ENVIRONMENT & SOCIAL TECHNICAL NOTE

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Testing a Modelling Approach to Shallow Landslide Erosion in New Zealand – Expanding the Model and Validation

Summary

In New Zealand, hill country covers 10 million hectares, of which 63% occurs in the North Island. Hill country erosion lowers economic returns, causes environmental damage, and can have serious off-site impacts. The ability to assess and quantify the risk of this erosion in detail would help land managers to make informed decisions. The current erosion susceptibility surface classifies New Zealand into four broad erosion categories, and is used to assess erosion risk nationally. To date, there is no fine spatial scale mapping tool available.

This study addresses the need for improved tools for best land management practices. We developed and tested the validity of a regression model created using high resolution digital elevation models, digitised shallow landslide erosion data and rainfall data. The original rainfall, slope and landslide data from two adjacent research catchments, Tamingimingi and Pakuratahi in Hawke's Bay, were updated and the subsequent model was tested at five sites spread across the lower North Island of New Zealand. All areas are prone to erosion and have detailed landslide data associated with them. While the updated model predicted the area affected by shallow landslide erosion in the original catchments of Tamingimingi and Pakuratahi, it could not predict total area affected by shallow landslide erosion with any accuracy in any of the new study sites. However, with rainfall, slope and landslide data from the new sites it would be possible to re-calibrate the original Pakuratahi model (R x S x V x A) and expect similar good predictive ability to those achieved at the Pakuratahi catchment.

Erosion risk maps produced from the regression model and the ArcMap classification scheme provided an increase in the representation of where shallow landslide could occur, with over 80% of known slips occurring in identified high risk areas.

Further work could be carried out for known high erosion prone areas using flow dynamics to indicate likely areas of sedimentation, debris flows and downstream damage. Productivity loss due to erosion could then be better calculated and further reduced.

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Introduction

Forestry generally mitigates hill country erosion by reinforcing the soil through its network of roots, interception of rainfall, and by evaporation from tree canopies. In New Zealand, hill country (slope > 15°) covers 10 million hectares (37% of national land area), the majority (63%) of which occurs in the North Island [1]. Hill country erosion and sedimentation reduces land productivity and increases downstream flooding damage[2]. Afforestation can significantly reduce pastoral land vulnerability to erosion (Figure 1).

Figure 1: Severe hill country erosion on pasture land (left), compared to erosion on adjacent pasture and forest (right).

Planted forests, have an increased erosion risk following harvesting and during earth works (Figure 2). This risk may increase in the future due to forests being established on more marginal land, and a predicted increase in frequency of extreme rainfall events [3].

Figure 2: Slips along a forest road (left) and a slope exposed to erosion following harvesting (right).

The Erosion Susceptibility surface classifies New Zealand into four broad erosion categories, and is used to assess erosion risk nationally [4]. The ability to assess and quantify the risk of erosion on a more detailed operational scale would help land managers to make more informed decisions (e.g., roading and harvest planning).

Landslide-susceptibility maps can identify the spatial probability of landslides occurring, and can assist in minimising the potential impacts of landslides. The process of producing such maps involves identifying geographical and topological factors that predispose an area to erosion, as well as the likelihood and severity of a trigger event. Once these components are defined, they are then incorporated into landslide-susceptibility maps.

The effectiveness of landslide-susceptibility maps depends on the availability and resolution of data inputs. The ability to create high resolution Digital Elevation Models (DEMs) with LiDAR (Light Detection and Ranging) optical remote sensing technology allows the modelling of terrain in more detail than was previously possible[5]. The production of high-resolution (i.e., 1 m x 1 m) landslide-susceptibility maps is now possible. High-resolution maps contain sufficient detail to aid spatial planning. Consequently, the potential now exists for smarter planning decisions to be made.

The previous study of landslide erosion in two adjacent catchments (Tamingimingi and Pakuratahi) in the Hawke's Bay[6] used SINMAP (a freely available ArcGIS tool) and statistical modelling to create and compare detailed high resolution erosion risk maps. Using high resolution DEMs, both methods produced good results, predicting 75-90% of shallow landslides for storm events with return periods of 80 and 100 years.

