COMPARING MODELLING APPROACHES FOR LANDSLIDE EARLY WARNING: A CASE STUDY OF BOGWONTO CATCHMENT, CENTRAL JAVA, INDONESIA.

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March 2018

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ABSTRACT

Rainfall induced landslides are a common natural hazard in mountainous areas which pose a significant threat to numerous communities residing near hilly terranes. Therefore, it is a societal and scientific interest to enhance understanding of the relationship between rainfall and occurrence of landslides for the development of effective landslide forecasting models. From this perspective, this study endeavoured to compare empirical and physically based modelling approaches of determining rainfall thresholds relevant for landslide early warning purposes. Since rainfall data availability is sparse in most remote locations the study exploited the usability of satellite rainfall products and forecasted rainfall data by first comparing them to observed rainfall measurements. The study was conducted in a landslide prone area in Bogowonto Catchment, Central Java, Indonesia. 169 landslides occurring in 48 event days over the period of 2003 to 2016 were analysed in this study.

Empirical rainfall thresholds were determined and tested by using both multiple antecedent-daily rainfall model and physically based model. To partly account for water loss by evapotranspiration and discharge especially for rainfall occurring several days before landslide occurrence the antecedent rainfall was multiplied by a decay coefficient based on recession of flood hydrograph for the region. Similarly, non-landslide triggering rainfall events of comparable magnitude with the landslide triggering events were randomly selected and subjected to the same conditions. Number of antecedent rainfall days that influence the occurrence of landslides were determined by manually fitting a line on the scatter plot of event day rainfall against antecedent rainfall for 3, 5, 10, 15, 20 and 30 days. The line was purposely drawn to separate triggering and non-triggering rainfall events as much as possible. The graph on which the fitted line achieved minimum mixing of triggering and non-triggering rainfall was chosen as being associated with occurrence of landslides. Due to unavailability of some data such as soil mechanical properties, a modified STARWARS PROBSTAB model was used to define physically based rainfall thresholds which also helped to add the spatial component to the modelling of landslides in the area.

Rainfall analysis indicate that TRMM data and ERA-Interim rainfall forecasts have poor correlation with observed daily rainfall however they were better at monthly scale and in detection of extreme rainfall events which are mostly associated with occurrence of landslides. The results from empirical model indicate that landslides in the catchment are generally influenced by 15 days antecedent rainfall and daily rainfall. Thresholds were also found to vary on different land uses and at different periods of the rainy season. The physically based model confirmed the importance of antecedent rainfall in landslide triggering conditions. On the 15 days antecedent rainfall graph two threshold lines representing minimum triggering rainfall conditions and maximum non-triggering rainfall conditions were drawn. The area below the line crossing minimum triggering rainfall conditions was assigned 10% probability of landslide occurrence and the area above maximum non-triggering rainfall conditions was assigned 90% probability of landslide occurrence. This was linked to a simple landslide early warning which had 87% overall accuracy in predicting landslide data from a nearby catchment. Thus, subject to improvement in the future, the threshold derived from this study can be used in as simple early warning system for landslides in the area. Basing on the results, empirical models are relatively easy to implement but they are not very precise especially for early warning purposes. Conversely physically based models are quite precise since they indicate exact possible slopes which are at danger of failing. However, these physical models tend to overpredict unstable areas and are data demanding hence difficult to implement in larger areas.

Keywords: Rainfall induced landslides, early warning, rainfall thresholds, antecedent rainfall, empirical models, physically based models.
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<td>Digital Elevation Model</td>
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<tr>
<td>ED</td>
<td>Event-duration</td>
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<td>EI</td>
<td>Event-intensity</td>
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<td>EWS</td>
<td>Early warning system</td>
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<tr>
<td>FN</td>
<td>False negatives</td>
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<td>FoS</td>
<td>Factor of safety</td>
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<td>FP</td>
<td>False positives</td>
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<tr>
<td>FS</td>
<td>Factor of Safety</td>
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<tr>
<td>GIS</td>
<td>Geographical Information System</td>
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<tr>
<td>GPM</td>
<td>Global Precipitation Measurement</td>
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<tr>
<td>ID</td>
<td>Intensity-duration</td>
</tr>
<tr>
<td>IFS</td>
<td>Intergrated Forecast System</td>
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<tr>
<td>NPP</td>
<td>Negative predictive power</td>
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<tr>
<td>PCC</td>
<td>Pearson Correlation Coefficient</td>
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<td>PPP</td>
<td>Positive predictive power</td>
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<tr>
<td>PROBSTAB</td>
<td>Probability of Stability</td>
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<td>RMSE</td>
<td>Root mean square error</td>
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<tr>
<td>SLIDE</td>
<td>SLope Infiltration Distributed Equilibrium</td>
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<tr>
<td>TN</td>
<td>True negatives</td>
</tr>
<tr>
<td>TP</td>
<td>True positives</td>
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<tr>
<td>TRMM</td>
<td>Tropical Rainfall Measurement Mission</td>
</tr>
<tr>
<td>UGM</td>
<td>University of Gadjah Mada</td>
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<tr>
<td>UNSDR</td>
<td>United Nations International Strategy for Disaster Reduction</td>
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1. INTRODUCTION

1.1. Background

There is a global concern about the huge devastating impacts that natural hazards are causing on societies (Banholzer et al., 2014; CRED, 2015; UNISDR, 2006). The vulnerability to natural hazards has lately been noticed to increase as more people are living in risky places such as mountainous areas due to rapid population growth (Gencer, 2013; Huppert et al., 2006). In addition, both the frequency and magnitudes of natural hazards has increased due to the advent of climate change which has led to an increase in extreme triggering weather events as observed from the 1950’s (IPCC, 2012). Landslides which are common in hilly terrains are ranked among the most devastating natural hazards that have caused numerous deaths and vast economic losses (CRED, 2015). The United Nations International Strategy for Disaster Reduction (UNISDR) postulated that despite material losses to disaster being not entirely inevitable; in some cases human injury and deaths could be avoided if proper measures had been in place (UNISDR, 2006). An Early Warning System (EWS) is one of such measures that have proved to be an effective way to circumvent adverse effects of natural disasters on people (Aleotti, 2004; Jian et al., 2015).

A thorough understanding of triggering mechanisms of slope failure and slope failure potential is of paramount significance for successful present and future landslide forecasting in an EWS (Uhlemann et al., 2016). Since precipitation is one of the main triggers of landslides, landslides frequencies and patterns are likewise expected to change in response to anticipated future precipitation pattern changes due to climate change (Gariano & Guzzetti, 2016; Uhlemann et al., 2016). Precipitation is expected to increase in winter and summers becoming drier in some regions while in some regions especially of high elevations, air temperature are expected to increase (Gariano & Guzzetti, 2016). With such scenarios, the strength of subsurface materials will decrease because of extensive weathering of surface and subsurface materials due to wetter winters and prolonged summers (Uhlemann et al., 2016). The reduction of materials strength will likely bring about frequent shallow slope failures. Increased precipitation patterns will among other things result into: wetter antecedent soil conditions, increase in weight of surface and subsurface soils, reduced shear strength and higher water tables (Gariano & Guzzetti, 2016). Ultimately, these conditions will collectively result into conditions that require less rainfall for landslides to be triggered.

1.2. Justification of the study

The Indonesia archipelago is a hotspot for various hydro-meteorological and geological hazards due to its geologic setting, climatic conditions and properties of surface and subsurface soils and lithologies (Kusumayudha & Ciptahening, 2016; Umar et al., 2013). Geologically, Indonesia lies on the active triple junction positioned on the subduction zone that has resulted to the formation of volcanic island (Umar et al., 2013). By its geological origin and its location, the country is often affected by geological hazards such as earthquakes, earth movements and volcanoes (Putri et al., 2013). Volcanic mountains with considerable steep slopes dominate the landscape of Indonesia hence making it prone to landslides (Umar et al., 2013). The country has average annual rainfall amounts ranging from 1800 mm to over 3500 mm; with such high rainfall amounts coupled with ubiquitous landslide conditioning factors such as steep slopes most landslides are triggered by rainfall hence dominate in the rainy season (Liao et al., 2010).
Landslides have been reported to be a secondary greatest disaster type that causes significant losses of lives and property in Indonesia (Cepeda, 2010). Java island being the economic hub and government centre of Indonesia leads in economic losses and fatalities due to landslides (Christanto et al., 2009). The risk has increased because the island has undergone infrastructural development such as construction of highways which simultaneously increases the potential for landslides occurrence and exposed elements at risk (Cepeda, 2010). Furthermore, the island is the most populated hence underprivileged people are forced to stay in landslide prone areas due to scarcity of settlement land (Ngadisih et al., 2017). In Java alone it was reported that in the period between 1981 to 2007, the island had an annual average of 49 landslide events with considerable damage (Liao et al., 2010).

Several measures have been tried to reduce landslide risk such as slope stabilization program and slope protection zonation which prohibits settlement or development on landslide susceptible slopes (Christanto et al., 2009; Fathani et al., 2008). However, despite all these efforts landslides remain a major problem in Indonesia (Fathani et al., 2008). Relocation of exposed communities is one of the measures that can help to reduce the impact of landslides; however, as noticed by Ngadisih et al., (2017), this is impractical for Indonesia due to socio-economic constraints. Structural mitigation measures such as: retaining walls, stone columns and drainage tunnels is another effective means of modifying the landslide hazard hence minimizing losses of lives and property (Ngadisih et al., 2017). But for developing countries like Indonesia such measures are yet to be fully adopted due to limited financial resources (Ngadisih et al., 2017). Thus, for such countries research about hazards is of great importance to inform the public about dangerous areas (Ngadisih et al., 2017). To avoid costly landslide mitigation measures Fathani et al., (2008) suggests landslide monitoring, prediction and early warning systems as viable options that are urgently needed to ensure safety of numerous communities living in landslides prone areas.

There exists numerous local scale landslide EWS in Indonesia and various attempts have been made by researchers to develop operational landslides EWS for the country or some specific regions. Liao et al., (2010) developed an experimental warning system for shallow landslides for Java island by using a physically based model to calculate safety factor. Safety factor is the ratio of resistance forces to driving forces to failure on a slope. A value of 1 for safety factor indicates equilibrium, a value of less than 1 indicates instability and a value of more than 1 indicates stability. It was observed by Liao et al., (2010) that a safety factor of 1 did not necessarily result into landslides but was rather just an indication that landslides could occur. Hadmoko et al., 2017 and Muntohar, 2008 empirically investigated the relationship between landslides and rainfall in Java and Yogyakarta, Central Java respectively. A minimum of 37 mm rain per day influenced shallow landslides in Yogyakarta if it had been raining for 5 days preceding the landslide occurrence day (Muntohar, 2008). Hadmoko et al. (2017) on the other hand found that for the whole Java island, shallow landslides were associated with at least 43 mm per day rainfall and 300 mm cumulative rainfall for the 30 days period prior to the day of slope failure. Recently Balai Litbang SABO (BLS), a research organization in Indonesia, which conducts research on sediment related topics including landslides and debris flows has developed an online landslide and lahars early warning platform (BLS, 2017). This EWS which is still undergoing development uses landslide initiation and runout models with an input of satellite rainfall estimates to provide warnings to specific localities (BLS, 2017).

1.3. Problem statement

Central Java is considered a high risk area for landslides due prevalent landslides conditioning factors and densely populated settlement on most risk zones hence early warning systems have been adopted as viable risk reduction measure (Karnawati et al., 2009). However, these monitoring systems are not very effective because most of the warning systems use extensometers installed on slopes that are likely to fail (Fathani et al., 2008; Sumaryono et al., 2015). Thus, such early warning systems are less effective on a regional scale
considering that there are numerous slopes where landslides are likely to occur. In addition to using extensometers and other instruments, rain-gauges are also installed to monitor rainfall from which warnings are sent to communities when some critical rainfall is reached or exceeded (50 mm rainfall for the study area). The critical rainfall conditions are however not rigorously determined by using available empirical methods and only consider high intensity rainfalls which are not the only landslides triggering rainfall events. In addition, since the monitoring instruments cannot be installed on all susceptible slopes there is need for subtle approaches to ensure that landslides on other slopes are also predicted consequently improving the performance of the landslide warning systems in the region.

From the foregoing discussion, it is evident that there is a need to exploit different methods of rainfall thresholds derivation to come up with more effective critical rainfall conditions that can be used for landslides early warning in various regions of Indonesia. This study therefore endeavoured to compare empirical and physically based methods in determination of rainfall thresholds for shallow landslides that can be used for a regional landslide early warning system to complement existing EWS's. This approach is advantageous since it adopts the strengths of both empirical and physically based methods hence likely to improve forecasting of shallow landslides in an early warning system.

1.4. Objectives and research questions

1.4.1. General objective

The general objective of this study is to compare physically based and empirical models for determination of rainfall thresholds for landslides initiation on a regional scale using a case study of Bogowonto Catchment, in Central Java, Indonesia.

1.4.2. Specific objectives

To achieve the general objective, the specific objectives listed below were formulated:

a. Isolation and classification of rainfall induced landslides from existing landslide inventories and historical sources.

b. Analysis of the spatial and temporal variability of rainfall by using both ground stations data and Tropical Rainfall Measurement Mission (TRMM) and Global Precipitation Measurement (GPM) satellite rainfall products.

c. Comparison of observed rainfall with satellite rainfall estimates and ERA-Interim rainfall forecasts.

d. Empirical correlation of landslides and rainfall by using rainfall on landslide occurrence day and antecedent rainfall for different periods to get spatially variable rainfall thresholds.

e. Modelling shallow landslide initiation by a physically based model to get dynamic rainfall thresholds.

f. Assessment of the usability and effectiveness of derived rainfall thresholds for a regional landslide EWS.

1.4.3. Research questions

The research answered the following research questions which were put forward to achieve the research goal:

i. What are the characteristics of rainfall induced landslides in the study area?

ii. How does TRMM and GPM satellite rainfall products and forecasted rainfall compare with ground stations rainfall measurements in the Catchment?
iii. Is there temporal variability in the relationship between past landslide events and rainfall in the study area?
iv. How do rainfall thresholds compare among slopes under different landcovers?
v. How can empirically derived landslide rainfall thresholds be improved?
vi. How does landslide rainfall thresholds derived from physically based method compare to those from empirical methods?
vii. Are the derived thresholds efficient in predicting rainfall induced shallow landslides?
viii. Which variables are essential when building an effective regional landslide EWS based on rainfall thresholds?

1.5. Methodology

To answer the research questions and eventually achieve objectives of this research the methodology summarised in the schematic flow diagram shown in figure 1.1 was followed. The research used both primary and secondary datasets. Primary data which included soil depth points, some soil parameters and some landslides points were obtained from field work. Secondary data for the study such as rainfall data, landslide inventory and thematic maps were provided by the University of Gadjah Mada. The methodology followed in this research can be divided into the following 4 parts as depicted by the colour coding in figure 1.1:

1. Preparation of input data for modelling (grey): This part involved preparation of datasets such as landslide inventory and rainfall data for both physical and empirical models. Rainfall data obtained from ground stations, rainfall forecasts and satellite rain products were used. Soil samples were collected from which saturated hydraulic conductivity for different soils in the study area was obtained after laboratory analysis of the samples. DEM at resolution of 12.5 m was used to derive catchment information layers such as flow network.

2. Empirical modelling for determination of landslides rainfall thresholds (blue): This part involved matching days on which landslides occurred with rainfall recorded on that day. Then rainfall information for the days preceding the day of landslide occurrence were extracted to see rainfall conditions before the landslide event days. To make the results more meaningful days with no landslides events but with high rainfalls comparable to those with landslides events were also extracted. Similarly, preceding rainfall conditions of these non-triggering rainfall events were also extracted. Finally, daily rainfall against 3, 5, 10, 15, 20, and 30 days cumulative antecedent rainfall scatter plots were separately drawn on which a line that best separates landslides events days and non-event days was manually drawn. The daily rainfall -antecedent cumulative rainfall scatter plot that best separates non-triggering and triggering rainfall was chosen as being related to the occurrence of landslides.

