



Evaluation of GIS-based topographic attributes and a soil wetness model for assessing landslide potential in the Middle Fork of the Payette River catchment, Idaho
by Mandy Alicia Lineback

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in
Earth Sciences
Montana State University
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Abstract:

Landslides on public lands result in loss of roads, removal of soil and vegetation, and sedimentation in rivers and streams. These problems have been exacerbated as demands for forest resources have increased, and road construction and logging activities have progressed to steeper areas that are more susceptible to landslides. Geographic information systems (GIS) provides a tool to analyze attributes contributing to landslides and to predict landsliding on public lands. The use of both deterministic hydrologic models and terrain analysis within a GIS for landslide prediction needs to be tested. This study examined: (1) which topographic attributes contribute most significantly to landsliding and (2) whether the process-based soil wetness model, DYNWET, predicts landsliding better than solely using topographic attributes for the 875 km² Middle Fork of the Payette River, Idaho catchment. Field mapped landslide points were used to validate each attribute's predictive capabilities. Thirty meter digital elevation model (DEM) data were used to calculate both the terrain attributes and DYNWET wetness index.

A sensitivity analysis was conducted to determine the sensitivity of DYNWET to soil input parameters; depth, hydraulic conductivity, and porosity, and to the critical drainage time since last rainfall. DYNWET was found to be relatively insensitive to all of these input parameters.

A chi-square analysis was conducted comparing "actual" and "expected" values of each topographic attribute and the wetness index within landslide and non-landslide cells. Elevation and slope had the strongest statistical association with landsliding in the study area.

To determine which combinations of variables should be used to predict landslides, a Bayesian analysis was performed. Probability grids resulted from this analysis. These grids were overlaid with the known landslides to determine how well the variables predicted mass movement. Results from the overlay indicated that elevation combined with slope provides the best prediction of landslides in the study area. Elevation, however, was used as a surrogate for vegetation cover, land use, and climate and may not be a good prediction variable in other settings. DYNWET was found to be ineffective at predicting landslides in the catchment.

In general, this research showed that a Bayesian probability approach has the potential to provide useful landslide predictions and hazard maps. A map produced from the analysis showed 40 percent of the landslides occurred in areas with high predicted probability which makes up 8 percent of the watershed. A moderate probability area makes up 22 percent of the catchment, while 40 percent of the landslides occur there. A low probability area makes up 23 percent of the catchment, while 15 percent of the landslides occur there. A very low probability area makes up 47 percent of the area, while 5 percent of the landslides occur there. Results might be improved with finer resolution DEMs and better maps of land use and land cover at regional scales.

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A thesis submitted in partial fulfillment
of the requirements for the degree

of

Master of Science

in

Earth Sciences

MONTANA STATE UNIVERSITY
Bozeman, Montana

August 1998

N378

26463

ii

APPROVAL

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This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

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ACKNOWLEDGMENTS

I would like to thank my advisor and committee chair, Dr. Andrew Marcus for his guidance and assistance throughout this research. I would like to also thank Dr. Richard Aspinall for lending his support to this project and serving on my thesis committee. Special gratitude should be given to Dr. Steve Custer for proposing this thesis topic and for serving on my thesis committee. I would also like to thank the Department of Earth Sciences at MSU for financial support in the form of teaching assistantships and the Geographic Information and Analysis Center for the technical expertise necessary to complete this project. Kim Rehm and Ann Parker deserve recognition for always supporting me with words of encouragement and helping me with scheduling.

I also need to thank the Intermountain Research Station of the Boise National Forest located in Boise, Idaho and especially Carolyn Bohn for allowing me to use their landslide database in this research. I also appreciate Tom Jackson of the Emmitt Ranger District of the Boise National Forest for assisting me with approximate locations of roads and timbering in the study area. Thanks to the girls in the GIAC, Ute Langner and Andrea Wright for always taking the time to help me. Thanks to Jason Griztner for listening.

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ABSTRACT

Landslides on public lands result in loss of roads, removal of soil and vegetation, and sedimentation in rivers and streams. These problems have been exacerbated as demands for forest resources have increased, and road construction and logging activities have progressed to steeper areas that are more susceptible to landslides. Geographic information systems (GIS) provides a tool to analyze attributes contributing to landslides and to predict landsliding on public lands. The use of both deterministic hydrologic models and terrain analysis within a GIS for landslide prediction needs to be tested. This study examined: (1) which topographic attributes contribute most significantly to landsliding and (2) whether the process-based soil wetness model, DYNWET, predicts landsliding better than solely using topographic attributes for the 875 km² Middle Fork of the Payette River, Idaho catchment. Field mapped landslide points were used to validate each attribute's predictive capabilities. Thirty meter digital elevation model (DEM) data were used to calculate both the terrain attributes and DYNWET wetness index.

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To determine which combinations of variables should be used to predict landslides, a Bayesian analysis was performed. Probability grids resulted from this analysis. These grids were overlaid with the known landslides to determine how well the variables predicted mass movement. Results from the overlay indicated that elevation combined with slope provides the best prediction of landslides in the study area. Elevation, however, was used as a surrogate for vegetation cover, land use, and climate and may not be a good prediction variable in other settings. DYNWET was found to be ineffective at predicting landslides in the catchment.

In general, this research showed that a Bayesian probability approach has the potential to provide useful landslide predictions and hazard maps. A map produced from the analysis showed 40 percent of the landslides occurred in areas with high predicted probability which makes up 8 percent of the watershed. A moderate probability area makes up 22 percent of the catchment, while 40 percent of the landslides occur there. A low probability area makes up 23 percent of the catchment, while 15 percent of the landslides occur there. A very low probability area makes up 47 percent of the area, while 5 percent of the landslides occur there. Results might be improved with finer resolution DEMs and better maps of land use and land cover at regional scales.

CHAPTER I

INTRODUCTION

Scope and Purpose

Mass movement causes damage with a value between one and two billion dollars in losses each year in the United States (Highland and Brown III, 1996). Landslides on public lands result in loss of roads, removal of soil and vegetation, and sedimentation in rivers and streams. These problems have become worse as demands for forest resources have increased, and road construction and logging activities have progressed to steeper areas that are more susceptible to landslides (Megahan et al., 1978). The increasing economic and environmental costs of landslides have heightened the concern of resource management agencies and established the need for more research to predict and reduce future landslide events on public lands.

Several variables influence landslides. These include vegetation, land use, road density, lithology, areas of faulting, seismic variables, slope, and soil moisture (Hadzinakos et al., 1991; Anbalagan, 1992; Pachauri and Pant, 1992; Maharaj, 1993; Ohmori and Sugai, 1995; Sarkar et al., 1995). Landscape shape may direct soil and ground water to areas of higher landslide potential (Megahan et al., 1978; Barling et al., 1994; Montgomery and Dietrich, 1994), but few studies have explored the use of hydrologic models or terrain analysis to predict landslide locations. Computer models,

and in particular, the combination of terrain analysis models with geographic information systems (GIS) may enhance landscape scale prediction of landslides.

The terrain model, TAPES-G and the wetness index model, DYNWET, have characteristics which might be expected to predict the location of landslides. TAPES-G (Gallant and Wilson, 1996) uses digital elevation models (DEMs) to derive terrain-based indices. DYNWET (Barling et al., 1994) is a model that predicts the spatial distribution of soil water content and the location and areal extent of zones of surface saturation in landscapes. If the shape of the landscape and the way water moves down slope influences landslides, then terrain analysis techniques and a soil wetness model may be able to successfully predict landslide location. An area of the Idaho Batholith was chosen as the study site for this research because geology in the Batholith is largely uniform and data on landslides are available for the area.

This study evaluates: 1) which topographic and hydrologic variables, as determined from GIS analysis using a DEM and the terrain model, TAPES-G, contribute most significantly to landslide events in the Idaho Batholith; 2) whether or not an association exists between the wetness index predicted by the soil moisture model, DYNWET, and the location of landslides in the Batholith; and 3) if the wetness index improves prediction of landslide potential over predictions based solely upon topographic parameters. The statistical probability model, BAYES, (Aspinall, 1992) is used to determine whether or not DYNWET improves landslide prediction over topographic attributes.

This approach to landslide prediction is significant because it may contribute to modeling techniques and in turn to hazard assessment of areas prone to landsliding. The study will contribute to modeling by determining whether the model approach can locate landslides and determine which topographic attributes best predict position. This study will also test whether the use of topographic attributes alone can adequately predict landslides and whether a process-based wetness model can enhance prediction. If successful, such a model may provide a simple method by which land managers can model landslide-prone areas within a GIS framework.

CHAPTER II

LITERATURE REVIEW

Methods for assessing landslide hazards usually fall into one of two broad categories: stochastic/statistical models and process-based, or deterministic models. Stochastic/statistical modeling approaches include: (1) multivariate statistical analyses of landscape characteristics associated with past landsliding (Jibson and Keefer, 1988; Pike, 1988; Carrara, 1989; Anbalagan, 1992; Maharaj, 1993; DeYoung, 1996); and (2) weighted hazard ratings based on environmental attributes related to landsliding (Bernknopf et al., 1988; Gupta and Joshi, 1990; Hadzinakos et al., 1991; Pachauri and Pant, 1992; Gökceoglu and Aksoy, 1996). The process-based approaches use deterministic models based on key geomorphic, hydrologic, geologic, and vegetation data (Okimura and Kawatani, 1986; van Asch et al., 1993; Montgomery and Dietrich, 1994; Miller, 1995; Van Westen and Terlien, 1996). Process-based methods usually couple landslide location with physical data collected either in the field or acquired digitally.

Landslide Prediction Variables and GIS

Shear stress is widely used to assess whether a landslide will occur. The stability of a slope is based upon the ratio between the shear stress (T), which tends to set the mass into motion, and the shear strength (S) of the materials, which resists motion (Hadzinakos

et al., 1991). The ratio is sometimes called the factor of safety (F):

$$F = S / T \quad (1)$$

If the strength factors exceed the stress factors, the factor of safety is greater than one, and the slope is stable. If the strength factors are less than the stress factors, the factor of safety is less than one, and the slope is expected to fail. The primary variables affecting the factor of safety in unconsolidated slope materials are cohesion, the internal angle of friction, the bulk density of the material, the depth of the material, the slope angle, the height of the slope, and the maximum pore water pressure conditions.

The strength, density, and hydrologic variables cannot be readily and inexpensively measured over entire landscapes and may be difficult to measure even at one site without the use of geotechnical borehole procedures. Therefore, many researchers have used surrogate variables to estimate the shear stress and strength variables. Maximum pore water pressure has been estimated by potential for groundwater saturation (Anbalagan, 1992) and rainfall (Hadzinakos et al., 1991). Cohesion has been estimated with indices for vegetation (Ohmori and Sugai, 1995), land use (Anbalagan, 1992), and road density (Maharaj, 1993). Lithological setting and composition (Sarkar et al., 1995), areas of faulting (Pachauri and Pant, 1992; DeYoung, 1996), and seismic variables, such as distance to past earthquake epicenters (Jibson and Keefer, 1988) also provide surrogate estimates of cohesion, the internal angle of friction, and bulk density. Slope and associated slope variables are generally measured in the field or taken directly from digital elevation models (DEMs).

Recently, the use of computer-based geographic information systems (GISs) has been shown to facilitate delineation of variables contributing to landslide hazard (Carrara et al., 1991; Miller, 1995). A GIS allows the rapid extraction of pertinent topographic information, such as slope and curvature, from DEMs. A GIS also efficiently organizes spatially distributed data in a digital format and allows assessment of spatial correlation between landslide-causing variables (Gupta and Joshi, 1990; Carrara et al., 1991). In recent years, GIS models have been proposed to predict the spatial distribution of slope instability.

Stochastic/Statistical Models

Three stochastic/statistical models have been compared in a 225 km² study area south of Lanzhou city on the Loess Plateau of China (Wang and Unwin, 1992). In the first technique, sieve mapping, landslide factors are mapped and overlaid using a GIS. Areas where all the overlapping layers meet the criteria for landsliding are considered areas susceptible to landslides. Although this method is simple to implement, its boolean (yes/no) nature produces abrupt spatial discontinuities which do not adequately reflect the degree of hazard or other variables which control movement (Wang and Unwin, 1992). The resulting map from the authors' study, which shows possible unstable areas, was a reasonable assessment of the most extreme hazard potential in the area (Wang and Unwin, 1992).

Weighting factors were also tested at the same site. This method reduces each category of a map layer to a single metric and then adds up the scores to produce an overall index (Wang and Unwin, 1992). Usually, the metric is a score for each category

based on a scale of susceptibility determined by the researcher. The authors' map, using the weighted factors technique, showed areas of high, moderate, and low risk of instability and was a satisfactory assessment of the spatial distribution of hazard according to hazards scientists (Wang and Unwin, 1992).

A specific example of the weighted ranking technique is illustrated by Gökçeoglu and Aksoy (1996). Field observations coupled with statistical analysis of landslide location at a 120 km² area in the Mengen region of Turkey revealed the major features contributing to instabilities. The authors utilized DEMs in a GIS framework to create maps of slope gradient, slope orientation (aspect), relative height of slope, and proximity of slope to drainage. Weights were assigned to different values of each attribute based on known characteristics of landslides. These topographically-derived maps were overlain with a vegetation layer, soil test results, and a two-dimensional stability analysis to produce a landslide susceptibility map based on weighted values for the attributes of each layer. This method created five zones of landslide susceptibility. All landslide areas fell in the zone with the highest hazard ranking. The weighted ranking method performed well (Gökçeoglu and Aksoy, 1996); the zones determined on the map accurately reflected zones of relative susceptibility. This method does not help determine which variables are most important in generating instability. However, this type of landslide hazard mapping is relatively simple to implement.

A third method tested in China is categorical data modeling, which uses regression techniques to determine the probability of landsliding based on aspect, slope, and lithology of previous landslides (Wang and Unwin, 1992). Categorical data

modeling enables each factor contributing to landslides to be optimally weighted based on past information to maximize the predictive capability of final landslide maps. This method yields a more detailed assessment in which the mapped data values can be interpreted as the long-term spatial risk of landsliding. This method also was implemented using well established standard probability methods to search for the most important factors to be included in an assessment. No disadvantages of this method were given.

