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# Incorporating variable cover in erosion algorithms for grazing lands within catchment scale water quality models

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**Abstract:** There is currently a high degree of interest in sediment loads being supplied to the Great Barrier Reef (GBR) lagoon. While monitoring provides an effective tool for quantifying the actual load of sediment being supplied to the reef, it is often difficult, without an exceptionally detailed monitoring network, to determine from this data where and why sediment is being produced. Also given the long duration of measurement required to ascertain trends in a highly dynamic system, and the vast areas needing to be assessed, it is generally impractical to quantify these impacts directly through monitoring. Broad scale catchment modelling has a role to play in helping land managers assess the temporal and spatial aspects of sediment generation.

In Australia there are currently two modelling paradigms typically applied to investigate broad scale catchment sediment generation. These are the USLE based steady state or long term average assessment (e.g. SedNet) style of model, and the temporal constant concentration (e.g. WaterCAST) models. While both of these approaches have their benefits in helping us understand catchment processes, they are limited in their ability to improve our understanding of the interactions of temporal and spatially variable sediment generation processes.

With recent developments in the remote sensing of ground cover and the development of the WaterCast catchment modelling framework, an opportunity to incorporate both temporally and spatially variable estimates of cover into broad scale catchment water quality modelling has arisen. This study reports the development of techniques to utilise the remotely sensed Bare Ground Index, a satellite estimate of ground cover, into the daily timestep WaterCast Modelling framework to improve our representation of sediment generation dynamics within catchments.

Both the highly calibrated EMC/DWC base model and the newly developed RUSLE Variable Cover model provide sound temporal estimates of sediment load generated within the catchment. The fixed EMC/DWC modelled sediment concentrations do not closely match observations, while the RUSLE Variable Cover model estimates do a better job at predicting concentrations.

The ability to incorporate spatially and temporally variable cover estimates for sediment generation into WaterCast is a useful advance in catchment water quality modelling. The variable cover estimates allow us to more realistically determine sediment generation hot spots within the catchment and hence gain a much better understanding of the management required in specific areas of the catchment.

***Keywords:*** *Water quality, remote sensing, USLE, WaterCast, sediment generation*

## 1. INTRODUCTION

### 1.1. Modelling Overview

There is currently a high degree of interest in sediment loads being supplied to the Great Barrier Reef (GBR) lagoon. While monitoring provides an effective tool for quantifying the actual load of sediment being supplied to the reef, it is often difficult, without an exceptionally detailed monitoring network, to determine from this data where and why sediment is being produced. Also given the long duration of measurement required to ascertain trends in a highly dynamic system, and the vast areas needing to be assessed, it is generally impractical to quantify these impacts directly through monitoring. Broad scale catchment modelling can help land managers assess the temporal and spatial aspects of sediment generation.

In Australia there are currently two modelling paradigms typically applied to investigate broad scale catchment sediment generation. These are the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) based steady state or long term average assessment (e.g. SedNet, Prosser *et al.* 2001) style of model, and the temporal timestep, constant concentration (e.g. WaterCAST, Argent *et al.* 2008a) models. Both of these models represent the three basic components of most water quality models – generation, delivery and transport. This paper deals only with the generation component of sediments.

SedNet is a catchment water quality model useful for estimating and understanding long term annual average sediment loads generated within (and exported from) a catchment. The model constructs sediment and nutrient budgets for river networks to identify patterns in the sediment transport. WaterCAST predicts daily flow and pollutant loads for a catchment. WaterCAST estimates loads for constituents (like total suspended solids, TSS) by multiplying the flow by a constituent concentration for each given land use considered.