These results represented a significant advance in assessing shallow landslide susceptibility compared to the generalised approach in the National Environmental Standards (NES) for forestry. However, validation of the statistical model in areas with the same soil types as the Pakuratahi study is needed. Expansion of the models into areas with different soil orders is needed to create a useful model applicable at a national level.

This research aims to investigate an alternative to the NES erosion susceptibility surface[4]. The specific objectives are to:

- validate testing of the statistical model created by Harrison *et al.* 2012; and
- determine the relationships between shallow landslide erosion and soil orders absent from the Pakuratahi study.

SINMAP was discounted as a suitable alternative to the NES erosion susceptibility layer, due to:

- complicated parameters that require a high level of soil science knowledge;
- difficulty in finding accurate parameter information without time consuming and expensive sampling; and
- lack of compatibility with ArcGIS 10 and subsequent developments.

Methods

The statistical model was evaluated using five new locations (Figure 3). Each of these new sites has digitised erosion events that cover a range of dates and soil orders (Table 1). Hi-resolution DEMs of 2 metres were derived from

LiDAR of each site, providing high quality data from which terrain attributes could be extracted.

Statistical Modelling Approach

An empirical nonlinear regression model was derived to predict the probability of shallow land sliding for a given intensive rainfall event. The dependent (erosion) variable was derived using a grid, equal to the size of the DEM, covering the site with value 100 if the grid location was on a slip, and 0 if not. This variable was derived from aerial images relating to rainfall events for each data set (Table 1), and represents the % slip area. The independent variables used in the regression were 72-hour rainfall (mm), slope (in 5-degree classes), soil type (Table 1), vegetation cover (pasture, indigenous scrub, exotic forest), and aspect. Other variables explored for inclusion in the regression model were various alternative terrain attributes (but slope and aspect were found to perform best), and lithography (this appeared to have some influence on slipping but less so than soil type).

Figure 3: Locations of the new research sites on the North Island of New Zealand. Source: Google Earth

Table 1: Date of Erosion events, and soil type for each site.

Site Name	Date of Events	Soil Type
Te Whanga	1941,1961,1977, 1991,2003,2009	Pallic
Tutira	1933,1938,1960, 1977,1988	Pallic and Pumice
Ruahines	1946,1974,1977, 2005	Gley, Brown and Recent
Pohangina	1946,1974,1995, 2005	Pallic
Pahiatua	1944,1979,1997, 2005,2011	Brown

Results and Discussion

During the validation process we found that the data extraction method could be improved, which led to a re-evaluation of the original Pakuratahi model.

The results were very similar to those of the previous research[6], with a similar predictive outcome. We found that land use had a significant impact on the predicted erosion susceptibility, with higher susceptible erosion ratings for pastoral land use than for exotic forestry and native scrub (Figure 4). The landslide data showed that less than 1% of landslides occurred after afforestation in the Pakuratahi catchment.

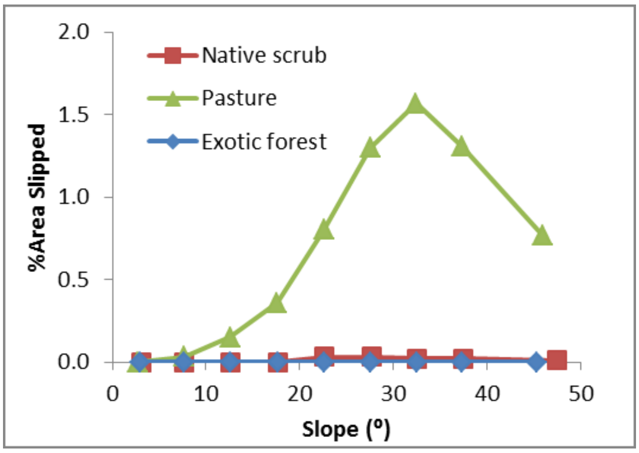

Figure 4: Observed land use area affected by shallow landslide erosion by slope class for the Pakuratahi catchment.