Carrara et al. (1991) provided another example of a GIS-based multivariate statistical landslide model. The study area covered a 60 km² area in the Umbria region of central Italy. Topographic attributes derived from DEMs were combined with lithologic and vegetative parameters in a GIS, to determine landslide risk based on correlations between landsliding and these attributes. Stepwise discriminant analysis was applied to classify stable and unstable areas on the basis of morphological, geological, and vegetational characteristics. The results from the discriminant analysis were grouped into three classes of risk of landslides: virtually none, low, and relatively high. The estimated risk areas agreed fairly well with field surveys. Multivariate statistical approaches of this type may be appropriate for locating areas in which landsliding is an important process, but they tend to classify relatively large areas into stability types, rather than fine-scale instability patterns (Montgomery and Dietrich, 1994). Moreover, such models tend to be site specific and cannot be used in other locations because of the empirical basis of GIS-based multivariate analysis (Montgomery and Dietrich, 1994).

Deterministic Models

Deterministic, or process-based GIS models, provide an alternative to statistical techniques for predicting sites of slope instability. GIS-based deterministic models specifically include the physical processes involved in landsliding and therefore can better pinpoint causes of mass movement (Miller, 1995). Process models also commonly use site-specific data and therefore model instability at a finer scale than is possible with statistical or weighted ranking hazard mapping. If the information needed for input to these models can be extracted from available topographic, geologic, and soil maps, then such models can be used for regional hazard assessment (Miller, 1995).

With the advent of GIS, deterministic slope stability models have increasingly been used in regional hazard analysis. Slope stability models typically use some variation of the factor of safety, incorporating components of slope, cohesion, and soil moisture. Within a GIS, the most suitable method is one-dimensional modeling because it calculates slope stability on a pixel basis, and is therefore suitable for use in a raster GIS (Van Westen and Terlien, 1996). Slope stability is calculated for the pixels on a map using information from maps of variables such as slope angle, soil depth, soil strength, and depth to ground water.

The attributes needed for deterministic slope stability models may be estimated using numerous methods. Slope components in GIS process-based studies are most often estimated directly from DEMs (Okimura and Ichikawa, 1985; Wang and Unwin, 1992; Montgomery and Dietrich, 1994; Miller, 1995), whereas the cohesion is most typically

measured with mechanical soils tests (Okimura and Ichikawa, 1985; Okimura and Nakagawa, 1988; Miller, 1995;).

The soil moisture component of most slope stability models has traditionally been difficult to estimate. Methods for estimation of soil moisture have included use of groundwater models (Okimura and Ichikawa, 1985; Okimura and Nakagawa, 1988) and process-based hydrologic models (Barling et al., 1994; Montgomery and Dietrich, 1994). Okimura and Ichikawa (1985) and Okimura and Nakagawa (1988) used a grid-based DEM with a model of shallow subsurface groundwater flow under steady rainfall to predict soil moisture. Predicted pore pressure values were used to calculate the stability of individual grid cells, using an infinite slope stability model. Their model correctly identified most of the landslide scars in a small (0.1 km^2) study catchment in the Takenotaira NW test field in Gifu Prefecture, Japan, although many more cells were predicted to be unstable than were actually observed.

Montgomery and Dietrich (1994) accounted for the fact that landslide areas are generally strongly controlled by surface topography through shallow subsurface flow convergence, increased soil saturation, and shear strength reduction. Montgomery and Dietrich combined a steady state rainfall and contour-based flow model, TOPOG, to simulate the spatial pattern of equilibrium soil saturation. This pattern was used to estimate the potential for shallow landsliding, assuming cohesionless soils of spatially constant thickness. Rainfall was applied at differing intensities until the critical rainfall value was reached. Model predictions in each study area were consistent with spatial patterns of observed landslide scars. In the Tennessee Valley catchment, occupying 1.2

km² in California, 78 percent of the actual landslides were predicted to be unstable using the critical rainfall model. For the Mettman Ridge catchment occupying 0.3 km² in the Oregon Coast Range, 84 percent of the actual landslides were predicted to be unstable. In 0.6 km² the Split Creek catchment in the Olympic Peninsula, all of the actual landslides were in locations predicted to be least stable by the model.

The Deterministic Wetness Model, DYNWET

A major limiting assumption of the Montgomery and Dietrich method to landslide prediction is the steady state approach. Barling et al. (1994) developed a quasi-dynamic wetness index, DYNWET, that accounts for variable drainage times since a prior rainfall event, thus relaxing the steady state assumption required by Montgomery and Dietrich (1994). DYNWET uses a simple subsurface flow model, topographic attributes derived from DEMs, and a user-specified drainage time and catchment soil parameters, (soil depth, saturated conductivity, and drainable porosity) to predict zones of surface saturation in a catchment. Barling et al. (1994) tested DYNWET by comparing the index to field measured wetness levels in the 0.07 km² Wagga Wagga catchment in southeastern Australia. They applied two different types of hypothetical rainfall events to the study site for 30 days, one event at 1mm/d for the 30-day simulation period, while in the second event, 30 mm of rainfall occurred during the first 3 hours (at a uniform rate of 10 mm/d). They found that the measured patterns of soil water were in close agreement with the spatial distribution of the DYNWET index, though no exact percentage of accuracy of the wetness index is noted. A series of maps were created which showed that

wetness contours between the known and predicted data were close in value. They found that the steady state model failed to predict the topographic hollows as focal areas of saturation while the quasi-dynamic DYNWET model did predict such zones (Barling et al., 1994). To date, no tests have been performed with the quasi-dynamic wetness index model, DYNWET, to determine if it can be used to enhance landslide prediction.

Literature Review Summary

The use of GIS methods for landslide assessment and hazard prediction has become more prevalent in recent years. GIS provides an efficient way of organizing spatially distributed data in a digital format and therefore has facilitated both landscape scale statistical and process-based modeling. The statistical techniques, which include multivariate correlations and weighted hazard ratings, are relatively easy to apply, but may not adequately reflect the ranges of landslide hazard or identify the controlling factors. Process-based models, on the other hand, may predict landsliding at a finer scale than statistical methods, but usually require more data and may be applicable only at the site being studied. These models also ignore the dynamic nature of soil wetting. Neither stochastic/statistical nor process-based techniques have been used in areas larger than 120 km² (Gökçeoglu and Aksoy, 1996). At this time, a landscape scale landslide analysis using a dynamic wetness model has not been performed. This thesis will develop probability-based estimates of landslide potential based solely on topographic variables extracted from TAPES-G and the quasi-dynamic wetness index, DYNWET.

CHAPTER III

STUDY AREA

The Boise National Forest (BNF) was chosen as a study area for three reasons: 1) the geology and soil characteristics are relatively homogenous throughout the area (Nelson, 1976); 2) landslides in the area were extensively mapped in 1975 (Megahan et al., 1978); and 3) Megahan et al. (1978) and Megahan and Bohn (1989) suggested that seepage forces were important to landslide development in the area. Since DYNWET produces a soil wetness index based on topographic modeling of water through soil, the model may prove useful in predicting areas of instability.

Geology, Topography and Soils

The study area covers 875 km² within the Middle Fork of the Payette River drainage (MFPR) in the BNF portion of the Idaho Batholith (Figure 1). Coarse textured quartz monzonite underlies approximately 65 percent of the study area. Medium to coarse grained granodiorite underlies approximately 32 percent of the study area in a north-south zone on the western side (Anderson, 1947; Nelson, 1976). A small area of quartz diorite underlies approximately 3 percent of the area along the western margins. All of these rocks weather to gruss and differences in rock type are not expected to produce significant differences in landslide potential.

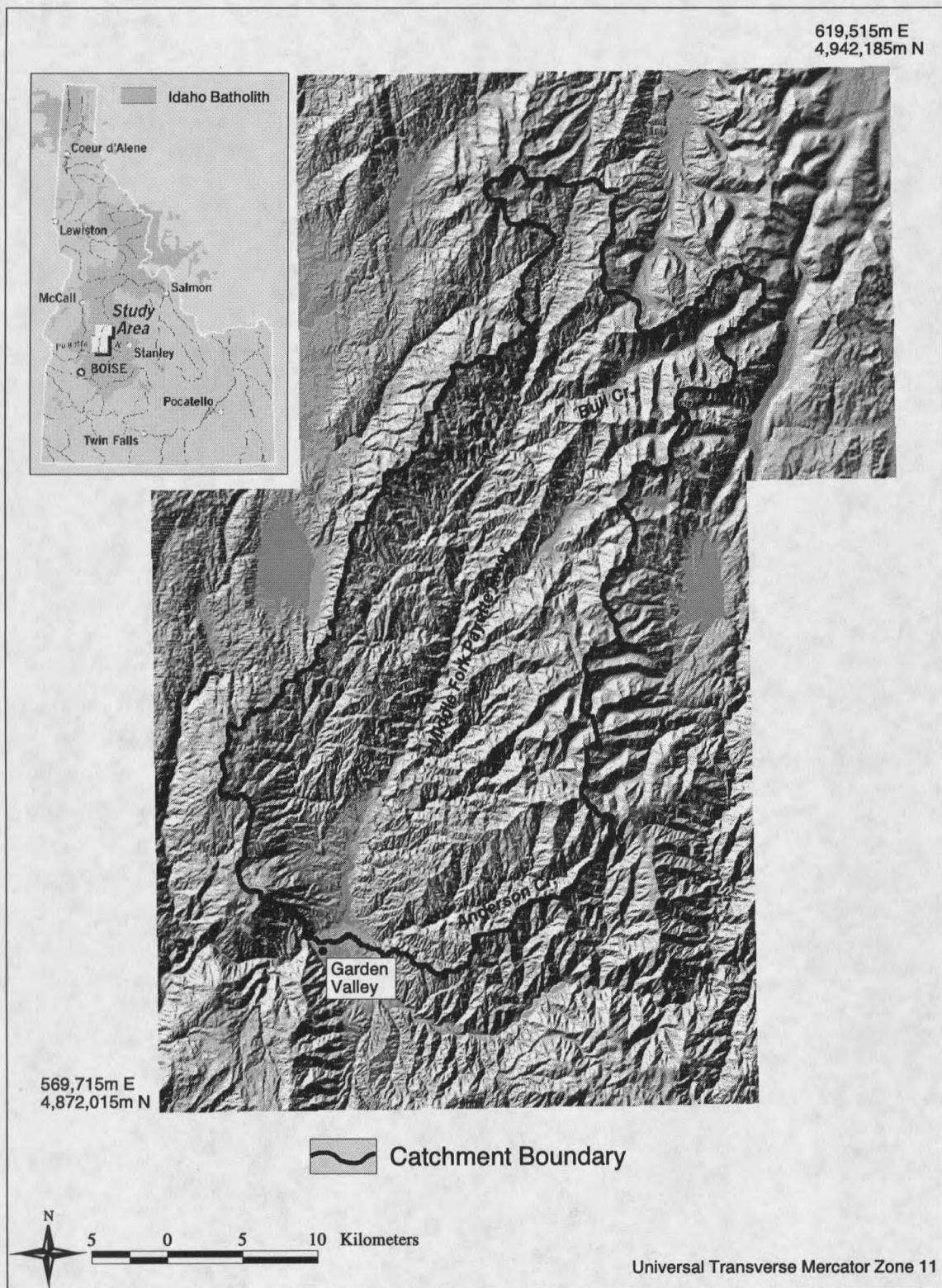


Figure 1. Middle Fork of the Payette River study area and location map.

Elevations in the study area range from approximately 900 to 2,500 m. The majority of slopes fall in the 11-30 degree range (Table 1). The dominant slope aspects of the catchment are southeast and west (Table 2).

Table 1. Slopes of the Middle Fork of the Payette River catchment as determined by TAPES-G with a 30 m DEM.

Degrees slope	Percent area
0-10	11.9
11-20	33.8
21-30	39.9
31-40	13.6
41-50	0.73
>50	0.03

Table 2. Aspect of slopes the Middle Fork of the Payette River catchment as determined by TAPES-G with a 30 m DEM.

Aspect	Cardinal degrees	Percent area
north	0-22, 337-360	8.4
northeast	23-67	8.6
east	68-112	13.4
southeast	113-157	16.0
south	158-202	13.3
southwest	203-247	12.2
west	248-292	14.6
northwest	293-336	13.3
flat	----	0.2

Fourteen soil series exist in the MFPR (Table 3). Mollisols compose 54 percent of the study area and have A horizons which range up to 75 cm thick. More poorly developed entisols and inceptisols occupy the remaining 46 percent of the study area (Table 3). Soils overlay moderately weathered granitic parent material. The depth to

unweathered bedrock is usually between 50 and 150 cm (Nelson, 1976). Soil textures are generally loamy sands to sandy loams.

Table 3. Classification, topographic properties, and approximate area of soil series found in the Middle Fork of the Payette River catchment (from Nelson, 1976).

