Journal of Hydrology: Regional Studies 50 (2023) 101592

Contents lists available at ScienceDirect

Journal of Hydrology: Regional Studies

journal homepage: www.elsevier.com/locate/ejrh

The Brigalow Catchment Study: A comparison of four methods to estimate peak runoff rate for small catchments before and after land use change in the Brigalow Belt bioregion of central Queensland, Australia

C.M. Thornton [a,*], B. Yu [b]

[a] *Department of Environment and Science, PO Box 1762, Rockhampton, Queensland 4700, Australia*
[b] *School of Engineering and Built Environment, Griffith University, Nathan, Queensland 4111, Australia*

ARTICLE INFO

Keywords:
Tree clearing
Modelling
Hydrology
Acacia spp
Paddock to Reef
Peak discharge

ABSTRACT

Study region: Brigalow Belt bioregion of north-eastern Australia.
Study focus: Dynamic SedNet is used to model erosion from 42.4 Mha of grazing land in the Great Barrier Reef catchments to guide the $3 billion Reef 2050 Long-Term Sustainability Plan 2021–2025. Improving Dynamic SedNet by incorporating the Modified Universal Soil Loss Equation requires spatially derived peak runoff rate. This study evaluated four simple methods to estimate peak runoff rate at a site representative of the 15 Brigalow Belt bioregion catchments that intersect with the 35 Great Barrier Reef catchments. Performance was assessed against measured data from three long-term catchments of the Brigalow Catchment Study both pre-clearing (1965–1982), when all catchments were virgin brigalow scrub prior to land use change, and post-clearing (1984–2004), after one catchment was converted to cropping and another to grazing.
New hydrological insights for the region: Useful estimations were obtained from the scaling technique ($R^2 = 0.90$; NSE $= 0.79$), multiple regression models ($R^2 = 0.90$; NSE $= 0.63$), and the variable infiltration rate method ($R^2 = 0.88$; NSE $= 0.71$). Estimations using the curve number and graphical peak discharge method gave an R^2 of 0.85; however, NSE was typically negative because the method systematically underestimated runoff rate. Despite different data requirements and complexity, all four methods were easily applied with parameters derived from widely available rainfall data, measured runoff volume data, and basic physical descriptors of the catchment.

1. Introduction

Estimation of runoff volume (Q_{tot}) and peak runoff rate (Q_p) for ungauged catchments has been the focus of substantial hydrological research worldwide (Dilshad and Peel, 1994; Hawkins, 1993; Jodar-Abellan et al., 2019; Post and Jakeman, 1999). For example, the International Association of Hydrological Sciences devoted a decade (2003–2012) towards achieving major advances in the capacity to make hydrological predictions in ungauged basins (Hrachowitz et al., 2013; Sivapalan et al., 2003). Despite the investment of more

* Corresponding author.
E-mail address: Craig.Thornton@des.qld.gov.au (C.M. Thornton).

https://doi.org/10.1016/j.ejrh.2023.101592
Received 12 July 2023; Received in revised form 2 November 2023; Accepted 22 November 2023
Available online 28 November 2023
2214-5818/

than 70 years of research in this field since the endeavours of Mockus (1949), limited availability of Q_p data, and a lack of models to estimate Q_p are both still identified as an impediment to soil erosion research (Silburn, 2011; Yu, 2020).

The need for hydrological predictions in ungauged catchments in Australia was highlighted by the Reef 2050 Long-Term Sustainability Plan 2021–2025 and the Reef 2050 Water Quality Improvement Plan 2017–2022 (Commonwealth of Australia, 2021; The State of Queensland, 2018). These programs have invested more than \$3 billion in a decade to protect and manage the Great Barrier Reef, which is a natural asset with an estimated value of \$56 billion (Commonwealth of Australia, 2021). In order to report progress towards targets and timeframes within the plans, a model framework supported by monitored data that links management action in catchments to water quantity, quality and ecological responses to receiving waters was required (Waterhouse, 2018). Within this framework, the Great Barrier Reef Dynamic SedNet (Dynamic SedNet) catchment model, built on the eWater Source modelling platform, was used to estimate erosion from the 32.6 Mha of grazing land across the 42.4 Mha Great Barrier Reef catchments via the Revised Universal Soil Loss Equation (RUSLE) (McCloskey et al., 2021b). The continual improvement of Dynamic SedNet has been an iterative process in response to research priorities (McCloskey et al., 2021a; McCloskey et al., 2021b, 2017a, 2017b; Wilkinson et al., 2014). Identified priorities include implementing the Modified Universal Soil Loss Equation (MUSLE) in place of RUSLE as it would likely improve estimates of sediment generation (Carroll and Yu, 2018; Yu, 2020). The primary reason being that MUSLE incorporates the hydrological parameters runoff and peak runoff rate which are better predictors of erosion than rainfall parameters alone as used in RUSLE (Tiwari et al., 2021). This substitution was shown to be successful at the small catchment scale within the Fitzroy Basin (Tiwari et al., 2021). The Fitzroy Basin is contained within the 36.7 Mha Brigalow Belt bioregion, of which 24 Mha overlays the Great Barrier

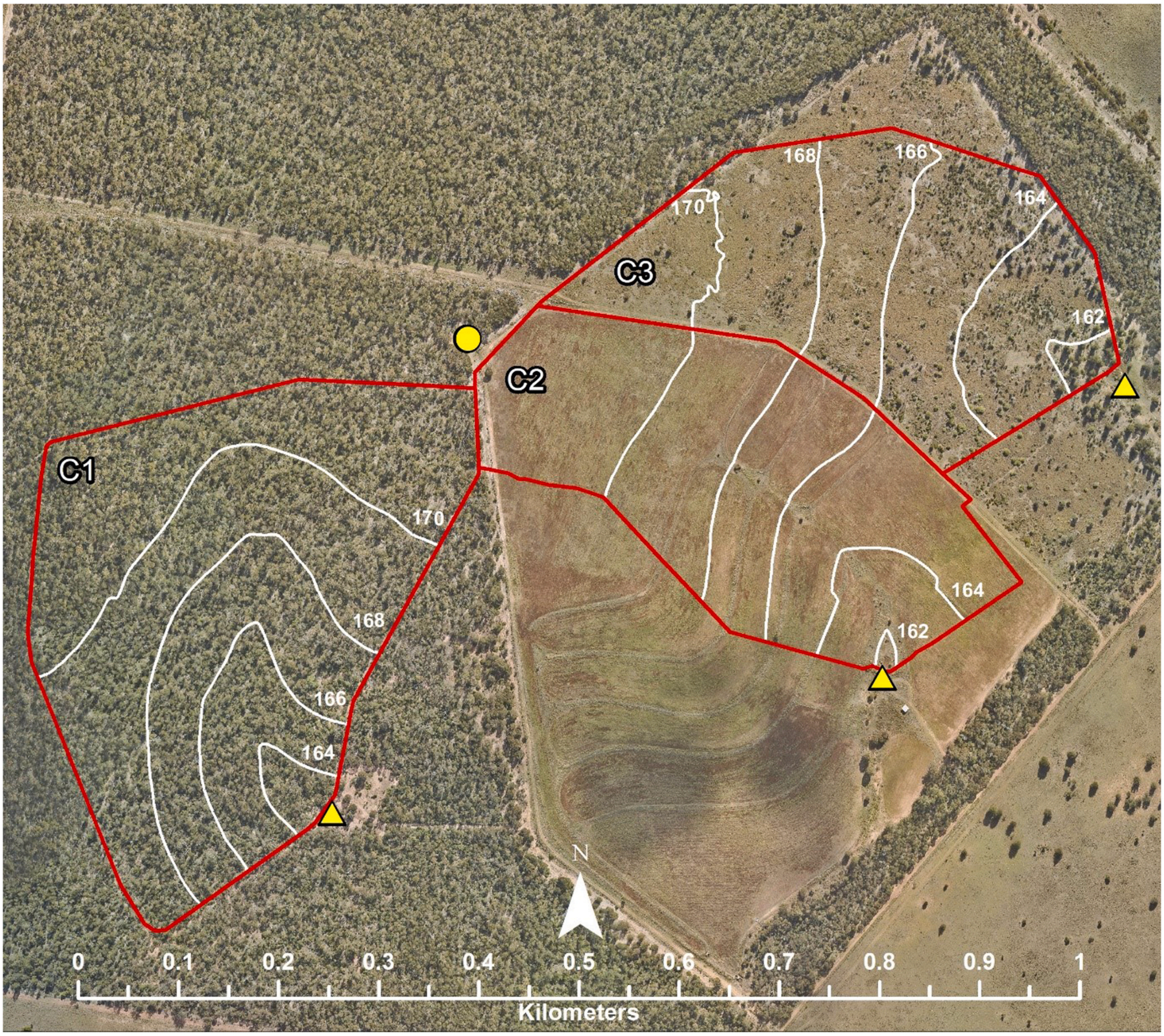

Fig. 1. Aerial photograph of the Brigalow Catchment Study showing catchment boundaries, topography and the location of monitoring equipment. The tipping bucket rainfall recorder at the head point of the catchments is indicated by the circle icon while runoff recording stations are indicated by the triangle icons. Spot heights are in metres.

Reef catchments (Tiwari et al., 2021). Effective parameterisation of MUSLE, which requires Q_p, is essential in order to operationalise the change from RUSLE to MUSLE in Dynamic SedNet and as such there is a requirement, and an identified research priority, to spatially derive Q_p (Carroll and Yu, 2018; Yu, 2020).

Individual hydrology and erosion investigations, such as those of the Brigalow Catchment Study (BCS) (Cowie et al., 2007), also require the ability to predict Q_p. The BCS is a long-term, paired, calibrated catchment study in the Brigalow Belt bioregion of Queensland, Australia, which has clearly demonstrated increases in Q_{tot}, Q_p and soil erosion when virgin brigalow scrub is cleared for cropping or grazing (Cowie et al., 2007; Elledge and Thornton, 2017; Thornton et al., 2007; Thornton and Elledge, 2021; Thornton and Yu, 2016). It is also the study that Tiwari et al. (2021) used to demonstrate that MUSLE was more suitable than RUSLE for estimating erosion at the small catchment scale. This was done by comparing observed event-based erosion from the land uses of virgin brigalow scrub, cropping and improved pasture with estimates of erosion generated with RUSLE and MUSLE. As with all long-term data collection, equipment failure and subsequent periods of missing data were unavoidable and methods to estimate Q_p were required so complete data sets were available for analysis (Thornton and Yu, 2016).

The first objective of this study was to examine the suitability of four simple methods for the estimation of Q_p using data from the three small (12–17 ha) long-term catchments of the BCS. Comparisons were made with data collected during two periods: (1) the calibration phase (1965–1982), monitoring virgin brigalow scrub prior to land use change, and (2) the land use comparison phase (1984–2004), when two of three catchments were converted for cropping and grazing, respectively. The four estimation methods were: (1) multiple regression models (Thornton and Yu, 2016), (2) the scaling technique (Yu and Rose, 1999), (3) the Natural Resources Conservation Service (NRCS) (formerly the Soil Conservation Service, SCS) curve number and graphical peak discharge method (U.S. Department of Agriculture, 1986; U.S. Department of Agriculture, 2004), and (4) the variable infiltration rate method (Yu et al., 1997b; Yu et al., 1999; Yu and Rosewell, 1998). Estimations of Q_p obtained using each of the four methods were assessed against observed Q_p using both graphical comparisons and the commonly used model performance indicators adjusted coefficient of determination (R^2) and coefficient of efficiency (NSE) (Nash and Sutcliffe, 1970; VSN International, 2011). After determining a suitable estimation method, the second objective of this study was to investigate simple processes to parameterise the method and operationalise it in Dynamic SedNet.

