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Variation in curve numbers derived from plot runoff data for New South Wales (Australia)

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Abstract:

The curve number method is a simple one parameter (the curve number) rainfall runoff model. While its theoretical underpinning has been questioned it remains a powerful hydrological tool in the absence of detailed data and is therefore used extensively in hydrological models. This study aims to characterize the variation in maximum retention values (S), which underlie curve numbers, for a range of agricultural treatments across a large spatial area in New South Wales (NSW), Australia. The data used for the analysis spans several decades of rainfall runoff observations. A range of different derivation methods result in variation in mean and variance of S. In particular, methods that emphasize the larger storms result in greater S and thus lower runoff. For larger spatial scales, emphasis on larger storms gives more reliable estimates of S. Systematic variation in S arises from variations in treatment, pre-runoff soil moisture, rainfall depth, and variations in cover. On the basis of the analysis, a table of curve number values for different land uses found in NSW is presented.

The resulting distributions of S and curve numbers provide guidance for rainfall runoff modelling studies in the agricultural important areas of NSW. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS rainfall runoff response; curve numbers; plot-scale; NEH630; maximum potential retention; Australia

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INTRODUCTION

Curve numbers (CN) have been widely used in hydrological modelling to predict the partitioning of rainfall into runoff and infiltration. In this approach, runoff is a direct function of daily rainfall, and the different runoff response curves are specified by a single parameter (CN) ranging from 0 (no runoff) to 100. The concept is neither new (Ponce and Hawkins, 1996) nor without criticism (Garen and Moore, 2005; Michel *et al*., 2005; Shaw and Walter, 2009). If detailed data are available, process-based models can give much more accurate answers than CN-based models (Goodrich *et al*., 1994; Garen and Moore, 2005). However, in the absence of detailed spatial and temporal information such as in many locations in Australia, a bulk parameter provides a useful estimate of temporal and areal average runoff because important sources of variability, such as spatial and temporal rainfall distribution, average out. As a result, Smith (1997) concluded that if only rainfall depth is available, there is currently no better method available for practical estimation of runoff than the curve number procedure.

Curve numbers (CN) are traditionally based on combinations of land use and soil type. The CN method recognizes four soil classes, primarily separated on profile hydraulic conductivities (Hawkins *et al*., 2009). Runoff variation within the soil hydrologic classes is, therefore, governed by the overlying land use, presumably through the influence on the infiltration loss (Ponce and Hawkins, 1996). Even though the CN methodology makes no direct assertion about the mechanisms involved in generating runoff, several authors have suggested interpretations of the physical process underlying the CN (Boughton, 1989; Steenhuis *et al*. 1995; Ponce and Hawkins 1996; Yu, 1998; Mishra and Singh 1999; Mishra *et al*. 2005). Simply put, the CN is a scaled version of the potential maximum retention (S). Runoff is generated after rainfall (P) exceeds the initial abstraction (Ia) that accounts for infiltration, interception, and surface storage in puddles and hollows. Runoff increases in time up to a maximum of $P - S$.

As the dependence of the hydrologic response on soil and land use is well documented (Michel *et al*., 2005), the simplicity of the model makes the CN method extremely powerful for large scale GIS-based modelling (Beven, 2001), particularly in the absence of detailed spatial data. It is therefore not surprising that many point-scale and catchment-scale hydrological models incorporate some version of the curve number equation (i.e. Foerster and Milne-Holme, 1995; Abbs and Littleboy, 1998; Arnold *et al*., 2000).

In Australia, Owens *et al*. (2003) reported that CN ranged from 97 under bare conditions to 57 under full cover on a hard setting Sodosol (Isbell, 1996)

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with low surface infiltration rates under bare conditions. For a heavy clay soil with varying levels of cover (25–90%), Foerster and Milne-Holme (1995) similarly found optimized *CN* ranging between 56 and 96 for runoff plots in Gunnedah under wheat for different tillage systems. These *CN* represented a much wider range than values for similar land use in the NEH630 tables (NRCS, 2004a). In contrast, in the same general area and using a catchment scale model and calibration on heavier (C & D) soils, values very similar to NEH630 tables were found (Sun and Cornish, 2005). Finally, for a group of 105 catchments with varying sizes in Queensland, estimated *CN* were highly variable and dependent on the method of determination (Titmarsh *et al*., 1995). These results suggest a large variation in *CN* values in agriculturally important areas of Australia, with, apart from the cover relationship highlighted by Owens *et al*. (2003), little indication of what determines this variation.

In general, variation in *CN* between events can result from variations in storm characteristics and surface conditions. Much of the variability in *CN* has been attributed to antecedent runoff content (ARC) such that soils that are wetter have a higher curve number, creating more runoff for a given amount of precipitation, than soils that are drier (Huang *et al*., 2007; Shaw and Walter, 2009). The ARC is generally divided into three classes: II for average conditions, I for dry conditions, and III for wetter conditions, each relating to different *CN* values within each land use class (NRCS, 2004b).

There has been some suggestion that the *CN* values in the NEH630 tables apply to 5% slopes and that the parameters need to be positively adjusted for steeper slopes (Neitsch *et al*., 2002; Huang *et al*., 2006). However, this relationship was never thoroughly tested and was based on some small watershed data in Texas (pers. comm. Dr. J. Williams, March 2008). As Hawkins *et al*. (2009) points out, there is also some literature that suggests negative slope adjustments for steeper slopes, which could be related to the erosion of potential surface seals before they can form.

Because of the local variation, calibration of *CN* is often used to match observed runoff to predicted runoff in hydrological models (Kim *et al*., 2010). While calibration is a useful tool for optimising large-scale hydrological models, a better indication of the range of possible *CN* values strengthens the calibration process.

Several methods have been suggested to estimate *CN* (Titmarsh *et al*., 1995; Ponce and Hawkins, 1996; McCuen, 2002; Feyereisen *et al*., 2008; Hawkins *et al*., 2009); most are based on graphical and least squares regression equations of observed rainfall runoff pairs, or their logarithmic transforms. As the minimum size of the storms included in the analysis is raised, lower *CN* result, because for small precipitation events, runoff only occurs for wet antecedent conditions and high-intensity storm conditions (Hawkins *et al*., 2009). Thus, *CN* based on the annual flood values will be lower than those based on analysis of more events per year; and *CN* derived from only rainfall events larger than some minimum size, such as 25 mm, will usually be lower than those derived using all available rainfall runoff pairs (see also Titmarsh *et al*. 1995).

The aims of this paper are to report the observed variation in the potential maximum retention values (S) underlying *CN* for a range of agricultural land uses in NSW, Australia, and to identify possible reasons for the variation. We concentrate on deriving S values as these have a physical interpretation in terms of maximum depth of water storage in the soil. The S values in this study were derived from a substantial historic database of rainfall-runoff data.

The CN method

The *CN* method is based on a water balance and two empirical hypotheses. The first states that the ratio of direct runoff (Q) to potential maximum runoff is equal to the ratio of infiltrated depth to potential maximum retention, S (both in length units). The second hypothesis is that the initial abstraction is some fraction of the potential maximum retention. Expressed mathematically, the water balance is

$$P = I_a + F + Q \tag{1}$$

and the two hypotheses are

$$\frac{Q}{P - I_a} = \frac{F}{S} \tag{2}$$

$$I_a = \lambda S \tag{3}$$

Where P is the rainfall, I_a is the initial abstraction, F is the cumulative infiltration depth excluding I_a, Q is the direct runoff, S is the potential maximum retention and λ is the initial abstraction ratio, which is suggested to be equal to 0·2 (NRCS 2004a).

There is some debate about the value of λ and whether this should be a calibrated parameter (Mishra *et al*., 2005; Descheemaeker *et al*., 2008; Hawkins *et al*. 2009). A recent re-analysis of the available data suggested that an initial abstraction equal to $0{\cdot}05 \times S$ would fit the data better (Woodward and Lomas, 2004; Hawkins *et al*., 2009). However, runoff predictions for most events would not be greatly altered by this change (Schneider and McCuen, 2005), and this is particularly true for higher rainfalls (Mishra and Singh, 2003). For this study, the standard value of 0·2 for λ was assumed. Combining Equations (1), (2), and (3), Q can be expressed as follows:

$$Q = \frac{(P - \lambda S)^2}{(P - \lambda S) + S} \quad for\ P > \lambda S \tag{4a}$$

$$Q = 0 \quad for\ P \leq \lambda S \tag{4b}$$

The relationship between S (in mm) and the *CN* is defined as

$$S = \frac{25\,400}{CN} - 254 \quad \text{or} \quad CN = \frac{25\,400}{254 + S} \tag{5}$$

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The CN ranges from 0 to 100 and is a transformation of S, which varies between $0 \leq S \leq \infty$. A value of S can be calculated from P and Q if $\lambda = 0{\cdot}2$ (Hawkins 1993):

$$S = 5\left[P + 2Q - \left(4Q^2 + 5PQ\right)^{0{\cdot}5}\right] \tag{6}$$

The calculation of CN from the S values is simple using (5).

