Application of satellite and airborne technologies for the development of probabilistic rainfall thresholds and susceptibility maps for landslides in Papua New Guinea

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Abstract

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Abstract

Landslides pose a significant risk to life and infrastructure in Papua New Guinea (PNG). The combination of rugged topography and high seismicity makes PNG highly susceptible to large-volume, earthquake-induced landslides, while the climate encourages widespread rainfall-induced landslides. Of the two triggering mechanisms, rainfall offers the best opportunities for the development of early warning/forecasting systems, as meteorological models continue to improve in skill and resolution. To understand the relationships between rainfall and landslides, studies have conventionally looked to develop landslide-triggering rainfall event thresholds. Such thresholds can form the basis for early warning/forecasting systems. In this thesis, satellite-based precipitation estimates from the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) are used to examine characteristics and relationships between rainfall and landslides. These data, in conjunction with Bayesian statistical approaches, were then used to develop landslide probabilities based on rainfall events of varying duration and magnitude.

Understanding the landslide triggers is only one aspect of slope instability. Environmental control factors, such as slope or curvature, can enhance or reduce the likelihood of slopes to fail. Therefore, multispectral imagery and high resolution GeoSAR (synthetic aperture radar) digital elevation models have been exploited to verify and map landslide scars in different regions of PNG. These data also support the development of landslide susceptibility maps, providing detailed information on the terrain and structures important for slope instability. Using fuzzy relation-based assessments these data were used to produce landslide susceptibility maps which differentiate areas of low/no susceptibility from those with high susceptibility. Overall, the satellite and airborne techniques have provided the tools to understand landslide occurrence relative to changes in rainfall and susceptibility, which can form the basis of early warning/forecasting models.
Acknowledgements

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<td>TMPA 3B42 daily, gauge-adjusted data</td>
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<td>TMPA 3B42 Real Time daily data</td>
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<td>3B42V6</td>
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<td>AMSR</td>
<td>Advanced Microwave Scanning Radiometer</td>
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<td>AMSU</td>
<td>Advances Microwave Sounding Unit</td>
</tr>
<tr>
<td>asl</td>
<td>above sea level</td>
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<td>AVHRR</td>
<td>Advanced Very High Resolution Radiometer</td>
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<td>Geostationary Orbiting Environmental Satellites</td>
</tr>
<tr>
<td>GPCC</td>
<td>Global Precipitation Climatology Centre</td>
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<td>GPS</td>
<td>Global Positioning System</td>
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<td>GSFC</td>
<td>Goddard Space Flight Centre</td>
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<td>HGCP</td>
<td>Hides Gas Conditioning Plant</td>
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<td>HGDC</td>
<td>Hides Gas Development Corporation</td>
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<tr>
<td>IR</td>
<td>Infrared</td>
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<tr>
<td>ITCZ</td>
<td>Inter-tropical Convergence Zone</td>
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<tr>
<td>JJA</td>
<td>June, July and August</td>
</tr>
<tr>
<td>LAM</td>
<td>landslide area mean</td>
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<td>LiDAR</td>
<td>Light Detection and Ranging</td>
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<td>LNG</td>
<td>Liquefied Natural Gas</td>
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<tr>
<td>LTE</td>
<td>Landslide Triggering Event</td>
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<td>MAM</td>
<td>March, April and May</td>
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<tr>
<td>MC</td>
<td>Maritime Continent</td>
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<td>MEI</td>
<td>Multivariate ENSO Index</td>
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<tr>
<td>Acronym</td>
<td>Definition</td>
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<tr>
<td>MJO</td>
<td>Madden-Julian Oscillation</td>
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<td>MRA</td>
<td>Mineral Resources Authority</td>
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<td>MSS</td>
<td>Multispectral Scanner</td>
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<td>MW</td>
<td>microwave</td>
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<td>National Aeronautics and Space Administration</td>
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<td>National Capital District</td>
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<td>Natural Disaster Centre</td>
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<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
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<td>NEIC PDE</td>
<td>National Earthquake Information Centre Preliminary Determination of Epicentres</td>
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<td>non-earthquake-triggered</td>
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<td>Nearest Neighbour Ration</td>
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<td>outgoing longwave radiation</td>
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<td>OSFZ</td>
<td>Owen Stanley Fault Zone</td>
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<td>OSMC</td>
<td>Owen Stanley Metamorphic Complex</td>
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<td>PERSIANN</td>
<td>Precipitation Estimation from Remotely Sensed Information Using Neural Networks</td>
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<td>PNG</td>
<td>Papua New Guinea</td>
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<td>POES</td>
<td>Polar Orbiting Environmental Satellites</td>
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<td>PR</td>
<td>Precipitation Radar</td>
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<td>PUB</td>
<td>Papuan Ultramafic Belt</td>
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<td>RMF</td>
<td>Ramu-Markham Fault</td>
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<td>regional monthly mean</td>
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<td>SAR</td>
<td>Synthetic Aperture Radar</td>
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<td>SLC</td>
<td>scan line corrector</td>
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<td>Southern Oscillation Index</td>
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<tr>
<td>SON</td>
<td>September, October and November</td>
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<tr>
<td>SPCZ</td>
<td>South Pacific Convergence Zone</td>
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<tr>
<td>SRTM</td>
<td>Shuttle Radar Topography Mission</td>
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<tr>
<td>SSM/I</td>
<td>Special Sensor Microwave/Imager</td>
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<tr>
<td>SST</td>
<td>Sea Surface Temperature</td>
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<td>TCT</td>
<td>Tasselled Cap Transformation</td>
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<td>TM</td>
<td>Thematic Mapper</td>
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<tr>
<td>TMI</td>
<td>TRMM Microwave Imager</td>
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<td>TMPA</td>
<td>TRMM Multi-satellite Precipitation Analysis</td>
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<tr>
<td>TOA</td>
<td>Top of Atmosphere</td>
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<tr>
<td>TRMM</td>
<td>Tropical Rainfall Measuring Mission</td>
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<td>USGS</td>
<td>United States Geological Survey</td>
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<tr>
<td>VIRS</td>
<td>Visible Infrared Scanner</td>
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<td>WMO</td>
<td>World Meteorological Organisation</td>
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1. Introduction
1.1 Background and rationale

Landslides, a term broadly used for mass movements which affect the land surface and consist of rock and/or soil, are critical for montane evolution (Petley, 2012; Hovius and Stark, 2006). They occur in a number of different styles and can move down slope at rates from mm/year up to m/s (Glade and Crozier, 2005a). As a key aspect of landform evolution, landslides can also be measured over decadal time scales (Glade and Crozier, 2005b; Cendrero and Dramis, 1996). The spatial and temporal scale of landslide processes makes them particularly problematic to mitigate against. This is because the processes involved are frequently complex and multi-faceted, and this means that any specific type or style of event can only be very generally linked to categorised environmental domains. In many instances, combinations of geomorphic characteristics and one or more (or no apparent) triggering event may be responsible for a landslide. The most extensively researched triggers of landslides are rainfall (references throughout) and earthquakes (Wasowski et al., 2011; Malamud et al., 2004a; Keefer, 2002; 1984), but day-to-day activities by humans can also results in slope movements (Alexander, 1992), as can rapid snowmelt and volcanic eruptions (Malamud et al., 2004a). It is often difficult to identify distinct causes and triggering conditions associated with individual landslides. This is because landslides can sometimes show a delayed response to a critical triggering event. The gradual increase in pore water pressures following prolonged rainfall is one such mechanism. On other occasions however, landslides can occur instantaneously in response to a trigger (Glade and Crozier, 2005a). The large number and wide range of factors, and combinations of factors, involved in landslide processes has meant that most work has been single-site, or basin-based (Crozier and Glade, 2005). The major drawback of these projects are that they are often completed without any consideration of factors outside of the immediate
vicinity of the slope and, although they are often very detailed, are not easily reproducible across larger areas.

Due to the nature of landslides, research to quantify their impact on humans has been difficult and the development of landslide event inventories is somewhat behind other natural hazard catalogues (Kirschbaum et al., 2010). There are a number of reasons for the disparity in landslide recording: (1) landslides frequently result in impacts over small areas compared to impacts associated with larger-scale natural hazards, (2) the areas affected by landslides are often remote and difficult to access, as well as being widely distributed relative to one another, (3) there is currently no systematic, universally adopted way to report landslides, with different organisations in different, and even in the same country, adopting different criteria for the development of event inventories. These reasons are particularly evident when trying to produce catalogues in developing countries, where additional issues including: (1) resource and funding, (2) poverty, (3) political issues and (4) crime, all further affect whether accurate landslide reporting occurs. Despite these constraints, a number of researchers have attempted to quantify the losses associated with landslides (Marano et al., 2010; Nadim et al., 2006; Guzzetti, 2000). Petley (2012) found that over 2500 fatal landslides occurred worldwide between January 2004 and December 2010, resulting in more than 32,000 recorded deaths. These records suggest a far greater number of fatalities associated with landslides than previously thought, which is particularly interesting given that the constraints outlined above are likely to mean that this remains an under-representation of the true extent of fatal landslides. Based on Petley’s (2012) findings, it can be argued that there is a disparity between regions where landslides have been extensively researched (Italy, North America) and regions which see large numbers of landslide-related fatalities (south-west Pacific, southern edge of the Himalayan Arc and
Central and South America; Petley, 2012), but less overall research into their occurrence. Some solutions to this have become available by the increased availability of low-cost, high resolution satellite data (Joyce et al., 2009; Hong et al., 2007; Nichol and Wong, 2005).

Remote sensing data and techniques have become a critical additional resource used to support the development of landslide inventories and have been found to be particularly useful for improving understanding of the spatial distribution and size of landslide events (Barlow et al., 2003; Petley et al., 2002). In addition, such datasets can be used to assess the environmental characteristics which enhance or reduce landslide susceptibility (Muthu et al., 2008; Ayalew et al., 2004), as well as to provide real-time information on potential triggering events such as rainfall (Hong et al., 2006) and/or earthquakes (Yang and Chen, 2010; Ratzinger et al., 2006). The introduction of satellite-based analysis has also allowed the first regional-to-global early warning and/or forecasting models to be developed (Krol and Bernard, 2012; Kirschbaum et al., 2012), although only in a few instances are these being used operationally in conjunction with the response community. These developments have predominantly focussed on the forecasting of rainfall-induced landslides, as meteorological forecasting and methods to merge satellite-derived data with ground-based observations have improved. However, these early warning prototypes remain relatively new concepts, even in westernised countries, where there is typically more equipment and funding to maintain and improve the computer modelling systems.

Papua New Guinea (PNG) is one developing country that suffers from a large number of landslides but which has only experienced moderate investment to improve understanding and monitoring. Due to the issues outlined above, the true extent of the hazard is difficult to identify, with much of the research focussing at the slope or
watershed scale, based on the requirements of development and engineering projects. In this research, the aim is to assess and understand landslide occurrence at a regional scale, and develop techniques which could facilitate the development of regional early warning/forecasting systems. As previously stated, the factors contributing to landslide events are frequently complex and multi-faceted, and therefore this research will focus on a number of key areas, specific to landslides in PNG (Fig. 1.1).

**Fig. 1.1.** Conceptual diagram outlining the range of triggers and causative factors associated with landslides in PNG, with dominant controls of variability associated with these factors also shown. Circles labelled with bold type are the dominant triggers/causative factors examined in this research. Circles marked with a red * indicate triggers/causative factors assessed through case study analysis. Greyed out circles are important research topics which will not be addressed in detail in this research. Abbreviations: ENSO, El Niño Southern Oscillation; ITCZ, Inter-tropical Convergence Zone; MJO, Madden-Julian Oscillation ; PDO, Pacific Decadal Oscillation; QBO, Quasi-biennial Oscillation.
Although there was an aspiration to include an assessment of landslide risk within this research, it quickly became apparent that limitations on the available data would inhibit such an analysis. There are a number of subtle variations to the definition of risk; however, the most widely accepted forms refer to risk as a function of a hazardous event and the vulnerability of the exposed elements (Birkmann, 2007). Crichton (1999) describes risk as “the probability of a loss and this depends on three elements, hazard, vulnerability and exposure. If any of these three elements in risk increases or decreases, then risk increases or decreases respectively”. This can be schematically illustrated using a three-dimensional pyramid diagram (Fig. 1.2).

![Fig. 1.2. Risk pyramid illustrating the three independent factors (hazard, vulnerability & exposure) which contribute to risk. Reproduced from Dwyer et al. (2004).](image)

Quantifying landslide risk is particularly problematic because it requires a number of complex components to be assessed, including: (1) the probability of landslides, (2) the run-out behaviour of landslide debris (which requires the landslide type and magnitude, geomorphology, moisture content and geology/stratigraphy to be ascertained), (3) the spatial and temporal distribution of exposed elements (people, buildings, infrastructure), (4) the varying degree of vulnerability of these assets to landslide activity and (5) how effective any policies for responding to, or mitigating against, landslides may be (Dai et al., 2002). Identifying the run-out behaviour is
1. Introduction

particularly challenging, especially in instances where landslide records are predominantly collated from non-technical sources. Frequently data pertaining to the landslide characteristics and physiography are not available. In this research therefore, the focus has been on understanding landslide hazard in terms of its spatial and temporal frequency. The development of landslide probabilities based on spatial and temporal variations of rainfall is addressed in this research, but aspects of landslide magnitude and type are only subjectively assessed. This will be discussed in more detail in Chapter 3 of this thesis.

Despite the necessary narrowing of scope, this research still offers the potential to extensively advance the body of knowledge related to landslide hazard in this region. This is particularly important as the region rapidly develops and encourages investment from global mining companies to exploit the abundance of natural resources. In fact, PNG offers a unique opportunity to identify, quantify and analyse landslide hazard prior to extensive, rapid infrastructure development, particularly throughout the central Highlands region. Developing an understanding of the landslide hazard at a regional scale and putting in place low-cost, integrated systems could allow sustainable development of high-risk areas, preventing additional fatalities and socio-economic impacts. Additional knowledge of a region which has not been extensively researched in either a meteorological or landslide context can also support those research groups who are attempting to develop robust global early-warning systems (Kirschbaum et al., 2012).

1.2 Aims and objectives

The principal aim of this thesis is to explore the possibilities for developing an early warning/forecasting approach for rainfall-induced landslides in PNG. In order to achieve this overall aim a number of objectives were identified including:
1. collate a historical landslide inventory for PNG, using a variety of different data sources;

2. determine the principal drivers of rainfall variability, at a synoptic scale, and assess whether relationships between the large-scale rainfall patterns and rainfall-related, landslide-triggering events can be established;

3. develop methods for using satellite-derived precipitation estimates to characterise rainfall patterns which have preceded known landslide events;

4. assess whether probabilistic rainfall thresholds can be developed based on the analysis conducted using the satellite-derived precipitation data;

5. generate a method for completing morphometric analysis on slopes in different climatological, geological and physiographical regions of PNG and develop maps showing the difference in landslide susceptibility based on semi-static causal factors, such as: geology, vegetation cover, proximity to watercourses and regional seismicity;

6. propose a model for integrating semi-static landslide susceptibility maps with probabilistic rainfall information for the production of warnings in PNG.

1.3 Thesis outline

This thesis comprises seven chapters, including this introduction. Chapter 2 provides a physiographic overview of PNG, including a description of PNG’s climate and the principal drivers of rainfall variability throughout the region. A broad outline of the country’s tectonic evolution and geology is also provided, focussing on the three main geological components of the region: (1) the Australian Craton, (2) the New Guinea Orogen and (3) the Melanesian Arc.

In Chapter 3 the development of a new landslide-triggering event inventory is described. This dataset forms the basis for all analysis in this and the subsequent
chapters of this thesis and is used to understand the first broad relationships between landslide occurrence and synoptic meteorology in PNG. Those landslide-triggering events, which are closely related to meteorological processes, are compared temporally and spatially with rainfall patterns over intraseasonal and interannual timescales, using gauge-based rainfall datasets.

It became evident during the analysis outlined in Chapter 3 that gauge-based data did not provide the spatial or temporal resolution required for detailed analysis of individual rainfall events preceding specific landslides. Chapter 4 therefore, describes a method for analysing landslide-triggering events, using satellite-derived precipitation methods. These data are explained in detail, including a summary of their interpretation and validation under different meteorological regimes and in different geographical regions. In addition, this chapter outlines a method for determining critical rainfall characteristics for landslide-triggering events, from which probabilistic rainfall event thresholds are established.

While undertaking this PhD a large landslide at a quarry in Southern Highlands Province occurred. The landslide resulted in numerous fatalities and additional socio-economic impacts. In Chapter 5 a description of this landslide, based on photographic and satellite-image interpretation, is provided. In addition, an outline of the potential triggers of the event is examined including, a review of rainfall, seismicity and anthropogenic activity in the Tagali Valley, preceding the landslide.

Although this thesis predominantly focuses on rainfall triggers, causal factors such as the underlying geology and geomorphology also contribute to slope movements. Following the findings in Chapter 5, Chapter 6 examines the morphometry of two case study regions in PNG and characterises the major causal factors contributing to
In this chapter, an introduction to the study of landslides in these different areas is provided. Based on these causal factors, a method to develop landslide susceptibility models and maps is described and evaluated.

Finally, Chapter 7 presents a synthesis of the main findings of the thesis research and includes a discussion of their application to PNG for the purposes of reducing losses associated with landslide hazards. In addition, recommendations for future developments and unresolved issues arising from the research are also outlined. Chapters 3-6 of this thesis have been written as discrete studies. This is particularly evident for Chapter 5 which comprises the published article by Robbins et al. (2013) and Chapter 3, which is currently being peer-reviewed for scientific publication. Due to the discrete nature of the chapters, there is inevitably some degree of overlap and repetition although this has been kept to a minimum.
2. Physiographical overview of Papua New Guinea
2.1 General Overview

PNG (Fig. 2.1) is located in the south-west Pacific, 160 km north of Australia, at approximately 147° E; 6° S. The island nation is made up of the eastern half of the island of New Guinea and over 600 additional islands. Covering an area of approximately 465,000 km², PNG is the third largest island country in the world. The region has a tropical maritime climate and experiences some of the highest annual rainfall accumulations globally (McAlpine et al., 1983). In many parts of the country rainfall is seasonal, being strongly influenced by shifts in the Intertropical Convergence Zone (ITCZ) and in the trade wind direction (McGregor, 1989; 1992). Imposed on this seasonal rainfall are larger scale variations, such as the El Niño Southern Oscillation (ENSO), and smaller scale influences induced by topography and land-sea thermal contrasts (McGregor and Nieuwolt, 1998). These encourage high spatial and temporal rainfall variability across the region. PNG has a wide variety of landscapes, from rugged mountainous terrain in the central highlands to extensive swamps which dominate the north and south mainland around the Sepik and Fly Rivers (Fig. 2.1). This variety is the result of PNG’s formation through the large-scale collision of the north-easterly migrating Indo-Australian Plate and the westerly-shifting Pacific Plate. Multiple arc-continent collisions encouraged rapid uplift of the New Guinea Mobile Belt, producing rugged mountainous regions with elevations in excess of 4000 m (Craig and Warvakai, 2009). This complex tectonic regime exposes PNG to regular moderate to high magnitude earthquakes, with return periods between 37 and 125 years for large-magnitude events (magnitude 7 and above; Anton and Gibson, 2008). The combination of rugged topography and high seismicity makes PNG highly susceptible to large-volume, earthquake-triggered landslides, while the climate encourages widespread rainfall-triggered landslides (Greenbaum et al., 1995; Stead, 1990).
Fig. 2.1. Location and geomorphology map of Papua New Guinea (PNG). The large towns/cities shown are also the locations of World Meteorological Organization (WMO) rainfall gauge stations.
2.2 Climate of Papua New Guinea

PNG’s climate is characterised by high rainfall accumulations, which alter between wetter and drier periods seasonally, and high maximum and minimum temperatures (Fig.2.2; McGregor, 1989). The spatial and temporal variability of these variables play important roles for landscape denudational processes, including landslide activity. Therefore, understanding the controls on weather and climate is essential for the development of landslide early warning and forecasting models.

![Figure 2.2](image)

**Fig. 2.2.** Mean monthly precipitation (bars) and mean daily minimum and maximum temperatures (lines) for Port Moresby (elevation~44 m) and Goroka (elevation~1600 m) meteorological gauge stations. For locations refer to Fig. 2.1.

2.2.1 General atmospheric circulation

PNG is identified as lying within the ‘maritime continent’ (MC; Ramage, 1968), a region which receives high solar radiation per unit area in comparison with the rest of the globe. This, in addition to high sea surface temperatures (SSTs), encourages evaporation and warm, buoyant air to rise, which condenses and ultimately falls as rain. This rainfall produces large quantities of condensational latent heat which drives the large-scale atmospheric circulation system (McGregor and Niewolt, 1998). These processes support the description of the region as a ‘global heat engine’ and have...
Physiographical overview of Papua New Guinea

consequently led to the MC representing the largest rainy area on Earth (Qian, 2008). Although lying within this highly dynamic region, PNG itself has received scarce attention from the meteorological research community. McAlpine et al., (1983) have written the most comprehensive outline of PNG climate, reviewing regional climatologies of surface winds, rainfall and temperature and developing a climate classification for the region. The dominant large-scale meteorological controls on weather and climate are: (1) the meridional heat transfer of the Hadley Cell and the temporal and spatial variability of the ITCZ, (2) the zonal Walker Circulation with its variability (ENSO) and associated oceanic currents, (3) the north-westerly monsoon circulation and (4) the physiography of the region.

The seasonal rainfall pattern of PNG and the wider western Pacific is recognised as being the result of the combined interaction of the east-west monsoon circulation and the north-south migration of the ITCZ. During northern hemisphere summers (June, July and August (JJA)), the zone of maximum vertical velocities (strongest warm air ascent) is displaced north of the equator and a corresponding intensification of descent occurs at approximately 10-15°S, causing the south-east trade winds to dominate. At this time the south-east trade winds, with an average strength of about 5 to 9 m s⁻¹ (Wheeler and McBride, 2005), are able to traverse the equator (Fig. 2.3) where they are forced to alter direction under the influence of the Coriolis force. This allows convergence and determines the location of the ITCZ and the ascending limb of the Hadley circulation (Waliser and Gautier, 1993). Rainfall during this period is generally confined to regions north of the equator and PNG typically experiences its drier season when the ITCZ is in this northerly position (McGregor, 1989; 1992). During the northern hemisphere winter (December, January and February (DJF)) maximum vertical velocities occur south of the equator and north-westerly flows are observed over PNG.
During this time PNG typically experiences its wetter season, the peak of which occurs in March. April and November are considered transitional periods when the ITCZ migrates north (during April) and south (during November; Fig. 2.3). McGregor (1989) highlighted that an early southerly transition of the ITCZ resulted in the wetter season starting earlier in PNG, while a delayed southerly transition allowed south-easterly trade winds to persist for longer, resulting in below-average rainfall.

![Diagram of seasonal rainfall and ITCZ migration](http://www.esrl.noaa.gov/psd/)

**Fig. 2.3.** Monthly climatology for January and July showing outgoing long-wave radiation (OLR) and NCEP/NCAR reanalysis 850hPa level vector winds, based on data from 1970-2010. Low values of OLR indicate cold cloud tops which are typically produced by precipitating cumulonimbus convection. *Images provided by NOAA/ESRL Physical Sciences Division, Boulder Colorado from their web site: http://www.esrl.noaa.gov/psd/*

The change in seasonal rainfall also coincides with reversals in tropospheric wind patterns, a key characteristic of the monsoon circulation (Wheeler and McBride, 2005).

The predominant driver of this circulation is land-sea thermal contrasts. This differential
2] Physiological overview of Papua New Guinea

heating occurs because the sun heats land and ocean surfaces at different rates. During JJA solar heating is most intense and the land heats up, forming a large low pressure system. The surrounding oceans heat up more slowly and are therefore cooler, relative to the land, causing a high pressure system to build up over the ocean. The winds alter in response to the changing and building pressure gradient, resulting in the start of the Asian-Australian Monsoon in late November or early DJF. Although the monsoon emerges as a clearly identifiable feature in January and February in PNG, it is not a constant or steady phenomenon. Much research over the last several years has focussed on understanding the variability of the monsoon system including: monsoon onset date (Hendon and Liebmann, 1990; Hendon et al., 1989), active and break periods within the wider monsoon season (McBride and Frank, 1999) and how these variations relate to both ENSO (Qian et al., 2010; Godfrey-Spenning and Reason, 2002) and the Madden-Julian Oscillation (MJO; Tam and Lau, 2005).

2.2.2 Non-seasonal variations of the tropical circulation

In addition to the meridional atmospheric circulation of the Hadley Cell, PNG is also influenced by the Walker Circulation. This is a zonal equatorial circulation spanning the Pacific Ocean, characterized by rising air in the western Pacific and descending air in the eastern Pacific (McGregor and Nieuwolt, 1998). The Walker Circulation is driven by the east-west SST gradient and the difference in specific heat capacity between land and ocean surfaces. Intense precipitation over the MC fuelled by strong solar forcing and evaporation from warmer SSTs releases latent heat, which enhances vertical air ascent and surface air inflow from the east and west. Cooler conditions in the eastern Pacific represent the location of the descending limb of the circulation. This differs from the Hadley Circulation which is driven by the difference in solar radiation per unit area received at different latitudes. Under normal conditions,
high pressure and cooler SSTs dominate in the eastern Pacific, while low pressure systems and warmer SSTs are dominant in the western Pacific and PNG. Extreme modes of this circulation have been recognised by an atmospheric pressure see-saw known as the Southern Oscillation (Bjerknes, 1969). This oscillation is described by the Southern Oscillation Index (SOI) which quantifies the pressure differences between Darwin, Australia (12.4°S, 130.9°E) and Tahiti (17.6°S, 149.6°W; Torrence and Webster, 1999). Negative SOI values are indicative of El Niño (warm) events, where the atmospheric pressure at Tahiti is less than the pressure at Darwin, while positive SOI values indicate a reversed pressure gradient (La Niña (cold) events). The Southern Oscillation and the corresponding index, describe the atmospheric component of ENSO (Troup, 1965). Being a coupled ocean-atmosphere system, ENSO is characterized by changes in both atmospheric and oceanic variables including: atmospheric pressure, trade wind dominance and strength, SSTs and the structure of the oceanic temperature profile across the equatorial Pacific. The changes in atmospheric pressure observed through the SOI, occur in concert with oceanic circulation variations. Under normal conditions south-east trade winds, fuelled by the semi-permanent subtropical anticyclone in the eastern Pacific, drive water towards the western Pacific, allowing upwelling of cooler water in this eastern region and hence lower SSTs (Fig. 2.4(a); McGregor and Nieuwolt, 1998). During La Niña this process is accentuated. Strengthening south-east trade winds enhance the equatorial current and cool water upwelling in the eastern Pacific. This produces anomalously cool SSTs in the east and anomalously low pressure in the western Pacific (Fig. 2.4(b)). El Niño events occur when south-east trade winds weaken causing internal oceanic waves (Kelvin Waves) of warm water from the western Pacific to move back towards the east. This causes a build-up of anomalously high SSTs in the eastern Pacific and inhibits cold water
upwelling along the South American coastline. The zone of deep convection, associated with the rising limb of the Walker Circulation, which normally dominates the western Pacific during ENSO-neutral and La Niña conditions, accompanies the eastward propagation of warmer SSTs (Fig. 2.4(c); Qian et al., 2010).

Under these extreme modes, ENSO can cause large changes in temperature and precipitation at both the basin scale and globally. In PNG extreme El Niño events can cause droughts, severe frosts and fires. In 1997 a severe drought event coincided with a particularly strong El Niño phase which resulted in below average rainfall for up to nine months (McVicar and Bierwirth, 2001). Ultimately the increase in plant stress and the reduction in food production led to 40% of the rural population suffering from severe food shortages (McVicar and Bierwirth, 2001). By contrast during La Niña phases, wetter conditions can lead to increases in floods and landslides and, in some circumstances, water-born and vector-born diseases (Kovats et al., 2003). Evidence of ENSO impact across the globe would suggest that a strong link between ENSO phase and rainfall would exist in PNG. However, McGregor (1989; 1992) found that although an inverse relationship between pressure changes and Port Moresby rainfall anomalies could be identified, the cross-correlation statistics were low. This, together with the work completed in 1992, indicated that the influence of ENSO was not uniform across PNG and that the degree to which ENSO affected rainfall patterns was associated with individual physiographic interactions with the zonal pressure gradient and the amplitude and phase of the monsoon circulation (McGregor, 1992).
Fig. 2.4. Schematic illustrations and data showing the changes to the Walker Circulation and the resultant change in monthly SSTs and vector winds associated with (a) normal conditions (using December 1993), (b) La Niña events (using December 1998) and (c) El Niño events (using December 1997). Images provided by the NOAA/PMEL Tropical Atmosphere Ocean Project from their website: http://www.pmel.noaa.gov/tao/jsdisplay

The complexities that ENSO introduces to seasonal rainfall patterns in PNG are further enhanced when other oscillations are considered. The MJO (Madden and Julian, 1971; 1994) has been identified as a source of intraseasonal variability which affects convective activity (Bellenger and Duvel, 2007). As with ENSO, the MJO is considered to be a coupled ocean-atmosphere system whose variability strongly influences rainfall patterns throughout the Indian Ocean and the MC. The oscillation is recognised as an eastwards propagating zone of convection with a periodicity of between 30 and 75 days.
The atmospheric signature is evident in surface pressure, lower and upper tropospheric wind strength (or divergence), and can be identified in variables such as relative humidity, outgoing longwave radiation (OLR) and precipitation. The oceanic signature is evident in SSTs, mixed layer depth, surface latent heat flux and surface wind stress variables. These signatures are most readily evident from November to March, during the Asian-Australian monsoon when the MJO experiences its maximum amplitude (around 10° latitude; Bellenger and Duvel, 2007). The MJO mechanism is schematically illustrated in Fig. 2.5. In brief this shows a split between regions of relatively suppressed convection and regions of relatively enhanced convection. The areas of suppressed convection are linked to anomalously strong trade wind inversions which enhance evaporation at the sea surface. In addition the clear skies, which dominant during these periods of suppressed convection, allow shortwave radiation to heat the sea surface slightly, increasing local SSTs. The increase in SSTs and evaporation from the sea surface causes warm air to rise, condense and produce rain-bearing clouds. Furthermore, the easterly winds weaken, allowing low-level moisture convergence which triggers deep convection. This marks the start of a zone of active convection, which comprises one or more super-cloud clusters which can produce heavy rainfall over a lifetime of one to two days. During the period of enhanced convection, increased cloud cover and surface wind speeds ultimately cause a slight, localized reduction in SSTs which subsequently leads to a period of suppressed convection (Woolnough et al., 2000). The mechanism by which these cycles of enhanced and suppressed convective activity propagate eastwards is linked to changes in lower and upper tropospheric wind circulations. Ahead of a zone of convection, low level cyclonic circulations cause anomalous easterly winds, while high level anti-cyclonic circulations result in
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anomalous westerly winds. The changes in high level wind direction are due to divergence over the zones of active convection.

Fig. 2.5. A schematic illustration showing the equatorial vertical cross section of the MJO as it propagates from the Indian Ocean to the western Pacific. Filled red arrows indicate the wind direction. Unfilled red SST labels indicate positive SST anomalies, while unfilled blue SST labels indicate negative SST anomalies respectively. Figure adapted from Madden and Julian, 1971; 1972

The influence of the MJO on PNG rainfall is not yet fully understood. This is primarily due to the complexities associated with this oscillation. For example, the MJO is typically considered to be a coherent mode of eastward propagating convection; however, Wheeler and McBride (2005) suggest that only half of the variance over the 30-75 day period can actually be attributed to a coherent mode. This makes determining relationships between the MJO and rainfall variability, challenging. Despite these complexities, a number of papers identified the MJO as important for intraseasonal variability. Hendon and Liebmann (1990) found that the oscillation influenced the onset of the Asian-Australian monsoon season and drove active and break periods (Fig. 2.5).
The super-cloud clusters, observed during enhanced convective episodes of the MJO, represent periods of enhanced activity (‘bursts’) while the periods of suppressed convection between the cloud clusters correspond to ‘break’ periods within the same monsoon season.

Further complexities have arisen through work which has looked to address the links between the MJO and ENSO. Hendon et al. (1999) identified strong year-to-year variability in MJO activity, some of which could be linked to ENSO. For example, strong periods of MJO activity have been observed to correspond with weak La Niña or ENSO-neutral periods, while weak or absent MJO activity coincides with strong El Niño years (Hendon et al., 1999; Zhang and Gottschalck, 2002). Furthermore, although the MJO has not been identified as a cause of El Niño, Kessler and Kleeman (2000) and Zhang and Gottschalck (2002), suggest that the MJO can modulate ENSO intensity and affect the speed with which an ENSO phase develops. The true nature of the MJO’s influence on PNG rainfall has not been specifically researched but the modulation of the Asian-Australian Monsoon would suggest that relationships should be identifiable.

2.2.3 Local modifications to the tropical circulation

In addition to the large-scale, interannual and intraseasonal variability, PNG is affected by localized, diurnal variability (McAlpine et al., 1983). The main mechanisms driving rainfall variability at the local scale include land-sea breezes and mountain-valley winds. These mechanisms are considered increasingly important in tropical regions where synoptic-scale pressure gradients tend to be weaker, while the local pressure gradients tend to be stronger, associated with differential heating between surface types (Qian, 2008). In the case of land-sea breezes, solar radiation warms land surfaces quickly during the day, while absorption by ocean surfaces occurs more slowly due to turbulence, waves and the difference in specific heat capacity. This causes a
convectional cell to develop. During the day warm buoyant air rises over the land, drawing air in from the ocean. During the night the land cools quickly while the thermal inertia of water means the ocean temperature remains close to its daytime temperature, causing the convective cell to reverse. Although sea-breezes rarely generate significant precipitation on their own, when they converge with winds from a different direction (i.e. trade winds) a sea-breeze front can develop (McGregor and Niewolt, 1998). Such fronts and zones of convergence are typical in the Fly Delta region of PNG and along the south coast of New Britain during the JJA season. These zones of active convection are organised dependent on the coastal alignment relative to the changing surface wind patterns (i.e. the seasonal reversal of trade wind direction) and this causes the location of such fronts to shift as the north-westerly monsoon develops. The zones of highest convergence move to the northern Sepik region of PNG and the northern coast of New Britain during DJF (McAlpine et al., 1983).

A similar process operates to generate mountain and valley winds. Differential heating of mountain slopes compared with lowland areas during the day causes upslope airflow, which draws air from the lowland valleys. Similar to the sea-breeze process, the convective cell is reversed at night. The upslope mountain airflow observed during the day is termed anabatic flow (valley wind), while the reversed downslope airflow, observed at night, is termed katabatic flow (mountain wind) and is the stronger of the two regimes. In the highlands anabatic flows of 12-13 m s\(^{-1}\) are observed, while katabatic flows at Mount Wilhelm have been recorded to gust at 15 m s\(^{-1}\) (McAlpine et al., 1983). As with sea-breeze driven convection, these orographically-driven processes are influenced by their interaction with synoptic scale processes. This gives rise to spatially and temporally varying zones of convergence across PNG (McAlpine et al., 1983). Ultimately, it is the complex combination of localized features driving local and
2| Physiographical overview of Papua New Guinea

diurnal variability and the intraseasonal and interannual variability imposed on the mean seasonal cycle which gives PNG its distinct rainfall patterns.

2.3 Tectonics and Geology of Papua New Guinea

PNG is a tectonically complex region being at the intersection between the Indo-Australian, Pacific, Philippine Sea and Caroline plates (Hill and Hall, 2003; Fig. 2.6).

![Tectonic map of Papua New Guinea](image)

Fig. 2.6. Tectonic map of Papua New Guinea with the main geological components shown in inset A, where yellow represents the Australian Craton, purple represents the New Guinea Orogen, pink represents the Melanesian Arc with oceanic plate and blue represents Pacific Oceanic Plate. Abbreviations: BSSL, Bismarck Sea Seismic Lineation; KT, Kilinauau Trench; MB, Manus Basin; MT, Manus Trench; MyT, Moresby Trench; NBA, New Britain arc; NBT, New Britain Trench; NGT, New Guinea Trench, OSF, Owen Stanley fault zone; PRi, Pocklington Rise; PT, Pocklington Trough; RMF, Ramu-Markham fault; SST, South Solomons Trench; TL, Tasman Line, TT, Trobriand Trough, WRI, Woodlark Rise; WSC, Woodlark Spreading Centre

The large-scale collision of the Indo-Australian and Pacific Plate at a rate of ~110 mm/yr (Davies, 2012) has strongly influenced the evolution, physiography and
seismicity of the region. Hill and Hall (2003) provide a comprehensive assessment of the evolution of the northern Australian margin, from the Proterozoic to the Holocene. The evolutionary model includes phases of igneous activity, rifting and subsidence, followed by periods of convergence and arc-continent collision. These processes have ultimately led to the modern tectonic setting of the region (Fig. 2.6). To simplify the complexities of the current tectonic formation, PNG can be divided into three broad geological components. These are: (1) the Australian Craton, (2) the New Guinea Orogen and (3) the Melanesian Arc (Williamson and Hancock, 2005; Fig. 2.6 (inset A)).

2.3.1 The Australian Craton

The tectonically stable Australian Craton extends across the continental shelf from the Arafura Sea in the west to the Coral Sea in the east. The craton is believed to make up the Precambrian and Paleozoic basement underlying the Fly Platform and the New Guinea Orogen (Fig. 2.6 (inset A; purple)). In comparison to the Precambrian basement on the western side of the Tasman Line, the Fly Platform is predominantly underlain by Paleozoic metasedimentary rocks, which have low lithospheric velocities consistent with young, hot and weak continental crust (Hill and Hall, 2003; Davies, 2012; Baldwin et al, 2012). This difference in craton composition influences how deformation is accommodated at the collisional margins, causing differences in fold-belt orogenesis between Indonesia (3-5 km high peaks) and PNG (1.3 km high peaks; Cloos et al., 2005; Hill and Hall, 2003). The granitic basement underlying the Fly Platform is overlain by Mesozoic and Cenozoic marine sediments. These, in turn, are overlain by terrestrial, fine grained sediments brought onto the platform by major river systems feeding into the Gulf of Papua. As the platform is predominantly stable, the geological units have only been subject to gentle warping, which contrasts sharply with the deformation of the northern margin of the platform, at the Papuan Fold Belt.
The formation of the Papuan Fold Belt and the New Guinea Mobile Belt is the result of deformation which has largely been driven by the Australian Craton’s involvement in numerous convergent collisions with volcanic arcs, oceanic crust and micro-continents (Baldwin et al., 2012). These collisions have been facilitated by interactions between multiple, rapidly rotating microplates including: the North and South Bismarck Plates, the Solomon Sea Plate and the Woodlark Plate (Wallace et al., 2004). Using Global Positioning System (GPS) techniques Wallace et al., (2004) identified six tectonic blocks linking these microplates and identified the Ramu-Markham Fault (RMF), New Britain Trench, Woodlark Spreading Centre, the Bismarck Sea Seismic Lineation (BSSL) and the Owen Stanley Fault Zone (OSFZ), as the major active plate boundaries connecting these blocks (Fig. 2.6). Subduction of the Solomon Sea Plate at the New Britain Trench has resulted in the formation of the New Britain Arc (Fig. 2.6) and drives seafloor spreading at the Woodlark Spreading Centre (Hall, 2002). The BSSL (Denham, 1969) acts as the interface between the North Bismarck Plate, which rotates anticlockwise at a rate of 0.3-1.25° Ma\(^{-1}\), and the South Bismarck Plate which rotates rapidly in a clockwise direction at ~9° Ma\(^{-1}\) (Wallace et al., 2004). This clockwise rotation has supported theories that the Finisterre, Sarawaget and Adelbert Mountains collided as an allochthonous terrane with the Australian Plate during the Oligocene to Late Pliocene (Abbott et al., 1994(a); Abbott et al., 1994(b); Davies, 2012). The importance of the Australian Craton, for this study, is that the deformation of its northern margin has resulted in the two geological components of particular relevance to landslides in PNG: (1) the New Guinea Orogen and (2) the Finisterre Terrane.
2.3.2 The New Guinea Orogen

The New Guinea Orogen is comprised of the Papuan Fold Belt and the New Guinea Mobile Belt. The two belts make up the central mainland cordillera, where elevations can exceed 4000 m above sea level (asl). The Papuan Fold Belt lies directly north of the Fly Platform, between approximately 140°E and 145°E, while the Mobile Belt extends from the border with Irian-Jaya in the west, to the south-easterly tip of the Papuan Peninsula (Fig. 2.6). The Fold Belt originated from oblique convergence between the Australian and Pacific plates during the Oligocene and Pliocene (Hill and Hall, 2003; Craig and Warvakai, 2009). As a result of north-east to south-west compressional deformation during the late Miocene-Pliocene, the fold belt has developed a series of north-westerly to westerly trending folds (Hill et al., 2010). Furthermore, the deformation and resultant tectonic shearing has led to extensive faulting throughout the belt. The dominant out crop rock is limestone, laid down during the late Oligocene to mid-Miocene, and is interspersed with tertiary volcanic deposits (Fig. 2.7). All out crop rocks are heavily denuded due to the climate and seismicity of the region. This, in conjunction with the heavily folded and faulted geological structure, results in numerous large magnitude landslides being observed.

In contrast to the predominantly sedimentary strata of the Papuan Fold Belt, the New Guinea Mobile Belt is dominated by metamorphic and igneous rocks (Fig. 2.7). The belt is separated into two sections by the Aure Trough which lies as a wedge between the eastern and western halves. This trough is composed of 15-16 km-thick marine strata, laid down rapidly during the Oligocene to Pliocene. Sequences of greywacke sandstones and interbedded limestone are folded on a north to south axis (Williamson and Hancock, 2005) as a result of the westward convergence of the Papuan Peninsula, at a rate of approximately 20 mm/year (Wallace et al., 2005). To the west of
the trough the New Guinea Mobile Belt is composed of Tertiary and Mesozoic volcanic, intrusive and metamorphic rocks (Hill and Gleadow, 1989; Baldwin et al., 2012). Island arc collision during the late Oligocene to early Miocene resulted in ophiolite emplacement. The April Ultramafics, which lie along the foothills and northern flanks of the central cordillera, and the Marum Ophiolite Belt, which lies along the northern flank of the Bismarck range, south of the Ramu Valley, are two examples (Jacques, 1981). In addition to the ophiolite belts, Miocene igneous rocks identified as the Maramuni Arc Volcanics outcrop along the northern flanks of the central cordillera (Hill and Hall, 2003). These calc-alkaline volcanic rocks are believed to have originated from south or south-westerly subduction during the mid-Miocene (Baldwin et al., 2012; Hill and Hall, 2003). However for this to be the case, subduction reversal over a very short time scale would have had to have occurred in order to accommodate the collision of the Melanesian Arc with the PNG mainland in the late Miocene. Therefore, hypotheses by Cloos et al. (2005) and Johnson et al. (1978), which look away from traditional plate tectonic subduction-generated magmatism, are believed to fit better with the localized nature of volcanic deposits.

The eastern half of the New Guinea Orogen is referred to as the Owen Stanley Range in the Papuan Peninsula and encompasses the northern Papuan Ultramafic Belt (PUB) and the southern Owen Stanley Metamorphic Complex (OSMC; Fig. 2.7). The two belts are separated by the OSFZ and bounded to the south by the Bogora Thrust (Fig. 2.7). Davies (2012; 1980), having completed the most extensive research in this area, identified that the OSMC was composed of a central sialic core composed of Mesozoic schist and gneiss, which extends 900 km in a west-north-westerly trending belt. The principle metamorphic event producing this complex is believed to have occurred during the early Eocene causing the original, unmetamorphosed Cretaceous
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sedimentary deposits to become altered. Parallel to, and north of, the metamorphic complex lies the basalt-gabbro-peridotite ophiolite of the PUB (Davies and Smith, 1971). This is composed of three layered units including a base of ultramafic rocks (4-8 km thick), a middle layer consisting of gabbroic rocks (4 km thick) and basalt volcanic rocks near the surface (4 km thick; Davies, 1980). The outcrop becomes more irregular moving towards the southern tip of the Papuan Peninsula, as many of the units have been significantly affected by horst and graben tectonics (Davies, 1980). Towards the end of the Owen Stanley Fault, volcanic rocks ranging in age from the Mid-Eocene to the present, overlie the ophiolite. The more recent deposits are associated with eruptions at Mount Lamington in 1956 and Victory in 1935. Mixed within the volcanic sequences are sedimentary and limestone rocks which were laid down during periods of volcanic quiescence (Davies, 2012).

