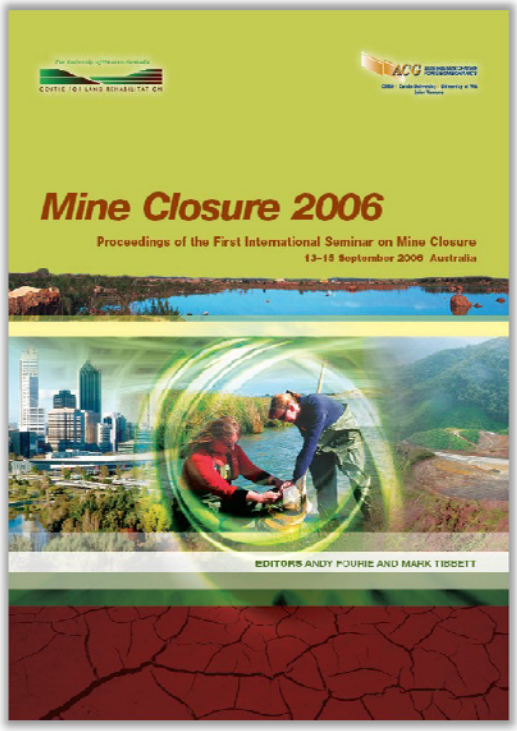

Mine Closure 2006 — Andy Fourie and Mark Tibbett (eds)


# Towards a Climate Based Risk Assessment of Land Rehabilitation

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## 1 INTRODUCTION

Successful rehabilitation of mined land is one of the key concerns for mine closures. Disturbance through mining is often so severe that rehabilitation must be viewed as the first step towards a long term evolution of the landscape and the ecosystem to a stable state that is in harmony with the surrounding land. To ensure that the rehabilitation measures will create a stable and sustainable landform, risk assessment needs to be carried out for the initial phase of rehabilitation, which may cover a time span of the first two decades depending on climate, soil and vegetation. This initial, short term assessment should also be complemented by long term risk assessment extending beyond decades.

The first years after rehabilitation are the most vulnerable to extreme weather events, especially for rock dumps and tailing storage facilities that involve the design of a new landform along with placement of soil material on the surfaces. It is often a single infrequent event such as a cyclone that causes excessive erosion and potentially significant leaching events contributing to acid mine drainage. This high risk period during these first years of rehabilitation is due to immature vegetation establishment and soil development. Understanding and quantifying water redistribution on mined landforms and rehabilitated dumps and tailing dams is therefore the key to risk assessment of rehabilitation success.

One of the first order controls of water redistribution is climate and in particular rainfall. While great effort has been placed on the use of detailed mechanistic understanding of small scale processes to predict and model surface runoff, infiltration, erosion and water movement in soils and rock dumps, little attention has been placed on climate forcing. In this paper we will outline a generic analysis on how the stochastic and episodic nature of rainfall contributes to the triggering of significant hydrological events that may cause damage to land rehabilitation and hence will provide us with a risk assessment tool. The analysis will focus on short term (years to decades) risk assessment aspects, as long term stability can only be realistically assessed when rehabilitation has been shown to be successful in the short term. We therefore promote a probabilistic event based approach that uses a minimalist description of hydrological processes and accurate and detailed information on rainfall as this is the most important first-order control of triggering relevant hydrological processes. We will use surface runoff as an example of our approach. This analysis will be further complemented by an analysis of the rainfall resolution required to predict surface runoff.

## 2 APPROACH

### 2.1 Background

In this section we will briefly outline the limitations of conventional methods used to predict hydrological processes at the plot and hillslope scale. Current trends in hydrological research have led us to question the use of large complex models for predicting hydrological processes at the catchment and hillslope scale for various reasons. These reasons include the uncertainties associated with large parameter sets and our inability to determine unique values for them and the assumption that by simply using small scale process description at each node on a spatial grid we realistically predict hydrologic responses at the next larger scale such as hillslope and first-order catchment. These problems are further exacerbated by the heterogeneities of surface and subsurface properties that are present at all scales and which are often poorly characterized.