METHODS

Study area

Daily rainfall and runoff from 6 New South Wales Soil Conservation Service research stations (Cowra, Gunnedah, Inverell, Scone, Wagga, and Wellington, Figure 1) were used for this study (Edwards, 1987) and this includes the data used earlier by Foerster and Milne Holme (1995). Average annual rainfall was fairly consistent across the 6 locations ranging from around 600 to 800 mm/year (Table I) and annual potential evapotranspiration ranged between 1300 and 1800 mm/year.

Over varying periods (from 6 to 33 years between 1943 and 1985) runoff plots were set up by the New South Wales Soil Conservation Service to develop the SOILOSS erosion prediction program (Edwards, 1987). At each location, several cropping and tillage treatments (Table I) were applied to the runoff plots, and at least three replications were carried out for every treatment. Briefly, cultivation treatments included several different wheat, sorghum, and maize rotations with different levels of tillage and fallow periods; Perennial pasture trials included a range of different pasture species, such as lucerne and grazing oats which were intermittently grazed or mowed; and finally grazing pressure trials which specifically studied the different levels of grazing pressure on presumably native pastures. The separation between the perennial pasture trials and the grazing pressure trials is not very well defined in the original documentation (Edwards, 1987). The grazing pressure trials were kept in this study as a separate group to highlight the effect of grazing pressure. The reader is referred to Edwards (1987) for the full description and time periods of each of the treatments. For this study, we grouped the trials into the three main groups: cultivated, perennial pasture and grazing trials. The soil erosion results from these locations have been summarized earlier (Edwards, 1987), but the rainfall-runoff results have not been studied in detail.

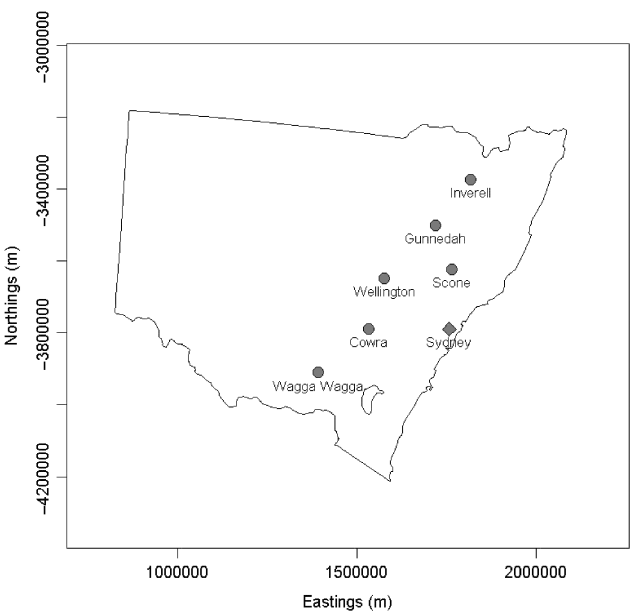

Figure 1. Map of NSW (Australia) with the locations of the research stations used in this study relative to the NSW capital Sydney

In general, the plots in the study were $41{\cdot}5 \times 2{\cdot}4$ m, or approximately 0·01 ha. In comparison, the watersheds on which the NEH630 tables are based were less than 1 square mile (256 ha) in size (NRCS, 2004a). This would still be considerably larger than the plots on which the runoff data in this study was derived.

Soils

For this study, we estimated the approximate saturated hydraulic conductivities (K_s) for the soils based on reported textures (Edwards, 1987) using the pedotransfer program Neurotheta (Minasny and McBratney, 2002). The definitions used to group soil hydraulic classes have varied since they were first introduced in 1955 (Hawkins *et al.*, 2009). However, using the present criteria (Hawkins *et al.*, 2009) and based on hydraulic conductivities of the top 0·5 m, soils at Cowra and Wagga Wagga are classified as C soils, while the others are D soils (Table I). We chose to classify the soils in Inverell as C soils, despite the low predicted K_s in the top 0·5 m, as these soils are very well structured and thus have a much higher K_s than would be predicted from the texture alone (McKenzie *et al.*, 2004). This soil hydraulic classification of the soils is needed to compare the derived S values in this study to values in the NEH630 tables (NRCS, 2004a).

Limitations to the data

There are some limitations to the data, as most of the detailed management records related to these studies are difficult to interpret (see comments in Edwards, 1987). In our study, rainfall (P) data was explicitly matched to the runoff (Q) data. Unreasonable and clearly wrongly recorded data were removed manually, such as Q data with missing P data. In addition, the daily Q data was manually matched to runoff generating storms in the P data. For example, in some cases rainfall was recorded on one day, while runoff was recorded on the next.

To account for possible differences in cover (Descheemaeker *et al.*, 2008), the data for the cultivation trials was split in growing (cropping) season and non-growing (fallow) season data to represent different land uses. Following Feyereisen *et al.* (2008), we based our cut-off dates on the mean sowing and harvest dates provided by Edwards (1987).

In the study, the fallow period in the wheat cropping trials was typical of the prevailing regional management, and consisted of wheat stubble management involving

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Table I. Average annual rainfall (1943–1975), average annual measured runoff from all plots, soil type, treatments, slope for the experimental plots at the 6 NSW Soil Conservation Service locations (Edwards, 1987). Est. K_s is the saturated hydraulic conductivity estimated from the average profile texture using pedotransfer functions (Minasny and McBratney, 2002). In the texture abbreviations, SClL is sandy clay loam, mCl is medium clay, hCl is heavy clay, SL is sandy loam and fSCl is fine sandy clay

Location	Average annual rainfall (mm)	Average annual measured runoff (mm)	Plots	Slope (%)	limiting texture within 0·5 m	Est. K_s (mm/hr)	Estimated Soil hydr. group
Cowra	659	17·3	Cultivation	7–8	SClL	21.7	C
					SClL	21.7	
					SClL	21.7	
			Grazing	12–13	SClL	21.7	C
Gunnedah	646	19·5	Cultivation	8–9	mCl/hCl	2.5/0.9	D
			Grazing	12	mCl	2.5	D
Inverell	783	50·4	Cultivation	9–12	hCl/mCl	2.5/0.9	C
					MCl	2.5	
			Grazing	14–15	mCl	2.5	C
Wagga Wagga	569	18·5	Cultivation	4	mCl/fSCl	2.5/12.5	C
					SL	21.24	
			Grazing	15			C
Wellington	644	17·4	Cultivation	4–4.5	lmCl	2.5	D
			Grazing	11	lmCl	2.5	D
Scone	683	16·3	Grazing	10	HCl	0.9	D
					HCl	0.9	
					HCl	0.9	
				30–36	HCl	0.9	D
					HCl	0.9	

occasional clipping or grazing of weeds and volunteer grasses by sheep followed by a series of tillage operations to prepare a seedbed for the next wheat crop (Edwards, 1987). Fallow management was not the same at all locations and some sites were grazed regularly, while others were not grazed at all. This very much depended on the amount of volunteer weeds and grass that grew during the fallow period. As a result of the opportunistic use of grazing, the amount of cover during fallow years is generally relatively low.

Deriving annual and monthly S values

Annual and monthly S values were determined by four different methods based on earlier studies (i.e. Feyereisen *et al.*, 2008; King *et al.*, 2008). These included the lognormal, least squares, censored data and 'Hawkins' methods and are discussed in detail below.

In general, annual S values were calculated from P and Q pairs using Equation (6). For the lognormal and censored data method, the P and Q data from the replicate plots in each treatment at a location were pooled. This resulted in a distribution of S values for which one mean S and standard deviation value by treatment and location could be calculated.

For the least squares and 'Hawkins' method, the replicate plots were not pooled as the underlying S distribution cannot be recovered from the fitting method. These methods therefore resulted in a maximum of 3 S values per treatment at each location.

Using the lognormal method we also calculated monthly CN to test if there were important seasonal trends. These were calculated by splitting the treatment datasets by month of the year and calculating average S values for the monthly subsets for each treatment at each location.

Lognormal method

The first method (the lognormal method) calculates S from all the P and Q data using Equation (6), generating a vector of S values. Any $S < P/0{\cdot}2$ (following Equation (4a)) were deleted. The scatter of the resulting S vector is assumed to be described by a lognormal distribution about the median (Hjelmfelt, 1991). The mean S value is subsequently calculated as exp (mean(log(S)) and the back-transformed standard deviation of log(S) is calculated using:

$$sd_{trans}(y) = \sqrt{\frac{(\exp(sd(\log(y))^2 - 1)}{\exp(2mean(\log(y)) + sd(\log(y))^2}} \quad (7)$$

Least squares method

The second method is the least squares method (King *et al.*, 2008). We used nonlinear least squares regression (using the function **nls**) in R (R Development Core Team, 2010) to fit Equation (4) to the P and Q pairs and derive S as a parameter. In this case, the underlying S distribution cannot be recovered, so the mean and standard deviation of S by treatment is calculated from the replicated plots.