Soil Series	Family	Order	Degrees Slope	Approx. Area (km ²)	Percent Area
Coski	Coarse-loamy, mixed	Mollisols	20-30	110	14.1
Coski Variant	Coarse-loamy, mixed, frigid	Mollisols	6-20	13	1.7
Koppes	Sandy, mixed	Mollisols	20-30	220	28.1
Naz	Coarse, loamy, mixed	Mollisols	20-30	18	2.3
Scriver	Coarse, loamy, mixed	Mollisols	10-20	58	7.4
Hanks	Coarse, loamy, mixed	Inceptisols	0-10	36	4.6
Josie	Coarse, loamy, mixed	Inceptisols	6-20	32	4.1
Ligget	Coarse, loamy, mixed	Inceptisols	20-30	31	4.0
Bryan	Sandy, mixed	Inceptisols	20-30	53	6.7
Pyle	Mixed	Entisols	20-30	72	9.2
Quartzburg	Sandy-skeletal, mixed, frigid	Entisols	20-30	79	10.1
Toiyabe	Mixed, frigid, shallow	Entisols	20-30	35	4.5
Whitecap	Mixed	Entisols	20-30	4	0.5
Graylock	Sandy-skeletal, mixed	Entisols	20-30	21	2.7

Climate

The climate of the study area is characterized by a warm, relatively dry period during the summer and early fall, followed by a wet late fall, winter and spring (Megahan et al., 1978). This pattern is common in the Rocky Mountain region of the Pacific

Northwest. Average annual precipitation varies with elevation from approximately 500 mm at 900 m to approximately 1,300 mm at 2,500 m (Megahan et al., 1978). Area records indicate that 43 percent of the moisture is received in winter, 25 percent in spring, 9 percent in summer, and 23 percent in fall. A monthly total precipitation greater than 254 mm occurs in one year out of eight. Daily totals of 12.7 mm or more occur on an average 20 days per year, and 25.4 mm or more on four days per year (Nelson, 1976).

Approximately 30 percent of the annual moisture at the lowest elevations and 60 percent at the highest elevations occurs as snowfall. Seasonal snowfall averages between 1,800 mm at low elevations to around 7,700 mm at elevations above 2,000 m. Snowmelt dominates the annual hydrograph with most of the total annual streamflow occurring during the peak snowmelt months of March through May (Megahan and Bohn, 1989).

At Garden Valley, 2.5 km south of the MFPR (Figure 1) at an elevation of 1,050 m, the average monthly maximum temperatures range from 0.6° C in January to 34° C in July, while average monthly minimums range from -8° C in January to 9° C in July.

Land Cover and Landslides

The MFPR drainage is mainly forested. The Douglas-fir (*Pseudotsuga menziesii*) zone is the most extensive zone in the MFPR and occurs at elevations below about 2,300 m. Few of the stands in this zone are pure Douglas-fir. Ponderosa pine (*Pinus ponderosa*) is a co-dominant species on south-facing slopes below 2,000 m, while Subalpine fir (*Abies lasiocarpa*), Engelmann spruce (*Picea engelmannii*), and Lodgepole

pine (*Pinus contorta*) are found in areas of cold-air drainage and along creek bottoms (Nelson, 1976). The spruce-fir zone occurs at elevations above 2,300 m.

Disturbance from roads and timber harvesting exists throughout the MFPR. Approximately 667 km (length) of roads are present in the study area (Jackson, personal communication, 1998). The majority of timber harvest in the study area occurred from approximately 1958 to 1978, though a few areas were logged from 1978 to 1994. The exact amount of area logged is unknown, but probably approaches 35 percent of the study area (Jackson, personal communication, 1998).

Mass movement occurs extensively throughout the study area. Data for 559 landslides were documented on the study area in 1975, however, this estimate is conservative because only events of 8 m³ or larger were sampled and some landslides were probably not detected (Megahan et al., 1978). The landslides sampled were located by: (1) aerial reconnaissance from fixed-wing or helicopter aircraft in inaccessible areas; (2) periodic aerial photography; (3) ground observations by forest workers familiar with the area; and (4) on-site reconnaissance along roads (Megahan et al., 1978). Seventy percent of the landslides are debris slides or debris avalanches, while 19 percent are slumps. Debris flows and torrents, account for 7 percent of the total. Only 2 percent of the mass movements consists of rock fall, all of which occurred on road cuts (Megahan et al., 1978). The average landslide is 12 m in length, 11 m in width, and 0.8 m in depth at the zone of failure. The largest landslide documented on the MFPR is 47.2 m in length, 37.8 m in width, and 2.4 m in depth.

The single most important factor triggering landslides in the study area was road construction, which accounts for 58 percent of the landslides (Megahan et al., 1978). The combination of roads plus timber harvest and/or fire accounted for another 30 percent of the landslides. In total, roads were associated with 88 percent of all documented landslides. Landslides associated with vegetation removal alone accounted for 9 percent of the slides; burning for 7 percent, and logging for 2 percent. Only 3 percent of the landslides occurred on completely undisturbed areas (Megahan et al., 1978).

CHAPTER IV

METHODS

In order to assess the relative ability of the topographic variables and DYNWET to predict landslide location, four general tasks were completed. First, existing landslide data were obtained and entered into a GIS. Second, DEMs of the study area were compiled and input to the TAPES-G model to generate topographic data. Third, the topographic output from TAPES-G was used in DYNWET to model hydrologic conditions. Finally, statistical techniques, including chi-square and a probability analysis using Bayesian statistics, were performed on the model output to determine which combinations of topographic and hydrologic variables provided the best predictions.

Landslide Data, DEMs, and Preprocessing

The Intermountain Research Station mapped and recorded numerous landslides within an 875 km² area in the Boise National Forest (BNF) in 1975 (Megahan et al., 1978). There are ten original 1:24000 scale hand-drawn maps which show the point locations of 559 landslides in the Middle Fork of the Payette River (MFPR) catchment. For this thesis, the field mapped data were digitized into an ARC/INFO coverage as points using the latitude/longitude coordinate system and were then projected into the Universal Transverse Mercator (UTM) coordinate system. Each landslide was given a unique identifier. The point coverages from the ten maps were then joined together as

one large coverage. Because DYNWET is a raster-based model, the vector point coverage of landslides was rasterized to create a grid with a 30 m cell resolution for comparison with the TAPES-G and DYNWET outputs.

The twenty 30 m DEMs covering the study area were obtained from the United States Geological Survey (USGS, 1997). Four are classified as Level 1, meaning they may contain more error than the other 16 DEMs that are classified as Level 2. In fact, visible systematic horizontal banding occurs in each of the Level 1 DEMs. These DEMs were used for analysis, however, because they lie on the perimeter of the MFPR watershed where they have little effect on the computer model outputs and because they are the only DEM data available at the 30 m scale (Figure 2). All 20 DEMs were imported into ARC/INFO using the DEMLATTICE command and were edgematched using the MOSAIC command to create one large DEM of the study area. The MFPR watershed was delineated on the large DEM using the ARC/INFO GRID module command WATERSHED.

Selection of Attributes for Evaluation

Specific topographic and hydrologic attributes important to the development of landslides were evaluated by this study. Slope, aspect, elevation, effective upslope contributing area, flow path length, plan and profile curvatures were chosen as the primary terrain attributes to analyze, based primarily on DEM data availability, ease of generation of the attributes by TAPES-G, and existing literature on landslides (Pike,

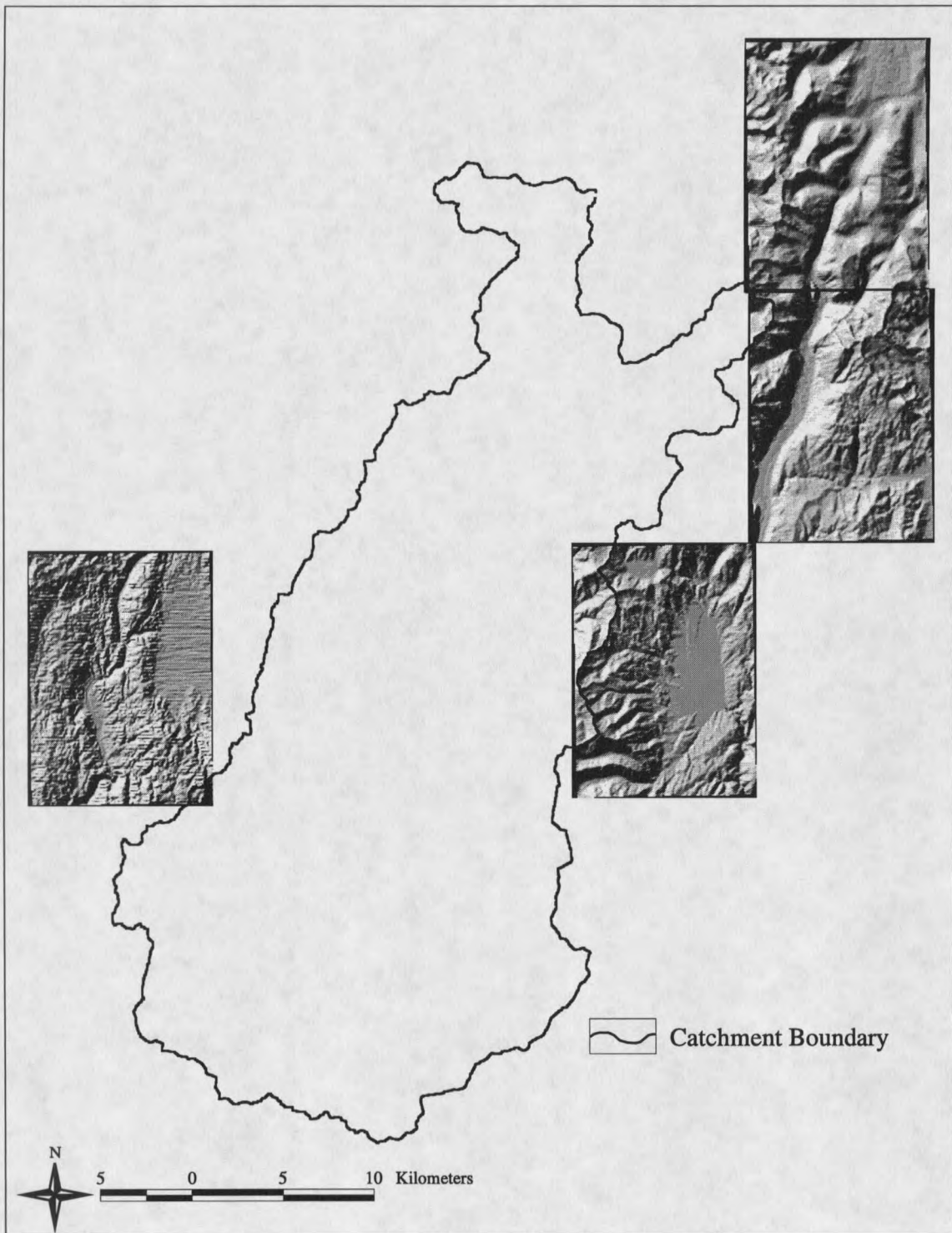


Figure 2. Level 1 DEMs located in the Middle Fork of the Payette River catchment used as input to TAPES-G.

1988; Wang and Unwin, 1992). Soil moisture was also evaluated because existing research indicates this variable affects landslides (Okimura and Kawatani, 1986; Montgomery and Dietrich, 1994).

Geology was considered to be uniform throughout the study area (Nelson, 1976; Ross, 1963). Precipitation and other climatic parameters were not included as variables because data were unavailable at appropriate spatial scales. Furthermore, over larger time spans it is likely that precipitation is relatively uniform across the watershed at a given elevation. Roads and vegetation attributes were not included because data sets of sufficient accuracy were unavailable. Disturbance data, including timber harvest and fire, were not considered in this study, because 97 percent of the landslide samples used in this research were on disturbed land (Megahan et. al., 1978) and adequate data on disturbance location do not exist. Although specific data on land use, precipitation, and vegetation did not exist for this study, elevation data were used as a surrogate for these attributes.

Calculation of Primary Terrain Attributes

Six topographic attributes of the study area were quantified using the grid-based terrain analysis program developed for use in the environmental sciences, TAPES-G (Gallant and Wilson, 1996). The seventh topographic attribute, elevation, was extracted directly from a DEM of the area by TAPES-G. TAPES-G was used because it easily calculates primary terrain attributes, including slope, aspect, upslope contributing area, profile curvature, plan curvature, and flow path length for each cell of a square-grid DEM. Most of the topographic attributes are calculated from the directional derivatives

of a topographic surface. These derivatives are computed using the DEM elevation values directly with a second-order finite-difference scheme.

The large DEM of the study area was converted to an ASCII file and ordered by row for input to TAPES-G. TAPES-G created a depressionless DEM from the original DEM and a flow routing algorithm, FRho8, was used to compute flow directions and upslope contributing area. The FRho8 method was developed to mimic 3-D flow by accounting for flow convergence and divergence (Quinn et al., 1991). The FRho8 algorithm calculates the proportion of upslope contributing area assigned to multiple downslope nearest neighbors on a slope-weighted basis using methods similar to those proposed by Freeman (1991) and Quinn et al. (1991).

TAPES-G produced an ASCII format output file of the seven terrain attributes considered for this study. All attributes calculated by TAPES-G were transferred to ARC/INFO using a FORTRAN program called TAPESOUT, which was written by Robert Snyder at Montana State University's Geographic Information and Analysis Center. Grids of the seven topographic variables of slope, aspect, elevation, upslope contributing area, flow path length and plan and profile curvatures at 30 m resolution were created from the ASCII attributes file with the ARC/INFO ASCIIGRID command.

Calculation of the Soil Wetness Index

The DYNWET model calculates a spatially distributed wetness index which indicates distribution of soil water and zones of soil saturation (Barling et al., 1994). The

model uses the attributes computed in TAPES-G to create an index based on either a steady-state or quasi-dynamic subsurface flow assumption.

The steady state wetness index (χ_i) is:

$$\chi_i = \ln [A_{si} / \tan \beta_i] \quad (2)$$

where A_{si} is the specific catchment area (catchment area draining across a unit width of contour) and β_i is the slope angle. This steady-state index approach predicts that points lower in a watershed, and especially those points near the outlets of the main channels, are the wettest points on the watershed and that the soil water decreases as the flow lines are traced upslope to the watershed divide (Wilson and Gallant, 1997). Every point on the catchment is assumed to have reached subsurface drainage equilibrium (Jones, 1986; O'Loughlin, 1986), which only rarely occurs in real world situations (Kirkby and Chorley, 1967; Barling et al., 1994). The steady-state method does not predict wetness well when soil piping plays a substantial role in the hydrologic patterns of a catchment (Jones 1987a, 1987b).

