Terrain Scaling for Continental Scale Soil Erosion Modelling

J.C. Gallant[a]

[a]*CSIRO Land and Water, GPO Box 1666, Canberra ACT 2601, Australia* (John.Gallant@csiro.au)

Abstract: Continental prediction of soil erosion and sediment transport poses many challenges, one of them being the difficulty of using coarse-scale topographic data to predict topographic influences on erosion at a scale commensurate with erosion processes. This paper describes the methods used in the Water-borne Soil Erosion and Sediment Transport project in the Sustainability Theme of the National Land and Water Resources Audit completed in early 2001. The RUSLE slope length and slope steepness factors were derived through a statistical modelling procedure based on a large number of measurements from high resolution DEMs across Australia. The statistical models provided usable predictions of slope length and steepness across the large areas of the continent included in the study with substantial improvements over values derived directly from the continental 9 second DEM.

Keywords: Scaling; Erosion; Hillslopes; Slope; Slope length

1. INTRODUCTION

1.1. Background

The water-borne erosion and sediment transport project (Project 4a of Theme 5 of the National Land and Water Resources Audit) provides predictions of hillslope erosion as one of the sources of sediment in river systems. The processes being modelled – routing of overland flow with detachment and deposition of sediment – are known to operate at a fine spatial scale, considerably finer than the resolution of the 9 second DEM [Hutchinson et al., 2001] which currently is the best Australia-wide digital elevation data set. This scale mismatch is a well-known problem and frequently occurs in hydrological modelling. While there is an extensive literature describing the problem and suggesting possible approaches, there is as yet no accepted operational procedure for dealing with it.

In this project erosion was modelled using the revised universal soil loss equation (RUSLE) [Renard et al., 1997] which includes topographic effects via length (L) and slope (S) factors. The spatial variation in these two factors combined is an important control on erosion intensity, comparable with the range of rainfall and soil erodibility [Rustomji and Prosser, in prep]. Deriving these factors directly from the 9 second DEM would be indefensible, as slopes would be underestimated and hillslope length overestimated in most areas.

The approach used for this project was to calculate slope and hillslope lengths from selected high resolution DEMs then build statistical models using predictive variables that are can be derived everywhere.

This paper follows on from Gallant et al. [1999] presented at MODSIM 1999, where the issues were identified and an approach proposed. The original concept was to use a spatially explicit sediment transport model at the 9 second DEM resolution, with topographic structure re-introduced to that DEM and the effects of sub-grid-scale structure parameterised in the model. The adopted solution was less detailed but provided information at a level of detail consistent with the continental scale of the project.

2. MEASUREMENTS FROM HIGH RESOLUTION DEMS

High resolution DEMs were obtained to cover most of the combinations of landform, climate and geology in Australia. An initial set of readily available DEMs was acquired, then gaps in the coverage were identified and additional DEMs obtained to fill those gaps. The final set of DEMs covered areas from all states, and included both coastal and inland areas. Resolutions were mostly 20 to 50 m and were derived either from 1:25 000 scale source data (1:50 000 in some cases) or from radar altimetry collected during airborne geophysical surveys. One DEM covering the wet tropics of northern Queensland is at 80 m resolution and is based on 1:100 000 scale source data.

Figure 1 shows the location and extent of the high resolution DEMs used for model building.

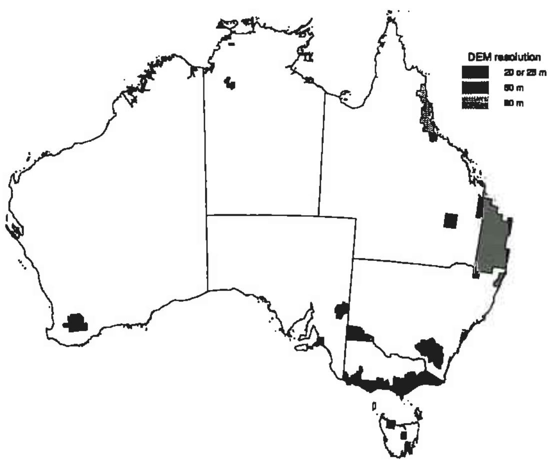

Figure 1. Figure 1. Location of high resolution DEMs used in the project. Shades indicate the DEM resolutions.

