Prediction of Sheet and Rill Erosion Over the Australian Continent, Incorporating Monthly Soil Loss Distribution

Hua Lu, John Gallant, Ian P. Prosser, Chris Moran, Graeme Priestley

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ABSTRACT

A major issue in Australian land management is soil erosion and the consequent reduction of productivity. The off-site effect of soil erosion is the degradation of water quality in streams and water storages. Measurement of soil erosion is time consuming and data on soil erosion rate is limited to a few sites. Those sparse measurements provide little information about the spatial distribution of soil loss rate across the nation. This report describes a spatial modelling framework which is used to predict an Australia-wide sheet and rill erosion. It is based on the Revised Universal Soil Loss Equation (RUSLE) using time series of remote sensing imagery and daily rainfall combining with updated spatial data for soil, land use and topography. The results are presented as a geo-referenced annual averaged soil loss map and its monthly distributions. It is found that the north part of the country has higher erosion potential than the south of the country. The prediction confirms that agricultural land use has higher erosion rate compared with most natural vegetated lands and that erosion potential differs significantly between summer and winter periods.
1 INTRODUCTION

Soil erosion caused by rainfall and runoff is recognised as a major environmental problem in Australia. Suspended sediment concentrations in streams and lakes affect water use and ecosystem health. High concentrations of sediment reduce stream clarity, inhibit respiration and feeding of stream biota, diminish light needed for plant photosynthesis, and require treatment for human water use. To minimise the decline of soil productivity and water quality and to optimise the use of resources for soil conservation, spatially distributed patterns of the hazard sources and associated soil loss rate is essential to identify crucial areas appropriate for more detailed investigation. Furthermore, the basic prerequisite for understanding the consequences of changes in land use and climate on soil erosion is to know the sources and rates of erosion rate under the present land use and climate conditions.

For the scale under consideration, a simplified version of the Revised Universal Soil Loss Equation (RUSLE) calibrated using New South Wales field data, was selected. Application of the RUSLE for the Australian continent affords the following advantages:

1. It requires a modest amount of parameters that can be derived for a continent and has been adapted to Australian conditions;
2. Used in conjunction with raster-based GIS, the RUSLE predicts erosion potential on a cell by cell basis for mapping spatial patterns; and
3. The factor-based nature of the RUSLE allows easy analysis of the role of individual factors in contributing to the estimated erosion rate.

A similar approach has been applied to the Australian continent before (Rosewell, 1996), as part of the 1996 National State of the Environment Report. This assessment provides a significant update on that assessment by inclusion of improved or new national datasets on rainfall, soils, vegetation cover, land use, and topography which were not available in 1996. Furthermore, we have been
able to incorporate seasonal patterns of rainfall and cover factors, which Rosewell (1997) suggested was needed for more accurate distinction of the continental pattern of soil erosion.

In this study, we present a spatial modelling framework designed for the Australian continent hillslope sheet and rill erosion prediction. Data used to generate the RUSLE variables include:

1. 13 years NOAA/NASA Pathfinder GAC 8km Advanced Very High Resolution Radiometer (AVHRR) derived 10-day maximum composite Normalised Difference Vegetation Index (NDVI) data (Data source: CSIRO Earth Observation Centre (EOC));
2. 20 years of daily rainfall interpolated from station measurements (Data source: Queensland Department of Natural Resources (QDNR));
3. Updated national soil attributes maps (Data source: Australian Soil Resource Information System (ASRIS) project, National Land and Water Resources Audit (NLWRA));
4. 1 km resolution National landuse map based on 1997 landuse distribution (Data source: Bureau of Rural Sciences (BRS) and NLWRA),
5. 9” National digital elevation model (DEM) (Data source: AUSLIG); and
6. Locally available higher resolution DEMs (Data source: CSIRO and State Agencies).

The updated soil attribute maps and the land use map together with this assessment of soil erosion are products of NLWRA.

2 METHODOLOGY

The RUSLE calculates mean annual soil loss ($Y$, t ha$^{-1}$ yr$^{-1}$) as a product of six factors: rainfall erosivity factor ($R$), soil erodibility factor ($K$), hillslope length factor ($L$), hillslope gradient factor ($S$), ground cover factor ($C$) and supporting practice factor ($P$):

$$Y = R K L S C P$$

(1)
The factors included in the RUSLE vary strongly across the Australia. Using available spatial information for each factor provides a means for estimating the spatial patterns of continental scale sheet and rill erosion. Due to lack of spatial data of contour cultivation and bank systems, an assessment of the supporting practice factor \( P \) is excluded.

The precise form of each factor is based on soil loss measurements on hillslope plots, mainly in the USA. Limited plot scale measurements of erosion have been undertaken in Australia \( (e.g. \) Edwards, 1987; McIvor \textit{et al.}, 1995; Scanlan \textit{et al.}, 1996) allowing limited local calibration of the USLE factors, particularly the \( C \) factor.

Mean annual values for rainfall erosivity and the cover factor are often used in direct application of Equation (1) to calculate mean annual hillslope erosion. This often neglects important seasonal patterns of rainfall erosivity and cover. Problematic to the standard annual application of the RUSLE is the pronounced wet-dry precipitation regime in Australian tropics and Mediterranean climate dominant areas such as south Western Australia. To adequately represent the erosive potential of rainfall for each temporally distinctive period, this study applies the RUSLE model on a monthly averaged basis by calculating appropriate erosivity and cover factors for each month. It can be shown that incorporation of seasonal effects reduces predicted mean annual soil loss in the tropics by a factor of 1.5. The modifications of Equation (1) discussed above yield monthly soil loss rate which can be calculated as:

\[
Y_j = R_j \cdot K \cdot L \cdot S \cdot C_j
\]  

(2)

where \( C_j = \sum_{i=1}^{12} \left( SLR_j \cdot \frac{R_j}{R} \right) \). \( R_j \) and \( SLR_j \) are cover management factor, rainfall erosivity and the soil loss ratio, respectively, for month \( j \).

