-based Landslide Reporter inventory.

This study will be using the GLC as its style of collecting landslide events is very similar to the GFLD in that it uses a metadata search to identify landslide activity (Kirchbaum et al., 2010; Kirchbaum et al., 2015, Kirchbaum et al., 2019). The GLC compiled a database that had all landslide events that were clearly triggered by rainfall conditions. The catalogue considers all types of landslide events, and some of the events have the information of which type it was if that information was available for the NASA team.

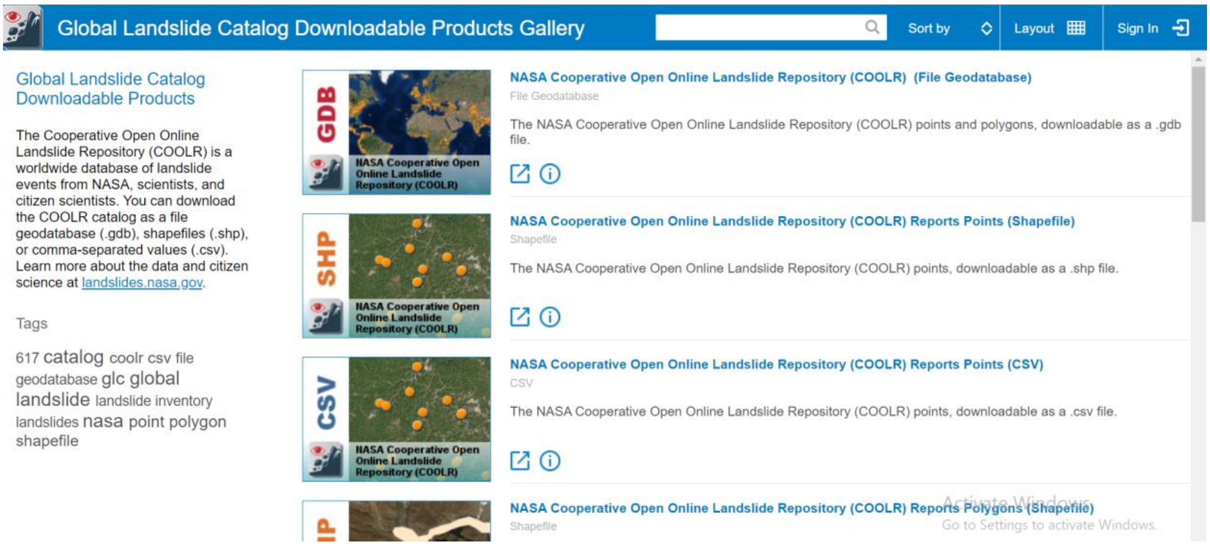
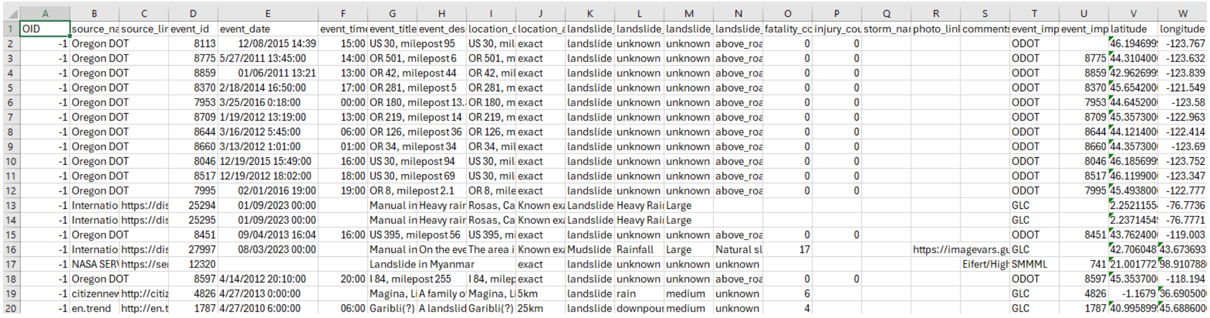


Figure 4.1: The NASA GLC downloadable products gallery where anyone can download the COOLR datasets in different formats (NASA, 2024).

The data is downloaded through the NASA website, where there is a products list available for public consumption. This list includes different types of files that can be downloaded and used for different applications. A view of this product gallery is in Figure 4.1. The datafile that was downloaded for this research was the comma separated values (.csv) file, as this file can be used in many of the different applications and software that has been used throughout the project.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	OID	source_na	source_lir	event_id	event_date	event_time	event_title	event_des	location_d	location_a	landslide_	landslide_	landslide_	landslide_	fatality_cc	injury_cou	storm_nar	photo_linl	comments	event_imp	event_imp	latitude	longitude
2	-1	Oregon DOT		8113	12/08/2015 14:39	15:00	US 30, milepost 95		US 30, mil	exact	landslide	unknown	unknown	above_roa	0	0				ODOT		46.194699	-123.767
3	-1	Oregon DOT		8775	5/27/2011 13:45:00	14:00	OR 501, milepost 6		OR 501, m	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8775	44.310400	-123.632
4	-1	Oregon DOT		8859	01/06/2011 13:21	13:00	OR 42, milepost 44		OR 42, mil	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8859	42.962699	-123.839
5	-1	Oregon DOT		8370	2/18/2014 16:50:00	17:00	OR 281, milepost 5		OR 281, m	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8370	45.654200	-121.549
6	-1	Oregon DOT		7953	3/25/2016 0:18:00	00:00	OR 180, milepost 13.		OR 180, m	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	7953	44.645200	-123.58
7	-1	Oregon DOT		8709	1/19/2012 13:19:00	13:00	OR 219, milepost 14		OR 219, m	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8709	45.357300	-122.963
8	-1	Oregon DOT		8644	3/16/2012 5:45:00	06:00	OR 126, milepost 36		OR 126, m	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8644	44.121400	-122.414
9	-1	Oregon DOT		8660	3/13/2012 1:01:00	01:00	OR 34, milepost 34		OR 34, mil	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8660	44.357300	-123.69
10	-1	Oregon DOT		8046	12/19/2015 15:49:00	16:00	US 30, milepost 94		US 30, mil	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8046	46.185699	-123.752
11	-1	Oregon DOT		8517	12/19/2012 18:02:00	18:00	US 30, milepost 69		US 30, mil	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8517	46.119900	-123.347
12	-1	Oregon DOT		7995	02/01/2016 19:00	19:00	OR 8, milepost 2.1		OR 8, mile	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	7995	45.493800	-122.777
13	-1	Internatio	https://dis	25294	01/09/2023 00:00		Manual in	Heavy rair	Rosas, Ca	Known exa	Landslide	Heavy Rai	Large							GLC		2.2521155	-76.7736
14	-1	Internatio	https://dis	25295	01/09/2023 00:00		Manual in	Heavy rair	Rosas, Ca	Known exa	Landslide	Heavy Rai	Large							GLC		2.2371454	-76.7771
15	-1	Oregon DOT		8451	09/04/2013 16:04	16:00	US 395, milepost 56		US 395, mi	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8451	43.762400	-119.003
16	-1	Internatio	https://dis	27997	08/03/2023 00:00		Manual in	On the eve	The area i	Known exa	Mudslide	Rainfall	Large	Natural sl	17			https://imagevars.gu		GLC		42.706048	43.673693
17	-1	NASA SER\	https://se	12320			Landslide in Myanmar			exact	landslide	unknown	unknown	unknown					Eifert/High	SMMML	741	21.001772	98.910788
18	-1	Oregon DOT		8597	4/14/2012 20:10:00	20:00	I 84, milepost 255		I 84, milep	exact	landslide	unknown	unknown	above_roa	0	0				ODOT	8597	45.353700	-118.194
19	-1	citizennew	http://citiz	4826	4/27/2013 0:00:00		Magina, Li	A family o	Magina, Li	5km	landslide	rain	medium	unknown	6					GLC	4826	-1.1679	36.690500
20	-1	en.trend	http://en.t	1787	4/27/2010 6:00:00	06:00	Garibli(?)	A landslid	Garibli(?)	25km	landslide	downpour	medium	unknown	4					GLC	1787	40.995899	45.688600

Figure 4.2: The spreadsheet when it is first opened, comprising of many different columns with different information collected within each one (NASA, 2024).

Figure 4.2 is the csv file once opened. There are 30 different headings within the document, including relevant information for this study, for example; event_date, latitude, longitude and landslide_trigger.

Global Fatal Landslide Database (GFLD)

The GFLD is formally known as the Durham Fatal Landslide Database due to the two researchers working at the University of Durham when compiling the database. The database was compiled using systematic metadata search tools which look to identify reports of landslide activity (based on the definitions set out by Hungr et al., 2014) on a daily basis (Froude & Petley, 2018). The dataset was collected and managed between 2004 and 2016, after the methods were developed between September 2002 and December 2003 (Petley, 2012; Froude & Petley 2018). This method of collecting landslide incidences differs from the methods of collection in the GLC (Kirchbaum et al., 2010; Kirchbaum et al., 2012, Kirchbaum et al., 2015; Froude & Petley, 2018). This is due to the counted landslide incidents being only those with fatalities and all landslide triggers are collected in the database, for example those triggered by seismic activity or anthropogenic means (Froude & Petley, 2018).

Other data sources I will be using within this chapter include my own personal experience and literature on landslide inventories and global disaster databases. These are detailed below.

My personal experience

I will be using my own personal experience of utilising global landslide inventories within my work in academic research. This is an important addition to the chapter as my experiences will be mirrored by other researchers in the field and the choices that I have made in choosing my landslide inventories for the study site that I'm working within.

Literature

There is an integral paper to this chapter which is referenced extensively throughout. This paper is a paper by Gómez et al. (2023) where they combine four of the largest global landslide databases, the GFLD, the GLC, the international disaster inventory (DesInventar) and the international disaster database (EM-DAT) to create a 'Unified Global Landslide Database' (UGLD). The Gómez et al. work was key in developing and understanding the methods I would need to employ to gather data for the largest possible number of landslide events in my study area to conduct my research in **Thesis Section 6.0 Research Chapter II** of this thesis.

4.3.2 Landslide Database Critical Reflections

NASA's Global Landslide Catalog (GLC) and the Global Fatal Landslide Database (GFLD) are valuable resources for landslide research, providing insights into the occurrence and impacts of these hazards. The GLC includes both fatal and non-fatal events, while the GFLD focuses exclusively on landslides that result in fatalities. These differing scopes offer a unique opportunity for complementary analysis, though they also present challenges due to biases, gaps, and methodological discrepancies.

One of the most significant advantages of combining these datasets lies in their potential to create a more holistic understanding of landslide dynamics. For instance, the GLC's inclusion of non-fatal events helps identify trends in landslide occurrence that are not always associated with human casualties. This broader dataset is critical for understanding environmental and anthropogenic triggers, such as extreme rainfall (Kirschbaum et al., 2015) and deforestation (Petley, 2012). Meanwhile, the GFLD provides a more focused lens on the societal impacts of landslides, including their disproportionate effects on vulnerable populations in regions like South Asia and Central America (Froude & Petley, 2018).

However, biases in reporting pose a significant challenge. The GLC relies on media and satellite data, which tend to overrepresent well-documented regions while underreporting events in remote or resource-poor areas (Kirschbaum & Stanley, 2018). Similarly, the GFLD is prone to underestimating fatalities in regions with weak disaster reporting infrastructure, such as sub-Saharan Africa (Froude & Petley, 2018). This disparity can skew global risk assessments, making certain regions appear safer or more dangerous than they truly are.

Another critical limitation stems from the databases' methodological differences. For example, the GFLD exclusively documents fatal events, omitting near-miss incidents that could provide vital information for future disaster mitigation (Dillon, 2020). In contrast, the GLC's non-fatal data, while useful, might include small-scale or low-impact landslides, potentially diluting insights into high-risk areas (Stanley & Kirschbaum, 2017). Additionally, inconsistencies in spatial and temporal resolution complicate efforts to integrate the datasets for predictive modelling or climate change impact studies.

Real-world applications illustrate these challenges. A study using the GLC to assess rainfall-induced landslide risks in Brazil (Martha et al., 2017) highlighted the importance of including non-fatal incidents in risk reduction strategies. Conversely, analysis of the GFLD in Nepal following the 2015 earthquakes underscored the disproportionate mortality risk in marginalized communities (Petley, 2012). These examples show the value of integrating the datasets to balance environmental triggers and human vulnerability in policy planning.

Ethical considerations also arise when prioritizing fatalities over broader impacts. While GFLD data underscores the human cost of landslides, it may divert attention from non-fatal events that devastate livelihoods and infrastructure. Incorporating both datasets equally into risk assessments could better support comprehensive disaster mitigation, addressing both immediate mortality risks and long-term societal resilience.

In conclusion, while NASA's GLC and the GFLD are invaluable individually, their integration demands careful attention to biases, methodological consistency, and ethical implications. Harmonizing these datasets would enhance their utility in understanding and mitigating landslide hazards globally, particularly in underrepresented regions.

Advantages of Using the GLC and GFLD Together

- **Comprehensive Dataset**:
  - The GLC includes non-fatal and fatal landslides, providing a broader perspective on landslide occurrence and environmental triggers (Kirschbaum et al., 2015).
  - The GFLD highlights the societal impacts of landslides by focusing on fatal incidents, emphasizing human vulnerability (Froude & Petley, 2018).
- **Complementary Insights**:
  - GLC data helps identify trends in landslide triggers (e.g., rainfall thresholds), while GFLD provides insights into fatalities and risk factors in vulnerable populations (Stanley & Kirschbaum, 2017).
  - Combining these datasets enables analysis of both physical and human dimensions of landslide risks, aiding holistic risk assessments.
- **Real-world Applicability**:
  - Studies using GLC data (e.g., rainfall-induced landslides in Brazil) and GFLD data (e.g., fatalities post-2015 Nepal earthquake) demonstrate the value of combining environmental and societal data for targeted mitigation strategies (Martha et al., 2017; Petley, 2012).

Weaknesses of Using the GLC and GFLD Together

- **Reporting Biases**:
  - The GLC overrepresents well-documented regions (e.g., developed countries) due to reliance on media and satellite data, while the GFLD underrepresents fatal events in areas with weak reporting infrastructure (Kirschbaum & Stanley, 2018).
  - Underreporting in remote or resource-poor regions skews global risk assessments (Froude & Petley, 2018).

- **Methodological Discrepancies**:
    - The GLC includes minor and low-impact landslides, which may dilute focus on high-risk areas.
    - The GFLD's exclusion of non-fatal events omits critical near-miss data that could inform preventative measures (Stanley & Kirschbaum, 2017).
- **Inconsistent Spatial and Temporal Resolution**:
    - Differences in data collection methods between the two databases complicate integration for predictive modelling or global hazard analysis (Kirschbaum & Stanley, 2018).
- **Ethical Considerations**:
    - GFLD's emphasis on fatalities risks sidelining non-fatal impacts (e.g., infrastructure damage or displacement), which are critical for comprehensive disaster mitigation strategies.

4.3.3 Methods

Thesis Section 5.0 Research Chapter I builds on the UGLD methods (Gómez et al., 2023), compared against alternative methods to evaluate different global landslide inventories. This evaluation includes spatial and temporal analysis of the landslide events using maps and graphs, globally and locally for the study area. I also create the study area's own specific merged LSI by combining and cleaning the global datasets for my study area. The commentary for the chapter also looks at specific clustering of landslide events from the combined inventory and discusses why this might be. An overall discussion on the choice of LSI is also included in this chapter with a proposed 'self-check' for researchers to reflect on their dataset choices, not only from a physical consideration, but also from a social and ethical perspective.

Unified Global Landslide Database Methods

The UGLD method (Gómez et al, 2023) of combining different global inventories to create a larger more spatially covered inventory is used within this chapter. The UGLD merges datasets to provide a more realistic and complete spatial and temporal distribution of landslide occurrences globally in a four-step process:

1. The GFLD data was compared with the GLC data where 98 landslides were matched in both datasets. This merged the GFLD and the GLC.
2. The merged GFLD + GLC database was compared to the EM-DAT database. 1 landslide matched to this. This results in a merged GFLD + GLC + EM-DAT dataset.
3. The GFLD + GLC + EM-DAT dataset was compared with the DesInventar database, where any of the same landslide events were removed. This then led to the merged GFLD + GLC + EM-DAT + DesInventar database.
4. Finally, a visual inspection was conducted to eliminate records that matched in country, date and where co-ordinates were the same.

Use of ArcGIS Pro for spatial analysis

When I combined any of the global landslide datasets, I examined the spatial coverage of the landslide inventories. I did this using ArcGIS pro to plot the landslide locations within the landscape, creating maps that can be compared and contrasted to each other. Other mapping software applications are available, like the free to use QGIS, but I used this application as it is used as the leading industry standard software and was available at my university.

Graphical Analysis of landslides globally and within Study Area

Using Python 3.10 within the visual learning environment of PyCharm Community Edition 1.2 I generated some graphs of landslide incidences in terms of numbers, triggers, fatalities and more. I utilised packages within Python such as pandas and matplotlib. A sample of the code I used is below (Figure 4.3).

```python
import pandas as pd
import matplotlib.pyplot as plt

# Load the data
df = pd.read_csv('combined_landslides_Dolan.csv', parse_dates=['date'])

# Filter data for the years 2006 to 2017
df = df[df['date'].dt.year.between(2006, 2017)]

# Group by year and count occurrences
landslide_counts = df.groupby(df['date'].dt.year).size()

# Plotting the data
plt.figure(figsize=(10, 6))
landslide_counts.plot(kind='bar', color='skyblue')
plt.title('Landslide Incidences from 2006 to 2017')
plt.xlabel('Year')
plt.ylabel('Number of Landslides')
plt.grid(True)
plt.show()
```

Figure 4.3: A example code for plotting landslide events over time from 2006-2017.

Python has been used as the primary coding language over other languages like R due to is reliability and application by many different industries and research disciplines. R for example can be used but has only recently been embraced by the hydrological community (Slater et al., 2019) (of which some of my MPhil thesis sits within) and so will not be used.

Statistical Analysis of Landslide Inventories

This chapter also used Python 3.10 within the visual learning environment of PyCharm Community Edition 1.2 to statistically analyse the LSI's in conjunction with the elevation and precipitation and also conduct statistical correlation plots of landslide numbers vs the South Asian Summer Monsson Index (SASMI) and Slope Angle (degrees). These statistical analysis additions have been established as standard statistical analysis for LSIs in Petley et al. (2007; 2018).

Case Study Analysis of Indian National Inventory

When conducting the research around the National Indian Landslide Inventory, I needed to do a case study analysis where I took three points of the National Indian Landslide Inventory where there was no additional data within the points and looked online at news and events pages to create in depth reports on the landslides. This is to promote the idea that a researcher can use news articles, NGO pages and online event pages to enhance the National Inventory to make it useful for application in identifying historical landslides for Thesis Section Research Chapter II.

Discussion of choices inferred by personal experience

The ability to use my own personal experience within the sciences will be used in research chapter I. I am a user of these interfaces and datasets and a researcher in the field of landslide science and so can use this experience within this research. These insights are valuable to discuss and use within a reflexive narrative, as it is a useful tool for considering decisions, bias, and potential personal limitations. This personal reflection exercise is valuable not only to me, but for the wider science community as I am a representative of the community and thus the data collected from this exercise can infer other's opinions and thoughts.

4.5 Data and Methods for 6.0 Research Chapter II 'Application'

This research chapter addresses a research gap highlighted in **Thesis Section 2.0 Literature Review** landslide predictive technologies are being developed in Italy, and in South America, yet is lacking in the Northeastern Indian Himalayas. There is also a gap in evaluating the potential of using global reforecasting datasets to forecast landslides using freely available global datasets in data poor areas. There could be a major application of this technology in many areas of the world.

This second main research chapter is tackling the second research question:

- Can precipitation triggered historical landslides in Darjeeling, India be identified with the global scale reanalysis precipitation dataset ERA5, and established Intensity Duration Thresholds?

To answer this question the following data and methodology is used.

4.5.1 Data

ERA5 Total Precipitation Hourly Dataset

The Darjeeling District in India is a very complex site in terms of its spatial heterogeneity, spatial coverage and differing topographic conditions. There are large differences in some of the regions within the Darjeeling District in terms of land use, slope aspects and geological significance (more site description can be seen in **Thesis Section 3.2 Study Area**). This makes it the ideal place for testing a coarse resolution global reanalysis product. This is good as it gives a variety of geographical features and landscapes to provide a comprehensive range of conditions. It also allows for identification of strengths and weaknesses and localised insights. It also allows for the testing of this product in real-world conditions, as most landscapes are diverse. The global reanalysis product that is being tested within this study area is the single level ERA5 Total Precipitation hourly data (ECMWF, 2025). This is a product created by the European Centre for Medium Range Forecasts (ECMWF) and is the 5th generation of their global atmospheric reanalysis product with a high temporal resolution (hourly). More information on ERA5 can be found in **Thesis Section 2.3 Precipitation Modelling.**

The ERA5 dataset is also complemented by enhanced global datasets which focus on one of the areas of application (land, atmosphere, and ocean) with products such as ERA-Land, which takes a deep dive into the global land process and the evolution of water and energy cycles. This has major advantages, for example; a 9km resolution compared to the ERA5 31km resolution (Munoz-Sabater et al., 2021; Gomis-Cebolla et al., 2023).

ERA5 has diverse research applications in climate research, monitoring of climate change, numerical weather prediction and commercial applications. It is valuable in understanding long-term climate trends and validating climate models. This makes ERA5 an important tool for policy-making in climate adaptations and mitigation strategies (Hersbach et al., 2020).

This project is using ERA5 for its reanalysis dataset of Total Precipitation. This dataset is used for understanding past precipitation patterns, validating hydrological models and has applications in water management and agriculture. Precipitation reanalysis products are also used in precipitation estimates in ungauged or data-sparse areas (Becker et al., 2020; Jiang et al., 2021). ERA5 total precipitation dataset has also been seen to have some reliable performance reliably predicting extremes in precipitation which also helps when looking at climate change and increased hazard analysis in data sparse areas (Hu & Frankie, 2020). However, despite some reliability in predicting extremes, the predictions tend to underestimate the intensity and frequency of extreme events, like rainfall. This also includes precipitation biases in areas with complex geography, orographic effects, and strong seasonal variations. To combat these limitations, there will be a critical evaluation of the data with the limitations in mind, which will add to mitigating the difficulties.

ERA5 does have some limitations, for example the assimilation of satellite-derived precipitation estimates can introduce uncertainties, especially in regions with data scarcity (Hersbach et al., 2020). It's coarse resolution also tends to smooth out local climatic and geographic variability. There are also some biases in the instrumentation in the observational datasets that are assimilated into ERA5.

More information on ERA5 and global models from ECMWF is in **Thesis Section 2.3 Precipitation Modelling.**

Combined GLC + GFLD landslide database from 6.0

Another data source I used in this chapter is the combined landslide inventory I created in the first research chapter seen in **Thesis Section 6.0: Research Chapter I.** I used this newly created and combined landslide inventory due to its ability to provide more landslide events within the study area, which allows for a more robust evaluation. It allowed more testing of the historical events against the global scale reforecasting models. Information on this can be seen in **Thesis Section 2.1 Landslide Science, Thesis Section 4.3 Data and Methods for 6.0 Research Chapter I.**

4.5.2 Methods

Python 3.10

The landslide inventories are downloaded as Microsoft Excel files, and the ERA5 Reanalysis product is downloaded as the format of NetCDF for use. In this work, the researcher is using Python programming language 3.10 within the PyCharm Community Edition 2023 1.2 integrated development environment (IDE) for the data processing, statistical analysis, and graphical analysis. A screenshot of an example of code can be seen below in Figure 4.6.


```
import netCDF4 as nc
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import matplotlib.dates as mdates

# Open the NetCDF file
file_path = "C:\\Users\\kn809485\\Downloads\\adaptor.mars.internal-1706532350.2220721-29255-11-c8c4e954-f851-45fa-8744-8c6a7913973f (1)
dataset = nc.Dataset(file_path, 'r')

# Read the total precipitation variable
tp = dataset.variables['tp'][:]  # Assuming the variable is named 'tp'

# Convert the time variable to datetime
time_var = dataset.variables['time']
dtime = nc.num2date(time_var[:], units=time_var.units, calendar=time_var.calendar)

# Convert cftime.DatetimeGregorian objects to standard Python datetime objects
dtime = [pd.Timestamp(dt.isoformat()) for dt in dtime]

# Calculate the mean precipitation and convert from meters to millimeters
monthly_mean_precip = tp.mean(axis=(1, 2, 3)) * 1000
df = pd.DataFrame({'Time': dtime, 'Precipitation': monthly_mean_precip})
df.set_index('Time', inplace=True)
```

Figure 4.6: An example piece of code for research chapter II.

I will be using Python again instead of other coding languages as it will add cohesion to my work and increase my understanding of the coding language in terms of its approach to landslide science and hydrology. As stated before in **Thesis Section 4.3.3 Methods** hydrology has only just recently adopted other coding languages and created libraries within them (like R) (Slater et al., 2019) and so it seems prudent to use a programming language that will be utilised by others in the field.

ArcGIS Pro

Landslide location maps, and geological maps are created in ArcGIS Pro for the **Thesis Section 3.0 Chapter 3: The Study Area** and will be used to discuss the results in this chapter and in **Thesis Section 7.0 Discussions and Future Considerations.**

Intensity Duration Thresholds

Intensity Duration thresholds are a tool which are used exclusively for landslides that are triggered by rainfall. An ID threshold is a threshold that is created from the relationship between precipitation intensity (I) and its duration (D), providing a threshold of conditions that if breached are likely to initiate landslide events. A schematic showing ID thresholds and the ideas behind the threshold being the line at which landslides do and do not occur can be seen in Figure 4.7 This Figure also shows the type of landslides that ID thresholds are more suited for – a) channel runoff vs b) deep seated landslides (Berti et al., 2012). The Indian Himalayas experiences both types of landslide events, however the channel runoff landslides are the ones that are most common, and the ones that happen most quickly. This is due to the climatic conditions of the Indian Himalayas, the orographic environment of steep slopes and fragmented surface geology and shallow soil profiles **(See Thesis Section 3.0 Chapter 3: The Study Area**).

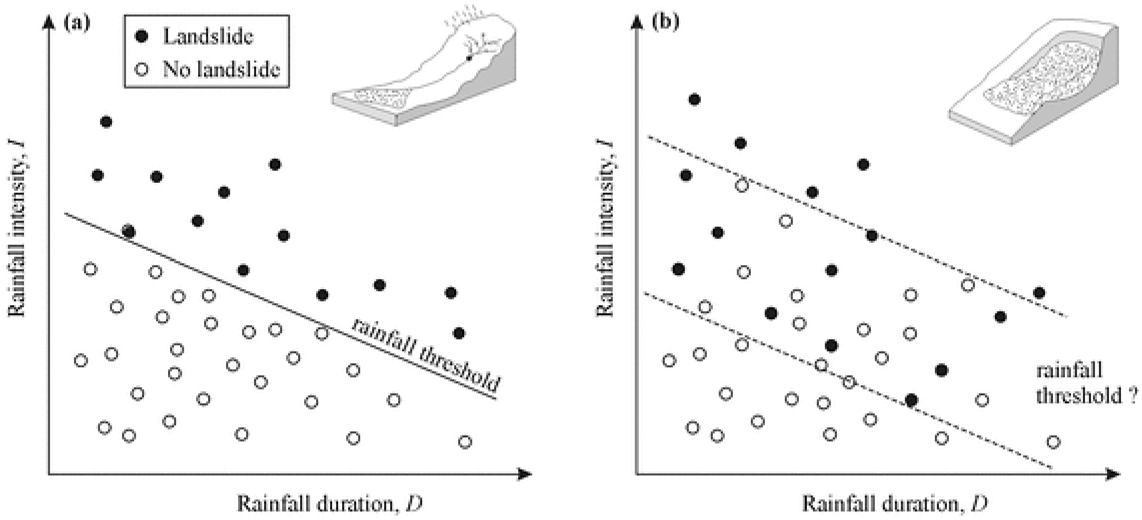


Figure 4.7: Rainfall ID thresholds in two conceptual Figures showing a) channel runoff and b) deep seated landslides. In the case of deep-seated landslides, it is difficult to identify a definite threshold because rainfall events that result in landslides of this nature are not the only triggering factors (Nikolopoulos et al., 2014).

ID thresholds are important as they try to establish a quantitative relationship between the intensity of rainfall (how much rain in a given period) and its duration (how long the rainfall event lasts) in terms of when a landslide is triggered. This relationship can not only identify the specific conditions at which landslides are initiated but has applications in LEWS for predicting landslide events, risk management strategies around land use planning and disaster preparedness.

The ID thresholds that are used in this research chapter will be pre-established thresholds as reviewed and assimilated in, Guzzetti et al. (2008) and Dikshit & Satyam (2017). Figure 4.8 is an ID graph from Guzzeti et al. (2008) who reviewed the worldwide ID thresholds to update Caine's 1980's Global ID threshold estimate.

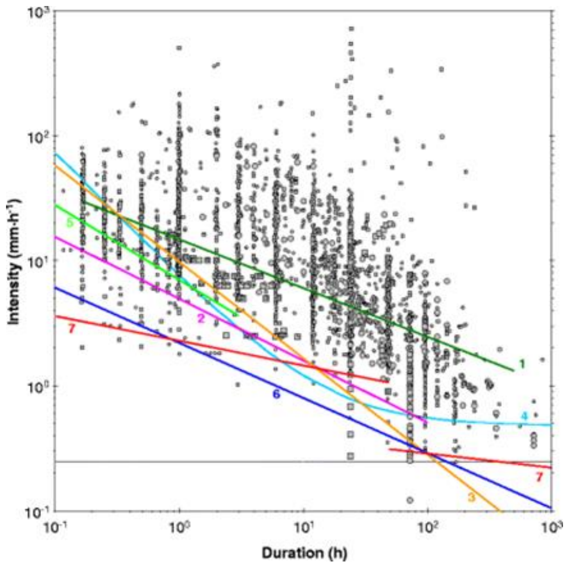


Figure 4.8: Comparison of the global ID thresholds. 1/Dark Green Caine (1980); 2/Pink Innes (1983); 3/Light Green Clarizia et al. (1996); 4/Light Blue Crosta and Frattini (2001); 5/Yellow Cannon and Gartner (2005); 6/Dark Blue (Guzzeti et al., 2008); 7/Red (Guzetti et al., 2008)

This work identified three ID global thresholds, line 6 which was the ID threshold for the entire set of ID rainfall data, and two lines (7) for different rainfall periods, D < 48hrs and D ≥ 48 h. This research chapter will be using line 6, the ID threshold for the entire ID rainfall period. Comparing this line to line 1, the initial ID threshold proposed by Caine (1980) there is a clear slope similarity, however, due to the information available to Caine, for example landslides – Caine's 73 events vs Guzzetti's 2626 events – the large differences seen between them could be ascribed to that. Dikshit & Satyam (2017) produced a paper estimating the ID thresholds of Kalimpong, India. Kalimpong is in the Eastern side of the site being investigated in this research chapter, and the threshold is the only one calculated within this site area.

In using established ID thresholds there are some associated advantages and disadvantages to this(Herchberg, 2021). The advantages are, consistency and comparability to other studies, proven reliability, ease of use and that these ID thresholds have already been accepted as a tool (Hong et al., 2017). There are limitations to using these ID thresholds, however. There is the regional variability to consider, especially when using the global ID threshold (Bogaaard & Greco, 2018). These thresholds are static, and they don't account for changes in land use, or climate change. This is especially true for the global ID threshold I am using from a 2008 paper, and so 16 years old already, and the climate is changing at an increasingly rapid pace. Using these thresholds with the coarse ERA5 precipitation data may undermine the effectiveness of the thresholds too. To overcome the limitations, I have also used a local threshold to compare the data in the local area. I took into consideration these limitations and by understanding the limitations, and it lead to a more robust discussion of the data analysis.

Contingency Tables and Model Metrics

Contingency Tables are a tool within hazard modelling to assess the accuracy of predictive models. They present data on the observed and predicted occurrences of natural hazards, and in this case, landslide events within Tables, which then allows for the calculation of performance metrics like sensitivity, specificity and accuracy (Brenning, 2005; Begueria, 2006). The contingency Table metrics that are used within this study are;

Contingency Table Metrics:

1. **Accuracy**:

    - Measures the proportion of true results (both true positives and true negatives) among the total number of cases examined.

Accuracy=TP+TNTP+TN+FP+FN

2. **Sensitivity (Recall)**:

    - Measures the proportion of actual positives that are correctly identified by the model.

Sensitivity (Recall)=TPTP+FN

3. **Specificity**:

    - Measures the proportion of actual negatives that are correctly identified by the model.

Specificity=TNTN+FPS

4. **Precision**:

- Measures the proportion of positive identifications that were actually correct.

Precision=TPTP+FP

5. **F1 Score**:

    - The harmonic mean of precision and recall, providing a balance between the two.

F1 Score=2×Precision×RecallPrecision+Recall

Alternatively: F1 Score=2×TP2×TP+FP+FN

These equations help evaluate the performance of a binary classification model using the values from the contingency Table.