3. Determination of landslide rainfall thresholds by physically based modelling (green): This part involved running STARWARS-PROBSTAB model, a coupled hydrological and slope stability physically based model. The input data which were used for the hydrological model, STARWARS are among others: DEM, soil depth map, soil hydraulic properties, land cover map and daily rainfall. Time series groundwater level and soil moisture content were the main outputs obtained from STARWARS model. These outputs were used as inputs for the simulation of slope failure in PROBSTAB model from which factor of safety (FoS) maps and other related maps for every timestep were obtained.

4. Comparison of the derived thresholds (white): Finally, this part of the research simply compared landslides rainfall thresholds derived by empirical modelling and physically based modelling.
Figure 1.1: Flowchart summarising the methodology of the research: preparation of input data (grey), empirical thresholds determination (blue), physically based modelling (green) and comparison (white).
1.6. Thesis structure

The thesis is structured into the following seven chapters:

Chapter one: This chapter explains the background of the research and describes the research problem being dealt with. The chapter further outlines objectives and research questions this research sought to answer. The chapter concludes by providing the general methodology that was used to answer research questions of this study.

Chapter two: The chapter provides a detailed review of the current literature on landslide early warning systems. Firstly, early warning systems are introduced in general followed by a theoretical background of landslide EWS. Secondly, different forecasting methodologies for landslide EWS are reviewed. The chapter concludes by reviewing the advantages and limitations of landslides forecasting methodologies which are used for EWS.

Chapter three: The chapter describes the study area and datasets used in the research.

Chapter four: The chapter provides results of the spatial and temporal analysis of rainfall patterns for the study area. In addition, comparison of satellite rainfall products, rainfall forecast and ground stations rainfall data for the Bogowonto Catchment is presented.

Chapter five: This chapter presents results of the landslides rainfall thresholds determination by empirical models used in the research. Empirical thresholds for different land uses and periods of the rainy season are presented. Finally, the chapter evaluates applicability of the derived empirical thresholds for a simple landslide EWS.

Chapter six: The chapter presents results of landslide modelling by a coupled hydrological-slope stability physical model. The chapter also evaluates the applicability of the results from a physically based model for an early warning of landslides.

Chapter seven: The chapter presents concluding remarks of this research.
2. LANDSLIDE EARLY WARNING SYSTEMS: A REVIEW

2.1. Early warning system (EWS)

Early warning is the provision of timely information before a catastrophic event which enables people exposed to a hazard to take preventive action hence reducing the possibility of harm or loss (UNISDR, 2009). EWS has a pivotal role in reduction of adverse effects of natural disasters. Rogers and Tsirkunov, (2010) attributes the reduction of mortality and injuries caused by natural hazards in the United States to the improvement of the country’s early warning systems over the years. Similar trends have also been observed in lower income countries like Bangladesh and Cuba after developing effective early warning systems to cyclones (Golnaraghi, 2012). According to UNISDR, (2009), there are four fundamental elements of an effective EWS which form a cycle as depicted in figure 2.1. For an EWS to effectively reduce impact of natural hazards the four elements must be adhered to and interlinked (UNISDR, 2006).

![Image of UNISDR early warning cycle](image-url)

Figure 2.1: The UNISDR early warning cycle.

The first element which is hazard mapping involves establishing knowledge of the risks and vulnerability of communities by making sure that necessary updated maps and data are available (UNISDR, 2006). Monitoring and forecasting which comes second is a technical component of the system which ensures that right parameters are being monitored and that accurate and timely warning can be generated when a disaster is imminent (UNISDR, 2006). The third element, warning dissemination ensures that understandable warnings are timely received and sent to communities who area at risk (UNISDR, 2006). Lastly response aptitude is the preparedness of the communities exposed to a hazard and their knowledge of required reaction after a warning is issued (UNISDR, 2006). This last component ensures that the concerned communities have comprehensive understanding of the implication and meanings of the warnings issued from the system. Considering landslide hazard, this work focuses on hazard mapping and monitoring and forecasting component of an EWS of rainfall induced landslides.
2.2. Landslide early warning

To come up with effective preventive measures or EWS for landslides; a thorough understanding of the triggering factors and the landslide process itself is very fundamental (Caracciolo et al., 2017). Rainfall and earthquake are the major triggers for landslides. Due to the unpredictability of earthquakes and the fact that rainfall is the major trigger for landslides, most landslides EWS attempts focus on rainfall triggered landslides (Aleotti, 2004; Thiebes & Glade, 2016). Numerous studies have been done to determine rainfall thresholds that are responsible for the occurrence of shallow landslides for example: Aleotti, (2004), Caracciolo et al., (2017) and Thiebes, (2012). Rainfall thresholds for landslides are defined by Guzzetti et al., (2007) as the minimum rainfall conditions that are likely to trigger landslides in an area.

Many factors such as: scale, type of landslide, risk scenarios and available resources must be considered for the selection of appropriate landslide EWS. Landslide EWS’s have been developed at various localities such as Italy (Camera et al., 2013; Rosi et al., 2012; Schilirò et al., 2015), Brazil (Calvello et al., 2015) and Central and Southern Europe (Guzzetti et al., 2007). Landslide EWS vary in scale from local, regional and global scales. The scale of an EWS determines the forecasting methodology and alerts that can be issued (Michoud et al., 2013; Thiebes & Glade, 2016). Local scale landslide EWS’s are implemented on a single or few slopes while the regional scale is implemented at a country or large region (Piciullo et al., 2016; Thiebes & Glade, 2016). Landslide EWS on a global scale has been attempted by various researchers such as: Guzzetti et al., (2008); Hong and Adler, (2007).

Numerous methodologies for landslides monitoring have been developed and are classified in several ways in the literature. Thiebes, (2012) suggested that landslide monitoring techniques can be broadly distinguished based on spatial scale into local and regional. Apart from considering scale these landslides monitoring methods can be classified based on the techniques and instrumentation used in the monitoring (Savvaidis, 2003) into the following 4 classes: (1) remote sensing or satellite techniques (2) photogrammetric techniques (3) ground-based geodetic techniques using various instruments such as total station and (4) geotechnical techniques which make use of sensors installed on the structures under consideration. Since landslide processes involves movement events in response to triggering mechanisms, understanding of the responses (movement ) to triggering events such as rainfall is essential (Uhlemann et al., 2016). Thus monitoring of the kinematic , hydrological and climatic parameters are essential for successful forecasting of landslides (Angeli et al., 2000). Basing on kinematic, hydrologic and climatic parameters of monitoring, a method of landslides monitoring classification can be devised. Table 2.1 shows a summary of types and classes of landslide early warning systems and their respective examples where they have been successfully applied.

2.3. Landslide rainfall thresholds

Rainfall is well recognised as the main trigger of landslides hence it has long been the scientific and societal interest to know the amount of rainfall that is responsible for the triggering of landslides in different areas (Guzzetti et al., 2007). Built up of water pressure in the underground soil because of infiltrating rain water is the mechanism which is used to explain how rainfall induced landslides are initiated (Guzzetti et al., 2007). Saturation from below due to perched ground water tables may also cause an increase in pore pressure apart from the direct means by infiltration of rain water (Thiebes, 2012). The increase in pore pressure may eventually trigger landslides due to reduced effective strength of the superficial soils (Thiebes & Glade, 2016). Understanding of these processes may lead to establishment of the relationship between landslide occurrence and rainfall which may be used in landslide forecasting for early warning purposes.
Table 2.1: Classification of landslide monitoring approaches used in the literature for landslide EWS.

<table>
<thead>
<tr>
<th>Type of parameter monitored</th>
<th>Instruments/Technique used</th>
<th>Applicable scale</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kinematic</td>
<td>Ground based monitoring instruments</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Tiltmeters and Extensometers</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Shape Acceleration Array (SAA)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Differential GPS</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Geophones</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>slope</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Uhlemann et al., (2016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Kunnath and Ramesh, (2010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Various</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Casagli et al., (2016) and Travelletti et al., (2012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hydrologic</td>
<td>Piezometers</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Water content sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tensiometers</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Local to medium</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Smith et al., (2015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Climatic</td>
<td>Empirical rainfall thresholds</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Various</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Physically based rainfall thresholds</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Local to medium</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

There are several complicating factors that hinder the establishment of the relationship that exists among rainfall, fluctuations of ground water and landslide occurrence (Gioia, 2015). Heterogeneity of earth materials over short distances such as infiltration capacity and cohesion and difficulties to precisely forecast triggering events are examples of the factors (Gioia, 2015). Despite these hindrances, some methods have been developed to describe the link between landslide occurrence and rainfall patterns. Through these methods, rainfall thresholds which trigger landslides have been determined by various researchers across
the world (e.g. Akcali, 2010; Camera et al., 2013; Dahal & Hasegawa, 2008; Guzzetti et al., 2007). Physically-based and empirical models are the main approaches that are used in determination of rainfall thresholds for landslide initiation (Guzzetti et al., 2007; Wu et al., 2010).

### 2.3.1. Physically based models for determination of landslide rainfall thresholds

Physically or process-based models attempt to simulate dynamic processes occurring in a slope and estimate the amount of water that moves into the ground and cause failure of slopes (Guzzetti et al., 2008). The essence of these models is to link rainfall patterns and slope stability by incorporating infiltration models such as the Richards equation model and Green and Ampt infiltration model and Slope stability models such as the infinite slope model (Guzzetti et al., 2007). Physically based models are often implemented on a local scale due to the complexity in obtaining spatially variable parameters such as hydrological and geotechnical properties of slopes which are fundamental inputs to the models (Floris et al., 2012 and Raia et al., 2014).

The purpose of physically based models for landslide rainfall threshold determination is threefold: firstly, these models intends to quantify rainfall conditions which are responsible for triggering landslides in a specific area (Frattini et al., 2004; Robbins, 2016). Secondly these models estimate when rainfall induced landslides are likely to occur (Baum et al., 2008). Thirdly, physically based models show the distribution and extent of expected landslides in an area (Baum et al., 2008). Due to their possibility of determining location and timing of possible landslides Guzzetti et al., (2007) recommends physically based models as suitable for a successful landslide warning system.

Various physically based models have been developed to simulate underground accumulation of infiltrated rainfall and eventually predict slope failure which can be applied for landslide early warning. An important component of most of them is the application of the infinite slope model, which make them mostly applicable for the analysis of shallow landslides. Such models can be developed in a Geographical Information System (GIS) environment. Some examples of these models include TRIGRS, SLIDE and STARWARS-PROBSTRAB just to mention a few. In general, these models assess the stability of slopes by using the Factor of Safety ($F_S$) (equation 2.1) at every pixel of a DEM.

$$F_S = \frac{C' + (\rho_s g z \cos^2 \theta - \rho_w g h \cos^2 \theta) \tan \phi}{\rho_s g z \sin \theta \cos \theta}$$

In this equation: $C'$ is the cohesion of the soil (N m$^{-2}$), $\rho_s$ is the wet soil density (kg m$^{-3}$), $g$ is acceleration due to gravity (ms$^{-2}$), $z$ is the depth of the soil layer, $\theta$ is the slope gradient (°), $\rho_w$ is bulk density of water (kg m$^{-3}$), $h$ is the vertical height of the water table and $\phi$ is the internal friction angle of the soil. In summary, the resisting forces constitute the Coulomb shear strength of earth materials or soils which results from the force of gravity, the cohesion and friction angle of the soil (Baum et al., 2008; Peres & Cancelliere, 2014). On the other hand, the driving force is the shear stress which consist of forces acting parallel to the slope in the direction of movement (Gioia, 2015; Peres & Cancelliere, 2014).

Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability (TRIGRS), is a physically-based model that predicts spatial distribution and timing of rainfall induced shallow landslides (Baum et al., 2008). In this model, one dimensional spatial pressure response to infiltration is combined with infinite slope stability calculation. Precisely TRIGRS models water table rise by comparing infiltrating water to available pore spaces above the water table and then calculates new pressure head for each timestep (Baum et al., 2008; Raia et al., 2014; Schilirò et al., 2015). When rainfall intensity exceeds infiltration rate TRIGRS disperse
excess water by its simple surface runoff routing scheme (Baum et al., 2008). By varying rainfall input, Schilirò et al., (2015) and Muntohar et al., (2017) used TRIGRS to define different triggering scenarios of shallow rainfall induced landslides respectively in Messina, north eastern Sicily, Italy and Banjarnegara, Central Java, Indonesia. 

The Slope Infiltration Distributed Equilibrium (SLIDE) model simulates the correlation between factor of safety and rainfall depth on the infinite slope model (Hong et al., 2015). As shown in figure 2.2, SLIDE highlights the influence of water infiltration process on the contribution of apparent cohesion to shear strength of soil and soil depth (Hong et al., 2015; Liao et al., 2010). SLIDE assumes a shallow slip surface which is above the water table in the unsaturated layer (Hong et al., 2015). Hong et al. (2015), recommended SLIDE model as a potential tool in landslides EWS due to its effectiveness in prediction of the spatial and temporal occurrence of rainfall induced shallow landslides.

![Figure 2.2: Schematic diagram for SLIDE model. (Source: Liao et al. (2010)).](image)

Lastly, STARWARS-PROBSTAB is a coupled dynamic hydromechanical slope stability model originally developed by Van Beek (2002). The coupled model is run in PCRaster which is a raster GIS environment. Storage and Redistribution of Water on Agricultural and Revegetated Slopes (STARWARS) simulates spatial and temporal dynamics of moisture content for different soil layers and ground water levels in response rainfall (van Beek, 2002). On the other hand, Probability of Stability (PROBSTAB) simulates slope stability and probability of failure based on infinite slope model using the simulated hydrological parameters as input (van Beek, 2002).

STARWARS basically simulates different subsurface processes such as soil water recharge and the movement of ground water considering the variability of soil hydrological properties which are governed by differences in land cover (Camera et al., 2013). The primary assumption of the model is that water that can enter the ground at a particular time is dependent on the infiltration capacity of soil and the availability of water which is governed by amount of precipitation and rate of loss due to evapotranspiration and canopy interception (Camera et al., 2013; van Beek, 2002). The model simulates the processes of infiltration and redistribution of the water in the subsurface by a one-dimensional model for the Richards’ equation which describe redistribution of water through unsaturated horizon (van Beek, 2002). The horizontal component of redistribution of the water is considered negligible (Camera et al., 2013). When the volume of water received by a cell exceeds the infiltration capacity, the excess water is routed to superficial runoff (van Beek,
Ignoring the mechanisms for the runoff, the path for the runoff water is based on the drainage direction map which is derived from DEM (Camera et al., 2013). At the end of each timestep of the model run, the excess water is moved out of the study area through an outlet point of the drainage direction map, discharge is also calculated at this outlet point (Camera et al., 2013).

The basis for assessment of slope stability by PROBSTAB is the limit equilibrium approach which assumes that failure occurs when driving forces exceed resisting forces (van Beek, 2002). The limit equilibrium approach uses the safety factor (equation 2.1) to assess the stability of slopes. A major advantage of physically based models is that it is possible to accurately predict slope failure considering site specific conditions hence these models are appropriate in areas with heterogenous material properties (Chen & Zhang, 2014). In addition, some models such as STARWARS-PROBSTAB and TRIGRS considers the variation of soils and materials in a spatially distributed manner, thus simulating real environmental conditions (Camera et al., 2013).

Despite their well performance in predicting slope failures, there are some limitations to the usage of physically based models. The major limitation of these models is the requirement of detailed spatial data on geotechnical, hydrological and morphological properties of the slopes under study. This makes these models less applicable over larger areas due to the difficulties in obtaining precise data required for the models (Martelloni et al., 2012; Robbins, 2016). Another limitation is that slope failures that are structurally controlled by fully or partial pre-existing sliding planes are not considered in physically based models. In addition, it is difficult to apply these models over large areas due to computational time that may be required to simulate the complex processes that occur in slopes (Rosi et al., 2017). Lastly, these models are well suited to simulation of shallow landslides due to the assumptions that are used by these models such as planar sliding surfaces which are not true for deep seated landslides (Guzzetti et al., 2007).

