Predictive Modelling of Rainfall Induced Landslides in a Tropical Environment
A case of Ang Khang and Wang Chin Districts in Northern Thailand

Sheila D.C. Namuwaya
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Predictive Modelling of Rainfall Induced Landslides in a Tropical Environment.
A Case of Ang Khang and Wang Chin Districts in Northern Thailand.

by

Sheila D.C. Namuwaya

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Disclaimer

This document describes work undertaken as part of a programme of study at the International Institute for Geo-information Science and Earth Observation. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the institute.
Dedication

I would like to dedicate this book to the Great and Faithful one.
Abstract

Landslides are one of the normal landscape building processes in mountainous areas. They become a problem when they interfere with human activity. The problem of landslides is of essential importance to a large number of countries not only because of the extensive damages, which are caused from time to time, but also because of the tragic loss of human life, which ensues.

Apart from earthquakes and human influence, climatic conditions are known to cause landslides. Landslides can be triggered by rainfall if some threshold intensity is exceeded so that pore water pressures are increased. The process is also exaggerated by the duration of the rainfall, slope angle, the distribution of shear strength, permeability particularly within the regolith thickness, antecedent weather and pore water pressure conditions.

Landslides together with their causal factors need to be mapped in order to be able to predict hazardous areas and those, which are not. The essential step for any hazard zonation is a landslide inventory. This can be based on aerial photo and/or satellite image interpretation, ground survey and a database containing historical information about landslide occurrences. The final product from the interpretation and the mapping is called a landslide inventory.

The main objective of this study was to investigate whether analysis of factors causing landslides in one area (Wang Chin in Northern Thailand), where landslides have been caused by a major rainfall event, can be used for building a model to assess landslide susceptibility in another area which has not had recent landslides (Ang Khang). A further objective was to evaluate the use of digital image processing for landslide mapping.

This study reveals that the analysis of rainfall data provides a means of predicting the return period of a rainfall event greater or lower than the event under investigation. The predicted rainfall return periods could only be relied upon if the rainfall data set is large. In such cases, the confidence level could be improved thus making the results more realistic and reliable.

Results indicate that Maximum Likelihood Supervised classification with Intensity Normalised bands gives the best results of the Digital Image analysis techniques with an accuracy of 70.6% followed by Maximum Likelihood Supervised Classification without Intensity Normalised bands with an accuracy of about 54%. An attempt to improve the results obtained from Maximum Likelihood Supervised Classification indicated that two band combination (Bands 1, 2, 3 and 2, 3& 4) yielded better results than all the other bands although the results were not as good as expected.

Prediction of future occurrence of rainfall induced landslides in Ang Khang indicated that 84% of the active landslides were located in the class with the highest occurrence of landslides, 14.1% in moderate class, and 1.9% of the active landslides in the class with the least occurrence of landslides. As a result of this it was observed that about only 45% of Ang Khang is susceptible to landslides. The other observation was that the landslide conditioning factors in Ang Khang can not be compared to those in Wang Chin which implies that separate studies ought to be carried out in Wang Chin.
Acknowledgements

I would like to appreciate the Dutch Government through the NFP for giving me this opportunity to come to ITC and pursue this programme. It has been a rewarding experience. I would also like to express my heartfelt gratitude to my supervisors Dr. D.P Shrestha and Dr. C. van Westen for all their provoking questions, guidance, support, advice and patience. Thank you so very much. I would also like to thank Dr. Paul van Dijk, the Programme Director, Drs. N. Kingma, Drs. R. Voskuil, Dr. A. Farshad, Drs. D. Alkema, Dr. D. G. Rossiter, Mr. Bart Krol, Ir. G. Parodi, Ir. B. Maathius, Mr. Gerard Reinink, Mr. Jan Hendrikse for all their advice, help and encouragement throughout the entire programme. Thank you all very much.

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I would like to thank the entire EREG 2004 group; Jimmee, Zul, Manuel, Li, Tommy, Hendrow, Chen, Mwale, Tesfaye, Fekerte, Dennis, Ms. Hoang and Samuel. It was great meeting and knowing you all. Thank you so much for all your help. To the rest of my friends……. words fail me …… Your friendship and company helped make this journey worth while. It’s been great knowing and working with you all.

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To the members of De Rot Church I would like to thank you for your warmth and love. To the Kollie’s – am grateful for everything. It’s been great knowing and fellowshipping with you. Special thanks go to my Dutch Family Adrie, Ginny and the children. Thank you so much for opening your home to me and making this a home away from home. It’s only God who can reward you.

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Chapter 1: Introduction

1.1. Background

Land degradation is a common problem in mountainous areas and is manifested in a variety of processes. Land degradation is the temporary or permanent lowering of the productive capacity of land. FAO and UNEP have six kinds of degradation: water erosion, wind erosion, salinization (excess of salts), chemical degradation, and biological degradation but they were reduced to the first three since its difficult to quantify chemical and biological degradation (Hudson 1986). Other types of degradation known include soil fertility decline, water logging, deforestation, rangeland degradation and lowering of the water table. There are various causes of land degradation which include direct causes (deforestation, overgrazing, intensive agriculture, shifting cultivation with short fallow periods, improper crop rotations etc), underlying causes (land shortage, economic pressures, poverty, population increase, short term or insecure tenancy, etc) and natural hazards like landslides (FAO, UNDP et al. 1994; Shrestha, Zinck et al. 2003).

“Landslides are one of the normal landscape building processes in mountainous areas. They become a problem when they interfere with human activity”(van Westen, Soeters et al. 1993). The problem of landslides is of essential importance to a large number of countries not only because of the extensive damages, which are caused from time to time, but also because of the tragic loss of human life, which ensues (Ercanoglu, Gokceoglu et al. 2003).

The term landslides refers to “the movement of a mass of rock, debris or earth down a slope” (Cruden and Varnes 1996). Soil is divided into two: debris and earth. The term Debris refers to material which contains a significant proportion of coarse material 20 to 80 percent of the particles are larger than 2mm and the remainder of the particles are less than 2 mm. Earth describes material in which 80 percent or more of the particles are smaller than 2mm. These movements are classified according certain criteria (Table 1.1). The first criterion is the type of movement and the second is the type of material. The types of movement include falls, topples, slides, spreads, flows and a complex type, which is a combination of two or more of the other types of movement mentioned earlier. The type of material is divided into two main classes: rock and soil (Varnes 1978; Cruden and Varnes 1996).
Table 1.1: Classification of Slope Movements (Varnes 1978)

<table>
<thead>
<tr>
<th>TYPE OF MOVEMENT</th>
<th>TYPE OF MATERIAL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SOILS</td>
</tr>
<tr>
<td></td>
<td>BEDROCK</td>
</tr>
<tr>
<td></td>
<td>Predominantly coarse</td>
</tr>
<tr>
<td>FALLS</td>
<td>Rock Fall</td>
</tr>
<tr>
<td>TOPPLES</td>
<td>Rock Topple</td>
</tr>
<tr>
<td>SLIDES</td>
<td>ROCKATIONAL</td>
</tr>
<tr>
<td></td>
<td>ROCK Slump</td>
</tr>
<tr>
<td></td>
<td>MANY UNITS</td>
</tr>
<tr>
<td></td>
<td>ROCK block slide</td>
</tr>
<tr>
<td></td>
<td>ROCK Slide</td>
</tr>
<tr>
<td></td>
<td>Earth block slide</td>
</tr>
<tr>
<td></td>
<td>Earth slide</td>
</tr>
<tr>
<td>LATERAL SPREADS</td>
<td>Rock spread</td>
</tr>
<tr>
<td>FLOWS</td>
<td>Rock flow</td>
</tr>
<tr>
<td></td>
<td>(deep creep)</td>
</tr>
</tbody>
</table>

Landslides have several causes or causal factors and these include geological, morphological, physical and human factors. These factors are also referred to as destabilising (Crozier 1986; Wieczorek 1996). The checklist in Figure 1.1 gives an outline of some factors that fall under these four main factors. Only a brief outline is given since description of landslide causal factors is not the focus of this study.

Table 1.2: Landslide Causative/ Causal Factors (Adopted from Cruden and Varnes 1996).

<table>
<thead>
<tr>
<th>Geological Causes</th>
<th>Morphological Causes</th>
</tr>
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<tbody>
<tr>
<td>i) Weak materials</td>
<td>i) Tectonic or volcanic uplift</td>
</tr>
<tr>
<td>ii) Sensitive materials</td>
<td>ii) Glacial rebound</td>
</tr>
<tr>
<td>iii) Sheared materials</td>
<td>iii) Fluvial erosion of slope toe</td>
</tr>
<tr>
<td>iv) Jointed or Fissured materials</td>
<td>iv) Wave Erosion of slope toe</td>
</tr>
<tr>
<td>v) Adversely oriented mass discontinuity (bedding, schistosity, etc.)</td>
<td>v) Glacial erosion of slope toe</td>
</tr>
<tr>
<td>vi) Adversely oriented structural discontinuity (fault, unconformity, contact, etc.)</td>
<td>vi) Erosion of lateral margins</td>
</tr>
<tr>
<td>vii) Contrast in permeability</td>
<td>vii) Subterranean erosion (solution and piping)</td>
</tr>
<tr>
<td>viii) Contrast in stiffness (stiff, dense material over plastic materials)</td>
<td>viii) Deposition loading slope and or its crest</td>
</tr>
<tr>
<td>ix) Vegetation loss (by fire or drought)</td>
<td>ix) Vegetation loss (by fire or drought)</td>
</tr>
</tbody>
</table>
Physical Causes | Human Causes
--- | ---
i) Intense rainfall | i) Excavation of slope and toe
ii) Rapid Snow melt | ii) Loading of slope or its crest
iii) Prolonged exceptional precipitation | iii) Draw down of reservoirs
iv) Rapid draw down of floods and tides | iv) Deforestation
v) Earthquakes | v) Irrigation
vi) Volcanic Eruptions | vi) Mining
vii) Thawing | vii) Artificial Vibration
viii) Freeze and Thaw weathering | viii) Water leakage from utilities.
ix) Shrink and swell weathering

The above factors can be classified into three main groups: preparatory, triggering and controlling (perpetuating) factors (Crozier 1986). These groups are explained here below and an illustration given in Figure 1.1

- **Preparatory factors** – factors (like rock type, soil texture etc.,) that make the slope susceptible to movement without actually initiating it and thereby tending to place the slope in a marginally stable state.
- **Triggering factors** like earthquakes, intense rainfall, volcanic eruption etc., initiate the movement and shift the slope from marginally stable to an actively unstable state.
- **The controlling or perpetuating factors** (like topography, etc.,) determine the condition of movement as it takes place. These factors control the form, rate and duration of mass movement.

Landslides problems have become more severe especially with increase of human activities on unstable hill slopes. It is not important to argue about which hazard is the most frightening and destructive. However necessity demands that they are evaluated in terms of their suddenness, severity, area extent, potential economic losses, degree of warning possible and the level of possible mitigatory measures.
The phenomena described as landslides are not limited to the land or to sliding (Turner and Jayaprakash 1996). (Crozier 1986) also notes that the term landslide has been used to refer to a category of mass movement excluding creep and subsidence. Landslides do not occur in isolation; they are a product of changes of several environmental factors and also influence the environmental conditions at a local level.

The landslide risk is increasing worldwide as the need for more land forces new development on unstable slopes. In recent years, the growth of populations and the diffusion of settlements over hazardous areas have increased the impact of natural disasters worldwide. According to (Smith 2001), landslides are an under recognized threat because the impacts tend to be on a small-scale, whilst the process itself is often attributed to other hazards, such as earth quakes and rainstorms.

Apart from earthquakes and human influence, climatic conditions are also known to cause landslides. Landslides can be triggered by rainfall if some threshold intensity is exceeded so that pore water pressures are increased. The process is also exaggerated by the duration of the rainfall, slope angle, the distribution of shear strength, permeability particularly within the regolith thickness, antecedent weather and pore water pressure conditions (Bell 1998).

Although a wealth of experience has been accumulated in recent years in understanding, recognizing and treating landslide hazards, this knowledge is still fragmented (Popescu 2005). In tropical countries, the making and updating of landslide inventories is even more difficult because of the high regeneration rate of the vegetation. Landslide inventories consist of surface mapping of existing slides in a given area. The inventories include a record of the location, size and an assessment of the state of activity of the landslides. The methods of mapping have not changed much over time and landslides can be detected by use of aerial photographs and satellite images supported by field surveys (Manunta, Farina et al. 2005).

The methods used for mapping and monitoring landslides include the application of remote sensing techniques combined with GIS analysis. The use of technologies like satellite imagery allows a quick acquisition of data over wide areas, reducing the time spent on field work and eventually the costs as well. Current satellites have been improved to allow for faster revisits, improved coverage and acquisition of not only cheap but useful data (Bakker, Grabmaier. et al. 2004; Manunta, Farina et al. 2005).

Landslides together with their causal factors need to be mapped in order to be able to predict hazardous areas and those, which are not. The essential step for any hazard zonation is landslide inventory. This can be based on aerial photo and/or satellite image interpretation, ground survey and a data base containing historical information about landslide occurrences. The final product from the interpretation and the mapping is called a landslide inventory. This gives a spatial distribution of the landslides which are represented either as points or to scale to indicate the affected areas (Soeters and van Westen 1996).
1.2. Problem Statement

While inventory mapping may define the spatial patterns of landslides, the temporal component of slide activity is more problematic (Lang, Moya et al. 1999). In sparsely vegetated terrain, landslides can be easily detected and mapped by the interpretation of air photos or multispectral imagery supported by field surveys. However, it is quite difficult to use the same methods in rugged terrain covered with dense vegetation. In particular, vegetated older dormant slides with subdued topographic expression may be unrecognizable on air photos or multispectral digital imagery. Landslides in tropical environment may revegetate within a remarkably short time, provided there exists a stable substrate. When ample nutrients are available, forests recover most characteristics they had before the landslides occurred. As a result of this, the vegetation covers up most of the evidence/scars of landslides thereby making their study and mapping difficult (McKean and Roering 2004).

Landslide inventorying becomes even more problematic when the area under investigation is inaccessible and there is no historical record of the landslides said to have occurred in the past (Cruden and Varnes 1996). This has a two fold implication. First, field surveys and ground truths may be almost impossible once the area is inaccessible. Secondly, prediction of the occurrence of landslides in the area in the future may be difficult since we rely on what happened in the past to predict what might happen in the future. These problems could be solved by selecting a test area (which has to be accessible) with similar climatic and physiographic conditions where ground surveys could be carried out. The selected test area should have a history of landslide activity to help in the prediction of the landslides. In addition to these methods, satellite imagery and aerial photography ought to be used to map and monitor landslide activity. These approaches are time consuming and expensive especially with the acquisition of aerial photographs.

Wang Chin in the Prae province of Northern Thailand has had problems of landslides over the last couple of years. The region experienced a heavy rainstorm of 285.5 mm in May 2001 which triggered off many landslides. Since Thailand is a tropical country, the landslide scars were covered by vegetation very quickly. This makes the landslide mapping very difficult.

On the other hand a different scenario exists in Angkhang in Northern Thailand, which is not under as much vegetation cover as in Wang Chin. Angkhang suffered heavy deforestation in the past due to the population pressure attracted by the soil fertility and the area’s good climate (Schubert, C, Backhaus, C et al. 1986.). Marginal lands have been opened up for agriculture. For a long time, the main form of agriculture practised was shifting cultivation which involved indiscriminate destruction of the native vegetation. This type of land use practice was changed with the introduction of the Royal Agricultural Station. Ang Khang is now under reforestation and better agricultural practices. With the presence of dense vegetation, landslide mapping and monitoring is becoming difficult especially since both Ang Khang and Wang Chin are located in the humid tropics.

Although aerial photography has been used extensively to produce landslide inventory maps, air photos are not readily available in all areas. Scientists increasingly have to rely on satellite data to help assess the
risk for potential landslides. Several studies have been conducted to assess use of satellite imagery in the investigation and modelling of landslides using deterministic and probabilistic methods (Carrara and Guzzetti 1995; Menard 1995; Western and Terlien 1996; Chung and Fabbri 1999; Guzetti, Carrara et al. 1999; Manunta, Farina et al. 2005). This study aims at analysing causal factors and model landslide based on a set of rules formulated by the analysis of those factors.

1.3. Main objective

The main objective of this study was to investigate whether analysis of factors causing landslides in one area (Wang Chin in Northern Thailand), where landslides have been caused by a major rainfall event, can be used for building a model to assess landslide susceptibility in another area which has not had recent landslides (Ang Khang). A further objective was to evaluate the use of digital image processing for landslide mapping.

1.4. Specific Objectives

- To assess the use of multispectral satellite data for mapping landslides caused by a single rainfall event. In this case an event which occurred in 2001 which caused many landslides in the Wang Chin area in Thailand.
- To identify the types of landslides and the landslide controlling factors in the Ang Khang
- To identify the landslide controlling factors in the Wang Chin area, with main emphasis on morphometric factors.
- To establish weights of these factors causing landslides in one area and apply them in landslide susceptibility modelling in another area
- To test the validity of the model using existing landslides.

1.5. Research Questions

- What is the accuracy of digital image analysis technique to map landslides which occurred in 2001 in Wang chin area as compared to aerial photo interpretation?
- What are the factors, which cause landslides in Wang Chin? Can they be ranked?
- Can we use the same combination of factors used to predict landslides in Wang Chin area to predict landslide susceptibility in the Doi Angkhang area?
- Which areas are more prone to landslides?
1.6. **Structure of the thesis**

This thesis is divided into 7 chapters. The first chapter states the problem and outlines the need of this study. The objectives and the research questions to be answered by this study are stated in this chapter. Chapter 2 gives a background based on literature review, for this study. It attempts to explain the theoretical concepts for predictive modelling and the factors surrounding the facilitation of rainfall induced landslides in tropical environments. This chapter also attempts to explain landslide mapping using satellite imagery and aerial photo interpretation. Chapter 3 describes the characteristics of the study areas, which have been used as case studies for this study. The location, climate, geology and soils are mentioned. Chapter 4 is a description of the digital image analysis techniques used in mapping landslides in Wang Chin. A comparison is made between the two remote sensing methods and the various methods used in the mapping. Chapter 5 comes next which describes the mapping of landslides in Ang Khang – the second study area. This chapter also gives a description of the landslides found in Ang Khang using already established landslides terminology. This is followed by Landslide susceptibility mapping in Ang Khang which is described in Chapter 6. This is followed by Chapter 7 which includes conclusions made based on the results of the study. Limitations to the study are highlighted and recommendations given.
Chapter 2: Literature Review

2.1 Introduction

Mass movement or mass wasting is the movement of masses of bodies of soil, bed rock, rock debris, soil, or mud which usually occur along steep-sided hills and mountains because of the pull of gravity as defined by (Schuster 1978; Crozier 1986; Cruden and Varnes 1996). They observed that the slipping of large amounts of rock and soil is seen in landslides, mud slides, and avalanches. (Varnes 1985) discussed that landslides may be very small or very large, and can move at slow to very high speeds. (Cruden and Varnes 1996; Popescu 2005) note that the landslides causal factors can be grouped as preparatory and triggering. Preparatory causal factors make the slope susceptible to movement without actually initiating it and thereby tend to place the slope in a marginally stable state. Triggering causal factors initiate movement and shift the slope from a marginally stable to an actively unstable state as discussed by (Popescu 2005). He then noted that these factors include exceptionally high rainfall events, earth quakes, land-use changes and volcanic eruptions.

According to (Varnes 1985), land sliding is the result of a wide variety of processes which include geological, geomorphological, meteorological factors and human induced activities. He observed that landslide occurrence depends on the inter-play of several parameters and therefore it is imperative to know the contribution of these parameters to slope instability. The important terrain factors include drainage, slope aspect, elevation, etc. A complete landslide hazard assessment requires an analysis of all these factors leading to instability in the region. Some of these factors can be derived by image interpretation. With the advancement in efficient digital computing facilities, the digital image analysis techniques have gained enormous importance (Carrara 1983; van Westen and Terlien 1996). Complementary to this, the spatial and temporal thematic information derived from remote sensing and ground based information need to be integrated for data analysis. This can be very well achieved using GIS which has the capabilities to handle voluminous spatial data as discussed by (van Westen and Terlien 1996). With the help of GIS, it is possible to integrate the spatial data of different layers to determine the influence of the parameters on landslide occurrence (Abdallah, Chorowicz et al. 2005).

2.2 Classification of Landslides

A slide is a down slope movement of soil or rock mass occurring dominantly on surfaces of rupture or on relatively thin zones of intense shear train (Cruden and Varnes 1996). Movement does not occur simultaneously over the surface of rupture. The first signs of ground movement are usually cracks along the main scarp (Cruden and Varnes 1996). Landslides are classified according the type of movement and material involved (see also Chapter 1: Table 1.1). There are several types of landslides which include falls, topples, slides, spreads and flows. In addition to this, there are two main subtypes of landslides and these are rotational and translational slides. A rotational slide is described by (Cruden and Varnes 1996) as a slide which occurs along a surface of rupture of a slope that is curved and concave. The head of the displaced material moves almost vertically.
downwards while the upper surface of the displaced material tilts back towards the scarp. Rotational slides occur most frequently in homogenous materials as observed by (Cruden and Varnes 1996). A translational slide is slide where material is displaced along a planar or undulating surface of rupture, sliding out over the original surface (Cruden and Varnes 1996).

### 2.3 Rainfall as a triggering factor

As part of slope instability assessment, the probability that a triggering event occurs, such as a rainfall event or an earthquake, ought to be determined. The step is taken further to establish the relationship between magnitude and the return period of this event in question. This provides grounds for better planning in the future (van Westen, Renger et al. 2003).

“Hydrologic systems are sometimes impacted by extreme events, such as severe storms, floods, and droughts. The magnitude of an extreme event is inversely related to its frequency of occurrence, very severe events occurring less frequently than more moderate events” (Parodi 2005).

Large rainfall amounts often lead to disastrous events, which prompt researchers to investigate the magnitude and frequency of such events in a particular area. An example of methods used is the The Gumbel Extreme value distribution method. It is a log normal method with constant skewness (Viessman, Lewis et al. 1989). The Extreme value method considers the distribution of the largest (or smallest) observations in a group of repeated samples. For N samples, the extreme values are taken for a representative period (Viessman, Lewis et al. 1989; Maidment 1993; Parodi 2005).

The data used for analysis of the rainfall consist of the largest events of each year depending on the time frame of the recordings. It could be 30 minutes, 1 hour or 24 hour recordings. A set of these recordings is then referred to as the annual- maximum series which is a sample of all in its category e.g 30 minute annual extremes (Viessman, Lewis et al. 1989). The objective of this method is to build a relation between the probability of the occurrence of a certain event, its return period and its magnitude (Viessman, Lewis et al. 1989). Frequency analysis of hydrologic data relates the magnitude of extreme events to their frequency of occurrence by making use of their probability distributions (Parodi 2005).
2.4 Mapping landslides

Landslide mapping can be based on one or a combination of any of the following activities: aerial photo interpretation, ground survey, and a data base of historical occurrences of landslides in an area (Schuster 1978; Soeters and van Westen 1996). However in the absence of historical data, one has to rely on field survey and photo interpretation technique. Satellite imagery is generally unsuitable for landslide mapping except where data products can be enlarged to at least 1:50000 scale (Soeters and van Westen 1996). Photographic and satellite information can be valuable in mapping other spatial information and for use in conjunction with computer mapping techniques as part of the development planning study (Naithani 1990).

Images are classified by categorising all pixels into land cover classes or theme as noted by (Lillesand, Kiefer et al. 2004). They also discussed that for any given image, the spectral pattern for each pixel is used as the numerical basis for the categorization. Different features exhibit different properties like spectral reflectance and emittance (Richards 1993; Lillesand, Kiefer et al. 2004). This is the most straightforward approach to landslide hazard zonation because aerial and space images contain a detailed record of features on the ground at the time of data acquisition.

2.4.1 Landslide mapping using Aerial photo interpretation.

Aerial photography can serve as the source for data on existing landslides, type of bedrock, and vegetation cover (Naithani 1990). Typically, large-scale photography is necessary for mapping existing landslides. The photo scale depends on the size of landslides common to the study area. Small-scale photography is less of a concern where bedrock and vegetation exist, since delineating areas with similar texture and appearance is easier than recognizing discrete features. Depending on vegetative cover, photo quality, experience and the skill of the interpreter, overall identification accuracy of 80 to 85 percent is realistic using aerial photography (Rib and Liang 1978; Hansen 1984).

The range of useful scales of aerial photography for landslide inventory work is limited to about 1:40,000 or larger. The selected scale will depend on the size of landslides common to the study area and, to some extent, the relief of the area. Where the majority of landslides are one hectare or smaller in size, large-scale photography on the order of 1:4,800 is necessary (Naithani 1990). The usefulness of black and white, color, or color-infrared photography for landslide inventory work will vary with local conditions and the reference level of the interpreter.

A map of existing landslides serves as the basic data source for understanding conditions contributing to landslide occurrence. Normally such a map is prepared by the interpretation of aerial photographs which is supported by field verifications (Cruden and Varnes 1996). While this map could also be compiled by field methods alone, the time and expense involved would only be justified by the unavailability of photo coverage. Either means of map preparation requires the skills and experience in landslide or landform interpretation.
The map may be prepared at different levels of detail concerning existing landslides (USGS 1985). A simple inventory identifies the definite and probable areas of existing landslides and is the minimum level required for a landslide hazard assessment.

There are several considerations to keep in mind when gathering data on existing landslides. First, the time and effort required to conduct an inventory varies with (1) geologic and topographic complexity; (2) size of an area; and (3) desired level of inventory detail (Varnes 1985). Second, more detailed inventories will require larger map scales to reveal the small features of this added detail. Third, additional data gathering can add detail to an existing inventory. This enables a previously completed simple inventory to be transformed into an intermediate inventory with less time and effort than producing the intermediate inventory solely from field work and aerial photography (Varnes 1984).

### 2.4.2 Landslide Mapping using image analysis techniques

Digital image processing involves the manipulation and interpretation of digital images with the aid of a computer. “There is no single “right” way to approach the image interpretation process” (Lillesand, Kiefer et al. 2004). Availability of images and interpretation equipment has a large influence on how the task of interpretation is undertaken. The objectives of the interpretation will then determine the methodology to be employed. What follows is the need for the criteria for a classification system to be set in order to categorise the various features occurring on the images under consideration (Lillesand, Kiefer et al. 2004).

Satellite images have the advantage of having multi-temporal characteristics which makes them useful for change detection. But on the other hand updating available data using satellite images requires intensive field work to fill in the missing details (Naithani 1990). This implies that satellite images ought to be used in combination with other data generation methods.