2.1. Hillslope Length

The algorithm used to calculate hillslope length is based on the classification of DEM cells into one of four classes: top, bottom, hillslope and indeterminate. The class is assigned by examining the set of cells within a circular context of a given size and marking the cells that are the maximum and minimum value in the circle. The circular context is constructed at every grid cell, so each cell is included within the context a number of times. Any cell that is never a maximum is classed as a bottom (valley) cell for that circle size; any cell that is never a minimum is classed as a top (ridge) cell; and cells that have been both maximum and minimum are classed as hillslopes. Those cells that were neither maximum nor minimum do not have a clear interpretation, although they include saddle cells, and are termed indeterminate cells. This analysis is performed using a range of different sized circular contexts, from one pixel in radius up to a user-defined maximum (1 km in this application).

The property that makes this classification useful for determining hillslope length is that most cells are classified as hillslope points at small radii but indeterminate at large radii. The radius at which the number of indeterminate points equals the number of hillslope points is a measure of the hillslope length. This radius cannot be determined for individual cells, since it is the frequency of different classes amongst a group of cells that determines the hillslope length at a site. The method therefore requires a user-defined length scale over which the frequency of cell classes is determined (1 km in this case). The resolution of the output grid is also user-specifiable (250 m in this case) but is rounded to the nearest multiple of the DEM resolution. This algorithm is implemented in the program `HillLength2`, available from the author.

Following calculation of the hillslope length at 250 m intervals, a mean length over a 1.5 km radius is computed. This step was performed to smooth out fine-scale variations in hillslope length that could not realistically be predicted from the coarser scale predictive variables. A further processing step was required to exclude areas with low relief, as hillslope length in very flat landscapes is unreliable both conceptually (what is a hillslope when there are no hills?) and practically (noise or subtle variations in DEM produce small hillslope length values). Low relief areas for this purpose were defined as areas having a standard deviation of elevation over a 2 km radius that was less than 5 m. A recently developed method for identifying depositional areas [Gallant and Dowling, in prep] provides a means for identifying length scales in these low relief parts of the landscape, but has not been incorporated in this analysis.

Figure 2 shows measured hillslope length (after smoothing) for the Warragul 1:250 000 map sheet in south-eastern Victoria including Wilson's Promontory (145°30′ E to 147° E, 39°15′ S to 38° S, approximately 130 × 130 km). Hillslope lengths in this landscape range from 60 to 400 m; in some other landscapes hillslope lengths up to 1 km are obtained.

2.2. Slope

Slope was calculated from the high resolution DEMs using conventional methods (the SLOPE function in ArcInfo Grid, with the percent option). For DEMs in geographic coordinates, corrections were applied to account for the different units of measure in the horizontal direction (degrees) and vertical direction (metres) and for the difference in spacing in the x and y directions due to the spherical coordinate system [Gallant, 2001]. From the raw slope, a mean slope over a circle of 250 m radius was calculated and the results converted to geographic projection at 9 second resolution.

Figure 3 shows mean slope calculated for the Warragul map sheet. Mean slope ranges from 0 to

50 % in this area which is the typical range for the steepest areas of Australia.

3. MODELLING METHOD

The statistical models were constructed using the Cubist data mining tool [version 1.08; Rulequest Research, 2001]. This software takes a set of samples, each with a target value and a collection of potential predictive variables, and constructs a number of rules each comprising a set of conditions and a linear model that provides the predicted value when the conditions are met. Cubist can also use an independent set of samples to test the model, and reports both summary statistics and the predictions for each validation datum. For this application 30% of the points in the 9 second resolution data were used for model building and a further 10% of points for model testing. The resulting sample set combined from all the high resolution results contained approximately 200 000 sample points, each with a calculated value and the values of all predictive variables at that location.