In a recent commentary Kirchner (2006) summarizes all these issues and provides compelling evidence that scientific progress will unlikely be driven by the development and application of parameter-rich models that are well capable of matching measured data, but not necessarily for the right reason. Instead, new theoretical insights along with innovative field observations will provide progress. One example that illustrates current limitations is how hillslope outflow responds to rainfall in a threshold like fashion due to a patchwork of localized water tables which eventually connect to produce a sudden outflow event (Tromp-van Meerveld and McDonnell, 2006; Lehmann et al., submitted). Conventional hydrological models are unlikely to capture this behaviour using averaged effective parameters for the entire hillslope (Kirchner, 2006).

Evidence for the problems associated with large model parameter sets has been provided by Jakeman and Hornberger (1993), who showed that rainfall-runoff data contain sufficient information to parameterize models with no more then four parameters. Furthermore, uncertainties associated with model parameters may be large due to their spatial variability and due to errors associated with their experimental determination amongst other factors. This in turn may cause great uncertainties for modelled output, such as drainage into a rock dump below a soil cover or runoff generation contributing to erosion. Minasny and McBratney (2002) analysed how uncertainty of pedotransfer functions (relationships between simple to measure soil properties such as texture and bulk density and hydraulic properties such as soil water retention and hydraulic conductivity functions) propagate into predictions of water flow and soil water storage using a numerical solution of Richards equation. Not only did they show that the resulting error is very large, but also that rainfall is one of the most important first-order controls for improving soil water storage predictions. The issue of model uncertainty is now well recognised and Pappenberger and Beven (2006) provide a strong case for making uncertainty measures a compulsory component of predictions made by hydrological models.

The general issues outlined above apply to all aspects of using hydrological models for making predictions concerning engineered landforms. Firstly, a number of models have relatively large parameter sets such as VADOSE/W (http://www.geo-slope.com/products/vadosew2004.aspx) and SIBERIA, for which accurate parameterisation seems very difficult, in particular considering the rather scarce data sets providing sufficient information content for estimating a unique set of parameters. Secondly, models applied to mine site rehabilitation often describe small scale processes at the plot scale and make the assumption that by modelling these processes on each node of a spatially distributed grid will provide all the answers for assessing hydrological response to climate. Thirdly, providing an uncertainty analysis of model predictions seems to be the exception rather than the rule. Finally, little focus has been placed on characterising the structure of climate and rainfall as the main driving force for causing damage to land rehabilitation.

We propose an alternative approach to assessing risk of rehabilitation of mined land by simply asking the question: What is the probability that rainfall will trigger a hydrological event which will cause damage to land rehabilitation? The underlying assumption of this question is that damages occur as discrete events. This is particularly true for erosion in semiarid and arid climates. But it is also relevant for leaching events in response to large rainfall events such as cyclones that may deposit 100 to 300 mm within a few days. This is a realistic situation in Western Australian regions where such conditions have to be considered for mine closure. Accordingly, the first step in our analysis is to fully quantify the statistical properties of rainfall. We use existing models describing daily and sub-daily rainfall. The second step involves an as-simple-as-possible and as-complex-as-necessary description of hydrological processes that will be able to predict their triggers, such as the onset of surface runoff, preferential flow through macro-pores and fractures and erosion. The emphasis of this approach is to capture the probability of the event occurring and not to produce a detailed time series. The third step is the statistical characterisation of the event triggering the hydrological processes such as runoff and erosion within the context of the rainfall statistics. Within this context we will look at the importance of the temporal resolution of rainfall. The following sections will outline each of these steps in detail.

## 2.2 Rainfall Description

Rainfall can be described by storm duration ($t_r$), a mean intensity (i), and an inter-storm period ($t_b$) which is the time between storm events (Figure 1). Assuming that a rainfall event occurs instantaneously (essentially with a storm duration of zero) with a given storm depth and maximum intensity simplifies the description of rainfall and is used in the analysis presented in the next section.

Storms occur independently of each other which has been shown to be a good assumption for a range of temporal scales. This assumption implies that the inter-storm period ($t_b$) is exponentially distributed and is the key statistical property characterizing rainfall at different time scales from a few hours to days. If we would like to quantify rainfall at smaller time scales, we need to describe within storm variability as shown in Figure 1. This requires a different approach and we used a multi-fractal method based on bounded random cascades that distributes rainfall into discrete time steps ranging from a few hours to minutes (Menabde and Sivapalan, 2000; Hipsey et al., 2003).