2.3.3 The Finisterre Terrane

The Adelbert and Finisterre Ranges and the Huon Peninsula make up the Finisterre Terrane on the PNG mainland (Fig. 2.7), while the islands of the Bismarck Arc make up the off-shore component of the terrane (Fig. 2.6 (inset A); Williams and Hancocks, 2005). Significant research has focussed on the Finisterre Range and the Huon Peninsula, as this is the site of ongoing arc-continent collision. The Finisterre range formed during the late Pliocene (3.0-3.7 Ma; Hovius et al., 1998) following the collision of the Finisterre Island Arc with the northern margin of the Australian Craton. Uplift rates are estimated to be between 0.8 and 2.1 mm/yr based on rock uplift rates determined from Quaternary coral terraces along the northern coastline (Chappell, 1974), and the calculated tectonic surface uplift across the limestone plateau (Abbott et al., 1997). The Range can be divided into three broad lithological belts including: (1) a north-dipping limestone sheet, (2) a central belt referred to as the Finisterre Volcanics,
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composed of basic to intermediate volcanic rocks and volcaniclastic sandstone and (3) a southerly, Eocene-Pleistocene sedimentary sequence (Abbott et al., 1994a; Fig. 2.7).

The rapid nature of uplift in this region and the westward propagation of the range provide opportunities to assess erosion and topographic evolution. Hovius and Stark (2006) suggest that the Huon Peninsula represents the initial stages of montane evolution, where drainage systems are in the early stages of initiation, with slot canyons intersecting large swathes of the limestone plateau. The western end of the range represents a developed ridge-and-valley landscape where processes such as fluvial incision and mass wasting counteract uplift. A major control on this evolution is landslide activity and the magnitude of events can be associated with the maturity of the range. Multiple-kilometre scale landslides drive erosion in the eastern range, where local topographical differences are small, causing low rates of fluvial incision and erosion. Ota et al., (1997) have recorded three typical landslide types in this region including: (1) landslides with steep, spoon-shaped headwalls and possible debris slides, (2) substantial debris flows and (3) smaller failures which occur at the steep heads of gullies. Type 1 and 2 are the most dominant in the Huon Peninsula where headwall heights can be anywhere between 20 and 100 m and almost vertical in profile (Ota et al., 1997). Such large-scale events are less frequent in the more mature, western range where fluvial incision results in smaller scale landslides, constrained by the local drainage network (Hovius and Stark, 2006).
Fig. 2.7. Geological map of PNG. Abbreviations: AOB, April ultramafics; AR, Adelbert Range; AT, Aure Trough; BT, Bogora Thrust; BTT, Bewani-Torricelli Terrane; DP, Doma Peaks; FR, Finisterre Range; HP, Huon Peninsula; MOB, Marum Ophiolite Belt; MP, Muller Plateau; NGMB, New Guinea Mobile Belt; OSFS, Owen Stanley Fault System; OSMC, Owen Stanley Metamorphic Complex OSTB, Owen Stanley Thrust Belt; PFTB, Papuan Fold and Thrust Belt; PT, Papuan Thrust; PUB, Papuan Ultramafic Belt; RMF, Ramu-Markham Fault.
Large-scale failures have also been recorded in New Britain (Hovius and Stark, 2006). Both New Britain and New Ireland are geologically similar to the early Finisterre Arc prior to its collision with the PNG mainland and have been produced from island-arc volcanism. Although New Ireland lies collinear with the Solomon Island Arc, its stratigraphy is more closely associated with New Britain. The exception to this is that the volcanic basement of New Britain is of Eocene origin (Williamson and Hancock, 2005), while the basement volcanics of New Ireland formed during the Oligocene. Hohnen (1978) provides a detailed overview of the geology and geomorphology of New Ireland, while Hine and Mason (1978), Heming (1978), Page and Ryburn (1973) and Macnab (1970) have completed geological assessments of key regions in New Britain. Interested individuals can obtain further information from these references. For both the Finisterre Range and the islands, the dominant factors for consideration with regard to landslide activity are: (1) the climate, (2) earthquake activity leading to landslides and (3) the denudational processes active in karst environments.

2.3.4 Earthquakes and their importance for landslides in Papua New Guinea

The evolution and interaction of the three broad geological components outlined above is dependent on the location and movement of current plate boundaries in and around PNG (Fig. 2.6). However, not all tectonic boundaries move in the same way, or to the same extent or frequency. It is this variability which influences the spatial distribution of earthquakes and the likelihood for earthquake-induced landslides. Data used by Curtis (1973; 1931-1970) and the United States Geological Survey (USGS) National Earthquake Information Centre (NEIC)/Preliminary Determination of Epicentres (PDE) database (http://earthquake.usgs.gov; Fig. 2.8) identify that the New Britain Trench and the northern Solomon Sea Trench are the locations with the highest frequency of earthquakes. Furthermore, these earthquakes tend be of greater magnitude
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and depth compared to events on other plate margins in the region. This can result in large-scale landslides across New Britain and New Ireland, but are generally too far away to significantly affect the PNG mainland.

In addition to these plate margins, seismicity is also high over the BSSL, the Huon Peninsula and the northern Sepik region (Fig. 2.8). The seismicity within the Huon Peninsula has been researched in significant detail as it is the product of the ongoing collision of the Finisterre Terrane with the PNG mainland (Kulig et al., 1993; Findlay, 2003). Tregoning et al. (1998) identified that epicentre depths ranged from 0 to 300 km around this zone. Shallower earthquakes (0 and 100 km) are confined mainly to the Huon Peninsula and the near-surface expression of the RMF, while deeper earthquakes (100-300 km) are predominantly observed at the western end of the Finisterre Range and off-shore, to the north of the Bismarck Arc. Mosusu (1999) suggested that the return period for a magnitude 6.0 earthquake is 50 years in a 1000 km² area of the Huon Seismic Zone. Earthquakes of this size have a high probability of triggering landslides which have the potential to cause substantial societal impacts. Furthermore, the wide variety of movements observed along this fault, including: left and right-lateral strike-slip and pure thrust has led to debate about the nature of the Finisterre Terranes emplacement (Weiler and Coe, 2000). This as well as numerous other reasons already highlighted, explains the importance of this region and why such intense research has been conducted in the area.

Earthquakes are also observed, although less densely and with generally lower magnitudes, across the central cordillera and northern Sepik (Fig. 2.8). There are some reasons to believe that earthquake activity in northern Sepik, along the Wewak Section of the New Guinea Trench (Cloos et al., 2005; Tregoning and Gorbatenko, 2004) is associated with the continuation of the BSSL along the southern margin of the Bewani-
Torricelli accreted arc. This is due to the dominance of strike-slip earthquakes in this region. However, thrust earthquakes have also been documented and this suggests that the Wewak section may represent a later phase of the processes being observed around the Huon Peninsula and along the RMF zone. Across both northern Sepik and the western central cordillera seismically-induced landslide failures have been recorded, for example during the magnitude 6.5 earthquake in January 1981 and magnitude 5.6 earthquake in April 1978 (Ripper and McCue, 1982). This illustrates that although boundaries may not produce the highest frequency or magnitude earthquakes, they can still pose a risk to communities through the instigation of large and numerous landslides.

Fig. 2.8. Epicentre map for earthquakes of magnitude 5 and greater recorded between 1973 and 2010. Data provided by the USGS Global Hazard Program NEIC/PDE Catalogue. Abbreviations: NBP, North Bismarck Plate; SBP, South Bismarck Plate; SSP, Solomon Sea Plate; WP, Woodlark Plate.
3. Landslides and rainfall variability at interseasonal and interannual timescales
Abstract

In PNG earthquakes and rainfall events form the dominant trigger mechanisms capable of generating many landslides. Large and numerous landslide events can cause widespread impacts which are felt particularly strongly in the largely subsistence-orientated communities which reside in the most susceptible areas of the country. An understanding of the characteristics of rainfall events, which lead to many landslides in PNG, is required to develop appropriate early warning systems and forecasting models. The spatial and temporal relationships between landslide occurrence and rainfall is still to be determined, particularly as this region is influenced by numerous synoptic meteorological interactions such as, for example, the El Niño-Southern Oscillation (ENSO). A newly developed landslide inventory collated for this research enables these relationships to be assessed on a variety of timescales (monthly-seasonal-annual). Analysis of gauge-based rainfall data identified that regionally averaged, mean monthly rainfall is correlated with the monthly frequency of observed landslides, supporting the widely held assumption that increased numbers of landslides are likely to occur during the north-westerly monsoon season. However, a closer examination of the patterns of landslides and rainfall alluded to a far more complex relationship related to rainfall accumulated throughout a complete seasonal cycle. This in turn is influenced by ENSO and rainfall patterns characterised over seasonal to annual timescales. These findings indicate that, dependent upon the quality of precipitation forecasts, there is a potential to use these broad relationships to inform models which aim to forecast heightened landslide susceptibility at timescales ranging from months to seasons.
3.1 Introduction

PNG is identified as a region with a significant landslide hazard, the true nature of which has been difficult to quantify due to inadequate data (Blong, 1986). However, the regularity of destructive landslide events, particularly in mining areas, has produced a number of scientific papers reviewing landslide activity. The combination of rugged topography, high seismicity and a tropical maritime climate makes the region highly susceptible to large-volume, earthquake- and rainfall-induced landslides (Greenbaum et al., 1995; Stead, 1990). The impacts of such events frequently affect the availability of essential commodities such as food, water and gasoline, and result in large numbers of injuries and fatalities. The development of early warning and forecasting systems is one approach which, if designed and used effectively, could reduce losses associated with landslides. The best opportunities for these types of developments come from rainfall-induced landslides, as rainfall forecasting continues to improve in spatial and temporal accuracy. However, investigations of landslide occurrence in PNG have largely been performed on a site specific basis or at most, the basin scale. This means that our baseline knowledge of the hazard at the regional scale is relatively poor. Furthermore, analysis of rainfall patterns preceding known landslide events has only been completed in a few isolated cases and not in sufficient depth to identify relationships. In this chapter therefore, the focus is to develop a broad understanding of when and where landslides occur across PNG and review this in the context of temporal and spatial rainfall variability.

3.2 Landslide occurrence in Papua New Guinea

Table 3.1 outlines the dominant failure mechanisms which have been observed in PNG.
<table>
<thead>
<tr>
<th>Landslide Type</th>
<th>Geology/Geomorphology</th>
<th>Affected areas</th>
<th>Images of PNG landslides</th>
</tr>
</thead>
</table>
| Debris slides/avalanches/flows | - Debris slides predominantly involve the soil and uppermost weathered material and occur on slopes of deformed rocks, thinly-bedded mudstones and closely foliated metamorphic rocks. They are usually wedged-shaped, tapering in width downslope.  
- Debris avalanches and flows generally occur in the soil and weathered rock. They tend to have larger deposits than debris slides, with extensive back scarps (> 200 m). When these movements occur in rock, as sometimes happens following very high magnitude seismicity, the largest debris avalanches/flows can occur.  
- All types typically occur from the crests of steep (> 45°), v-shaped valleys.                                                                                                                                                                                                 | - Debris slides, of varying size, are frequently observed around the Ok Tedi (Hearn, 1995; Fookes et al., 1991) region of Western Province and along the Highlands Highway.  
- Debris avalanches and flows have been recorded in a number of locations which experience very high magnitude seismic activity (Nakanai Mountains, New Britain (King and Loveday, 1985)). They are also seen in areas where tectonic uplift outpaces many denudational processes, (eastern Finisterre Range and the Huon Peninsula; Hovius et al., 1998; Ota et al., 1997).                                                                 | ![Fig. 3.1. The complex (translational/debris flow) Wantoat Landslide in Morobe Province (Kuna, 2002)](image1)                                                                                                                                                                                                                                             |
| Rotational slumps              | - Rotational slumps typically move as a single unit along well defined internal slip planes and often include backward rotation of the failed mass (Stead, 1990). They generally occur in homogeneous sedimentary rocks, such as mudstones, marls, sandstones and greywacke, although very large slumps have also been observed in the metamorphics of the Suckling-Dayman massif in the Papuan Peninsula (Löffler, 1977; Davies, 1980).  
- These movements can occur on slopes as low as 10°, although in such cases displacement is generally limited. Where they occur on steeper slopes (> 30°), deposits can exceed volumes of 500,000 m³ (e.g. Dinidam Landslide; Blong, 1986).                                                                                                                                 | - Numerous slumps, of varying size, have been observed following geotechnical appraisals of routes along the Highlands Highway (Tutton and Kuna, 1995; Kuna, 1998) and these can regularly lead to road closures and property damage.                                                                                                           | ![Fig. 3.2. Back scarp of a rotational slump which affected Gera Village in 2008 (photograph courtesy of Gabriel Kuna, PNG Mineral Resources Authority)](image2)                                                                                                                                                                                                              |
Mudslides

- Mudslides are defined by Stead (1990) as ‘masses of argillaceous, silty or very fine sandy debris’ which displace material by ‘sliding on discrete boundary surfaces in relatively slow moving lobate forms’.
- Numerous examples have been associated with the Chim Formation. This is comprised of dark grey, thinly laminated mudstone with siltstone with some interbedded volcaniclastic sandstone. The mudstones are generally weak, but break down further to form highly plastic silty clay (Peart, 1991a). A 3-tiered classification includes: (1) fresh mudstone, (2) weathered mudstone or ‘Chim Shale’ and (3) colluvium, which represents the silty clay matrix supporting varying sizes of rock fragments.
- Most mudslides in Chimbu and Enga Provinces typically involve the colluvium.

Translational slides/ rockslides

- The mechanism of failure in translational slides and rockslides is strongly influenced by bedding planes, joints, faults and the interface between weathered material and fresh bedrock (Stead, 1990).
- Deeply incised terrain around the Highlands Highway, combined with geologies comprising silty-sand and weathered volcanic material results in numerous failures being observed.
- Translational slides along the highways typically occur on slopes of 30 to 50°.

- The Yakatabari Mudslide in Enga Province (Blong, 1985). Recorded mean velocities equal ~60 mm/year, along a surface slope of 8 to 12°.
- In some instances large areas are covered with multiple adjacent mudslides reacting to localized changes in shear strength and pore water pressure.
- Their generally slow nature, the variability that can exist within a single mudslide (width, depth, rate of movement and style of movement; Comegna et al., 2007) and the fact that they can occur on slope angles between 6 and 15° (Blong, 1981), makes them particularly problematic to mitigate against.

Table 3.1. The geology and geomorphology associated with the main landslide types which affect PNG
Of the landslide types shown in Table 3.1, debris slides, avalanches and flows (Fig. 3.1) are considered the most common, but rotational slumps (Fig. 3.2), mudslides (Fig.3.3) and translational slides (Fig. 3.4) have also been widely documented in PNG. Individual landslides range from small-scale events of the order of a few cubic metres of material, to some of the largest recorded failures in the world. The Kaiapit Landslide deposit, for example, has a volume in excess of $180 \times 10^6$ m$^3$ (Peart, 1991b; Drechsler et al., 1989) and its morphology has many similarities with large sturzstroms such as the Frank Slide (Canada 1903; Cruden and Hungr, 1986) and Mayunmarca (Peru 1974; Hutchinson and Kojan, 1975). As well as large volume landslides, PNG is also affected by high-density landsliding associated with seismic activity. A magnitude 7.0 earthquake close to Madang in 1970 resulted in large numbers of debris avalanches covering an area of approximately 240 km$^2$ in the Adelbert Range (Pain and Bowler, 1973). In 1993 two earthquakes (magnitudes 6.9 and 6.7) resulted in more than 4700 landslides being mapped across the Finisterre and Sarawaget mountain ranges (Meunier et al., 2007).

### 3.3 Landslide Inventory for Papua New Guinea

#### 3.3.1 Collation of landslide-triggering events

Understanding landslide occurrence, in the context of changing rainfall patterns, requires information about historical landslide events. Therefore a new, regionally-focussed landslide inventory has been established for PNG. The development of landslide databases is frequently challenging due to inconsistencies in landslide reporting, sparse population densities in many of the affected areas (Kirschbaum et al., 2009) and the remoteness (Petley, 2012) of landslide events. In the new PNG inventory, the inclusion of a landslide event was based on strict criteria. Only those landslides where both the date and location could be established with reasonable accuracy were
entered into the database, as this information is critical for analysing the characteristics of potential trigger mechanisms. However, it became evident that these criteria would limit the size of the inventory because regular and detailed landslide recording remains relatively sparse in PNG. This meant that although large numbers of landslides have been identified by their scars and deposits (Kuna, 1998) the dates of the events were rarely recorded. Therefore records of landslide activity were obtained from a range of sources including: (1) technical reports and site inspection logs obtained from the PNG Mineral Resource Authority (MRA) and the Department of Mineral Policy and Geohazards Management archives (Itiogen, 2007; Kuna and Moihoi, 2006; Browne, 1994; Tutton and Buleka, 1993; Peart, 1991c and references throughout), (2) accessible journal publications (Fookes and Dale, 1992; Griffiths et al., 2004; King et al., 1989 and references throughout), (3) newspaper records, (4) internet publications and (5) supplementary archives (i.e. Dartmouth Flood Observatory and USGS NEIC PDC). The variety of sources meant that details for each landslide event varied in completeness and scientific content. Each data source used to construct the new PNG landslide inventory has its own uncertainties and limitations, and to understand these, an examination of the metadata is required. Metadata in this context describes the dominant attributes of the other data sources by providing information on: (1) how these data sources were produced, (2) the spatial and temporal coverage of these data, (3) the type of author (e.g. scientist or media correspondent), (4) the publications purpose and (5) the date when the document was created. Table 3.2 provides a broad overview of the metadata associated with each data source used to construct the new PNG landslide inventory. The term metadata can also be used to describe the types of data which make up a database. A full description of the parameters collected in the landslide inventory can be seen in Appendix A.
<table>
<thead>
<tr>
<th>Data source</th>
<th>Author type</th>
<th>Spatial coverage</th>
<th>Temporal coverage</th>
<th>How is information obtained?</th>
<th>Purpose of the data source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical site reports</td>
<td>Geologists</td>
<td>Single slope; watershed area; specific limited area domain (e.g. sections of Highlands Highways)</td>
<td>Representative of data collected during a single days field work or data collected over a few months of a field campaign</td>
<td>Field assessment &amp; geotechnical appraisals conducted by local/in-country specialists</td>
<td>Document Hazard &amp; Impacts</td>
</tr>
<tr>
<td>Journal publications</td>
<td>Research scientists</td>
<td>Single slope; watershed area; limited area domain (e.g. Finisterre Range; Greenbaum <em>et al.</em>, 2005)</td>
<td>Continuous; individual paper represents data relevant to research topic time frame (single event; long-term trends of events)</td>
<td>Field research or desk-based research conducted by in-country &amp;/or external research scientists with interest &amp; expertise in a specific field of research</td>
<td>Document Scientific Method &amp; Knowledge</td>
</tr>
<tr>
<td>Online newspaper articles</td>
<td>Media correspondents</td>
<td>Global; Event article specific to area affected (typically village/district level)</td>
<td>Continuous; limited archive in developing countries; Specific to individual event</td>
<td>In-country correspondents visiting sites, conducting interviews &amp;/or collating information from existing data for publication</td>
<td>Inform &amp; Encourage readership</td>
</tr>
<tr>
<td>Internet publications: ReliefWeb</td>
<td>Varied</td>
<td>Global; Event documentation specific to area affected (typically district/national level)</td>
<td>1996 to present; continuous updates as and when events occur</td>
<td>Content from &gt; 2500 organisations, including from non-governmental organisations; international organisations, academic and research institutes, government, media &amp; Red Cross/Red Crescent movement</td>
<td>Document Disasters (Humanitarian Focus)</td>
</tr>
<tr>
<td>Supplementary archives: Dartmouth Flood Observatory</td>
<td>Research scientists</td>
<td>Global; Event documentation specific to area affected (typically village/district/national level)</td>
<td>1985 to present; continuous updates as and when events occur</td>
<td>Archive is derived from news, governmental, instrumental, and remote sensing sources</td>
<td></td>
</tr>
<tr>
<td>Supplementary archives: USGS NEIC PDC</td>
<td>Automated seismometers &amp; research scientists</td>
<td>Global; Latitude &amp; Longitude of individual earthquakes, shakemaps showing earthquake intensity across areas are provided. Secondary hazards (landslides) noted in comments</td>
<td>Monthly data available from 01/01/1973 to present; Weekly data available from 01/04/2011 to present; Daily data available from 14/10/2012 to present</td>
<td>Data available from national and regional seismic networks &amp; collated into a single database. Impact information &amp; secondary hazards obtained from media, government &amp; non-governmental sources</td>
<td></td>
</tr>
<tr>
<td>Supplementary archives: Munich Re (personal communication)</td>
<td>Varied</td>
<td>Global; Event documentation specific to area affected (typically village/district/national level)</td>
<td>From 1980 to present all loss events; retrospectively all great disasters since 1950; All major historical events from 79AD Mt. Vesuvius eruption</td>
<td>Information source from 6 major groups: (1) insurance industry, (2) science and research, (3) UN, EU, administrations, governmental and non-governmental organisations, (4) meteorological, geological, etc., services, (5) news agencies, (6) other sources (Kron et al., 2012)</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2. Broad overview of metadata related to the source datasets used in the collation of the new PNG landslide inventory.
Although the strict selection criteria introduced limitations, the method is essential to improve accuracy when collecting relevant rainfall accumulation and earthquake event histories prior to each landslide event. This becomes a particularly important issue in Chapters 4 and 5. Despite the selection criteria used, it was possible to log 126 landslide events between 1970 and 2009 (40 years). Each entry represents either an individual landslide (e.g. the Wantoat Landslide in April 2002; Kuna, 2002) or a cluster of landslides (e.g. landslides associated with the magnitude 7 earthquake in October 1970; Tutton and Browne, 1994) that are the result of 83 different trigger events. Triggering events are typically defined as external factors which change the state of the slope and result in movement. The trigger of a landslide differs from the cause of a landslide because causal factors represent aspects of the environment which make the slope inherently susceptible to movement (e.g. geological structure, slope). The triggering events captured in the PNG inventory include earthquakes, floods, storms or high rainfall accumulations and tropical cyclones. Each triggering event can instigate more than one landslide and affect more than one community, meaning that each landslide-triggering event recorded represents the occurrence of 1 or more landslides. These entries are obtained from a region covering mainland PNG, New Britain and New Ireland (Fig. 3.5).

Based on the limitations and uncertainties of the source data and the database entry criteria, it is likely that the landslide-triggering events collated in the PNG inventory represent medium-to-large landslides, while smaller events are under-represented. The availability of quantifiable size (volume, area extent, number of failures associated with a single trigger) information related to landslide events was very difficult to acquire, with only a handful of the data sources providing this information. Therefore, the assumption that the inventory contains predominantly
medium-to-large landslide events is based only on the fact that larger landslides (or large numbers of landslides triggered by a single event) tend to cause the greatest socio-economic impacts, and are generally recorded with higher accuracy. This is particularly the case in PNG where there is a culture of providing compensation rewards for damage associated with landslides perceived as anthropogenic (Kuna, 1998). It should be recognised therefore, that where determinations of size (medium-to-large) are used throughout this thesis, the actual reference is subjective and is predominantly based on the impacts of the landslide event and the media or scientific interest it encouraged. This assumption is distinct from the identification of shallow and deep-seated landslides completed in Chapter 6.

![Fig. 3.5. Location of all landslide-triggering events collated in the landslide inventory over the period between 1970 and 2010.](img)

Of the 83 landslide-triggering events in the inventory, there are 21 earthquake-triggered (EQ) events and 62 non-earthquake-triggered (NEQ) events. Where there was
ambiguity regarding the trigger mechanism, the landslide event was allocated to the NEQ category. The interpretation of triggering mechanism was based on information held in the source datasets, which given their variety, introduced uncertainty. Accurately identifying the trigger mechanism for landslides is often difficult, particularly when the landslide is secondary to an initial natural hazard (Kirschbaum et al., 2009). This frequently occurs in the case of earthquakes where subsequent landslides are rarely reported. However, earthquakes themselves are widely recorded by a global network of seismographs and their dates and epicentres are systematically catalogued. This means that certain triggering events recorded in the new PNG inventory could be identified and preliminarily verified with more accuracy than individual landslides in PNG. The following section outlines the approaches used to reduce temporal and spatial uncertainty in the new PNG landslide inventory. It should be noted that at this stage, the methods used are aimed at broadly reducing temporal and spatial uncertainty of the identified triggering-events and verifying whether the events have been allocated to the correct EQ- or NEQ-triggering category.

3.3.2 Methods for improving temporal and spatial uncertainty in landslide inventories

Given the sources used to collate the PNG landslide inventory, it was inevitable that there would be some uncertainty associated with the time and location of landslide entries. Temporal uncertainty is predominantly associated with the timing and duration of the triggering event and where, within the triggering event period, landslides were induced. This is particularly problematic for flood events, where the start and end dates can be ambiguous. Some of this uncertainty was reduced by cross-referencing multiple data-sources to constrain the landslide-triggering event within a set time period. The Dartmouth Flood Observatory archive was particularly useful, as it compiles flood
inundation extents and additional impact information, including secondary hazards such as landslides. This information has been collected since 1985 using news, governmental, instrumental, and remote sensing sources. In a similar way, triggering events thought to be associated with earthquakes were cross-referenced with the date and location of earthquake epicentres obtained from global (USGS NEIC PDE) and local earthquake catalogues.

By carefully cross-referencing each landslide-triggering event in the inventory against a variety of hazard and disaster databases, the uncertainty around the time and duration of each landslide-triggering event was reduced. For 83% of the entries, the duration of the landslide-triggering event was constrained within a period of 10 days or less. For the remaining 17% of entries, landslide-triggering event durations exceed 30 days. In these instances the documented landslides, could have been instigated at any point within this 30-day period. The absolute maximum temporal uncertainty is two months, which coincides with a prolonged flood event in Central Province in 2006. For the purposes of this Chapter’s analysis aims, the temporal uncertainty is acceptable. However, in cases where the aim is to analyse higher resolution rainfall patterns preceding an individual landslide-triggering event (Chapter 4) a more detailed method to constrain the temporal uncertainty is required. This secondary method will be explained in detail in Chapter 4.

In addition to temporal uncertainty, spatial uncertainty also proved to be a concern. Often journal publications and site inspection reports use latitude and longitude grid coordinates to determine the location of a landslide. However, on closer inspection of the meta-data used to collate the PNG inventory, it was found that the nearest village or point of interest was frequently used as a reference. Village names change and/or are misspelt, particularly in media reports, making it difficult to orientate
the locations of landslides with suitable accuracy. Moreover, some village names are used in multiple provinces throughout PNG, causing confusion when trying to locate the true landslide site. To address these issues the landslide-triggering event entries were first cross-referenced against settlement data provided by the PNG MRA. This allowed the correct province and administrative district to be identified in the majority of cases. In the second step, all triggering events were cross-referenced with 30 m False Colour Composite (FCC) Landsat satellite images (Vohora and Donoghue, 2004; Petley et al., 2002). This technique has proven successful for identifying landslide scars in PNG and globally (Greenbaum et al., 1995).

Freely available Landsat satellite images were obtained from the Earth Resources Observation and Science (EROS) data centre and downloaded from the USGS Global Visualization Viewer (GLOVIS; http://glovis.usgs.gov/) website. The images had already been terrain-, radiometrically- and geographically-corrected, reducing the pre-processing requirements for FCC image analysis. For each landslide-triggering event, images were selected based on the amount of cloud cover over the affected area (<30%) and their acquisition date, which needed to be as close as possible to the time of landslide occurrence or the associated triggering event. The temporal and spatial uncertainties acknowledged above are not a concern for the identification of useful Landsat tiles due to the repeat cycle time frames (16 days) and the wide swath of the Landsat images (183 km wide and 170 km long). Both Landsat 4-5 Thematic Mapper (TM) and Landsat-7 Enhanced Thematic Mapper (ETM+) were used in this analysis, as they offer the highest resolution (30 m) compared with the longer-running Landsat 1-5 Multispectral Scanner (MSS; resolution of 60 m). Landsat-4 and -5 have provided continuous imagery since 1982, while Landsat-7 has been providing imagery since 1999. Unfortunately, in May 2003 the scan line corrector (SLC) which is used to
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remove the zigzag motion associated with the along- (provided by the forward velocity of satellite) and across-track (provided by the Scan Mirror) motion, failed. This has resulted in data loss within Landsat-7 images from this date. Using both Landsat-5 TM and Landsat-7 ETM+, data were available for 29 out of the 40 year length of the landslide inventory. As both satellites use the same suite of bands, except for the addition of the panchromatic band on Landsat-7, a continuous record of earth observation could be achieved (Table 3.3).

<table>
<thead>
<tr>
<th>Landsat 5 (TM)</th>
<th>Wavelength (µm)</th>
<th>Resolution</th>
<th>Landsat 7 (ETM+)</th>
<th>Wavelength (µm)</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 1</td>
<td>0.45-0.52</td>
<td>30 m</td>
<td>Band 1</td>
<td>0.45-0.515</td>
<td>30 m</td>
</tr>
<tr>
<td>Band 2</td>
<td>0.52-0.60</td>
<td>30 m</td>
<td>Band 2</td>
<td>0.525-0.605</td>
<td>30 m</td>
</tr>
<tr>
<td>Band 3</td>
<td>0.63-0.69</td>
<td>30 m</td>
<td>Band 3</td>
<td>0.63-0.69</td>
<td>30 m</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.76-0.90 [NIR]</td>
<td>30 m</td>
<td>Band 4</td>
<td>0.75-0.90 [NIR]</td>
<td>30 m</td>
</tr>
<tr>
<td>Band 5</td>
<td>1.55-1.75 [SWIR]</td>
<td>30 m</td>
<td>Band 5</td>
<td>1.55-1.75 [SWIR]</td>
<td>30 m</td>
</tr>
<tr>
<td>Band 6</td>
<td>10.4-12.5 [Thermal]</td>
<td>120 m</td>
<td>Band 6</td>
<td>10.4-12.5 [Thermal]</td>
<td>60 m</td>
</tr>
<tr>
<td>Band 7</td>
<td>2.08-2.35 [SWIR]</td>
<td>30 m</td>
<td>Band 7</td>
<td>2.09-2.35 [SWIR]</td>
<td>30 m</td>
</tr>
<tr>
<td>Pan Band</td>
<td></td>
<td></td>
<td>Pan Band</td>
<td>0.52-0.90</td>
<td>15 m</td>
</tr>
</tbody>
</table>

Table 3.3. Suite of bands available for Landsat 5 TM and Landsat 7 ETM+

Greenbaum et al., (1995) used an approach which generated FCC images using bands 4 (near infrared; reflected 0.75-0.90 µm), 5 (mid-infrared; reflected 1.55-1.75 µm) and 7 (mid-infrared; reflected 2.08-2.35 µm) where bare rock (dark blue tones), which becomes exposed following landslide events, can be differentiated from vegetated slopes (variations of red tones). When overlain with digital terrain (90 m; Shuttle Radar Topography Mission (SRTM)) and settlement data, the size and geographical position of landslides can be identified (Fig. 3.6). In order to confirm that the blue tones observed in the FCC images were associated with landslide scars, the Digital Number (DN) values in each of the 7 bands were extracted from the area believed to be a landslide (Fig. 3.6) and were compared against the typical spectral ranges indicative of active landslides (Table 3.4; Petley, 2002). If the values were found
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to correspond well, the landslide entry was considered spatially verified. The latitude and longitude of the landslide head scarp or the centre point of the landslide polygon were recorded in the landslide inventory.

<table>
<thead>
<tr>
<th>Band Number</th>
<th>Wavelength (micrometers)</th>
<th>DN Values of active landslide</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.45-0.515</td>
<td>73-100</td>
</tr>
<tr>
<td>2</td>
<td>0.525-0.605</td>
<td>60-102</td>
</tr>
<tr>
<td>3</td>
<td>0.63-0.69</td>
<td>50-120</td>
</tr>
<tr>
<td>4</td>
<td>0.75-0.90</td>
<td>48-107</td>
</tr>
<tr>
<td>5</td>
<td>1.55-1.75</td>
<td>57-132</td>
</tr>
<tr>
<td>6</td>
<td>10.40-12.5</td>
<td>130-186</td>
</tr>
<tr>
<td>7</td>
<td>2.09-2.35</td>
<td>41-110</td>
</tr>
</tbody>
</table>

Table 3.4. DN values obtained from the Wantoat Landslide FCC 457 image compared against the typical spectral ranges of active landslides (Petley, 2002).

Using bands 4, 5 and 7 allowed greater atmospheric penetration as there was no visible band included in the FCC production. However, cloud cover and shadowing remained a major issue because of the tropical climate and mountainous terrain in the locations affected by the majority of landslides. This restricted the availability of satellite images for some landslide-triggering events. In addition, the resolution of Landsat images prevents some smaller landslides being identified. Petley (2002) suggested that landslides with a width and length of 50 m are the smallest events that can be resolved confidently with this technique and satellite data. As the landslide inventory primarily comprises medium-to-large events, the later issue was less of a concern, while cloud cover proved to be a greater hindrance. For these reasons, not all triggering events could be spatially verified using this method. However additional scars, not recorded in the landslide database, became apparent on review of the FCC images. For example, the identification of the Kikiapa Rockslide and an additional debris flow in Fig. 3.6 were observed in the same scene as the Wantoat Landslide (April 2002 in Morobe Province; Kuna, 2002). Acquiring dates for these additional scars is
very difficult. A review of earlier Landsat images did not prove effective because cloud cover, shadow and haze prevented a detailed timeline of images being available. This meant that even identifying which month these events occurred in was not possible. In fact it was found that the Kikiapa Rockslide occurred several years prior to the Wantoat Landslide (no date recorded) and that, although activity had continued at the site through toppling and slumping (Kuna, 2002), no movement was recorded at the time of the Wantoat Landslide. These additional scars are useful when assessing causal factors associated with landslides and this is addressed further in Chapter 6.

3.4 Interseasonal rainfall variability and landslide-triggering events (Temporal Analysis)

Rainfall and its variability strongly influences slope stability by affecting the degree to which water interacts with slopes. Larger accumulations of rainfall increase water loading and can cause water tables to rise which can reduce sliding resistances as pore pressures increase along (potential) slip surfaces. Intense rainfall also affects surface runoff and river flow velocities, which in turn changes erosion potential and the efficacy to modify slopes. Surface erosion and river undercutting can cause over-
steepening and the removal of landslide toe deposits, both of which can further reduce local slope stability, resulting in translational slides that retrogress upslope. Variations in rainfall can also mobilise shrink-swell processes in certain geological materials. This can lead to a gradual weakening of these materials and potentially result in pathways for enhanced (bypass) infiltration producing slopes that are much more sensitive to being triggered by rainfall. Fuhrmann et al. (2008), Zêzere et al. (2005), Chowdhury and Flentje, (2002) and Glade et al. (2000) all recognise that rainfall over durations up to and exceeding 3 months could be influential for instigating larger magnitude landslides. Over such timescales, rainfall values in PNG are strongly influenced by the interactions of synoptic meteorological processes and the local environment, and therefore an analysis of landslide occurrence relative to these large-scale meteorological controls is warranted. To do this, the 62 NEQ landslide-triggering events that occurred between 1970 and 2009 are used, in addition to two rainfall datasets, both derived from gauge station records. The first was obtained from the World Meteorological Organisation (WMO; http://worldweather.wmo.int/077/m077.htm) and the second from the Global Precipitation Climatology Centre (GPCC; http://kunden.dwd.de/GPCC/Visualizer).

3.4.1 **WMO regional monthly mean (RMM) approach**

WMO monthly rainfall climatology data, obtained from gauge stations between 1973 and 2007, were used to identify the seasonal and spatial variability of rainfall across PNG. These data represent the average monthly rainfall accumulation at 9 gauge sites (Fig. 2.1), based on rainfall collected over a period of between 9 and 35 years, depending on the station (Fig. 3.7). As anticipated for a region influenced by a seasonal monsoon, all stations experience drier and wetter periods. Eight sites exhibit wetter periods from December to May, coinciding with the Asia-Australian monsoon (McGregor, 1992; Salinger et al., 1995) and drier periods, from June to November (Fig.
3.7). However, Lae City has a wetter period from June to November. This, together with the variability observed between the remaining eight stations, provides a first indication of the degree to which mean annual climate is influenced by regional physiography. The southern coastal gauge stations at Daru and Port Moresby (Fig. 3.7) have the lowest mean monthly rainfall during July, August, September, October and November due to their position relative to the south-east trade winds that dominate during these months. Gauge stations along the north coast (Vanimo, Wewak and Madang) and across the islands (Rabaul and Kavieng) generally observe higher monthly rainfall accumulations than the southern coastal gauges (Fig. 3.7), although there is a large amount of variability between the rainfall totals observed at these stations throughout the year. The difference between rainfall accumulations observed during the wetter and drier seasons is greatest for the southern gauge stations, particularly Daru. Other stations, such as Wewak, see only minor changes in mean monthly rainfall throughout the year, illustrating that some parts of PNG experience less distinct wetter and drier seasons. This variability is associated with the change in trade wind direction from the drier to the wetter season and the interaction between these trade winds and physiographic aspects of the PNG landmass, including coastal orientation. These interactions can produce localized convective regimes, such as land-sea breezes, which can cause rain-bearing systems, such as sea breeze fronts (McGregor and Niewolt, 1998), to develop. These occur on both the north and south coasts of PNG and the islands at different times of the year. Lae City is an accentuated example of this process as large off-shore convective zones are produced by the interaction of the south-easterly trade winds and both land-sea breezes and mountain-valley winds. This results in a combined sea breeze-valley-wind system (McGregor and Niewolt, 1998) and causes Lae City to have the highest mean monthly rainfall during June, July and August (Fig. 3.7).
Fig. 3.7. Average monthly rainfall for nine gauge stations across PNG (for location refer to Fig. 2.1). The reference period used for the climatology is shown next to each station label. Climatologies of the different regions are categorised as: northern coastal (shown in blue) and southern coastal (shown in red) gauge sites, gauges on the adjacent islands (shown in green), gauge site at Goroka (representing the Highlands; shown in orange) and the gauge site at Lae City (shown in grey).

In a similar way to rainfall, landslide-triggering event frequency also varies with the transition from wetter to drier seasons. Although landslide-triggering events occur in every month, the highest frequencies are observed during March, April and May (MAM) and the lowest frequencies are seen between June and October. To identify whether, and how strongly, monthly rainfall is related to monthly landslide frequency, a regional mean monthly rainfall distribution, based on the 9 WMO gauge stations, was produced (Fig. 3.8). A regionally-averaged mean, herein referred to as the WMO regional monthly mean (RMM), is appropriate here because of the regional distribution of landslide-triggering events. When compared with the landslide-triggering event frequency distribution a correlation coefficient of 0.86 was obtained, indicating a strongly positive relationship between the two variables.
As Lae City exhibits a dramatically different rainfall pattern to the other 8 stations, a second distribution was created with the gauge data from Lae City removed (Fig. 3.8). This enhanced the seasonality of the WMO RMM, making the drier season drier, while maintaining the wetter season values (Fig. 3.8). There was a small reduction in the correlation coefficient ($R^2 = 0.82$) which suggests that there may be a spatial component contributing to the correlation. To assess this, Fig. 3.9 was produced, showing landslide-triggering event frequency by administrative province and month of the year. As would be expected given the landslide-triggering event frequency distribution, nearly all provinces record events during the wetter season, particularly from January to May. From May onwards triggering events decline to zero in most provinces, except for the Islands, Morobe (in which Lae City lies), Madang and Western Provinces, which all record events during June, July, August and September.

The high rainfall totals observed in Lae City during the ‘typical’ drier season are associated with localized convection, which also drives rainfall along the north coast and the adjacent Islands. This variability is no longer captured by the WMO RMM when the data from Lae City is removed.
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Fig. 3.9. Landslide-triggering events by province and month. Inset map shows the location of the different provinces. Landslide-triggering events have been aggregated across all the islands (labelled 'Islands') and East and West Sepik Provinces (labelled 'Sepik'). NCD = National Capital District.

Furthermore, rainfall in Western Province is known to be consistently high throughout the year (McAlpine et al., 1983) and therefore seasonal changes in rainfall may be less distinct in this and adjacent inland regions. Given the sparse number of stations available and that 8 of the sites lie in coastal positions it is very likely that the WMO RMM’s under-represent accumulations in every month and that the change in rainfall from wetter to drier periods is over-emphasized. A gridded dataset with better representation of rainfall across the areas most prone to landslides is required to fully assess the spatial and temporal variability identified.

3.4.2 GPCC regional monthly mean (RMM) approach

The GPCC Full Data Reanalysis Product Version 5 (Adler et al., 2003) uses near real-time and non real-time gauge stations held in the GPCC database to produce gridded (0.5° resolution or ~55km) monthly precipitation accumulations over land areas around the globe. Rainfall gauge data from National Meteorological and Hydrological...
centres, as well as other sources, are interpolated to produce the gridded datasets. These
gridded data allow for temporal and spatial comparisons between rainfall and landslide-
triggering events to be made. To spatially and temporally match the landslide-triggering
event inventory, 221 grid squares, covering mainland PNG, New Britain and New
Ireland were extracted from the global dataset, for all months between 1970 and 2009.
For consistency with the WMO RMM analysis a regional monthly mean, based on all
grid squares and months, was calculated.

The GPCC RMM is shown in Fig. 3.8. As anticipated monthly mean rainfall
accumulations are higher for all months and although there remains a distinct wetter and
drier season, the differences between the two seasons are less than that seen for the
WMO RMM’s. This reflects the addition of gridded rainfall data in the interior and
higher elevation regions of the PNG mainland. However, rather than improving the
correlation coefficient, only 64% of the variance in the number of landslide-triggering
events is explained by the GPCC RMM rainfall (Fig. 3.8). This reduction is the result of
a larger number of, and greater variability between, the data points used to generate the
multi-year, regionally-based mean. Although this RMM can be considered more
representative of the rainfall over the whole of PNG than the WMO RMM, it is not
necessarily representative of the areas most prone to landslide-triggering events.
Therefore a second GPCC mean monthly rainfall distribution was generated, based on
only those GPCC grid squares which lie coincident with recorded landslides. This
second distribution, referred to as the GPCC landslide area mean (LAM), uses the same
number of months (all between 1970 and 2009) but only 34 grid squares. This was
compared against the monthly frequency of landslide-triggering events (Fig. 3.10
(Inset)). Firstly, it is interesting to note that the GPCC LAM reintroduces a well defined
wetter and drier period, where there is a steep decline in monthly rainfall totals after
April. Secondly, the differences introduced into the GPCC LAM yielded a slightly higher correlation coefficient ($R^2 = 0.66$; Fig. 3.10) than the GPCC RMM, but not as high as either of the coefficients identified using WMO data. Even with a reduced number of GPCC points, the range of rainfall values between the 25$^{th}$ and 75$^{th}$ quartiles suggests that there is large year-to-year variability in the monthly totals (Fig.3.10). The differences between the GPCC RMM and the GPCC LAM indicate that areas which are affected by landslides vary substantially in terms of their seasonal rainfall profile.