For all the benefits of applying catchment water quality models there are still a number of major considerations which limit the utility of these models. One of these limitations is that both SedNet and WaterCAST use steady state representations of sediment generated from a parcel of land. The WaterCAST model allows us to predict sediment loads on a daily basis, but is lumped spatially to the subcatchment level. The SedNet model is steady state, but raster surface inputs allow spatially explicit estimates of sediment generation using the using the USLE. The USLE is an empirical relationship designed to calculate long term average soil losses from sheet and rill erosion under specified conditions. The amount of sediment generated annually is a function of rainfall, soil erodibility, slope steepness, slope length, management and soil cover. Typically when using the USLE at sub-catchment scale, one value of cover is estimated and applied over the whole catchment for each land use. This cover level does not vary over time, i.e. it is a steady state parameter. Obviously in the case of grazing lands this is rarely the case. The amount of ground cover is directly affected by climatic variations and management practices. This limits how realistically these steady state models can represent the effects of seasonality, droughts and land management.

In recent times a spatially and temporarily variable estimate of ground cover has become available for all of Queensland – the Bare Ground Index (BGI) (Byrne *et al*. 2004). The BGI uses satellite remote sensing to estimate ground cover utilising Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) images. The images have been collected and analysed annually for the time period 1988-2004 over the entire State and provide a snapshot of ground cover at a given point in time, as illustrated by figure 1.

The purpose of this study was to investigate and develop methods by which the BGI could be incorporated into WaterCast to provide a variable estimate of cover, allowing a more realistic estimate of the impacts of climate and land management on catchment water quality.

### 1.2. Study Area

The Fitzroy River Catchment covers an area of approximately 140, 000 km$^2$ in central Queensland, Australia (refer figure 2). The Fitzroy River flows to the Great Barrier Reef, and is therefore seen as a significant region in terms of water quantity and quality. This is a region of diverse climate and land management regimes, however the most significant land use in the catchment from a spatial context is grazing, with some conservation, cropping, resource extraction and horticulture also present. The Fitzroy Catchment is also topographically diverse, and the soils and landscapes just as variable.

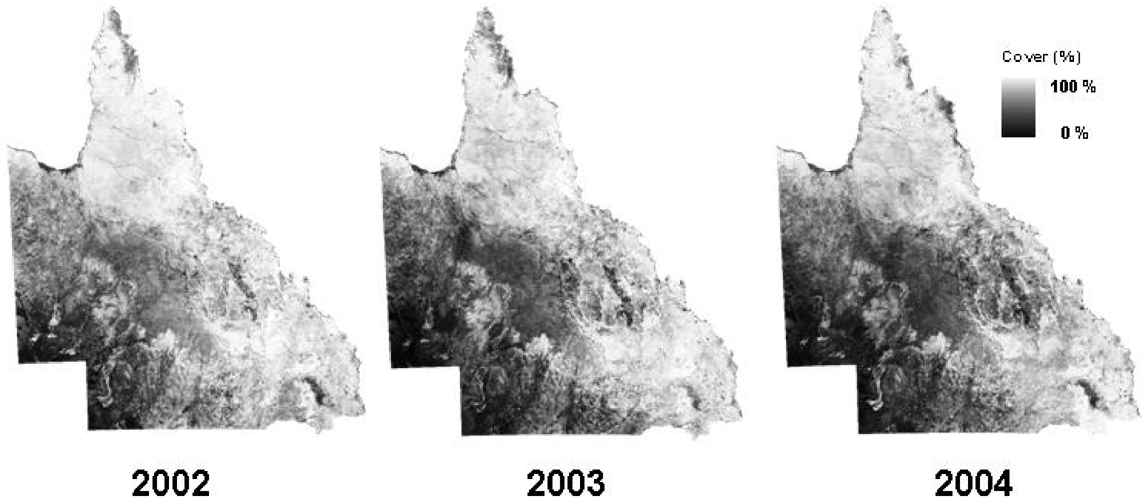


**Figure 1.** Example of the bare ground index product over Queensland for the years 2002 - 2004

## 2. METHODS

### 2.1. Base WaterCast Model Development

The main model structure of WaterCAST is “subcatchment-node-link”, where subcatchments feed water and material fluxes into nodes, from where they are routed along links.

To develop and test the new spatiotemporal models a base WaterCast model for the Fitzroy River Catchment was generated with 396 subcatchments (Ellis *et al.* 2009). This high level of detail allows users to identify areas within the catchment that are considered ‘hot spots’ for erosion, at a scale that would allow useful interpretation. Each subcatchment had 7 Functional Units (FUs) nominally assigned based on land use. Each FU instance was assigned a rainfall-runoff model, each link in the node-link network was assigned a flow routing model, with 12 links representing water storages.