Evaluating the suitability of simple methods for the estimation of Q_p at the small catchment scale, and by extension the 36.7 Mha of Brigalow Belt bioregion in Queensland and northern New South Wales, will be of direct benefit to hydrological modelling by providing a necessary hydrologic parameter for runoff-driven soil erosion modelling in this landscape. It facilitates the next iteration of model improvement for the Reef 2050 Long-Term Sustainability Plan 2021–2025 and the Reef 2050 Water Quality Improvement Plan 2017–2022 (Commonwealth of Australia, 2021; The State of Queensland, 2018), which is essential to ensure the ongoing health of the Great Barrier Reef.

2. Materials and methods

2.1. Site description

The BCS was established in 1965 to determine the impact on hydrology, productivity and resource condition when brigalow land was cleared for cropping or grazing. It is a paired, calibrated catchment study consisting of three contiguous catchments, identified by topographic survey. The areas of the catchments were 16.8 ha (catchment 1 or C1), 11.7 ha (catchment 2 or C2) and 12.7 ha (catchment 3 or C3). The catchments comprised good quality agricultural land, all equally suitable for cropping or grazing (Webb, 1971). The BCS is located in central Queensland, Australia, at 24.81°S, 149.80°E using the Geocentric Datum of Australia 1994 (Australian Government - Geoscience Australia, 2006). A location map is presented in Cowie et al. (2007) and an aerial photograph annotated with catchment boundaries, topography and the location of monitoring equipment is shown in Fig. 1. The topography in Fig. 1 was determined by LiDAR survey, which has greater accuracy than the historical survey data previously presented in the literature.

The BCS rationale, aims and history, along with physical characteristics including location, experimental design, climate, vegetation and soils, have been documented extensively (Cowie et al., 2007; Lawrence and Sinclair, 1989; Radford et al., 2007; Silburn et al., 2009; Thornton et al., 2007; Thornton and Elledge, 2016; Thornton and Shrestha, 2021; Thornton and Yu, 2016). Land use and hydrological data used in this study were collected as part of the long-term BCS. Changes in runoff as a result of land development and land use change are given in Thornton et al. (2007), while changes in peak runoff rate are given in Thornton and Yu (2016). A brief description of the site and experimental treatments follows.

2.1.1. Climate

The climate is semi-arid to subtropical with wet summers and low winter rainfall. Average maximum monthly temperature (1890–2004) for summer was 33.1 °C, while minimum temperature in winter averaged 6.5 °C. Annual hydrological year rainfall during the study period (October 1965 to September 2004) ranged from 342 to 785 mm with an average of 646 mm. Spring and summer rainfall (September to February) is characterised by high intensity, short-duration storms with high temporal and spatial variability. Average annual potential evaporation at the nearby Bureau of Meteorology station 035149 was in excess of 2100 mm/yr during the study period. Average monthly evaporation exceeds average monthly rainfall in all months of the year (Cowie et al., 2007; Thornton et al., 2007).

2.1.2. Soil types

Soil types in the catchments comprise associations of Black and Grey Vertosols, some with gilgais, Black and Grey Dermosols, and subdominant Black and Brown Sodosols (Cowie et al., 2007; Isbell, 1996). Clay soils (Vertosols and Dermosols) occupy approximately 70% of C1 and C2, and 58% of C3. Sodosols occupy the remaining area in these catchments. Soils have a plant available water capacity ranging from 160 to 200 mm in the surface 1.4 m. Mean slope of the catchments is 2.5% (Cowie et al., 2007).

2.1.3. Vegetation

Before clearing, the study site was composed of three major vegetation communities, identified by their most common canopy species: brigalow (*Acacia harpophylla*), brigalow–belah (*Casuarina cristata*) and brigalow–Dawson Gum (*Eucalyptus cambageana*). Understories of all major communities were characterized by *Geijera* sp. either exclusively, or in association with *Eremophila* sp. or *Myoporum* sp. (Johnson, 2004). Projected canopy cover ranges from zero in non-vegetated areas to 100% in treed areas. Litter levels (both leaf and wood) range from 1.9 t/ha in non-vegetated areas to 29 t/ha in treed areas (Dowling et al., 1986). The extant uncleared vegetation of the site is classified as regional ecosystems 11.4.8, *Eucalyptus cambageana* woodland to open forest with *Acacia harpophylla* or *Acacia argyrodendron* on Cainozoic clay plains, and 11.4.9, *Acacia harpophylla* shrubby woodland with *Terminalia oblongata* on Cainozoic clay plains (The State of Queensland, 2020).

2.1.4. Site history and management

The study has been divided into three distinct experimental stages (Table 1) (Thornton et al., 2010). Stage I, the calibration phase, commenced in 1965 with the three catchments retained in their virgin state for calibration purposes. Rainfall and runoff data were collected to describe differences in catchment hydrological responses to a range of weather sequences. The empirical calibrations mathematically describing differences in runoff and peak runoff rate between the catchments are given in Thornton et al. (2007) and Thornton and Yu (2016), respectively.

Stage II, the land development phase, commenced in March 1982 with C2 and C3 cleared by bulldozer and chain. The fallen timber was burnt in situ in October 1982. In C2, residual unburnt timber was raked to the contour line and burnt. Narrow based contour banks at 1.5 m vertical spacing were then constructed and a grassed waterway later established. In C3, unburnt timber was left in place, and in November 1982 the catchment was sown to improved pasture by throwing buffel grass seed (*Cenchrus ciliaris* cv. Biloela) on the soil surface. Stage II hydrology was not analysed in detail due its short duration, the marked changes in catchment condition and a high incidence of equipment failure (Thornton et al., 2007).

During Stage III, the land use comparison phase, comparison of the effect of land use change commenced with cropping in C2 and grazing in C3. Sorghum was planted in C2 in September 1984 followed by nine annual wheat crops commencing in 1985. Fallow management in this period was entirely mechanical tillage. A minimum tillage and opportunity cropping philosophy was adopted in the early 1990s and has continued with either a summer (sorghum) or winter (wheat) crop sown whenever soil moisture was adequate. Grazing in C3 commenced in December 1983. Stocking rates varied between 0.29 and 0.71 head/ha (each beast typically 0.8 adult equivalents), adjusted to maintain pasture dry matter levels greater than 1000 kg/ha. There was no feed supplementation.

2.1.5. Rainfall and runoff data

Rainfall and runoff data were analysed on an event basis. A rainfall event was defined as one or more wet days separated from other events by at least one dry day. A daily 9 am rainfall total greater than zero was considered a wet day while a daily total of zero was considered a dry day. Only rainfall events that produced runoff were considered in this study. Rainfall and runoff observations for the BCS are presented in Thornton et al. (2007), while peak runoff rate observations are presented in Thornton and Yu (2016).

In this study rainfall data was collected from a 0.5 mm tipping bucket recorder located at the head point of the catchments typically at a 6-minute or lower time step to about 2000, and 1-minute or instantaneous from 2000 onwards (Fig. 1). Raw data was stored and processed using the Hydstra database (Kisters, 2014). Where data was aggregated, 15-minute totals commenced from midnight while daily totals were the previous 24 h to 9 am. Rainfall intensity (I_x) was calculated as the peak intensity over x minutes within the event. Antecedent rainfall (A_x) was calculated as the sum of daily rainfall totals over x number of days until 9 am on the day the event commenced.

Storm energy (E) was not measured at this site. The technique of Rosewell (1986) was used to estimate the total storm energy from observed tipping bucket rainfall intensity data. Storm erosivity (EI_{30}) was calculated as the product of storm energy and peak 30-rainfall intensity (Yu and Rosewell, 1998).

Each catchment was instrumented to measure runoff using a 1.2 m steel HL flume with a 3.9 m by 6.1 m concrete approach box located at the outlet point of each catchment (Fig. 1) (Brakenseik et al., 1979). Water height through the flumes was recorded with

Table 1
The land use history of the three catchments of the Brigalow Catchment Study.

		Land use by experimental stage		
Catchment	Area (ha)	Stage I (Jan 1965–Mar 1982)	Stage II (Mar 1982–Sep 1984)	Stage III (Sep 1984–Dec 2004)
C1	16.8	Virgin brigalow scrub	Virgin brigalow scrub	Virgin brigalow scrub
C2	11.7	Virgin brigalow scrub	Development	Cropping
C3	12.7	Virgin brigalow scrub	Development	Improved pasture

mechanical float recorders typically at a 15-minute or lower time step to about 2000, and 1-minute from 2000 onwards. Raw runoff data were also stored and processed using the Hydstra database (Kisters, 2014). Observed stage height data (m) were converted to runoff depth (mm) and flow rate (mm/hr), eliminating the effect of catchment size. Peak runoff rate was calculated on an event basis from the observed instantaneous peak height.

2.2. *Methods to estimate peak runoff rate*

2.2.1. *Multiple regression models*

Thornton and Yu (2016) developed linear multiple regression models to estimate Q_p for each catchment and stage using local climate and catchment condition data. All regression models considered the parameters total runoff (Q_{tot}), total rainfall (P), storm energy (E), storm erosivity (EI_{30}), peak rainfall intensity (I), antecedent rainfall (A) and total soil water (TSW). Each parameter was tested individually for a significant correlation ($P < 0.05$) with dependent parameter Q_p. Significant parameters were then combined and an all-subsets regression performed using the statistical software program GenStat v14.1 (VSN International, 2011). The final models only included significant constants and coefficients. To allow numerical evaluation of Q_p regression models, a split sample approach was used. The models were developed on data collected in odd years and then validated on data collected in even years. The models for each of the catchments in Stage I and III of the study are given in Table 2.

2.2.2. *The scaling technique*

The scaling technique relates peak runoff rate to rainfall, runoff volume and peak rainfall intensity as follows:

$$Q_p = \alpha_p \times \frac{Qtot}{Ptot} \times I_x \tag{1}$$

where Q_p is the peak runoff rate (mm/hr), Q_{tot} is total runoff volume (mm), P is total rainfall (mm), I_x is rainfall intensity for a given time interval x and α_p is a dimensionless scaling parameter (Yu and Rose, 1999). As rainfall intensity data for the site was available on a number of time intervals, a simple calibration was undertaken to determine the best estimate of α_p given peak rainfall intensity during 6, 10, 15, 20 and 30-minute intervals and 1, 2, 3, 4, 6, 12, 18 and 24-hour intervals. This was done by estimating Q_p using α_p derived from each of the 13 rainfall intensity intervals and selecting the interval that gave Q_p estimates with the highest NSE.

2.2.3. *The Natural Resources Conservation Service curve number and graphical peak discharge method*

The NRCS curve number and graphical peak discharge methods are based on empirical relationships derived from thousands of infiltrometer plots and decades of observations from at least 12 experimental catchments (Rallison, 1980; Woodward et al., 2002). The methods are ubiquitous and enduring (Boughton, 1989; Lyon et al., 2004). Application of the methods is guided by National Engineering Handbooks and a body of literature which means that local determination of variables such as curve number are seldom pursued (U.S. Department of Agriculture, 2004; Van Mullem et al., 2002).

2.2.4. *The Natural Resources Conservation Service curve number method*

The NRCS curve number (CN) method estimates runoff from total storm rainfall based on the underlying principle that the relationship between rainfall and runoff from a natural watershed can be described by a curve (U.S. Department of Agriculture, 2004). That is, when accumulated natural rainfall is plotted versus accumulated natural runoff, runoff starts after some rainfall has accumulated and the relationship between rainfall and runoff curves becomes asymptotic to a 1:1 line for large rainfall events (Rallison, 1980; Woodward et al., 2002). Within the method, curve number is a dimensionless parameter used to describe the rainfall-runoff relationship for a catchment, as influenced by physical factors such as soil type, land use and management practice (Boughton, 1989; Hawkins, 1993). Curve number varies between 0 and 100 with a CN value of 0 producing no runoff and a CN value of 100 resulting in all rainfall becoming runoff (Hawkins, 1993). The NRCS CN method provides an estimate of Q_{tot} and the parameters S and I_a (defined below), which are then used with the NRCS graphical peak discharge (GPD) method (U.S. Department of Agriculture, 1986) to estimate Q_p.