The quasi-dynamic wetness index, DYNWET, is a new index that recognizes that the subsurface flow regime in a watershed rarely, if ever, reaches the steady-state condition (Moore, 1992; Barling et al., 1994). DYNWET calculates: (1) the time for subsurface flow to travel the length of each cell; and (2) the effective upslope contributing area per unit width of contour for each cell (Iida, 1984; Barling et al., 1994; Wilson and Gallant, 1997). The quasi-dynamic version of DYNWET requires the user to specify uniform or spatially varying soil properties including soil depth, hydraulic conductivity, drainable porosity and a drainage time. Studies by Moore et al. (1993a,

1993b) and Wilson et al. (1994) show that the soil wetness index indicates the location and degree of saturation of a watershed and helps describe the abundance and distribution of erosion and deposition, soil properties, and vegetation in complex landscapes.

Sensitivity of DYNWET to Soil Parameters

DYNWET accepts either uniform or spatially variable values for porosity, hydraulic conductivity, and depth; which are used to calculate travel time. Available data consisted of a soil map of the MFPR (Nelson, 1976), which placed the fourteen soils series (Table 3) comprising the study area into eight soil management areas. Each management area had ranges of values for soil attributes, including porosity, depth, and saturated conductivity (Nelson, 1976; NRCS, 1997) for each of the fourteen soil series in the watershed and percent area of each soil series within each soil management area (Nelson, 1976). Soils were grouped by Nelson into management areas based on dominant soil types, drainage systems and patterns, geologic factors that affect plant growth and water supply, pronounced variations in climate over short distances, and relief features on the landscape. Although a detailed soil survey map exists for the MFPR area (Nelson, 1976), the entire study area is not covered, so uniform rather than spatially variable soil attributes were used for input to the DYNWET model.

Uniform values for the soil attributes, depth, hydraulic conductivity, and drainable porosity were calculated using the data from Nelson (1976) and NRCS (1997) with the following methods. First, weighted mean minimum and mean maximum values for the soil attributes were calculated based on percent area for each soil series present in each of

the eight soil management areas. For example, to calculate a weighted mean minimum value for soil depth for the eight management areas comprised of the fourteen soil series, the following equation was used:

$$\sum_{n=1}^{14} (\text{min depth}_n * \% \text{ area of management area}_n) \quad (3)$$

These minimum and maximum weighted means were then further weighted by the percent area each soil management group covers in the basin (Table 4). To calculate a weighted mean minimum for the entire study catchment comprised of the eight management areas, the following equation was used:

$$\sum_{n=1}^8 (\text{min depth}_n * \% \text{ area of study catchment}_n) \quad (4)$$

This same approach was used for the other weighted mean calculations for all other attributes. Overall weighted minimum and maximum means were calculated for each soil attribute and the overall mean was then derived resulting in one value each for soil depth, hydraulic conductivity, and drainable porosity (Table 4).

A sensitivity analysis was conducted in order to assess DYNWET's response to the input parameters of porosity, soil depth and hydraulic conductivity. The minimum or maximum values for each soil parameter were used individually while holding the other two parameters constant at their mean values in six DYNWET runs with a drainage time held at 4000 hours. Difference grids comparing the DYNWET grid derived with the minimum value and the maximum value of each parameter were created to indicate the sensitivity of DYNWET to variations in each soil property. Two subsequent DYNWET runs with drainage times of 4000 and 400 hours were also completed, using the mean

Table 4. Soil management group properties of the Middle Fork of the Payette River catchment. All minimum, maximum, and mean values are weighted means, weighted to the percent area the soil management group covers in the basin.

Soil Management Group	Percent of study area	Soil depth (m)		Saturated hydraulic conductivity (mm/hr)		Drainable porosity (m ³ /m ³)	
		min	max	min	max	min	max
Scriver-Bryan	6.7	0	1.6	63.4	111.8	0.54	0.67
Koppes-Coski	17.8	0	1.3	100.8	201.6	0.56	0.66
Pyle-Bryan	7.8	0	1.2	114.2	230.2	0.61	0.71
Ligget-Pyle	6.7	0	1.4	97.3	196.9	0.58	0.66
Koppes-Toiyabe	11.1	0	1.2	108.9	228.4	1.53	0.64
Koppes-Quartzburg	33.3	0	1.2	105.8	212.7	0.55	0.65
Koppes-Rock Land	3.3	0	1.2	107.8	217.8	0.56	0.65
Josie-Hanks-Graylock	13.3	0	1.4	63.2	133.4	0.58	0.66
Overall weighted means		min	max	min	max	min	max
		0	1.3	96.2	195.6	0.56	0.66
Overall mean values		0.64		145.9		0.61	

values of porosity, hydraulic conductivity and soil depth. Four thousand hours was initially chosen as a drainage time because it is approximately 167 days, or 5.6 months (the approximate length of winter in the study area). The 4000 hour time thus simulates the amount of time between significant snowmelt events, which is the time for available subsurface water to redistribute across the catchment. Use of a 400-hour, or 17 day, drainage time evaluates whether or not an order of magnitude variation in drainage time affects the DYNWET index. Wilson and Gallant (1996) used a 10 day drainage time for their DYNWET runs in the Cottonwood Creek catchment south of Norris, Montana, so the 400 hour drainage time is representative of drainage times from previous work in the region. Results of the sensitivity analysis are presented in the next chapter.

Creation of Development and Validation Data Sets for Analysis

A development grid and validation grid of landslides was needed for subsequent statistical analyses of the topographic attributes and DYNWET. Therefore, the grid of 559 landslides was randomly divided into two grids of 280 and 279 landslides each, using the ARC/INFO command RANDOM (Figure3). The development grid was used to develop statistical models of the relationship between topography, the wetness index, and landslides. The validation grid was used to test if the statistical models of the relationship between topography, DYNWET, and landslides successfully predicts landslides.

To input data to the Bayesian probability model for statistical analysis, each cell value in a grid must be in an integer class representing a range of values of the attribute (e.g., for elevation, a 1 represents 900-975 m, a 2 represents 976-1050 m, etc.). Table 5

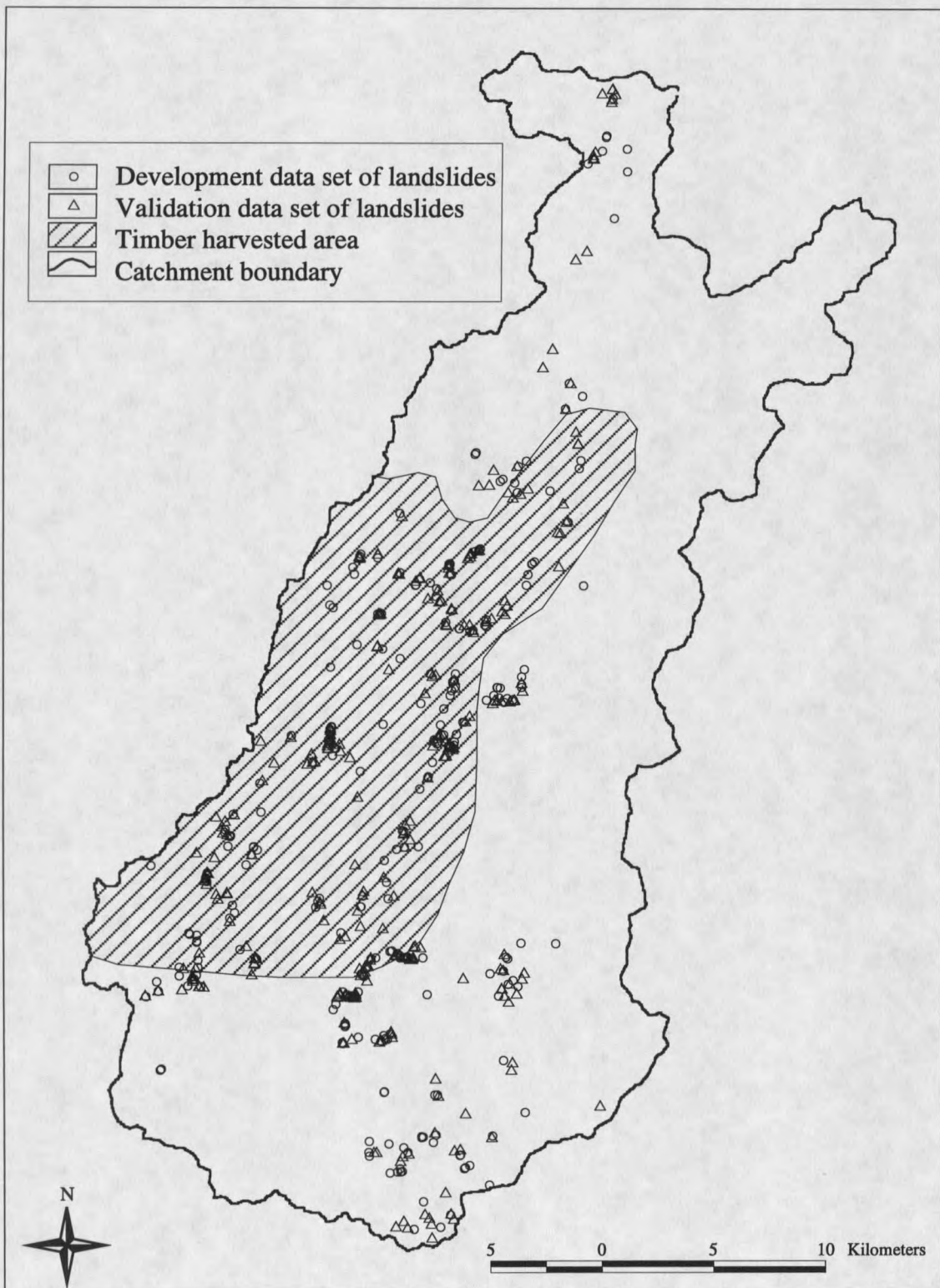


Figure 3. Development and validation landslide data sets and the approximate location of areas timber harvested from 1958 to 1978 in the Middle Fork of the Payette River catchment.

shows how each TAPES-G attribute and DYNWET grid was divided into ranges for input to the Bayesian model. The number of categories each variable was divided into varied to meet the requirements of the statistical test, as discussed in later sections.

Table 5. Division of attribute values into ranges for input to the Bayesian model.

Attribute	Range	Number of categories	Increments
Slope	0 to 64 degrees	63	1 degree
Aspect	0 to 360 degrees	72	5 degrees
Elevation	900 to 2575 m	68	25 m
Plan curvature	-173 to 267 1/100m ¹	15	Variable ²
Upslope contributing area	1-999585 cells	25	Variable ²
DYNWET with 400 hours	2.8-5.5 index values	77	approx. 0.03 index value
DYNWET with 4000 hours	2.7-10.3 index values	77	1 index value

¹ Curvature is the reciprocal of the radius of the curve. A gentle curve has a large radius and a low curvature, while a tight curve has a small radius and large curvature. The curvature values are small so they are multiplied in TAPES-G by 100 to give values with fewer zeroes.

² Increments for plan curvature and upslope contributing area vary based on natural breaks within the distribution of the data values.

Statistical Analysis

To determine which topographic variables are the most closely related to landslides and to ascertain whether or not DYNWET enhances landslide prediction, two statistical methods were employed: a chi-square analysis and a Bayesian model of probability. The chi-square analysis (Griffith and Amrhein, 1991) was used to determine which topographic attributes are significantly different in cells with and without landslides and should be included in the Bayesian predictive model. Probabilities of

topographic attribute values and DYNWET values occurring in cells with landslides are called “actual” probabilities, while probabilities in cells without landslides are called “expected” probabilities. The chi-square test is used to determine if the actual and expected probabilities are significantly different from one another.

Subsequent Bayesian analysis assumes conditional independence among driving variables, so a correlation analysis was performed to assess which TAPES-G topographic variables could be used with DYNWET output in a multivariate prediction. The conditional Bayesian probabilities (Davis, 1986) are derived by comparing attributes of the data set to be modeled with attributes of a number of predictor data sets. For example, the distribution of Red deer was predicted throughout the Grampian Region in Scotland by combining a small subset of known locations for the distribution of Red deer with habitat data sets including frost, altitude, and land cover of the region using Bayesian analysis (Aspinall, 1992). The distribution of other Red deer habitat in the region was then predicted based on these variables.

In this study, the Bayesian analysis was used to ascertain the probability of a landslide occurring based on the selected topographic and moisture index attributes. The Bayesian conditional probabilities are derived by comparing attributes of the cells containing landslides to attributes of cells without landslides. The development data set (cells with landslides) contains 280 cells, while the remainder of the catchment (cells without landslides) contains 973,378 cells. To obtain the probabilities, ten Bayesian analyses were completed using the development data set of landslides, and combinations of the variables slope, aspect, elevation, and DYNWET. Two analyses were completed

with slope, aspect, elevation and DYNWET at 4000 hours and 400 hours, respectively, four using each variable on its own, three using combinations of the topographic variables, and one using the three topographic variables, for a total of 10 probability grids of landslide occurrence. A difference grid comparing the probability grids run at 400 and 4000 hours drainage times showed little difference between the grids. Consequently, because the 4000 hour drainage time had been used for most of the previous DYNWET runs, the 4000 hour DYNWET grid was used for the subsequent Bayesian analysis involving DYNWET. All nine grids containing Bayesian probabilities of landslide occurrence were overlain with the validation grid of 279 known landslides. The predicted conditional probabilities of occurrence in each known landslide cell were used to create cumulative frequency diagrams of predicted vs. actual probability of landslides. A hazard map using the Bayesian predicted probabilities of landslides was derived from the variables deemed by this researcher as most viable for landslide prediction.

Two software packages were used to conduct the statistical analyses. The Bayesian probability model, BAYES, (Aspinall, 1992) was used to determine the actual and expected probabilities of landslides being associated with a specific attribute. The actual and expected probabilities for each topographic attribute and DYNWET were then input to Microsoft EXCEL for the chi-square analysis.