This contingency Table has been created by doing stratified random sampling of the wet days from the ERA5 total precipitation dataset. Stratified random sampling is a statistical method to make sure that subgroups of a population of data are adequately represented by a sample. In this case the rainfall events were stratified based on the temporal characteristics, so that wet days and potential landslide days were randomly sampled from each month for each year in the study (Thompson, 2012). The process is detailed here;

Stratified Random Sampling

- **Process**:
    1. Divide the dataset into strata based on a specific characteristic (e.g. month like in the study).
    2. Perform random sampling within each stratum.
    3. Combine the samples from all strata to form the final sample.
- **Purpose**: To ensure that each subgroup is adequately represented in the sample, which increases the precision of the estimates.
- **Advantages**:
    - Ensures representation of all subgroups in the population.
    - Reduces sampling error compared to simple random sampling.

The advantages listed are especially important for this study. All of the months need to be represented so that landslides events or wet days that could lead to landslide events that may occur outside of the monsoon can also be shown, and that the intense rainfall experienced in te monsoon period will not dominate the sampling.

Relative Operating Curves

The Area Under Relative Operating Curves (ROC) also known as Receiver Operating Characteristics is an evaluation tool that measures the performance of a forecast by plotting the true positive rate on the X axis and the false positive rate on the Y axis. A ROC graph is a diagram that shows the trade-offs between the benefits (true positives) and costs (false positives) (Tsagalidis & Evangelidis, 2011) and illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. It is created by plotting the True Positive Rate (TPR, or Sensitivity) against the False Positive Rate (FPR, or 1-Specificity) at various threshold settings.

True Positive Rate (TPR)

Also known as Sensitivity or Recall, TPR measures the proportion of actual positives that are correctly identified by the model.

TPR=TPTP+FNTPR=TP+FNTP

where:

- **TP**: True Positives (correctly predicted positive cases)
- **FN**: False Negatives (actual positive cases that were incorrectly predicted as negative)

False Positive Rate (FPR)

FPR measures the proportion of actual negatives that are incorrectly identified as positives by the model.

FPR=FPFP+TNFPR=FP+TNFP

where:

- **FP**: False Positives (actual negative cases that were incorrectly predicted as positive)
- **TN**: True Negatives (correctly predicted negative cases)

For this study I used a ROC curve showing the performance of the ERA5 data use in conjunction with the landslide ID thresholds. I used this because the ROC curve is a standard method for evaluating the diagnostic ability of binary classifiers, in this case, the ability of the model to predict landslides. It's crucial for assessing the model's accuracy and reliability. A ROC curve is also not dependant on a specific decision threshold and contains just a single performance metric. This simplifies the model comparison and selection. ROC curves can also have limitations in their use. They can lead to misleading interpretations, leading mostly to instances of model overestimation of performance. Having the single performance metric, although useful for simplifying the analysis, this could lead to oversimplification. This means that aspects of the model's behaviour can be overlooked. When interpreting the ROC Curve, it is important to see examples of one. The closer a point is to the top left corner, the better it is (high sensitivity, low false-positive rate). An example of this can be seen in Figure 4.9 The central red dotted line shows the point at which the TPR and the FPR are equal, and so is the same as random guessing. Anything below the red dotted line would be considered 'worse than random guessing' and would be considered that if you switched the prediction the outcome would be more accurate.

The Area Under the Curve (AUC) can also be calculated for each threshold. A larger AUC indicates a better overall performance of the threshold. An AUC score is used to measure the overall performance of a binary classification model, with the value ranging from 0 to 1. The scores generally mean these things;

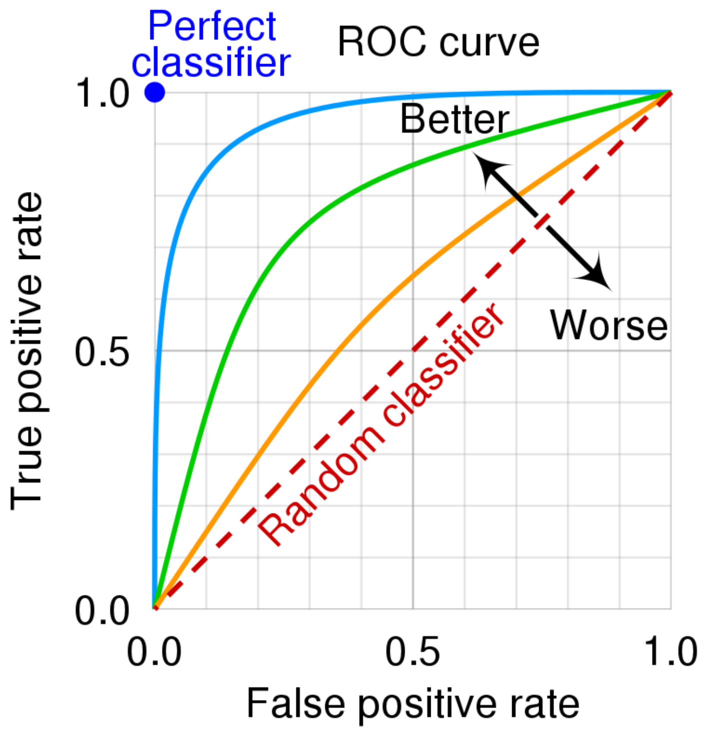


Figure 4.9: A ROC curve graph with annotations on what each shape might mean (Created by Author).

- AUC = 0: The model's performance is perfectly incorrect
- 0 < AUC < 0.5: The model's performance is oppositely predicting the hazard events.
- AUC = 0.5: The model's performance is equivalent to random guessing.

- 0.5 < AUC < 0.7: The model performs poorly to fairly.
- 0.7 < AUC < 0.8: The model performs moderately well.
- 0.8 < AUC < 0.9: The model performs very well.
- AUC > 0.9: The model performs exceptionally well.
- AUC = 1: The model is perfectly correct.

Chapter 5: Research Chapter I: 'Data'

Analysing the Global Landslide Inventories available for Darjeeling District, India, statistically evaluating their use, and critiquing the choices made by landslide researchers.

5.1 Introduction

Landslides are a major natural hazard in mountainous areas around the world and pose a high risk to people, economies, and infrastructure. It is an important venture to understand landslides, where they're likely to occur and their potential impacts (Emberson et al., 2022). Landslides are small, localised events compared to hazards with a larger footprint, such as cyclones or earthquakes. However, landslide triggering events like intense rainfall can be over a wide region and contain many landslide events which mirror the extent of the triggering region (Marc et al., 2017, 2018; Tanyaš and Lombardo, 2019; Emberson et al., 2022).

Landslide information, such as morphology, geology, land cover, seismic and hydrological factors, can be used to construct landslide susceptibility models, and landslide inventories which hold this information also need to include the date and time of a landslide occurrence as this is used to calibrate and validate these susceptibility models (Guzzetti et al., 2012; Van Den Eeckhaut & Hervás, 2012; Reichenbach et al., 2018; Emberson et al., 2022).

A landslide inventory (LSI) is usually a database of landslide records that document landslide events. These can be categorised as event or historical LSIs. Event LSIs are associated with a triggering event, while historical LSIs are just a collection of landslides which is a count of landslides over a given area (Malamud et al., 2004). An LSI will normally contain information on the event, such as characteristics, location, size, type, triggers and timing (Guzzetti et al., 2012). The purpose of an LSI is to provide a detailed and systematic record of past and present landslide events to use in research to understand hazards, assess the risks and implement effective disaster management plans (Guzzetti et al., 2012; Emberson et al., 2022).

LSIs are compiled through a variety of methods, and there is no international standard or method for compiling databases and inventories. Different methods include field surveys, satellite imagery, aerial photography, historical reports and news reporting. Due to the advancement of technology and Geographical Information Systems (GIS), LSIs are becoming more accurate and efficient, enabling the analysis of large areas and integration of different data sources (Van Den Eeckhaut & Hervás, 2012). Combining different technological approaches has yielded good results when compiling landslide inventories, for example, combining social media information with artificial intelligence led to a precision of 76% of landslide event detections (Pennington et al., 2022).

LSIs are important data resources due to their application in the landslide hazard assessment and prediction fields. Researchers can use these LSIs to analyse the patterns and triggers of past landslide events, to identify areas at risk of future landslides or to understand factors leading to slope instability, all of which can be useful in developing appropriate mitigation measures. LSIs can also be used in the validation and improvement of predictive models of landslide occurrence (Guzzetti et al., 2012).

LSIs can be created and catalogued in Global LSIs and there are examples of these inventories from organisations such as NASA (Kirchbaum et al., 2019) and the University of Durham (Froude & Petley, 2018). All Global LSIs and disaster databases are created by institutions from the Global North or international bodies such as the United Nations (Gómez, García & Aristizábal, 2023). National LSIs are common in countries that have many landslide hazards, with many examples of this in the UK, India, France, Switzerland, China and Brazil (Pennington et al., 2015; Batar & Watanabe, 2021; Thiery et al., 2024; Hervas & Van Den Eeckhaut, 2012; Lin et al., 2017; Dias, Holbling & Grohmann, 2021)

Landslide research is predominantly (70%) produced by the Global North, with the top 10 countries being China, Italy, USA, Japan, UK, Germany, Switzerland, Canada, Taiwan and France (Wu et al., 2015; Carrión-Mero et al., 2021). The research conducted in these Global North countries consistently uses LSIs that are either produced through satellite analysis and construction of LSIs from aerial images or taking the data from Global LSIs. An example of this is through a 'World Centre of Excellence on Landslide Risk Reduction' at the Charles University in Prague, Czech Republic. A 2010 study by Vilímek et al. looked at three study areas that the centre had focused on – the Peruvian Andes, the Jemma River Basin, Ethiopia and selected regions of the Himalaya and Karakoram. In all these areas either a Global Disaster Database was used for the landslide event count, a Global North contractor and institution had created one from satellite imagery, or an inventory wasn't used at all (Vilímek et al., 2010). This is despite a national inventory being available in Peru (from the Instituto Nacional de Defensa Civil) and in the areas of the Himalayas and Karakoram the study looked at.

5.1.1 Research Questions

The research question being answered in this research chapter has been created from the gaps in literature highlighted in **Thesis Section 2.4 Literature Review: Research Question – 5.0 Research Chapter I**. The research question is as follows;

- What global and national landslide inventories are available for researchers when researching Darjeeling, India?

This will be answered by looking at some specific points.

- What Global LSIs are available in the study area?
- Will using a unified database approach increase the coverage of landslide events in my study area?
- Analysis of physical characteristics from my study site to highlight any correlations between the physical properties of the study area and the combined LSI.
- Will there enough landslide events in the study area to do any validation/skill analysis?
- Why did I personally not choose to look at India's National Inventory?

Each of the following sections will tackle each of these specific points to answer the research question.

5.2 Analysis of Global Landslide Inventories – What's available in the study area?

I started by conducting an analysis of the currently available global LSIs by collecting information from each LSI or database containing landslide event data and creating a Table to compare landslide numbers, coverage over the globe, and information recorded by each individual LSI (Table 5.1). I have done this to quantify what landslide data is available from the global inventories in the study area, and what kind of information would be available for use when using the inventories. Indian landslides are counted in all the databases listed, with other databases such as the preventionweb (PreventionWeb, 2021), DesInventar (DesConsultar, n.d) or catastrophes-naturelles (Cat-Nat, n.d) not containing any landslides within India not being represented in Table 5.1.

Table 5.1: Overview of the current publicly available global inventories containing data on landslide occurrence in India, divided into "Global Landslide Inventories" which has exclusively landslide data and "Global Disaster Inventories" which has data comprising of landslides and other type of natural hazards that can lead to disasters. "#LS" is the number of global landslides, "#LS India" is the number of landslides in India and "# Study Area" is the number of landslide events recorded in the thesis Study Area in Darjeeling District, India – location in ***Thesis Section 3.0 Study Area.*** *Table structure taken from: (Monsieurs et al., 2018)*

Name	**Institution (Country/ Union)**	**Included Processes**	**Start**	**End**	**# LS**	**# LS India**	**# Study Area**	**Website***
Global Landslide Inventories								
GFLD – Global Fatal Landslide Database	University of Durham (UK)	Fatal non-seismic triggered soil/rock failures, including slides, flows and fails. Debris flows are included when the movement can be clearly differentiated from a flood.	2004	2010	5536	992	71	[1]
GLC – Global Landslide Catalog	NASA – National Aeronautics and Space Administr	All types of mass movements triggered by rainfall.	1968	2024	11033	1265	111	[2]

	ation (USA)							
Global Disaster Inventories								
EM-DAT – Emergency Disaster Data Base	CRED – Centre for research on the Epidemiology of Disaster, at the Catholic University of Louvain (Belgium)	Biological, climatological, geophysical, hydrological, meteorological, and technical disaster which have killed 10 or more people, affected 100 or more people, or resulted in a declaration of a state of emergency or call for international assistance	2000	2024	460	29	0	[3]
GLIDE – The Global Disaster Indentifier Number	ADRC – Asian Disaster Reduction Center (Japan)	Cold Wave, Complex emergency, Drought, Earthquake, Epidemic, Extratropical Cyclone, Extreme Temperature, Famine, Fire, Flashflood, Flood, Heat Wave, Insect Infestation, Land Slide,	Approx. 1900	Present	152	3	0	[4]

		Mud Slide, Other, Severe Local Storm, Slide, Snow avalanche, Storm Surge, Technological Disaster, Tornadoes, Tropical Cyclone, Tsunami, Violent Wind, Volcano, Wave/Surge, Wild fire						
NatCatSERVICE – Natural catastrophe loss database	Münich Reinsurance Company (Germany)	Natural disaster (excluding technological disasters): Avalanche, Drought, Earthquake, Eruption, Flooding, Landslide, Rock Fall, Storms, Subsidence, Volcanic Extreme temperatures, Wildfire	79	Present	Approx. 6149	66	0	[5]
Relief Web	UN Office for the Coordination of Humanitarian Affairs (OCHA)	Cold Wave, Drought, Earthquake, Epidemic, Extratropical Cyclone, Fire, Flashflood, Flood, Heat Wave, Insect Infestation, Land Slide, Mud Slide, Other, Severe Local Storm, Snow Avalanche, Storm Surge, Technological Disaster,	1980	Present	Approx. 222	15	0	[6]

		Tropical Cyclone, Tsunami, Volcano, Wild Fire						

** https://shefuni.maps.arcgis.com/apps/webappviewer/index.html?id=8458951270904fc29527254492517063 [1], https://gpm.nasa.gov/landslides/data.html [2], https://www.emdat.be/ [3], https://www.glidenumber.net/glide/public/search/search.jsp [4], https://www.munichre.com/en/solutions/for-industry-clients/natcatservice.html [5], https://reliefweb.int/ [6]*

From Table 5.1 it is apparent that from the global landslide databases and natural hazard databases landslides cover many events in India, however, fail to represent the landslides within the study area in many cases. Within those that have been included in the Table above, the number of databases that contain landslides within the study area is the GFLD and the GLC. The global disaster inventories have no instances of landslides within the study area, and so cannot be used in the application of validation of models using historical landslide instances. Of the two remaining datasets, consideration into duplicate events needs to be taken, and if the events are different, perhaps the landslide events could be used in a combined, unified dataset to make a larger more complete LSI.

5.2.1 Will using a unified database approach increase the coverage of landslide events in my study area?

Gómez et al., (2023) combined four of the global landslide and disaster databases to create a Unified Global Landslide Database (UGLD) which combined contained 161 countries, 37,946 landslides and 185,753 fatalities between 1903 and 2020. The paper used the GLC, the GFLD, EM-DAT and the DeInventar databases to compile the new UGLD, and its findings showed that there were few overlapping events, indicating that each of the databases collect unique and different landslide data and balance each other (Gómez et al., 2023). American and Asian continents contained the most landslide incidences and fatalities, and rainfall was one of the most frequent triggers (Gómez et al., 2023). The characteristics of this thesis study area combined with the aim to understand more about rainfall triggered landslides should mean that there are many relevant landslide events in the UGLD, or within a combined LSI in general. Using a unified approach as seen in Gómez et al., (2023) is therefore the approach that would contain as much information as possible for landslide events, increasing the coverage and increasing the amount of landslide events captured. Considering Table 5.1, when considering landslide inventories that encompass the study location there are only two inventories that have landslide events for the study area. By combining these two datasets a larger combined inventory will enable a more representative dataset when validating models with historic events. The two databases have a combined 16569 landslides, with a combined number of landslides of 2257 in India.

Table 5.1 illustrates that there is limited global landslide data available for the study area in the Darjeeling District. The landslide specific datasets are the only datasets to include landslides in the study area, with only 4 of the many global disaster databases available having landslides events shown in India. Table 5.2 shows general information of the global landslide databases that have been chosen to combine for this study site.

Global disaster databases are known to have a geo-political component to them, either from international data sharing agreements (Adindu et al., 2024; Yang et al., 2024), or political boundaries creating significant challenges in collecting and sharing data due to sovereignty and control over information (Richmond & Pogodda, 2016). Due to some of these restrictions some of the international disaster databases that do not contain landslide events in India also do not contain information on other countries in Asia, such as China (PreventionWeb, 2021; DeConsultar, n.d). Analysis of these various omissions from the datasets is beyond the scope of this research piece, however **Thesis Section 3.0 Study Area** contains more information on India's position on the world stage, and the historical and present relationships with other countries and organisations.

Table 5.2: General Information for landslide records for the two combined datasets, the GLC (Kirchbaum, 2019) and the GFLD (Froude & Petley, 2018).

Information in database	*Global landslide databases*	
	GLC	**GFLD**
Scope of Collected data	Analysis of global landslides triggered by rainfall	Analysis of landslide activity resulting in the loss of human life
Time Range	2006-2017	2004-2017
Number of Records	11033	5536
Number of Fatalities	31061	64149
Fatalities/Landslides (2d.p)	2.82	11.59
Continents with the highest number of landslides	North America and Asia	Asia
Number of countries with reported data	124	138
Most affected countries	USA, India and the Philippines	India, Nepal and China.

5.2.2 Global Analysis of GFLD and the GLC

I have created some maps to show the spatial distribution of the two LSIs, GLC and the GFLD and these can be seen in Figure 5.1 & 5.2. From these two Figures some comparisons can be made. The

GLC has more landslide events within its database, but has a higher spatial coverage in the US, while the GFLD has a higher spatial coverage in Asia, including the study site. Despite this, the number of landslides is similar in India, with 262-716 landslides in India in the GLC and 346-721 landslides in the GFLD. It is apparent that using the two databases combined would increase the spatial coverage of the landslide events

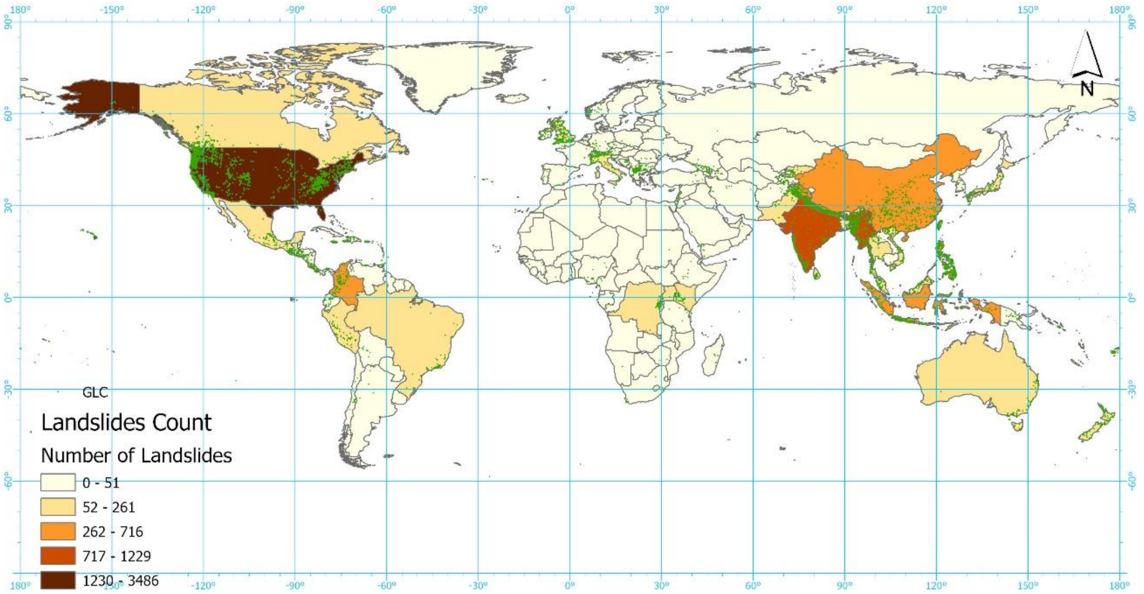


Figure 5.1: Spatial distribution of the GLC (Kirchbaum et al., 2019) with shading to show the countries with the most coverage of landslide events in these.

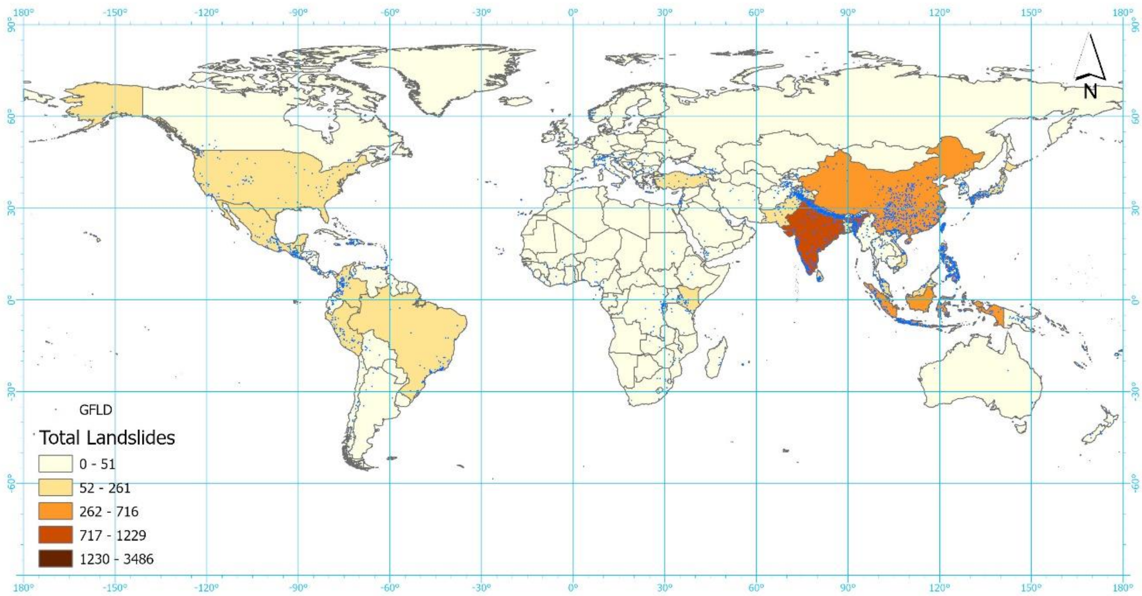


Figure 5.2: Spatial distribution of the GFLD (Froud and Petley, 2018) with shading to show the countries with the most coverage of landslide events.

There are several differences in the LSIs in terms of numbers of incidences and numbers of fatalities. In Figure 5.3 there is a clear difference in the number of fatalities and landslide events recorded for both datasets. The details of specific numbers are in Table 5.2. Figure 5.3 shows that although the GFLD has less landslides reported; it contains many more fatalities then the GLC. The GLC does have many more landslides reported then the GFLD yet, does not contain as many fatalities. This could be due to underreporting of landslides in national new reports when they are initially logged, with no follow up on the number of fatalities as more bodies are found or people are missing. It could also be due to the geographical location of the number of landslides reported. For example, the GLC has many more landslides reported in the North Americas, where the reporting of landslides is more structured, even when the landslides are not fatal, whereas the GFLD has more landslides in Asia, where landslide reports are usually reported upon when there are fatalities. The GFLD has a focus specifically to log human losses and fatal landslide events which also adds to the disparity between the GLC and GFLD regarding fatalities.

It is important to look at the data in this way as it allows researchers to understand how useful the dataset is and how useful the dataset is for studying landslides. When considering how useful a dataset is going to be for research, the researcher needs to know what they need from the dataset. If the researcher was focusing on non-fatal landslides from the US, then the GLC would be a perfect match for the study. A researcher who was focusing on fatal landslides in Asia would find that the GLC had little coverage in Asia. It is also important to consider the associations and objectives of the institutions that are creating the LSIs as this does impact the recording and the data availability within the databases. The GLC is created by NASA, a US government agency, and this is reflected in the US coverage of landslide incidences. The GFLD has been created at the University of Durham, a UK based university. The main researchers have had extensive experience and professional associations with peers in Asia, and so the information presented in the GFLD is predominantly in Asia. There are always social implications when considering data availability and data acquisition (Umber et al., 2024).

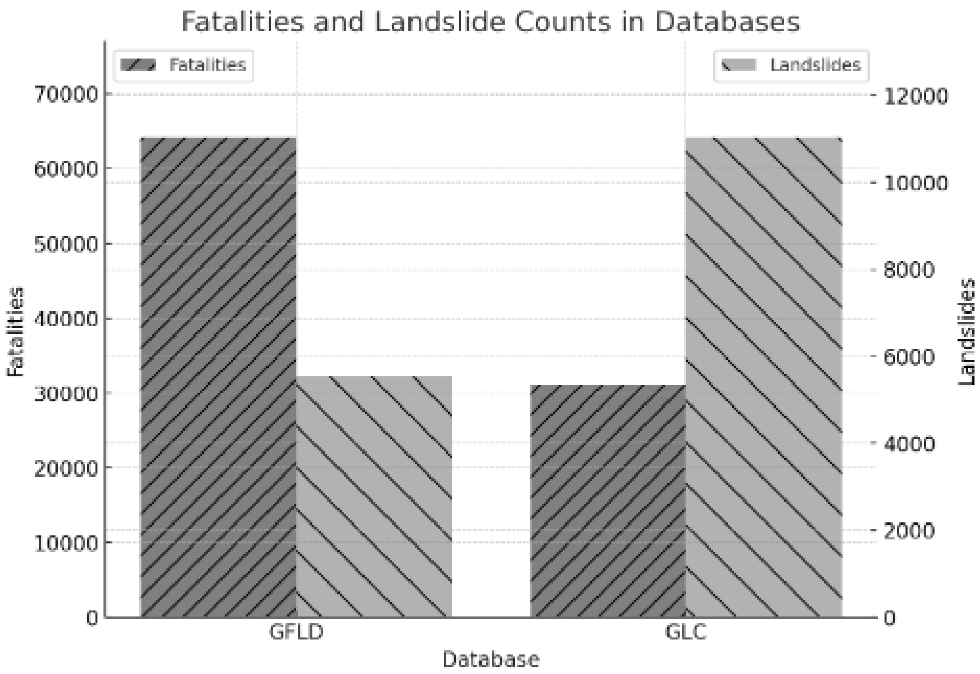


Figure 5.3: Comparison between the number of landslides recorded and the number of fatalities for the two datasets, GFLD (Froude and Petley, 2018) and GLC (KIrchbaum et al., 2019).

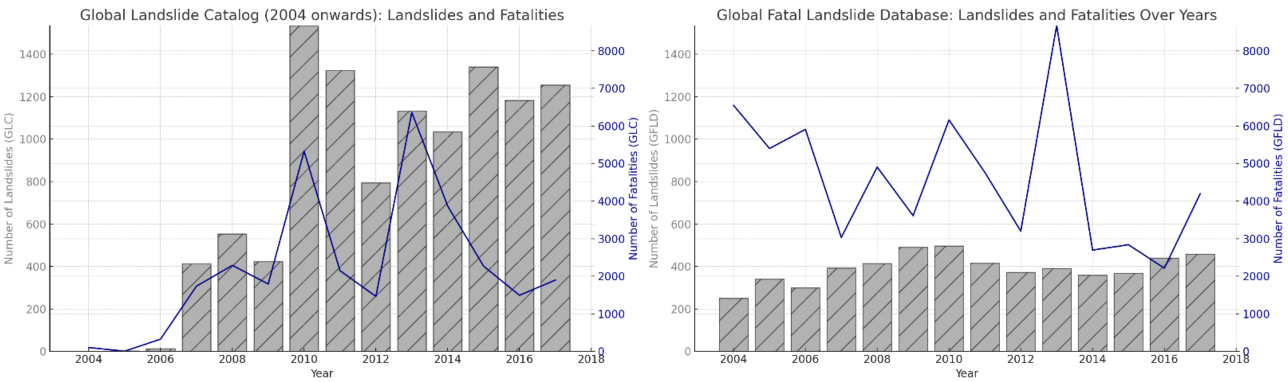


Figure 5.4: The temporal differences between the GLC and the GFLD.

Figure 5.4 shows the temporal differences in the GLC and the GFLD. From this graph the higher fatalities count for the GFLD is more apparent, despite the much lower number of reported landslide events seen each year compared to the GLC. The two datasets only show the most recent events from 2004. This is much later than the discounted DesInventar and EM-DAT which contain events from 1906 and 1903 respectively. This longer time period would be useful for a larger historical verification for models for example, but in this case, this is useless because it does not contain the landslides needed for this study or thesis.

The GLC in Figure 5.4 shows a trend of increasing landslide counts over time with the GFLD showing a very slight increasing trend in landslide counts. The GLC also shows a slight increase in fatalities over time, with the GFLD showing an even trend in fatalities. This increase in landslides over time is a trend seen in other longer datasets, for example the DeInventar dataset, where there is a marked increase in landslide events from 1900 to 2020 (Gómez, García & Aristizábal, 2023; Fidan et al., 2024). The increase in landslides is thought to be due to climate change increasing the extreme weather events globally and pushing what scientists consider normal (Prakash, 2024). This is an important point to consider for my research, as with an increasing risk to hazards, the utilisation of landslide inventories, and the way in which the data is collected and stored will be an important dataset when developing tools to combat the increased vulnerability and landslide incidents.

The implications of this on my research and study is that any verification of models could only happen within the smaller window of temporal time covered by the GLC and GFLD and not the larger window covered in the other databases. It is usual for model verification to happen over many decades, and the dataset and model hoping to be verified within my own research has data from 1940 to the present day. This means that although there could be 80 years of verification analysis to do, the study would have to be limited to the 12 years available in these LSIs

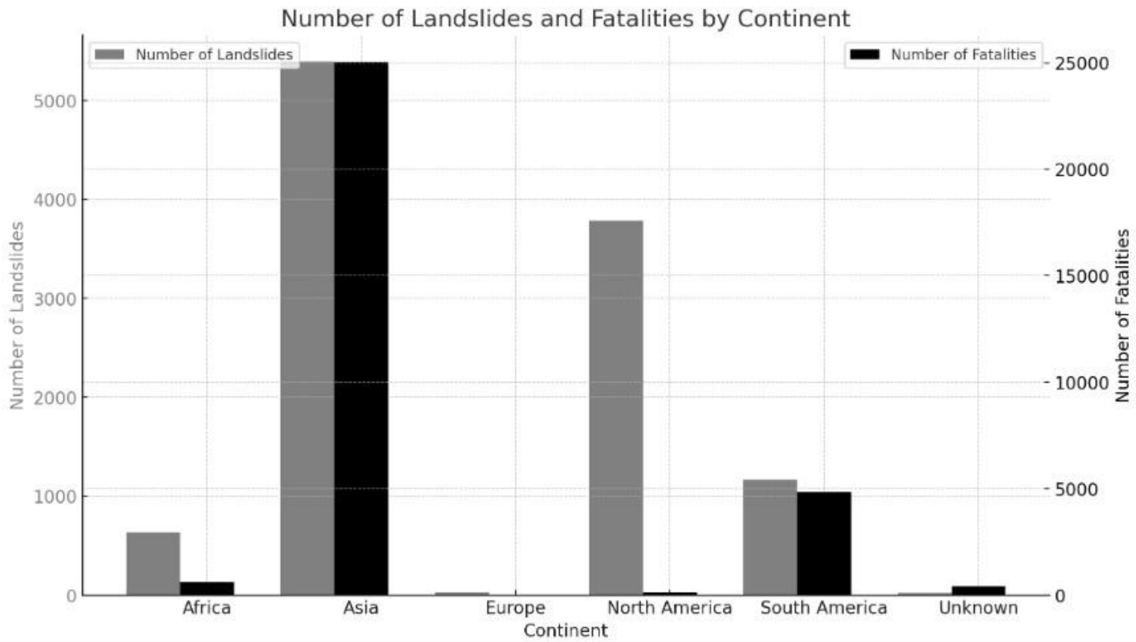


Figure 5.7: The GLC number of fatalities and landslides per continent.

The GLC when split into continents shows the spatial distribution graphically of both the landslide counts and the fatalities (Figure 5.7) compared to the map in Figure 5.1. This shows that the map in Figure 6.1 is correct in terms of landslide counts, however this Figure contains information about the fatalities, which shows something else. The GLC shows that the fatality count is much higher in South America and Africa, despite having fewer landslide events compared to the North American Continent (Figure 5.7). This could be due to several reasons. It could be due to the reporting techniques in the GLC. The reports that make it to the news, or that are deemed most important in the Global South are generally ones that are fatal. All landslides in the Global North are considered to be important due to ideas based in post-colonialism (ideas such as importance, wealth and ability to maintain safety for citizens) and so most are catalogued and reported upon when they happen. The robust nature of reporting landslides in the Global North, coupled by the fact that the GLC has been created by a North American agency could also be the reason why there are more landslides reported in North America even though they are not fatal landslide events.