2.3.2. **Empirical models for determination of landslide rainfall thresholds**

Empirical models are sometimes referred to as black box models because they ignore the complex processes which are involved in landslide initiation (Martelloni et al., 2012). Instead empirical models adopt a simple and functional statistical correlation between the trigger (rainfall) and the resulting effect (landslide) by using historical records of rainfall and landslides (Guzzetti et al., 2007; Martelloni et al., 2012). By adopting the principle that the past is key to the future, empirical models aim to derive equations representing the thresholds beyond which landslides have occurred in the past and assuming that they will occur again in the future when similar conditions are met (Martelloni et al., 2012).

Guzzetti et al., (2008) listed several common rainfall and climate variables used in the determination of rainfall thresholds for landslides initiation found in the literature. These thresholds were later grouped into three based on type of rainfall measurement used for their definition (Guzzetti et al., 2008): (1) thresholds that use precipitation characteristics of specific rainfall events, (2) thresholds that utilize antecedent rainfall conditions and (3) other thresholds such as hydrological thresholds. Thresholds established using characteristics of specific rainfall events are further divided into: intensity-duration (ID) thresholds, total rainfall event based (E) thresholds, rainfall event-duration (ED) thresholds and rainfall event-intensity (EI) thresholds (Guzzetti et al., 2007; Guzzetti et al., 2008).

Landslide rainfall thresholds determined by intensity-duration (ID) approach are the most common and well document in the literature (e.g. Brunetti et al., 2010; De Luca & Versace, 2017; Melillo et al., 2015; Picuillo et al., 2016). ID thresholds are derived from a log-log plot of maximum intensity (I in mm per hour) and duration (D in hours) of rainfall events which resulted to landslides (Brunetti et al., 2010; Guzzetti et al., 2008).
The general form of the threshold equation which obeys the power law form is shown in equation 2.2:

\[ I = \alpha D^{-\beta} \]  

(2.2)

Where \( I \) is rainfall intensity (mm/hr.), \( D \) is duration (hr.), \( \alpha \) is the intercept and \( \beta \) is the slope that defines the slope of the power law curve (Guzzetti et al., 2008). It is possible to deduce probable duration of rainfall events which can initiate slope failure in an area by using its derived ID equation (Mathew et al., 2014).

Rainfall thresholds for landslides initiation which consider antecedent rainfall conditions were later developed after observing that some landslides occur either after short duration and low intensity rainfalls or during the rainy season when soils are relatively moist (Chleborad et al., 2006; Glade et al., 2000; Guo et al., 2013). Proponents of the thresholds which consider antecedent rainfall conditions argue that certain soil moisture levels must be reached or exceeded before intensity-duration thresholds can be effective (Aleotti, 2004; Chleborad et al., 2006). Antecedent precipitation influence groundwater levels and soil moisture which are the basic factors that predispose landslide susceptible slopes to failure (Guzzetti et al., 2007). Thus, antecedent precipitation conditions can be used to determine when slope failures are likely to happen (Guzzetti et al., 2007). The simplest method of establishing antecedent precipitation thresholds is based on the calculation of the amount of antecedent precipitation before slope failures are initiated (Glade et al., 2000; Guzzetti et al., 2007).

Empirical methods for derivation of rainfall thresholds for landslides initiation have been widely used in various places ranging from local to global scales. Guzzetti et al., (2007), evaluated minimum intensity and duration of rainfalls that are likely to cause landslides when reached or exceeded for various climatic regions. In this study, it was established that minimum average rainfall intensity and durations that are likely to trigger landslides decreases linearly with an increase of rainfall duration from 10 minutes to 35 days (Guzzetti et al., 2007).

The main advantage of empirical methods for deriving landslide rainfall thresholds is that they are simple hence can be used at various scales ranging from local to global scales as long as historical rainfall and landslides data is available (Martelloni et al., 2012). Furthermore, since these methods require limited input data and are rapid, they can be easily implemented into an operational landslide early warning system (Martelloni et al., 2012).

Conversely, several limitations for the application of empirical landslide rainfall thresholds have been reported in the literature. The first limitation is that despite these thresholds being relatively simple to derive, they perform well only in the region where they were developed hence cannot be exported elsewhere (Guzzetti et al., 2007). The second limitation is the assumption that conditions which triggered landslides in the past will be the same in the future which may not be the case in a dynamic environment we live in (Gioia, 2015). Lastly, unavailability of landslides and rainfall data of superior quality and resolution results into unacceptable levels of rates of thresholds exceedance without any landslides being triggered and sometimes landslides occurring below determined minimum thresholds (Gioia, 2015).
3. STUDY AREA AND DATA

3.1. Introduction

This chapter presents a brief description of the study area focusing on the physical environment, landscape characteristics and occurrence of landslides. Furthermore, the chapter provides a description of datasets used in the study and how and where they were acquired.

3.2. Location of the study area

Bogowonto catchment is bounded by latitude 7° 023' to 7° 054' S and longitude 109° 056' to 109° 010' E, it is one of the largest catchments in Central Java, Indonesia. Large part of the catchment is in Purworejo, a regency in Central Java, figure 3.1 below shows the map and location of the study area. The size of the catchment is about 600 km², the altitude of the area ranges from 0 to 3305 m above the sea level. The catchment has of late often been hit by flooding and landslide disasters (Pawestri et al., 2017). The area experiences numerous shallow landslides almost every year during the rainy season with an average of 10 events per year according to the landslide inventory. Additionally, landslides data from Karangkobar catchment which is located to the north west of Bogowonto was used to assess the derived rainfall thresholds. The size of the catchment is about 42 km². Due to prevalent hilly terrane and high rainfall landslide often happen in Karangkobar (Muntohar et al., 2017).

Figure 3.1: Map of Bogowonto Catchment. The insert shows location of the catchment and Karangkobar catchment within Java Island, Indonesia
3.3. Data collection

The study used both primary and secondary data which were respectively collected during fieldwork which was conducted in the period between September to October 2017 and from secondary sources. Landslide inventory was developed by collecting landslides data from other studies and events reported by the media. In addition, some landslide occurrence information was obtained during field mapping by interviewing village authorities on areas where they had occurrence of landslides in their respective jurisdiction. Other datasets essential for the study such as DEM, landsuse map, ground measured rainfall data and drainage map were collected from various sources as shown in table 3.1 below.

Table 3.1: List of datasets used in this study.

<table>
<thead>
<tr>
<th>Data</th>
<th>Format</th>
<th>Resolution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital Elevation Model</td>
<td>Raster</td>
<td>12.5m</td>
<td>ASF portal</td>
</tr>
<tr>
<td>Geological map</td>
<td>Photo copy</td>
<td>1:100 000</td>
<td>Geological Survey of Indonesia</td>
</tr>
<tr>
<td>Landslide inventories</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>a. Covering Bogowonto Catchment</td>
<td>Points</td>
<td></td>
<td>Indonesian National Board for Disaster Management (BNPB)</td>
</tr>
<tr>
<td>b. Covering central Kodil sub catchment</td>
<td>Points</td>
<td></td>
<td>MSc thesis by Ulfa (2017)</td>
</tr>
<tr>
<td>c. Covering Kodil Catchment</td>
<td>Points</td>
<td></td>
<td>MSc thesis by Rusdiyatmoko (2013)</td>
</tr>
<tr>
<td>d. Covering Bogowonto Catchment</td>
<td>Points and polygons</td>
<td></td>
<td>Field interviews and mapping</td>
</tr>
<tr>
<td>Landcover map</td>
<td>Shapefile</td>
<td></td>
<td>University of Gadjah Mada (UGM)</td>
</tr>
<tr>
<td>Drainage map</td>
<td>Shapefile</td>
<td></td>
<td>UGM</td>
</tr>
<tr>
<td>Rainfall data</td>
<td>Excel sheets</td>
<td></td>
<td>UGM</td>
</tr>
<tr>
<td>a. Ground station data (1990-2016)</td>
<td>CSV</td>
<td>0.25° and 0.1°</td>
<td>NASA portal</td>
</tr>
<tr>
<td>b. Satellite rainfall estimates (2000-2016)</td>
<td>NetCDF</td>
<td>80 km</td>
<td>ECMWF portal</td>
</tr>
<tr>
<td>Road network</td>
<td>Shapefile</td>
<td></td>
<td>UGM</td>
</tr>
<tr>
<td>Administrative boundaries</td>
<td>Shapefile</td>
<td></td>
<td>UGM</td>
</tr>
</tbody>
</table>

3.4. Physiography of the study area

Mass wasting processes including landslides are influenced by physiographic factors such as high relief, steep slopes and soil development (Ballabh et al., 2014). It is therefore imperative to have a thorough understanding of the physiography of an area to eventually understand spatial and temporal patterns of landslides in an area. The Bogowonto river and its main tributary, the Kodil river flow from mount Simbung
which has the highest altitude of 3,375 m above sea level (Pawestri et al., 2017). Volcanic mountains and denudational hills are a prominent characteristic of the northern and eastern part which constitutes the upper part of the catchment (Nugroho et al., 2014). The upper catchment has peaks exceeding 3,000 m altitude and slopes of more than 35 percent. The lower catchment is dominated by coastal floodplain characterised by slopes of less than 2 percent (Mursid et al, 2015).

Geologically the study area is made up of four formations namely: Old andesite breccia, Sentolo, Andesite and alluvium formations (DGWRD, 1996). Andesitic breccia, tuff, lapilli tuff and intercalations of andesitic lava flows are the prominent lithologies within the Old andesite breccia formation (DGWRD, 1996). The andesite formation is composed of the variants of the compositional range from hypersthene andesite to hornblende-augite andesite and trachyandesite (DGWRD, 1996). The Sentolo formation is composed of limestone and marl sandstone lithologies. Lastly the alluvium formation is composed of gravel, sand, silt and clay; the formation is mostly confined to coastal plain and in streams (DGWRD, 1996). The old andesite formation is prominent in the northern part followed by Sentolo formation.

Based on origin the area can be divided into three main geomorphological units (Nugroho et al., 2014). The denudational hills, which is an old volcanic formation and is consistent with the Andesite Breccia formation. Many rocks belonging to this unit have undergone extensive weathering processes (Nugroho et al., 2014). The denudational hillslope unit is the second unit, located on the foot slope with moderate slope between 8 and 25%. It is mainly composed of reworked materials from the upper units; it’s lower part is made up of marl limestone (Nugroho et al., 2014). The alluvium plain unit is the third, it generally has flat relief with slopes between 0 and 3%. The morphological and geological differences are believed to control the occurrence of landslides in the study area (Fathani et al., 2008). Landslides are absent in the flat relief but dominate in the slopes of high relief north east area, this is further influenced by strong weathering and fracturing of andesite and andesitic breccias which are dominant in the north east part (Fathani et al., 2008).

3.5. Climate

As the rest of Java island, the study area has a tropical climate characterised by two seasons which vary with equatorial air circulation and meridian air circulation (Ngadisih et al., 2017). A long, wet monsoon season from the month of October to May (figure 3.2) characterised by high intense rainfall and a dry season from June to September are the main seasons.

Figure 3.2: Average monthly precipitation for Bogowonto catchment (2000-2016) and corresponding monthly total number of landslides recorded over the same period.
The average annual precipitation of the catchment varies from the upper and lower parts of the area; the upper catchment area receives relatively higher precipitation than the lower catchment (Nugroho et al., 2014). The average annual precipitation of the upper catchment is about 3000 mm while for the lower catchment is about 2500 mm. Average air temperature ranges between 25 and 27 degrees Celsius whilst humidity ranges from 70 percent to 90 percent (Mursid et al., 2015).

3.6. Landslides in the study area

Vast areas especially the central east part is continuously affected by landslides due to its geomorphic setting coupled with high precipitation amount. Numerous rice fields, parts of settlement areas and roads are the main elements that are exposed to the recurrent landslides hazard. The most recent event is the June 2016 landslides which affected most parts of Central Java, this resulted into over 28 deaths and several others missing in the study area (Petley, 2016). Several houses were destroyed and many roads blocked which made access to the affected sites difficult (Petley, 2016). The 2011 rainfall was extreme leading to numerous (33 reported) landslides in the study area.

Due to unavailability of an official landslide inventory, various means were used to generate a landslide inventory for this study. A landslide inventory is documentation of the information pertaining to past landslides which contains amongst other things: the location, classification, volume, date of occurrence and other characteristics of landslides in an area (Fell et al., 2008). Some of the techniques used for preparation of landslides inventory mapping include: using historical data, image interpretation and automatic classification (Van Westen et al., 2012).

In this study firstly, the Indonesian National Board for Disaster Management (BNPB) database which is a national archive for disasters in Indonesia (BNPB, 2017) was checked to get landslides events that have occurred in Bogowonto Catchment. Despite this database having numerous landslide events (over 4500
between the years 2001 and 2017), only 4 landslides were found in Bogowonto area. Secondly, landslide information was sought from landslide research that have been conducted in the area; two MSc theses were found which were done in the area. From these theses, 190 landslide points which were used in these studies were added to the inventory. Lastly during field work 24 landslides points were also mapped, during the field, in addition, some landslide points obtained from other sources were also visited to verify and collect some other information such as date of occurrence. In total 218 landslides were collected from the sources described and fieldwork which are mostly covering the central part of the study area as shown in figure 3.3. 167 landslides have date of occurrence known; they were triggered on 48 different dates. The compiled landslide database covers a period of 13 years from 2003 to 2016. However, the inventory was not detailed enough to provide other characteristics such as type of landslide (deep vs shallow) and initiation areas and runout.

During field work period it was realised that landslides older than one year were hardly traceable due to revegetation because of prevalent fertile soils and high precipitation amounts. In addition, ubiquitous high tropical trees made it difficult to map landslides in the area using satellite images. For the landslides that were still traceable, landslide type, soil type and soil depth were recorded. Shallow debris slides are a common type which was mapped during field work. Landslides occurring in built up areas were mostly associated with cut slopes.

3.7. Land cover

Land cover is a significant factor that influence the occurrence of landslides. Land cover may influence slope failure mechanisms since it alters hydro-morphological response of slopes by for example adjusting infiltration and runoff capabilities and soil cohesion which eventually affect shear strength (Beguería, 2006). Thus, it is important to consider land cover in landslide studies, this study used an existing land use map which was reclassified into 6 classes as shown in figure 3.4. As shown in the map: forest and rice plantations are the major land uses. Landslide occurrence dominate in the forest landcover followed by built up areas.

Figure 3.4: Landcover map showing six major landcovers (left) and pie chart of area percentage covered by each land cover (right).
3.8. **Digital Elevation Model (DEM)**

DEM is one of the most fundamental datasets in topographically based modelling of catchment processes such as flooding and landslide occurrence (Claessens et al., 2005). The accuracy of landslide physical models are based on quality of DEM since most input factor maps that are used for modelling of landslides such as slope, elevation and drainage direction are derived from DEM (Mahalingam & Olsen, 2015). In this study the DEM used was ALOS PALSAR DEM at a resolution of 12.5 m by 12.5 m which was downloaded freely from Alaska Satellite Facility (ASF) website (ASF DAAC, 2017). A high resolution or quality DEM for the catchment was not available as this 12.5m resolution could not capture cut slopes which were abundant in the central part of the study area. The poor-quality DEM affected results of the physically based model to some extent since most of the input factor maps for the physical model are derived from DEM.

3.9. **Soil texture and Soil depth**

Soil is a fundamental factor for the investigation of superficial hydrological and geomechanical dynamics of slopes for landslide assessment (Kuriakose et al., 2009). Due to unavailability of a local soil map, a soil map was downloaded from the Soil Grids which is a coarse resolution (250 m) global soil information system (Hengl et al., 2017). The coarse resolution soil map which had 3 soil textures for the catchment was used to determine minimum number of soil samples to be collected for measurement of different soil properties which are important for the landslide physical modelling. Six soil samples were collected from various locations from which different soil properties such as hydraulic conductivity and porosity were tested at the University of Gadjah Mada geomorphology laboratory.