In principle, classification of multipsectral data should be straightforward but it is never the case. For one to obtain an acceptable accuracy result from the classification, then they ought to be careful during the selection of analytical tools during the classification (Richards 1993).

### 2.4.3 Supervised Classification

In remote sensing, classification is the main tool for extracting information about the surface cover type of an area represented. Conventional classification methods assign each pixel to one class (Sabins 1996). The class could represent forest, soil or vegetation or cloud. The classification methods (algorithms) generate a map showing classes with the highest concentration. According to (Richards 1993), Supervised classification is a procedure for identifying spectrally similar areas on an image by identifying ‘training’ sites of known targets and then extrapolating those spectral signatures to other areas of unknown targets.
He also discussed that supervised classification is the procedure used most often for quantitative analysis of remote sensing image data. It makes use of suitable algorithms to label the pixels in a given image as a representative of specific land cover types or classes (Richards 1993).

The analyst makes a choice of land cover types or land classes for use in segmenting the image. This is because supervised classification relies on the \textit{a priori} knowledge of the location and identify of land cover types that are in the image (Richards 1993). According to (Lillesand, Kiefer et al. 2004), this can be achieved through field work, study of aerial photographs or other independent sources of information and selecting representative pixels from each of the required land cover types or land cover classes.

This is referred to as training the data. This is the most important step where the analyst performs a prior identification of the selected classes during the training of the pixels (Richards 1993; Lillesand, Kiefer et al. 2004). This requires ground truth either by field visits or by use of reference data like topographic maps and air photographs. The training data is then used to estimate the parameters of any given classifier algorithm to be used. The selected set of parameters for any given class is sometimes referred to as the signature of that class.

(Richards 1993) also discussed that the analyst ought to have sufficient known pixels for each class of interest for which representative signatures can be developed. Then using a trained algorithm, every pixel in the image is labelled into one of the classes in which case, the whole image is then classified. By training the data, the analyst teaches the algorithm to recognise the spectral characteristics of each class, thus the term Supervised classification. It is important as with all training procedures based upon field or reference data, that the training data be recorded at about the same time as the multispectral data to be classified. Otherwise errors resulting from temporal variations may arise (Richards 1993).

(Richards 1993; Lillesand, Kiefer et al. 2004) note that it is of necessity that training data be identified for at least all classes of interest and preferable for all apparent classes in the area of interest of the image to be analysed. They then discussed that it is therefore wise to use some threshold or limit if the classification is of minimum distance or maximum likelihood variety. This ensures that any pixel which is poorly characterised is not erroneously labelled. In the case of maximum likelihood, a limit is applied by making use of the thresholds. By so doing, the pixels which were not well represented during the training phase will not be classified.

\subsection*{2.4.3.1 Maximum Likelihood Classifier}

According to (Richards 1993; Sabins 1996), Maximum Likelihood classifier is the most common algorithm used in supervised classification. The observed that the algorithm has been statistically developed and makes use of conditional probabilities. The pixels of the image are described basing on their respective spectral characteristics. For any given pixel at any given position, the class with the largest probability of likelihood is assigned (Richards 1993; Sabins 1996).
In agreement, Lillesand, Kiefer et al. (2004) noted that this algorithm quantitatively evaluates both the variance and covariance of the spectral patterns when classifying an unknown pixel. In addition to this, they noted that Maximum Likelihood makes assumption of normality and a response pattern can thus be described using the mean vector and the covariance matrix. The statistical probabilities of each pixel of any given class are computed. Each pixel is then assigned to the most likely class or the class with the highest probability value or some might even be given an “unknown” value if their probabilities are below the threshold set by the analyst (Lillesand, Kiefer et al. 2004).

2.5 Landslide Modelling and Susceptibility Mapping

Landslide modelling and susceptibility mapping, for any given area, involves predicting the occurrence of future landslides based on observed preparatory factors. (Abdallah, Chorowicz et al. 2005) observed that in order to predict the occurrence of landslides in the future, it’s important to establish a statistical relationship between landslides and any possible factor. They also discussed that future events would occur if similar conditions which have led to landslides in the past are present.

“Prediction of landslide occurrence for areas currently not subject to landsliding is based on the assumption that hazardous phenomena that have occurred in the past can provide useful information for prediction of the landslide occurrences in the future” (Tamire 2001).

By examining existing landslides in an area, it is possible to recognize how permanent factors contributed to these slope failures. Identifying conditions and processes promoting past instability makes it possible to use these factors to predict future landslides (Varnes 1984). Factors influencing where landslides occur can be divided into two sets, permanent and variable (Sharpe, 1938). Permanent factors are characteristics of the landscape which remain unchanged or vary little from a human perspective. The steepness of a slope or the type of rock, for example, present changes only with the passage of long periods of time. Permanent factors such as rock type and slope steepness can be recognized and identified for specific landslides long after their occurrence (DeGraff, 1978). By examining existing landslides in an area, it is possible to recognize how permanent factors contributed to these slope failures. Identifying conditions and processes promoting past instability makes it possible to use these factors to estimate future landslides (Varnes 1984).

Variable factors are landscape characteristics that change quickly as a result of some triggering event (Popescu 2005). Ground vibration due to earthquakes, a rapid rise in groundwater levels, and increased soil moisture due to intense precipitation are examples of variable factors (Sidle, Pearce et al. 1985; Oliver, F. G. Bell et al. 1994). Due to the lack of long-term records relating landslide activity to historic earthquakes, storms, or other initiating factors, permanent factors are usually used to estimate landslide hazard. At best, landslide and landslide susceptible areas can be identified along with expected triggering events. At worst, some areas may not be detected at all.
Three principles guide landslide hazard assessment. First, landslides in the future will most likely occur under geomorphic, geologic, and topographic conditions that have produced past and present landslides. Second, the underlying conditions and processes which cause landslides are understood. Third, the relative importance of conditions and processes contributing to landslide occurrence can be determined and each assigned some measure reflecting its contribution (Varnes, 1985). The number of conditions present (as discussed in Section 2.5.1) in an area can then be factored together to represent the degree of potential hazard present.

Landslide hazard zonation can be divided into two methods: direct and indirect. Direct methods require the expertise of a geomorphologist who, based on his/her knowledge of the terrain conditions of the study area determines the degree of susceptibility to landslides. On the other hand indirect methods either use statistical or deterministic models to predict landslide prone areas based on landslide occurrence and their conditioning factors. This study focuses its method of prediction on the use of indirect methods.

2.5.1 Landslide conditioning factors

According to (Carrara 1988; Cruden and Varnes 1996) it can be noted that landslides are caused by one or a combination of two or more of the following factors: (a) change in slope gradient, (b) increasing the load that the land must bear, (c) shocks and vibrations, (d) change in water content, (e) ground-water movement, (f) frost action or wedging, (g) weathering of rocks, and (h) removal or changing the type of vegetation covering slopes, etc. Of these factors, five (a, b, c, d, and h) can be man-related.

In an attempt to identify the reasons for landsliding in the Ang Khang area, a number of landslide conditioning factors were identified during the field work and their importance discussed in the sections that follow.

2.5.1.1 Slope Gradient

(Varnes 1978) describes landslides as rock, earth, or debris flows on slopes due to gravity. He then observed that they can occur on any terrain given the right conditions of soil, moisture, and the angle of slope. He also observed that the steeper the slope of the land, the more likely that mass wasting will occur.

He noted that the steeper slopes have a greater chance of landsliding and Slope gradient also influences the velocity of the water travelling over the land surface. This does not prevent failures from occurring on gentler slopes. Other factors may make a gentle slope especially sensitive to failure, and thus in this situation could be determined to have a relatively high hazard potential (Crozier 1986; Cruden and Varnes 1996).

For example, high ground water conditions occurring in sandy soils may liquefy during an earthquake. This can cause a landslide on a slope as gentle as 5 to 10 percent. Conversely, the steepest slopes may not always be the most hazardous. Steep slopes are less likely to develop a thick cover of superficial material.
conducive to certain types of landslides. Slope gradient can be mapped using topographic maps or calculated from a DEM generated from digitized contours through contour interpolation.

2.5.1.2 Slope Direction (Aspect)

Slope direction (aspect) refers to the direction a slope faces. It can be an indirect measure of climatic influence on the hydrologic characteristics of the landscape (Ercanoglu, Gokceoglu et al. 2003). They observed that important characteristics associated with landslides are related to such factors as subsurface recharge resulting from prevailing winds and their influence on local frontal storms or accumulated snow. In other cases, a slope may experience more freeze/thaw cycles or wet/dry cycles which can reduce the strength of the soil and make the area more susceptible to landslides (Crozier 1986). In general, due to the complexity of these factors and existing development activities, there is usually no direct observable correlation between slope orientation and landslide hazard (Cruden and Varnes 1996).

2.5.1.3 Drainage – Flow Accumulation

Following rainfall events, water flows from areas of convex curvature and accumulates in areas of concave curvature. This is known as flow accumulation, or upstream catchment area. Flow accumulation is a measure of the land area that contributes surface water to an area where surface water can accumulate (Chen and Lee 2003). This parameter was considered of relevance to the study because it defines the locations in which water concentrates, such as at the head of the gullies, where there is a high landslide incidence.

Water is recognized as an important factor in slope stability-almost as important as gravity (Crozier 1986). Water plays a key role in producing slope failure. In the form of rivers and wave action, water erodes the base of slopes, removing support, which increases driving forces. The weight (load) on the slope increases when water fills previously empty pore spaces and fractures. The shear strength of the slope material is decreased by increasing the pore water pressure (pressure that develops in pore spaces due to the increased amount of water) (Capecchi and Focardi 1988; Oliver, F. G. Bell et al. 1994; Chen, Kao et al. 1995; Chen and Lee 2003). By so doing, water plays an important role in increasing the potential to mass movements. To represent the hydrologic factor in landslide hazard assessments, indirect measures can be used which can be mapped to show the influence of the area's hydrology, such as vegetation, slope orientation (aspect), or precipitation zones (Popescu 2005).

In analysing the correlation between landslides and vegetation, (Crozier 1986) said that the type of vegetation and its density over an area will often reflect the variation in subsurface water. Certain species are water-loving or phreatophytes. He then went on to say that the presence of these species shows near-surface water table conditions and springs. In mountainous regions, microclimatic differences produce
different hydrologic conditions which in turn result in plant communities that vary according to the moisture available to the slope and its distribution throughout the year.

## 2.5.1.4 Distance to Roads

In addition to natural phenomena, human development activities may increase the natural tendency for a landslide to occur. Development activities such as cutting and filling along roads and the removing of forest vegetation are capable of greatly altering slope form and ground water conditions (Swanson and Dyrness 1975). These altered conditions may significantly increase the degree of landslide hazard present (Sidle, Pearce et al. 1985; Varnes 1985).

(DeGraff 1979) illustrated that building a road which cuts off the toe of a steep slope can increase landslide susceptibility. (Kockelman 1985) in agreement observed that it is possible to reduce the potential impact of natural landslide activity and limit development-initiated landslide occurrence by early consideration of these effects.

## 2.5.1.5 Geology

According to (Geological Survey Division 1974) of Thailand, the main geological eras that describe the formations of the area are of the Quaternary, Permian and Carboniferous (lower and upper) ages. The main rock types which dominate the Eastern part of the area (running from North to South) include Shale, Limestone, Sandstone and Conglomerates. The Western part of Ang Khang which runs from North to South is dominated by Limestone and Karst formations. Shale is highly weatherable and once its cleavage is in the direction of the dip, landslides are bound to occur when it rains (Way 1973). In addition to this, he observed that the soils formed from shale are relatively impermeable therefore when it rains, their weight increases as the amount of rain increases leading to mass movement.

## 2.5.1.6 Soil (Texture, Depth and Sub group)

According to the (Soil Survey Staff 1999), the word “soil,” is used to several meanings. They say that soil in its traditional meaning, soil is the natural medium for the growth of land plants, whether or not it has discernible soil horizons. People consider soil important because it supports plants that supply food, fibers, drugs, and other wants of humans and because it filters water and recycles wastes. Therefore wastage of soil in terms of degradation is bound to arouse concern.

According to (Soil Survey Staff 1999), soil is the natural medium for the growth of plants, whether or not it has discernible soil horizons. In addition to this they observed that a large percentage of the life on earth, if not all life on earth, derives its livelihood from the soil in one way or the other. As a result of this, the loss of loss either through erosion or natural hazards is of great significance.
Soils are classified with respect to their respective or specific characteristics and properties. However this study does not focus on soil classification but soil as an important landslide conditioning factor. To establish its importance to the occurrence of landslides, this study considered Soil sub groups, Texture and Depth which are discussed in the sections that follow:

a) Soil Sub Groups

According to the classification system used by (Soil Survey Staff 1999), three classification levels (order, suborder, and great group) precede Subgroup and they are focused on categorizing soils based on major features or geological/environmental processes that dominated the direction and/or extent of soil development. They noted that the subgroup classification seeks to recognize distinctive soil features across different soils within a given soil great group. They also discussed that the subgroup name includes the great group name, modified by one or more descriptive adjectives. These descriptive adjectives fall into three general categories termed Typic, intergrade, and extragrade. A Typic subgroup soil lacks any significant properties that would suggest it is in a transition phase between related great groups or some other soil taxonomic level. Intergrade subgroup soils are those that belong to one soil great group but share various soil properties common to another recognized great group, suborder, or order. Extragrade subgroup soils reflect specific properties that are otherwise anomalous to the main concept of the great group (Rice, Gilbert et al. Reviewed March 2005). These are simple explanations, however since this research focused on landslides and the conditioning factors a detailed definition of the subgroup was not given.

b) Soil Texture and Depth

(Soil Survey Staff 1999) use the term Soil texture to designate the proportionate distribution of the sand, silt and clay mineral particles in a soil. They also discussed that these mineral particles vary in size from those easily seen with the unaided eye to those below the range of a high-powered microscope. According to their size, these mineral particles are grouped into "separates."

A soil separate is a group of mineral particles that fit within definite size limits expressed as diameter in millimetres as defined by (Soil Survey Staff 1999). Since various sizes of particle have quite different physical characteristics, the nature of mineral soils is determined to a remarkable degree by the particular separate that is present in larger amounts. Thus, a soil possessing a large amount of clay has quite different physical properties from one made up mostly of sand and/or silt. Soil textural classes therefore reflect the percentages of Sand Silt and clay (Soil Survey Staff 1999). The higher the percentage of clay the lower the permeability and the higher the chances of sliding.

Soils formed from mixed alluvial materials (e.g., limestone, quartzose sandstone and shale and siltstone) on terraces and flood plains are predominately well-drained, fine-sandy loam, loam and silt loam soils with high moisture availability and moderate fertility (Rice, Gilbert et al. 2005). Less extensive soils are somewhat poorly drained or have a fragipan, which restricts root growth and permeability.
According to (Soil Survey Staff 1999), soils on ridges are formed in weathered residuum from shale, siltstone, and sandstone, and to a limited extent, limestone, and carbonaceous shale and siltstone. They are mostly moderately deep-to deep, well-drained, loam, silt loam, and silty clay loams with moderate fertility.

Soils on upland slopes are usually formed from colluvial materials of mixed mineralogy, derived from a variety of rock types. Soils on steep upper slopes range from moderately deep to shallow. They are well drained with the gravelly and channery silt loam and sandy loam textures commonly associated with rock outcrop. These soils generally have severe erosion potential from exposed or bare soil areas and a greater risk of slope failure (Soil Survey Staff 1999).

The effective depth of a soil for plant growth is the vertical distance into the soil from the surface to a layer that essentially stops the downward growth of plant roots. The barrier layer may be rock, sand, gravel, heavy clay, or a cemented layer (The University of Arizona 1998).

Soils that are deep, well-drained, and have desirable texture and structure, are suitable for the production of most garden or landscape plants (Soil Survey Staff 1999). Deep soils can hold more plant nutrients and water than can shallow soils with similar textures. Depth of soil and its capacity for nutrients and water frequently determine the yield from a crop, particularly annual crops that are grown with little or no irrigation. Plants growing on shallow soils also have less mechanical support than those growing in deep soils. Trees growing in shallow soils are more easily blown over by wind than are those growing in deep soils. This leaves the land exposed to agents of land degradation of which landslides play an important role as illustrated by (USGS 1985; Soil Survey Staff 1999; Popescu 2005).

2.5.1.7 Land use/ Land cover

(Swanson and Dyrness 1975) observed that in addition to natural phenomena, human activities may increase the natural tendency for landslides to occur. When homes are constructed on unstable soils, or roads are cut into steep hillsides in critical areas, when we fail to properly manage our forests, we may be accelerating landslide activity. They also observed that landslides, which result from development activities such as these, are usually caused by increasing moisture in the soil or changing the form of a slope. Development activities such as removing of forest vegetation are capable of greatly altering slope form and ground water conditions. These altered conditions may significantly increase the degree of landslide hazard present (Sidle, Pearce et al. 1985).

2.5.2 Weights of Evidence Modeling

For more hundreds of years, landslides have been occurring, destroying not only property worth millions of dollars but also human lives. Several studies (Carrara 1983; van Westen, Renger et al. 1997; Chung and Fabbri 1999) have been carried out in order to predict their occurrence and also to try and understand why they do occur. As a result of these studies several methods were devised which include
Deterministic, Heuristic and Statistical approaches (Soeters and van Westen 1996). This study however focuses on the use of Weights of Evidence modelling which is a statistical approach: Bivariate Statistics.

Several studies have been carried out using the weights of evidence modelling (van Westen 1993; Bonham-Carter 1994; Alleotti and Chowdhury 1999; Chung and Fabbri 1999; Carranza 2002; van Westen, Renger et al. 2003) who discovered that this method has its own shortcomings. The first shortcoming is the fact that it takes into account only those landslide conditioning factors which can be easily mapped and in so doing it over simplifies the factors. The next shortcoming is the fact that while using Bivariate statistics, an assumption is made that all landslides in a given study area occur under the same combination of factors. The third is that each type of landslide has its own causal factors and should therefore be analysed separately. And the fourth is that the method is open to subjectivity since it is mostly used by people other than earth scientists (van Westen, Rengers et al. 2003).

The advantages of Weights of Evidence modelling with respect to Bivariate Statistics are that the method is simple, easy to use and less time consuming (Soeters and van Westen 1996; Suzen and Doyuran 2004). Bivariate Statistics can be used to establish the correlation between landslide occurrences at a factor level (Carrara and Merenda 1976). This allows for less important factors to be left out for further processing.
Chapter 3: Characteristics of the study Areas

3.1 Introduction

Two study areas were selected for this study, Wang Chin and Doi Ang Khang (Ang Khang). The first study area, Wang Chin, experienced a high rainfall event in 2001 which caused many landslides. Unfortunately because the area was inaccessible, limited field was carried out. It was based on observations from afar using binoculars. Although limited field work was carried out in the area, a cloud free satellite image was available for the area and thus Wang Chin was used as a focus for image analysis to detect landslides.

The second study area was Ang Khang. Although there was no historical data base with a spatial distribution of landslides in the area, Ang Khang was accessible and so field work was possible. In this area, the landslide conditioning factors could be identified and used to predict the future occurrence of landslides in the area. The assumptions for this study are Angkhang has fewer landslides and the rules derived from in one area will apply in another.

3.2 Wang Chin

3.2.1 Location

Mae Suary sub–watershed is located in Wang Chin District in the Prae province of Northern Thailand (Figure 3:1) The district is about 200km (North/West/East etc.) from Chiang Mai, It lies between 99° 25’ and 99° 38’ East longitudes and between 17° 41’ and 17° 53’ North latitudes and covers a surface area of 250 km². Elevation varies from 105 to 1,222 m above mean sea level. Wang Chin is administratively divided into Soy, Mae Pung, and Pah Sak sub districts.
3.2.2 Climate

Wang Chin is characterised by a tropical climate that is influenced by both north eastern and south western monsoons. The area experiences an annual average rainfall of 1739 mm based on 8 years (1997 to 2004, Wang Chin District) of daily rainfall records, most of which falls during rainy season (May to October) as shown in the Figure 3:2 below.

![Figure 3.2 Average Monthly Rainfall for Wang Chin](image)

From the above figure, we notice a double peaked rainfall regime in Wang Chin, one in May and the other in September. The months of October to April are relatively dry months compared to the rest of the year with February being the month with least rainfall (about 10mm).

Temperatures range from a minimum of about 12°C during the winter season (November to March), to a maximum of about 35°C during the summer season (May to September).

3.2.3 Geology and Geomorphology

The study area lies in the northern highlands of Thailand. The main geological ages of the area include Quaternary and Permian ages. The upper portion of the area comprises of Rhyolite, Phyllite and undifferentiated sandstone. The middle part of the area, which is a lateral valley, comprises of colluvial and alluvial deposits also called River and terrace gravel. The lower part of the area comprises mainly of shale and sandstone rocks.
Wang Chin has two basic landscapes: a lateral valley in the centre and mountainous areas on either side of the valley, running from North East to South West.

### 3.2.4 Soils

Wang Chin is classified into two main Soil orders; Inceptisols and Alfisols. Inceptisols have profiles features more weakly developed than many of the other soils but retain a resemblance to their parent rock material. They have an umbric, mollic epipedon or a cambic horizon. A Cambic horizon is one in which the parent material has been changed into soil by formation of soil structure, liberation of iron oxides, clay formation and obliteration of the original rock structure. Mollis and Umbris horizons are both dark coloured surface horizons but Mollis horizons are typical of steppe slopes with over 50 percent of the exchange capacity dominated by base cations. Umbris horizons have less than 50 percent of the exchange capacity dominated by base cations (Bridges 1997; Buol, Hole et al. 1997).

Wang Chin soils have an argillic horizon and moderate to relatively high base content (calcium, magnesium, sodium and potassium). An argillic horizon is an illuvial horizon enriched with clay to a significant extent. The Alfisols are further classified into a suborder called Udalfs while the suborder for Inceptisols is Tropepts (Bridges 1997; Buol, Hole et al. 1997). They have a soil textural classification range from Silty Loam to Gravely Loam. The moisture regime in Wang Chin is Udic.

### 3.2.5 Land cover and Land use

The Mae Suay sub–watershed consists of five major land cover types. These include forests (both degraded and undegraded), irrigated rice, mixed cultivation, which includes vegetables of various types and other staple foods, and shrub. The land use is mainly forest and shrub on the sloping area while there are some orchards on low and medium terraces of the Yom river, which passes through the Wang Chin District covering about 27 km length. Paddy rice areas occupy the flood plain of the Yom river which was damaged by mass movement in 2001.

### 3.3 Doi Ang Khang (Ang Khang)

#### 3.3.1 Location

Located on Tanaosri Mountain, **Angkhang** is just five kilometers from the Thai-Burmese border. Ang Khang lies between 99° 03’ and 99° 04’ East longitudes and between 19° 51’ and 19° 55’ North latitudes. Situated 160 kilometres north of Chiang Mai (40 km from Fang district) and 1,400 meters above sea level, Doi Angkhang is cool all year round. The weather not only allows the growth of temperate plants, but it also attracts thousands of visitors each year especially during the cool winters (November to February). Land use in the past consisted of shifting cultivation by local inhabitants, which is now prohibited. Because of strict government policy, dense forests exist in some areas while it is degraded elsewhere.
The name Doi Ang Khang was derived from a northern dialect meaning a bowl which is due to the physiography of the area that has steep mountain ridges stretching about 5 km in length and 3 km in width forming a bowl in the centre.

The Royal Agricultural Station Ang Khang is situated 1,400 meters above sea level in Mae Ngom sub district, Phang district, Chiang Mai Province in Northern Thailand (Figure 3:3). The research station covers a total area of about 37.49 km² with a population of approximately 2,785 people from 6 villages; Ban Luang, Ban Khum, Ban Pangma, Ban Khodont, Ban Pak and Ban Norlae.

Figure 3.3 Ang Khang District (with the road network) in Northern Thailand.

3.3.2 Climate

The average temperature for the region is about 17.7 degrees Celsius with an average annual rainfall of about 2,075 mm calculated for a period of 16 years (1989 – 2004, Ang Khang Station). Maximum temperatures are in the high of 32 degrees Celsius (average maximum) in April and while minimum temperatures are as low as -3 degrees Celsius in January which causes frost. The rainfall season lasts from July to November although a considerable amount of rainfall is received in May (Figure 3-4). August is the month with the highest amount of rainfall with an average of about 400mm. The figure below shows the average annual rainfall of Ang Khang.
### 3.3.3 Geology and Geomorphology

Ang Khang is dominated by sedimentary rocks of different ages which are Quaternary and Permian. The North-eastern side of the study area is dominated by Carboniferous lower rocks, which include Sandstone, Greywacke and Shale. The mid-section comprises of carboniferous upper rocks. They comprise of Sandstone, Shale, and Conglomerates. Between the mid-section running from North to South and the Western section are small areas with Quaternary rocks. These rocks are characterised by gravel and sandstone. Rocks of the Permian age comprising of limestone dominate the Western section of the study area. Unfortunately the geology of the area on the extreme Western section – running from North to South of the study area, is unknown and thus classified as so.

In Figure 3.5 the codes q, u, p2, h1 and h2 refer to the Geological ages of the study area. T Upper, and lower respectively. The legend of these codes is given in Table 3.1

Ang Khang can be described as an area with a complex geomorphology comprising of sinks holes of Karst landforms mostly in the centre part of the study area. In the past, area used to be composed of steep mountain slopes but they were eroded to leave a bowl like shape. What is left are mountain slopes on the Eastern and the Western sections of the study area and a Piedmont in the middle (Figure 3.6). Ang Khang is also described as a relatively high terrain with elevation ranging from 1040m to 1920m above sea level.
Table 3.1 Table showing the Legend of the Geological map of Ang Khang (explanation of the symbols used)

<table>
<thead>
<tr>
<th>Age</th>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neozoic</td>
<td>q</td>
<td>Fluvial deposit and colluvium</td>
</tr>
<tr>
<td>Paleozoic</td>
<td>p2-1</td>
<td>Limestone</td>
</tr>
<tr>
<td>Carboniferous (upper)</td>
<td>h2</td>
<td>Sandstone, shale, chert, greywacke, conglomerate</td>
</tr>
<tr>
<td>Carboniferous (lower)</td>
<td>h1</td>
<td>Sandstone, greywacke, shale</td>
</tr>
</tbody>
</table>

The Geopedological map of Ang Khang is given in Figure 3.6 and the legend given in Table 3.2. It is referred to as the Geopedological map because a Pedological approach was used in the preparation of the map. The procedure involved aerial photo interpretation and screen digitizing in ILWIS 3.3 version.