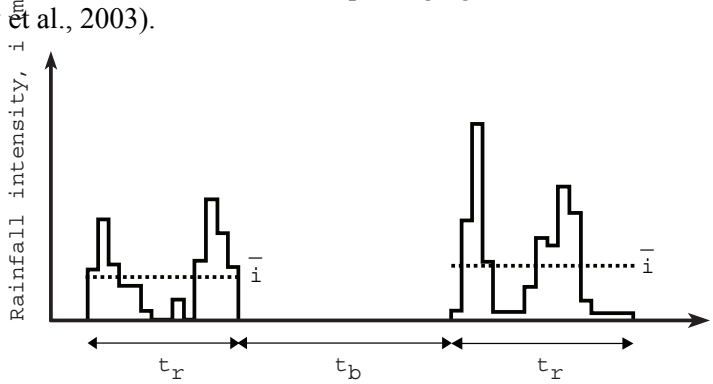


**Figure 1 Rainfall representation with mean intensity *i*, storm duration $t_r$, and inter-storm period $t_b$ (from Struthers et al., 2006b)**

## 2.3 Modelling Triggers of Hydrological Events

### *2.3.1 Stochastic description of event triggering*

The first approach that provides us with statistical information on the triggering of critical events is to model directly the statistical properties of the hydrological event that is being triggered. Here we consider runoff generation as one example that is of great importance for assessing risk of reconstructed landforms to erosion. Runoff is generated by either infiltration excess or saturation excess. Figure 2a represents an example of infiltration excess. Rainfall is described as an instantaneous event with maximum intensity $I_{max}$. Infiltration excess is triggered once the rainfall intensity exceeds a critical value, here an infiltration capacity of 80 mm/day (Figure 2a). All the rainfall above this threshold value is turned into surface runoff. We are interested in the time between these threshold events denoted as $\tau$ (also referred to as inter-event time). The statistical properties of interest are in particular the mean and variance of the inter-event time. By focussing on the event triggering rather then the generation of a complete runoff time series, we represent runoff in a similar way to rainfall, making it compatible for a systematic comparison. Recalling that the inter-storm period (which is the inter-event time for rainfall) follows an exponential distribution, our aim is to determine what distribution the inter-event time for runoff has and how it depends on the rainfall distribution.

A slightly different picture emerges when we look at saturation excess (Figure 2b). Runoff triggered by saturation excess is due to the complete filling of the water storage capacity of the soil. Once the soil is saturated all rainfall thereafter is converted into surface runoff. To model this in the simplest way we need to use a mass balance representation of soil moisture which is essentially a bucket-type model. Figure 2b shows the concept, where rainfall is represented similar to Figure 2a and the soil water storage response is shown as the solid line at the bottom. Each time the soil water storage reaches a value of one, saturation excess is triggered and again we are interested in the time between these events.