An updated empirical nonlinear regression model was fitted to predict % slip area at Pakuratahi. The model had the following form:

Probability of slipping = R x S x V x A

Where;
R = rainfall effect = max(Rain-R_threshold, 0)
S = soil/slope factor
V = vegetation cover factor
A = aspect adjustment = 1 + g x cos(Aspect - f)

R_threshold is the threshold (72-hour rainfall in mm) below which no slipping is predicted to occur for each soil type (Table 2).

Table 2: Updated Rainfall thresholds for Pallic, Pumice and Recent soil type over a 72-hour period.

Soil type	R_threshold
Pallic soil	123.1
Pumice or Recent soil	149.0

The soil and slope class factors S (Table 3) provide estimates of the % slip area for each millimetre increase in 72-hour rainfall above the threshold for land under pasture. For example, in a 323-mm event (i.e., 200 mm above the threshold for Pallic soil – Table 2), the % area slipping in the 25-30^0 slope class for Pallic soil is predicted to be 200 x 0.00569 = 1.1%.

The vegetation cover factor V has values 1, 0.245 and 0.0071 for pasture, indigenous scrub, and exotic forest.

Table 3: Updated Soil and slope class factors to be used to estimate the % slip area for each millimetre increase in 72-hour rainfall above the threshold for land under pasture.

Slope class °	Pallic soil	Pumice or Recent soil
<5	0.000119	0.000042
5-10	0.000503	0.000054
10-15	0.00107	0.000141
15-20	0.00205	0.000288
20-25	0.00391	0.00068
25-30	0.00569	0.00143
30-35	0.00672	0.00201
35-40	0.00618	0.00253
>40	0.00434	0.00378

The mean actual and predicted percentage eroded area showed good agreement, with no bias for each event (Figure 4). These results demonstrate that the model accurately predicts the likelihood of slipping (as a percentage by area) for a rainfall event of known intensity at any location within the study site.

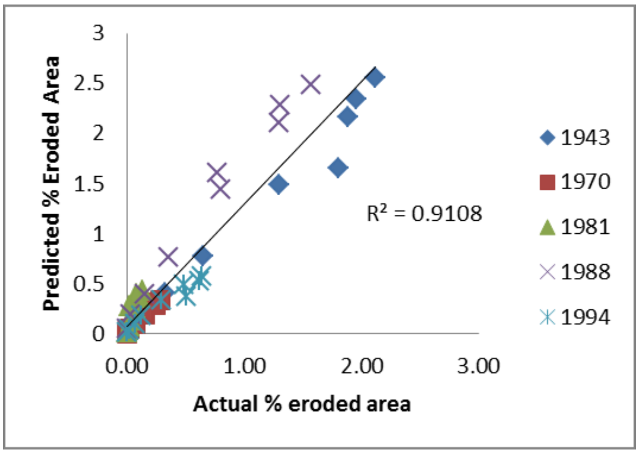

Figure 4: Pakuratahi actual versus predicted % landslide area for each of the five rainfall events (R^2 = 0.91).

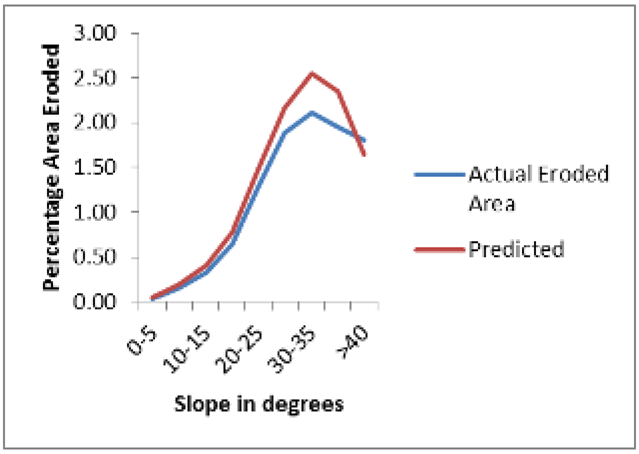

Figure 5: Pakuratahi actual versus predicted % landslide area for a rainfall event of 503mm/72 hr.