The following equation describes the rainfall-runoff relationship used in the NRCS CN method (U.S. Department of Agriculture, 2004):

Table 2
Multiple regression models for the estimation of peak runoff rate from the three catchments of the Brigalow Catchment Study. Log Q_p is log transformed (log $(x + 1)$ peak runoff rate, log Q_{tot} is log transformed (log $(x + 1)$ total runoff, P is total rainfall, E is storm energy, $A_{2\ day}$ is antecedent rainfall in the two days prior to the event and EI_{30} is storm erosivity (Thornton and Yu, 2016).

Stage	Catchment	Land use	Regression model of peak runoff rate ($logQ_p$)	R^2
Stage I	C1	Brigalow scrub	$0.524 \times \log Q_{tot}$	0.82
	C2	Brigalow scrub	$0.8483 \times \log Q_{tot} - 0.0188 \times P + 0.0787 \times E$	0.96
	C3	Brigalow scrub	$0.5767 \times \log Q_{tot} + 0.0122 \times E + 0.0073 \times A_{2\ day}$	0.94
Stage III	C1	Brigalow scrub	$0.6767 \times \log Q_{tot}$	0.82
	C2	Cropping	$0.815 \times \log Q_{tot} - 0.0238 \times P + 0.1096 \times E$	0.75
	C3	Pasture	$0.466 \times \log Q_{tot} + 0.0006 \times EI_{30}$	0.92

$$Q_{tot} = \frac{(P - I_a)^2}{(P - I_a) + S} \text{ if } P > I_a \text{ and } Q_{tot} = 0 \text{ if } P < I_a \tag{2}$$

where Q_{tot} is runoff, P is rainfall, I_a is an initial abstraction or retention parameter (rainfall that does not become runoff) and S is a site index defined as the maximum detention, or the maximum possible difference between P and Q_{tot} as P approaches infinity. P, Q_{tot}, I_a, S are all measured in inches.

Historical NRCS field data gave the empirical relationship:

$$I_a = 0.2S \tag{3}$$

Substituting (Eq. (3)) into (Eq. (2)) gives what is commonly termed the familiar equation:

$$Q_{tot} = \frac{(P - 0.2S)^2}{P + 0.8S} \tag{4}$$

The retention parameter S is related to a curve number as follows:

$$S = \frac{1000}{CN} - 10 \tag{5}$$

where S is measured in inches. Curve number equals 100 when $S = 0$, and approaches 0 as S goes to infinity. Tables of CN values exist for a range of hydrologic soil groups, cover types, land use treatments and antecedent conditions (USDA NRCS 1986). Estimating Q_{tot} for a rainfall event on a particular catchment is done by selecting an appropriate CN value, substituting the value into Eq. (5) and solving for S, then substituting S and the known rainfall total into Eq. (4) and solving for Q_{tot}.

As local determination of CN values was always the intention of the method (Van Mullem et al., 2002), CN values for each catchment by experimental stage were calculated from pairs of P:Q_{tot} observations for a single storm. A CN was calculated by solving Eq. (4) for S given known P and Q_{tot} (as shown in Eq. (6)), then substituting S into Eq. (5) and solving for CN (Boughton, 1989; Hawkins, 1973; Hawkins, 1993):

$$S = 5[P + 2Qtot - (4Qtot^2 + 5PQtot)^{1/2}] \tag{6}$$

The observation that rainfall events of similar magnitude generate varying amounts of runoff demonstrates that CN values vary from event to event (U.S. Department of Agriculture, 2004). The original NRCS CN method stated that antecedent moisture condition (AMC) was the most significant variable explaining this variation (Van Mullem et al., 2002). The method classifies antecedent rainfall in the five days preceding runoff into three AMC conditions. During the growing season, antecedent rainfall less than 36 mm is classified as AMC I; 36–53 mm is classified as AMC II; and greater than 53 mm is classified as AMC III (Boughton, 1989; Chow et al., 1988; Dilshad and Peel, 1994). Classifications for the dormant season also exist, but as the BCS is dominated by perennial vegetation and opportunity cropping, the AMC classifications for the growing season were adopted. To make the locally determined CN values applicable to climatic sequences other than those under which they were calculated, some method of optimisation to account for AMC must be undertaken and an average set of CN values produced (Boughton, 1989).

Three methods of optimising CN values were evaluated in this study. All three methods use the equations of Chow et al. (1988) to determine CN values for AMC I (CN(I)) and AMC III (CN(III)) based on the CN value for AMC II (CN(II)). The first method uses the statistical theory that as sample size increases, the sample mean more closely reflects the population mean. Thus as many event-based CN values were calculated for each catchment using pairs of P:Q_{tot} observations, the mean of the calculated CN values should be a reasonable estimation of the true average CN value for the catchment. This average CN value is then considered as CN(II), and CN(I) and (III) were calculated for each catchment via Chow et al.'s (1988) equations.

The second method assumes that each CN value calculated using a pair of P:Q_{tot} observations is CN(II). Chow et al.'s (1988) equations were then used to determine CN(I) and (III) based on the calculated CN(II). This results in a set of three CN values for each event. The average CN(I) value for the catchment was then determined by averaging all the calculated event-based CN(I) values. The average CN(II) and CN(III) values were determined in the same manner.

The third method grouped the calculated event-based CN values into the three AMC classifications based on the observed antecedent rainfall. The average CN(I), CN(II) and CN(III) values for the catchment were then determined by averaging each group of event-based CN values, respectively.

The three optimisation methods were assessed by comparing Q_{tot} estimated using the NRCS CN method to observed Q_{tot}. Estimates of Q_{tot} were made on an event basis using the average CN value for either AMC I, II or III, depending on the observed five-day antecedent rainfall.

2.2.5. The Natural Resources Conservation Service graphical peak discharge method

Once Q_{tot} and the parameters S and I_a have been determined with the NRCS CN method, the NRCS GPD method is used to estimate Q_p. The NRCS GPD method was developed from hydrograph analyses with TR-20 Computer Program for Project Formulation – Hydrology (U.S. Department of Agriculture, 1983; U.S. Department of Agriculture, 1986; Ward, 1995).

The equation for calculating Q_p is:

$$Q_p = q_u A Q_{tot} F \tag{7}$$

where Q_p is peak discharge with units of cubic feet per second (cfs), q_u is unit peak discharge with units of cfs per square mile per inch of runoff (csm/in) (see Eqs. (8) to (10)), A is drainage area in square miles (mi^2), Q_{tot} is total runoff volume in inches, and F is an adjustment factor for ponds and swamps. In this study, observed Q_{tot} was used as the input parameter for the NRCS GPD method.

Unit peak discharge (q_u) for use in Eq. (7) requires an estimation of the time of concentration (t_c) for the catchment. Time of concentration was estimated by the NRCS lag method, as this method has been shown to have one of the lowest biases (Ward, 1995). The NRCS lag equation is:

$$t_l = \frac{L^{0.8}(S+1)^{0.7}}{1900Y^{0.5}} \tag{8}$$

where t_l is lag time (hr), L is the hydraulic length of the catchment with units of feet (ft), S is a function of the NRCS CN method (Eqs. (2) to (5)) and Y is the average land slope (%) (Ward, 1995). Lag time is related to t_c as follows (Ward, 1995):

$$t_l = 0.6t_c \tag{9}$$

Having estimated t_c using Eqs. (8) and (9), estimation of q_u was undertaken using the United States Department of Agriculture Natural Resource Conservation Service (1986) equation-based method for a Type II rainfall distribution. This distribution represents regions in which high rates of runoff from small areas are usually generated from summer thunderstorms (U.S. Department of Agriculture, 1973), which was applicable to the study site.

The equation for estimating q_u is:

$$\log(q_u) = C_0 + C_1 \log(t_c) + C_2[\log(t_c)]^2 \tag{10}$$

where q_u is unit peak discharge (csm/in), t_c is time of concentration (hr) (Eqs. (8) and (9)) and C_0, C_1 and C_2 are coefficients chosen from lookup tables in U.S. Department of Agriculture (1986), which depend on the rainfall distribution, and ratio of I_a/P from Eqs. (2) to (5). The estimation of q_u is then substituted into Eq. (7), which is then solved for Q_p.

2.2.6. The variable infiltration rate method

From first principles, the variable infiltration rate (VIR) method assumes runoff is equal to rainfall minus abstraction, which can include infiltration, surface storage, interception and evapotranspiration (Connolly et al., 1997; Thornton et al., 2007). Assuming that at the commencement of runoff, surface storage, interception losses and evapotranspiration are negligible, runoff rate (Q_i) (mm/hr) can be estimated as rainfall rate (P_i) (mm/hr) less infiltration rate (f_i) (mm/hr) for a given time interval (Yu et al., 1998). This is written as:

$$Q_i = P_i - f_i \tag{11}$$

The unknown infiltration rate f_i is constrained by two limitations as follows (Yu et al., 1998):

$$\sum_{i=1}^{n}(P_i - f_i)\Delta t = Q_{tot} \tag{12}$$

and

$$f_i \le P_i \tag{13}$$

where Q_{tot} is the total runoff volume (mm) for the event, P_i is the rainfall rate (mm/hr), f_i is the infiltration rate (mm/hr), Δt is the time interval at which rainfall rate is measured and $n\Delta t$ is the duration of the runoff event.

Maximum infiltration rate has been shown to vary spatially across the landscape (Yu, 1997; Yu et al., 1998; Yu et al., 1997b). This spatial variation in maximum infiltration rate can be described by an exponential distribution, with the actual rate of infiltration given by:

$$f_i = I(1 - e^{P_i/I}) \tag{14}$$

where I is interpreted as a spatially-averaged maximum infiltration rate (mm/hr) (Yu et al., 1998; Yu et al., 1997b). To determine I, Eq. (14) is substituted into Eq. (12) as follows:

$$\sum_{i=1}^{n}[P_i - I(1 - e^{P_i/I})]\Delta t - Q_{tot} = 0 \tag{15}$$

Next, Eq. (15) is solved numerically when both rainfall rate (P_i) and total runoff volume (Q_{tot}) are known (Yu et al., 1998). Eq. (15) presents a root-finding problem which can be solved by numerical methods, of which the most suitable for this purpose is Brent's method (Press et al., 1989). Brent's method combines root bracketing, bisection and inverse quadratic interpolation (Brent, 1973; Press et al., 1989), guaranteeing a unique solution for I, the spatially–averaged maximum infiltration rate from which Q_p is calculated (Yu, 1997). Once I is known, peak rate of rainfall excess, R_p, is evaluated as follows:

$$R_p = P_p - I(1 - e^{-\frac{P_p}{I}}) \tag{16}$$

where P_p is the peak rainfall intensity. R_p is an approximation of Q_p for small areas where time lag can be ignored.

In this study, assessment of the VIR method will also consider the need to route localised runoff to the catchment outlet. For large areas, the literature shows that VIR estimations of runoff rate can be routed to a catchment outlet using a linear approximation to a kinematic wave, assuming a constant lag time between rainfall excess and runoff (Yu, 1999; Yu et al., 1997b; Yu et al., 2000b). The routing equation is written:

$$Q_i = \alpha Q_{i-1} + (1 - \alpha)R_i \tag{17}$$

where Q_i is the estimated runoff rate at the catchment outlet and R_i is the rainfall excess rate. The parameter α is related to the lag time of runoff within the catchment (t_l, Eq. (9)) and the time interval of measurement (Δt), and is given as (Yu et al., 1997b):

$$\alpha = \frac{t_l}{t_l + \Delta t} \tag{18}$$

This study will use the software program Generation Of Synthetic Hydrograph (GOSH) (Yu, 1997) to solve Eq. (15) and hence Q_p. GOSH uses Brent's method to solve Eq. (15) given known rainfall rates and Q_{tot}. GOSH outputs include both I and Q_p.

2.3. Assessment of method performance

Method performance was assessed against observed runoff data using several criteria, similar to the approaches of Refsgaard and Knudsen (1996), Lørup et al. (1998) and Legates and McCabe Jr (1999). Graphical comparison comprised overlay plots of observed and estimated Q_p data. Numerical evaluation compared R^2 and NSE between observed and estimated Q_p data.