![Image](image-url)  
**Fig. 3.10.** Comparing GPCC LAM and monthly landslide-triggering event frequency. The spread of rainfall values between the lower (25th) and upper (75th) quartiles is shown in addition to a linear trend line (black dashed). Inset graph shows the WMO RMM, GPCC RMM and the GPCC LAM rainfall distributions and the monthly frequency of landslide-triggering events.

Given that there is such large variability in monthly rainfall totals, it might be assumed that a large number of the landslide-triggering events occurred in months where rainfall was greater than the GPCC LAM. To assess this Fig. 3.11 shows the monthly rainfall, obtained for the specific month and year at the location of each landslide-triggering event, compared against the GPCC RMM and the GPCC LAM. It should be noted that because triggering events can induce landslides in a number of different areas simultaneously, there are a number of events which span multiple GPCC
grid squares. All landslide-triggering events covering all the various GPCC grid squares are shown in Fig. 3.11.

**Fig. 3.11.** Monthly rainfall observed in the month and year, at the location of each landslide-triggering event (from GPCC data), compared against the GPCC RMM and GPCC LAM. The temporal and spatial reference for the RMM climatologies is shown in brackets.

59% of landslide-triggering events occur in months where rainfall exceeded the GPCC RMM and GPCC LAM (Fig. 3.11). However, 41% of landslide-triggering events occur in months where rainfall was below the GPCC LAM monthly average. This illustrates that landslide-triggering events can occur in months with very different rainfall totals, driven by different meteorological processes. However, this analysis does not illustrate whether the rainfall at the landslide location was high or low compared to the local mean for that grid square, or to what degree the spatial variability of rainfall affects both the frequency and distribution of landslide-triggering events.

### 3.5 Interseasonal rainfall variability and landslide-triggering events (Spatial Analysis)

To examine rainfall and landslide occurrence spatially, four seasonal composite mean monthly rainfall fields were generated for the PNG domain (Fig. 3.12). Average monthly rainfall observed within each season was calculated based on all months in that season (DJF, MAM, JJA and SON (September, October and November)), using the 40 years (1970-2009) of monthly GPCC data. Grid based means are produced for each of the 221 grid squares in PNG. For comparison landslide-triggering events, split over the four seasons, were overlain on the appropriate rainfall composite (Fig. 3.12).
Fig. 3.12. GPCC seasonal composite mean monthly rainfall fields (based on 40 years of monthly data), with the location of landslide-triggering events (from the PNG landslide inventory) split over the four seasons; (a) DJF, (b) MAM, (c) JJA and (d) SON, with isohyets at 200 mm/month intervals shown as a guide. Red tones denote less rainfall and drier conditions, and blue tones denote more rainfall and wetter conditions.
To support the seasonal rainfall composites, the maximum, mean and median monthly rainfall for each season have been calculated, as well as the standard deviation, coefficient of variation and percentage coverage of rainfall greater than 200 mm/month (Table 3.5). In addition, landslide-triggering event statistics were produced including:

1. a Nearest Neighbour Ratio (NNR) to assess how clustered or dispersed events are;
2. the triggering event frequency and
3. the number of administrative provinces affected by landslide-triggering events (Table 3.5). The NNR technique uses the following equations (Ebdon, 1985; Mitchell, 2005):

\[
ANN = \frac{\bar{D}_o}{\bar{D}_E} 
\]

EQ 3.1

where \( \bar{D}_o \) is the mean distance between each feature and their nearest neighbour,

\[
\bar{D}_o = \frac{\sum_{i=1}^{n} d_i}{n} 
\]

EQ 3.2

and \( \bar{D}_E \) is the expected mean distance of the features given a random pattern.

\[
\bar{D}_E = \frac{0.5}{\sqrt{n/A}} 
\]

EQ 3.3

d\(_i\) equals the distance between the feature (i) and its nearest feature, while \( n \) refers to the total number of features and \( A \) represents the area under study. If the average distance determined between the feature and the nearest neighbour points is less (more) than the average obtained from a random distribution, the features are considered clustered (dispersed). The resulting index value (ANN) indicates the level of clustering where values less than 1 indicate clustered features and values greater than 1 indicate dispersed features. To ensure that the NNR index values are comparable across the seasons, the same area parameter has been used for all the calculations.
### Table 3.5
Seasonal rainfall variability indicators and corresponding seasonal landslide-triggering event statistics. CV denotes Coefficient of Variation, calculated by dividing the standard deviation by the mean, and NNR denotes the Nearest-Neighbourhood Ratio value (Ebdon, 1985; Mitchell, 2005).

<table>
<thead>
<tr>
<th>Season</th>
<th>Season Rainfall Variability Indicators (mm/month)</th>
<th>% grid cells &gt;200 mm/month</th>
<th>Landslide-triggering event frequency</th>
<th>Provinces affected</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
<td>Mean</td>
<td>StDev</td>
<td>Median</td>
</tr>
<tr>
<td>DJF</td>
<td>1353.5</td>
<td>285.2</td>
<td>138.4</td>
<td>267.5</td>
</tr>
<tr>
<td>MAM</td>
<td>1370.7</td>
<td>290.2</td>
<td>140.5</td>
<td>270.2</td>
</tr>
<tr>
<td>JJA</td>
<td>2752.3</td>
<td>230.0</td>
<td>201.2</td>
<td>176.6</td>
</tr>
<tr>
<td>SON</td>
<td>1397.3</td>
<td>219.0</td>
<td>137.5</td>
<td>199.2</td>
</tr>
</tbody>
</table>
3| Landslides and rainfall variability at interseasonal and interannual timescales

At the broad scale, both the seasonal composites (Fig. 3.12) and the statistics (Table 3.5) point to a definitive split in rainfall distribution and landslide-triggering event activity between the wetter season (DJF and MAM) and the drier season (JJA and SON). From a rainfall perspective this is a function of the time when the north-westerly monsoon is active over PNG (DJF and MAM) and when orographic and physiographically–induced rainfall is the more dominant process driving rainfall (JJA and SON). This difference can be observed in the seasonal rainfall variability indicators where greater than 80% of PNG is affected by rainfall greater than 200 mm/month during DJF and MAM, and less than 50% of PNG is affected by rainfall greater than 200 mm/month during JJA and SON. The use of a 200 mm/month reference threshold is subjective and was selected purely on the basis that it allowed the differences in rainfall patterns across all four seasonal composites to be shown with greatest clarity. The characteristics of the DJF and MAM seasons include high mean and median rainfall and maximum rainfall totals reaching between 1350 and 1380 mm/month. JJA and SON are characterised by lower mean and median rainfall but higher maximum rainfall totals in excess of 1390 mm/month and reaching peaks of 2752.3 mm/month in JJA (Table 3.5). This illustrates the degree of variability between JJA and SON (coefficient of variation > 60% for both seasons) and DJF or MAM (coefficient of variation ~ 48% for both seasons).

Landslide-triggering events also show some characteristics suggestive of a wetter and drier season split. In terms of landslide frequency, DJF and MAM see the greatest number of events (19 and 26 for DJF and MAM respectively) compared with the lower numbers of events observed during JJA and SON (8 and 9 events respectively; Table 3.5). Furthermore, triggering event clustering appears to inversely mirror the change in rainfall coverage. For example, during DJF and MAM when rainfall in excess of 200
mm/month covers the greatest percentage of the country, landslide-triggering events are generally more clustered (0.17 and 0.46 for DJF and MAM respectively). The reverse is true during JJA and SON, where rainfall greater than 200 mm/month is restricted to less than 50% of the country, yet landslide-triggering events are much more dispersed (0.64 and 0.61 respectively). This is not unexpected, given that during JJA and SON, rainfall is predominantly associated with localized convective activity. By their nature, they are typically isolated, short-lived rainfall events and, therefore, landslide-triggering events associated with this type of rainfall are likely to show similarly dispersed and isolated characteristics. During DJF and MAM, rainfall is generally more consistent and widespread. This can lead to a single landslide-triggering event, such as a flood, covering a wider geographical extent, relative to an individual rainstorm. This therefore, increases the number of individual landslides recorded across the relatively wide area of the triggering-event, causing clustering to increase relative to the widely dispersed nature of isolated rainstorms identified in JJA and SON. This also suggests that environmental control factors for landslides may play a more significant role in determining the spatial distribution of landslide events during the wetter seasons, than during the drier seasons.

Despite this definitive split, a closer assessment of the occurrence of landslide-triggering events, relative to the pattern of high and low mean rainfall accumulations, suggests a far more complicated spatial relationship. Although rainfall during DJF and MAM is driven by the north-westerly monsoon, the distribution of rainfall is not uniform across PNG. The highest totals are seen in Western Province, the Adelbert Mountain Range in Madang Province and the northern coastlines of New Britain and New Ireland. Areas with lower rainfall totals (< 200 mm/month) are mainly confined to the southern coasts around Daru and Port Moresby, the northern coastline near Wewak.
and along the Ramu Valley (Fig. 3.12 (a); Fig. 3.12 (b)). In some respects the distributions of the two variables are similar. During DJF for example, landslide-triggering events occur in Western Province and the northern coastline close to Madang; both areas which see average rainfall accumulations in excess of 400 mm/month. However, the majority of events are confined within the central cordillera in Chimbu, Western Highlands and Eastern Highlands Provinces. Monthly mean rainfall totals in these areas lie between 250 and 350 mm/month during DJF. Furthermore, in a small number of cases landslide-triggering events are observed in areas where rainfall is between 150 and 200 mm/month (Morobe Province; Fig. 3.12 (a)). The same is true in MAM, JJA and SON (Fig. 3.12 (d)). During MAM the distribution of landslide-triggering events extends beyond the central cordillera, reaching into the Sepik basin, the Huon Peninsula and the southern coast of the Papuan Peninsula. All of these areas are prone to lower mean monthly rainfall totals, between 150 and 250 mm/months (Fig. 3.12 (b)). In JJA, the majority of landslide-triggering events occur in areas where mean rainfall is less than 200 mm/month. Only in the coastal areas and Western Province, are landslide-triggering events observed in conjunction with rainfall totals which remain above this amount.

One consistent feature between the four seasons is the continuation of triggering event activity within the central cordillera. Chimbu, Western Highlands and Eastern Highlands Provinces maintain a high proportion of landslide activity throughout the year and see relatively consistent mean monthly rainfall totals, between 200 and 300 mm/month (except for JJA; Fig. 3.12 (c)). Chimbu Province, in particular, observes triggering events throughout all seasons, despite the fact that mean monthly rainfall totals fall to less than 200 mm/month during JJA (Fig. 3.12 (c)). This activity is likely to be associated with the fact that isolated and intermittent convective cells and localized,
Landslides and rainfall variability at interseasonal and interannual timescales

Orographically-enhanced rainfall are poorly resolved in the GPCC dataset, due to the sparse coverage of rainfall gauges throughout PNG. Therefore, intense thunderstorms which can result in landslides during these seasons are not accurately captured. In addition to the central provinces, Western Province also continues to observe landslide-triggering events throughout the year. This is a reflection of the continuation of high rainfall totals throughout all seasons in this area. Overall, the analysis above indicates that areas with the highest rainfall do not implicitly relate to locations with the greatest density of landslide-triggering events, and areas with lower mean rainfall do not preclude landslide-triggering events from occurring. This would further suggest that factors other than the mean distribution of rainfall play a role in determining the spatial distribution of landslide-triggering events throughout the year. These additional factors are analysed in detail in Chapters 5 and 6.

One aspect which is important to remember throughout this analysis is that rainfall derived from different meteorological processes is likely to be captured with different degrees of accuracy. During DJF and MAM, rainfall is predominantly related to the north-westerly monsoon. This affects the majority of the country and can be widely captured by gauge stations, due to its relative coherency. During JJA and SON, where rainfall is largely the product of intermittent and isolated thunderstorm activity, or spatially specific convective regimes, the accurate capture of high intensity rainfall events is more difficult. Furthermore, the spatial resolution of GPCC data (0.5°) precludes detailed assessments to quantify the localized variability within the mountainous regions of PNG. Rainfall in these areas likely varies significantly from one valley to the next and therefore the true nature of rainfall and its association with landslide-triggering events cannot be captured accurately at this scale. Therefore, although broad-scale relationships between the temporal and spatial variability of
rainfall and landslide-triggering events can be established, the analysis above indicates two things: (1) that monthly rainfall patterns alone do not dictate where a landslide will occur and (2) that the broad-scale seasonal patterns cannot resolve localized temporal and spatial rainfall variability. Furthermore, it is important to remember that the climatologies used throughout this section are based on 40-years of monthly rainfall data. Given the location of PNG within the MC, year-to-year variability would be expected to be high due to variations in the amplitude and coherency of the north-westerly monsoon and the influence of ENSO. To assess this year-to-year variability the following section reviews the impact of ENSO on both rainfall and landslide-triggering event occurrence.

3.6 The impact of ENSO on PNG rainfall and landslide-triggering event occurrence

ENSO is known to influence rainfall patterns throughout the Pacific and globally, and can subsequently cause large changes in the timing and frequency of natural hazards (McPhaden et al., 2006; Kitzberger et al., 2001; Bouma et al. 1997). Therefore, an assessment of the impact of ENSO on PNG rainfall and the frequency of landslide-triggering events has been completed. At a broad scale, El Niño introduces ‘typically’ drier than normal conditions, while La Niña brings ‘typically’ wetter than normal conditions to PNG (McVicar and Bierwirth, 2001). The Multivariate ENSO Index (MEI) has been used to identify pairs of years representing each ENSO phase (El Niño, La Niña and ENSO-neutral). Pairs of years were used because ENSO phases typically begin towards the end of the north-westerly monsoon season (March or April) of year 1 and continue to affect synoptic weather patterns across multiple seasons, extending into year 2. In some cases, episodes can extend into years 3 and 4, as has been seen in a number of La Niña events since 1970. Wolter and Timlin (1993; 1998) described the
production method of the MEI in detail. In brief it is calculated as the first unrotated principal component of six variables including: sea level pressure, zonal and meridional components of surface wind, sea surface temperature (SST), surface air temperature and total cloudiness for each bimonthly period (Dec/Jan, Jan/Feb etc.). For comparability, the values are standardized across the seasons and the reference period (1950-1993).

The NOAA/ESRL/PSD generates a bimonthly, ranked index of the MEI which is freely available from their website (http://www.esrl.noaa.gov/psd/enso/mei/) and provides data from December 1949/ January 1950 up until the present. At the time of acquiring data (2012) there were 63 years of ranked data available. Each bimonthly period was therefore ranked between 1 and 63, where strong-to-weak La Niña events are identified by MEI ranks 1-19 (with 1 being the strongest La Niña event) and weak-to-strong El Niño events are identified by MEI ranks 45-63 (with 63 being the strongest El Niño event). Near-normal conditions (ENSO Neutral phases) are represented by values between 19 and 45. Using these ranks, years associated with each ENSO phase were recognised (Table 3.6; Fig. 3.13). In each case all months within the years are categorised as being associated with a specific episode. Based on the 40 years of the landslide inventory, 13, 11 and 16 years were identified representing La Niña, El Niño and ENSO-neutral events respectively.

<table>
<thead>
<tr>
<th>La Niña years</th>
<th>El Niño years</th>
</tr>
</thead>
</table>

Table 3.6. La Niña and El Niño years (Jan to Dec in each case) identified from the bimonthly MEI ranks (based on data sourced in 2012). All other years between 1970 and 2009 not shown in the table are classified as ENSO-neutral years.
3.6.1 Annual recurrence of ENSO and its influence on rainfall and landslide-triggering events

To understand the temporal recurrence of ENSO, an annual time series has been produced (Fig. 3.14). Using the same GPCC data (221 grid squares; 40 years) analysed earlier in this chapter, regionally-averaged rainfall statistics were calculated and compared against the annual frequency of medium-to-large landslide-triggering events. To identify changing ENSO phases each boxplot (Fig. 3.14) is colour coded, with pink tones representing years associated with La Niña phases, green tones with years associated with El Niño phases and blue tones for years associated with the ENSO-neutral phases. The resulting rainfall box-plots show the large variation in rainfall accumulations over PNG at this temporal and spatial scale (Fig. 3.14). As these regional statistics cover the same 221 grid squares used in the previous temporal and spatial analysis, it is possible to state that the majority of the observed rainfall variability is
associated with the JJA season and the very large differences in rainfall related to location specific convection (Fig. 3.12(c)).

At annual timescales the influence of ENSO phase on annual rainfall appears to be minimal (Fig. 3.14). The mean and median rainfall accumulations remain consistent throughout the time series, at around 3000 mm/year, and the variability within each year does not appear to vary substantially from one ENSO phase to the next. This is likely to be a product of the ENSO phase intensity, onset, duration and degree of interaction with the seasonal rainfall cycle. One observation which can be made however is that the 1st year of 3 out of the 5 El Niño events show reductions in the mean annual rainfall (1972-1973; 1982-1983; 1997-1998). Values return to the near-average annual rainfall totals (3000 mm/year) in the 2nd year of the ENSO phase in these instances (Fig. 3.14). For all of these episodes, no landslide-trIGGERing events are observed in the 1st year, while the numbers begin to increase in the 2nd year, reflecting the increase in average rainfall also observed in this 2nd year of the phase (except for the 1972-1973 episode where no triggering events are observed in either year 1 or 2). The remaining 2 El Niño events observed between 1970 and 2009 do not share these characteristics however. There is also minimal year-to-year variability in average annual rainfall observed across the remaining La Niña and ENSO neutral episodes.
In addition to rainfall, there does not appear to be a clearly identifiable relationship between the occurrences of landslide-triggering events and ENSO phase, at the annual timescale. Triggering events are recorded during all phases in PNG, although larger numbers are observed during La Niña phases. During the 13 La Niña years identified, 28 (45%) landslide-triggering events were recorded. This is compared with 13 (21%) triggering events over the 11 El Niño years and 21 (34%) triggering events recorded over the 16 ENSO-neutral years. Across all the La Niña phases, the largest triggering event frequencies are observed during the most recent La Niña event where 5, 4 and 7 medium-to-large landslide-triggering events were recorded during 2007, 2008 and 2009 respectively (Fig. 3.14). Of these triggering events the majority are linked to flooding in the central Highlands, although flash floods and tropical storms affecting Milne Bay Province and the Papuan Peninsula have also been recorded. Rainfall-induced landslides associated with tropical cyclones are particularly interesting because the likelihood of these systems making landfall on mainland PNG is relatively low, due
to the country’s proximity to the equator. However, on the 12th November 2007 Tropical Cyclone Guba made landfall along the northern coast of the Papuan Peninsula. Revell and Goulter (1986) found that during periods of positive SOI (La Niña), tropical cyclones had a tendency to form at more westerly longitudes (i.e. closer to PNG and northern Australia), increasing the likelihood of tropical cyclones and tropical depressions, associated with the South Pacific Convergence Zone (SPCZ), affecting the region. Although tropical cyclones do not appear as a landslide-triggering event during any of the other La Niña phases, severe storms and tropical depressions affecting the southern coast of Central Province and NCD occurred during the 2000-2001 La Niña event.

The 2007-2009, La Niña episode is classified as one of the top six strongest La Niña events to have occurred since 1949. It would be easy therefore, to suggest that the intensity of this event played a role in the higher frequency of landslide-triggering events observed over this period. However, when compared against other La Niña episodes between 1970 and 2009, this most recent event was in fact considered to be relatively weak. Moderate-to-strong La Niña events were recorded during 1974-1976 and 1999-2001, with 1974 being the strongest recorded. However, annual average rainfall and annual landslide-triggering event frequency do not reflect the changes in ENSO intensity. Therefore, additional factors such as improved landslide recording, accessibility, transport and infrastructure and increased availability of satellite data should be considered as contributors to the apparent increase in landslide-triggering events recorded from 2006 onwards. Therefore, although more landslide-triggering events appear to occur in PNG during La Niña episodes, care should be taken, particularly as greater than 50% of those observed were recorded during this most recent La Niña event (2007-2009; Fig. 3.14). Moreover, when landslide-triggering event
frequencies are compared across the different phases there are a number of other years which see comparable numbers of triggering events to those observed between 2007 and 2009. These include the 1983 and 1991 El Niño episodes (Fig. 3.14) where, in both cases, four medium-to-large landslide-triggering events were recorded. For the 1983 event, in particular, this highlights the complexity of determining robust relationships between landslide-triggering events and ENSO phase. Although El Niño is associated with causing drier conditions in PNG, it also influences the Hadley Cell circulation and the position of the ITCZ. During 1983, the ITCZ migrated further south during MAM than usual (Waliser and Gautier, 1993), prolonging the period over which the ITCZ migrated over PNG and this ultimately increased rainfall during this season. The study by Waliser and Gautier (1993) did not extend to 1991, preventing a similar argument being made for the number of landslide-triggering events observed in that year.

These results suggest that ENSO phase and intensity only have a minor impact on annual average rainfall and annual landslide-triggering event frequency, at this temporal scale. However, work by Waliser and Gautier (1993), McGregor (1989; 1992) and Revell and Goulter (1986) suggest that relationships may be more apparent at the seasonal scale. Therefore, the impact of ENSO at monthly time scales was also analysed.

3.6.2 The affect of ENSO on rainfall and landslide-triggering events over monthly time scales

Again using GPCC monthly data, multi-year, regionally-averaged monthly rainfall accumulations were generated for each of the ENSO phases. These averages were calculated using all months, across all the years which were assigned to a specific ENSO phase (13 years representing La Niña events, 11 years representing El Niño events and 16 years representing ENSO-neutral episodes). The landslide-triggering
events were redistributed to illustrate the monthly frequency of events across each ENSO mode. For reference the 40-year GPCC RMM, produced in section 3.4, is also shown (Fig. 3.15).

The RMM rainfall accumulations for each ENSO phase indicate that La Niña months are generally wetter than average and El Niño months are generally drier than average, consistent with the widely held assumption of ENSO’s impact across the south-west Pacific. Almost all La Niña months have average rainfall greater than the GPCC RMM, with the greatest differences being observed from May to December (Fig. 3.15(a)). By comparison, El Niño months show notably lower rainfall accumulations than those calculated for the GPCC RMM, from May to November (Fig. 3.15(b)). As expected, ENSO-neutral rainfall closely follows the forty-year, monthly climatology represented by the GPCC RMM (Fig. 3.15(c)).

A number of interesting points can be drawn from these plots. Firstly, although the monthly distributions show differences across the ENSO modes, the absolute difference in mean monthly rainfall is small. This is likely to be the result of using regionally-averaged data. McGregor (1992) suggested that the degree to which ENSO altered rainfall patterns varied spatially, and noted that the use of smoothed, regionally-based parameters could prevent key aspects of the spatial variability being identified. This will be discussed further in section 3.7. Secondly, neither of the extreme modes of ENSO appear to inhibit or dampen the occurrence of the north-westerly monsoon. This has ultimately resulted in only slight modifications in average rainfall during these months. It is not within the scope of this thesis to analyse the complex interactions between ENSO and the north-westerly monsoon. However, the fact that monsoon-driven rainfall remains a consistent feature of the monthly distribution is likely to be one reason why landslide-triggering events are observed throughout all ENSO phases.
Changes in landslide-triggering event frequency, associated with each ENSO phase (Fig. 3.15), are equally pronounced and variable when reviewed at monthly time scales. Of the three landslide-triggering event distributions, Fig 3.15(a) has the greatest similarities to the original monthly distribution of landslide-triggering events (Fig. 3.8). However, the seasonal distribution of landslide-triggering events identified in Section 3.4.1, remains a feature of both El Niño and ENSO-neutral distributions. This reflects the fact that ENSO appears to have minimal influence on the north-westerly monsoon in PNG. Despite this, there are greater numbers of triggering events observed from December through to May for La Niña episodes (20 triggering events), than during both El Niño (10 triggering events) and ENSO-neutral periods (15 triggering events).

Given that it is evident that ENSO does not significantly alter the regional mean rainfall or significantly affect regional mean rainfall during the north-westerly monsoon season, other factors must be involved in affecting landslide-triggering event frequency. One important contribution which can be drawn out of the plots in Fig. 3.15 is the effect that each ENSO phase has on the complete seasonal rainfall cycle. For example, average monthly rainfall is consistently higher from May to December during La Niña episodes. This means that although rainfall accumulations fall as the north-westerly monsoon wanes in April, the rainfall does not reduce to the level observed during El Niño or ENSO-neutral phases. This would prevent groundwater levels dropping significantly and could potentially maintain soil moisture and stream flows well into the typical drier season. Therefore, conditions would remain favourable for slope instability throughout the drier season (7 recorded failures observed during the drier seasons of La Niña; Fig. 3.15(a)). Hence, although there is not a large difference in any single month’s rainfall accumulation, the combined effect of every month in the La Niña distribution having slightly higher average rainfall totals could be enough to encourage the distinct
changes in landslide-triggering event frequency observed. This is reversed for El Niño phases, where rainfall throughout the drier season is further suppressed. This would allow greater volumes of water to be lost from the environment, reducing groundwater levels, river flow rates and soil moisture. The reduction in water loading would potentially increase the stability of many slopes during these months. This is reflected in the lower numbers of landslide-triggering events observed during the drier seasons of El Niño episodes (3 triggering events; Fig 3.15(b)). However, following these periods of accentuated drier conditions, landslide-triggering event frequency appears to increase substantially during December. A review of geology is likely to be critical to understanding why this occurs. For example, excessive drying of clay-rich soils can cause cracks which thereby allows for enhanced infiltration producing slopes which are more sensitive to being triggered by rainfall.

Although the impact of ENSO appears subtle for rainfall, there are clear differences in the landslide-triggering event frequency between the ENSO phases. Therefore it is possible that distinct patterns of triggering event activity could exist. To address this possibility Fig. 3.16 was produced showing the monthly rainfall and monthly landslide-triggering event frequency in a scatterplot. The majority of points lie within a central, oval envelope labelled as ‘La Niña triggering event activity’ (Fig. 3.16). All months associated with the La Niña phase fall within this envelope, which shows that the landslide-triggering event frequency begins to increase once mean rainfall accumulations exceed ~225 mm/month. As expected given the results of the GPCC RMM and WMO RMM analysis, there is a general trend indicating that monthly landslide-triggering event frequency increases as monthly rainfall accumulations increase. The majority of ENSO-neutral points also fit within this envelope, although the maximum frequency observed in any single month is less than that observed during
La Niña episodes. There are also two distinct outliers from the ENSO-neutral points which define the maximum upper boundary and minimum lower boundary of the wider envelope of triggering event activity.

Fig. 3.16. Landslide-triggering event frequency and monthly rainfall accumulation by ENSO phase, with an overall envelope of triggering event activity identified (grey region), within which specific zones of activity for La Niña phases and El Niño are shown.

In addition to this envelope there is a distinct pattern associated with the observed El Niño landslide-triggering events. Rather than a single envelope, the distribution is split over two distinct zones. These are labelled as ‘El Niño triggering event activity’ on Fig 3.16. The first envelope is associated with higher mean rainfall accumulations greater than 280 mm/month. Each point within this envelope occurred during the wetter season, in January, February or March. The second envelope is linked to lower mean rainfall accumulations less than 250 mm/month. Each of these triggering events coincides with months in drier season. Despite these patterns, it must be reiterated that the data is based on multi-year, regionally-based averages. Given that ENSO
predominantly affects rainfall values during the drier season, it is likely that localized changes in the frequency and spatial distribution of small-scale convective activity are not being observed.

3.7 Discussion

A major aim of this chapter was to understand the broad-scale relationships between landslide-triggering events and interseasonal and interannual rainfall variability. Initially, the relationships appeared broadly straightforward, with the monthly frequency of landslide-triggering events correlating (positively) well with regional (GPCC RMM) and landslide-area (GPCC LAM) means. However, the availability of the gridded GPCC data allowed more detailed analysis of the relationships, both spatially and temporally to be assessed, allowing more complex relationships to be identified.

Firstly, a review of mean monthly rainfall over seasonal time scales found that changes in absolute mean monthly rainfall, within the monsoon period, were small (DJF = 285.2 mm/month and MAM = 290.2 mm/month; equivalent to a 1% increase from DJF to MAM) compared with changes in landslide-triggering event occurrence (~46% increase from DJF to MAM; Table 3.5). Similarly, during the ENSO analysis, the differences in absolute mean monthly rainfall were small and yet there were marked changes in landslide-triggering event frequency during the wetter seasons of the different phases (28 events during the 13 La Niña years, 13 events during the 11 El Niño years and 21 events during the 16 ENSO-neutral years). In both instances, this suggests that rainfall accumulated throughout the seasonal cycle (rainfall durations greater than one month) is important for landslide-triggering events to be instigated. This effectively identified the importance of antecedent conditions for landslide-
triggering events during DJF and MAM. The same characteristics are not observed for the drier seasons.

A key aspect of the antecedent condition of the environment is geology, as this determines how moisture infiltrates and moves through the strata. This not only influences the temporal distribution of landslide-triggering events within the seasonal cycle but also results in distinct spatial patterns. In Chimbu, Western Highlands and Eastern Highlands Provinces, where the Chim Formation outcrops, there is a significant clay fraction ‘dominated by monmorillonite-illite inter-stratification’ (Blong, 1985). In this strata hydraulic conductivity values could be anywhere between $5 \times 10^{-7}$ and $5 \times 10^{-3}$ m/day (Lewis et al., 2006). Having these weaker layers has been found to make slopes more responsive to rainfall. This results from a reduction in shear strength which occurs as monmorillonite absorbs water and swells. In the spatial analysis, it was possible to identify those provinces where the Chim Formation outcropped regularly, as being more responsive to changes in monthly rainfall because landslide-triggering events were initiated early in the seasonal cycle, as soon as rainfall moved into the mountainous regions during SON (Fig. 3.12). Triggering events continue to occur in these provinces throughout DJF and MAM, increasing to a maximum number of events in DJF and remaining at this level throughout MAM. In some cases (e.g. the Yakatabari Mudslide; Blong, 1985) it is likely that environmental recharge, delivered in SON and DJF, would allow slow-moving creep-style movements to reactivate during these seasons, as well as to support mudslide surges in MAM following the re-saturation of the geology. Other areas of PNG, particularly Southern Highlands Province, appear to be less responsive, with events only being observed during MAM (Fig. 3.9 and Fig. 3.12). This is a karst limestone environment with high conductivity values of the order of $10^1$ to $10^3$ m/day (Lewis et al., 2006). This would suggest a system highly responsive to rainfall over
shorter durations. However, the landslides in this region are frequently large, translational and/or complex in nature, encouraged by ongoing denudation of faults and bedding-planes within the limestone structure or undercutting associated with stream erosion. The environmental recharge delivered in DJF, including enhanced stream flow and erosion potential, could allow additional rainfall during MAM to instigate landslides in materials which have been weakened over previous seasonal cycles. The importance of geology and morphology in affecting the spatial and temporal distributions of landslides will be examined in more detail in Chapters 5 and 6 of this thesis.

The spatial distribution of landslide-triggering events becomes additionally complex when the impacts of ENSO phase are considered. Correlations between regionally-averaged monthly rainfall and landslide-triggering events were weak for all the ENSO phases, although distinct patterns of activity were obtainable for both La Niña and El Niño years (Fig. 3.16). As McGregor (1992) suggested, this is likely to be a function of the use of regionally-averaged rainfall statistics. Plots showing monthly rainfall (percentage) differences for La Niña (Fig. 3.17(a)) and El Nino years (Fig. 3.17(b)) compared against the ENSO-neutral rainfall composite, illustrate how rainfall varies spatially between the extreme modes of ENSO in PNG. For both anomaly plots, the JJA season is used, as this is the season where ENSO phase results in the greatest deviations in monthly rainfall when compared against the ENSO-neutral and GPCC RMM rainfall distributions (Fig. 3.15). Although these rainfall anomaly plots hint at the degree of spatial variability which can be induced by the two extreme modes of ENSO, subtle interactions in high topography regions are not clearly evident. Such interactions include changes to katabatic flows which can enhance the likelihood of frosts affecting regions in the central Highlands during El Niño phases (McGregor and Nieuwolt, 1998;
McVicar and Bierwirth, 2001). Moreover, subtle changes in local wind patterns, in addition to the impact ENSO has on synoptic wind patterns, will result in complex localized interactions affecting the spatial and temporal distribution of rainfall during different phases of ENSO. These interactions will induce rainfall variability at higher resolution than the GPCC data can resolve, and therefore these rainfall events cannot be captured robustly at the 0.5 x 0.5° resolution.

In addition to rainfall data resolution, there is a degree of subjectivity involved in the method used to identify the different phases of the ENSO cycle. There are a number of different indices available to make this assessment (MEI, SOI, Bivariate ENSO time series (BEST); Smith and Sardeshmukh, 2000). Each index uses different meteorological parameters, numbers of parameters and methods for defining the index and data reference periods. One of the main reasons for the subjectivity in determining distinct ENSO phases comes from the fact that the processes involved are continuous in nature and each parameter used to identify the onset of a phase has its own degree of noise and variability. Furthermore, categorising index values to represent distinct ENSO phases can prove to be problematic given that the individual signatures of a specific ENSO event are often unique. The decision to use the bimonthly ranked MEI was based on the fact that it used the greatest number of meteorological parameters and provided a clear and intuitive method for categorising periods associated with the different ENSO phases. It should be noted however, that the use of a different ENSO index could result in a different number of years being assigned to each ENSO phase which could, in turn, impact the relationships identified in this analysis.
One important consideration when contextualising the results of this chapter’s analysis is to understand how representative the GPCC Full Data Reanalysis product (Version 5) is at providing reliable monthly rainfall data. The representativeness of the data is not only a function of the grid resolution, which as mentioned earlier is too coarse to resolve the majority of isolated, localized convective storms, but also the data used to generate the reanalysis product itself. The GPCC Full Data Reanalysis product (Version 5) is for the period 1901 to 2009 and uses quality-controlled data from 65,000 stations world-wide that have records with durations of 10 years or longer. The major sources of error for gauge-based gridded precipitation datasets are: (1) systematic gauge-measuring error and (2) the sampling error dependent on the gauge network.
density (Schneider et al., 2013). The predominant source of error in PNG is associated with the sampling error induced by the sparse gauge network density. Investigations by WMO (1985) and GPCC (Rudolf et al., 1994) have indicated that the relative sampling error of the gridded monthly rainfall data is between ±7 to 40% of the true area mean, if five rain gauges per grid square are used. Alternatively, where ten stations are used a sampling error range of ±5 to 20% of the true area mean can be expected. The error range for a given number of stations reflects the spatial variability of the precipitation in the region and is dependent on orography, season and type of precipitation (convective, stratiform) being recorded (Schneider et al., 2013). Fig. 3.18 shows the gauge network coverage, in numbers of stations per grid, for the DJF season of 4 years which fall within the 40 years studied in this chapter.

![Gauge Network Coverage](image)

**Fig. 3.18.** Rainfall gauge network coverage in PNG and surrounding areas for the DJF season in years (a) 1969/70, (b) 1979/80, (c) 1989/90 and (d) 1999/2000. Colours indicate the number of gauges per grid square.
The very low numbers of gauges, particularly in 2000 indicate that sampling error is likely to be high in PNG and that this would have a significant impact on how precipitation data is interpolated across the region (using the SPHEREMAP interpolation method (a spherical adaptation to Shepard’s weighting interpolation method; Willmott et al., 1985; Shepard, 1968)). The combination of poor gauge network coverage and the relatively coarse nature of the GPCC grid (0.5°) means that confidence in area statistics are relatively low for this region. Furthermore, the coarse nature of the GPCC grid means that individual convective storms produced by rapidly changing topography are not captured regularly. This introduces bias to the dataset, with rainfall accumulations recorded during the north-westerly monsoon being more accurate, due to the widespread nature of convective rainfall during this time, than rainfall accumulations obtained during the drier season, when intermittent, localized convective storms are more dominant. For this reason, GPCC data can be considered applicable for use at a broad scale only. It can be used to identify changing rainfall patterns seasonally but cannot be used to identify a single rainfall threshold which triggers a single landslide event. The limitations outlined here for rainfall data are similar to those previously outlined (section 3.3) for the landslide inventory.

3.8 Conclusions

This analysis has identified the temporal and spatial variability of both rainfall and landslide-triggering events at interseasonal and interannual time scales. The results suggest that the high frequency of landslide-triggering events observed during the wetter seasons (DJF and MAM) are likely to be associated with rainfall totals accumulated over a month or more, with antecedent conditions over consecutive seasons being an important additional factor for landslide-triggering events during these months. By contrast, rainfall accumulated over shorter timescales is likely to be
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important for the majority of events which occur in JJA and SON. Unfortunately, the GPCC dataset is unable to accurately capture rainfall at a relevant scale to assess this in detail and therefore another source of rainfall data are required to allow further assessments of this relationships to be completed. At the interannual timescale, comparisons between ENSO phases indicated that La Niña phases are the most active with regard to landslide-triggering events, with 45% of events occurring during this phase, while only 21% and 34% of landslide-triggering events occurred during El Niño and ENSO-neutral phases, respectively. Patterns of triggering event activity associated with changing monthly rainfall were established for La Niña and El Niño phases, with unique envelopes of activity being identified.
4. Probabilistic approaches for assessing landslide-triggering event rainfall
Abstract

The relationships between rainfall and landslide occurrence are frequently complex, particularly for larger, deeply-seated and/or complex mass movements. This complexity is amplified due to the inconsistency and incomplete nature of many landslide catalogues and the frequently sparse nature of available rainfall data. For these reasons, probabilistic techniques are being developed so that some of these uncertainties can be captured within empirical analysis. Here, a modified Bayesian technique is used to determine landslide probability related to rainfall events of specific magnitude and duration. This involves assessing the detailed rainfall patterns in the days preceding landslide events, to determine the characteristics of landslide-triggering rainfall events. These are then compared against rainfall patterns where no landslides have been recorded (non-landslide-triggering rainfall events). In both cases, satellite-derived precipitation estimates have been used to derive representative rainfall for events with different rainfall durations (5, 10, 15, 30, 45, 60, 75 and 90 days). The Bayesian technique is then applied to the two rainfall-variable combinations: (1) accumulation-duration and (2) intensity-duration, using relative frequencies to assess the probabilities of landslides. The method has been successful in distinguishing between non-landslide and landslide-triggering rainfall events. It has also quantified landslide probabilities related to changing accumulation-duration and intensity-duration rainfall events, working particularly well for the accumulation-duration combination. Furthermore, the first proxy probability thresholds have been developed for PNG. These have the potential, following further testing, verification and calibration, to be used within an early warning/forecasting framework to help decision-makers prepare for landslide hazards.
4 Probabilistic approaches for assessing landslide-triggering event rainfall

4.1 Introduction

Defining rainfall event thresholds for landslide activity has been extensively researched in a range of different climatological and geological regions. Frequently, the findings illustrate that there is not a direct cause and effect relationship between rainfall and landslide events, but that complex additional factors are also important (e.g. Chowdhury and Flentje, 2002). The strength of any relationship is linked to the type, size, and kinematics of the landslide and the variable chosen to explain the rainfall characteristics (Aleotti, 2004). Shallow landslides are typically associated with short, high-intensity rainfall while most large, deeply-seated landslides are affected by the interaction between long-term rainfall and natural denudational processes. The methods used to analyse these relationships are typically model-based being either empirically-based or physically-based. Physically-based models are those which aim to explain the dynamic processes occurring within a slope during a landslide (Capparelli and Versace, 2011). They typically look to extend slope stability models, such as the ‘infinite slope model’ and often include hydrological models, which explain groundwater and infiltration processes (Guzzetti et al., 2007). These models require a significant volume of data in order to accurately represent the dynamic processes occurring prior to, and during, slope movements. Parameters input into such process-based models include: soil thickness, groundwater conditions and shear resistance. Such detailed data are both difficult to acquire and to apply to large areas, particularly in PNG. Empirical models, on the other hand, use statistical approaches, based on historical landslide catalogues, to assess the rainfall patterns most likely to be associated with landslides. These models have been used to develop different rainfall thresholds at local (Zêzere et al., 2005; Lee et al., 2014), regional (Aleotti, 2004; Larsen and Simon, 1993) and global scales (Caine, 1980, Crosta and Frattini, 2001).
All models are affected by the uncertainties of the datasets used to create them. For example, physically-based landslide models have rarely accounted for the spatial and temporal variability of geotechnical parameters and pore water pressures when calculating the conventional factor of safety (Aleotti and Chowdhury, 1999). Empirically-based models, by contrast, have uncertainties inherent to the methodology used to produce landslide and rainfall event inventories. Quantifying the uncertainty and variability introduced by numerous aspects of a model’s development has become an increasingly important consideration, resulting in a shift towards increased use of probabilities in both physically and empirically-based models. In conventional approaches, using the deterministic framework, two types of rainfall threshold are typically used for landslide early warning. The first identifies the maximum amount of rainfall required to cause a change of state to take place and the second identifies the minimum rainfall threshold which defines the lowest level below which a process does not occur (Guzzetti et al., 2007; Staley et al., 2012). In both cases, these thresholds become ‘on/off’ switches which indicate whether a slope will or will not fail given a specified amount/intensity of rainfall. This can prove ineffective and inaccurate for early warning systems, particularly for highly complex events such as landslides. Probabilistic approaches, however, offer information about the likelihood of a process to occur given changes in the rainfall parameter. This can be extended further to look at the probabilities of slope movement associated with variability in geotechnical parameters, such as cohesion, angle of friction and shear strength (physically-based model; Aleotti and Chowdhury, 1999) or the temporal and spatial variability of quasi-static landslide susceptibility indicators (empirically-based model). A number of different probabilistic techniques have been examined for landslide early warning development (First Order Second Moment Method; Point estimate method; Monte Carlo simulation; Bayesian approaches).
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Carlo simulation method, (Chowdhury, 1984) Bayesian approaches (Guzzetti et al., 2007) and multivariate logistic regression (Brunetti et al., 2010)), however; few have been pulled through and developed into real-time landslide early warning/forecast systems. An exception to this is the ELDEWAS system, which aims to detect landslides in Austria using a nowcasting weather forecasting system combined with fuzzy logic to describe the landslide susceptibility (Krol and Bernard, 2012).

The limitations on data availability in PNG have resulted in an empirically-based focus to this research. The methods employed in Chapter 3 and throughout this thesis rely heavily on the historical landslide inventory (section 3.3) and on the availability of reliable rainfall data. In this chapter, approaches which build on those discussed in Chapter 3 are used to understand the detailed rainfall patterns which occur preceding known landslide events. Based on these analyses, a modified Bayesian approach is used to develop probabilistic rainfall thresholds for medium-to-large landslide events in PNG.

4.2 Satellite-derived precipitation estimates

In Chapter 3, gauge-based rainfall data were used to understand the broad relationships between rainfall variability and landslide occurrence in PNG. However, the analysis was restricted by the poor coverage of the rainfall gauge network and the temporal and spatial resolution of the available datasets. To address the limitations identified in Chapter 3, satellite-derived rainfall products were considered.

4.2.1 Background to satellite-derived precipitation estimation techniques

Satellite observations of precipitation have been in use since the 1970’s, where early estimation algorithms were largely based on data from infrared (IR) and visible satellite sensors. These were used to infer surface rainfall intensity based on the
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brightness (reflectivity of clouds) and the temperature of the cloud tops (Ebert et al., 2007). These techniques relied on the assumption that clouds penetrating deeper into the atmosphere have colder cloud tops and produce heavier rainfall. Ebert et al. (2007) suggested that the link between precipitation and cloud properties is relatively weak and can only produce crude estimates of precipitation. However, the advantages of IR and visible sensors are associated with the regularity and high temporal frequency with which measurements can be made. In North America, for example, satellite-derived precipitation data can be provided at 15 minute intervals at a resolution of ~4 km (Vicente et al., 1998).