In addition, during fieldwork 53 soil depth measurements were done at various localities. The locations of the soil samples and their respective measurements are shown in appendix 2. Hydraulic and slope stability models are strongly affected by soil depth hence caution has to be exercised when producing soil depth to ensure the reliability of hydraulic and slope stability models (Camera et al., 2013; Tang et al. 2017). The soil depth map (appendix 2) used in this study was modelled using topographic attributes by modifying the methodology proposed by Kuriakose et al., (2009). The model uses slope steepness, profile curvature, distance to coast and channels to predict soil depth but in this study, distance to the coast was not used and elevation factor was introduced. The soil depth is calculated by the following equation:

\[
SD = \text{Intercept} + a \times DEM + b \times D_{\text{channel}} + c \times S + d \times C
\]

(3.1)

Where SD is the soil depth (m), a, b, c, d are constants (-) derived from statistical analysis, DEM is the digital elevation model (m), \(D_{\text{channel}}\) is the distance to the nearest channel (m), S is the slope of the surface (m m\(^{-1}\)) and C is the profile curvature of the surface (m\(^{-1}\)). The values for the constants (table 3.2) used for this study were derived using the field soil depth measurements and the aforementioned topographic factors. The correlation of the predicted soil depth map with field measured soil depth was 0.41

Table 3.2: *Predictors for the soil prediction model constants and their respective derived values*

<table>
<thead>
<tr>
<th>Constant</th>
<th>Predictor</th>
<th>Value</th>
<th>Intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>DEM</td>
<td>-0.0011</td>
<td></td>
</tr>
<tr>
<td>b</td>
<td>Channel-distance map</td>
<td>0.0007</td>
<td>3.2829</td>
</tr>
<tr>
<td>c</td>
<td>Slope map</td>
<td>0.9938</td>
<td></td>
</tr>
<tr>
<td>d</td>
<td>Curvature map</td>
<td>9.2238</td>
<td></td>
</tr>
</tbody>
</table>
4. RAINFALL ANALYSIS

4.1. Introduction

The significance of considering precipitation patterns in landslide assessment cannot be overemphasised, a high percentage of landslides especially in tropical regions and mountainous areas are caused by intense rainfall (Aristizábal et al., 2017; Calvello et al., 2015). A thorough understanding of precipitation patterns prior to occurrence of landslide events is fundamental for the development of effective landslide forecasting in an EWS (Robbins, 2016). Therefore, before evaluation of the correlation between landslide occurrence and rainfall; the behaviour of the triggering factor (rainfall) was analysed. Many studies dealing with determination of rainfall thresholds use gauge-measured rainfall data which might have limitations such as: missing data, inaccuracies of observations due to instrument mechanical defects and sparse coverage of gauge network (Robbins, 2016; Sene, 2013). To overcome rainfall data availability challenges, a combination of gauge measured rainfall data and satellite measurements is recommended as a way of simultaneously improving rainfall estimations accuracy and resolution at the catchment scale (Ouatiki et al., 2017).

The Tropical Rainfall Measuring Mission (TRMM) and the Global Precipitation Measurement (GPM) are the satellite rainfall products which were used in this study. Additionally, rainfall forecast data from European Centre for Medium-Range Weather Forecasts (ECWMF) was used to link the determined thresholds to an early warning system. The details about ECWMF data are provided in section 4.6 TRMM, a joint mission of NASA and the Japan Aerospace Exploration Agency has been providing rainfall measurements at various temporal and spatial scales since November 1997 up to March 2015 (Kirschbaum et al., 2016; NASA, 2016). Building on the success story of TRMM, GPM which is a constellation of satellites designed to provide high resolution precipitation observations was launched in February, 2014 (Hou et al., 2014). Due to its high spatial and temporal resolution, GPM observations are expected to improve the forecasting of freshwater resources and hydro-meteorological hazard such as floods and landslides (Kirschbaum et al., 2012; Wu et al., 2012).

Since the ultimate aim of this study was to link rainfall thresholds to landslides EWS, it is essential to have reliable rainfall estimates to come up with an effective landslides forecasting. It is therefore the aim of this chapter to provide a comparison of different rainfall data sources and to eventually find appropriate rainfall data to be used for derivation of rainfall thresholds. Specifically, 3B42 v7 rainfall product of TRMM was used, this is a daily rainfall estimate at a spatial resolution of 0.25° (~25 km) (Huffman et al., 2010). For GPM, the data product used was daily IMERG final precipitation level 3 at a resolution of 10 km by 10 km which is derived from half hourly IMERG rainfall (Hou et al., 2014). Details about the algorithms which are used to derive rainfall estimates for both TRMM 3B42 v7 and GPM IMERG daily rainfall products is available on the NASA website.

The subsequent parts of the chapter are structured as follows: section 4.2 explains the coverage of TRMM and GPM in the catchment, sections 4.3 and 4.4 presents findings on spatial correlation of rainfall stations which was done to investigate if there is spatial precipitation variability in the catchment. Section 4.5 presents results on comparison of gauge measured and satellite estimated rainfall at daily and monthly scales. Sections 4.6 presents results of comparison of rainfall forecast data and gauge measured, TRMM and GPM rainfall products. In section 4.7 the rainfall products are compared based on extreme precipitation indices. Lastly, section 4.8 discusses the overall findings of the rainfall analysis for the catchments and presents some concluding remarks.
4.2. Rainfall stations, TRMM and GPM coverage in the study area

As shown in figures 4.1a and 4.1b, the area is covered by 6 TRMM pixels and by about 15 GPM pixels. However, since the study is dealing with historical landslides, the usage of GPM data is limited since its data is only available from April 2014 onwards. As a result, the coarse resolution TRMM was mostly used since its data is fully available for the whole period of study in this research (2003-2016).

A total of 13 rainfall stations data were available for this study, of these stations 4 are automatic weather stations located within the University of Gadjah Mada (UGM) field laboratory, the remaining stations are manually recorded. The automatic UGM rainfall stations were not used in this study since their data extend over a period of less than one year because they have been recently installed. The spatial distribution of the rainfall stations is shown in figure 4.1 which also shows the coverage of TRMM and GPM.

![Figure 4.1a: Coverage of TRMM pixels over Bogowonto Catchment.](image1)

![Figure 4.1b: Map showing coverage of GPM pixels over Bogowonto Catchment and location of rainfall stations.](image2)

The central part, where most of the landslides occur is well covered with rainfall stations as shown in figure 4.1. However most of the stations have a lot of gaps in the records due to broken instruments as commented in the rainfall stations logbook. Table 4.1 shows the details of each station, only three stations have continuous data for the measurement period they cover. Two of the three complete stations are in the flat areas where landslides are not a problem and the third is outside of the catchment. The mean annual rainfall recorded by rainfall stations ranges from 2063 mm to 3397 mm.
4.3. Spatial correlation of rainfall stations

6 rainfall stations of the 9 listed in table 4.1 were compared by using their daily precipitation measurements to explore if there is a correlation of the rainfall measurements at these various localities. The comparison was done for the years 2009 to 2016, a common period amongst the 6 stations with continuous data record. The other three rainfall stations were not considered in the comparison due to intermittent data records. Table 4.2 shows results of Pearson Correlation Coefficient (PCC) amongst rainfall stations.

Table 4.1: Meta data on 9 rainfall stations used in this study (Abbreviations link to the locations indicated in figure 4.1b).

<table>
<thead>
<tr>
<th>Station Name</th>
<th>Elevation (m)</th>
<th>South Latitude</th>
<th>East Longitude</th>
<th>Average annual rainfall (mm)</th>
<th>Period covered</th>
<th>Missing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benyuasin (Bn)</td>
<td>210</td>
<td>-7.6637</td>
<td>110.105</td>
<td>2619</td>
<td>1990-2016</td>
<td>1 year</td>
</tr>
<tr>
<td>Banyuurip (Bp)</td>
<td>22</td>
<td>-7.7621</td>
<td>110.978</td>
<td>2063</td>
<td>1992-2012</td>
<td>5 years</td>
</tr>
<tr>
<td>Bener (Br)</td>
<td>31</td>
<td>-7.6328</td>
<td>110.05</td>
<td>2372</td>
<td>2008-2016</td>
<td>6 months</td>
</tr>
<tr>
<td>Guntur (Gr)</td>
<td>216</td>
<td>-7.6215</td>
<td>110.029</td>
<td>3350</td>
<td>1990-2016</td>
<td>21 months</td>
</tr>
<tr>
<td>Kedungputri (Ki)</td>
<td>107</td>
<td>-7.6712</td>
<td>110.042</td>
<td>2960</td>
<td>1990-2016</td>
<td>0</td>
</tr>
<tr>
<td>Maron (Mn)</td>
<td>148</td>
<td>-7.7674</td>
<td>110.032</td>
<td>3149</td>
<td>1990-2016</td>
<td>0</td>
</tr>
<tr>
<td>Purworejo (Po)</td>
<td>66</td>
<td>-7.2123</td>
<td>110.005</td>
<td>2521</td>
<td>1990-2012</td>
<td>14 months</td>
</tr>
<tr>
<td>Salaman (Sn)</td>
<td>300</td>
<td>-7.5967</td>
<td>-110.14</td>
<td>3331</td>
<td>1986-2016</td>
<td>0</td>
</tr>
<tr>
<td>Wutujagir (Wt)</td>
<td>331</td>
<td>-7.4769</td>
<td>109.97</td>
<td>3397</td>
<td>1990-2012</td>
<td>5 months</td>
</tr>
</tbody>
</table>

Table 4.2: Pearson correlation coefficients for observed daily rainfall between various rainfall stations (2009-2016).

<table>
<thead>
<tr>
<th></th>
<th>Br</th>
<th>Bn</th>
<th>Gr</th>
<th>Ki</th>
<th>Mn</th>
<th>Sn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Br</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bn</td>
<td>0.248</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gr</td>
<td>0.470</td>
<td>0.267</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ki</td>
<td>0.674</td>
<td>0.248</td>
<td>0.365</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mn</td>
<td>0.754</td>
<td>0.247</td>
<td>0.438</td>
<td>0.769</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Sn</td>
<td>0.472</td>
<td>0.279</td>
<td>0.301</td>
<td>0.447</td>
<td>0.470</td>
<td>1</td>
</tr>
</tbody>
</table>

* All correlations are significant at the 0.01 level (2-tailed)

Stations Maron (Mn) and Kedungputri (Ki) are highly correlated amongst all stations (0.726), this could be expected since the stations are also spatially closest to each other (figure 4.1b). Station Benyuasin (Bn) poorly correlates with all the station with PCC’s of less than 0.25 possibly because it is isolated from all the stations. In general, for the correlations between the other stations there is poor to moderate correlations signified
by low correlation coefficients. These results roughly imply that rainfall over the catchment is spatially variable as there is not high correlation of rainfall measurements amongst the various stations that have been analysed.

4.4. Correlation between station elevation and rainfall

It is theoretically known that topography affects precipitation distribution and amount but the extent of variability is not straightforward (Brunsdon et al., 2001; Sindosi et al., 2015). Since the study area is orographically diversified the mean annual precipitation was correlated with the station’s elevation to explore the effect of topography on precipitation.

![Graph of correlation between station elevation and rainfall](image)

Figure 4.2: Correlation of rainfall stations elevation (m) and measured mean annual rainfall in Bogowonto Catchment over the period 1990-2016.

The correlation of mean annual rainfall and elevation is shown in figure 4.2. Stations at lower elevations have relatively lower mean annual rainfall compared to rainfall stations at higher elevations. With a correlation coefficient of about 0.71, the variation cannot be attributed to mere random variation; thus, much of the variation can be explained by elevation differences amongst the rainfall stations.

4.5. Comparison of satellite rainfall products and station data

The accuracy of satellite rainfall products needs to be assessed due to some inherent shortcomings resulting from amongst other things: random errors, non-uniform field of view of the sensors that are used and uncertainties in the algorithms used to retrieve precipitation measurements (Li et al., 2014). Thus, it is essential to assess how satellite rainfall products compare with conventional ground-based rainfall measurements. The comparison was performed using statistical measures and methods such as: correlation analysis, the root mean square error (RMSE) and relative bias which are measures widely used in the literature (Li et al., 2014; Wehbe et al., 2017).

Table 4.3 shows formulas for the statistical metrics which were used to compare satellite precipitation estimates and gauge measured rainfall. The correlation coefficient (R) reflects the degree of agreement
between two variables, in this case satellite rainfall estimates and ground-based rainfall measurements. The values of correlation coefficient ranges from -1 to 1 where positive values indicate positive correlation and negative values indicates negative correlation. The RMSE measures the average error magnitude and relative bias measures the systematic bias between satellite precipitation estimates and gauge measured rainfall data (Tan & Duan, 2017; Toté et al., 2015). Relative bias reflects the degree of over estimation or underestimation of a rainfall product in estimating rainfall (Toté et al., 2015). Lastly, Bias evaluate the average estimation error of satellite rainfall products in millimetres (Toté et al., 2015).

According to Tan & Duan, (2017), good performance of satellite based daily precipitation estimates should be characterised by RB values ranging from -10% to 10% and correlation coefficient of more than 0.7. Negative values of relative bias and bias signifies under estimation of satellite precipitation products (Tan & Duan, 2017). Satellite precipitation pixels which covers at least one rainfall station were the ones consider in the analysis. The following sections presents the results of the comparison.

### 4.5.1. Comparison of daily rainfall estimates

Table 4.4 shows the results of the correlation analysis between satellite estimated rainfall with Gentur Station which exhibited relatively higher correlation coefficient with Satellite rainfall estimates compared to the other stations. The results for the other three stations are shown in appendix 1. Generally, for daily rainfall in all stations, there is low agreement between ground measured rainfall and satellite rainfall estimates evidenced by their low R values. For Gentur station (table 4.4), there is a moderate agreement with GPM estimates (R=0.521) which is better than that with TRMM (R=0.356). Looking into the other correlation metrics, both TRMM and GPM underestimates the daily rainfall amounts signified by their negative bias. Furthermore, the relative bias is beyond the acceptable limits of -10% to 10% for acceptable performance of satellite rainfall products.

### Table 4.3: Statistical metrics used for comparison of satellite rainfall estimates (S) and gauge rainfall measurements (G) (adapted from Li et al., (2014); Toté et al., (2015) and Wehbe et al,( 2017) ).

<table>
<thead>
<tr>
<th>Statistical metric</th>
<th>Formula</th>
<th>Perfect score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation coefficient</td>
<td>$R = \frac{\sum_{i=1}^{n}(G_i - \bar{G})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(G_i - \bar{G})^2 \sum_{i=1}^{n}(S_i - \bar{S})^2}}$</td>
<td>1</td>
</tr>
<tr>
<td>Root mean square</td>
<td>$RMSE = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (S_i - G_i)^{2}$</td>
<td>0</td>
</tr>
<tr>
<td>Relative bias</td>
<td>$RB = \frac{\sum_{i=1}^{n}(S_i - G_i)}{\sum_{i=1}^{n}G_i} \times 100%$</td>
<td>0</td>
</tr>
<tr>
<td>Bias</td>
<td>$Bias = \frac{\sum_{i=1}^{n}(S_i - G_i)}{n}$</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 4.4: Results of correlation of daily satellite rainfall estimates and observed rainfall from station Gentur.

<table>
<thead>
<tr>
<th></th>
<th>TRMM</th>
<th>GPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>0.356</td>
<td>0.521</td>
</tr>
<tr>
<td>RMSE (mm/day)</td>
<td>23.084</td>
<td>19.034</td>
</tr>
<tr>
<td>Relative Bias (%)</td>
<td>-28.068</td>
<td>-24.342</td>
</tr>
<tr>
<td>Bias</td>
<td>-3.016</td>
<td>-2.589</td>
</tr>
</tbody>
</table>

4.5.2. Comparison of monthly rainfall totals

Since one of the objectives of this study is to determine rainfall thresholds for landslide occurrence by considering antecedent rainfall conditions of up to 30 days; monthly rainfall measurements were also compared. Both daily observed rainfall measurements and daily satellite rainfall estimates by TRMM and GPM products were aggregated to monthly precipitation totals.

Figure 4.3: Scatter plots for TRMM and GPM monthly rainfall estimates against two rainfall stations.