Sections 2.1 – 2.5 describe the calculation procedure for each factor in Equation (2). The calculation was applied for each grid cell at an appropriate resolution determined by the source data resolution. More specifically, 0.05° for \( R \) factor
determined by QDNR daily rainfall data, 0.01° for C factor determined by the NLWRA/BRS landuse data, 0.0025° for LS factor determined by the 9” AUSLIG DEM, and 0.0025° for K factor determined by the ASRIS soil attributes. The resulted images with resolution coarser than 9” were re-sampled to 0.0025°, which is NLWRA Theme 5.4b, sediment delivery and transport project required resolution. The bilinear option was used to re-sample R factor and its monthly distributions and the nearest neighbour option was used for C factor re-sampling. All the images were then extended to the coast line using nibble command in ARC/INFO. The re-sampled images were finally multiplied using Equation (2) to produce monthly hillslope erosion rate (in the unit of t ha⁻¹ yr⁻¹) maps. The annual hillslope erosion map is the sum of the twelve monthly erosion maps.

2.1 Rainfall erosivity (R)

Rainfall erosivity (R) is defined as the mean annual sum of individual storm erosion index values, EI₃₀, where E is the total storm kinetic energy and I₃₀ is the maximum rainfall intensity in 30 minutes. To compute storm EI₃₀, continuous rainfall intensity data are needed. Wischmeier and Smith (1978) recommended that at least 20 years of pluviograph data be used to accommodate natural climatic variations. However, the spatial and temporal coverage of pluviograph data is often very limited.

Yu and Rosewell (1996a, 1996b) and Yu (1998) proposed a rainfall erosivity model in which storm EI₃₀ for the month j is related to daily rainfall amount, R_d, in the form:

\[
EI_{30}(j) = \alpha \left[ 1 + \eta \cos(2\pi f \cdot j - \omega) \right] \sum_{d=1}^{N} R_d^\beta \quad \text{for } R_d > R_0
\]

where \( R_d \) is the daily rainfall amount, \( R_0 \) is the threshold rainfall amount to generate runoff (set to 12.7 mm; Wischmeier and Smith, 1978), and \( N \) is the number of days with rainfall amount in excess of \( R_0 \) in the month. The first part of the equation is a sinusoidal function with a wavelength of twelve months (\( f = 1/12 \)). It is used to describe the seasonal variation of rainfall erosivity for a
given amount of daily rainfall. The parameter $\omega$ is set at $\pi/6$, implying that for a given amount of daily rainfall the corresponding rainfall erosivity is the highest in January, when the temperature is the highest for most part of the continent. Regional relationships were derived using 79 stations located in NSW, SA, and the tropics for parameters $\alpha$, $\beta$, $\eta$:

\begin{align*}
\alpha &= 0.395 \left[1 + 0.098 \exp(3.26 \Psi/M)\right] \\
\beta &= 1.49 \\
\eta &= 0.29
\end{align*}

where $M$ is the mean annual rainfall and $\Psi$ is the mean summer rainfall (November to April; Bureau of Meteorology 1989).

The model was applied to the Australian continent using 0.05° resolution daily rainfall data interpolated by Queensland Department of Natural Resources. The description of daily rainfall interpolation can be found in Jeffrey et al. (2001). Ordinary kriging is firstly used to spatially interpolate monthly rainfall values. Then, for each grid cell, the daily distribution of rainfall throughout the month is calculated by accessing the rainfall record for the station nearest the points of interest, and partitioning the interpolated monthly rainfall onto individual days according to the long-term distribution of daily rainfall at the nearest rain gauge station. In this study, 20 years of grided daily rainfall from 1\textsuperscript{st} of January, 1980 to 31\textsuperscript{st} of December, 1999 are used. The ratio $\Psi/M$ was calculated using the same daily rainfall data. The resulting rainfall erosivities calculated are the mean annual $R$ factor (averaged annual $EI_{30}$), and mean monthly $R$ factors for the 20 year period.

The $R$ factor, estimated using the daily model, and that of several previous researchers (McFarlane et al., 1986; Rosenthal and White, 1980; Yu and Rosewell, 1996a,b; Yu, 1998) have been compared for 120 stations across Australia. Figure 1 shows the comparison between the modelled and actual $R$ factor. The linear correlation coefficient (Pearson’s $r$) is 0.903 (SSE = 5.1e8, $\sigma = 1909.5$). The standard deviation of measured $R$ is 4311 and 4428 for predicted
$R$. No noticeable bias of the model is observed. In general, the model compares well with various $R$ factors calculated using pluviograph data.

The estimated spatial pattern of the $R$ factor and the monthly distributions for selected locations across the continent are shown in Figure 2. For the northern

![Figure 1. Comparison between modelled and actual $R$ factor for 142 points at 120 locations (shown in the bottom map, with references to the ILZ and the NLWRA defined regions). Multiple values for the same rainfall gauge station given by different authors using different period of pluviograph data are included. 1:1 line (solid blue) is shown. The unit of $R$ factor is MJ mm ha$^{-1}$ hr$^{-1}$ yr$^{-1}$.](image-url)
Figure 2. Map of rainfall erosivity ($R$ factor) and its monthly distributions for selected locations.
part of the continent, the monthly distributions of $R$ factor estimated using Equation (3) generally show peaks in summer period, from December to February. Approximately 80% of the annual rainfall erosivity occur between December and March. A negligible fraction occurs in the months from April to October in northern Australia. This is consistent with the common rainfall pattern in the Australia’s tropics of intense storms during summer and little rainfall during winter (McIvor et al., 1995; Rosenthal and White, 1980). For the south-eastern part of the continent, predicted monthly $R$ factor distributions change gradually from summer dominance to uniform when moving from north to south, which is comparable with continent rainfall intensity distribution (Bureau of Meteorology, 1989; Yu and Rosewell, 1996a,b; Yu 1998). Winter dominant monthly $R$ factor distributions are obtained for the coast area of southwestern part of Western Australia. The pattern then changes to a summer dominance inland within one hundred kilometres from the coast (Figure 2). This is also comparable with the distributions of the $R$ factor estimated using pluviograph data for the region (McFarlane et al., 1986). Quantitative assessment of the monthly distribution of $R$ factor is technically challenging as many previously existing $R$ factors were calculated using short periods of pluviograph data. This causes serious bias for monthly distribution of the $R$ factor toward single large storms in the period.

