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A new empirical model of sub-daily rainfall intensity and its application in a rangeland biophysical model

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Abstract. Sub-daily rainfall intensity has a significant impact on runoff and erosion rates in northern Australian rangelands. However, it has been difficult to include sub-daily rainfall intensity in rangeland biophysical models using historical climate data due to the limited number of pluviograph stations with long-term records. In this paper a new empirical model ('Temperature I15' model) was developed to predict the daily maximum 15-min rainfall intensity (I15) using daily minimum and maximum temperature and daily rainfall totals from 12 selected pluviograph stations across Australia. The 'Temperature I15' model accounted for 46% ($P < 0.01$) of the variation in observed daily I15 for an independent validation dataset derived from 67 Australia-wide pluviograph stations and represented both geographical and seasonal variability in I15. The model also accounted for 70% ($P < 0.01$) of the variation in the observed historical trend in I15 for the full record period (average record period was 37 years) of 73 Australia-wide pluviograph stations.

The 'Temperature I15' model was found to be an improvement on a past empirical model of I15 and can be easily implemented in biophysical models by using readily available daily climate data. However, as the 'Temperature I15' model only represented 46% of the variation in daily observed I15, the model is best used in simulation studies on 'timeframes' in excess of 5 years.

The new 'Temperature I15' model was implemented in the runoff equation of the Australia-wide spatial pasture growth model AussieGRASS, which predicts daily water balance and pasture growth for 185 different pasture communities. This resulted in an improved simulation of green cover for 71% of pasture communities but was worse for 25% of communities, with no change for 4% of communities.

Additional keywords: Australian rangelands, climate change, hydrological factors, precipitation intensity, runoff water, soil erosion.

Introduction

The degradation of Australian rangelands and downstream impacts from excessive runoff and erosion has been well documented (Tothill and Gillies 1992; Rogers *et al*. 1999; Pringle and Tinley 2003; McKeon *et al*. 2004; Pringle *et al*. 2006). Hillslope scale runoff and erosion can have a range of impacts including loss of pasture productivity (Miles 1993; Silburn *et al*. 2011), deposition of disaggregated sediment ready for remobilisation in larger events (Bartley *et al*. 2007) and increased sediment loads in river systems (Packett *et al*. 2009) which, in Queensland, has led to increased sediment deposition on near-shore reefs (Brodie *et al*. 2003; McKergow *et al*. 2005). The results of these studies has led to an increased focus on grazing land management practices and their impacts on hillslope runoff and erosion rates (e.g. O'Reagain *et al*. 2005; Bartley *et al*. 2010). One approach to developing sustainable management practices is to assess management options using grazing systems models (e.g. GRASP – GRASs Production, Rickert *et al*. 2000). These models can assess the impacts of grazing management on hillslope runoff, soil erosion and animal production attributes over long timeframes (>100 years) thereby accounting for long-term climate variability (McKeon *et al*. 2000, 2004; McIntosh *et al*. 2005). To undertake these studies, grazing system models need to adequately represent physical processes that determine hillslope runoff and erosion rates.

Sub-daily rainfall intensity – importance and use in models

Sub-daily rainfall intensity has been found to be a key factor in determining hillslope scale runoff in several field studies in Australian grazing and cropping lands (Freebairn and Wockner 1986; Scanlan *et al*. 1996; Fraser and Waters 2004; Waters 2004). Several studies have found that models which are based on sub-daily rainfall intensities, give more accurate estimates of daily runoff and soil loss than models which are based on daily rainfall (Freebairn *et al*. 1996; Fentie *et al*. 2002). However, there are limited long-term measurements of sub-daily rainfall intensity in Australia with only 184 pluviograph stations having records exceeding 30 years.

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Various options have been employed to estimate sub-daily rainfall intensity. For example, this problem has been addressed in other countries by using estimates of sub-daily rainfall intensity generated by stochastic climate models such as CLIGEN (CLImate GENerator), as input for, agricultural production-runoff-erosion system models such as SWAT (Surface Water Assessment Tool) and WEPP (Water Erosion Prediction Project). However, Yu (2005) indicated that there are limitations in applying sub-daily stochastic models across Australia, given the poor spatial distribution of long-term pluviograph stations.

In Australia the grazing systems model GRASP, has used sub-daily rainfall intensity estimates, based on a 'time-of-year' model developed by Scanlan *et al*. (1996). The 'time-of-year' model estimates sub-daily rainfall intensity by multiplying the daily rainfall total by a constant for a given Julian day. The fixed Julian day constant is derived from a cosine wave with the maximum values representing summer and the minimum values representing winter. However, in order to account for changes in sub-daily rainfall intensity between locations the model needs to be parameterised against observed sub-daily rainfall intensity on a site-by-site basis.

Although, maximum sub-daily rainfall intensities can be estimated for any location in Australia from manuals which provide intensity-frequency-duration curves for recurrence intervals of 1–100 years (e.g. Australian Rainfall and Runoff, Pilgrim 1987), these estimates are temporally too coarse to be applied in daily time-step agricultural systems modelling.

Another option may be to interpolate sub-daily rainfall records. However, this would not overcome the limitation of the short length of records. Furthermore, given the low number of pluviograph stations with long-term records, spatial interpolation of sub-daily rainfall intensities across Australia is likely to be problematic and probably, for this reason, has not been attempted (unlike daily rainfall for which there are ~8000 stations with records exceeding 30 years).

Given the limited options to obtain estimates of sub-daily rainfall on a comparable spatial and temporal scale to daily climate records in Australia, in this paper we explore the possibility of deriving estimates of sub-daily rainfall intensity from historical daily climate data records. Daily climate records are readily available (e.g. DERM and BoM 2011) and have been interpolated across Australia on a daily time-step basis from 1889 to the present (Jeffrey *et al*. 2001). Meteorological studies in other countries have found that storm prediction and sub-daily rainfall intensity rates were related to other more commonly measured meteorological variables such as humidity and temperature (e.g. Eltahir and Pal 1996; Lenderink and Van Meijgaard 2008, 2010). In this study we hypothesised that sub-daily rainfall intensity could be related to daily rainfall amount and other climate elements related to synoptic scale processes (e.g. convection).