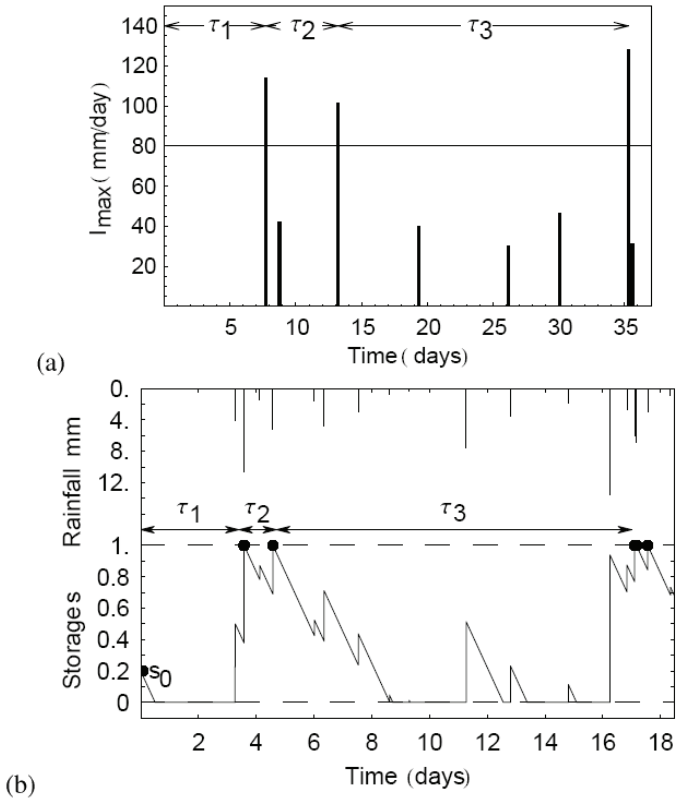


**Figure 2 Representation of threshold triggering based on a simple value of 80 mm/day for the maximum rainfall intensity $I_{max}$ (a). Hypothetical time series of normalised soil water storage *s* reaching a critical threshold at a value of 1 shown in (b) along with the rainfall signal. τ is the time between events also referred to as inter-event time (from McGrath et al. submitted)**

A blueprint of how to analyse soil water balance problems using a stochastic approach was presented by Milly (1993). A detailed description of our approach is given by McGrath et al. (submitted) and we present only a brief summary here. As previously pointed out this approach is based on predicting the statistical properties directly and this requires the formulation of a stochastic differential equation of the water balance. It is represented in terms of a simple bucket with a fixed storage capacity $w_0$[L]. The bucket wets during rainfall events and dries during the inter-storm period with a constant evaporative demand $E_m$ [L/T]. Soil water is represented by dimensionless storage $s=w/w_0$. At a threshold value of one ($s_\xi$=1 [-]) runoff through saturation excess is triggered. The resulting stochastic balance equation for water storage $s$[-] is:

$$\frac{\mathrm{d}s}{\mathrm{d}t} = \begin{cases} F[s,t] & \text{for} \quad s = 0 \\ F[s,t] - \dfrac{E_m}{\mathrm{w}_0} & \text{for} \quad 0 < s \le 1 \end{cases} \tag{1}$$

where $t$ [T] denotes time and F[$s,t$] [-] instantaneous random infiltration events (normalised by $w_0$), occurring at discrete times $t_i$. Infiltration is limited by the available storage capacity i.e. F[$s,t$]=min[1-$s_i$,$h_i/w_0$] where $s_i^-$ [-] denotes the antecedent soil moisture and $h_i$[L] the random storm depth.

Two similarity parameters can be defined: (i) the supply ratio $\alpha= w_0/\gamma$ where $\gamma$ is the mean storm depth and (ii) the demand ratio $\beta= w_0/(E_m\, t_b)$. The supply ratio relates the storage capacity of the soil to the mean storm depth, whereas the demand ratio relates the storage capacity to the mean potential evaporation during the inter-storm period. Large values of $\alpha$ indicate that the storage capacity is much larger than the average amount of water supplied through rainfall which can also be interpreted as either having a very deep soil or

very small average storm events. Similarly, small values of β indicate that evaporative demand is much larger than the soil water store or that the soil water store is very small for example given by very shallow soil depth. Large β values indicate negligible evaporative demand relative to the storage capacity. These two similarity parameters relate to climate in general and as we will show below, it is useful to analyse how saturation excess triggering occurs in climates of different aridity. Accordingly, we define the aridity index $AI=(E_m\ t_b)/\gamma=\alpha/\beta$ relating evaporative demand to rainfall supply. For arid climates we have $AI>1$ and for humid climates we have $AI<1$. Further details of the analytical derivation of mean, variance and coefficient of variation for the inter-event time of saturation excess can be found in McGrath et al (submitted).

### *2.3.2 Modelling event triggering in the time domain*

The method above is ideally suited to assess statistical properties of hydrological triggers directly from the probability density function of rainfall properties and has been used to model time scales in the same order of storm events which occur at time steps of several hours to at most a day. There is mounting evidence that accurate prediction of runoff requires high resolution rainfall measured at intervals of a few minutes to a few hours (Milly, 1994; Bronstert and Bardossy, 2003). This resolution captures within storm variability. To assess how within storm variability affects triggering of runoff through infiltration and saturation excess, we firstly have to use a rainfall model such as the bounded random cascade model to assess the structure of within storm rainfall. This requires us to model the statistical response to rainfall in the time domain in contrast to the approach introduced above. We follow however the same philosophy in describing the triggering with an as simple as possible model such as a bucket model for soil water storage. Hearman and Hinz (submitted) presented such an analysis for which a simple bucket model was used to describe infiltration and saturation excess. In summary, the model partitions rainfall into infiltration, infiltration excess (represented by a simple infiltration capacity threshold), soil water storage, deep drainage and saturation excess. Evaporation is neglected as we focus on the response during a single rainfall event of four hours. This analysis has important implications for other processes triggered by runoff such as erosion. Errors in predicting runoff and runoff intensities will make it very difficult to assess erosion triggers. The underlying question here is therefore: What is the appropriate rainfall resolution for making realistic hydrological predictions? Details of the model and its parameterisation is presented by Hearman and Hinz (submitted).