Table 3.2 showing the terminologies used in the Geopedological map of Ang Khang (Figure 3.6)

<table>
<thead>
<tr>
<th>Landscape</th>
<th>Relief Type</th>
<th>Lithology</th>
<th>Landform</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mountain of predominantly Shale</td>
<td>Ridge</td>
<td>Residuum and colluvium from sandstone</td>
<td>Slope Facet complex</td>
<td>MOS111</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Residuum and colluvium from Phyllite and some shale</td>
<td>Slope Facet complex</td>
<td>MOS121</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Residuum and colluvium from shale</td>
<td>Summit Shoulder complex</td>
<td>MOS131</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Back_foot slope complex</td>
<td>MOS132</td>
</tr>
<tr>
<td>Hill</td>
<td></td>
<td>Residuum and Colluvium from shale</td>
<td>Slope Facet complex</td>
<td>MOS211</td>
</tr>
<tr>
<td>Vale</td>
<td></td>
<td>Alluvio_colluvium</td>
<td>Bottom_side complex</td>
<td>MOS311</td>
</tr>
<tr>
<td>Mountain of predominantly Limestone</td>
<td>Hill</td>
<td>Limestone associated with residuum from shale</td>
<td>Slope Facet complex</td>
<td>MOL11</td>
</tr>
<tr>
<td></td>
<td>Tower Karst</td>
<td>Limestone</td>
<td>Slope Facet complex</td>
<td>MOL21</td>
</tr>
<tr>
<td></td>
<td>Polje (undulating to rolling surface)</td>
<td>Residuum and colluvium derived from shale associated with limestone</td>
<td>Sinkhole</td>
<td>MOL31</td>
</tr>
<tr>
<td>Piedmont</td>
<td>Hill</td>
<td>Residuum and colluvium derived from shale</td>
<td>Slope Facet complex</td>
<td>Pi111</td>
</tr>
<tr>
<td></td>
<td>Tower Karst</td>
<td>Limestone</td>
<td>Slope Facet complex</td>
<td>Pi211</td>
</tr>
<tr>
<td></td>
<td>Erosional glacis</td>
<td>Colluvium over residuum derived from shale</td>
<td>Slope Facet complex</td>
<td>Pi311</td>
</tr>
<tr>
<td></td>
<td>Polje (gently sloping surface)</td>
<td>Colluvium and residuum derived from shale associated with limestone</td>
<td>Sinkhole</td>
<td>Pi411</td>
</tr>
<tr>
<td></td>
<td>Vale</td>
<td>Alluvio_Colluvium</td>
<td>Bottom_side complex</td>
<td>Pi511</td>
</tr>
</tbody>
</table>

(Adapted from Udomsri, 2005)
Figure 3.5 Showing the Geological map of Angkhang

Figure 3.6 Showing the Geopedology map of Ang Khang (proper legend given in Table 3.2)
3.3.4 Soils

Ang Khang consists of two main soil Orders (Inceptisols and Alfisols). The soil subgroups names of Ang Khang include Fluventic Eutrudepts, Lithic Eutrudepts, Oxyaquic Eutrudepts, Rhodic Paleudalfs, Typic (Mollic) Paleudalfs, Typic Hapludalfs, Typic Paleudalfs, Ultic (Mollic) Hapludalfs, Ultic Eutrudepts, and Ultic Hapludalfs.

According to (Bhubharuang 1980), the soils found in the valleys of Ang Khang are of a sandy loam texture derived from alluvium material. He also discussed that the mountain of predominant shale have soils of clayey texture derived from colluvio-alluvio material while the mountain of predominantly limestone associated with shale rock types have soils of a clayey texture and are red in colour.

3.3.5 Land cover / Land use

Shifting cultivation was the traditional farming system in the highlands of northern Thailand which involved indiscriminate slashing and burning of available vegetation to create land for cultivation. It was appropriate as long as the highland population was small and an abundance of land per farm owned by a family permitted long fallow periods. But rapid population growth, (caused mainly by migration from the lowlands of Thailand, Burma and Laos and high birth rates) led to a rapid decline in the amount of land available to each family. With the increasing scarcity of land, fallow periods became shorter and marginal and forested areas were turned into agricultural land (Schubert., Backhaus. et al. 1986).

In the late eighties with the establishment of the Royal Agricultural Station, the slash and burn system which was considered exploitive has been eliminated (Schubert, Backhaus et al. 1986). This has enabled the hill tribe people to settle down on permanent lands and practice subsistence farming using modern agricultural techniques and profitable crops introduced by the Royal Agricultural Station in Ang Khang. The crops grown include temperate vegetables, flowers, fruits, forest plants including various kinds of bamboo, Chinese tea, linseed etc. The land cover map (Figure 3.7) was prepared from aerial photo interpretation (2002).
3.4 Analysis of the rainfall pattern in the study areas

Landslides can be triggered by a number of factors which include earthquakes and rainfall. These triggering factors cause the slope to shift from marginally stable to an actively unstable state (Capecchi and Focardi 1988). This study was focused on rainfall triggering or induced landslides. Because of this focus, rainfall data (recorded on a daily basis) was obtained during field work for both Wang Chin (8 years) and Ang Khang (16 years).

This study used the Gumbel Extreme value distribution method (Chapter 2: Section 2.3) to analyse the rainfall data of Wang Chin and Ang Khang. The objective of this method is to build the relation between the probability of the occurrence of a certain event, its return period and its magnitude. In the case of the study, the event is a rain storm. The main advantage of this method is that it can be used even with small data sets and it also considers extreme values. This is important since in the case of this study, the available data sets were for 8 and 16 years in Wang Chin and Ang Khang respectively.
3.4.1 Gumbel Extreme Distribution value Method

The rainfall data obtained during fieldwork for the 2 study areas was explored and the total of number of years (N) established. The maximum amount of rainfall per year was extracted from the original data and then the steps (1, 2 and 3) were taken to predict the return periods of various rainfall amounts in the two areas.

Since the data obtained was recorded on a daily basis and the theory considers, only maximum values, the monthly peaks were extracted. From these monthly peaks the annual maximum values were extracted. This set is referred to as the annual maximum series which is a sample of all observations (Dunne and Leopold 1978). Then the maximum annual rainfall values were sorted and ranked from high to low. The lowest rank 1 was assigned to the lowest data value and the highest rank N to the highest data value.

Steps used in the Gumbel Extreme Distribution value method

1. Using equation 3.1, the left sided probability was calculated for each observation (sorted maximum rainfall amounts):

\[ P_L = \frac{R}{N + 1} \] \hspace{1cm} (3.1)

Where:

- \( P_L \) = left sided probability (probability that a certain rainfall amount is lower than the one considered)
- \( R \) = is the rank of a given amount/value of rainfall
- \( N \) = number of observations

2. For each observation, the return period (\( T_r \)) was determined using equation 3.2.

\[ T_r = \frac{1}{P_R} = \frac{1}{1 - P_L} \] \hspace{1cm} (3.2)

Where:

- \( P_R \) Right sided probability is the probability that a certain rainfall is higher than the one under consideration
3. To determine the plotting position for each observation, equation 3.3 was used.

\[ Y = -\ln (-\ln P_L) \]  

(3.3)

### 3.5 Results and Discussions

The results obtained from using equations 3.1 to 3.3 are presented and discussed in the sections that follow with respect to the 2 study areas.

#### 3.5.1 Wang Chin

<table>
<thead>
<tr>
<th>Year</th>
<th>Rainfall</th>
<th>N=</th>
<th>Plotting Position</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mm</td>
<td>Sorted Rank</td>
<td>Left Prob</td>
</tr>
<tr>
<td>1997</td>
<td>94.4</td>
<td>66.3</td>
<td>1</td>
</tr>
<tr>
<td>1998</td>
<td>66.3</td>
<td>72.2</td>
<td>2</td>
</tr>
<tr>
<td>1999</td>
<td>82.6</td>
<td>82.6</td>
<td>3</td>
</tr>
<tr>
<td>2000</td>
<td>99.1</td>
<td>94.4</td>
<td>4</td>
</tr>
<tr>
<td><strong>2001</strong></td>
<td><strong>285.5</strong></td>
<td><strong>94.8</strong></td>
<td><strong>5</strong></td>
</tr>
<tr>
<td>2002</td>
<td>127.3</td>
<td>99.1</td>
<td>6</td>
</tr>
<tr>
<td>2003</td>
<td>72.2</td>
<td>127.3</td>
<td>7</td>
</tr>
<tr>
<td>2004</td>
<td>94.8</td>
<td>285.5</td>
<td>8</td>
</tr>
</tbody>
</table>

In a period of 8 years, the highest amount of rainfall received in Wang Chin was 285.5mm, which was an extreme event. Apart from this the maximum amount of rainfall received ranged from 66.3mm to 127.3mm (Table 3.3). As the rainfall amounts increase from 66.3mm to 127.3mm, their return periods increase. Unfortunately, the predictions from this data can not be relied upon since the period under consideration is too small (only 8 years).

The left and right probabilities of the sorted maximum annual rainfall values were calculated and plotted using the Gumbel plot (Figure 3.8) to determine the return periods of different thresholds or amounts. The amount highlighted for 2001 was the amount of rainfall received in May 2001 triggering of landslides on the 3rd and 4th of May the same year.
Figure 3.8 Showing the Gumbel Plot for Wang Chin

For the case of the 2001 rainfall event (which is highlighted in Table 3.3), the return period is 9 years. From the probability calculations, it could therefore be assumed that the next rainfall event is likely to occur in 2010, assuming that all other factors remain constant. However, the degree of confidence for this result is too low considering the fact that the amount of data available was limited.

From Figure 3.8 it can be noted that the 2001 rainfall event was an extreme event and therefore appears as an outlier on the plot. From the records (8 years) of Wang Chin such an event has only occurred once in 2001 and never before. Being extreme and an outlier, it thus largely affects the results of the plot and eventually the prediction of the return periods.

The plot is not realistic because it uses a high range determined by a single rainfall event. The rainfall received in May 2001 (285.5mm) was extremely high in comparison to other years, and yet it greatly affects the results of the plot. The range is from 0 to 300 mm and yet the actual range should have been from 0 to slightly above 130 since before May 2001 the highest amount of rainfall received in Wang Chin (records of 8 years) was 127 mm. In reality, 8 years it’s too short a period to determine the return periods for any amount of rainfall received in the area. We can not even predict the return period for the next 10 years which disqualifies the results of the Gumbel plot in the case of Wang Chin. Therefore based on the available data, it is neither possible to predict any other rainfall event nor determine the threshold or the return period of the 2001 rainfall event. What could be agreed upon is that the maximum amount of rainfall which
could be received in Wang Chin in a period of 10 years is not likely to exceed 285.5 mm if all contributing factors remain constant.

### 3.5.2 Ang Khang

Rainfall data was available for a period of 16 years. The results from equations 3.1, 3.2 and 3.3 were tabulated in Table 3.4 and used for the Gumbel plot to determine the return period of various rainfall amounts received in the district.

**Table 3.4 Sorted and Processed annual maximum rainfall data for Ang Khang**

<table>
<thead>
<tr>
<th>Year</th>
<th>Rainfall</th>
<th>N= 16</th>
<th>Plotting Position</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mm</td>
<td>Sorted</td>
<td>Left Prob</td>
</tr>
<tr>
<td>1989</td>
<td>59.8</td>
<td>59.8</td>
<td>1</td>
</tr>
<tr>
<td>1990</td>
<td>184.2</td>
<td>63.4</td>
<td>2</td>
</tr>
<tr>
<td>1991</td>
<td>80.0</td>
<td>65.2</td>
<td>3</td>
</tr>
<tr>
<td>1992</td>
<td>125.2</td>
<td>72.2</td>
<td>4</td>
</tr>
<tr>
<td>1993</td>
<td>131.4</td>
<td>76.0</td>
<td>5</td>
</tr>
<tr>
<td>1994</td>
<td>87.8</td>
<td>80.0</td>
<td>6</td>
</tr>
<tr>
<td>1995</td>
<td>100.2</td>
<td>86.8</td>
<td>7</td>
</tr>
<tr>
<td>1996</td>
<td>167.2</td>
<td>87.8</td>
<td>8</td>
</tr>
<tr>
<td>1997</td>
<td>126.8</td>
<td>91.6</td>
<td>9</td>
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<tr>
<td>1998</td>
<td>65.2</td>
<td>99.8</td>
<td>10</td>
</tr>
<tr>
<td>1999</td>
<td>63.4</td>
<td>100.2</td>
<td>11</td>
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<tr>
<td>2000</td>
<td>99.8</td>
<td>125.2</td>
<td>12</td>
</tr>
<tr>
<td>2001</td>
<td>76.0</td>
<td>126.8</td>
<td>13</td>
</tr>
<tr>
<td>2002</td>
<td>86.8</td>
<td>131.4</td>
<td>14</td>
</tr>
<tr>
<td>2003</td>
<td>72.2</td>
<td>167.2</td>
<td>15</td>
</tr>
<tr>
<td>2004</td>
<td>91.6</td>
<td>184.2</td>
<td>16</td>
</tr>
</tbody>
</table>

After sorting out the maximum annual rainfall amounts, the left and right probabilities were calculated and so were the plotting positions. The plotting positions are used to determine the return periods for various rainfall amounts using the Gumbel plot (Figure 3.9).

From Table 3.3, it can be noted that the probability that an amount of rainfall greater than 59.8mm might be received is 0.941 and the return period is about 1 year. 59.8 mm (highlighted) of rainfall were received in 1989 and the following year (1990), the amount of rainfall received was 184.2mm this was indeed greater than 59.8mm. As the years went by (from 1989 – 2004), the amount of rainfall increased and so did their left probabilities. For example in 1991, 80 mm of rainfall were received and the left probability was 0.176. This implies that the probability of receiving a rainfall amount less than 80mm was less than 0.5.
Therefore an amount greater than 80mm was to be expected the following year. Indeed in 1992, 125.2mm of rainfall were received which was greater than the 80mm received in 1991, the previous year.

Taking another example, for a rainfall amount of about 184mm (in 1990), the probability that a greater amount of rainfall would be received was 0.059 less than 0.1 while the probability that an amount less than it (184mm) would be received was 0.94 (close to 1). Indeed in 1991, only 80mm were received which was less than 184mm received in the previous year. The Gumbel plot (Figure 3.9) can be used to determine the return periods for different amounts of rainfall not exceeding 200 mm with respect to Ang Khang.

![Gumbel Plot](image)

**Figure 3.9 Gumbel plot for Ang Khang**

Figure 3.9 uses a more realistic range given the period for which the climatic data was available. This is because, based on the figures in Table 3.2, the minimum value was 58.9 while the maximum was 184.2. The range used in the plot was from 0 to 200. Then using the Gumbel plot (Figure 3.9) we can predict the return period for rainfall amount greater than 180mm. The return period is 17 years. The return period is a range (in terms of years) within which a rainfall event is expected to happen.
3.6 Discussions

One of the most important triggering factors of landslides is the pressure exerted by water in the ground part of this water is supplied by rainfall. Since the water, which filters into the soil, regulates the extent of this pressure the landslides due to natural causes usually occur after a period of heavy rainfalls. In the consideration of rainfall events and their return periods, a satisfactory amount of data is needed. The Gumbel Extreme Value method can use at least 10 years. Then the determined return periods would have a fair level of confidence.(Capecchi and Focardi 1988).

If the amount of climatic data available is sufficient enough, the probabilities of different thresholds of rainfall occurring in any given area can be determined and so can their return periods. Although as regards to climate, just like all other aspects of nature, one can never be 100% certain of statistical predictions but they help not only planners but also other scientists in designing life saving models and evacuation plans in case of hazards.

In the case of Wang Chin, the predictions and probabilities are rejected given that the data was insufficient. But in the case of Ang Khang the predictions made can be relied upon even though they were not 100% correct. If data set was bigger (more than 16 years), then a more accurate prediction could have been determined.

So in agreement with (Dunne and Leopold 1978; Maidment 1993; Parodi 2005) we can say that although, basing on the results in Table 3.2, we can not predict the exact amount of rainfall to be received, we can predict whether the amount of rainfall to be received would be greater or lesser than the amount under consideration. In addition to this, we can also predict the return periods of large rainfall amounts with a relatively higher level of confidence.

4.1 Introduction

Digital image processing involves the manipulation and interpretation of digital images with the aid of a computer. “There is no single “right” way to approach the image interpretation process” (Lillesand, Kiefer et al. 2004). This implies that when interpreting images, one ought to combine as many techniques as are available to them, whilst optimising their advantages to obtain the best possible results. Availability of images and interpretation equipment has a large influence on how the task of interpretation is undertaken. The objectives of the interpretation will then determine the methodology to be employed. What follows is the need for the criteria for a classification system to be set in order to categorise the various features occurring on the images under consideration (Lillesand, Kiefer et al. 2004).

Digital image analysis techniques are useful in not only mapping landslides but also in the monitoring and updating of landslide inventories. In situations where limited or not historical landslide data is present, digital analysis can prove to be of vital importance (Manunta, Farina et al. 2005). The purpose for which a landslide map is intended largely influences the scale at which one operates. But in cases where availability of data is not guaranteed, the issue of scale comes in later (Naithani 1990). One is then forced to work with whatever is available and therefore makes best use of it. To map ground features like towns, villages, wetlands, forests, one can use colour multi-spectral satellite images and air photos. Standard image classification models work on the spectral components of each ground cover in remotely sensed imagery (Sabins 1996). Some methods are completely automatic while others take advantage of one’s ability to identify known ground cover in sample locations (Lillesand, Kiefer et al. 2004).

Wang Chin area is the focus of this study. Because the area was inaccessible, minimum field work was carried out. Landslide inventory mapping therefore relied on the remote sensing techniques. The main objective of this chapter was to assess the reliability of using digital image analysis techniques in mapping landslides in inaccessible areas. The landslide inventory map prepared using aerial photos interpretation was used to assess the accuracy and reliability of the different techniques. Thus the main purpose of landslide inventory mapping using aerial photos was for this purpose only.
4.2 Materials and Methods

The materials available for mapping landslides in Wang Chin included the following:

- Geo-coded ASTER image bands 1, 2, 3N with 15m resolution and bands 4, 5, 6 and 7 resampled to 15m resolution were used. The image was taken on 28th November 2001.
- 5 runs of coloured aerial photographs containing a total of 24 photographs with a scale of 1:25000 taken at an altitude of about 4800m. The flying direction was east to west and the period during which they were taken was January 2002 and December 2002.
- Mirror stereoscope.
- Software used in processing the ASTER data: ERDAS Imagine version 8.7 and ILWIS version 3.3.

4.3 Landslide mapping using satellite imagery

Satellite images offer an efficient and quick data source (of the earth’s surface) to obtain the most recent and the urgently needed topographic or thematic maps. Present technology provides the possibility of accelerating the production of these maps (Sabins 1996). One of the means of extracting data from images is by means of classification. Digital image classification is based on the different spectral characteristics of the earth’s surface which include soil, vegetation, rocks, water bodies, etc (Sabins 1996). During this process, the operator instructs the computer to perform an “interpretation” according to certain conditions, which are specified during the training phase (to be explained in the sections that follow).

4.3.1 Satellite Image: ASTER image and its features

For digital image analysis, this study used the ASTER image. ASTER is a Japanese and American high performance sensor operated by the Japanese Ministry of Economy, Trade and Industry. The term ASTER stands for Advanced Spaceborne Thermal Emission and Reflection Radiometer. The features of the ASTER sensor are:

- Wide spectrum of wavelength (VNIR 3 bands, SWIR 6 bands, TIR 5 bands)
- Stereoscopic data in a single orbit using the near – infrared bands
- High geometric and radiometric accuracy
- World wide coverage and reasonable prices

The image processing and classification methods which have been selected for this study include Normalized Difference Vegetation Index, Maximum Likelihood Supervised classification without Intensity Normalisation, Maximum Likelihood Supervised classification with intensity normalisation, Spectral Angle Mapper and incorporation of Slope map and Geology map to improve Maximum Likelihood Classification.
4.3.2 Selection of the test area

In order to carry out the classification and landslide mapping in particular using the digital analysis techniques, a test area was selected and the results of this area would be extrapolated to the rest of the Wang Chin watershed. The procedure followed for selection of the test area is given in the sections that follow.

The selected area in Figure 4.1 shows the test area used for landslide mapping. The landslides in this watershed seem to be localized in this specific area. Some possible reasons for this are:

The differences in the geology of the area are clearly highlighted. The first among these differences is the drainage pattern. The south eastern area has a concentrated drainage network, dendritic in particular. This type of drainage is characteristic of Shale which is characterized by its low resistance to erosion (Way 1973). The Geology map indicates that this area is covered by Shale, Sandstone and Conglomerates. Another observation was the fact that the landslides seem to occur on the face slopes of the ridges. The back slopes appear not to be less prone to landslides.

Figure 4.1 A false colour composite showing the test area zoomed in to indicate location of the landslides (white patches)
4.3.3 Normalised Difference Vegetation Index (NDVI)

In NDVI the vegetated areas yield high values because of their high NIR reflectance and low visible reflectance; clouds, water and snow, which have higher visible reflectance then NIR reflectance yield negative NDVI values. According to (Lillesand, Kiefer et al. 2004), rocks and soils have similar reflectance in both the NIR and Red NIR/R–images can serve as a crude classifier of images, and indicate vegetated areas in particular. Therefore this ratio has been developed into a range of different vegetation indices. For an Aster image, the NIR and Red bands correspond to bands 3 and 2 respectively which are incorporated by the Visible and Near Infrared (VNIR) system of the ASTER instrument. These bands are very essential in distinguishing between vegetation and soil as discussed by (Richards 1993; Lillesand, Kiefer et al. 2004).

Using ERDAS Imagine 8.7, a subset of the ASTER image was obtained. This area represented a test area showing bare land on steep slopes. This is the only area from which landslides can be identified since the rest of the area is either under dense vegetation which masks the evidence of prior landslide activity. NDVI was calculated using the equation 4:1. The result was classified in order to differentiate the bare land from the rest of the area from the land cover classes.

\[
NDVI = \frac{(NIR - Red)}{NIR + Red}
\]

Where  NIR is Near Infra red Band (ASTER band 3N)
Red is visible spectra Band (ASTER band 2)

Band 2 (0.63 – 0.69um) is used for distinguishing between vegetation and soil in monitoring vegetation health(Richards 1993). In this study it was useful in distinguishing between the areas with dense humid tropical forest and those with bare soil. Band 3 (0.76 – 0.90um) which is the NIR band, is useful in providing a contrast with bright reflectance for soil and vegetation so it helps in defining the water/land interface (Lillesand, Kiefer et al. 2004).

The resultant classified map was then overlaid with the district boundary and the areas which had been classified as bare soils were then digitized, using ILWIS 3.3. The polygons were then labelled and the map was rasterised. A histogram was generated (Table 4:1) which provided information on the number of pixels and the area which had been mapped as having landslide activity. To obtain the accuracy of the resultant landslide map, raster map was then crossed with the raster map (landslide) obtained from aerial photo interpretation (ortho photo) and a confusion matrix (Table 4:2) was obtained.
4.3.4 Maximum Likelihood Supervised Classification

The Maximum Likelihood classifier is a parametric classifier which relies on the assumption that each class has a probability distribution (Richards 1993). He also observed that Maximum Likelihood is considered to give the best results because it does not only consider shape, size of the clusters but also their orientation. (Lillesand, Kiefer et al. 2004) observed that it calculates the statistical distance based on the mean values and covariance matrix of the clusters. The statistical distance is a probability value based on “equiprobability contours”. Each pixel had fair chance of representation during the classification. The advantage of the maximum likelihood classifier above the other algorithms is that it assumes equal probability of occurrence and cost of misclassification for all classes. But its limitation is that large numbers of computations are required to classify each pixel and can thus be time consuming (Lillesand, Kiefer et al. 2004).

To make a classification for a given pixel belonging to class I, given that this pixel has a feature vector f, then the probability \( p(i|f) \), can be calculated using Bayes’ rule (Schowengerdt 1997):

\[
p (i | f) = \frac{p (f | i)p(i)}{P(f)} \quad \text{.............................. (4.2)}
\]

Where

\[
p(f) = \sum_{i} p(f | i) p(i) \quad \text{.............................. (4.3)}
\]

A decision rule is then made with the \textit{a posteriori} probabilities based on equation (4.2). Then a pixel is assigned to a particular class if its \textit{a posteriori} probability is greater than all the other classes. Then the following Bayes’ decision rule is applied:

\[
\text{If } p (i | f) > p (j | f), \text{ for all } j \neq I, \text{ assign pixel to class } i
\]

In order to carry out supervised classification, a map list was created in ILWIS. The map list contained three bands of the ASTER image and these were Bands 1, 2 and 3N. A sample set was then created and given its own domain which included the different land cover classes needed for the classification.

In Supervised Classification, a training set needs to be generated which identifies representative sample areas for each of the desired output classes. The process determines the statistical properties (which properties, specify) of each of the training classes, and then uses these properties to classify the entire image. To yield acceptable results, training data must be both representative and complete (Lillesand, Kiefer et al. 2004).
This therefore called for developing training statistics from all spectral classes constituting each information class to be discriminated by the classifier. After training the sample sets, the image was then classified using Maximum Likelihood algorithm.

During the classification, different threshold values were set to determine the ones which gave the best results (accuracy). The threshold value which gave the best accuracy (Table 4.2), in comparison to the other thresholds, was 20.

During the training stage, 2-dimesional feature space plots were made (using 2 bands at a time) to indicate the occurrence of the different classes and their feature vectors. The clouds of the different classes are plotted as feature vectors representing the trained in the image. Visualisation of these clouds in various band combinations is important because the analyst can identify the best band combination to differentiate between the land cover classes. In the case of the ASTER image the best band combination (in comparison to other band combinations like Figure 4.2(b) to different between bare soil and vegetation is band 3 and band 2 as shown in Figure 4.2(a).

![Feature Space plots without Intensity Normalisation](image)

**Figure 4.2 Feature Space plots without Intensity Normalisation**

### 4.3.5 Maximum Likelihood Classifier with Intensity Normalised Bands (NML)

Knowing that intensity \( I \) (photon count) depends mostly on external factors, such as sun angles, surface orientation, shadow, band normalization was used which splits the intensity and reflectance(s) for proper feature extraction. Intensity normalisation was applied to the spectral bands to reduce the effect of illumination differences on the surface reflectance according to (Shrestha and Zinck 2001). This was carried out by summing up the similar bands as those used in the Maximum Likelihood Supervised Classifier and then dividing each of the original bands of the image by the sum of the three bands. The dividend was then multiplied by 255 as shown in Formula 4.4.
NBi=255 \left( \frac{OBi}{\sum OBi} \right), \ i = 1 \ to \ n \ ........................................ (4.4)

Where

NBi is the band normalised by total intensity

OB is the original spectral band of the ASTER image

i the band used

A new map list was created using Intensity normalized bands and the maximum likelihood classifier was run to classify the trained data set.