Characterising sub-daily rainfall intensity

The daily maximum 15-min rainfall intensity (I15) is one measurement of sub-daily rainfall intensity that has been found to be important for modelling hillslope runoff and erosion rates in northern Australia rangelands (e.g. Scanlan *et al*. 1996; Fraser and Waters 2004). Observations of I15 vary markedly from location to location across Australia. For example, considering a north–south transect in eastern Australia, the average I15 on days when the daily rainfall exceeded 15 mm are 41 mm/h in tropical north Queensland (Thursday Island, −10°35′S, 142°13′E); 30 mm/h in sub-tropical Queensland (Samford, −27°22′S, 152°53′E); 18.5 mm/h in temperate New South Wales (Scone, −32°4′S, 150°56′E); and 12 mm/h in Tasmania (Hobart, −42°50′S, 147°30′E). Observations of I15 also vary seasonally for a given location with summer months generally having the highest recorded I15 values. For example, at Tamworth (−31°5′S, 150°51′E) the summer average I15 is 22 mm/h in contrast to the winter average I15 of 7 mm/h. At Kingaroy (−26°33′S, 151°51′E) the summer average I15 is 40 mm/h compared to the winter average of 15 mm/h.

Study outline

The aim of this study is to estimate historical I15 values on a daily basis for any location in the northern Australian rangelands (north of latitude −27°28′S). These values can then be used as an input for the GRASP model, thereby increasing the utility of this model in assessing runoff and erosion in northern Australian rangelands.

In this study we describe the development of an I15 model based on daily rainfall, daily diurnal temperature range and daily minimum temperature. We then describe the validation of this I15 model using an independent dataset. The robustness of the I15 model was then assessed by testing its capacity to represent observed geographical, seasonal and temporal variability in I15. The performance of the I15 model was also compared to a 'time-of-year' I15 model which had previously been used in GRASP. The degree to which errors in representing I15 are propagated to errors in calculated runoff was then tested for time periods of 1−10 years. Finally, the I15 model was incorporated in an Australia-wide spatial implementation of the point scale GRASP model (AussieGRASS – Australian Grassland and Rangeland Assessment by Spatial Simulation, Carter *et al*. 2000). We assess whether the inclusion of this new I15 model leads to an improved simulation of green cover, which has been 'observed' continentally by satellite. This is currently the only model test against observed data which can be made at a continental scale (on a 5 × 5-km grid) and any improvement in the AussieGRASS models simulation of green cover may imply an improvement in the simulation of the soil water balance, of which runoff is an important component.

Site selection and data preparation

Selection of I15 calibration sites

Initially the major application of the new I15 model was in northern Australia, which is dominated by high-rainfall intensities in summer, hence 11 sites from northern Australia were selected (north of latitude −27°28′S, Fig. 1*a*). Because northern Australian pastoral regions cover a diverse range of climatic environments (i.e. sub-tropical to arid), an I15 model developed for this area may be applicable at a larger continental scale. For this reason an additional location from southern Australia with a winter-rainfall regime (Hobart) was included in the calibration dataset to test for possible extrapolation to other

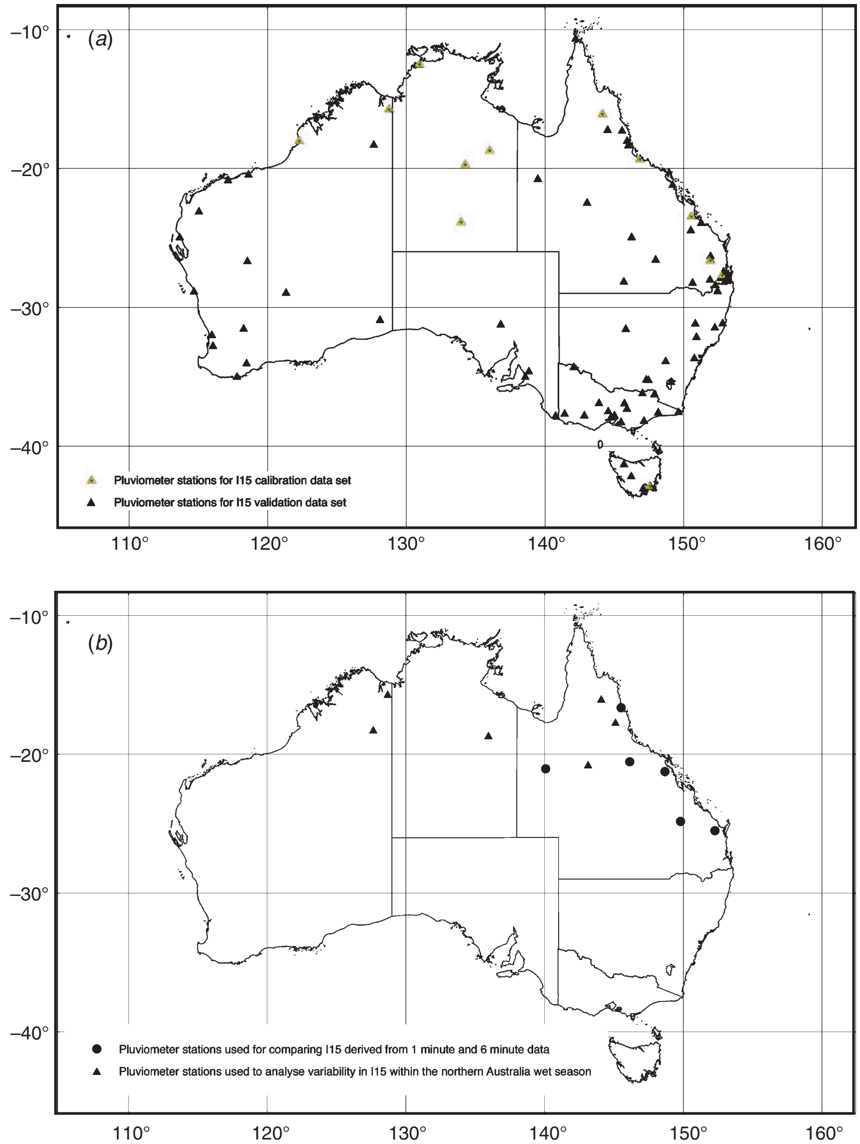

Fig. 1. Pluviometer stations used in this study: (*a*) stations used for the model calibration and validation datasets; (*b*) stations used for comparing I15 derived from 1- and 6-min data, and stations used to analyse variability in I15 within the northern Australia wet season.

locations in the southern rangeland regions. The I15 model was tested across an additional 67 Australia-wide locations which provides a strong independent test of the model.