### 2.2 Soil erodibility ($K$)

Soil erodibility ($K$) is a measure of the susceptibility of the soil to erosion. In the RUSLE, it is a quantitative value determined experimentally. For a particular soil, it is the rate of soil loss per erosion index unit as measured on a unit plot maintained under continuous bare fallow. For satisfactory direct measurement of soil erodibility, erosion from field plots needs to be studied for periods generally well in excess of 5 years (Loch et al., 1998). This is costly and time-consuming, and data from field studies of adequate duration are available for only a few Australian soils (Loch et al., 1998). Therefore, considerable attention has been paid to estimate soil erodibility from soil attributes such as particle size distribution, organic matter content and density of eroded soil (e.g. Wischmeier
et al., 1971; Loch and Rosewell, 1992). Even these data, however, are not readily available at regional or continental scales.

In this study, a modified nomograph equation (Wishmeier et al. 1971) was used to estimate $K$ factor for Australian soils. The soil erodibility surface has been generated using the equation (Loch and Rosewell, 1992):

$$K = 2.77 \times 100 (P_{125})^{1.14} (10^{-7})(12 - 2 O_{c}) + 3.29 \times 10^{-3} (Pr - 3)$$

where $P_{125}$ is the percentage of particles with diameter less than 0.125 mm, $O_{c}$ is organic carbon in percentage, and $Pr$ is the soil permeability rating. These soil attributes were obtained using data including polygon-based soil information from various state agencies, the digital Atlas of Australian Soils (Northcote et al. 1960-1968), and a digital polygon coverage of the Soil-Landforms of the Murray-Darling Basin. An organic carbon surface is obtained by statistical modelling using point observations, climatic data, elevation data and LANDSAT MSS satellite data. Using a look-up table linking unique soil type described as Principle Profile Form (PPF) with interpreted soil attributes (McKenzie et al. 2000), a weighted mean approach was taken to average soil attribute values in each polygon. Based on the area occupied by each PPF, the final soil attribute value for a polygon was calculated by the addition of the area weighted soil attribute value for each PPF. Rosewell’s (1993) classes for soil permeability were used to categorise the saturated hydraulic conductivity of the A-horizon derived by the Australia Soil Resource Information System (ASRIS) project of NLWRA. The $K$ factor surface is a product of ASRIS project.

It is found, nationally, that heavy clay soils (Vertosols) are highly erodible as they are structurally unstable. Relatively large $K$ values are estimated for chemically dispersible sodic soils (Sodosols). Kandosols and Calcarosols with sandy topsoil are slightly less erodible. Rocky soils (Rudosols) and weakly developed soils (Tenosols) are least erodible. Soils with high organic matter content are less erodible than those with low organic matter content. There is an obvious state boundary between SA and Victoria, partly due to land management differences and to original map sources of soil data.
2.3 Cover and crop management factor (C)

The cover and crop management factor (C) measures the combined effect of all the interrelated cover and crop management variables. It is defined as the ratio of soil loss from land maintained under specified conditions to the corresponding loss from continuous tilled bare fallow. It is an estimate of the combined effects of prior land use, crop canopy cover, surface cover, surface roughness, and organic material below the soil surface. It is usually expressed as an annual value for a particular cover and crop management system but is calculated from the soil loss ratios for shorter periods of time within which cover and management effects are relatively uniform. The soil loss ratios are combined in proportion to the applicable percentages of erosivity (R) to derive annual C values. At continental scale, deriving the appropriate C values essentially requires accurate estimation of canopy cover and ground cover as they offer very different erosion control protection. Although tree canopy cover can be estimated at annual averaged basis due to it relatively slow growth, there are strong seasonal patterns to ground cover in the Australian continent, reflecting seasonal patterns in rainfall. We, therefore, calculated mean monthly values of C to reflect seasonal variations in cover. The best way to assess cover patterns across a large area is by interpretation of remote sensing data because satellite remote sensing offers the only practical means of continuously and consistently monitoring vegetation cover on a continent scale.

For each grid cell, the calculation of C factor involves the following distinct steps:

1. Separating the NDVI signals into three components, perennial NDVI, seasonal NDVI and random NDVI using time series decomposition;
2. Estimating vegetation covers by regression equations between long-term annual averaged perennial NDVI and woody cover, and between monthly averaged seasonal NDVI and ground cover using site measurements;
3. Calculating monthly soil loss ratio (SLR) using a simplified version of SOILLOSS (Rosewell, 1993); and
4. Calculating annual C factor values by weighting SLR with the fraction of rainfall erosivity (R) associated with the corresponding month.
2.3.1 Pathfinder AVHRR NDVI

This NDVI time series was derived from the AVHRR sensor on the National Oceanographic and Atmospheric Administration (NOAA) series of meteorological satellites (NOAA–7, -9, and –11) and made available by the NASA Goddard Space Flight Distributed Active Archive Centre (GDAAC) (James and Kalluri, 1994). The spatial resolution is 0.08° (approx. 8 km) and the

Table 1: The NDVI time series used in this study (Note: ULHC is upper left hand corner, BRHC is bottom right hand corner).

<table>
<thead>
<tr>
<th>Spatial Coverage</th>
<th>ULHC: 112°E, 10°S</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BRHC: 155°E, 10°S</td>
</tr>
<tr>
<td>Pixel size:</td>
<td>0.05°</td>
</tr>
<tr>
<td>Number of columns:</td>
<td>860</td>
</tr>
<tr>
<td>Number of rows:</td>
<td>700</td>
</tr>
</tbody>
</table>

Temporal Coverage: 10-day composite, middle July 1981 to midle April 1994, 460 images

Original Data Source: NASA Goddard Space Flight Centre

Calibration and Filtering: Modified BISE (Lovell and Graetz, 2000).