This is reinforced by using the model to predict the percentage area eroded during the largest rainfall event (Figure 5). The predicted area follows the actual area closely, but diverges once the slope increases above 25°, the model having a propensity to over-predict the % landslide area on these steeper slopes. We are unsure why the % eroded area tracks downwards on the steepest slopes (>35°). We presume that soil has already been eroded from these steep slopes, which are now or always were rock faces.

In the validation, the probability of slipping equation (R x S x V x A), is used to predict the areas lost to shallow land slide erosion during known rainfall events (Table 1) for each new site. The R^2 gives an indication as to whether the model will be a good predictor or not. The closer the R^2 value is to one (1) the better the model can be assumed to perform. Using the largest rainfall event, a direct comparison between the actual and predicted is shown.

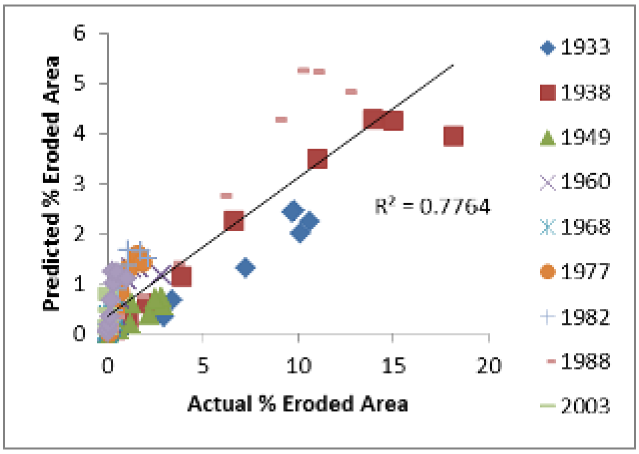

Figure 6: Tutira actual versus predicted % landslide area for each of the rainfall events (R2 = 0.78).

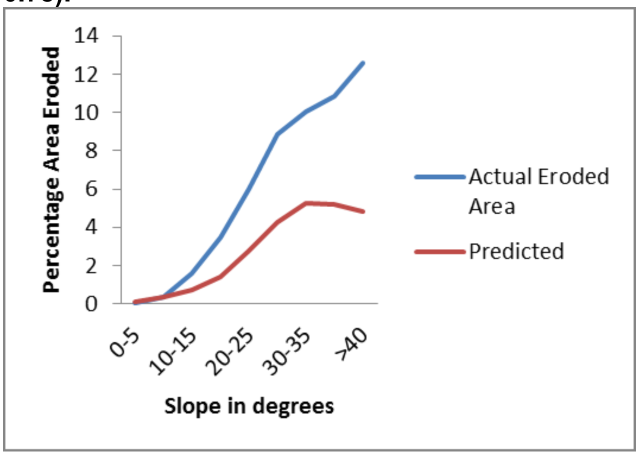

Figure 7: Tutira actual versus predicted % landslide area for a rainfall event of 730mm/72 hr.

In Tutira (which has a similar soil type to that of Pakuratahi), the model had a lower R^2 value of 0.78. When used to predict a 730mm/hr rain fall event (Figure 7), the predicted and actual figures begin to diverge at slopes of 10° and greater. The model under-predicts the area effected by landslides.

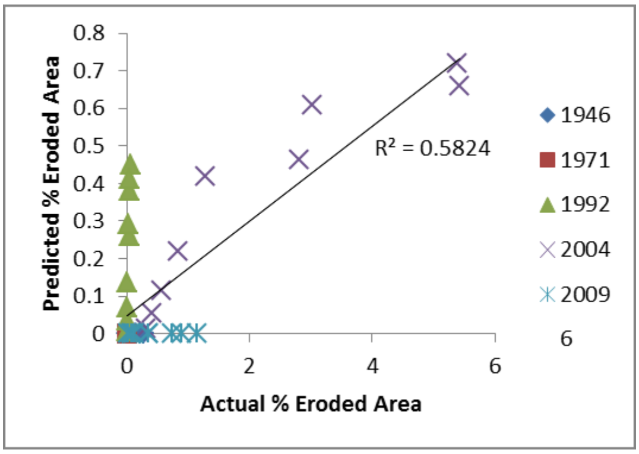

Figure 8: Pohangina Actual versus predicted % landslide area for each of the rainfall events (R2 = 0.58).