Extraction of observed I15 and daily climate data

In northern Australia, annual potential evapotranspiration is usually much larger than annual rainfall and hence daily rainfall totals of less than 15 mm often do not produce significant runoff and erosion events (e.g. Scanlan *et al*. 1996). For example we found that in the analysis of two grazing runoff trials undertaken in central Queensland (with more than 145 runoff events) greater than 97% of all recorded runoff occurred on days when the daily rainfall total was greater than or equal to 15 mm. Hence in the study reported here, we developed an I15 model only for days when the daily rainfall total was greater than or equal to 15 mm.

The Bureau of Meteorology pluviograph data have been recorded on a midnight-to-midnight time basis. These records were reformatted to a 9 a.m. to 9 a.m. time period in order to enable comparison with daily rainfall data, which have been recorded at 9 a.m. As part of data quality assurance, the daily total rainfall recorded from the pluviograph record was compared to the independently recorded station daily rainfall total. Errors may occur in both pluviograph and daily climate data records. For example, Yu (2005) reported that for the long-term Sydney pluviograph station there are periods of missing data and obvious discrepancies between daily cumulated pluviograph data and daily rainfall totals. Similarly, errors can occur in daily rainfall records because of simple issues, such as rainfall gauges not being read on Sundays (Viney and Bates 2004). Records were assessed to determine when the daily pluviograph total was within ±5%

of the total daily rainfall reported from the gauge. This arbitrary threshold was chosen as the basis to indicate that the two independent recordings of daily rainfall total were in agreement. Using this threshold, ~70% of all daily rainfall events greater than 15 mm were retained for further analysis.

The Bureau of Meteorology pluviograph data have been recorded as rainfall totals over 6-min time intervals, therefore only allowing indices of rainfall intensity at time periods which are in multiples of 6 min. As we required I15 data in order to be consistent with findings from previous field hydrology studies (e.g. Scanlan *et al*. 1996), for this study, I15 values were estimated by taking the average of the daily maximum I12 and I18 measurements. Field hydrology studies which have measured I15, have often been calculated from pluviometer measurements recorded on a 1-min time interval. In order to test the validity of this averaging approach we examined the 1-min interval recorded rainfall data for six locations across Queensland (Fig. 1*b*). The average record length for these six locations was 8.1 years and when combined, resulted in 645 individual rainfall events greater than or equal to 15 mm. We found that the I15 calculated from 1-min time interval data on these days was on average 2% greater than the I15 estimated from averaging the daily maximum I12 and I18 measurements. On this basis we concluded that averaging the I12 and I18 measurements was an appropriate method to estimate I15 for use in the existing empirical runoff models.

As the daily rainfall is recorded at 9 a.m. each day, the daily climate variables associated with that daily rainfall total, potentially cover 2 calendar days. An analysis of a dataset combining 43 pluviograph stations located across Australia found that 68% of the daily rainfall total fell on the previous day between 9 a.m. and midnight. Thus, climatic variables measured on the day before the recording of the daily rainfall total were more likely to indicate the conditions before, and or during the rainfall event. Daily climate data (minimum temperature and maximum temperature, vapour pressure, solar radiation and pan evaporation) were extracted from the SILO patched-point dataset for each location on the day before the recording of the daily rainfall total.

The importance of a given daily climate variable in determining I15 was analysed using linear regression based on the least-squares method, using the 12 locations (shown in Fig. 1*a*) as a single group. Linear regression analysis was also used to assess the relationships between I15 and the multiplication of two or more daily climate variables.

Model development

The coefficient of determination (r^2) for the linear regression relationships between I15 and a single daily climate variable can be seen in Table 1. Daily rainfall had the strongest correlation with daily I15 of any single climate variable with a coefficient of determination of 0.19 (Table 1).

Analysis of the multiplication of two climate variables indicated that daily rainfall × solar radiation explained 40% of the variation in daily I15, while daily rainfall × diurnal temperature range explained 36% of the variation in daily I15 (Table 2).

In selecting the most appropriate model, some consideration needs to be given to the availability and integrity of historical data. Historical estimates of solar radiation have relied on visual assessment of cloud cover. In Australia, the method for assessing cloud cover changed in 1949 from visual estimates of cloud cover in tenths (e.g. cloud cover estimates derived by segmenting the sky from 1 to 10) to cloud cover estimates in eighths (i.e. from 1 to 8). Rayner *et al*. (2004) found that the solar radiation

Table 1. The coefficient of determination (r^2) between I15 and each individual climate variable

	Maximum temp. (°C)	Minimum temp. (°C)	Diurnal temp. range (°C)	Daily rainfall (mm)	Pan evaporation (mm)	Solar radiation (MJ/m^2)	Vapour pressure (hPa)
I15 (mm/h)	0.18	0.07	0.06	0.19	0.08	0.15	0.09

Table 2. The coefficient of determination (r^2) between I15 and the product of multiplying two daily climate variables together

For example, the coefficient of determination between maximum temperature and I15 was 0.18 and the coefficient of determination between maximum temperature × minimum temperature and I15 was 0.14

	Minimum temperature (T_{min}, °C)	Diurnal temperature range (DTR, °C)	Daily rainfall (DR, mm)	Pan evaporation (PE, mm)	Solar radiation (SR, MJ/m^2)	Vapour pressure (VP, hPa)
Maximum temperatur(°C)	(T_{max} × T_{min}) 0.14	(T_{max} × DTR) 0.10	(T_{max} × DR) 0.29	(T_{max} × PE) 0.11	(T_{max} × SR) 0.17	(T_{max} × VP) 0.15
Minimum temperature (°C)	–	(T_{min} × DTR) 0.15	(T_{min} × DR) 0.22	(T_{min} × PE) 0.09	(T_{min} × SR) 0.16	(T_{min} × VP) 0.08
Diurnal temperature range (°C)	–	–	(DTR × DR) 0.36	(DTR × PE) 0.11	(DTR × SR) 0.11	(DTR × VP) 0.16
Daily rainfall (mm)	–	–	–	(DR × PE) 0.25	(DR × SR) 0.40	(DR × VP) 0.22
Pan evaporation (mm)	–	–	–	–	(PE × SR) 0.12	(PE × VP) 0.10
Solar radiation (MJ/m^2)	–	–	–	–	–	(SR × VP) 0.18

surfaces were systematically lower in the post-1949 period than in the pre-1949 period. It could not be determined whether this represented a climate trend, or a discontinuity associated with the change in observation practice. The possibility of a discontinuity in these data poses a concern in using solar radiation in an empirical model to reconstruct historical I15.