# 3 RESULTS AND DISCUSSION

## 3.1 Trigger Variability as a Function of Climate

In this section we will summarize the most important finding of how runoff is being triggered assuming independent storms as outlined in section 2.1. If we recall that we are looking at the two runoff mechanisms: infiltration excess represented by a simple cut-off threshold intensity and saturation excess which is a storage trigger. It turns out that a simple cut-off threshold (Figure 2a) eg a critical rainfall intensity triggering runoff by infiltration excess will have very similar statistical properties as the rainfall itself. More specifically, if the inter-storm period of rainfall is exponentially distributed then the time between infiltration excess events (inter-event time) will also be exponentially distributed but with a different set of parameters (Rodriguez-Iturbe et al., 2000). This is not true for saturation excess, triggered by a storage threshold (Figure 2b). The statistical properties of rainfall are not preserved and the probability density function of inter-event times will not be exponentially distributed. In fact, the often used assumption in engineering design that runoff events occur independently is not satisfied by saturation excess. The carry over of soil moisture storage between storms implies that saturation excess events occur in clusters or in other words when one event is triggered the probability that a second event will follow is high. Once the water storage is high, it takes only a small rainfall event to fill this store to its maximum triggering a second saturation excess event. Obviously, temporal clustering is an important feature that needs to be considered during risk assessment.

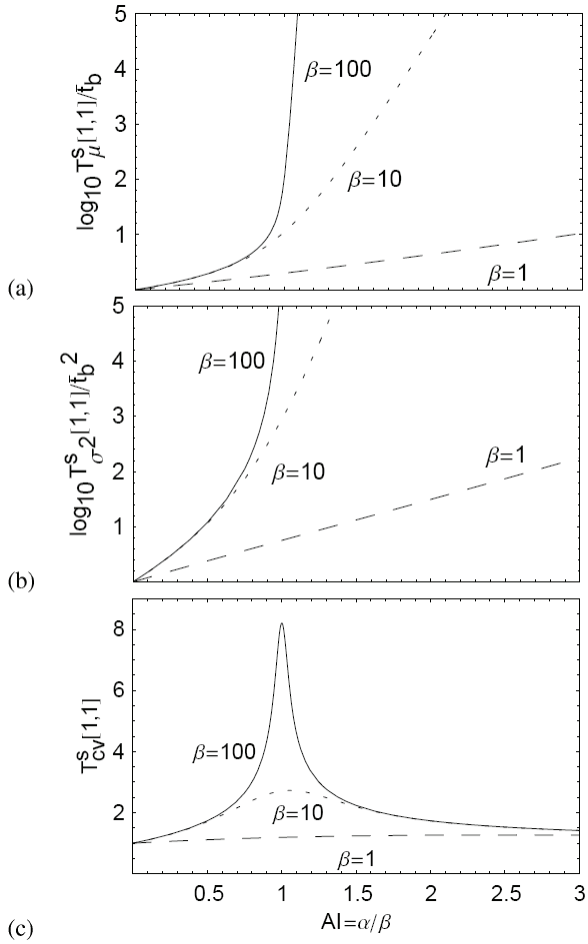


**Figure 3 Logarithmic mean (a), logarithmic variance (b) and coefficient of variation (c) of the inter-event time for saturation excess as a function of aridity (AI) (from McGrath et al, submitted)**