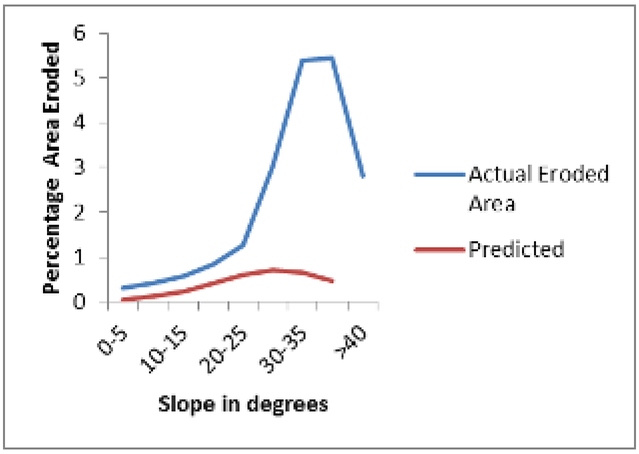

Figure 9: Pohangina actual versus predicted % landslide area for a rainfall event of 230mm/72hr.

For the Pahiatua area, the model explains just over half of the observed variation in % landslide area (R^2 0.58, Figure 8). The predicted and actual values (Figure 9) are similar until the slopes are greater than 25°. Where the values differ, the actual data increase substantially while the prediced data show only a slight increase.

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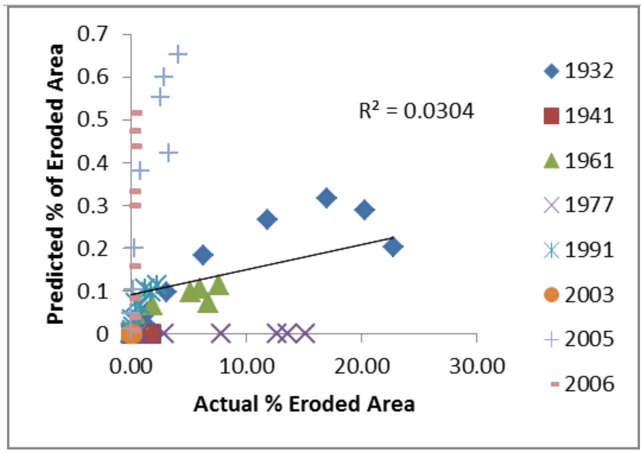

Figure 10: Te Whanga actual versus predicted % landslide area for each of the rainfall events (R2 = 0.03).

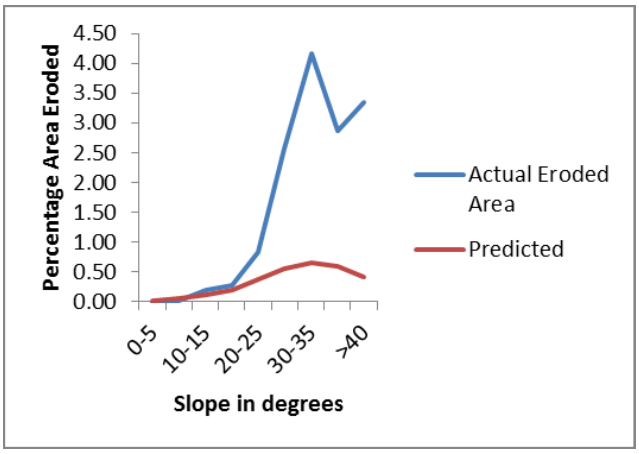

Figure 11: Te Whanga actual versus predicted % landslide area for a rainfall event of 220mm/72hr.

The Te Whanga R^2 of 0.03 (Figure 10) indicates that the model was unable to predict the actual data. When using actual data from a 220mm/72hr event (Figure 11), the predicted and actual values for % areas eroded were similar until the slope rose above 15°. The actual data then increased sharply to 4% of total area eroded while the predicted stayed well below 1%.