Then observed monthly rainfall totals were compared with the estimated monthly totals by TRMM and GPM. The scatter plot for observed rainfall monthly and monthly estimated rainfall by both TRMM and GPM for stations Salaman and Gentur are shown in figure 4.3 and table 4.5. Results for other stations are
shown in appendix 1. As shown in the figure the correlation of the observed rainfall and satellite estimated rainfall at monthly scale improves significantly with higher correlation coefficients being observed in all cases as compared the daily scale. Like the daily scale, GPM rainfall estimates showed better performance than TRMM with higher correlation coefficients (for example 0.91 for Station Gentur) and lower RMSE’s. However, even at the monthly scale the relative bias is still negative hence the satellite products still underestimate monthly rainfall estimates. The relative bias is also beyond the recommendable limits of 10% and -10%.

Table 4.5: Results of correlation of monthly satellite rainfall estimates and observed rainfall for Gentur station.

<table>
<thead>
<tr>
<th></th>
<th>TRMM</th>
<th>GPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>0.831</td>
<td>0.914</td>
</tr>
<tr>
<td>RMSE (mm/month)</td>
<td>149.619</td>
<td>126.251</td>
</tr>
<tr>
<td>Relative Bias (%)</td>
<td>-21.563</td>
<td>-25.8</td>
</tr>
<tr>
<td>Bias</td>
<td>-56</td>
<td>-79.5276</td>
</tr>
</tbody>
</table>

4.6. Rainfall forecast data

In addition to TRMM and GPM, ERA-Interim rainfall forecast data was explored for its usability for a landslide early warning system. ERA-Interim is a global atmospheric reanalysis produced by the ECWMF (Berrisford et al., 2011). ERA-Interim is produced using the Intergrated Forecast System (IFS) using 12 hour analysis cycles (Dee et al., 2011). Datasets produced are: 4 analyses per day at 00, 06, 12 and 18 Coordinated Universal Time (UTC) and 2 forecasts per day initialized from analyses at 00 and 12 UTC (Berrisford et al., 2011). The forecasted data for a given day, made on the day before was correlated with the measured rainfall from stations, TRMM and GPM on the day itself. Forecast data for the period 2003 to 2016 was analysed. The purpose of analysing this data was to check if the forecasted rainfall can be linked to a landslide early warning system based on antecedent rainfall thresholds. With reliable rainfall forecast, warning of possible occurrence of landslides can be issued by plotting the forecasted rainfall on the antecedent rainfall threshold graph. The study used ERA-Interim daily rainfall forecast data with step 12 initialised at 00:00 UTC with a horizontal grid resolution of 0.125 by 0.125.

<table>
<thead>
<tr>
<th></th>
<th>TRMM</th>
<th>GPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation Coefficient (R)</td>
<td>0.23</td>
<td>0.37</td>
</tr>
<tr>
<td>RMSE (mm/day)</td>
<td>19.45</td>
<td>14.44</td>
</tr>
<tr>
<td>Relative Bias (%)</td>
<td>19.45</td>
<td>29.26</td>
</tr>
<tr>
<td>Bias</td>
<td>-19.45</td>
<td>2.18</td>
</tr>
</tbody>
</table>

The results in table 4.6 indicates that there is generally a poor agreement between forecasted rainfall data and observed rainfall and the two satellite rainfall estimates signified by R values less than 0.5 in all cases. The forecast data overestimates rainfall data when compared to observed rainfall measurements, TRMM and GPM signified by positive relative bias and bias. Additionally, the relative bias is out of the tolerable range of -10% to 10% for acceptable performance of rainfall estimates. These results are in agreement with
the findings of Kidd et al., (2013) who found that ECWMF forecast model overestimated rainfall in the tropics by about 15%. In this research Kidd et al., (2013) particularly pointed out poor performance ECWMF precipitation model over Indonesia due to complex land-sea interactions.

4.7. Comparison on extreme precipitation indices

As extreme precipitation often results into disastrous events such as floods and landslides, analysis of extreme precipitation is fundamental when designing mitigation strategies (Yazid & Humphries, 2015). Therefore, all rainfall datasets were compared by investigating their performance in detection of extreme daily precipitation events. Extreme rainfall events were determined by indices provided by the World Meteorological Organisation (WMO) (Tank et al., 2009) which are widely used in the literature (e.g. Balling et al., 2016; Rahmani et al, 2016; Yazid & Humphries, 2015). The definitions of the 11 indices that were used in the analysis of extremes in this study are shown in table 4.7.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Name</th>
<th>Definition</th>
<th>Calculation</th>
</tr>
</thead>
<tbody>
<tr>
<td>RX1day</td>
<td>Daily maximum rainfall</td>
<td>Highest precipitation amount in 1 day</td>
<td>RX1day$<em>i$ = max (RR$</em>{ij}$)</td>
</tr>
<tr>
<td>RX5day</td>
<td>5 days maximum rainfall</td>
<td>Highest precipitation amount in 5 days</td>
<td>RX5day$<em>i$ = max (RR$</em>{kj}$)</td>
</tr>
<tr>
<td>R10mm</td>
<td>Number of heavy rainfall days</td>
<td>Count of days when precipitation ≥ 10mm</td>
<td>Count (RR$_{ij}$ ≥ 10 mm)</td>
</tr>
<tr>
<td>R20mm</td>
<td>Number of very heavy precipitation</td>
<td>Count of days when rainfall ≥ 20mm</td>
<td>Count (RR$_{ij}$ ≥ 20 mm)</td>
</tr>
<tr>
<td>R50mm</td>
<td>Number of extremely heavy rainfall (defined for this study)</td>
<td>Count of days when rainfall ≥ 50mm</td>
<td>Count (RR$_{ij}$ ≥ 50 mm)</td>
</tr>
<tr>
<td>SDII</td>
<td>Simple daily intensity index</td>
<td>Mean rainfall when precipitation ≥ 1 mm</td>
<td>SDII$<em>i$ = sum (RR$</em>{wj}$) / W</td>
</tr>
<tr>
<td>R95PTOT</td>
<td>Precipitation due to very wet days</td>
<td>Contribution to precipitation by very wet days</td>
<td>R95Ptot % = Sum if { (RR$_{ij}$ &gt; R95p) / PRCPTOT } *100</td>
</tr>
<tr>
<td>R99PTOT</td>
<td>Precipitation due to extremely wet days</td>
<td>Contribution to precipitation by extremely wet days</td>
<td>R99Ptot % = Sum if { (RR$_{ij}$ &gt; R99p) / PRCPTOT } *100</td>
</tr>
<tr>
<td>PRCPTOT</td>
<td>Wet-days (&gt;1mm) precipitation total</td>
<td>Total precipitation in wet days</td>
<td>PRCPTOT$<em>i$ = sum (RR$</em>{w}$)</td>
</tr>
</tbody>
</table>

The results are summarised in table 4.8 which was done for Station Kedungputri only and its corresponding TRMM and ERA-Interim pixels. This station was chosen because of its proximity to landslide points cluster.
and it has continuous data from 2000 to 2016. GPM rainfall estimates were not considered in the analysis of extremes since its data is only available from 2015. As shown in table 4.8, using Kedungputri station as a standard, the station has high scores for all indices except number of heavy rainfall days (R10mm). Number of heavy rainfall days is higher for ERA-Interim (2124 days) followed by TRMM (1381 days) and finally ground Station data (1194 days). The high number of heavy rainfall days (rainfall ≥ 10 mm) for ERA-Interim and TRMM can be attributed to the overestimation of small rainfall events by these products. The overestimation of small rainfall events is also reflected in number of wet days (rainfall ≥ 1mm) which is high for Era-Interim (3414 days) followed by TRMM (2525 days) and lastly station data (2022).

Looking at very heavy and extremely heavy precipitation ERA-Interim performs poorly in detection of such events. For instance, over the study period, ERA-Interim only predicts 47 days with rainfall of greater than or equal to 50 mm while TRMM detects 138 days and 223 days are observed at rainfall station. The inferior performance of ERA-Interim in this case is probably due to underestimation of extreme events. This is further evidenced by the 95\textsuperscript{th} and 99\textsuperscript{th} percentile for ERA-Interim data which is respectively at 28 mm and 58 mm signifying that there are less high amount precipitation events. For Kedungputri station data the 95\textsuperscript{th} and 99\textsuperscript{th} percentile is at 69 mm and 116 mm respectively and for TRMM at 52 and 72 mm respectively. Lastly, total precipitation on wet days over the period is recorded high for ground station data (44180 mm) followed by ERA-Interim (43980 mm) and lastly TRMM (40819 mm). The contribution of very wet days to total precipitation varies from 18.2 % for ERA-Interim to 23 % for Station data, with TRMM on the middle at 21%.

Table 4.8: Summary of results for extreme precipitation analysis for Station data, TRMM and ERA-Interim rainfall data over the period 2003 to 2016.

<table>
<thead>
<tr>
<th></th>
<th>Station Data</th>
<th>TRMM</th>
<th>ERA-Interim</th>
</tr>
</thead>
<tbody>
<tr>
<td>RX1day</td>
<td>332 mm</td>
<td>182.8 mm</td>
<td>191.3 mm</td>
</tr>
<tr>
<td>RX5day</td>
<td>358 mm</td>
<td>256.9 mm</td>
<td>328.5 mm</td>
</tr>
<tr>
<td>R10mm</td>
<td>1194 days</td>
<td>1381 days</td>
<td>2124 days</td>
</tr>
<tr>
<td>R20mm</td>
<td>772 days</td>
<td>741 days</td>
<td>521 days</td>
</tr>
<tr>
<td>R50mm</td>
<td>223 days</td>
<td>138 days</td>
<td>47 days</td>
</tr>
<tr>
<td>SDII</td>
<td>21.9mm/day</td>
<td>16mm/day</td>
<td>12.8mm/day</td>
</tr>
<tr>
<td>R95Ptot %</td>
<td>23%</td>
<td>21%</td>
<td>18.2%</td>
</tr>
<tr>
<td>R99Ptot %</td>
<td>7%</td>
<td>6%</td>
<td>6.9%</td>
</tr>
<tr>
<td>PRCTOT</td>
<td>44180 mm</td>
<td>40819 mm</td>
<td>43980 mm</td>
</tr>
</tbody>
</table>

4.8. Discussion

Generally, the correlation between TRMM daily rainfall estimates and observed daily rainfall in the study area is poorer compared to GPM rainfall estimates. One possible cause for the poor correlation is the coarser resolution of TRMM grids (25km) compared to GPM grid size (10 km). Additionally, as indicated in the results of spatial correlation of rainfall stations, there is moderate to poor correlation between rainfall stations even those falling within one TRMM grid. This implies there is a spatial heterogeneity of rainfall in the catchment hence to give one rainfall value for the pixel size of TRMM, spatial variability details may be smoothened. The correlation with GPM is better possibly due to higher spatial resolution and improved algorithm for estimating precipitation. On a monthly scale however, the two satellite rainfall products
perform reasonably well with higher correlation coefficients with observed monthly rainfall measurements. A probable explanation to good correlation at the monthly scale is that satellite rainfall products are calibrated towards monthly precipitation rather than daily (Toté et al., 2015).

Era-Interim daily rainfall forecast data was also compared with observed rainfall and the two satellite estimates. In general, there is a poor agreement between the rainfall forecasts and observed rainfall and estimated rainfall by the two satellite products. The lack of agreement of ERA-Interim forecast and observed rainfall could be attributed to uncertainties in the parameterization of convection in the IFS (Bumke, 2016). The issue of spatial resolution can also be considered here, the resolution of the forecasts data is coarse (80 km) hence it is difficult to give accurate forecast in areas with spatially heterogenous rainfall patterns.

Analysis of extreme rainfall with respect to number of days with rain, by using TRMM and ERA-Interim rainfall datasets indicates that ERA-interim overestimates, but the total amount of precipitation is very similar to observed rainfall for the period 2003 to 2016. TRMM has larger number of days with very heavy and extremely heavy precipitation as compared to ERA-Interim, which implies TRMM performs well in detection of high rainfall events. For indices such as maximum 1 and 5 days rainfall and days with heavy precipitation; ERA-Interim forecasts outperform TRMM estimates. ERA-Interim forecasts however underestimate days with heavy and extremely heavy precipitation.

Overall due to its high spatial and temporal resolutions coupled with better performance compared to TRMM, the use of GPM rainfall estimates is favourable at a catchment scale. However, since GPM rainfall estimates are only available from 2015, TRMM can reasonably be used when rainfall estimates before 2015 are needed in ungauged areas or where observed data is missing. In addition, since TRMM performs well in detection of very heavy precipitation, it can reasonably be used in forecasting of effects of extreme rainfall events such as landslides. The limitation of using TRMM rainfall estimates for derivation of rainfall thresholds is that due to its low resolution, the spatial variability of rainfall thresholds due variablity in spatial rainfall patterns may not be well depicted. Similarly, ERA-Interim rainfall predictions have been found similar to TRMM in terms of relationship with observed daily rainfall hence can also be used in prediction of rainfall induced landslides. The only limitation to using the rainfall forecast like TRMM is the large spatial scale which means the thresholds would be generalised since one rainfall amount has to be applied over a large area. Furthermore, due to poor performance in detection of extreme and very extreme rainfall events, the rainfall forecasts are less appropriate for forecasting landslides influenced by high and extreme rainfall events. It would be desirable to perform bias correction to the rainfall estimates to improve the correlation with observed rainfall, but this is beyond the scope of this study.
5. DETERMINATION OF RAINFALL THRESHOLDS BY AN EMPIRICAL MODEL

5.1. Introduction

Physically-based modelling and empirical modelling are the two main methods for determining landslides rainfall thresholds, these approaches have been introduced in chapter 2. The basis of all the approaches is to characterize landslide triggering rainfall to derive a plausible relationship that exists between rainfall and occurrence of landslides. To derive the correlation between landslides occurrence and rainfall various rainfall parameters are used such as: rainfall intensity, antecedent rainfall, cumulative rainfall and duration of rainfall. The rainfall intensity-duration thresholds are the most common since a majority of landslides are triggered by extreme rainfall events characterized by high intensities and durations (Dahal & Hasegawa, 2008).

It is well understood that changes in ground water levels and soil moisture conditions which eventually induce pore-water pressure changes are the main factors which are associated with occurrence of landslides (Guzzetti et al., 2007; Rahardjo et al., 2008). Since antecedent rainfall conditions affect groundwater levels thus, in a simplistic way antecedent rainfall conditions can be used as a proxy for antecedent suction and ground water levels in landslide susceptible slopes (Guzzetti et al., 2007; Ma et al., 2014). The influence of antecedent rainfall on the occurrence of landslides is particularly well exhibited in soils with low permeability as compared to those with high permeability (Rahardjo et al., 2008). The influence of particular antecedent rainfall events to the occurrence of landslides decreases with time due to processes of transpiration and discharge (Ma et al., 2014). Thus the success of using antecedent rainfall conditions to define landslide rainfall threshold hinges on the prudent choice of the time period over which to consider the antecedent rainfall (Guzzetti et al., 2007).

This chapter presents results of the derived empirically based rainfall thresholds that can be used for landslide early warning in Bogowonto catchment. It is evident that the occurrence of landslides in the study area is influenced by antecedent rainfall conditions since most of the landslides occur in the middle of the rainy season and in some cases even occur with no rainfall recorded on the day of occurrence (Hadmoko et al., 2017; Muntohar, 2008). In addition, the study area is mostly composed of clayey soils which are characterized by low permeabilities hence the impact of antecedent rainfall is highly probable. Therefore, this study considered antecedent rainfall conditions to determine rainfall thresholds for the occurrence of landslides. The thresholds were determined using TRMM rainfall estimates for antecedent rainfall and station rainfall data only for days of landslide occurrence with very low or no estimated TRMM rainfall. An analysis was also done to investigate if there is a spatial and temporal variability of the rainfall thresholds in the study area. In addition, the applicability of the determined thresholds for an early warning system was investigated. Further, the usability of ERA-Interim rainfall forecasts for a landslide early warning was explored.