To add to IR measurements, data from passive microwave (MW) sensors became available in the 1980’s and are now included within a number of current satellite-derived precipitation estimation algorithms. Such sensors identify the degree to which the Earth’s radiation is modified by hydrometeors. This is most easily accomplished over the ocean, where the contrast between the brightness temperatures of raindrops (radiatively warm) and the brightness temperature of the sea surface (radiatively cool) can be identified with reasonable accuracy in the 10-50 GHz range (Ebert et al., 2007). A greater contrast between the brightness temperatures indicates heavier rainfall. Land surfaces, however, are both stronger radiation emitters and more variable with regards to surface coverage (ice, rainforests and desert). Therefore over land areas, observations of precipitation-sized ice particles are made using the high-frequency microwave range (~85 GHz). Measurements of colder brightness temperatures, at these higher frequencies, register greater concentrations of ice particles which typically represent convective clouds, which are known to produce heavy rainfall at the surface (Ebert et al., 2007). Although effective for identifying convective rainfall, the method is less successful at identifying rainfall resulting from stratiform clouds (Ebert et al., 2007). In
addition, although MW measurements are frequently made from low-altitude, low-inclination orbits, which allows for high spatial resolution, the temporal resolution is reduced to, at best, a point being observed twice a day (Schumacher, 2000). This can prove to be problematic for observing the high spatial and temporal variability of precipitation. There are therefore, pros and cons to each method and it was not until Adler et al. (1993) that the best components of each were combined successfully. Since then, validation of multi-sensor algorithms suggests that precipitation estimates are often more accurate using combined sensor information (IR-MW) than earlier single-sensor algorithms (Ebert et al., 2007; Kidd et al., 2003).

Following on from the work by Adler et al., (1993) a number of satellite-based rainfall estimation algorithms have become available for meteorological and hydrological research. The most widely used include Tropical Rainfall Measuring Mission (TRMM; Simpson et al., 1988; Kummerow et al., 2000) Multi-satellite Precipitation Analysis (TMPA; Huffman et al., 2007), Climate Prediction Centre Morphing product (CMORPH; Joyce et al., 2004) and Precipitation Estimation from Remotely Sensed Information Using Neural Networks (PERSIANN; Sorooshian et al., 2000). The TRMM TMPA method uses MW measurements to calibrate IR precipitation estimates and then merges the estimates together to produce a single precipitation estimate per TRMM grid square. In this technique, rainfall estimations are made from MW estimates where MW data are available and use IR-derived estimates where MW data are not available. This differs from both CMORPH and PERSIANN. The CMORPH method uses MW data to derive rainfall estimates and only uses IR data to generate a field representing cloud motion. This is then used to propagate raining pixels spatially and temporally. PERSIANN, on the other hand, uses IR data to derive rainfall estimates. In this method, relationships between IR and MW data are determined
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through neural networks and then applied to the IR data to generate precipitation estimates. All three products have a spatial resolution of 0.25° and 3-hourly temporal resolution, although both CMORPH and PERSIANN offer data at finer resolutions for more recent data. Furthermore all products offer good coverage in the tropics and have been evaluated extensively for different applications and regions. However, of the three methods, TRMM TMPA has the longest data archive, with precipitation estimates available from 1998 through to the present. CMORPH data are available from December 2002 to the present, while PERSIANN data are available from March 2000 to the present.

4.2.2 Evaluations of satellite-derived precipitation estimation products

To decide which satellite-based estimation product is most appropriate for analysing rainfall characteristics related to landslides in PNG, a review of the literature was conducted. There have been numerous studies evaluating TMPA, CMORPH and PERSIANN performance in a range of different regions (Huffman et al., 2007, Ebert et al., 2007, Tain et al., 2007, Dinku et al., 2010). The studies of particular relevance to this thesis are those which evaluate performance in tropical regions using the following products:

- TMPA 3B42 Real Time (3B42RT) daily data,
- TMPA 3B42 (3B42) daily, gauge-adjusted data,
- CMORPH daily data and
- PERSIANN daily data.

4.2.2.1 General performance of satellite-derived precipitation estimates

Ebert et al. (2007) compared twelve operational precipitation estimates, including five multi-sensor algorithms (including 3B42RT, CMORPH and PERSIANN), three IR-only algorithms and four global Numerical Weather Prediction (NWP) models. In all
cases, the focus of the validation was on daily rainfall estimate performance. Focussing on the findings for tropical northern Australia, due to the proximity of the region to PNG, it was found that satellite estimate performance was better during the southern hemisphere summer (DJF) than the winter (JJA). This suggested that the satellite-based algorithms produced more accurate precipitation estimates as the precipitation regime tended towards deep convection (Ebert et al., 2007) and that the high frequency MW range is useful for measuring convectively-driven rainfall. However, the multi-sensor algorithms had difficulty detecting non-convective rainfall when examined at daily time-scales (Fig. 4.1). In tropical northern Australia, non-convective rainfall is usually the product of remnant mid-latitude frontal systems or orographic uplift, both of which are dominant mechanisms for rainfall during JJA (Ebert et al., 2007). Of the satellite estimation products examined, CMORPH appeared to perform better in both winter and summer situations, with correlations in excess of 0.6 during both periods in the tropics (Ebert et al., 2007).

Fig. 4.1. Example validation of the CMORPH daily rainfall estimates (05/01/2005) over Australia. The satellite algorithm correctly diagnosed the heavy precipitation in northeastern Australia but overestimated light rain extent to the south. It also failed to capture the light rainfall in the far southeast, a problem that is common to most satellite precipitation algorithms when dealing with rain in shallow clouds (Ebert et al, 2007). Reproduced with permission.
Unfortunately the daily, gauge-adjusted 3B42 data were not assessed in the analysis completed by Ebert et al. (2007). However, studies by Romilly and Gebremichael (2011), Behrangi et al., (2011), Dinku et al., (2008), Yu et al., (2009) and Su et al., (2008) have shown that gauge-adjusted 3B42 suffers similar biases to 3B42RT, particularly over shorter timescales. Based on these studies the following general statements can be made:

(1) MW-based products (3B42, 3B42RT and CMORPH) outperform IR-based products (PERSIANN).

(2) Rainfall occurrence and amount is more accurately represented by satellite-derived precipitation estimates during the summer (DJF in the southern hemisphere, JJA in the northern hemisphere) and at lower latitudes.

(3) The estimates become more accurate as the precipitation regime tends towards deep convection (Ebert et al., 2007)

(4) There is a general indication that estimation products suffer from under-estimation during the drier season and over-estimation during the wetter season, particularly in tropical regions.

(5) The degree of bias observed across the products is variable and dependent on the occurrence and variability of the dominant rainfall regimes within the season and the geomorphology of the region (Romilly and Gebremichael, 2011; Ebert et al., 2007).

4.2.2.2 Physiographically-specific comparison of TMPA, CMORPH and PERSIANN

The influence of geomorphology on the accuracy of satellite-derived precipitation estimates is particularly important in PNG. As an archipelago of islands with rapidly-varying rugged terrain, rainfall processes are strongly influenced by the combination of land and sea areas, the mountainous topography and the alignment of coastal regions in
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relation to the trade winds. Further validation studies have looked specifically at the ability of satellite-derived precipitation algorithms to accurately represent rainfall in mountainous and/or island nations. Hirpa et al. (2010) evaluated 3B42RT, CMORPH and PERSIANN over the complex topographic region of the Awash River basin, in north-eastern Ethiopia. They found that the PERSIANN algorithm produced precipitation estimates with a smaller range of variability and underestimated large rainfall accumulations, when compared to CMORPH and 3B42RT. Rainfall gauge observations taken within the basin show that rainfall accumulations increase with increasing elevation. This trend was captured by CMORPH and 3B42RT but not the PERSIANN algorithm which considerably underestimated rainfall accumulations at high elevations (Hirpa et al., 2010). Similar findings have been documented in a number of different geographical locations (Vernimmen et al., 2012; Romilly and Gebremichael, 2011; Li et al., 2014). The gauge-adjusted 3B42 product was evaluated by Dinku et al., (2008) and Dinku et al., (2010) for the western highlands of Ethiopia and the highlands of Columbia, in South America. In both instances, 3B42 underestimated the total rainfall amounts by ~14% and ~16% for Ethiopia and Columbia, respectively. This underestimation was also recorded by Ward et al., (2011) for the Paute Basin in Ecuador and the Baker Basin in Chile/Argentina.

A number of studies have also explored the effect being a small island or archipelago has on the performance of satellite-derived precipitation estimates. Jamandre and Narisma (2013) reviewed the accuracy of 3B42 and CMORPH against rain gauge and gridded precipitation data for the Philippines. Their results indicated that both algorithms struggled to accurately capture low daily rainfall accumulations (< 50 mm/day), particularly in the south of the archipelago. In this southern region rainfall is predominantly driven by orographic uplift and the contrasting thermal interactions.
between the land and sea, resulting in lower correlation coefficients than those obtained in the north-eastern part of the country, where the south-west monsoon and typhoon activity are observed. CMORPH and 3B42 appear to perform better in this northern region, particularly during the periods of deep-convective activity. However, the 3B42 estimates performed notably well for precipitation accumulations in excess of 100 mm/day, indicating that 3B42 is favourable for applications using heavy or extreme rainfall information in this region.

The findings of these different studies can be broadly summarised using the outcomes of research by Vernimmen et al. (2012). In this study 3B42RT, CMORPH and PERSIANN were compared against the annual and monthly rainfall accumulated within six basins with high spatial rainfall gauge network coverage in Java, Indonesia. The main findings were:

(1) PERSIANN had larger relative accumulation differences, when compared to the annual average rainfall estimates obtained from CMORPH and 3B42RT over the period 2003-2008. This supports the findings of Hirpa et al. (2010).

(2) The differences between PERSIANN and the CMORPH and 3B42RT algorithms were found to be particularly evident when reviewed spatially in Indonesia, where PERSIANN showed lower precipitation estimates in high elevation regions compared with the other two estimates.

(3) As in work by Jamandre and Narisma (2013), Ebert et al. (2007) and Tian et al. (2007), performance was strongly associated with seasonal rainfall regime changes. For all algorithms used in the Indonesian study, performance dropped during the dry season. Greater relative biases were calculated over these periods when compared with biases calculated for the wet season.
4| Probabilistic approaches for assessing landslide-triggering event rainfall

(4) Of the algorithms examined TRMM 3B42RT performed the best over Indonesia, producing the smallest relative bias compared to CMORPH, which produced large negative biases (underestimates of rainfall accumulations), and PERSIANN, which produced large positive biases (overestimates of rainfall accumulations).

The studies reviewed above highlight some of the strengths and weaknesses of the different algorithms, both temporally and spatially and illustrate the need for caution when applying these data. 3B42 is considered to have higher accuracy over aggregated rainfall durations (greater than 1 day) due to the addition of rainfall gauge data (Ebert et al., 2007). CMORPH performs better at shorter rainfall durations of a day or less and both CMORPH and 3B42 perform better than PERSIANN in high altitude regions. The larger-scale landslides captured in the PNG landslide inventory are likely to be associated with rainfall produced from weather systems lasting at least a day or more (Fuhrmann et al., 2008). Therefore, aggregates of daily rainfall data will be required to study the rainfall events preceding landslide activity. In fact, research by Zêzere et al., (2005) suggest that rainfall accumulated over periods of one day, up to three months are required to analyse rainfall characteristics associated with shallow and deep-seated landslide types. Based on these requirements and the evaluations of satellite-derived precipitation estimates outlined above, the decision was made to use the gauge-adjusted 3B42 data for the analysis of rainfall patterns preceding landslide events conducted in this chapter.

4.3 TRMM satellite and TRMM TMPA products

The gauge-adjusted 3B42 Version 6 (3B42V6) product is generated at the National Aeronautics and Space Administration (NASA) Goddard Space Flight Centre (GSFC) from TRMM TMPA (Huffman et al., 2007) and made available through data collected by TRMM and other satellites. Launched in 1997, the TRMM satellite follows
a circular, non-sun-synchronous orbit at an altitude of approximately 400 km (Fig. 4.2). With an orbital inclination of 35° to the equator, raw data is available between 35° north and 35° south. Using and processing data from other satellites can increase data coverage to a region between 50° North and 50° South across the globe (180° West to 180° East). The satellite completes a full Earth orbit in approximately 90 minutes and makes 16 orbits per day. On-board the TRMM satellite a suite of sensors measure a range of precipitation-related variables (Fig. 4.2). The primary instruments making up the ‘Rain-measuring Package’ include the Precipitation Radar (PR), the TRMM Microwave Imager (TMI) and the Visible Infrared Scanner (VIRS).

4.3.1 Precipitation Radar (PR)

The PR on-board the TRMM satellite is an active microwave sensor which has a horizontal ground resolution of approximately 5 km and a swath width of 247 km. It is able to generate a 3-dimensional profile of storm structure over both land and sea areas, as it observes both the vertical structure of precipitation and the spatial coverage (Iguchi et al., 2000). This allows estimates of latent heat release to be made which are related to large-scale tropical dynamics. The sensor is able to detect rain rates to a minimum of 0.5 mm/hr and is also able to discern between convective and stratiform rain (Schumacher and Houze, 2003). These types of precipitation develop under different dynamic processes and result in different precipitation rates being observed (Houze, 1993; 1997), which could have important implications for the timing of different landslide types.
4.3.2 **TRMM Microwave Imager (TMI)**

The TMI is a passive microwave sensor, the design of which has largely been based on the Special Sensor Microwave/Imager (SSM/I) which has been operating continuously on-board Defence Meteorological Satellites since 1987 (Kummerow *et al.*, 1998). The sensor is designed to measure absorption, emission and scattering of microwave energy from the earth and atmosphere. The intensity of the radiation is recorded at five different frequencies: 10.7, 19.4, 21.3, 37, 85.5 GHz. The addition of the 10.7 GHz frequency, which is not available on SSM/I, provides a more linear response at the higher rainfall rates observed in the tropics. Furthermore, the reduced
orbit of the TRMM satellite improves ground resolution of the TMI sensor, resulting in a swath width of 878 km. The TMI retrievals are tuned using the observations made by the PR sensor and the measurements made by TMI are then processed using a number of algorithms based around Planck’s radiation law, to generate values of precipitation rate (Braun, 2011).

4.3.3 Visible Infrared Scanner (VIRS)

The VIRS measures radiation in five spectral regions: 0.63µm; 1.6µm; 3.75µm; 10.8µm and 12µm (Kummerow et al., 1998). These spectral ranges correspond to the visible to infrared regions of the electromagnetic spectrum and allow precipitating clouds to be differentiated from non-precipitating clouds and the Earth’s surface. Under clear sky conditions the temperatures recorded will correspond to the surface temperature. When clouds are present the temperature typically corresponds with the cloud tops. Higher cloud top heights, which are characteristic of cumulonimbus-type convective clouds, will record colder temperatures due to their higher altitude and therefore produce high intensities in the shorter wavelengths. Lower altitude clouds and the Earth’s surface will record warmer temperatures due to their reduced altitude and will therefore record higher intensities in the longer wavelengths. In addition to providing information on cloud-top temperatures and structure, VIRS also links the TRMM measurements from TMI and PR with long-running visible and infrared observations recorded from Polar Orbiting Environmental Satellites (POES) and Geostationary Orbiting Environmental Satellites (GOES; Kummerow et al., 1998).

4.3.4 Production of 3B42V6 daily rainfall estimates

The 3B42V6 product is available at 3-hourly and daily temporal resolution. Both are available on 0.25° x 0.25° regular, latitude-longitude grids and have coverage from 50° north to 50° south around the globe. Huffman et al., (2007) provide a detailed
overview of the processing algorithms involved in multi-satellite precipitation analysis
and a schematic illustration of this process is shown in Fig. 4.3. In brief, the product is
generated in four steps:

(1) The precipitation estimates from all the available microwave sensors are
calibrated and combined. This involves converting data from TRMM and other
satellites (SSM/I, Advanced Microwave Scanning Radiometer (AMSR) and the
Advanced Microwave Sounding Unit (AMSU)) to precipitation estimates and
then adjusting these estimates using probability matching of precipitation rate
histograms. These histograms are developed from coincident data. Once all the
estimates have been calibrated, the 0.25° grid is populated with the ‘best’ data
generated across all the overpasses.

(2) The infrared estimates obtained from two satellite sources (the National Climatic
Data Centre (NCDC) GridSat-B1 and the Climate Prediction Centre (CPC)
Merged IR) are calibrated using the microwave precipitation estimates.

(3) In step three, these IR estimates are used to fill any grid cells which have not
been covered by the microwave precipitation estimates, calibrated in step one.

(4) In the final step, the microwave and IR estimates are summed over a calendar
month to generate a monthly multi-satellite product. The monthly data is then
combined with gauge data from GPCC or the Climate Assessment and
Monitoring System (CAMS) to generate a post-real-time, satellite-gauge
monthly product (3B43). The 3-hourly 3B42V6 product is then generated by
scaling the monthly data using a computed field of satellite-gauge/multi-satellite
ratios. The daily rainfall accumulations are then derived from these 3-hourly rain
rates.
4.3.5 Pre-processing of 3B42V6 rainfall data

To analyse rainfall characteristics associated with larger-scale landslides, continuous rainfall data with the same spatial and temporal coverage as the PNG landslide inventory are required. 3B42V6 daily rainfall data (Fig. 4.4(a)) are available from the 1\textsuperscript{st} January, 1998 to the present, providing representative rainfall over 12 years of the landslide inventory. These data were downloaded from the Goddard Earth Sciences Data and Information Services Centre (GES DISC), using their Mirador data archive search interface. Each rainfall field (4383 days) was then clipped to produce a subset of data coincident with the PNG domain (Fig. 4.4(b)). To obtain daily rainfall time series for any grid square in the domain, the centre point of each TRMM grid was used to extract the daily rainfall data (Fig. 4.4(c)). Data was only extracted for TRMM grid squares covering land areas, as these are the only locations where rainfall-triggered landslides will occur. Daily data were then appended together to produce time series (Fig. 4.4(d)).
Fig. 4.4. 3B42V6 pre-processing steps with (a) showing the raw data obtained from GES DISC, (b) the clipped data for the PNG domain, (c) the extraction of daily rainfall to the land-based TRMM grid squares and (d) the development of daily rainfall time series plots for each TRMM grid square. TP = TRMM Point.
4.4 Deriving rainfall-event thresholds for landslide activity in PNG

4.4.1 Background to rainfall threshold analysis

A range of empirically-based rainfall thresholds are commonly derived. These include: (1) intensity-duration (ID) thresholds, (2) thresholds based on the total event rainfall, (3) rainfall event-duration (ED) thresholds and (4) rainfall event-intensity (EI) thresholds (Guzzetti et al., 2007). Typically, these approaches examine the rainfall characteristics in the days preceding a landslide and compare these characteristics against rainfall events where no landslides were recorded. Rainfall thresholds are then defined as the best separators between these two datasets, with ID thresholds being the most commonly used within the research literature (Guzzetti et al., 2007; Frattini et al., 2009). ID, ED and EI thresholds require rainfall to be accurately reconstructed over varying durations. In many conventional approaches only one combination of rainfall intensity-duration or accumulation-duration is considered critical to the initiation of a landslide, resulting in unique rainfall events defined by a specific magnitude and duration, for each landslide. It is therefore critical to be able to accurately and robustly identify the start and end date of the critical rainfall period which resulted in landslide activation. Despite the importance of this, the approaches used to identify and classify rainfall events are often very subjective, with many authors choosing not to specify how rainfall events were categorised (Berti et al., 2012).

Rainfall intensity is the most widely used rainfall parameter for landslide threshold analysis because ID thresholds are frequently applied to shallow landslides or debris flows, which have been more extensively researched for the purposes of landslide early warning system development (Guzzetti et al., 2007). The typical method of deriving ID thresholds is through the application of a power law equation in the form of:

\[ I = \alpha D^\theta \]
where $I$ is the rainfall intensity, $D$ is the duration and coefficient $\alpha$ and exponent $\beta$ are empirically derived parameters defining the location of the critical rainfall intensity within the ID plane (Staley et al., 2011). Rainfall durations examined in the literature tend to extend from 1 hour up to 100 hours (Guzzetti et al., 2007). For larger, complex failures, such as those recorded in the PNG inventory, short rainfall durations are unlikely to generate the critical rainfall required for movement. Therefore, this analysis will focus on the development of ED and ID thresholds for rainfall event durations up to 3 months.

Conventionally ID thresholds are typically deterministic and are drawn as straight lines across a log-log space, representing the rainfall intensity and rainfall duration required to change the state of the system and result in landslides. However, the move to develop probabilistic rainfall thresholds is well established. For empirically-based models the techniques include: (1) logistic regression to define ID thresholds (Frattini et al., 2009; Glade et al., 2000), (2) using control datasets to estimate landslide probability after the ID threshold has been exceeded (Jaiswal and Van Westen, 2009) and (3) Bayesian statistical approaches (Berti et al., 2012; Guzzetti et al., 2007). The Bayesian approach is particularly appealing due to its use of prior and marginal probabilities to accurately obtain conditional probabilities based on all available rainfall data (rainfall which resulted in landslides and rainfall which did not). Using these probabilities allows for a more informative model and is preferable to some of the more subjective methods, which are insensitive to the prior probability (Berti et al., 2012). The Bayesian approach can be applied to develop ED, EI and ID thresholds. In the following sections, therefore, a modified Bayesian methodology is outlined for the development of probabilistic ED and ID thresholds for PNG. Furthermore, a detailed examination of the classification of a landslide-triggering rainfall events is provided.
4.4.2 Terminology

Before proceeding into a detailed description of the analysis methodology, an outline of the terminology used in the following sections is provided for clarity.

1) *Landslide-triggering event (LTE)* – these are meteorological, hydrological or geological events or hazards which have led to landslides. In the PNG landslide inventory, landslide-triggering events include earthquakes, floods, storms or high rainfall accumulations and tropical cyclones. These natural hazards can alter the environment leading to conditions which are favourable for landslides to occur. Each triggering event can instigate more than one landslide and affect more than one community, and therefore a single landslide-triggering event can represent a cluster of one or more landslides.

2) *Landslide-triggering event episode* – this is the duration of the identified landslide-triggering event, as determined by the supplementary metadata used to collate the PNG landslide inventory. This represents the total duration of a flood event or the time when a tropical cyclone is active and resulted in landslides. The landslide-triggering event episode may be shorter or longer than the critical rainfall duration which led to landslides.

3) *Critical rainfall start date* – the start of the critical rainfall event which led to the activation of landslides. This date has been determined in a number of different ways in the research literature and is considered the greatest source of uncertainty when tying to derive accurate reconstructions of rainfall associated with landslide events (Berti et al., 2012).

4) *Critical rainfall end date (CRED)* – the date when landslides were initiated. This can coincide with the date or end date of the landslide-triggering event episode or can occur within the period of the landslide-triggering event episode.
(5) **Critical rainfall duration** – the duration over which rainfall is contributing to the eventual landslide initiation. This period is typically represented by a sharp increase in rainfall intensity or a prolonged period of persistent rainfall, with the end of the critical rainfall duration being defined by the occurrence of a slope movement (the critical rainfall end date). The critical rainfall duration is equal to the number of days between the critical rainfall start date and the critical rainfall end date.

(6) **Rainfall event** – rainfall characterised by variables such as accumulation, intensity and/or duration. A rainfall event can either be associated with a landslide or can occur independently of any recorded landslides. For rainfall events resulting in landslides the term “*triggering rainfall event*” will be used for distinction.

### 4.4.3 Identifying triggering rainfall events

For all empirically-based landslide models, the first requirement is to review the rainfall characteristics associated with historical landslide events. Ideally, landslide-triggering rainfall events would be well defined and clearly associated with an individual landslide or a cluster of landslides. Unfortunately, this is rarely the case. In order to identify the specific landslide-triggering rainfall event associated with a landslide or cluster of landslides, criteria for the start and end of the rainfall event need to be determined. Once the start and end date are defined the duration of the event can be established and the rainfall associated with initiating the landslide can be accurately reconstructed.

#### 4.4.3.1 Locating representative rainfall data for landslide-triggering events

Of the 83 landslide-triggering events recorded between 1970 and 2009, 39 were recorded between 1998 and 2009, coinciding with the rainfall data available from 3B42V6. Of these, 7 were identified to be earthquake-induced resulting in 32 landslide-triggering events being available for this analysis (Table 4.1). To identify triggering
rainfall events, representative daily rainfall was extracted from the 3B42V6 preprocessed data (Fig. 4.4) for all grid squares in which landslides were observed. By overlying the landslide events onto the TRMM grid, representative grid squares were identified as the single 0.25° x 0.25° pixel within which landslide-triggering events were located (Fig. 4.5). In 9 cases (Table 4.1) triggering events affected multiple TRMM grid squares. In such instances, daily rainfall across all the affected grid squares was extracted (Fig. 4.5; Table 4.1). This allowed the rainfall variability, both spatially and temporally within a single triggering event, to be observed. This is a preferable method over calculating the mean across the grid squares, as it allows key characteristics such as peak rainfall intensities and the number of non-rain days to be identified across all landslide affected areas.

![Fig. 4.5. Identifying the representative TRMM grid squares for the production of representative daily rainfall time series.](image-url)
To generate a time series for each landslide-triggering event, daily rainfall data were extracted for 100 consecutive days preceding the end date of each landslide-triggering event (Table 4.1). The decision to use 100 consecutive days was taken based on the fact that the landslide-triggering events recorded tend to be biased towards larger-scale landslides, which are frequently associated with complex rainfall patterns observed over durations of 90 days or more (Zêzere et al., 2005; Fuhrmann et al., 2008;
Chowdhury and Flentje, 2002). Therefore, extracting 100 days of data should capture the rainfall characteristics across most of the major landslide types which are recorded in the landslide inventory. Furthermore, there remains uncertainty associated with the exact time of landslide initiation, within the wider triggering event episodes. Therefore, by extending the time series by an additional 10 days, some lee-way is provided so that the critical rainfall end date can be accurately determined. The extracted time series are plotted and labelled based on the landslide-triggering event it is associated with (indexed between 1 and 32; Fig. 4.6). For those events which occurred across multiple TRMM grid squares (9 events) a further index is used to distinguish between the plots (e.g. LTE2_1 = landslide-triggering event (LTE) 2, representative TRMM point 1). 52 time series plots were produced representing the 32 landslide-triggering events which occurred between 1998 and 2009. Each plot represents a unique rainfall pattern which led to recorded landslides within a TRMM grid square (Fig. 4.6). Therefore, all further analysis uses these 52 rainfall time series to identify critical rainfall characteristics for the development of rainfall thresholds.

Fig. 4.6. Example time series plots showing daily rainfall accumulation in the 100 days preceding the landslide-triggering event end dates shown in Table 4.1
4.4.3.2 Determining critical rainfall durations

The 100 day time series represent the daily rainfall leading up to the landslide-triggering event end date. However, for triggering events with durations greater than a single day, the actual time of landslide initiation, within the triggering event episodes, remains unknown. Therefore, the critical rainfall end date has not been robustly identified for these events. Furthermore, the critical rainfall start date is also unknown and this prevents accurate reconstructs of the rainfall associated with the landslides. The following sections discuss the issues and methods used to determine first, the critical rainfall end date and second, the critical rainfall start date.

4.4.3.2.1 Determining critical rainfall end dates

Identifying the critical rainfall end date is particularly problematic for larger-scale landslides because instability is regularly caused by long-term rainfall interacting with natural denudational processes. Furthermore, for prolonged triggering events, such as floods, the date of landslide initiation is rarely recorded. To address these issues Frattini et al. (2009) use the general assumption that landslide activation, particularly for debris flows, is likely to correspond to the day when maximum rainfall intensities over the period are observed (normally associated with a convective storm in the case of shallow landslides). Although this is a rather simplistic assumption and not necessarily the case for all types of mass movement, the approach appeared feasible for the PNG landslides because the likely time of initiation had already been constrained between the dates of the landslide-triggering event episode (Table 4.1; Table 4.2). For example, a flood event in New Ireland during 2003 (LTE15) lasted for 10 days, ending on the 10/08/2003. Having identified that the flood was the trigger for the recorded landslides, it was likely that their initiation occurred between 01/08/2003 and the 10/08/2003. Therefore rainfall during the period was examined to determine the likely initiation date.
<table>
<thead>
<tr>
<th>Label</th>
<th>Landslide Trigger Event (LTE) No.</th>
<th>Representative TRMM Pixel Number</th>
<th>LTE episode length (Days)</th>
<th>Original LTE End Date (dd/mm/yy)</th>
<th>Revised CRED (dd/mm/yy)</th>
<th>Max. daily rainfall during LTE episode (mm/day)</th>
</tr>
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<tr>
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<td>2</td>
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<td>01/02/2007</td>
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<td>24.43</td>
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<td>23.68</td>
</tr>
</tbody>
</table>

**Table 4.2.** Critical rainfall end dates (CRED; revised entries shown in grey) for landslide trigger events lasting 2 or more days.
Adopting the method proposed by Frattini et al., (2009) meant identifying all landslide-triggering events lasting 2 or more days (14 triggering events; 33 time series) and isolating the daily rainfall accumulations over the triggering event episode in each case. The maximum daily rainfall within this period was then identified (Fig. 4.7) and this date became the critical rainfall end date for the time series (Table 4.2). In instances where the triggering event lasted 2 or more days and affected more than one TRMM pixel, the maximum daily rainfall during the triggering event episode was identified for each unique time series, and the critical rainfall end date revised in each case (Table 4.2). For all events where the landslide-triggering event episode corresponds to a single day, no review of maximum daily rainfall was conducted and the single landslide-triggering event date shown in Table 4.1 is assumed to correspond to the critical rainfall end date.

Out of the 33 time series examined, 13 were found to have their maximum daily rainfall on the original landslide-triggering end date and therefore, there was no requirement to alter the time series end dates for these cases (Table 4.2). For the remaining 20 time series, new critical rainfall end dates were identified (Table 4.2). For each of these entries, the 100 day time series was temporally shifted so that the last day of the series coincided with the new critical rainfall end date (e.g. the date, within the landslide-triggering event duration, which saw the highest rainfall accumulations). Following this, a new set of time series were produced representing 90 days of consecutive daily rainfall preceding the newly identified critical rainfall end date. This was completed for all 52 time series, following the earlier suggestion that 90 days represents the maximum duration over which rainfall events are likely to result in landslides (Zêzere et al., 2005; Fuhrmann et al., 2008; Chowdhury and Flentje, 2002).
Fig. 4.7. Plots illustrating the method used to define the critical rainfall end date for landslide-triggering events lasting 2 or more days. Red, dotted lines illustrate the start and end of the landslide-triggering event episode (9 days in this case). MDR = maximum daily rainfall; CRED = critical rainfall end date.

4.4.3.2.2 Determining the critical rainfall start dates

In order to accurately reproduce the critical rainfall up to the point of landslide initiation, criteria to identify the start of a critical rainfall event needs to be established. A number of techniques have been used for this purpose, including: (1) the use of author or expert judgement (Aleotti, 2004; Berti et al., 2012), (2) periods of rainfall quiescence, defined either by a certain period without rainfall or a period over which limited rainfall occurred (Larsen and Simon, 1993; Brunetti et al., 2010) and (3) the use of multiple time frames (Frattini et al., 2009). The technique’s efficacy to identify
rainfall episodes both for triggering and non-triggering rainfall events is dependent on the types of landslides being examined and the rainfall regimes which affect the region. It is essential that the same objective criteria are used to identify triggering and non-triggering rainfall events.

Cumulative rainfall curves offer an easy way to identify peak accumulations or prolonged periods of rainfall quiescence within a time series. Therefore the 52, 90-day rainfall time series were converted into cumulative rainfall curves (Fig. 4.8). Visual inspection of the curves was then conducted to identify: (1) different types of rainfall patterns which lead to landslides in PNG and (2) changes in the profile (steps, plateaus) of the curves which could be used to truncate the time series into distinct rainfall events. Based on the methods adopted by Aleotti (2004), Larsen and Simon (1993) and Brunetti et al. (2010), each cumulative time series was examined to identify occasions where sharp rises in daily rainfall and/or changes in the slope angle occurred. These are shown with grey vertical lines in Fig. 4.8, and represent potential critical rainfall start dates for each landslide event. This was based purely on the visual examination of the curves and independent judgement. The different possible critical rainfall durations are shown by horizontal, double-headed arrows in Fig 4.8, extending from each of the potential critical rainfall start dates to the critical rainfall end date (90th day of the time series). Durations of shorter than a few days prior to the critical rainfall end date could not be illustrated with horizontal arrows, but grey, vertical dotted-lines are shown to indicate potential start dates close to the end of the time series.

The curves show that numerous, different critical rainfall durations could be determined using this ‘break-in-slope’ method. 42 out of the 52 cumulative rainfall curves showed profiles where more than 1 critical rainfall start date could be identified. Although each cumulative rainfall curve is unique, two broad types of rainfall pattern
were determined from the plots. The first type includes accumulation curves with stepped rainfall profiles (LTE16; Fig.4.8). Identifying critical rainfall start dates is potentially easier for these curves because changes in rainfall intensity are very obvious. LTE15, LTE16, LTE18, LTE23 and LTE24 are all examples of this stepped profile. Typically this type of pattern represents the occurrence of short duration, high intensity rainfall events interspersed with periods of no rainfall (horizontally, flat profile) or low rainfall accumulations (Fig. 4.8). Although, changes in rainfall can be identified more easily, these profiles regularly show one or more steps, indicating that one or more high intensity rainfall events occur, intermittently throughout the time series. Given that the primary goal is to identify the critical rainfall associated with landslide initiation, those high intensity events which occur closest to the end of the time series would typically be considered the most relevant. However, careful consideration of the magnitude of rainfall intensity changes and the number of high magnitude changes throughout the time series needs to be given, as these are all potentially relevant in affecting when/if landslides are activated, particularly for larger-scale landslides. Thus, it should not be broadly assumed that the high intensity event closest to the end of the time series, is the rainfall event responsible for the recorded landslides.

The second type of cumulative rainfall curve is shown as an almost exactly diagonal increase in rainfall across the plot. LTE10, LTE17, LTE21_1 and LTE27 are examples of this type of curve (Fig. 4.8). It is particularly problematic in these instances, to identify distinct rainfall events because daily rainfall accumulations remain steady and continuous throughout the time series. Without distinct high intensity rainfall or periods of prolonged rainfall quiescence, used in research by Larsen and Simon (1993) and Brunetti et al. (2010), the time series cannot be truncated. Therefore, the whole sequence must be assumed to be relevant to the recorded landslides.
Fig. 4.8. Cumulative rainfall curves for each landslide-triggering event and representative TRMM point. The x-axis represents each day within the 90 day sequence. The 90th day represents the critical rainfall end date while vertical, grey dotted lines represent possible critical rainfall start dates. The black arrows represent that possible critical rainfall durations which could be associated with each landslide-triggering event.
Fig. 4.8. Continued
Fig. 4.8. Continued
Any of the potential critical rainfall start dates (grey dotted lines; Fig. 4.8) identified within the cumulative time series plots could be correct and therefore, any of the critical rainfall durations could have initiated the observed landslides. In only 10 of the 52 time series, were single critical rainfall start dates identified. Four of the profiles (LTE10, LTE17, LTE21_1 and LTE31_2; Fig. 4.8) were almost exactly diagonal across the plot area and therefore the start date of the critical rainfall event is considered to be day 1, resulting in a critical rainfall duration equal to 90 days. Another four cumulative rainfall curves (LTE18_1, LTE18_2, LTE18_3 and LTE18_4; Fig. 4.8) have large increases in rainfall intensity towards the end of the time series, associated with the landfall of tropical cyclone Guba. The remaining 2 curves (LTE13 and LTE28) had only one identifiable, sharp increase in rainfall during their time series. For LTE13 this increase occurred on day 49, when a daily rainfall total of ~75 mm was recorded. For LTE28 the increase occurred on day 24 when a daily rainfall total of ~110 mm was recorded (Fig.4.8).

For all cumulative rainfall time series where more than one potential critical rainfall start date was identified, determining which start dates provides the best reconstruction of rainfall for a recorded landslide, is not straightforward. This is because unless the change in rainfall intensity is several orders of magnitude larger than any other increase in the time series, as in the case of Tropical Cyclone Guba (LTE18_1, LTE18_2, LTE18_3 and LTE18_4; Fig. 4.8), identifying which of the possible critical rainfall durations is critical cannot be achieved by visual interpretation alone. Identifying quantifiable rainfall criteria that can be used to systematically truncate a time series into discrete rainfall events is one approach used in the research literature. Berti et al. (2012), for example, use an algorithm which scans the time series, identifying new rainfall events when precipitation accumulated over 3 days exceeds 5
Probabilistic approaches for assessing landslide-triggering event rainfall

mm. These thresholds are applicable to the individual area of study; in this case the Emilia-Romagna region of Italy. This region is influenced by a mild Mediterranean climate with distinct cold and dry seasons (Berti et al., 2012), opposed to the wetter and drier seasons experienced in PNG. This distinction results in different storm types, driven by different meteorological processes. For example, during the north-westerly monsoon, large swathes of PNG are affected by high accumulation and persistent rainfall events. During the drier season there is greater variability, from convective storms which are typically isolated and occur over short durations to longer duration rainfall (5 days or more) brought about by meridional troughs. The broad range of rainfall patterns lead to different dynamic processes prior to resultant landslides. Therefore, the approach used by Berti et al. (2012) is more suitable for landslide databases where one type of mass movement, such as debris flows, are being analysed or where landslide events can be linked to extreme rainfall events. Neither is the case for the PNG datasets.

The variability illustrated in the cumulative rainfall curves, the known differences in the climatological regimes which affect PNG and the diversity of landslides types being analysed, suggests that identifying a single objective set of rainfall variables to truncate the time series adequately, will not be robust. The visual analysis of the cumulative rainfall curves only yielded 10 (of 52) time series where a single, clearly identifiable, critical rainfall start date and duration could be determined. The remaining 42 time series exhibited multiple critical rainfall durations, all of which could be considered important to trigger landslides. This supports the assumption made by Frattini et al. (2009) that the exact combination of rainfall variables actually critical for each failure is generally unknown. Therefore, the ‘multiple time frames’ method
Probabilistic approaches for assessing landslide-triggering event rainfall

(Frattini et al., 2009; Zêzere et al., 2005; Fuhrmann et al., 2008) was considered, to establish relationships between triggering and non-triggering rainfall events.

### 4.4.4 Generating rainfall events using the ‘multiple time frames’ method

The ‘multiple time frames’ method aims to truncate a rainfall time series into discreet rainfall events based on a number of different rainfall durations. Precipitation variables such as accumulation and/or mean intensity are then calculated over the selected duration to define a rainfall event. The number of rainfall durations and the length of the durations have been selected based on the types of landslides which are known to populate the PNG landslide inventory and the meteorological regimes which drive rainfall in the region. Total rainfall accumulations and mean rainfall intensities were calculated for 5, 10, 15, 30, 45, 60, 75 and 90 day durations preceding the critical rainfall end dates. This was completed for all 52 rainfall time series. The processing method involved calculating the accumulated rainfall over the specified duration leading up to the critical rainfall end date. For example for LTE1, the critical rainfall end date is 01/04/2002, therefore the 5 day rainfall accumulation equates to the amount of rain which fell between 28/03/2002 (inclusive) up until 01/04/2002 (inclusive). The 5 day, mean daily rainfall intensity for LTE 1 is calculated over the same 5 day period.

All landslide-triggering rainfall events, for the different durations and time series, were calculated based on the pre-extracted daily rainfall data used throughout the preceding sections.

For comparison accumulations and mean intensities need to be calculated for rainfall events where no landslides were recorded. To conform to the same objective methodology, moving rainfall accumulations and moving mean intensities were calculated for each duration (5, 10, 15, 30, 45, 60, 75 and 90 days) using the 12 years of TRMM data available. As there are no critical rainfall end dates for rainfall events
which have not resulted in recorded landslides, moving sum and moving mean values are calculated over the complete 12 year record, for each discreet rainfall-duration. For the 5 day rainfall-duration, for example, rainfall accumulations are calculated by summing data for days 1 to 5, then for days 2 to 6, then for days 3 to 7, and so on using equation 4.1:

\[
Acc(sum) = (Acc(t) + Acc(t + 1) + \ldots + Acc(t + n))
\]  

\[
Int(mean) = \frac{Acc(t) + Acc(t + 1) + \ldots + Acc(t + n)}{n}
\]

where \(Acc(sum)\) is the total rainfall accumulated over \(n\) number of days of daily rainfall \(Acc(t)\). This equation is modified to equation 4.2:

Conventionally ID and ED thresholds are defined by reviewing linear relationships across a log-log plot. The rainfall accumulation totals, for each rainfall duration and landslide-triggering time series are compared against the rainfall accumulation totals obtained for all non-landslide-triggering rainfall events (Fig. 4.9(a)). The same categorization is made for the mean rainfall intensity values (Fig. 4.9(b)).
Fig. 4.9. Log duration-log accumulation (top panel) and log duration-log intensity (bottom panel) plots for landslide-triggering rainfall events and non-landslide-triggering rainfall events. Lower (blue) and upper (red) envelope lines are used as approximate separators of the data across the different durations.
An upper envelope representing the lower limit of rainfall accumulations above which landslides occur has been drawn for the longer duration rainfall events (30 days or more), while a lower envelope, representing the lower limit of rainfall accumulations above which landslides occur has also been drawn for the shorter duration rainfall events (5 to 15 days; Fig. 4.9(a); Fig. 4.9(b)). Of the two plots, linear trends can be identified with greater clarity in the log-accumulation – log-duration plot (Fig. 4.9(a)) than in the log-intensity – log-duration plot (Fig. 4.9(b)). This made defining upper and lower limits easier for the accumulation-based plot than for the intensity-based plot. For the accumulation-based plot the separation between long duration, landslide-triggering rainfall events and short duration, landslide-triggering rainfall events was clearly visible. However, the very low mean intensity rainfall events, particularly over shorter durations, meant that identifying lower limits for the intensity-based plot was more difficult. Although upper and lower envelopes were identified for the two log-log plots, these cannot be used as thresholds for early warning systems. This is because rainfall events across the different rainfall-durations are not distinct from one another. For example, the lowest triggering rainfall event seen in Fig. 4.9 (a) for durations of 5 and 10 days, are both associated with LTE13. This results in triggering and non-triggering rainfall events overlapping within the log-log space (Frattini et al., 2009). In this regard, the envelope limits drawn across Fig. 4.9(a) and Fig. 4.9(b) represent tentative representations of linear limits within the data.

4.4.5 **Defining probabilistic rainfall thresholds: the Bayesian approach**

One of the greatest limitations of conventional ID and ED approaches is that they are generally insensitive to the rainfall climatology of the region. In order to translate Fig. 4.9(a) and Fig. 4.9(b) into useful information, triggering rainfall events need to be separated from non-triggering rainfall events. Although this determination cannot be
Probabilistic approaches for assessing landslide-triggering event rainfall made from Fig. 4.9(a) and Fig. 4.9(b), using Bayesian statistics it is possible to assess the probability that a rainfall event of specific magnitude and duration can initiate landslides. The Bayesian technique estimates the probability of one event given the occurrence of another event. In its simplest form, the equation is:

\[
P(A|B) = \frac{(P(B|A) \cdot P(A))}{P(B)}
\]

EQ 4.3

where:

- \( P(B|A) \) is the conditional probability of \( B \) (rainfall event of certain magnitude) given \( A \) (landslides), also referred to as the likelihood,
- \( P(A) \) is the prior probability of \( A \) (landslides) and represents our best understanding of the probability before any additional information is provided,
- \( P(B) \) is referred to as the marginal probability and represents the probability of observing \( B \) (rainfall event of certain magnitude) regardless of whether \( A \) (landslides) occurs or not,
- \( P(A|B) \) is the conditional probability of \( A \) (landslides) given \( B \) (rainfall event of certain magnitude). This is also called the Posterior probability.

In the PNG analysis, the aim is to estimate the probability of landslides given different rainfall accumulation-duration or rainfall intensity-duration combinations. For this, the equation needs to be modified to extend the analysis to what Berti et al., (2012) refer to as the two-dimensional Bayesian approach. Equation 4.4 shows how Equation 4.3 is extended to include two variables \( B \) and \( C \):

\[
P(A|B, C) = \frac{(P(B, C|A) \cdot P(A))}{P(B, C)}
\]

EQ 4.4

If \( B \equiv I \), where \( I \) is the rainfall intensity and \( C \equiv D \), where \( D \) is the rainfall duration, then Equation 4.4 calculates the probability of a landslide occurring given a rainfall
event of specific intensity and duration. Alternatively, if $B \equiv E$, where $E$, is the rainfall accumulation then the probability of a landslide occurring given a rainfall event of specific rainfall accumulation and duration is calculated.