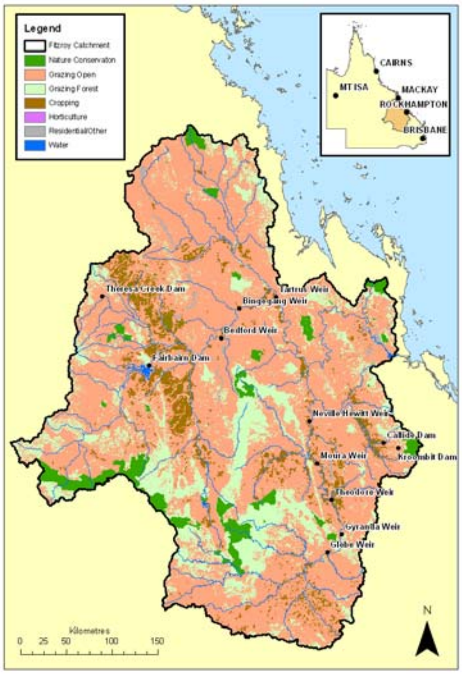


**Figure 2.** Land uses of the Fitzroy River Catchment, Queensland, Australia

An Event Mean Concentration / Dry Weather Concentration (EMC/DWC) model (Argent *et al.* 2008b) was applied to each FU to generate sediment from each subcatchment. The EMC/DWC values used were sourced from a calibration project in the Dawson Valley sub-region of the Fitzroy catchment (Ellis *et al.* 2009). The WaterCAST model implementing the EMC/DWC approach forms the basis for assessment of the dynamic models investigated in this paper.

To assess the validity of TSS predictions from the WaterCAST model, daily TSS concentration (mg/L) observations were processed at numerous locations throughout the catchment. Where multiple observations occurred on any day, an average concentration value was calculated. This daily concentration value can be multiplied by flow volume to provide an estimate of daily TSS load.

### 2.2 Implementing the spatially and temporally variable sediment generation model

The Variable Cover model is based on the spatial and temporal processing of raster surfaces representing the components of the Revised USLE (RUSLE) (Renard *et al*. 1997). The RUSLE can be represented as (Rosewell, 1993):

$$\mathbf{A = R \times K \times L \times S \times C \times P} \tag{1}$$

Where A is the annual average soil loss (t/ha/yr), R is the rainfall erosivity factor (MJ mm ha/hr/yr), K is the soil erodibility factor, L is the slope length factor, S is the slope steepness factor, C is the crop and cover management factor, and P is the support practice factor.

For the purposes of this study, the support practice factor (P) is held constant at 1, as not enough data is available throughout the study area to apply this with any confidence. This means that estimates of soil loss depicted in this study are representative of land management with no soil conservation practices.

The raster spatial data for the RUSLE Variable Cover model is pre-processed using routines which generate a KLSC time series summary for each FU. Initially the K factor, L factor and S factor pixel values are multiplied together for each pixel in each FU. Given that these components of the RUSLE do not vary significantly over time this calculation is only done once. The resulting KLS term for each pixel in a functional unit is multiplied by the C factor value derived from the BGI surfaces for each year. These values within each FU are summed to generate a KLSC series for each FU for each time step.

These KLSC time series values are then read into the WaterCast model as model inputs. When the model is run the daily R factor is calculated at each time step for each FU from the daily rainfall using a spatially averaged empirical model developed by Yu *et al.* (2008). This R factor is multiplied by the input KLSC time step value for the FU to estimate the hill slope sediment generation for each day.