Geo-re-registered and re-sampled by D. Barret

temporal coverage is 10-day maximum NDVI composite from July 1981 through to the middle of 1994. The Pathfinder NDVI is corrected for change in sensor calibration, ozone absorption, Rayleigh scattering and normalised for changes in solar zenith angle. The CSIRO Earth Observation Centre (EOC) obtained a subset covering the Australian continent from NASA. The NDVI time series was further noise reduced by using a modified Best Index Slope Extraction (BISE) algorithm using a search window of 6 decades and a NDVI change threshold of 0.1 per decad (Lovell and Graetz, 2000). The data set was
geo-re-registered and re-sampled to 0.05° by D. Barret at CSIRO Land and Water using the nearest neighbour option in ARC/INFO. Although the time series NDVI has been greatly improved, noticeable errors remain including effects of volcanic aerosols, water vapour, background soil colour and occasional missing values due to satellite drifting. In this study, 460 Pathfinder 10-day composite NDVI images from July 1981 to April 1994 were obtained from EOC and used for vegetation cover estimation. Later images were excluded as large area of southern part of Australia has missing data as a result of the orbital drift. The information of the NDVI data set is summarised in the Table 1.

2.3.2 Time Series Decomposition and NDVI Baseline Estimation

Estimating annual averaged woody canopy cover and monthly averaged ground vegetation cover involves separating the NDVI signals into two components, perennially green vegetation and seasonally green vegetation. Roderick et al. (1999) proposed a robust method for estimating the evergreen and raingreen cover for Australian condition. The evergreen cover is assumed to track along the base of the NDVI time series, which is assumed to be equivalent to the woody vegetation cover. However, the time series decomposition method they used required error free time series without missing values. As Pathfinder NDVI does have missing values, it made us using more advanced time series analysis tools. Our analysis was carried out by applying a time series decomposition scheme in the form:

\[ NDVI_i = T_i + S_i + R_i \]  

where \( i = 1 \) to \( N \), with \( N \) is the total number of images in the time series, \( T_i \) is the trend component, \( S_i \) is the seasonal component, and \( R_i \) is the irregular component. Frequency components of variation are obtained through a sequence of locally weighted regression smoothing LOESS (LOcal rEgreSSion). A backfitting algorithm produces a seasonal component with a period equal to 12 months. This decomposition scheme has a simple design and allows fast computation for the 860 pixel by 700 pixel time series over Australia. It also has
the ability to decompose time series with up to 5% randomly distributed missing values and outliers and ensure robust estimates of the trend and seasonal components that are not distorted by aberrant behaviour in the time series. Areas that often have more than 5% missing values in some continuous periods due to orbital decay, such as Tasmania, were statistically data filled before the decomposition was carried out. A detailed description of the decomposition procedure can be found in Cleveland et al. (1990).

It is assumed that the perennial component tracks along the base of the time series. This is augmented with seasonal vegetation during the growing season. So we define:

\[
B_i = T_i - \lambda \left| \min_{i=1}^{N}(S_i) \right| \\
G_i = S_i + \lambda \left| \min_{i=1}^{N}(S_i) \right| 
\]

(5)

where \(B_i\) is the perennial component (mainly due to tree cover) and \(G_i\) is the component due to variations of seasonal cover and \(\lambda\) is a parameter greater or equal to 1. The value of \(\lambda\) is determined by:

\[
\lambda = 1 + \frac{RG}{\overline{T} + RG} 
\]

(6)

with constraints subjective to:

\[
1 \leq \lambda \leq \frac{\min_{i=1}^{N}(T_i)}{\left| \min_{i=1}^{N}(S_i) \right|} \quad \text{if} \quad \min_{i=1}^{N}(T_i) > \left| \min_{i=1}^{N}(S_i) \right| \\
\lambda = 1 \quad \text{if} \quad \min_{i=1}^{N}(T_i) \leq \left| \min_{i=1}^{N}(S_i) \right| 
\]

(7)

to make both \(B_i\) and \(G_i\) positive, where \(\overline{T}\) is the mean value of trend and \(RG = \max_{i=1}^{N}(S_i) - \min_{i=1}^{N}(S_i)\) is the amplitude of the seasonal component. Equation (6) suggests that the adjustment of trend to the base of time series of NDVI be linearly related to the ratio between amplitude of the seasonal component and the mean amplitude of the time series. The larger this ratio, the lower the base NDVI will be and the smaller the perennial component.
The mean annual perennial component of NDVI was calculated by averaging the base track line. The monthly mean NDVI component due to seasonal cover was averaged for each month. The irregular component resulting from short-term rainfall variation and sensor errors was ignored in this analysis.

### 2.3.3 Conversion from NDVI Vegetation Cover

McVicar et al. (1996a, b) have established regression equations between the simple ratio, $SR = \frac{1 + NDVI}{1 - NDVI}$, of the reflective channels recorded by the AVHRR sensor and field measured Leaf Area Index (LAI) for different types of covers. It was found that the estimated tree cover is too high using the regression equation given in McVicar et al. (1996a), where the uncorrected NDVI images were used. The NDVI values extracted from Pathfinder images for the same period is about three times larger than the uncorrected NDVI used by McVicar et al. (1996a). We refitted the ground measurements of McVicar et al. (1996a) against Pathfinder NDVI time series for the same period time (10th – 20th of March, 1990) when the ground measurements were undertaken. Empirical relationship of the form:

$$F_c = 140 * NDVI$$  \hspace{1cm} (8)

where $F_c$ is the perennial woody cover in percentage, is found to the best among other possible forms between remote sensed data and ground measurements. Note that LAI can be converted into percentage vegetation cover using the relationship:

$$F_c = 100 * (1.0 - e^{-LAI/2})$$  \hspace{1cm} (9)

assuming random distribution of foliage above the soil and uniform leaf-angle distribution (Choudhury, 1989). It was used to relate NDVI to perennial woody cover.