Bayesian probabilities are normally calculated based on relative frequencies and can be approximated using Equations 4.5(a), 4.5(b) and 4.5(c):

$$P(A) \approx \frac{N_A}{N_R} \quad \text{EQ 4.5 (a)}$$

$$P(B, C) \approx \frac{N_{(B,C)}}{N_R} \quad \text{EQ 4.5 (b)}$$

$$P(B, C | A) \approx \frac{N_{(B,C | A)}}{N_A} \quad \text{EQ 4.5 (c)}$$

$N_R$ represents the total number of rainfall events recorded during a given time reference and $N_A$ represents the total number of landslides recorded over the same reference period. The notation $N_{(B,C)}$ is then the number of rainfall events of specific magnitude and duration, while $N_{(B,C | A)}$ is the number of rainfall events of specific magnitude and duration which resulted in landslides.

### 4.4.5.1 Modifications to the Bayesian approach

The Bayesian method outlined above, and adopted here, is similar to that used by Berti et al. (2012) to examine landslides in the Emilia-Romagna region of Italy. However, there are number of important differences between the two methods when applied to PNG. These differences affect how the data is processed and how probabilities are ultimately produced. The first difference involves the integration of the ‘multiple time frames’ method. This integration is completed by altering the way that relative frequencies are calculated. In the approach by Berti et al. (2012), each rainfall event, regardless of whether it was associated with a landslide or not, was unique across all the durations examined and therefore the total population of rainfall events resulting
4| Probabilistic approaches for assessing landslide-triggering event rainfall

in landslides was the sum of all events over all durations. This was also true for the total population of rainfall events which did not result in landslides. This is not the case for the PNG data shown in Fig 4.9(a) and Fig 4.9(b). Here, data across the different durations overlap because of the assumption that all combinations (accumulation-duration or intensity-duration) could be critical to the initiated landslides. In order to integrate the Bayesian approach with the results of the ‘multiple time frames’ method, the relative frequencies and the subsequent Bayesian calculations are applied to each set of rainfall duration data separately (5, 10, 15, 30, 45, 60, 75 and 90 days). By applying the calculations in this way, the definitions for notation $N_R$ and $N_A$ are modified to:

$N_R$ – is the total number of rainfall events recorded during a given time reference, for a specific duration,

$N_A$ – is the total number of landslides recorded over the same reference period and duration.

Values for $N_R$ and $N_A$ are shown in Table 4.3 and are consistent for analysis of the accumulation-duration combination and the intensity-duration combination. Variables $N_{(B|C)}$ and $N_{(B,C|A)}$ are defined and calculated as per the original method for both variable combinations.

<table>
<thead>
<tr>
<th>Rainfall Event Duration (Days)</th>
<th>Total number of rainfall events ($N_R$)</th>
<th>Total number of landslide-trIGGERING rainfall events ($N_A$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>4327</td>
<td>52</td>
</tr>
<tr>
<td>10</td>
<td>4322</td>
<td>52</td>
</tr>
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<td>15</td>
<td>4317</td>
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<td>52</td>
</tr>
<tr>
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<td>4257</td>
<td>52</td>
</tr>
<tr>
<td>90</td>
<td>4242</td>
<td>52</td>
</tr>
</tbody>
</table>

Table 4.3. Total number of rainfall events and landslide-triggering rainfall events for each rainfall duration examined.
The second difference addresses the use of multiple TRMM grid squares to obtain representative rainfall data. This is an issue which affects how frequencies of non-landslide-triggering rainfall events are calculated. Forty representative TRMM pixels were identified coinciding with the locations of recorded landslides (section 4.4.3.1). In Section 4.4.4, non-landslide-triggering rainfall events were produced for each grid square and rainfall duration. To create relative frequencies of rainfall events of specific magnitudes, rainfall from all the representative pixels needed to be included so that the different climates across PNG were captured. However, the major drawback of using each of the representative TRMM pixels is that the number of landslide events which fall within each pixel can be very small, leading to inaccurate estimates of landslide probability (Berti et al., 2012). Therefore, to avoid data splitting but still account for the diversity of the different climates across the TRMM pixels, magnitude–frequency distributions were produced using 50 mm rainfall increments (bins) for the accumulation-duration analysis and 5 mm/day increments for the intensity-duration analysis. Frequency distributions were produced for each representative TRMM pixel separately and then the mean frequency within each magnitude increment was calculated. Frequency-magnitude distributions were generated in this way for each of the durations being examined (5, 10, 15, 30, 45, 60, 75 and 90 days) and for both the accumulation-duration and intensity-duration combinations.

4.4.5.2 Application of the modified Bayesian approach to PNG data

The modified Bayesian approach was performed on the accumulation-duration and the intensity-duration combinations separately. Given that the linear relationship within the log-log space appeared stronger for the accumulation-duration combination (Fig. 4.9(a)), this analysis was completed first. Graphs of the probability distributions obtained for each rainfall accumulation-duration are shown in Fig. 4.10.
Probabilistic approaches for assessing landslide-triggering event rainfall
4 | Probabilistic approaches for assessing landslide-triggering event rainfall
Fig. 4.10. (Pages 145 and 146). Bayesian analysis for rainfall event accumulations and durations; with the left hand charts showing the prior ($P(A)$), marginal ($P(B, C)$) and conditional ($P(B, C|A)$) probabilities and the right hand charts showing the posterior probabilities ($P(A|B, C)$), with the prior probability added for comparison.

The plots on the left compare the magnitude-frequency distributions of triggering rainfall events against non-triggering rainfall events, for the 12 years examined. On the right are the computed posterior probabilities. In both sets of plots, the prior probability is provided for comparison. The difference between $P(A|B, C)$ and $P(A)$ illustrate how effective the two variables (B and C) are at improving our prior knowledge. If the variables were of no relevance then the two probability distributions, $P(B, C)$ and $P(B, C|A)$ would be similar to each other and the posterior probability and prior probability would be roughly equal. This is not the case for the distributions observed in Fig.4.10, where there are marked differences between $P(B, C)$ and $P(B, C|A)$. In addition, $P(A|B, C)$ is well above $P(A)$, particularly for higher magnitude rainfall events. As might be expected, there is a general trend where increases in the magnitude of the rainfall events result in increases in the probability of landslides. Peak probabilities across the durations are observed for rainfall events with durations of 10 days and accumulations between 350 and 400 mm ($> 0.65$). Such a high probability needs to be used cautiously however, because probabilities which are obtained for such extreme events are likely to lack significance as sample sizes within the bins at this end of the distribution are frequently small. A second, small peak of landslide probabilities is observed for rainfall events with durations of 75 days and accumulations $> 1200$ mm ($> 0.2$), while probabilities are relatively low across all magnitudes of rainfall accumulated over 30, 45 and 60 days. This could suggest that two types of rainfall event are more likely to lead
Probabilistic approaches for assessing landslide-triggering event rainfall to landslides: the first being high accumulation, shorter duration (< 15 days) rainfall events and the second being long duration (> 75 days), high accumulation rainfall events.

Although these plots allow easy comparisons between the different probability distributions within a single rainfall-duration period to be made, it is not easy to compare the probabilities across the durations. Furthermore, identifying thresholds in a similar style to the ID and ED methods is not intuitive from these plots. Therefore, the resultant posterior probabilities have been interpolated onto a 2D plot comparing the probabilities across the log-accumulation, log-duration space (Fig. 4.1). The very high probability value obtained for 10-day rainfall in excess of 350 mm has been removed due to the distortion it introduces in the bilinear interpolation. Given that there is likely to be very low significance for this result, this was deemed appropriate so that the best proxy of the “true” landslide probability could be obtained based on the PNG data available.

High accumulation (logA > 2.39; 250 mm), short duration rainfall events show the highest probabilities, with values greater than 0.2 observed for 5-day (logD = ~0.7) and 10-day (logD = 1.0) durations. The secondary peak, observed at 75-day durations from Fig. 4.10, is also evident in Fig 4.11. It is more difficult to obtain higher probabilities for long duration rainfall events, because extreme rainfall rarely lasts over such prolonged periods and landslides are frequently initiated by the gradual effects of increasing pore water pressure. Therefore, relationships between rainfall and landslide occurrence are more complex at these longer durations. However, the band of probabilities narrows after about 40 days (logD = 1.6), to a more confined envelope of activity, compared with the wide band of probabilities observed across shorter durations. This is likely to be a product of the wider distributions (i.e. events seen across
a greater number of bin ranges) for both non-triggering and triggering rainfall events at longer durations (P(B,C) and P(B,C|A); Fig. 4.10), which results in fewer samples per bin and which affects the ratio between the two distributions.

Fig. 4.11. Landslide probabilities as a function of rainfall accumulation and duration, with lines of equal probability illustrated for 0.05 and 0.1 probabilities. Probabilities refer to any one of the 40 TRMM grid squares where landslides have previously been recorded. The original upper envelope from Fig. 4.9(a) is also shown as a reference.

Using the probability contours, it is possible to identify linear relationships, where lines of roughly equal probability can be drawn across the log-log space. This is particularly evident for the shorter-duration events, where isolines of equal probability can be identified for 0.05 and 0.10, respectively (Fig. 4.11). These isolines represent rainfall events with changing magnitude and duration, which result in the same
probabilities of landslide occurrence. In order for this information to be useful for decision-making and early warning, an acceptable probability isoline needs to be identified. This is by no means straightforward as it is relates to the coping capacity of the region and sub-regions of PNG. There are, as in many countries, different areas of PNG which can accept different levels of risk and different degrees of loss. In highly vulnerable areas even very low probabilities could be considered unacceptable if the potential losses result in devastating consequences for the community. The very lowest probabilities coincide quite nicely with the original ‘upper’ linear envelope obtained from visual inspection of the data in the original log-accumulation, log-duration plot (Fig. 4.9(a)). This could be used as an early ‘heads-up’ indicator by forecasters and geotechnical specialists to identify regions which could potentially be at heightened levels of risk in the near future. Above 0.05 there is an abrupt increase in landslide probability and this, it is suggested by Berti et al., (2012), indicates that a radical change in the state of the environment has occurred. Therefore, the additional probability thresholds (0.05 and 0.1) could be used for issuing warnings to the public or to hazard-related responders so that people are informed and can respond appropriately to mitigate potential losses before the hazard occurs. Obviously, these plots do not provide any indication of where within a single TRMM grid square a landslide might occur and therefore no engineering-type mitigation, above and beyond existing precautions, could be administered. However, providing awareness of potential increases in the landslide hazard before time could help to induce behavioural changes in a population which is generally more attuned to their environment, so as to limit fatalities and injuries.

The modified Bayesian approach was also applied to the intensity-duration combination. Generally the distributions, \(P(B,C)\) and \(P(B,C|A)\) show greater similarities to each other and this resulted in smaller differences between \(P(A|B,C)\) and \(P(A)\). This
indicates that mean intensity is poorer at informing the posterior probability, than the accumulation-duration combination. The highest probabilities were again found for the shorter-duration rainfall events. This conforms to the findings of conventional research, where the link between short-duration, high-intensity rainfall and landslide occurrence is frequently illustrated (Staley et al., 2011; Guzzetti et al., 2008). As with the accumulation-duration, the highest probabilities (> 0.6) were obtained for 10-day rainfall events with mean intensities greater than 35 mm/day. In contrast to the accumulation-duration, a secondary peak (> 0.6) is observed for 45-day rainfall events with mean intensities greater than 25 mm/day. The same limitations identified in the earlier analysis apply here and therefore both of these very high accumulations have been removed for the production of the 2D plot (Fig. 4.12).

Similar to the accumulation-duration analysis, landslide probabilities are greatest where mean intensities are high. In contrast to Fig. 4.11, linear trends are harder to identify in this plot. However, it is evident from Fig. 4.12 that high-intensity, shorter-duration (< 10 days) events produce the highest probabilities, with an additional, smaller peak evident at longer durations (> 45 days). Small isolines, representing rainfall events with changing magnitude and duration, which result in the same probabilities of landslide occurrence, can be drawn across the log-log space, although these are only really apparent for shorter-duration events (Fig. 4.12). These isolines should be considered cautiously however, because the uneven distribution of data in this analysis could produce artefacts of the interpolation. Unlike the accumulation-duration analysis, the original ‘upper’ linear envelope obtained from visual inspection of the data in Fig. 4.9(b) does not correspond well with the lower end of the posterior probabilities. This illustrates how the conventional method of ID threshold analysis can provide inaccurate threshold limits.
Fig. 4.12. Landslide probabilities as a function of mean rainfall intensity and duration. Probabilities refer to any one of the 40 TRMM grid squares where landslides have previously been recorded. The original upper envelope from Fig. 4.10(b) is also shown as a reference.

Of the two variable combinations analysed, accumulation-duration offers the best scope for producing useable probabilistic thresholds for landslides in PNG. The different probability thresholds offer the potential to have a staggered warning system, whereby certain responders or the public receive warnings only when certain probability thresholds are reached or exceeded. It should be remembered that the Bayesian approach is used here to define a proxy of the “true” landslide probability, because the landslide inventory for PNG under-represents the true numbers of landslides occurring in the region. Furthermore, the probabilities obtained for both rainfall combinations,
Probabilistic approaches for assessing landslide-triggering event rainfall indicate the landslide probability within any one, single TRMM grid square (~ 625 km²) from the 40 identified in section 4.4.3.1. Although the variation in rainfall across these grid squares has been partially captured by the modified Bayesian approach, it should be noted that there has been no consideration of the spatial variability of event control factors (i.e. geology and slope) which would add information on the likely spatial distribution of possible landslide occurrences within a TRMM grid square. This is addressed in Chapters 5 and 6 of this thesis.

4.5 Discussion

4.5.1 Uncertainties associated with defining triggering rainfall events

Uncertainties are an inherent component of model design. However, within this methodology there are some specific uncertainties which potentially lead to large changes in the probabilistic thresholds identified. The first of these is the method used to define the triggering rainfall events, and more specifically, the critical rainfall end date. Despite, working well for those triggering events which were temporally well defined, such as Tropical Cyclone Guba (LTE18_1, LTE18_2, LTE18_3 and LTE18_4; Fig. 4.7), the general assumption that landslide activation is likely to correspond to the maximum rainfall intensity over the landslide-triggering event episode (Frattini et al., 2009) is very simplistic and tends to be less relevant for larger-scale landslides. Furthermore, the assumption does not account for landslides which occurred sometime after the triggering rainfall event. This is common for deep-seated failures and means that additional, contributory rainfall after the triggering rainfall event has ended, is not captured. In order to determine how much this assumption affected the reconstruction of triggering rainfall, revised and un-revised 90-day accumulations and 5-day accumulations were compared for all time series where the critical rainfall end date was altered from the original landslide-triggering end date (Table 4.2; Table 4.4).
<table>
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<th>Label</th>
<th>Original LTE end date (dd/mm/yy)</th>
<th>Revised CRED (dd/mm/yy)</th>
<th>Difference between revised CRED and original LTE (revised – unrevised accumulations)</th>
<th>Mean daily rainfall over 90 days (mm/day)</th>
<th>Cumulative rainfall profile type (Description)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td></td>
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<td>5 day accum. (mm)</td>
<td>Original 90 days</td>
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Table 4.4. Computed differences between revised and un-revised accumulations over 90 day and 5 day durations, respectively, where negative values indicate that revised values have lower accumulations than those obtained using the original LTE end date and positive values indicate that revised values have high accumulation than those obtained using the original LTE end date. The description of the cumulative rainfall profile is based on visual interpretation of Fig. 4.8 only. Grey, shaded entries are those with large differences (> 40 mm) in rainfall accumulations.
In the majority of cases (65%), differences between the revised and unrevised rainfall accumulations for both the 90-day and 5-day durations are less than 40 mm. Of these cases, there is generally a small reduction in the rainfall accumulation observed over the revised 90-day accumulations (negative difference values), compared with the original 90-day accumulation (using the original landslide-triggering event end date). The revised 5-day accumulations tend to be larger than the unrevised 5-day accumulations (positive difference values). However, given that the relative frequencies produced for the Bayesian calculations are obtained by classifying each rainfall event into bin (increment) ranges of 50 mm for the accumulation-duration frequency distributions and bin ranges of 5 mm/day for the intensity-duration frequency distributions, the small differences observed would not have significantly altered the classification of any of these events.

The remaining 7 time series (35%) have differences between the revised and unrevised rainfall accumulations for both the 90-day and 5-day durations greater than 40 mm. For these events, the revised 5-day rainfall accumulations were dramatically higher (positive difference values) while the majority of 90-day rainfall accumulations were lower (negative difference values). This suggests that the original landslide-triggering event end date under-represented, by a large margin, the “true” rainfall likely to have triggered landslides and that the revisions made provide a better representation of rainfall events at shorter durations. Although there are negative differences for many of the 90-day accumulations, these are either smaller than the magnitude-frequency bin ranges or occur in cumulative rainfall curves with stepped profiles. Stepped profiles suggest that higher-intensity, shorter-duration events are more likely to have initiated the landslides observed. Based on this overview, the method used to determine the critical rainfall end date works well for shorter-duration events, while having a minimal
Probabilistic approaches for assessing landslide-triggering event rainfall

(negative) effect on longer-duration rainfall events. Furthermore, as the mean daily rainfall remains relatively consistent across the 90-day periods for both revised and unrevised time series, the variability within the time series has not been significantly altered by applying this assumption.

4.5.2 Uncertainties associated with defining non-triggering rainfall events

Forty TRMM grid squares coinciding with the locations of landslide activity (section 4.4.3.1) were used to define the non-triggering rainfall events. Rather than use a single grid square to represent all affected regions, the mean frequency per bin range (50 mm for accumulation and 5 mm/day for intensity) was calculated based on all the frequency distribution across the 40 representative grid squares. This allowed the magnitude-frequency distributions across all the grid squares to be incorporated into the analysis, while preventing the need to split the landslide events over the 40 TRMM grid squares. This method results in probabilities which refer to the extent of a single TRMM grid square (~ 625 km²) but which could affect any of the 40 grid squares analysed (approximate areal extent 25,000 km²). Of course, using the mean of the magnitude-frequency distribution prevents any grid squares with markedly different climatologies being captured accurately and results in small rainfall event samples at the extreme tails of the distribution. This can distort the probabilities calculated.

One approach which could improve on the above method, is defining climatologically-similar regions from the 40 grid squares, and defining magnitude-frequency distributions for rainfall events within each sub-region. Based on the literature review (Chapter 2) and the rainfall climatology work completed in Chapter 3, unique climatological domains could be determined from the 40 grid squares. These include: (1) the Papuan Peninsula (15 TRMM grid squares), (2) the Highlands or central cordillera (14 TRMM grid squares) and (3) the northern coastal areas, including the
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Sepik basin and the neighbouring islands (11 TRMM grid squares). This would produce better representations of the rainfall events which affect each sub-region and would ultimately alter the magnitude-frequency distributions used in the Bayesian calculations. The major drawback of this approach is that the total number of landslide-triggering events would need to be split over the different sub-regions. With the current landslide data availability for PNG, this is impractical and would produce inaccurate estimates of landslide probability. However, the advantage of the Bayesian approach is that the methodology can be easily updated as new data becomes available, by shifting the posterior probability, $P(A|B,C)$, into the likelihood, $P(B,C|A)$. Additional future research and more extensive landslide mapping across the region could, therefore, be included into this methodology to improve its robustness.

4.6 Summary and conclusions

A modified Bayesian approach has been used to calculate landslide probabilities associated with changing rainfall accumulation-duration and intensity-duration. These probabilities are based on a catalogue of medium-to-large landslides which occurred in PNG between 1998 and 2009 and daily, satellite-derived precipitation estimates (3B42V6). The results of this analysis should be tempered by the fact that the landslide inventory on which this research is based is incomplete and that the rainfall data used has a relatively coarse resolution. However, the results show clear relationships between rainfall and landslide occurrence and illustrate the successful application of a reproducible and flexible method for the production of probabilistic rainfall thresholds in a region with poor observation data (both landslides and rainfall) and limited data and resource availability.

The modified Bayesian approach proved successful in distinguishing between non-triggering and triggering rainfall events. This was essential because of the use of
the ‘multiple time frames’ method to determine critical rainfall durations (Frattini et al., 2009; Zêzere et al., 2005). Joining these two approaches reduced the subjectivity associated with conventional methods, which typically use generalised rainfall characteristics to obtain critical start and end dates for triggering rainfall events. The method also quantified landslide probabilities related to changing magnitude-duration and intensity-duration rainfall events. The development of linear isolines of equal probability, particularly for the accumulation-duration combination (Fig. 4.11), provides the first insights into how this approach could be used within operational early warning and forecasting systems in PNG. With any such system, choosing the appropriate probability threshold is not straightforward, particularly if the population you are forecasting for has a highly variable vulnerability and/or exposure. The use of multiple probability isolines offers the potential for a staggered warning system, where different probabilities result in different sectors of the response community being notified. Prior to any such integration and use, the model would need extensive testing, calibration and verification to ensure that missed alerts and false alarms were kept to a minimum and that decisions could be effectively made using the probabilities obtained.
5. Reviewing rainfall thresholds in the context of the Tumbi Landslide

This chapter is derived from:

Abstract

On the 24th January 2012, a fatal landslide with an estimated volume of 3 Mm$^3$ hit villagers and infrastructure in the Tagali Valley, in Southern Highlands Province. The associated human casualties and infrastructure destruction give a human as well as a scientific need to review the potential causes for the event. PNG experiences numerous landslides annually, most of which are triggered either by rainfall or seismic activity. Although direct triggers are difficult to distinguish in the case of deep-seated landslides, there are occasions when such events can be seen as the ‘straw which breaks the camel’s back’. Here, short-term rainfall patterns preceding the landslide are reviewed and compared against rainfall events which resulted in landslides between 1998 and 2009 (Chapter 4, section 4.4.3). In addition long-term rainfall, 6 months prior to the landslide, is examined to determine whether changes in interseasonal rainfall could have contributed to the slope movement. As rainfall is not the only potential trigger for this event, seismic activity both temporally and spatially was also reviewed. The results suggest that a seismic trigger is very unlikely to have led to the observed failure at Tumbi Quarry. However, an increase in rainfall over the two weeks preceding the landslide could have played a more significant role in destabilizing the slope. Furthermore, a high intensity rainfall event at the end of October 2011 could also have been influential. In addition to analysing the potential triggering mechanisms, geology, morphometry and anthropogenic activity within the Tagali Valley are also reviewed. Causal factors are particularly important for this event because of the controversy surrounding the landslide and its link to the quarry. Results suggest that geology and geomorphology, as well as the anthropogenic activity in the area could all have served to enhance rather than restrain slope failures.
5.1 Introduction

Between 4 and 5am on January 24th, 2012 a moderate landslide occurred in Southern Highlands Province of PNG. The failure happened in close proximity to an aggregate quarry site on the slopes above the Tagari River (142°47’21.715”E, 5°57’27.71”S), in Komo-Margarima District (ESSO Highlands Limited, 2010; Fig. 5.1). Although the estimated volume of the landslide is moderate by PNG standards, the failure affected the villages of Tumbi and Tumbiago and resulted in 60 fatalities (Wilson, 2012), damage to property, food gardens and led to a key road in the province being blocked. Additionally, the landslide engulfed a large proportion of Tumbi Quarry (Quarry QA1) which was being used to supply aggregate for the development of haulage roads and the Komo Airfield, in support of the Liquefied Natural Gas (LNG) Project. Following a site inspection conducted by the National Disaster Centre (NDC), the trigger for the event was suggested to be heavy rainfall which weakened the limestone formation making up the face of the quarry (Papua New Guinea National Disaster Centre (NDC) Technical Assessment team, 2012). However, the poor coverage of rainfall gauge stations in the region makes this hard to substantiate. Furthermore, photographs of the landslide suggest it was deep-seated. Such movements rarely result from a single rainfall event and the relationship between landslide occurrence and rainfall is often complex in these instances. This, therefore, provides an opportunity to examine a complex landslide using similar approaches and data to that used in Chapter 4. This allows the rainfall patterns observed prior to the Tumbi Landslide to be compared against rainfall patterns associated with historical landslides recorded in the PNG inventory. Furthermore, it provides a means of examining the important role of additional environmental factors (geological structure, geomorphology, and
Reviewing rainfall thresholds in the context of the Tumbi Landslide

anthropogenic activity) play in landslide initiation and how these factors interact with potential triggers to induce landslides.

Fig. 5.1. Map showing the location of the Tumbi Landslide within Southern Highland Province and the dominant geographic features of Papua New Guinea.

As discussed in Chapter 2 and 3, PNG experiences numerous landslides annually, although it has been difficult to fully quantify the hazard due to the lack of systematic reporting and the remoteness of communities which tend to be affected (Blong, 1986). Recorded landslides tend to range from slips and slumps of a few cubic metres of material to failures with estimated volumes of $1.8 \times 10^9 \text{m}^3$ (Kaiapit landslide; Peart, 1991). The most common failure types to occur in PNG were identified by Stead (1990) to be debris slides, avalanches and flows, although translational slides, rotational slumps and mudslides have also been widely documented. The majority of landslides are triggered by rainfall and/or earthquakes, although there a number of cases where mining activity has been linked to large failures (Walker, 2005; Griffiths \textit{et al.}, 2004).
Typically, mining and quarrying affects landslide susceptibility by altering the environment through over-steepening, vegetation clearance or modifications to waterways and drainage, rather than being a direct trigger. However, in instances where blasting or unsafe waste and spoil management are involved, direct relationships can be identified.

Despite being a moderate-sized landslide, the number of fatalities and the link to the aggregate quarry has made the Tumbi Landslide of particular interest. This is especially true because the event occurred in a region where compensation payouts for perceived anthropogenic influences to landslides have increased in recent years (Kuna 1998). In this chapter a brief description of the landslide will be provided, with the main aims being: (1) to review the rainfall accumulations in the Tagali Valley prior to the landslide event and to contextualise the results with the climatology of the region and the rainfall patterns which have resulted in previously recorded landslides, (2) to review the likelihood that seismicity could have played a role in the failure and (3) to provide an overview of the landslide in relation to the land use and activities at the quarry site.

### 5.2 Regional geological setting

PNG has undergone significant tectonic deformation associated with a number of complex collision and orogenic uplift events (Findlay, 2003). The Tumbi Landslide occurred within the Papuan Fold Belt, which formed through the collision of the northeast-migrating Indo-Australian plate and the north-west moving Pacific plate (Fig. 5.1). The Fold Belt, together with the New Guinea Mobile Belt, make up the central mainland cordillera where elevations can exceed 4000 m asl. This region is dominated by rugged terrain, with densely forested slopes and ridge and ravine features (Löffler, 1977). The fold and thrust belt lies between the New Guinea Mobile Belt and the tectonically stable Fly Platform which lies to the south. Compressional deformation
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during the late Miocene-Pliocene has resulted in a series of north-westerly to westerly
trending folds. In the south-western part of the belt, directly north of the Fly Platform,
the folds are predominantly overthrust anticlines which become ‘tightly folded
anticlines with broad synclines’ (Löffler, 1977) moving into the central and north-
eastern Highlands. The deformation and resultant tectonic shearing has led to extensive
faulting throughout the belt, resulting in Cretaceous and Tertiary sedimentary deposits
having dip angles of 30-40° (Hill and Gleadow, 1989).

Limestone is the dominant outcrop rock and has been heavily weathered to form
widespread karst landforms including, arête and pinnacle karst, tower karst, cone karst
and doline karst (James, 2006; Williams, 1972). On the Muller Plateau, limestone is
overlain by the Lai Formation, composed of siltstones and mudstones (James, 2006).
This formation, as well as the Orubadi/Pnyang and the Era Beds observed in the
Strickland-Cecilia area (south of the Muller Plateau), represent a period of post-
Miocene sedimentation associated with the growth of the fold belt. Underlying the Darai
Limestone, and the post-Miocene siliclastic deposits, is the Ieru Formation consisting of
marine mudstone and shale, with siltstone and sandstone interbeds. This formation was
laid down during the Cretaceous, when the northern edge of the Australian Craton was
passive. The formation is considered less competent than the overlying Darai Limestone
and is believed to be the zone from which listric thrust faults extend into the above units
(Craig and Warvakai, 2009). Underlying the Ieru Formation the dominant lithological
units include (from basement to Ieru Formation): (1) the granitic basement of the
Australian craton, (observed as outcrops of Triassic granodiorite and small amounts of
Palaeozoic metamorphic rocks in the Muller and Kubor anticlines); (2) the Late Jurassic
Imburu Formation, laid down during a period of subsidence and flooding at the
collisional margin; and (3) the Toro Sandstone laid down during the Jurassic and early
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Cretaceous. To the south and east of the Muller Plateau, the limestone outcrop gives way to subaerial volcanic deposits produced from Quaternary volcanic centres, such as the Doma Peaks (Davies, 2012).

All outcrop rocks in the north-western area of Southern Highlands Province are extensively denuded through landslide activity and weathering, enhanced by the climate and seismicity of the region. The annual precipitation throughout the fold belt varies significantly but can exceed 8000 mm/year in areas of Western Province (McAlpine et al., 1983). Within Southern Highlands Province this is reduced to between 3000 and 4000 mm/year. Seismically, the fold belt lies within the boundary of seismic zone 3, where ground accelerations are expected to be less than 0.54 g (Anton and Gibson, 2007) and earthquakes of magnitude 6 and above have been recorded in recent history (Ripper and McCue, 1982). In addition to climatic and seismic denudational processes, the region has also experienced increased levels of anthropogenic activity since numerous hydrocarbon accumulations have been discovered. Drilling for both oil and natural gas (Hill et al., 2010) has led to a requirement for conditioning plants, such as The Hides Gas Conditioning Plant (HGCP) and quarries to support infrastructure development. Tumbi Quarry is one such supporting quarry site and has been identified as the location of the Tumbi Landslide.

5.3 Tagali Valley and Tumbi Landslide site

5.3.1 Geology and morphometry

The Tagali Valley, which lies within the wider Tari Basin, is situated close to the western boundary between Southern Highlands Province and Western Province. The Tumbi Landslide occurred on the western slope of a north-west to south-east trending valley above the Tagari River. The western slope above 1300 m is composed of part massive, part bedded limestone (Darai Limestone Formation) which was laid down
Reviewing rainfall thresholds in the context of the Tumbi Landslide during the late Oligocene to Mid Miocene (Fig. 5.2(a)). Although some strata are pure, there are a number of impure limestone interbeds which are made up of calcareous clastic strata (James, 2006). The presence of these weaker layers, that are less permeable, can result in basal sapping and undercutting of the limestone unit which can subsequently lead to rockfalls and slope retreat. The limestone surface expression on which the failure occurred is a continuation of the extensive Muller Plateau which lies to the north. The limestone varies in lithology throughout the Plateau from strong micrites which are seen at the landslide site to weaker, chalkier rock elsewhere (James, 2006). The lower porosity implied by the micrite lithology is countered by the state of almost permanent saturation of the epikarst, brought about by high rainfall accumulations and extensive stream runoff over the Plateau and into the Tagali Valley. Denudation rates for the wider Plateau have been estimated at 200 m$^3$ km$^{-2}$ a$^{-1}$ (James, 1980) and large scale limestone slab slumps have been mapped in adjacent valleys (Bryan and Shearman, 2008). The part-massive nature of the limestone suggests that the development of internal slip-surfaces, favourable for rotational slumps, would have been less likely to occur. However, bedding planes can clearly be observed in Fig. 5.2(b). These types of discontinuity can develop into slip surfaces, encouraging movement if they lie coincident with the slope geometry. It is difficult to ascertain the degree to which the limestone has been folded at the landslide site. This makes determining whether the dip angle and direction, both of which are important indicators for slope stability, are coincident with the geometry of the slope at Tumbi Quarry. However, although the precise dip cannot be determined, a photograph of the intact, exposed limestone to the north-western side of the Tumbi Landslide back scarp (Fig. 5.2(b)), provides a tentative indication of potential dip (25-30°) and direction (which appears to be down-slope). The steep dip angle and the down-slope orientation suggest
that the limestone unit is in a structural position which will encourage rather than restrain landslide activity. Add to this the fact that the landslide site lies within the highly folded and faulted Papuan Fold Belt and it is likely that numerous discontinuities exist within the rock. The combination of bedding planes, faults and fractures, means that fracture nets can develop which allows water to penetrate throughout the limestone unit. Over time this can further enhance existing weaknesses, which in turn increases the likelihood of collapses and landslides.

Fig. 5.2. Location of Tumbi Quarry including: (a) geological map of the Tagali valley (b) photographic interpretation of the limestone dip angle and direction and (c) a slope profile and schematic geological cross-section (line A-A’ in a) of the area around the landslide site

A schematic geological cross-section and map (Fig. 5.2), illustrates the location of Tumbi Quarry and the adjacent outcrop rocks. Of relevance to the Tumbi Landslide event is the contact between the limestone unit and the underlying Ieru Formation (Fig. 5.2(c)). This formation was laid down during the late Cretaceous and is split into the upper Ieru, which is predominantly sandstone, and the lower Ieru which is composed of
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shale and mudstone (Hill and Gleadow, 1989). Although this formation is not observed at outcrop within the valley, based on estimates of the thickness of the Darai Limestone (James, 2006; Davies, 2012) and the break in slope angle observed in the slope profile (Fig. 5.2(c); Fig. 5.3), the approximate depth of contact between the limestone unit and the Ieru Formation is believed to be at approximately 1300 m asl. This also corresponds to the approximate location of a watercourse which emerges from below the face of the quarry (Fig. 5.3).

![Fig. 5.3. A pre-failure slope profile of the landslide site derived from a 5 m DEM.](image)

Based on the geological cross-section (Fig. 5.2(c)) and slope profile (Fig. 5.3) it is evident that the quarry site was located on a very steep slope. Angles of between 30 to 50° were calculated as secondary derivatives of a digital elevation model (DEM) produced at 5 m resolution by Fugro Earthdata’s dual band interferometric radar system (GeoSAR). Such slope angles have been identified by Greenbaum et al. (1995), to experience higher incidences of landslides in PNG and would therefore be an additional structural element encouraging rather than restraining slope movement. Further additional extraction of aggregate material from the quarry would have been likely to
further steepen this slope. It is therefore necessary to understand the land use and anthropogenic activities which were ongoing within the vicinity of the Tagali Valley.

5.3.2 Landuse and anthropogenic activity

The area surrounding the Tagali Valley has been the focus of increasingly intense natural gas extraction, particularly with the initiation of the PNG LNG Project. This project aims to commercialise natural gas from the Hides, Angore and Juha fields in Southern Highland Province. With an operational life of thirty years and a high demand for the development of extensive supporting infrastructure, numerous existing quarry sites within the Tagali Valley have been leased to ESSO Highlands from Hides Gas Development Corporation (HGDC; D’Appolonia S.p, 2011a). The Tumbi Quarry is one such site, with a second quarry, Tameya Quarry (QA2) also operating in close proximity, along the same limestone ridge. The digital elevation data acquired to produce the pre-failure slope profile (Fig. 5.3) was obtained via GeoSAR overpasses during 2006. The date of acquisition suggests that the slope angles obtained are representative of the pre-failure slope, although it is unlikely that the slope angles are natural due to the pre-existence of a quarry at this location for a considerable period of time prior to the initiation of the LNG project. It should also be noted that as these data were obtained in 2006, they will not have captured any additional modifications made to the quarry between 2010 and 2012, leading up to the time of the failure. ESSO Highlands detail that aggregate, reaching a volume of approximately 100,000 m³, had been extracted between the start of Project activities and 2010 (ESSO Highlands Limited, 2010). This suggests that possible further steepening could have occurred. In addition to the continued extraction of material from the site, there were a number of plans outlined in the Resettlement Action Plan (ESSO Highlands Limited, 2010) to extend the quarry. These extensions include the development of an adjacent spoil area,
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as well as large zones of cleared forest. These modifications will be discussed in more
detail in section 5.4 with the aid of satellite images, photographs and a land use
schematic of the quarry.

Although the failure appears to have originated within the quarry’s access
boundary, activities and land use surrounding the quarry could have influenced water
drainage and infiltration or have affected local slope stability around the quarry and
therefore warrants a review. The area around Tumbi Quarry is largely comprised of
secondary rainforest and agricultural areas (Fig. 5.4(a)). Coffee, pandanus (screw pine
trees), casuarinas and castanopsis trees are all grown in close proximity to quarry the
site, as well as a wide range of food-producing plants. There is therefore a mixture of
subsistence-style crop production as well as trees which are producing goods of
commercial value to the community. The majority of food gardens can be observed
downslope of the quarry (Fig. 5.4(a)). This coincides with the main road linking the
Nogoli Transit Camp to the north, with the HGCP facility in the south of the valley.
Additional infrastructure includes an elementary school, close to the quarry access road,
and the villages of Tumbiago and Handamanda which lie upslope of the quarry. These
were significantly impacted by the landslide event. There are also numerous shelters in
areas downslope of the quarry, a number of which had been erected following the
implementation of the resettlement and relocation plan developed in 2010 (Esso
Highlands Limited, 2010).

The above information suggests that the geometric profile of the site, combined
with the structural alignment of the geology would have encouraged rather than
inhibited any potential slope movements. In addition, the continued extraction of
aggregate at the site could also have excessively steepened the pre-existing slope,
further enhancing potential slope instability within the quarry. A review of the landslide
5| Reviewing rainfall thresholds in the context of the Tumbi Landslide characteristics using satellite images and photographs taken pre- and post-failure will now be provided.

5.4 Tumbi Landslide Characteristics

5.4.1 Pre- and post-failure image analysis

In order to understand the characteristics of a landslide it is useful to be able to review the pre-failure slope. This is possible using the interferometric radar data, obtained in 2006, and photographs of the site prior to the Tumbi Landslide event. Fig. 5.4(a) shows Tumbi Quarry photographed on the 27th January 2010, two years prior to the landslide (Petley, 2012). For comparison Fig. 5.4(b), a photograph taken from a helicopter overpass shortly after the landslide occurred, is provided to illustrate the location and extent of the deposit following the failure on the 24th January, 2012. Although the two images are taken from different perspectives; Fig. 5.4(a) is looking along the western slope to the north-west from a south-easterly position, while Fig. 5.4(b) is taken from a northerly position looking along the western slope to the south-east, it is clear that the failure has encompassed the majority of the quarry area. To the extreme left of Fig. 5.4(b) is a glimpse of a secondary quarry site, named QA2 (Tameya Quarry), which is smaller but still active.
Fig. 5.4. Aerial photographs of (a) Tumbi Quarry on the 27th January, 2010 and (b) the Tumbi Landslide shortly after failure on the 24th January, 2012.
Although Fig. 5.4(b) suggests that vegetation above the landslide back scarp remained relatively intact prior to the failure, there are some grassy areas evident between the trees, which suggests that some degree of clearance had been completed. Given that the pre-failure image was taken in 2010 prior to the development of the Resettlement Action Plan (Esso Highlands Limited, 2010), it is likely that this clearance is associated with activities from the up-slope villages mentioned earlier. However, the Action Plan does indicate that further clearance was planned after 2010 with an area of approximately 1.4 Ha identified as the ‘initial clearance area’ in the north-eastern area of the quarry, close to the break in the tree line observed in the pre-failure image (Fig. 5.4(a); Esso Highlands Limited, 2010). It can be assumed that the planned extensions to the quarry had at least started to be implemented at the site, as there is a distinct difference between the size of the quarry in Fig. 5.4(a) and Fig. 5.4(b). Furthermore, an area to the north-west of the quarry appears to have been cleared (Fig. 5.4(b) and Fig. 5.5(a)) and this was not evident in the pre-failure image (Fig. 5.4(a)). A schematic land use map of the proposed changes within the quarry access boundary is shown in Fig. 5.5(b). In this image the north-western area of the site has been assigned for use as a spoil area, with an access road leading up to the upper quarry area (Fig. 5.5(a) and Fig. 5.5(b)). This area has remained intact, adjacent to the main landslide deposit, and there does not appear to be evidence of large spoil heaps in the post-failure image (Fig. 5.4(b)). It is therefore, difficult to determine to what extent the proposed extensions had been completed and whether significant amounts of spoil were being temporarily held in this north-westerly area of the quarry site or whether large amounts of vegetation upslope of the quarry had been cleared. However, these potential modifications are important to consider, particularly the location of spoil areas which can be very important for changing the overburden pressure on slopes.
Fig. 5.5. (a) Annotated aerial photograph of the upper and medial regions of the Tumbi Landslide, with (b) schematic diagram of the land-use within the quarry’s land access boundary shown for reference.

In addition to these modifications, there is some evidence to suggest that there was pre-existing instability at the quarry. The back scarp can be identified in both the
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pre- and post-failure images respectively (Fig. 5.4(a) and Fig. 5.4(b)). A small break in the tree line follows the approximate upper edge of the slip plane annotated on the IKONOS satellite imagery in Fig. 5.6(a). This linear feature, identified in the pre-failure image (Fig. 5.4(a)), suggests that there was a fault or highly weathered joint within the limestone unit at this point above the quarry face. Alternatively this could have been a tension crack opening up at this location, suggesting instability along the limestone ridge. This is not the only indication of pre-existing instability around the quarry. Again, in the pre-failure image (Fig. 5.3(a)) small, shallow failures can be identified. These appear to be predominantly soil slips or at most shallow failures within the colluvium layer at the base of the ridge and would be considered superficial in comparison to the Tumbi Landslide. However, larger failures have been known to affect this area; a mudslide at HGCP in November, 2010 (D’Appolonia S.p.A., 2011a) is one such example and almost exactly a year following the Tumbi landslide another failure near Komo Airfield occurred.

An assessment of the landslide, made by the PNG NDC, estimates that the landslide deposit covers an area of 0.195 km$^2$ and has a volume of 0.003 km$^3$ (Papua New Guinea National Disaster Centre Technical Assessment Team, 2012). The total length of the deposit is 845 m and has an estimated depth of 30 m where the landslide has buried the road (Fig. 5.3; Fig. 5.6(a)). Pools of water were identified within the landslide deposit and these were believed to be associated with increases in groundwater prior to the failure. This will be addressed further in section 5.5.
Fig. 5.6. (a) Annotated IKONOS satellite image showing the outline of the Tumbi Landslide deposit and aerial photographs of the (b) upper, (c) medial and (d) distal regions of the landslide deposit. All photographs in this figure are courtesy of the Geohazards Management Division in Papua New Guinea.
5.4.2 Photographic interpretation of landslide characteristics

A closer look at the different parts of the landslide provides an overview of the characteristics of the failure. The depth of the back scarp (Fig. 5.6(b)) indicates that the failure was deep-seated (i.e. the failure plane is within the regional bedrock unit) and the straight angle of the failure plane shows limited rotation or backward tilting, suggesting that the primary failure was translational. The intact clump of trees shown by the red circle in Fig. 5.6(a) and Fig. 5.6(b) also favours a translational slip, where the slope failed along a planar surface causing the forested area to become detached where the zone of weakness intersects the surface. The middle and lower parts of the deposit have clearly visible flow characteristics (Fig. 5.6(c) and Fig. 5.6(d)). Following the initial translational failure, secondary back scarps within the failed deposit allowed the previously, relatively intact landslide debris to break up and mobilise as a debris flow. Such failure mechanisms can often produce levee-type formations, due to their Non-Newtonian flow dynamics (Ancey, 2007) and these can be observed in Fig. 5.6(c) and Fig. 5.6(d). Reviewing these together with Fig. 5.5(a), it seems that as the debris flow moved downslope the levees produced were of sufficient thickness to cause subsequent failures. This resulted in numerous additional back scarps in the lower regions of the landslide deposit. Other characteristics of this type of flow include super-elevation scars, produced as material flows around a corner, causing it to “superelevate or climb up on the bend side” (Ancey, 2007) as it moves down slope. Typically, debris flows need to be moving at considerable speed for this to occur and the bend would need to be prominent. Although, the speed of the event is unknown, the deposit does not appear to have mobilised around any substantial corners. There is however possible evidence of a super-elevation scar in Fig. 5.6(d), as the debris is forced around a more resistant bulge of material on the south-eastern side of the landslide deposit (Fig. 5.6(a)). Alternatively,
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this prominent scar could be representative of the depth of the slip surface within the limestone unit.