The resultant normalised bands have a property that the sum of any pixel value is 255 due to normalisation. After the normalisation of the Bands (1, 2 and 3N), a map list and training sample sets were created together with a domain with similar classes as in the case of classification without Intensity Normalisation. A feature space was opened and 2 bands at a time were selected. As the sample sets were being selected, they were plotted in the feature space. Care was taken to avoid overlapping and also to maintain a low standard deviation. The same procedure was followed for all the classes. Feature space plots after normalization (Figure 4.3) showed that the clouds of the training samples are not elongated indicating that the classes are free from intensity variation. With the Intensity Normalised bands, the clouds of the land cover classes in the feature space during the training stage were not elongated. This ensured a reduction in the effects due to illumination variations and a better plot in the feature space. There was also a reduction in overlapping of the clouds representing the land cover classes as shown in Figure 4.3(a) resulting in better results during the classification. After training the samples, classification was run using the ML classifier.

An example of the feature space plots used in the training phase is shown in figure 4.3. These feature space plots were 2-dimensional in nature. This implies that only two bands were used at any given time. Various normalised band combinations were used to indicate the occurrence of the different classes and their feature vectors. The clouds of the different classes are plotted as feature vectors when selected for training the pixels for the selected land cover classes. Visualisation of these clouds in various band combinations is important because the analyst can identify the best band combination to differentiate between the land cover classes. In the case of the ASTER image the best band combination (in comparison to other band combinations like Figure 4.3(b) to different between bare soil and vegetation is band 3 and band 2 as shown in Figure 4.3(a). With the use of normalised bands, the clouds are not as elongated as those that plotted whilst using non normalised bands. This implies that the illumination differences between the pixels have been reduced and so pixels which would have otherwise been classified to different classes are assigned to the most appropriate classes.
4.3.6 Spectral Angle Mapper Classifier (SAM)

The Spectral Angle Mapper (SAM) uses the n-dimensional angle to match pixels to reference spectra (Lillesand, Kiefer et al. 2004). The algorithm determines the spectral similarity between two spectra by calculating the angle between the spectra, treating them as vectors in a space with dimensionality equal to the number of bands as illustrated by (Lillesand, Kiefer et al. 2004). SAM performs supervised classification given a set of spectral records which define each class. SAM assumes that spectral image data have been reduced to "apparent reflectance", with all dark current and path radiance biases removed. The thresholds of this algorithm are expressed in radians since; classification is carried out basing on the given angle of separation between reflectance spectra of the different pixels of the image.

In ILWIS version 3.31 academic Alpha the SAM operates as a supervised classification algorithm. In this case the original ASTER bands, the same as those used in Maximum Likelihood supervised classifier without Intensity normalisation. The same procedure as was described in Section 4.4.2 was applied but then after the training the Spectral Angle Mapper Supervised Classifier was run. In this algorithm, the thresholds are expressed in radians because an angle is computed between the class-centers and each pixel to be classified. The computations are based on an inverse cosine and yield at most an angle of 90 degrees, which in approximation is equivalent to about 1.7 radians. Hence a threshold between 0 and 1.7 is meaningful; the best threshold is difficult to predict, and depends on the samples and the images. However the best threshold for this study was found to be 0.25 radians which is an equivalent of about 12 degrees.
4.4 Accuracy Assessment

After the image was classified using the three different algorithms results were filtered using the majority filter to reduce the number of undefined pixels and also to determine whether filtering would improve the accuracy of the different classification algorithms.

In order to determine the accuracy of the results from the three classifications, the landslide map obtained from aerial photo interpretation of the area was used. The sections that follow give a detailed explanation of the whole procedure.

4.4.1 Landslide mapping using Aerial Photo interpretation

Aerial photos at a scale of 1:25,000 were supplied by Land Development Department (LDD), Ministry of Agriculture and Cooperatives, Bangkok, Thailand. The aerial photos were scanned and a few were selected to produce an orthophoto. Scanning of aerial photos reduces the differences between them and the satellite images. (Scanning converts the analogue data into digital format but that does not make it similar to satellite image) The scanned photographs were imported into ERDAS Imagine 8.7 as a step towards producing an ortho photo. The ASTER image was used for georeferencing the selected photographs since ground control points from field observations or a base map were not available. The Interior orientation was set using the fiducial marks and camera information, read off the photographs, like focal length and the type of camera.

Three runs out of the five runs were selected. This was because from studying the photographs using the stereoscope, these runs appeared to have more landslide activity in comparison to the other runs. In addition to this, since the process of producing an ortho photo is laborious, a decision had to be made to select those photos which would give a better representation of the area in terms of landslide activity.

The ortho photo generation was carried out in ERDAS Imagine version 8.7. Using the geo-coded ASTER image as a reference on the left, the first scanned photo was loaded on the right. The scanned photo was rotated 90 degrees anticlockwise, for orientation towards the north. Ground control points were generated in reference to the ASTER image for the first photo. The georeferenced photo was then used as a reference for the next overlapping photo in the run. This process was continued until all the selected photos were georeferenced.

Automatic generation of tie points produced a root mean square error (RMSE) of 0.115. The swipe tool (in ERDAS 8.7 imagine) was used to check whether the ASTER image and the ortho photo were perfectly overlapping. The result was a perfect overlap of the ortho photo and the ASTER image. Unfortunately the resultant ortho photo had an uneven contrast.
Feathering was then applied to the ortho photo to improve its contrast especially in the areas of overlap. With feathering, the intensity of one photo decreases as the intensity of the second photo increases over the area of overlap thus evening them out. Not only was the contrast not even, but also the colors within the ortho photo. Therefore image dodging was used to improve on the color contrast throughout the resultant ortho photo shown in Figure 4.4

Figure 4.4 Showing the ortho photo of the Wang Chin test area for landslides mapping.

Using the ortho photo (Figure 4.4: red circles indicate some of the landslides observed in the test area) as a base and screen digitizing in ILWIS 3.3, a landslide map of a test area in Wang Chin was produced. The resultant map (Figure 4.5) indicates the spatial distribution of the landslides in the selected test area (the Mae Suary Sub watershed) in Wang Chin.

The resultant Landslide inventory (Figure 4.4) for the Mae Suary sub water shed indicates only the active landslides. No other type of landslides could be recognised during the aerial photo interpretation. Mae Suary sub- watershed is under a dense humid forest whose vegetation covers the landslide scars. The type of landslides identified and mapped in this sub- watershed are small rotational slides. Since there is no historical record of the landslides in this area not much can be side about how frequently they do occur.
4.5 Results and Discussions

Only recent slides could be recognised by the digital image analysis technique and were thus classified as unvegetated scarps. The identified landslides were small in size, most of which were concentrated on the South Eastern side of the study area which runs parallel to the lateral/tributary valley. The Landslide inventory derived from aerial photo interpretation was used as the ground truth to test the accuracy of the landslide maps obtained from digital image analysis techniques.

Results show that areas covered by landslides vary depending on the type of techniques used (Table 4.1). Areas under landslides were computed using histogram calculations. Histogram information reveals that NDVI is the technique with not only the least coverage (13.1 ha) in terms of area but also one with the least accuracy (18.88%). NDVI is a classification best designed for differentiating between land cover classes most especially between vegetation, water and bare soil (Sabins 1996). As a result it is too general and its ratios are only indicative and not specific.
Table 4.1 Histogram Results showing coverage of landslides by area using the different techniques

<table>
<thead>
<tr>
<th>Analysis Technique</th>
<th>Number of Pixels</th>
<th>Area (m)</th>
<th>Area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>40427</td>
<td>131172</td>
<td>13.1</td>
</tr>
<tr>
<td>SAM</td>
<td>67756</td>
<td>271024</td>
<td>27.1</td>
</tr>
<tr>
<td>Maximum Likelihood (without Intensity Normalisation) ML</td>
<td>234587</td>
<td>938348</td>
<td>93.8</td>
</tr>
<tr>
<td>Maximum Likelihood (with Intensity Normalisation) NML</td>
<td>176620</td>
<td>706480</td>
<td>70.6</td>
</tr>
<tr>
<td>Digital Aerial photos Interpretation (Ortho photo)</td>
<td>40427</td>
<td>161708</td>
<td>16.2</td>
</tr>
</tbody>
</table>

In addition to extracting areal coverages of land sliding, confusion matrices were calculated for each of the techniques using the results from the digital aerial photo interpretation as the ground truth and means of assessment. A summary of the overall accuracy for each of the techniques is given in Table 4.2

Table 4.2 Accuracy Results from the Confusion matrix

<table>
<thead>
<tr>
<th>Analysis Technique</th>
<th>Classified Pixels</th>
<th>Area of no interest</th>
<th>Total No. of pixels</th>
<th>Overall Accuracy (%) (before filtering)</th>
<th>Overall Accuracy (%) (after filtering)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>6118</td>
<td>34309</td>
<td>40427</td>
<td>18</td>
<td>18.8</td>
</tr>
<tr>
<td>SAM</td>
<td>11420</td>
<td>29007</td>
<td>40427</td>
<td>28.25</td>
<td>32.06</td>
</tr>
<tr>
<td>ML</td>
<td>22110</td>
<td>18137</td>
<td>40427</td>
<td>50.18</td>
<td>54.69</td>
</tr>
<tr>
<td>NML</td>
<td>27228</td>
<td>13199</td>
<td>40427</td>
<td>67.38</td>
<td>71.20</td>
</tr>
</tbody>
</table>

The SAM classifier yielded an accuracy of 28.25% before filtering and 32.6% after majority filtering at a threshold of 0.25 radians. This is equivalent to about 12 degrees. Any threshold above or below 0.25 radians lowers the accuracy of the algorithm in the eventual mapping of the landslides. A decrease in the threshold means that there is a decrease in the angle of separation between the pixels trained for the various classes. In which case, the algorithm is likely to assign wrong classes to certain pixels if not properly distinguished from neighbouring ones. When the threshold is increased, the angle of separation between the pixels and the classes is increased and this would increase the errors of omission. Certain pixels are bound to be misclassified since classification is largely dependent on the distance of separation between the pixels and the class centres.

Maximum Likelihood without intensity normalisation, at a threshold of 20 yielded an overall accuracy of 50.18% before majority filtering and 54.69% after majority filtering. When carrying out supervised classification, a value may or may not be selected. It is important to select a value also known as the threshold during the running of the algorithm.

The selected value sets boundaries and pixels which fall within such boundaries are assigned a value of the class of the category they belong to depending on their reflectance values. The value
which sets boundaries is what is called a threshold (Sabins 1996). In reality it is difficult to set the most appropriate threshold. One ought to keep trying until the most optimal results are obtained. In this study a threshold of 20 meant that for any given class any pixel within a boundary of 20 is assigned to that class. If it falls outside this boundary its labelled “unknown” (Richards 1993).

When the illumination differences within the image were reduced by the application of Intensity Normalisation, the accuracy of Maximum Likelihood (with a threshold of 45) improved. The results indicate 67.38% and 71.20% before and after majority filtering respectively. Therefore it can be said that for this study the best digital imaging analysis technique for the mapping of landslides was Supervised Classification using Maximum Likelihood, with Intensity Normalised Bands, as the classification algorithm.

There are a number of reasons as to why better results were not obtained in terms of area. Histogram information reveals that all the image analysis techniques had larger areas mapped with landslide activity. The first being the difference in between the time of capture of the satellite image and taking of the aerial photographs. Whereas the satellite image was taken in November 2001, only 6 months after the rain storm which caused the landslides under investigation, the aerial photos were taken in January and December 2002. It is very likely that most of the landslides in the image could not be recognised in the aerial photos as they had already been covered by the vegetation.

The other reason is that 3D view is possible aerial photos, it is not so with the normal satellite image. In addition to this, there is a big difference in the resolution between the satellite image (15m) and the aerial photos (2m) which implies that the amount of detail seen from the satellite image is far less than the amount of detail which can be seen on the aerial photographs.

Having obtained the results which are discussed in Section 4.6, an attempt was made to try and improve the results from the Maximum Likelihood supervised classification and also determine which band combination would provide the best results. In addition to selecting the best band combination post processing of the image classification results was carried out. By so doing it was assumed that the results obtained in the Sections 4.3.3 to 4.3.5. The processes involved in this phase are explained in the sections that follow.
4.6 Use of Maximum Likelihood Supervised Classification with Slope and Geology maps in Digital Image Analysis.

This section involved the selection of bands which would result into the best classification results once compared with the landslide map from aerial photo interpretation. The selection helps the expert to different between the classes (or features) being classified since spectral characteristics of different features vary in the different bands (Lillesand, Kiefer et al. 2004). The selection of bands is also dependent on what purpose the classification is supposed to serve. This could be land use/land cover or Geology or landslide mapping like in this study. Before this process was started, a Level 1B Geo-coded ASTER image was obtained and a sub set was created in an attempt to reduce the size of the image.

4.6.1 Selection of band combinations for the map lists used in the training and classification phase.

Bands 1, 2 and 3 were selected as the first band combination to establish how much could be obtained using the bands from VNIR region of the spectrum. The other band combinations were based on the correlation amongst the various bands of the ASTER image. The correlations were calculated using correlation matrices (see table 4.1 and 4.2).

When analyzing satellite data, the various spectral bands often show a degree of correlation (Lillesand, Kiefer et al. 2004). This means that when spectral values in one band are high the values in another band are expected to be high as well as discussed by (Richards 1993). He observed that plotting values from highly correlated bands in a feature space will result in an ellipsoid denoting that the two bands contain dependent information. From a set of highly correlated bands only one adds real value whilst the other ones may be derived or estimated (Richards 1993). Calculating a correlation matrix helps to detect the redundancy and identifies possible reductions in the number of bands to be used in a color composite.

Correlation coefficients are normalized covariance values. A correlation coefficient ranges from -1 to +1 (Lillesand, Kiefer et al. 2004). Diagonal elements are always 1. (Lillesand, Kiefer et al. 2004) noted that a correlation close to +1 indicates a direct relationship between two bands. They then suggested that if the reflectance of a pixel in one band is known, the reflectance of that pixel in the other band can be derived or estimated. A correlation close to -1 indicates an inverse relationship between the reflectance values of one band and the reflectance values in the other one (Lillesand, Kiefer et al. 2004).
a) Bands 1, 2 and 3 from the VNIR regions (RGB: 321 respectively)

Bands 1, 2 and 3 are the bands from the VNIR region of the spectrum. Figure 4.7 shows a false color composite made using these 3 bands. The landslide results obtained from this map list are presented in Table 4.3.

Figure 4.6 Showing the color composites for Band Combinations 1, 2, 3 (a); Bands 2, 3, 4 (b) and Bands 1, 3, 7 (c), used in the Post processing phase

b) Bands 2, 3 and 4 from both VNIR and SWIR regions respectively

To establish the correlation for the bands of the ASTER image used in this study, 4 bands were selected. These were bands 1, 2 and 3 of the Visible Near Infra red (VNIR) region and band 4 of the Short Wave Infra red (SWIR) region of the spectrum. The results of the correlation matrix are presented in Table 4.3. Bands 1 and 2 are highly correlated with a correlation coefficient of 0.95. The high correlation between bands 1 and 2 suggests that one of these bands could be removed from the band combination. In addition to this, band 1 has the highest correlation with the rest of the bands in this group in comparison to band 2. So band 1 was left out and band 2 was used. Therefore a map list of bands 2, 3 and 4 was created and used. Band 4 of the SWIR region was resampled to 15m resolution before the map list was created.
Table 4.3 Showing results of the Correlation Matrix for four band combinations used in this study

<table>
<thead>
<tr>
<th>Bands</th>
<th>Band 1</th>
<th>Band 2</th>
<th>Band 3</th>
<th>Band 4</th>
<th>Band 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 1</td>
<td>1.00</td>
<td>0.95</td>
<td>0.88</td>
<td>0.82</td>
<td>0.71</td>
</tr>
<tr>
<td>Band 2</td>
<td>0.95</td>
<td>1.00</td>
<td>0.72</td>
<td>0.78</td>
<td>0.80</td>
</tr>
<tr>
<td>Band 3</td>
<td>0.88</td>
<td>0.72</td>
<td>1.00</td>
<td>0.77</td>
<td>-0.01</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.82</td>
<td>0.78</td>
<td>0.77</td>
<td>1.00</td>
<td>0.69</td>
</tr>
<tr>
<td>Band 7</td>
<td>0.78</td>
<td>0.63</td>
<td>1.00</td>
<td>0.69</td>
<td>1.00</td>
</tr>
</tbody>
</table>

The band combination (RGB: 432 respectively Figure 4.6b) was useful in visualisation of the Geology of the area. One type of Geology (Shale, Sandstone and Conglomerates) is prone to landslides (with respect to the study area). This band combination helped in identifying possible reasons for the localization of the landslides. In addition during the training phase, the bare land was clearly visible which helped in the reduction of errors during the training phase.

**c) Bands 7 (SWIR), 3 and 1 from and VNIR regions (RGB:731 respectively Figure 4.6 c)**

Selection of these bands was based upon their correlation (Table 4.3). Although the correlations seem to be high, they are relatively lower than the correlations amongst the other bands ensuring a maximization of the spectral characteristics of the features shown on the image. The result is less overlap and clear differentiation between the classes during the training phase and classification.

Apart from the relatively lower correlation, this band combination gives a visualisation that is almost a true color composite. This is because vegetation is clearly visible as green (real color of healthy vegetation naturally), built up areas as purplish while the bare soil is clearly distinguished (area of focus) as shown in figure 4.9. The clear visualisation reduces the error during the training phase since there is a clear distinction between built up areas and bare soil.

**d) Bands 1,2,3 (from VNIR region) and 4,5 and 6 (from SWIR region)**

Bands from the SWIR region were used to determine whether use of a SWIR region band would have any impact on the results of the classification. Thus results from the classifications of the above band combinations are presented in Table 4.3.

The increase in the number of pixels classified as “unvegetated scarps” with the use of SWIR bands as opposed to VNIR could be due to the fact that in the SWIR region, the spectral characteristics of the bare soil have improved. This probably resulted in an improvement in the reflectance of the bare soil and a resultant improvement in the classification.
This band combination involved the use of bands 1, 2 and 3N of the VNIR region of the spectrum. The other set of bands were band 4, 5 and 6 of the SWIR region of the spectrum. The bands of the SWIR region were resampled to a 15m resolution (from 30m) and a map list created using all the six bands. Although during the training phase, the feature space plots shows only two bands at a time, the specified algorithm (using maximum likelihood supervised classifier) uses all the bands in the map list during the classification. Results of the classification using these six bands are presented in Tables 4.4.

The classification process involved use of only three classes: unvegetated scarps, bare soil and others. The bare soil in the test area shown on the ASTER image was classified as the unvegetated scarps while all the bare soil in the valley was classified as bare soil the rest of the other features (vegetation, built up area, clouds) were classified as others. This was because the class of interest was that of bare soils on the steep slopes. The results of the image classification using the selected band combinations as mentioned above are presented in Table 4.4 indicating class of interest.

After establishing the correlation amongst the various bands as indicated in Table 4.3, map lists for the band combinations were created. That is for the combination of Bands 1,2 &3, Bands 2,3 &4, Bands 1,3,&7 and Bands 1,2,3,4,5&6. A sample set then created for each of these map lists but the same domain was maintained and it contained three classes; bare soil, unvegetated scarps and others. The next phase was to train the data set for each of the map lists and then run the classification algorithm. The results were then post processed in an effort to improve the classification results and the accuracy.

### Table 4.4 Showing results of the classification of the image using the selected band combinations

<table>
<thead>
<tr>
<th>Band Combination</th>
<th>Unvegetated Scarps (No. of Pixels)</th>
<th>Percentage of Whole map (%)</th>
<th>Number of Pixels of the whole image</th>
</tr>
</thead>
<tbody>
<tr>
<td>123</td>
<td>2815755</td>
<td>4.49</td>
<td>62672550</td>
</tr>
<tr>
<td>234</td>
<td>1489696</td>
<td>2.38</td>
<td>62672550</td>
</tr>
<tr>
<td>731</td>
<td>6812782</td>
<td>10.87</td>
<td>62672550</td>
</tr>
<tr>
<td>123456</td>
<td>437189</td>
<td>0.70</td>
<td>62672550</td>
</tr>
<tr>
<td>Map (for testing accuracy)</td>
<td>Number of Pixels</td>
<td>Area (m²)</td>
<td></td>
</tr>
<tr>
<td>Slide01</td>
<td>52921</td>
<td>211684</td>
<td></td>
</tr>
</tbody>
</table>
The results in Table 4.4 indicate that band combination 1,3, & 7 has the highest percentage of pixels classified as unvegetated scarps and while band combination 1,2,3,4,5&6 indicates the least number of pixels classified as unvegetated scarps. Bands 1,2 & 7 seem to indicated (based on the results Table 4.4 that the presence of Band 7 improves on the classification results. This could be due to the fact that this band combination is good for visualization and reduces the user’s error of accuracy during the training phase.

To find out how many of the pixels classified as unvegetated scarps were actual landslides; the classification results for each of the band combinations were filtered using Geology and Slope in a post processing phase described in Section 4.6.2.

4.6.2 Post Processing Stage

This stage involved the use of GIS operation statements/commands in ILWIS version 3.3 with Geology and Slope gradient as the conditions. Through this approach the pixels that were wrongly classified as “unvegetated scarps”, meaning that they do not satisfy the two conditions, would then be masked out.

The test area indicated that the landslides were localized in the area composed of Shale, Sandstone and Conglomerates. Therefore after running the maximum classification algorithm, the post processing stage started with eliminating all the pixels which had been classified as “unvegetated scarps” and were located on a different Lithology. The unvegetated scarps in the area of interest were masked using the following command in ILWIS 3.3 version:

\[ \text{Slide}_g=\text{iff}(X=\text{“unvegetated scarps”}) \text{ AND } (\text{Geol}=”\text{TR3}”) \ X,? \]

Where: \( X \) is the classified map

\( \text{Geol} \) is the Geology Map and “TR3” the code given to the Lithology of interest (Figure 4.7)

The next stage in the post processing phase involved eliminating all those pixels classified as “unvegetated scarps” which occurred on flat terrains. Therefore to establish the slope gradient of interest for the study, the landslide inventory (produced from aerial photo interpretation) was overlaid on the slope gradient map.

A Slope map for the Wang Chin area was generated from a DEM. This DEM was generated from the ASTER image using band 3N (Nadir and Forward Looking) with the ERDAS software. VNIR has 2 (two) near infra red bands which have similar wavelengths, those are 3N (nadir looking) and 3B (backward looking) (Lillesand, Kiefer et al. 2004).
The 3B band is used to achieve the backward looking. The setting angle between the backward looking and the nadir looking is designed to be 27.60° (ERSDAC 2002). The objection of band 3b addition is to obtain stereoscopic image that will be processed to generate the height of land surface or DEM (Digital Elevation Model).

The overlay of the landslide map on the slope gradient map indicated that the slides were located on slope gradients ranging from 5 degrees to about 40 degrees. Therefore the GIS command statement using slope gradient as a condition started from Slope gradient = 5 degrees. This was gradually increased up to a slope gradient of above 20 degrees.

\[
\text{Slide}_{gs} = \text{iff}((\text{Slide}_g = \text{"unvegetated scarps"}) \ \text{AND} \ (\text{Slope}>5), \ Slide_g,?)
\]

Where:

- \text{Slide}_{gs} \text{ is the resultant raster map which fulfills the "Geology = "TR3" and "Slope>5" conditions.}
- \text{Slope} \text{ is the Slope gradient map (Figure 4.8)}

The results of the post classification using the above mentioned conditions are presented in Table 4.6 Once the results of the classification fulfilled the 2 conditions, the resultant maps (from the 4 selected band combinations) were crossed with the landslide map from aerial photo interpretation for accuracy assessment. The results are presented and discussed in the sections that follow.

### 4.6.3 Results and Discussions

After identifying the Geology of interest and the Slope classes of interest, the unvegetated scarps outside the area of interest were masked out using the two conditions. The results are presented in Table 4.5

<table>
<thead>
<tr>
<th>Band Combination</th>
<th>Geol=&quot;TR3&quot;</th>
<th>Geol=&quot;TR3&quot; and Slope&gt;5</th>
</tr>
</thead>
<tbody>
<tr>
<td>123 (VNIR)</td>
<td>104428</td>
<td>49545</td>
</tr>
<tr>
<td>234 (VNIR+SWIR)</td>
<td>1031091</td>
<td>431361</td>
</tr>
<tr>
<td>731 (VNIR+SWIR)</td>
<td>168127</td>
<td>64478</td>
</tr>
<tr>
<td>123456 (VNIR+SWIR)</td>
<td>59556</td>
<td>23060</td>
</tr>
</tbody>
</table>

Although it’s true that the remote sensing tool is useful for landslide hazard mapping, a true picture for the comparison of results obtained from the use of the various techniques (as mentioned above) is only possible if the temporal conditions are similar.
Figure 4.7 Showing the Geology map of the test area (after masking out the Geology of the other areas)

Figure 4.8 Showing the Slope map of the test area (after masking out the Geology of the other areas)
4.6.4 Accuracy Assessment

In order make an accuracy assessment, the classification results of the various band combinations, after masking out the landslide features using the masks from Geology and Slope gradient, were crossed with the Landslide map produced from aerial photo interpretation.

![An overlay of Landslide map (aerial photo interpretation) on Classified Landslide map]

Figure 4.9 Showing an overlay of the ortho photo on the test area of the ASTER image to show that the two did not have a perfect match (a) and (b) showing an overlay of landslide boundaries from aerial photo interpretation on the classification results (bands 2,3 and 4) from digital image analysis.

Although the overall accuracy was high, it was discovered that the error of omission and commission were equally high. Therefore it was not necessary to test the accuracy of the classification results from the other band combinations. For an accuracy test to be carried out, both the Image and the photo ortho photo should have had a perfect match which was not the case in this study as indicated in Figure 4.9 (a) and (b). It was not clear what the cause of the shift was. Unfortunately there was not enough time to identify what the cause of problem was and also to rectify it or even to carry out post processing with the other algorithms.
As a result only the number of pixels that were correctly classified as landslides (obtained from a cross between the classification results and the landslide map from the aerial photo interpretation) for all the band combinations are presented in Table 4.6.