### 2.3 Input spatial data layers

#### K Factor

The soil polygons for which the K factor is calculated is based on the Queensland Combined Soils Coverage (Brough *et al.* 2006)**.** This data set contains the spatial polygon information and a range of soil attributes forming the Queensland component of the Australian Soil Resource Information System (ASRIS) (McKenzie *et al.* 2005). Each polygon in this layer is the best possible scale data available at a given location . The value of K is calculated using attributes contained in the Combined Soils Coverage via an empirical equation, employing a slightly modified form of the nomograph in which the particle size term (M) has been adapted to account for Australian conditions (Loch *et al*. 1998):

$$K = [(2.77 \times 10^{-7}) \times (100P_{125})^{1.14} \times (12 - OM) + (4.28 \times 10^{-3}) \times (SS - 2) + (3.29 \times 10^{-3}) \times (PR - 3)] / (d_s - 1) \tag{2}$$

where $K$ is the USLE soil erodibility factor. The K factor for Queensland surface has been developed using pedotransfer functions to estimate the required soil parameters. $OM$ is organic matter (%), $SS$ is a soil structure code, $PR$ is a soil permeability rating, $100P_{125}$ and $d_s$ relate to particle size and sediment density.

#### L Factor

Both the L and S Factors were generated using the DERM 25m DEM. The slope length factor is evaluated using the equations in the RUSLE (McCool *et al*. 1989b). The slope length component of the slope length factor is calculated from the DEM using the drainage network as the slope length cut off point. An ArcGIS flow path length algorithm was used to generate the surface.

#### S Factor

The slope steepness factor is defined as the ratio of soil loss from the field slope gradient to that from a 9% slope under otherwise identical conditions. The slope steepness factor is calculated using the equations:

$$S = 10.8 \times \sin\theta + 0.03 \qquad \sigma \leq 9\% \tag{3}$$

$$S = 16.8 \times \sin\theta + 0.03 \qquad \sigma > 9\%$$

where $\theta$ is the angle of slope and $\sigma$ is the slope gradient in percentage (McCool *et al.* 1989a). The slope values are generated from the DEM using the standard ArcGIS algorithms.

**C Factor**

Key to the application of the Variable Cover RUSLE model presented in this study is the spatially and temporally variable estimate of C Factor derived from the BGI product. To avoid estimates of ground cover from the BGI being significantly biased by tree and litter cover, in this project the BGI is only being used to infer ground cover where tree influence is minimal. This is achieved by designing "Grazing Open Forest" and "Grazing Closed Forest" FUs into the system. The BGI is converted to cover, i.e. the inverse of BGI, which is then converted to a C factor using the relationship described by Rosewell (1997):

$$C = e^{(-0.799-(4.74\times10^{-2} \times \text{cover}) + (4.49\times10^{-4} \times \text{cover}^2) - (5.2\times10^{-6} \times \text{cover}^3))} \quad \textbf{(4)}$$

## 3. RESULTS & DISCUSSION

Figure 3 shows a reasonably good correlation between predicted and observed sediment loads for the EMC/DWC base model. This is probably due primarily to the hydrology model being well calibrated. In this catchment most of the load tends to be generated by relatively few large events over time. If the hydrology is correct then it makes estimates of the loads more likely to be realistic when sensible EMC/DWC values are used. In this base model the EMC/DWC values are also relatively well calibrated, leading to acceptable load estimates. Figure 4 shows an even better correlation for the RUSLE Variable Cover load estimates. This suggests that the RUSLE Variable Cover model is making sensible erosion estimates.