The GFLD dataset split into continents (Figure 5.8) shows a different split between the continents to the GLC as expected from the differences in Figure 5.1 and Figure 5.2. The focus of the GFLD is on Asia, with little landslide events in other countries. South America is the second largest number of landslide events outside of Asia.

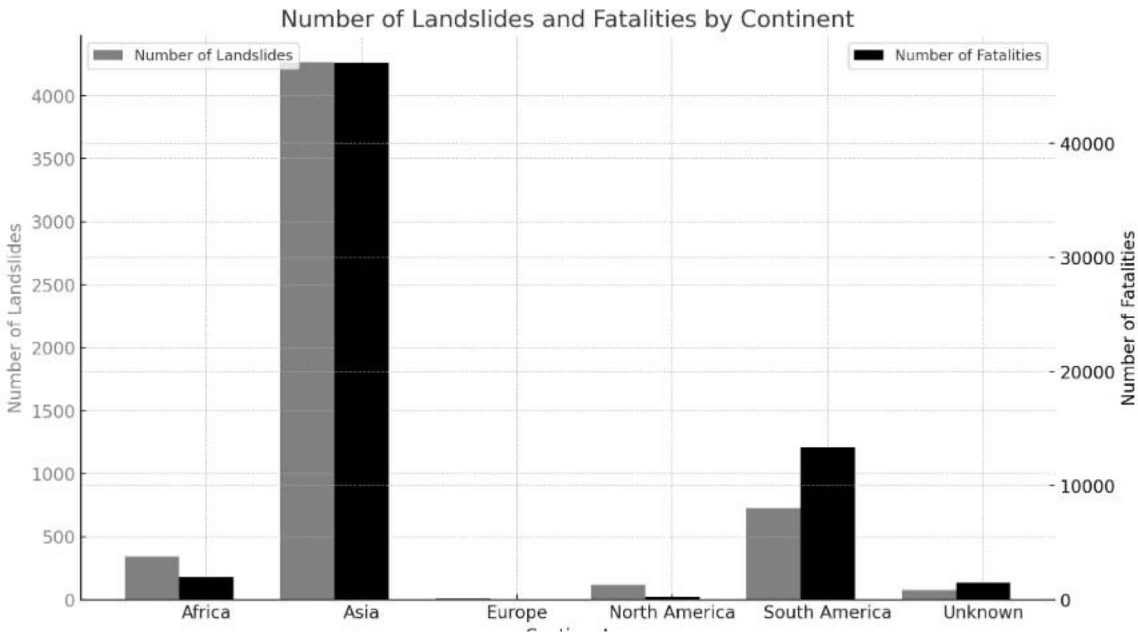


Figure 5.8: The GFLD and the fatalities and landslides per continent

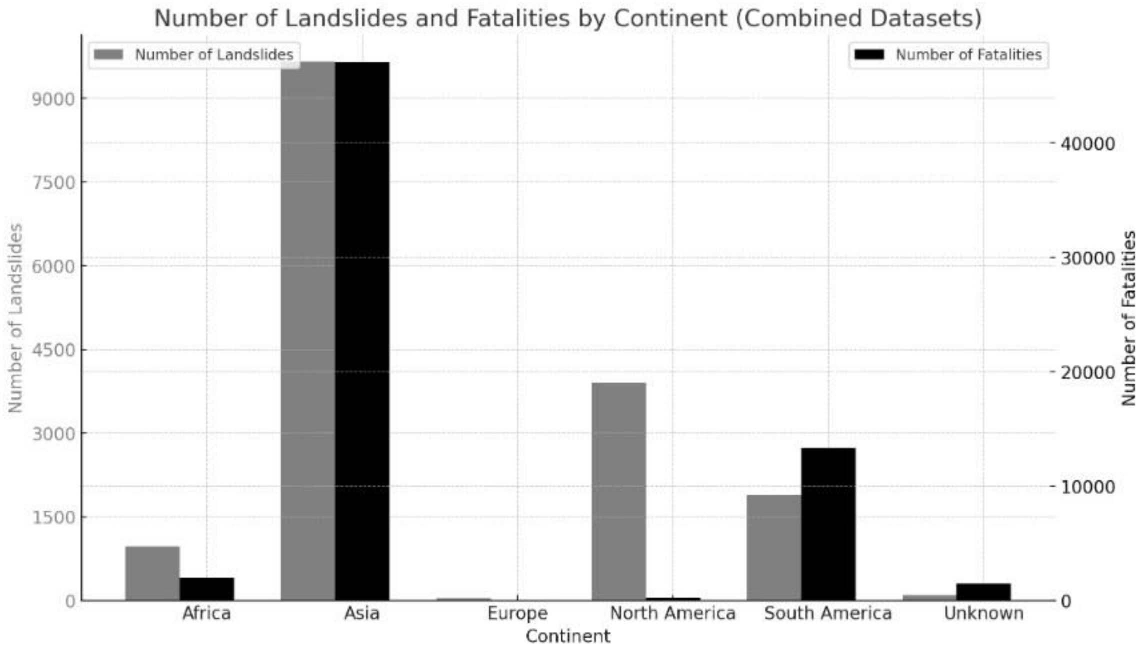


Figure 5.9: The combined (GLC & GFLD) fatalities and landslide numbers per continent

Combining both the GLC and GFLD LSIs data and splitting them between continents seen in Figure 5.9, provides an illustration of the spatial coverage that can be gained from using the combination of both the datasets together for research purposes. The areas that had less coverage in either have been bolstered by the other – for example, the GFLD had little North American landslides, and the GLC had little South American landslides. Overall, the landslide events that are gained from combining both datasets make for a more comprehensive dataset globally.

5.2.3 The GFLD and GLC LSIs and combined LSI at the study site

Now if we focus the spatial outlook to observe the LSIs at the study site specifically, we can see that the landslide incidences can indeed be used in combination to increase the spatial and temporal coverage of landslide events at my study site. We can see this through Figure 5.10, which shows the specific site region within this study and the locations of the landslide events for each global landslide database. These Figures show that although the GLC has more landslide points within the site, the global spatial distribution is less than the GFLD. This shows further that combining both the GLC and the GFLD would increase the coverage over the specific site of interest and that the landslide points are converging on sometimes very specific points.

This does not however mean that there are no other susceptible areas of landsliding that are not covered by both sets of data – and a more comprehensive image of landslide counts can be seen in **Thesis section 5.2.4** in **Figure 5.14.** This Figure shows the Indian national landslide inventory and is discussed in detail there.

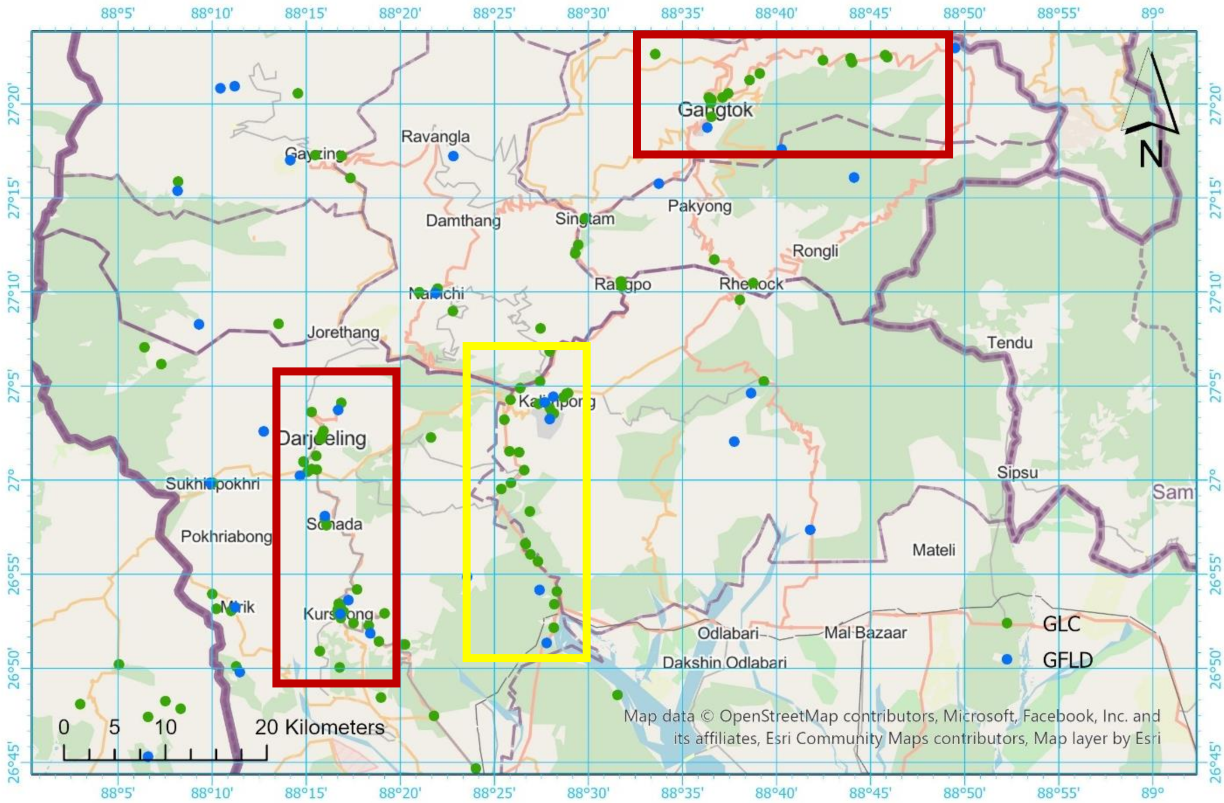


Figure 5.10: The location of landslides in the study area, with the green points the landslide locations of the GLC landslides and the blue points of the GFLD landslides.

In Figure 5.10 the specific points that the landslides seem to be converging on are by national highways and in built up urban areas. The boxes highlighted in Figure 5.10 are the 4 largest settlements in the Darjeeling and Sikkim areas; Darjeeling, Kalimpong, Kursong and Gangtok. The landslides are clustered in and around these areas and follow two major features – rivers and national highways. This could show that the landslides are occurring due to anthropogenic means, however both LSIs are news/ citizen science report based, and so it would make sense if the only reported landslides within these inventories were where people lived and travelled along.

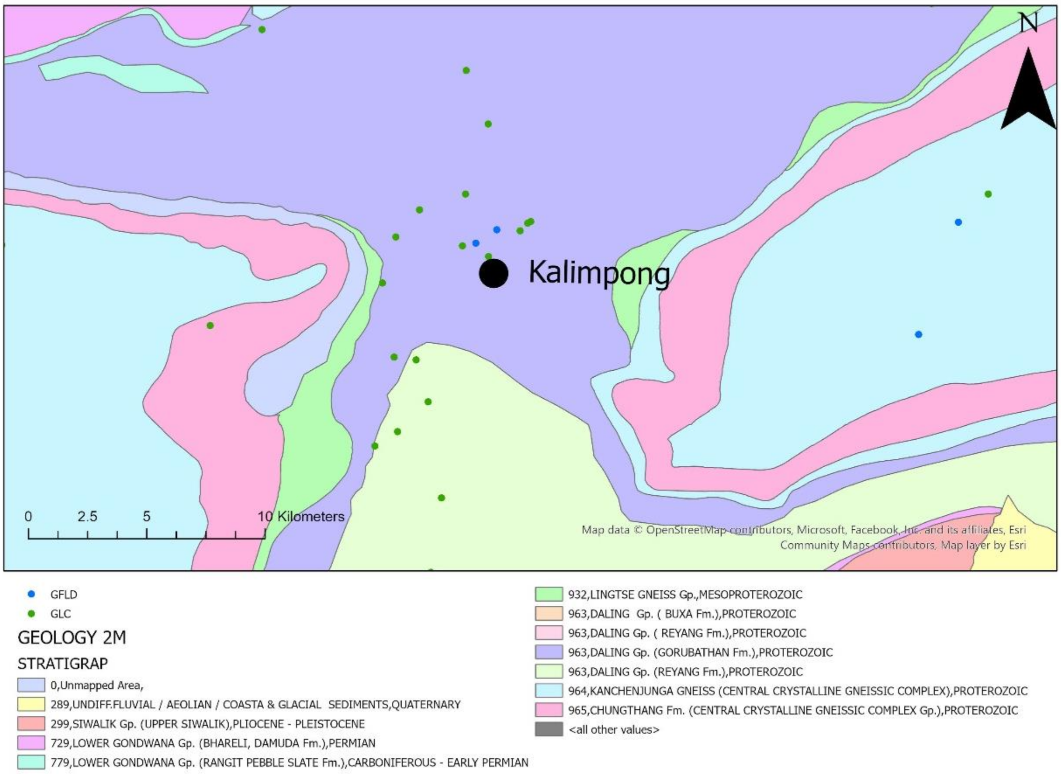


Figure 5.11: The geological stratigraphy at Kalimpong, with the landslide locations mapped.

The yellow box in Figure 5.10 corresponds to the Kalimpong region seen in Figure 5.11. From this Figure it is apparent that geological changes or features does not impact landslide locations. This is important to note as geological changes can lead to inconsistencies, changes in erosion stages and weathering, and ingress and pooling of water. This all relates to how landslides can be formed and triggered (Vasudevan and Ramanathan, 2016). There are no reported large faults or thrusts in this area either.

5.2.4 Statistical Analysis

The combined LSI should be analysed against physical characteristics from my study site to highlight any correlations between the physical properties of the study area and the combined LSI as part of the **Thesis Section 5.1.1 Research Questions** as we can see if the combined inventory works with the physical characteristics and the usual ways in which landslides are triggered and formed.

Some analysis is required to understand how these LSIs work in the study area itself in terms of geographical location, meteorological drivers and trends with other datasets that are used in the area by other researchers, such as the South Asian Monsoon Index (SASMI) , which has been used in conjunction with LSI data before (Petley et al., 2007)

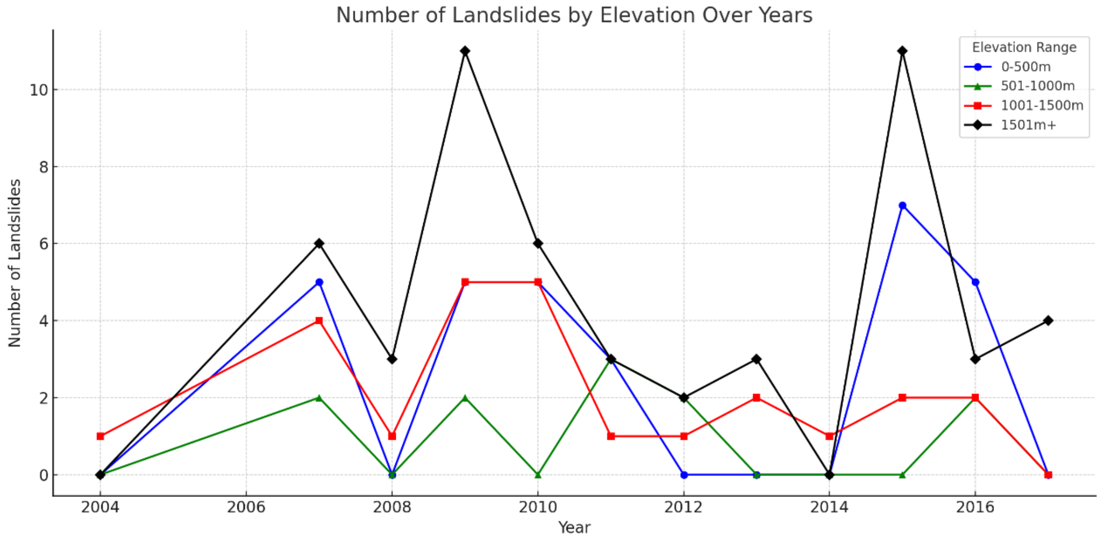


Figure 5.12: Combined landslide inventory for my study area: Temporal trends in the number of landslides across different elevation ranges (0–500 m, 501–1000 m, 1001–1500 m, and 1501+ m) from 2004 to 2016.

The graph highlights that within my study area, higher elevations (1501+ m) experience the most frequent landslides, with significant peaks in 2008 and 2014. Lower elevation ranges (0–500 m) exhibit fewer landslides overall, while mid-elevation ranges (501–1500 m) show moderate activity. These patterns suggest that elevation plays a critical role in landslide susceptibility in the Study Area, influenced by factors such as slope steepness, rainfall intensity, and geomorphological conditions (McColl, 2022). Chen et al. (2024) discusses the elevation dependant shift of landslide activity within the high mountains of China and found that elevation plays a critical role in influencing landslides, due to the increase in angle of repose (Beakawi Al-Hashemi and Baghabra Al-Amoudi, 2018), increased rainfall due to the orographic effect and general mountain range evolution (Korup et al., 2010).

Guzzetti (2021) discussed the role that each condition has within predictions of landslides within an invited perspective. Guzzetti highlighted that “convergence research” is needed within landslide science to design tools and strategies going forward in landslide science.

Temporal spikes may correspond to extreme weather events or specific years of heavy monsoons (Bogaard and Greco, 2016) (Kirchbaum et al., 2020) (Bellugi et al, 2021). Kirchbaum et al. (2020) examined changes in extreme precipitation and landslide incidences in the High Mountain Asia area and concluded that extreme monsoonal rainfall triggers more landslides in this area.

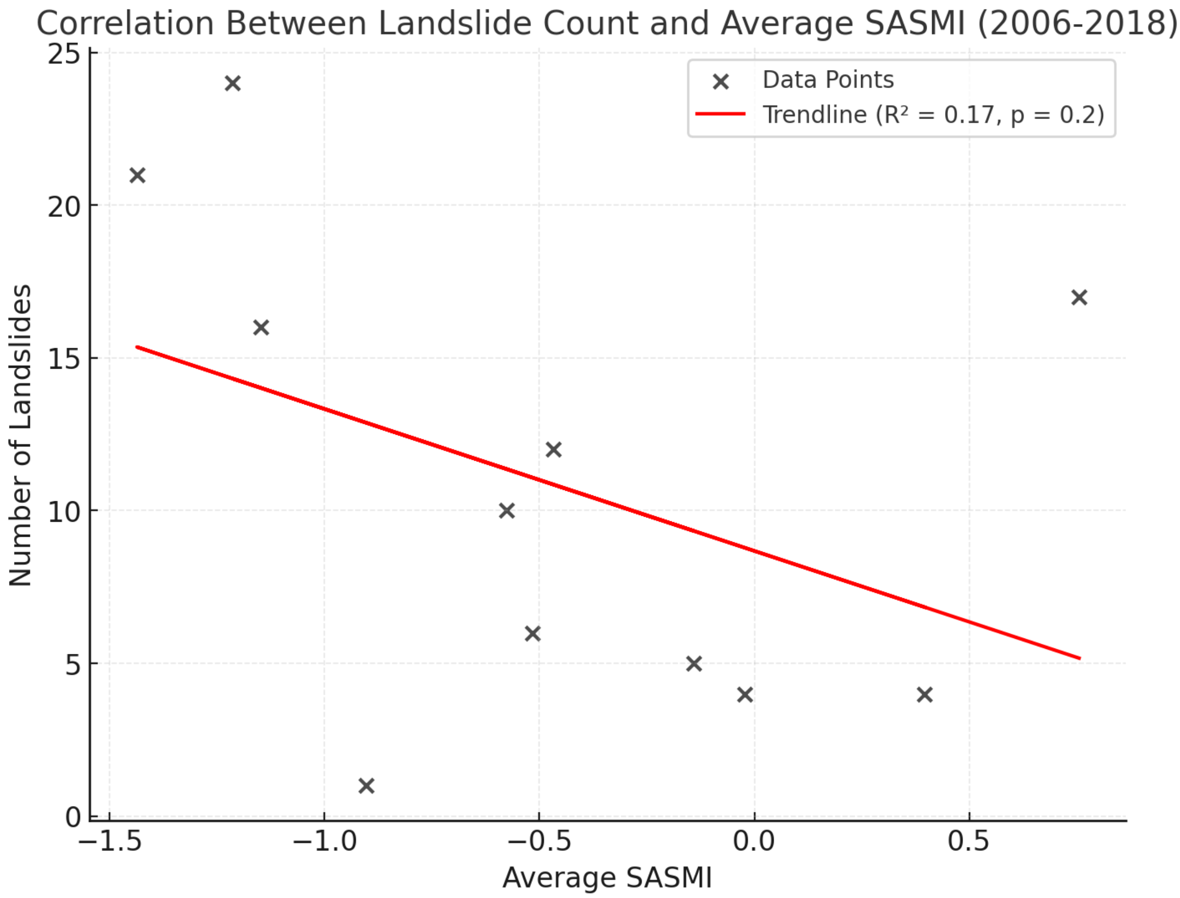


Figure 5.13: Relationship between the South Asian Summer Monsoon Index (SASMI) and landslide occurrences (2006–2018). The plot highlights a negative correlation between average monthly SASMI values and the number of landslides, with a fitted trendline (red) showing the general pattern.

The statistical metrics ($R^2 = 0.17$, $p = 0.2$) provide insights into the strength and significance of this relationship, suggesting that weaker monsoons (lower SASMI) may correspond to higher landslide activity. If the slope of the trendline is negative (as it appears here), it suggests that higher average SASMI values (indicating stronger or more consistent monsoons) might correspond to fewer landslides. Conversely, lower SASMI values (weaker monsoons) might lead to more landslides. This is not consistent with the scientific consensus on how landslides trigger (**See Thesis Section 2.1 Landslide Science**) or consistent with the case studies in **Thesis Section 5.3.1 Case Study Analysis of Indian LSI events**. This could be due to the reporting nature of the landslide events, only being reported by citizens, and therefore isn't representative of real landslide event patterns happening in and around larger extreme monsoons and monsoonal rainfall.

A higher R^2 value (close to 1) would mean the SASMI explains much of the variation in landslide occurrences. A lower R^2 suggests the relationship is weaker and other factors might be more influential. The p-value assesses the statistical significance of the trend. A value less than 0.05

indicates a significant relationship between SASMI and landslides. The R^2 value in this context of 0.17 means that the relationship between the SASMI and landslide events is weaker than other factors (for example, soil saturation or anthropogenic triggers) and the p value of 0.2 means that the trend in this graph is not significant. This plot provides a visual and statistical insight into how monsoon intensity (as captured by SASMI) might influence landslide occurrences. Further investigation could involve exploring other factors (e.g., soil saturation, terrain, or extreme rainfall events) that contribute to landslide risk.

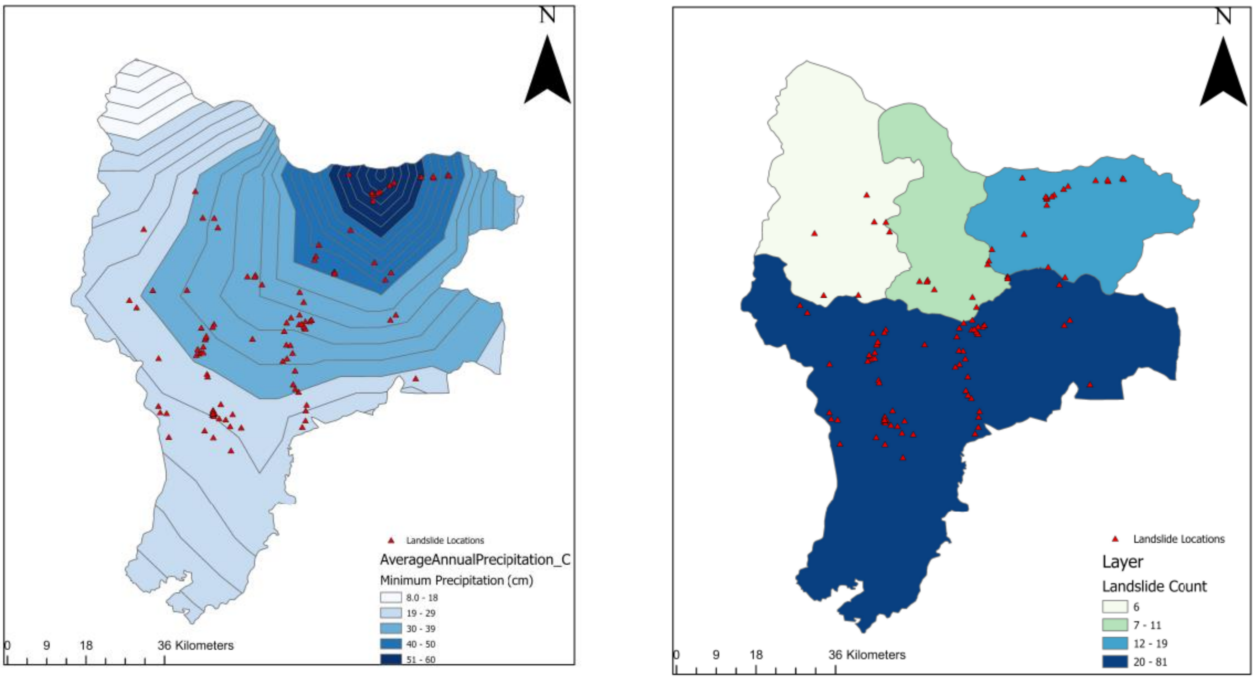


Figure 3.14: Maps illustrating the spatial distribution of landslide occurrences in relation to precipitation (IMD, 2024) and regional landslide density in the Study Area (Combined LSI from GFLD & GLC).

The left map (A) depicts average annual precipitation contours (in cm), highlighting a concentration of landslides in areas with moderate to high precipitation (30–60 cm). The right map (B) categorizes regions based on landslide count, with darker shades indicating higher incidence (20–81 landslides), emphasizing southern and central areas as major landslide hotspots. Red triangles represent specific landslide locations. These maps show that the annual precipitation is not indicative of higher landslide counts. However, this may be explained by the features outlined in **Thesis Section 5.2.3 The GFLD and GLC LSIs and combined LSI at the study site**. Figure 5.10 from this section shows that the landslides are clustered around highways and urban areas, probably due to the nature of the landslide reporting by citizens and thus being reported when they are seeing the landslides when travelling in and around the area (Rohan et al., 2020). This means that the landslides in unoccupied areas are not being adequately represented, and so this would skew landslide counts. These discrepancies in citizen reported LSIs and satellite created LSIs have been studied before. Spatial uncertainties and reporting biases are common when using news and citizen-based reports (Rohan et al., 2020) and so this is likely what is happening within the study area due to the nature of the combined LSIs reporting.

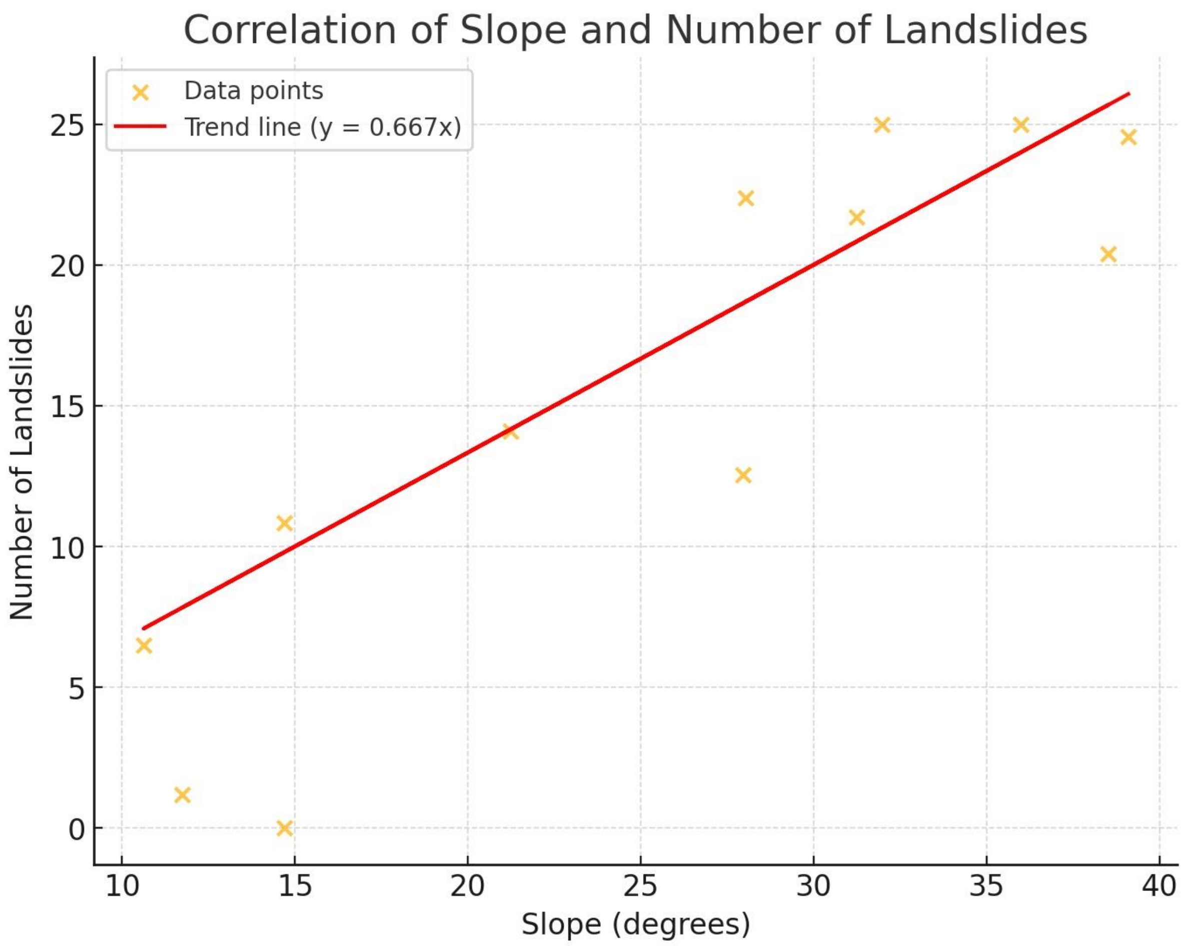


Figure 5.15: Relationship between slope steepness and the number of landslides in the northeastern Himalayan region of India.

The graph shows a clear link between slope steepness (angle) and landslide occurrence, reflecting the challenges of managing such risks in the mountainous terrain of Northeast India, particularly in the study area. As the slope increases from 10 to 40 degrees, the number of landslides rises moderately, with a maximum of 25 recorded. This aligns with the region's characteristics, where steep slopes, intense rainfall, and some seismic activity make it highly prone to landslides.

The trend highlights those steeper slopes, especially those above 30 degrees, are more vulnerable. However, the moderate correlation (0.667) suggests other factors, like soil type, vegetation cover, and human activity (e.g., deforestation or road construction), also play a significant role (McColl, 2022). A few outliers hint at localised impacts of such factors. **Thesis Section 5.2.3** looked at the location of the landslides recorded on the LSIs and found that there were areas associated exclusively around roads and infrastructure, and so this could be partially the reason why the correlation isn't much stronger. Salini & Rahul (2024) looked exclusively at road networks and landslide risk and vulnerability and highlights that infrastructure planners must develop design strategies and mitigation measures for road building in these mountainous areas due to the negative impact roads can have on slopes.

5.3 The Indian national landslide database

India's national landslide inventory is gathered by the Geological Survey of India and has been recorded from the 1900's to the present day. The dataset can be accessed through the Geological Survey of India's webpage and interactive service called Bhukosh.

It is a very comprehensive and informative dataset which contains lots of information about the landslide itself as well as the antecedent conditions present. Table 5.3 shows the information available in the national dataset.

Table 5.2: Information collected in Bhukosh Indian National Landslide Inventory. Initiation and Reactivation 1-3 have been highlighted to show references to temporal data collection.

Bhukosh Indian National Landslide Inventory	*Information Recorded*	
	Landslide specific	**Other**
	Slide Number	Longitude & Latitude
	Depth	Structure
	Geology	Abstract
	Length	Citation
	Width	Remarks
	Height	Alert
	LS_Area	State
	Triggering	District
	LS_Volume	Topo Sheet
	Slide Name	**Initiation**
	Activity	Photos

	Style	Report
	Runout Distance	NH_SH_Location
	Material Type	Persons Death
	Movement Type	People Affected
	Movement Rate	Livestock Affected
	Distribution	Communication Affected
	Failure Mechanism	Land use Affected
	Reactivation 1-3	Pre-Remedial Measures
	Geomorphology	Infrastructure Affected
	Hydrological Condition	Geoscientific Cause

The information recorded within the Bhukosh landslide inventory is ambitious and is a clear representation of what the Indian Geological Society would like to record within the dataset. In comparison with the Global Landslide datasets, it records significantly more information on the landslide and antecedent conditions. However, when downloading the data and viewing the data, it is apparent that the breadth of available data fields is generally not recorded for many of the landslide events.

For example, Initiation and Reactivation 1-3 is the only reference to a temporal dataset. This is important for using landslide inventories for model verification, as a clear date (and time if possible) is needed. When investigating what data is stored within these fields, initiation is usually in year format, or not recorded at all. In the Reactivation 1-3 data field, this is shown as a blank field within the study site, but again is shown as a year if the landslide had reactivated at some point.

Figure 5.12: The Bhukosh System screen (Bhukosh, 2024)

The Bhukosh system can be seen in Figures 5.12 And 5.13. These Figures show the web-based application at which the Indian National Landslide Dataset can be accessed and downloaded. Figure 5.13 shows the different 'toposheet' numbers each section of the study area sits on. To download the data the researcher needs to create a free account so that any data downloads can be sent to the email address that is registered on the account. This is a standard practice when offering earth data for free downloads and is the same for the GLC and GFLD.