Table 4.6 Table Showing the results of the cross between the classified maps and the landslide map from aerial photo interpretation.

<table>
<thead>
<tr>
<th>Band Combination</th>
<th>Unvegetated scarps</th>
<th>Landslide Present</th>
</tr>
</thead>
<tbody>
<tr>
<td>123</td>
<td>49545</td>
<td>6050</td>
</tr>
<tr>
<td>234</td>
<td>431361</td>
<td>6185</td>
</tr>
<tr>
<td>731</td>
<td>64478</td>
<td>1365</td>
</tr>
<tr>
<td>123456</td>
<td>23060</td>
<td>681</td>
</tr>
</tbody>
</table>

Using the results in Table 4.6, it is indicated that the best band combination for mapping landslides using digital image analysis is bands 2, 3 (from the VNIR region) and band 4 from the SWIR region of the spectrum. The rest of the band combinations (7,3,1 and 1,2,3,4,5,6) indicate poor results.

4.7 Comparison between landslide mapping using aerial photos and digital images

Both aerial photos and digital images can be used not only in mapping but also for monitoring of landslides. During the mapping of landslides from the digital image, it was impossible to get 100% accuracy from the resultant maps. A number of observations were made to give an explanation for the difference in results between landslides mapping using the different digital image analysis techniques.

Although digital images are becoming increasingly cheap and easily available, they have their own limitations due to spatial resolution. Identification of features like roads, buildings, and other infrastructure may not be possible in low resolution data.

The advantages of aerial photographs include its high spatial resolution for topographic mapping (Naithani 1990). The other advantage is that aerial photographs can be flown at any desired scale to suit requirements for a given task at hand. There is no real alternative to aerial photographs at present for medium scale mapping like the one used in this study.

During the mapping of landslides, the use of digital imagery is time consuming and quite demanding. The process also requires and depends a lot on the knowledge of the expert especially during the classification process. This raises the issue of subjectivity. Training samples in the various land cover classes demand that the expert be careful to minimise errors and also avoid the
overlapping of the classes. On the other hand mapping using aerial photography is also
demanding but overlapping is impossible since no training phase is employed. In addition to this
stereoscopic view enhances the visualisation of the different landforms thus improving the results
of the mapping.

The features identifiable on aerial photographs are much more that those which can be identified
from a satellite image. In addition to this, when aerial photographs are being taken, a desired
scale can be set in order to meet specified requirements. This is further improved by the
availability of high performance cameras and the possibility of using less sensitivity films
(Naithani 1990).

The interpretability of slope instability features on remotely sensed images is based on the
recognition and identification of elements associated with slope movements. The study of these
features and the deduction of their significance for a particular type of slope instability are
dependent on the absence or presence of other features or factors. This implies that slope
instability phenomena are seldom identified as such, but interpreted by the analysis of a certain
number of elements pertaining to the slope failure and characterising its nature. The
interpretability of slope instability phenomena depends in the first place on the spatial resolution
of the images and size of the features which can be recognised or identified and which are
characterising the slope movement. Spectral information by itself seldom allows for the
interpretation of slope movements, it only influences the contrast of the features which are
usually interpreted on the basis of their land form and pattern.

A comparison was made between satellite imagery taken in November 2001 to aerial photographs
taken in January and December, 2002. Since there were no aerial photographs taken in 2001, it is
not possible to make a change detection of the state of slope instability in Wang Chin. The
differences between digital images and aerial photographs are summarised in Table 4.7
Table 4.7 Differences between digital images and aerial photos: A summary

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Satellite Images - ASTER</th>
<th>Aerial Photographs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resolution</td>
<td>15m does not give much detail and small landslides can not be mapped</td>
<td>2m gives a lot of detail and small landslides can be mapped</td>
</tr>
<tr>
<td>Stereo vision (3D)</td>
<td>ASTER has an along-track stereoscopic capability, using a near-infrared spectral band, from which high quality DEM’s can be generated for virtually any location on the Earth’s surface.</td>
<td>Readily available as long as a stereoscope is available</td>
</tr>
<tr>
<td>Time of acquisition</td>
<td>Taken in November 2001 (6 months after the rain storm)</td>
<td>Taken in January and December 2002 – long after the rain storm.</td>
</tr>
<tr>
<td>Type of Landslides</td>
<td>Their identification not possible</td>
<td>Their identification possible</td>
</tr>
<tr>
<td>Means of extraction</td>
<td>Classification and on screen digitizing</td>
<td>Stereoscopic view and on screen digitizing.</td>
</tr>
<tr>
<td>Cost</td>
<td>Cheap and have a regular revisit time.</td>
<td>Can be expensive especially if required on a regular basis at large scale.</td>
</tr>
</tbody>
</table>

Therefore in agreement with the findings of (Naithani 1990), the multi-temporal characteristics of digital images can be fully exploited, but feature extraction and mapping from the digital images requires extensive field work to fill in the missing details. Thus the use of aerial photographs in combination with satellite imagery is recommended to reduce field work to a minimum since it can be costly.

Based on the results from the post processing (using the 4 selected band combinations), the following conclusions can be made:

The results from the Post processing phase were not as good as were expected but they indicate that the best band combination for mapping landslides in this study are bands 1, 2 and from the VNIR region. The results are improved further by using band combination 2, 3 (from the VNIR) and 4 (SWIR) region of the spectrum as indicated in Table 4.7. This implies that use of a band from the SWIR region of the spectrum improves the results from digital image analysis with respect to mapping landslides.

When a band from the SWIR region of the spectrum is included in the map list used to classify landslides, the results are improved. Bands in the SWIR are useful for detection of high temperatures and therefore improve the spectral characteristics of the features in the image under investigation making landslide identification easier since landslides have an influence on the spectral characteristics of bare soils (Richards 1993; Lillesand, Kiefer et al. 2004; ERSDAC 2005).
The errors of commission and omission are high in all cases. This could be due to the fact that the Image and the aerial photo ortho photo were not matching perfectly causing a shift. As a result some pixels that were landslides could have been omitted while those that were not landslides were considered as so during the accuracy assessment.

The other reason could be due to the fact that the Image used in this study was a Level 1A for the processing part and level 1B for the post processing part which was not corrected for Aspect. Aspect not only influences the amount of sun received but eventually influences the energy reflected by various features captured by an image. This could have been improved by using Intensity Normalised bands.

Although the results obtained from digital image analysis are less than half of those obtained from aerial photo interpretation, it does not imply that satellite imagery cannot be used for mapping landslides. The errors could have been during the training phase were classes could have overlapped as a result of poor selection. Selection of pixels during the training phase is heavily reliant on the user’s ability to differentiate between the pixels of the various classes. This is in agreement with (Soeters and van Westen 1996), who observed interpretation of landslides from remote sensing sources requires knowledge of the distinctive features associated with slope movements and of the image characteristics associated with these features. They also noted that adequate interpretation depends on image characteristics.

The difference in time of capture of the ASTER image and the aerial photos could also have an effect on the accuracy of the results from the classification. The interpretability of features in an image is influenced by the contrast that exists between the features and their background. When interpreting landslides, this contrast results from spatial differences that exist between the landslide and its surroundings. This is affected by the period that elapsed since the failure. (Soeters and van Westen 1996).

The other reason for the low number of pixels which were correctly classified as landslides could be in the difference in size. The ASTER image was at 15m resolution while the ortho photo had a spatial resolution of 2m. The higher the spatial resolution, the greater the detail and the higher the accuracy. The reverse is true implying that since the ASTER had a smaller spatial resolution, it affected the accuracy. This is in agreement with (Soeters and van Westen 1996; Lillesand, Kiefer et al. 2004) who observed that the spatial resolution of the remote sensing images provides the primary control of the interpretability of landslides and thus the application of any remote sensing data for landslide studies.

With respect to the post processing phase, the results could be improved by correcting the shift and ensuring the Image and the ortho photo have a perfect match. Another way of improving the results could have been by randomly selecting a sample set from the landslides produced by aerial
photo interpretation and using them during the training phase. The rest of the landslides would then be used to test the accuracy of the classification process. If Maximum Likelihood Classification had been used with Intensity Normalised bands, the results would have been improved. Intensity Normalised bands reduce the effect of the sun angle (Richards 1993).

Although the aerial photo interpretation results were basically for testing accuracy, it is very likely that during the generation of the ortho photo there could have been errors as a result of radial distortions which in turn affected the results from the interpretation. On the other hand, errors could have arisen during the interpretation and mapping of the landslides using the aerial photos. Therefore a combination of all these errors greatly reduced the accuracy of the digital image analysis techniques in mapping landslides.
Chapter 5: Landslide mapping in Ang Khang using aerial photos

5.1 Introduction

The most important component of any landslide hazard zonation is the preparation of a detailed landslide inventory, since in order to be able to predict the occurrence one needs to know where and how landslides have happened before. A landslide inventory is a spatial distribution of landslides, represented as points or drawn to scale, defining the type and activity of the landslides. The mapping of landslides in Ang Khang, as explained in the sections that follow, involved the use of aerial photos interpretation and ground survey (field work), including several interviews with the local population.

The main objective of this chapter therefore, was to produce a landslide inventory which was used as an evidence map in landslide hazard zonation (Chapter 6). There are two basic methods of landslide hazard zonation: the direct and indirect mapping methods. The direct mapping method is a knowledge-driven geomorphic technique (Schuster 1978). During field surveys, the analyst establishes and evaluates the relationship between landslides and their geologic and geomorphic settings. The indirect mapping technique is an approach which involves the mapping of the parameters considered to be of potential effect on the occurrence of landslides. This is then followed by an analysis of all the factors contributing to the occurrence of landslides. This study employed the indirect method to produce the landslide hazard zonation and eventually produce susceptibility maps.

5.2 Materials and Methods

Several materials were available during the field work preparation but some others were provided only while in the field. The field work which commenced on September 10th and ended on 10th October 2005. The materials used during the field work and in the mapping of landslides in Ang Khang are listed here under.

- 12 Coloured aerial photographs covering Ang Khang with an east to west flight path (photo scale 1:25,000 taken in January 2002)
- An IPAQ together with a GPS which contained data about Ang Khang like the district boundary, roads, rivers, and villages: secondary data provided by LDD.
- A pocket stereoscope.
- A Laptop for recording field data on a daily basis.
- Software used to produce the landslide inventory, the factor maps and the landslide susceptibility maps was ILWIS 3.3
5.3 Field work in Ang Khang

Field work activities in Ang Khang involved verifying the landslides identified during preliminary photo interpretation. Other landslides which were not on the aerial photos were also recorded. The length, width, and depth of these landslides were measured and recorded (Appendix: 1 Table 1)

The landslide terminology used in this study was based on (Cruden and Varnes 1996) with minor modifications to suit the conditions present in Ang Khang. The modifications were necessary to identify the type of landslides and to distinguish between their various stages of activity.

Old Landslides observed during the field work and mapped on the aerial photo. The red lines are indicating the landslide boundaries.

A stabilized landslide whose toe was cut off by the construction of the buildings in the foreground of the photo.

Figure 5.1 showing some of the landslides recognised in the field.

A total of 33 landslide sample points were observed in the field. Appendix: Table 2 shows the description of the sample points. Figure 5.1 shows some of the landslides observed during the field work while Figure 5.2 shows diagrammatic representation of the type of active landslides in Ang Khang.

In classifying landslides, emphasis was placed on the type of movement and the type of material (Chapter 1: Table 1.1). The movements are divided into falls, topple, slides, spreads and flows.
The type of material involves debris, earth or rocks. The name of a landslide can become even more elaborate once more details are obtained. These details describe the distribution, style and the rate of movement (Cruden and Varnes 1996).

Figure 5.2 Showing a diagrammatic representation of the type of landslides in Ang Khang (Rotational Slides: Slumps)

Table 5.1 Descriptive Statistics of the Landslides recorded during the Field work (as indicated in Figure 5.3).

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Type</th>
<th>Number of Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide Type (Lanstyp)</td>
<td>Slide</td>
<td>33</td>
</tr>
<tr>
<td>Sub Type (subtype)</td>
<td>Rotational</td>
<td>33</td>
</tr>
<tr>
<td>Material (mate)</td>
<td>Debris</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>Rocks</td>
<td>3</td>
</tr>
<tr>
<td>Lithology</td>
<td>Shale</td>
<td>33</td>
</tr>
<tr>
<td>Soil Type (Soil)</td>
<td>Clay</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Clay Loam</td>
<td>28</td>
</tr>
<tr>
<td>Land cover</td>
<td>Forest</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Degraded Forest</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>Agriculture</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Abandoned land with Shrubs and Grass</td>
<td>3</td>
</tr>
<tr>
<td>Slope Percentage (Slop_perc)</td>
<td>&lt;50%</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>&gt;50%</td>
<td>31</td>
</tr>
</tbody>
</table>
Field Sample Points taken in Ang Khang

![Field Sample Points](image)

<table>
<thead>
<tr>
<th>Shape</th>
<th>Station_id</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DA010</td>
<td>505050</td>
<td>2203093</td>
<td>1519</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lanstyp</th>
<th>Subtyp</th>
<th>Dep(m)</th>
<th>Wide(m)</th>
<th>Leng(m)</th>
<th>Soil</th>
<th>Mate</th>
<th>Slop_perc</th>
<th>Slop_deg</th>
<th>Sa</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>CL</td>
<td>2</td>
<td>88</td>
<td>42</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Figure 5.3 showing the field sample points overlaid on the mosaic of Ang Khang (together with some of the recorded attributes).

A record of the sample points together with the check list used during the field work are indicated in the Appendices 1 and 2.

### 5.4 Landslide Inventory Mapping

A Landslide inventory is a type of map which shows the locations and outlines of landslides. It is a data set that may present a single event, a regional event, or multiple events. Small-scale maps may show only landslide locations whereas large-scale maps may distinguish landslide sources from deposits and classify different kinds of landslides and show other pertinent data.

Classification of the landslides was based on the procedure suggested by Crudens & Varnes.
A sketch of the type of landslides identified in Ang Khang is shown in Figure 6.1. These landslides were later classified as active, stable or Dormant slides. Active landslides are those that indicated a state of activity. Their scars were bare of vegetation but in some cases some grasses had started growing. The landslides whose movement was still apparent were classified as dormant. In some cases some young shrubs were visible but had not covered the scars entirely. Stabilized landslides were those whose movement had stopped and had some remedial measures like vegetation and some artefacts. The classification borrowed ideas from (Varnes 1978; Cruden and Varnes 1996). Although there are several landslide activity classes, like reactivated, relict, abandoned, and suspended, the nomenclature was kept simple since the monitoring of the landslides in this tropical area without a historical data base of landslides was not an easy task.

5.4.1 Generation of Epipolar Stereo pairs

To generate an Epipolar stereo pair, the aerial photos of Ang Khang were scanned and imported into ILWIS. Out of the scanned photos five were selected for on screen digitizing and mapping of the landslides. The scanned aerial photos had to be rotated 270 degrees clockwise (using the ILWIS mirror rotate function) for stereoscopic view.

An epipolar creation window (Figure 5.4) was opened in ILWIS and the input (rotated scanned photo) left and right (rotated mosaic) candidates selected, the right candidate having a georeference system. The three fiducial marks (FM) on the left photo were marked and the principal point (PP) was automatically calculated. This PP was transferred onto the right candidate (mosaic). The mosaic did not have fiducial marks. So, using the paper prints of the scanned aerial photos, 2 lines, (one running from top to bottom and the other from left to right), were drawn and their point of intersection determined. The determined point corresponded to the PP of the mosaic. The PP was manually added onto the mosaic and then transferred to the left candidate.

The PP is only an approximation of the best possible rotation point or pivot. Theoretically, the nadir point (i.e. the terrain point perpendicular under the camera) is the point around which the photos should be rotated to make the photos Epipolar to each other. The FM, PP and the PP, two Scaling Points SP were marked on both the left and then the right scanned photos. The same procedure was repeated for the rest of the photos.
5.4.2 Generation of the Landslide inventory

The Epipolar pairs generated in Section 5.4.1 were opened one at a time and the pane with the georeferenced mate (the mosaic) was activated. Using the screen scope, the areas with landslide activity were digitised and a segment map produced. With the segment editor, the segments were then checked for self overlaps, dead ends, code consistency and intersection. Once these were all completed, the segment map was polygonised by labelling the points. Using the raster operation, the polygon map was then rasterised and a layout produced indicating the spatial distribution and landslide activity in Ang Khang (Figure 5.5).
5.5 Results and Discussions

Although the Lithology in Ang Khang includes Limestone, Sandstone and Shale, Shale was the most affected by slides occur only in Shale. The soil types ranging from clay and clay gravely loam on the mid slopes are predominant in these areas which were most affected by the slides. The slopes most affected have a slope percentage of 20% and more.

A further confirmation of the type of landslides, apart from field observations, involves the use of depth and length (Appendix Table field measurements). A ratio of depth and length gives a range
which can be used to determine whether landslides under investigation are translational or rotational slides. Translational slides in soils usually have a depth to length ratio below 0.1 (Depth of surface of rupture /Length of surface of rupture: D/L) and usually rotational slides have a D/L ratio between 0.15 and 0.33 (Cruden and Varnes 1996). The slides in Ang Khang have a D/L ratio ranging from 0.21 to 0.67 which confirms the fact that most of the observed landslides are rotational slides.

### Table 5.2 Mapping Statistics

<table>
<thead>
<tr>
<th>Aerial Photos</th>
<th>Mapped</th>
<th>Not mapped</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mapped</td>
<td>27</td>
<td>91</td>
</tr>
<tr>
<td>Not mapped</td>
<td>8</td>
<td>5</td>
</tr>
</tbody>
</table>

Simple calculations indicate that about 81% of the field observations could be mapped. In addition to the 27 mapped field slides, 91 more slides were mapped from the aerial photographs. The difference between what could be mapped and could not be mapped (from the field observations) plus the extra slide, is quiet understandable since the aerial photos were taken in January 2002 and the field work was carried out in September to October 2005. Based on the results of mapping landslides using aerial photo interpretation in Ang Khang, the same interpretation techniques were employed in Wang Chin to map the landslides.

The landslide inventory produced in Section 5.4.2 was then used as the evidence map in modelling landslides and producing the landslide susceptibility maps (Chapter 6).

### 5.6 Conclusions

The following conclusions can be drawn:

Aerial photos, as remote sensing tools, are useful for mapping landslides and production of a landslide inventory for an area under study. Because of the third dimension (Elevation) available due to stereoscopic vision, it was possible to identify the type of landslide activity in Ang Khang.

The type of landslides which occur in Ang Khang were not only identified but also mapped. Ang Khang is predominantly affected by rotational slides (slumps) which are small and shallow. Although there is no historical data to indicate for how long this area has been affected by landslides, the landslides in this study area include active, dormant and stable and the Eastern part was more affected by the landslides than the western part. The Eastern part of the area is dominated by shale which is prone to landslides.
Chapter 6: Landslide modelling and Susceptibility mapping

6.1 Introduction

The unpredictable state of natural hazards is one of the major uncontrolled impacts on local and global economies. Almost no portion of the earth’s surface is free from the impact of natural hazards. The impact is made worse by the continuous increase in population which creates situations where more human beings are made vulnerable to hazards. Also the increase of extreme precipitation related to global change, combined with a lack of proper disaster preparedness plans have caused the loss of many lives and property in many parts of the world. Natural hazards include earthquakes, floods, Forest Fire, volcanic eruptions, Tsunamis, droughts landslides, etc (Süzen and Doyuran 2004).

Landslides are triggered mainly under the influence of earth quakes and / or rainfall. Based on the spatial and temporal distribution of the landslides and their triggering factors, it is possible to identify areas susceptible to similar slides. In this study, the triggering factor for the landslides was considered to be rainfall.

The main objective of this chapter is to assess the various landslide conditioning factors and then use them to predict the future occurrence of landslides in the area. A variety of new tools are available for use in GIS for evaluating the distribution of phenomena in a statistical framework. Weights of Evidence is one such tool which was initially applied in GIS to predict the occurrence of minerals based on known mineral deposits but has been expanded to the study of landslides. Weights are estimated for a set of evidential themes associated with the known occurrences. These weights are then evaluated for the evidential themes in an area to produce a map of potential values for occurrence of that mineral or hazard. This chapter describes the application of the weights of evidence method for predicting the occurrence of landslides in Ang Khang district, Northern Thailand.

6.2 Materials

The materials used included the following:

- Landslide map produced using aerial photos and those mapped from the field (explained in chapter 5)
- A georeferenced digital Contour Map at a 10m interval provided by LDD.
- Software used to produce the landslide inventory, the factor maps (Slope gradient, slope aspect, Distance to roads, Soil attributes (soil classification at Subgroup level, Texture class and soil depth), Flow Accumulation, , Land use/ Land Cover) and the landslide susceptibility maps was ILWIS 3.3.
6.3 Modelling Landslides

Over the past two decades, many scientists (Carrara and Guzzetti 1995; Soeters and van Westen 1996) have attempted to assess landslide hazards and produced hazard / susceptibility maps portraying their spatial distribution. There are approaches which have been used and these are: statistical, geomorphological (expert dependent) or deterministic approaches. Despite the methodological and operational differences amongst these methods, they are all founded upon one basic conceptual model. The deterministic approach on the other hand is based on physical models. The basic conceptual model requires first the identification and mapping of a set of factors (e.g. geomorphological, topographical, landuse or geological) which are directly or indirectly correlated with slope instability. The model then estimates the relative contribution of these factors in slope failure and ends with the classification of the study area into different hazard zones or susceptibility degrees (Soeters and van Westen 1996; Aleotti and Chowdhury 1999; Guzzetti, Carrara et al. 1999).

Modelling of the landslides is a factor analysis process. A factor analysis process is a step-by-step approach used to prepare landslide hazard zones of an area (Carrara 1983; Carrara 1988). There are four steps that are followed to complete the factor analysis and produce a hazard map: (1) map the existing landslides and combine the factor maps one by one (Geology, slope gradient, Aspect, Soil subgroup, texture, depth, the hydrologic factors, etc ) into individual map units; (2) overlay the landslide inventory on the combined factor map; (3) prepare a combined factor analysis for all combinations of the factors and group combinations of these factors in a way that defines the three levels of landslide hazard; and (4) produce a map with landslide hazard zones from the grouped combinations. The software used to produce both the evidence maps and the factor maps was ILWIS version 3.3.

6.3.1 Landslide Inventory maps

According to (Carrara, Cardinalli et al. 1991), landslide inventory maps are the most important input data for predicting future landslide occurrence and susceptibility mapping since they contain the spatial attributes of the landslides. They also contain other attributes like state of activity, type and subtype of the landslides. The location of these landslides can give an idea of the factors which may cause future landslides.

Two landslide maps were produced for Ang Khang using interpretation of aerial photos taken in January 2002 (Figure 6.2) and field observations in the period between September and October 2005 (Figure 6.3). The landslide maps were for the years 2002 and 2005. Both maps were produced by making use of on screen digitizing and Epipolar stereo pairs generated in ILWIS. The steps used to generate the landslide inventory for both years were explained in Section 6.4.2. The Landslide inventory from aerial photos of 2002 was used as the evidence map in the
modelling and generation of weights for the different factors while the landslide map of the field observations of 2005 was used to test how well the model performed. The main types of landslides identified in Ang Khang were rotational slides (Slumps).

### 6.3.2 Landslide Causal and Conditioning Factors

Landslides are complex geological and/or geomorphological processes caused by a large number of factors which makes the classification of existing landslides and prediction of their future occurrence also fairly complex. (Carrara and Merenda 1976; Carrara and Guzzetti 1995) noted that the first important step in a GIS-supported landslide susceptibility assessment is to gather existing data related to the occurrence of landslides. The factors selected for this study, based on field observations, include Geology (Lithology), Slope gradient, Aspect, Land use/Land cover, Flow accumulation, Soil Depth, Texture class, and soil classification at Sub group level, and Distance from Roads. Production of each factor map is evaluated under separate headings in the sections that follow.

#### 6.3.2.1 Slope gradient

Slope is defined by a plane tangent to a topographic surface, as modelled by the DEM at a point (Burrough 1986). Slope is classified as a vector; as such it has a quantity (gradient) and a direction (aspect). Slope gradient is defined by (Burrough 1986) as the maximum rate of change in altitude.

Material (in the form of debris or rocks) can move down slope in response to gravity. Movement can range from very slow, barely perceptible over many years, to devastatingly rapid, within seconds. Whether or not slope movement occurs depends nearly always on slope steepness. Shrestha (2000), (Ercanoglu, Gokceoglu et al. 2003) argue that Slope gradient can be considered the most important landslide conditioning factor. It is however not easy to directly determine which slope class is more susceptible to landslides. Slope angles can be used as such for mostly they are classified in a limited number of slope classes.

To produce slope gradient classes for the watershed, a digital elevation model (DEM) was generated from digitized contour lines at 10 m intervals which were digitized from a topographic base map at a scale of 1:50,000. A Digital Elevation Model with a spatial resolution of 10m was obtained. The slope classes were computed using height differences in the X and Y directions. The resultant Slope gradient map (Figure 6.4) was then classified into 5 classes (in degrees) The slope classes include: 0 -6.5 degrees, 6.5 – 12.5 degrees, 12.5 – 22.5 degrees, 22.5 – 45 degrees and the last class with a range between 45 and 90 degrees.

Based on the field observations, slopes with a gradient 20 degrees and above were more susceptible than those of a lower gradient. The 5 classes correspond to the slope classification
system used in Thailand. Since the results of this study are to be applied in Thailand it was deemed necessary to maintain a similar classification system. Therefore the slope gradient map was classified into appropriate classes to identify which slope gradient was most prone to the occurrence of landslides.

6.3.2.2 Slope Aspect

Slope is defined as the compass direction of the maximum rate of change and is considered by some researchers as a landslide conditioning factor (Ercanoglu, Gokceoglu et al. 2003). In Mountainous areas, the direction of the slopes (Aspect) is such that some slopes face the direct rays of the sun while others receive indirect sunlight (Guzzetti, Carrara et al. 1999). They continue to state that this may also have an influence on the vegetation condition, which is often different for various aspect classes. Also because of their exposition some slopes experience more rain than others and this has influence on the local climatic conditions of the given area. Once there is a difference in the amount of rainfall received at a local level even the susceptibility to landslides may be different. In order to establish which Slope direction is more susceptible to landslides, a map was produced and classified into 8 different direction classes according to the geological compass. The Slope Aspect was computed from the DEM using height differences in the X and Y directions. The slope direction map (Figure 6.5) was classified according to the geological compass. These classes include North, North East, East, South East, South, South West, West and North West.

