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DISTRIBUTION OF HYDROLOGICAL LOSSES FOR VARYING RAINFALL AND ANTECEDENT WETNESS CONDITIONS

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Abstract: Hydrological loss is a vital component in many hydrological models, which are used in forecasting floods and evaluating water resources for both surface and subsurface flows. Due to the complex and random nature of the rainfall runoff process, hydrological losses are not yet fully understood. Consequently, practitioners often use representative values of the losses for design applications such as rainfall-runoff modelling which has led to inaccurate quantification of water quantities in the resulting applications. Therefore, the existing hydrological loss models must be revisited. This study is based on three unregulated catchments situated in Mt. Lofty Ranges of South Australia (SA). The paper focuses on analysing initial loss (IL), continuing loss (CL) and proportional loss (PL) with rainfall and antecedent wetness conditions. The paper introduces IL_TR_AW nomogram that can be implemented to estimate IL as a function of TR and AW, using statistical approach. This study will yield improvements to existing loss models and will encourage practitioners to utilise multiple data sets to estimate losses, instead of using hypothetical or representative values to generalise real situations.

INTRODUCTION

The rainfall that does not contribute to direct runoff is termed as a hydrological loss. Hydrological losses can be caused by various processes such as infiltration, depression storage, evapotranspiration and interception. Available loss models that are used to estimate hydrological losses can be broadly classified as conceptual and theoretical models. Conceptual models include the Initial Loss-Continuous Loss model (IL-CL) and the Initial Loss-Proportional Loss model (IL-PL). These are based on the spatial lumped response of a catchment (Nandakumar *et al.* [1]). The theoretical models are usually based on infiltration equations, and then treat other loss elements such as depression storage, evaporation, and interception as relatively minor losses. In some cases, the infiltration loss can only be 30% of the total precipitation (Chow [2]). However, evaporation or evapotranspiration may account for up to 75% of total annual precipitation (Gray [3] and Brutsaert [4]). Also, the interception may account for 20 to 40% of the total precipitation in humid forest regions (Chow *et al.*[5], Gash *et al.*[6], Teklehaimanot *et al.*[7], Viville *et al.* [8]and Tallaksen *et al.* [9]). Ullah and Dickinson [10] found that depression storage, also plays a significant role in the hydrologic response of a catchment. Therefore sometimes these elements of hydrological loss cannot be treated as minor. Also, infiltration equations (theoretical models) are not particularly appropriate for the loss estimation of catchments, since they

only provide point estimations (Ilahee [11]). In contrast, lumped conceptual models can define the losses at the catchment scale (Nandakumar *et al*.[1]) and incorporate losses from all the elements. Therefore, this study will focus on lumped conceptual models.

Lumped hydrological models estimate the loss values in a catchment individually in the case of a storm event. During a rain storm in a catchment, these loss values vary temporally as well as spatially. Therefore, the accumulated response of runoff to rainfall is highly nonlinear. However, when incorporating losses in hydrologic models, these variations are often neglected. Instead, the models use representative single values such as mean or median loss. Even Australian Rainfall and Runoff (ARR) (IEAust [12]), which is the national guide for flood estimation in Australia, provides only representative single values (median or mean) for hydrological losses. These single representative values of the losses are likely to introduce a high degree of uncertainty and possible bias in the resulting flood/flow estimates (Hill and Mein [13], Waugh [14] and Walsh *et al*. [15]).

The aim of this paper is to investigate the variability of each loss components (IL, CL and PL) and to identify the distribution of the losses with respect to rainfall and antecedent wetness condition. For selected catchments in SA, this study will 1) investigate the variability of the IL, CL and PL with rainfall characteristics and antecedent wetness conditions, and 2) develop a nomogram to describe the IL as a function of Total Rainfall (TR), and Antecedent Wetness (AW).