The chapter is structured into 11 sections including the current section (introduction). Sections 5.2 to 5.4 presents results of determination of rainfall thresholds by using unweighted and weighted antecedent rainfall models. Sections 5.5 and 5.6 presents results for spatial and temporal variability of rainfall thresholds in the catchment. Section 5.7 presents probability-based rainfall thresholds which are used in section 5.8 to link the determined thresholds to landslide forecasting. Section 5.9 assess the effectiveness of using ERA-Interim rainfall forecast for landslide early warning. Section 5.10 evaluates the performance of the determined thresholds and lastly, section 5.11 discuss the overall results presented in this chapter.
5.2. Methodology for deriving antecedent rainfall threshold

5.2.1. Reconstruction of unweighted antecedent rainfall thresholds

Antecedent rainfall thresholds were first derived by simply considering the amount of rainfall for specified periods preceding the landslide occurrence day. The daily rainfall amounts on the landslide occurrence day was plotted against different antecedent rainfall amounts for different period of days prior to the occurrence of landslides (Zêzere et al., 2005). To determine relevant number of antecedent days for the triggering of landslides; daily rainfall on the day of landslide occurrence was separately plotted against 3, 5, 10, 15, 20 and 30 days cumulative rainfall amounts. Similarly, on the same plot non-triggering rainfall events were also plotted against their respective antecedent rainfall conditions to make the method more objective. The non-triggering rainfall events were randomly selected from rainfall events of at least the minimum recorded triggering rainfall event (equal or greater than 10 mm). A line was manually fitted to the daily rainfall-antecedent rainfall scatter plot. The line was purposely fitted to separate triggering and non-triggering rainfall events as much as possible. The graph on which the fitted line achieved minimum mixing of triggering and non-triggering rainfall was considered as the possible combination that influence occurrence of landslides (Zêzere et al., 2005).

5.2.2. Reconstruction of effective antecedent rainfall

The problem with thresholds derived from unweighted antecedent rainfall is that not all recorded amount of rainfall infiltrates into the ground due to overland flow and evapotranspiration hence the derived rainfall thresholds may be an overestimation (Ma et al., 2014). Considering the processes of discharge and evapotranspiration, the actual amount of water that infiltrates into the ground during and after rainfall events preceding the occurrence of landslides is referred to as effective antecedent rainfall (Ma et al., 2014). For the prediction of landslide, the interest is knowing the actual amount of water that infiltrates into the ground and contribute to the slope failure process. In order to derive effective antecedent rainfall from rainfall events preceding landslide occurrence Glade et al., (2000) used the antecedent daily rainfall model to define landslide triggering rainfall thresholds in New Zealand. The derived effective antecedent rainfall thresholds are regarded as an index of soil moisture for the respective days preceding the landslide occurrence day (Glade et al., 2000). The effective antecedent rainfall is calculated by weighting the antecedent rainfall using formula 5.1 (Glade et al., 2000; Zêzere et al., 2005).

\[ AR_x = K P_1 + K^2 P_2 + \ldots + K^n P_n \]  

(5.1)

Where \( AR_x \) is the calibrated effective antecedent rainfall for a day \( x \), \( P_1 \) is the daily rainfall for the day before \( x \), \( P_n \) is the daily rainfall for the \( n \)th day before day \( x \). Lastly, \( K \) is an empirically derived calibration constant ranging from 0.8 to 0.9 based on recession of flood hydrographs which is governed by local catchment hydrological characteristics. Applying the constant \( K \) makes rainfall events occurring several days before the landslide to become negligible. In this study \( K \) was assumed to be 0.9 based on the work of Adji and Misqi (2010) where they derived distribution of flood hydrograph recession constants in Central Java. The weighted antecedent rainfall totals were subjected to the same procedure described in the previous section to determine the thresholds.

5.3. Thresholds for unweighted antecedent rainfall

Rainfall thresholds were first determined by unweighted antecedent rainfall values. Rainfall conditions for every landslide point were extracted from corresponding TRMM grid and plotted on a graph of event day rain against antecedent rainfall. To derive the unweighted thresholds, a line was manually fitted on the scatter
plots for the daily rainfall and antecedent cumulative rainfall for 3, 5, 7, 10, 15, 20 and 30 days. The results of this statistical analysis are shown in figure 5.1.

Figure 5.1: Scatter plots for daily rainfall against unweighted antecedent rainfall periods of: 3 days, 5 days, 10 days, 15 days, 20 days and 30 days. Triangular dots symbolise landslide triggering rainfall events and round dots symbolise non-landslide triggering rainfall events.
As illustrated in figure 5.1, from the scatter plot of 15 days and onwards the best separation of landslide triggering, and non-triggering rainfall events is achieved. This is evidenced by simultaneously having few landslides triggering events below the fitted line and few non-triggering events above the line. It was not possible to achieve a complete separation of landslide triggering and non-triggering rainfall events due to uncertainties in reporting of landslide dates and inherent uncertainties of rainfall estimation by TRMM and rainfall recording by manual ground stations. Therefore the choice was based on the scatter which results into minimal mixing of triggering and non-triggering rainfall events (Garcia-Urquia, 2016).

There are several other possible explanations for this lack of complete separation between triggering and non-triggering rainfall events. Firstly, this lack of complete separation between triggering and non-triggering rainfall events can be attributed to the simplification adopted by empirical models by ignoring many other physical processes that occur in the slope to the infiltrating rainfall (Rosi et al., 2012). Secondly, another probable reason for the occurrence of non-triggering rainfall events above the line is that they may have triggered small sized landslides hence were not identified or reported in the literature or media (Zêzere et al., 2005). Lastly the antecedent rainfall being unweighted makes rainfall occurring several days before the event day being equally important with rainfall occurring few days before the event day which is unrealistic. Basing on the presented results, the occurrence of landslides is in general influenced by 15 days antecedent rainfall. The equation for the line on the 15 days antecedent rainfall is given below:

\[ y = -0.3284x + 80 \]  

(5.2)

where \( y \) is the daily rainfall on the day of landslides occurrence and \( x \) is the unweighted cumulative antecedent rainfall for 15 days. From this equation, a decreasing amount of 15 days cumulative antecedent rainfall results into high amount of daily rainfall being required for landslides to be triggered.

### 5.4. Effective antecedent rainfall landslide rainfall thresholds

To partly account for these processes of evapotranspiration and discharge, rainfall thresholds that weights antecedent rainfall for different days were calculated. The accumulated effective antecedent rainfall for different periods preceding the landslide event were calculated using equation 5.1. A series of the results for 3, 5, 10, 15, 20 and 30 days are shown in figure 5.2.
Like the pattern observed from thresholds with unadjusted antecedent rainfall, the best separation for weighted antecedent rainfall is observed from 15 days and upwards. From the results of the 15 days weighted rainfall graph, landslides are in general triggered when 15 days cumulative effective rainfall exceed 50 mm coupled with a minimum of 10 mm up to 95 mm daily rainfall. When the 15 days cumulative effective rainfall increases the amount of daily rainfall required to trigger landslides decreases down to a minimum of 10 mm. The equation for the 15 days weighted antecedent rainfall is given below:

\[ y = -0.7619x + 80 \]  

where \( y \) is the daily rainfall on the day of landslides occurrence and \( x \) is the weighted cumulative antecedent rainfall for 15 days calculated by equation 5.1.

### 5.5. Rainfall thresholds for different land uses

Rainfall thresholds presented in the previous two sections are general for the area without considering any factors which are obviously spatially variable in the catchment. It is interesting to explore the variability of rainfall thresholds for rainfall induced landslides under different land uses since land use or landcover is an
Important factor which influences slope failure (Gioia et al., 2015; Lu et al., 2015). Landcover affect the hydrology of slopes and mechanisms of slope stability hence directly influencing the response of slopes to rainfall (Lu et al., 2015). The land use map (figure 3.4) was further reclassified into two main classes namely: built up area and forested areas. The built-up areas due to human intervention are dominated by cut slopes resulting from construction of roads and buildings and cultivation. The forested areas on the other hand consisted of: forests and shrubs. 107 of the 166 landslides occurred in forested areas while the remaining 59 occurred in the built-up area. Figure 5.3 shows graphs for these two land uses from which their respective weighted antecedent rainfall was determined. The graphs for the other antecedent periods for these land uses are shown in appendix 3.

For the built-up area the best minimum mixing of landslide triggering rainfall events and non-triggering rainfall events is observed from 15 days antecedent days and upwards while for the forested areas is from 10 days and above. Landslides in both land use classes are in general triggered when cumulative antecedent rainfall amounts exceed 50 mm. Thus, the observed difference may be due to differences in water conductivity between the two land use classes. Under forested areas groundwater may rise faster than in built up area where soil compaction and paved surfaced dominate hence rainwater infiltrates at a slower rate as compared to the forested areas.

5.6. Temporal variability of rainfall thresholds

As shown in chapter 3 (figure 3.2), the occurrence of landslides in Bogowonto Catchment is spread throughout the rainy season from October to May. The landslide inventory was therefore classified according to the landslide date of occurrence into groups spanning two months to explore if the rainfall conditions vary for these different periods of the rainy season. Many landslides (79) occurred in the months of December to January followed by October to November (42) then February to March comes third with 28 landslides and lastly April to May with 19 landslides. Series of results of the determined threshold using weighted antecedent rainfall for different periods of the rainy season are presented in figures 5.4. Graphs for the other antecedent days are shown in appendix 4.

![Figure 5.3: Scatter plots for determining rainfall thresholds for different land uses: built-up area (left) and forested area (right). Round dots represent non-triggering rainfall and triangles represent triggering rainfall.](image-url)
The results suggest that landslide occurrence at the beginning of the rainy season (October–November) are influenced by 7 days effective cumulative antecedent rainfall of at least 60 mm coupled with daily rainfall of at least 20 mm (figure 5.4a). For the period between December and January, which has most of the landslide occurrence; 10 days effective antecedent rainfall is related to the occurrence of landslides. Lastly the period from February to March and at the end of the rainy season between April and May; landslides occurrence is related to 15 days antecedent rainfall. One noticeable pattern observed through different periods is that the landslides at the beginning of the rainy season are related to relatively lower amounts of antecedent rainfall as compared to the other periods. This may be related to the type of the landslides that dominant (shallow versus deep seated landslides), however the landslide inventory was not detailed enough to explore probable causes.

5.7. Probability based antecedent rainfall thresholds

Previous three sections presented general rainfall thresholds for landslide occurrence in the study area and thresholds considering different land uses and period of the rainy season. In principle, the determined thresholds are supposed to always discriminate landslide triggering and non-triggering rainfall conditions (Chleborad, et al., 2006). But as observed in the previous sections it is difficult to draw a line that perfectly discriminates the two rainfall conditions. This indicates the uncertainty that is met with when using such

Figure 5.4: Graphs for daily rainfall against cumulative antecedent rainfall thresholds for different periods of the rainy season. Round dots represent non-triggering rainfall and triangles represent triggering rainfall.
Probability based antecedent rainfall thresholds were derived by adapting the method presented by Zhuang et al., (2014) and Jian et al., (2015). In this methodology, a line is manually fitted that joins lowest daily rainfall and lowest cumulative antecedent rainfall that triggered landslides. This line is referred to as the lower envelope of landslides occurrence; although no landslide occurrences have been observed for rainfall lower than this threshold, a 10% probability is assigned to take into account inherent uncertainties (Zhuang et al., 2014). A second line referred to as the upper envelope is drawn above the lower envelope crossing the highest rainfall that failed to trigger landslides; the probability of landslide occurrence above this line is 100% but is assigned 90% to give the forecasting an uncertainty margin (Huang et al., 2015; Zhuang et al., 2014). Based on the lower and upper envelope different lines of warnings with different probabilities can be drawn using equation 5.6 (Huang et al., 2015; Zhuang et al., 2014):

$$C = C_{10} + (C_{90} - C_{10}) \frac{(Pro - 0.1)^2}{0.64}$$  \hspace{1cm} (5.6)

Where $C$ is the variable for the probability line (Pro) selected, $C_{10}$ is the parameter for the lower envelope or the 10% probability value and $C_{90}$ is the parameter for the upper envelope. The plot for deriving probabilistic daily rainfall and 15 days effective antecedent rainfall which can be used as a preliminary forecasting tool for landslides early warning for the area is shown in figure 5.5 below:

![Figure 5.5: Plot for 15 days effective antecedent rainfall and daily rainfall: black dots symbolise non-landslide triggering rainfall events and triangular dots symbolise landslide triggering rainfall events.](image_url)

From the graph (figure 5.5), the green line is the lower envelope of rainfall conditions that trigger landslides. The rainfall conditions under the green line are assigned a 10% probability of triggering landslides (Huang et al., 2015). Above the green line, the red line is the upper envelope; the probability of landslides occurrence above the red line is 90% (Huang et al., 2015). Thus, based on this plot, any probability line of landslide can
be drawn after adapting equation 5.6 by the values for $C_{10}$ and $C_{90}$ shown in the graph (Huang et al., 2015; Lee et al., 2013). The adapted equation for the study area is presented in equation 5.7.

$$
C = 122 + 77 \times (Pro - 0.1)^2/0.64
$$

(5.7)

5.8. Use of empirically derived thresholds for landslide EWS

The utility of the determined daily rainfall- antecedent rainfall thresholds is that it can be applied for a landslide early warning by defining different probability lines on the graph of antecedent rainfall- daily rainfall plot. Using the thresholds presented in figure 5.5 and applying the same method to the thresholds derived for different periods of the rainy season and land covers a landslide EWS can be established. The graph (figure 5.5) can be divided into three regions corresponding to their respective probabilities of landslides occurrence. Based on the landslide inventory used in this study 10% and 90% probability lines for landslide occurrence were drawn on the antecedent rainfall-daily rainfall scatter. These lines of probability can be linked to zones for landslide early warning with different meaning in the warning such as: normal, alert and severe warning. The three main warning levels corresponds to the region below the lower threshold, the region between the lower thresholds and upper threshold and the region above the upper threshold. The scheme for the proposed landslides EWS is presented in table 5.1 below:

Table 5.1: Proposed landslide warning levels based on the derived rainfall thresholds and their respective responses. (adapted from Huang et al., 2015)

<table>
<thead>
<tr>
<th>Warning Level</th>
<th>Definition</th>
<th>Suggested Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1</td>
<td><strong>Normal:</strong> Daily rainfall less than 50 mm and effective cumulated antecedent rainfall less than 40 mm</td>
<td>Business as usual</td>
</tr>
<tr>
<td>Level 2</td>
<td><strong>Alert:</strong> Daily rainfall more than 50 mm coupled with effective cumulated rainfall of more than 50 mm or daily rainfall more than 70 mm when antecedent rain is less than 50 mm.</td>
<td>Concerned communities alerted; Data checked regularly</td>
</tr>
<tr>
<td>Level 3</td>
<td><strong>Warning:</strong> Daily rainfall more than 50 mm coupled with effective cumulated rainfall antecedent rainfall of more than 75 mm</td>
<td>Warning issued; Data checked more regularly</td>
</tr>
<tr>
<td>Level 4</td>
<td><strong>Severe warning:</strong> Daily rainfall of at least 40 mm coupled with cumulated antecedent rainfall of more than 85 mm. Or effective cumulated antecedent rainfall of more than 100 mm coupled with daily rain of at least 20 mm</td>
<td>Critical situation; data checked more frequent. Warning issued</td>
</tr>
</tbody>
</table>

5.9. Linking rainfall forecasts to landslide early warning system

The effectiveness of an early warning system hinges on timely issuance of information to concerned exposed communities about imminent danger (UNISDR, 2006). However most early warning systems for hydrometeorological hazards are based on weather radar and gauge measured rainfall rather than forecasts hence warnings are issued while the events are occurring or only few hours before (Alfieri & Thielen, 2015). This study explored the effectiveness of linking ERA-Interim rainfall forecasts to an early warning system
for landslides. Since in this study, rainfall thresholds are based on antecedent rainfall and daily rainfall; the essence of using rainfall forecasts is to consider observed antecedent rainfall for say past 15 days including the present day and predicted rainfall for the next day. This would enable warning messages of possible occurrence of landslides on the next day to be issued timely if the forecasted rainfall leads to exceedance of the thresholds.