The predictive variables were selected to represent the major factors presumed to control landscape form:

- Material (geology and soil)
- Climate (temperature, rainfall and seasonality)
- Geomorphology (relief, slope, slope position)

Sixteen variables were used for prediction:

- Two aggregated geology classifications derived from the 1:2.5M scale geology map of Australia (geol_agec and geol_lith)
- A more detailed lithology surface provided by the Bureau of Rural Sciences (lithology)
- The Australian Soil Classification derived from the Atlas of Australian Soils
- Mean annual rainfall, rainfall seasonality index and annual moisture index
- Mean annual temperature, temperature seasonality and diurnal temperature range
- Relief, relative elevation and slope position within land units defined by ridge and stream networks from the 9 second DEM
- Standard deviation of elevation and elevation percentile (an indicator of slope position) within 2 km radius circular regions from the 9 second DEM
- Slope from the 9 second DEM

A stepwise model building approach was adopted. For the first step, each variable was used independently and the best variable identified using statistical diagnostics from the modelling package (correlation and relative error). This one variable was then used with each other variable, and the best second variable identified. This procedure was repeated until all variables were included.

As more variables were introduced into the model and the rule conditions derived by Cubist became more selective, the number of points that do not match any condition increased, leaving undefined cells in the predicted result. This is an undesirable effect that influenced the selection of model complexity.

Final selection of the model was based on the statistical diagnostics, visual comparisons of predicted and measured maps and the relative rates of unpredicted points.

3.1. Model of Hillslope Length

Models for hillslope length with few variables performed poorly, and the performance continued to improve slowly as more variables were included. There were few problems with unpredicted values, so the selected model included all the 16 variables and contained 56 rules.

Lithology was the most predictive single variable (correlation = 0.35), with three climate variables (mean annual temperature, diurnal temperature range and mean annual rainfall) producing slightly lower correlations. The order in which variables were selected is:

- lithology
- mean annual temperature
- temperature seasonality
- standard deviation of elevation
- mean annual rainfall
- diurnal temperature range
- slope position
- rainfall seasonality
- elevation percentile
- annual moisture index
- Australian soil classification
- slope from 9" DEM
- relief
- relative elevation
- geology (geol_lith)
- geology (geol_agec)

The final model comprised 55 rules and has a correlation coefficient of 0.71 on the validation data.

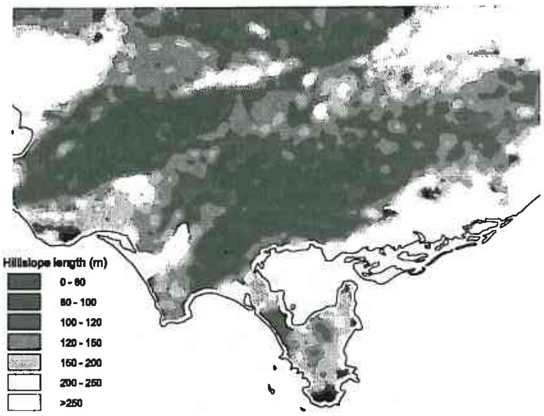

Figure 2. Measured hillslope length for Warragul map sheet, southeastern Victoria.

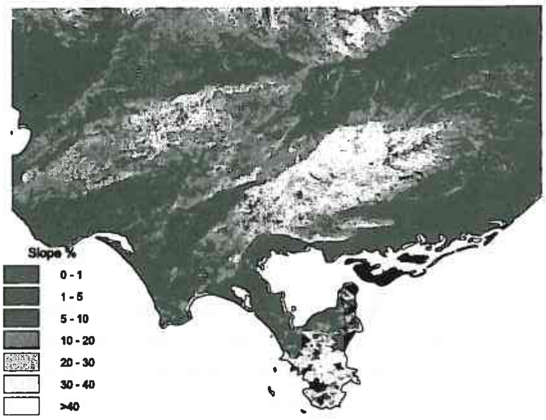

Figure 3. Measured slope for Warragul sheet.