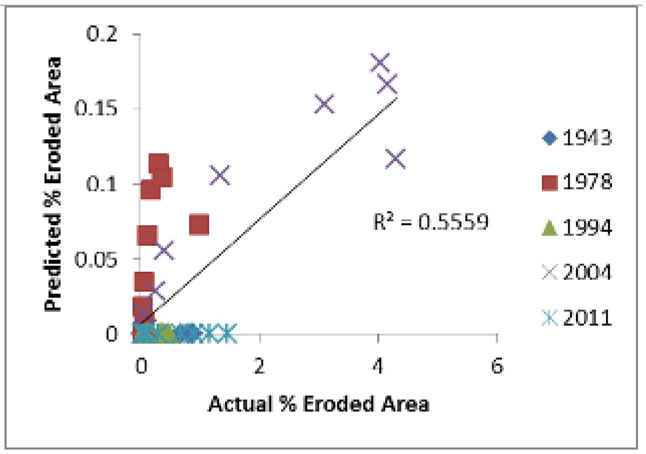

Figure 12: Pahiatua actual versus predicted % landslide area for each of the rainfall events (R2 = 0.55).

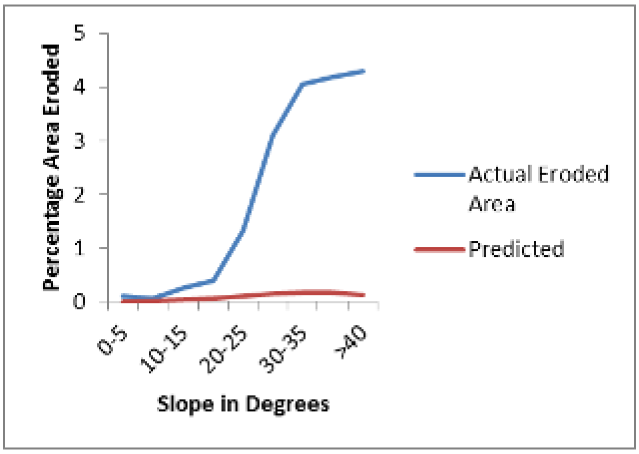

Figure 13: Pahiatua actual versus predicted % landslide area for a rainfall event of 230mm/72hr.

Using the model to predict the area of land affected by landslide erosion in the Pohangina research area resulted in a R^2 of 0.55 (Figure 12). When comparing predicted and actual data for a 230mm/72hr event, the model underpredicts, especially when the slope is above 15°.

Our results showed that the probability of landslip damage on all sites is strongly influenced by the rainfall intensity, slope, vegetation cover and soil type. Aspect had a marked influence on the probability of shallow landslides, although the effect varied in both direction and extent for each rainfall event. On all new sites the model under-predicted the extent to which shallow landslides would occur.

Risk maps produced using the method for categorising risk suggested by Sticker and Moon[7] were a good indicator of where shallow landslides would occur. This method uses Jenks natural breaks to categorise erosion. This is a method available in ArcMap, where data are partitioned into classes based on natural groups in the data distribution.

Using the statistical model and data from a known rainfall event, erosion risk maps were produced for Te Whanga, Pohangina and Tutira (Figures 15, 17, and 19 respectively). The actual shallow landslide data for the corresponding site and event were used to calculate the number of shallow landslides that occurred in each risk category (Tables 4, 5, and 6). The 4 class erosion susceptibility maps are also shown as a comparison (Figures 14, 16, 18).

When comparing the differences between the two risk maps it is important to understand what each map represents. The Erosion susceptibility 4 class layer indicates the overall risk of that area slipping at any time, while the statistical model represents the risk that a particular area will erode during a specific rainfall event.