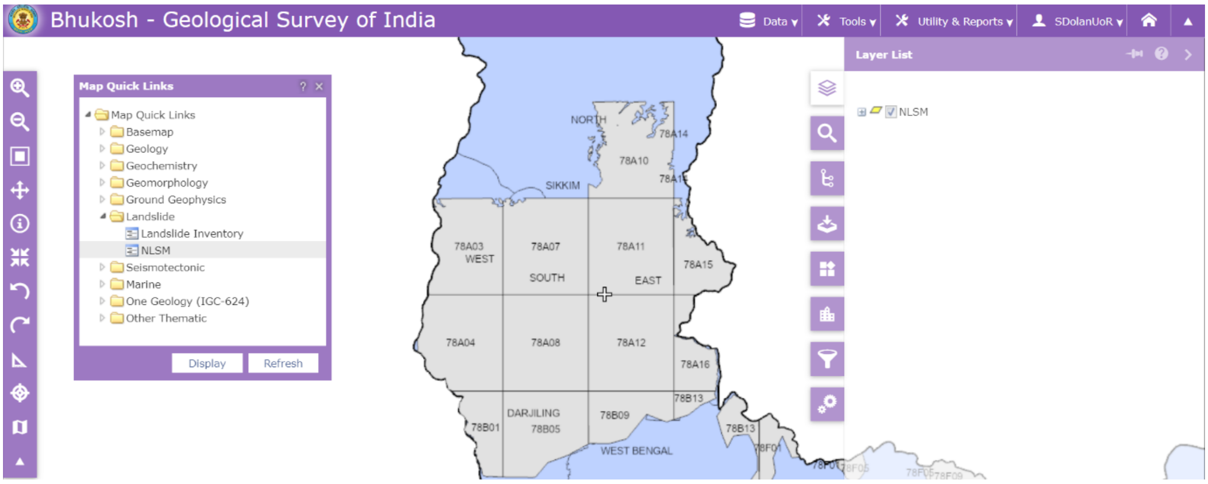


Figure 5.13: The toposheet numbers for the study site (Bhukosh, 2024).

The GSI's national LSI is shown in Figure 5.14. This Figure shows the sheer number of landslides experienced in this area. This is far more landslide counts then is recorded in the combined GLC and GFLD and has an even spatial coverage of landslides across the entire district.

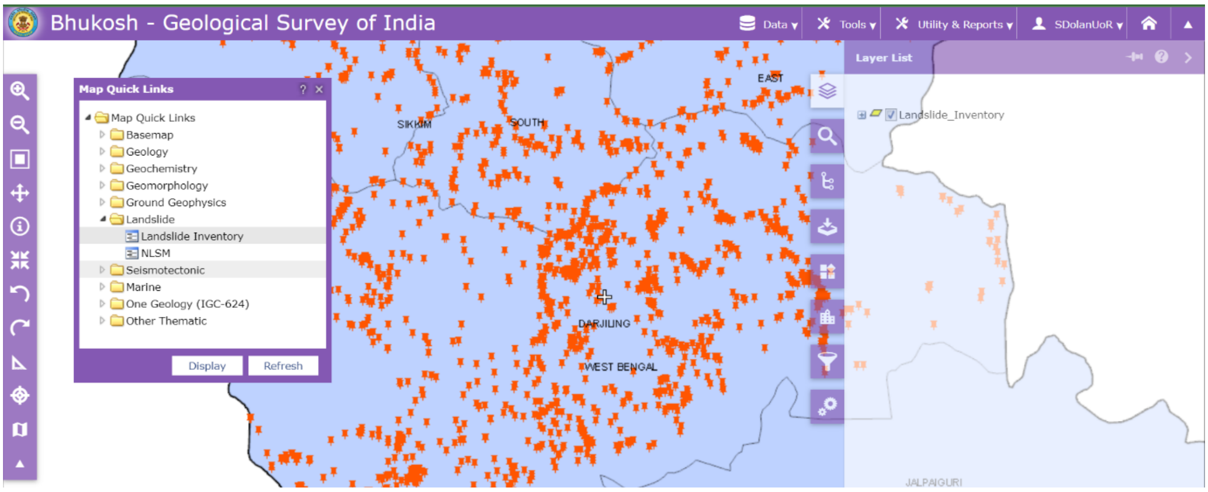
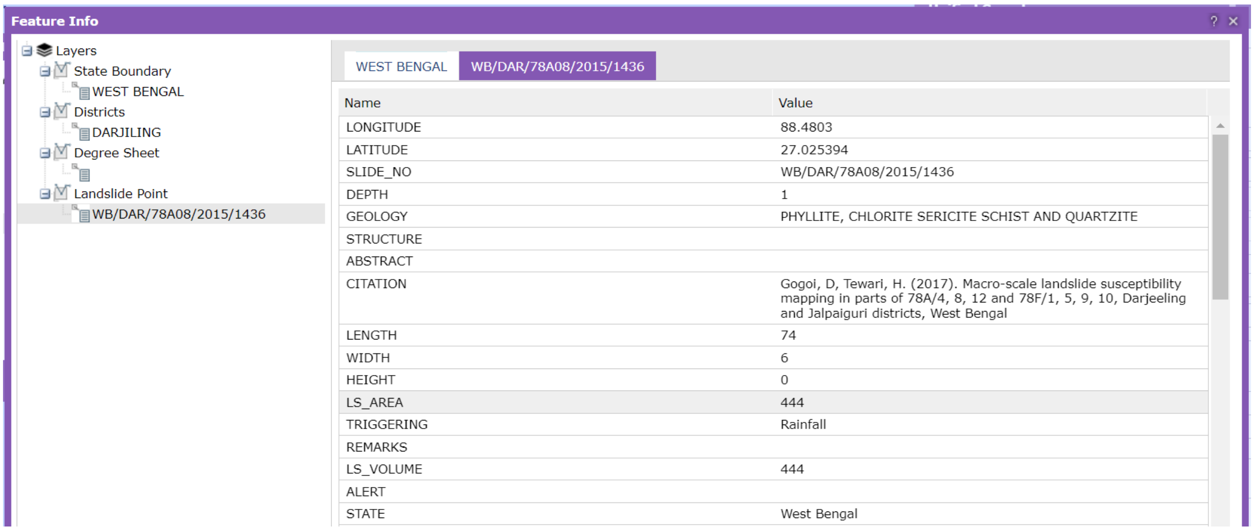
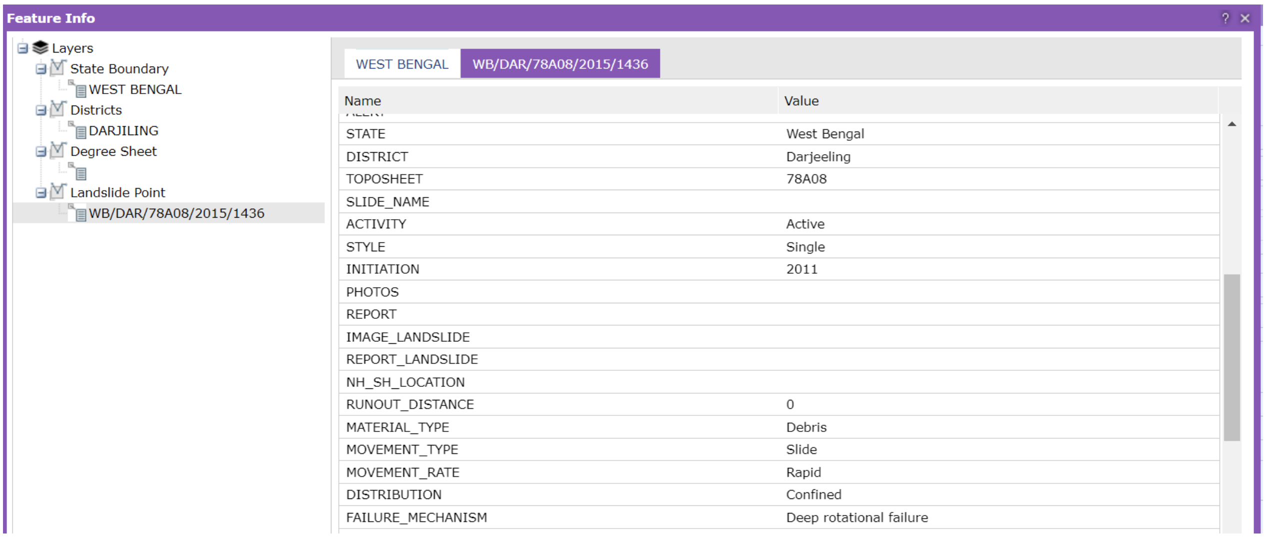


Figure 5.14: The landslide locations in the National LSI that are within the study area (Bhukosh, 2024).

Despite there being a larger number of landslides for the study area for this research, Figure 5.15 show the data available for most of the landslide points featured in the study site area. From these screenshots it is apparent that there is no usable temporal information for the validation of hourly or even daily models.





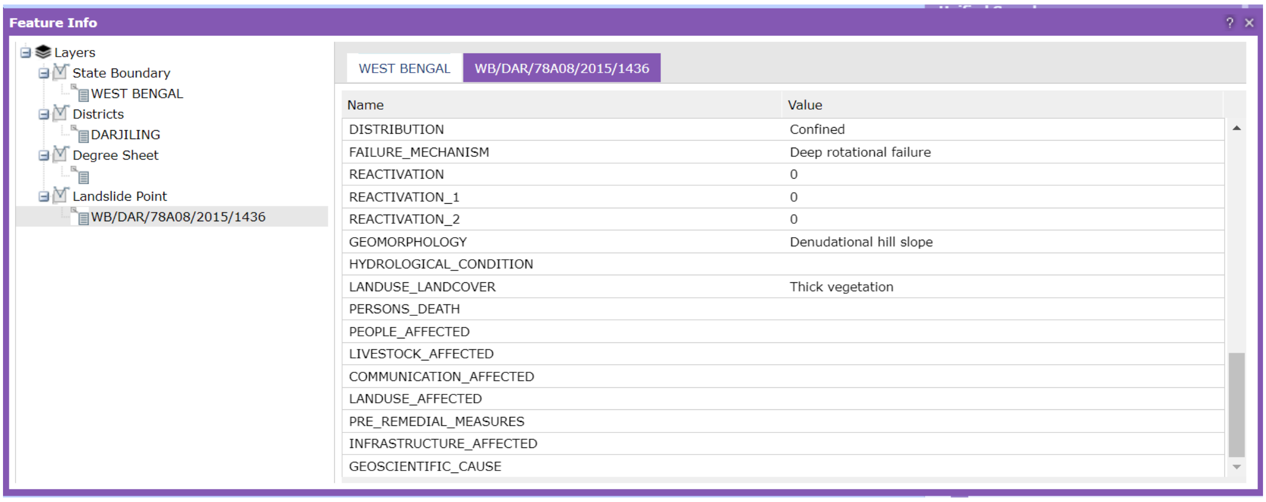


Figure 5.15: The Information within one of the landslides, this shows the depth of information the GSI want to achieve, but the blank spaces also show that this is often not covered in the landslides shown on the map (Bhukosh, 2024).

Not only is there not the information needed to use within the study that I would like to do in this study area, but the web application is clunky to use, and had strange limitations within it. For example, you cannot download more than 5 toposheet data points at one time (Figure 5.16). This is also coupled with the fact that the researcher cannot download across district or state borders – for example, the study area is over the boarder of West Bengal and South Sikkim without making multiple applications to the data portal. This in general makes the system hard to use and creates a longer more frustrating user experience.

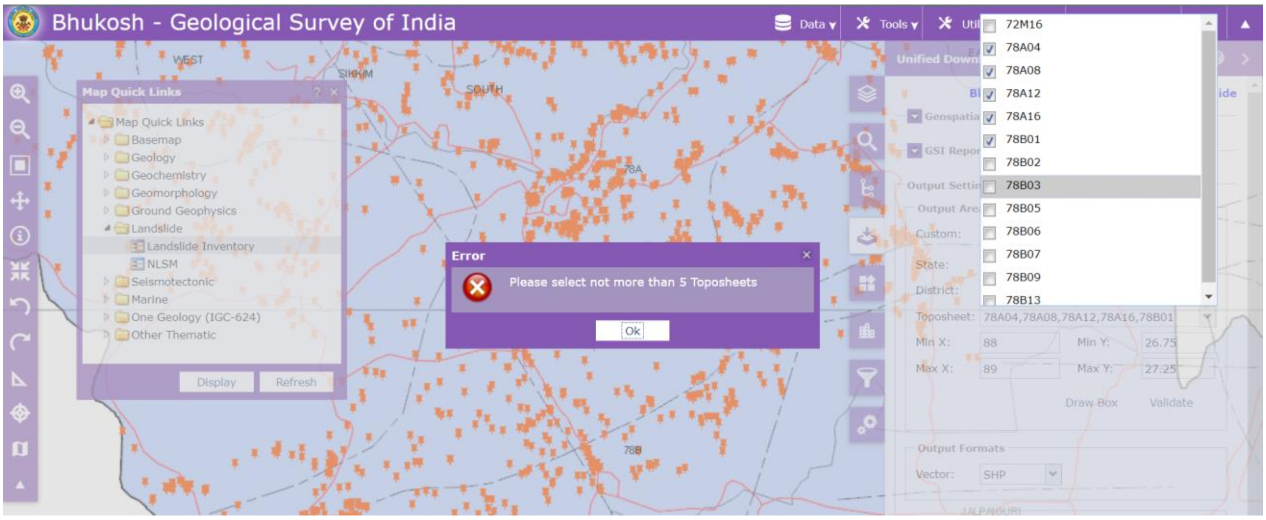


Figure 5.16: The toposheet download cannot exceed 5 sheets, and does not cover across state boundaries (Bhukosh, 2024).

Although the dataset is very comprehensive, it lacks the temporal information needed for different applications, such as model verification using historical events. In this case, the national landslide inventory is all but useless for my intentions for the dataset, which meant that I could not use it for my intended research in any case. However, there are other considerations to this question. The temporal shortcomings were not discovered until I had already started using the global datasets, the GLC and the GFLD I didn't consider the national dataset as my colleagues and peers drew my attention to the global datasets for use in my research. It was apparent that the research I was reading online from journals and blogs were using the many global landslide databases like the GLC or GFLD as discussed in **Thesis Section 5.1 Introduction**.

In reflection of my choices in the beginning of my research journey, I also held a belief that the national databases would be of lower quality or accuracy as the Global landslide databases. I believe that this was an unconscious bias on my part, fostered from a life sheltered in the UK - a society which still holds post-colonial and nationalistic values. This unconscious bias has been documented and researched in many subjects and is a well-established theory (Oberai & Anand, 2018).

5.3.1 Case Study Analysis of Indian LSI events

I have chosen three of the landslides in the Darjeeling/Kalimpong area that are points within but do not have any information contained within the Indian LSI. I have created detailed case studies for each, gleaning information from journals and news agencies.

Case Study 1: The 2018 Jurey Landslide in Darjeeling

Background

The Jurey landslide occurred in August 2018 after an extended period of monsoonal rainfall. Jurey, a small village in the Kalimpong district, has been historically prone to landslides due to its precarious geological conditions and heavy seasonal rainfall. The event caused widespread destruction and loss of life, bringing attention to the urgent need for improved landslide mitigation strategies in the region (SaveTheHills, 2018).

Meteorological Factors

The primary cause of the Jurey landslide was intense monsoonal rainfall. Over a span of 72 hours, the region experienced more than 350 mm of precipitation, which saturated the soil and elevated pore water pressure. These conditions weakened the slope's stability, leading to its eventual collapse (Bhattacharya et al., 2019). Antecedent rainfall over the preceding weeks had already left the soil in a vulnerable state, exacerbating the effects of the heavy downpour.

The rainfall was associated with a low-pressure system typical of the monsoon season, which brought prolonged and intense precipitation to the Eastern Himalayan region (Ghosh et al., 2020).

With climate change increasing the frequency and intensity of such extreme weather events, the risks of landslides in the Darjeeling region have grown significantly (Roy & Saha, 2019).

The Event

On August 14, 2018, a massive slope failure occurred in the Jurey area, resulting in a debris flow that buried multiple homes and agricultural fields. The landslide disrupted a main road connecting Kalimpong to other parts of the district, cutting off essential supplies and evacuation routes. The debris covered an area of approximately 3 square kilometres, displacing over 120 families and resulting in 18 fatalities (SaveTheHills, 2018).

The event also destroyed a significant portion of terraced farmland, which was a primary source of livelihood for the local population. Infrastructure damage included the collapse of roadways, bridges, and water supply systems, leaving the affected communities isolated for weeks (Ghosh et al., 2020).

Aftermath

The immediate response to the disaster involved rescue and relief operations by local authorities and the National Disaster Response Force (NDRF). However, ongoing rainfall and landslide debris hampered these efforts. Emergency shelters were set up for displaced families, and relief materials were distributed by both governmental and non-governmental organizations (Bhattacharya et al., 2019).

The disaster exposed significant gaps in the region's disaster preparedness and early warning systems. Although signs of slope instability were observed in the weeks leading up to the landslide, no evacuation orders were issued. This lack of proactive measures significantly increased the human and economic toll of the event (Roy & Saha, 2019).

Conclusion

The 2018 Jurey landslide underscores the interplay between extreme meteorological events and the region's fragile geologies. Addressing these challenges requires a comprehensive approach that includes advanced weather monitoring, sustainable land-use planning, and community engagement. By implementing these strategies, the Darjeeling region can mitigate the risks of future landslides and protect its vulnerable communities (Ghosh et al., 2020).

Case Study 2: The 2020 Kalimpong Landslide in Darjeeling

Background

The 2020 Kalimpong landslide occurred in July 2020. The landslide followed an extended period of heavy monsoonal rainfall, resulting in extensive destruction and loss of life. Kalimpong, situated in the eastern part of Darjeeling district, has long been recognized as a high-risk area for landslides due to its steep terrain, fragile geology, and intense seasonal rainfall patterns (SaveTheHills, 2020).

Meteorological Factors

The primary trigger for the 2020 Kalimpong landslide was a severe monsoonal downpour, with the region receiving over 400 mm of rainfall within three days. This excessive precipitation led to rapid saturation of the soil, significantly weakening the slope stability. Antecedent rainfall from the preceding weeks had already elevated the moisture content in the soil, creating conditions ripe for slope failure (Roy & Saha, 2019). The rainfall event was associated with a low-pressure system, which brought prolonged and intense precipitation across the Eastern Himalayas (Dolui & Chakraborty, 2023).

Extreme rainfall events like this have become increasingly common in the region, with climate change contributing to more frequent and intense monsoonal depressions. These changing weather patterns have heightened the vulnerability of already fragile slopes, making large-scale landslides an annual threat (Dolui & Chakraborty, 2023).

The Event

On July 12, 2020, a massive slope failure occurred near the village of Sangsey in Kalimpong. The landslide involved a rapid debris flow that engulfed several homes, agricultural fields, and portions of a main road connecting Kalimpong to other parts of the district. Reports indicate that the debris flow covered an area of approximately 2.5 square kilometres and displaced over 100 families (SaveTheHills, 2020). Tragically, the event resulted in 15 fatalities and numerous injuries. Infrastructure damage included the destruction of critical roadways and water supply systems, further isolating affected communities (McGowran, 2022).

Aftermath

The immediate aftermath of the landslide was marked by rescue operations conducted by local authorities and disaster response teams. However, access to the affected areas was severely hampered by ongoing rainfall and blocked roads. Emergency shelters were established for displaced families, and relief materials, including food and medical aid, were airlifted to remote locations (Singha & Sarkar, 2024).

The event highlighted deficiencies in early warning systems and the lack of real-time monitoring of high-risk slopes. Local residents reported minor slope movements in the weeks leading up to the landslide, but no formal evacuation orders were issued. This lack of preparedness exacerbated the human and economic toll of the disaster.

Conclusion

The 2020 Kalimpong landslide serves as a stark reminder of the interplay between extreme meteorological events and fragile geologies in the Darjeeling region. Addressing these challenges requires an integrated approach involving advanced weather monitoring, sustainable land-use planning, and community engagement to mitigate the risk of future disasters (McGowran, 2022).

Case Study 3: The 2017 Tingling Landslide in Darjeeling

Background

Tingling, located near the Kurseong subdivision, is known for its vulnerability to landslides due to steep terrain and fragile geology. This landslide occurred in July 2017 after heavy monsoon rains and resulted in considerable destruction to life and property, emphasizing the need for effective landslide mitigation measures (SaveTheHills, 2017).

Meteorological Factors

The primary cause of the Tingling landslide was prolonged and heavy rainfall. Over 250 mm of rain was recorded within 48 hours, leading to saturated soils and increased pore water pressure. This rapid saturation weakened the soil's cohesion, triggering slope failure (Ghosh et al., 2018). Antecedent rainfall during the preceding weeks had already left the slopes highly unsTable, creating conditions ripe for a disaster (Das et al., 2019)

The heavy rains were attributed to a low-pressure system moving across the Bay of Bengal, a common meteorological phenomenon during the monsoon season. This system brought consistent and intense precipitation across the Darjeeling hills, which are particularly susceptible to landslides due to their steep gradients and weathered rocks (Bhattacharya et al., 2018).

The Event

On July 13, 2017, the Tingling landslide occurred, causing widespread destruction. The debris flow swept through the Tingling tea garden, burying several workers' quarters and farmland. Approximately 20 families were displaced, and 12 fatalities were reported (SaveTheHills, 2017). Infrastructure damage included the destruction of roads and bridges, cutting off access to the affected area for several days.

The debris covered an area of nearly 2 square kilometres, and significant economic losses were incurred due to the destruction of tea plantations, which are a vital source of livelihood for the local population. The landslide also disrupted water supply systems, further complicating the recovery process (Das et al., 2019).

Aftermath

The response to the disaster involved coordinated efforts by local authorities, the National Disaster Response Force (NDRF), and community volunteers. However, ongoing rains and blocked roads delayed rescue operations. Emergency relief shelters were established, and food and medical aid were provided to displaced families (Bhattacharya et al., 2018).

The Tingling landslide exposed critical gaps in early warning systems and preparedness. While signs of slope instability had been noted, including small cracks and minor landslips in the weeks prior, no evacuation orders were issued. This oversight underscored the need for better predictive tools and community education regarding landslide risks (Ghosh et al., 2018).

Conclusion

The 2017 Tingling landslide underscored the vulnerability of the Darjeeling hills to extreme rainfall and highlighted the need for improved mitigation strategies. Addressing these challenges requires a multidisciplinary approach that integrates advanced technology, community engagement, and sustainable land-use planning to reduce the risk of future disasters (Das et al., 2019).

Lessons Learned from the Case Studies

1. Improved Weather Forecasting: The event highlighted the need for advanced weather monitoring systems capable of providing timely and localized rainfall predictions (Ghosh et al., 2020).
2. Slope Stabilization Measures: Engineering solutions, such as retaining walls and improved drainage systems, are critical for preventing landslides in high-risk areas (Bhattacharya et al., 2019).
3. Community Awareness and Engagement: Educating local communities about the signs of slope instability and evacuation protocols can reduce casualties (SaveTheHills, 2018).
4. Climate Adaptation Strategies: Long-term measures to address the increasing intensity of monsoonal rainfall due to climate change are essential for enhancing resilience in the region (Roy & Saha, 2019).

5.4 Choosing the LSI for my site – Discussion & Future Considerations

When considering the research above and the research question 'What global and national landslide inventories are available for researchers when researching Darjeeling, India' there are many things to consider when evaluating current practice and the use of global LSIs and if the current practice and current global LSIs can be used for scientific enquiry and in particular equiTable scientific enquiry. We can first look at the tools that are being used by researchers and evaluate if there is sufficient data within the global LSIs that are being used. Then we can discuss why these global LSIs are being used over the national inventory, and then we can encourage a best practice for collecting and storing LSIs. Finally, we can discuss what would be the 'ideal practice' when moving the needle in DRR landslide science towards a more equiTable and usable global LSI.

5.4.1 Insufficient Comprehensive Data.

From the data analysed in **section 5.2.2** it is proven that combining both datasets make for a more spatially and temporally diverse and covered database. Figure 5.10 and the subsequent maps processed how this combination would affect the study area's landslide counts and locations. In Table 5.1, it shows that the GLC has 111 counts of landslides within the study area and the GLFD has 71 landslide event counts. Combined this makes 178 landslide counts for the study area. Although this appears to be a method of increasing the coverage spatially and temporally for the global LSI's, the consideration of the number of landslides reported means that this number is unfortunately still far too low for use in landslide studies for the area. This number of landslides is a very low number of events, and if we were to create an average over the years that the datasets span, then this would be only 14 landslides a year, a very small amount compared with the actual number of landslides reported using landslide inventories that are created in the field using observations or when creating an inventory through satellite imagery (Berti et al., 2012; Dikshit et al., 2019). **See Thesis Section 6.3.3 Research Chapter II: Data Limitations** for more information.

The nature of the reporting of landslides for both the GFLD and the GLC means that the clusters of landslides we see spatially (Figure 5.10) are based on where landslides are more likely to be reported in the news, through its impact to communities, rather than the landslides that are occurring away from towns and roads. This specifically skews the data towards an interaction with society-based LSI rather than a more comprehensive dataset that is representative of the landslides within the study area.

5.4.2 Best practice for the collection of and storing landslide inventories.

When considering the current practice, it is obvious that there are improvements that can be made regarding how the global LSIs can be created, collected, stored, and distributed. At the current level, the global LSIs on offer are just not good enough.

There are several improvements that could be made. The first would be using other methods to collect landslide events. This could be through continual monitoring of satellite imagery to collect location data and approximate timing (Novellino et al., 2024), to automated data collection methods (e.g. accelerometers) placed in the field (Njafabadi et al., 2024). Pairing these events with additional data taken from other datasets, such as meteorological (rainfall), environmental (land use) and geological (soil type) datasets could add a plethora of additional data to the identified landslide events.

Even if the mode of reporting was the same – through direct landslide reporting by the communities, or using news reports to collate a database, there can be alternative improvements made. An effort to make the reporting easier to do. This could be done with a wide range of methods. For example, creating and developing an application for mobiles where the input of the citizen can be regulated and made easier to accomplish would allow LSIs to have information that is desirable, and have more incidences recorded. For example, Rohan et al. (2020) investigated a dedicated phoneline and mobile service for this type of reporting. Engaging community groups is another way in which citizens can be utilised to create LSIs in this way, and with additional training the community groups would be able to provide high quality and relevant information for the landslides to be used in research. Training in the community in general would promote awareness in the community of the importance of LSIs in not only the research, but in ways that would impact the community directly if used in tools like the one proposed in **Thesis Section 6.0 Research Chapter II.** The role of community networks in preparing and responding to landslides has been investigated in the Alps, with positive outcomes (Pedoth et al., 2023).

There are many different studies that are creating landslide inventories through intensive and resource consuming ways such as field studies, sampling, and the use of Unmanned Aerial Vehicles (UAV) or drones when creating landslide inventories (Rossi et al., 2018). If there was a better protocol to share and distribute these datasets to the wider use in global LSIs rather than the gatekeeping of data, or the idea of 'ownership' of data then collaborative global LSIs could be far more usable and represent the actual spatial and temporal coverage of study areas like my own. Collaboration and data sharing would also extend to sharing 'best practice' and lead to standardisation of the collection and storage of these global LSIs in a way that would impact the accessibility and quality of the data that is available to researchers.

5.4.3 Which inventory is best for Darjeeling District, India?

While the research suggests that using a combined landslide inventory from the global LSIs and disaster databases that are available increases spatial and temporal coverage of landslide events globally, for specific local areas the results are less ideal, and show some biases in location and timing. Using a combined dataset is the most suiTable 'current practice' and is a method that is being used by landslide researchers today, however this global LSI method is not suiTable for specific applications in the Darjeeling District, India. In Figure 5.1 it is apparent that the GLC, which has the most landslide events recorded within it, has many more landslides recorded in the United States and South America. This means that potentially the application of using global LSIs combined could work for local application in other areas of the world, and specifically with the United States. Dandridge et al. (2023) also identified that the US would be the best place for using global LSIs as there is a reporting bias for English speaking countries with high GDP. Something to consider for future research would be to analyse the combination of these global LSIs and disaster datasets in different local locations to compare spatial and temporal coverage and differences in community reporting biases.

This focus on the United States from the GLC is a bias that needs to be considered by the landslide researcher. Additionally, the focus on Nepal from the GFLD is also something to consider. The GLC has a focus on the US as it is produced by NASA, a US funded national institution (Kirchbaum et al., 2019). The GFLD is created by two researchers, who have long research ties to Nepal (Froude & Petley, 2018). The global LSIs that are being used here are being influenced by geo-politics, but also from the intentions of the individuals that are collecting the information and setting up the LSIs in general. Social checks on the how and why datasets are created and being used needs to be part of a landslide researchers toolkit, and this type of dataset checks can be encouraged for early career researchers through adequate additional training either through university courses, PhD skills training or through workplace training courses. The Equality and Human Rights Commission advocates these types of training as they're seen to be effective when training is provided for employees in business (EHRC, 2018).

When considering the future of landslide inventories there is a strong case for creating a universal standard for collecting and storing landslide events, despite the organisations, institutions or national establishment that collects the information. McColl & Cook (2024) have already began looking into a universal size classification system for landslides due to inconsistency within literature. Not only could there be a best practice implemented for the collection and storage of landslide information in LSIs globally and nationally, but there also seems to be the need for creating a best practice for researchers in the earth sciences or the disaster risk reduction sciences to create some form of 'social check' on their decisions surrounding data selection and use. These considerations are also discussed in **Thesis section 7.2 Discussion and Future Considerations: Research Chapter I.**

5.5 Future Considerations

While databases like the Global Fatal Landslide Database (Froude & Petley, 2018) and NASA's Global Landslide Catalogue (Kirschbaum et al., 2015) provide invaluable global-scale insights into landslide occurrences and trends, conducting a manual landslide inventory offers critical advantages for localized prediction efforts. These global datasets are inherently limited by their coarse resolution and broad focus, often prioritizing fatal or large-scale events while neglecting smaller, non-fatal, yet significant landslides that contribute to regional susceptibility patterns.

For example, the Global Fatal Landslide Database focuses on landslides with reported fatalities, omitting many non-fatal but frequent events that may provide important clues about susceptibility factors (Froude & Petley, 2018). Similarly, NASA's Global Landslide Catalogue relies on satellite-derived data and media reports, which may miss smaller or vegetated landslides and lack site-specific characteristics like slope gradient, soil type, or drainage conditions (Kirschbaum et al., 2015).

By complementing these global datasets with a detailed manual inventory, researchers can address these gaps, ensuring local topography, geology, and anthropogenic influences are accurately represented. This integration enhances the predictive capacity of landslide models and aids in the design of targeted mitigation strategies, particularly in high-risk regions like the Himalayas (Guzzetti et al., 2012).

5.6 Conclusion

The global LSIs that are available for researchers are separate entities that have different objectives and agendas which mean that the spatial and temporal coverage of databases and inventories can have gaps. Using different LSIs in combination with each other can create a larger dataset that has a more spatial and temporal coverage for study areas of interest for researchers. For example, in the study area specified in this research chapter the increase spatial and temporal coverage of landslide inventories has been apparent, however inadequate.

There is also a consideration for physical science researchers in respect to the choices made when deciding on which datasets to use. The researcher needs to understand what details they need from the LSI to be able to conduct their research. After this, the researcher needs to consider all available datasets, from international and national organisations. After the choice is made by the researcher there needs to be another 'social check' on why they have chosen to use the LSI they chose.

Overall, the current practices of using global LSIs in research when researchers do not have the time or resources to conduct more intensive site investigations and produce their own local LSIs fall short of producing something that fully represents the local areas. This means that a wider application of using a free, available dataset for the globe that can be used in conjunction with other freely available datasets for application in tools for prediction (as in **Thesis Section 6.0 Research Chapter II**) is much harder to create due to the lack of events in a micro spatial scale.

Chapter 6: Research Chapter II ‘Application’

Utilizing ERA5 Climate Reanalysis Data for Landslide Prediction in Darjeeling, India: A Statistical Approach

6.1 Introduction

The research question for this chapter is;

- Can precipitation triggered landslides in Darjeeling, India be predicted with the global scale reanalysis precipitation dataset ERA5, and established Intensity Duration Thresholds?

This research question explores a gap in the literature which is explored in **Thesis Section 2.6 Literature Review.** This research gap can be condensed into a singular sentence. Using precipitation Intensity Duration thresholds for landslides in conjunction with ECMWF’s reanalysis dataset ERA5 has never been investigated before, and landslide prediction has never been researched in the Northeastern Indian Himalayas. This research is needed to fill the gap as encouraging the use of freely available global datasets in areas that are data sparse or technologically unadapt could change the risk that landslides have to the population living in this area and advance the science and understanding of the technologies for others in similar areas. To do this, this chapter will use the combined landslide inventory (See **Thesis Section 5.0 Research Chapter I**). The implications of using these two very different LSIs have been critically discussed in **4.3.2 Landslide Database Critical Reflections.** As I am using a combination of both an occurrence LSI and a Fatal LSI, the main objective of this research is investigating the predictability of landslide risk to the population. This combined LSI begins the process of verifying historical landslide events with established ID thresholds and the historical ERA5 reanalysis datasets. To verify these events, I will be using ROC curve analysis to assign hits and misses to the events based on the ERA5. Before I do this, I will need to do a sensitivity analysis on the ERA5 Total Precipitation dataset due to the known limitation of the ERA5 ‘Drizzle Effect’ (See **Thesis Section 2.2.3.2 Drizzle Effect**) as to complete this verification I need established ‘dry days’ during the Indian Monsoon season, rather than the constant wetness that ERA5 projects. The ROC analysis will hopefully give a statistical significance to using ERA5 total precipitation in conjunction with the ID thresholds to successfully predict the historical landslide events in the combined landslide inventory, and thus be able to be used in the future, after additional studies, to be used for additional information and warning in this area.