As with all landslides, the debris from the translational and subsequent debris flow failures flowed under gravity and therefore followed channels. During this movement the debris flow material was constrained to the stream channels and the access road which, prior to the failure, led up to the quarry face (Fig. 5.5(b)). In addition, the area of elevated, non-disturbed ground (Fig. 5.5(a)) to the north-west of the landslide deposit restrained the debris flow and funneled the material downslope, restricting lateral spread. The material remained channelised as it moved into the Tagari River flood plain. There are two streams which interact with the landslide deposit and which could have aided mobilisation of the landslide material once it had failed: the first is Tumbi Creek which previously flowed from the quarry face, and the second is a stream running parallel to the south-eastern edge of the quarry’s land access boundary (Fig. 5.5(b)). The use of stream channels to encourage downslope movement is secondarily supported by the morphology of the slide toe region: one main deposit in the medial region is channelised within two separate drainage networks in the distal region (Fig. 5.6(d)). As seen on the annotated IKONOS satellite imagery (Fig. 5.6(a)) and documented in the site inspection report (Papua New Guinea National Disaster Centre Technical Assessment Team, 2012), Tumbi Creek was temporarily blocked by the landslide debris before its course was ultimately altered towards to the south-east. This could explain the pools of water which were observed throughout the medial and distal regions of the deposit (Fig. 5.6(b)).

Based on the analysis of these photos, the sequence of events is likely to have been a joint- or fault-controlled translational slide followed by subsequent debris flow failures within the deposit. Such a sequence of events could have been triggered by: (1)
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heightened rainfall accumulations, as suggested in the Technical Assessment Report (Papua New Guinea National Disaster Centre Technical Assessment Report, 2012); (2) seismic activity or (3) an external environmental factor such as anthropogenic interventions.

5.5 Rainfall preceding the Tumbi Landslide

The photographic interpretation of the pre- and post-failure images suggests that the Tumbi Landslide was a deep-seated failure. The initial translational movement occurred within the Darai Limestone, which made up the outcrop rock of the western slope of the Tagali Valley. Typically, the triggers of deep-seated failures are complex and in terms of rainfall, require a review of both the short-term and long-term rainfall patterns out to seasonal time scales. Here, rainfall is compared to the rainfall climatology for the valley. In addition, rainfall characteristics observed before the movement are assessed against other rainfall events which have resulted in landslides, using the methods in Chapter 4 of this thesis.

Due to the remoteness of the landslide site and the sparse distribution of rainfall gauges throughout the PNG Highlands, satellite-derived precipitation estimates from the TRMM TMPA dataset were used for the shorter-term (up to 90 days preceding the landslide) rainfall analysis. Unlike the assessments completed in Chapters 4, the 3B42 Real Time product (3B42RT; Huffman et al., 2007) has been used to obtain representative rainfall prior to the Tumbi event, as at the time that this analysis was conducted, gauge corrected data (TRMM TMPA 3B42) were unavailable. The 3B42RT data is generated in the same way as the gauge-corrected TRMM TMPA 3B42 data, in that it takes microwave (MW)-derived precipitation estimates and uses infrared (IR) estimates, calibrated against the MW-derived values, to fill any missing data. It also has the same data coverage (from 50° North to 50° South and from 180° West to 180° East)
Reviewing rainfall thresholds in the context of the Tumbi Landslide and spatial (0.25°) and temporal (3-hourly) resolution. The main difference is that the 3B42RT product does not include any gauge adjustment and therefore it should be noted that the biases, discussed in Chapter 4, section 4.2.2, will apply to these data. As completed in the previous analyses, the 3-hourly rainfall estimates are aggregated into daily rainfall accumulations and downloaded using the Mirador data archive. Daily data is most applicable for this assessment because of the uncertainties associated with the TRMM precipitation estimates at fine temporal resolution and because the focus of this analysis is to determine whether rainfall could have contributed to a deep-seated landslide. Such landslide types are rarely triggered by short (< 1 day) duration rainfall events and therefore aggregated rainfall accumulations are more relevant. To obtain representative rainfall data, 90 days of daily rainfall accumulations were extracted from the near-global, raw 3B42RT data. This involved identifying the most representative TRMM grid square (0.25 x 0.25°) using the location of the Tumbi Landslide relative to the TRMM grid (Chapter 4; section 4.4.3.1). Using data from the representative TRMM grid square, a 90-day time series of daily rainfall was constructed (Fig. 5.7(a)), with the 90th day representing rainfall which fell on the day of the landslide’s initiation (24th January 2012).

5.5.1 Shorter-term rainfall analysis

In the 90 days preceding the Tumbi Landslide (27/10/2011 to 24/01/2012), 739 mm of rainfall fell over the Tagali Valley and the landslide site. The mean daily rainfall for the period is approximately 8 mm/day with the highest daily rainfall total observed on the 27th October, 2011 (40.9 mm; Fig. 5.7(a)). As the rainfall accumulation obtained for the 27th October was significantly higher than the daily rainfall amounts observed in the rest of the time series, the decision was made to review rainfall in the 3 days leading up to this heavier rainfall event. The aim of this was to determine whether the
heightened accumulation estimated by 3B42RT was part of a longer stormy period or an isolated high rainfall intensity event. In actual fact there was no rainfall estimated to have fallen at the site on the 26\textsuperscript{th} October, 2011 and only 22 mm was estimated to have fallen between the 23\textsuperscript{rd} and 26\textsuperscript{th} October. Therefore, the high rainfall accumulation observed on the 27\textsuperscript{th} October can be identified as a ‘high intensity’, short duration rainfall event. The term ‘high intensity’ is used in a relative context here, as it is evident from the analysis conducted in Chapter 4, that significantly larger daily accumulations occur across PNG and that these larger accumulations are more likely to trigger landslide events. Over the remaining days in the time series there were 8 occasions when daily rainfall totals exceeded 20 mm/day; 4 of these were clustered into the last 10 days of the time series. To examine this period of rainfall activity in more detail, a 30-day time series (26/12/2011 to 24/01/2012; highlighted in grey in Fig. 5.7(a)) was also produced (Fig. 5.7(b)).

In this shorter time series (Fig. 5.7(b)), 6 non-rain days were identified, all occurring early in the period (December 31\textsuperscript{st}, January 1\textsuperscript{st}, 7\textsuperscript{th}, 8\textsuperscript{th}, 11\textsuperscript{th} and 14\textsuperscript{th}). This caused the first half of the 30 day period (26\textsuperscript{th} December to 9\textsuperscript{th} January) to have a slightly lower average daily rainfall (7 mm/day) than observed in the 90-day time series (8 mm/day). However, in the second half of the 30-day period (10\textsuperscript{th} to 24\textsuperscript{th} January), the mean daily rainfall increased to 14.7 mm/day, double the mean daily rainfall obtained for the first half of the time series (Fig. 5.7(a)). To determine the relevance of the rainfall observed prior to the Tumbi event, the 10-, 30-, 60- and 90-day rainfall accumulations were calculated and compared against rainfall accumulations associated with previous landslide events and the magnitude-duration of rainfall events over a 12-year period (1998-2009). These four durations were selected as they represent key time intervals over which rainfall totals result in changes to hydrological systems and slope
Reviewing rainfall thresholds in the context of the Tumbi Landslide conditions, which may result in movement (Fuhrmann et al., 2008). The decision was made not to assess mean rainfall intensity preceding the Tumbi event due to the results in Chapter 4, which suggest that relationships between landslide occurrence and rainfall intensity are less well defined for the medium-to-large landslides contained and analysed in the PNG landslide inventory.

Fig. 5.7. (a) Daily rainfall accumulations derived from 3B42RT, for 90 days preceding the Tumbi Landslide with (b) the final 30 days of the time series (shaded grey) shown in more detail.

Total rainfall accumulations over 10 days (15th January 2012 to 24th January 2012), 30 days (26th December 2011 to 24th January 2012), 60 days (26th November 2011 to 24th January 2012) and 90 days (27th October 2011 to 24th January 2012) prior to the Tumbi Landslide have been calculated totalling 190.02, 325.95, 583.10 and 739.14 mm, respectively. Using the 90-day rainfall time series, generated for the 52 landslide-triggering events which were analysed in Chapter 4, histograms of landslide frequency per 50 mm rainfall accumulation bins were produced (Fig. 5.8). The rainfall
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event frequency distributions for all non-landslide rainfall events are also shown (Fig. 5.8). These were produced using the method outlined in Chapter 4, section 4.4.4. In brief, a running sum calculation was applied to 12 years of 3B42V6 daily rainfall data so that running accumulations at each of the different rainfall durations could be produced. The accumulations observed for the Tumbi Landslide were also plotted to correspond to a 50 mm rainfall accumulation bin, so that the event could be compared against the historical landslides and rainfall frequency distributions. The 10-, 30-, 60-, and 90-day accumulations for the Tumbi event mean that it falls into the 150-199.9 mm/10 day, 300-349.9 mm/30 day, 550-599.9 mm/60 day and 700-749.9 mm/90 day rainfall bins, respectively.

Fig. 5.8. Comparison between landslide frequency distributions, rainfall event climatology and the Tumbi Landslide event, based on rainfall accumulations for (a) 10 days, (b) 30 days, (c) 60 days and (d) 90 days. Landslide frequencies are obtained using rainfall accumulations prior to 52 slope movements identified over the period 1998 to 2009. The rainfall event frequency distributions (climatology) are obtained from analysing 12 years (1998-2009) of TRMM daily rainfall data.
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The rainfall which occurred prior to the Tumbi Landslide lies towards the right of the rainfall and landslide frequency distribution peaks in all cases. This suggests that the rainfall which fell tended towards the extreme end of the distribution, although only marginally, in all cases. Furthermore, the Tumbi event when compared against the landslide frequency distributions appears to fit well, in that the rainfall accumulations observed for this event have also been associated with a number of historical landslides of similar magnitude. In the 10-day duration distribution (Fig. 5.8(a)), 4 of the 52 landslide events from the PNG inventory have occurred with rainfall totals between 150 and 199.9 mm/10 days, coinciding with the rainfall observed prior to the Tumbi Landslide. Three (LTE19_2, LTE25 and LTE23) of these are linked to flooding which resulted in landslides across the Highlands and Port Moresby. The fourth event of similar magnitude is the Wantoat Landslide in Morobe Province (LTE1). This landslide is particularly interesting as it falls within the same rainfall bin as the Tumbi Landslide in 3 out of the 4 rainfall durations examined (10-, 30- and 60-days). Based on examinations by an engineering geologist from the Geological Survey of Papua New Guinea, Department of Mining between the 16th and 27th of April 2002, it is believed that the Wantoat Landslide was triggered by increased rainfall in the two weeks prior to the slope movement (Kuna, 2002). This is the same assessment provided for the Tumbi event (Papua New Guinea National Disaster Centre (NDC) Technical Assessment Team, 2012).

In order to understand the similarities and differences between the rainfall characteristics of historical landslide events and the Tumbi Landslide, all landslide-triggering events that recorded rainfall accumulations of similar magnitude to the Tumbi Landslide were examined in more detail. Cumulative rainfall curves were produced for the Tumbi Landslide and each of the historical landslides falling within the coincident
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rainfall accumulation bin as the Tumbi event (Fig. 5.9). This resulted in 15 cumulative rainfall curves being produced, inclusive of the Tumbi rainfall curve, and provides a means of placing the rainfall patterns observed prior to the Tumbi Landslide in context with other known landslide events recorded in the PNG landslide inventory.

The similarities in rainfall distribution prior to both the Tumbi and Wantoat Landslides can now be visualised (Fig. 5.9). The similarities in rainfall accumulation and the way that the rainfall was distributed over the 90-day period would suggest that similar mechanisms of failure may have been active at the two sites. In some respects this is true. Both landslides are believed to have initiated as translational failures which evolved into debris flows. The failures also occurred on very steep slopes (> 30° and up to 50°) in areas which were predominantly covered with secondary rainforest, cultivated cropland and grassland. Despite these overall similarities, however, the geology of the Wantoat area consists of greywacke, argillite and volcanolithic conglomerate and limestone lenses (Kuna, 2002). Furthermore, the Wantoat Landslide had no association with quarry or mining activities. Therefore, the similarities between the two events need to be considered cautiously, as each landslide event is unique in terms of the dynamics which result in failure.
Fig. 5.9. Cumulative rainfall curves for the 90 days preceding the Tumbi Landslide and 14 landslide-triggering events with similar magnitude-duration rainfall events.

The Tumbi Landslide rainfall accumulation coincides with the greatest number of similar magnitude landslide-triggering rainfall events in the 30-day duration plot (Fig. 5.8(b)). 7 landslide-triggering events were recorded to have similar rainfall magnitudes to the Tumbi event in this instance. This is approximately 14% of the non-earthquake induced landslides analysed in Chapter 4. Analysis of these events indicate that four were associated with flooding (LTE12 and LTE23) and/or flash-floods (LTE21_4) and severe storms (LTE20), while one was associated with mining activity in combination with intense rainfall (LTE14). Unfortunately, there is limited information related to LTE14, although it is known is that the landslide occurred at Lihir gold mine, which lies
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on Lihir Island and is part of the Tabar-Lihir-Tanga-Feni chain of volcanic islands positioned parallel to New Ireland. The remaining two were individually recorded landslide events; one being the already identified Wantoat Landslide (LTE1) and the other being the Watabung Landslide (LTE4), which occurred in the Daulo Pass area of Eastern Highlands Province in March 2009. At 60- and 90-day rainfall durations there are fewer historically recorded landslide events associated with similar rainfall magnitudes to the Tumbi Landslide (2 in the 60-day landslide frequency distribution and 5 in the 90-day landslide frequency distribution; Fig. 5.8(c) and Fig. 5.8(d)).

Assessing the landslide frequency distributions, it is evident that the Tumbi Landslide fits well within the frequency distributions of previous landslide events, particularly for the 10-, 30- and 90-day rainfall duration periods (Fig. 5.8). It is evident therefore, that the rainfall accumulations, observed prior to the Tumbi Landslide, have been associated with a number of landslides in recent history. This is not a confirmation that rainfall triggered the Tumbi event but rather provides further understanding into the relevance of the values obtained, in the context of previous non-earthquake-induced landslide activity. The further analysis comparing those cumulative rainfall curves which resulted in similar magnitude rainfall preceding other historical landslide events showed that similar magnitude rainfall can be produced by very different distributions of rainfall over the same time period (Fig. 5.9). This illustrates the complexities involved in determining whether rainfall was the true trigger of the Tumbi Landslide. As discussed earlier, the Wantoat and Tumbi landslides share a number of similar rainfall characteristics over a range of time scales. By contrast LTE23, which refers to landslides in Port Moresby associated with flash flooding, shows stark differences in the way that the rainfall was distributed over the 90-days. The stepped nature of the LTE23 cumulative rainfall curve in the final 30-days preceding the landslides, supports the
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theory that flash-flooding was ultimately responsible for the landslides observed. The difference between this and the rainfall patterns preceding the Tumbi Landslide suggest that very different mechanisms of failure were involved in each case.

Rainfall of similar magnitude has been associated with a number of different types of landslide-triggering event including: flash-flooding, widespread flood events and severe storms. There are a number of ways in which the same accumulation of rainfall can lead to different triggering events including: (1) the rainfall characteristics themselves, (2) the geology and geomorphology on which the rainfall falls and (3) the antecedent condition of the environment (i.e. groundwater, soil moisture and drainage network capacity). To address the issues of antecedent rainfall, a review of rainfall patterns 6-months prior to the Tumbi landslide will now be provided.

5.5.2 Interseasonal rainfall analysis

As previously acknowledged, deep-seated failures are often complex and are rarely associated with a single, well-defined, rainfall event. Furthermore, the underlying groundwater and soil moisture conditions play an important role in how/when and where a landslide ultimately occurs and whether additional hydrological events, such as floods, are involved. Therefore, a review of rainfall variability between the preceding seasons (up to 6 months prior to the failure) has also been completed. The Tumbi Landslide occurred in January, within PNG’s wetter season which extends from December to May (McAlpine et al., 1983). To review longer-term rainfall variability, a coarser temporal resolution than that applied to the short-term rainfall analysis is used. The GPCC Full Data Reanalysis Product (Adler et al., 2003), used in Chapter 3 of this thesis, is very effective for analysing longer-term rainfall patterns and in particular allowing comparisons between a single month’s rainfall and the climatology. The monthly estimates of rainfall accumulation are produced using the GPCC real and non-
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real time gauge station data, which is interpolated onto a 0.5 x 0.5° grid. Using GPCC grids which covered the area of the Tagali Valley, rainfall climatology fields were produced by calculating the mean monthly rainfall for each consecutive month (January to December) using a forty-year reference period (1970-2009). Using the average monthly climatology grids, rainfall totals for the Tumbi Quarry were generated (Fig. 5.10). As these data are interpolated from rainfall gauge stations, which have both sparse coverage and a coastal bias in PNG, it is anticipated that the average rainfall accumulations estimated have been under-represented. However, the research findings from Chapter 3 indicate that GPCC data can accurately represent the seasonal profile.

Fig. 5.10. A comparison between mean monthly rainfall in the 6 months prior to the Tumbi Landslide (derived from TRMM 3B42RT) and the mean monthly rainfall climatology (period 1970-2009)

Following the production of the seasonal profile it was compared to the rainfall which occurred prior to the Tumbi Landslide. Again using TRMM 3B42RT, gridded daily rainfall accumulations were reproduced to generate monthly rainfall totals covering the period July 2011 to January 2012. Due to the difference in grid size between the TRMM and GPCC datasets, the GPCC grids were re-sampled to the same grid resolution as the 3B42RT data and the centre point of the pixel shifted by 0.125° to capture the spatial variability in rainfall accumulations in the 3B42RT dataset. Fig. 5.10 illustrates the monthly rainfall accumulation for the 6 months prior to the Tumbi
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landslide and compares the totals with the monthly rainfall climatology derived from
GPCC data. The difference between the satellite-derived rainfall accumulations and the
monthly climatologies are shown as percentage differences of the climatology for each
month. It is evident that for the 6 months leading up to the landslide event, monthly
rainfall had been consistently below the forty-year average. August shows an extremely
low monthly rainfall (78.5 mm) and shows the largest percentage difference (66%)
between the monthly accumulation and the climatology. This large difference is in
addition to below average rainfall in July. This departure from climatology would likely
have been observed in the Tagali Valley as reduced surface runoff and stream discharge.
The rainfall from September and October, which had accumulations close to the
climatology (94% and 96% respectively), would have contributed to re-charging the
volumes of water within the surface geology and would have gone part of the way to
replenish stream flows in the area. However, this recharge would have been relatively
slow given that November and December had 37% and 21% less rainfall than the
monthly climatology. The 6 months of below-average rainfall prior to the failure
suggests that both groundwater and water held within both the limestone and sandstone
units would have been at lower levels than anticipated.

5.6 Seismic activity

To assess whether seismic activity could have contributed to the Tumbi Landslide,
a review of earthquake activity throughout the PNG mainland for the coincident 90-day
period used for the short-term rainfall analysis has been completed. Earthquake data
were extracted from the USGS NEIC/PDE Catalogue, initially at a global spatial scale.
The epicentres of the earthquakes were then plotted and those which fell within the
landmass boundary of the PNG mainland were retained for further analysis. Fig. 5.11(a)
illustrates the geographic distribution of the earthquake epicentres, while Fig. 5.11(b)
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indicates the magnitude-distance relationship between the earthquake events and the location of Tumbi Quarry. This was produced by calculating the distance between each earthquake epicentre and the quarry site, in kilometres. Additionally, the temporal distribution of each earthquake is provided (Fig. 5.11(c)) along with the daily rainfall totals over the 90-day period prior to the landslide failure.

Fig. 5.11. (a) A map showing the location and magnitude of all earthquake events recorded within the PNG mainland between 27th October 2011 and 24th January 2012 and (b) a magnitude-distance plot of these earthquakes relative to the location of Tumbi Quarry. (c) A time series plot spanning the same temporal periods as a, comparing the daily rainfall and the dates and magnitudes of the recorded earthquakes.
Twenty earthquakes occurred over the period 27/10/2011 and 24/01/2012, within the PNG mainland (Fig. 5.11(a)). All were greater than magnitude 4, which is considered the minimum magnitude at which landslides, disrupted slides and falls are likely to be triggered (Wilson and Keefer, 1985). However, the distances between the earthquake epicentres and the location of Tumbi Quarry and the landslide site exceed 150 km in all cases. The nearest event is recorded as a magnitude 5.0 earthquake, 153 km from the landslide. Analysis of a global earthquake catalogue completed by Wilson and Keefer (1985) suggests that only earthquakes in excess of magnitude 6.5 would have the required seismic energy to induce slope failures at such distances from the rupture zone. Within the 90-day period analysed there was only 1 event which exceeded magnitude 6.5; a magnitude 7.1 earthquake recorded on the 14th December, 2011. This occurred in the Owen Stanley Range of Morobe Province, on the eastern side of the mainland, 478 km from the location of Tumbi Quarry. An earthquake of similar magnitude occurred in October 1993, with the epicentre located in the Finisterre Range of Morobe Province (Meunier et al., 2007). This earthquake and the numerous high magnitude aftershocks caused landslides across an area of 3000 km² (Tutton and Browne 1994). Using satellite data, Greenbaum et al. (1995) mapped the approximate limits of both ground movements and large landslides resultant from this earthquake. The maximum distance at which landslides were observed was between 60 and 80 km from the fault rupture. Another magnitude 7.0 earthquake occurred near Madang, to the north of Morobe and the Finisterre Range, in November 1970. This caused landslides across an area of 240 km² within the Adelbert Range (Pain and Bowler, 1973). The area with the highest density of landslides occurred within 30 km of the earthquake epicentre. It is evident, both from the analysis conducted by Wilson and Keefer (1985) and from these historic events in PNG, that the high magnitude earthquake on the 14th
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December 2011 is unlikely to have increased instability at Tumbi Quarry due to the large distance (478 km) between the epicentre and the Tumbi Landslide site.

In addition to the distance-magnitude relationship, there is also a need to consider the temporal distribution of earthquakes relative to the timing of the Tumbi Landslide (Fig. 5.11(c)). A magnitude 4.7 earthquake occurred on the day of the Tumbi failure, although the epicentre is located 446 km from the landslide site, again in Morobe Province. All other events including the larger magnitude 7 earthquake occurred prior to 8th January, 2012. Given the magnitudes, epicentral distances and timings of these earthquakes, it can be concluded that all of the recorded events would have been unlikely to have contributed to the Tumbi Landslide. We therefore rule out seismicity as a likely trigger on the grounds of epicentral distance, timing and relatively low seismic energy expended during this period.

5.7 Discussion and conclusion

Based on the satellite and photograph interpretations, the Tumbi Landslide is believed to have moved initially as a translational slide. After failure the landslide debris subsequently evolved into multiple debris flows, with one main central flow moving downslope using stream channels and the road leading up to the original quarry face. Identifying a single trigger for a deep-seated failure such as the Tumbi Landslide is not straightforward. The shorter-term rainfall analysis indicates that there was an increase in rainfall accumulations in the 10 days prior to the slope movement.

Furthermore, rainfall accumulations over 30- and 90-day durations coincide with a number of similar magnitude rainfall events which are associated with recent landslides. This indicates that the shorter-term rainfall accumulations seen prior to the Tumbi event were equivalent to previous rainfall events which had triggered landslides in the region. This is not however, confirmation that short-term rainfall triggered the Tumbi
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Landslide. In fact closer inspection of the rainfall characteristics preceding other known landslides, observed between 1998 and 2009, suggest that additional complex interactions need to be considered. For example, it has been seen that for a number of previously identified landslides (LTE12, LTE19_2, LTE23, LTE25, LTE21_1, LTE21_4, LTE27_1 and LTE30; Fig. 5.9) flooding was a major contributor to the initiation of slope movement. This was not the case for the Tumbi Landslide. This highlights a number of important issues for understanding landslide initiation. Firstly, similar magnitude-duration rainfall events can distribute rainfall differently across similar time scales (i.e. stepped cumulative rainfall curves illustrative of high-intensity, short-duration events (LTE23; Fig. 5.9) and shallow, diagonal rainfall curves illustrative of lower-intensity, longer-duration events (LTE21_1; Fig. 5.9)). These differences have the potential to alter the failure mechanisms involved in the landslide. Secondly, how rainfall interacts with the surface is strongly affected by the antecedent conditions of the environment. This includes consideration of underlying groundwater levels and soil moisture. Thirdly, the ability of rainfall to interact and mobilize potential slip surfaces is strongly dependent on the geology, geological structure, land use and the level of environmental modification by humans.

The antecedent conditions of the Tagali Valley were examined through the analysis of monthly rainfall accumulations for all months in the six months leading up to the Tumbi Landslide. All months analysed had monthly rainfall totals lower than the 40-year climatological mean. However, August and November, with differences of 66% and 37% respectively, showed the greatest deviation from climatology. This result suggests that the JJA season would have been particularly dry, followed by a very slow recovery of ground water re-charge and stream flows through September, October and November (SON). The recurrence of below-average monthly rainfall, particularly in
November and December, and the timing of the slide at the start of the wet season, rather than at the end, suggests that groundwater would have been close to the dry season low point or even lower, given the exceptionally low rainfall in August 2011. It seems unlikely therefore that groundwater played a significant role in the failure. This would also suggest that stream discharge would have been lower over this period, resulting in reduced surface runoff and infiltration through the bedding planes and joints within the limestone unit. This is likely to be why there was no flooding associated with the Tumbi Landslide, while other landslide-triggering rainfall events, of similar magnitude and duration were accompanied by flooding. This therefore supports the theory that short-term rainfall accumulations, observed over the 90-, 30- and 10-day periods, was more likely to have enhanced the slope’s susceptibility to failure, than the antecedent conditions observed over the 6 months prior to movement.

In addition to the potential rainfall triggers, the analysis highlighted the importance of the underlying susceptibility and the natural denudational processes which act on the slope over decadal time scales. The denudational processes of the region are known to be predominantly erosion by streams (James, 2006), although earthquakes have also been known to weaken surrounding geological units. Hovius et al., (1998) documented the drainage network evolution in the Finisterre Range of PNG; an area also dominated by micritic limestone, and showed that landslides are a critical component in the evolution of the range. Signs of denudation, such as the proposed weathered joint or tension crack close to the location of the back scarp and the shallow failures surrounding the quarry, were evident prior to the failure (Fig. 5.4(a)). The streams surrounding the site would also have played a role in gradually weakening the surrounding limestone structure of the quarry. In addition to these natural denudational processes, the geomorphology of the site also appears to have resulted in a slope with a
naturally high susceptibility to landsliding. Through photographic interpretation and analysis of 5 m DEM data it is evident that the limestone unit was in a favourable structural position for landslide occurrence. The potential bedding-plane angles, estimated to be between 25 and 30°, and the downslope direction suggest that the unit had structural characteristics which were likely to enhance rather than restrain any potential failure. Additionally steep slope angles, derived from 5 m DEM data obtained in 2006, were calculate to be between 30 and 50° at the site prior to failure. These slope angles have been identified to experience higher incidences of landslides in PNG (Greenbaum et al., 1995) and would have further served to increase the ridge’s susceptibility to landslides. Proof of this natural landslide susceptibility is evident in the number of limestone slumps which have been mapped within this and adjacent valleys, which have not been affected by significant anthropogenic activity.

Although, the natural processes affecting the Tumbi area could have ultimately resulted in landslides without any additional external influences, it can be argued that the changes made to the slope during quarrying would have been very likely to enhance landslide susceptibility. Since the start of Project activities in the area, approximately 100,000 m³ of material has been extracted from the quarry site (Esso Highlands Limited, 2010). This material was extracted prior to 2010 when the Resettlement Action Plan was written. Based on this report, further re-development of the quarry, with additional extraction from the surrounding area, was to be completed post-2010 and this included an expansion of the work site to include a storage area for topsoil and spoil overburden. This storage area was to be located on the west, north and south sides of the worksite, within the quarry’s land access boundary (Fig. 5.5(b); Esso Highlands Limited, 2010). As mentioned previously, it is difficult to determine to what extent further modification and extraction had been completed at the site. The still intact
storage area (Fig. 5(a and b)), positioned to the north-westerly side of the site on an area of elevated ground, is evidence that some of these changes had already begun to be implemented. Based on the location of this storage area it is unlikely that it enhanced the slope’s instability prior to the event, although additional clearance and activity with heavy machinery could have allowed pre-existing discontinuities in the surrounding rock to expand. However, the main factor likely to further enhance landslide susceptibility at this site is the additional extraction of material from the base of the already identified steep slope (Fig. 5.3). This is likely to have weakened the integrity of the unit above through over-steepening. An IESC report from November 2011 did indicate that the site was ‘benched and slopes have been stabilized such that the quarry is safe and could be re-occupied should this be required in the future’ (D’Appolonia S.p.A., 2011b). Such measures would have been put in place to increase the stability of the slope and quarry area following material extraction. However, such methods of slope stabilization are insufficient for deep-seated landslides.

Although it has been possible to identify that rainfall could have been the ‘straw which broke the camel’s back’, it is evident that a number of complex factors were involved in the Tumbi Landslide. The natural geomorphology of the slope and the anthropogenic activity at the site were all likely to be as important in this failure. It should be reiterated that the rainfall data used to understand the rainfall preceding the landslide were obtained from 3B42RT estimates. These data suffer from both under- and over-estimation at different times of the year and their ability to reflect the rainfall at the Tumbi site is strongly influenced by the dynamical processes of the rainfall (i.e. convective or ‘warm rain’ processes) being observed. The fact that the Tumbi Landslide occurred at the start of the wetter season, when convectively driven rainfall associated with the north-westerly monsoon is more consistent suggests that the estimates should
be reaching their highest level of skill. However, the limitations in temporal monitoring mean that rainfall could be under-represented at the Tumbi site.

The initial translational failure of the Tumbi Landslide occurred following a 90-day rainfall total of 739.14 mm, the result of an intense heavy rainfall event on the 27\(^\text{th}\) October, 2011 and a subsequent longer-duration, lower intensity rainfall event between the 15\(^\text{th}\) January 2012 and the landslide failure on the 24\(^\text{th}\) January 2012. The pre-failure slope conditions, including bedding-plane orientation and angle, the steep angles of slope and reduced vegetation cover, as well as the numerous drainage channels, were contributory factors which were likely to enhance rather than restrain a failure at the location. The additional anthropogenic activities would also have served to enhance the landslide susceptibility, although there were clearly attempts made to reduce the impact of quarrying through modifications made at the site (D’Appolonia S.p.A., 2011b). As this is a complex, deep-seated failure, there is no single factor which can be identified as a trigger to this event; rather a number of factors which, combined, enhanced the slope’s susceptibility to failure.
6. Characterising topographical and lithological controls on landsliding in PNG
Abstract

To fully understand landslide hazard, consideration of both the potential triggers (rainfall, earthquakes) and the environmental control factors is essential. There has been a substantial volume of research developing and validating approaches for landslide susceptibility analysis. In the majority of cases susceptibility maps are produced using geo-information and geographic information system (GIS) tools. In this chapter, satellite and airborne techniques are used to develop new landslide inventory maps for two case study domains in PNG. Ultimately, the sample size of events in each domain were increased substantially (n=191 in Western Province and n = 366 in Chimbu Province). Using these newly mapped landslides, the dominant control factors for each case study area were identified through frequency ratio analysis. The generation of fuzzy membership maps, based on the frequency ratio statistics, allowed fuzzy relation-based modelling of landslide susceptibility to be completed for a range of different control factor combinations. The best maps for each case study region were identified through 2x2 contingency table analysis. Model 2-3 was found to perform the best for Western province, with ~ 75% of all forecasts being correct. In Chimbu Province, Model 1-3 was found to perform the best overall with ~ 72% of all forecasts being correct.
6.1 Introduction

Landslide susceptibility is broadly defined as the likelihood of a landslide occurring in a specific area based on the local terrain conditions of that area (Brabb, 1984). This typically involves a two step process whereby: (1) landslides are identified and classified within a historical landslide inventory and (2) environmental causal factors (or event control factors) are identified and classified for the different landslide types and integrated to produce a landslide susceptibility map. Although it was possible to identify landslide-triggering events and collate them into a landslide inventory for PNG using archived data sources (Chapter 3), the limitations induced by the necessary selection criteria and sparse data availability, meant that the sample size was severely restricted. Therefore, alternative methods to develop a broader landslide inventory map for PNG were explored in this chapter.

6.1.1 Approaches for landslide identification and classification

Typically the development of landslide inventory maps involves depicting the location, extent and types of landslides which have left visible features in the landscape (Malamud et al., 2004b). In conventional methods, this has involved interpreting landscape features from stereoscopic aerial photographs, where expert interpreters use a range of different features (e.g. shape, size, texture) to identify and map landslide scars (Van Westen, 2004; Guzzetti et al., 2012; Mondini et al., 2013). The identified landslides are then validated through field investigations (Martha et al., 2013). This technique, although robust, is difficult to apply to large areas and regions which are very remote or inaccessible due to, for example, dense rainforest cover. There has therefore been a move towards the use of remote sensing techniques, which generally allow for rapid assessments to be made over greater areal extents. A range of satellites
and sensors have been used for this purpose and are documented in the research literature. Typically very high resolution imagery (e.g. Quickbird, Ikonos (Nichol and Wong, 2005; Petley et al., 2002), CARTOSAT-1, CARTOSAT-2 and Spot-5 (Moine et al., 2009)) allows the greatest numbers and types of landslides to be identified (Van Westen et al., 2008). However, the costly nature of these datasets inhibits large-scale, spatial and temporal analysis. Therefore, coarser resolution datasets acquired from LANDSAT and/or ASTER, which are freely available, provide a more economic assessment of landslide hazard across large areas. These satellites and their sensors have proven to be effective in identifying larger magnitude landslide scars and the high-density scars associated with earthquakes (Greenbaum et al., 1995). They also offer the opportunity to use multi-spectral data. This takes advantage of the different spectral characteristics of surface types, such as bare earth, dense forest, cropland etc. and uses these classifications to indicate possible landslide sites (Huang and Li, 2009; Whitworth et al., 2005). Two approaches of multi-spectral analysis are widely employed.

1) The first uses raw sensor data (DN values), available across a variety of electromagnetic spectral band widths, to identify the spatial distribution of pixels associated with bare earth and other landslide characteristics. This is traditionally completed by generating colour composite images (FCC; Chapter 3) for each satellite acquisition data, using specific combinations of bands to draw out and identify the likely landslide pixels (Greenbaum et al., 1995).

2) The second method assesses changes in the spatial distribution of spectral signatures across multiple, temporally-varying images (change detection; Lu et al., 2011; Basith et al., 2010; Cheng et al., 2004).

Both of these approaches are predominantly conducted on a pixel-basis, which can preclude landslide features from having realistic morphometry. In addition, it is
difficult from these spectral-based approaches to easily distinguish the source area of
the landslide from the deposition area, due to the coarse nature of the data (typically ~30
m). This is an important aspect of landslide classification prior to susceptibility analysis
because the assessment of event control factors for the deposition area would not
necessarily represent the control factors found at the source area, which encouraged the
failure. This issue is being addressed by the emerging and growing use of high
resolution DEM datasets which are based on Light Detection and Ranging (LiDAR) and
Synthetic Aperture Radar (SAR) interferometry (Haneberg et al., 2005; Jaboyedoff et
al., 2012; Bürgmann et al., 2000). These applications have the ability to identify high
resolution, geomorphologic characteristics of landslides (Lin et al., 2014) and to
monitor the deformation rates of unstable slopes. Terrestrial-based LiDAR for example,
has been used extensively to monitor the Åknes rockslide in Western Norway
(Oppikofer et al., 2009) and the collapse of the eastern flank of the Eiger in the Swiss
Alps (Oppikofer et al., 2008). These approaches have also been used to map the
geological structures of unstable slopes (Sturzenegger and Stead, 2009; Lato et al.,
2012), to identify regions likely to fail in the near future. In addition, both technologies
can also be fitted to aircraft for airborne data collection. In these instances, larger areas
can be mapped quickly, at high resolution. The production of detailed DEMs allows
landslides to be identified by their geomorphic characteristics. This approach has
proven particularly successful for identifying large-scale landslides, with features such
as: (1) cracks and fractures above the crown, (2) arcuate head scarps, (3) step-like
deposition features associated with backward tilting and (4) the bulging, undulating and
blocky textures associated with the deposited mass (Fig. 6.1; Lin et al., 2014; Varnes,
The use of both LiDAR and SAR are therefore important additional techniques, which reintroduce some of the intuitive analysis, traditionally completed by expert interpreters of aerial photographs, into the more modern, semi-automatic landslide identification process (van Westen et al., 2008). The techniques are further advantageous because they are able to penetrate both cloud and dense forest cover. This makes the approach ideal for use in tropical regions. The major draw-back however, is that the data can be expensive to collect and process, and depending on the mode of collection (satellite, airborne or terrestrial) the repeat cycle time of data acquisition can be very long, meaning that multi-temporal analysis is difficult.

6.1.2 Methods for landslide susceptibility modelling

In almost all the recent landslide susceptibility research, the two step susceptibility process has been completed using Geographical Information System (GIS) and Remote Sensing tools (Van Westen, 2004). This has increased the speed with which landslide susceptibility maps can be created and has allowed the first global susceptibility maps to be produced (Hong et al., 2007). Due to the complexity of many landslide processes, a wide range of terrain variables are typically used to explain the causal or event-controlling factors important for slope movement. Such preparatory variables include slope, curvature, aspect, lithology, soil, land cover and hydrology (Dai and Lee, 2002; Van Westen et al., 2008). As evident in the analysis conducted in
Chapter 5, determining the degree to which each variable may enhance or reduce the likelihood of landslide occurrence is challenging. In a number of approaches, all available data sources are used, with little consideration of the “true” influence each factor has on landslide initiation. However, Fabbri et al. (2003) found that greater numbers of data layers did not improve the accuracy of resultant susceptibility maps for a case study area in Portugal. Therefore, it is important to assess which event control factors are most important for the observed landslides in the area of study.

The production of susceptibility maps requires a method to combine the geospatial event control factors into a single output that can be used for decision making. Numerous techniques have been documented within the research literature, with Guzzetti et al. (1999) providing a good overview of the techniques employed and their limitations and assumptions. In brief, these techniques include:

1. qualitative methods of categorising landslide susceptibility using expert evaluation (Dahl et al., 2010) and
2. quantitative methods to generate a numeric scale of landslide susceptibility.

Quantitative approaches are generally easier to reproduce and can be quantitatively validated. Methods which are regularly used as part of the quantitative approach include: (1) weighted linear combination (WLC; Hong et al., 2007; Ayalew et al., 2004), (2) multivariate logistic regression (Lepore et al., 2012), (3) Bayesian inference (Mondini et al., 2013), (4) frequency ratio approaches (Lee et al., 2007; Lee and Pradhan, 2006) and (5) process-based models with expert judgement (Muthu and Petrou, 2007). More recent methods include data mining, fuzzy logic and neural network models. From these approaches the combination of event control factors most relevant to initiate landslides in a certain area can be determined and susceptibility maps produced.
In PNG landslide susceptibility analysis has primarily been completed at the slope or catchment scale. The work by Greenbaum et al. (1995) is the most extensive susceptibility research conducted in the region, focussing on the Finisterre range. The major aims of their analyses were to identify methods that could be applied rapidly to large areas, while remaining cost effective. This remains a critical requirement for any approach being used in PNG and any method which looks to address landslide susceptibility at a regional scale, as this thesis does. In this chapter therefore, satellite and airborne techniques were employed to generate a new set of landslide event maps for two case study regions in PNG. The spatial occurrence of these landslides was then analysed relative to a range of event control factors to establish which variables and combinations of variables were most appropriate for inclusion in a susceptibility model. Using fuzzy logic approaches, susceptibility maps were then produced using the best combinations of control factors for each case study region.

### 6.2 Overview of case study regions

For this analysis, two case study regions have been selected to examine the causal factors related to landslides. One case study area lies in Western Province, while the other lies in Chimbu Province (Fig. 6.2). These areas were selected because they represent regions with different geology, climatology, levels of seismicity and anthropogenic activity, which affect denudation rates and the greater or lesser importance of different causal factors. Each case study domain represents an area of approximately 2300 km². Fig. 6.2 outlines the geology, geomorphology and rainfall climatology of the two case study domains.
Fig. 6.2. Geology, geomorphology and rainfall climatology for case study areas in Western Province (CS1) and Chimbu Province (CS2).
6.3 Satellite and airborne data analysis for landslide identification

The original landslide inventory outlined in Chapter 3 (section 3.3) was constrained by the scarcity of landslide records and the need for each landslide-triggering event to have a verifiable date. This was an essential criterion so that representative rainfall could be analysed and probabilistic rainfall thresholds produced (Chapter 4). Given that the exact date of landslide occurrence is less of a concern for the landslide susceptibility analysis, new maps of landslide scars and deposits were produced for each case study area. Landslides were identified using both multi-spectral and SAR methods, so that both shallow and more deeply-seated landslides could be captured. Both techniques were required for this process because shallow landslides are most easily identified through multi-spectral methods; while the morphological characteristics of larger-scale landslides are easier to identify using high resolution DEMs (Van Den Eeckhaut et al., 2005). The data required and the methods used are outlined in the following sections.

6.3.1 Satellite material and processing

6.3.1.1 Landsat satellite images

To map landslide scars, a series of Landsat-5 TM and Landsat-7 ETM+ images were used. As completed in Chapter 3, images were obtained from the EROS data centre and downloaded from the USGS GLOVIS website. The selection of each image was based on the following criteria: (1) minimum cloud cover (< 30%) over the entire scene, (2) least amount of cloud cover over the case study domain area and (3) only one image per 6 months was kept for the purpose of change detection analysis. Table 6.1 shows the selected Landsat images used for each case study domain, based on an examination of the available images acquired between 1985 and 2010. All bands for
each scene were clipped and re-projected to a local geographic coordinate system (WGS_1984_UTM_Zone_55s), to produce a subset of data corresponding to the domain areas of each case study region.

<table>
<thead>
<tr>
<th>Western Province (path/row = 100/64)</th>
<th>Chimbu Province (path/row = 98/64)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Acquisition Date</strong></td>
<td><strong>Cloud Cover</strong></td>
</tr>
<tr>
<td>23/04/1989</td>
<td>12%</td>
</tr>
<tr>
<td>26/04/1990</td>
<td>17%</td>
</tr>
<tr>
<td>13/02/1993</td>
<td>4%</td>
</tr>
<tr>
<td>10/01/1998</td>
<td>9%</td>
</tr>
<tr>
<td>08/01/2000</td>
<td>19%</td>
</tr>
<tr>
<td>19/04/2002</td>
<td>29%</td>
</tr>
<tr>
<td>28/02/2004</td>
<td>10%</td>
</tr>
<tr>
<td>20/10/2008</td>
<td>9%</td>
</tr>
<tr>
<td>08/01/2009</td>
<td>7%</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6.1. Landsat-5 TM and Landsat-7 ETM+ images used for multi-spectral landslide identification

6.3.1.2 Landsat satellite image pre-processing

6.3.1.2.1 FCC image production

There are a number of approaches which can be used to detect landslides from multi-spectral data. The method employed in Chapter 3 to spatially verify the landslides held in the PNG landslide inventory (Greenbaum *et al.*, 1995), proved to be successful in identifying additional landslide scars (Fig. 3.6). In this approach FCC images were produced using bands 4 (near infrared; reflected: 0.75-0.90 \( \mu m \)), 5 (mid-infrared; reflected: 1.55-1.75 \( \mu m \)) and 7 (mid-infrared; reflected: 2.09-2.35 \( \mu m \)), allowing bare rock (dark blue tones) to be differentiated from vegetated slopes (red tones). Other combinations of bands have also shown success, including the use of bands 5, 4 and 2 (green; reflected: 0.52-0.60 \( \mu m \); Petley, 2002). Based on this, the decision was made to generate two sets of FCC images (a 457 composite and a 542 composite) per acquisition date (Table 6.1), for both case study areas using ERDAS Imagine 2013 software (Fig. 6.3).
Fig. 6.3. FCC images (acquired 19/04/2002) for the Western Province case study domain area with (a) showing a 542 band combination and (b) showing a 457 band combination. The colours associated with different features are illustrated in insets A1, A2, B1 and B2 where settlements (Tabubil) and landslide scars are labelled and green vegetated areas and rivers are illustrated by green and purple tones (FCC 542) and red and blue tones (FCC 457), respectively.