All R^2 presented are adjusted R^2. Adjusted R^2 has the advantage over statistic r^2 in that it takes account of the number of parameters that have been fitted in the model (VSN International, 2011). As Q_p was not normally distributed, log transformation $\log(Q_p + 1)$ was performed on both observed and estimated data to allow for valid statistical testing.

The NSE expresses the proportion of variance of the observed data which can be accounted for directly by the estimated data (Nash and Sutcliffe, 1970). This is a better indicator of model performance than statistic r^2, which has been shown to be insensitive to additive and proportional differences between observed and estimated values (Legates and McCabe, 1999). Values of NSE range from -∞.to 1. An NSE value of 1 means perfect agreement between the observed and estimated data. An NSE value of 0 means that the modelled estimate is no better a predictor than the observed mean. A negative NSE value means that the modelled estimate is a worse predictor than an estimation made using the mean of the observed data (Chiew and McMahon, 1993; Legates and McCabe, 1999; Yu et al., 2000a; Yu et al., 2000b).

3. Results

3.1. Multiple regression models

3.1.1. Estimations of peak runoff rate using multiple regression models

Regression models of Q_p during Stage I, the calibration phase, gave good estimations of both the development (odd years) and validation (even years) data (Fig. 2). Little bias is evident despite the wide range of observed Q_p data. However, C2 regressions yielded poor results for very small observed Q_p values. In the worst instance, model calibration included two pre-clearing events both with

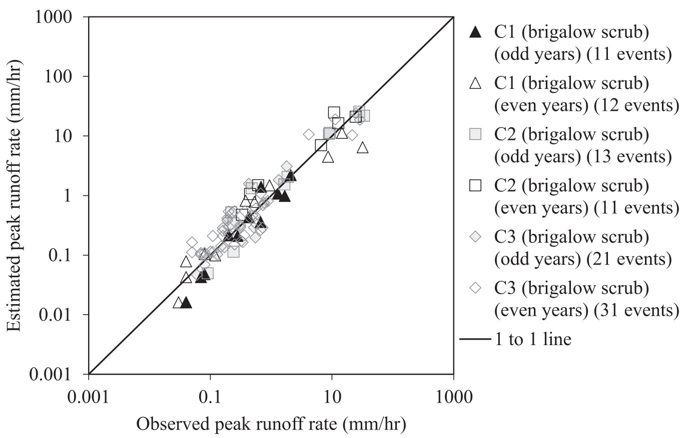

Fig. 2. Observed peak runoff rate compared with peak runoff rate estimated using multiple regression model equations (Table 2) for the three catchments during Stage I.

negligible Q (less than 0.1 mm) and observed Q_p less than 0.1 mm/hr which yielded negative results when validated against observed Q_p values less than 0.4 mm/hr (data not shown). Regression models of Stage III, the land use comparison phase also gave good estimations of both the development and validation data; however, events with Q_p greater than 1 mm/hr were better estimated than events with Q_p less than 1 mm/hr (Fig. 3). No parameter describing I or TSW was significant in any all-subsets regression analysis.

3.2. The scaling technique

3.2.1. Simple optimisation of the scaling technique parameters

During Stage I, the best estimates of α_p for all catchments (highest NSE values) were obtained using peak one-hour rainfall intensity measurements. During Stage III, the best estimates of α_p for C1, C2 and C3 were obtained using peak six-hour, one-hour and two-hour rainfall intensity measurements, respectively. The median and mode of these rainfall intensities was one-hour (Table 3). Estimates of α_p optimised using observed event-based Q_{tot}, P and I data are given in Table 3.

3.2.2. Estimations of peak runoff rate using the scaling technique

During Stage I, the scaling technique gave good estimations of Q_p from C1 and C2; however, the method typically underestimated Q_p from C3 where observed Q_p data was less than 1 mm/hr (Fig. 4). During Stage III, the scaling technique gave good estimations of Q_p from C1. Estimates from C2 showed wide scatter in across the range of observed Q_p data. Estimates from C3 continued to be poor where observed Q_p data was less than 1 mm/hr (Fig. 5). When the average of all α_p estimates was used in place of the individual α_p estimate for each catchment and stage, the overall average NSE reduced by 34%.

3.3. The Natural Resources Conservation Service curve number and graphical peak discharge method

3.3.1. Calculation of curve numbers to estimate runoff volume prior to the estimation of peak runoff rate

The average CN calculated from pairs of observed Stage I P:Q_{tot} data was CN 58 for all catchments. Average CN decreased to CN 53 for C1 in Stage III; however, CN increased for both C2 and C3 to CN 67 and CN 64, respectively (Table 4). Observed peak runoff rates showed that during Stage III, C3 had proportionally more small events than the other catchments. This bias was eliminated by removing all events where Q_{tot} was less than 1 mm, and subsequently, the average calculated CN for both C2 and C3 in Stage III was CN 67.

Optimisation of CN values was undertaken using two equation-based methods and by averaging the calculated CN values for individual events grouped according to AMC conditions. Both equation-based methods gave similar results when used to calculate CN(I) and CN(III) values. The difference in CN values between the equation-based methods was a maximum of three for CN(I) values and one for CN(III) values. Optimising CN values using observed AMC resulted in CN(I) and CN(II) values being higher than those calculated by the equation-based methods, and CN(III) values typically lower than the equation-based methods. In all instances, CN values optimised using the observed AMC condition provided the best estimate of Q_{tot} (Table 4).

3.3.2. Estimations of peak runoff rate using the graphical peak discharge method

The NRCS GPD method gave good estimations of Q_p across all catchments in Stages I and III; however, more scatter is evident in Stage III estimations (Fig. 6 and Fig. 7). The method typically underestimated Q_p in small events and overestimated Q_p in large events. For Stage I events, where observed Q_p data was greater than 5 mm/hr, 83% of estimated Q_p values were greater than observed values. This overestimation decreased in Stage III events. For Stage III events, when observed Q_p data was greater than 5 mm/hr, only 56% of estimated values were greater than observed values.

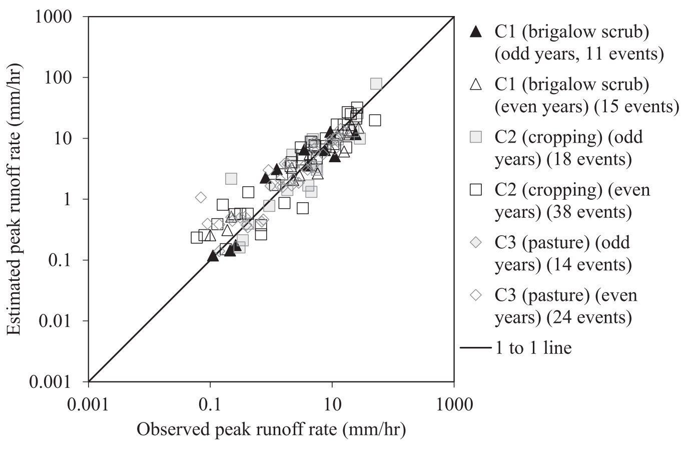

Fig. 3. Observed peak runoff rate compared with peak runoff rate estimated using multiple regression model equations (Table 2) for the three catchments during Stage III.

Table 3
The optimised intensity intervals and scaling parameter (α_p) values, determined from observed rainfall total, rainfall intensity and runoff data.

Catchment	Stage	Intensity interval	α_p
C1	I	1 hr	1.123
	III	6 hr	4.466
C2	I	1 hr	1.024
	III	1 hr	1.383
C3	I	1 hr	1.104
	III	2 hr	1.271
Average α_p			1.729

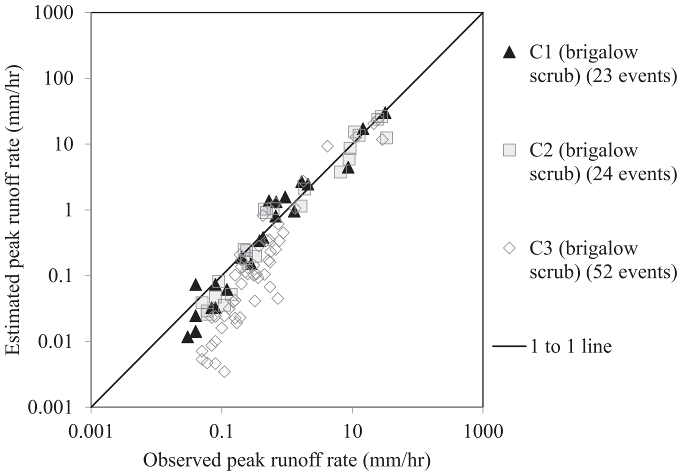

Fig. 4. Observed peak runoff rate compared with peak runoff rate estimated using the scaling technique for the three catchments during Stage I.

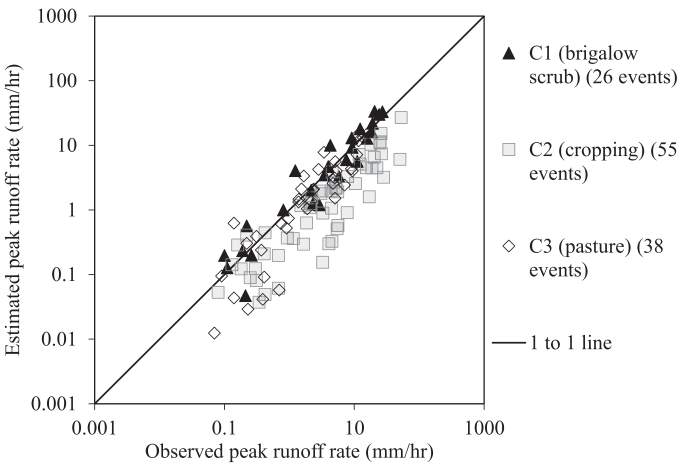

Fig. 5. Observed peak runoff rate compared with peak runoff rate estimated using the scaling technique for the three catchments during Stage III.

3.4. The variable infiltration rate method

3.4.1. Estimations of peak runoff rate using the variable infiltration rate method

On average, the VIR method with no routing component overestimated Q_p for 88% of events, with the time of peak runoff occurring prior to the observed peak in 92% of events. In all cases, routing of VIR-estimated runoff resulted in a Q_p equal to or smaller than the non-routed estimations. During Stage I, the routed VIR method gave good estimations of Q_p from C1 and C2; however, the method typically underestimated Q_p from C3 where observed Q_p data was less than 1 mm/hr (Fig. 8). During Stage III, the method gave good estimations of Q_p from all catchments; however, for C2 and C3, events with Q_p greater than 1 mm/hr were better estimated than events

Table 4
Curve number values calculated using the NRCS method and their suitability for estimating total runoff, based on the numerical indicators R^b and Nash-Sutcliffe coefficient of efficiency (NSE). Curve number (*CN*) values were calculated from observed event-based rainfall and runoff data and optimised using either the average of all event based *CN* values[a] or the average of event based CN values grouped according to antecedent moisture condition[b].

						R^2 log *Q* (obs) v log *Q* (est)	
Catchment	Stage	Average *CN*[a]	*CN* (II)[b]	*CN* (I)[b]	*CN* (III)[b]	Using average *CN*[a]	Using AMC Grouped *CN*[b]
C1	I	58	61	58	69	0.53	0.53
	III	53	68	53	55	0.54	0.55
C2	I	58	59	55	78	0.6	0.65
	III	67	81	65	71	0.51	0.54
C3	I	58	62	56	71	0.58	0.64
	III	64	67	61	77	0.2	0.23

[a] Calculated on an event basis using the method of Hawkins (1993) and averaged across all events.
[b] Calculated on an event basis using the method of Hawkins (1993) and averaged across all events grouped according to AMC condition.