Figure 5.6 shows results of using forecasted rainfall data for the previous day before landslide occurrence day compares with using observed rainfall. Of the 41 landslides used, 2 are below the lower threshold (figure 5.6) and 6 landslides are above the upper threshold while the remaining are between the upper and lower threshold lines. These results imply that most of the landslides could not have happened unawares since according to the proposed warning levels the communities could have been on alert. It could be desirable that most of the points based on forecast rainfall data fall above the upper threshold. But as shown in chapter 4, the forecasted rainfall underestimates high rainfall events; thus, this is possibly the reason why most points are not above the upper threshold.

![Figure 5.6: Thresholds based on observed 15 days antecedent rainfall and ERA-Interim rainfall forecasts for the day before the landslide overlaid on the determined 15 days antecedent rainfall and daily rainfall thresholds.](image)

### 5.10. Evaluation of the derived thresholds

To test the performance of the determined thresholds, landslide data from Karangkobar area, a catchment near Bogowonto area was used. The landslides data for this area consisted of 17 landslides which occurred from the year 2014 to 2016 with their respective dates of occurrence reported. TRMM rainfall data was used to derive rainfall conditions that caused these landslides. Rainfall condition on the day of occurrence of these landslides and their respective effective antecedent rainfall conditions were plotted on the graph of the of the proposed thresholds.

The results of overlaying the independent dataset is shown in figure 5.7. Most of the landslides from the Karangkobar region fall in the red zone (above the upper threshold) signifying satisfactory performance of the determined thresholds. However, one of the landslides falls in the green zone (below the lower threshold) which is not desirable for early warning. Both satellite rainfall products did not detect rainfall on
the day which is reported for the landslide falling below the lower threshold. With more data on landslides and their respective rainfall information the thresholds can be improved in the future.

To further evaluate the effectiveness of the derived thresholds, a confusion matrix of how the determined thresholds classified landslides from Karangkobar was produced. Table 5.2 shows the contingency matrix for the results of evaluation from which true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) were calculated. True positives are days with landslides correctly detected by the model (Begueria, 2006). True negatives are days without landslides which the model correctly classified as non-landslide days (Begueria, 2006). False positives (false alarms) are days which are classified as landslide days but no landslides occurred (Begueria, 2006). Lastly, false negatives (missed alarms) are days with at least a landslide occurrence but the model classified as no landslide day (Begueria, 2006). To simply the evaluation all landslide points from Karangkobar below the upper threshold were considered as false negatives and non-triggering points above the upper threshold as false positives.

![Figure 5.7: Scatter for Karangkobar landslides on the graph for determined thresholds used for testing performance of the determined thresholds.](image)

Table 5.2: Contingency matrix for the results of evaluation of the empirically derived rainfall thresholds applied on landslides from Karangkobar.

<table>
<thead>
<tr>
<th>Observed</th>
<th>Landslide</th>
<th>No landslide</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Landslide</strong></td>
<td>13 (TP)</td>
<td>2 (FP)</td>
</tr>
<tr>
<td><strong>No landslide</strong></td>
<td>4 (FN)</td>
<td>26 (TN)</td>
</tr>
</tbody>
</table>

From the matrix above, the evaluation of the thresholds was done based on the following four indices commonly used in the literature (e.g. Begueria, 2006; Lagomarsino et al., 2015; Martelloni et al., 2012):
(1) The positive predictive power (PPP) which is the proportion of positive results that are true positives (Beguería, 2006). Calculated as follows: $PPP = \frac{TP}{FP + TP}$. Thus, here: $PPP = 13 / (2 + 13) = 0.8666$. A perfect classifier would have a score of 1 for PPP, this result implies that the derived thresholds are practically good as they are close to 1.

(2) Negative predictive power (NPP) is the proportion of predicted negatives that are true negatives (Beguería, 2006). $NPP = \frac{TN}{FN + TN} = 26 / (4 + 26) = 0.8666$ which is also close to the perfect score of 1 hence the thresholds are also precise in detecting non-landslide days.

(3) Sensitivity (true positive rate) is the proportion of positive cases (landslides) which are correctly classified as such (Lagomarsino et al., 2015). Sensitivity = $\frac{TP}{TP + FN} = 13 / (13 + 4) = 0.765$. This result implies that the thresholds is moderately good in detecting landslides as some are missed.

(4) Specificity (true negative rate) is the proportion of days without landslides which are correctly classified as such (Lagomarsino et al., 2015). Specificity = $\frac{TN}{TN + FP} = 26 / (26 + 2) = 0.929$. which implies the thresholds rarely registers false positives as the value is close to 1.

(5) Efficiency (overall accuracy) is an index that measures the overall performance of a model by calculating the proportion of correct predictions with respect to the total (Lagomarsino et al., 2015). Efficiency = $\frac{(TP + TN)}{(FP + FN + TP + TN) *100} = (13 + 26) / (2 + 4 + 13 + 26) *100 = 87\%$

The results presented above implies that the derived empirical rainfall thresholds are reasonably good with an overall accuracy of 87%. In addition, it is only one landslide which falls below the lower threshold where landslides are not expected. The other three points falls between the lower and upper threshold where landslides are expected but with a lower probability of occurrence. With the inherent uncertainties of the input data such as landslide dates and rainfall inputs the performance is satisfactory; hence the thresholds can be practically used as a basis for a simple early warning of landslides. With more accurate landslide observations and rainfall measurement the thresholds can eventually be improvement for the better.

5.11. **Summary on empirical rainfall thresholds**

The occurrence of landslides in Java island, Indonesia is believed to be influenced by antecedent rainfall conditions (Hadmoko et al., 2017). However, the exact antecedent rainfall conditions that influence landslides occurrence in different areas is not known. In this study, landslides in Bogowonto catchment have been empirically correlated with weighted antecedent rainfall conditions by taking daily rainfall as dependent variable and different periods of antecedent rainfall as independent variable. Following this analysis, the 15 days weighted antecedent rainfall totals and daily rainfall on the landslide event day has been found to be correlated to the occurrence of landslides. The weighted thresholds are preferable because they reduce mixing of landslide days from non-landslide days as they make rainfall occurring several days before the event days to be less important.

Results of rainfall thresholds for different land uses and period of the rainy season suggest that there is a spatial and temporal variability of rainfall conditions that trigger landslides in the catchment. The spatial variability of the thresholds can be attributed to the effect of the land covers on the sub-surface and surface soil hydrological and mechanical properties which influence occurrence of landslides (Begueria, 2006). For example, in settlement areas soils may be compacted thereby reducing the soil’s infiltration capacity as compared to forested area. This eventually influences the response of the slopes to incoming rainfall as it may take longer to infiltrate. On the other hand, the variation of the thresholds at different periods of the rainy season may be due to type of landslides occurring in these periods (shallow vs deep seated landslides).
Overall, the results imply that these factors (land cover and month of occurrence) can be used to improve the forecasting of landslides in the area. This can eventually help improve the performance of a landslide EWS as the thresholds are not static and generalised for the whole catchment but rather dynamic and different for various land covers.

Evidenced by non-occurrence of landslides when conditions that triggered landslides in the past are reached or exceeded; the relationship between rainfall and landslides occurrence is not straightforward (Robbins, 2016). This inherent uncertainty is partly dealt with when the determination of thresholds is probability based (Berti et al., 2012). Considering the uncertainties in the landslides dates and rainfall data, probability-based thresholds were also determined. To partly deal with uncertainties of the input data this study recommends the linking of probability based empirical thresholds to landslides early warning system. However, despite the probability-based thresholds being favoured caution need to be exercised in using them as they have been determined from limited data. Thus, further study is needed before integrating these thresholds in an early warning system for landslides.

Although the derived probabilistic thresholds performed generally well in predicting landslides from Karangkobar area the derived thresholds are solely based on data for Bogowonto Catchment. Thus, transferring the thresholds to other areas may lead to poor results as it has also been shown in chapter 4 there is spatial variation of rainfall in the area. In addition, the thresholds may be an underestimation as they are mostly based on TRMM rainfall estimates and it has been shown in chapter 4 that TRMM rainfall underestimate rainfall in the study area. Lastly, the derived thresholds give no distinction on different types of landslides although it has been shown elsewhere that the effect of antecedent precipitation differs based on various landslide types for example deep seated and shallow landslides (e.g. Muntohar, 2008; Zêzere et al., 2005).
6. DETERMINATION OF RAINFALL THRESHOLDS BY A PHYSICALLY-BASED MODEL

6.1. Introduction

Apart from empirical models physically based models are also utilised to model rainfall induced landslides. These physically based models are advantageous over empirical models because they provide more theoretical basis for understanding the response of slopes to hydrologic processes (Hong et al., 2015b). These models use various topographic, geotechnical and hydrologic parameters to simulate mechanisms of slope failure. Physically based models are preferred over empirical models for the prediction of the location of possible rainfall induced landslides (Raia et al., 2013). A limitation of using physically based models is the difficulty in obtaining accurate spatially variable data for several parameters that describe the material properties of slopes over large areas (Raia et al., 2013; Robbins, 2016).

In this study the STARWARS+PROBSTAB physically based model was used to simulate rainfall induced landslides. Due to the poor data setting of the study area, a modified version of the coupled STARWARS+PROBSTAB model was used for hydrological and slope stability modelling. STARWARS is a dynamic hydrological model while PROBSTAB is a slope stability model (Camera et al., 2013; van Beek, 2002). The outputs from the hydrological model for every timestep are used as inputs for the slope stability modelling. The model is an open source script which allows customisation of the model to specific environmental settings and data availability issues. The coupled model is run in a PCRaster GIS environment. The model was run for the 2014 to 2015 rainy season. To reduce the computing time the physically-based model was run for the Kodil sub catchment only since most of the landslides in the inventory were in this sub-catchment.

STARWARS model was developed by van Beek (2002) to assess the influence of vegetation on hillslope hydrology in a Mediterranean environment. The model incorporates various processes including interception, evapotranspiration and infiltration. The source of the water into the model is rainfall which is assigned an amount for every time step of the model duration. The amount of water that reaches the ground at every time step is governed by infiltration capacity (Camera, 2011). The effect of vegetation on evapotranspiration (ETP) was ignored hence average ETP value for the dry and wet season were calculated by using average temperature (Bhat et al., 2016).

PROBSTAB on the other hand models slope stability by calculating the safety factor for the soil column boundary with bedrock based on the variation of water level and moisture content (Kuriakose et al., 2009). The PROBSTAB slope stability model ignores the lateral interaction between cells hence the stability is based on properties of individual cells (Camera, 2011).

6.2. Input data for the coupled hydrological- slope stability model

Most of the required input data for the coupled model were unavailable or were of poor quality to successfully implement the physical model. Consequently, various means such as literature derived values, pedo-transfer functions and simple empirical models were exploited to parameterize the model for the catchment. In addition, the model itself which requires many input parameters and is highly data demanding was modified to adapt it to the study area which can be described as a data poor environment. The main data required for the model mainly include: topographical data, pedological data, climatic data and soil mechanical parameters. The main data inputs that were used in this study are described in chapter 3. The
following subsections presents some of the remaining parameters and data required for the physically based model and how they were obtained.

### 6.2.1. Meteorological data

The main meteorological data used was rainfall data and temperature data. Rainfall data for the model was obtained from rainfall stations at a daily temporal resolution. The daily rainfall data for the 2014 to 2015 rainy season was used because a lot of landslides (39) occurred in this season. Evapotranspiration (ETP) for the dry and rainy season was calculated by using respective average seasonal temperatures using the following equation proposed by Bhat et al., (2016):

\[ E = 221.5 + 29.0 \times T \]  \hspace{1cm} (6.1)

Where \( E \) is evaporation and \( T \) is average annual temperature. With an annual average temperature of 27°C the annual estimated evapotranspiration of the study area is 1004.5 mm, averaging 2.75 mm per day. This is close to the average 2.6mm/ day derived during detailed evaporation studies in the region by Calder et al., (1986).

### 6.2.2. Soil hydrological parameters

Soil hydraulic conductivity (Ksat) was measured from six samples that were collected from various locations the study area. The tests were done at University of Gadjah Mada laboratory. Ksat measurements for three samples were used whose results are: 0.138 m/day, 0.22 m/day and 0.59 m/day. The other three measurements were not used as they were out of the range of the reported samples which compares well with values used in other studies conducted in the area (Muntohar et al., 2017; Putra et al., 2017). Test results for all soil samples is shown in appendix 2c.

### 6.2.3. Other important parameters

After supplying all the necessary base maps such as: DEM, land use and soil depth, the parameters shown in table 6.1 were used in the model. In addition, some initial conditions were also defined, these included surface detention, interception storage and snow cover which were set to 0. Some initial conditions were set to minimal values ranging from 0.01 to 0.03, these included: initial water level above the lithological contact, and soil moisture for different soil layers. The model time step was set at 1 day, this daily timestep is favourable because it reduces the amount of error introduced at different steps in calculation of different processes (Camera, 2011).

### Table 6.1: List of some parameters used in the coupled hydrological- slope stability model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Value(s)</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c )</td>
<td>Cohesion</td>
<td>15-30kPa</td>
<td>Literature (Putra et al., 2017)</td>
</tr>
<tr>
<td>( \theta_s )</td>
<td>Porosity</td>
<td>0.4-0.51</td>
<td>Literature (Muntohar et al., 2013)</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>Unit weight of soil</td>
<td>17kN/m³</td>
<td>Constant</td>
</tr>
<tr>
<td>( h_A )</td>
<td>Air entry value</td>
<td>0.06</td>
<td>Constant</td>
</tr>
<tr>
<td>( \phi )</td>
<td>Internal friction angle</td>
<td>24-35°</td>
<td>Literature (Putra et al., 2017)</td>
</tr>
<tr>
<td>( \Psi )</td>
<td>Matric suction</td>
<td>0.5</td>
<td>Constant (Muntohar et al., 2017)</td>
</tr>
</tbody>
</table>
6.3. Model Results

6.3.1. Results of STARWARS

The main outputs of the hydrological model are the soil moisture conditions for every timestep and respective ground water levels. Before running the model for the 2014 to 2015 rainy season, the model was run for the period preceding this rainy season to set initial soil moisture and groundwater conditions. Figure 6.1 shows the temporal variation of ground water levels in response to daily rainfall input (July 2014 to June 2015) for one of the measurement points that was set in the model. The pattern of temporal water variation in response to input rainfall is similar for other points that were set in the model. As shown in the figure, generally the peaks of groundwater levels follow peaks of rainfall. No piezometer measurements were available to calibrate the groundwater levels for the study period. Therefore, the results were directly used as input for the slope stability modelling.

![Temporal variation of ground water level in response to rainfall (2014/2015 rainy season).](image)

6.3.2. Results of PROBSTAB

The slope stability component of the coupled model provides among other things the safety factor for every timestep of the model run and number of unstable steps out of the model duration. Figure 6.2 presents the spatial distribution of the factor of safety for the dry condition (rainfall was set at 0 mm/day at all timesteps) and after applying the 2014 to 2015 daily rainfall. For the dry conditions, the safety factor is in all cases higher than 1.4 with most pixels having a safety factor between 3 and 10. With such a range of safety factor under dry conditions, the area can be described as generally stable under conditions of no rainfall according to the model results. Figure 6.3 on the other hand depicts spatial variation of safety factor for the conditions after applying rainfall. The safety factor under rainfall conditions reduces to as low as 0.2 in some locations. The maps shown in figure 6.2 and 6.3 have been classified into three landslide stability classes according to simulated safety factor. The unstable class represents pixels with safety factor less than 1.1, the moderate class represents pixels with safety factor between 1.1 and 2 and lastly the stable class represents all pixels with a safety factor above 2.
The results of the slope stability simulation presented in figure 6.3 are a general scenario expected in an area which is prone to landslide for the instability to arise after applying rainfall. However, when the predicted unstable areas are compared with observed rainfall induced landslides, not all landslides are correctly predicted by the model, but they are found in areas which have been predicted stable or moderately stable. This pattern is particularly exhibited in the settlement areas where most of the landslides are associated with cut slopes. Figures 6.4 and 6.5 shows how the predicted stability map compares with observed landslides. The probable reason for lack of agreement between predicted and observed landslides especially in the cut slopes area is due to poor DEM which was used in the modelling, and uncertainties in the parameterization of the physically based model such as initial soil moisture and initial ground water level. The settlement areas have a lot of cut slopes on which most of the landslides occur, but the DEM could not capture these cut slopes.