As the memory effect depends on both the evaporative demand and the rainfall we expect that temporal clustering will be different in different climates. Recall that the aridity index characterises climate in terms of the ratio of evaporative demand and rainfall supply, we can now look at the statistical properties of saturation excess as a function of the aridity index *AI* for different demand ratios β. Figure 3 displays the statistics of the saturation excess inter-event times for *AI* values ranging between 0 and 3 showing lines of demand ratios of 1, 10 and 100 which were derived based on Equation 1 and simple statistical models of rainfall timing and magnitude. Both the mean and the variance increase with increasing aridity. This increase is most severe for β =100 which represents a very large storage capacity of the soil compared to the evaporative demand. This value is extremely high and could also be interpreted as a very deep soil. As β decreases the increase of the mean and variance is less pronounced. The most interesting result is how the coefficient of variation, the ratio of variance and mean, behaves as a function of aridity. In terms of temporal dynamics the coefficient of variation of the inter-event time is also a measure of temporal clustering. Coefficient of variations greater than 1 indicate a degree of clustering and the higher the more clustered. For deep soils the coefficient of variation peaks at about an aridity index near one, where evaporative demand and rainfall is balanced. The coefficient of variation is a measure of variability relative to the mean, which implies that intermediate climates may experience most variability.

## 3.2 Effects of temporal resolution on runoff triggering

The findings of the previous section focussed on the effect of the temporal structure of runoff generation. This section will focus on the effect of rainfall resolution on predicting runoff. As the analysis was done in the time domain by modelling infiltration excess, saturation excess, deep drainage and water storage in soil, we will first look qualitatively at the pattern of runoff triggering as modelled for rainfall resolutions of 1.875 min and 120 min for a 4 hour storm.

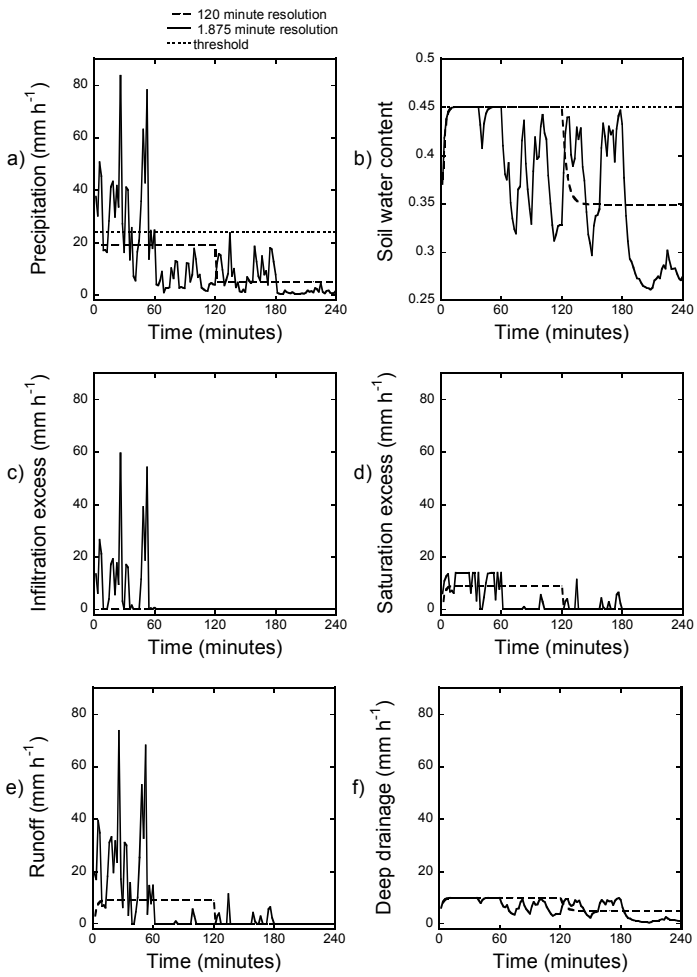


**Figure 4 Comparison of 1.875 and 120 min resolution of rainfall (a), soil water content (b), infiltration excess (c), saturation excess (d), runoff (e), and deep drainage (f) (from Hearman and Hinz, submitted)**

From Figure 4 it can be seen that the higher resolution rainfall has higher peaks in intensities than the low resolution rainfall. This leads to infiltration excess being triggered in the high resolution rainfall input and no infiltration excess triggered with the low resolution rainfall. As a result more water is able to enter the soil for the low resolution rainfall and the soil is saturated for a longer period of time. Figure 4 shows that the dynamics of runoff generation is markedly different for the two resolutions. The peaky rainfall of the high resolution produces a peaky response of infiltration excess in particular. Furthermore, high resolution rainfall generates more runoff. Considering that both resolutions are at a sub-daily time scale and that the differences are pronounced, implies that daily rainfall resolution is incompatible with accurate prediction of runoff. In fact, calibration of hydrological models using daily rainfall will obviously generate unrealistic parameter values for hydraulic properties.