CATCHMENT SELECTION AND DATA

The selected catchments were unregulated and in the small to medium size range with no major land-use changes. Under these conditions, it can be assumed that the temporal patterns of the pluviograph data provide representative temporal patterns for the whole catchment (Ilahee [11]). Both rainfall and streamflow record lengths of the catchments were sufficient to provide a robust analysis. According to several studies (Boni *et al*. [16], Jingyi and Hall [17], Kumar and Chatterjee [18]), the record length of data should be at least 10 years for adequate empirical analysis. Three catchments were selected for this study: Scott Bottom (A5030502), Mt Pleasant (A5040512) and North Para (A5050502). A location map of the selected catchments is given in Figure 1.
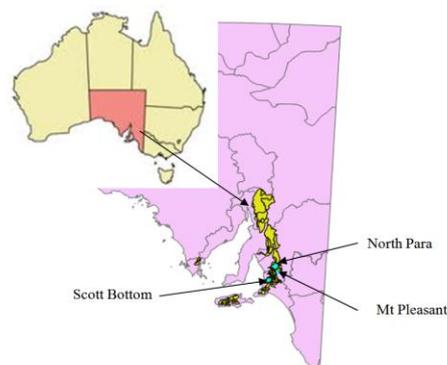

Figure 1: Location map.

METHODOLOGY

Quantifying losses

The process of calculating losses involves three steps: 1) extracting events, 2) baseflow separation and 3) calculating IL, CL and PL components. The rainfall events that have potential to produce significant runoff were selected in order to calculate the losses. The

criterion described by Hoang *et al*. [19] was adopted in this study for selecting suitable rainfall events. Then the rainfall and streamflow data were plotted (synchronized) and corresponding streamflow events were extracted for the selected rainfall events using the HYDSTRA software.

The measured streamflow data comprise of Quickflow (QF) (rainfall excess) and Baseflow (BF) components. For hydrological loss estimations, only the QF should be considered. Therefore the BF should be separated from the original streamflow data set. The Lyne and Hollick algorithm (Nathan and McMahon [20]) in the HYDSTRA program was used for BF separation.

The IL, which is defined as the amount of rainfall that occurs before the start of the runoff, was calculated according to Equation 1.

$$IL = \sum_{i=1}^{n} I_i \tag{1}$$

where n is the duration in hours of the storm burst that ends before runoff begins, and I_i is hourly rainfall in mm.

The Total Rainfall (TR) can be expressed according to Equation 2. This can be rearranged as in Equation 3 to calculate the CL, which is defined as the average rate of loss in mm/h throughout the remainder of the rainfall event.

$$TR = IL + CL \times t + QF \tag{2}$$

$$CL = \frac{(TR - IL - QF)}{t} \tag{3}$$

where TR, IL and QF are in mm, CL is in mm/h and t is the time in h elapsed between the start of the surface runoff and end of the rainfall event.

The PL, which is assumed to be a fixed proportion of the storm rainfall, was estimated using Equation 4.

$$PL = 1 - \frac{TSV}{TRV - IL} \tag{4}$$

where, TSV is the total surface-runoff volume and TRV is the total rainfall volume. TSV and TRV were calculated using Equations 5 and 6, respectively.

$$TSV = \sum_{i=1}^{n} n \times q_{f(i)} \tag{5}$$

where n is the duration of the streamflow event.

$$TRV = \sum_{i=1}^{r} r \times A \tag{6}$$

where r is the hourly rainfall in mm and A is the catchment area in m^2.

Analysing variability of losses with rainfall characteristics and antecedent wetness
In this study, the variability of the losses (IL, CL and PL) with rainfall characteristics and antecedent wetness conditions was investigated. The rainfall characteristics considered include the total rainfall volume of the event expressed in terms of the average depth of total rainfall (TR) in mm over the catchment. In order to represent the antecedent moisture content, the five-day antecedent wetness (AW) was considered. AW is defined as the total rainfall that the catchment receives in the five days prior to the start of the selected event. A

bivariate analysis was performed to investigate the relationship between the loss components and the other variables.