Landslides in the Darjeeling and Sikkim Himalayas are a major concern for the mountain region as they are the most vulnerable areas to landslides primarily due to their geological and geomorphological characteristics. The Darjeeling and Sikkim Himalayas are 40% of India's landslide prone areas (Dikshit & Satyam, 2017). Heavy rainfall and seismic activity are the main natural triggers for landslides in the area (Biswas & Pal, 2016). These landslides affect key infrastructure in the area, such as transportation links, energy supplies and agriculture (Dikshit et al., 2020). Fatal landslides in the Indian Himalayas triggered by precipitation accounted for 14.52% of global fatal landslides between 2006 and 2017 (Froude & Petley, 2018), with the potential for this number to rise when considering other global landslide databases (Froude and Petley, 2018) (Dikshit et al., 2020).

6.2 Site Information

The study site is between 27.4°N and 26.8°S latitude and longitude between 88.0°E and 88.8°W. It is in the Darjeeling District of the Indian Himalayas and comprises of the towns Darjeeling and Kalimpong. The northern boundary reaches the Southern Sikkim cities of Singtam and Namchi, while the southern boundary reaches the town of Kurseong, still within the district of Darjeeling. The Highest elevation in the site area is Tiger Hill, a mountain South of Darjeeling which as an elevation of 2590m. The study area spans over an area ~1730km^2. This site area can be seen in **Thesis Section 3.2 Study Area Figure 3.7**.

The hydrological significance of this study area is that the rainfall has a seasonal monsoon pattern. This means that the study area is subject to heavy rainfall. The beginning and end of the season changes from year to year, although the scientific community uses June – September as the monsoon period for ease of research (Recchia, Griffiths & Douglas 2021; Kulkarni & Koteswara Rao, 2023). Climate change is making monsoons experience more rainfall and have more erratic and volatile events (Maharana, Agnihortri & Dimri, 2021; Sandeep & Kumari, 2023).

This research chapter focusses on the landslides triggered by rainfall alone, as there is evidence that the study area experiences most landslides that have been triggered in this way (Basu and De, 2024) (BGS, 2025). Knowing what the area's major trigger of landslides is will help when designing early warning systems for landslides in this area.

There are other things to consider when thinking about landslides in an environment. For example, the underlying geology. The geology of Darjeeling (featured in **Thesis Section 3.2 Study Area**) and the surrounding areas is very complex, due to its geological history of the broader tectonic formation of the Himalayas and subsequent evolution over millions of years. A detailed view of the geological significance of the area is in **Thesis Section 3.0 The Study Area.** The geological environment of the

Darjeeling and Sikkim Himalayas does affect landslide occurrence. Geological factors affecting landslides include the regional geology and rock type and the structure of bedrocks, for example, faults and rock foliations (Rawat et al., 2015). This geological environment does control certain aspects of hydrology, for example the way in which the underlying geology controls landscape and landforms e.g. topography which would affect the physical catchment characteristics. The geological environment and subsequent landslide occurrence are also affected by the hydrological action of river basins, and the Tista Basin is one of the largest in the Darjeeling Himalayas, with approximately five sub-basins situated in the Kalimpong region alone (Dikshit & Satyam, 2017), and is highly vulnerable to landslides. Land use, agricultural practices and expansion of highways and anthropogenic engineering also interacts with landslides in this area. These things can increase the likelihood of landslides through different mechanisms such as undercutting at the toe of landslides, deforestation on slopes and heavy machinery vibrations (Highland et al., 2008) (Rohan et al., 2020). This is detailed within **Thesis Section 3.0 The Study Area.**

Despite there being other triggers and considerations, this chapter will solely be focusing on rainfall and its triggering effect on landslides in the study area.

6.3 Data Used

The full extended information for the data used in this research chapter can be seen in **Thesis Section 2.6 Literature Review and Thesis Section 4.5 Data and Methods.**

6.3.1 ERA5 climate reanalysis data for the Darjeeling region

ERA5 is the fifth generation of atmospheric reanalysis of the global climate system by the European Centre for Medium-range Weather Forecasts (ECMWF). Reanalysis is a method of reconstructing past weather and climate datasets by combining specific global models and observations. ERA5 produces datasets for a vast number of atmospheric, land and oceanic climate variables covering dates from the 1950’s to the present day. ERA5 is a significant improvement from the ERA-Interim dataset that was used previously; improving in resolution, accuracy and the range of parameters involved (Dee et al., 2011; Hersbach et al., 2020).

The spatial resolution of ERA5 is 31km, while ERA-Interim was 79km. This is better for representing the regional and small-scale weather features (Hersbach et al., 2020). ERA5 also includes a better representation of the atmospheric column and incorporates recent and more advanced observation techniques including satellite observations, which were not used in the earlier reanalysis products from ECMWF. A more accurate and comprehensive representation of the past state of the Earth’s climate system is created by ECMWF’s Integrated Forecast System (IFS) and this allows for an assimilation of a large array of observational data in a dynamically consistent manner (Hersbach et al., 2020). This project uses ERA5 Total Precipitation (m) (ECMWF, 2024). This dataset is used for understanding past precipitation patterns, validating hydrological models and has applications in water management and agriculture (Grassman et al., 2007; Beven, 2011). ERA5 has been evaluated to be quite good in general (Tarek, Brissette & Arsenault, 2020; Arshad et al., 2021). Precipitation reanalysis products are also used for precipitation estimates in ungauged or data-sparse areas, such as my study area (Becker et al., 2020; Jiang et al., 2021).

ERA5 has also been evaluated to be quite good at high extremes, which is an important consideration when looking at rainfall triggered landslides, as the landslide events are usually triggered from storm events (Gariano & Guzzetti, 2016; Marc et al., 2019). ERA5 total precipitation dataset has some reliable performance predicting extremes in precipitation which also helps when looking at climate change and increased hazard analysis in data sparse areas (Hu & Frankie, 2020). ERA5 does have some limitations, for example the assimilation of satellite-derived precipitation estimates can introduce uncertainties, especially in regions with data scarcity (Hersbach et al., 2020).

You can find out more information through a full description of ECMWF's ERA5 reanalysis system which can be seen in **Thesis Section 2.2 Precipitation Modelling Science.**

6.3.2 Historical landslide event records – combined landslide inventory.

The historical landslide events that will be used in this study will be taken from the combined landslide inventory that was created in **Thesis Section 5.0 Research Chapter I.** The combined inventory combines the NASA Global Landslide Catalogue (GLC) and the Global Fatal Landslide Database (GFLD) from the University of Durham. More information on these landslide inventories and how they were combined can be found in **Thesis Section 5.0 Research Chapter I.**

6.3.3 Data Limitations

There are some data limitations that need to be discussed before their use in both the precipitation dataset and the landslide datasets.

Taking the landslide datasets into consideration first, in **Thesis Section 5.0 Research Chapter I** we have seen that the Geological Survey of India has their own national landslide inventory which contains hundreds of landslides not identified within the landslide inventories this study is using (GSI, 2024). However, to effectively analyse the datasets for statistical analysis through the use of the intensity duration graphs and ROC curve analysis (**Thesis Section 4.5.2.5 Relative Operating Curves**), the specific date and time is essential. The national landslide inventory does not include these dates within its database; however, this information is recorded in the GLC and the GFLD. The landslide databases also do not contain temporally long data. For example, the GLC is from 2007-2019 while the GFLD is from 2005-2017. This research will be inclusive of both datasets, and so the date range will be between 2007-2017. This does limit the study, as only having a small number of years means that the method cannot be tested over a longer temporal period..

However, there may not be enough landslide events for assessing the skill of the ID threshold and ERA5 dataset together to assess the prediction tool. Guzzetti et al. (2008) used over 700 landslides to define and validate their ID thresholds for central Europe. Within regional studies a LSI of 9000 landslides were used for developing preliminary ID thresholds in Italy (Berti et al., 2012). A localised study on a singular road in Bhutan used 248 landslides in an ID study (Dikshit et al., 2019). This means that current literature seems to use landslides in their hundreds and thousands to calibrate and assess their ID thresholds, and so there may not be enough for this type of study. Information taken from **Thesis Section 5.0 Research Chapter I** shows both landslide datasets have a combined total of 131 landlsides within the site area itself. The event counts of the overall landslide events can be seen in Table 6.1.

Table 6.1: Landslide event counts for both datasets, also showing the matched values removed in a combined event count.

	GLC (Kirchbaum et al., 2017)	GFLD (Froude and Petley, 2018)	Combined Counts (minus matched events)
Global	11033	5536	14195
India	1265	992	1678
Study Area	111	71	131

The ERA5 Total Precipitation Reanalysis dataset also has its limitations. The 31km resolution of the reanalysis means that it is very difficult to specifically look at slopes, specific landslides and geologically significant areas. This means there is an assumption made that the whole grid square is experiencing the same precipitation. The coarse nature of ERA5 reanalysis also brings up another limitation, when researching its use with ID thresholds (**Thesis Section 4.5.2.3 Intensity Duration Thresholds)**, which is the 'drizzle effect'. Although reanalysis datasets like ERA5 are known to perform better than satellite datasets like the GPM and TRMM in many areas of the world (Beck et al., 2019) this study also showed that in complex topography satellite precipitation may perform better than the ERA5 due to satellite precipitation being a higher spatial resolution compared to the ERA5. However, ERA5 has been showed to be reliable at capturing extreme rainfall events in some areas of the world (Gao et al., 2020; Hersbach et al., 2020; Zhu et al., 2021), and this is important with rainfall triggered landslides and the mechanism of failure.

Drizzle Effect -ERA5

The limitation in using ERA5 with ID thresholds is the ‘Drizzle Effect’. This is a known limitation in that it struggles to resolve the difference between dry days and days with low precipitation leading to a continuous ‘drizzle effect’ (Hersbach et al., 2020; Pappenberger, 2024). This can skew statistical analysis of precipitation. To correct for this difficulty a threshold can be applied to the data, setting any precipitation values under the threshold to zero. For example, a threshold of 1mm will mean that any values of precipitation in ERA5 under 1mm will be set to zero.

In this study this means that, without correction, the ERA5 precipitation for the monsoon over the site area has no ‘dry days’ between June and September. This means it is difficult to create an event duration of the precipitation before each landslide, as this is usually taken from the first instance of continuous rainfall until the landslide event itself. This suggests that a threshold correction of the drizzle effect is required.

However, there is no evidence currently of whether the 1mm threshold is appropriate in different geographical locations and rainfall situations. For example, the 1mm threshold is used globally, in areas as diverse as the Gobi Desert to the Amazonian Rainforest (Beck et al., 2019; Hersbach et al., 2020; Pappenburger, 2024). Therefore, to create ‘dry days’ that take into consideration the hydrological and seasonal conditions of the monsoon, a sensitivity analysis has been undertaken. This analysis considers the conventional 1mm threshold that ECMWF places to combat this drizzle effect, as well as a greater 5mm and 10mm threshold and a 25th percentile threshold. These larger thresholds are considered as the site area is within the sub-tropical monsoon climate, and so the amount of rainfall is extreme in this area and so the generic worldwide drizzle effect threshold of 1mm might be too small still for gaining much ‘dry day’ activity in the study area.

6.3.4 ERA5 Usability Explanation

ERA5 is increasingly being utilized in the prediction of future landslide events due to its high-resolution, globally consistent, and long-term climate data, which are essential for understanding the atmospheric conditions that contribute to landslides. Landslides are complex natural disasters triggered by multiple factors, including intense rainfall, soil saturation, and steep terrain. The relationship between weather patterns and landslides is well-documented, with studies showing that heavy rainfall, rapid soil moisture increase, and seismic activity are often critical triggers (Mao et al., 2020; Guzzetti et al., 2008; Corominas et al., 2014). ERA5 offers a comprehensive reanalysis of atmospheric conditions, providing hourly data on key variables such as precipitation, temperature, wind, and humidity, spanning from 1950 to the present. This makes it an invaluable resource for understanding how weather and climate influence landslide events over time.

By analysing historical ERA5 data, researchers can model the environmental conditions that preceded past landslides. For example, heavy rainfall events and rapid increases in soil moisture are frequently associated with landslides, especially in regions with steep slopes and loose soil. ERA5's high spatial and temporal resolution allows for the detailed modelling of these events on a local or regional scale, which is essential for understanding landslide dynamics in specific areas. Several studies have demonstrated that heavy rainfall and prolonged wet periods are key indicators of landslide occurrence (Fell et al., 2017; Guzzetti et al., 2008). ERA5 enables researchers to assess how often these weather patterns occur and their correlation with landslide events.

Using historical data, like that from ERA5, is an important first step in predicting future landslides. By studying the conditions that caused landslides in the past, scientists can understand what kinds of weather patterns are most likely to trigger them. This helps them create models to forecast similar conditions in the future. For example, if a certain amount of rainfall in a specific region triggered landslides before, ERA5 data can help predict if similar weather is likely to happen again. These predictions are important because they allow scientists and emergency services to be prepared in advance, reducing the risk of damage and saving lives. So, even though ERA5 doesn't directly predict the future, it gives scientists the tools to understand patterns and improve future predictions of landslides. For example, Botto et al (2025) used ERA-5 LAND reanalysis data to evaluate the performance of the Italian regional shallow landslide early warning system in Piemonte in Northwest Italy when looking at predicting changes in landslides due to climate change in the future.

ERA5 has also been widely used to validate predictions for other natural disasters, such as flooding. For example, ERA5 data has been used to compare past flood events with rainfall predictions, helping to assess the accuracy of flood models (Zhou et al., 2020). Similarly, ERA5 has improved the accuracy of cyclone predictions by validating the intensity and paths of past storms (Cameron et al., 2020). These applications demonstrate how historical reanalysis products like ERA5 are essential for validating predictive models. By comparing the actual outcomes of past events with model forecasts, researchers can refine their predictive tools, ensuring more accurate future predictions for landslides and other weather-related hazards.

6.4 Methods

The detailed methodology can be seen in **Thesis Section 4.5 Data and Methods.** Within that section the computer packages used, example coding and more can be seen. I will briefly mention the types of products and methods I am using below as a recap, in particular ID thresholds and ROC curves as this will be the focus of this research chapter.

6.4.1 Intensity Duration (ID) thresholds for landslides triggered by precipitation.

Intensity Duration thresholds are a tool which are used exclusively for landslides that are triggered by rainfall. An ID threshold is a threshold that is created from the relationship between precipitation intensity (I) and its duration (D), providing a threshold of conditions that if breached are likely to initiate landslide events (Guzzeti et al., 2008; Biswakarma & Joshi, 2023).

ID thresholds are important as they try to establish a quantitative relationship between the intensity of rainfall (how much rain in a given period) and its duration (how long the rainfall event lasts). This relationship can not only identify the specific conditions at which landslides are initiated but has applications in LEWS for predicting landslide events, risk management strategies around land use planning and disaster preparedness.

6.4.2 Why ID thresholds for this site?

Intensity-duration (I-D) thresholds are critical for understanding and predicting landslide occurrence, particularly in the landslide-prone regions of Northeast India. This region, characterized by steep slopes, high rainfall, and fragile geological formations, experiences frequent landslides that threaten lives, infrastructure, and ecosystems. Establishing I-D thresholds is an effective approach to mitigate these risks.

I-D thresholds correlate rainfall intensity and duration to the likelihood of landslide events, enabling the identification of critical conditions that trigger slope failures. Real-life applications of these thresholds have proven their utility in disaster risk reduction. For example, Caine's (1980) global thresholds have been adapted regionally, such as in Italy (Guzzetti et al., 2007) and Hong Kong (Jibson, 2005), showing their scalability and effectiveness. In the Indian context, Jain et al. (2022) successfully implemented localized I-D thresholds to predict landslides during monsoons in the Darjeeling Himalayas, a region with similar geomorphic and climatic conditions as Northeast India.

The use of I-D thresholds provides early warning systems with actionable data, enhancing preparedness and response strategies. For instance, the real-time monitoring of rainfall and landslide prediction in Japan (Osanai et al., 2010) highlights the potential for reducing casualties and property damage. In Northeast India, where traditional warning systems are scarce, this approach could bridge critical gaps in disaster management.

I-D thresholds integrate seamlessly with GIS and remote sensing technologies, enabling spatial mapping of high-risk zones. This is particularly relevant for Northeast India, where dense forests and remote terrains complicate ground-based assessments.

Overall, implementing I-D thresholds in Northeast India aligns with global best practices and leverages proven methodologies to address regional challenges. Their adoption promises significant advancements in landslide risk mitigation and resilience building.

The selection of intensity-duration (I-D) thresholds for landslide prediction offers distinct advantages over alternative tools, particularly in the context of Northeast India. These advantages stem from their simplicity, real-time applicability, and proven effectiveness in diverse geological and climatic settings.

1. Simplicity and Accessibility

I-D thresholds rely on straightforward parameters: rainfall intensity and duration. Unlike complex models such as physically-based or probabilistic approaches, they do not require extensive datasets on soil properties, slope stability, or subsurface conditions, which may be difficult to obtain in data-scarce regions like Northeast India. For example, studies in Japan (Osanai et al., 2010) and Italy (Guzzetti et al., 2007) have demonstrated that these thresholds are easy to calculate and interpret, making them accessible for local governments and communities.

2. Real-Time Applications

I-D thresholds are highly effective for real-time landslide warning systems. By integrating rainfall monitoring data with predefined thresholds, authorities can issue timely warnings. This capability has been successfully implemented in Hong Kong (Jibson, 2005), where real-time threshold models have significantly reduced landslide-related fatalities. In Northeast India, where monsoonal rainfall is intense and unpredicTable, such real-time monitoring could dramatically improve disaster response.

3. Cost-Effectiveness

Compared to physically-based models, which require detailed field investigations and laboratory analyses, I-D thresholds are cost-effective. They minimize the need for expensive instrumentation or long-term data collection, making them ideal for resource-limited settings.

4. Proven Performance in Diverse Regions

I-D thresholds have shown high reliability across different terrains and climates. For instance, they have been adapted to the steep slopes of the Himalayas (Jain et al., 2022) and tropical regions of Southeast Asia (Glade et al., 2000), showcasing their versatility. This reliability makes them an attractive option for the varied and complex terrains of Northeast India.

5. Integration with GIS and Remote Sensing

I-D thresholds can be integrated with Geographic Information Systems (GIS) and remote sensing tools to map high-risk zones. This approach, used effectively in countries like Japan (Osanai et al., 2010), allows for the visualization of spatial and temporal landslide risks, aiding in targeted mitigation efforts.

While alternative tools like physically-based models or probabilistic approaches offer detailed analyses, they are often data-intensive, costly, and time-consuming, making them less practical for immediate application. In contrast, I-D thresholds offer a robust, efficient, and scalable solution to address landslide risks in Northeast India.

This research chapter will be using pre-established thresholds as reviewed and assimilated in, Guzzetti et al. (2008) and Dikshit & Satyam (2017). From now I will be referring to Guzzetti et al.'s ID threshold as GIDT and Dokshit & Satyam's ID threshold as DSIDT. GIDT has a value of $I = 2.20xD^{-0.44}$ while the DSIDT has a value of $I = 3.52 \times D^{-0.41}$. A graphical representation of these Figures can be seen in Figure 6.1

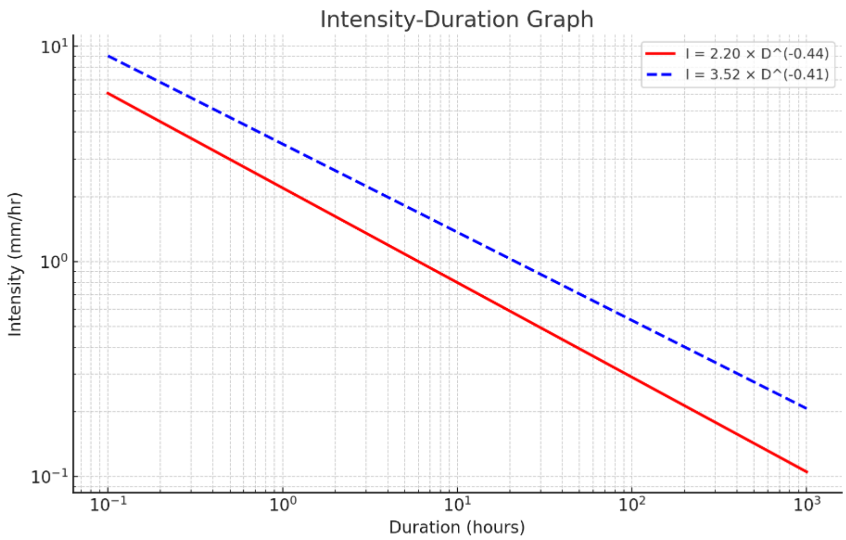


Figure 6.1: The two thresholds I will be using in this study. GIDT in red and DSIDT in dotted blue.

From this graph (Figure 6.1) it is apparent that the DSIDT threshold calculated for the Darjeeling and Sikkim area has been calculated to be higher than the global GIDT threshold. This means that the DSIDT has the triggering of landslide events occurring with a higher intensity of precipitation, even over the longer durations, compared to the GIDT threshold. The angle of each ID threshold however is similar, leading to the suggestion that all landslides that are triggered by precipitation have a similar pattern of failure over a long duration of rainfall. The DSIDT threshold has a smaller angle then the GIDT threshold, showing that the triggering of landslide events over the duration needs more intensity than Global landslide events. These differences between DSIDT and the GIDT are expected. The Kalimpong region experiences seasonal monsoon rainfall unlike a large portion of the globe, so in terms of a global average, the drier and less intense perception experienced in some of the world would push this ID threshold lower than the wetter Kalimpong region.

6.4.3 ROC Analysis

When dealing with multiple thresholds in a landslide prediction model, the ROC curve becomes a valuable tool to evaluate and compare the performance of each threshold. Let's expand on this with a hypothetical example involving four different intensity-duration thresholds for landslide prediction.

A ROC curve is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. It is created by plotting the True Positive Rate (TPR, or Sensitivity) against the False Positive Rate (FPR, or Specificity) at various threshold settings. The threshold settings in this research are the established intensity duration thresholds, the GIDT and the DSIDT specified above in **Thesis Section 6.4.1.**

Once the threshold is established the construction of the ROC curve begins. This begins with the data preparation – deciding if the ERA5 precipitation intensity constitutes the historic landslide event as a 'hit' (if it correctly predicts a landslide) or a 'false alarm' (if it predicts a landslide that doesn't occur). The 'misses' (landslides that occurred without prediction) and 'true negatives' (correctly predicted non-landslide events) are also calculated at this stage.

After this, a True Positive Rate (TPR) and a False Positive Rate (FPR) is calculated by; TPR (hits divided by the sum of hits and misses) and FPR (false alarms divided by the sum of false alarms and true negatives). On the ROC graph, the TPR is then plotted against the FPR for each of the two ID thresholds used.

To interpret the ROC curve, the 'best' result would be a point that is closer to the top left corner, as this signifies a high sensitivity but also a low false-positive rate. The Area Under the Curve (AUC) can also be calculated for each of the two thresholds. A larger AUC indicates a better overall performance of the threshold.

The full explanation and methods for ROC curve analysis can be found in **Thesis Section 4.5.2.5 Relative Operating Curves.**

6.5 Results and Discussion

6.5.1 Analysis of ERA5 Precipitation Data

To illustrate the climatological intensity changes throughout the year I used the ERA5 hourly precipitation to first create a spatial hourly mean, and then make an hourly intensity of the day for all years (Figure 6.2). It shows that the monsoon period is a specific period of the year where the intensity of rainfall is higher than any other part of the year in this study area (Takahashi, 2016; Kulkarni & Rao, 2022). This is important to understand for this thesis as it means that any prediction tool that works with ID thresholds would potentially only work within the four months of the monsoon period. A more detailed insight into the monsoon period (Figure 6.3) shows that the intensity of the precipitation during this period, over all the years in this study, is consistent over the monsoon, with a lessening in intensity in the September month.

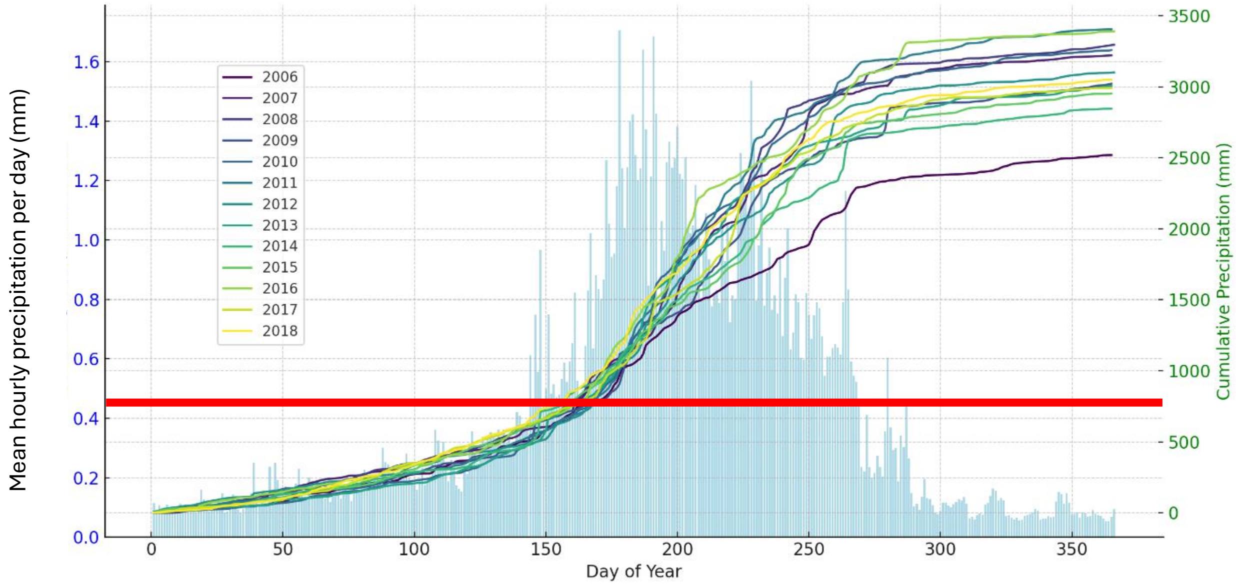


Figure 6.2: Spatial average over the 9 gridded cells in the study area, daily mean of hourly intensity, and the mean across all years. With the cumulative hourly rainfall for each year. Mean. hourly Intensity is 0.422mm and is shown by a red line.

Focusing in on the monsoon period (JJAS), the overall pattern of precipitation intensity over the monsoon can be seen (Figure 6.3).

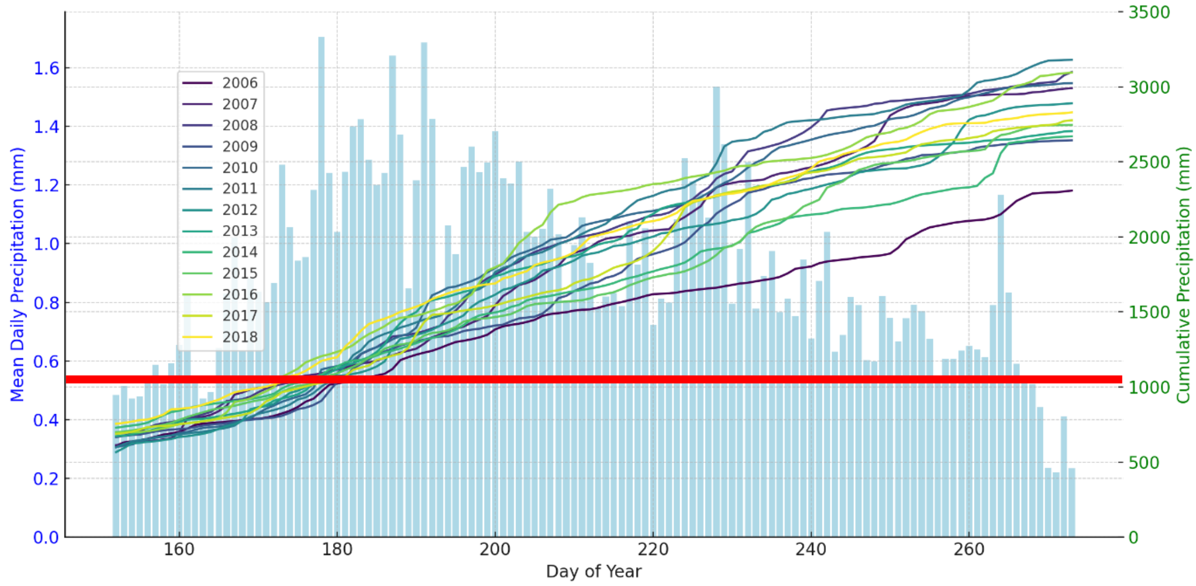


Figure 6.3: Spatial average over the 9 gridded cells in the study area, daily mean of hourly intensity, and the mean across all years. With the cumulative hourly rainfall for each year. Mean. hourly Intensity is 0.422mm and is shown by a red line. (Showing the months of June, July, Aug and Sept – the monsoon period).

Figure 6.3 illustrates daily and cumulative precipitation trends across multiple years (2006–2018). The bars represent mean daily precipitation, highlighting seasonal fluctuations, with peaks suggesting wetter periods. The cumulative precipitation lines indicate yearly variability, showing how rainfall totals accumulate over time.

Key observations include significant differences in annual totals, with wetter years (e.g., 2016) and drier years (e.g., 2006) evident. Steeper slopes on cumulative lines suggest intense rainfall periods, while flatter sections indicate dry spells. Most years follow a similar pattern, but anomalies suggest unusual weather events or climatic variability.

The monsoon season's total precipitation for each month can be seen in Figure 6.4 Where both the study area's precipitation has been plotted with data taken from observed gauges by the IMD. From this graph we can see that the ERA5 totals are higher than those from the IMD, especially at the beginning of the monsoon season. By September it appears that the IMD and ERA5 datasets have a similar value.

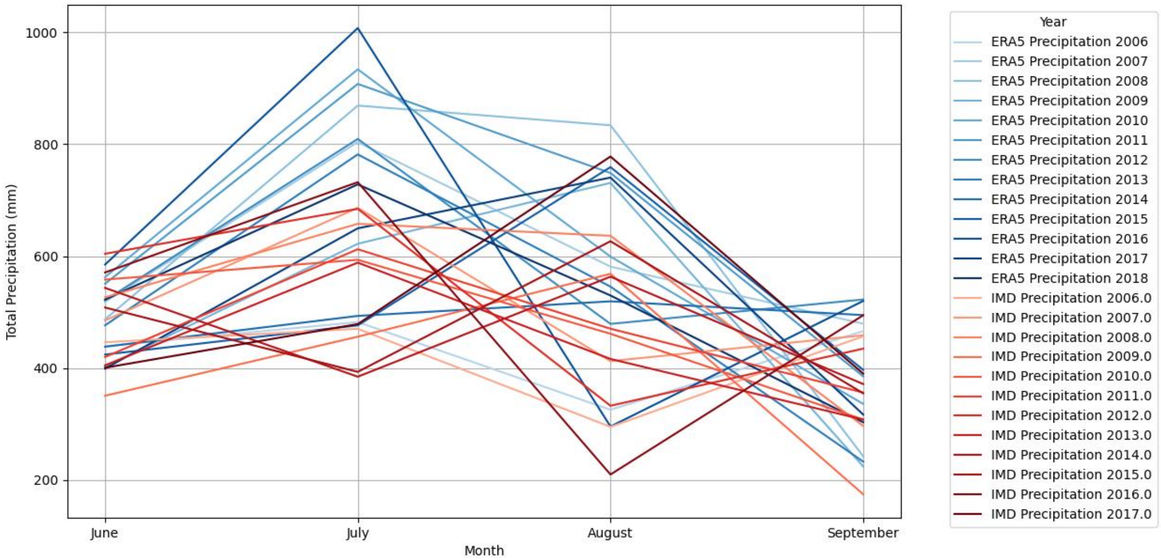


Figure 6.4: The monthly totals of the monsoon season (JJAS) for the ERA5 data in the study area, and the IMD data in the West Bengal and Sikkim Regions

Studies suggest that while ERA5 provides valuable precipitation estimates, it may overestimate rainfall in certain regions compared to observational data, just like Figure 6.4 (Hassler & Lauer, 2021; Alexandridis et al., 2023; Cavallari et al., 2024). For example, Cavallari et al., conducted a multi-scale assessment of high-resolution reanalysis precipitation fields over Italy. They observed an overall overestimation of precipitation in the reanalysis climatological fields over the Po Valley and the Alps, while noting underestimations in other regions (2024).