For ground cover, regression equations proposed by McVicar et al. (1996b) of the form:
were used. Parameters $a$ and $b$ were empirically determined by relating AVHRR vegetation indexes to LANDSAT TM LAI estimates, derived from field observations (McVicar et al., 1996a). The values of $a$ and $b$ for four different vegetation cover types are listed in Table 2. Detailed calibration and validation of the estimated vegetation cover surfaces will be given elsewhere.

Table 2. Parameters of Equation (10) for cropping, pasture, grasses and woody cover. (From McVicar et al., 1996b).

<table>
<thead>
<tr>
<th>Landcover Type</th>
<th>$a$</th>
<th>$b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropping</td>
<td>-1.47</td>
<td>1.22</td>
</tr>
<tr>
<td>Pasture</td>
<td>-0.90</td>
<td>0.72</td>
</tr>
<tr>
<td>Grasses</td>
<td>-1.15</td>
<td>0.96</td>
</tr>
<tr>
<td>Woody Cover</td>
<td>-4.65</td>
<td>4.22</td>
</tr>
</tbody>
</table>

$LAI = a + b \left( \frac{1 + NDVI}{1 - NDVI} \right)$

(10)

2.3.4 Calculation of Monthly Soil loss Ratio (SLR) and C Factor

To calculate the soil loss ratio factor, land use data is required in addition to percentage cover. The recently produced National Land and Water Resources Audit (NLWRA) land use mapping of Australia (with spatial resolution of 1 km$^2$) was used to assign land use to one of 19 groups aggregated from the original data (Table 3).

The land use and mean percentage cover for each month were used to calculate monthly $SLR$ and $C$ factor following the procedure described in SOILLOSS (Rosewell, 1993). Small $SLR$ values (0.00001 and 0.0001, respectively) were assumed for land use groups 11 and 12 irrespective of cover. The calculations of $SLR$ for groups 21 to 25 and 51 (forests, woodland and native pasture land) follow the tables D4 and D5 in SOILLOSS for estimated canopy cover and ground cover from the NDVI data. The monthly $SLR$ for groups 31 to 42
(cropping lands and improved pasture) were calculated using the land use sub-factor approach of splitting the crop cycle into growth phases. It was assumed that the sowing date for crops is four months prior to the month with maximum greenness and the harvest date occurs two months after the month with maximum greenness. Although our program can be run with different tillage system options, without sensible spatial data, it was assumed that conventional tillage system is used everywhere, which is the worst scenario and gives the highest erosion rate due to tillage. Other parameters, such as maximum canopy height, canopy height after harvest, residue coefficient, rate of decay of surface and incorporated residue, temperature factors for residue decay rates, etc are assigned to the same values as the closest cropping type given in SOILLOSS (Rosewell, 1993). Finally, annual cover and management factor values were calculated by weighting SLRs with the fraction of rainfall erosivity ($R$) associated with the corresponding month.

Table 3: Landuse groups used to calculate soil loss ratio.

<table>
<thead>
<tr>
<th>Groups</th>
<th>Land use Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Perennial watercourse and lake, Licensed airport, Mangrove, Reservoir, Saline, Coastal flat, Swamp, Built-up area</td>
</tr>
<tr>
<td>12</td>
<td>Non-perennial watercourse and lake</td>
</tr>
<tr>
<td>21</td>
<td>Closed forest</td>
</tr>
<tr>
<td>22</td>
<td>Open forest</td>
</tr>
<tr>
<td>23</td>
<td>Woodland</td>
</tr>
<tr>
<td>24</td>
<td>Commercial native forest production, Plantation fruit, Agroforestry, Apples, Citrus, Grapes, Stone fruit, Pears, Plantation</td>
</tr>
<tr>
<td>25</td>
<td>National Park</td>
</tr>
<tr>
<td>31</td>
<td>Cereals excluding rice</td>
</tr>
<tr>
<td>32</td>
<td>Legumes</td>
</tr>
<tr>
<td>33</td>
<td>Other non-cereal crops</td>
</tr>
<tr>
<td>34</td>
<td>Oilseeds</td>
</tr>
<tr>
<td>35</td>
<td>Non-cereal forage crops</td>
</tr>
<tr>
<td>36</td>
<td>Rice</td>
</tr>
<tr>
<td>37</td>
<td>Cotton</td>
</tr>
<tr>
<td>38</td>
<td>Potatoes</td>
</tr>
<tr>
<td>39</td>
<td>Sugar cane</td>
</tr>
<tr>
<td>40</td>
<td>Other vegetables</td>
</tr>
<tr>
<td>41</td>
<td>Nuts</td>
</tr>
<tr>
<td>42</td>
<td>Improved Pastures</td>
</tr>
<tr>
<td>51</td>
<td>Residual/Native Pasture</td>
</tr>
</tbody>
</table>
2.4 Slope length factor ($L$) and slope steepness factor ($S$)

Slope length factor ($L$) is defined as the ratio of soil loss from the field slope length to that from a 22.13 metre length under otherwise identical conditions. It represents the increase in storm runoff volume with increasing hillslope length. For cropping land, $L$ is evaluated by the equations used in RUSLE (McCool, et al., 1989; Renard et al., 1997) with:

$$L = \left( \frac{X_h}{22.13} \right)^m$$  \hspace{1cm} (11)

where $X_h$ is the horizontal slope length in metres and $m$ is a variable slope length exponent. $m$ is related to the ratio $\varepsilon$ of rill erosion to interrill erosion by the following equation:

$$m = \frac{\varepsilon}{1 + \varepsilon}$$  \hspace{1cm} (12)

$\varepsilon$ is calculated for conditions when the soil is moderately susceptible to both rill and interrill erosion using the following equation:

$$\varepsilon = \frac{\sin \theta}{0.0896 \times [3.0 \times (\sin \theta)^{0.8} + 0.56]}$$  \hspace{1cm} (13)

where $\theta$ is the slope angle.