Distribution patterns of the IL

Identifying the distribution of IL with respect to the other variables was the next step. First, a multiple-regression analysis was carried out to estimate the combined effect of the independent variables TR and AW on the dependent variable IL. Then contour and dot maps were used to examine the effect of variables on each other. On these maps, each loss value was mapped in the third dimension as it improves the interpretability of the loss distribution patterns. The possibility of forming either a contour map or a dot map, and the patterns of distribution of each loss component compared to two other independent variables were investigated. In order to identify the clusters, all the observed IL values were ranked and aggregated to 8 arrays, as shown in Table 1. Finally, an IL_TR_AW nomogram was introduced to describe the IL distribution patterns. IL values for 582 events were used and 500 were used for developing the method while 82 independent randomly selected values were used for validation.

Table 1 : Loss aggregations

Aggregation	1	2	3	4	5	6	7	8
Loss values (mm)	0 -5	6-10	11-15	16-20	21-25	26-30	31-40	41-50

IL_TR_AW nomogram

In this study, the IL values were graphically interpreted using a Cartesian grid with TR values taken as variable X and AW values taken as variable Y. The IL values were aggregated as shown in Table 1 and the aggregation numbers were marked on the Cartesian grid for each event. The (X, Y) coordinates of the corresponding point represent the observed TR and AW values for the same event. Only the aggregations 1-5 were used in this method, as there were only a few events that fell into aggregations 6-8.

Central tendency was investigated to identify the distribution pattern of the IL values with respect to TR and AW. In the central tendency method, the centre value and the dispersion of IL in each aggregation were investigated. The centre values are calculated using Equations 7 and 8.

$$\bar{X} = \sum_{i=1}^{n} \frac{X_i}{n} \tag{7}$$

$$\bar{Y} = \sum_{i=1}^{n} \frac{Y_i}{n} \tag{8}$$

where (Xi, Yi), i=1,2,...,n are the coordinates of a given set of n points for each aggregation.

The dispersion of IL of each aggregation was determined using deviation, the difference in value of an observation from a central value mean. The Standard Distance (SD) is directly related to the standard deviation. The distances between each observation and the mean center were squared and summed, and this sum was divided by the number of observations. The standard distance of the point distribution of each aggregation was calculated by using the coordinates of each point in Equation 9.

$$SD = \sqrt{\sigma_x^2 + \sigma_y^2} \tag{9}$$

where

$$\sigma_x^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n} \qquad \text{and} \qquad \sigma_y^2 = \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}{n}$$

The IL distribution that corresponds to each aggregation was then drawn as circles with a radius equal to the standard distance around the mean center of the distribution.

RESULTS AND DISCUSSION

The results are based on events that have been extracted from the three selected catchments over the 25 year observation period. All the events selected for the analysis had the potential to produce significant runoff.

One objective of this study was to investigate the variability of loss components (IL, CL and PL) with the rainfall characteristics and antecedent moisture content. AW is used as a substitute for the antecedent moisture content, because AW is an easily measurable parameter that has a direct relationship with antecedent moisture content. Similarly TR and AW are easily measurable parameters, which should increase the usability of the developed model. When analysing the variability of IL, CL and PL with the parameters TR and AW, it was found that the variability of IL and CL changed considerably with TR. Figure 2 shows the variability of IL, CL and PL with TR. In Figure 2, the selected events were ranked in ascending order of TR values.
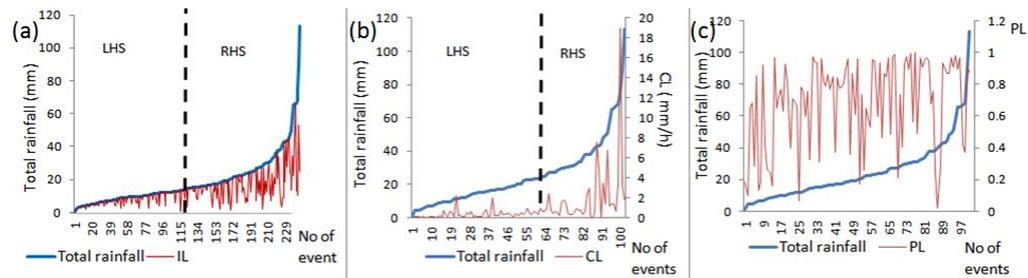

Figure 2: Variability of (a) IL, (b) CL and (c) PL with total rainfall.