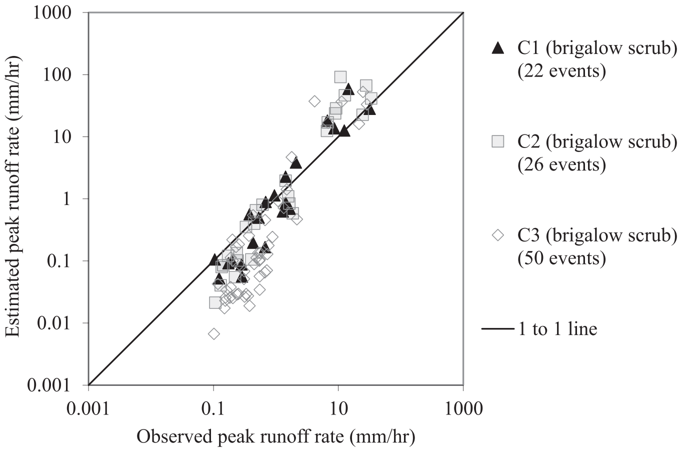

Fig. 6. Observed peak runoff rate compared with peak runoff rate estimated using the NRCS method for the three catchments during Stage I.

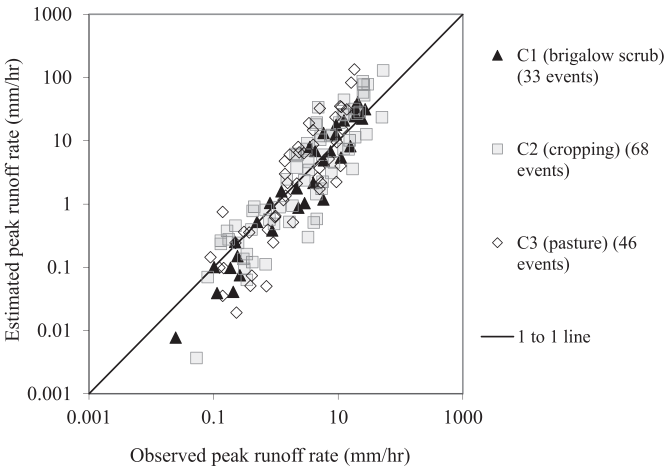

Fig. 7. Observed peak runoff rate compared with peak runoff rate estimated using the NRCS method for the three catchments during Stage III.

with Q_p less than 1 mm/hr (Fig. 9). Routing typically delayed the estimated peak, with an average of 97% of Stage I peaks and 100% of Stage III peaks occurring after the estimated non-routed peak. However, the delay was not long enough and on average 91% of routed peaks occurred prior to the observed peak.

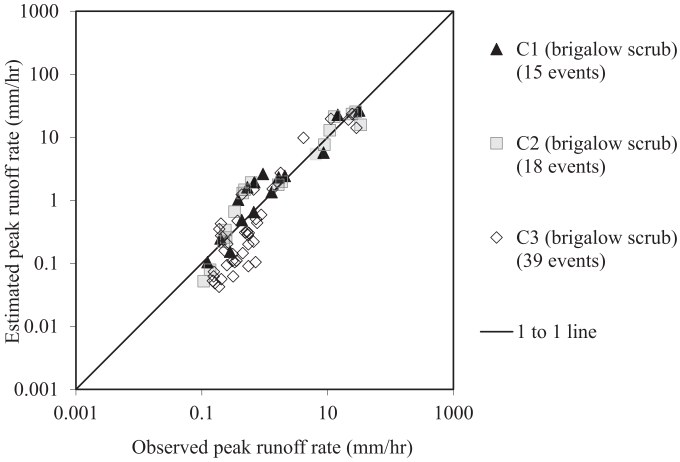

Fig. 8. Observed peak runoff rate compared with peak runoff rate estimated using the routed VIR method for the three catchments during Stage I.

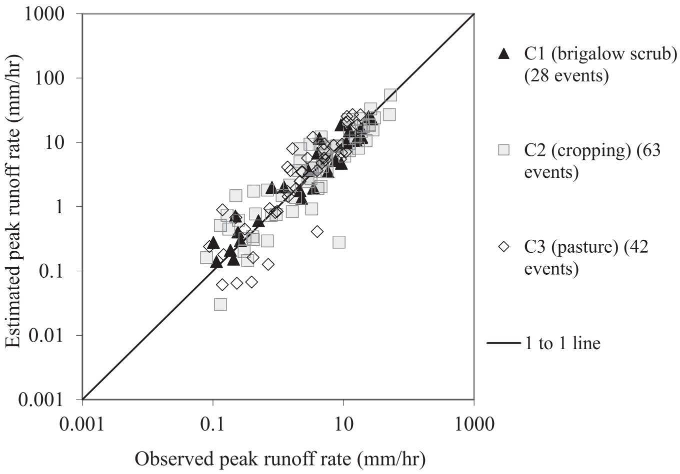

Fig. 9. Observed peak runoff rate compared with peak runoff rate estimated using the VIR method for the three catchments during Stage III.

3.5. Quantitative assessment of method performance

Numerical evaluation criteria R^2 and NSE calculated using observed and estimated Q_p data for all methods is shown in Table 5. When averaged across all catchments and stages, regression models and the scaling technique had the equal highest R^2 while the scaling technique had the highest NSE.

Using a split sample approach, regression models of Q_p developed on data collected in odd years were validated against Q_p data collected in even years. During Stage I, regression models gave an R^2 of 0.89 or greater for all catchments. There was little change in R^2

Table 5
Comparison of method performance based on the numerical indicators R^2 and Nash-Sutcliffe coefficient of efficiency (NSE).

		Regression models		Scaling technique		NRCS method		VIR method	
		R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Catchment	Stage	(R^2 based on log-transformed data; NSE based on normal data)							
C1	I	0.9	0.35	0.95	0.97	0.92	-0.75	0.91	0.9
	III	0.93	0.67	0.92	0.77	0.89	0.47	0.89	0.81
C2	I	0.94	0.64	0.96	0.77	0.92	-3.29	0.94	0.81
	III	0.89	0.68	0.78	0.62	0.78	-1.5	0.81	0.8
C3	I	0.89	0.59	0.93	0.82	0.87	-0.44	0.92	0.82
	III	0.87	0.86	0.85	0.79	0.73	-19.69	0.82	0.11
Stage I average		0.91	0.53	0.95	0.85	0.9	-1.49	0.92	0.84
Stage III average		0.9	0.74	0.85	0.73	0.8	-6.91	0.84	0.57
Overall average		0.9	0.63	0.9	0.79	0.85	-4.2	0.88	0.71

in Stage III with an R^2 of 0.87 or greater for all catchments; however, NSE values improved to 0.67 or greater for all catchments.

Regression analysis of NRCS GPD estimated Q_p against observed Q_p gave R^2 greater than 0.73 in all instances. These high R^2 values disguise the tendency of the method to underestimate Q_p in small events and overestimate Q_p in large events. This is evident in the negative NSE values for all catchments in Stage I, and in C2 and C3 in Stage III. The NRCS GPD method consistently gave the lowest R^2 and NSE of all four methods.

Regression analyses of Q_p estimated using VIR without routing against observed Q_p showed strong correlations with R^2 greater than 0.7 in all instances; however, the tendency of the method to overestimate Q_p resulted in low and negative NSE values. When Q_p was estimated using VIR and routing was performed, an improved R^2 was obtained for all catchments, with R^2 greater than 0.9 in Stage I and greater than 0.8 in Stage III. As the routed method did not suffer the gross overestimation of Q_p that the non-routed method exhibited, all values of NSE were greatly improved. Despite typical R^2 and NSE values greater than 0.8, the method gave poor estimations of C3 in Stage III, with a NSE value of 0.11.

The minimum variable and parameter set required to utilise each of the methods varies considerably (Table 6). For example, multiple regression models to estimate Q_p from C1 only required Q_{tot}. In contrast, nine descriptors of a catchment, its climate and hydrology were required to estimate Q_p using the NRCS GPD method.

4. Discussion

4.1. Comments on the Natural Resources Conservation Service curve number method for estimating runoff volume

A measurement of Q_{tot} is required to apply any of the four methods to estimate Q_p that were evaluated in this study. If Q_{tot} is unknown, it has to be estimated. The *CN* values calculated in this study provide a basis for estimating Q_{tot} from these and other semi-arid subtropical catchments.

The best agreement between observed Q_{tot} and NRCS *CN* method estimations of Q_{tot} was obtained using *CN* values optimised based on the observed antecedent rainfall. This was the third method evaluated. This method gave substantial improvement in Q_{tot} estimations compared to using *CN* values optimised by formula in the first and second methods. As daily rainfall data for Australia is widely available via tools such as SILO (Queensland Government, 2019), assigning an AMC condition to a calculated *CN* value based on the NRCS classification of AMC is straightforward.

An average *CN* value for brigalow scrub, calculated from pairs of observed P:Q_{tot} data on an event basis, is *CN* 57, given *CN* 58 for all catchments in SI and *CN* 53 for C1 in SIII. An average *CN* value for brigalow scrub, optimised using observed AMC, is *CN* 63, given *CN* 61, *CN* 59 and *CN* 62 for C1 to C3, respectively, in SI and *CN* 68 for C1 in SIII. These *CN* values are similar to the *CN* values of 58 and 59 initially reported for brigalow scrub by Boughton (1989) who analysed the first three years of BCS data. Boughton (1989) also reports optimised *CN* values of 73, 71 and 70 for C1, C2 and C3, respectively, based on 15 years of BCS data from 1965 to 1979. The *CN* values for the three-year period reported in the Boughton (1989) study were from a dry period with little runoff. Thus the *CN* values from the latter 15-year period are considered more representative, with the comparison highlighting the concern in undertaking local calibration with a limited data set (Boughton, 1989).

The optimised *CN* value of 81, calculated for cropping under average (AMC II) antecedent moisture conditions, is within the range reported by Freebairn and Boughton (1981) for cropping on cracking clays in southern Queensland. The AMC II-optimised *CN* value of 67 calculated for grazed pasture is greater than the range reported by Cao et al. (2011) for pasture and grazing treatments on predominantly medium and heavy clay soils throughout New South Wales. However, the AMC III-optimised *CN* value of 77 calculated for grazed pasture in this study was within the range reported by Cao et al. (2011).

The average *CN* values calculated for the catchments in this study are lower than those suggested by the NRCS *CN* tables, irrespective of the optimisation method used in their calculation. The selection of a *CN* value from the NRCS *CN* tables requires each catchment be assigned a hydrological soil group. It is assumed that the two main soil types of the BCS are described by hydrological soil group B or C. Hydrological soil group of B has moderate infiltration rates respectively when thoroughly wetted; moderately fine to moderately course textures; and moderate rates of water transmission. Hydrological soil group C has low infiltration rates when thoroughly wetted; moderately fine to fine textures; and low rates of water transmission.

Suggested NRCS *CN* values for cropping on hydrological soil group B are 83 for fallows with residual stubble, 75 for straight rowed crops with residual stubble and 74 for contoured crops with residual stubble. When cropping on hydrological soil group C, these *CN* values increase to 88, 82 and 81, respectively. Suggested NRCS *CN* values for continuously grazed pasture with greater than 75% cover are 61 and 74 for hydrological soil groups B and C, respectively, which are closer to those calculated in this study than the suggested *CN* values for cropping. The calculated *CN* value for brigalow scrub is similar to the suggested *CN* value of 55 for woodland on hydrological soil group B, and less than the suggested *CN* value of 70 for woodland on hydrological soil group C.

Table 6
Minimum variable and parameter sets required to utilise each of the methods evaluated.