Data censoring method

The third method is a data-censoring method that uses only the larger storms in the record. Various criteria have been proposed for selecting the larger storms (Hawkins

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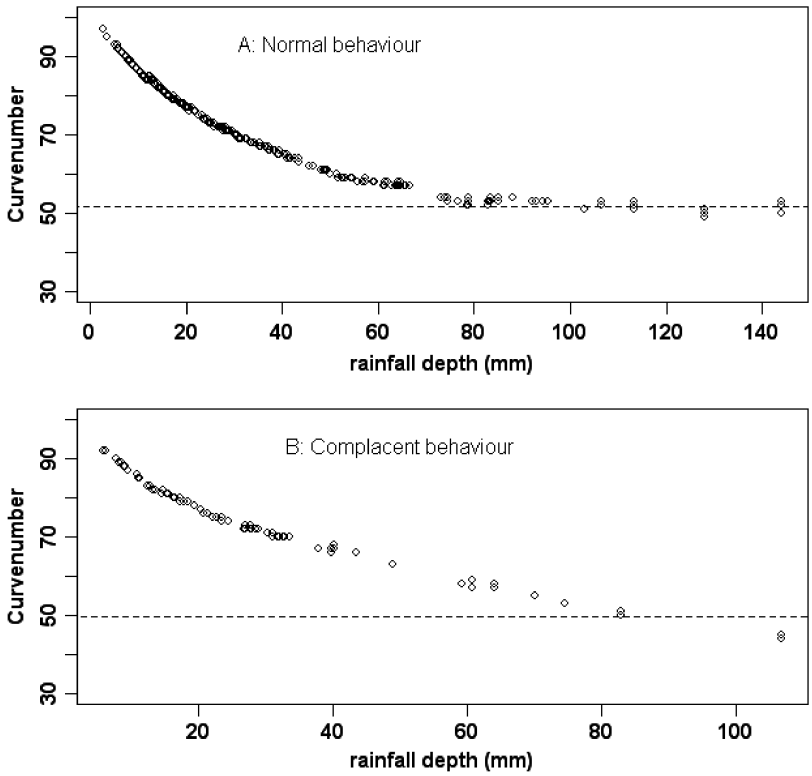

Figure 2. A: Normal, and B: complacent behaviour of the *CN* rainfall depth relationship as defined by (Hawkins 1993) for two example ordered series at Cowra. In the 'normal' case the *CN* can be calculated as the asymptotic value as the rainfall depth goes to infinity. In the 'complacent behaviour' case, a *CN* cannot be calculated

et al., 1985; Ponce and Hawkins, 1996). Following earlier work (Hawkins *et al.*, 1985; Feyereisen *et al.*, 2008), we used the partial-duration rainfall series for which $P/S > 0{\cdot}46$ to represent the annual or monthly 'flood' series, or censored dataset (Hawkins *et al.* 1985; Feyereisen *et al.* 2008). Subsequently, the lognormal method described above is used to calculate the S distribution, mean, and standard deviation for each treatment.

Asymptotic method

Finally, we applied the asymptotic method (Hawkins, 1993), which regards the *CN* as an asymptotic limit as P approaches ∞. In this method, the 'Hawkins' method, *CN* calculated using Equations (4) and (5) are plotted against the respective P values, and the asymptotic value at high rainfalls is taken as the final *CN* (Figure 2a). The analysis can be done on ordered or unordered data, and we have plotted ordered data to increase the clarity of the figure. The actual analysis used unordered data as this should give more accurate results (Hawkins *et al.*, 2009). In some cases however, the *CN* does not reach an asymptotic value but keeps declining, and the *CN* cannot be calculated (Figure 2b). This is called complacent behaviour (Hawkins, 1993) and is possibly due to insufficient data in the series. The opposite is violent behaviour, in which the *CN* values suddenly increase after an initial decline (Hawkins, 1993). We again used nonlinear least squares (nls) in R (R Development Core Team, 2010) to calculate the asymptotic S_∞ related to CN_∞ values by inserting Equation (5) into the suggested empirical equations (Hawkins, 1993) to fit standard behaviour:

$$CN(P) = \frac{25\,400}{S_\infty + 254} + \left(100 - \frac{25\,400}{S_\infty + 254}\right)\exp(-kP) \tag{8}$$

or violent behaviour depending on the data:

$$CN(P) = \frac{25\,400}{S_\infty + 254}(1 - \exp(-kP)) \tag{9}$$

In these equations, k is a fitting constant that describes the slope of the $\log(CN) - \log(P)$ relationship. The nls function maximizes the logLikehood, therefore, separation between standard and violent behaviour was based on which Equation ((8) or (9)) gave the highest logLikehood. Additionally, if the asymptotic S value was greater than the maximum calculated S value based on Equation (5) we assumed complacent behaviour (Hawkins, 1993).

Comparison between methods and with NEH630

A more classical statistical comparison (such as using an ANOVA) is not possible due to unequal S samples in each method and the overall incomplete statistical design of the runoff study.

We therefore used linear mixed models in Genstat 13 based on a REML (restricted maximum likelihood) analysis to analyse the data by location, treatment, and method of derivation (shown above), which corrects for uneven variances and unbalanced designs. Given the complexity of the standard errors in REML, graphical displays are used to highlight statistical differences between the

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Table II. Comparable *CN* values from the NEH630 tables (NRCS, 2004) for the NSW soil conservation study treatments and soil combinations selected for this study. (C = contoured, CR = Crop residue, SR = Straight row, HG = Hydrologic Group)

Land use	Soil HG	NEH630 *CN* choice crop	NEH630 *CN* choice fallow	Description
	Cultivation treatment trials			
2-year wheat rotation	C	81	88	Small grains C good/fallow CR
2-year wheat rotation	D	84	90	Small grains C good/fallow CR
2-year wheat rotation-stubble mulched	C	80	88	Small grains C + CR/fallow CR
3-year wheat rotation	C	81	86	Small grains C good/pasture poor
3-year wheat rotation	D	84	89	Small grains C good/pasture poor
4-year wheat rotation	C	81	79	Small grains C good/pasture fair
Annual wheat-stubble burned	C	82	91	Small grains C poor/bare Soil
Annual wheat-stubble burned	D	85	91	Small grains C poor/bare Soil
Annual wheat-stubble incorporated	C	82	90	Small grains C poor/fallow
Annual wheat-stubble mulched	D	84	88	Small grains C + CR poor/fallow CR
Corn-horizontal rows	C	85	90	Row crops SR/fallow
Corn-vertical rows	C	85	90	Row crops SR/fallow
Grain sorghum	C	85	90	Row crops SR/fallow
	Permanent pasture trials			
Grazing oats	C	81		Legumes SR good
Land retired	C	74		Pasture good
Land retired	D	80		Pasture good
Lucerne	C	81		Legumes SR good
Lucerne	D	85		Legumes SR good
Mixed pasture	C	74		Pasture good
Native pasture	C	74		Pasture good
Permanent pasture	D	80		Pasture good
Phalaris/Lucerne pasture	C	74		Pasture good
Rhodes/Lucerne pasture	C	74		Pasture good
Sown pasture	D	85		Legumes SR good
Sudan grass	D	85		Legumes SR good
Volunteer pasture	D	80		Pasture good
	Grazing pressure trials			
Heavy grazing	C	86		Pasture poor
Heavy grazing	D	89		Pasture poor
Medium grazing	D	84		Pasture fair
Medium grazing-burned	D	89		Pasture poor
Light grazing	C	74		Pasture good
Light grazing	D	80		Pasture good
No grazing	D	78		Land protected from grazing

individual treatments and tables are used for statistical summaries by location and method. Standard deviations were approximated by multiplying the standard errors by the square root of the number of observations.

To benchmark the derived *S* values in this study, comparable *S* values were selected from ARC-II *CN* for similar land uses in the NEH630 tables (Table II). If there was no grazing or cropping, a good hydrologic condition was assumed, otherwise the condition was adjusted (Table II; NRCS, 2004b).

Antecedent moisture and rainfall intensity effects

Following earlier work (Dabney *et al*., 2011) a monthly correction factor for the annual derived *S*, reflecting water balance effects, was calculated based on average monthly temperature and rainfall for each of the locations using RUSLE2. The original approach was based on northern hemisphere (US) climate data and we directly applied the Northern Hemisphere correction (taking into account the reversal in seasons) to see if the adjustment, reflecting seasonal variation in antecedent moisture, explained observed patterns of runoff and derived *S* values. Similarly, an empirical correction factor for rainfall intensity, based on the ratio of average monthly EI30 for the different locations (reported by Rosewell and Turner, 1992) divided by average monthly rainfall depth, was applied (Dabney *et al*., 2011).