The importance of lithology in this model is not surprising, but the degree to which climatic variables explain hillslope length is surprising. Climatic variables make up 5 of the 8 most predictive variables. Standard deviation of elevation, essentially a measure of relief, is the only geomorphic variable appearing high on the list. Mean annual temperature, the second variable included, could be acting as a surrogate for elevation above a base level since temperature decreases systematically with elevation. Temperature seasonality, the third variable included, may be a direct measure of climatic regime distinguishing alpine, arid and coastal environments.

Figure 4 shows the predicted hillslope length for the Warragul map sheet. Compared with the measured values of Figure 2, the predicted map

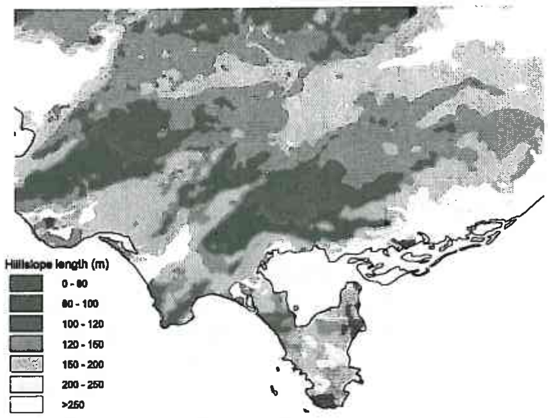

Figure 4. Predicted hillslope length for Warragul sheet. Compared to measured values, the predictions have reduced range and detail but similar patterns.

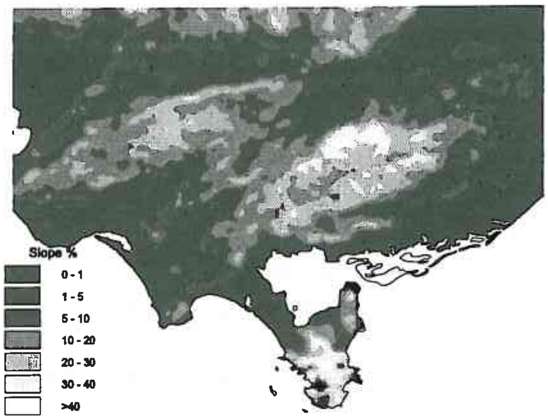

Figure 5. Predicted slope for Warragul sheet. Compared to the measured values, general patterns and values are similar although much detail is lost.

shows similar overall patterns with differences in detail, and a reduced range: both short and long hillslopes are under-represented in the predictions. The variation between shorter and longer hillslopes at the regional scale is the desired result, and this prediction is considered to be a satisfactory result for the purposes of this project.

3.2. Model of Slope

While slope from the 9 second DEM was considered unreliable compared to slope from the higher resolution DEMs, it was expected to be well correlated with mean slope. This was indeed the case, and slope was by far the best single predictor, but additional variables improved the result both in terms of statistics and spatial patterns (as assessed by the visual comparison of the predictions and measurements). The results ceased to improve after 10 variables, and the frequency of unpredicted values increased with increasing numbers of variables, so the final model used only the first 10 variables:

- slope from 9" DEM
- standard deviation of elevation
- lithology
- rainfall seasonality
- annual moisture index
- annual mean temperature
- elevation percentile
- relative elevation
- diurnal temperature range
- slope position

This model comprised 53 rules and had a correlation coefficient of 0.87.

The list of included variables contains a mixture of geomorphic, geologic and climatic variables. As expected, slope is the most predictive single variable. The early inclusion of standard deviation of elevation and lithology is unsurprising. What is surprising is the lack of predictive power from annual mean rainfall; instead rainfall seasonality and moisture index appear as relatively important predictors. It may be that the effect of mean annual rainfall is already captured by the 9" slope, with the seasonality and moisture index accounting for subtler effects of rainfall-related climate.