6.3.2.3 Soil

Landslides, as a type of natural hazards, are classified not only in terms of rate or style of movement but also in terms of the material involved. The materials are either soil (Debris and earth) or rocks (Cruden and Varnes 1996). Baring this in mind together with the observations during the field work, soil was selected as one of the landslide conditioning factors in this water shed.

Soils are classified into groups, subgroups, orders, suborders and families according to Soil taxonomy (Soil Survey Staff, 1999). Soil has several characteristics which include texture class, Depth, PH, Cation Exchange Capacity (CEC) etc. But for the purposes of this study, soil classification at Subgroup level, Texture class and soil depth were selected and the steps taken to produce the corresponding factor maps are outlined under the respective headings.

A Soil map together with an attribute table containing data on its classifications and characteristics were supplied by Land Development Department (LDD), Ministry of Agriculture and Cooperatives, Bangkok, Thailand. This data was used to produce the attribute maps of the soil subgroup, texture and depth.
a) Subgroup

Three classification levels (order, suborder, and great group) precede Subgroup and they are focused on categorizing soils based on major features or geological/environmental processes that dominated the direction and/or extent of soil development. The subgroup classification seeks to recognize distinctive soil features across different soils within a given soil great group. The subgroup name includes the great group name, modified by one or more descriptive adjectives. These descriptive adjectives fall into three general categories termed Typic, intergrade, and extragrade. A Typic subgroup soil lacks any significant properties that would suggest it is in a transition phase between related great groups or some other soil taxonomic level. Intergrade subgroup soils are those that belong to one soil great group but share various soil properties common to another recognized great group, suborder, or order. Extragrade subgroup soils reflect specific properties that are otherwise anomalous to the main concept of the great group (Rice, Gilbert et al. 2005). These are simple explanations, however since this research focused on landslides and the conditioning factors a detailed definition of the subgroup was not given.

The study area consists of two main soil Orders (Inceptisols and Alfisols). The soil Great Groups include Hapludalfs, Eutrudepts and Paleudalfs. They are further classified into the following Subgroups: Fluverntic Eutrudepts, Lithic Eutrudepts, Typic Hapludalfs, Typic (Mollic) Paleudalfs, Ultic Eutrudepts, Ultic (Mollic) Hapludalfs, Oxyaquic Eutrudepts, and Rhodic Paleudalfs. Using these Subgroup classes, an attribute map (Figure 6.6) was generated. In order to establish the relation between Soil and the occurrence of landslides it was deemed fit to select a classification group which was not too general (like the Order, Suborder, or Great Group which had only 2 classes) or those which had too many classes like the Family. In case of over generalisation, it is difficult to establish which soils are susceptible to landslides. Also if the classes are too big, (like in the case of Soil family) then there is a risk of overlap. Thus the Soil Subgroup was selected as a predictor.

b) Soil Texture

The soil textural classes were obtained for the soil map provided by the LDD office based on soil classification which were carried out in this study area.

An attribute map (Figure 6.7) was produced by making use of the Soil map linked to an attribute table. The resultant soil Subgroup map indicated the soil textural classes of the area. These classes include Clay Loam, Silty Loam, Slightly Gravel Silt Loam, Slightly Gravel Clay Loam, Loam, Gravel Sandy Loam and Slightly Gravel Loam.
c) Soil Depth

The University of Arizona (1998) defines the effective depth of a soil for plant growth as the vertical distance into the soil from the surface to a layer that essentially stops the downward growth of plant roots. They then give examples of barrier layer which can be rock, sand, gravel, heavy clay, or a cemented layer. Terms that are used to express effective depth of soil in the study area are (Soil Survey Staff 1999):

- **Shallow** - the surface is less or equal to 150 cm from a layer that retards root development.
- **Moderately deep to deep** - the surface is 150 to 200 cm from a layer that retards root development.
- **Very deep** - the surface is 200 cm or more from a layer that retards root development.

Soil Survey Staff (1999) observed that soils that are deep, well-drained, and have desirable texture and structure, are suitable for the production of most garden or landscape plants. In addition to this they say that deep soils can hold more plant nutrients and water than can shallow soils with similar textures. As a result, the depth of the soil and its capacity for nutrients and water frequently determine the yield from a crop, particularly annual crops that are grown with little or no irrigation. Plants growing on shallow soils also have less mechanical support than those growing in deep soils (Soil Survey Staff 1999). Trees growing in shallow soils are more easily blown over by wind than are those growing in deep soils. This leaves the land exposed to agents of land degradation of which landslides play an important role.

The dependent raster map indicating Soil Depth (Figure 6.8) was produced using the Soil map and the attribute Depth from an attribute table linked to the soil map. The classes in the Soil Depth map include Shallow, Moderately Deep to Deep, and Very Deep largely dependent on the rock types from which they are derived.

6.3.2.4 Drainage: Flow Accumulation

Following rainfall events, water flows from areas of convex curvature and accumulates in areas of concave curvature. This is known as flow accumulation, or upstream catchment area. Flow accumulation is a measure of the land area that contributes surface water to an area where surface water can accumulate. This parameter was considered of relevance to the study because it defines the locations in which water concentrates, such areas are likely to have a high landslide incidence.

The drainage pattern of a watershed can be obtained from a DEM of the area. The DEM can be produced by interpolating digitized contours (from topographic maps) of the area. Hydrologic
functions on a DEM enable the determination of the drainage pattern and networks of drainage network ordering, flow depth, topological optimisation and flow accumulation, etc. But this study focused only on flow accumulation.

Using Figure 6.1 as a model, Flow accumulation can be explained as the number of cells, or area, which contributes to runoff of a given cell A. Once accumulation reaches a threshold appropriate to this region, a drainage channel is formed. Flow accumulation measures the area of a watershed that contributes runoff to the cell. For this region represented, cell A is the point of accumulation for all the drainage flow in this area.

![Flow accumulation in a DEM](image)

**Figure 6.1 Diagrammatic Representation of Flow Accumulation**

To generate the factor map – Flow accumulation, the DEM-hydro processing operation in ILWIS, (Figure 6.9) was produced. The Flow Accumulation map was classified into 5 classes using the histogram information and the calculated Cumulative percentages (Table 6.1).

This implies that about 60% of the area has only 1 cell contributing their flow, about 13% with 3 cells contributing and the maximum accumulation in about 10% of the area is 15500 cells, which are probably the outlet points.

<table>
<thead>
<tr>
<th>Value</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
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</tr>
<tr>
<td>6</td>
<td>8.00</td>
</tr>
<tr>
<td>16</td>
<td>9.13</td>
</tr>
<tr>
<td>15500</td>
<td>9.76</td>
</tr>
</tbody>
</table>
6.3.2.5 Lithology

The main geological eras that describe the formations of the area are the Paleozoic and Neozoic eras. The main rock types include Shale, Limestone, Sandstone and Conglomerates. The digital geological map showing these rock types was generated by digitizing a scanned Geological map at a scale of 1:50,000 (Geological Survey Division 1974). The resultant factor map is shown in Figure 6.10. Basing on field observations, an assumption was made that Shale is more prone to landslides than the other rock types.

6.3.2.6 Land use / Land cover

The interaction between land cover and landslide activity is a highly complex phenomenon. Some researchers (Gokceoglu and Aksoy 1996; Jakob 2000) emphasise the positive effects of dense vegetation on the stability of slopes. While other researchers (Greenway 1987; Wu 1995) also mention some negative effects of dense forest cover on the stability of slopes in addition to its positive effects. Theoretically tree roots reinforce the soil, increasing soil shear strength, if the roots penetrate through the shear zone. In addition, roots extract moisture from the soil which is lost to the atmosphere via transpiration, leading to lower pore water pressures (Greenway 1987). For example, tree roots in the landslide area generally do not reach the failure surface. For this reason, the vegetation cover in the area adds weight to the slipped mass thus having an adverse effect on the stability.

The Land cover/ Landuse (Figure 5.11) map of the study area was produced from aerial photo interpretation at a scale of 1:25000 using a screen scope and the Epipolar pairs (see Chapter 5: Section 5.4.1). Seven land cover classes were recognised. These are Agriculture, Bare land, degraded forest, open forest and rock outcrops.

There are several factors that were considered during the interpretation and production of these land cover classes. In the case of Agriculture, the areas interpreted and classified as such, were of a regular shape and most appeared to have rows of vegetation which indicated human activities.

Bare land appeared as bright pieces of land on the aerial photo. Bare land had regular shapes indicated that there was a possibility that at the time when the photographs were taken, these pieces of land were not under use but had been used for agricultural purposes before. The other reason for this is that the area in which these features were located belongs to the Royal project of Ang Khang and could have been under rest until the following season. During field work, it was observed that there was a change in land use of the area. The areas under agriculture had increased and the bare land has reduced although it was not established by how much.

The forests of Ang Khang were classified into three classes: dense, open and degraded forests. The criteria for this classification included tone, roughness and vegetation density per unit (not to
scale). Those areas classified as dense forests were of the darkest colour and tone amongst the three classes. The dense forests appeared rough and had the highest tree density per square unit. The open forests were of a lighter green and less dense then the dense forest. Their canopies appear smoother than those of the dense forests. The open forest is likely to be younger than the dense forest. This is because the tone of the forest was lighter than that of the dense forests.

In the case of degraded forests, in comparison with the other two classes of forests, the tree density was the lowest. The tone of the trees was very light green to almost white in some patches indicating that the trees in these areas had been cut. Rock out crops stood out as complete separate and recognisable land cover units. They were clearly visible under stereoscopic vision thus classified as such. The water reservoirs were features that were square in shape closely associated with the agricultural areas.

### 6.3.2.7 Distance to Roads

Swanson and Dymness (1975) observed that in addition to natural phenomena, human activities may increase the natural tendency for a landslide to occur. When homes are constructed on unstable soils, or roads are cut into steep hillsides in critical areas, when we fail to properly manage our forests, we may be accelerating landslide activity. They also said that landslides, which result from development activities such as these, are usually caused by increasing moisture in the soil or changing the form of a slope. Development activities such as cutting and filling along roads and the removing of forest vegetation are capable of greatly altering slope form and ground water conditions. These altered conditions may significantly increase the degree of landslide hazard present (Sidle, Pearce et al. 1985).

For example, converting a forested area to grassland or one where crops are cultivated can increase the moisture in the soil enough to cause landslide problems (DeGraff 1979). Building a road which cuts off the toe of a steep slope can increase landslide susceptibility. It is possible to reduce the potential impact of natural landslide activity and limit development-initiated landslide occurrence by early consideration of these effects (Kockelman 1985).

During the field work, a number of landslides were observed to have occurred close to the roads. It was also observed that the most of the roads in this area were constructed on mid slopes rather than on the more gentle slopes. In so doing these ridges had been excavated to make room for the road construction. As a result of this development, slopes were left bare and exposed to the impacts of rainfall. It was thus assumed that road construction and distance to roads had an influence on the occurrence of landslides in this area. In order to produce the map showing distance to roads, the road segment map was rasterised and the distance to these roads calculated in meters. The resultant map was then sliced to give a raster map (Figure 6.12) showing distance to roads divided into 5 classes. The Five classes are 0 -10, 10 – 20, 20 – 30, 30 – 50, and 50 – 500.
(meters). Those roads which are located in flat areas were filtered out by giving them a value greater than 500m. This is because flat areas are not an area of interest and so the roads in these areas were not of interest in this study. No landslides are expected to have occurred in the flat areas.
Figure 6.2 Showing the Landslides mapped through aerial photo interpretation (2002)

Figure 6.3 Showing the Landslides mapped in the field 2005
Figure 6.4 Showing the slope gradient map of Ang Khang

Figure 6.5 Showing the Aspect Map of Ang Khang
Figure 6.6 Showing the Soil Sub group Map of Ang Khang
(The blue areas are not indicated in the legend of the Soil Texture map because they do represent water reservoirs and are undefined in terms of soil texture)

Figure 6.7 Showing the Soil Texture Map of Ang Khang
Figure 6.8 Showing the Soil Depth Map of Ang Khang:  
Figure 6.9 Showing the Flow Accumulation Map of Ang Khang

Note that in the Soil Depth map: the areas indicated as urban area and water did not have soil depth and were indicated as “is” but were indicated as undefined in the model.
PREDICTIVE MODELLING OF RAINFALL INDUCED LANDSLIDES IN A TROPICAL ENVIRONMENT.
A CASE OF ANG KHANG AND WANG CHIN DISTRICTS IN NORTHERN THAILAND

Geology Map of Ang Khang showing the different Lithologies

Landcover map of Ang Khang

Figure 6.10 Showing the Geological map of Ang Khang

Figure 6.11 Showing the land cover map of Ang Khang (aerial photo interpretation 2002)
Figure 6.12 Showing the ranges of the distance to the roads of Ang Khang based on the Road network where the class indicated as green are the actual roads which were filtered out by being given a high value (>500m)

Now that the general points with regard to mapping the various factors have been covered, Section 6.4 provides details on the techniques used in the Weights of evidence modelling in addition to presenting a step-by-step approach for preparing a landslide hazard map.
6.4 Weights of Evidence Modelling

Weights of evidence modelling is a quantitative method for combining evidence in support of a hypothesis. Weights are estimated from the measured association between known occurrences and the values on the maps to be used as predictors. In this study the known occurrences are landslides and the predictors are the selected factor maps which include Slope gradient, Aspect, Soil (Subgroup, Texture class and Depth), Geology, Flow Accumulation, Land cover and Distance to roads.

Several studies have been carried out using the weights of evidence modelling (van Westen 1993; Bonham-Carter 1994; Aleotti and Chowdhury 1999; Chung and Fabbri 1999; Carranza 2002). It has been discovered that this method has its own shortcomings. The first short coming is the fact that it takes into account only those landslide conditioning factors which can be easily mapped and in so doing it over simplifies the factors. The next short coming is the fact that while using Bivariate statistics, an assumption is made that all landslides in a given study area occur under the same combination of factors. The third is that each type of landslide has its own causal factors and should therefore be analysed separately. And the fourth is that the method is open to subjectivity since its mostly used by people other than earth scientists.

Although several disadvantages have been mentioned, the method has advantages as well. It is simple and less time consuming. In addition to this each landslide conditioning factor can be assigned weights in terms of its correlation with the occurrence of landslides.

Before carrying out the Bivariate Statistical Analysis to establish the correlation between the various factors and landslides, a number of important rules were followed. These rules were, all the factor maps had to have the same this was because of running a script (van Westen, Renger et al. 2003):

- Georeference and size
- Class domains but each factor map had the same domain as the name of the factor map.
- The name of the factor map had \( \leq 7 \) characters
- No attribute table as the different attribute tables were made during the running of the script.
- All these factor maps had the same georeference as the Landslide map.
Table 6.2 Inputs maps used in the Weights of Evidence modelling

<table>
<thead>
<tr>
<th>Factor</th>
<th>Description</th>
<th>File Type</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>Slope classes in degrees</td>
<td>Raster</td>
<td>Class: Slope</td>
</tr>
<tr>
<td>Geol</td>
<td>Lithology</td>
<td>Raster</td>
<td>Class: Geol</td>
</tr>
<tr>
<td>Depth</td>
<td>Soil depth of the soils</td>
<td>Raster</td>
<td>Class: Depth</td>
</tr>
<tr>
<td>Aspect</td>
<td>Slope direction classes</td>
<td>Raster</td>
<td>Class: Aspcls</td>
</tr>
<tr>
<td></td>
<td>(Aspect?)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FA</td>
<td>Flow Accumulation</td>
<td>Raster</td>
<td>Class: FA</td>
</tr>
<tr>
<td>Landuse</td>
<td>Landuse / Land cover classes</td>
<td>Raster</td>
<td>Class: Landuse</td>
</tr>
<tr>
<td>Roadis</td>
<td>Distance to Road</td>
<td>Raster</td>
<td>Class: Roadis</td>
</tr>
<tr>
<td>Texture</td>
<td>Soil Textural Classes</td>
<td>Raster</td>
<td>Class: Texture</td>
</tr>
<tr>
<td>Subgrp</td>
<td>Soil Subgroup</td>
<td>Raster</td>
<td>Class: Subgrp</td>
</tr>
</tbody>
</table>

The rules for assigning weights for the preparatory factors were largely based on field observations during which time the following causal factors were identified (Table 6.2). The main triggering factor for these landslides was assumed to be rainfall since there is no historical data to prove otherwise. In addition to this further observation (during field work) on 28th September 2005, about 238mm of rainfall was received and it triggered off a number of landslides in the area. With these maps, a landslide hazard map was prepared. Hazard zonation is a means of identifying areas with differing landslide hazards.

It is rare that all landslides in a study area are examined owing to difficulties of access and time. For this reason the terrain parameters identified on the basis of field work alone as contributing factors to land sliding may not be correct. To avoid such errors, a statistical data analysis technique was employed where all data taken from the landslides was treated the same.

To establish the correlation between each of the factors and the occurrence of landslides, three scenarios were set. The first involved only active landslides. The second involved both active and dormant landslides. The third scenario involved all the landslides mapped in the area.

The step-by-step approach, or factor analysis, used to prepare a landslide hazard map is described below (adapted from (van Westen, Renger et al. 2003)):

**Step1: Calculating prior probability**

An attribute map indicating only the active landslides was created from the landslide inventory (Chapter 5: Figure 5.1). Then the prior probability was that a certain pixel in the activity map will have a landslide was calculated. It is the density of landslides in the entire area as expressed in equation 6.1.
PREDICTIVE MODELLING OF RAINFALL INDUCED LANDSLIDES IN A TROPICAL ENVIRONMENT.
A CASE OF ANG KHANG AND WANG CHIN DISTRICTS IN NORTHERN THAILAND

The conditional probability that a landslide could occur is referred to as conditional if we were on “Clay Loam” soils, the probability of the occurrence of the landslide is larger than when we are on “Gravely Loam” soils.

The conditional probability of having landslides in Ang Khang, given that one is in a certain unit, is the density of the landslides in the unit. It’s calculated as the number of pixels with the landslides in the unit divided by the total number of pixels in the unit as expressed as (equation 6.2).

\[ P\{ S \mid B \} = \frac{P\{ S \cap B \}}{P\{ B \}} = \frac{N_{pix}\{ S \cap B \}}{N_{pix}\{ B \}} \quad \text{Equation 6.2.} \]

Where:

\[ P\{ S \mid B \} \] is the conditional probability of having a landslide(S) while in a certain unit B

\[ N_{pix}\{ S \mid B \} \] is the number of pixels with landslides in the unit

\[ N_{pix}\{ B \} \] is the total number of pixels in the unit
Step 3: Calculating Positive and Negative Weights

Weights of evidence modelling was selected for the indirect landslide susceptibility mapping and it requires that positive \( W_i^+ \) and negative \( W_i^- \) weights to be calculated. These values are assigned to each pixel in each of the factor maps and are defined as:

\[
W_i^+ = \log_e \frac{P(B_i|S)}{P(B_i|S)}
\]

Equation 6.3

and

\[
W_i^- = \log_e \frac{P(\overline{B}_i|S)}{P(\overline{B}_i|S)}
\]

Equation 6.4

where,

- \( B_i \) = presence of a potential landslide conditioning factor,
- \( \overline{B} \) = absence of a potential landslide conditioning factor,
- \( S \) = presence of a landslide, and
- \( \overline{S} \) = absence of a landslide

The method was performed using the individual factor maps each factor map had a range of classes indicating the conditions present in the study area. For example the Land cover factor map had 8 classes indicating eight categories of land cover representing the area.

For each factor, \( W_i^+ \) was used to indicate the importance of the presence of the factor, for example Clay Soils, for the occurrence of landslides. If \( W_i^+ \) was positive the presence of the factor is favourable for the occurrence of landslides, and if \( W_i^+ \) is negative it is not favourable.

\( W_i^- \) was used to evaluate the importance of the absence of the factor for the occurrence of landslides. When \( W_i^- \) is positive the absence of the factor is favourable for the occurrence of landslides, and when it is not. Weights with extreme values indicate that the factor is a useful for the susceptibility mapping, while factors with a weight around zero have no relation with the occurrence of landslides.

The positive and the negative weights expressed in Equations 6.3 and 6.4 were simplified and expressed in terms of the number of pixels and are thus re-written in equations 6.5 and 6.6.
\[ W_i^+ = \log_e \frac{N_{pix_1}}{N_{pix_1} + N_{pix_2}} \]

\[ W_i^- = \log_e \frac{N_{pix_2}}{N_{pix_1} + N_{pix_2}} \]

\[ W_i^{final} = \log_e \frac{N_{pix_3}}{N_{pix_1} + N_{pix_2}} \]

Where:
- \( N_{pix1} = n_{slclass} \)
- \( N_{pix2} = n_{slide} - n_{slclass} \)
- \( N_{pix3} = n_{class} - n_{slclass} \)
- \( N_{pix4} = n_{map} - n_{slide} - n_{class} + n_{slclass} \)

And
- \( N_{map} = \) column with the total number of pixels in the map
- \( N_{slide} = \) column with the number of slides with landslides in the map
- \( N_{class} = \) column with the number of pixels in the class

Because of the nature of the process of weights of evidence modelling (long and time consuming if carried out manually), all the steps described above were incorporated into a weight script (Appendix 3) which was run to produce the negative and positive weights for each of the factor maps. These results are given and discussed in Section 6.5

### 6.4 Results and Discussions

Extrapolating the data to areas with characteristics similar to those found associated with past landslides was an effective tool for forecasting where, but not when, landslides are more likely to occur in the future. The results are discussed in the sections that follow for each of the different scenarios set during the modelling.

Three types of weights for the different factor maps are presented in the sections that follow; \( WPLUS, WMIN \) and \( WFINAL \). **WPLUS** is a positive weight. If the weight of a class for any given factor is positive then it implies that the presence of that class has a positive correlation with the occurrence of landslides. Thus the presence of that factor and class in particular facilitates the occurrence of landslides. **WMIN** is the negative weight. If on the other hand the weight of a certain factor and a class is negative, then it implies that the absence of that class favours the occurrence of landslides. **WFINAL** is the final weight of the
class in the weight map of that factor. It is these final weights (for each factor) that were added to produce the final weight map for the various factors in the three scenarios. The correlations of each factor and class with the occurrence of landslides are discussed in the sections that follow.

6.5.1 Scenario 1: Using a Landslides map indicating Active Landslides only
The type of landslides observed in the study area was small rotational slides (Slumps). The correlation between the different factors and the occurrence of active landslides is discussed in the sections that follow. Because of the large size of conditioning factors, the results have been grouped and presented in sections. The factors derived from the digital elevation model (Slope, Aspect and Flow Accumulation) were grouped together. The second group composed of Lithology, Soil Subgroup, Soil Texture, Soil Depth and Land cover. The third group composed of distance to roads.

6.5.1.1 Slope direction, Aspect and Flow Accumulation
The results of this group are presented in Table 6.3. In the Slope gradient map, the slope class between 12.5 degrees and 45 degrees shows a good positive relationship with the occurrence of the slides as the slope class have a higher weight than all the other slope classes.

In the Aspect map, it was observed that the directions South East, South, South West and West show a good positive correlation with the slides. The South west direction showed the highest positive correlation with the slides. The slopes in the West direction are more prone to the occurrence of landslides which is directly linked to the fact that this is where the road construction has been most active. An overlay of the Aspect, and Geology maps indicated that these slopes are dominated by Shale. Shale is less permeable than Limestone to sandstone and also has very little resistance to runoff. As a result, it is more prone to landslides. In addition to this, Shale is easily weatherable making it easy for the soils which are derived from it to be moved: sliding off.

In the Flow Accumulation map, all classes apart from the class with value 1 indicate a good positive correlation with the occurrence of landslides. But the class with the maximum Flow Accumulation i.e. 15500 has the highest positive correlation with the landslides. 4 out of the 5 classes have positive weights implying that the classification was not good. The class with the highest flow accumulation value (15500) indicates a high positive relation but no landslides are expected to occur in this place because of the presence of the Karst formations. They are very permeable thus a high flow accumulation value.
### Table 6.3 Weights for the Input maps with respect to Active Slides

<table>
<thead>
<tr>
<th>Theme Class</th>
<th>WPLUS</th>
<th>WMIN</th>
<th>WFINAL</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Slope Gradient</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 - 6.5 degrees</td>
<td>-1.0479</td>
<td>0.0562</td>
<td>-1.1733</td>
</tr>
<tr>
<td>6.5 – 12.5 degrees</td>
<td>-0.1211</td>
<td>0.0151</td>
<td>-0.0692</td>
</tr>
<tr>
<td>12.5 – 22.5 degrees</td>
<td>0.1981</td>
<td>-0.0996</td>
<td>0.2285</td>
</tr>
<tr>
<td>22.5 – 45 degrees</td>
<td>0.1138</td>
<td>-0.0946</td>
<td>0.1392</td>
</tr>
<tr>
<td>&gt; 45 degrees</td>
<td>-1.3024</td>
<td>0.0536</td>
<td>-1.4252</td>
</tr>
<tr>
<td><strong>Aspect</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>-1.6473</td>
<td>0.10854</td>
<td>-1.7986</td>
</tr>
<tr>
<td>NE</td>
<td>-2.2899</td>
<td>0.0164</td>
<td>-2.4967</td>
</tr>
<tr>
<td>E</td>
<td>-0.8333</td>
<td>0.0788</td>
<td>-0.9549</td>
</tr>
<tr>
<td>SE</td>
<td>0.4307</td>
<td>-0.0643</td>
<td>0.4523</td>
</tr>
<tr>
<td>S</td>
<td>0.5533</td>
<td>-0.0876</td>
<td>0.5981</td>
</tr>
<tr>
<td>SW</td>
<td>0.7215</td>
<td>-0.1930</td>
<td>0.8717</td>
</tr>
<tr>
<td>W</td>
<td>0.4012</td>
<td>-0.0776</td>
<td>0.4360</td>
</tr>
<tr>
<td>NW</td>
<td>-0.2852</td>
<td>0.0284</td>
<td>-0.3563</td>
</tr>
<tr>
<td><strong>Flow Accumulation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.89294</td>
<td>0.6381</td>
<td>-1.3133</td>
</tr>
<tr>
<td>3</td>
<td>0.2948</td>
<td>-0.0535</td>
<td>0.5660</td>
</tr>
<tr>
<td>6</td>
<td>0.5089</td>
<td>-0.0591</td>
<td>0.7858</td>
</tr>
<tr>
<td>16</td>
<td>0.7476</td>
<td>-0.1172</td>
<td>1.0826</td>
</tr>
<tr>
<td>15500</td>
<td>0.9674</td>
<td>-0.1906</td>
<td>1.3758</td>
</tr>
</tbody>
</table>

#### 6.5.1.2 Lithology, Soil: Subgroup, Texture, and Depth

The results from Table 6.4 indicate that in the Lithology Map, the rock formation containing Sandstone, Shale and Conglomerates has the highest positive correlation with the occurrence of landslides. In this watershed, the rock type shale is under laid by Sandstone and Conglomerate rock types (Baum and Hahn 1977). In areas where shale is underlain by more permeable rock types there is a high chance of soils to slip off. Once the Shale absorbs water, it becomes heavy and slips off the underlying rock. In the Soil subgroup map, the class Ultic has the highest positive weights showing a good correlation with the slides. In the Soil Texture, the textural classes Slightly Gravely Clay Loam and Silty Loam have the highest positive correlations with the occurrence of landslides while the Soil Depth map indicates that the class moderately deep to deep has the highest positive correlation. These are the type of soils derived from Shale.
Table 6.4 Weights for Input Maps with respect to Active Landslides.