RESULTS

Annual data

The results indicate a considerable variability in *S* values for the cultivation trials (Figure 3). The figure indicates the mean and one standard deviation of the derived *S* distribution, which for the least squares and Hawkins method consists of only three values per treatment (one for each rep). In Figure 3, *S* values based on similar treatments from the NEH630 tables (Table II) have been used on the *x*-axis as a reference. The least squares method of

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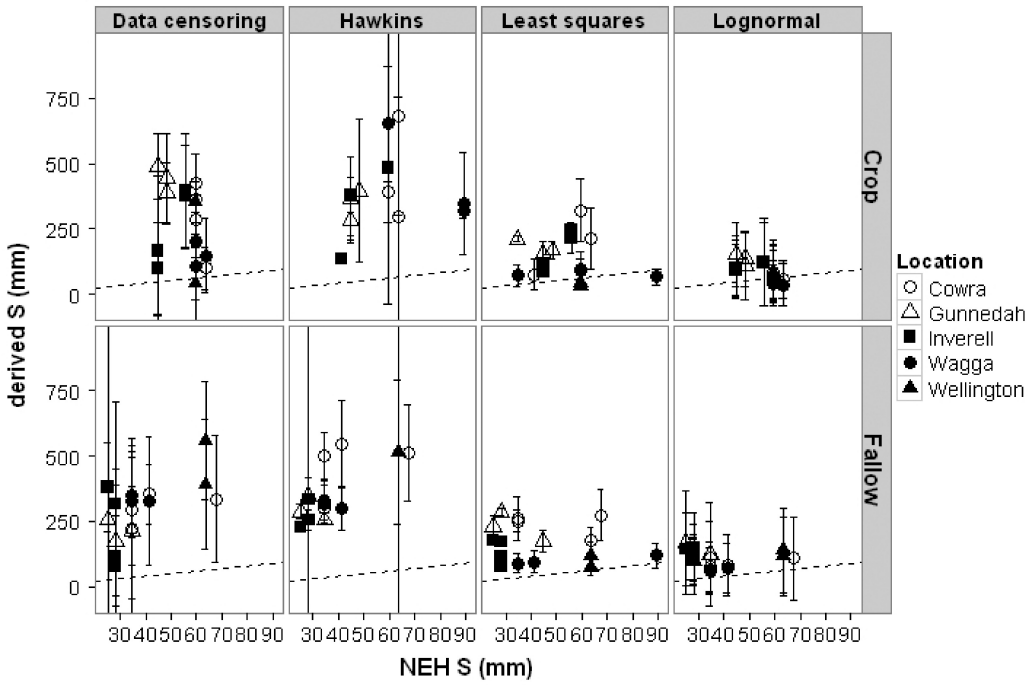

Figure 3. Calculated mean *S* values (mm) for the NSW data using the 4 different methods, plotted against *S* values (mm) derived from *CN* for similar land uses suggested in the NEH630 tables (i.e. Table II), limited to the cultivation treatments. Error bars indicate one standard deviation (mm) and the dashed line (–) indicates a 1 : 1 relationship with the NEH630 *S* values

analysing *CN* resulted in the lowest variability, while the data censoring and Hawkins method resulted in the highest variability in *S* values. Except for the lognormal method, most mean *S* values are higher than for similar treatments in the NEH 630 tables.

Cultivation trials

For the cropping season of the cultivation trials (wheat, maize, and sorghum rotations), the derived *S* values are lowest for the lognormal method. In contrast, the least squares, data censoring and Hawkins methods result overall in much greater *S* values (Figure 3 and Table III). Only a few of the Hawkins method fits indicated complacent behaviour and none indicated violent behaviour. A majority of standard behaviour would be expected for agricultural runoff data (Hawkins *et al*., 2009).

Based on REML means, the fallow season data indicates statistically greater *S* values than the cropping season using the lognormal method and data censoring method (Table III), indicating lower runoff during this period. For the least squares method and the Hawkins method this is the reverse, with the cropping season data resulting in greater *S* values.

REML mean *S* values for similar land uses clearly vary between locations (Figure 4). For example, using the lognormal method the mean *S* value for the 2-year wheat rotation in Gunnedah is higher than the values calculated for Wellington even though these locations both have D soils. This might be due to differences in the slopes, since at Wellington slopes were only 4–5%, while the slopes at Gunnedah were 8–9%, thus suggesting a negative relation between slope and runoff. Similarly, on C soils, the *S* values for the 2- and 3-year wheat rotations at Cowra are greater than those in Wagga Wagga, and Wagga Wagga again has gentler slopes.

This can also be seen in the REML results summarized for the cropping and fallow season by location (Table III). This indicates that for the lognormal and least squares methods, Cowra and Gunnedah gave consistently higher *S* values (and thus, lower runoff) than Wagga and Wellington. The data censoring method is based on fewer *P* and *Q* pairs than the other three methods (Table IV), while for the least squares and Hawkins methods the underlying *S* distribution cannot be recovered and which means there was a maximum of three *S* values per treatment to calculate the standard deviations (Figure 4).

At all locations, the mean REML *S* values from the lognormal and least squares method tended to increase with increasing length of the wheat rotation (2 to 3 to 4-year wheat rotation) during both the cropping and the fallow season indicating decreased runoff due to more water storage (Figure 4).

Perennial pasture and grazing pressure trials

The *S* values from the perennial pasture and grazing pressure trials are also quite variable (Table III and Figure 5). The data censoring and Hawkins method result in higher standard deviations than the log normal and least squares methods. The lognormal method again has *S* values closest to those derived from the NEH630 tables.

Statistical analysis indicated differences between different treatments for the perennial pasture trials, but because the treatments were very inconsistent across the locations this comparison is not shown, but rather the

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Table III. REML mean *S* and standard deviations (sd) for *S* values (in mm) calculated using the four methods for the NSW database based on the replicate plots at each site for the cultivation, perennial pasture and grazing pressure trials. The results are summarized by location and reported separately for the cropping and fallow season part of the year. NA means 'cannot be calculated'. (For the overall REML means, different letters on a row (a, b, c) indicate significant differences at the 5% level)

Location	Lognormal		Least squares		Hawkins		Data censoring	
	Cultivation trials: Cropping							
	S (mm)	sd	*S* (mm)	sd	*S* (mm)	se	*S* (mm)	se
Cowra	82·5	96·6	216·5	54·3	404·8	36·9	311·1	94·1
Gunnedah	148·4	93·8	176·8	81·9	367·8	53·9	446·6	94·5
Inverell	115·5	74·2	142·2	77·8	327·8	39·3	151·4	332·7
Wagga Wagga	54·3	79·2	83·9	53·2	308·3	48·2	148·0	166·7
Wellington	68·3	94·1	37·5	94·6	NA	NA	90·7	94·2
REML overall mean *S*	**87·7a**	**93·5**	**156·4b**	**71·4**	**356·5c**	**275·9**	**163·0b**	**219·5**
	Cultivation trials: Fallow							
Cowra	111·5	93·7	241·8	52·3	436·5	30·7	349·0	94·4
Gunnedah	142·6	93·6	217·6	81·9	283·1	54·0	248·6	95·0
Inverell	120·1	71·15	113·3	68·9	192·7	45·7	131·4	62·2
Wagga Wagga	85·1	83·3	110·0	53·2	322·7	39·3	375·4	76·5
Wellington	135·3	95·3	97·7	59·8	696·8	51·6	531·3	94·5
REML Overall mean *S*	**108·8a**	**93·8**	**166·1b**	**65·1**	**386·5c**	**44·2**	**228·1c**	**217·8**
	Perennial pasture trials							
Cowra	96·1	123·7	300·6	72·4	532·7	217·0	326·6	113·0
Gunnedah	164·0	74·3	325·3	55·9	406·5	58·0	379·6	73·3
Inverell	162·0	124·0	214·3	55·9	325·0	60·1	430·5	125·4
Wagga Wagga	117·4	126·3	245·1	72·4	471·6	72·4	508·9	125·2
Wellington	179·0	38·4	404·0	72·4	517·3	72·4	632·1	63·9
REML overall mean *S*	**132·5a**	**132·8**	**285·7b**	**119·9**	**406·1c**	**80·2**	**391·9d**	**249·2**
	Grazing pressure trials							
Cowra	177·1	125·0	485·9	88·5	636·7	108·4	455·9	125·2
Gunnedah	132·5	131·3	344·9	88·5	510·6	88·5	491·1	163·9
Inverell	183·3	125·5	211·8	88·5	313·7	97·0	382·8	125·1
Scone	145·5	125·3	322·6	36·2	505·0	39·0	422·3	125·4
Wagga Wagga	98·7	124·6	186·8	88·5	560·2	108·4	506·0	125·4
Wellington	206·0	124·8	887·2	88·5	794·6	88·5	531·4	125·1
REML overall mean *S*	**145·9a**	**139·8**	**368·4b**	**108·9**	**532·9c**	**74·2**	**434·9d**	**285·4**

overall variation by location is shown in Table III. In general, the lognormal method again results in the lowest *S* values compared to the least squares, Hawkins and data censored methods (Table III), but there are no clear trends across the locations.