Method	Variable and parameter requirements
Multiple regression modelling of Q_p	Q_{tot} (as a minimum)
Scaling technique	α_p, Q_{tot}, P, I
NRCS graphical peak discharge	A, Q_{tot}, F, t_c, L, S, Y, P
Variable infiltration rate	P_i, Q_{tot}, t_l, α

Subtle variations in how the NRCS *CN* method is applied, such as determination of AMC and hydrological soil group, likely explains differences between the locally calibrated *CN* values determined in this study and those noted in Boughton (1989) and other literature, including the NRCS *CN* tables. For example, the hydrological soil group for this study site is a D based on global interpretation of soil data provided by the Food and Agriculture Organisation (Ross et al., 2018). However, the most likely explanation for the locally-calibrated *CN* values in this study being lower than those suggested by the NRCS *CN* tables is the definition of a rainfall event used in this study. As the minimum size of the storms included in the analysis is raised, lower *CN* values result. This is because for small precipitation events, runoff only occurs for wet antecedent conditions and high-intensity storm conditions. For example, *CN* values calculated from annual runoff values will be lower than those based on analysis of more events per year (Cao et al., 2011). This shows that *CN* values calculated from a rainfall event consisting of multiple wet days, as defined in this study, will always be lower than those calculated from a single wet day, which is the classical interpretation of the NRCS method (U.S. Department of Agriculture, 2015). Pairing of daily rainfall and runoff values in this study showed instances where runoff on the falling limb of a hydrograph continued into a dry day. Successfully implementing the classical interpretation of the NRCS method in these circumstances requires additional complexity to consider time of concentration, hence the pragmatic decision to simply define a rainfall event as one or more wet days separated from other events by at least one dry day.

4.2. Comparing the performance of the four estimation methods

This study has shown that regression models, the scaling technique and the VIR method all produce acceptable estimations of Q_p when compared using both graphical and numerical assessments of method performance. Numerical assessment of method performance across all catchments and stages using R^2 indicated that the site-specific regression models and the scaling technique gave the best estimation of Q_p, followed by the VIR and the NRCS GDP method. Assessment of method performance using NSE indicated that the scaling technique continued to give the best estimation of Q_p, followed by the VIR method, regression models and the NRCS GDP method. A greater number of input variables and parameters did not equate to better estimation of Q_p.

Typically, all methods gave better estimations during Stage I than Stage III of the study. This is likely due to the smaller variability in catchment hydrology when all catchments contained virgin brigalow scrub compared to their changed dynamics when converted to land uses of cropping or grazing (Thornton et al., 2007; Thornton and Yu, 2016). Regression models gave good estimations throughout the range of observed Q_p data with the exception of two very small events where total runoff was less than 0.1 mm, or essentially negligible. Events where observed Q_p data was less than 1 mm/hr were most difficult to estimate using the scaling technique, the NRCS *CN* and GPD method and the VIR method, with pre-clearing Q_p from C3 consistently underestimated. This is not necessarily reflected in the NSE values, particularly for the VIR method and scaling technique. This is likely explained by the fact that as a numerical indicator comparing observed and estimated data, NSE tends to overemphasise the matching of high flow values at the expense of low flow values (Krause et al., 2005; Patil and Stieglitz, 2014; Patil et al., 2014).

It is not surprising that regression models, the scaling technique and the VIR method generate good estimates of Q_p given that they all capture relationships between observed rainfall and runoff data. Given that rainfall is the primary driving mechanism controlling watershed runoff (Fernandez and Garbrecht, 1994) and that total rainfall was the best single estimator of Q_{tot} in regression models at this site (Thornton and Yu, 2016), the regression models of Q_p inherently capture the dynamic between rainfall, runoff and peak discharge. This dynamic is directly captured in the VIR method and scaling technique, whereas the NRCS GDP method relies on empirical relationships, such as the NRCS curve number runoff equation (U.S. Department of Agriculture, 1973).

This study clearly showed that regression models, the scaling technique and the VIR method gave the best estimations of Q_p. However, the choice of which method is best employed can also be influenced by external factors, such as the different data and computational requirements of each method. As previously noted, all methods require a measurement or an estimation of Q_{tot} and if estimation is required, the *CN* values calculated in this study provide a basis for doing so. Regression models to estimate Q_{tot} could also be developed; however, regression models of Q_{tot} for this site did not perform as well as regression models of Q_p (Thornton and Yu, 2016; Thornton, 2012). Daily time-step hydrological modelling at this site has yielded better estimates of Q_{tot} than either regression modelling or the NRCS *CN* method evaluated in this study (Thornton et al., 2007). This is not surprising as, where data are available, process-based models have been shown to give more accurate answers than the NRCS *CN* method (Cao et al., 2011).

All methods require rainfall data. Easily obtainable rainfall total data is necessary for the scaling technique, the NRCS method and the VIR method, while also improving regression models for C2 both pre- and post-clearing. Rainfall data at a sub-daily timescale is not required for the NRCS method; however, it does allow the calculation of parameters such as E and EI_{30}, which improved regression models for C2 and C3 both pre- and post-clearing. Rainfall data at a sub-daily timescale is essential for the VIR method and scaling technique. It is relatively simple to obtain sub-daily rainfall data in formats such as six-minute rainfall data, which is available on request from the Australian Bureau of Meteorology (Bureau of Meteorology, 2019).

Unlike regression models and the scaling technique, both NRCS and VIR methods require some physical knowledge of the catchments to estimate lags and time of concentration. Information such as slope, hydraulic length and ponded area are all simple parameters easy to determine and should not preclude the use of either method. Examination of contour mapping should provide the basic physical catchment characteristics required.

All four methods have simple computational requirements. With a known or estimated Q_{tot}, an estimation of Q_p can be obtained by simple calculation using regression models. If no local calibration is undertaken, simple calculation allows estimations of Q_p to be obtained using the scaling technique. The NRCS method is only marginally more complicated, and with the assistance of tables of coefficients, the majority of the method is reduced to simple calculation. The GOSH Software used to implement the VIR method has very basic computational requirements by modern standards, and the input files are easily compiled by simple spreadsheet packages, which can also be utilised to perform routing calculations (Yu, 1997).

In this study, the NRCS method was the least suitable for the estimation of Q_p. In contrast, someone seeking to estimate Q_p in an ungauged catchment should not exclude multiple regression models, the scaling technique, or the VIR method on the basis of performance. The optimal method is likely to be determined by data availability and the experience and proficiency of the user. If these methods were being implemented in catchments with dissimilar climate, geography or land use to the catchments in this study, an ensemble modelling approach should be undertaken. Comparison of Q_p estimates from multiple methods provides a simple check on their validity and improves confidence, particularly in ungauged catchments where no data exists to undertake model validation.

4.3. Spatially deriving Q_p to operationalise MUSLE in Dynamic SedNet

As the scaling technique was the best method to estimate Q_p, using it to parameterise MUSLE in place of RUSLE in Dynamic SedNet would be appropriate. It would also be appropriate given its success at other sites in south-east Queensland (Yu et al., 1997a), southern Queensland (Yu, 2020), central Queensland (Fentie et al., 2002), and Asia (Yu and Rose, 1999). Additionally, it is likely the only method that has a real chance of being applied in a consistent manner throughout the subcatchments of the Great Barrier Reef (Yu, 2020). Operationalising MUSLE in place of RUSLE in Dynamic SedNet is likely to improved model performance across Great Barrier Reef catchments given its success when tested at the small catchment scale using Brigalow Catchment Study data. Across all catchments and land uses, comparison of observed event-based erosion with estimates of erosion generated with MUSLE gave an average R^2 of 0.65, compared to estimates of erosion generated with RUSLE which gave an average R^2 of 0.07 (Tiwari et al., 2021). Operationalising this change would require spatially derived measures of total runoff volume, total rainfall, peak rainfall intensity (typically derived from six-minute or shorter time step data) and an assessment of an appropriate scaling parameter for each Functional Unit represented in Dynamic SedNet. A Functional Unit is the smallest scale of subcatchment, about 65 km^2, based on common hydrological and water quality response or characteristic (McCloskey et al., 2021b). As discussed, in general terms these are easily obtainable parameters. In this specific example, the following approaches could be used for parameterisation.

Within Dynamic SedNet, an estimate of total runoff volume is generated for each Functional Unit via the Sacramento rainfall runoff model and is therefore immediately available for use with the scaling technique (McCloskey et al., 2021b). Daily rainfall data used within Dynamic SedNet is obtained from SILO, a collaboration which includes the Australian Bureau of Meteorology who, as discussed, provide six-minute interval rainfall data on request (Bureau of Meteorology, 2019; McCloskey et al., 2021b; Queensland Government, 2019). This time-step of sub-daily rainfall data is the preferred input for the scaling technique (Yu et al., 1997a). This collaboration can therefore provide both total rainfall and rainfall intensity parameters.

An appropriate scaling parameter is the only input to the scaling technique not immediately available for each Functional Unit within Dynamic SedNet. This study and that of Fentie et al. (2002), both conducted within a Great Barrier Reef catchment of central Queensland, provide two sources of scaling parameters. Scaling parameters have also been determined for sites in south-east Queensland (Yu et al., 1997a) and southern Queensland (Yu, 2020), while estimates of generic scaling factors based on data from six sites in Australia and South-East Asia are given in Yu and Rose (1999).

Given the reduction in NSE in this study when using the average scaling parameter in place of the individual catchment and stage scaling parameters, and the observation that scaling parameters vary with catchment area, there is value in undertaking local optimisation of scaling parameters where possible (Yu, 2020). Existing programs for the continuous improvement of Dynamic SedNet could also be used to optimise scaling parameters. These programs are integrated into the modelling framework that supports the Reef 2050 Long-Term Sustainability Plan 2021–2025 and the Reef 2050 Water Quality Improvement Plan 2017–2022 and are referred to in totality as the Paddock to Reef Integrated Monitoring, Modelling and Reporting program (Paddock to Reef program) (Carroll et al., 2012; Commonwealth of Australia, 2021; The State of Queensland, 2018; Waterhouse, 2018). Within the Paddock to Reef program, the calibration, validation and improvement of models is underpinned by numerous real-world field monitoring studies, including the Brigalow Catchment Study. The optimisation of scaling parameters in this study and the numerical assessment of model performance can be replicated for all Paddock to Reef monitoring studies in the same manner as done for this study to provide yet another source of scaling parameters. This has the benefit of all the input data having been collected from multiple sites and industries within Great Barrier Reef catchments. This includes horticulture and sugarcane in the Burnett Mary region (Nachimuthu et al., 2016; Nachimuthu et al., 2017), grain and grazing in the Fitzroy region (Elledge and Thornton, 2017; Murphy et al., 2013; Thornton and Elledge, 2021), sugarcane in the Mackay Whitsunday and Wet Tropics regions, and bananas in the Wet Tropics region (Department of Resources, 2021). Scaling parameters could also be derived from Paddock to Reef rainfall simulation trials conducted on grazing and sugarcane paddocks throughout the Great Barrier Reef catchments (Cook et al., 2021; Department of Resources, 2021; Melland et al., 2022). Calibration of erosion estimates from MUSLE in Dynamic SedNet could be undertaken using the same approach as currently employed for estimates from RUSLE in Dynamic SedNet. That is, manual calibration of Dynamic SedNet to best match measured end-of-system and sub-basin loads provided by the Great Barrier Reef Catchment Loads Monitoring Program (Turner et al., 2013). A detailed explanation of the manual calibration of Dynamic SedNet undertaken as part of the continuous improvement approach is given in McCloskey et al. (2021b).

5. Conclusions

The aim of this study was to evaluate the suitability of four simple methods to estimate peak runoff rate in small (12–17 ha) catchments with land uses of virgin brigalow scrub, cropping or grazing in the semi-arid subtropical Brigalow Belt bioregion of central Queensland, Australia. This was a research priority to facilitate the continuous improvement of the Dynamic SedNet model, which was used for estimating erosion in the modelling framework which supports the Reef 2050 Long-Term Sustainability Plan 2021–2025 and the Reef 2050 Water Quality Improvement Plan 2017–2022. The four methods evaluated were (1) multiple regression models, (2) the scaling technique, (3) the Natural Resources Conservation Service curve number and graphical peak discharge method, and (4) the variable infiltration rate method. Numerical assessment of estimated peak runoff rate compared to observed peak runoff rate both pre- and post-land clearing gave R^2 greater than 0.8 irrespective of method. Numerical assessment using the Nash-Sutcliffe coefficient of efficiency showed that the best estimations of peak runoff rate were obtained using the scaling technique, then the variable infiltration rate method, then multiple regression models. The Nash-Sutcliffe coefficient of efficiency for estimations of peak runoff rate using the Natural Resources Conservation Service method were typically negative, rendering the method unsuitable for use at the tens of hectares scale in the Brigalow Belt bioregion. All methods typically gave better estimations pre-clearing when the catchments contained virgin brigalow scrub. This is likely due to the smaller variability in catchment hydrology compared to their changed dynamics when converted to land uses of cropping or grazing.