Although FCC image analysis has proven very successful for the identification of recently failed landslides, where a significant amount of the surficial material has been removed from the slope, the method is less successful for identifying slower moving failures or those which displace material over very small distances. However, additional satellite-based techniques can be used to complement FCC image analysis including the use of the Normalized Difference Vegetation Index (NDVI) and Tasselled Cap Transformations (TCT). Both of these techniques have proven useful for landslide identification and classification (Basith et al., 2010; Petley and Bulmer, 2004) by effectively identifying land use change over multi-temporal satellite scenes, particularly changes in the distribution, stress-level and moisture content of vegetated areas. In order
for these image enhancement methods to be used effectively a number of pre-processing steps were completed. These steps include:

1. converting the raw image DN values to physical units of reflectance
2. producing NDVI images using specific spectral bands and
3. generating TCT images for brightness, greenness and wetness.

The conversion from DN values to reflectance is crucial for multi-temporal and multi-spectral analysis because it helps to remove variations between different satellite images. These differences can arise because of variations between the sensors used to capture information, the Earth-sun distance and the solar zenith angle (caused by different acquisition dates and overpass times). The methods and data used to complete these steps are outlined over the following sections.

6.3.1.2.2 Pre-processing for NDVI and TCT image production

The majority of the scenes obtained for this analysis use the Landsat 5 TM sensor. In order for TCT images to be produced effectively, these data need to be converted to the equivalent values of the Landsat 7 ETM+ sensor. This is because the transformation coefficients developed by Huang et al. (2002) for TCT analysis are applicable to ‘Top of Atmosphere’ (TOA) reflectance data from Landsat 7 ETM+. Although coefficients have been developed for Landsat 5 TM (Crist and Cicone, 1984; Crist, 1985), they have been based on ground measurements which only observe slight atmospheric effects. Therefore, these earlier coefficients cannot be applied to Landsat data unless it has been atmospherically corrected. There are however, numerous uncertainties associated with atmospheric correction algorithms, including the lack of ground and atmospheric data over wide areas which are necessary to perform the correction (Cohen et al., 2001). This is a particular issue for PNG. Therefore, the use of an ‘at-satellite’ or TOA transformation is more appropriate for this analysis. To convert from Landsat 5 TM DN
values, a similar approach to that described by Vogelmann et al. (2001) is used in conjunction with the following expression:

\[ \text{DN7} = (\text{Slope} \times \text{DN5}) + \text{intercept} \quad \text{EQ. 6.1} \]

where \( \text{DN7} \) is the Landsat 7 ETM+ equivalent DN values and \( \text{DN5} \) is the Landsat 5 TM DN values. The slope and intercept represent band-specific coefficients, shown in Table 6.2 and are the inverse of those provided by Vogelmann et al. (2001). This step is completed only where Landsat 5 TM data is being used.

<table>
<thead>
<tr>
<th>Band</th>
<th>EQ 6.1 coefficients</th>
<th>EQ 6.2 coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope</td>
<td>Intercept</td>
</tr>
<tr>
<td>1</td>
<td>0.943</td>
<td>4.21</td>
</tr>
<tr>
<td>2</td>
<td>1.776</td>
<td>2.58</td>
</tr>
<tr>
<td>3</td>
<td>1.538</td>
<td>2.50</td>
</tr>
<tr>
<td>4</td>
<td>1.427</td>
<td>4.80</td>
</tr>
<tr>
<td>5</td>
<td>0.984</td>
<td>6.96</td>
</tr>
<tr>
<td>7</td>
<td>1.304</td>
<td>5.76</td>
</tr>
</tbody>
</table>

**Table 6.2.** Coefficients required for EQ 6.1, where Landsat-5 TM data are converted to Landsat-7 ETM+ equivalent, and for EQ 6.2, where DN values are converted to radiance values (Chander et al., 2009)

Following this initial conversion, TOA reflectance values were generated using a two-step process. The first step involved converting the DN values into radiance values using the gain and bias method (EQ. 6.2):

\[ L_\lambda = (G_{\text{rescale}} \times \text{DN7}) + B_{\text{rescale}} \quad \text{EQ. 6.2} \]

where:

- \( L_\lambda \) = spectral radiance at the sensors aperture in watts/(meter squares*ster*µm)
- \( G_{\text{rescale}} \) = rescaled gain in watts/ (meter squares * ster * µm)
- \( \text{DN7} \) = the Landsat 7 ETM+ DN values (or the equivalent calculated in step 2)
- \( B_{\text{rescale}} \) = rescaled bias in watts/ (meter squares * ster * µm)
The band specific gain and bias coefficients are shown in Table 6.2 (Chander et al., 2009). The second step of the process involved converting the radiance values to TOA reflectance values using equation 6.3:

\[ \rho_\lambda = \frac{\pi d^2 L_\lambda}{E_{\text{sun}} \cos \theta_s} \]  

where:

- \( \rho_\lambda \) = planetary reflectance (unitless ratio)
- \( L_\lambda \) = spectral radiance at the sensors aperture
- \( d \) = Earth-Sun distance in astronomical units
- \( E_{\text{sun}} \) = band-specific mean solar exoatmospheric irradiances in watts/(meter squares * ster * µm)
- \( \theta_s \) = solar zenith angle in degrees

\( L_\lambda \) are the radiance values calculated using equation 6.2, while \( E_{\text{sun}}, d \) and \( \theta_s \) are all values which can be obtained from look-up tables or the image metadata file. Firstly, the mean solar exoatmospheric irradiances were obtained for each band from the Landsat 7 Science Data Users Handbook (http://landsathandbook.gsfc.nasa.gov/data_prod/prog_sect11_3.html). \( d \) and \( \theta_s \) are scene specific variables, affected by the day of the year and the time of day that the image was acquired. The solar elevation angle (\( \theta_s \)) and the day of the year for the specific image acquisition date were found in the satellite image header file. The Earth-Sun distance was then obtained by referring to the look-up table provided by Chander et al., (2009), using the day of year value.

6.3.1.2.3 NDVI image production

The NDVI (Fig. 6.4) is used to assess changes in the distribution and health of vegetated areas, using the visible and near-infrared bands of the electromagnetic
6| Characterising topographical and lithological controls on landsliding in PNG

spectrum. To compute the NDVI, the TOA reflectance values from bands 3 and 4 are used in conjunction with equation 6.4:

\[
NDVI = \frac{NIR_{Band4} - RED_{Band3}}{NIR_{Band4} + RED_{Band3}}
\]

where \(NIR_{Band4}\) represents the TOA reflectance values of band 4 and \(RED_{Band3}\) represents the TOA reflectance values of band 3. NDVI values range from -1 to 1, with extremely negative values representing deep water, values around 0 representing bare soil and values of 0.6 and above representing dense green vegetation.

**Fig. 6.4.** Landsat satellite image (a) showing the NDVI (b) the FCC 542 image and (c) a classified NDVI, to illustrate values typically associated with bare earth areas in PNG. Landsat satellite scene acquired on 13/02/1993 for the Western Province case study area
The NDVI data were then classified to draw out values which are typically associated with bare earth areas. During this classification it became evident that cloud cover within the images could influence the accurate identification of landslide scars. Therefore, a basic cloud mask was used to reduce the amount of cloud cover being captured within the classification. However, even with this mask, some of the outline edges of the cloud cover remained within the NDVI image and showed values similar to that for bare earth pixels (Fig. 6.4). For this reason, further analysis of the NDVI data needed to be conducted cautiously. A review of the geometry of a cluster of classified pixels could usually distinguish those areas associated with cloud cover from those areas associated with bare soil and/or a potential landslide scars. This was a time consuming process and therefore, the NDVI was used predominantly for cross-validation purposes, rather than being used as a ‘stand-alone’ landslide identification tool.

6.3.1.2.4 Tasselled Cap Transformations (TCT)

TCT is a method used to enhance and compress the spectral information content of Landsat TM data. It takes advantage of the spectral properties of different surfaces, such as vegetation or bare soil, and uses orthogonal transformation to produce weighted sums of reflectance along three primary axes (Kauth and Thomas, 1976; Crist and Kauth, 1986). The first component is brightness, which accounts for the majority of variability in the satellite image, and is associated with bare soil or sparsely-vegetated areas (Fig. 6.5(a)). Orthogonal to the first component, the second component is greenness which is associated with green vegetated areas (Fig. 6.5(b)), while the third component is wetness, which is related to soil moisture and water (Fig. 6.5(c)). To compute these components the following equation is used:
Characterising topographical and lithological controls on landsliding in PNG

\[ \text{tas}. \text{cap}_i = (\text{coeff}_1 \times \text{band}_1) + (\text{coeff}_2 \times \text{band}_2) + (\text{coeff}_3 \times \text{band}_3) + (\text{coeff}_4 \times \text{band}_4) + (\text{coeff}_5 \times \text{band}_5) + (\text{coeff}_7 \times \text{band}_7) \]

EQ 6.5

where \( \text{tas}. \text{cap}_i \) is the calculated tasseled cap index for brightness, greenness and wetness depending on which band specific coefficients, given by Huang et al., (2002; Table 6.3) are used. The band variables are the TOA reflectance values for each band, calculated in equation 6.3.

<table>
<thead>
<tr>
<th>TCT Index</th>
<th>Coefficient (Band 1)</th>
<th>Coefficient (Band 2)</th>
<th>Coefficient (Band 3)</th>
<th>Coefficient (Band 4)</th>
<th>Coefficient (Band 5)</th>
<th>Coefficient (Band 7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brightness</td>
<td>0.3561</td>
<td>0.3972</td>
<td>0.3904</td>
<td>0.6966</td>
<td>0.2286</td>
<td>0.1596</td>
</tr>
<tr>
<td>Greenness</td>
<td>-0.3344</td>
<td>-0.3544</td>
<td>-0.4556</td>
<td>0.6966</td>
<td>-0.0242</td>
<td>-0.2630</td>
</tr>
<tr>
<td>Wetness</td>
<td>0.2626</td>
<td>0.2141</td>
<td>0.0926</td>
<td>0.0656</td>
<td>-0.7629</td>
<td>-0.5388</td>
</tr>
</tbody>
</table>

Table 6.3. Band specific coefficients required for TCT for brightness, greenness and wetness indices (Huang et al., 2002)

Fig. 6.5. (a) Brightness, (b) Greenness and (c) Wetness indices produced using the TCT equation (EQ 6.5) and the appropriate coefficients in Table 6.3.
6.3.2 GeoSAR material and processing

GeoSAR is a single-pass, dual frequency, interferometric radar mapping system. X- and P-band data are collected simultaneously in 10-14 km wide swaths, at a height of between 10,000 to 12,500 m using a Gulfstream-II jet aircraft. The X-band (9630-9790 MHz) frequency provides a record of the first surface, recording scatter from vegetation and other surfaces. The P-band (270-430 MHz) frequency records the substructure of the underlying surface as it is able to penetrate vegetation. Both bands record data at high spatial resolution, (P-Band data have spatial resolutions of 5 m, while X-band data have spatial resolutions of 3 m) but due to costs and logistics of producing the data, the temporal frequency is usually very low. In the case of PNG, one mapping project to collect this high resolution data was completed in 2006, however there has not been a repeat set of overpasses since this date. Despite this low temporal frequency, the availability of high resolution P-band data offered great advantages for the identification of large-scale landslides in PNG, through an assessment of morphology and structural features consistent with more deeply-seated landslides (Van Den Eeckhaut et al., 2005; Tarolli et al., 2012; Lin et al., 2014; Fig. 6.1).

Prior to the identification of landslide features, the individual 10-14 km swaths of XYZ GeoSAR data needed to be processed to obtain a single DEM representative of the case study areas. Each tile (12 per case study domain) was reformatted from ASCII text format to gridded datasets using ‘Surfer’ software and the kriging interpolation method. The gridded datasets were then mosaicked together, with the overlapping edges processed through bilinear interpolation, to produce a single DEM representative of the case study area. Once these data existed as a single file, shaded relief maps were produced (Fig. 6.6).
Fig. 6.6. Shaded relief maps of the (a) Western Province and (b) Chimbu Province case study domains.

6.3.3 Integrating satellite and airborne techniques for the identification of landslides

Fig. 6.7 outlines how the different multi-spectral and DEM analysis methods were used and integrated to produce the new landslide inventory maps for the Western and Chimbu Province case study regions.
Fig. 6.7. Schematic illustration of the method used to generate a single landslide occurrence map, based on multi-spectral and DEM image analysis.
The FCC, NDVI and TCT images make up the multi-spectral and multi-temporal component of the landslide identification methodology. The FCC images were primarily used to identify pixels which have DN values consistent with previously identified active landslides (FCC; Chapter 3; Petley, 2002), while the NDVI images identified spectral signatures consistent with bare earth or stressed and/or minimal vegetation cover (NDVI). The FCC images identified landslide scars within each Landsat image, separately. The output was an aggregated shapefile of FCC-derived landslide polygons based on all the satellite acquisition dates (Table 6.1). The NDVI and TCT images are then used to identify pixels that change classification (i.e. change from vegetated to bare earth or from bare earth to vegetated pixels) between the image acquisition dates. Pixels which change classification could indicate landslides which have occurred at some point between the times the two images were collected (e.g. Basith et al., 2010; Nichol and Wong, 2005). In these instances, the changed pixels were extracted from the NDVI and TCT images and used to support the FCC landslide identification method. Of course, there was also the possibility that classification changes were occurring associated with agricultural practices. In the Western Province case study area, the agricultural practices are largely subsistence farming through the use of food gardens. Ohtsuka (1994) found that these gardens were normally located within 1 or 2 km of the village settlements which they support. Therefore areas identified as showing significant changes in classification, with the potential to be landslide scars, were further cross-referenced with settlement data provided by PNG MRA. Any cluster of pixels thought to be a possible landslide scar and lying in close proximity to a settlement, could then be visually assessed based on the pixel-cluster’s shape and size to determine whether the classified pixels were more likely to be associated with landslide activity or agriculture.
In Chimbu Province, this was more problematic. Firstly, the valleys within the case study domain are far more densely populated than observed in Western Province. Therefore, there is a higher density of food gardens required to support the communities there. Secondly the Highlands Highway, a well established trade route which runs from Lae City into the Highlands, traverses through the case study domain. There is therefore a greater diversity of farming practices in this area, including commercially grown crops, such as coffee. In the majority of cases, there was ambiguity around the identification of landslide polygons in areas close to villages, particularly if there were only 2 or 3 pixels assigned to the landslide classification. Only in cases where there was a clear, dense cluster of pixels associated with the landslide classification were the polygons retained. In all other instances, polygons were disregarded from the final multi-spectral, landslide inventory maps.

Adjacent to the multi-spectral, multi-temporal analysis, a method to derive landslide polygons from shaded relief maps was also investigated. In this approach, larger-scale landslides were identified using maps generated with eight different sun azimuth angles (45°, 90°, 135°, 180°, 225°, 270°, 315°, 360°) and a consistent sun elevation of 45° (Lin et al., 2014). The use of different aspects allowed different distinct characteristics of the landslides to be observed. It also provided a means of cross-referencing some of the more difficult to identify features under different light conditions. This was particularly useful in the steep, narrow valleys observed in Chimbu Province. In conjunction with the shaded relief maps, high resolution slope maps were generated for each case study region. These provided additional evidence for features such as the landslide toe region, where swelling and bulging can often be observed (Fig. 6.8(b); Lin et al., 2014; Martha et al., 2010). The shaded relief maps were also draped over high resolution elevation data in a 3D environment, so that the features
could be put into context within the wider topography. This also allowed terrain profiles of possible landslide deposit to be generated (Fig. 6.8(c)). These additional techniques helped to identify further landslide features such as the related sliding blocks and minor scarps which can be present in larger, rotational failures (Fig. 6.8; Lin et al., 2014).

Fig. 6.8. A large-scale landslide identified in the Western Province case study area where (a) shows the shaded relief map (sun azimuth 315°) with the landslide head scarp (orange dotted line) and gully erosion features (green dotted line) highlighted. While (b) shows the slope map for the same geographical area and (c) is the slope profile for line A-A’ shown in a (red dashed line).

The separate polygon files output from the multi-spectral analysis and the DEM analysis were appended together to produce a single landslide polygon file for each case study area (Fig. 6.9). As part of the mapping and identification process, it was also necessary to identify the landslide initiation location for each landslide. This involved identifying the upslope end of each polygon and digitizing (as a linear feature) the landslide head scarp (Fig. 6.9). It was also important to gain basic information on the
mapped landslides. This included calculating the area of the landslide polygons and the length and orientation of the landslide head scarps.

Fig. 6.9. Mapped landslide polygons (red outlines with hashed interiors) and head scarps (black lines) for Western Province (top panel) and Chimbu Province (bottom panel), based on multi-spectral and DEM analysis outputs. Both sets of mapped landslides are overlain on high resolution shaded relief maps (sun azimuth 315°).
The multi-spectral and DEM approaches proved to be very successful for identifying additional potential landslide scars in the two case study areas. 191 potential landslides were mapped in the Western Province case study area and 366 were identified in the Chimbu Province case study area. This substantially increased the number of potential landslides available for susceptibility analysis. Furthermore, a greater range of landslide types and sizes were identified. This is important as it allows control factors associated with different failure mechanisms and environments to be analysed and captured. Ultimately this should produce a better representation of the landslide hazard in the two case study areas. Although, the techniques proved successful in identifying additional potential landslide scars, it should be noted that there has been no field investigations conducted to verify the locations of these scars. In some instances, it was possible to cross-reference events against the pre-defined landslides in the PNG inventory. However, this was only possible for a very small number of cases. The total numbers of landslides in each area are still likely to be underestimated, as both the multi-spectral and DEM methods are not very effective at identifying small-scale failures (Lin et al., 2014; Petley, 2002).

6.4 Topographical and lithological control factors for landslides

In order to determine the topographic and lithological controls that contribute to landslide susceptibility, a number of different geospatial datasets needed to be examined. As in the earlier rainfall analysis (Chapter 4), it was important to investigate these datasets across areas where landslides have been observed and areas where landslides have not been observed. This allows event control factors associated with landslides to be differentiated from the general geomorphology of the area. Furthermore, to develop accurate susceptibility maps, the control factors of greatest relevance to landslides need to be determined for the different geological and
geomorphological settings of the case study domains. Therefore, a range of control factors were analysed relative to the mapped landslides (Fig. 6.9), to assess the ‘reliability’ of each event control factor for use within a landslide susceptibility model (Greenbaum et al., 1995). The geospatial data used to complete this analysis are shown in Table 6.4.

<table>
<thead>
<tr>
<th>Data – Main type</th>
<th>GIS data layer</th>
<th>GIS data format</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide Inventory</td>
<td>Landslide areas</td>
<td>Polygons</td>
<td>Multi-spectral &amp; DEM interpretation</td>
</tr>
<tr>
<td></td>
<td>Landslide head scarps</td>
<td>Polyline</td>
<td>Multi-spectral &amp; DEM interpretation</td>
</tr>
<tr>
<td>Terrain</td>
<td>Elevation</td>
<td>Raster</td>
<td>GeoSAR DEM</td>
</tr>
<tr>
<td></td>
<td>Slope</td>
<td>Raster</td>
<td>GeoSAR DEM</td>
</tr>
<tr>
<td></td>
<td>Aspect (slope direction)</td>
<td>Raster</td>
<td>GeoSAR DEM</td>
</tr>
<tr>
<td></td>
<td>Plan curvature</td>
<td>Raster</td>
<td>GeoSAR DEM</td>
</tr>
<tr>
<td></td>
<td>Profile curvature</td>
<td>Raster</td>
<td>GeoSAR DEM</td>
</tr>
<tr>
<td>Geology</td>
<td>Rock type</td>
<td>Raster</td>
<td>1:250,000 scale geology map (PNG MRA)</td>
</tr>
<tr>
<td></td>
<td>Lithology</td>
<td>Raster</td>
<td>1:250,000 scale geology map (PNG MRA)</td>
</tr>
<tr>
<td>Linear structures</td>
<td>Lineaments</td>
<td>Polyline</td>
<td>Satellite-derived, automatic processing (PCI Geomatica)</td>
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<td></td>
<td>Drainage (Rivers)</td>
<td>Polyline</td>
<td>PNG MRA Province data</td>
</tr>
<tr>
<td>Environmental</td>
<td>Land cover</td>
<td>Raster</td>
<td>AVHRR Global Land Cover Facility (GLCF)</td>
</tr>
</tbody>
</table>

Table 6.4. Geospatial datasets used to investigate event control factors for landslides

6.4.1 Terrain-based control factors: data processing

The high resolution GeoSAR DEMs proved to be very useful for identifying larger-scale landslides. However, to better integrate the variable resolutions of the different event control factors (DEM, geology, land cover), the decision was made to resample all the datasets to a common resolution of approximately 160 m. To compare the geospatial datasets across both landslide-affected and non-landslide-affected areas, a pixel/point-based approach was used. In the first instance, this involved converting a single DEM dataset (160 m resolution) to a point shapefile within ArcMAP. Each point represents the centre of a 160 x 160 m pixel, within the case study domain. This point
grid represents a root database, to which all control factor data are appended. Following this, each point was classified based on whether it was associated with landslide areas or not. To do this, all points lying within 150 m of the landslide head scarps were classified with the value 1 (indicating that the point is associated with a landslide initiation region), while all other points were allocated a 0 (indicating that the point is not associated with a landslide initiation region). All landslide depositional areas, shown by the extent of the landslide polygons (Fig. 6.9), were allocated values of 0. This reflects the fact that geospatial data within these deposition zones are unlikely to be representative of the control factors observed at the landslide head scarp, which contributed to the failure.

Following the point-based classification, ArcMap tools were used to generate a range of grid-based, terrain derivatives from the GeoSAR DEMs. These included slope, aspect and plan and profile curvature datasets for each case study area. Profile curvature assesses the degree of concavity or convexity parallel to the direction of maximum slope (Fig. 6.10(a)), while planform curvature (plan curvature) assesses the degree of concavity or convexity perpendicular to the direction of maximum slope (Fig. 6.10(b); Buckley, 2010). Combinations of these two datasets are important for understanding acceleration and deceleration of flow, and for identifying where erosion rates are likely to be higher or lower. Both of these aspects are important for landslide occurrence and landslide risk assessment.
Once all these datasets were produced and extracted to the point file database, frequency distributions, as a percentage of the total area \( f(p_i) \) were generate, and compared against frequency distributions as a percentage of the total landslide-initiation areas \( fl(p_i) \); Coe et al., 2004). Ultimately a ratio \( R(p_i) \) between the two distributions was calculated using the following equation:

\[
R(p_i) = \frac{fl(p_i)}{f(p_i)} \quad \text{EQ 6.6}
\]

where \( p_i \) represents the event control factor (i.e. slope, aspect, etc.). Values of \( R(p_i) \) greater than 1 indicate that there is a higher density of landslide points within the class, than observed in the overall dataset. This suggests that the factor and class are more favourable for landslide occurrence (Coe et al., 2004; Lee et al., 2002; Pradhan, 2011). Table 6.5 illustrates the class ranges used to produce the frequency distributions for each event control factor. The ratio value calculated for each factor and class are also shown, for both the Western and Chimbu Province case study areas.
Table 6.5. Distribution of frequency ratio values for terrain-based event control factors in the Western and Chimbu Province case study areas.

<table>
<thead>
<tr>
<th>Event control factor/class</th>
<th>Western Province case study area</th>
<th>Chimbu Province case study area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of points (domain area)</td>
<td>% of points&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>Elevation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 200</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>400</td>
<td>1,354</td>
<td>1.40</td>
</tr>
<tr>
<td>600</td>
<td>5,765</td>
<td>5.98</td>
</tr>
<tr>
<td>800</td>
<td>6,344</td>
<td>6.58</td>
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<td>8.86</td>
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<tr>
<td>&gt; 3000</td>
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<tr>
<td><strong>Slope</strong></td>
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<td></td>
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<tr>
<td>&lt; 5</td>
<td>9,110</td>
<td>9.44</td>
</tr>
<tr>
<td>10</td>
<td>23,781</td>
<td>24.65</td>
</tr>
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<td>15</td>
<td>23,212</td>
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<tr>
<td>20</td>
<td>16,564</td>
<td>17.17</td>
</tr>
<tr>
<td>Aspect</td>
<td>Flat (0.03 - 0.03)</td>
<td>Convex (+)</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------------</td>
<td>------------</td>
</tr>
<tr>
<td>North</td>
<td>13,622</td>
<td>30,808</td>
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<tr>
<td>North east</td>
<td>12,740</td>
<td>28,366</td>
</tr>
<tr>
<td>East</td>
<td>9,390</td>
<td>17,557</td>
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</tr>
<tr>
<td>North west</td>
<td>17,557</td>
<td>16,861</td>
</tr>
</tbody>
</table>

Table 6.5. Continued.
6.4.2 **Terrain-based control factors: data evaluation**

Based on Table 6.5 and Fig. 6.11, the relative importance of each control factor can be identified. Furthermore, the areas preferentially susceptible to landslides can also be discerned, as discussed below:

(1) **Elevation**: Although there is no identifiable correlation between the elevation control factor and the calculated ratio, for both case study domains, there are class ranges which indicate preferential susceptibility. ~ 76% of landslides were initiated at elevations between 1,000 and 2,400 m in Western Province. Six of the seven elevation classes in this range recorded ratio values greater than 1 indicating that areas with elevations between 1,000 and 2,000 m and between 2,200 and 2,400 m are preferentially susceptible to landslide events (Fig. 6.11(a1)). The 1,600 to 1,800 m class \(R(p_l) = 1.79\) and the 1,800 to 2,000 m class \(R(p_l) = 1.45\)) have the highest calculated ratios and therefore areas with elevations between 1,600 and 2,000 m are the most susceptible to landslides, in this region. In Chimbu province, only four classes had calculated ratio values greater than 1. This is due to the domain lying at generally higher elevations when compared against the Western Province case study area. The four classes equate to an elevation range from 1,800 m to 2,600 m, within which ~ 66% of landslides were initiated. Two of the four classes had notably high ratio values. These were the 2,000 to 2,200 m class \(R(p_l) = 2.07\) and the 2,200 to 2,400 m class \(R(p_l) = 1.99\), indicating that these two elevation classes are particularly susceptible to landslides in Chimbu Province.

(2) **Slope angle**: As might be expected, in Western Province there is a clear positive correlation whereby increases in the slope angle result in higher ratio values (Fig. 6.11(b1)). Ratio values begin to exceed 1 once slope angles increase above 20°, indicating that slope angles greater than 20° are preferentially susceptible to landslides.
and that this preference increases as slope angles increase (up to the maximum ratio value of $R(p_i) = 9.66$, for slope angles greater than $50^\circ$). In contrast, there is little or no correlation observed between the calculated ratio and the slope angle in Chimbu Province (Fig. 6.11(b2)). ~85% of landslides were initiated on slopes with angles between 10 and $40^\circ$, however, preferential susceptibility is only noticeably evident for slope angles between $45$ and $50^\circ$ ($R(p_i) = 3.62$). These findings suggest that slope is a less important control factor for landslide initiation in this region.

Fig. 6.11. Graphs showing the study area frequency distributions (as a percentage of total), landslide area frequency distributions and frequency ratios for event control factors ($p_i$), (a) elevation, (b) slope and (c) aspect. Graphs related to Western Province are shown on the left (a1, b1 and c1) and graphs related to Chimbu Province are shown on the right (a2, b2 and c2). The susceptibility indicator represents where the ratio equals 1. Ratio values greater than this indicate preferred susceptibility in that class.
(3) **Aspect**: As found in previous studies (Greenbaum *et al*., 1995) there appears to be no significant association between aspect and landslide occurrence in either case study area. This is likely to be related to the types of landslides being analysed. Aspect would be considered important if for example, the trigger mechanism was related to the prevailing wind direction, which in turn led to high-intensity rainfall events occurring more frequently on one side of a range than another (Greenbaum *et al*., 1995). In PNG, the prevailing wind direction changes seasonally with the transition of the north-westerly monsoon and localized temperature variations and orography, results in highly variable rainfall accumulations across the highly dissected mountain ranges. Furthermore, the larger-scale landslide events used for this analysis typically have complex triggering mechanisms associated with prolonged rainfall.

(4) **Plan and profile curvature**: These data have been tabulated across three classes each (Table 6.5). One class represents convex terrain, another represents concave terrain and the third flat or linear terrain. For profile curvature (Fig. 6.10(a)), both Western and Chimbu Provinces saw greater than 50% of landslides being initiated on convex slopes. In both cases, the ratio values exceed 1 \( R(p_c) = 1.66 \) for Western Province and \( R(p_c) = 1.63 \) for Chimbu Province), indicating that convex slopes are preferentially susceptible to landslides in both of these regions. Similar results are observed for the plan curvature analysis (Fig. 6.10(b)). In Western Province ~49% of landslides were initiated from convex slopes, while in Chimbu Province ~ 58% of landslides were initiated from convex slopes, resulting in both classes having ratio values greater than 1 \( R(p_i) = 1.36 \) for Western Province and \( R(p_i) = 1.49 \) for Chimbu Province). Although the ratio values of the convex classes indicate preferential susceptibility, the actual variability between the classes is small, suggesting that there is
not a significant difference in landslide susceptibility across the classes of these two event control factors.

### 6.4.3 Lithology and geomorphology-based control factors: data processing

The lithology and geomorphology-based control factors are discussed separately, as these geospatial datasets are not derived from a single DEM, as is the case for the terrain-based control factors. Despite this, the same pixel/point-based approach was used to collate information into the 160 m resolution, point shapefile database used in the previous method. The first control factors to be processed were those based on PNG geological data. The rock type and lithology number were converted from their raw data format (polygon features) to a 160 m resolution raster dataset, using maximum area assignment. This method determines that if there is only one vector feature overlapping the pixel, then it must overlap by greater than 50% for that pixel to be assigned the feature value. If there are multiple features overlapping the cell, the value of the feature with the largest overlapping area is assigned to the pixel. This method produced a single, 160 m gridded rock type dataset for each case study area and a single, 160 m gridded lithology type dataset for each case study area. The rock type number and the lithology number at each pixel in the two domains were then extracted to the point shapefile database.

Structural information, including the proximity of pixels to lineaments (a linear feature at the surface, such as a fault or scarp), is also considered relevant to landslide initiation. Lineaments can be manually digitized or automatically derived from either high resolution DEM data or satellite imagery (Qari, 2011; Mallast *et al.*, 2011). As both case study areas are extensively dissected by drainage features the decision was made to use an automatic lineament extraction algorithm, with PCI Geomatica software. The PCI LINE algorithm consists of edge detection, thresholding and curve extraction.
processing, to derive linear features from different images. To ensure accuracy it was necessary to conduct the lineament extraction process on shaded relief maps with different sun azimuth angles. To do this the eight shaded relief maps, produced for each case study domain during the landslide identification process (Section 6.3.3), were used in conjunction with the PCI LINE algorithm to produce eight separate lineament extraction maps. The values assigned to each parameter used in the algorithm are shown in Table 6.6. A single map of lineament features, for each case study area, was then produced by combining the results of PCI LINE algorithm and removing the duplicate features (Fig. 6.12)

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
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<td>RADI</td>
<td>Filter radius (pixels)</td>
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</tr>
<tr>
<td>GTHR</td>
<td>Edge gradient threshold</td>
<td>100</td>
</tr>
<tr>
<td>LTHR</td>
<td>Curve length threshold (pixels)</td>
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</tr>
<tr>
<td>FTHR</td>
<td>Line fitting error threshold (pixels)</td>
<td>3</td>
</tr>
<tr>
<td>ATHR</td>
<td>Angular difference threshold (°)</td>
<td>30</td>
</tr>
<tr>
<td>DTHR</td>
<td>Linking distance threshold (pixels)</td>
<td>20</td>
</tr>
</tbody>
</table>

**Table 6.6.** Parameter values used by PCI LINE algorithm for automatic lineament extraction

Additional linear features relevant for landslide initiation include drainage networks. PNG MRA has collated Province-based data, such as rivers, settlements, schools, roads and bridges over a number of years and have these datasets mapped in GIS-based software. All major and minor rivers were appended and clipped, based on the case study domain size, to generate a subset of data illustrating the spatial distribution of drainage networks. Distances between each point in the point shapefile database and both sets of linear features (lineaments and rivers) were then calculated using buffer tools in ArcMAP.
The final control factor analysed was land cover. Based on the difficulties associated with making land cover maps in regions of very dense vegetation cover, the decision was made to use the Advanced Very High Resolution Radiometer (AVHRR) land cover dataset at 1 km resolution. These data were produced using AVHRR images acquired between 1981 and 1994, to generate a simplified classification of land cover types across the globe. The data were downloaded from the Global Land Cover Facility (GLCF) website (http://glcf.umd.edu/data/landcover/) and clipped to produce subsets of data for the two case study domains. The land cover value of each grid cell was then extracted to the point shapefile database to sit alongside the other control factor information. Frequency distributions as a percentage of the total area, and as a percentage of the total landslide-initiation areas, were then calculated, as were the frequency ratio ($R(p_i)$) values (EQ6.6; Coe et al., 2004). These are shown in Table 6.7.
Table 6.7. Distribution of frequency ratio values for lithology and geomorphology-based control factors in the Western and Chimbu case study areas

<table>
<thead>
<tr>
<th>Event control factor/class</th>
<th>Western Province case study area</th>
<th>Chimbu Province case study area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of points (domain area)</td>
<td>% of points</td>
</tr>
<tr>
<td>Distance from Lineaments (m)</td>
<td>&lt; 100</td>
<td>9,229</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>9,777</td>
</tr>
<tr>
<td></td>
<td>300</td>
<td>9,358</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>9,167</td>
</tr>
<tr>
<td></td>
<td>500</td>
<td>8,376</td>
</tr>
<tr>
<td></td>
<td>600</td>
<td>7,533</td>
</tr>
<tr>
<td></td>
<td>700</td>
<td>6,761</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>5,707</td>
</tr>
<tr>
<td></td>
<td>900</td>
<td>4,959</td>
</tr>
<tr>
<td></td>
<td>&gt; 900</td>
<td>25,605</td>
</tr>
<tr>
<td>Distance from Drainage (m)</td>
<td>&lt; 200</td>
<td>29,839</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>25,373</td>
</tr>
<tr>
<td></td>
<td>600</td>
<td>17,907</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>10,880</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>5,817</td>
</tr>
<tr>
<td></td>
<td>1200</td>
<td>3,016</td>
</tr>
<tr>
<td></td>
<td>1400</td>
<td>1,490</td>
</tr>
<tr>
<td></td>
<td>&gt; 1400</td>
<td>2,150</td>
</tr>
</tbody>
</table>
### Rock Type

<table>
<thead>
<tr>
<th>Rock Type</th>
<th>Area</th>
<th>Percent of Area</th>
<th>Water Content</th>
<th>Area</th>
<th>Percent of Area</th>
<th>Water Content</th>
<th>Area</th>
<th>Percent of Area</th>
<th>Water Content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-calcareous sedimentary rock</td>
<td>32,549</td>
<td>33.74</td>
<td>1.00</td>
<td>26,081</td>
<td>26.40</td>
<td>33.64</td>
<td>551</td>
<td>33.64</td>
<td>1.00</td>
</tr>
<tr>
<td>Calcereous sedimentary rock</td>
<td>53,752</td>
<td>55.72</td>
<td>1.01</td>
<td>4,928</td>
<td>4.99</td>
<td>56.17</td>
<td>920</td>
<td>56.17</td>
<td>1.01</td>
</tr>
<tr>
<td>Alluvial deposits</td>
<td>8,279</td>
<td>8.58</td>
<td>0.00</td>
<td>13,708</td>
<td>13.88</td>
<td>9.28</td>
<td>152</td>
<td>9.28</td>
<td>0.00</td>
</tr>
<tr>
<td>Igneous rock</td>
<td>1,691</td>
<td>1.75</td>
<td>0.52</td>
<td>34,581</td>
<td>35.00</td>
<td>0.92</td>
<td>15</td>
<td>0.92</td>
<td>0.52</td>
</tr>
<tr>
<td>Metamorphic rock</td>
<td>33</td>
<td>0.03</td>
<td>0.00</td>
<td>19,474</td>
<td>19.71</td>
<td>0.00</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Water</td>
<td>168</td>
<td>0.17</td>
<td>0.00</td>
<td>17</td>
<td>0.02</td>
<td>0.00</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

### Land cover

<table>
<thead>
<tr>
<th>Land cover</th>
<th>Area</th>
<th>Percent of Area</th>
<th>Water Content</th>
<th>Area</th>
<th>Percent of Area</th>
<th>Water Content</th>
<th>Area</th>
<th>Percent of Area</th>
<th>Water Content</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evergreen broadleaf forest</td>
<td>22,366</td>
<td>23.18</td>
<td>0.77</td>
<td>13,876</td>
<td>14.05</td>
<td>17.89</td>
<td>293</td>
<td>17.89</td>
<td>0.77</td>
</tr>
<tr>
<td>Deciduous broadleaf forest</td>
<td>385</td>
<td>0.40</td>
<td>0.76</td>
<td>252</td>
<td>0.26</td>
<td>0.31</td>
<td>5</td>
<td>0.31</td>
<td>0.76</td>
</tr>
<tr>
<td>Woodland</td>
<td>30,962</td>
<td>32.09</td>
<td>0.72</td>
<td>52,921</td>
<td>53.57</td>
<td>23.26</td>
<td>381</td>
<td>23.26</td>
<td>0.72</td>
</tr>
<tr>
<td>Wooded grassland</td>
<td>919</td>
<td>0.95</td>
<td>2.44</td>
<td>21,784</td>
<td>22.05</td>
<td>2.32</td>
<td>38</td>
<td>2.32</td>
<td>2.44</td>
</tr>
<tr>
<td>Open Shrub land</td>
<td>15,050</td>
<td>15.60</td>
<td>1.57</td>
<td>5,166</td>
<td>5.23</td>
<td>24.42</td>
<td>400</td>
<td>24.42</td>
<td>1.57</td>
</tr>
<tr>
<td>Grassland</td>
<td>20,245</td>
<td>20.99</td>
<td>3.71</td>
<td>103</td>
<td>1.42</td>
<td>18.07</td>
<td>296</td>
<td>18.07</td>
<td>0.86</td>
</tr>
<tr>
<td>Cropland</td>
<td>1,967</td>
<td>2.04</td>
<td>0.00</td>
<td>0</td>
<td>0.00</td>
<td>1.34</td>
<td>22</td>
<td>1.34</td>
<td>0.66</td>
</tr>
<tr>
<td>Bare ground</td>
<td>4,578</td>
<td>4.75</td>
<td>0.00</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
<td>203</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Urban and Built</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 6.7. Continued
6.4.4 Lithology and geomorphology-based control factors: data evaluation

Based on the tabulated data in Table 6.7 and the graphical interpretations of the lineament and drainage data (Fig. 6.13), the relative importance of each lithology and geomorphology-based control factor was assessed and the findings discussed below:

![Graphs showing the study area frequency distributions (as a percentage of total), landslide area frequency distributions and frequency ratios for event control factors \( p_i \), (a) distance from lineaments and (b) distance from drainage. Graphs related to Western Province are shown on the left (a1 and b1) and graphs related to Chimbu Province are shown on the right (a2 and b2). The susceptibility indicator represents where the ratio equals 1. Ratio values greater than this indicate preferred susceptibility in that class.]

(1) **Lineaments**: Both case study areas show that there is a clear negative relationship between the calculated ratio and lineament distance (Fig. 6.13 (a1 and a2)). This indicates that as the distance from lineaments increases the landslide susceptibility decreases. When landslide frequency is tabulated in 100 m distance increments, the
highest percentages of landslides (~27% in Western Province and ~25% in Chimbu Province) initiated within 100 m of a lineament feature (Table 6.7). Over the three shortest-distance classes (< 100 m, 100-200m and 200-300m) ~ 57% and ~ 59% of all landslides were initiated in Western and Chimbu Provinces, respectively. This illustrates that for both case study regions, areas within 300 m of a lineament are preferentially susceptible to landslides.

(2) **Drainage:** There is little or no correlation between the drainage distance and the calculated ratio values for both case study areas. For Western Province, there is a tentative indication that as drainage distance increases, the ratio value also increases (Fig. 6.13(b1)). However, this trend was only observed for classes up to 1000 m and on review of the calculated ratio values it was evident that the range of values was small across all of the first 6 classes (from \( R(p_d) = 0.93 \) to \( R(p_d) = 1.35 \)). This suggests that all areas within a distance of 1,200 m of a river are roughly equally susceptible to landslides in Western Province. In Chimbu Province, the highest percentage of landslides (~29%) initiated between 200 and 400 m of a river, with subsequent high percentages of landslides (~23%) initiated between 400 and 600 m of a river. These two classes represent the highest ratio values (\( R(p_d) = 0.93 \) to \( R(p_d) = 1.35 \)) indicating that they are particularly susceptible to landslides, while all areas between 200m and 1,400 m can be considered preferentially susceptible to landslides relative to the remaining classes.

(3) **Rock type:** The rock type data did not provide a significant amount of additional information, particularly for Western Province. The highest percentage of landslides (~56%) initiated in areas with calcareous sedimentary rocks and subsequent high percentages of landslides (~33%) initiated in areas with non-calcareous sedimentary rocks (Table 6.7). However, given the dominance of these rock types
within the domain this is not particularly useful. In Chimbu Province the geology is more variable, allowing clearer distinctions between the rock types to be made. ~ 13% of all initiated landslides occur in areas comprised of calcareous sedimentary rocks; however, only ~5% of points within the entire domain area fall within this class. This results in a ratio value of $R(p_i) = 2.81$, indicating that areas comprised of this rock type are preferentially susceptible to landslides, by some margin compared to other rock types.

4) **Lithology**: This control factor proved more informative than the rock type control factor. In Western Province, 11 of the 31 lithology classes have values greater than 1 (Fig. 6.14(a)) and therefore have preferred susceptibility. The mudstone/siltstone classes (JKi and Jui) show the highest ratio values ($R(p_i) = 3.39$ and $R(p_i) = 2.59$, respectively), with subsequently high ratio values being calculated for sandstone (KTf2 and JKt) and limestone deposits (Tmpf3). This was expected as a number of documented failures have been associated with these units (Fookes and Dale, 1992; Peart, 1991c). The remaining classes with ratio values in excess of 1 (Jb, Jk, KTf1, Kie, Qs2 and Tmd7), are all roughly equally susceptible to landslides, even though ~ 50% of landslides were initiated in areas comprised of Tmd7 (micritic limestone). In Chimbu Province, 6 of the 30 lithology classes have calculated ratio values greater than 1 (Fig. 6.14(b)). Of these, three of the classes relate to limestone lithologies (P-Rk, Teoc and Tmo2), two relate to siltstone units (Jum3 and Tmo1) and the final class relates to a conglomerate of greywacke, sandstone, siltstone and shale (Jlg). Areas comprised of limestone (Teoc) have the greatest susceptibility to landslide occurrence, with a ratio value of $R(p_i) = 3.24$, which is substantially higher than any other lithological unit in the domain. However, the highest percentage of landslides (~ 17%) initiated in areas comprised of Jlg (conglomerate).
(5) **Land cover**: The potential of these data to provide additional information which might enhance a susceptibility map was considered relatively low. This proved largely correct. In Western Province, the majority of classes have ratio values between 0.66 and 0.86. However, 3 of the 9 classes had ratio values greater than 1, indicating that areas of wooded grassland, open shrubland and bare ground were preferentially susceptible to landslides (Table 6.7). In the Chimbu Province areas of deciduous broadleaf forest, woodland and grassland were considered particularly susceptible to landslides, however the actual percentages of landslides initiated in these areas was less than 6%.