The *S* values generally decrease with increasing grazing pressure or burning, as a result of poorer hydrologic conditions, although this is not consistent across all six locations (Figure 6). Increased grazing pressure is expected to decrease the infiltration capacity of the soil and increase runoff (Owens *et al*., 2003), but this trend is not observed in the REML means (Figure 7). In fact, at Inverell, Wellington and Scone, light grazing often results in lower REML mean *S* values, and thus, higher runoff than heavy grazing (Figure 7). The database management notes indicate that the grazing trial was not well controlled at Inverell, and that the validity of some of the data at Wellington is in doubt (Edwards, 1987).

Monthly data

Using the lognormal method, monthly mean *S* values are lower in winter and higher in summer as demonstrated for the wheat treatments at Cowra (Figure 8). This trend is clearer in the regular wheat treatments than in the mulched treatment at Cowra. High to very high *S* values are also observed in December under all wheat treatments, corresponding to harvest time for the wheat treatments.

One way to adjust the *S* values for soil moisture and/or rainfall erosivity is using the empirical method suggested by Dabney *et al*. (2011). The continuous line in the graph indicates the soil moisture adjusted *S* values based on the average annual *S* value for the wheat-based treatments (Figure 3). This adjustment removes some of the variation in the data (Figure 8 and Table V), but this is mainly in the fallow periods of the wheat treatments. More intense summer storms can sometimes result in a lower *S* value (Dabney *et al*., 2011). However, the RUSLE2 rainfall intensity adjustment had little effect at Cowra (Figure 8, Table V) because of generally low-intensity rainfall. The dashed line in Figure 8 indicates the annual *S* value adjusted for the combined influence of erosivity and soil moisture and is nearly the same as the continuous line that reflects only soil moisture variation.

For the grazing and perennial pasture treatments at Wagga Wagga a similar monthly soil moisture response to

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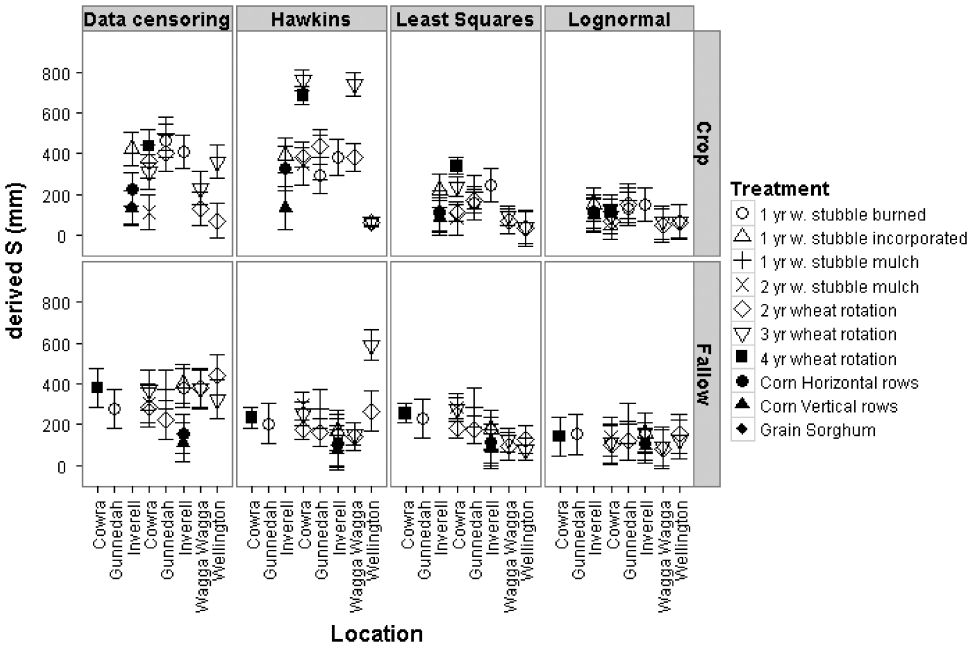

Figure 4. REML mean *S* values (mm) and standard deviations (mm) for the different cultivation treatments by cropping and fallow season and by location. Error bars indicate 1 standard deviation (mm) based on the REML analysis

Table IV. Number of storms used for the derivation of *S* values in the different methods for the cultivation treatments. LN is 'Lognormal', LS is 'Least Squares' and H is 'Hawkins', the same number of storms was used for the analysis of these 3 methods

Location	Treatment	LN, LS and H methods	Data censoring
		Cropping	
Cowra	2-year wheat	1076	2
	2-year wheat stubble mulched	83	7
	3-year wheat	523	22
	4-year wheat	433	10
Gunnedah	Annual wheat-stubble burned	107	6
	Annual wheat-stubble mulched	91	3
	2-year wheat	93	6
Inverell	Annual wheat-stubble burned	189	17
	Annual wheat-stubble incorporated	171	3
	Corn-horizontal rows	136	25
	Corn-vertical rows	175	88
	Grain sorghum	284	141
Wagga Wagga	2-year wheat	555	51
	3-year wheat	449	8
Wellington	2-year wheat	51	45
	3-year wheat	45	3
		Fallow	
Cowra	2-year wheat	2279	45
	2-year wheat stubble mulched	131	5
	3-year wheat	1844	86
	4-year wheat	936	46
Gunnedah	Annual wheat-stubble burned	158	30
	Annual wheat-stubble mulched	127	12
	2-year wheat	473	89
Inverell	Annual wheat-stubble burned	151	3
	Annual wheat-stubble incorporated	173	3
	Corn-horizontal rows	76	23
	Corn-vertical rows	71	59
	Grain sorghum	131	67
Wagga Wagga	2-year wheat	857	12
	3-year wheat	1066	9
Wellington	2-year wheat	91	6
	3-year wheat	232	9

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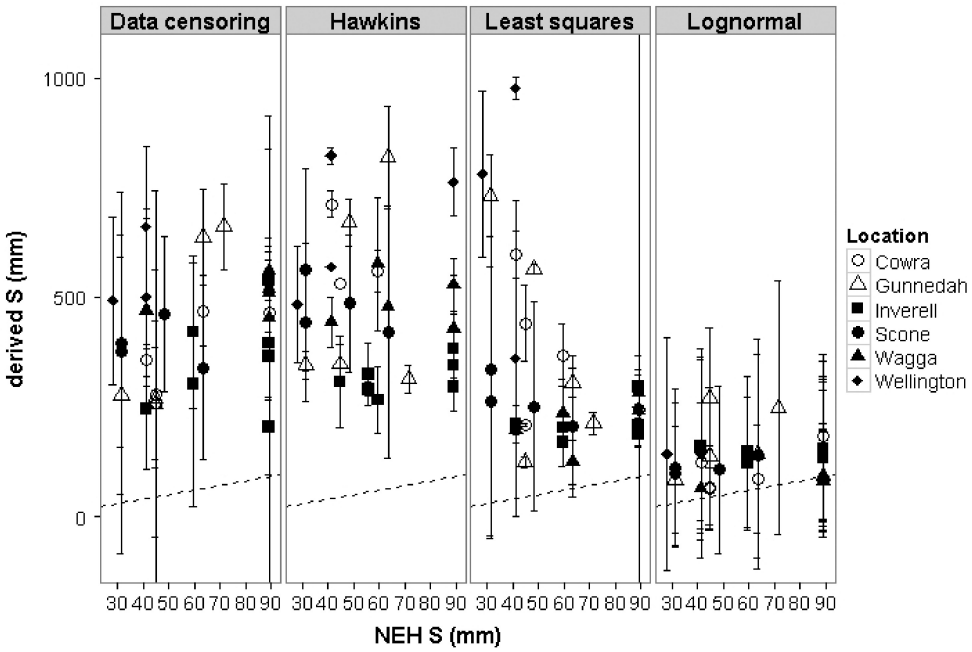

Figure 5. Calculated mean *S* values (mm) for the NSW data using the 4 different methods, plotted against *S* values (mm) derived from *CN* for perennial pasture and grazing land uses suggested in the NEH630 tables (i.e. Table II). Error bars indicate one standard devation (mm) and the dashed line (–) indicates a 1 : 1 relationship with the NEH630 *S* values. For the grazing trials a decrease in the hydrologic condition was used to adjust for increased grazing pressure on the *CN* from the NEH630 tables (Table II)