None of the four methods should be excluded on the basis of data requirements. Parameterisation is a straightforward task for all methods, utilising widely available rainfall data, measured runoff volume data or alternatively, an estimate of runoff volume obtained from one or more widely available models, and basic physical descriptors of the catchment. Where possible, an ensemble modelling approach provides a simple check on the validity of Q_p estimates. This improves confidence, particularly in ungauged catchments where no data exists to undertake model validation.

Improving erosion predictions from Dynamic SedNet by operationalising MUSLE in place of RUSLE requires spatially derived estimates of Q_p. These estimates are best obtained using the scaling technique. It had the best numerical performance of all methods, and three of the four input parameters are immediately available. The fourth is available from published literature but could also be calculated from plot and small catchment studies monitoring rainfall and runoff. Such data is collected by the Paddock to Reef Integrated Monitoring, Modelling and Reporting program specifically for the purpose of calibrating, validating, and improving the suite of models, including Dynamic SedNet, in the framework that underpins the Reef 2050 Long-Term Sustainability Plan 2021–2025 and the Reef 2050 Water Quality Improvement Plan 2017–2022.

Declaration of funding

This study was funded by the Queensland Department of Environment and Science, the Queensland Department of Resources, and the Australian and Queensland Governments Paddock to Reef Integrated Monitoring, Modelling and Reporting program.

CRediT authorship contribution statement

C.M. Thornton: Conceptualization, Methodology, Investigation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **B. Yu:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

Many staff have contributed to the design and execution of the Brigalow Catchment Study. We thank you H Pauli, J Rosser, A Webb, P Lawrence, R Bryant, A Dowling, H Hunter, N Cocaris, J Kalnins, R Scarborough, R Pushmann, R Gillespie, D Sinclair, B Kitchen, A Key, P Hansen, G Thomas, E Anderson, P Back, D Miles, W Burrows, M Nasser, A Lloyd, A Barnes, M Jeffery, T James, N Purvis-Smith, B Radford, B Cowie, D Reid, A Elledge and staff of the former Department of Primary Industries Brigalow Research Station.

References

Australian Government - Geoscience Australia (2006) Appendix M - The Geocentric Datum of Australia. Available at: ⟨http://www.ga.gov.au/mapspecs/250k100k/appendix_m.html⟩ [accessed 19 November 2019].
Boughton, W.C., 1989. A review of the USDA SCS curve number method. Aust. J. Soil Res. 27 (3), 511–523. DOI:10.1071/SR9890511.
Brakenseik, D.L., Osborn, H.B., Rawls, W.J., 1979. Field Manual for Research in Agricultural Hydrology. Agriculture handbook No. 224. United States Department of Agriculture. U.S. Govt. Print. Office,, Washington DC.
Brent, R.P., 1973. Algorithms for Minimisation without Derivatives. Prentice-Hall,, Englewood Cliffs, N.J.
Bureau of Meteorology (2019) Climate and oceans data and analysis. Available at: ⟨http://www.bom.gov.au/climate/data-services/⟩ [accessed 19 November 2019].
Cao, H., Vervoort, R.W., Dabney, S.M., 2011. Variation in curve numbers derived from plot runoff data for New South Wales (Australia). Hydrol. Process. 25 (24), 3774–3789. DOI:doi:10.1002/hyp.8102.
Carroll, C., et al., 2012. A Paddock to reef monitoring and modelling framework for the Great Barrier Reef: Paddock and catchment component. Mar. Pollut. Bull. 65 (4–9), 136–149. DOI:10.1016/j.marpolbul.2011.11.022; 10.1016/j.agee.2012.02.002; Williams, M., Longstaff, B., Buchanan, C., Llanso, R., Dennison, W.,

Development and evaluation of spatially-explicit index of Chesapeake bay health (2009) Marine Pollution Bulletin, 59, pp. 14-25; Yang, X., Integrated use of remote sensing and geographic information systems in riparian vegetation delineation and mapping (2007) International Journal of Remote Sensing, 28, pp. 353-370.
Carroll, C., Yu, B., 2018, QWMN water model catalogue. A catalogue of water models used by the Queensland Government. October 2017.
Chiew, F.H.S., McMahon, T.A., 1993. Assessing the adequacy of catchment streamflow yield estimates. Aust. J. Soil Res. 31 (5), 665–680.
Chow, V.T., Maidment, D.R., Mays, L.W., 1988. Applied Hydrology. McGraw-Hill,, United States of America.
Commonwealth of Australia, 2021. Reef 2050 Long-Term Sustainability Plan 2021-2025. Canbera, ACT,.
Connolly, R.D., Ciesiolka, C.A.A., Silburn, D.M., Carroll, C., 1997. Distributed parameter hydrology model (Answers) applied to a range of catchment scales using rainfall simulator data. IV. Evaluating pasture catchment hydrology. J. Hydrol. 201 (1–4), 311–328. DOI:10.1016/S0022-1694(97)00052-8.
Cook, F.J., Bosomworth, B., Melland, A.R., Silburn, D.M., Eyles, M., 2021. Solutes in runoff under simulated rainfall on fertilised sugarcane (Saccharum sp.) beds: Measurements and results. Agric., Ecosyst. Environ. 313, 107343. DOI:https://doi.org/10.1016/j.agee.2021.107343.
Cowie, B.A., Thornton, C.M., Radford, B.J., 2007. The Brigalow Catchment Study: I. Overview of a 40-year study of the effects of land clearing in the brigalow bioregion of Australia. Aust. J. Soil Res. 45, 479–495.
Department of Resources (2021) Great Barrier Reef Paddock and Catchment Science. Available at: ⟨https://apps.information.qld.gov.au/StoryMaps/GBR_PaddockCatchmentScience/⟩ [accessed 8 June 2023].
Dilshad, M., Peel, L.J., 1994. Evaluation of the USDA curve number method for agricultural catchments in the Australian semi-arid tropics. Aust. J. Soil Res. 32 (4), 673–685.
Dowling, A.J., Webb, A.A., Scanlan, J.C., 1986. Surface soil chemical and physical patterns in a brigalow- Dawson gum forest, central Queensland. Aust. J. Ecol. 11 (2), 155–162.
Elledge, A., Thornton, C., 2017. Effect of changing land use from virgin brigalow (*Acacia harpophylla*) woodland to a crop or pasture system on sediment, nitrogen and phosphorus in runoff over 25 years in subtropical Australia. Agric., Ecosyst. Environ. 239, 119–131. DOI:https://doi.org/10.1016/j.agee.2016.12.031.
Fentie, B., Yu, B., Silburn, M.D., Ciesiolka, C.A.A., 2002. Evaluation of eight different methods to predict hillslope runoff rates for a grazing catchment in Australia. J. Hydrol. 261 (1), 102–114. DOI:https://doi.org/10.1016/S0022-1694(02)00017-3.
Fernandez, G.P., Garbrecht, J., 1994. Effect of trends and long-term fluctuations of rainfall on watershed runoff. Trans. Am. Soc. Agric. Eng. 37 (6), 1841–1844.
Freebairn, D.M., Boughton, W.C., 1981. Surface runoff experiments on the eastern Darling Downs (Greenmount, Australia). Aust. J. Soil Res. 19 (2), 133–146.
Hawkins, R.H., 1973. Improved prediction of storm runoff in mountain watersheds. J. Irrig. Drain. Div. 99 (4), 519–523.
Hawkins, R.H., 1993. Asymptotic determination of runoff curve numbers from data. J. Irrig. Drain. Eng. - ASCE 119 (2), 334–345.
Hrachowitz, M., et al., 2013. A decade of Predictions in Ungauged Basins (PUB)-a review. Hydrol. Sci. J. 58 (6), 1198–1255. DOI:10.1080/02626667.2013.803183.
Isbell, R.F., 1996. The Australian Soil Classification. CSIRO Publishing,, Collingwood, Victoria.
Jodar-Abellan, A., Valdes-Abellan, J., Pla, C., Gomariz-Castillo, F., 2019. Impact of land use changes on flash flood prediction using a sub-daily SWAT model in five Mediterranean ungauged watersheds (SE Spain). Sci. Total Environ. 657, 1578–1591. DOI:https://doi.org/10.1016/j.scitotenv.2018.12.034.
Johnson, R.W., 2004. Vegetation survey of the Brigalow Research Station, Theodore, Queensland. Proc. R. Soc. Qld. 111, 39–61.
Kisters (2014) Hydstra/TS Time Series Data Management V10.4. Available at: ⟨http://www.kisters.com.au⟩ [accessed 19 November 2019].
Krause, P., Boyle, D.P., Bäse, F., 2005. Comparison of different efficiency criteria for hydrological model assessment. Adv. Geosci. 5, 89–97.
Lawrence, P.A., Sinclair, D.P., 1989. Catchment hydrology and soil loss. In: Lawrence, P.A., Thorburn, P.J. (Eds.), Changes in Hydrology, Soil Fertility and Productivity of Brigalow Catchments Following Clearing. Department of Primary Industries Departmental Report RQR89002, Queensland, pp. 2.5–2.90.
Legates, D.R., McCabe, G.J., Jr, 1999. Evaluating the use of 'goodness-of-fit' measures in hydrologic and hydroclimatic model validation. Water Resour. Res. 35 (1), 233–241. DOI:10.1029/1998WR900018.
Lørup, J.K., Refsgaard, J.C., Mazvimavi, D., 1998. Assessing the effect of land use change on catchment runoff by combined use of statistical tests and hydrological modelling: Case studies from Zimbabwe. J. Hydrol. 205 (3–4), 147–163. DOI:10.1016/S0168-1176(97)00311-9.
Lyon, S.W., Walter, M.T., Gerard-Marchant, P., Steenhuis, T.S., 2004. Using a topographic index to distribute variable source area runoff predicted with the SCS curve-number equation. Hydrol. Process. 18 (15), 2757–2771. DOI:10.1002/hyp.1494.
McCloskey, G.L. et al., 2017b, Modelling pollutant load changes due to improved management practices in the Great Barrier Reef catchments: updated methodology and results – Technical Report for Reef Report Cards 2015, Brisbane, Queensland.
McCloskey, G.L. et al., 2017a, Modelling pollutant load changes due to improved management practices in the Great Barrier Reef catchments: updated methodology and results – Technical Report for Reef Report Cards 2014, Brisbane, Queensland.
McCloskey, G.L., et al., 2021a. Modelled estimates of dissolved inorganic nitrogen exported to the Great Barrier Reef lagoon. Mar. Pollut. Bull. 171, 112655. DOI:https://doi.org/10.1016/j.marpolbul.2021.112655.
McCloskey, G.L., et al., 2021b. Modelled estimates of fine sediment and particulate nutrients delivered from the Great Barrier Reef catchments. Mar. Pollut. Bull. 165, 112163. DOI:https://doi.org/10.1016/j.marpolbul.2021.112163.
Melland, A.R., Bosomworth, B., Cook, F.J., Silburn, D.M., Eyles, M., 2022. Impacts of sugarcane (Saccharum sp.) soil and fertiliser management practices on nutrients and sediment in plot-scale runoff from simulated rainfall. Soil Tillage Res 216, 105259. DOI:https://doi.org/10.1016/j.still.2021.105259.
Mockus, V., 1949. Estimation of total (and peak rates of) surface runoff for individual storms. Exhibit A of Appendix B. Interim Survey Report Grand (Neosho) River Watershed. U.S. Gov. Print Office,, Washington, D.C.
Murphy, T., Dougall, C., Burger, P., Carroll, C., 2013. Runoff water quality from dryland cropping on Vertisols in Central Queensland, Australia. Agric., Ecosyst. Environ. 180, 21–28.
Nachimuthu, G., Halpin, N.V., Bell, M.J., 2016. Effect of sugarcane cropping systems on herbicide losses in surface runoff. Sci. Total Environ. 557–558, 773–784. DOI:https://doi.org/10.1016/j.scitotenv.2016.03.105.
Nachimuthu, G., Halpin, N.V., Bell, M.J., 2017. Impact of Practice Change on Runoff Water Quality and Vegetable Yield—An On-Farm Case Study. Agriculture 7 (3), 30.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I - A discussion of principles. J. Hydrol. 10 (3), 282–290.
Patil, S., Stieglitz, M., 2014. Modelling daily streamflow at ungauged catchments: What information is necessary? Hydrol. Process. 28 (3), 1159–1169.
Patil, S.D., Wigington, P.J., Leibowitz, S.G., Comeleo, R.L., 2014. Use of hydrologic landscape classification to diagnose streamflow predictability in Oregon. J. Am. Water Resour. Assoc. 50 (3), 762–776.
Post, D.A., Jakeman, A.J., 1999. Predicting the daily streamflow of ungauged catchments in S.E. Australia by regionalising the parameters of a lumped conceptual rainfall-runoff model. Ecol. Model. 123 (2–3), 91–104.
Press, W.H., Flannery, B.P., Teukolsky, S.A., Vetterling, W.T., 1989. Numerical Recipes: The art of scientific computing (FORTRAN version). Cambridge University Press,, New York.
Queensland Government (2019) SILO Patched Point Datasets for Queensland. Available at: ⟨https://data.qld.gov.au/dataset/silo-patched-point-datasets-for-queensland⟩ [accessed 19 November 2019].
Radford, B.J., Thornton, C.M., Cowie, B.A., Stephens, M.L., 2007. The Brigalow Catchment Study: III. Productivity changes on brigalow land cleared for long-term cropping and for grazing. Aust. J. Soil Res. 45 (7), 512–523.
Rallison, R.E., 1980. Origin and Evolution of the SCS Runoff Equation, Symposium on Watershed Management. American Society of Civil Engineers,, Boise, Idaho, pp. 912–924.
Refsgaard, J.C., Knudsen, J., 1996. Operational validation and intercomparison of different types of hydrological models. Water Resour. Res. 32 (7), 2189–2202. DOI:10.1029/96WR00896.
Rosewell, C.J., 1986. Rainfall kinetic energy in eastern Australia. J. Clim. Appl. Meteorol. 25 (11), 1695–1701.
Ross, C.W., et al., 2018. Global Hydrologic Soil Groups (HYSOGs250m) for Curve Number-based Runoff Modeling. Oak Ridge,, Tennessee, USA.