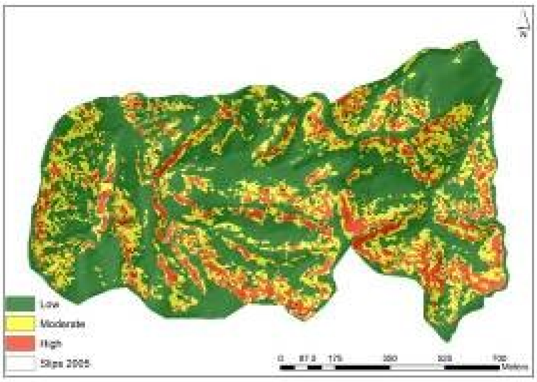

Figure 15: Statistical model for 2005 220mm/72hr rainfall event Te Whanga

Table 4: Actual shallow landslides by risk class for 2005 220mm/72hr event Te Whanga

	Te Whanga	
Erosion risk category	**Number of Landslides**	**Percentage**
High	171	80.3
Moderate	38	17.8
Low	4	1.9
Total	213	100

The tables show that over 80% of erosion occurred in areas indicated as high risk. The 4 class erosion susceptibility maps are also shown as a comparison (Figures 14, 16, 18).

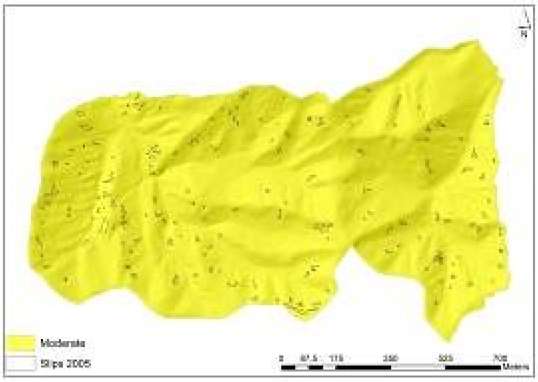

Figure 14: Erosion susceptibility 4 class surface for Te Whanga.

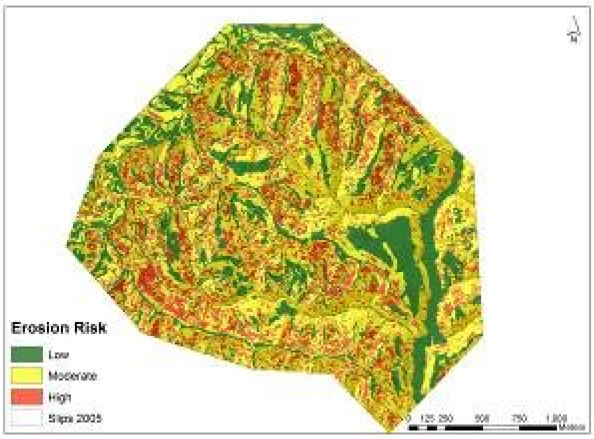

Figure 17: Statistical model for 2005 230mm/72hr rainfall event Pohangina

Table 5: Actual shallow landslide by risk class for 2005 230mm/72hr event Pohangina

	Pohangina	
Erosion risk category	**Number of Landslides**	**Percentage**
High	998	98.3
Moderate	5	0.5
Low	12	1.2
Total	1015	100

Risk maps produced using the statistically modelled data show marked differences in the allocation of erosion risk across the landscape when compared to the erosion susceptibility layer. This is most evident at Pohangina (Figures 16 and 17), where areas classified as very high risk by the erosion susceptibility 4 class layer are re-classified as low erosion risk in the statistical model risk maps.