The Drizzle Effect – Sensitivity Analysis

There are two things that need to be tested to look at the ERA5 'Drizzle Effect'. The number of dry days and the total precipitation over the monsoon season. Usually in climate model studies the researcher would use bias correction (Themessl et al., 2011; Hempel et al., 2013), adjusting both at the same time – removing the 'dry days' while distributing the drizzle onto the remaining days.

To look at the total number of dry days, I will be counting the number of dry days from the mean precipitation over the study area. I will be doing this for different thresholds, to see how well the

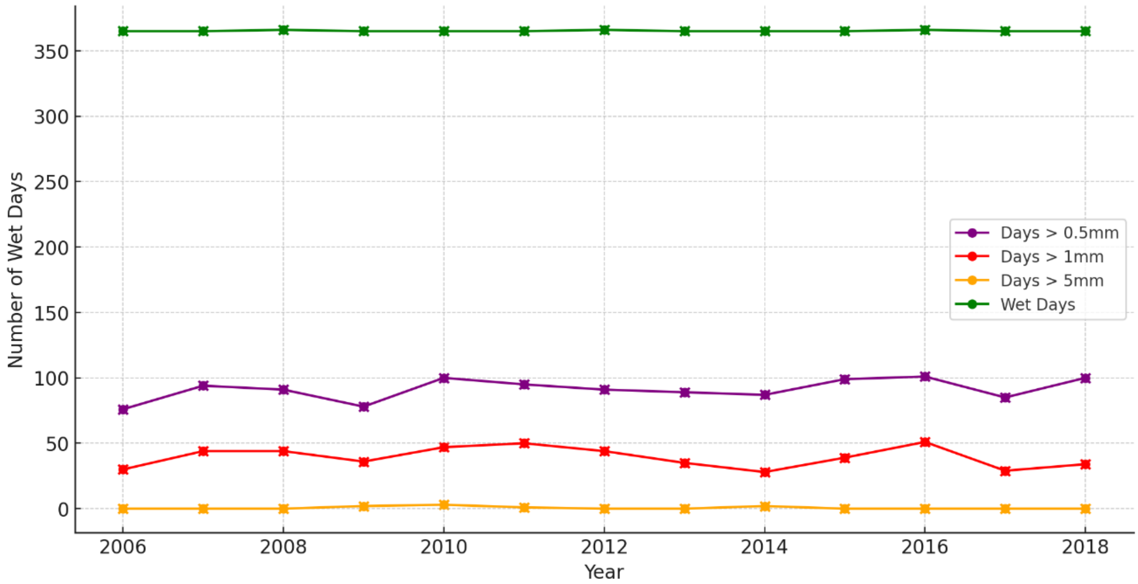


Figure 6.5: Number of 'wet days' in each year over the Study Area. There are threshold counts for wet days exceeding 0.5mm, 1mm and 5mm.

1mm adjustment that is usually used for determining dry to wet days. From Figure 6.5 We can see that the initial count of 'wet days' of any precipitation measured, is very high, at over 350 days, and in 2008 and 2016 ERA5 had precipitation in the study area for all 365 days of the year. This is an example of the ERA5 drizzle effect, with ERA5 showing some precipitation every day in a small area.

The Indian Meteorological Department (IMD) has average rainy days in the town of Darjeeling to be around 105 days a year (averaged between 1901-2012) (Saicharan & Rangaswamy, 2023; IMD, 2024).

However, the town of Darjeeling is only a small area within the study area, and so to estimate the sensitivity of the threshold I am going to look at the separate datapoints in the ERA5 dataset over the study area. There are 20 separate data points over the study area, and the 1mm 'wet day' total can be seen for each point in Figure 6.6.

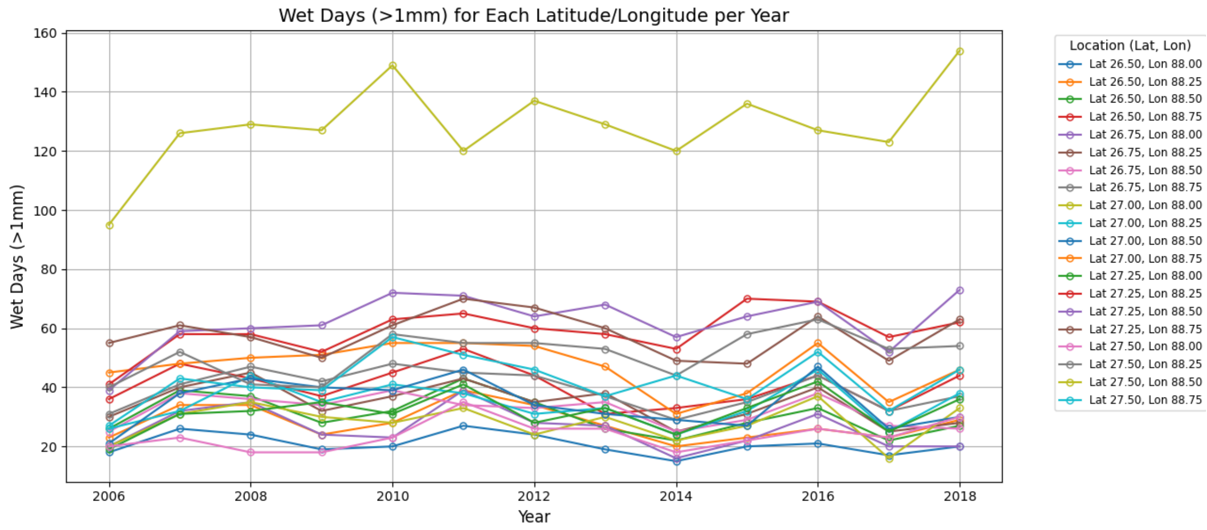


Figure 6.6: the ECWMF 1mm threshold for 'wet days' to combat the 'drizzle effect' – the count for each latitude/longitude pairing in the study area showing the variability of each data point for 'wet' and 'dry' days.

From this Figure (6.6) it is apparent that each of the spatial data points do have a large amount of variability that may be missed in the mean taken across the study area.

Figure 6.7 shows the spatial variability over the area in a spatial map taken from the year 2006. This Figure also shows the four different thresholds considered in this study. From this Figure it shows that the northern area experiences more 'wet days' in every iteration of the threshold.

The Northeast of the map has the most wet days, with the grid square in 27 .4°N and 26.8°S having the most wet days in all four cases. This is still the case when the 5mm wet day threshold is considered, the wetter latitude and longitude areas are the same, there are just less days counted in the area due to the shift in threshold. These areas do shift in subsequent years, 2008-2017, and the 'wettest' area doesn't remain constant. This means that if a case study analysis was to be completed, then each area could be taken into consideration, however during a mean across the whole area, it should be noted that this may lead to some limitations and difficulties in obtaining meaningful results. In my study I will still be using the mean for the area, as I am trying to simplify the processes to a simple 'hit' or 'miss' for landslides in the area, instead of creating a spatial map or location-based analysis of landslide events, as this would require modelling of slope angles, geology, soil information, soil moisture levels etc.

Overall, when considering how to combat the ECMWF's ERA5 total precipitation 'drizzle effect' for this study area there must be two approaches, depending on the aims of the research. If a case study of landslide events is being used, then researchers should consider using the exact location precipitation data due to the variability over the area. Secondly, if using a mean over the whole area some thought should be surrounding the limitations this may have due to the variability of the area's 'wetness' and how this might affect the physical properties of landslide initiation and if this replicates 'real world' scenarios. Considering other research endeavours in other localities and regional studies, there must be some thought into which of the two approaches should be used as is appropriate for their research objectives.

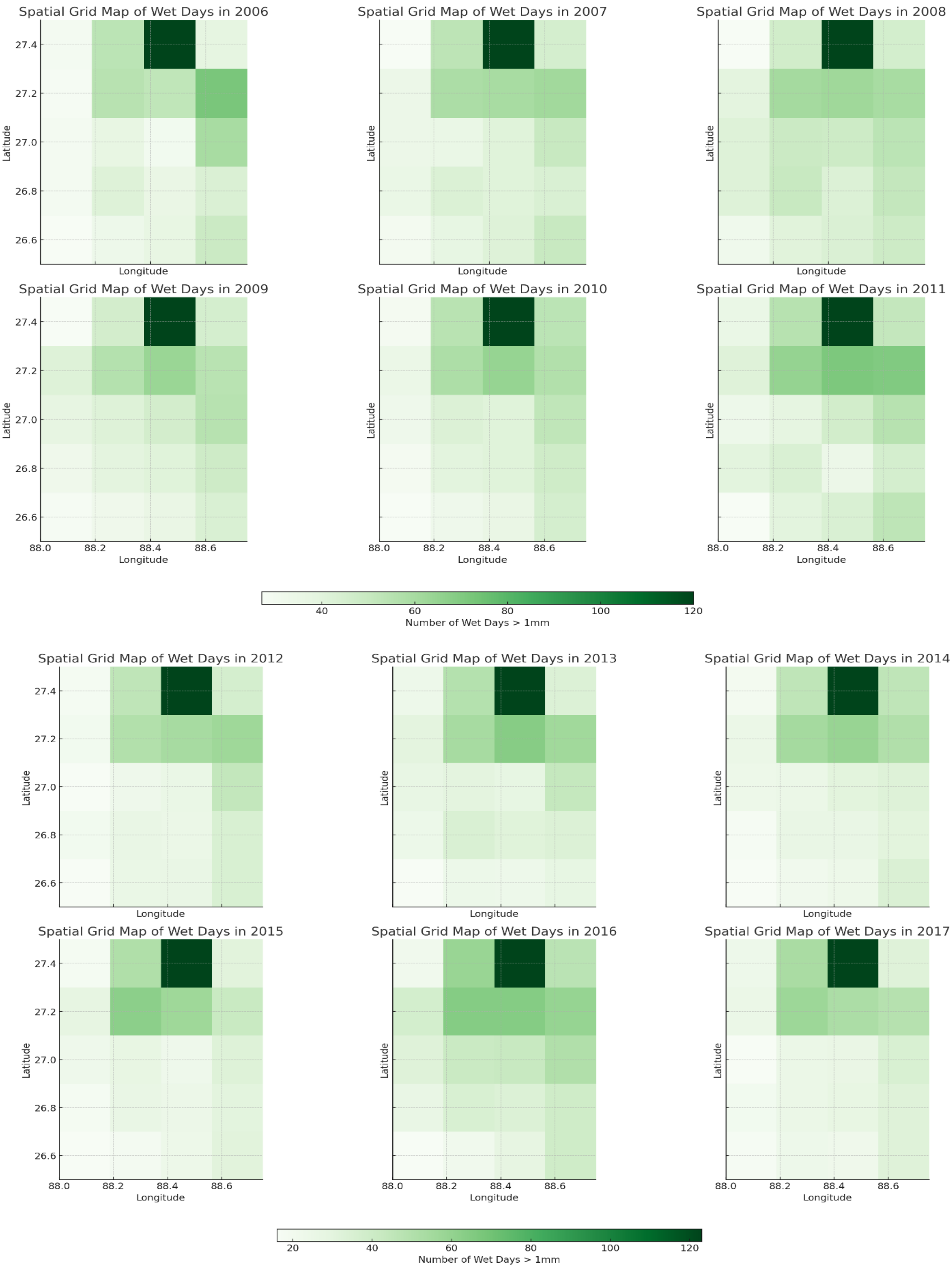


Figure 6.7: The spatial distribution of wet days (<1mm) in the site area.

6.5.2 Combining Landslide and Precipitation Data

The initiation of landslides from precipitation events in relation to intensity and duration of the precipitation is usually completed mathematically. The mean precipitation across all years with landslide events can be seen in Figure 6.8. The use of a graph to try and see these relationships can be seen in Figure 6.9, where the daily mean precipitation annually with the monsoon period has been plotted with landslide events from both landslide inventories. The pattern usually seen, is either long periods of rainfall, followed by landslides, or a sharp increase in precipitation, leading to an intense precipitation event, proceeded by a landslide event.

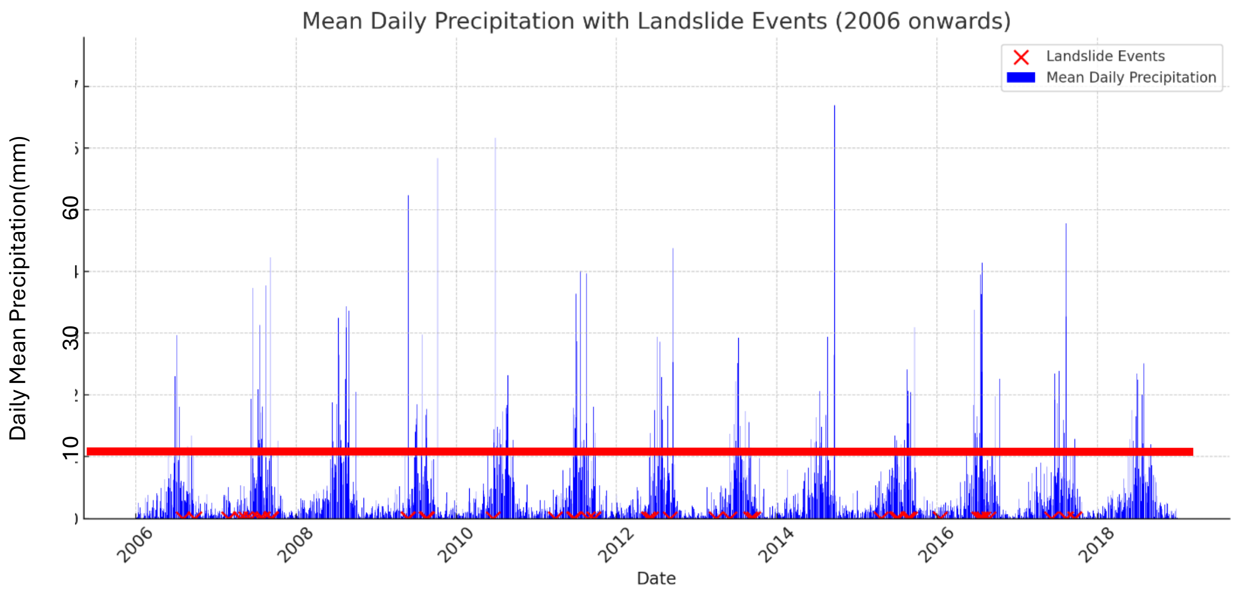


Figure 6.8: Spatial daily mean over the 9 gridded cells in the study area and landslide events plotted for the whole period of research (2006-2018). The average daily spatial mean is 10.12mm and is indicated on the graph by a red line.

Figure 6.8 is showing the spatial daily mean over the entire study period and shows the landslide within it. This illustration is a useful tool when examining the relationship between precipitation and rainfall triggered landslides

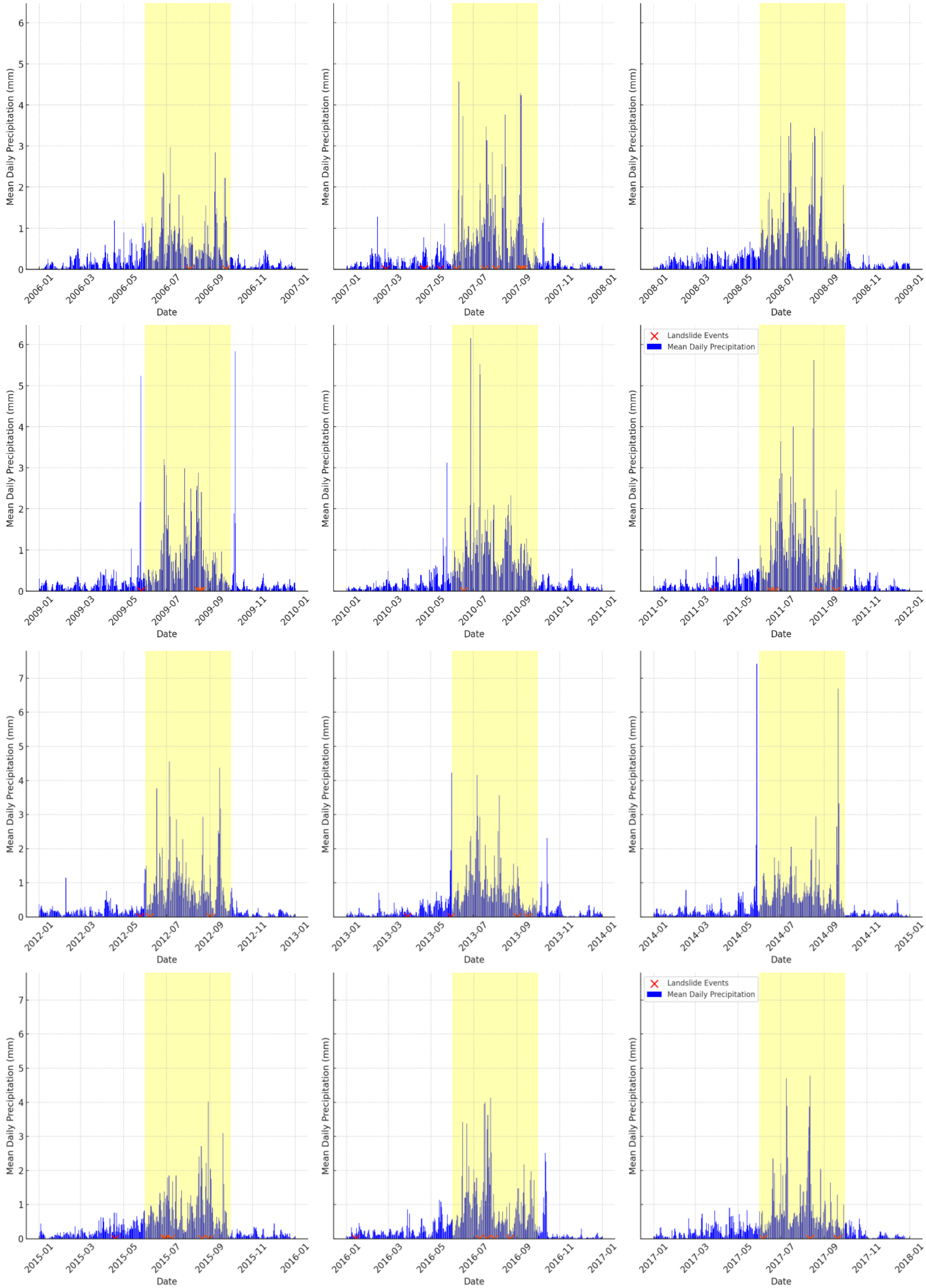


Figure 6.9: Each year of the study with mean daily intensity of precipitation (mm) and the landslide incidences plotted. The monsoon period (JJAS) is highlighted in a yellow to show the increased intensity for the period.

Figure 6.9 is different from Figure 8.8 as the graph is showing this daily intensity for each year. With this illustration I am trying to visually see if there is a link to the daily intensity felt each year and the landslides that were reported by the combined LSI from Thesis Section 5.0 Research Chapter: I. There are a few years (2009, 2011, 2012, 2013, 2017) on this panel of graphs that show the initiation of landslide events as soon as the intensity increases. This could be due to the intensity itself increasing above the threshold for triggering of the event, or it could be due to the antecedent conditions that predated the monsoon season. A lot of rain being deposited on very dry earth after a period of non-monsoonal precipitation could rapidly lift the water Table and trigger a landslide, or rapidly load a slope that has less soil cohesion due to air pockets and cracks (see **Thesis Section 2.1 Landslide Science**). Two years, 2008 and 2014, have no landslide events recorded within them, showing that the global landslide inventories do not capture the events needed for a comprehensive study, however most years do contain landslide events. From this graph we can also see that most of the landslides are triggered within the monsoon season. This is usual to see as previous studies and data have shown that the monsoon season has the most incidences of landslides within it (**Thesis Section 3.1.2.1 Meteorology**).

The theory of ID thresholds is that accumulated rainfall plus duration over time triggers a landslide. I am looking at precipitation in this way to potentially see if there is a pattern of extreme rainfall peaks before landslide events, or if it appears more like a low but prolonged period of rainfall causes these landslide events.

Figure 6.9 Illustrates these usual patterns, with long periods of less intense rainfall followed by landslide events in the first half of the monsoon period, and then in the second half of the monsoon, showing the large intense precipitation events triggering landslide events.

6.5.3 ID Thresholds and Landslide events

In this section historic landslides for the study area are placed within the DSIDT and GIDT ID thresholds. To do this I have calculated the mean precipitation for the study area per day and used the 1mm and below as an indication of a 'dry day' to combat the drizzle effect. As I am working in 24-hour intervals the landslide events will appear on the logarithmic scale as lines, for example in Figure 6.10 there are quite a few landslides which have different intensities over the course of one 24hr period – 10^0 – and would have actually been triggered after less than 24hrs of rainfall.

The following ID graph (8.10) is for this calculation with the 1mm or less as a 'dry hour'.

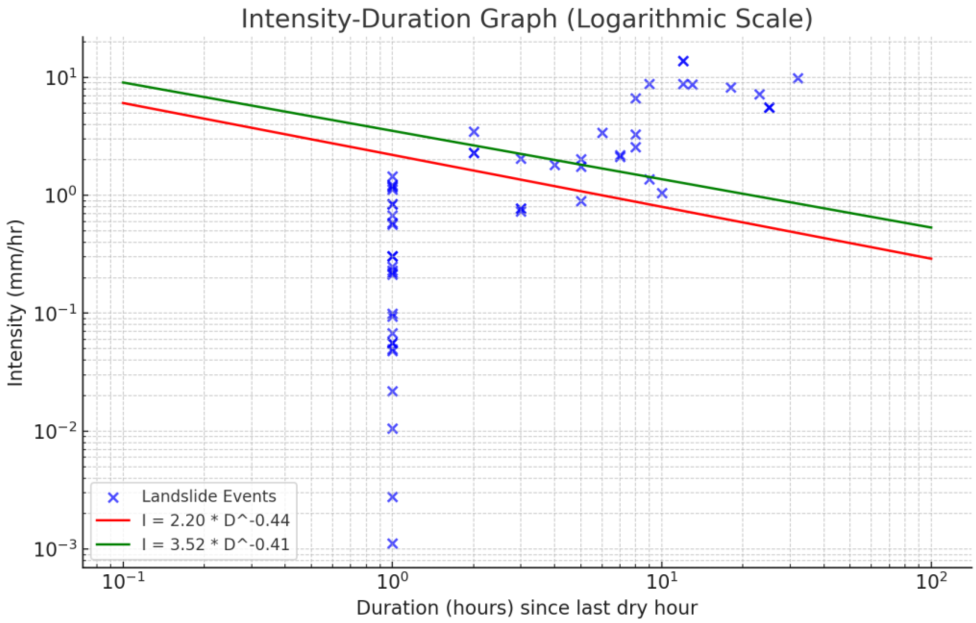


Figure 6.10: The spatial mean of the ERA5 total precipitation hourly data for the landslide events in my study area.

As the intensity and duration rises, there are more landslide events, and in some more extreme circumstances where the rainfall is quite intense the landslides are far beyond the GIDT and even the DSIDT. My only query would be the shorter, less intense landslides that fall below the line within an hour of the landslide event are strange.

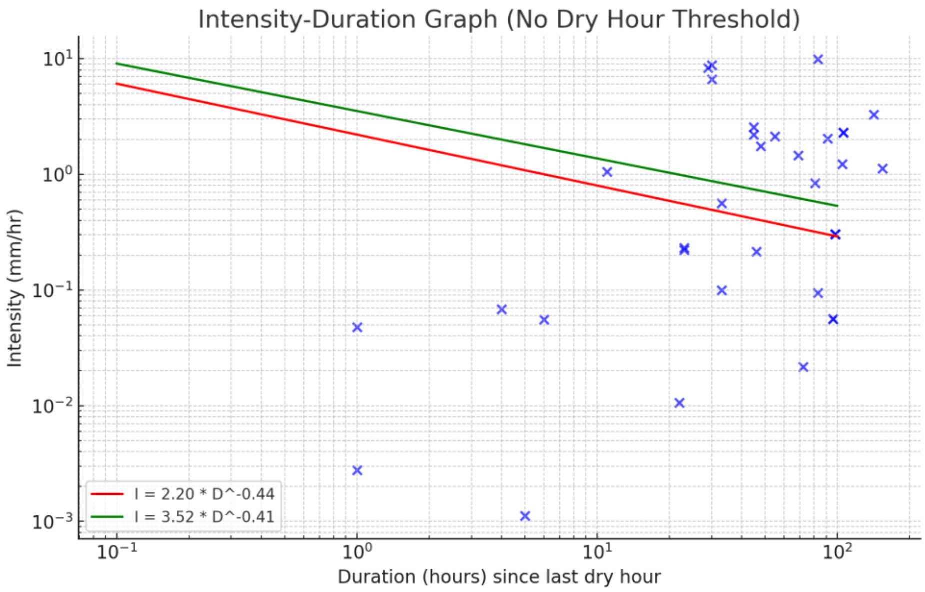


Figure 6.11: Without the 1mm or less dry hour threshold.

The 1mm drizzle effect alteration is for 1mm a day, and so when looking at an hourly dataset that's 0.0416mm/hr. Figure 6.11 is a representation of this adjustment rather than using 1mm. However, this means that a lot of the landslides are not being represented as they fall into the ‘0 hours’ duration mark and are not being plotted.

This final graph (6.12) is now plotting all the available landslide events for the study area without the

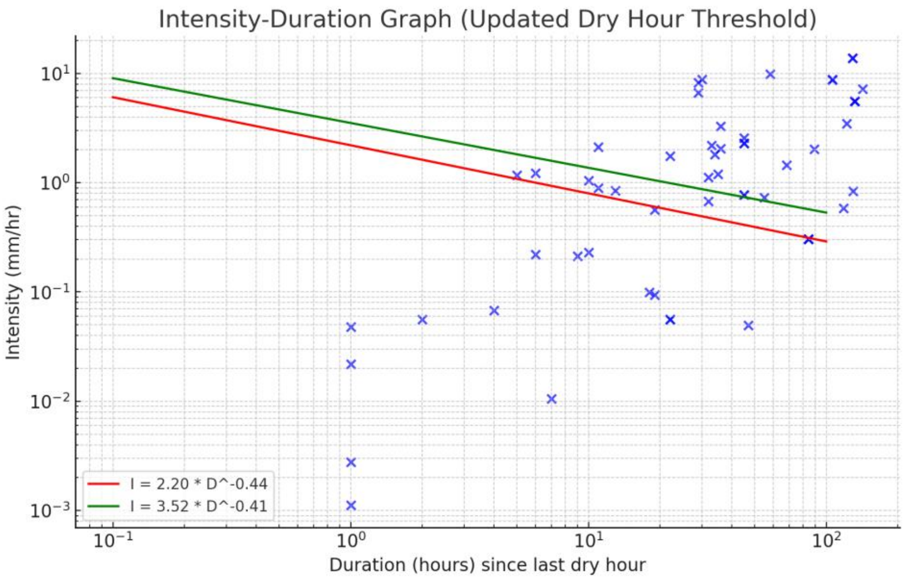


Figure 6.12: The dry hour set at 0.0416mm

drizzle effect threshold. There are still a fair number of landslides falling under the ID thresholds, but I believe that the events are being as accurately depicted as they can be given the limitations of each dataset. From this graph it is apparent that longer more intense rainfall triggered landslides are being identified by these intensity duration thresholds. However, it also appears that some of the landslides are now not being identified in the graph. This could be due to the lack of drizzle effect threshold for ‘dry days’ making the landslides have a larger duration and thus not be shown on the graph.

Looking at both Figure 6.11 and Figure 6.12 we can consider the underlying datasets that make these graphs. The LSIs that are being used here have two different agendas, one for risk (fatalities) and the other just for occurrence. A more intense rainfall event would indicate there would be little to no lead time when mitigating the risks associated, and the proceeding landslide event. This means that the underlying landslide dataset will have a slight bias towards intense rainfall events anyway, as these would be the landslides captured within one of the LSIs used within this study. This can be seen in both 6.11 and 6.12 where there is a cluster of intense events in the upper left of the graph.

6.5.4 How well can the rainfall and ID thresholds predict landslides? - ROC Curve Analysis

In this research chapter the landslide events are being used with ID thresholds to produce ROC curve analysis. This is to test the skill of both ID thresholds in predicting the historical landslides to see if they can be used as tools in the medium range with ECMWF's prediction model.

From the Intensity Duration graph above there are several things we can take away from this. Firstly, we can discuss a simple contingency Table for the ID thresholds and their ability to either give a true positive (hit) or a false negative (miss). The true positives will be above the line and the true negatives will be below the line.

Table 6.1: The contingency Table for the two ID thresholds (GIDT and DSIDT) with the 0.0416mm drizzle effect alteration.

ID thresholds	*True Positives*	*False Negatives*
GIDT	37	20
DSIDT	31	26

From Table 6.2 we can make a few initial judgements. The number of misses is quite large, and in the DSIDT threshold nearly half of the landslide incidences are missed. To produce ROC curves there needs to be non-landslide events. I will use a stratified random sampling technique to uniformly distribute across different months and locations. This will provide a better representation of typical rainy hours. These days will be labelled 'landslide events' and 'non-landslide events'. Then the established ID threshold will be used to predict the landslides based on the precipitation intensity and duration. The True Positive Rate (TPR) and the False Positive Rate (FPR) will be calculated from that (**See Thesis Section 4.4.2 Methods**).

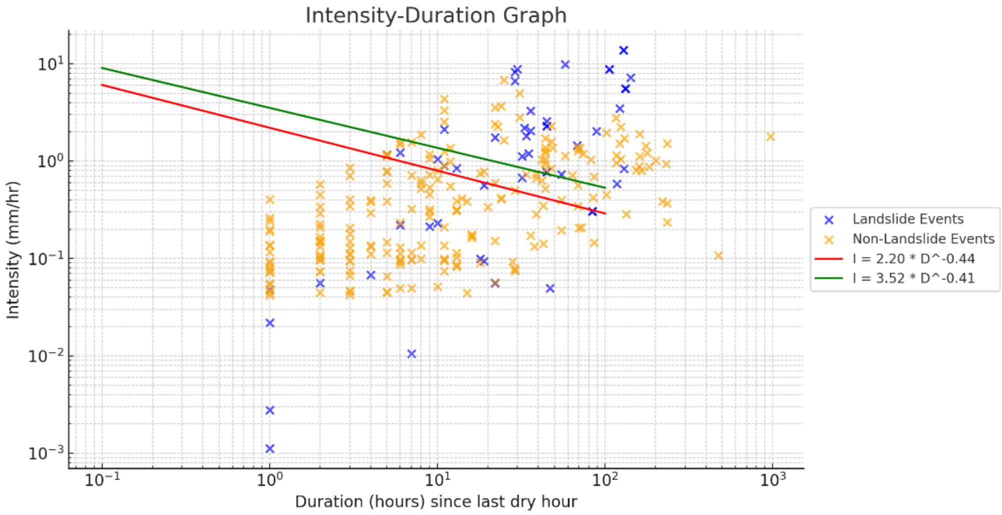


Figure 6.13: The ID graph showing landslide events in blue and non-landslide events in orange.

This graph (6.13) then allows for a more complete contingency Table to be completed for the ROC analysis. From this contingency Table it is apparent that there are quite a lot of false alarms within the system.

Table 6.2: Final contingency Table for the two intensity duration thresholds.

ID Threshold	*True Positive (hit)*	*False Positive (False Alarms)*	*True Negative*	*False Negative (miss)*
GIDT	37	81	142	20
DSIDT	31	53	170	26

The model metrics for each of the lines are below. The way we work out model metrics from the contingency Table can be seen in **Thesis Chapter 4.5.2.4 Methods: Contingency Tables and Model Metrics.**

Metrics for Line: ($I = 2.20xD^{-0.44}$)

- Accuracy: 0.639

This means that for 63.9% of the time the model correctly identified if a landslide occurred or not.

- Sensitivity (Recall): 0.649

The model correctly identified 64.9% of the actual landslide events.

- Specificity: 0.637

The model correctly identified the rainy hours without landslides 63.7% of the time.

- Precision: 0.314

A precision of 31.4% means that the model predicted a very high number of false positives.

- F1 Score: 0.423

This is the mean of precision and recall – and a score close to 50% shows that the models performance is moderate but leans towards having a higher recall than precision.

Metrics for Line: DSIDT ($I = 3.52 \times D^{-0.41}$)

- Accuracy: 0.718

This means that the model correctly identified if it was a landslide or not 71.8% of the time.

- Sensitivity (Recall): 0.544

The model correctly identified 54.4% of the actual landslide events.

- Specificity: 0.762

The model correctly identified 76.2% of the non-landslide events.

- Precision: 0.369

Out if all the predicted landslide events only 36.9% were actual landslide events.

- F1 Score: 0.440

This is still a moderate score and slightly higher than the GIDT. This means that there is a better balance between precision and recall.

From these metrics it seems that GIDT is performing better than DSIDT at catching more of the landslide events, but at a cost of more false alarms (lower precision). Line 2 however is better at correctly identifying non-landslide events and has fewer false alarms but misses more actual landslide events. The use of ROC curves in this research is to determine the effectiveness of the rainfall intensity and duration metrics when predicting landslides using the two ID thresholds from Guzzetti et al. (2008) and Dikshit & Satyam (2017).