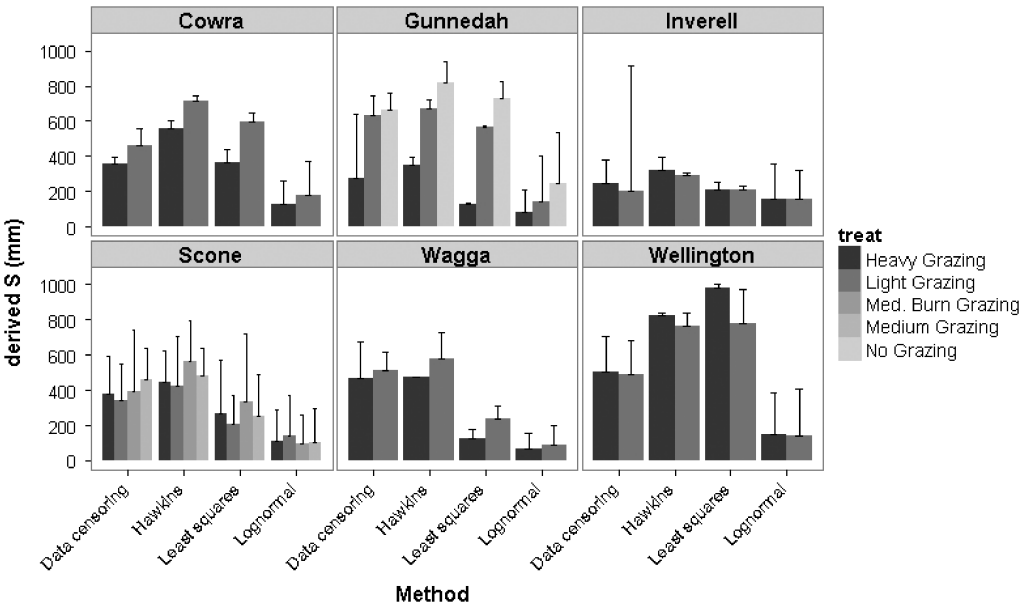

Figure 6. Calculated mean *S* values (mm) for grazing treatments using the 4 different methods sorted by the intensity of the grazing treatment. Error bars indicate one standard deviation (mm)

the wheat treatments in Cowra exists (continuous line in Figure 9). However, in Wagga Wagga (which is located approximately 200 km southwest of Cowra, Figure 1), there is a greater effect of summer storm intensity on the *S* values in January and February (dashed line). However, the variation in the monthly *CN* appears to be better matched by the soil moisture variation alone, indicating that the empirical erosivity adjustment (Dabney *et al.*, 2011) is possibly less appropriate in Australia. The overall adjustment is generally small and quite variable for the treatments in Figures 8 and 9 (Table V). For some, e.g. 3-year wheat, of the treatments the standard deviation increased as a result of the moisture adjustment, while for example, for lucerne at Wagga Wagga, the standard deviation decreased for the moisture adjustment, but increased again when the erosivity adjustment was added.

DISCUSSION

The NSW SCS rainfall-runoff datasets contains considerable variation in runoff responses across many years of

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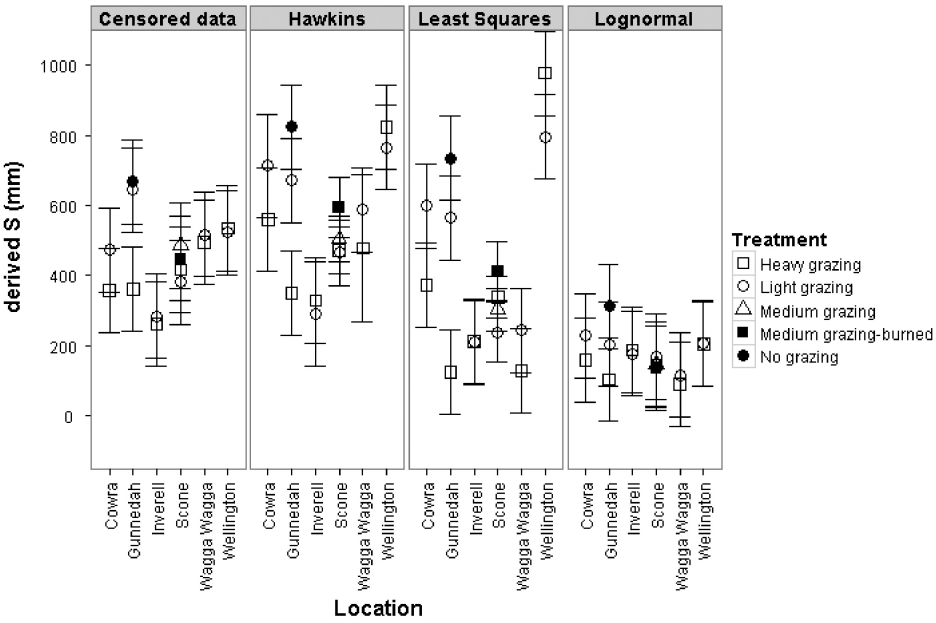

Figure 7. REML mean *S* values (mm) and standard deviations (mm) for the different grazing treatments by location. Error bars indicate 1 standard deviation based on the standard error of the REML analysis

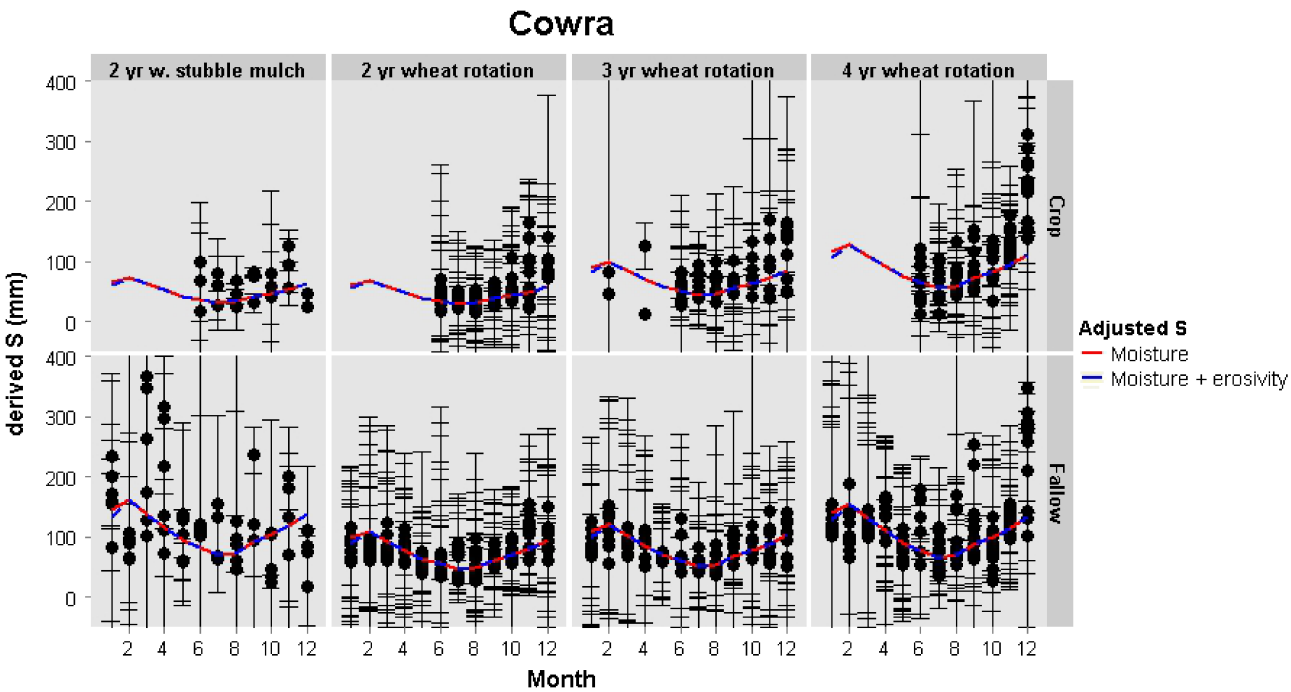

Figure 8. Calculated mean monthly *S* values (mm) and standard deviations using the lognormal method for wheat treatments in Cowra. Monthly adjusted annual mean *S* values for moisture and for moisture and erosivity are plotted as continuous and dashed lines, respectively

data, even for the same treatment. However, the variation in mean *S* values in this study for the wheat treatments is in line with other studies in Australia (Foerster and Milne-Holme, 1995; Titmarsh *et al*., 1995).