Silburn, D.M., 2011. Hillslope runoff and erosion on duplex soils in grazing lands in semi-arid central Queensland. II. Simple models for suspended and bedload sediment. Soil Res 49 (2), 118–126.

Silburn, D.M., Cowie, B.A., Thornton, C.M., 2009. The Brigalow Catchment Study revisited: Effects of land development on deep drainage determined from non-steady chloride profiles. J. Hydrol. 373 (3–4), 487–498. DOI:10.1016/j.jhydrol.2009.05.012.

Sivapalan, M., et al., 2003. IAHS Decade on Predictions in Ungauged Basins (PUB), 2003-2012: Shaping an exciting future for the hydrological sciences. Hydrol. Sci. J. 48 (6), 857–880. DOI:10.1623/hysj.48.6.857.51421.

The State of Queensland, 2018. Reef. 2050 Water Qual. Improv. Plan 2017-2022.

The State of Queensland (2020) Regional ecosystems. Available at: ⟨https://www.qld.gov.au/environment/plants-animals/plants/ecosystems⟩ [accessed 3 September 2021].

Thornton, C., Radford, B., Silburn, M., Cowie, B., 2010, The Brigalow Catchment Study: More than 20 years of monitoring water balance and soil fertility of brigalow lands after clearing for cropping or pasture, 19th World Congress of Soil Science; Soil Solutions for a Changing World, Brisbane, Queensland, pp. 106–109.

Thornton, C.M., Elledge, A.E., 2016. Tebuthiuron movement via leaching and runoff from grazed Vertisol and Alfisol soils in the Brigalow Belt bioregion of central Queensland, Australia. J. Agric. Food Chem. 64 (20), 3949–3959. DOI:10.1021/acs.jafc.5b05393.

Thornton, C.M., Elledge, A.E., 2021. Heavy grazing of buffel grass pasture in the Brigalow Belt bioregion of Queensland, Australia, more than tripled runoff and exports of total suspended solids compared to conservative grazing. Mar. Pollut. Bull. 171, 112704. DOI:https://doi.org/10.1016/j.marpolbul.2021.112704.

Thornton, C.M., Shrestha, K., 2021. The Brigalow Catchment Study: V. Clearing and burning brigalow (*Acacia harpophylla*) in Queensland, Australia, temporarily increases surface soil fertility prior to nutrient decline under cropping or grazing. Soil Res. 59, 146–169. DOI:https://doi.org/10.1071/SR20088.

Thornton, C.M., Yu, B., 2016. The Brigalow Catchment Study: IV. Clearing brigalow (*Acacia harpophylla*) for cropping or grazing increases peak runoff rate. Soil Res. 54 (6), 749–759. DOI:10.1071/SR15121.

Thornton, C.M., Cowie, B.A., Freebairn, D.M., Playford, C.L., 2007. The Brigalow Catchment Study: II. Clearing brigalow (*Acacia harpophylla*) for cropping or pasture increases runoff. Aust. J. Soil Res. 45, 496–511.

Tiwari, J., Thornton, C., Yu, B., 2021. The Brigalow Catchment Study: VI. Evaluation of the RUSLE and MUSLE Models to assess the impact of clearing brigalow (*Acacia harpophylla*) on sediment yield. Soil Res. 59, 778–793.

Turner, R., et al., 2013. Monitoring to enhance modelling–A loads monitoring program for validation of catchment models, MODSIM2013, 20th International Congress on Modelling and Simulation. Model. Simul. Soc. Aust. N. Z. 3253–3259.

U.S. Department of Agriculture (1973) A method for estimating volume and rate of runoff in small watersheds. Technical paper Tp-149. Available at: ⟨https://www.wcc.nrcs.usda.gov/ftpref/wntsc/H&H/TRsTPs/TP149.pdf⟩ [accessed 19 November 2019].

U.S. Department of Agriculture, 1983. Computer Program for Project Formulation-hydrology. Technical Release TR-20. U.S. Department of Agriculture,, Washington, DC.

U.S. Department of Agriculture (1986) Urban hydrology for small watersheds. Technical Release TR-55. Available at: ⟨https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1044171.pdf⟩ [accessed 19 November 2019].

U.S. Department of Agriculture (2004) National Engineering Handbook (NEH) Part 630 Hydrology. Chapter 10. Estimation of direct runoff from storm rainfall. Available at: ⟨https://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/water/manage/hydrology/?cid=stelprdb1043063⟩ [accessed 19 November 2019].

U.S. Department of Agriculture (2015) National Engineering Handbook (NEH) Part 630 Hydrology. Chapter 4. Storm rainfall depth and distribution (draft). Available at: ⟨https://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/water/manage/hydrology/?cid=stelprdb1043063⟩ [accessed 19 November 2019].

Van Mullem, J.A., Woodward, D.E., Hawkins, R.H., Hjelmfelt, A.T., Jr., 2002, Runoff curve number method: beyond the handbook, Second Federal Interagency Hydrologic Modeling Conference; Hydrologic Modeling for the 21st Century, Las Vegas, Nevada, pp. 1–10.

VSN International (2011) Genstat V14.1. Available at: ⟨https://www.vsni.co.uk/software/genstat/⟩ [accessed 19 November 2019].

Ward, A., 1995. Environmental Hydrology. CRC Press, Inc.,, United States of America.

Waterhouse, J., 2018, Paddock to reef integrated monitoring, modelling and reporting (Paddock to Reef) program design, 2018–2022. Queensland Government, Queensland.

Webb, A.A., 1971. Soil survey of Brigalow Research Station. Queensland Department of Primary Industries,, Brisbane, Queensland.

Wilkinson, S.N., et al., 2014. Development of a time-stepping sediment budget model for assessing land use impacts in large river basins. Sci. Total Environ. 468–469, 1210–1224. DOI:https://doi.org/10.1016/j.scitotenv.2013.07.049.

Woodward, D.E., Hawkins, R.H., Hjelmfelt, A., Van Mullem, J., Quan, Q.D., 2002, Curve number method: Origins, applications and limitations, Second Federal Interagency Hydrologic Modeling Conference; Hydrologic Modeling for the 21st Century, Las Vegas, Nevada, pp. 1–10.

Yu, B., 1997. GOSH 1.2: A Program for Calculating Runoff Rates Given Rainfall Rates and Runoff Amount. Faculty of Environmental Sciences, Griffith University, Nathan, Australia.

Yu, B., 1999. A comparison of the green-ampt and a spatially variable infiltration model for natural storm events. Trans. Am. Soc. Agric. Eng. 42 (1), 89–97.

Yu, B., 2020, Prediction of cover-dependent runoff amount and peak runoff rate for grazing land in Queensland. Final Report., Queensland.

Yu, B., Rose, C.W., 1999. Application of a physically based soil erosion model, GUEST, in the absence of data on runoff rates I. Theory and methodology. Aust. J. Soil Res. 37 (1), 1–11.

Yu, B., Rosewell, C.J., 1998. RECS: A program to calculate the R-factor for the USLE/RUSLE using BOM/AWS pluviograph data. Faculty of Environmental Sciences. Griffith University,.

Yu, B., Rose, C.W., Ciesiolka, C.A.A., Coughlan, K.J., Fentie, B., 1997a. Toward a framework for runoff and soil loss prediction using GUEST technology. Aust. J. Soil Res. 35 (5), 1191–1212.

Yu, B., Rose, C.W., Coughlan, K.J., Fentie, B., 1997b. Plot-scale rainfall-runoff characteristics and modeling at six sites in Australia and Southeast Asia. Trans. Am. Soc. Agric. Eng. 40 (5), 1295–1303.

Yu, B., Cakurs, U., Rose, C.W., 1998. An assessment of methods for estimating runoff rates at the plot scale. Trans. Am. Soc. Agric. Eng. 41 (3), 653–661.

Yu, B., Rose, C.W., Yin, D., Anecksamphat, C., 1999. Re-interpretation of USLE datasets for physically based erosion models with examples from southern China and northern Thailand. In: Stott, D.E., Mohtar, R.H., Steinhardt, G.C. (Eds.), Sustaining the global farm. Selected papers from the 10th International Soil Conservation Organisation Meeting. International Soil Conservation Organization in cooperation with the USDA and Purdue University, West Lafayette, Indiana, pp. 929–934.

Yu, B., Ciesiolka, C.A.A., Rose, C.W., Coughlan, K.J., 2000a. A validation test of WEPP to predict runoff and soil loss from a pineapple farm on a sandy soil in subtropical Queensland, Australia. Aust. J. Soil Res. 38 (3), 537–554.

Yu, B., Sombatpanit, S., Rose, C.W., Ciesiolka, C.A.A., Coughlan, K.J., 2000b. Characteristics and modeling of runoff hydrographs for different tillage treatments. Soil Sci. Soc. Am. J. 64 (5), 1763–1770.

Thornton, C.M., 2012. Effects of land development on peak runoff rate and its prediction for brigalow catchments in central Queensland, Australia. Master's Thesis, Griffith University. DOI:https://doi.org/10.25904/1912/744.