The rainfall that corresponds to the dates when the model indicates the occurrence of slope instabilities was studied to see the relationship between stability conditions and rainfall. The results of the time series variation of percentage of unstable areas in relation to rainfall is shown in figure 6.6. As shown in the diagram, generally there is a lag time after rainfall peaks before unstable pixels peaks. This may be explained as being caused by low infiltration rates associated with clay soils since the catchment is mostly composed of clayey soils. In addition, this may also be explained that slope failure in the catchment is strongly influenced by antecedent rainfall conditions rather than daily rainfall conditions. This agrees with the results from empirical modelling presented in chapter 5 where landslides were found to be correlated with 15 days
antecedent rainfall. It was also found in previous studies that the occurrence of landslides in the region is influenced by antecedent rainfall of up to 30 days (Hadmoko et al., 2017).

Figure 6.4: Zoom in on the UGM field laboratory area which is dominated by cut slope landslides.

Figure 6.5: Map showing observed landslides and predicted stability condition by physically based model.

Figure 6.6: Timeseries of input daily rainfall input to the physically based model and the resulting predicted percentage of unstable area.
Apart from depicting the spatial distribution of possible slope failures, PROBSTAB model also gives the number of timesteps that pixels are unstable over the period of the model run. Thus, the usefulness of the model for landslides early warning can also be evaluated based on this output. It is desirable that pixels should be predicted unstable for a limited period for effective use of the results in an early warning system. Figure 6.7 shows the results for periods over which pixels are unstable. As shown in the figure, the model overestimates the number of days on which instability occurs in some pixels. Most of the pixels are predicted to be unstable for period of 0-50 days and 150-260 days in a year. This implies that the results of the model cannot be reliably used for early warning as warnings have to be issued for prolonged periods which is usually not the case in reality.

![Figure 6.7: Map showing number of days over which instability conditions occur in a pixel for the period July 2014 to June 2015 (left) and zoom in on part of the UGM field laboratory showing the same (left).](image)

### 6.4. Summary and conclusions

A modified STARWARS-PROBSTAB coupled model has been used to model hydrology and slope stability. The results indicated that slope failure is influenced by antecedent rainfall conditions as there was a lag time between rainfall peaks and rise of instability. The maximum predicted unstable area by the model was 3% of the area under study. The predicted unstable areas did not match well with observed landslides especially for failures occurring in cut slopes. This can be explained by the fact that mechanisms of slope failure in natural slopes are different from that of cut slopes (Leroueil, 2001). The poor agreement between predicted and observed failures is exacerbated by poor input data especially the DEM and uncertainties in some input parameters that were used in the physically based model.
Most of the input parameters used for the physical model were not based on field measurements but rather obtained from the literature. This increased uncertainty in the modelling of landslides of the study area. Thus, the model result can be better than what has been realised now if precise values of the various parameters that are required could be obtained. Further, lack of calibration data made it impossible to check the accuracy of the model outputs which would eventually lead to adjustment of the outputs for better performance of the model. This suggests that for the physically based model to be used for early warning purposes much attention need to be given to precise parameterization of the model.

Overall, the model provides the spatial distribution of possible failure areas with their respective period of instability. This is advantageous especially when considering early warning since it is possible to specifically point areas of possible failures rather than issuing general warning for the whole area as does empirical methods. However, the model overestimates the period of instability of the areas predicted as unstable. This limits the application of the model for an early warning system since for an early warning to be effective precise outputs are required to eventually issue unambiguous warnings.
7. DISCUSSION AND CONCLUSIONS

The main aim of this research was to compare empirical and physically based modelling with respect to determination of rainfall thresholds applicable for landslide early warning. Empirical rainfall thresholds were derived by analysing historical landslides and rainfall data for Bogowonto catchment from 2003 to 2016. Physically based modelling was done using STARWARS-PROBSTAB model. Both approaches were assessed for their eligibility for an effective landslide early warning system for the area.

Correlation of observed rainfall measurements and TRMM and GPM satellite rainfall products and ERA-Interim rainfall forecast indicate that these products underestimate rainfalls at the daily scale. The underperformance amongst other possible reasons may be attributed to their coarse spatial resolution: 25km, 10 km and 80 km respectively for TRMM, GPM and ERA-Interim being compared to point gauge rainfall measurements. It is difficult for these products to correlate well with observed rainfall in such a catchment which showed spatially variable rainfall patterns after analysing different gauge rainfall measurements. The spatial heterogenous rainfall characteristics of the catchment suggests that rainfall measurement for every landslide point should be site specific which is difficult to achieve even when using gauge measured rainfall due to sparse network of rainfall stations. However, since the satellite rainfall estimates correlated well with observed rainfall at scales other than daily, the rainfall estimates were still used since landslide in the area are mostly influenced by antecedent rainfall (Hadmoko et al., 2017). Furthermore, the satellite rainfall products especially TRMM were good in detection of heavy and very heavy rainfall events which are mostly associated with occurrence of landslides hence could still be reliably used. Still, the effect of uncertainties in the TRMM rainfall inputs especially on the day of landslide cannot be ruled out.

Both weighted and unweighted antecedent rainfall threshold models were applied in this study to determine empirical rainfall thresholds. Weighted antecedent rainfall thresholds model was favoured since it can differentiate recently occurring and old rainfall events by multiplying the rainfall with a decay coefficient. The weighting of rainfall events occurring on different days is essential since the water is not stationary in the ground due to processes of discharge and evapotranspiration. Correlation of antecedent rainfall condition for up to 30 days before the day of landslide occurrence indicated that landslides in the area are generally influenced by 15 days antecedent rainfall. This can be explained by soil texture of the catchment which is dominantly clayey that are characterized by low permeability hence the response of groundwater to rainfall is slow. The result agrees with the finding of Hadmoko et al., (2017) and Muntohar, (2008) who found that landslides in the region are influenced by antecedent rainfall of up to 30 days. However as pointed out already since these thresholds were derived by using TRMM rainfall inputs the reported thresholds may be an underestimation. Despite this limitation, TRMM rainfall data has been successfully incorporated into an operational landslide early warning in the region by Balai SABO organisation (BLS, 2017).

Many factors need to be considered to come up with precise site-specific rainfall thresholds for landslide occurrence due to the spatial heterogeneity of earth surface materials such as geology and soil type. This was portrayed when thresholds were analysed for different land uses in the catchment where it was observed that the thresholds differ for forest and built up areas. This variation may be caused by differences in infiltration rates for the two land uses possibly due to changes in soil structure which may be altered when subjected to some uses (Granados-olivas et al., 2016). Built up areas for example may have increased extent of paved surfaces which are poorly drained. Thus, by extension, apart from land use, several other factors related to properties of surface and subsurface materials such as geomorphology and geology need to be
considered in derivation of rainfall thresholds. Eventually, this may lead to an improvement of landslide forecasting hence making the performance of a landslide early warning system to be remarkably high.

It was further noticed that apart from factors related to the properties of surface materials, time of landslide occurrence need to be considered in forecasting of landslides. Number of antecedent rainfall influencing landslide occurrence changed at different periods of the rainy season. This may be due to the reason that deep seated landslides which require considerable amounts of antecedent rainfall dominate towards the end of the rainy season, but the landslide inventory was not detailed enough to investigate the possibility of this explanation. Nonetheless, even with the same landslide type, rainfall conditions causing landslide at the beginning of the rainy season cannot be the same at the beginning and at the middle or end of the rainy season due to differences in pre-existing soil moisture and ground water levels (Guzzetti et al., 2008).

STARWARS-PROBSTAB physical model was also used to simulate the stability of slopes in response to rainfall. It was evident from the physically based coupled model that antecedent rainfall influences the occurrence of landslides as percentage of unstable areas increased following peaks of rainfall. The model predicted up to 3% of unstable pixels out of the whole catchment. However, the predicted unstable areas did not match very well with observed landslide. The inferior performance of the physically based model is mainly attributed to poor quality input data mainly: soil data, DEM and landslide inventory. The modelling lacked the essential element of calibration due to unavailability of field observed measurements such as discharge and piezometer measurements. The physical model also overestimated the length of period on which pixels were unstable in a year which is not practical for use in an early warning system since it is uncertain when exactly warnings must be issued. Therefore, the usage of the physically based modelling results at this stage can only be limited to a landslide susceptibility map.

Overall findings of this study suggest that GPM rainfall estimates compared to TRMM have a better correlation with observed rainfall. Hence, the usage of GPM could be good but the limitation is that it has not been available for most of the period this study covered. Since for landslides monitoring high rainfall events are of interest, TRMM rainfall estimates are still applicable because TRMM performed well in estimation of high rainfall events. This study also indicates that ERA-Interim rainfall forecasts are good at detection of rainfall days but poor in detection of high rainfall events. Hence the rainfall forecasts are less useful for early warning of landslides influenced by high rainfall events.

The study concludes that for landslide early warning in the study area antecedent rainfall of up to 15 days need to be monitored. The study also concludes that empirically derived rainfall thresholds are relatively easy to derive even in a data poor environment as where this study was conducted. However, empirically based approach generalises the thresholds as they do not consider the spatial variability of slope geotechnical and hydrological properties. In addition, for landslide early warning purposes empirically derived rainfall thresholds are less precise as they just indicate that landslides may occur when thresholds are reached or exceeded without specifying exact locations. On the other hand, physically based methods, specify possible locations of slope failures and they also try to simulate complex processes that occur in slopes before slope failure. Physically based models however as observed in this study are highly sensitive to input data therefore are less suitable for large areas as it is difficult to get detailed data over large areas.

Finally, the applicability of the rainfall thresholds derived in this study for landslide early warning is subject to some limitations. The thresholds have been determined from limited landslide data and the available data was not detailed enough in terms of type, size and accuracy of date of occurrence. Thus, the thresholds can be improved when more landslide observations become available. Lastly, the input rainfall data was TRMM which showed poor correlation with observed daily rainfall hence the thresholds may be an underestimation.
LIST OF REFERENCES


environmental variables in an anthropogenic landscape, a case study in the Western Ghats of Kerala, India. *Catena*, 79, 27–38. https://doi.org/10.1016/j.catena.2009.05.005


Pawestri, M. T., Sujono, J., & Istiarto, I. (2017). Flood hazard mapping of bogowonto river in Purworejo...


Thiebes, B. (2012). Landslide analysis and early warning systems: local and regional case study in the Swabian Alb,
COMPARING MODELLING APPROACHES FOR LANDSLIDE EARLY WARNING: A CASE STUDY OF BOGOWONTO CATCHMENT, CENTRAL JAVA, INDONESIA


van Beek, L. P. H. (2002). Assessment of the influence of changes in land use and climate on landslide activity in a Mediterranean environment.


APPENDIX 1: Correlation between gauge and satellite estimated rainfall.

Table A 1.1: Correlation results between observed rainfall from rainfall stations and TRMM estimated rainfall.

<table>
<thead>
<tr>
<th></th>
<th>Bener</th>
<th>Salaman</th>
<th>Maron</th>
<th>Banyuasin</th>
<th>Kedungputri</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>0.354</td>
<td>0.238</td>
<td>0.177</td>
<td>0.172</td>
<td>0.162</td>
</tr>
<tr>
<td>RMSE (mm/day)</td>
<td>18.884</td>
<td>19.398</td>
<td>21.349</td>
<td>19.854</td>
<td>21.216</td>
</tr>
<tr>
<td>Relative Bias (%)</td>
<td>-19.989</td>
<td>-14.302</td>
<td>-11.75</td>
<td>4.244</td>
<td>-7.592</td>
</tr>
<tr>
<td>Bias</td>
<td>-1.874</td>
<td>-1.167</td>
<td>-0.949</td>
<td>0.291</td>
<td>-0.579</td>
</tr>
</tbody>
</table>

Table A 1.2: Correlation results between observed rainfall from rainfall stations and GPM estimated rainfall.

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>0.340</td>
<td>0.289</td>
<td>0.303</td>
<td>0.273</td>
<td>0.262</td>
</tr>
<tr>
<td>RMSE (mm/day)</td>
<td>27.892</td>
<td>20.391</td>
<td>22.473</td>
<td>14.759</td>
<td>22.108</td>
</tr>
<tr>
<td>Relative Bias (%)</td>
<td>-104.3</td>
<td>-10.375</td>
<td>-20.458</td>
<td>15.112</td>
<td>-12.362</td>
</tr>
<tr>
<td>Bias</td>
<td>-11.017</td>
<td>-1.006</td>
<td>-2.227</td>
<td>0.823</td>
<td>-1.014</td>
</tr>
</tbody>
</table>

Table A 1.3: Monthly correlation results between observed rainfall from rainfall stations and TRMM estimated rainfall.

<table>
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<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>0.924</td>
<td>0.86</td>
<td>0.899</td>
<td>0.814</td>
<td>0.873</td>
</tr>
<tr>
<td>RMSE (mm/month)</td>
<td>108.370</td>
<td>116.1</td>
<td>101.972</td>
<td>106.204</td>
<td>105.037</td>
</tr>
<tr>
<td>Relative Bias (%)</td>
<td>-17.420</td>
<td>-14.403</td>
<td>-11.767</td>
<td>8.654</td>
<td>-7.502</td>
</tr>
<tr>
<td>Bias</td>
<td>-47.269</td>
<td>-35</td>
<td>-28.417</td>
<td>17.857</td>
<td>-17.159</td>
</tr>
</tbody>
</table>

Table A 1.4: Monthly correlation results between observed rainfall from rainfall stations and GPM estimated rainfall.

<table>
<thead>
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<th>Banyuasin</th>
<th>Kedungputri</th>
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<tbody>
<tr>
<td>Correlation Coefficient</td>
<td>0.886</td>
<td>0.907</td>
<td>0.832</td>
<td>0.82</td>
<td>0.851</td>
</tr>
<tr>
<td>RMSE (mm/month)</td>
<td>128.923</td>
<td>82.051</td>
<td>144.925</td>
<td>92.797</td>
<td>116.301</td>
</tr>
<tr>
<td>Bias</td>
<td>-50.6</td>
<td>-36.47</td>
<td>-68.405</td>
<td>22.55</td>
<td>-31.802</td>
</tr>
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APPENDIX 2: SOIL RELATED MAPS USED FOR PHYSICAL MODELLING

Appendix 2a: maps showing field soil depth measurement points and modelled soil depth (left) and soil texture map derived from soil grids and pedo-transfer function (right).

Appendix 2b: correlation of field soil depth measurements and modelled soil depth (PCC= 0.4075)
Appendix 2c: Table showing field soil depth measurement points

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Appendix 2d: Ksat results

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*Not used in the model
APPENDIX 3: GRAPHS FOR RAINFALL THRESHOLDS FOR DIFFERENT LAND USES

Figure A3.1: series of graphs for antecedent rainfall thresholds for Built up area. Black dots represent non-triggering rainfall conditions and grey triangles represent triggering rainfall.
Figure A3.2: series of graphs for antecedent rainfall thresholds for Forest area. Black dots represent non-triggering rainfall conditions and grey triangles represent triggering rainfall.
Figure A4.1: series of graphs for antecedent rainfall thresholds for October to November. Black dots represent non-triggering rainfall conditions and grey triangles represent triggering rainfall.
Figure A4.2: series of graphs for antecedent rainfall thresholds for December to January. Black dots represent non-triggering rainfall conditions and grey triangles represent triggering rainfall.
Figure A4.3: series of graphs for antecedent rainfall thresholds for February to March. Black dots represent non-triggering rainfall conditions and grey triangles represent triggering rainfall.
Figure A4.4: series of graphs for antecedent rainfall thresholds for April to May. Black dots represent non-triggering rainfall conditions and grey triangles represent triggering rainfall.