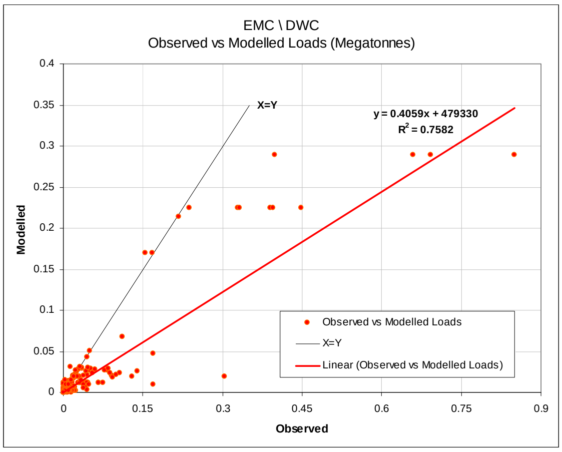


**Figure 3.** Modelled vs observed values for sediment loads using the EMC/DWC model.

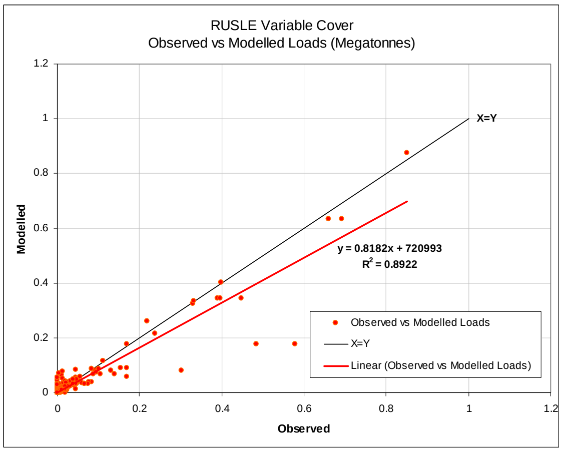


**Figure 4**. Modelled vs observed values for sediment loads using the RUSLE Variable Cover model.

Figure 5 shows poor correlation between predicted and observed sediment concentrations for the EMC/DWC base model results. This to be expected as the sediment concentrations for each FU are held constant over time and can not hope to mimic the dynamic processes of sediment generation. Figure 6 shows a slightly better correlation between predicted and observed sediment concentrations for the RUSLE Variable Cover model. This improvement in correlation suggests that the RUSLE Variable Cover model is more adequately dealing with the inherent variability surrounding sediment generation, spatially and temporally. While not perfect these results suggest the model is capturing some of the variability in the sediment generation processes over time.

It is important to note that typically models based on the RUSLE approach would employ some manner of sediment delivery ratio (SDR) to reduce the amount of sediment reaching the streams from that which is actually generated. There is no SDR applied in this particular RUSLE Variable Cover model. Hence it could be suggested that the RUSLE Variable Cover model is underestimating sediment generation, but given the correlation it is foreseeable that the magnitude of the values could be adjusted as data becomes available.

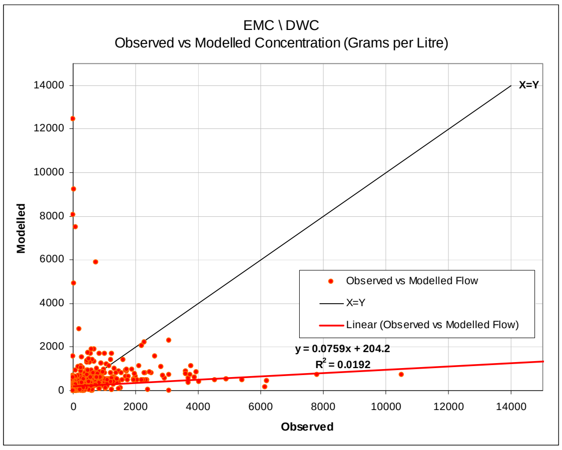


**Figure 5**. Modelled vs observed values for sediment concentrations using the EMC/DWC model.

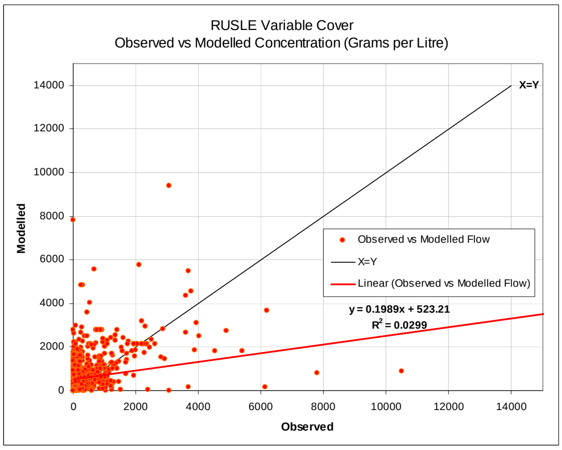


**Figure 6**. Modelled vs observed values for sediment concentrations using the RUSLE Variable Cover model.

It should also be remembered that we are only predicting part of the sediment generation budget. In this particular application of the RUSLE Variable Cover model we are ignoring sediment produced from gullies and stream bank erosion and subsequent landscape deposition and re-entrainment. The measured data includes sediments from all sources, hence it is not particularly useful to analyse in further detail until the rest of the sediment budget is explicitly accounted for.