An additional model using just 9" slope as the sole predictive variable was developed for use in the interior of the continent where many of the predictive variables were not available and the extrapolation of the model is not appropriate. This model contained 17 rules (correlation = 0.80), and the composite effect of those linear models was manually modelled with a single non-linear model:

$$s_{pred} = 1 + s_9 \frac{2.1}{1 + \frac{.014 s_9}{1 + 0.001 s_9}}$$

where s_{pred} is predicted slope and s_9 is slope from the 9" DEM. This model predicts a minimum slope of 1%, increasing with 9" slope at a rate that decreases as 9" slope increases.

Figure 5 shows predicted slope for the Warragul map sheet. As for hillslope length, the predictions are similar in overall pattern with considerable differences in detail. The predicted slope has fewer areas of high slope and less detail, but for the purposes of this project the prediction is once again considered to be satisfactory.

3.3. Calculation of L and S Factors

The RUSLE L and S factors are calculated from mean hillslope length and mean slope using the standard RUSLE equations [Renard et al., 1997]. In some land use classes where surface runoff does not appear to increase with flow path length, the L factor is set to 1.

Some applications of hillslope length for erosion prediction require an L factor for the interior of the continent. In this non-agricultural area no high resolution DEMs were obtained to provide samples for rule building. Extrapolation of the rules into the different geomorphic and climatic conditions of this area was considered to be inappropriate, so a unit L factor value was used. For low relief areas this is reasonable as the L factor is close to 1 when slope is low. High relief areas would in reality have a higher L factor.

Further details of these calculations are presented in Lu et al. [2001].

4. ASSESSMENT OF RESULTS

The hillslope length algorithm has not been thoroughly validated although manual measurements from contours in a small number of locations agreed with the results of `HillLength2`. The error from calculating hillslope length is considered to be small. The error in calculating mean slope is also expected to be small.

The accuracy of the predictions is assessed both by the statistical diagnostics of the Cubist program and visual comparisons of patterns. The correlations reported by Cubist are 0.71 for hillslope length, which indicates a reasonably good prediction but with substantial variation unaccounted for, and 0.87 for slope indicating quite a good model accounting for most of the variation.

Root-mean-square (RMS) error for each prediction was analysed using the approximately 67 000 pairs of measured and predicted values. For hillslope length the RMS error was 85 m, compared to a mean hillslope length of about 200 m. Error generally increases with the magnitude of the predicted hillslope length, and the mean relative error is about 30% for predicted lengths between 100 and 500 m. The model performs poorly for low hillslope lengths; for predicted lengths less than 70 m, the average error is over 100 m. It also under-predicts large hillslope lengths: there are few predictions greater than 400 m in spite of the measured values reaching 1000 m.

For slope the RMS error was 7% slope, compared to a mean slope of 13%. Error generally increases with slope value, with under-prediction increasingly prevalent at higher slopes. The mean relative error is about 0.6 for slopes less than 5% decreasing to 0.1 for slopes above 60%. The error is approximately 0.4 times the slope value up to 20% slope, above which the error is 8% slope. The minimum predicted slope is about 0.5%, so very low slopes are not correctly represented.

5. CONCLUSIONS

Overall, the results are considered adequate for the purpose of this project. The errors form a significant but not overwhelming contribution to the error budget for hillslope soil erosion.

The value in this modelling approach based on high resolution data is demonstrated by two observations. Firstly, the average hillslope length (200 m) is less than the resolution of the 9 second DEM. Secondly, the model of slope based solely on the 9 second DEM slope demonstrates that the mean slope is more than twice the value measured directly from the 9 second DEM, although this factor reduces as slope increases above 10%. Determining hillslope lengths and slopes directly from the 9 second DEM would have caused gross errors in erosion estimates.

The rules produced by Cubist have not yet been analysed from a geomorphic perspective. It is possible that some of the variables are acting as surrogates for other effects, in which case more physically realistic models could be constructed by using a predictive variable more closely related to the effect. One example of this could be temperature, which is a strong predictor of hillslope length but may be reflecting some effect of elevation on hillslope length, rather than temperature *per se*. A close analysis of the rules may suggest areas for research into the physical processes underlying the development of slope forms, but this has not yet been attempted.

6. ACKNOWLEDGEMENTS

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