CHAPTER V

RESULTS

The results of this study are presented in four parts: (1) an evaluation of DYNWET's sensitivity to input soil parameters and drainage time; (2) a correlation analysis testing conditional independence among TAPES-G topographic variables and DYNWET; (3) the results of the chi-square analysis to determine which topographic variables are associated with landslides in the study area; and (4) the Bayesian analysis to evaluate the ability of selected topographic variables and DYNWET to enhance landslide prediction of landslides.

DYNWET's Sensitivity to Input Soil Parameters and Drainage Time

The sensitivity of DYNWET to the soil parameters of depth, hydraulic conductivity, and porosity is shown in Table 6. Variations in soil depth had no effect on the DYNWET index. When two DYNWET runs were completed with minimum and maximum soil depths of 0.0 m and 1.3 m, the moisture index was identical for each DYNWET grid as determined by difference grids.

When the minimum and maximum values of the drainable porosity and hydraulic conductivity were used as input to DYNWET, wetness index values varied slightly (Table 6). In a difference grid comparing the minimum porosity and maximum porosity-

Table 6. Mean, standard deviation, and range of DYNWET wetness index values for all 973,378 cells in study area with DYNWET run at 4000 hours drainage time and calculated with minimum and maximum values of soil depth, hydraulic conductivity, and porosity. Only one parameter at a time was varied, with the other parameters held at mean values.

	DYNWET inputs (4000 hours)	DYNWET index outputs		
Soil parameters	Parameter values	Mean	Standard deviation	Range of values
Soil depth (m)	Min 0.0	5.6	1.2	2.8-10.3
	Max 1.3	5.6	1.2	2.8-10.3
Hydraulic conductivity (mm/hr)	Min 96.2	5.5	1.0	2.8-9.3
	Max 195.6	5.7	1.3	2.8-10.9
Porosity (m ³ /m ³)	Min 0.56	5.7	1.2	2.8-10.5
	Max 0.66	5.6	1.2	2.8-10.2

based indices, 80 percent of the cell values in the difference grid were zero, indicating little change between index values of each grid. In the difference grid comparing the minimum hydraulic conductivity and maximum hydraulic conductivity-based indices, 72 percent of the cell values in the difference grid were zero, indicating little change between index values of each grid. Even where index values were not identical between difference grid cells, the values were similar, generally within 0.1 of an index value.

The slight sensitivity to the hydraulic conductivity and porosity parameters is expected, because the velocity (v) of subsurface flow in DYNWET is given by

$$v = q/\eta = (K_s/\eta) \tan \beta \quad (5)$$

where q is the flux density, K_s is the saturated hydraulic conductivity, and η is the effective porosity. The velocity of subsurface flow is inversely proportional to the drainable porosity and directly proportional to the saturated hydraulic conductivity. Thus the time necessary for the catchment to reach a given wetness pattern is accelerated or

delayed by variations in these variables, but the overall wetness patterns are not altered (Barling et al., 1994).

DYNWET is also relatively insensitive to the user specified drainage time, although the upper range of DYNWET index values did shift notably when drainage time was increased tenfold (Table 7). Changes in the drainage time affect how long it takes a cell to reach saturation. Changing drainage times does not, however, alter the relative wetness patterns (Barling et al., 1994).

Table 7. Mean, standard deviation, and range of DYNWET wetness index values calculated with mean values of soil depth, hydraulic conductivity, porosity, and varying drainage times since a prior rainfall event.

Drainage time (hrs)	DYNWET inputs (mean values)			DYNWET outputs		
	Soil depth (m)	Hydraulic conductivity (mm/hr)	Porosity (m^3/m^3)	Mean	Standard deviation	Range of values
4000	0.64	145.9	0.61	4.2	0.21	2.8-5.5
400				5.6	1.2	2.7-10.4

Based on results from the sensitivity analysis, mean parameter values for soil depth, hydraulic conductivity, and drainable porosity of 0.64 m, 145.9mm/hr, and 0.61 m^3/m^3 , respectively, were input with drainage times of 4000 and 400 hours to the DYNWET model. These DYNWET runs produced two wetness index grids differing only in drainage times, which were used in further analysis.

Correlation Analysis of Topographic Variables and DYNWET

A correlation analysis was conducted to assess whether topographic variables and DYNWET violate the assumption of independence among variables, which is necessary for the Bayesian analysis. Correlations between topographic variables and wetness index values are generally low (Table 8), although five combinations of TAPES-G and DYNWET grids had r values greater than 0.10. These were upslope contributing area and flow path length; plan and profile curvatures; DYNWET and slope; DYNWET and plan curvature; and DYNWET and profile curvature. Therefore, flow path length and profile curvature were omitted from the remainder of the analysis because these variables are partially correlated to other variables in the study. Slope, elevation, upslope contributing area, and plan curvature were retained as potentially key topographic variables. DYNWET, despite being correlated with slope and plan curvature, was kept because its inclusion in the final analysis is fundamental to the objectives of this study.

Determining Variables Relating to Landsliding: Chi-square Analysis

A chi-square analysis was performed with slope, aspect, plan curvature, elevation, upslope contributing area, and the DYNWET grids run at 400 and 4000 hours to determine which attributes significantly contribute to landsliding in the study area. The sample sizes of actual and expected probability values for each attribute are listed in Table 5 as number of categories.

Table 8. Correlation matrix for topographic variables and DYNWET showing correlation r values. UCA is upslope contributing area, FPL is flow path length and DWET is DYNWET. Correlation r values greater than 0.10 are bolded.

	Slope (degrees)	Aspect (degrees)	Planc ^a	Profc ^b	Elev- ation (m)	UCA (#of cells)	FPL (m)	DWET (index values)
Slope	X							
Aspect	0.008	X						
Planc	0.001	0.000	X					
Profc	0.001	0.000	0.160	X				
Elev	0.005	0.004	0.001	0.006	X			
UCA	0.008	0.000	0.001	0.004	0.005	X		
FPL	0.000	0.000	0.014	0.023	0.008	0.810	X	
DWET	0.160	0.000	0.281	0.168	0.001	0.005	0.008	X

^a Plan curvature (convex curvatures are negative) (1/100 m)

^b Profile curvature (convex curvatures are negative) (1/100 m)

Probability histograms and the chi-square statistic of association indicate which variables were uniquely associated with landslides and should be included in the final Bayesian analysis. The actual distribution represents the distribution of attribute values in the 280 cells with landslides. The expected distribution represents the distribution of attributes in the 973,378 cells without landslides. Each chi-square statistic was evaluated at the 0.10 significance level for the appropriate degrees of freedom. The chi-square statistics at the 0.10 level showed that no significant difference exists between expected and actual landslide distributions for the plan curvature and upslope contributing area variables (Figure 4). Therefore, these attributes were omitted from further analysis.

The actual and expected distributions of landslides were significantly different at different elevations (Figure 5a). Figure 5a indicates that there is a higher probability of

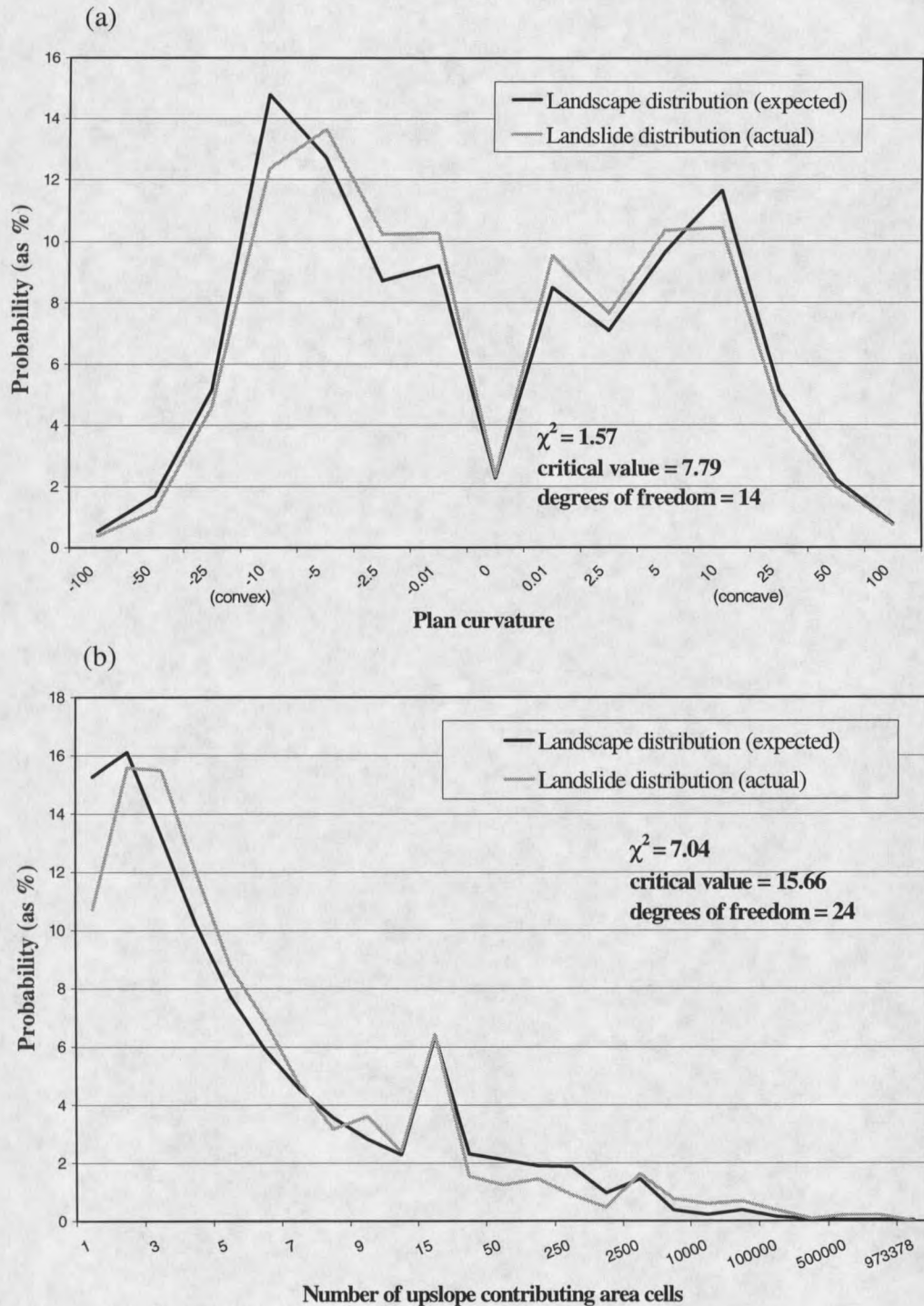


Figure 4. Probability histograms and the chi-square statistic (χ^2) for (a) plan curvature values and (b) upslope contributing area cells. Distributions are considered significantly different if χ^2 is greater than the critical value at the 0.10 significance level.

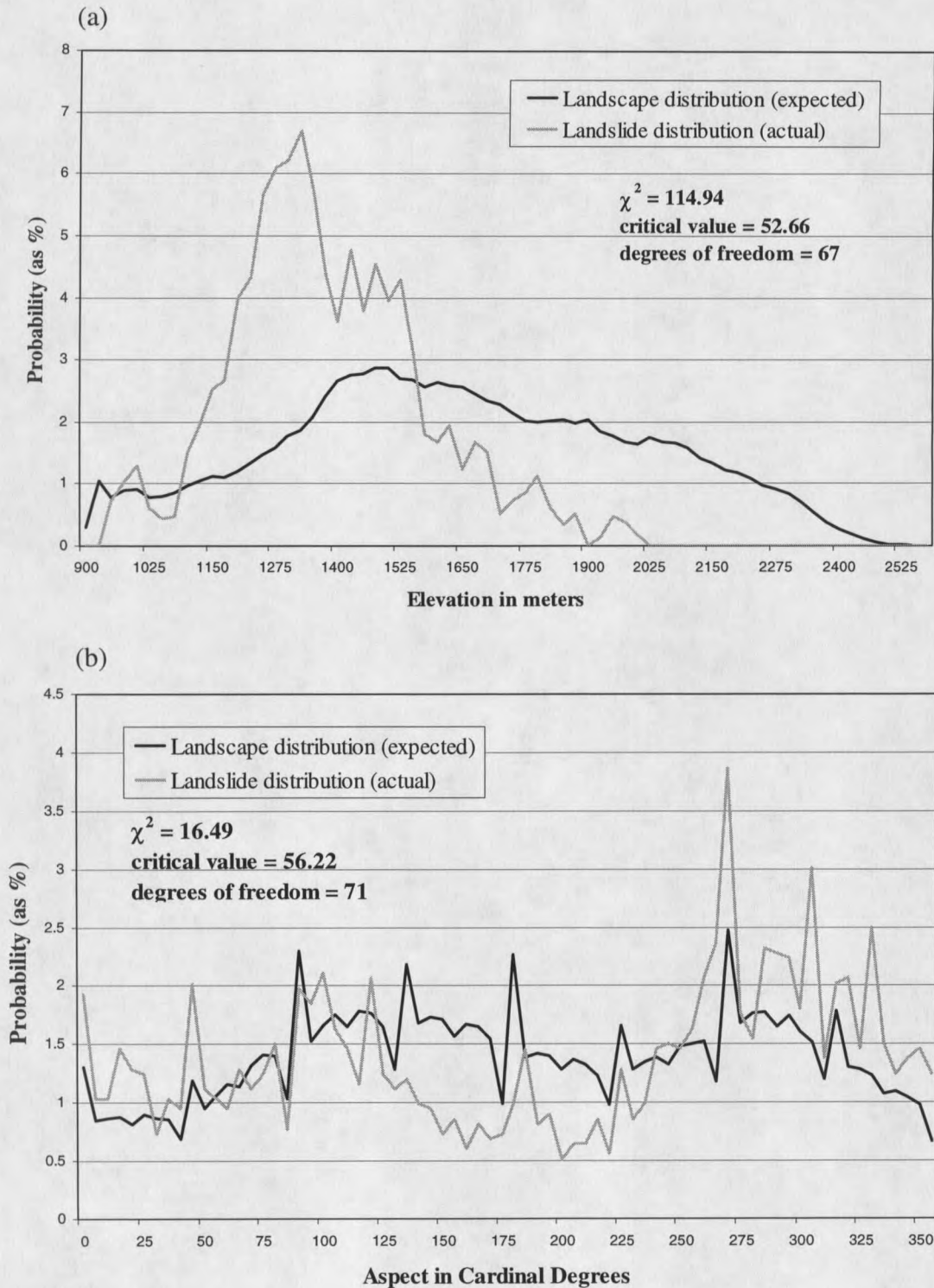


Figure 5. Probability histograms and the chi-square statistic (χ^2) for (a) elevation and (b) aspect values. Distributions are considered significantly different if χ^2 is greater than the critical value at the 0.10 significance level.

finding landslide cells at elevations between 1125 and 1575 m than at other elevations. Elevation was therefore retained in the Bayesian analysis based on the chi-square analysis and the assumption that it served as a surrogate measure of land use, vegetation, and climate variability.