Figure 7 shows the rainfall, cover and sediment generation for a particular model sub-catchment for part of the model period. These data show that the RUSLE Variable Cover model is working how we would expect it to be. If we take the period from mid 1993 to late 1996 we can see that there is relatively low ground cover. During this time moderate rainfall events cause relatively large erosion events, reflecting the inverse sediment generation to cover relationship inherent in the RUSLE. For the period late 1996 to 2000 during which we have somewhat higher cover, similar sized rainfall events to those in the preceding period cause

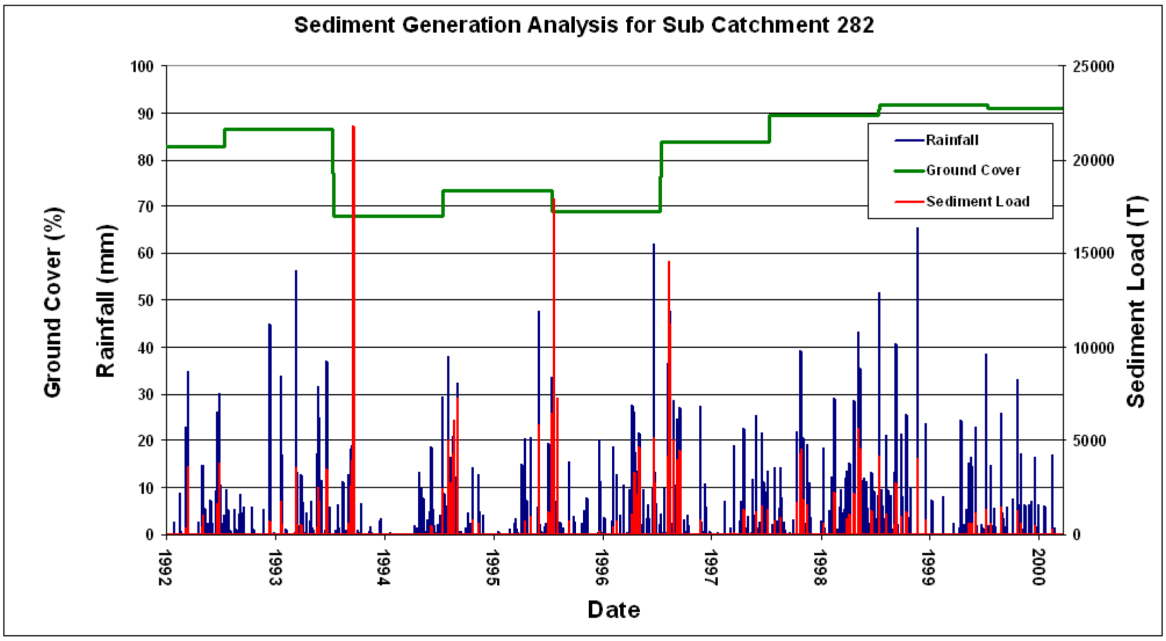


**Figure 7**. Cover, rainfall and modelled sediment load generated from subcatchment 282 using the RUSLE Variable Cover model.

much smaller erosion events. Having this cover to erosion relationship working effectively in the RUSLE Variable Cover model allows us to investigate how ground cover management can affect the spatial and temporal distribution of sediment generation within the catchment.

## 4. CONCLUSION

The ability to incorporate spatially and temporally variable cover estimates for predict sediment generation into WaterCast is a useful advance in catchment water quality modelling. The variable cover estimates allow us to more realistically determine sediment generation hot spots within the catchment and hence gain a much better understanding of the management required in specific areas of the catchment. This model is hopefully just the first of a number these style of models to be developed that will further refine our ability to represent the spatial and temporal processes of broad scale sediment generation.

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