In order to obtain general information on runoff generated from different soil properties and rainfall intensities the g* parameter was constructed. The *g** parameter is the ratio of the drainage parameters to the

average storm intensity, essentially comparing the supply rate (rainfall) with the potential output rate (drainage). The higher this parameter is the faster the soil drains compared to the average rainfall intensity. To capture variations in within storm rainfall intensities 500 realizations were generated for each mean rainfall intensity then the mean runoff for both infiltration and saturation excess was calculated for each resolution. Figure 5 shows the difference in runoff predicted using two different rainfall resolutions (1.875 min and 120 min). It shows that at a value of approximately ln $g^*$=2 runoff predictions are most sensitive to these rainfall resolutions. It must be noted however, that although at low values of ln $g^*$ the difference between runoff generated by the two resolutions diminishes this is the result of high amounts of infiltration excess being produced by the high resolution rainfall in comparison to high amounts of saturation excess produced by the low resolution rainfall.

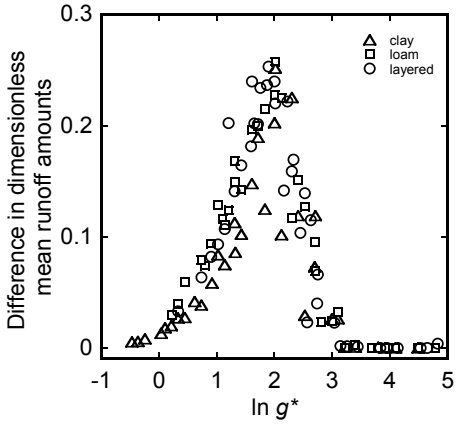


**Figure 5 Difference between average runoff generated by 500 realisations of 1.875 and 120 min resolutions as function of effective drainage rate to average storm intensity (from Hearman and Hinz, submitted)**

In summary, high temporal resolution of rainfall may be important to capture all runoff events. If this is so, rainfall models that disaggregate low temporal resolution into high temporal resolution have to play an important role for predicting relevant hydrological events.

# 4 IMPLICATIONS FOR MINE SITE REHABILITATION

This paper has summarized some of our findings concerning the triggering of hydrological events by rainfall. We currently have made progress in testing this approach for contaminant leaching through preferential flow as measured in lysimeters. The generic analysis of trigger statistics of storage threshold systems has direct applications to regions with clear climate gradients. One such region for which we do this research is Western Australia. Rainfall usually diminishes from the coastal areas in the West to the inland areas in the East. This decrease in rainfall is also associated with an increase in potential evapotranspiration. This creates a very clear gradient of the aridity index *AI*. Hence the results as presented in Figure 3 can be directly applied to identify areas for which the variability of hydrological events is very high and therefore associated with a more difficult risk assessment that is less predictable. Using rainfall information from the weather service (Bureau of Meteorology) this could provide an *a priori* risk assessment by geographical areas.

Our analysis has shown that rainfall, as a first-order control, can be used in a probabilistic framework to assess the timing of critical events. This timing is expressed not only in the frequency of event triggering but also in the temporal structure of events. This temporal structure we expressed simply in terms of the coefficient of variation of inter-event times a measure of temporal clustering. Our results suggest how this clustering changes across an aridity gradient. Such clustering could therefore pose a greater risk to engineered landscapes than would otherwise be predicted from a simple risk assessment based upon a simulated 1 in 5 year storm for example. Understanding how the temporal structure of events occurs may allow improved design and risk assessment of post mined landscapes.

Critical to our analysis is the identification of the critical values of infiltration and soil moisture that triggers an event like erosion. While the complexity of the model is greatly reduced, we still need to better establish these critical threshold values.

## ACKNOWLEDGEMENTS

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