The slope steepness factor ($S$) is defined as the ratio of soil loss from the field slope gradient to that from a 9% slope under identical conditions. As it has been shown that the original slope steepness factor of USLE overestimates the soil loss from slopes steeper than 9%, as recommended in SOILLOSS, the RUSLE slope steepness equation is used in this study. The equations are:

$$S = 10.8 \times \sin \theta + 0.03 \hspace{1cm} \sigma \leq 9\%$$  \hspace{1cm} (14)

$$S = 16.8 \times \sin \theta - 0.50 \hspace{1cm} \sigma > 9\%$$

where $\theta$ is the angle of slope and $\sigma$ is the slope gradient in percentage. McIsaac et al. (1987) reviewed the soil loss data from several experiments on disturbed and undisturbed lands at slopes of up to 84%. An equation similar to (14) was recommended.
The topographic complexity manifested in steep slopes and ravine networks presents significant challenges to estimating the slope length and slope steepness factors. The RUSLE is directly applicable for hillslopes up to 300 m in length. Quantitative spatial models of sediment transport normally use fine-scale representations of topography, with a resolution of no coarser than 50 m. Using the AUSLIG 9" (approx 250 m × 250 m) digital elevation model (DEM) of Australia, we found it impossible to directly estimate slope length and resolve convergent or divergent terrain due to missing representation of local terrain curvature. A statistical modelling approach was used to estimate slope length and steepness and described in short here.

Hillslope length and mean slope were measured directly from available high resolution DEMs. The hillslope length measurement technique examines the landscape over a range of scales and identifies the average distance from ridges to valleys. This analysis is repeated at regular intervals across the DEM, producing a regular grid of hillslope length values. Mean slope was computed as the mean slope value over a 250 m radius circular window. The DEMs used in this analysis cover a range of topographies, geologies and climatic zones in WA, NT, northern and southern Queensland, the western slopes of NSW, coastal NSW, southern Victoria and north-western, central and south-eastern Tasmania. Some of the DEMs were derived from contour and streamline data while others were derived from data obtained during airborne geophysical surveys. Resolutions ranged from 20 to 80 m. Figure 3 shows the location and resolution of these high resolution DEMs used in this study.

Statistical predictive models for hillslope length and mean slope were constructed using the Cubist data mining tool (decision rules based upon piecewise linear regression, Quinlan, 1993) based on variables available for the Australian intensive landuse zone (ILZ). The predictive model was then used to derive estimates of the slope length and steepness across the entire study area, using geology, soil class and several climatic and topographic attributes as predictive variables. Details of estimating hillslope length and slope can be found in a forthcoming technical report.
In woodlands and forests there is evidence that runoff volume grows only weakly or not at all with hillslope length (Bonell and Williams, 1987; Prosser and Williams, 1998). In these landscapes there are patches of runoff generation and patches of runoff infiltration and longer hillslopes do not necessarily yield more sediment than short ones. Thus the $L$ factor is set to 1 for those landuse categories. $L$ factor is also set to 1 for all the pixel outside of ILZ, where there is little rill erosion. $m$ is set to zero for all pasture land due to lack of spatial data for the calibration of the slope length effect on erosion rate. This results a large area in the continent has a slope length factor ($L$) with value of 1, which is equivalent to slope length equal to standard USLE fallow length 22.13 m. The effect of errors due to the simplified estimation of slope length factor ($L$) is expected to be relatively minor as RUSLE is less sensitive to slope length than to any other factor (Renard, 1997). For typical slope conditions, a 10% error in the slope length results in a 5% error in the computed erosion rate.

Figure 3. The location and resolution of the high resolution DEMs used in this study are shown.
2.5 Supporting practice factor \((P)\)

Supporting practice factor \((P)\) accounts for the effects of contours, strip cropping or terracing. It is defined as the ratio of soil loss with a specific supporting practice to the corresponding soil loss with certain cultivation. Due to a lack of spatial data on existing contour locations and tillage practices, it is assumed that the values of \(P\) factor are 1 everywhere. Given this scenario, the estimated soil loss rate reflects erosion potential under current conditions with no soil conservation support practices.

3 RESULTS

3.1 Current Erosion

Figure 4 shows the predicted sheet and rill erosion, and Figure 5 shows the monthly distributions. It is predicted that north part of the country has considerably more erosion than the southern part of the country. This predicted trend is consistent with measurements (Freebairn, 1982; Edwards, 1993).

It was found that about \(4.8 \times 10^9\) tonnes of soil is moved annually on hillslopes over the continent. It is 3-4 times smaller than previous estimation (Wasson et al., 1996). Comparing with globe estimation \((75 \times 10^9\) t yr\(^{-1}\), Pimentel et al., 1995), it is predicted that Australia contributes 6.4% of globe soil erosion from 5% of the world land area. The average soil erosion is 6.3 t ha\(^{-1}\) yr\(^{-1}\). If we denote that a pixel with soil loss rate below 0.5 t ha\(^{-1}\) yr\(^{-1}\) as low erosion, larger than 10 t ha\(^{-1}\) yr\(^{-1}\) as high erosion, and in between as medium, it is estimated that about 23% of the continent experiences low erosion, 16% faces high erosion and 61% of the continent experiences medium hillslope erosion. Overall, 25% of the area is eroded at a rate greater than the continental average rate, showing the potential to target erosion control to problem areas. Under any given rainfall regime, the map shows that the reduction of protective ground cover increases the risk of high soil losses.

Table 4 divides hillslope erosion into land use classes. In general, agricultural lands have higher erosion rate compared with forest, but not necessarily more
Figure 4: Prediction of annual hillslope erosion hazard for the Australia continent.
Figure 5. Predicted monthly soil erosion rate patterns for the Australian continent.
erodible than native pasture lands. The predicted average erosion rates for cereals are relatively low because they are often located in floodplains where the slope is low. However, the rates are higher compared with surrounding non-cropping area with similar climatic, soil and topographic conditions. This confirms that land use and management practices have a major impact on soil erosion. However, as our prediction is more or less based on the worst scenario assumption for cropping land, the predicted rate for those lands could be higher than the actual rate. The maps also identify areas of high soil erosion potential within some of the National Parks in the tropics, but these are the natural conditions in steep lands experiencing high intensity rainfall, and do not represent elevated soil erosion rates.