Diurnal temperature range has been used as an indicator of solar radiation (Bristow and Campbell 1984) as the diurnal range in temperature reflects (in part) the amount of energy received at the surface on a daily time scale. Daily rainfall × diurnal temperature range explained almost as much of the variation in I15 (36%), as daily rainfall × solar radiation. As such, given the concerns with the integrity of solar radiation data, diurnal temperature range may be a more robust variable to include in an empirical model, hence, daily rainfall × diurnal temperature range was chosen as the basis of the empirical model. To build on this model, further interactions between daily rainfall × diurnal temperature range and the remaining climate variables were investigated. The three-way interaction, daily rainfall × diurnal temperature range × minimum temperature was found to explain 42% of the variation in I15 across these calibration sites ($P < 0.01$). Thus, daily rainfall, daily diurnal temperature range and daily minimum temperature were the input variables used in the daily I15 model. A single parameter (i.e. coefficient) was optimised to minimise the root mean square error (RMSE).

This model was further refined by applying constraints to the model to minimise errors due to excessively large or small values. The maximum possible I15 for any given day occurs when the total daily rainfall falls within a 15-min time period (at these times I15 = 4 × daily rainfall), hence the empirical model has an upper limit of four times the daily rainfall total. The positive correlation relationship between rainfall and I15 did not continue for rainfall events greater than 100 mm, thus daily rainfall was constrained to a maximum value of 100 mm. Only 3% of all daily rainfall totals exceeded 100 mm. In terms of low values of I15, it was found that I15 was rarely less than one-quarter of the daily rainfall total. This figure is equivalent to one-sixteenth of the daily rainfall total occurring in a 15-min time period, which is approaching the minimum possible I15 wherein the daily rain occurs evenly over 24 h. This constraint also prevents I15 values being negative (or equal to zero) in the event of daily minimum temperatures being less than or equal to zero degrees Celsius. This empirical I15 model will now be referred to as the 'Temperature I15' model.

$$\text{'Temperature I15' Model} : \mathrm{I15}(a) = \text{Minimum Temperature} \times \text{minimum}\ (100,\ \text{Daily Rainfall}) \times \text{Diurnal Temperature Range}/k$$

$$\mathrm{I15}\ (b) = \text{minimum}\ [4 \times \text{Daily Rainfall},\ \mathrm{I15}\ (a)]$$

$$\mathrm{I15} = \text{maximum}\ [0.25 \times \text{Daily Rainfall},\ \mathrm{I15}\ (b)]$$

where I15 is the daily 15-min peak rainfall intensity in mm/h, I15 (*a*) and I15 (*b*) are estimates of daily 15-min peak rainfall intensity in mm/h before applying all the model constraints; Minimum Temperature is the daily minimum temperature in °C; Diurnal Temperature Range is the daily temperature range in °C; Daily Rainfall is the daily rainfall total in mm; *k* is a coefficient which was found to be 150 when optimising to minimise the RMSE between measured and estimated I15.

Daily, seasonal and geographical validation of the 'Temperature I15' model

The validity of the calibrated model was assessed using a further 67 randomly selected Australia-wide independent validation datasets (Fig. 1*a*), which included more than 29 000 daily I15 events. Figure 2 shows the observed I15 and predicted I15 for; five climatologically different locations in Australia (Fig. 2*a–e*); and as a combined dataset consisting of the 67 validation stations (Fig. 2*f*). Figure 2*f* shows that for this large observed I15 dataset, the 'Temperature I15' model represents the monthly variability in I15 and also represents the event size distributions in I15. However, the I15 model only accounts for 46% of the variation in observed daily I15 and hence the model may not predict specific I15 events on a day-to-day basis with a high degree of accuracy. Figure 2*a–e* shows that the results from these five independent validation climate stations were similar to the combined group of 67 validation stations, with the model adequately representing long-term average event class sizes and monthly averages but in some cases only poorly representing individual daily I15 events. These results indicate that the 'Temperature I15' model accounts for long-term monthly averages of I15 and also event class distributions in I15 for a wide variety of climatic regions.

For the 67 validation stations the 'Temperature I15' model's performance over the long-term (average station record length 37 years) was statistically significant ($r^2 = 0.46$, $n > 29\,000$, $P < 0.01$) and the model's capacity to replicate historically observed I15 event size distributions and monthly variability indicates that the model is unlikely to be biased to particular event classes. Due to the limitations of the model to predict individual daily I15, the 'Temperature I15' model is best applied in long-term simulation studies (i.e. 5 years or more, as described later).

Alternative I15 models

The I15 model developed for this study requires the input of daily climate variables, including minimum temperature, diurnal temperature range and daily rainfall amount. These daily climate variables vary systematically across continental Australia and Tasmania, given the range in climate types (wet tropics to winter-dominant rainfall). Such variations in climate may be explained using factors such as 'time of year', latitude, longitude and the distance from the coastline. We evaluate alternative approaches below.