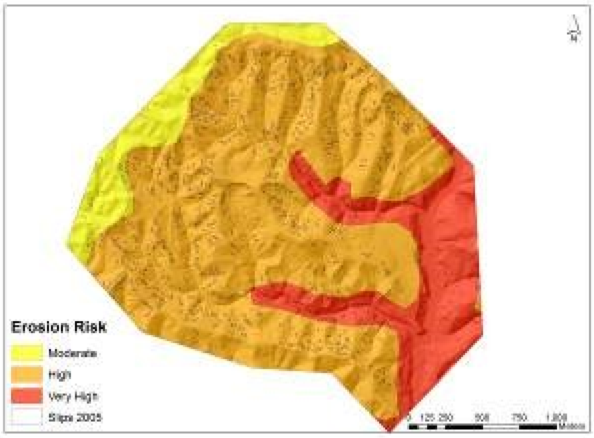

Figure 16: Erosion susceptibility 4 class surface for Pohangina

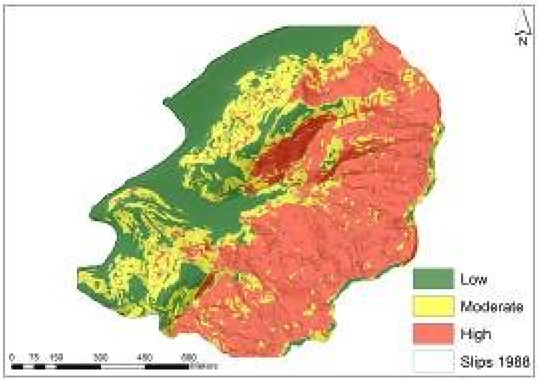

Figure 19: Statistical model for 1988 730mm/72hr rainfall event Tutira

Table 6: Actual shallow landslide by risk class for 1988 730mm/72hr event Tutira

	Tutira	
Erosion risk category	**Number of Landslides**	**Percentage**
High	446	83.7
Moderate	40	7.5
Low	47	8.8
Total	533	100.0

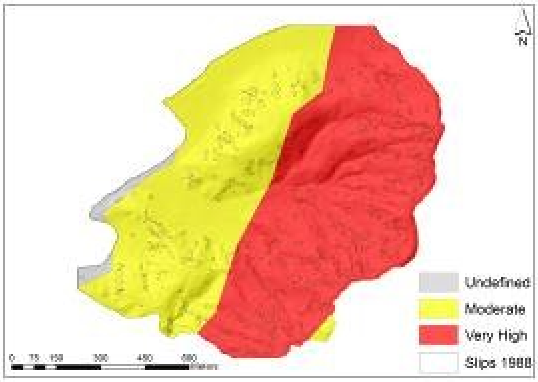

Figure 18: Erosion susceptibility 4 class surface for Tutira

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Conclusions

The recalibrated Pakuratahi model performed well at predicting the percentage of area that will be affected by shallow landslides with changing rainfall intensity. The model followed actual data in the Pakuratahi study area closely through all slopes, with a tendency for over-prediction. When run in other study areas, the model mirrored actual data only at the lower slopes where little or no erosion would be expected. With increasing slope angles the model under-predicts the percentage landslide area. Therefore the model has not been validated because actual area affect by erosion can vary considerably from the predictions generated by the model.

While the model has not been validated to predict erosion in areas other than Pakuratahi, it could be calibrated with relative ease to use in new areas. However the calibration process requires each new area to have data that identifies landslides that were caused by a known rainfall event. A high-resolution DEM of the eroded area is also required. These data are very difficult to acquire as there is currently no coordinated collection of erosion data in New Zealand. The accuracy of the re-calibration improves with the size of the rainfall event. A rainfall event of 300m/72hr produces better results than a 200mm/72hr, and an event of 500mm/72hr produces better results than the 300mm/72hr.

A very strong relationship between shallow landslides and slope was found to be consistent in all soil types. This means that slipping occurs above a certain degree of slope (about 15 degrees), and regardless of rainfall, the amount of erosion will increase as slope increases. This relationship can be used to indicate risk with some confidence (Tables 4, 5, and 6) when using high resolution DEMs. The resulting risk maps (Figures 15, 17, and 19) appear to provide a better indication of shallow landslide erosion than the four class erosion susceptibility surface[4].

This research demonstrates that with the correct data, the statistical model can produce accurate predictions of areas affected by shallow landslides. It also highlights the difference between the ability to indicate erosion risk and the ability to model soil loss due to erosion. With high resolution DEMs, simple and accurate erosion risk maps can be produced. If an area of erosion is known, further work could be carried out, using flow dynamics to indicate likely areas of sedimentation, debris flows and downstream damage. Productivity loss due to erosion could then be calculated.

Acknowledgements

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