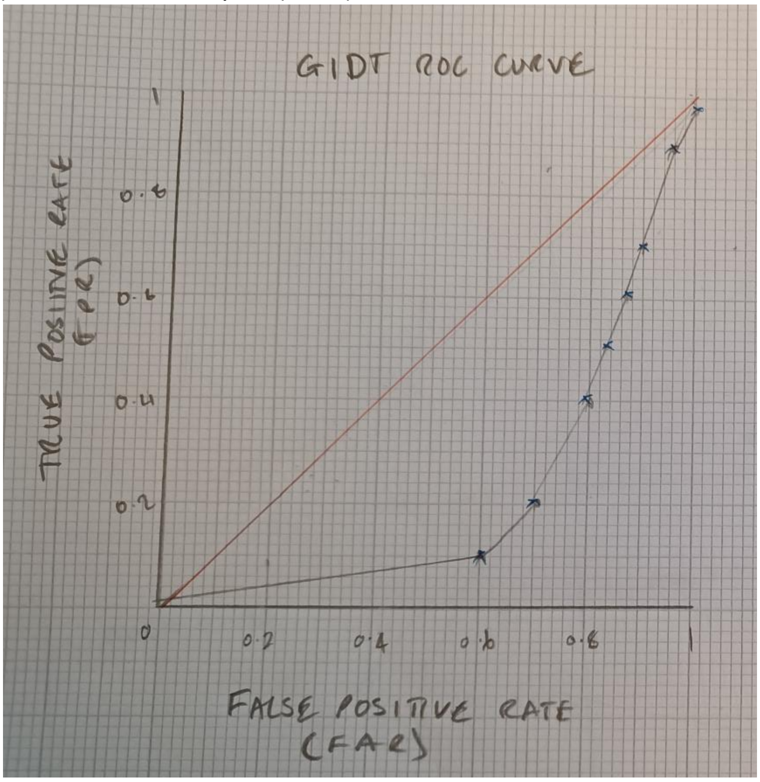


Figure 6.14: The ROC curve for the GIDT (Guzzeti et al., 2008). AUC = 0.19.

This curve (6.14) is less indicative of the ability of ERA5 to predict landslides in this area using a predetermined ID threshold. The AUC score of 0.19 is not in an accepTable range. When the ROC curve is aligned more to the upper left of the graph, above the red baseline, it can be considered that the model is more accurate. This is because each datapoint is the relationship between the true positive rate and the false positive rate. The true positive rate is measuring the proportion of actual positives that are identified by the model while the false negative rate is measuring the proportion of actual negatives that are incorrectly identified as positive by the model.

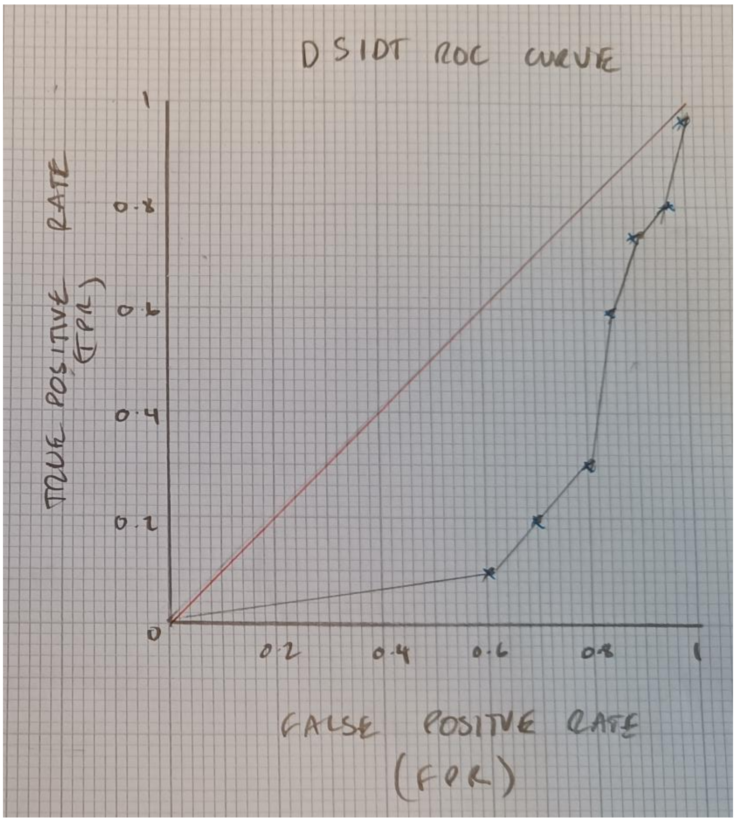


Figure 6.15: The ROC curve for the DSIDT (Dikshit & Satyam, 2017) AUC = 0.19

Overall, an area under curve score of under 0.5 shows that the model is performing even worse than random guessing (Figure 6.15). It indicates that the model is systematically making incorrect predictions. Its misclassifying the landslide events to a significant extent. In practical terms, if we changed the negative predictions to positive predictions, it would perform better than it does currently. There could be a few different reasons for this.

- **Data quality**: There are major limitations with using the ERA5 and the Global LSIs in this way
- **Model Simplicity**: The model may just be too simple to capture underlying criteria – such as soil moisture levels and slope angle.
- **Imbalanced data**: If the datasets are imbalanced, which they are – there are more non-landslide events then there are recorded landslide events.

If we take the four years with the most landslides, 2007, 2009, 2011, and 2015, and create the ID threshold graphs again just for those specific years, will the ROC graphs produce better results?

Individual year analysis

The individual year graphs can be seen in Figure 6.16 and 6.17 where the AUC can be seen too.

The AUC for the year 2007 was 0.21 for both GIDT and DSIDT and so a bit higher than that of the overall years, but still under 0.5 and so significantly worse than random guessing. The cluster of rainy days but non landslide days is concentrated in the middle to the bottom left of the graph, meaning that there were less intense, shorter rainfall events this year.

The AUC for the year 2009 was 0.13 and so a bit lower than both the GIDT and the DSIDT in the overall years' intensity duration graph. Significantly worse than random guessing. The cluster of orange rainy events is more spaced out in this year, concentrated on the middle to bottom right of the graph, showing that the rainy events this year were longer and less intense.

The AUC for the year 2011 was 0.33. A large improvement seen and larger than the overall years. Maybe this is due to the rainfall in this year being more intense for longer durations, meaning that the systematic random sampling for the non-landslide days focused more in the top right corner of the intensity duration graph. The orange cluster is situated on the upper right of the graph, showing that the rainy events were more intense over a longer duration.

The AUC for the year 2015 was 0.15 and so a bit lower than both the GIDT and the DSIDT in the overall years' intensity duration graph. Significantly worse than random guessing. The orange rainy events this year are on the bottom half of the graph, showing that the intensity of the rainfall this year was low.

As before there are a few reasons why this might be the case in this instance. It is interesting to note that the years with intense rainfall incidences had a higher AUC score then those that had less intense rainfall events recorded.

Overall, this is not a good indication of the datasets to be used at any systematic level in the foreseeable future.

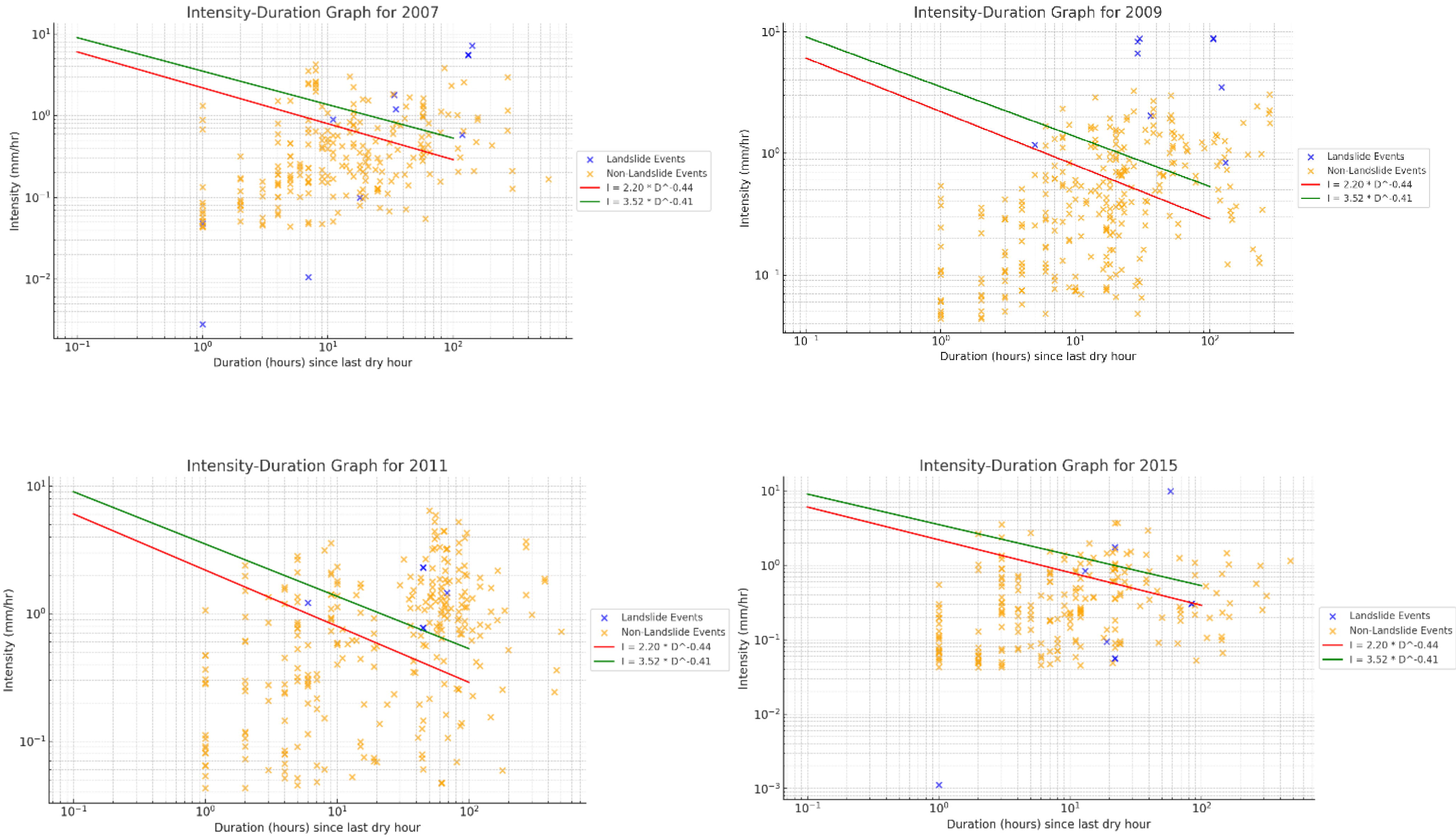


*Figure 6.16: The ID graphs for 2007, 2009, 2011 and 2015 - the years that had the most landslide events recorded within them from the combined global LSI (**See Thesis Section 6.0 Research Chapter I**). The red line is the GIDT (Guzetti et al., 2008) and the green line is the DSIDT (Dikshit & Satyam, 2017)*

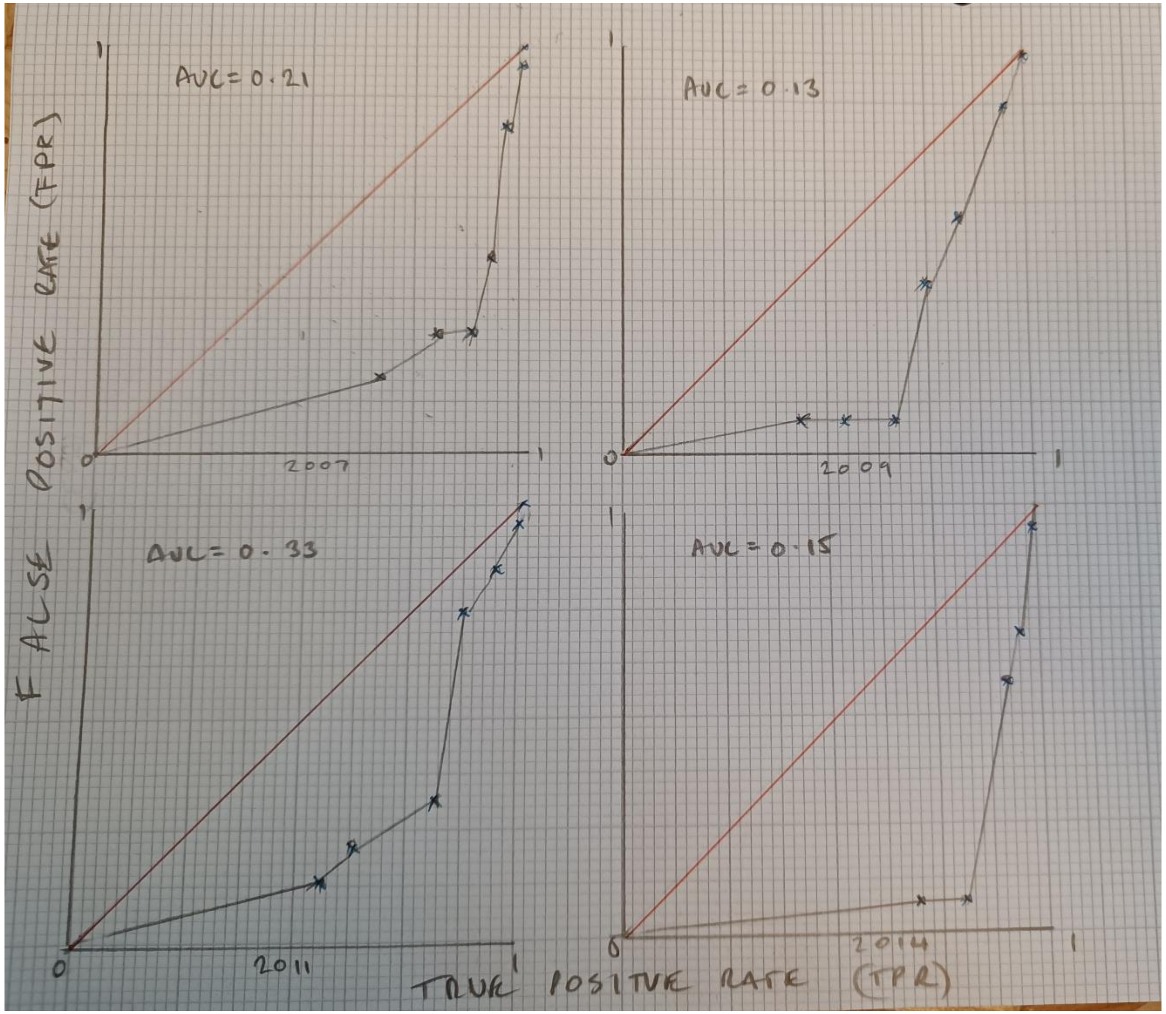


Figure 6.17: The ROC curves for the individual years that have been examined in this study. The red line is the 'random' threshold at 0.5 and most ROC curves would sit above this. The ROC curves pictured here look different from the original ROC curves as they are so far below the line that the 'usual' representation would make it hard to see the details. AUC is: 2007 = 0.21, 2009 = 0.13, 2011 = 0.33, 2014 = 0.15.

6.5.5 Case Study Analysis

To understand why the ROC curve analysis could be wrong, and to see if in individual cases that this tool may have been useful to use, a couple of case studies from the year which had the best AUC score can be used to look at this tool in detail.

The year with the best AUC score is the 2011 year, which had an AUC score of 0.33. This year had 6 landslide events, with the rainfall event days being clustered in the upper right of the graph – meaning that the rainy days this year were of a higher intensity over a longer duration.

Table 6.4: The Landslides from the combined dataset (GFLD and GLC) in 2011.

Latitude	Longitude	Date of Landslide (YYYY-MM-DD)
26.86445	88.30685	2011-03-26
26.89348	88.28743	2011-06-17
27.2833	88.23596	2011-06-23
27.34711	88.17392	2011-06-23
27.02306	88.15570	2011-08-24
26.86455	88.30746	2011-09-18

From Table 6.4 we can see that there are instances where there are landslides happening in the similar area and date in this year. On the 23rd of June 2011 there was two landslides reported, with another on the 17th of June, just 6 days previously. For this case study I will use the 23rd of June and the 24th of August landslide events for case studies as these happened during the Monsoon period that year.

26th June 2011 - 27°20'49.6"N 88°10'26.1"E – Gyalshing-Dentam and Gyalshing-Sabdong road, Sikkim.

This landslide was hard to find, as there was little reporting on the slide itself. The report that I did find was from a blogspace called 'SikkimNOW' a blog space that was used as a notice board for political and local news. This blog post showed that the Relief Commissioner has handed over a cheque of Rs. 30 lakhs (£28k) to deal with the damage to roads, crops, and buildings due to the landslide here.

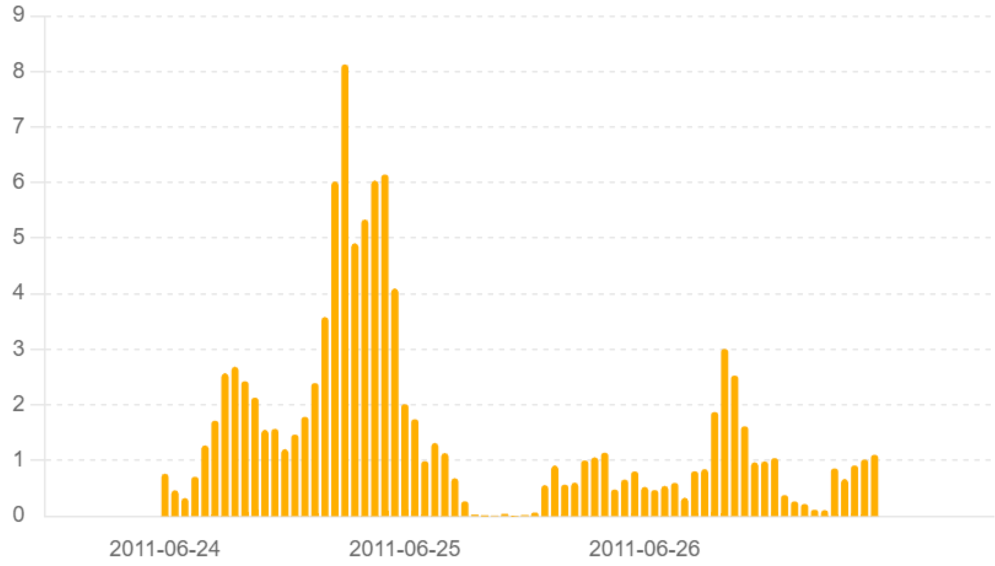


Figure 6.18: Hourly ERA5 Total Precipitation in the 48hrs and 24hrs of the 26th of June 2011.

Figure 6.18 shows the ERA5 total precipitation for the 48hours before the day in which the landslide event occurred, as well as the 24hours of the day at which the landslide occurred in June 2011.

24th August 2011 – 27°02'30.6"N 88°15'57.0"E - Darjeeling Town, Darjeeling District

On this day the landslide was within Darjeeling town and has been recorded on the Save the Hills (STH) blogspace. STH is a NGO based in the Himalayas over North Western India, Nepal and North Eastern India. In this blog post the rainfall was shown to be from the STH rain gauges:

- Rainfall in Darjeeling on 24Aug2011: 129mm
- Rainfall in Kalimpong on 24Aug2011 : 6mm
- Rainfall in Gangtok on 24Aug2011 : 7mm

This landslide was reported to happen in the early hours of the morning and so had no casualties, despite happening at a busy tourist destination, and so would have incurred some casualties if it had happened during the day. The report also noted that prolonged rainfall in August 2011 was surprisingly small, and this landslide happened during a period of prolonged rainfall.

Figure 6.19 shows the ERA5 total precipitation for the 48 hours before the day in which the landslide event occurred, as well as the 24 hours of the day at which the landslide occurred in August 2011.

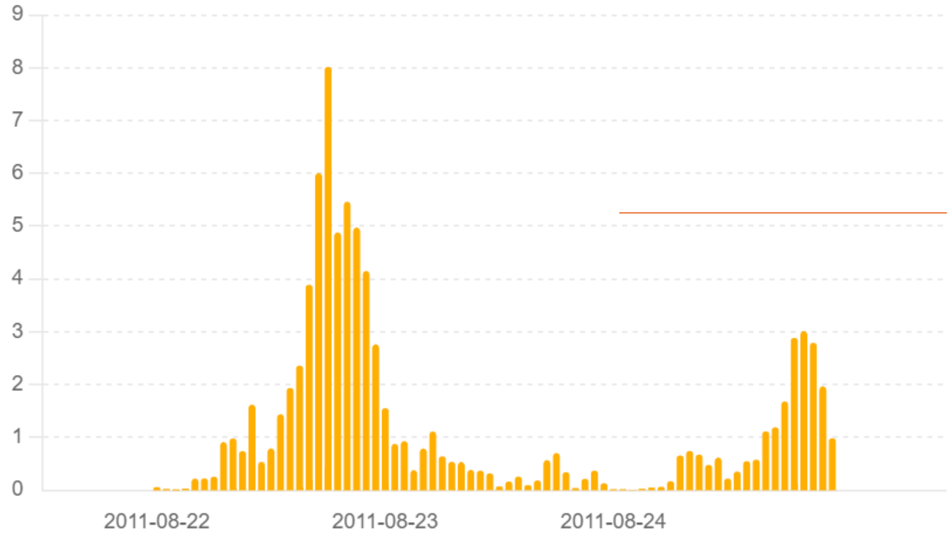


Figure 6.19: Hourly ERA5 Total Precipitation in the 48hrs and 24hrs of the 24th of August 2011. The red line indicates the STH hourly mean from the 129mm recorded in the area on the 24th of August 2011 when the landslide incident happened (5.38mm).

From Figure 6.19 we can see that perhaps the hourly rainfall from ERA5 is underestimating the rainfall in the area, either from being on a coarse gridded system and so thus unable to capture such a local event, or from not capturing extreme rainfall incidences skilfully, or from being early with the peak rainfall event (see **Thesis Section 2.3 Precipitation Modelling** for more information on limitations and extreme rainfall capture).

From both the case studies in June and August 2011, it is obvious that there has been an intense rainfall event before the landslide event. However, the ERA5 precipitation data in both cases has the larger intense peak 24hours before the day of the landslide event itself. This could be due to the ERA5 reanalysis being 24hours out of where the rainfall occurred, or it has something to do with the mechanisms of landslide initiation. For example, the peak rainfall could have saturated the soil before the smaller rainfall event, and thus moved with a smaller precipitation event.

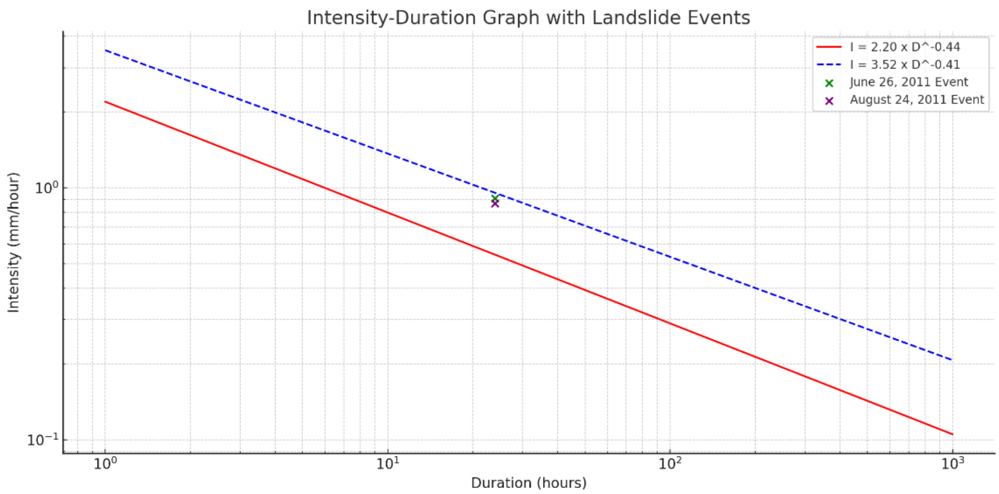


Figure 6.20: The two events in an ID graph with the GIDT (red line) and the DSIDT (blue dashed line) on the graph.

Figure 6.20 shows these two events on the ID graph. From this graph we can see that the GIDT does capture the events, yet the DSIDT just falls out of 'predicting' these events.

Going forward, a more in depth case study of landslides in this area should be conducted, with soil moisture data and geological surveys to indicate why these events were triggered, and f the ERA5 precipitation would have been a good indication of the trigger of the landslide event.

Other rainfall triggered landslides I saw when researching the June 2011 landslides in the global combined datasets from one blog source – STH:

1. 17th June 2011 – Kuresong, Darjeeling District (Within Study Area)

12 hours of rainfall causes a slide that kills 3 children and 1 man, and a slip that causes National Highway 31A to come to a stop for 5 hours, stranding 500 plus vehicles on either side.

Observational rainfall data from the STH website and rain gauges:

a) Kurseong :- 180mm (source STH ARG at Dow Hill, Kurseong)

b) Kalimpong :-31mm (source STH ARG at Tirpai, Kalimpong)

c) Darjeeling :- 54mm (source STH ARG at Gandhi Road, Darjeeling)

2. 19th June 2011 – Many happened in Kuresong and Darjeeling (Within Study Area)

60mm of rainfall in 3-hour period in Kalimpong recorded, no deaths or casualties.

3. 23rd of June 2011 – Pelling, West Sikkim (Within Study Area)

5-hour torrential downpour causing numerous landslides causing 16 confirmed deaths, also associated with anthropogenic building or human interference of the hills and mountains (Save the Hills, 2011).

These three are just a small number of landslides that are reported by STH, and this is only one of the agencies that work in my study area. It wasn't hard to find this data, and I wonder why this hasn't been reported in the global landslide inventories that I have been using to make my combined inventory.

6.6 Discussion

Can I answer my research question: *Can precipitation triggered landslides in Darjeeling, India be predicted with the global scale reanalysis precipitation dataset ERA5, and established Intensity Duration Thresholds?*

The answer right now is no. However, I think that there could be great application in this if there were more historical landslide events to consider. **Thesis Section 6.3.3 Data Limitations** discussed the lack of historical landslide events compared to other studies looking at ID thresholds, and these studies were using hundreds and thousands of landslides for validation studies.

If doing this study again, I would consider using a bootstrapped approach to 'create' more landslide events to try and test the theory behind using both the Global LSIs and the ERA5 Total Precipitation dataset. This method was used by Hwang et al. (2023) when doing a probabilistic analysis of rainfall triggered shallow landslides when confronted with limited/insufficient landslide data. Moradmand et al. (2025) also used bootstrapping aggregation with other statistical methods for enhancing landslide susceptibility mapping. I would also like to use an area of the world that has more reported historical landslides to test my theory – for example the US.

Overall, the global landslide inventories, even when combined for more coverage is not good enough for this type of predictive tool development in the study area. Not only this, but reported landslides are not being added to these inventories, despite these inventories being the most comprehensive global landslide inventories in the world. This could be due to a number of different reasons, such as lack of international cooperation when reporting landslides to the larger global inventories, or, perhaps, it is due to the lack of interest in creating a more complete inventory by organisations such as the team at NASA in areas such as this one in the Darjeeling District, India. This surprises me as the study area is one of the most at risk areas for landslides worldwide and has some of the largest landslide fatalities in the world. There are three ways to view the discussion and how the chapter fills the research gaps highlighted in **Thesis Section 2.6 Literature Review: Research Question 6.0 Research Chapter II**, and these have been summarised below.

6.6.1 Application of ERA5 Data in Landslide Prediction

While ERA5 reanalysis data has been widely used for various meteorological studies, its application in landslide prediction remains underexplored. This chapter fills this gap by evaluating the potential of ERA5 total precipitation data combined with intensity-duration thresholds for landslide prediction.

6.6.2 Sparse Historical Landslide Records

The northeastern Indian Himalayas lack comprehensive historical records of landslide events, impeding the development of predictive models. This research highlights the critical need for improved landslide monitoring and documentation, addressing the gap in historical data availability.

6.6.3 Evaluation of Predictive Methods

The effectiveness of using predefined intensity-duration thresholds for predicting landslides has not been thoroughly assessed in regions with limited historical data. This research identifies the limitations of this approach in data-scarce environments, addressing the gap in the evaluation of predictive methods under such conditions.

These three points and additional discussion are discussed in more detail in **Thesis Section 7.4: Discussion and Future Considerations: Research Chapter II.**

6.7 Future Considerations

The research has shown that with the current Global LSIs there are not enough landslide events to use a system like this so far. To try to combat the issues faced in this research chapter it may be prudent to take individual case studies and compare precipitation patterns and accumulations. The lack of data is a problem that I think should be an international point of policy change – a larger effort for a collaborative, comprehensive international database that is updated and reported to by national agencies would be a start. Discussions on the future of a worldwide collaborative database for a global LSI is discussed in **Thesis Section 5.0 Research Chapter I & Thesis Section 7.2 Discussion and Future Considerations: Research Chapter I.**

6.8 Conclusion

There is a systematic error when using the Global LSI's and the established ID thresholds together to try and predict landslides in the Darjeeling District, India. This is due to the lack of historical landslides available for use in this way. With a considerably larger historical landslide database this type of testing could be done again, as there is merit to trying to have a predictive landslide tool in this region as landslides are one of the most frequent and life-threatening natural hazards in this study area.

Chapter 7: Discussion and Future considerations

7.1 Introduction

The thesis I am presenting is looking at the way in which current practice in DRR research is failing to be sufficient for working within an equitable parameter when working across the Global North – Global South divide. The thesis is answering the following research questions:

- Are the global landslide inventories fit for use when validating historical reforecasting of precipitation triggered landslides in Darjeeling, India?
- Can historical precipitation triggered landslides in Darjeeling, India be identified with the global scale reanalysis precipitation dataset ERA5, and established Intensity Duration Thresholds?

These research questions were tackled in two main research chapters, **5.0 Research Chapter I and 6.0 Research Chapter II.** To discuss the chapters, the research gaps have been distilled into subheadings of which I discuss my results and their contribution to filling each of these gaps within the DRR discipline. The discussion of each of these chapters and the discussion surrounding the research questions is below, with a further overall discussion on the way these chapters interact with each other for the contribution to knowledge within the DRR discipline.

7.2 Research Chapter I – 'Data'

In the **Thesis Section 2.0 Literature Review** there was a clear and obvious research gap in the current literature. This gap was that LSIs are unregulated and un-standardised and have not been used in any larger global studies in the creation of rainfall-triggered prediction tools with global scale precipitation models. This leads to current literature researching the creation of combining many different global LSIs and disaster datasets to create something that is 'more representative' of the global landslide landscape. **Thesis Section 5.0 Research Chapter I** has demonstrated that this global representation is not actually representing landslide conditions in the local areas, which is especially important when considering the locality of this study, the Darjeeling District, India – as this area of the world is one of the major areas in the globe that suffer fatal and non-fatal landslides (**See Thesis Section 3.0 The Study Area**). The discussion in the research chapter centred around 3 main topics, insufficient data, 'best practice' for LSIs and which of the available LSIs should be used in the case of the Darjeeling district, India.

7.2.1 Insufficient Comprehensive Data

Previous landslide inventories often lacked comprehensive spatial and temporal coverage, leading to fragmented data that hindered global analysis. Kirchbaum et al. (2019) emphasised that most LSIs were focused on local or national scales, lacked temporal information and thus made it difficult to correlate landslide events with their triggering events. By integrating multiple inventories, this research fills the gap in comprehensive landslide data, providing a completer and more robust dataset for analysis (Gómez et al., 2023). This type of combination of landslide data has good results in terms of creating a global landslide inventory with increased temporal and spatial size but now my research has shown this is not the case at a regional or local level in the Darjeeling district, India. In looking at this specific area the results have shown that despite good indications on the extension of spatial and temporal coverage of landslide events globally (Kirchbaum et al., 2019), for regional areas like the Darjeeling District the options become far more limited and does not represent the observed temporal or spatial landslide events that happen in the study area (Emberson et al., 2020). Emberson et al. (2020) used global LSIs combined with satellite data to provide a more consistent estimate of landslide exposure worldwide, including more remote and data sparse areas like Darjeeling, India. More studies into other local regions should be done to see if this is the case elsewhere. This type of study would be best placed to be done in both Global North countries like the United States (where the GLC coverage is more complete (Dandridge et al., 2023)) and Nepal (where the GFLD data is more complete (Petley and Froud, 2018)).

7.2.2 Best practice for the collection of and storing landslide inventories

In order to move towards 'best practice' for landslide inventories it is prudent to suggest some improvements to the 'current practice'. In this section I discussed the methods of collecting landslide events, either with new methods being implemented by the global LSI's, including monitoring by either on the ground sensors or through satellite imagery (Emberson et al., 2020). I discussed the importance of using additional datasets to add additional information to be collected about specific landslide events – for example pairing the event time and date with meteorological precipitation datasets to understand the current weather conditions, accumulated precipitation (24hr, 48hr, 72hr), temperature and more (Petley, 2007) (Kirchbaum et al., 2010). Banfi et al. (2024) did an investigation where they looked at temporal clustering of precipitation for detection of potential landslides in Portugal, in the hope that it could outperform traditional rainfall thresholds. The result from this small case study was that they performed similarly, but perhaps they could be used differently. The clustering approach was better at detecting deep landslides while the traditional rainfall thresholds detected shallow landsliding better (Banfi et al., 2024).