Total soil loss is dominated by the pastoral industries, including grazed woodlands, because of the vast areas that these land uses occupy. Thus the sediment loads of large regional catchments such as the Burdekin and Fitzroy catchments of Queensland will be dominated by sediment derived from pastoral land. Cropping land of high erosion hazard is more restricted in extent but can cause local problems as indicated by the high soil loss rates, and will be

Table 4: Soil Loss from land use categories.

<table>
<thead>
<tr>
<th>Landuse Description</th>
<th>Approx. Total area (km²)</th>
<th>Total Erosion (t yr⁻¹)</th>
<th>Average Erosion Rate (t ha⁻¹ yr⁻¹)</th>
<th>Rate of acceleration Since European Settlement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closed Forest</td>
<td>25,116</td>
<td>2,772,706</td>
<td>1.10</td>
<td>1.1</td>
</tr>
<tr>
<td>Open Forest</td>
<td>285,796</td>
<td>9,896,968</td>
<td>0.35</td>
<td>1.0</td>
</tr>
<tr>
<td>Woodland (unmanaged lands)</td>
<td>2,179,326</td>
<td>1,102,649,750</td>
<td>5.06</td>
<td>1.2</td>
</tr>
<tr>
<td>Commercial native forest production</td>
<td>157,460</td>
<td>5,864,068</td>
<td>0.37</td>
<td>1.0</td>
</tr>
<tr>
<td>National Parks</td>
<td>183,303</td>
<td>188,824,306</td>
<td>10.30</td>
<td>1.1</td>
</tr>
<tr>
<td>Cereals excluding rice</td>
<td>182,936</td>
<td>39,517,812</td>
<td>2.16</td>
<td>10.3</td>
</tr>
<tr>
<td>Legumes</td>
<td>22,568</td>
<td>795,556</td>
<td>0.35</td>
<td>3.2</td>
</tr>
<tr>
<td>Oilseeds</td>
<td>6,242</td>
<td>2,390,087</td>
<td>3.83</td>
<td>9.5</td>
</tr>
<tr>
<td>Rice</td>
<td>1,573</td>
<td>115,250</td>
<td>0.73</td>
<td>5.9</td>
</tr>
<tr>
<td>Cotton</td>
<td>4,053</td>
<td>2,784,581</td>
<td>6.87</td>
<td>11.3</td>
</tr>
<tr>
<td>Sugar Cane</td>
<td>4,736</td>
<td>18,694,681</td>
<td>39.47</td>
<td>56.8</td>
</tr>
<tr>
<td>Other agricultural landuse</td>
<td>2,138</td>
<td>2,402,811</td>
<td>11.24</td>
<td>33.6</td>
</tr>
<tr>
<td>Improved Pastures</td>
<td>200,295</td>
<td>46,307,300</td>
<td>2.31</td>
<td>5.1</td>
</tr>
<tr>
<td>Residual/Native Pastures</td>
<td>4,257,824</td>
<td>3,388,486,244</td>
<td>7.96</td>
<td>1.9</td>
</tr>
</tbody>
</table>
significant in relatively small catchments dominated by intensive land use. The relatively high average erosion rates predicted for national parks is primarily due to most national parks being located on north part of the country, where the rainfall intensity is high, or in the arid inland, where the cover is low.

Figure 6 shows the monthly distribution of total soil loss. It is found that over

90% of the erosion occurs in the summer period (from November to April). This summer dominant erosion pattern is clearly shown in Figure 5 especially for tropical Australia, which is mainly caused by intensive summer monsoon rainfall. However, the high erosion zone detected within the east part of Murray-Darling Basin, is one of weaker summer dominance.

3.2 Prediction Evaluation of Current Hillslope Erosion

Researchers have undertaken a wide range of hillslope erosion plot measurements in the past. The measurements methods include USLE plots (Edwards, 1987), farm dam sediment survey (Neil and Fogarty, 1991; Throne, 1997), Caesium-137 (Loughran and Elliot, 1996) and sediment yield from small catchment (Prove, 1991; Freebairn and Wockner, 1984). Figure 7 shows the comparison between the predicted and measured hillslope erosion for the
location where the measurements were undertaken. The comparison was made by taking the 5%, mean and 95% (approximately) for both measurements and predicted values for given landuse and locations. There are 103 points shown in the Figure 7. Because it is often the case that latitudes and longitudes of the nearest towns were given rather than the precise location of the measurements, the predicted values shown in Figure 7 were calculated by taking 5%, average and 95% for the given landuse near the town. The radius used for the average is within the range from 1 km to 50 km according to individual literature. In some cases, additional information, such as slope percentage is used for better targeting the measurement location. Figure 7 shows, in most cases, that the differences between prediction and measurements are within a factor of 10, which is comparable to the range of measurements for the same location. The linear correlation coefficient (Pearson’s r) between measured and modelled mean erosion rate is 0.815. No significant bias was obtained in the data. Given the wide range of measurements we used for comparison, the quality of our input data, and the scale of the analysis, we conclude that the results are encouraging. We also found that it is often the case that our predicted values are smaller than
Caesium-137, but larger than farm dam sedimentation or sediment yield measurement. This is because the Caesium-137 accounts for all types of erosion, including mass movement and wind erosion. On the other hand, farm dam sedimentation and sediment yield should be smaller than hillslope erosion because of deposition. The prediction matches USLE plots measurements (Edwards, 1987) better, especially for cropping land, simply because the model is initially calibrated from those data.