Derivation methods

The difference in derived *S* values between the different methods also agrees with the study by Titmarsh *et al*. (1995) and indicates that understanding the method of estimation is crucial in the selection of an *S* value for runoff estimates.

Rainfall runoff series are often characterized by unequal variance. The lognormal method intends to correct for this and therefore emphasizes smaller storms through the log transformation of the *S* values. As a result the derived *S* values tend to be lower compared to the other three methods which put more weight on the larger storms (Titmarsh *et al*., 1995; Hawkins *et al*., 2009). In addition, the high variability of the data censoring method reflects the limited number of storms used in this method (Table IV). This is a drawback of the data censoring method and means that even the relatively long

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Table V. Standard deviations (sd) for the S distribution (in mm) calculated before and after adjustment for monthly variation due to moisture and erosivity (Dabney *et al*., 2011) based on the lognormal method

Location	Treatment	Original (Figure 3)	Adjusted for moisture	Adjusted for erosivity and moisture
			Cropping season	
		sd (mm)	sd (mm)	sd(mm)
Cowra	2-year wheat	98·5	98·7	98·7
Figure 8	2-year wheat stubble mulched	77·6	88·6	88·6
	3-year wheat	108·2	113·7	113·7
	4-year wheat	119·3	115·9	115·9
			Fallow season	
Cowra	2-year wheat	103·1	94·0	94·7
Figure 8	2-year wheat stubble mulched	153·7	143·0	145·3
	3-year wheat	117·2	106·8	107·5
	4-year wheat	163·1	147·1	148·5
			Perennial pasture trials	
Wagga Wagga	Lucerne	119·5	107·9	110·3
Figure 9	Mixed pasture	104·2	91·5	93·4
	Land retired	115·4	101·5	103·8

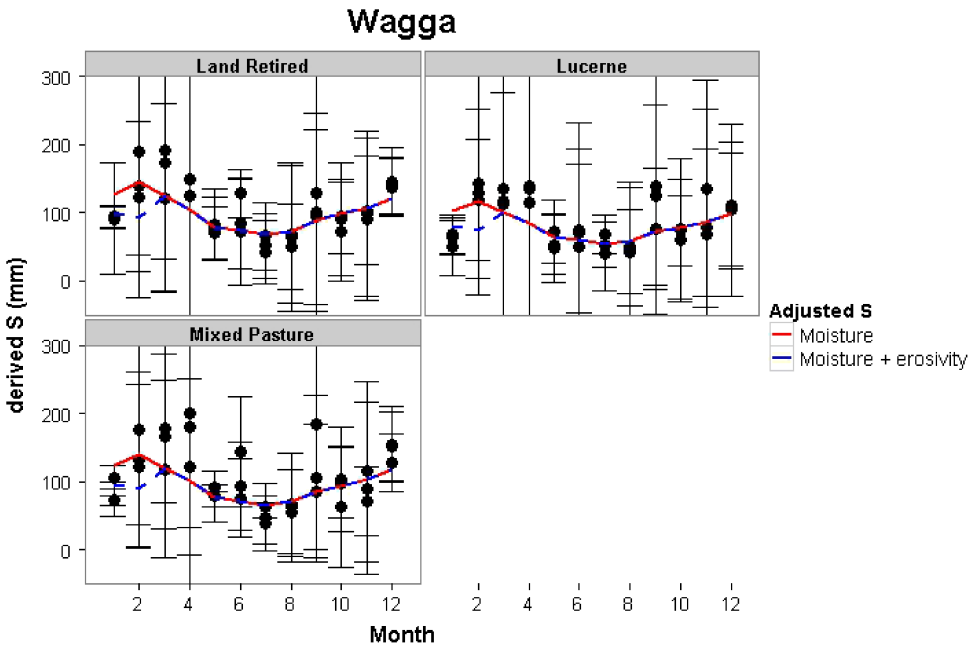

Figure 9. Calculated average monthly S values (mm) and standard deviations using the lognormal method for pasture cropping and grazed treatments in Wagga Wagga. Monthly adjusted annual mean S values for moisture and moisture and erosivity are plotted as continuous and dashed lines, respectively

data series in this study were insufficient to develop good estimates.

If the S values are plotted against the rainfall amounts of the respective events (Figure 10), it is clear that lower rainfall events tend to have lower S values (relatively more runoff and higher CN) than higher rainfall events because only high intensity storms generate runoff for these low rainfall events. If an annual storm series (for example based on a 2-year return value) is used in a data censoring method rather than the $P < 0{\cdot}46S$ cut-off, the variability in the S estimates would also be large. For example the 2-year storm return value for Cowra for the period under consideration is around 56 mm in Figure 10.

The sharp upper boundary of S in Figure 10 corresponds to events with only a trace of runoff. This represents $S \sim 5 \times P$ (based on $\lambda = 0{\cdot}2S \sim P$). The fact that this boundary occurs even at much larger rainfall events means that for a significant fraction of larger rain events, there was relatively little runoff. As a result, the variability in S values increases with increasing storm size because for larger (daily and multi day) storm sizes there is more possible variation in runoff responses due to greater variation in rainfall intensities. This can also be seen in the variability in the data censoring method.

The analysis of S values in this study was based on P and Q pairs where $Q > 0$. Excluding the rainfall data

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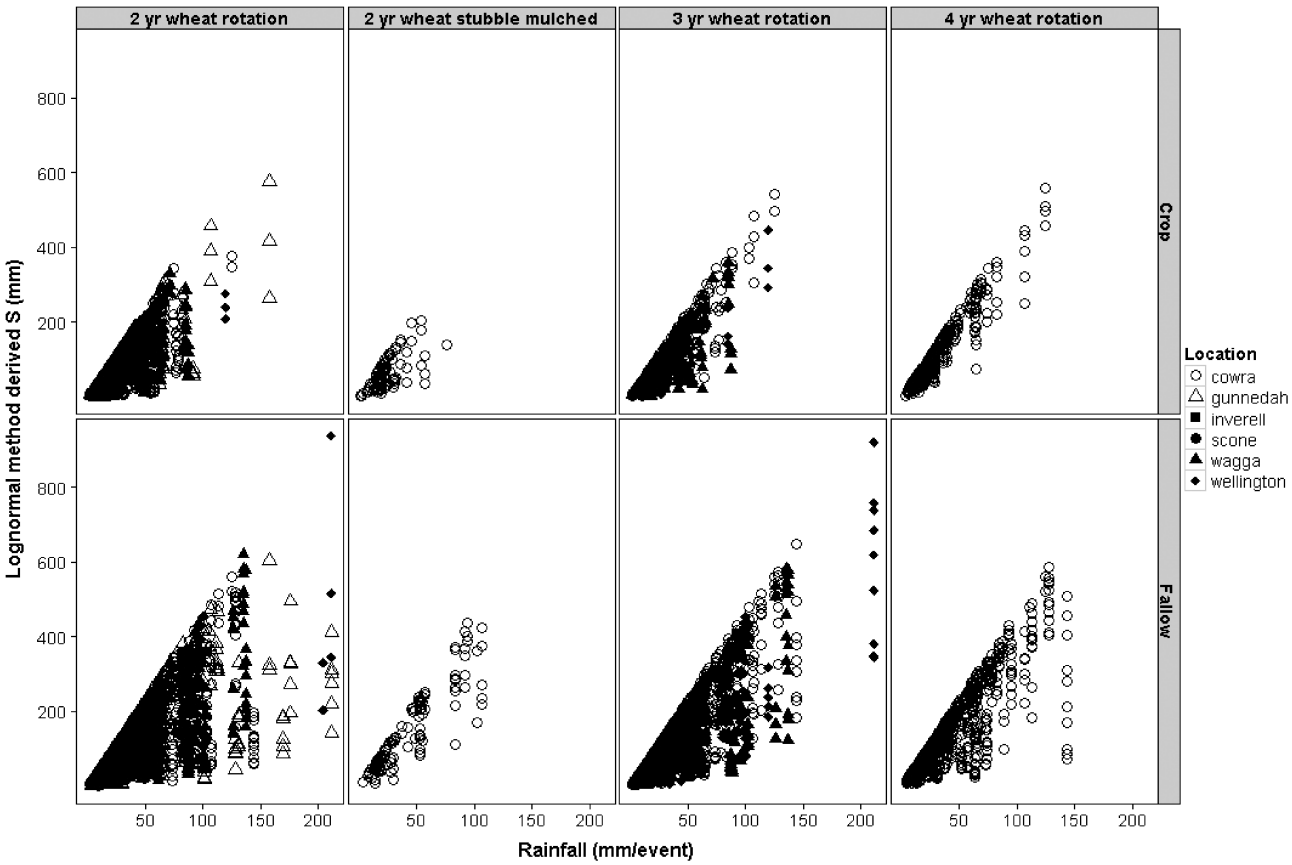

Figure 10. Calculated S values using the lognormal method for 2-year and longer wheat treatments plotted against event rainfall amounts across all locations

where $Q = 0$ can lead to lower overall S values, as this data would increase the number of $S \sim 5 \times P$ values in the distribution. As far as we can determine, this effect could possibly influence the lognormal method. As a result, predicted runoff using the derived CN in this study could over-estimate true runoff, but some preliminary analysis suggests this effect is minor. How including the zero runoff data affects estimates of both S and Ia could be an interesting avenue for further research.