### 6.5 Landslide susceptibility maps

The principle aim of susceptibility analysis is to provide information on the spatial variability of control factors relevant to landslide initiation. In this regard, susceptibility
6| Characterising topographical and lithological controls on landsliding in PNG

maps can enhance purely meteorologically-based models (Chapter 4), by providing additional information on slopes that are most susceptible to failure. Ultimately, combining probabilistic rainfall thresholds with susceptibility maps can provide a model that identifies areas where rainfall could trigger landslides and the most susceptible slopes within these areas.

There have been a number of methods used to integrate different geospatial datasets for the development of landslide susceptibility maps. One approach, which is particularly favourable for capturing the uncertainty and variability associated with landslide susceptibility modelling, is fuzzy set theory (fuzzy logic; Zadeh, 1965). This considers the spatial objects within a map as part of a set. In classical set theory (Hines, 1997), an objects membership is either true (= 1), indicating that it is a member of a set, or false (= 0), indicating that it is not a member. This would result in a control factor, such as slope, being considered either important for slope instability (1) or not important for slope instability (0). Fuzzy set theory, however, is based on the concept of partial truth. In this approach a membership function is employed to determine the degree of membership within a set, using any value between 0 and 1 (Pradhan, 2011; Shahabi et al., 2012). Values of 1 indicate full membership while values of 0 represent full non-membership. The values in between 0 and 1, allow different degrees of membership to be assigned to different instability factors.

The presence of various classes within a specific set means that each control factor may have numerous fuzzy membership values associated with it. In addition, any number of different maps can have membership values supporting a single proposition (Bonham-Carter, 1994). In the case of landslide susceptibility the proposition may be “areas prone to landslide hazard”. Any maps used in support of this are assigned fuzzy membership values reflecting the relative importance of each map, and class within
each map, to the proposed proposition. The maps are then combined using one of a range of different fuzzy operators (fuzzy OR, fuzzy AND, fuzzy algebraic product, fuzzy algebraic sum and fuzzy gamma operator). These operators are explained in detail by Bonham-Carter (1994) and Pradhan (2011), while those relevant to this analysis will be explained in detail over the following sections.

6.5.1 Fuzzy membership values for topographical and lithological control factors

The frequency ratio analysis completed in the previous section offers an easy way to generate fuzzy membership values (Table 6.5; Table 6.7). It has already been illustrated that ratio values which are greater than 1 indicate preferred susceptibility, while values less than 1 indicate a lower degree of relationship between the factor/class and landslide events. Therefore, the ratio values already act to represent the degree of membership between factors/classes and landslides. In order to convert these ratios into values which conform to fuzzy set theory, the data are normalized to generate values between 0 and 1 (Pradhan, 2011; Fig. 6.15). This was completed for all control factors and classes where data was available and for both case study areas. The fuzzy membership values were then allocated to the root point shapefile database, so that each point had a fuzzy membership value assigned according to its control factor and class (Fig. 6.15). Once the membership values had been assigned to all points in each case study domain, the data were converted to 160 m resolution, gridded maps (Fig. 6.15). A single fuzzy membership map was created for each control factor and case study area.

Once these gridded data were produced two decisions needed to be made:

1. which control factors best represent conditions favourable for landslides and
2. which fuzzy operator is most applicable for combining the selected control factor maps.
6.5.2 Application of fuzzy logic to PNG case study domains

Pradhan (2011) successfully implemented the fuzzy gamma operator to combine a number of different fuzzy membership maps, for case study areas in Malaysia. In each case, the output maps allowed areas associated with no landslide susceptibility to be differentiated from areas with very high landslide susceptibility. This is essential for useful forecasting and decision-making. The fuzzy gamma operator used by Pradhan (2011) and adopted here is defined as:

$$\mu_{\text{combination}} = (fuzzy \ \text{algebraic sum})^\lambda \times (fuzzy \ \text{algebraic product})^{1-\lambda} \quad \text{EQ. 6.7}$$

where $\lambda$ is a value between 0 and 1 (Zimmerman and Zysno, 1980) and the fuzzy algebraic product is calculated as:
and the fuzzy algebraic sum is calculated as:

\[ \mu_{combination} = \prod_{i=1}^{n} (1 - \mu_i) \quad \text{EQ 6.9} \]

In both equation 6.8 and equation 6.9, \( \mu_i \) represents the fuzzy membership values for the \( i \)-th map where \( i = 1, 2, \ldots, n \) (depending on the number of control factors used). In equation 6.7, \( \lambda \) is a subjectively determined value which when equal to 1, produces fuzzy values equal to the fuzzy algebraic sum (EQ 6.9). When \( \lambda \) is equal to 0, the output of the fuzzy gamma operator is equal to the fuzzy algebraic product (EQ 6.8; Pradhan, 2011). This fuzzy operator proved to be more successful than some of the other operators discussed by Bonham-Carter (1994), as it can be used to compromise between the ‘increasive’ tendencies of the algebraic sum and the ‘decreasive’ tendencies of the algebraic product. This can ultimately result in fuzzy values spread between 0 and 1, rather than producing very small values (as observed when using the fuzzy algebraic product) or very large values (as observed when using the fuzzy algebraic sum) which can make distinguishing different classifications of landslide susceptibility difficult (Pradhan, 2011).

The selection of the fuzzy gamma operator was relatively straightforward based on pre-existing research findings (Pradhan, 2011). However, selecting the most appropriate control factors for use in a susceptibility model was less straightforward. The frequency ratio analysis conducted in section 6.4, identified that all the examined control factors had at least one class with a ratio value greater than 1. This indicates that
at least one class in every control factor showed preferential susceptibility to landslides and that this factor/class was important for landslide initiation. In a number of cases however, it was possible to identify control factors which were particularly strongly associated with landslide occurrence. For example, the correlations observed between slope and the calculated frequency ratio values in Western Province, indicate that this factor is important for landslide susceptibility in this region (Fig. 6.11; Table 6.5).

Based on the analysis completed in section 6.4, it was evident that different combinations and numbers of controls factors may combine to produce maps with different degrees of accuracy. Therefore, the decision was made to test a number of different susceptibility models (using different numbers and types of control factors). In total four models were examined for each case study region. In three of the models, favourable control factors (i.e. those which showed correlation between the factor and the ratio) were used, while the other model acted as a dummy, using variables which were not considered particularly important for landslide susceptibility (Table 6.8).

In addition to testing various combinations of control factors, relevant values of $\lambda$ also needed to be tested. A range of possible $\lambda$ values were suggested by Pradhan (2011), however, it was unclear which of the suggested values would be most appropriate for use in PNG and how this value would alter the gamma operator when different control factors were examined. Therefore, a number of different values for $\lambda$ were also considered. The different models and $\lambda$ values used are shown in Table 6.8.
Western Province case study area | Chimbu Province case study area
--- | ---
Model no. | Control factors used | # CFs | \( \lambda \) value | Control factors used | # CFs | \( \lambda \) value
--- | --- | --- | --- | --- | --- | ---
1-1 | Slope, lineament distance, lithology, elevation | 4 | 0.975 | Elevation, lineament distance, lithology | 3 | 0.975
1-2 | 0.9 | Elevation, lineament distance, lithology | 3 | 0.95 | Elevation, lineament distance, lithology | 4 | 0.95
1-3 | 0.95 | Elevation, lineament distance, lithology | 4 | 0.95 | Elevation, lineament distance, lithology, slope | 5 | 0.95
2-1 | Slope, lineament distance, lithology | 3 | 0.975 | Elevation, lineament distance, lithology | 3 | 0.95
2-2 | 0.9 | Elevation, lineament distance, lithology, slope | 4 | 0.95 | Elevation, lineament distance, lithology, slope | 5 | 0.95
2-3 | 0.95 | Elevation, lineament distance, lithology, slope | 5 | 0.95 | Elevation, lineament distance, lithology, slope | 6 | 0.95
3-1 | Elevation, aspect, drainage distance | 3 | 0.975 | Elevation, aspect and drainage distance | 3 | 0.95
3-2 | 0.9 | Elevation, aspect and drainage distance | 4 | 0.95 | Elevation, aspect and drainage distance | 5 | 0.95
3-3 | 0.95 | Elevation, aspect and drainage distance | 5 | 0.95 | Elevation, aspect and drainage distance | 6 | 0.95
4-1 | Slope, lineament distance, lithology, drainage distance, elevation | 5 | 0.975 | Elevation, lineament distance, land cover, lithology, slope | 5 | 0.95
4-2 | 0.9 | Elevation, lineament distance, land cover, lithology, slope | 5 | 0.95 | Elevation, lineament distance, land cover, lithology, slope | 6 | 0.95
4-3 | 0.95 | Elevation, lineament distance, land cover, lithology, slope | 6 | 0.95 | Elevation, lineament distance, land cover, lithology, slope | 7 | 0.95

Table 6.8. The control factor models and \( \lambda \) values (used in the fuzzy gamma operation) tested for the development of susceptibility maps for the Western and Chimbu Province case study areas. (# CFs = number of control factors)

### 6.6 Results and discussion

The output from the fuzzy gamma operator varied depending on which model and \( \lambda \) value was used in the calculation. Therefore, to ensure easier comparison across the different map outputs, a landslide susceptibility index was produced by classifying the fuzzy output values into equal increments (0.2). This resulted in 6 landslide susceptibility classes ranging from ‘no susceptibility’ up to ‘very high susceptibility’.

Fig. 6.16 shows the landslide susceptibility index produced for the four control factor models, for Western Province (all using \( \lambda = 0.9 \)). The variability across the four maps indicates the importance of selecting and combing the most relevant control factors, with the dummy model (Fig. 6.16(c)), correctly producing output that would be difficult to apply in a decision-making environment. Nearly all fuzzy values in Fig. 6.16(c) lie between 0.6 and 1.0 and are therefore classified as high or very high susceptibility areas. The extensive coverage of such high susceptibility values means that the variability associated with landslide initiation is not accurately being captured.
Furthermore, if one considers that a single TRMM grid square has a resolution of 0.25 x 0.25°, the output from the dummy model would not significantly enhance a ‘forecast’ of landslide probability.

![Fig. 6.16. Landslide susceptibility maps for (a) model 1-2, (b) model 2-2, (c) model 3-2 and (d) model 4-2 (Table 6.8), for the Western Province case study domain. All maps use λ = 0.9. Observed landslides are shown by black, hashed polygons.](image)

In addition to the control factor models, the influence of the λ value in the fuzzy gamma operator was tested. Fig. 6.17 visually compares models, using the same control factors, but different λ values. It is possible to identify λ values decreases, the distribution of fuzzy output values moves towards lower values, associated with the growing importance of the ‘decreasive’ tendencies of the fuzzy algebraic product. In order to quantitatively compare the outputs of the all the models, 2x2 contingency tables were used so that the most effective combinations of control factors and λ values could be ascertained. These tables compare observed landslides (points associated with mapped landslide head scarps) against the forecast of enhanced landslide susceptibility.
The aim is to find a model which is able to accurately forecast the locations susceptible to landslide initiation, while not producing too many false alarms.

Two sets of 2x2 contingency tables were produced for each model (excluding the dummy model (3)) and λ value (Table 6.8). The first set compared forecast data above a fuzzy value of 0.4 (moderate susceptibility), while the second set examined forecast data above a fuzzy value of 0.6 (high susceptibility). This allowed comparisons between models based on a hypothetical warning threshold. The frequency of points associated with hits, misses, false alarms and correct non-events were calculated and converted to percentages for easier comparison across the models (Fig. 6.18; Fig. 6.19). Higher percentages of hits and correct non-events are desirable, as these indicate that a greater fraction of forecasts were correct. It is also desirable to have low percentages of false alarms and misses, as these indicate that there are a lower fraction of incorrect forecasts.
Fig. 6.18. 2x2 contingency tables for landslide susceptibility models in Western Province using different control factors (models 1, 2 and 4) and \( \lambda \) values (0.975, 0.9 and 0.95). Models which performed the best overall are outlined in red.

<table>
<thead>
<tr>
<th>Event Forecast</th>
<th>Event Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>HIT</td>
</tr>
<tr>
<td>No</td>
<td>MISS</td>
</tr>
<tr>
<td>Marginal Total</td>
<td>Obs Yes</td>
</tr>
</tbody>
</table>

- **hit** - event forecast to occur, and did occur
- **miss** - event forecast not to occur, but did occur
- **false alarm** - event forecast to occur, but did not occur
- **correct non-event** - event forecast not to occur, and did not occur

Total landslide initiation observations = 1,485

Total non-landslide initiation observations = 94,987

Sum total (points in case study domain) = 96,472
Fig. 6.19. 2x2 contingency tables for landslide susceptibility models in Chimbu Province using different control factors (models 1, 2 and 4) and λ values (0.975, 0.9 and 0.95). Models which performed the best overall are outlined in red.
Broadly speaking the models tested for Western Province, proved to be the most successful at correctly forecasting events (areas of moderate or high landslide susceptibility coincide with areas of observed landslide events) and non-events (areas with no landslide susceptibility coincide with areas with no observed landslides). These models also produced lower percentages of false alarms and misses, than the Chimbu Province models. This was not unexpected given the poor correlations seen between the Chimbu Province control factors and the frequency ratio values in section 6.4. The contingency table results indicate that the control factor models used in Chimbu Province, struggle to capture the processes which result in landslide initiation in this region, and that other control factors, above those analysed, must also play a contributory role in landslide events. Despite this, preferable landslide susceptibility models can be identified for each case study domain and these would therefore be favourable to take forward for testing and calibration.

**Western Province:** The best overall landslide susceptibility model produced using the fuzzy technique, and applied to Western Province, was model 2. This used elevation, lineament distance, lithology and slope to differentiate between areas of higher landslide susceptibility and lower landslide susceptibility. When the susceptibility maps for model 2 were compared against the mapped (observed) landslides, models which use a warning threshold of 0.4 (moderate susceptibility) were identified as performing better (Fig. 6.18). In these instances the percentage of hits, ranged from 57% (Model 2-2) up to 71% (Model 2-1), indicating that between 57 and 71% of forecasts correctly coincided with observed landslide initiation zones. This decreased to between 34% (Model 2-2) and 53% (Model 2-1) for models using a warning threshold of 0.6 (high susceptibility). When the model-2 contingency tables were compared based on which value of $\lambda$ performed best, there was very little to
discriminate between them. Model 2-1 using $\lambda = 0.975$, had the highest percentage of hits (71%) but also a greater percentage of false alarms (37%), which ultimately reduced the total fraction of correct forecasts to $\sim 63\%$ (calculated as (hits + correct negatives/sum total)). By comparison, Model 2-2 (using $\lambda = 0.95$) showed the greatest total fraction of correct forecasts ($\sim 79\%$), but had higher percentages of missed forecasts (43%). Therefore, of the 3 models (Model 2-1, 2-2 and 2-3), Model 2-3 provides the best all-round performance, with $\sim 71\%$ of all forecasts being correct, while percentages of misses and false alarms were 34% and 29%, respectively. Based on this analysis, Model 2-3 provides the best combination of control factors to identify zones of moderate to high landslide susceptibility in Western Province. Furthermore, of the $\lambda$ values examined, $\lambda = 0.95$ provided the best spread of fuzzy values for the determination of different landslide susceptibility classes.

**Chimbu Province**: For Chimbu Province, a single control factor model could not be identified as preferentially suitable for differentiating between different degrees of landslide susceptibility. A number of models produced hit rates in excess of 80% (9 out of the 18 models tested; Fig. 6.19). However, in each of these cases, high percentages of false alarms were also observed, ranging between 60 and 75%. This indicates that, in these instances, the models are significantly over-forecasting the number of points associated with moderate to high susceptibility, when compared against the observed landslide distribution. This would result in large areas of the domain being subject to landslide susceptibility warnings, where no landslides would then be observed. There is a concern in such situations that warnings will not be trusted because they are issued with relative regularity compared with the actual occurrence of events. However, in a similar way to the selection of an appropriate rainfall-based, landslide probability thresholds (0.05 or 0.1; *Chapter 4*), the delicate balance between over-forecasting
6] Characterising topographical and lithological controls on landsliding in PNG

landslide susceptibility and under-forecasting landslide susceptibility needs to be carefully addressed. This can largely be accomplished through model calibration and integration with meteorological models, and discussions with the decision-making and response community. It should be noted, however, that landslide susceptibility models are prone to over-forecasting, because control factors normally cover wider geographical extents than the isolated occurrences of landslides on which they are based. Furthermore, where head scarp regions are identified as point or line features, the number of pixels used to assess coincident control factor information is limited, and therefore the number of pixels associated with a control factor is generally always larger than the number of pixels associated with a landslide – even in areas where landslide density is very high.

Two of the Chimbu Province susceptibility models appear to balance higher hit rate percentages, with lower false alarm percentages. Model 1-3 and Model 4-3, both perform well using a λ value equal to 0.95 (Fig. 6.19). However Model 1-3 performs better when the warning threshold is 0.4 (moderate susceptibility), while Model 4-3 performs better when the warning threshold is 0.6 (high susceptibility). When forecasts of susceptible areas are compared against the mapped landslides, the total fraction of correct forecasts is equal to 72% for Model 1-3 and 77% for Model 4-3. Both models also show low percentages of misses (42 and 47% for Model 1-3 and Model 4-3, respectively) and false alarms (28 and 23% for Model 1-3 and Model 4-3, respectively). These two models are therefore very similar. Model 1-3, which arguably performs slightly better out of the two models, combined elevation, lineament distance and lithology, while Model 4-3 combined elevation, lineament distance, land cover, lithology and slope. This supports the findings of Fabbri et al., (2003), illustrating that
the inclusion of more control factors does not necessarily produce susceptibility maps with greater accuracy.

One aspect which must be remembered for all of these models is that the fuzzy relation-based methodology is strongly affected by the accuracy and choice of the input data. This includes the accuracy and completeness of the landslide maps produced in section 6.3, and the selection and accuracy of the control factor maps, produced in section 6.4. Furthermore, the method is additionally sensitive to which control factors are identified to be the most relevant to landslide initiation and the fuzzy membership values are sensitive to the size of the increments used to determine frequency ratio distributions for each control factor. In Western Province for example, the relationships between different control factors and landslide initiation appeared better defined, illustrated by the greater correlations between the control factors and the frequency ratio values (Fig. 6.11; Fig. 6.13). For Chimbu Province, the fuzzy membership values were harder to differentiate, because the correlations between the control factors and the frequency ratio values were less obvious. It is possible that additional control factors, other than those examined, or higher resolution data is required to accurately ascertain the control factors most relevant to the landslides in Chimbu Province.

6.7 Conclusions

The fuzzy relation-based methodology has been successfully applied to two case study regions in PNG. The landslide inventory was successfully expanded using satellite and airborne technologies to map landslide scars in Western Province (n= 191) and Chimbu Province (n= 366). Using the GeoSAR DEM and a number of additional freely available, datasets, control factors maps were also produced. Based on these maps, fuzzy membership values for different event control factors were produced, indicating which factors/classes enhanced or reduced a slopes susceptibility to failure.
The product of the fuzzy gamma operator was a range of landslide susceptibility maps, based on a variety of control factors and $\lambda$ values (Table 6.8). Using 2x2 contingency tables, the most successful models for each case study area were identified. In Western Province, Model 2-3 performed the best overall with $\sim 75\%$ of all forecasts being correct. In Chimbu Province, Model 1-3 was found to perform the best overall with $\sim 72\%$ of all forecasts being correct.
7. Synthesis and conclusions
7.1 Introduction

This thesis set out to explore the possibilities for developing early warning/forecasting approaches for rainfall-induced landslides in PNG, using cost-effective methods and data. Given that almost all research into landslide occurrence in PNG has focussed on site-specific and/or basin scale analysis, there was a significant knowledge gap related to the regional, temporal and spatial occurrence of landslides, and their relationship with broad-scale rainfall patterns. Therefore in Chapter 3, a new, regionally-focussed landslide inventory was collated and the entries analysed in the context of rainfall patterns over a range of time scales (months-seasons-years). Typically, early warning/forecasting systems use thresholds to differentiate between events that will trigger landslides and events that will not. In the case of rainfall-induced landslides this required detailed analysis of rainfall patterns preceding known landslide events. Therefore in Chapter 4, daily TRMM TMPA 3B42 data were used to understand the characteristics of triggering and non-triggering rainfall events, so that probabilistic rainfall thresholds could be determined. Triggering events are however, only one aspect of landslide initiation. Therefore, this research additionally sought to understand how event control factors varied throughout the country (Chapter 5 and 6). This is broadly referred to as modelling the landslide susceptibility. Based on these analyses fuzzy logic approaches were used to develop landslide susceptibility maps which could compliment the probabilistic rainfall thresholds. This chapter provides a synthesis of the main findings of this research and uses this information to establish the possibility for developing early warning/forecasting approaches for rainfall-induced landslides in PNG.
7.2 Regional review of landslide occurrence and rainfall patterns

Developing a landslide inventory is rarely straightforward due to the inherent nature of landslides (Kirschbaum et al., 2009; Petley, 2012). However, information from journal publications, site inspection reports and technical notes made by engineering geologists (Tutton and Kuna, 1998; Kuna, 2002), newspaper and internet publications, relief agency websites and supplementary global archives (USGS NEIC/PDC, Dartmouth Flood Observatory) allowed pertinent information (date, location, type, size/number, possible trigger and impacts) to be extracted and collated within a single database. This method posed a number of challenges because of the sparse availability of information pertaining to many landslide events, the variety of data sources from which the information was derived and the selection criteria used to determine whether or not a landslide event was included in the database. Ultimately a set of landslide-triggering events were collated (n=126 entries) from mainland PNG and the adjacent islands (New Ireland and New Britain). Although there were a number of biases and restrictions on these data, the database offered the first opportunities to review the spatial (Fig. 3.5; Fig. 3.12) and temporal (Fig. 3.8; Fig. 3.14) occurrences of landslides, relative to the regional rainfall climatology.

In conventional analyses of rainfall-induced landslides, events are compared against rainfall gauge data, which are typically considered more accurate. One of the greatest challenges with this type of analysis is the availability of representative rainfall data, coincident to the areas affected by landslides. This was particularly problematic in PNG because the reliable rainfall gauge network is very sparse, with the main recording stations all being positioned at coastal sites rather than the central cordillera (Fig. 2.1), where the majority of landslides are recorded (Fig. 3.5). The restrictions on available rainfall data, including the fact that hourly rainfall data was not made available at the
time this research was conducted, meant that alternative gauge-based data sources needed to be considered. WMO climatology data and GPCC monthly accumulation data both illustrated positive correlations between regionally-averaged, monthly rainfall and the monthly frequency of landslide-triggering events (WMO-based data produced $R^2$ values of 0.86 and 0.82; GPCC-based data produced correlation coefficients of 0.64 and 0.66). These correlations and the additional analysis completed in Chapter 3 confirmed two widely held assumptions:

(1) that landslide events occur more frequently during the wetter season (December to May) than during the drier season (June to November) and

(2) that more landslide events are observed during years associated with La Niña episodes (generally wetter), than years associated with either El Niño or ENSO neutral in PNG.

Of particular importance however, was the identification that, particularly for the latter half of the wetter season, absolute month-to-month rainfall variability was found to be small, while changes in landslide occurrence were relatively large by comparison. This indicated the importance of antecedent rainfall conditions and that rainfall over durations in excess of one month were important for landslide initiation in these instances. Furthermore, the findings hinted that rainfall driven by different dynamic mechanisms could induce different numbers and types of failure. Therefore, despite the limitations and data restrictions affecting the analysis, Chapter 3 demonstrates the first regionally-based relationships between landslide occurrences and rainfall over monthly, seasonal and annual time scales.
7.3 Satellite-based precipitation data for the development of probabilistic rainfall thresholds

Conventional methods of determining landslide-triggering rainfall thresholds have been based on a deterministic framework. Furthermore, the majority of research has focused on the development of short-duration rainfall thresholds applicable to shallow-landslides (Guzzetti et al., 2007; Staley et al., 2011; Aleotti, 2004; Caine, 1980). By comparison, research to develop rainfall thresholds for larger-scale and/or deep-seated landslides is relatively sparse. This is largely because of the complex dynamics involved in their initiation. Such complexity and uncertainty typically favours a probabilistic approach to warning and/or forecasting, as this framework offers information about the likelihood of an event, rather than a simple Boolean response (Chowdhury, 1984; Guzzetti et al., 2007; Brunetti et al., 2010; Berti et al., 2012; Glade et al., 2000). Given the nature of the landslides in the PNG inventory and the extensive societal impacts which can result from such movements (Robbins et al., 2013), methods to develop probabilistic, landslide-triggering rainfall thresholds for larger-scale landslide initiation, are both timely and essential.

In Chapter 4 therefore, the issue of developing probabilistic rainfall thresholds for larger-scale landslide events, was addressed. The dominant feature of all empirically-based thresholds (deterministic and probabilistic), is the necessary understanding of how rainfall characteristics change between those that induce landslides and those that don’t. This requires rainfall data representative of the landslide area and a suitable temporal and spatial resolution to capture the rainfall variability. The limitations of gauge-based data in PNG were made evident in Chapter 3, and therefore an alternative source of rainfall data was required. Satellite-based precipitation algorithms were considered, for their extensive (spatial) and consistent (temporal) data coverage. The TRMM TMPA 3B42 daily rainfall data have proven useful in a number of hydrological
Synthesis and Conclusions

studies (Su et al., 2008; Behrangi et al., 2011) at basin and regional scales. TRMM TMPA 3B42 also has the longest running archive, compared to CMORPH or PERSIANN, and is routinely calibrated by the inclusion of gauge-based data. In addition, the data are freely available and in a format easily compatible with many GIS-based software packages, without any additional formatting. Therefore, satellite-based techniques provided a cost effect means of analysing detailed rainfall characteristics for landslide events in PNG.

Although probabilistic threshold determination for landslides is not a new concept, it has yet to be pulled through successfully into real-time early warning and forecasting systems, as observed for meteorological hazard forecasting (Neal et al., 2013) and flood warning (Gouweleeuw et al., 2005). A number of considerations are essential to ensure that this ‘pull-through’ happens: (1) the method used to determine the probabilistic thresholds needs to be robust and reproducible, as well as (2) straightforward to understand and implement and (3) provide outputs that are genuinely helpful for decision-making and planning. In Chapter 4 therefore, a combined approach, using the ‘multiple times frames’ method (Frattini et al., 2009; Zêzere et al., 2005; Fuhrmann et al., 2008) and Bayesian statistics (Berti et al., 2012), was considered. In this analysis the two techniques proved useful for ensuring clarity and reducing subjectivity throughout the threshold determination process. The ‘multiple time frames’ method limited the uncertainty associated with defining critical rainfall events. The method also proved to be flexible, allowing any number of rainfall durations to be examined, while remaining robust across different seasons (wetter vs. drier), climate regimes and geographical areas. The Bayesian methodology used by Berti et al., (2012) and applied here is similarly robust, as it uses the concept of relative frequencies to
obtain probabilities of landslides. This captures the overall uncertainty and spread of rainfall events which do and do not, result in landslides.

The combined statistical approaches and the satellite-derived precipitation estimates used in Chapter 4 proved successful for identifying the characteristics of rainfall events associated with landslides. Based on this, landslide probabilities based on changing accumulation-duration or intensity-duration rainfall combinations were developed (Fig. 4.11; Fig. 4.12). Of the two combinations, the analysis of rainfall events defined by accumulation and duration proved the most successful. This was not unexpected given the nature of the landslides (larger-scale) used for the analysis. Larger-landslide types are more likely to be triggered by the influence of accumulated rainfall interacting with slopes. Typically, larger rainfall accumulations result in increased water loading and pore water pressures, which can reduce sliding resistance. Peaks in landslide probability were calculated for both extreme, short-term rainfall and longer-duration, high-accumulation rainfall. The 2D landslide probability plots allowed linear relationships to be identified, where lines of roughly equal probability could be drawn across the log-log space (i.e. for probabilities of 0.05 and 0.1 in Fig. 4.11). Broadly speaking the analysis suggested that two types of rainfall event were more likely to lead landslides in PNG: the first being high-accumulation, shorter duration (< 15 days) rainfall events and the second being long duration (> 75 days), high accumulations rainfall events.

In terms of applying the information from this analysis to reality, the isolines drawn in Fig. 4.11 and Fig. 4.12 represent an important question with regard to probabilistic forecasting – which landslide probability isoline should be used to initiate a warning? In highly vulnerable areas of PNG for example, even very low landslide probabilities could be considered unacceptable due to the potentially devastating
consequences a large-scale landslide could have on the population. The 0.05 isoline was tentatively identified as an ‘early, heads-up warning threshold’ for landslides in PNG, but further calibration of the model would be required to identify the most applicable isoline for effective warning. Overall, the findings illustrate that it is possible to produce rainfall thresholds in areas with sparse data availability, in a cost effective and straightforward manner. The development of probability isolines has also identified a possible mechanism for warning deployment. The different probability isolines could represent different levels of warnings to different responder communities, helping to increase preparedness and mitigation planning, while limiting the false-alarm rates observed by the wider population. It is anticipated that these approaches can be readily updated as new data becomes available (i.e. as the landslide inventory in PNG expands) and that the methods can be easily reproduced to accommodate different rainfall data which may potentially become available in the future.

7.4 Landslide susceptibility in PNG

The probabilistic thresholds determined in Chapter 4, do not address the spatially-varying environmental control factors, which can increase or decrease the inherent susceptibility of a slope to landsliding. The occurrence of the Tumbi Landslide in January, 2012 illustrated this issue (Chapter 5; Robbins et al., 2013). The rainfall accumulated at the site was not particularly extreme for the area (Southern Highlands Province) but was sufficient to result in a landslide probability greater than 0.02 for a number of rainfall accumulation-durations (Fig. 4.11). However, the calculated probabilities refer to any one of 40 TRMM grid squares analysed (Chapter 4, section 4.4.3.1), which each have a resolution of 0.25 x 0.25°. This is a substantial area of warning, with no means of providing further information related to locations, within the grid squares, which are more susceptible to failure than others. Therefore, in Chapter 6
a detailed analysis of event control factors associated with landslide initiation was conducted.

A major issue for the susceptibility analysis was the limited sample size of collated events in the PNG inventory. However, having a verifiable date for a landslide event was less important for the susceptibility analysis, and therefore methods to expand the landslide inventory were considered. Once again, satellite and airborne technologies appeared the most favourable option. The use of Landsat data had already proven successful for identifying landslide scars in the Finisterre Range of PNG (Greenbaum et al., 1995) and was seen as a cost effective and timely method to rapidly assess landslide prone areas (Petley, 2002). Given, that this thesis focuses on larger-scale landslides, additional techniques were also required because multi-spectral methods are less effective at identifying the morphological characteristics of some deep-seated landslide events (Van Den Eekhaut et al., 2005). Therefore, high resolution DEM data were also used to map landslide scars in the two case study areas (Lin et al., 2014). It should be noted that although GeoSAR DEM data are not generally freely available and are not particularly cost-effective, these data are already available for the entire mainland region of PNG. Therefore the techniques and methods detailed in this chapter can be extended to other areas of PNG at no extra cost.

The multi-spectral and DEM analysis proved very successful at identifying landslide scars across the two case study regions examined (Fig. 6.9) and significantly increased the number of landslide events available for susceptibility analysis (n=191 in Western Province; n=366 in Chimbu Province). Of course without any field investigations to robustly verify the mapped landslides, the true success of the techniques cannot be fully established. However, the mapped landslides proved to be invaluable for understanding the relationships between landslide events and spatially-
Synthesis and Conclusions

varying environmental control factors. By comparing the frequency ratio statistics (Table 6.5; Table 6.7), control factors important for landslides were differentiated from those that were less important in each case study region, resulting in the basic information required for landslide susceptibility modelling using fuzzy logic (Pradhan, 2011).

7.5 Early warning/forecasting landslides in PNG

The analysis completed throughout this thesis has been driven by a desire to identify a means of modelling periods when landslide activity is likely to increase, associated with changes in rainfall and local morphology. Having the ability to warn communities of periods of heightened landslide susceptibility offers opportunities for mitigation, to reduce potential losses from these natural hazards. A schematic illustration of the modelling framework which could be developed, to bring together the different aspects of this research into a useable early warning/forecasting model for rainfall-induced landslides in PNG, is shown in Fig. 7.1. This framework requires real-time (TRMM) or forecast rainfall information to provide the temporally- and spatially-dynamic component of the model. Forecast models are currently limited in this region, but research and model development underway at the Australian Bureau of Meteorology could be used once it is made available. The landslide susceptibility model would require extending, to encompass the complete mainland of PNG. It would then provide higher-resolution, spatial information, within the resolution grid of the rainfall data, on areas with low/or no landslide susceptibility. Ultimately the output from this combined, conceptual model framework (Fig. 7.1) would provide temporal and spatial information on areas likely to experience heightened landslide susceptibility, based on changing weather conditions, over the coming days/months (depending on rainfall data used). This information could then be provided, depending on the landslide probabilities, to
different civil contingency members (e.g. Natural Disaster Centre in PNG, MRA, government) or to the public, to encourage vigilance and/or mitigating actions to be taken, during the warning period.

**Fig. 7.1.** Conceptual model framework for a rainfall-induced landslide early warning/forecasting system for PNG.

### 7.6 Recommendations and future work

It is evident that remotely sensed information can significantly enhance landslide mapping and inventory development in PNG. However, these techniques cannot occur in insolation, as field-based mapping continues to be the most robust and accurate way for indentifying landslides. This is particularly true for smaller scale events. Therefore, the most time- and cost-effective method for landslide inventory development is through a combination of fieldwork and remote sensing, particularly when considering a regionally-based hazard. In order for the two methods to work together, there needs to be a systematic and consistent approach to landslide recording. The development of a
checklist of pertinent information is recommended, which could be used by all geologists who visit a landslide site. This would require geologists to provide basic information on each landslide they visit, including: the latitude and longitude of the landslide site, the date of occurrence (or the date of field inspection if the date of occurrence is unknown), the size, type and main characteristics of the slide, the basic geology, land use and the impact of the event on the surrounding community. These data could then be collated into a single, GIS-based landslide inventory, similar to that outlined by Flentje and Chowdhury (2005) for the Wollongong area of Australia. Satellite-imagery would then complement this database to provide spatial verification. This would dramatically increase the scope for regionally-based hazard assessments.

Irrespective of the current availability of landslide data, it has been shown that the addition of satellite and airborne methods can significantly enhance our understanding of landslide triggers and event control factors. A key component of this research, going forward is validation of the techniques. TRMM offers real-time data (3B42RT) from which a conceptual model environment, utilizing the probabilistic rainfall thresholds and susceptibility maps produced in this research could be tested. Collaboration with PNG MRA and the Department of Mineral Policy and Geohazards Management would be essential to ensure that: (1) the system sat well within existing infrastructure, (2) that monitoring of landslide events and fieldtrips could be organised and (3) so that the true value of this type of model, in terms of decision-making and response, could be ascertained.

Additional aspects that are also worthy of further investigation include: (1) using the higher-resolution TRMM data to assess the relative importance of convective or stratiform rain for landsliding, (2) validate the fuzzy membership techniques across other regions of PNG and (3) investigate the most appropriate methods to integrate the
susceptibility models with the rainfall thresholds to produce an optimal warning/forecasting system.

7.7 Conclusions

This thesis explores the possibilities of developing cost effective early warning/forecasting tools for rainfall-induced landslides in PNG. Overall, it has been demonstrated that probabilistic rainfall thresholds can be developed using satellite-based precipitation estimates, and that satellite and airborne techniques can provide valuable information for the development of complimentary landslide susceptibility maps, both of which can be utilized in early warning/forecasting systems. To summarise, the main conclusions are:

- Landslide occurrence is strongly influenced by the interseasonal rainfall variability in PNG and therefore rainfall over periods up to 90 days preceding a landslide can be important for initiation;
- The characteristics of rainfall events associated with landslides and non-landslides can be differentiated using satellite-based precipitation estimates;
- The ‘multiple time frames’ method and a modified Bayesian approach (Chapter 4) are capable of producing landslide probabilities based on both accumulation-duration and intensity-duration rainfall combinations;
- For the landslides recorded in the PNG inventory, rainfall events defined by accumulation and duration proved most successful for developing landslide probabilities. The analysis suggests that two types of rainfall event are more likely to lead to landslides in PNG: the first being high
accumulation, shorter duration (< 15 days) rainfall events and the second being long duration (> 75 days), high accumulation rainfall events;

- Satellite and airborne-based technologies, together with the methodologies applied in Chapter 6, can significantly enhance landslide inventory map production for PNG;

- Fuzzy logic methods have proven successful for developing landslide susceptibility models which can complement probabilistic rainfall thresholds, for the development of integrated warning/forecasting systems.

- Overall, the use of satellite and airborne techniques have the potential to significantly enhance landslide research in PNG and proved to be successful in providing data for the development of warning/forecasting systems which could reduce losses associated with landslide hazard.
References


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References


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References


Capparelli G, Versace G (2011) FLaIR and SUSHI: two mathematical models for early warning of landslides induced by rainfall. Landslides, 8:67–79


References


References

http://pnglnc.com/media/pdfs/commitment/PGHUEHSPZZZ410003_Tumbi_Qarry__QA_1__RAP_Rev_0_Website_48956.pdf (accessed February 2012)


276
Greenbaum, D., Tutton, M., Bowker, M.R., Browne, T.J., Greally, K.B., Kuna, G.,
McDonald, A.J.W., Marsh, S.H., Northmore, K.J., O’Connor, E.A. & Tragheim,

reactivation of a landslide during the construction of the Ok Ma tailings dam,
Papua New Guinea. *Quarterly Journal of Engineering Geology and
Hydrogeology, 37*, 173-186

Guzzetti, F. (2000). Landslides fatalities and the evaluation of landslide risk in Italy.
*Engineering Geology, 58*, 2, 89-107

evaluation: a review of current techniques and their application in a multi-scale
study, Central Italy. *Geomorphology, 31*, 181-216

Guzzetti, F., Mondini, A.C., Cardinali, M., Fiorucci, F., Santangelo, M., Chang, K.
Reviews, 112*, 42-66

initiation of landslides in central and southern Europe. *Meteorology and
Atmospheric Physics, 98*, 239–267

Hall, R. (2002) Cenozoic geological and plate tectonic evolution of SE Asia and the SW
Pacific: computer-based reconstructions, model and animations. *Journal of Asian
Earth Sciences, 20*, 353–431

Haneberg WC, Creighton AL, Medley EW, Jonas DA (2005) Use of LiDAR to assess
slope hazards at the Lihir gold mine, Papua New Guinea. In: Hungr O, Fell R,
Couture R, Eberhardt E (Eds) Proceedings of the international conference on
landslide risk management. Vancouver, Taylor & Francis Group, Supplementary
Volume (CD), Canada

Hearn, G.J. (1995) Landslide and erosion hazard mapping at Ok Tedi copper mine,

*Geological Society of America Bulletin, 85*, 1253-1264


Summer Monsoon. *Journal of Atmospheric Sciences, 47*, 18, 2227-2240

Hendon, H.H., Zhang, C. & Glick, J.D. (1999). Interannual variation of the Madden-
Julian Oscillation during austral summer. *Journal of Climate, 12*, 2538-2550

margin in a west Pacific context. *In: Hillis, R. & Müller, R.D (Eds) Defining
References


References


References


References


References


Mondini, A.C., Marchesini, I., Rossi, M., Chang, K., Pasquariello, G. & Guzzetti, F. (2013) Bayesian framework for mapping and classifying shallow landslides exploiting remote sensing and topographic data. *Geomorphology*, 201, 135-147

References

the Technical Meeting on Exodynamic Geohazards in East and Southeast Asia, Pattaya, Thailand


References


Pradhan, B. (2011) Use of GIS-based fuzzy logic relations and its cross application to produce landslide susceptibility maps in three test areas in Malaysia. Environmental Earth Science, 63, 329-349


Qian, Jian Hua. (2008). Why precipitation is mostly concentrated over islands in the Maritime Continent. Journal of Atmospheric Sciences, 65, 1428-1441

Qian, Jian Hua, Robertson, A.W. & Moron, V. (2010). Interactions among ENSO, the monsoon and diurnal cycle in rainfall variability over Java, Indonesia, Journal of Atmospheric Science, 67, 3509-3524


References


References


References


References


References

region – an earth-science perspective, USGS Professional Paper 1360, pp. 316-345

WMO (1985) Review of requirements for area-averaged precipitation data, surface based and spaced based estimation techniques, space and time sampling, accuracy and error, data exchange. WCP-100, WMO/TD-No. 115


### Table A-1: Variables and formats for data collated within the new PNG landslide inventory

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<th>Variable Name</th>
<th>Format</th>
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<td>ID</td>
<td>Numeric</td>
</tr>
<tr>
<td>2</td>
<td>Date</td>
<td>day.month.year (numeric) or month.year (text)</td>
</tr>
<tr>
<td>3</td>
<td>LTE Start Date</td>
<td>Day Numeric (1-31)</td>
</tr>
<tr>
<td>4</td>
<td>Monthly</td>
<td>Numeric (1-12)</td>
</tr>
<tr>
<td>5</td>
<td>Year</td>
<td>Numeric (1970 – 2010)</td>
</tr>
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<td>6</td>
<td>LTE End Date</td>
<td>Day Numeric (1-31)</td>
</tr>
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<td>7</td>
<td>Monthly</td>
<td>Numeric (1-12)</td>
</tr>
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<td>8</td>
<td>Year</td>
<td>Numeric (1970 – 2010)</td>
</tr>
<tr>
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<td>Duration in days</td>
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<td>Event descriptor</td>
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<tr>
<td>13</td>
<td>Location Coordinates</td>
<td>Y – Long Decimal Degrees</td>
</tr>
<tr>
<td>14</td>
<td>Coordinates</td>
<td>X – Lat Decimal Degrees</td>
</tr>
<tr>
<td>15</td>
<td>Location Coordinates</td>
<td>Y – Long Decimal Degrees</td>
</tr>
<tr>
<td>16</td>
<td>Location</td>
<td>Village, Town or landmark (text)</td>
</tr>
<tr>
<td>17</td>
<td>Province</td>
<td>Name (text)</td>
</tr>
<tr>
<td>18</td>
<td>Trigger descriptor</td>
<td>R = Rainfall</td>
</tr>
<tr>
<td>19</td>
<td>River close to landslide site</td>
<td>Name (text)</td>
</tr>
<tr>
<td>20</td>
<td>Mountain Range landslide</td>
<td>Name (text)</td>
</tr>
<tr>
<td>21</td>
<td>Earthquake magnitude</td>
<td>Richter Scale (numeric)</td>
</tr>
<tr>
<td>22</td>
<td>Earthquake depth in km</td>
<td>Numeric</td>
</tr>
<tr>
<td>23</td>
<td>Modified Mercalli Intensity</td>
<td>12 levels (roman numerals)</td>
</tr>
<tr>
<td>24</td>
<td>Landslide affected area in sq km</td>
<td>Combined slides (numeric)</td>
</tr>
<tr>
<td>25</td>
<td>Landslide volume in m³</td>
<td>Combined slides (numeric)</td>
</tr>
<tr>
<td>26</td>
<td>References</td>
<td>Reference for the landslide (journal article reference/database name/ MRA report number / hyperlink to media article)</td>
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