### 3.3 Erosion Rate between Current and Pre-European Settlement

To understand the impact of landuse and management practises on hillslope erosion more, the predicted hillslope erosion needs to be put in the context of erosion under natural vegetation cover. We predicted natural erosion using the same procedure, with a cover factor for native vegetation and keeping the other factors as for the present day.

We conducted a simple modelling framework to predict pre-European settlement (undisturbed) USLE cover factor ($C$). Under this framework, we assume that under certain similar climatic, geological and soil conditions, the natural vegetation remains similar in terms of vegetation cover effect on erosion. As only 3% of the continent areas are used as permanent cropping, we also assume that the climate and geology do not change since European settlement. Namely, landuse changes have relatively larger impact on cover management factor but limited impact on climate. In each zone there are areas of reserve where native vegetation cover is retained and for which the USLE $C$ factor was determined from remote sensing data for the assessment of current erosion rate. By only sampling the pixel with limited human disturbance, such as National Parks, Natural Forest and Crowned Aboriginal Conservation Land from the NLWRA/BRS landuse map, statistical models were built relating cover and management factor $C$ to other climatic, geological and soil attributes using the decision tree model Cubist. Figure 8 shows the comparison between samples of $C$ values extracted from the current $C$ map and modelled $C$ values for those natural landuse pixels. The model was applied to the ILZ only because of the minor disturbance and low input data quality in the areas outside of the ILZ. The
minimum value of predicted $C$ and current $C$ factor is used to get pre-European settlement cover management factor with an underlying assumption that the current $C$ factor is always larger than native vegetation cover factor. The maximum $C$ value for natural vegetation cover is set to 0.45 as it is often observed for the natural non-disturbed bare soil condition (RUSLE, Renard, et al., 1997). Assuming $L$ factor and $P$ factor equal to 1 everywhere and other factors unchanged, a map of pre-European hillslope erosion was calculated by the same USLE equation $Y = R K L S C P$.

![Figure 8. Comparison between actual cover and management factor $C$ values and modelled $C$ using Cubist. The line of best fit is shown.](image)

The acceleration of current mean annual soil loss above natural rates was predicted as the ratio of current to pre-European hillslope erosion rates. The ratio map (Figure 9) highlights those cropping lands and grazing lands where the acceleration of erosion is high. It shows that erosion rate increased considerably in the cropping areas, such as the Darling Downs, Colac in Victoria, wheat belt of Western Australia, and Hunter Valley. It also shows erosion rate increases in the areas experiencing intensive grazing land clearance after settlement. Those areas include central and upper Burdekin (along the Burdekin River), Fitzroy catchment and most eastern part of Murray-Darling Basin. Also shown in the
Figure 9. Map shows the acceleration of hillslope erosion since European settlement. It is modelled by the ratio between current and pre-European settlement hillslope erosion rate. Negligible (ratio 0 – 1.5), Low (ratio 1.5 – 3), Moderately low (ratio 3 – 5), Moderate (ratio 5 – 10), High (ratio 10 – 25), Very High (ratio > 25).
last column of Table 4, the predicted rates of acceleration of erosion since European settlement are considerably higher for agricultural landuse groups compared with other less disturbed landuse groups.

4 DISCUSSIONS AND CONCLUSIONS

Based on recently available topographic, rainfall, soil, landuse and time series analysis of remotely sensed data, a nationwide prediction of hillslope erosion has been developed. This study applied the USLE model on a monthly averaged basis, calculating appropriate erosivity and cover factors for each month, to represent the erosive potential of rainfall and runoff for each temporally distinct period. The slope steepness factor is better handled by topographic scaling using high resolution DEMs.

The broad predicted hillslope erosion patterns are consistent with a qualitative analysis of plot data gathered from literature (Edwards, 1993). It is predicted that hillslope erosion increases from south to north, which is mainly determined by continental scale rainfall intensity pattern. Temporally, the erosion rate is higher in summer for most of the continent, especially for the tropics, which also follows the large scale climatic trend. Erosion rate is high for the area with steep gradients. Regions such as Tasmania and SW Western Australia are predicted to have low soil erosion rates, largely a result of low rainfall intensity at times of low cover. Most of the predicted patterns are supported by the available field data (Edwards, 1993; Throne, 1997).

The acceleration of erosion is studied by modelling the ratio between current and pre-settlement hillslope erosion rate. The results show that although the current erosion rates of cropping lands are not high compared with some landuse groups, acceleration of erosion is high when it was put in context of erosion under natural vegetation cover for the same location. It provides essential information for the assessment of landuse impact in terms of possible environmental degradation and pollution of both land and water resources.
The amount of gross erosion needs to be adjusted to account for rock cover. The full erosion potential may not be realised for some of the areas predicted as highly erodible (such as upper Queensland and Northern Australia) because of the high percentage of rock cover and shallow soil depth.

This study is aimed to provide broad scale (first order) nationwide erosion estimation at a reconnaissance level. It could be useful for the purposes:
1. Identifying crucial catchments or sub-area appropriate for more detailed soil erosion investigation;
2. Indicating the environmental health and agricultural Productivity and sustainability at regional scale;
3. Providing sediment sources for modelling sediment transport in the river system; and
4. Assessing the relative impact of landuse management on soil erosion.

It is not encouraged to use the results from this study for the estimation of soil erosion rate at a fine scale, such as a specific paddock. Readers are reminded that the vegetation covers were estimated using 8km resolution remotely sensed data. The heterogeneous of cover can cause a great amount of variation in soil erosion rate at a resolution smaller than 8km. Similar reason can be applied for other factors.

Better prediction could be achieved by bringing in more information. For example, prediction for cropping land can be improved by specifying tillage types, crop rotation, contour cultivation and bank management. For pasture lands, the erosion rate can be better predicted by giving grazing pressure for the location. For forests, providing density of roads and logging frequency can improve the prediction. However, more input data do not always guarantee better prediction. Low quality inputs may introduce more errors and make the overall prediction worse off. Therefore, it is important to check the input data quality and its suitability before using them.
5 ACKNOWLEDGEMENTS

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6 REFERENCES