It is clear from Figure 2 that the higher the TR in an event, the greater the variation in IL and CL. The variations of the IL and CL values are lower in lower rainfall events. The threshold between the Left Hand Side (LHS) and the Right Hand Side (RHS) of the graph was selected based on the median value of the TR. The difference of Mean, Median and Variance for the LHS and RHS are summarised in Table 2.

Table 2: Summary statistics for the loss components, based on changes in TR

	Mean		Median		Variance	
	LHS	RHS	LHS	RHS	LHS	RHS
IL (mm)	7.90	17.20	8.10	16.39	13.70	80.10
CL(mm/h)	0.37	2.10	0.25	0.94	0.16	10.71
PL (mm/h)	0.64	0.73	0.75	0.86	0.07	0.07

This is an important finding for applications such as rainfall runoff modelling where the mean or median value of IL is used as an input parameter. For design applications, it is important to identify the TR of the event before assigning a representative value for the IL or CL parameters. However, as shown in Figure 2 (c), the variation of the PL with TR is quite low and the variance is only 0.07. Not only PL is independent of TR, it is also shows much less sensitivity to the high outliers. Therefore, it can be inferred that the PL model is

more suitable than the CL model. However, the IL needs further investigation before it can be efficiently incorporated into design applications.

IL distribution with respect to TR and AW

This paper will now discuss the distribution of the IL with respect to the TR and AW conditions. Before analysing the distribution patterns, it is useful to determine the combined effect of TR and AW on IL. Hence a multiple-regression was carried out and it was found that the adjusted R^2 was 0.7, which indicates that 70% of variation of IL can be explained by using TR, and AW.

In order to provide a better representation of the distribution, IL was described with respect to at least two variables, rather than examining one variable at a time. The first approach used to identify the distribution pattern with respect to two other parameters was the use of contour and dot maps. As no contour patterns were found data aggregation was performed to minimise the complexity. The aggregation was done carefully as too few aggregations can mask the real variation portrayed by the observed data. In this study, the data was aggregated into 8 arrays (Table 1), minimising the inevitable loss of information during the aggregation.

The application of IL_TR_AW nomogram, for ascertaining the distribution of the IL with respect to AW and TR, is shown in Figure 3. A sample of randomly selected events that occurred between the period 1989-2010 was selected to develop this map. In Figure 3, the red colour cells indicate the mean centers of each aggregation and the radius of each circle represents the standard distance. Together with the mean center, the standard distance can be used to compare and contrast the point distributions. Therefore, the circles drawn around each center represent the distribution of losses with respect to AW and TR. More dispersed point patterns will have large standard distances. However both measures are very sensitive to extreme observations. The overlapping sections indicate the variability of the losses in the same range of TR and AW values. Based on the overlapping sections of the map, regions that can represent a certain range of IL values were identified and shown in Figure 3. This map can be used to predict the IL value of an event if TR and AW values are known. For example, if the TR and AW values of an event are 14mm and 13mm respectively, from the map it can be determined that the IL value for the same event ranges from 5 to 15mm.
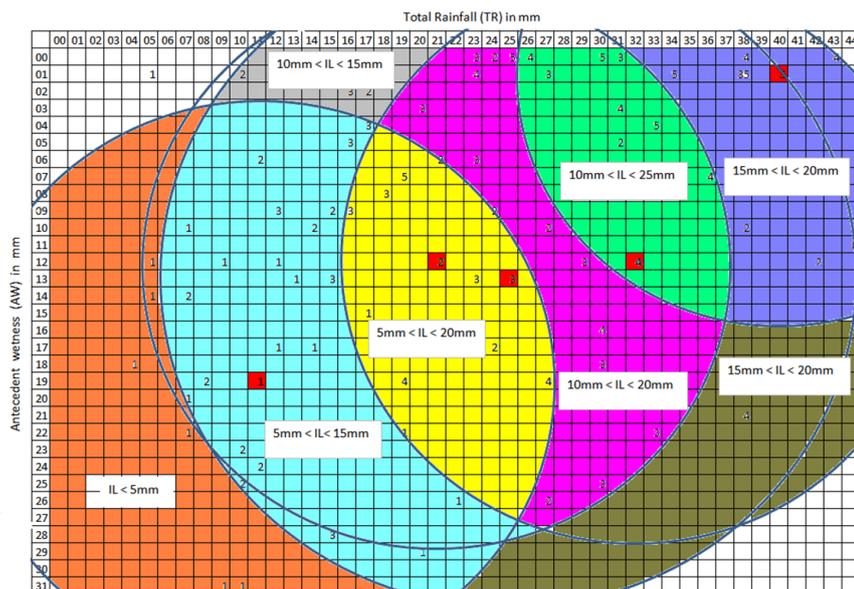