Aspect was also included in the Bayesian analysis, despite a chi-square statistic ($\chi^2 = 16.49$) that suggests no relation between aspect and landslides (Figure 5b). The actual and expected curves appear distinctly different. As expected, wetter north facing aspects have a higher proportion of landslide cells, while fewer landslides occur in dryer south facing aspects. The chi-square analysis may be misleading in the case of aspect, because when 280 landslide cell values of aspect are grouped into 72 categories, some categories contain fewer than five landslide cells. This invalidates one of the key assumptions of chi-square analyses. Dividing the 280 landslide cells of aspect into fewer than 72 categories did not improve the chi-square p-value, because some aspect classes still had less than five values.

The chi-square statistic for slope, $\chi^2 = 45.65$, indicates significant association of slope and landslides at the 0.10 level. Based on Figure 6, which demonstrates that the landslide cells tend towards 25 to 40 degree slopes, slope was included in the final probability analysis.

Histograms depicting both the expected and actual curves for the DYNWET grids at 400 and 4000 hours are shown in Figure 7. A chi-square analysis conducted on both DYNWET grids indicates no significant difference between actual and expected wetness

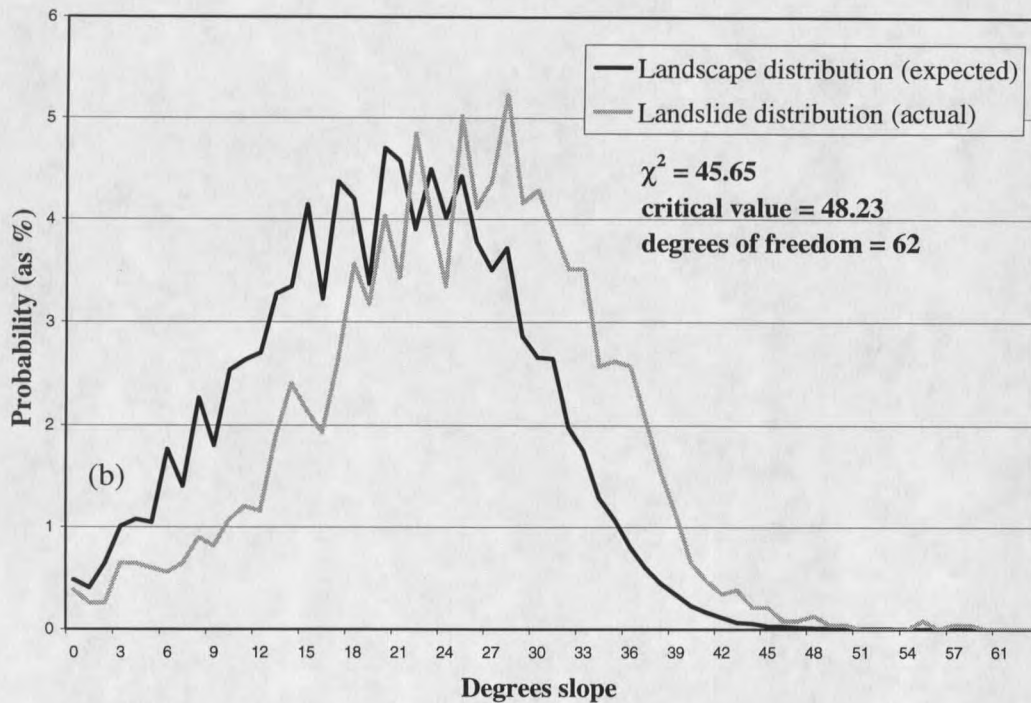


Figure 6. Probability histograms and the chi-square statistic (χ^2) for slope values. Distributions are significantly different if χ^2 is greater than the critical value at the 0.10 significance level.

index values at the 0.10 level of significance. DYNWET output was still included in the final analysis, however, because its ability to enhance landslide prediction was a central question of this study.

Multivariate Landslide Prediction: Bayesian Analysis

The chi-square and probability histogram analysis suggested that elevation, slope, and aspect are the best predictors of landslides in the study area. Although the wetness index did not demonstrate a significant chi-square statistic, it was retained for inclusion in further statistical tests. Chi-square, however, is unable to clearly specify which variable

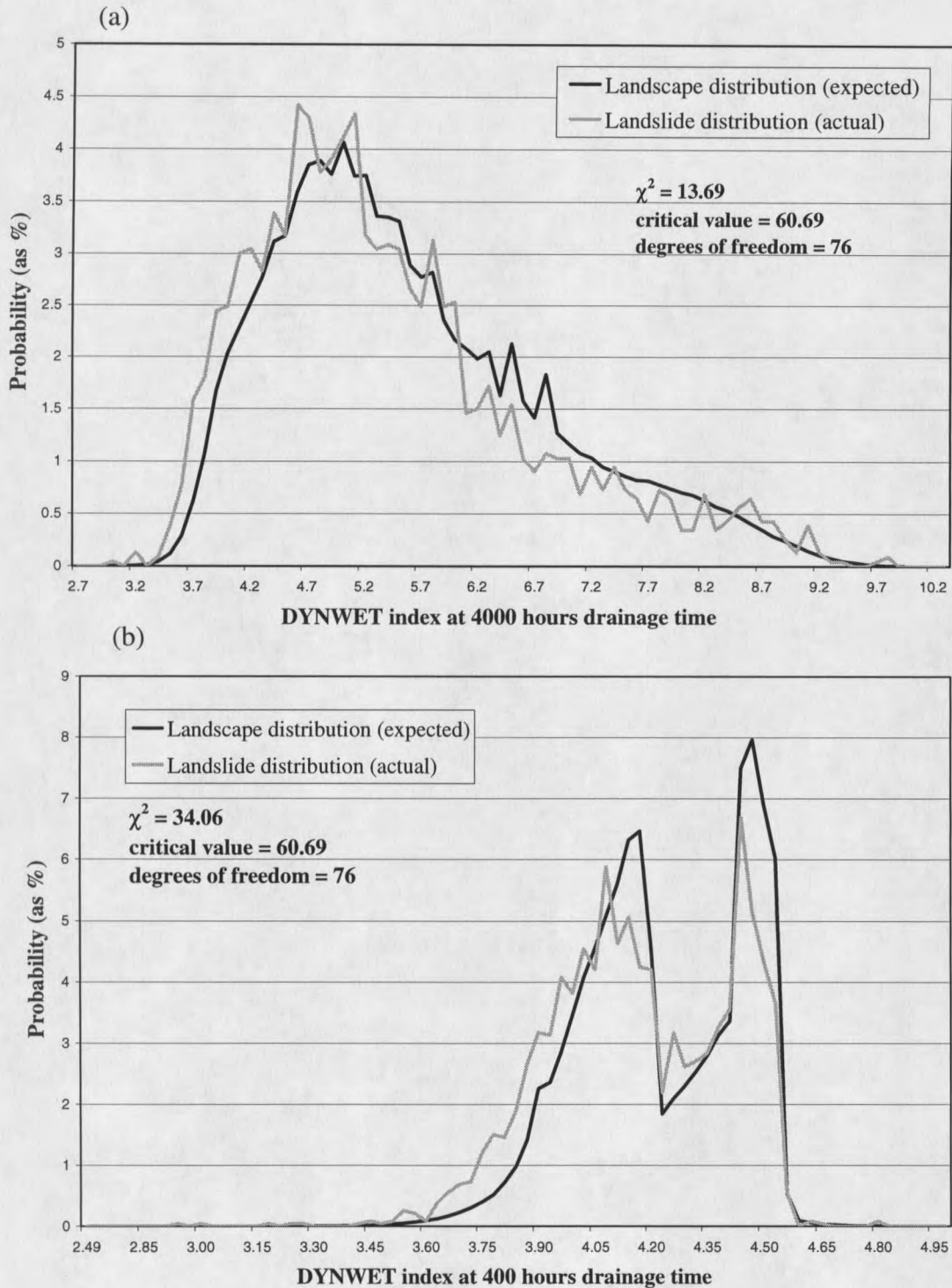


Figure 7. Probability histograms and the chi-square statistic (χ^2) for DYNWET index values with (a) a 4000 hour drainage time and (b) a 400 hour drainage time. Distributions are significantly different if χ^2 is greater than the critical value at the 0.10 significance level.

is the best predictor or evaluate how well combinations of variables predict landslides. Therefore, Bayesian analysis was used to predict the probability of landslides in each cell based on different combinations of elevation, slope, aspect, and the wetness index. The Bayesian probability grids were then overlain with the validation grid of known landslides. Cumulative frequency curves were developed from these overlays to show how well the predictions fit the actual landslide distributions.

Cumulative frequency curves can be used to evaluate the effectiveness of the different combinations of attributes for predicting landslides. Figure 8 shows two hypothetical examples of cumulative frequency diagrams. The upper curve shows a good fit. A good fit exists if 100 percent of the known landslides occur in cells where there is a predicted Bayesian probability of 90 percent or higher (Figure 8). This situation is a good fit because a very large percentage of landslide sites is associated with high predicted probabilities (Figure 8). The location of the y-intercept for the upper curve at 90 percent probability also indicates a good fit because this means that known landslide sites only occur in cells with high probabilities (Figure 8). The lower curve shows a relatively poor fit. This fit is poor because most of the known landslide sites occur where there are low predicted probabilities (Figure 8). The location of the y-intercept in this case also indicates a poor fit because some known landslides occur in cells where the Bayesian predicted probability is zero (Figure 8).

The actual cumulative frequency diagrams of Bayesian predicted probabilities using individual topographic attributes and combinations of topographic attributes are

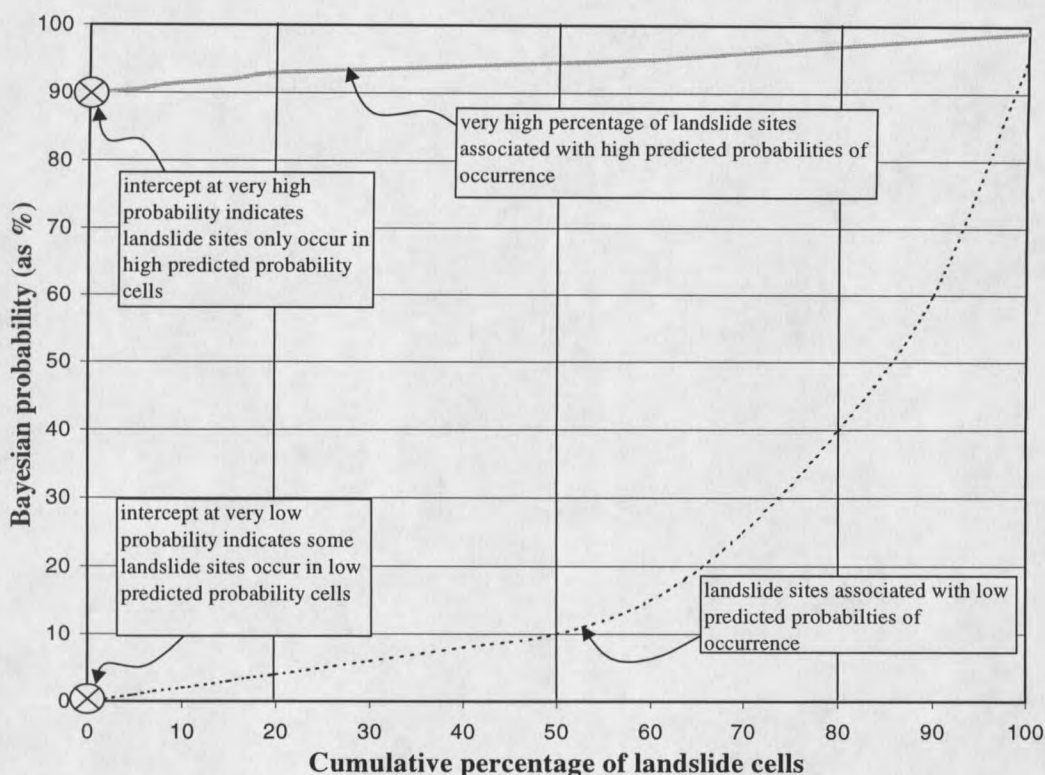


Figure 8. Illustration of cumulative frequency diagram showing Bayesian predicted probabilities (y-axis) occurring in cumulative percent of total cells with landslides (x-axis). Explanation of curves is in the text.

presented in Figure 9. The vertical line at 50 percent cumulative percentage (median) provides an excellent point of reference. Figure 9a illustrates the individual variables which best predict landslide occurrence in the study area. Fifty percent of all known landslides occur in cells where, based on elevation alone, there is a 65 percent or higher probability of a landslide occurring. In contrast, when slope, aspect, or DYNWET are used individually for prediction, the results are relatively poor. The slope frequency curve (Figure 9a) shows that only 50 percent of the known landslides occur in cells where