An empirical I15 model which uses the effect of the 'time of year' on I15 has previously been applied in runoff equations within the GRASP grazing systems model (Scanlan *et al.* 1996; Littleboy and McKeon 1997). This general 'time-of-year' I15 model was compared to the new 'Temperature I15' model for several locations in eastern Australia (Townsville, Rockhampton, Kingaroy and Hobart), which represent a range of climatic zones (e.g. tropical, sub-tropical, temperate). For these four stations, the general 'time-of-year' I15 model accounted for 25, 17, 39 and 5% of the variation in I15, respectively, while the new 'Temperature I15' model accounted for more of the variation

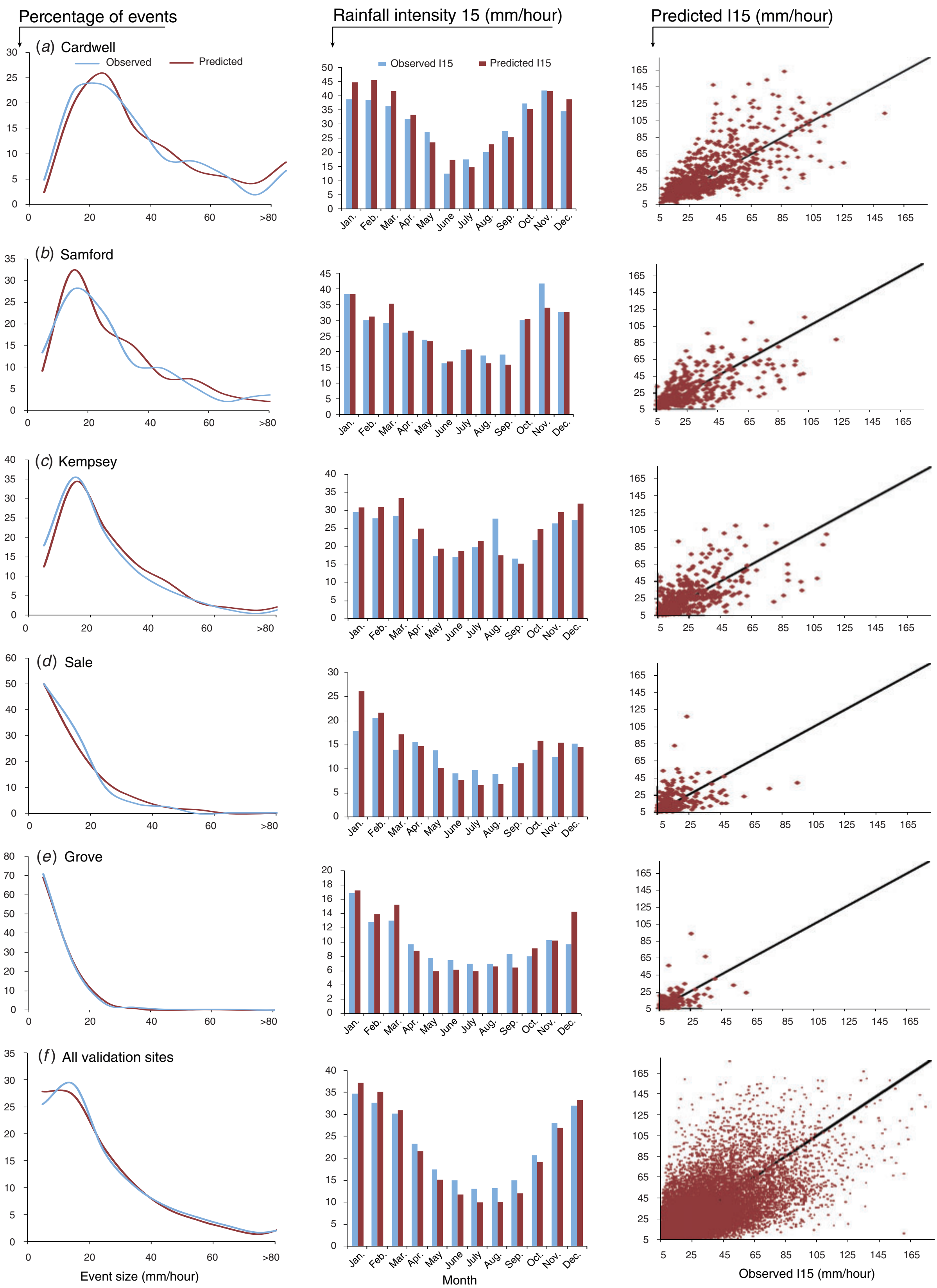

Fig. 2. Observed and predicted I15 event size distributions, seasonal distribution and daily graphs for validation locations (*a*) Cardwell (Qld); (*b*) Samford (Qld); (*c*) Kempsey (NSW); (*d*) Sale (Vic.); (*e*) Grove (Tas.); and (*f*) all 67 validation stations.

(35, 41, 55 and 18%, respectively) (Table 3). An alternative *site-specific* 'time-of-year' model was also tested using optimised parameters based on minimising the RMSE for each location. Fitting the optimised parameters to the *site-specific* 'time-of-year' model only explained slightly more of the variation but substantially improved the RMSE. The new 'Temperature I15' model, (which does not include any site specific calibration) had similar or improved coefficient of determination and lower RMSE when compared to the *site-specific* 'time-of-year' model. Most importantly the 'Temperature I15' model was more closely aligned with the event size distributions for each location than either of the 'time-of-year' models (e.g. Fig. 3).

Temporal trends in I15

The importance of the daily climate variables in the predictive I15 model was also assessed by determining the capacity of the I15 model to account for temporal trends in the observed historical I15 data. To investigate whether the model accounts for historical trends in I15 (including decreases and increases), linear regression equations were fitted to the observed I15 and modelled I15 time series for 73 pluviograph stations. The average station record length was 37 years. Of the 73 stations, 27% had statistically significant ($P < 0.05$) trends of increasing intensity, 64% also had increasing trends, which were not statistically significant ($P > 0.05$) and 9% had decreasing trends,

Table 3. The coefficient of determination (r^2) and the root mean square error (RMSE) for the three I15 model predictions: (*a*) 'time-of-year' I15 using GRASP parameters; (*b*) 'time-of-year' I15 using optimised parameters; and (*c*) the new 'Temperature I15' model

Location	Time-of-year I15 GRASP parameters		Time-of-year I15 Optimised parameters		Temperature I15	
	RMSE	r^2	RMSE	r^2	RMSE	r^2
Townsville, –19.25°S, 146.77°E	45.4	0.25	21.4	0.25	19.9	0.35
Rockhampton, –23.38°S, 150.48°E	30.8	0.17	20.2	0.20	17.9	0.41
Kingaroy, –26.55°S, 151.85°E	21.1	0.39	19.4	0.40	17.4	0.55
Hobart, –42.80°S, 147.50°E	24.2	0.05	8.8	0.05	8.4	0.18