Figure 3: IL_TR_AW nomogram.

One point that needs to be highlighted in the application of this method is that the mean value of losses is not used to represent an aggregation. For example, in Table 1 Aggregation 1 represents the range of losses (i.e. from 0 to 5) and not the average loss (2.5mm). Therefore, in Figure 3 the regions are also marked as a range. If the average loss of each aggregation was used to construct the map in Figure 3, the interpretation could have been different. For instance, if average loss values were used, then in Figure 3, the red cell that indicate Aggregation number 1 would have been replaced by the average loss value of 2.5mm and that for Aggregation number 4 would be replaced by 17.5mm. Then the light blue region would represent losses between 2.5mm to 17mm. This might look generally correct with the numbers given in the example, but using the mean values actually leads to several problems. One possible problem is that if the unit and the size of the aggregation change, the map will give a different interpretation. Also even if we use the same number, size and shape of units, different partitions can yield different values for the correlation coefficients for the same data. In statistical theories, this is known as a "modifiable unit problem" (Burt and Barber [21]). The problem does not invalidate the use of correlation coefficients for real data, but might cause specific interpretation problems. Therefore, to minimize the interpretation problem, in this study the aggregations are given as a range of values not just as the mean value.

The validity of the map is investigated by using 82 randomly selected testing events within the region. For the testing events, the IL values were calculated, aggregated and plotted on the map shown in Figure 3. However, this map can only be used for hydrologically similar catchments. The method can be generalised by incorporating a wide range of catchments or developing similar maps for different hydrological catchments. It must also be noted that the method is suitable for unregulated catchments. Also, when implementing such nomogram, it is very important to use a large number of data sets. If data are aggregated into fewer and larger units, it may mask the important associations between variables or it may overemphasize other associations. Also, if correct aggregations are not used, there can be substantial variations in the value of most statistics. For example, the correlation coefficient can be changed dramatically with the aggregations, especially if there are fewer data points or if there are fewer aggregations. Indeed, sometimes correlations coefficient can be changed from negative to positive in value.

This nomogram can overcome the problems associated with using representative single values for a wide range of events.

CONCLUSION

This paper provides a comprehensive analysis of the variability of IL, CL and PL with selected rainfall characteristics and antecedent wetness conditions. The effects of individual parameters as well as the combined effect of those parameters on losses were investigated. The issues associated with current practices and errors caused by using representative single loss values in design applications were also discussed. Although the IL–PL model is clearly superior to the IL–CL model, the IL model itself needs further modifications to improve design applications. IL should be determined as a function of other parameters, here as a function of the independent variables TR and AW. These independent variables were selected because they are not only easily measurable but they can also explain up to 70% of the IL. An IL_TR_AW nomogram was introduced, as s new model to determine the IL when minimum of two independent variables are present. The method was tested for the selected region and the possibility of generalising the methods and the limitations of this were also discussed. The results presented in this paper should be useful for improving existing conceptual (lumped) loss models.