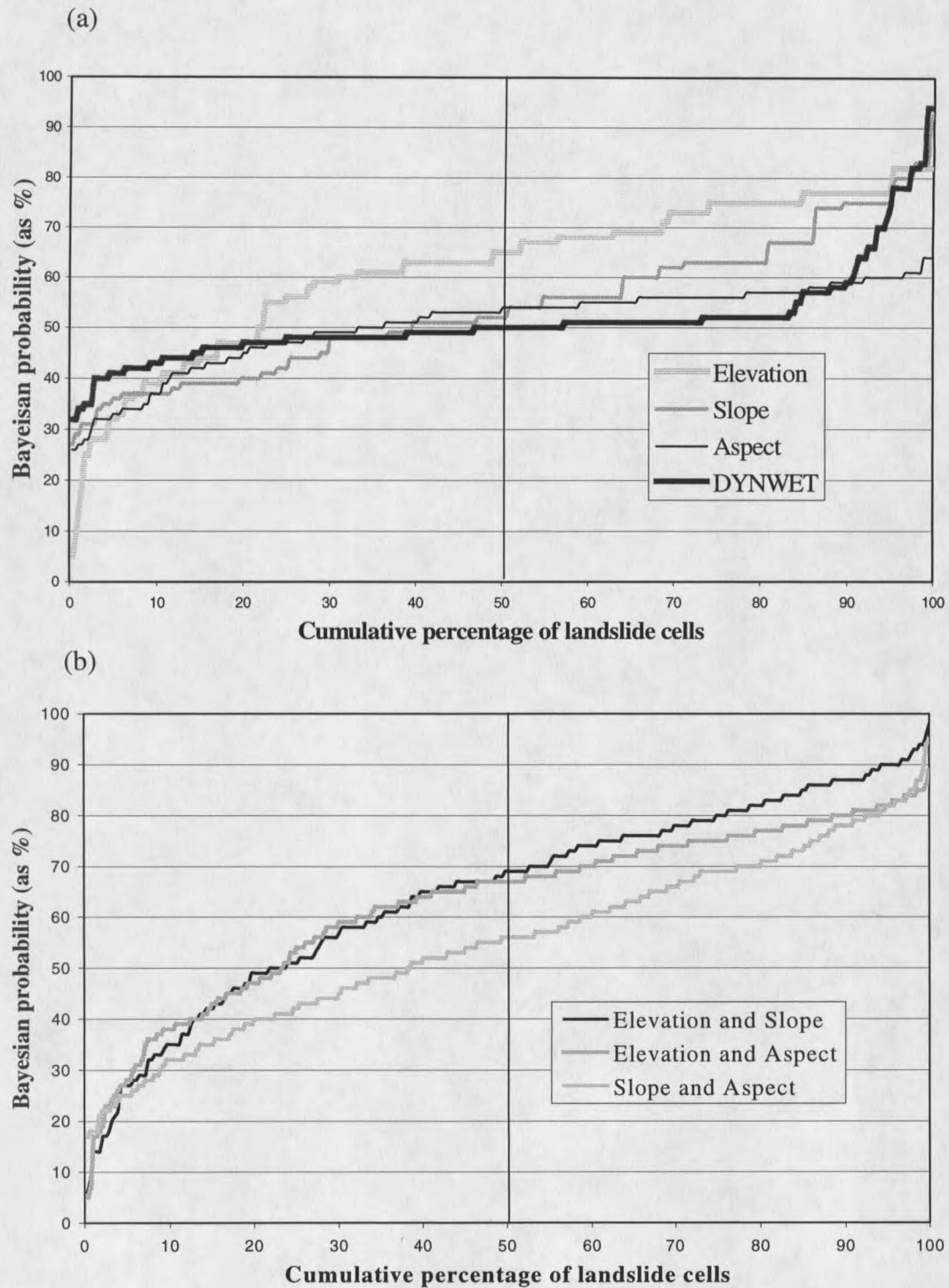


Figure 9. Cumulative frequency diagrams showing cumulative percent of landslides falling in grid cells of a given predicted probability for (a) individual attributes and (b) combinations of attributes.

the predicted probability of landsliding is greater than 53 percent. The aspect frequency curve (Figure 9a) shows that 50 percent of the known landslides occur in cells with greater than 54 percent probability of occurrence. When compared with the other frequency curves, however, the predicted probability of occurrence based on aspect alone does not rise above 64 percent for the landslide cells. The DYNWET frequency curve of Figure 9a shows that 50 percent of the known landslides occur in cells with less than 50 percent probability of occurrence, while the other 50 percent of landslides occur in cells with greater than 50 percent probability of occurrence. These results suggest a poor fit and mean that DYNWET alone does not enhance the prediction of landslide prone areas.

The cumulative frequency results for combinations of topographic variables show a slightly different pattern (Figure 9b). Slope and elevation combined provide the best results with 50 percent of the landslide cells occurring where there is a predicted probability of 68 percent or greater. This probability is not much better than using elevation alone, which yields 50 percent of landslides occurring where there is a predicted probability of 65 percent or greater. The combination of aspect and elevation yield similar results with 50 percent of the landslide cells having a 66 percent or greater probability of landslide occurrence. The combination of slope and aspect yields poorer results with 50 percent of landslide cells showing a 55 percent or greater probability of landslide occurrence.

Another method of interpreting the cumulative frequency diagrams is to analyze the area above the 50 percent Bayesian probability line (a horizontal line). With this method, elevation is still the best individual predictor of landslide occurrence, with

approximately 80 percent of all known landslides occurring in cells where there is a 50 percent or greater probability of landslide occurrence (Figure 9a). For the other three individual variables, approximately 50 percent of landslides occur in cells with a 50 percent probability or greater. The combination of elevation and slope yields similar results (Figure 9b).

The two best variables for predicting landslides based on the Bayesian analysis are elevation, and elevation and slope (Figure 10). The combinations of elevation, slope, and aspect; and elevation, slope, aspect, and DYNWET also yield relatively good results (Figure 10). Figure 10 shows that in the study area given this scale of data and the present analytic techniques, no gain in accuracy is achieved by the addition of the DYNWET-based wetness index or aspect. The Bayesian analysis generally confirms the chi-square analysis; elevation and slope are the most critical variables for predicting landslides.

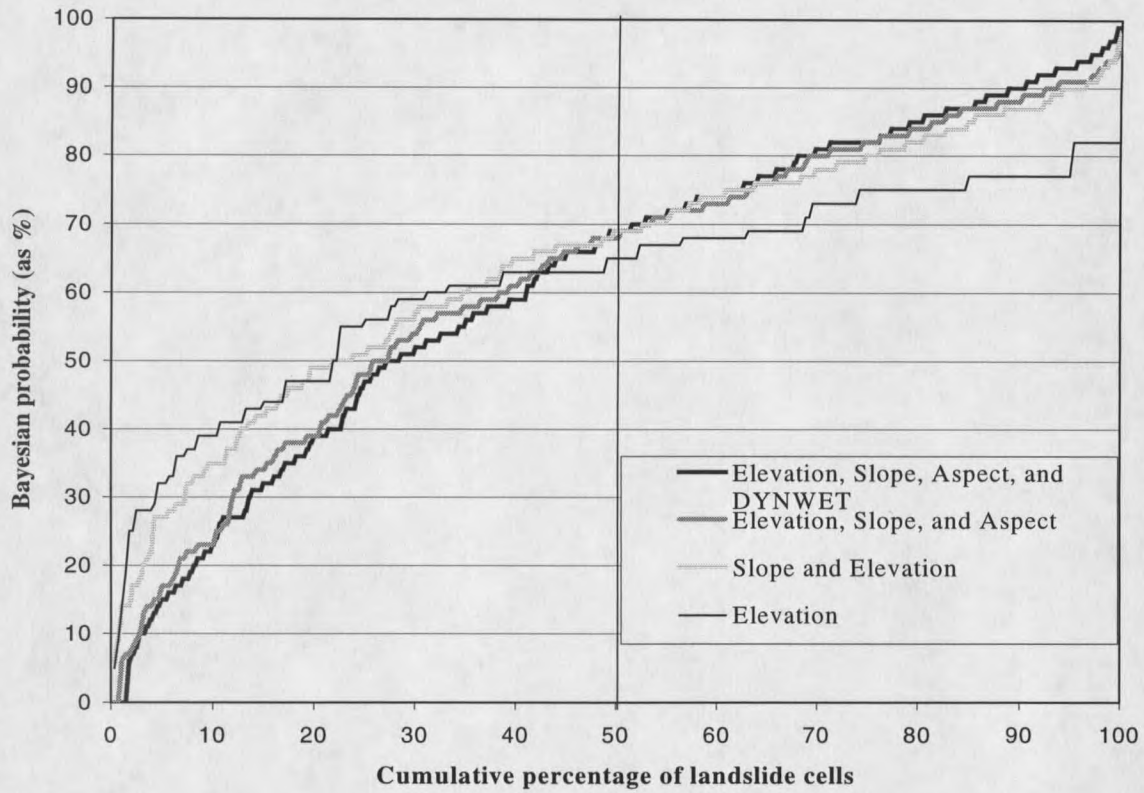


Figure 10. Cumulative frequency diagram showing useful combinations of variables for landslide prediction.

CHAPTER VI

DISCUSSION AND CONCLUSIONS

This study evaluated which landscape scale topographic and hydrologic variables contribute most significantly to landslide events in the Middle Fork of the Payette River area of the Idaho Batholith and whether GIS modeling can contribute to regional landslide prediction. Topographic variables were calculated from a digital elevation model (DEM) with the terrain model, TAPES-G, and a wetness index was estimated using the wetness model, DYNWET. The combination of elevation, a surrogate for vegetation, land use, and climate, and slope provided the best predictions of landslide events in the study area. Aspect, plan curvature, profile curvature, upslope contributing area and flow path length did not improve prediction of landslides in the MFPR relative to elevation and slope. The more computationally complex DYNWET soil wetness model did not improve landslide prediction when compared to more direct topographic variables.

Topographic Variables Contributing to Landslides

Both a chi-square and Bayesian analysis indicate that the topographic variables of elevation and slope are most strongly associated with landslides in the study area. Although results from the chi-square analysis did not show aspect to contribute significantly to landsliding, aspect was included in the final Bayesian analysis because

probability histograms of aspect (Figure 5b) suggest that landslides with aspects of 125 to 250 degrees have a different distribution than expected based on the distribution of all aspects in the study area. DYNWET was included in the final Bayesian analysis because its use as a landslide prediction tool was one of the central questions of this research.

Elevation was analyzed in this study as a possible surrogate measure for land use, vegetation, and climate, which are not mapped for the MFPR catchment. The Bayesian analysis indicated that elevation was the factor with the greatest statistical association with landslides in the study area. This study shows that 76 percent of mapped landslides in the MFPR occur between 1100 and 1600 m. Ten percent occur between 900 and 1099 m, and 14 percent occur between 1601 and 2000 m (Figure 5a). The strong association between elevation and landsliding was somewhat surprising since elevation is not known to be a causative factor of landslides elsewhere. Rather elevation is more likely linked to other variables such as land use or vegetation, which influence landslides in other studies.

One reason for the association of elevation and landslides may be that the sample data set of landslides is biased towards the elevation range 1100 to 1600 m. Alternatively, based on a hand-drawn map from the Emmett Ranger District of the U.S. Forest Service (Jackson, 1998), road cuts and subsequent timber harvest occur mainly at this elevational range (Figure 3). Disturbance may explain the association between elevation and landslides. Douglas-fir and Ponderosa pine also correspond to the landslide elevation range, with all landslides occurring at approximately the same elevation as Douglas-fir and Ponderosa pine (Figure 5a). Douglas-fir occurs at elevations below 2,300 m and Ponderosa pine occurs below 2,000 m. All landslides occur at or below

2,025 m (Figure 5a). Most of the past harvest was evenly divided between the Douglas-fir and Ponderosa pine species (Nelson, 1976).

The association of elevation and landslides may also be related to the topography at high elevations. At high elevation, it may be less likely for a landslide to occur because there may be less soil and loose debris on convex and steep slopes. Slopes at higher elevations are usually steeper, therefore there may be little landslide activity because small sloughs are continuously occurring. Therefore, the soils are thinner at higher elevations, and large observable landslides may seldom form on the steeper higher slopes.

Based on the chi-square and Bayesian analyses, slope is the second most significant variable related landslides in the study area. Fifty-seven percent of the documented landslides in the MFPR occur on slopes between 10 and 30 degrees. Thirty-five percent of occur on slopes greater than 30 degrees. Five percent of landslides occur on slopes less than 10 degrees, while 3 percent occur on slopes greater than 40 degrees. No landslides occur on slopes greater than 58 degrees slope. Eighty-two percent of landslides with slope greater than 30 degrees fall in the elevation range 1100 to 1600 m, however, 100 percent of landslides fall in the elevation range, 1000 to 1700 m. These data indicate that an association between slope and elevation exists in landslide cells, even though Table 8 indicates no correlation exists overall in the study area. The steepness of slope is related to the gravitational force necessary to move earth material, and the greater the slope angle, the stronger the shearing stress. In most cases, slope alone is an important variable associated with landslides. Because slope and elevation

are correlated in landslide cells in this study, other factors such as timber harvest or road cuts may also be playing a role in the landsliding (Megahan et al., 1978), but there is no solid location data to analyze the role of timber harvest and roads.

DYNWET's Ability to Enhance Landslide Prediction

The addition of DYNWET did not improve landslide prediction in this study. Based on the chi-square analysis (Figure 7), there was no difference between the distribution of landscape and landslide frequency of the DYNWET index. The index values produced by DYNWET suggest moisture may not be a primary control driving landslides in the MFPR. According to Megahan et al. (1979), the large number of roads in the area and the timber activities are the most important factors contributing to landslides. DYNWET might be able to enhance prediction given other types of mass movements than the types located in the study area. Seventy percent of the landslides were debris slides or debris avalanches. Perhaps DYNWET would be better at enhancing prediction of more fluid types of landslides, like debris flows or mudflows. Another study site would likely be necessary to test this, because only 7 percent of the mass movements in this study area fail as debris flows or debris torrents.