Depending on the runoff estimate that is needed, a different method might need to be used. The lognormal method with the emphasis on the smaller events is only useful for plot scale estimates for a specific location. Many of the smaller runoff events can disappear at larger spatial scales, particular in semi-arid conditions, due to transmission losses (e.g. Simanton *et al.*, 1996). This means that for larger spatial scale applications the least squares or Hawkins method is more applicable. In contrast, for peak runoff estimates related to hydrological design the data censoring method is most appropriate.

If exact estimates of runoff for a specific location are needed in a hydrological model, calibration of CN on local data is the best solution (i.e. Hawkins *et al.*, 2009; Kim *et al.*, 2010). However, the results from this study can give some guidance on the expected values for such calibrations and possible temporal variations which is important for dynamic modelling. The overall distribution in the S values can also be useful for larger regional studies, for example, using SWAT (Arnold and Fohrer, 2005), that need to include stochastic variation in the runoff generating processes across the landscape with variable land use. In particular, in such models, the relationship between P and S is crucial because models include all rainfall storms rather than design storms with a specific return interval. Given that all methods develop a direct relationship between S and P, this can be used to further adjust the curve number values in such dynamic hydrological models.

Comparison with NEH630

Several studies have earlier indicated that there was little correspondence between the CN listed in the NEH630 tables and derived CN using different methods (Hawkins *et al.*, 2009), possibly because of inaccuracies in the original determination of CN. More specifically, little correlation was found between NEH630 values and CN based on Queensland catchment data (Titmarsh *et al.*, 1995). One reason which makes it unlikely that the NEH630 values are comparable to the derived S values in this study is that many of the treatments do not match the listed NEH630 land uses exactly (Table II). For example, fallow treatments in NSW are much more variable than in the US and can stretch over several years. Grazing by sheep is often used to control grass and weed growth during such long fallow periods. Additionally, due to the Australian climate, locations in NSW would be

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Table VI. Curve numbers for NSW land use on 'C' and 'D' soil hydrologic groups (HG) for ARC I–ARC III conditions for fallow and cropping seasons based on the least squares method

Land use	Soil HG	ARC I	ARC II	ARC III	ARC I	ARC II	ARC III
		Cropping season			Fallow season		
2-year wheat rotation	C	46	72	89	46	59	71
2-year wheat rotation	D	32	72	94	45	64	80
2-year wheat rotation-stubble mulched	C	51	77	92	32	48	64
3-year wheat rotation	C	34	65	87	34	59	80
3-year wheat rotation	D	75	87	93	61	78	88
4-year wheat rotation	C	28	44	61	42	50	58
Annual wheat-stubble burned	C	46	51	56	56	60	63
Annual wheat-stubble burned	D	48	63	75	44	53	62
Annual wheat-stubble incorporated	C	42	54	66	58	59	60
Annual wheat-stubble mulched	D	52	55	57	45	47	50
Corn-horizontal rows	C	68	68	69	65	69	72
Corn-vertical rows	C	68	75	80	68	76	83
Grain sorghum	C	69	71	72	65	71	76
		Perennial pasture trials					
Grazing oats	C	45	60	74			
Land retired	C	34	47	61			
Land retired	D	9	51	91			
Lucerne	C	46	54	63			
Mixed pasture	C	36	51	66			
Native pasture	C	50	57	64			
Permanent pasture	D	21	26	31			
Phalaris/Lucerne pasture	C	15	41	74			
Rhodes/Lucerne pasture	C	40	46	53			
Sown pasture	C	50	55	60			
Sown pasture	D	54	55	56			
Sudan grass	D	40	45	51			
Volunteer pasture	D	49	55	60			
		Grazing pressure trials					
Heavy grazing	C	28	37	46			
Heavy grazing	D	30	54	77			
Medium grazing	D	13	47	83			
Medium grazing-burned	D	21	50	80			
Light grazing	C	14	43	77			
Light grazing	D	22	45	70			
No grazing	D	13	41	75			

expected to have a much drier average antecedent runoff condition (ARC) and lower average rainfall intensity than the climate in the US on which the values for similar treatments in the tables were calibrated.

Sources of variation in the derived S values

Besides reporting *S* values and thus related *CN* for specific Australian treatments and for different locations, this paper aimed to explain some of the variation in the derived *S* values to better understand the variation in hydrological responses from agricultural land. As demonstrated, part of the annual variation is likely due to seasonal variation in available soil moisture content. Higher rainfall and lower evapotranspiration in winter (due to lower radiation) would cause higher seasonal soil moisture and higher runoff. Initial moisture is therefore a key variable that causes variations in runoff response, and the *CN* method has long recognized this through adjustment (ARC I–ARC III) for antecedent runoff conditions. If the 5 and 95% confidence intervals of the *S* distributions are adopted as ARC I and III conditions, and using the lognormal method (Hjelmfelt, 1991) then the range of possible *CN* can be developed for different NSW treatments based on this dataset (Table VI). This table indicates quite reasonable variation in treatments, soil hydrologic groups and ARC, even though the variation due to ARC is high. Adjustments for monthly variation in moisture content and rainfall erosivity (Figures 8 and 9) remove some, but not all, of the variation in the lognormal method (and by extension, in the other methods) which means inherent variation remains a key feature of the *CN* method.

Given the overall variability, the range of locations and length of the experiments in the database, there are several other reasons that explain variation in *S* values such as effects of differences in slope on the runoff, non-stationarity in the runoff response due to changes in management, or recording errors (Hawkins *et al.*, 2009). Besides increased interception due to crop canopy closure, an increase in *S* values in the later part of the crop growing season (December) can be related to increasing soil cover (Owens *et al.*, 2003;

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Descheemaeker *et al*., 2008). This can also explain the higher variability in monthly *S* values in the stubble mulched treatment (Figure 8), being caused by variations in soil cover from season to season. Finally, the increase in monthly *S* values in December for the cropping season of the cultivation treatments (Figure 8) can be due to increased transpiration due to higher temperatures and increased biomass in that period of the year, thus lowering the soil moisture store steeply (Huang *et al*., 2007).

Despite all the variation, some clear differences between the treatments can be observed (Figures 4 and 7) and the table of resulting *CN* (Table VI) indicates logical trends. However, some interesting future research could concentrate on the actual treatments in the *CN* table (Table VI). One could argue that there is little difference between the different length of wheat rotations (1 year, 2 year, etc.) and that thus the length of the fallow period has only a minor influence on the soil infiltration and runoff. In contrast, the development stage of the crop would be a more important classification than the crop type or rotation length in the different cropping treatments. In the end, the *CN* aim to represent broad land use soil class combinations, which can be expected to include considerable internal random variation due to variation in storm intensities and ARC (Hjelmfelt, 1991). This is probably more true in semi-arid environments such as Australia (Pilgrim *et al*., 1988).

In this study, we did not attempt to validate the derived *CN*. Given the overall variation in the treatments in the dataset, it was difficult to split the data into a validation and calibration set. Furthermore, as the high variability in the derived *S* values indicates, such a validation would be unlikely to indicate good performance. Given the simplicity of the 1 parameter rainfall runoff model that the *CN* method represents, this is not surprising. We therefore believe that the stochastic variation indicated by the results in this paper is of more use to a hydrologist than a validation attempt.

CONCLUSIONS

Values of *S* for *CN* calculations were derived for a wide range of specific Australian land use soil combinations extending the available estimates for *CN* specifically for Australian conditions. Depending on the method used to calculate *S*, considerable variation in *S* related to one land use soil combination was found.

Part of the variation in *S* can be explained by differences in seasonal antecedent moisture content and increases in cover from a growing crop. However, there was little evidence that rainfall intensity impacted the *S* estimates.

Rainfall depth introduces further variation in *S* and this should also be taken into account in dynamic hydrological models.

Different derivation methods result in differences in *S*, and changes the variance and this should be considered when deriving *CN*. The lognormal method emphasizes smaller rainfall events, which only result in runoff under high rainfall intensities. This is unlikely to be useful for estimation of runoff at larger spatial scales and in catchment models.

The derived distributions of *S* values for agricultural treatments in NSW are a useful addition to the Australian hydrologist's toolbox and put in perspective the expected variation in runoff responses from agricultural land uses.

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