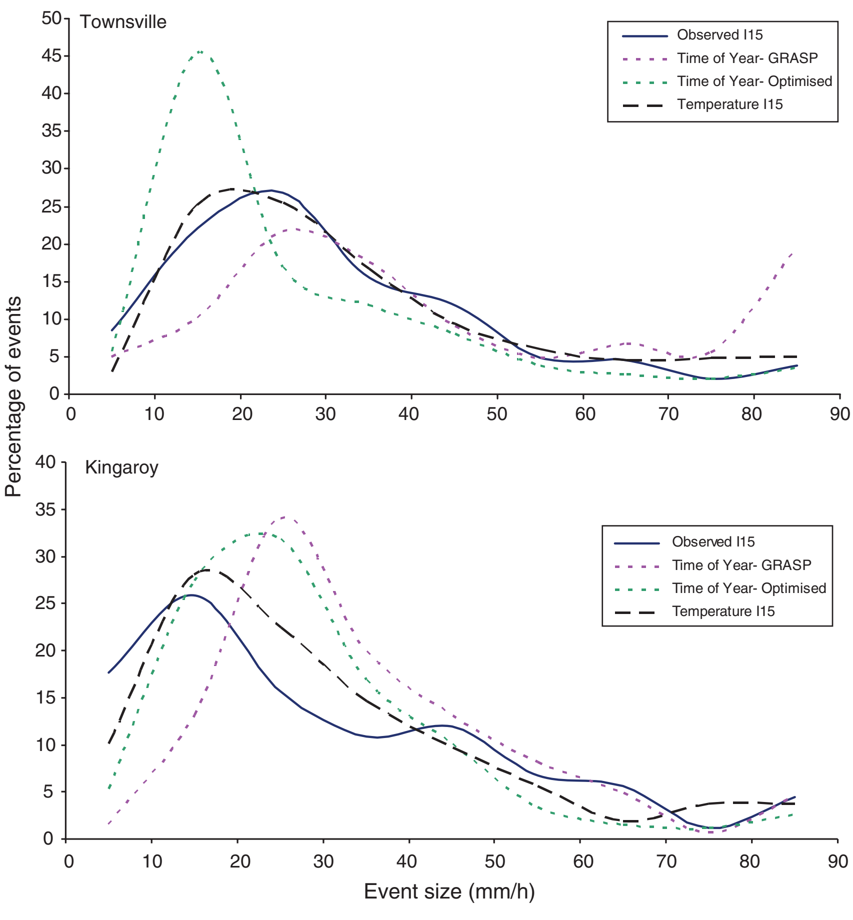

Fig. 3. A comparison of the event size distributions for: (*a*) historical observed I15, (*b*) 'time-of-year' I15 using GRASP parameters; (*c*) 'time-of-year' I15 using optimised parameters; and (*d*) the general 'Temperature I15' model. Note events at 85 mm/h include all events >85 mm/h.

which were not statistically significant ($P > 0.05$). The median change in I15 for all locations was +13%. The observed historical trends in I15 for the 73 pluviograph stations (ranging from small decreases to substantial increases) were well represented ($r^2 = 0.70$, $P < 0.01$) by the 'Temperature I15' model (Fig. 4*a*).

To assess the more recent trends in I15, analysis of the shorter period from 1990 to 2005 was undertaken (Fig. 4*b*). For this shorter time period, 22% of stations had trends of increasing intensity ($P < 0.05$), 4% had trends of decreasing intensity ($P < 0.05$) and for 74% the trends were not statistically significant ($P > 0.05$). The median change in I15 for all locations was +23%. The model accounted for 67% ($P < 0.01$) of the variation in the observed changes in I15 for the period from 1990 to 2005. The model tended to under-predict the observed trend of increasing I15 (slope = 0.71), although the model accounted for a high proportion of the variability ($r^2 = 0.67$, $P < 0.01$) in trends across the nation.

Errors associated with applying the empirical I15 model when modelling rangeland runoff

It is important to ascertain the most appropriate timeframe for applying the 'Temperature I15' model in daily time-step biophysical models, given that it only explains 46% of the variation in observed daily I15 measurements. The location of Rockhampton (central coastal Queensland), where estimates of I15 (using I12 and I18 measurements) were available from 1940 to 2004, was chosen to undertake this analysis. For these 600 rainfall events (when daily rainfall was >15 mm), I15 was calculated using the 'Temperature I15' model. The difference between the modelled I15 and the observed I15 was used to calculate the average absolute percentage error in modelled I15 for simulation time periods ranging from 1 to 10 years (Fig. 5). The average percentage error in modelled I15 decreased from 25% for simulation time periods of 1 year to 16% for simulation time periods of 3 years. The average percentage error in modelled I15 becomes relatively stable for simulation time periods in excess of 3–5 years.

As the modelled I15 estimates are used to predict hillslope runoff in the GRASP biophysical model we investigated the errors which are propagated when estimating hillslope runoff. Simulated runoff was calculated with the GRASP–Scanlan runoff equation (Littleboy and McKeon 1997) for a factorial combination of surface cover (0–50%) and soil water deficit (0–50 mm) using both the observed I15 and the 'Temperature I15' model. The difference between these two estimates of simulated runoff was used to calculate the average absolute error in simulated runoff and the average absolute percentage error in simulated runoff. The average error (in mm) increased with increasing soil water deficit and decreased with increasing cover. When expressed as a percentage of runoff (Fig. 5), the average absolute percentage error increased with soil water deficit (i.e. as runoff declined). We found that the absolute percentage errors in runoff were amplified when the daily runoff values were low; however, the errors in runoff were dampened when daily runoff values were high (e.g. errors in runoff were <10% when runoff was >20 mm/event). The percentage error in simulated runoff was relatively stable for simulation periods greater than 3–5 years (Fig. 5).