I also discussed improvements to the global LSI inventories if the system of reporting via news or citizens stayed the same and sought to promote collaboration with other researchers – reporting/collaborating/combining their datasets to the global LSI. This would be to stop the gatekeeping when the data is seen as 'owned' by the funding body that provided the researcher with the funds to conduct the research. Part of this would also be developing ways in which to encourage participation as citizens to contribute to the global LSIs, through development of a simple mobile app, to training community groups to collect pertinent information on the landslide events that were being recorded, as discussed in Pedoth et al. (2015) where they looked at the role of community networks in landsliding in the dolomites.

7.2.3 Which Inventory is best for Darjeeling District, India

At the end of this chapter, I sought to answer the main research question and discuss my thoughts on which inventory is 'best practice' for my study area – and if this was different to the 'current practice' that I have experienced. Combining the current global LSIs seems like it would be an excellent idea to increase the spatial and temporal coverage (Gómez et al., 2023). However, it was apparent that that for the Darjeeling District, India, utilizing the global LSIs would not work in the locality. There was an increase in landslide events both spatially and temporally but this number of landslides that were recorded in the combined landslides inventory did not fully represent the landscape and the landslide incidences that happen in the area (Bhukosh, 2024). A study in 2019 (Roy and Saha) identified 326 landslides just from using google satellite imagery alone. The 'current practice' in global LSI inventories is not currently good enough for representing smaller localities like the study area. Moving forward to create a more equitable 'best practice' in landslide or the DRR discipline, there are a few things to try and implement. Training researchers, either at the undergraduate, post graduate or within the workplace on how to 'social check' the datasets they're using is one way of moving the practices towards a more equitable use. This additional training will allow the researchers to understand the often implicit biases in the datasets they're using, and also allow the researchers to discover if another method, or indeed LSI would work better than the current one they're using, despite any unconscious bias or misgiving they might have that influences their decisions (ECHR, 2018) (Oberai and Anand, 2018).

Overall **Thesis Section 5.0 Research Chapter I** discusses the global and national LSI datasets that are available for the region in the study and found that the global LSI datasets are not very representative spatially or temporally of the region and the landslides that are there (Kirchbaum et al., 2010). The national inventory, although more representative, does not contain the information specified as needed in this thesis – for example the date and/or time of the landslide event. This led to recommendations on how we could change the current practice to a practice that would lead to more cohesion, more comprehensive LSI databases and more equitable partnerships and data collection and sharing strategies.

7.3 Research Chapter II – 'Application'

Research chapter II has a very clear research question: Can historical precipitation triggered landslides in Darjeeling, India be identified with the global scale reanalysis precipitation dataset ERA5, and established Intensity Duration Thresholds? This research question was born from a gap in the literature surrounding landslide prediction systems within the wider scope of Landslide Early Warning Systems (LEWS). Landslide prediction systems have only begun to be developed and used, and only within areas of the world like the US and Italy (Rossi et al., 2018) (Guzzetti et al., 2019) (Kirchbaum et al., 2019). Landslide prediction using freely available datasets and predetermined landslide ID thresholds has never been attempted in the literature either. For me it was important to try to create a prediction system that used freely available datasets due to the lack of observation data and funding available in the thesis study area of the Darjeeling district, India – and also the application of the same method being able to be used in other areas, even if it is used as a precursory look for hazards at areas being considered for refugee housing, aid delivery and other endeavours that require quick decision making.

The research question was answered by the research chapter, however the ideal result of having a simple, freely accessible, prediction tool was not the case. This was due to the lack of historical landslide data available from freely accessible global LSI databases, even when combined as seen in **Thesis Section 5.0 Research Chapter I**. The results showed that the prediction model that was used in this study was not only inaccurate to random, but showed results that were worse than random, and instead, if the prediction model was used in an opposite approach (when the model says 'hit' record a 'miss') it would be more skilful. This type of result is very peculiar and indicates that there were not enough historical landslide events to operate the prediction system with any type of skill.

There are three defined topics when discussing this research chapter. There is the discussion on the application of ERA5 for landslide prediction, the sparse historical landslide records and the evaluation of predictive methods in general.

7.3.1 Application of ERA5 Data in Landslide Prediction

While ERA5 reanalysis data has been widely used for various meteorological studies, its application in landslide prediction remains relatively unexplored, with some studies in Europe (Bordoni et al., 2023) (Distefano et al., 2023) and more in Italy (Reder and Rianna, 2021) (Botto et al., 2025) using ERA5 but not in this study area, and not in conjunction with established ID thresholds. This chapter fills this gap by evaluating the potential of ERA5 total precipitation data combined with intensity-duration thresholds for landslide prediction in the Darjeeling district, India. ERA5 is a reanalysis product that provides a long temporal dataset at a high spatial resolution, and its ability to be used as a dataset for precipitation is important for landslide prediction studies as precipitation is a primary trigger for landslides – as water infiltration reduces the soils shear strength and increases pore water pressure leading to slope failure (**See Thesis Section 2.1 Landslide Hazards**). The chapter unfortunately cannot sufficiently say if ERA5 total precipitation can be used for a predictive model when used in conjunction with established ID thresholds in the Darjeeling district, India because of the lack of historical landslide data to verify the skill. For future consideration, using case studies would be advantageous to try to answer this question, as a more in-depth analysis of the weather systems, the antecedent conditions and the topographical characteristics can be taken into consideration (Reder and Rianna, 2021). For example, Reder and Rianna used a case study to show that ERA5 could be used as a proxy for slope wetness (2021). The ERA5 reanalysis itself could also be placed under more scrutiny, with the most extreme ensemble members being interrogated (Hersbach, 2020) (Soci et al., 2024).

7.3.2 Sparse Historical Landslide Records

The northeastern Indian Himalayas lack comprehensive historical records of landslide events, impeding the development of predictive models. This research highlights the critical need for improved landslide monitoring and documentation, addressing the gap in historical data availability, and fills in more of the story surrounding the lack of data in global LSIs continuing from **Thesis Section 5.0 Research Chapter I**. Guzzetti (2012) championed for more resources, technology and innovation in landslide inventories, as this would improve the quality of landslide tools, maps and have a positive effect on all products and analyses. In a 2023 paper Sharma et al. did a systematic review in which they looked at research gaps for the future of landslides specifically around the impact of climate change. Sharma et al. identified lack of advanced prediction models based on poor data were the major research gaps. For future studies into using ERA5 with established ID thresholds doing this study again, but in a country which has more historical landslide events available for testing the predictive system, for example the United States.

7.3.3 Evaluation of Predictive Methods

The effectiveness of using predefined intensity-duration thresholds for predicting landslides has not been thoroughly assessed in regions with limited historical data. Italy have been at the forefront of using historical precipitation and landslide datasets in order to derive rainfall thresholds (Caracciolo et al., 2016) and this is due to their expansive and varied historical datasets. This research identifies the limitations of this approach in data-scarce environments, addressing the gap in the evaluation of predictive methods under such conditions.

Overall, the research chapter tries to use the most recent and used current practice when developing an idea or predictive model. The failure to produce something is a symptom of the condition of the 'current practice' and is indicative of the failures in our discipline's current practice.

When considering this chapter as a singular research piece, I must reflect on its ideology that began at the start of my PhD journey. My thoughts at the time were: I am going to make a predictive landslide model for the Northeastern Indian Himalayas because my technology and tool will save the communities from unnecessary deaths. My own unconscious white saviourism began my research into this prediction model and I must admit that I am sad to see that it currently doesn't work. However, considering the technocratic push by the Global North based on technological superiority born from a colonial and imperial past, I wonder if this tool would be needed at all. **Thesis section 2.2.1 DRR** discussed the UN initiative 'Early Warnings for All' but also the trap that Global North researchers fall into when researching Global South Countries. Jefferess (2022) discusses white saviourism and humanitarian projects and talks about the way in which humanitarian aid and research has been represented to Global North populations and how problematic this can be (Dogra, 2012) (Fassin, 2012). A paper in 2016 looked at community challenges to the saviour mentality of researchers in aid agencies and concluded that it was a problematic way of approaching research (Flaherty, 2016).

I think that the future consideration of this chapter should also reflect what would be the *actual* impact on those living in the community in the Darjeeling district, India and if this type of tool would make any impact at all. This research should be conducted with the communities in the Darjeeling district and highlight any local and indigenous knowledge that already exists and informs the community about landslide risk and predictions. Few et al. (2022) did a critical reflection on the cross-disciplinary practice they engaged in while working with communities and concluded that working collaboratively with communities would produce the most meaningful and effective research.

7.4 Discussion of overall thesis and outcomes in relation to DRR

The findings in the two research chapters show significant limitations in using freely available global landslide inventories for historical verification of reanalysis models like ERA5 for landslide prediction. These LSIs, while valuable for broad trend analysis, often lack the spatial and temporal resolution, completeness, and quality required for robust historical validation. Issues such as underreporting of small-scale events, inconsistent data collection methods, and regionally biased coverage hinder their utility in accurately verifying reanalysis model outputs. Also research chapter II compounded this as the ERA5-based model demonstrated poor performance in verifying historical landslide events. This suggests that the model's precipitation parameter, may not adequately represent the complex, localized triggers of landslides. Moreover, the coarse resolution of ERA5 data likely fails to capture the microclimatic and geomorphological factors critical to accurate landslide prediction, especially in heterogeneous terrains like the Himalayas.

Freely available landslide inventories (LSIs) that lack quality and completeness undermine efforts to develop effective early warning systems and disaster preparedness strategies. These inventories often suffer from inconsistent reporting, regional bias, and missing small-scale or historic events, limiting their utility for validating prediction models like those using ERA5. Poor LSIs lead to unreliable predictions, directly affecting the UN's Early Warning for All initiative, which relies on accurate data to protect vulnerable populations **(See Thesis Section 2.2 DRR and Landslide Early Warning)**. Without robust LSIs, communities are deprived of actionable information, conflicting with SDG 16.10's mandate to ensure public access to reliable information for effective disaster risk reduction.

The UN's Early Warning for All initiative faces criticism for its reliance on global datasets and models (Troglic et al., 2022) that often fail to address the localized and complex nature of disasters such as landslides **(See Thesis Section 2.2 DRR and Landslide Early Warning)**. This critique aligns closely with the research findings, which reveal that freely available global landslide inventories are incomplete, regionally biased, and unsuitable for validating reanalysis models like those using ERA5. These gaps limit the reliability of prediction models and, in turn, the effectiveness of early warning systems, particularly in high-risk areas like the Himalayas, where disasters are influenced by localized factors such as rainfall variability, soil conditions, and seismic activity.

The initiative's dependency on such flawed datasets risks delivering inaccurate or inadequate warnings to vulnerable communities, undermining its goal of universal disaster preparedness. To address this, there is an urgent need for investments in localized data collection, refinement of prediction models, and the integration of regional knowledge to ensure reliable, actionable early warning systems (WMO, 2024).

However, the goal is ambitious and sorely needed in the global community. To align with these global goals, investment in high-resolution, localized data collection, integration of diverse datasets, and refinement of reanalysis models is essential. By bridging these gaps, we can move closer to achieving effective early warning systems that save lives and foster resilient communities worldwide.

7.5 Conclusion

By investigating the current practice within landslide science in the DRR discipline through looking at the data and an application of a freely available and simple historical identification of hazards tool I have been able to identify and highlight research gaps, results and recommendations for the future within this DRR discipline. I propose that the current practice is poor, and that by investing in more reliable and accurate LSIs then we can move towards achieving the global goals set by the UN, to codevelop and cocreate innovative, accessible and impactful prediction tools.

Chapter 8: Conclusion

8.1 Overall Conclusion

To begin with the thesis interrogated the 'data' elements of freely available global LSI datasets. It found that although combining the datasets, it did not represent the regional area and concluded to make a more accessible dataset then recommendations on collection, storage and dissemination needed to be carried out. This in turn would make it more accessible for use in the DRR discipline in relation to the UN's Early Warning for All strategy. The current practice in 'data' needs to be pushed towards a best practice which is more equiTable (**Thesis Section 5.0 Research Chapter I**).

The second research question and objective were answered in **Thesis Section 6.0 Research Chapter II** where ERA5 and established ID thresholds were used as a tool for historical landslide identification. To validate this tool, this chapter used the combined global LSI created in **Thesis Section 5.0 Research Chapter I** to provide historic landslide events to try and validate the skill of this prediction tool. The aim of this chapter was to try and investigate if current practice in 'data' and 'people' could be applied to an 'application'. The results were very poor. There were not enough landslide events to be able to accurately provide a skill analysis on the prediction tool, and the results that did come from this study showed that if we reversed the decision from the prediction tool, it would be more skilful.

Overall, it is apparent that the thesis objectives were met by the research chapters, and the research gaps highlighted by the research questions, filled. There was also a comprehensive section in each research chapter and highlighted in **Thesis Section 7.0 Discussion and Future Considerations** which makes recommendations for changes to policy, training and institutional structures both in Higher Education and within the government run UK funding bodies.

8.2 Research Significance

The thesis set out to fill in some of the current research gaps that were identified in **Thesis Section 2.7 Research Questions.**

1. Are the landslide inventories identified fit for use when validating historical reforecasting of precipitation triggered landslides in Darjeeling, India?

The gaps found were that found for my first research question to fill was that there is no current research in using global LSIs in a regional context, or any specific literature on recommendations for unifying the collection, storage and dissemination of LSIs in general. Another unique input by the first research chapter was the idea of ‘social checks’ on data choices by DRR researchers. This research chapter has significant research potential and contributes scientific value to the DRR and landslide sciences by showing the shortcomings in global LSIs and considering recommendations, including a new concept surrounding the training of DRR researchers in ‘social checks’.

2. Can historical precipitation triggered landslides in Darjeeling, India be identified with the global scale reanalysis precipitation dataset ERA5, and established Intensity Duration Thresholds?

The second research chapter fills in gaps found in the literature. The gaps in the literature were that ERA5, freely available global LSIs and predetermined ID thresholds have not been used in conjunction together to try to create a simple and accessible landslide prediction tool. This has also never been applied to the Darjeeling district, India. My research chapter tests the theory if these datasets can be used in this way, and if they could be used in a LEWS. The overall results for this research chapter adds to the narrative surrounding best practice for reporting, maintaining, storing and disseminating free and available global LSIs, which is also an area of the literature where there has been limited research.

Overall, my thesis has begun not only answering questions on if the current practice is good enough for the future of DRR in our changing climate but also has begun *asking* the next sets of questions on making the discipline more equiTable to make steps towards best practice. It has produced some original science that can be built upon during my next steps as an Early Career Researcher and hopefully lead towards some industry and academic changes from recommendations stated within.

Chapter 9: References

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Postgraduate student, Geography Education Program, State University of Malang, Indonesia, ifana@unikama.ac.id, Sari, Y. I., Sumarmi, S., Prof., Department of Geography, State University of Malang, Indonesia, sumarmi.fis@um.ac.id, Utomo, D. H., Assoc. Prof., Department of Geography, State University of Malang, Indonesia, dwiyono.hari.fis@um.ac.id, Astina, I. K., & Ph.D., Department of Geography, State University of Malang, Indonesia, komang.astina.fis@um.ac.id. (2021). The Effect of Problem Based Learning on Problem Solving and Scientific Writing Skills. *International Journal of Instruction*, *14*(2), 11–26. https://doi.org/10.29333/iji.2021.1422a

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Appendix 1 – Working collaboratively in tropical cyclone rapid response teams as an expert at data analysis of ECMWF's Copernicus storm hydrographs and forecasted flooding.

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Recommendations to improve the interpretation of global flood forecasts to support international humanitarian operations for tropical cyclones

Linda Speight[1,2] | **Elizabeth Stephens**[1,3,4] | **Laurence Hawker**[5] | **Calum Baugh**[6] | **Jeffrey Neal**[5,7] | **Hannah Cloke**[1,3,8] | **Stephen Grey**[9] | **Helen Titley**[1,10] | **Katherine Marsden**[10,11] | **Tim Sumner**[11] | **Andrea Ficchì**[1,12] | **Christel Prudhomme**[6,13,14] | **Leanne Archer**[5] | **Juan Bazo**[4,15] | **Jânio Dambo**[16] | **Siobhan Dolan**[1] | **Anna Lena Huhn**[17] | **Francesca Moschini**[6] | **James Savage**[7] | **Andy Smith**[7] | **Jamie Towner**[1] | **Maureen Wanzala**[1]

My contributions to this paper were an integral part of the rapid response team responding to a developing Tropical Cyclone (TC Eloise) that was going to make landfall in Mozambique, Africa.

My contribution was as a data analyst to provide not only interpretation of the data, but also to report on what that data meant in terms of the impact to the surrounding areas, using established risk and vulnerability matrices.

This contributed to reports that were then presented to the UK government, who then used this information in meetings with the Mozambique Government, local NGOs and to determine what kind of aid to send to the area.

This paper directly uses these developed reports within this paper to make recommendations for improvements for the support of international humanitarian operations for tropical cyclones.

Appendix 2 – The Summer Exhibition at the Royal Society

In the summer of 2023, I attended the Royal Society's Summer Exhibition as a member of the University of Reading 'Beware Floods!' team on day 2 of the exhibition. The following report shows some of the findings and insights from the exhibition.

I have included this as an appendix as I have reflected on my time there in the context of my PhD and I think that it is a very valuable contribution to the PhD framing and the idea that working reflexively is an important skill that needs to be constantly developed and improved upon, especially within the context of searching within our own intentions and feelings in and around colonialism and post colonialism.

Figure A.1: Siobhan Dolan at the 'Beware Floods!' stand at the Royal Society, Summer 2023 (Dolan, 2023).

Figure 1 is a picture I took while at the event, just before the day began. On page 7 of the report an image of me interacting with the public on the day can also be seen (Knowles, 2023).

During the exhibition I spoke with probably hundreds of children, adults and students about flooding, climate change (as the climate stripes were on show here) and about natural hazards in general. Some individuals were there to learn more, some were there to see what was on offer while others were there to argue about the existence of climate change overall.

My main takeaway from this event was the feeling that I was part of something that didn't align with my overall values, and the fledgling values that I have been fostering over the PhD journey. It seems very strange to me to be talking about natural hazard events due to climate change (more extreme events happening in the Global South, mainly from a culture of overconsumption in the Global North and those ideals being coveted by the Global South) with middle to upper class British white people with Selfridges bags, or designer clothes. Talking about my research felt like I was cheapening it, allowing it to be used as a form of 'poverty porn' for those that could come to the Royal Society in London, during the working hours of a weekday.

This experience gave me an insight into the British nation's need for stroking the ego, for the ability to perpetuate the 'white saviour syndrome'. Reflecting on this day, at the time I was doing the same thing – describing my research as something that would 'change lives' or 'save people'. This event was not only the public performing for the felling of feeling good about themselves, but also an opportunity for me to perform and feel good about myself. It shows that despite my own self-development after the epiphany in Nepal 2018, I was still using instances like this without thinking about the connotations or the implications of what I was doing or why.

I think that these types of exhibitions are good for increasing public understanding of certain scientific findings and important information transfers for Universities and the public, but when you're covering something like climate change and natural hazards there needs to be a bit of additional thought given by the Universities showing these issues. For example, the University of Reading sent an all-white, all British team to showcase the research at the university despite there being other members of staff within the research groups that could have diversified the staff and allowed for more diverse conversations in and around climate change and natural hazards.

Royal Society Summer Science Exhibition 2023: Report on participation

CK: 7 August 2023

1. Overview

The Summer Science Exhibition is the Royal Society's week-long flagship public engagement event. It is held in July each year in the beautiful surroundings of the Royal Society in central London and provides a free, annual display of cutting-edge science and technology in the UK (selected by competition). It is attended by schools and the public, as well as science journalists, policymakers and politicians, members and Fellows of the Royal Society.

A team from Water@Reading (Geography & Environmental Sciences) led by Professor Hannah Cloke was invited to exhibit at the 2023 Summer Science Exhibition with a smaller version of the stand that had been selected for the 2020 exhibition (cancelled due to the pandemic). We were one of only a few of the 2020 exhibitors who were invited, which is a positive reflection on the original application and the efforts we made to adapt our activities for the replacement digital event in 2021.

We attended on Thursday 6 July (a schools day, with the Royal Society 'soiree' in the evening) and on Friday 7 July (a public day). On both days we received extremely positive feedback on our activities and team energy, from the public, other exhibitors, and Royal Society staff.

The Royal Society welcomed a total of 9,700 visitors to the Exhibition which ran for 6 days from Tuesday 4 July to Sunday 9 July 2023. There were 1,100 visitors during the day on 6 July plus 460 for the evening Soiree, and 1,470 visitors on 7 July – so over 3,300 people saw our stand over the two days we attended. We are currently still awaiting the evaluation report from the Royal Society.

Beware: Floods Ahead! (description from Royal Society website)

Floods are becoming more likely as the climate warms – as we've seen in recent years, from Somerset or Whaley Bridge to Pakistan and Mozambique. Forecasting floods is tricky but has improved thanks to research and improved prediction by meteorologists and hydrologists. Flood defences and the choices we make about where to build houses can help reduce the impact of floods. Join scientists from the University of Reading to try your hand at flood prediction and managing the risk that it may flood, and to discuss our interactive climate stripes – a graphic representation of how the world is warming. Find our more: https://research.reading.ac.uk/toohttps://research.reading.ac.uk/too-much-water/much-water/

2. Aims of attending

- To showcase the best of Reading research and raise the University's profile among Royal Society audiences (schools and the public, science journalists, policymakers and politicians, members and Fellows of the Royal Society).
- To raise the profile of Reading research among other exhibitors and peer universities.
- To gain experience of public engagement in a high-profile environment and to foster links with the Royal Society's public engagement team for future opportunities.

3. Our stand and activities

As an invited exhibitor, we were allocated a smaller space (2m x 2m) than the 'flagship' stands which had been selected in the 2023 competition (4m x 4m) – although in the event we had more space than we expected. The stand was based on the activities which had been planned for 2020 and designed and built by the Technical Services team led by Andy Whittam. They worked closely with Stuart Mitchell from ECMWF, who developed the computer programme for the flood prediction game. We are extremely grateful to Stuart, Andy and the team for the time and effort they put into this, both for the initial build in 2020 and to get the activities out of storage and overhaul them, since the interactive nature of the stand was a major factor contributing to its success.

The build of the activities had been almost complete in April 2020 when that year's Exhibition was postponed due to the pandemic. At that point we decided to complete them as far as we could, not knowing how long the lockdown would last. This proved to be a good value-for-money decision since they have also been used by Professor Sarah Dance (Meteorology) for schools visits days in 2022 and 2023. We hope to use them again in future (provided we have researchers to staff the stand), for example at Swindon Science Festival or the University's Community Festival in 2024.[1]

The stand we took to the 2023 Exhibition consisted of:

a. **Flooding Table:** a model landscape, involving trees, movable model buildings and flood barriers, which can be flooded with water, enabling visitors can see directly how land management and flood defences can protect (or not) from flooding.

b. **Flood prediction game:** a fruit machine which visitors can play to understand the range of factors that can combine to contribute (or not) to flooding, and its unpredictability.

c. **Climate stripes banners:** provided a backdrop to the stand and a conversation starter. Visitors are able to identify their country and year of birth and how the climate has changed over time. [Note: due to space constraints we substituted this static activity rather than the interactive stripes originally developed for the 2020 stand.]

We also had:

d. **Climate stripes badges:** as small take-home reminders, intended to be a conversation starter for people to wear/use in their daily lives. These were not cheap to purchase, so the team was encouraged to give them to visitors who had engaged in interested conversation (not just wandered past the stand).

e. **Website** with online version of flood prediction game; climate stripes activity; cloud-spotting activity; short 'Meet the scientist' videos about the different roles researchers play in flood prediction and prevention; online version of 2021 public lecture by Professor Cloke.

f. **Cloud-spotting guide:** which we had developed as an online activity for the digital version of the exhibition (although in the event we did not use this, and will keep it for another opportunity).

The effective use of the climate stripes for branding on t-shirts (with the University logo on the back) and for stand backdrop was commented on by other PER professionals who attended the event.

We should acknowledge here the work of Jeremy LeLean (former Senior Research Communications Officer) who developed the activities with the Technical Services team in 2020 and took them online in 2021 but has since left the University.

Other activities

- Professor Cloke attended the Summer Science Exhibition Soiree, a black-tie and invitationonly evening for senior scientists, science policymakers, journalists and Royal Society Fellows. This is a useful networking and profile-raising opportunity. Unfortunately, the ViceChancellor was unable to attend due to a prior commitment, so we invited Dr Florence Rabier (Director-General of

ECMWF) as a guest. Two of the University's Royal Society Fellows also attended.

- Professor Cloke was invited to give a talk on 6 and 7 July about her work as a scientist which filled the lecture theatre each day: What happens when there's too much water?
- She was also interviewed for the Exhibition podcast: Summer Science Live (1h13mins in), which has been viewed over 4,200 times to date.

4. Team members

Although hugely enjoyable, it is very tiring to be on your feet and 'on show' all day, so we would usually expect to have a team of between 6 and 8 people each day to staff a 'flagship' stand (allowing a proper rota of breaks and rest periods). Because we were offered a much smaller space this year, we took a smaller team, although in the event, we had more space than expected, and the team worked very hard both days.

Thursday 6 July • Professor Hannah Cloke (lead researcher), Geography & Environmental Sciences • Dr Jessica Neumann, Geography & Environmental Sciences • Helen Titley, Met Office (staff) / University of Reading (PhD student) • Dr Stuart Mitchell, ECMWF (retired) • Connie Seamer, Research Communications Officer
Friday 7 July • Professor Hannah Cloke (lead researcher), Geography & Environmental Sciences • Dr Jessica Neuman, Geography & Environmental Sciences • Dr Siobhan Dolan, Geography & Environmental Sciences • Pete Castle, External Relations & PR Manager

5. What we learned

- Our stand compared very well with those of other bigger universities, who had clearly spent a lot more money on presentation (see section on resources below).
- Most of the other universities attending are from the Russell Group, represented by the 'hard' sciences. Our approach of focusing on our environmental/sustainability issues for our applications allows the University to stand out with our own profile among them.
- Interactive hands-on activities draw people in – and were popular with all ages.
- It is inspiring for children and young people to meet 'real-life scientists'.
- The University's climate science is recognised by the public to varying degrees. The climate stripes are well known in meteorology circles, but not more widely; their simplicity and strong message was acknowledged.
- The University's strong position on sustainability is attractive to students (extrapolated from a small sample).

Feedback from the team

Participation in the Exhibition was fun and exhausting – and it was both inspiring, energising and a learning experience:

> "Pretty much everyone I spoke to was interested to talk about flooding. It was a bit of a change for me to be on my feet all day and talking to people rather than just sat at a computer... I'm very glad I did it as it was brilliant to chat to people, with a massive range of ages from about 8 to 80!"
>
> "I was amazed and inspired to see my academic colleagues in action, particularly seeing Jess and Siobhan who are clearly absolute naturals at engaging kids and adults and drawing them in with their personality and knowledge."
>
> "I only had immensely positive feedback. People loved it. Stayed for ages. Returned. Chatted to me in the queue for the toilets. Talked about current flooding around the world, or how safe they were. They laughed in delight. Many of the kids enjoyed the freedom to flood everyone and wash all the houses downstream. Some really interesting conversations on the back of this."
>
> "Hold some more public events at UoR or local venues? People travelled from Scotland for the day to visit RS so I reckon there'd be enough local interest to make it worthwhile."

Feedback on the activities

> "The flood Table was incredibly popular with younger children and teenagers. It's ideal as an activity to get a whole school group engaged with as there is plenty of room to get people all around the Table (I had up to 12 gathered around for one demo)."
>
> "Nearly everyone stopped at the flooding Table and watched. Anything that visitors can physically get their hands on and try for themselves was really popular. Having the ability to create different outcomes really sparks conversation too (flood machine and moving the houses / water jugs). The climate stripes were good because they are well-recognised but (in my opinion) did not generate the same level of discussion and interest with most people as they were more static. The stripes did appeal to those already with a background knowledge of climate change though so I think it's good to have a variety of activities to appeal to a larger audience."

Feedback on the University

> "It was very rewarding though to inspire kids and adults about flooding and climate change - lots of interest in the topic area and also UoR as an institution."
>
> "I was actually surprised at how few people had seen or knew about the climate stripes. I feel like I see them everywhere (which is great!) but I clearly move in lots of Uni of Reading / meteorology circles, so it was a good reminder to me ... it's clear that the potential to continue to expand their use as an educational tool is massive. ... People were really interested and impressed by this and it shows them that the potential of Reading research to make wider impacts across the community and the world.
>
> "I had some conversations with some nutcases who insisted climate change was a hoax. But equally, I met a student who said she is coming to Reading in September to study English specifically because she loves our climate focus as an institution. I spoke

to loads of people who knew about the climate stripes, but more who were fascinated to learn about them."

Practical lessons for the Research Communications team

- We delivered a well-conceived and engaging stand – visitors loved the hands-on activities.

This made it easy for the research team to strike up conversations and explain their science.

- However, we were not quite so successful at conveying an overarching research message about the link between science and practical (or policy action) on the stand (although the research team was very good at doing this). We should put more thought into this for the design of future stands.
- We need to develop a briefing sheet about the climate stripes for any staff working on a stand like this – pointing out information about key years/regions that stand out on the display e.g. Europe being colder in World War 2 and in 2010.
- It would also be helpful to have supporting material (either printouts or a QR code) to provide scientific backing for the arguments that climate change is caused by human activity.
- There were several small logistical details we learned – e.g. adding QR codes to direct people to the website and give access to further information; having business cards available; ensuring there was tech support on hand for technically complex activities.
- The flooding Table in particular and the fruit machine were heavy and cumbersome to move and transport costs were not inconsiderable. This may limit re-use off campus, and we must consider this in any future exhibition design.
- We needed a better briefing about the Soiree (what we got from the Royal Society team was virtually non-existent. Particularly we should consider inviting one or two senior external stakeholders (relevant to the stand), ensure all of our own Royal Society Fellows know we will be there and ask them to attend to support the team, with networking and general University profile-raising.

6. Budget and resources

We were granted £29,000 from RETF to cover participation in the 2020 Exhibition and this was used to build the activities in 2020 and adapt them for the online Exhibition in 2021. There was, of course, a considerable underspend in the physical delivery (based on previous years' costs, we had budgeted £6000 for travel, accommodation and subsistence; £5200 for communications and training including and a dry-run 'practice' event; £5000 for a small giveaway item).

We were given permission to request money from HEIF to fund the 2023 Exhibition, but in the event were able to use an underspend in the Research Communications team's activity budget.

2020 costs	
Activity build costs	3,355
Technical Services labour costs	5,301

Stand design and printing	659
	9,315
2021 digital exhibition	
Poetry video, workshop, competition	2,600
Cloud-spotting guides (printing)	1,696
Website costs and video recording/edit	526
	4,822
2023 costs	
Checking and finalising build of activities*	520
Transport	1019
Travel and subsistence (9 staff in total/2 days)	775
Climate stripes t-shirts and badges	2249
	4563

*Note: 2023 labour costs have not yet been charged by Tech Services, but can be expected to be about 6 days.

This total spend represents exceptional value for money and compares very favourably with the Royal Society's published data on what it costs to exhibit:

Total spend	**Rough budget breakdown (%)**
25% spent £25k	40% Exhibit design and build
25% spent £20k - £25k	25% Displays and interactives
32% spent £15k - £20k	25% Accommodation, travel and subsistence
19% spend £10k - £15k	10 % Freebies, T-shirts, insurance
0% spend under 10k	

We must of course also factor in staff time, which is not inconsiderable:

- **Lead Researcher:** It is essential to have a senior researcher who is committed to the process and will help with conceptualisation of the stand and activities, representation at the Royal Society, and is fully committed to attend as many days of the event as possible (total time commitment: estimate 15 days for full delivery of a 'flagship' stand).
- **Research Communications team:** The time necessary to develop the application, conceive of and design the activities, supervise the design and build, develop communications outputs, liaise with the Royal Society team, deliver the event should not be underestimated Conceptualisation, stand build (estimate 10 full weeks of work for one person).
- **Technical Services:** design and build of hands-on activities: estimate 10 days.
- **Research team to deliver:** A full 'flagship' stand needs a team of 5 or 6 post-docs and PhD students for the full 8 days of the Exhibition, plus the Lead Researcher and other senior researcher. In 2023, with a smaller stand, we managed with a team of 4 (plus comms officer) on 6 July (schools day) and 3 (plus press officer) on 7 July – but this was very hard work.
- **Press/Comms on the day:** We can benefit greatly from the dedicated support of a Press Officer at the event (especially if we are running a 'flagship' stand for 8 days). This is a highprofile event with significant

opportunities – for example, Professor Cloke was featured on Radio 4's 'The Life Scientific' after meeting presenter Jim Al-Khalili at the online 'soiree' in 2021.

Future plans

We have now attended the Summer Science Exhibition for three of the last four times it has been held (Soil Science in 2019; Covid and llama nanobodies in 2022; and Flooding in 2021/23) and we have gathered considerable experience of putting on a stand of this nature and can certainly hold our own against our comparator universities.

We are currently in discussions with the School of the Built Environment about revising the submission focused on sustainability that we made with them for the 2022 Exhibition (which we were told had narrowly missed being shortlisted). We have also approached the School of Agriculture to explore whether we could submit an application about the future of agriculture. We hope to be able to submit one of these for the 2024 exhibition (deadline 2 October) and one for 2025.

Caroline Knowles Head of Research Communications & Engagement August 2023