REFERENCES

[1] Nandakumar N., Mein R. and Siriwardena L., *"Loss modeling for flood estimation - a review"*. Cooperative Reserch Center for Catchment Hydrology, (1994).

[2] Chow V. T., Maidment D. R. and Mays L. W., *"Applied hydrology; 2 edition"*, McGraw-Hill New York, (2013).

[3] Gray D. M., *"Handbook on the principles of hydrology : A General Text with Special Emphasis on Canadian conditions"*, Water Information Center, Inc, Port Washington, N.Y., (1973).

[4] Brutsaert W., *"Hydrology : an introduction"*, Cambridge Univeristy Press, New York, (2005).

[5] Chow V. T., Maidment D. R. and Mays L. W., *"Applied hydrology"*. McGraw-Hill, New York, (1988).

[6] Gash J. H. C., Wright I. R. and Lloyd C. R., "Comparative estimates of interception loss from three coniferous forests in Great Britain". *Journal of Hydrology*, Vol. 48, No.(1–2) (1980), pp 89-105.

[7] Teklehaimanot Z., Jarvis P. G. and Ledger D. C., "Rainfall interception and boundary layer conductance in relation to tree spacing", *Journal of Hydrology*, Vol. 123, No. (3–4), (1991), pp 261-278.

[8] Viville D., Biron P., Granier A., Dambrine E. and Probst A., "Interception in a mountainous declining spruce stand in the Strengbach catchment (Vosges, France)", *Journal of Hydrology*, Vol.144, No. (1–4), (1993), pp 273-282.

[9] Tallaksen L. M., Schunselaar S. and Van Veen R., " Comparative model estimates of interception loss in a coniferous forest stand", *Nordic Hydrology*, Vol. 27, No.3, (1996), pp 143-160.

[10] Ullah W. and Dickinson W. T., "Quantitative description of depression storage using a digital surface model: I. Determination of depression storage" , *Journal of Hydrology*, Vol. 42, No. (1–2), (1979), pp.63-75.

[11] Ilahee M. *"Modelling Losses in Flood Estimation"*, Queensland University of Technology, Queensland, (2005).

[12] IEAust. *"Australian rainfall and runoff: a guide to flood estimation"*. Institution of Engineers, Australia, Barton, ACT, (1987).

[13] Hill P. I. and Mein R. G. *"Incompatibilities between storm temporal patterns and losses for design flood estimation"*, Institution of Engineers, Australia, City, (1996).

[14] Waugh A. *"Design losses in flood estimation"*, Institute of Engineers, Australia City, (1991).

[15] Walsh M., *"Initial losses for design flood estimation in New South Wales"*, University of New South Wales, NSW, (1991).

[16] Boni G., Ferraris L., Giannoni F., Roth G. and Rudari R. "Flood probability analysis for un-gauged watersheds by means of a simple distributed hydrologic model". *Advances in Water Resources*, Vol. 30, No. 10, (2007), pp 2135-2144.

[17] Jingyi Z. and Hall M., "Regional flood frequency analysis for the Gan-Ming River basin in China". *Journal of Hydrology*, Vol. 296, No. (1-4), (2004), pp 98-117.

[18] Kumar R. and Chatterjee C., "Regional flood frequency analysis using L-moments for North Brahmaputra region of India", *Journal of Hydrologic Engineering*, Vol. 10, No.1, (2005), 1-7.

[19] Hoang T., Rahman A., Weinmann P., Laurenson E. and Nathan R., *"Joint probability description of design rainfalls"*, Institution of Engineers, Australia, City, (1999).

[20] Nathan R. and McMahon T., "Evaluation of automated techniques for base flow and recession analyses", *Water Resources Research*, Vol.26, No.7, (1990), pp 1465-1473.

[21] Burt J. E., Barber G. M. and Rigby D. L. *"Elementary statistics for geographers"*, Guilford Press, NY, (2009).