Variability in I15 within the wet season of northern Australia

In northern Australian grazing systems, soils may be most susceptible to runoff and erosion events during the mid-to-late spring period because of the greater likelihood of relatively low groundcover at the end of the dry season. Furthermore, late spring in northern Australia is referred to as the 'storm season' reflecting the general observation that rainfall intensity during this time of year is greater than that which occurs later during the summer-rainfall season. For November and February we compared the observed and predicted median I15 for a combined group of six pluviometer stations across northern Australia (Fig. 1*b*). These

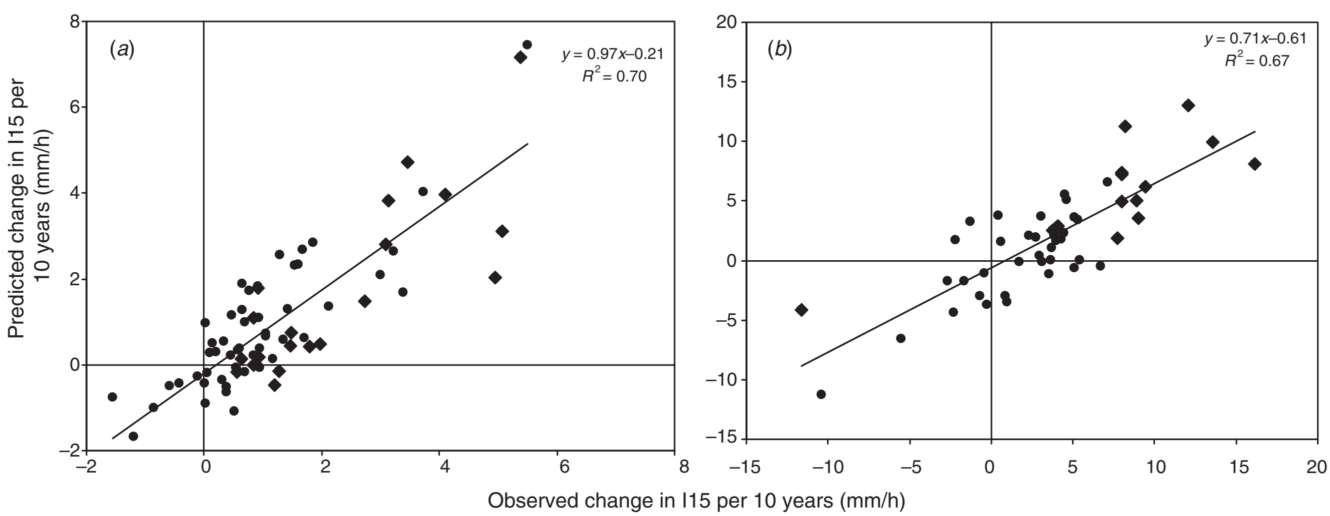

Fig. 4. The observed and predicted change in I15 for: (*a*) the full recording period (average ~37 years) of the pluviograph stations; and (*b*) the period 1990–2005. Diamonds indicate that the trend in the observed pluviograph record was significant at $P < 0.05$.

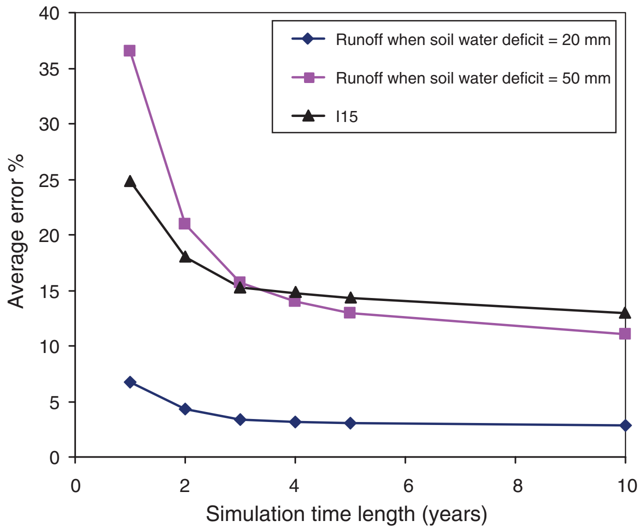

Fig. 5. The average absolute percentage error for runoff calculated over different time periods when using two soil water deficits 20 mm (diamonds) and 50 mm (squares), and I15 (triangles) when applying the temperature I15 model.

datasets consisted of 128 and 521 observed rainfall events greater than 15 mm for November and February, respectively.

The observed median November I15 was 27.8% greater than February. Similarly, the median November I15 from the 'Temperature I15' model was 27.9% greater than February. However, the median I15 rainfall event calculated by the 'Temperature I15' model was +9.6% and +9.5% greater than the observed median I15 for November and February, respectively. These findings indicate that the 'Temperature I15' model captures the potentially important impacts that 'storm season' rainfall may have on runoff and erosion processes in Northern Australia.

Application of the 'Temperature I15' model in the AussieGRASS model

One approach that can be used to assess the value of the new 'Temperature I15' model (and hence, the effect rainfall intensity has on surface runoff and water balance) is to evaluate the impact in a major model application in simulating pasture growth (e.g. Ive *et al*. 1976). The Australia-wide spatial pasture growth model AussieGRASS was used to evaluate the impact of the new 'Temperature I15' model on the simulation of green cover for 185 pasture communities across Australia (after Carter *et al.* 1996). Due to the lack of spatially representative I15 data, AussieGRASS rainfall intensity had been parameterised using a 'time-of-year' I15 with generalised 'time-of-year' parameters. The AussieGRASS model had been calibrated to simulate observed green pasture cover from 1981 to 1996 (Carter *et al.* 2000). Values of modelled green pasture cover (derived from modelled green biomass) are calibrated based on the satellite-derived indices of green cover (i.e. Normalised Differential Vegetation Index). The AussieGRASS model parameters, such as pasture regrowth rate and transpiration efficiency had been optimised for each pasture community and hence, represented the best simulation that could be achieved with the 'time-of-year' I15 model. Inclusion of the 'Temperature I15' model (~15 lines of FORTRAN code) improved simulation of green cover for 132 (71%) of pasture communities but was worse for 47 (25%) of communities, with no change for six (4%) communities. Thus, the results support the general use of the 'Temperature I15' model in simulations of pasture growth and further improvement is likely if the pasture growth parameters are re-calibrated with the new I15 model.