<table>
<thead>
<tr>
<th>Theme Class</th>
<th>WPLUS</th>
<th>WMIN</th>
<th>WFINAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lithology</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gravel, Shale</td>
<td>0.4177</td>
<td>-0.0227</td>
<td>-0.8978</td>
</tr>
<tr>
<td>Limestone</td>
<td>-5.4987</td>
<td>0.2156</td>
<td>-7.0524</td>
</tr>
<tr>
<td>Limestone, Sandstone</td>
<td>-2.4903</td>
<td>0.2910</td>
<td>-4.1195</td>
</tr>
<tr>
<td>Sandstone, Shale</td>
<td>-4.1136</td>
<td>0.0491</td>
<td>-5.5010</td>
</tr>
<tr>
<td>Sandstone, Shale, Conglomerate</td>
<td>0.7180</td>
<td>-1.8712</td>
<td>1.2511</td>
</tr>
<tr>
<td>Soil Subgroup</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fluverntic</td>
<td>-1.0841</td>
<td>0.0016</td>
<td>-1.2492</td>
</tr>
<tr>
<td>Oxyaquic</td>
<td>-1.2770</td>
<td>0.0021</td>
<td>-1.4426</td>
</tr>
<tr>
<td>Rhodic</td>
<td>-5.4858</td>
<td>0.2125</td>
<td>-5.8619</td>
</tr>
<tr>
<td>Lithic</td>
<td>-3.6238</td>
<td>0.0295</td>
<td>-3.8169</td>
</tr>
<tr>
<td>Typic</td>
<td>0.1489</td>
<td>-0.0871</td>
<td>0.0725</td>
</tr>
<tr>
<td>Typic (Mollic)</td>
<td>-1.2940</td>
<td>0.0021</td>
<td>-1.4597</td>
</tr>
<tr>
<td>Ultic</td>
<td>0.5810</td>
<td>-0.3735</td>
<td>0.7909</td>
</tr>
<tr>
<td>Ultic (Mollic)</td>
<td>-4.1621</td>
<td>0.0517</td>
<td>-4.3773</td>
</tr>
<tr>
<td>Soil Texture</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clay Loam</td>
<td>-0.0993</td>
<td>0.1937</td>
<td>-0.2020</td>
</tr>
<tr>
<td>Gravely Sandy Loam</td>
<td>-3.6235</td>
<td>0.0295</td>
<td>-3.5620</td>
</tr>
<tr>
<td>Loam</td>
<td>-3.4165</td>
<td>0.0237</td>
<td>-3.3493</td>
</tr>
<tr>
<td>Silty Loam</td>
<td>1.2765</td>
<td>-0.0006</td>
<td>1.3681</td>
</tr>
<tr>
<td>Slightly Gravely Silty Loam</td>
<td>-0.9845</td>
<td>0.0013</td>
<td>-0.8949</td>
</tr>
<tr>
<td>Slightly Gravely Clay Loam</td>
<td>0.5857</td>
<td>-0.1559</td>
<td>0.8326</td>
</tr>
<tr>
<td>Slightly Gravel Loam</td>
<td>-1.2766</td>
<td>0.0021</td>
<td>-1.1877</td>
</tr>
<tr>
<td>Soil Depth</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>-4.7869</td>
<td>0.0303</td>
<td>-0.7312</td>
</tr>
<tr>
<td>Moderately Deep to Deep</td>
<td>0.4358</td>
<td>-0.3230</td>
<td>0.7362</td>
</tr>
<tr>
<td>Very Deep</td>
<td>-0.2617</td>
<td>0.2392</td>
<td>-0.5235</td>
</tr>
</tbody>
</table>

6.5.1.3 Land cover and Distance to Roads

Using Table 6.4 the Land cover map indicates that the classes, Bare land and Degraded Forests have positive correlations with the occurrence of landslides in with the class Degraded Forests is showing the highest correlation. It is possible that the water reservoirs are artificial open water tanks constructed with concrete to provide water for irrigation in the project agricultural lands.
Table 6.5 Weights of Input maps with respect to Active Landslides

<table>
<thead>
<tr>
<th>Theme Class</th>
<th>WPLUS</th>
<th>WMIN</th>
<th>WFINAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land cover</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>-1.4091</td>
<td>0.0303</td>
<td>-1.5918</td>
</tr>
<tr>
<td>Bare Land</td>
<td>0.9195</td>
<td>-0.1253</td>
<td>0.8925</td>
</tr>
<tr>
<td>Built-up Area</td>
<td>-2.9393</td>
<td>0.0144</td>
<td>-3.1060</td>
</tr>
<tr>
<td>Degraded Forest</td>
<td>0.8729</td>
<td>-0.6185</td>
<td>1.3391</td>
</tr>
<tr>
<td>Dense Forest</td>
<td>-1.2473</td>
<td>0.4262</td>
<td>-1.8258</td>
</tr>
<tr>
<td>Open Forest</td>
<td>-0.7165</td>
<td>0.1105</td>
<td>-0.9794</td>
</tr>
<tr>
<td>Rock Out crop</td>
<td>-2.6526</td>
<td>0.0106</td>
<td>-2.8155</td>
</tr>
<tr>
<td>Distance to Roads</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 – 10 m</td>
<td>-0.4143</td>
<td>0.0475</td>
<td>-0.4960</td>
</tr>
<tr>
<td>10 – 20 m</td>
<td>0.2188</td>
<td>-0.0849</td>
<td>0.2696</td>
</tr>
<tr>
<td>20 – 30 m</td>
<td>0.2901</td>
<td>-0.1102</td>
<td>0.3662</td>
</tr>
<tr>
<td>30 – 50 m</td>
<td>-0.1446</td>
<td>0.0419</td>
<td>-0.0221</td>
</tr>
<tr>
<td>50 – 500 m</td>
<td>-1.1261</td>
<td>0.0152</td>
<td>-1.1754</td>
</tr>
<tr>
<td>500 – 1000 m</td>
<td>-0.5219</td>
<td>0.0564</td>
<td>-0.6124</td>
</tr>
</tbody>
</table>

6.5.2 A combination of the three scenarios: Scenario 1: Using Active slides only, Scenario 2: Using Active & Dormant Slides and Scenario 3: Using All Slides.

In this section, the results from the model using the 3 scenarios were combined and presented in Table 6.6. In Scenario 1 only the Active slides were used, while in Scenario 2 the Active and dormant slides were used and in Scenario 3 all the landslides (active, dormant and stable) mapped in the study area were used. A comparison was then made amongst the three scenarios the results of which are discussed in the sections that follow.

6.5.2.1 Slope Gradient, Aspect and Flow Accumulation

For a better comparison, the results from the 3 scenarios (indicating only the final weights) are indicated in Table 6.6. Using the Slope Gradient map, only 1 class indicates a positive correlation with the occurrence of landslides. This class indicates slope gradient between 22.5 to 45 degrees. This class indicates the slope of highest instability. Slopes may fail due to the angle. In this watershed once the steep slopes are covered by highly weatherable material, the occurrence of landslides is increased. Once water is availed through rainfall in terms of runoff, then the material on the steep slopes are facilitated to slide. The high landslide occurrence could be related to the fact that these slopes are facing the West. Table 6.6 indicates that the slopes in the West have a high positive correlation with the occurrence of landslides. This is directly related to the fact that the slopes in the West have active road construction. In the study area, most of the roads are constructed on the mid slopes (of relatively high elevation) of the ridge which explains the high
positive correlation between slopes between 22.5 and 45 degrees and the occurrence of landslides. Another relation is indicated by the Slope Aspect North West which shows a positive weight. This implies that in the North West there is slope instability giving rise to the occurrence of landslides. An overlay of the land cover, Geology, and Soil texture maps indicates that Slopes facing the North West direction are dominated by degraded forests, located on the shale, sandstone and conglomerate rock formation with mostly clay loam soil textures. Degraded forests expose the soil to rainfall making it easy for landslides to occur. Clay Loam soils have a relatively low permeability (Way 1973) because of the presence of clay. These soils are derived from Shale which inhibits internal drainage and creates more surface runoff (Way 1973).

The South West facing slopes seem to be more prone to landslides than the rest of the slope directions. This could be due to the general orientation of the main lithological units and the slope forms in the area. The slope map indicates that most of the lithological units are in the North – South direction perpendicular to the slope forms hence the occurrence of more slides.

Table 6.6 Weights of the Input maps with respective to the 3 scenarios

<table>
<thead>
<tr>
<th>Theme Class</th>
<th>Active Slides</th>
<th>Active &amp; Dormant</th>
<th>All Slides</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Slope Gradient</strong></td>
<td><strong>WFINAL</strong></td>
<td><strong>WFINAL</strong></td>
<td><strong>WFINAL</strong></td>
</tr>
<tr>
<td>0 - 6.5 degrees</td>
<td>-1.1733</td>
<td>-1.5936</td>
<td>-1.8642</td>
</tr>
<tr>
<td>6.5 – 12.5 degrees</td>
<td>-0.0692</td>
<td>-0.8178</td>
<td>-1.0413</td>
</tr>
<tr>
<td>12.5 – 22.5 degrees</td>
<td>0.2285</td>
<td>-0.0088</td>
<td>-0.1460</td>
</tr>
<tr>
<td>22.5 – 45 degrees</td>
<td>0.1392</td>
<td>0.3977</td>
<td>0.4761</td>
</tr>
<tr>
<td>&gt; 45 degrees</td>
<td>-1.4252</td>
<td>-0.9819</td>
<td>-0.5060</td>
</tr>
<tr>
<td><strong>Aspect</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>-1.7986</td>
<td>-1.2193</td>
<td>-1.0584</td>
</tr>
<tr>
<td>NE</td>
<td>-2.4967</td>
<td>-2.3085</td>
<td>-2.266</td>
</tr>
<tr>
<td>E</td>
<td>-0.9549</td>
<td>-1.4877</td>
<td>-1.8777</td>
</tr>
<tr>
<td>SE</td>
<td>0.4523</td>
<td>0.0809</td>
<td>-0.3752</td>
</tr>
<tr>
<td>S</td>
<td>0.5981</td>
<td>0.6474</td>
<td>0.3274</td>
</tr>
<tr>
<td>SW</td>
<td>0.8717</td>
<td>0.8550</td>
<td>0.8289</td>
</tr>
<tr>
<td>W</td>
<td>0.4360</td>
<td>0.6012</td>
<td>0.8751</td>
</tr>
<tr>
<td>NW</td>
<td>-0.3563</td>
<td>-0.1287</td>
<td>0.2742</td>
</tr>
<tr>
<td><strong>Flow Accumulation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-1.3133</td>
<td>-1.3133</td>
<td>-1.2763</td>
</tr>
<tr>
<td>3</td>
<td>0.5660</td>
<td>0.5660</td>
<td>0.6221</td>
</tr>
<tr>
<td>6</td>
<td>0.7858</td>
<td>0.7858</td>
<td>0.7334</td>
</tr>
<tr>
<td>16</td>
<td>1.0826</td>
<td>1.0826</td>
<td>1.0820</td>
</tr>
<tr>
<td>15500</td>
<td>1.3758</td>
<td>1.3758</td>
<td>1.3515</td>
</tr>
</tbody>
</table>
In the Flow Accumulation map (Table 6.6), in all the three scenarios, 4 out of 5 classes indicate a positive correlation with the occurrence of landslides. It can thus be concluded that this classification was not good. The exceptionally high flow accumulation values correspond to the areas in the West with the Karst formations and sink holes as indicated on the Geology map by (Baum and Hahn 1977). According to (Way 1973) Limestones are sedimentary rocks which have calcium carbonate in proportions to affect their overall characteristics. He illustrated that once water seeping through the joint patterns of limestone dissolves the calcium carbonate, a roof of one of the channels collapses forming a depression which is referred to as a sink hole. He also discussed that in humid and tropical climates, (like Ang Khang) limestone contains many joints and solution cavities thus increasing its drainage capacity of the soil and reducing its risk to landslide occurrence.

6.5.2.2 Lithology, Soil: Subgroup, Texture and Depth

In Table 6.7, the Lithology map, the formation which includes Sandstone, Shale and Conglomerates has a high positive weight indicating a good correlation with respect to all scenarios although Scenario 3 shows the highest correlation.

In the Soil Subgroup map, the class Urtic showed the highest positive correlation. Urtic soils are acid soils with clayey and/ or organic illuvial features in subsoil horizons as discussed by (Soil Survey Staff 1999). They also stated that these soils are developed in clayey weathering products of siliceous sediments or acid igneous rocks and usually contain mixtures of clay minerals. The clay in the eastern part of this water shed is derived from the easily weatherable Shale. The soil textural classes with the presence of clay showed a positive weight (Table 6.7) indicating that presence of clay facilitates the occurrence of landslides. Soil texture classes Clay Loam and Slightly Gravely Clay Loam show positive weights with the Slightly Gravely Clay Loam showing the highest positive weight in all the three scenarios. Out of the 7 textural classes, in Scenario 1: 2 classes (Silty Loam and Slightly Gravely Clay Loam) have positive weights; Scenario 2: three classes (Clay Loam, Slightly Gravely Sandy Loam and Slightly Gravely Clay Loam) while Scenario 3 indicates that classes Clay Loam and Slightly Gravely Clay Loam have positive weights. Basing on this observation, the classification of the Soil texture classes was good. Soil textural class Slightly Gravely Clay Loam shows a positive weight indicating a good correlation with the occurrence of landslides.

Field observations indicate that the most dominant type of landslides in Ang Khang were Slumps which were predominant on Shale underlain by sandstone and conglomerate rock formations. These findings are in agreement with the findings of (Way 1973), which indicate that in thickly bedded clay shale regions, the major forms of mass wasting are soil creep and slumps.

In addition to the above, (Way 1973) observed that shales interbedded with sandstones and/ or limestones (in the case of Ang Khang Shale is interbedded with sandstone) are very unstable.
This observation could explain the dominance of Slumps on the rock formation which includes Shale, sandstone and conglomerates since they are unstable a condition which favours the occurrence of landslides.

Table 6.7 Weights of Input Maps with respect to Active and Dormant Landslides

<table>
<thead>
<tr>
<th>Theme Class</th>
<th>Active Slides</th>
<th>Active &amp; Dormant Slides</th>
<th>All Slides</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Lithology</strong></td>
<td>WFINAL</td>
<td>WFINAL</td>
<td>WFINAL</td>
</tr>
<tr>
<td>Gravel, Shale</td>
<td>-0.8978</td>
<td>-2.5604</td>
<td>-3.7176</td>
</tr>
<tr>
<td>Limestone</td>
<td>-7.0524</td>
<td>-9.0504</td>
<td>-10.1976</td>
</tr>
<tr>
<td>Limestone, Sandstone</td>
<td>-4.1195</td>
<td>-5.9095</td>
<td>-7.0338</td>
</tr>
<tr>
<td>Sandstone, Shale</td>
<td>-5.5010</td>
<td>-7.4970</td>
<td>-8.6418</td>
</tr>
<tr>
<td>Sandstone, Shale, Conglomerate</td>
<td><strong>1.2511</strong></td>
<td><strong>1.3753</strong></td>
<td><strong>1.4321</strong></td>
</tr>
<tr>
<td><strong>Soil Subgroup</strong></td>
<td>WFINAL</td>
<td>WFINAL</td>
<td>WFINAL</td>
</tr>
<tr>
<td>Fluventic</td>
<td>-1.2492</td>
<td>-0.1786</td>
<td>-0.6606</td>
</tr>
<tr>
<td>Oxyaquic</td>
<td>-1.4426</td>
<td>-2.5861</td>
<td>-3.1741</td>
</tr>
<tr>
<td>Rhodic</td>
<td>-5.8619</td>
<td>-7.0078</td>
<td>-7.5988</td>
</tr>
<tr>
<td>Lithic</td>
<td>-3.8169</td>
<td>-4.9607</td>
<td>-5.5491</td>
</tr>
<tr>
<td>Typic</td>
<td><strong>0.0725</strong></td>
<td>0.1655</td>
<td><strong>0.0526</strong></td>
</tr>
<tr>
<td>Typic (Mollic)</td>
<td>-1.4597</td>
<td>-2.6031</td>
<td>-3.1912</td>
</tr>
<tr>
<td>Ultic</td>
<td><strong>0.7909</strong></td>
<td><strong>0.7067</strong></td>
<td><strong>0.7587</strong></td>
</tr>
<tr>
<td>Ultic (Mollic)</td>
<td>-4.3773</td>
<td>-0.3730</td>
<td>-0.2476</td>
</tr>
<tr>
<td><strong>Soil Texture</strong></td>
<td>WFINAL</td>
<td>WFINAL</td>
<td>WFINAL</td>
</tr>
<tr>
<td>Clay Loam</td>
<td>-0.2020</td>
<td><strong>0.08158</strong></td>
<td><strong>0.0349</strong></td>
</tr>
<tr>
<td>Gravelly Sandy Loam</td>
<td>-3.5620</td>
<td>-4.9392</td>
<td>-5.4706</td>
</tr>
<tr>
<td>Loam</td>
<td>-3.3493</td>
<td>-4.7265</td>
<td>-5.2578</td>
</tr>
<tr>
<td>Silty Loam</td>
<td><strong>1.3681</strong></td>
<td>-0.0088</td>
<td>-0.5399</td>
</tr>
<tr>
<td>Slightly Gravelly Silty Loam</td>
<td>-0.8949</td>
<td><strong>0.0562</strong></td>
<td>-0.4810</td>
</tr>
<tr>
<td>Slightly Gravelly Clay Loam</td>
<td><strong>0.8326</strong></td>
<td><strong>0.1897</strong></td>
<td><strong>0.2921</strong></td>
</tr>
<tr>
<td>Slightly Gravel Loam</td>
<td>-1.1877</td>
<td>-0.0088</td>
<td>-3.0957</td>
</tr>
<tr>
<td><strong>Soil Depth</strong></td>
<td>WFINAL</td>
<td>WFINAL</td>
<td>WFINAL</td>
</tr>
<tr>
<td>Shallow</td>
<td>-0.7312</td>
<td>-4.8398</td>
<td>-5.4319</td>
</tr>
<tr>
<td>Moderately Deep to Deep</td>
<td><strong>0.7362</strong></td>
<td><strong>0.7362</strong></td>
<td><strong>0.8022</strong></td>
</tr>
<tr>
<td>Very Deep</td>
<td>-0.5235</td>
<td>-0.5235</td>
<td>-0.6530</td>
</tr>
</tbody>
</table>

A further exploration of the results in table 6.7 indicates that whereas Scenario 1 and 2 show a relatively low negative weight for the Slightly Gravelly Loam Soil textural class, Scenario 3 shows a high negative weight for the same class. This implies that the absence of Slightly
Gravely Loam soils facilitates the occurrence of landslides. The soil texture class, as the name suggests, is composed of gravel and coarse texture sand. Soils containing sand allow the rapid percolation of rainfall which explains the high negative correlation to the occurrence of landslides as discussed by (Way 1973). For landslides to occur the soils ought to have limited porosity, once loaded with water, the soil then becomes heavy and thus easily slides down the slope hence the occurrence of landslides.

Results from Table 6.7 also indicate that in all the 3 Scenarios, the most affected Soil depth is Moderately Deep to Deep. According to (Way 1973; Bridges 1997; Soil Survey Staff 1999) soils derived from Shale are thin and moderately deep. An overlay of the Soil Depth Map on the Geological mp of Ang Khang indicates that the eastern part of the water shed is predominantly covered by soils which are moderately deep to deep. The landslide inventory map indicates that the eastern map is more prone to landslides then the rest of the study area. These observations explain the positive weight indicated by the moderately deep to deep soils which implies that the presence of moderately deep to deep soils facilitates the occurrence of landslides in Ang Khang.

### 6.5.2.3 Land cover and Distance to Roads

Table 6.8 shows the final weights obtained from correlating land cover and Distance to roads maps with the occurrence of landslides with respect to the three scenarios. All the final weights indicate that the Land cover class Degraded Forest has the highest positive weight. This implies that degraded forests facilitate the occurrence of landslides in the study area. However land cover class dense forest shows a positive weight in scenario 2 and 3. This is because in both Scenarios dormant slides were included in the evidence map.

These observations could be explained by (Sidle, Pearce et al. 1985; Crozier 1986; Greenway 1987), who observed that vegetation plays an important role in the stability of slopes. They also discuss that the removing of forest vegetation is capable of greatly altering slope form and ground water conditions. These altered conditions may significantly increase the degree of landslide hazard present (Sidle, Pearce et al. 1985).

Another factor and class presented in all the three scenarios is the distance to the roads; the class which is shown to be of greatest influence on the occurrence of landslides is that within the range of 20 – 30m from the roads. This could be related to the upslope distance to the scarp. A cross of the road distance map and the slope map indicates that the areas that fall within the road distance class 20 – 30m from the roads predominantly occur on slopes between 22.5 to 45 degrees. Excavation
Table 6.8 Weights of the Input Maps with respect to the 3 Scenarios

<table>
<thead>
<tr>
<th>Theme Class</th>
<th>Active Slides</th>
<th>Active &amp; Dormant Slides</th>
<th>All Slides</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WFINAL</td>
<td>WFINAL</td>
<td>WFINAL</td>
</tr>
<tr>
<td>Agriculture</td>
<td>-1.5918</td>
<td>-2.6409</td>
<td>-2.6409</td>
</tr>
<tr>
<td>Bare Land</td>
<td><strong>0.8925</strong></td>
<td>-0.3505</td>
<td>-0.3505</td>
</tr>
<tr>
<td>Built-up Area</td>
<td>-3.1060</td>
<td>-4.2051</td>
<td>-4.2051</td>
</tr>
<tr>
<td>Degraded Forest</td>
<td><strong>1.3391</strong></td>
<td><strong>0.2922</strong></td>
<td><strong>0.2922</strong></td>
</tr>
<tr>
<td>Dense Forest</td>
<td>-1.8258</td>
<td><strong>0.1367</strong></td>
<td><strong>0.1367</strong></td>
</tr>
<tr>
<td>Open Forest</td>
<td>-0.9794</td>
<td>-0.3428</td>
<td>-0.3428</td>
</tr>
<tr>
<td><strong>Distance to Roads</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 – 10 m</td>
<td>-0.4960</td>
<td>-1.1455</td>
<td>-1.1455</td>
</tr>
<tr>
<td>10 – 20 m</td>
<td><strong>0.2696</strong></td>
<td>-0.0290</td>
<td>-0.0290</td>
</tr>
<tr>
<td>20 – 30 m</td>
<td><strong>0.3662</strong></td>
<td><strong>0.4586</strong></td>
<td><strong>0.4586</strong></td>
</tr>
<tr>
<td>30 – 50 m</td>
<td>-0.0221</td>
<td>-0.0204</td>
<td>-0.0204</td>
</tr>
<tr>
<td>50 – 500 m</td>
<td>-1.1754</td>
<td>-0.9981</td>
<td>-0.9981</td>
</tr>
<tr>
<td>500 – 1000 m</td>
<td>-0.6124</td>
<td>-0.0973</td>
<td>-0.0973</td>
</tr>
</tbody>
</table>

Having analysed and discussed the results of the final weights obtained from the various factor maps, it was noted that scenario 2 performed better that scenarios 1 and 3. This was shown by crossing the final weight map (obtained from combining, by addition in ILWIS, the factor maps from this scenario) and the landslide inventory map of 2002 obtained from aerial photo interpretation. The results of this cross are presented in Figure 6.13 indicating how well the model performed.
Figure 6.13 Showing the Success Rate Curve for Scenario 2: Active and Dormant Slides

About 90% of all the landslides is already accounted for by 40% of the Predicted Map

6.6 Landslide Susceptibility Maps from the three Scenarios (models)

Landslide susceptibility is defined by (Hansen 1984; Cruden and Varnes 1996), as the proneness of the terrain to produce slope failures. Susceptibility is usually expressed in a cartographic way as discussed by (Brabb 1984). A landslide susceptibility map depicts areas likely to have landslides in the future by correlating some of the principal factors that contribute to landsliding with the past distribution of slope failures (Brabb 1984). The landslide susceptibility maps are a spatial representation of the degree to which an area is prone to landslides. These maps are classified into classes ranging from Low to High hazard zones depending on the factors under consideration. In this study the landslide susceptibility maps were classified into three classes as discussed in section 6.6.1.
6.6.1 Landslide Susceptibility Categories

Three landslide susceptibility classes or categories were used in the landslide susceptibility maps and they are explained here below and the resultant Susceptibility maps are shown in Figures 6.14 to 6.16. The three susceptibility classes are:

**Low Susceptibility**: indicated as the low hazard class (colour code-green): Areas for which the combination of factors is less likely to adversely affect the stability provided that the existing ground conditions are not radically altered to facilitate site development.

**Moderate Susceptibility**: indicated as the moderate hazard class (colour code- yellow): Areas for which the combination of factors may adversely influence slope stability.

**High Susceptibility**: indicated as the high hazard class (colour code- red): Areas for which existing ground conditions are likely to create serious landslide problems. In general, these areas are unsuitable for site development. The cost of carrying out standard geologic-geotechnical investigations and remedial/preventive work for slope stabilization may be very high. Therefore, it is best to avoid these slopes as far as possible except for the most essential use. A thorough ground investigation report by competent persons should be required before any site development is undertaken.