Another reason DYNWET did not improve landslide prediction may relate to soil piping. DYNWET may not predict soil wetness well when soil piping plays a substantial role in the hydrologic response of a catchment (Barling et al., 1994). In the case of the MFPR catchment, gopher holes exist in many of the landslides in the area (Ladson,

personal communication, 1990). These gopher holes may act as soil pipes and affect the ability of the DYNWET model to predict the wetness index.

Data availability, quality, and resolution, may also be factors limiting DYNWET's prediction capabilities. DEMs presently available in the United States are limited to a minimum grid-spacing of 30 meters. The 30 m resolution of the digital elevation model may be too coarse to accurately represent key terrain features used to model the hydrologic processes with the DYNWET model. Zhang and Montgomery (1994) concluded that a DEM grid size of 10 m was the best compromise between model accuracy and data processing time. They also found that grid sizes of 30 and 90 m may be too large for modeling complex topography.

Limitations of the DYNWET model may also affect its ability to predict landslides. In the study area, DYNWET was found to be relatively insensitive to the soil input parameters of soil depth, saturated hydraulic conductivity, and drainable porosity (Table 6). Perhaps this is due to the minimum, mean, and maximum values for these parameters being close to each other in value. Barling et al. (1994, p. 1043) concluded that "although the quasi dynamic index requires the user to specify the drainage time, saturated hydraulic conductivity, and drainable porosity, the results of simulations indicate that the resulting wetness patterns are not sensitive to these parameters." This lack of sensitivity may be enhanced by the very thin soils and narrow range of soil depth, hydraulic conductivity, and porosity values in the catchment.

DYNWET may also be insensitive to the soil input parameters because uniform soil parameters were input to DYNWET across the entire watershed. DYNWET is thus

distinguishing differences in soil moisture based mainly upon the DEM (the topographic hollows) and the time between significant rainfall or snowmelt events (the user-specified drainage time), not upon local variations in soils. However, even inclusion of a spatially variable map of the soil input parameters might not generate change in modeled moisture patterns because the values of parameters were so close in value initially (Table 6). Soil depth was generalized as ranges and may not have captured thickness.

DYNWET was also largely insensitive to the drainage time input (Table 7). Even though the wetness indices calculated with 4000 hours drainage time were greater in magnitude than with the 400 hour time, little effect was detected on DYNWET's ability to predict landslides. If DYNWET were more sensitive to drainage time, perhaps the model could better locate those areas that were completely saturated, and thus were more likely to fail.

Implications of this Study for Land Management

Based on this research, elevation and slope are statistically associated with and are the best predictors of landslides in the MFPR catchment. Little, if any improvement is gained by the addition of other variables such as aspect or DYNWET (Figure 10).

Figure 11 shows a cumulative frequency diagram of the Bayesian predicted probabilities of both the development and validation data sets calculated with elevation and slope only as predictor variables. This figure was first used to determine if the cumulative frequencies of predicted probabilities were similar for the development and validation data sets and second to assess cut-off values for creating a landslide hazard

map. Based upon the slope of the development data set line on Figure 11, cut-off values of predicted probability were determined and assigned hazard ratings for the landslide hazard map covering the entire study area. Zero to 30 percent predicted probability is very low hazard, and 5 percent of the landslides occur in this zone. Thirty-one to 50 percent predicted probability is low hazard, and 15 percent of the landslides occur in this

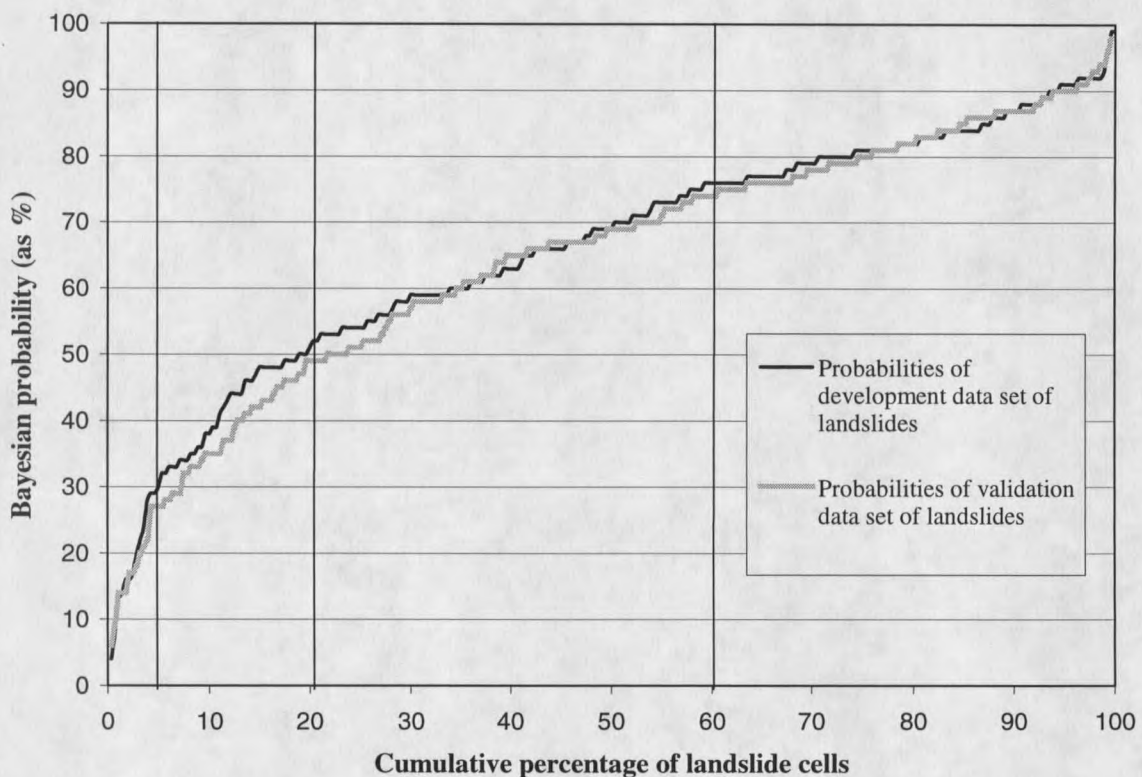


Figure 11. Cumulative frequency diagram showing cumulative percent of both development and validation data sets of landslides falling in grid cells of a given predicted probability. Only elevation and slope were used as predictor variables in the Bayesian analysis.

zone. Fifty-one to 75 percent predicted probability is moderate hazard, and 40 percent of the landslides occur in this zone. Seventy-six to 100 percent predicted probability is high hazard, and 40 percent of the landslides occur in this zone.

Figure 12 shows a hazard map with areas of very low, low, moderate, and high landslide hazard based solely on elevation and slope as Bayesian predictor variables. The high hazard area makes up 8 percent of the catchment, and 40 percent of the known landslides occur in this hazard zone, while the moderate hazard area makes up 22 percent of the catchment, and 40 percent of the known landslides occur in this hazard zone (Figure 12). The low hazard area makes up 23 percent of the catchment, and 15 percent of the landslides occur in this hazard zone, while the very low hazard area comprises 47 percent of the catchment, and 5 percent of the landslides occur in this zone (Figure 12). Given the combination of elevation and slope used as inputs, this hazard map indicates where landslides are likely and unlikely to occur.

Such a map might be used by a land manager to determine where activities which may induce landslides, such as timber harvest or road building, could be performed with less likelihood of landsliding. This assumption may be somewhat misleading however, as the areas with very low or low hazards of landsliding generally occur in areas which have not seen previous timber harvest and do not contain roads, and the areas with high hazard of landslides occur in previously logged areas with a high concentration of roads (Figure 3). Therefore, although elevation and slope are statistically associated with

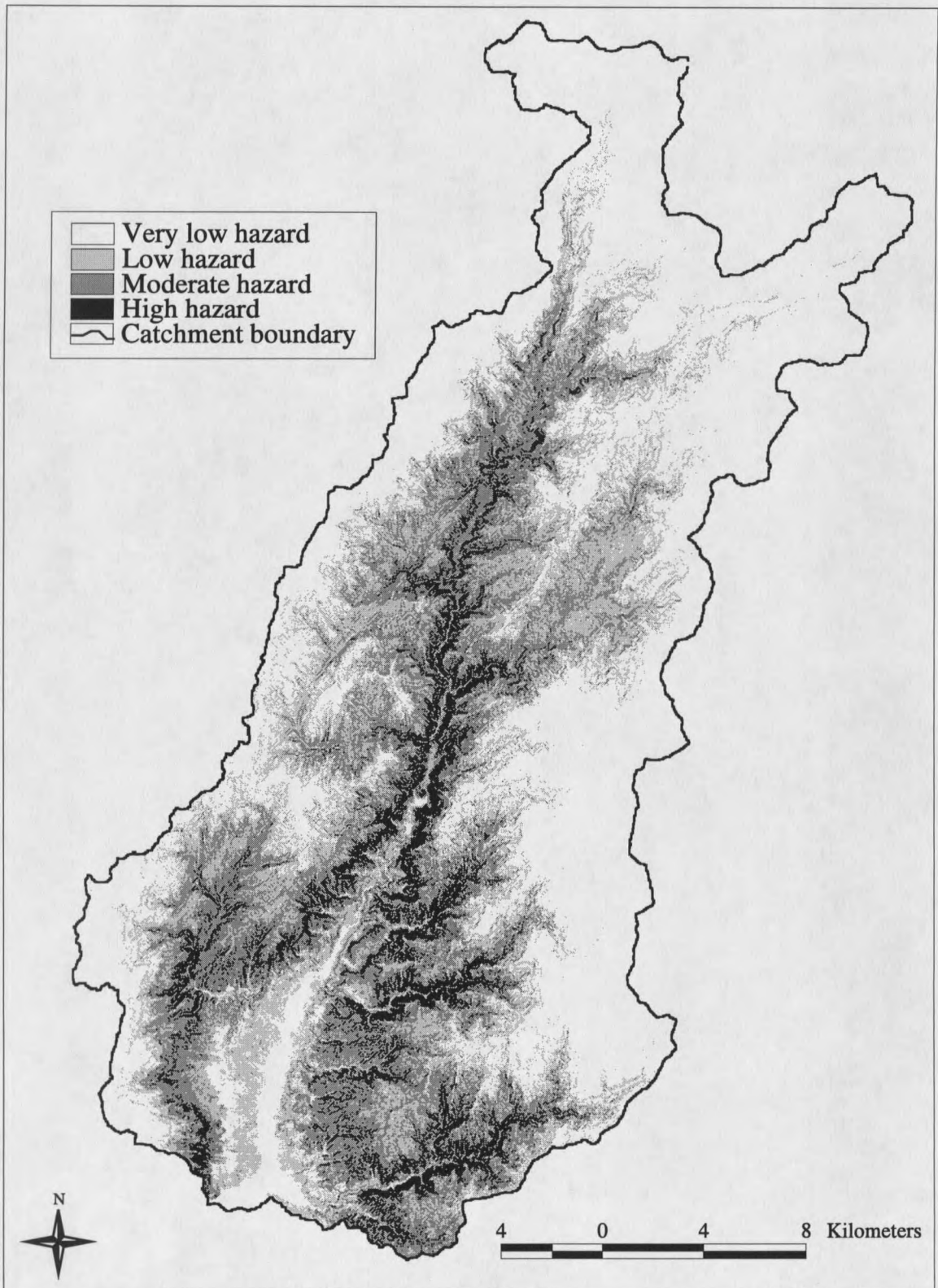


Figure 12. Landslide hazard map for the Middle Fork of the Payette River catchment created with elevation and slope only as predictor variables.

landsliding, a more reasonable answer may be that the timber harvest and roads in the area are inducing the landslides. The analysis described in this thesis does not show whether the low landslide hazard areas truly represent areas not prone to mass movement, or they exist because timbering and road building have not occurred there. Since elevation was used as a surrogate measure for unavailable data on land use and vegetation in the study area, this variable is likely capturing the spatial variation of land use and vegetation with regard to the known landslides.

Conclusions

GIS offers an efficient method of linking spatially variable data with models of earth processes. Recent advances in deterministic modeling, availability of data, and computing power will likely lead to more use of computer models to predict landscape processes. With more modeling software available, users need to be aware of the underlying physics and assumptions of the models and the sensitivity of the models to input data. Users should also be conscious of the appropriateness of the type of model for specific applications. As illustrated in this research, DYNWET was inappropriate for modeling landslides in the MFPR, although it may be effective in areas dominated by debris flows and debris torrents.

This research showed that GIS analysis using a Bayesian approach has the potential to provide useful prediction of landslides (Figure 12), but problems do exist with data resolution and potential sample bias related to land use in the MFPR. The combination of elevation and slope afford the best landslide prediction. Other

topographically-derived variables including aspect, plan curvature, profile curvature, upslope contributing area, flow path length, and the DYNWET wetness index did not improve the prediction of landslides. However, elevation is likely a surrogate for vegetation and land use. Elevation and slope may not work the same elsewhere.

Some recommendations do exist which may improve DYNWET's landslide modeling success. First, a detailed spatially variable instead of generalized spatially uniform soil parameter grid could be used for input to the model. Such input would require a much more intensive measurement program than currently exists on most forests. Second, if possible, DYNWET could be tested in an area free of gopher activity and soil piping.

To improve GIS landslide analyses, landslide modelers need to have good spatial data for all key processes which may be occurring in their study areas. For example, in the MFPR catchment, road building and timber harvest may play the most significant role in landslides in the area, however the road and timber harvest maps were not adequate for inclusion in this analysis. The use of more data sets appropriate to landslide analysis might significantly improve results.

Though GIS provides a very efficient way of predicting landslides, whether or not it provides an accurate method for assessing landslide potential depends mainly on the scale of area studied and the availability of data used for analysis. With the advent of better resolution data sets and computer models which represent processes more accurately, GIS may become an efficient way to analyze landslide hazard. However, with the data and techniques available at this time, GIS did not provide highly predictive

results for determination of potential landslide locations. Rather, GIS did provide generalized maps of landslide hazard based on Bayesian probability.

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