Discussion

Applying the 'Temperature I15' model using historical climate data

The empirical I15 model is regarded as robust because the model accounts for: (1) geographical variations in I15 across Australia; (2) seasonal variations in I15 at each location; and (3) some of the historical trends in observed I15. The simplicity of the model in terms of data requirements and because there is no requirement to calibrate the I15 model on a site-by-site basis, suggests that the model has potential for wide application across Australia's rangelands. The model utilises readily available climate variables (daily maximum temperature, daily minimum temperatures and the daily rainfall amount) allowing it to be readily applied at the same grid scale as SILO climate data (Jeffrey *et al*. 2001).

Daily climate variables in the 'Temperature 15' model

The 'Temperature I15' model was derived from empirical relationships and hence, this paper has not focused on how each of the daily climate variables in the 'Temperature I15' model may impact on I15. The sub-daily rainfall intensity measurement I15 is a 15-min interval measurement of rainfall and hence climate variables measured at a daily time scale are clearly insufficient to develop a detailed understanding of the physical processes that determine sub-daily rainfall intensity. Nevertheless, we are restricted to using daily climate variables to develop retrospective models of I15. There are a number of reasons as to why the daily climate variables in the 'Temperature I15' model could be related to I15. Daily rainfall amount was found to have the highest positive correlation of any of the daily climate variables with observed I15 (Table 1). This result was expected given that I15 and daily rainfall amount are both measurements of rainfall at different time scales. While it is possible to have low I15 values on days of high rainfall, in general, I15 increases as the daily rainfall amounts increase.

The second variable in the 'Temperature I15' model, diurnal temperature range, is considered as a representation of the surface interception of solar radiation. Dai *et al.* (1999) undertook a study of the weather conditions which lead to intense 1-hourly-rainfall events across the United States. This study found that intense summer-rainfall events primarily occurred on late afternoons to early evenings after a day of clear conditions (high solar radiation incidence) that allowed the build-up of high levels of convective available potential energy. Similar conditions precede late afternoon 'thunderstorms' for many areas in Queensland, which produce intense rainfall events. These conditions are in contrast to rainfall events which occur on very cloudy days (hence, low surface solar radiation interception and low diurnal temperature range) and are probably more likely to result in lower rainfall intensity.

The third variable of the 'Temperature I15' model, minimum temperature, is an indicator of the capacity of the atmosphere to hold water in a vapour form based on the theoretical Clausius–Clapeyron relationship, with a warmer atmosphere able to hold more water vapour.

Thus, while the 'Temperature I15' model was empirically derived, each of the variables in the 'Temperature I15' model may be 'partially' linked to the processes that cause variability in sub-daily rainfall intensity.

Temporal trends in I15

The analysis of trends in observed I15 found that I15 has generally increased over the relatively short time of data collection (average record length 37 years). The rate of increase in I15 has been greater in more recent times (between 1990 and 2004) (Fig. 4). Our study was limited to developing a 15-min rainfall intensity model from the longer period of historical daily climate data (~100 years) and hence, further analysis of trends in I15, as well as other sub-daily rainfall intensity timeframes needs to be undertaken. A preliminary investigation (results not presented) of daily peak 30-min (I30) and 60-min (I60) rainfall intensity suggests that minor changes in the 'Temperature I15' model can be made to also predict these rainfall intensities. This preliminary investigation also indicated that for the majority of pluviometer stations, observed I30 and I60 have also been increasing and that these temporal trends can also be represented by I30 and I60 models.

Applying the 'Temperature I15' model in climate change studies

The 'Temperature I15' model did represent some of the historical trends in observed I15 (Fig. 4). However, given its empirical derivation, it is uncertain as to how the model will represent I15 under future climate change. One problem associated with implementing the 'Temperature I15' model in a climate change study is determining what will be the impact of climate change on each of the daily climate variables in the 'Temperature I15' model (i.e. minimum temperature and diurnal temperature range on rainfall days and daily rainfall amount). This may involve several issues such as: (1) lack of available daily climate data due to poor temporal and spatial resolution global circulation model (GCM) projections; to overcome this problem, monthly GCM rainfall data can be disaggregated to daily rainfall data, but this may not be a simple process, especially where changes in both daily rainfall amount and the number of rain days may occur; (2) diverging projections of daily climate variables from a range of GCM; and (3) differing rates of change in daily climate variables due to different greenhouse gas emissions scenarios. These issues are common to climate change studies which use daily time-step biophysical models and should be addressed by careful consideration of GCM projections and by applying a range of potential climate change outcomes (e.g. McKeon *et al.* 2009).

A second problem associated with applying the 'Temperature I15' model in climate change studies is determining whether the empirical equation will adequately represent the impact of changing daily climate variables on I15. Daily climate variables will potentially be outside the historical observed ranges. It is not clear to what extent the empirical relationships can be extrapolated without consideration of the underlying mechanisms causing variation in rainfall intensity.

The effects of climate change are often related as spatial shifts in physical phenomena. For example, Leslie *et al.* (2007), predicts that under future climate change (2000–50), cyclone genesis will move 200 km farther south, which will increase the potential for cyclones to track across south-eastern Queensland or northern New South Wales. Further, Lough (2008) has reported an observed (1950–2007) 200-km southerly movement of sea surface temperatures along the Queensland coastline due to historical climate change. The 'Temperature I15' model represented the spatial variability in observed I15 across Australia. If climate change impacts can be represented by spatial shifts in daily climate variables used in the 'Temperature I15' model, then the model may be useful in representing the likely impacts of climate change on future I15. A further research paper is being developed to explore the potential impacts of climate change on future I15 and also the subsequent impacts on rangeland hillslope runoff and soil erosion rates.

Conclusion

The empirical 'Temperature I15' model developed in this study was an improvement on an existing empirical I15 model (e.g. Scanlan *et al.* 1996), which has been applied in daily time-step biophysical models. The 'Temperature I15' model has potential to effectively synthesise a peak sub-daily rainfall intensity dataset for locations across Australia. The simplicity of the model allows it to be easily implemented in existing biophysical models and hence, improves our capacity to assess the impacts that rainfall intensity may have on runoff and soil erosion in agricultural systems using long-term historical climate datasets.

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