After calculating the weights for each of the factors in relation to the occurrence of landslides, to obtain the final weight map from each of the models (scenarios), all the weights of the factor maps were added using the following command statement in ILWIS 3.3 version.

\[
W_{\text{final}} = w_{\text{slop}} + w_{\text{aspcls}} + w_{\text{geol}} + w_{\text{roadis}} + w_{\text{subgp}} + w_{\text{depth}} + w_{\text{texture}} + w_{\text{FA}} + w_{\text{landcover}}.
\]

Where:
- \( w_{\text{slop}} \): weight map for the Slope gradient factor
- \( w_{\text{aspcls}} \): weight map for the Slope Aspect factor
- \( w_{\text{geol}} \): weight map for the Geology Factor
- \( w_{\text{roadis}} \): weight map for the Road distance factor
- \( w_{\text{subgp}} \): weight map for the Soil Sub group factor
- \( w_{\text{depth}} \): weight map for the Soil Depth factor
- \( w_{\text{texture}} \): weight map for the Soil texture factor
- \( w_{\text{FA}} \): Weight map for the Flow Accumulation Factor
- \( w_{\text{landcover}} \): weight map for the Land cover factor.

Since three models were used, three final weight maps were produced. Using the slicing operation in ILWIS 3.3 version, each of the final weight maps was classified into three hazard classes. Classification was based on histogram information for each of the final weight maps generated from each of the three models. The best scenario was selected. The result was the landslide susceptibility map for each of the models as indicated in Figures 6.14 to 6.16.
Figure 6.14 Showing a landslide susceptibility map (Active slides only)  Figure 6.15 Showing the landslide susceptibility map (Active & Dormant slides)
Figure 6.16 Showing Landslide susceptibility map (All slides)

6.7 Validation of the results

In order to evaluate the performance of the model, scenario 2 was selected. This because it provided better results compared to scenario 1 and 3.

To test the prediction rate, the weighted map from scenario 2 was crossed with the landslide map from the field (2005). The results of the cross are presented in Table 6.8.
Table 6.9 Showing the results from testing the prediction rate of the model used in Scenario 2

<table>
<thead>
<tr>
<th>Susceptibility Class</th>
<th>Percentage of active slides in the class (%)</th>
<th>Percentage of total Area %</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Hazard</td>
<td>84</td>
<td>45</td>
</tr>
<tr>
<td>Moderate Hazard</td>
<td>14.1</td>
<td>17</td>
</tr>
<tr>
<td>Low Hazard</td>
<td>1.9</td>
<td>38</td>
</tr>
</tbody>
</table>

The results in Table 6.9 indicate that 84% of the observed landslides are located in the area predicted to have the highest occurrence of landslides. Since more than 70% of the active landslides are accounted for, then it can be said that the model was a good prediction for the occurrence of landslides in Ang Khang. The results in the table (6.9) indicate that only 45% of the area is highly susceptible to landslides which is less than half of the total area of Ang Khang. This is expected since about half of the area, the Western part if dominated by Limestone which is pervious and therefore not susceptible to landslides.

6.8 Comparison between Ang Khang and Wang Chin (with respect to weights of evidence modelling using morphometric parameters)

Although the original objective could not be met because of the different availability of data, and different Lithological units, some DEM derived factors could be used to compare the two study areas. The DEM for the Wang Chin area was generated from the ASTER image using band 3. Having generated the DEM, the Slope, Aspect and Flow Accumulation were derived and a script (also used in Chapter 6 with respect to Ang Khang) was run to establish the weights of these three factors with the occurrence of landslides. The resultant weights were then tabulated and compared to the weights of the similar factors in Ang Khang. The final weights for the Slope gradient, Aspect and Flow Accumulation maps for the two areas are presented in Table 6.9 and a comparison made.

The weights that are bolded (Table 6.10) are the positive weights of the classes in the factor maps under investigation with respect to the occurrence of landslides.
Table 6.10 Showing the weights of the morphometric parameters in Ang Khang and Wang Chin

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Ang Khang</th>
<th>Wang Chin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>WFINAL</td>
<td>WFINAL</td>
</tr>
<tr>
<td>0 – 6.5 degrees</td>
<td>-1.5936</td>
<td>-1.9420</td>
</tr>
<tr>
<td>6.5 – 12.5 degrees</td>
<td>-0.8178</td>
<td>0.4454</td>
</tr>
<tr>
<td>12.5 – 22.5 degrees</td>
<td>-0.0088</td>
<td>0.6509</td>
</tr>
<tr>
<td>22.5 – 45 degrees</td>
<td>0.3977</td>
<td>0.4525</td>
</tr>
<tr>
<td>&gt;45 degrees</td>
<td>-0.9819</td>
<td>0.3176</td>
</tr>
<tr>
<td>Aspect</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North</td>
<td>-1.2193</td>
<td>-0.9283</td>
</tr>
<tr>
<td>North East</td>
<td>-2.3085</td>
<td>-0.4892</td>
</tr>
<tr>
<td>East</td>
<td>-1.4877</td>
<td>-0.6175</td>
</tr>
<tr>
<td>South East</td>
<td>0.0809</td>
<td>-0.1734</td>
</tr>
<tr>
<td>South</td>
<td>0.6474</td>
<td>0.5132</td>
</tr>
<tr>
<td>South West</td>
<td>0.8550</td>
<td>0.8592</td>
</tr>
<tr>
<td>West</td>
<td>0.6012</td>
<td>-0.1190</td>
</tr>
<tr>
<td>North West</td>
<td>-0.1287</td>
<td>0.2019</td>
</tr>
</tbody>
</table>

Using the results presented in Table 6.10, with respect to slope gradient, in Ang Khang slopes with a gradient between 22.5 and 45 degrees indicate the highest vulnerability to landslides. This was also seen when the landslide map of Wang Chin was overlaid on the slope gradient map, the result indicated slope instability as low as 5 degrees. The other possibility is that whereas in Ang Khang there seems to be no influence of lineaments on slope stability, landslides in Wang Chin might be influenced by the presence of lineaments. Lineaments are lines of weakness which adversely affect the slope stability of any area in which they are located. However since the relationship between lineaments and the occurrence of landslides in Wang Chin was not investigated in this study, a concrete conclusion can not be drawn with regards to their influence on the occurrence of landslides in the area.

Whereas in Ang Khang slopes with a gradient between 22.5 – 45 degrees indicate the highest positive weight, In Wang Chin slopes with a gradient 12.5 – 45 degrees indicate the highest positive weight. Also the weights of the slope gradient map of Wang Chin are relatively higher than those of Ang Khang. Since a positive weight indicates a positive correlation with the occurrence of landslides in an area, then a higher positive value indicates a higher correlation. Therefore it can be concluded that with respect to landslides, slopes seem to play a higher role in the occurrence of landslides in Wang Chin than in Ang Khang.

With respect to Aspect, the slope direction which indicates the highest susceptibility to landslides is the South West direction with similar weights in both areas. In this implies that in both watersheds, the South West facing slopes are more prone to landslides than the other slopes. This could be due to the fact that since both districts are located within a similar local climate in Northern Thailand (about 350 km from each other), and are orientated towards the sun in a comparable way. As a result they are influenced by similar climatic conditions thereby showing similar tendencies towards susceptibility to landslides.
In the case of the Flow Accumulation map, different classes were made because of the difference in the number of cells that contribute water cumulatively in the two areas as was indicated in the histograms for both areas respectively. This could imply that there is a difference in surface runoff in the two areas probably because there is a difference in the amount of rainfall received. However because of the lack of data most especially in the Wang Chin area, this could not be established.

Table 6.11 Showing the weights of the Flow Accumulation in Ang Khang and Wang Chin

<table>
<thead>
<tr>
<th>Class</th>
<th>WFINAL</th>
<th>Class</th>
<th>WFINAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - 3</td>
<td>-1.3133</td>
<td>1 – 5</td>
<td>0.2200</td>
</tr>
<tr>
<td>3 - 6</td>
<td>0.5660</td>
<td>5 - 22</td>
<td>0.1800</td>
</tr>
<tr>
<td>6 - 16</td>
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A number of conclusions can be drawn with respect to the water accumulation on slope in the Ang Khang and Wang Chin catchments as indicated in Table 6.11.

Whereas in Ang Khang the classification of the Flow Accumulation map was not a good one (indicated by the fact that 4 out of 5 classes had positive weights), whereas the results from Wang Chin indicate that the classification was better. In Ang Khang, flow accumulation is influenced by the presence of Karts formations and sink holes as a result of the presence of limestone in the area. Since limestone is more pervious than Shale, ground water flow is inevitably improved in Ang Khang.

On the contrary, in Wang Chin, there seems to be no indication of Limestone and presence of Karst formations or sink holes. Flow accumulation classes between 1 – 22 indicate a good correlation with the occurrence of landslides while the higher classes indicate negative higher values. The morphometric parameters from both areas are really different and if we were to use those from one area in another there would be a problem. This is typical of soils derived from Shale which are clayey in nature and therefore impervious thus reducing ground water flow and accumulation. This is in agreement with (Way 1973) who observed that Shale related soils are prone to landslides because they are impervious and so absorption of water on their part, increases their weight thus increasing their instability.
6.9 Conclusions

The main objective of this Chapter was to assess the landslide conditioning factors and then use them to predict the future occurrence of landslides in the area. Based upon the results discussed in the sections above, the following conclusions were drawn.

The model from Scenario 2, which used active and dormant slides, provided better results in comparison to the other 2 models. If only active landslides are considered, then the sample under consideration is too low. Stable landslides are those landslides which do not indicate an active state of activity as defined by (Cruden and Varnes 1996). When investigating the state of activity of landslides in a given area, priority should be given to those landslides which indicate their state of activity and have not been stabilised either by human activity or vegetation (Crozier 1986; Cruden and Varnes 1996).

The weights of evidence model is a good predictor for the future occurrence of landslides once the landslide inventories (for various periods in time) are available. A combination of field work, secondary data and aerial photo interpretation is important in identifying and mapping the landslide conditioning factors.

The study reveals that the rock types Shale underlain by Sandstone and Conglomerates are the most vulnerable to Landslides. This is because in all three models they have positive weights indicating a positive correlation with the occurrence of future landslides. This finding is concurrent with field observations. This is due to the fact that Shale is easily weathered leaving it less resistant to landslide triggering factors like rainfall. Another characteristic of Shale which makes it more vulnerable to landslides is the fact that its permeability is poor and this reduces the speed with which it releases water to surrounding areas. As a result of this clay has a lower saturation point and high pore water pressure all of which facilitate the occurrence of landslides.

In terms of Slope gradient, Slopes with a gradient between 22.5 degrees and 45 degrees are the most vulnerable. This is because they indicated the highest positive weight (a good correlation with the occurrence of landslides) in comparison to the other slope gradient classes. With respect to Aspect, the South West facing slopes showed a good correlation with the occurrence of landslides and therefore play a vital role in the occurrence of landslides.

With respect to Soil, Soil Subgroup Ultic with a Soil textural class of Slightly Gravely Clay Loam and a moderately Deep to Deep Soil depth indicated the highest correlation with the occurrence of landslides. These type of soils are predominant in areas with degraded forests which indicated a high correlation with the occurrence of landslides. This is largely due to human influence. Deforestation involves the cutting of trees which act as slope stabilisers by their ability, through their roots, to hold the soil together and also absorb water which if in case (in clay soils) will facilitate the sliding of the soils thus the occurrence of landslides (Crozier 1986).

Soils derived from Shale (Sedimentary rocks) are commonly found to have a moderate to deep depth and the presence of clay which has a high correlation with the occurrence of landslides (as a result of its poor porosity) (Way 1973).
The study area may not have a historical record of the landslides but their threat cannot be ignored. It is therefore imperative that remedial and preventive measures are designed to protect life and property from future landslides.
Chapter 7: Conclusions, Recommendations and Limitations of this study

7.1 Conclusions

The main objective of this study was to investigate whether analysis of factors causing landslides in one area (Wang Chin in Northern Thailand), where landslides have been caused by a major rainfall event, can be used for building a model to assess landslide susceptibility in another area which has not had recent landslides (Ang Khang). A further objective was to evaluate the use of digital image processing for landslide mapping.

The specific objectives could be divided into three and they include Analysis of rainfall data, use of Digital Image analysis techniques to map landslides and susceptibility modelling using weights of evidence modelling.

The use of the Gumbel Extreme value method in Analysis if rainfall data yielded good results for Ang Khang but not for Wang Chin. This is because Wang Chin had a very small data set (8 years) while Ang Khang had a fairly good amount of rainfall data (6 years). With reference to Chapter three Section 3.4, in the case of Wang Chin, analysis of rainfall data yielded poor results because of the small data set. Therefore the return period in this area cannot be relied upon. With respect to Ang Khang, the data set was of 16 years and so the results are fairly good. However in all it can be noted that prediction of the return periods gives us the range within a rainfall amount is to be expected.

Satellite Imagery, such as ASTER which was used in this study, can be used to map landslides. However better results are obtained when they are combined with aerial photo interpretation. The Maximum Likelihood Supervised classification algorithm with intensity normalisation provided the best results in comparison with the other selected algorithms. The best band combination, with respect to this study was that which included bands 2, 3N (both from the VNIR region of the spectrum) and 4 from the (SWIR region).

The results (see Chapter 4 Table 4.3) indicate that the use of a SWIR band with VNIR band in digital image improves the results from the classification. This is because bands in the SWIR of the spectrum make use of the short waves which are vital for high temperature detection (ERSDAC 2005). This is because landslides modify the spectral properties of vegetated slopes and weathered rock surfaces, exposing bright soils and bare rock surfaces. Bare rock surfaces would thus have higher reflectance than vegetated surfaces thus the unvegetated scars can be clearly identified and classified. The scars left behind have a higher reflectance especially if they are not revegetated since its bare soil. As a result the unvegetated scars can easily be recognized by virtue of a higher reflectance. This therefore results in an improvement on there reflectance characteristics of the features on the image under investigation(Lillesand, Kiefer et al. 2004).

As the study area in northern Thailand is in a tropical environment, most of the new landslides are quickly covered by vegetation. From photo interpretation it was not clear whether they were stable, dormant or stabilised. (Cruden and Varnes 1996) suggest that within regions, standard criteria can be developed to help in distinguishing between different landslides. These criteria could be used to
describe the growth of vegetation on the landslide scars. But with the lack of a historical landslide database to compare with and establish possible dates of occurrence of most of the landslides that were recognised in the aerial photos of Wang Chin a simplified nomenclature was adopted. Field work was not possible as the landslide areas were not accessible.

Landsliding is a complex process that involves the interaction of different factors such as terrain topography, land cover, climate, etc. In particular, rainfall induced shallow landslides take place in Northern Thailand affecting many areas thus the identification of slope instability indicators is necessary.

The use of factors such as topography, soil, geology, and vegetation is important in landslide susceptibility analysis and could provide a quick and cheap analysis (Turner and Schuster 1996). These factors were available and used in landslide susceptibility mapping in Ang Khang.

The landslide conditioning factors identified in Ang Khang included rock types of Shales, Sandstones and Conglomerates, slopes with a gradient range between 22.5 to 45 degrees combined with Slightly Gravelly Clay Loam soils. All these factors play an important role in the occurrence of landslides in Ang Khang.

The model which made use of active and dormant landslides as the landslide evidence map in predicting future landslide occurrence yielded better results (with respect to this study) than using only active landslides or all available landslides in the area. This is based on the fact that about 90% of the active landslides in Ang Khang could be explained by 40% of the map with the highest susceptibility scores. Concerning the prediction rate, the model predicted that 84% of the landslides occur in the class which is highly susceptible to landslides, 14.1% in the class which is moderately susceptible and 1.9% of the landslides in the class which is less susceptible to landslides.

As to the areas that are prone to landslides, the Eastern part (running from North to South) is the Ang Khang area which indicated the highest vulnerability to the occurrence of landslides with a South West Slope Aspect.

7.2 Recommendations

Having made conclusions in section 7.1, some recommendations ought to be made with respect to the two study areas and they are presented in Section 7.2 below.

7.2.1 Ang Khang

Concerning the mitigation of landslides in this watershed, the following recommendations have been made.

The stability of the landslide prone areas could be improved by increasing the factor of safety. This can be done by eliminating the slope, removing the unstable soil and rock materials, or applying one or more appropriate slope stabilization methods (such as buttress fills, sub drains, soil nailing, crib walls, etc.). This is theoretically true, in practice it is expensive and may even increase slope instability once the weight on the point of weakness is increased. For deep-seated slope instability, strengthening the
design of the structure (e.g., reinforced foundations) is generally not by itself an adequate mitigation
measure.

With respect to rotational slides (slumps), which are the dominant type of landslides experienced in
Ang Khang, the main cause of instability is loss of shear strength, and road construction resulting in
sliding of a soil or rock mass along a rupture surface within the slope. As a result the following
mitigation measures could be applied.

- **Reduce driving force**, by reducing the weight of the potential slide mass (cutting off the head
  of the slide, or totally removing the landslide), flattening the surface slope angle (‘laying back’
  the slope face) through grading, preventing water infiltration by controlling surface drainage,
  or reducing the accumulation of subsurface water by installing sub drains; (Turner and
  Schuster 1996; Thampi and Mathai 1998), and/or

- **Increase resisting force**, by replacing slide debris and especially the rupture surface with
  compacted fill, installing shear keys or buttresses, dewatering the slide mass, pinning shallow
  slide masses with soil or rock anchors, reinforced caissons, or bolts, or constructing retaining
  structures at the edge of the slide (Kockelman 1985; Popescu 2005).

Since results indicated that the most susceptible land cover were degraded forests, the people of Ang
Khang ought to plant more trees to restore the lost forests and thereby increasing the stability of the
region since it is of a rugged terrain and so prone to landslides with once a sufficient amount of rainfall
is received. In addition to this the slopes which were exposed as a result of the road constructions
could be layered with concrete and the soils nailed.

### 7.2.2 Wang Chin

Further studies should be carried out in Wang Chin to establish the factors which cause landslides in
this area and also the landslide prone areas. In addition to this the type of landslides endemic to this
area ought to be identified. Based upon this, it is therefore recommended that a comprehensive study
be carried out to establish the landslide conditioning factors in Wang chin and how they differ from
those in Ang Khang.

It is also recommended to carry out studies to establish whether landslide conditioning factors are
identified in one area and tested in another area. Although preliminary results indicate that this is not
possible with respect to Ang Khang and Wang Chin, it might be possible for other areas.

In addition to this, studies ought to be carried out to establish the influence of lineaments on the
occurrence of landslides in the Wang Chin water shed. There is also a need to study the threshold
values for the occurrence of landslides for the factors under investigation.

Further research should be carried out on the use of ASTER images for mapping landslides. Although
the results obtained in this study are weak, they could be improved by the use of Level 2 images which
are corrected for Aspect.
In general, while it is not always possible to prevent slope failures occurring within an area, it is sometimes possible to protect the site from the run out of failed slope materials. This is particularly true for sites located at or near the base of steep slopes which can receive large amounts of material from shallow disaggregated landslides or debris flows. Methods include catchment and/or protective structures such as basins, embankments, diversion or barrier walls, and fences (Wu 1995). Diversion methods should only be employed where the diverted landslide materials will not affect other sites.

To carry out a comparative study (with respect to morphometric parameters) between the Ang Khang and Wang Chin area, a topographic map would have been of great use. Contours could have been extracted and a DEM generated with limited errors.

In addition to a topographic map a large rainfall data set, a detailed geological map, detailed soil map and temporal landslide data would have made the analysis of the landslide conditioning factors in Wang Chin easier. Also the comparison to Ang Khang would have been more meaningful.

### 7.3 Limitations.

Although this study has come to an end, some limitations ought to be mentioned.

Lack of time.

Two study areas, Ang Khang and Wang Chin were selected for use in this study but a comprehensive study on the landslide conditioning factors in the second area (Wang Chin) was hampered because of lack of data. For example the rainfall data was insufficient, the Geology map was too general (at a scale of 1:250,000) and as a result the landslide conditioning factors for this area could not be established satisfactorily. The discussions made relied on visual interpretation and preliminary findings.

There was not sufficient time to obtain a level 2 ASTER image to carry out landslide mapping using a radiometrically corrected satellite image. It was hoped that the results obtained from mapping landslides using digital image analysis techniques would have been better with the use of a radiometrically corrected image.

There was insufficient field verification in the Wang Chin area. In addition, there was a lack of a good DEM for the Wang Chin area. The DEM used was derived from the ASTER image which had unknown errors. Another limitation was the lack of good rainfall data which made it difficult to explain why the rainfall event only caused so many landslides in a localised area in Wang Chin.

In the case of Ang Khang, there was lack of temporal landslide information.
References


APPENDICES

Appendix 1: Showing a record of the Field Sample Points as kept while doing Field work.

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<td>30</td>
<td>1</td>
<td>SF</td>
<td>BSELE</td>
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</tbody>
</table>

Where:
- Station ID refers to the point from which the sample was taken.
- X, Y are coordinates taken for the point.
- Z is the Elevation.
- Landslip is the Landslide Type.
- Subtype is the Landslide Subtype.
- Depth is the Depth of the Scarp.
- Width = the Width of the scarp.
- Length = the Length.
- Soil = The Soil texture.
- Mate = material of the landslide.
- Slope = Slope percentage.
- SA = State of Activity.
- Lancover = Land cover.
- LITH = Lithology.
## Appendix 2: Field checklist for landslides

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Date:</th>
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### General information

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<tr>
<th>OP</th>
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<th>Photo- Number</th>
<th>GPS</th>
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<tbody>
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<tbody>
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</tbody>
</table>

### Landslide description:

#### Landslide type

- 1. Fall
- 2. Topple
- 3. Slide
- 4. Spread
- 5. Flow
- 6. Creep
- 0. Unknown

#### Material involved

- 1. Rock
- 2. Debris
- 3. Earth

#### Subtypes

- 1. Rotational
- 2. Translational
- 3. Wedge
- 4. Complex
- 5. Unknown

#### States of activity

- 1. Active
- 2. Suspended
- 3. Reactivated
- 4. Abandoned
- 5. Dormant
- 6. Stabilized
- 7. Stabilized
- 8. Relict
- 0. Unknown

#### Distribution of activity

- 1. Advancing
- 2. Retrogressive
- 3. Enlarging
- 4. Diminishing
- 5. Confined
- 6. Moving
- 7. Widening
- 0. Unknown

#### Styles of activity

- 1. Complex
- 2. Composite
- 3. Successive
- 4. Single
- 5. Multiple
- 0. Unknown

#### Age

- 1. Recent Landslides
- 2. Old Landslides

#### Width

- 1. Very Wide (> 25m)
- 2. Wide (10-25 m)
- 3. Moderate (2-10 m)
- 4. Shallow (< 2 m)
- 0. Unknown

#### Depth of landslide

- 1. Very Deep (> 25m)
- 2. Deep (10-25 m)
- 3. Moderate (2-10 m)
- 4. Shallow (< 2 m)
- 0. Unknown

#### Total landslide length

- 1. 0 - 50 m.
- 2. 50 - 100 m.
- 3. 100 - 250 m.
- 4. > 250 m.
- 0. Not determined
## Important factors for occurrence of landslide:

<table>
<thead>
<tr>
<th>Lithology</th>
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<tbody>
<tr>
<td>Soils</td>
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<td>Landuse/Landcover</td>
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<tr>
<td>Gemorphology</td>
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<td>Topography</td>
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<tr>
<td>Other causes</td>
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</tbody>
</table>

**Explain in words why the landslide has occurred at this place:**

**Please sketch the landslide:**
Appendix 3: Script used for calculating the weights of the Factor maps in the three scenarios (in ILWIS version 3.3)

The parameter %1 refers to the name of the factor map. It should be less than 7 characters long.
// Make sure that each map has a domain with the same name
//The landslide map is parameter %2 It should have 1 or 0 values.

//FIRST WE WILL DELETE EXISTING RESULT FILES
// the crosstable s%1.tbt
//The attribute table %1.tbt
// and we make a new attribute table

del s%1.*
del w%1.*
del %1.tbt
crtbl %1 %1

//NOW WE CROSS THE FACTOR MAP WITH THE ACTIVITY MAP
// This activity map was create with the script WEIGHTIN
// The cross table is called s%1
s%1=TableCross(%1.mpr,%2.mpr,IgnoreUndefs)
calc s%1.tbt

//Now we calculate one column in the cross table to indicate only the pixels with landslides.
Tabcalc s%1 npixact=iff((%2=1),NPix,0)

//NOW WE USE AGGREGATION FUNCTION, WITH OR WITHOUT A KEY TO CALCULATE:
//NCLASS = number of pixels in the class. We sum the values from columns Npix and group them by %1
//nslclass = number of pixels with landslides in the class.We sum the values from columns Npixact and group
//nmap = number of pixels with landslides in the map. We sum the values from columns Npix and don't group
//nslide = number of pixels with landslide in the map. We sum the values from columns Npixact and don't
//THE RESULTS ARE NOT STORED IN THE CROSS TABLE S%1 BUT IN THE ATTRIBUTE TABLE
%1

Tabcalc s%1 %1.nclass = ColumnJoinSum(s%1.tbt,Npix,%1,1)
Tabcalc s%1 %1.nslclass = ColumnJoinSum(s%1.tbt,Npixact,%1,1)
Tabcalc s%1 %1.nmap = ColumnJoinSum(s%1.tbt,Npix,,1)
Tabcalc s%1 %1.nslide = ColumnJoinSum(s%1.tbt,Npixact,,1)

//NOW WE CALCULATE THE FOUR VALUES NPIX1 - NPIX4 AS INDICATED IN THE EXERCISE BOOK. THIS IS DONE IN THE ATTRIBUTE TABLE
// We correct for the situation when Npix1 - Npix3 might be 0 pixels, and change it into 1 pixel

Tabcalc %1 npix1 = IFF((nslclass>0), nslclass, 1)
Tabcalc %1 npix2 = IFF((nslide-nslclass)=0, 1, nslide-nslclass)
Tabcalc %1 npix3 = IFF((nclass-nslclass)=0, 1, nclass-nslclass)
Tabcalc %1 npix4 = nmap-nslide-nclass+nslclass

// NOW WE CALCULATE THE WEIGHTS IN THE ATTRIBUTE TABLE
Tabcalc %1 wplus {dom=value.dom; vr=-10:10:0.00001} =
LN((npix1/(npix1+npix2))/(npix3/(npix3+npix4)))
Tabcalc %1 wminus {dom=value.dom; vr=-10:10:0.00001} =
LN((npix2/(npix1+npix2))/(npix4/(npix3+npix4)))

// NOW WE CALCULATE THE CONTRAST FACTOR
Tabcalc %1 Cw = wplus - wminus

// NOW WE CALCULATE THE FINAL WEIGHT
// The final weight is the sum of the positive weight and the negative weights of the other classes
Tabcalc %1 WminSum = aggsum(wminus)
Tabcalc %1 Wmap = wplus + WminSum - Wminus

// NOW WE MAKE AN ATTRIBUTE MAP OF THE FINAL WEIGHTS
w%1.mpr = MapAttribute(%1,%1.Wmap)
calc w%1.mpr