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Modelling the sensitivity of agricultural systems to climate change and extreme climatic events

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ABSTRACT

Little is known about the impacts of increased frequencies of extreme climatic events (ECEs) on agricultural landscapes, though such events may be much more detrimental than those of gradual climate change alone. Here we develop an approach for examining the sensitivity of agricultural systems to climatic variability and ECEs on pasture-based dairy farms.

Using a combination of spreadsheet formulae, biophysical and economic tools, we compared two approaches for generating future climate scenarios: a 'Gradual' approach, wherein climate projections of changes in monthly average temperature and rainfall were applied without altering the pattern of ECEs, and a 'Variable' approach, where monthly change projections were combined with more heatwaves, longer droughts and more extreme rainfall events to generate future scenarios with increased variability.

The sensitivity of each approach was compared by modelling whole-farm system impacts on pasture and milk production, feed intake and profit under 'Low' and 'High' climate change projections based on the Representative Concentration Pathways with the highest greenhouse emissions in 2080 (RCP8.5) at three sites in southern Australia. 'Low' change projections had average warming of 1.6–2.0 °C and rainfall 10–18% higher than the historical climate, while the 'High' change scenario had 2.5–3.2 °C of warming and 15–30% reductions in rainfall. Both future climate scenarios applied the same average monthly change in rainfall and temperature relative to historical climates, but the relative frequency of events falling in the tails of the historical climate distribution was increased in the Variable approach. When used to simulate impacts on whole farm systems, the Variable approach translated into lower annual pasture growth and utilisation, and greater variation within and across years. Exposure to more frequent ECEs led to greater reliance on purchased feeds and lower long-term profitability, particularly in the High change scenarios.

We conclude that increased climate variability associated with more frequent ECEs has impacts on agricultural systems over and above those of gradual climate change, which may have two main implications. First, climate change projections following RCP8.5 will progressively depress pasture yields and profitability of pasture-based dairy systems. Second, future modelling of climate change impacts on agricultural systems must adopt methodologies that account for the variability associated with ECEs in projected climate data, since the sensitivity of losses in production and profitability becomes greater with more frequent ECEs, even if gradual long-term changes in climate are accounted for.

1. Introduction

While the biophysical, economic and social impacts of gradual climate change on agriculture have been scrutinised for some time, research of the impacts of extreme climatic events (ECEs) on agro-ecosystems is in its infancy. Recent reviews have highlighted the dearth of work on climate variability and have underscored the need for more knowledge on the timing and interactions of different climatic stresses on plant growth and development, as well as the need for knowledge of the cascading impacts through farming systems caused by ECEs (Thornton et al., 2014; Tubiello et al., 2007; White et al., 2011). Although there has been some research on the nonlinear and threshold responses to extreme heat in crops (Porter and Semenov, 2005; Tubiello et al., 2007), impact studies of extreme events on pasture and livestock systems are rare (Soussana et al., 2010; White et al., 2011). Given that the Intergovernmental Panel on Climate Change (IPCC) has documented significant increases in global extreme precipitation events, regional trends towards more severe and longer droughts, and high certainty that heat waves will increase in frequency and magnitude during the 21st century (Seneviratne et al., 2012), it is now imperative that further

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studies to quantify the impacts of ECEs on agricultural landscapes are conducted.

Past studies of climate change impacts on crop and pasture production typically adopt data from global circulation models (GCMs) (e.g. Cullen et al., 2009; Harrison et al., 2014; Jones and Thornton, 2003; Parry et al., 2005). The majority of these studies examine drought (and to a lesser extent) heat stress (White et al., 2011). GCM data is often downscaled to a daily time-step and to a given site (e.g. Tubiello et al., 2000), as required if the intended use is inputs for ecophysiological or biophysical crop and livestock models. Climate data produced in this way are generally fixed according to the method chosen and are not subject to modification to account for local differences projected in ECEs. To overcome this, studies often compare biophysical results generated using either several Representative Concentration Pathways (RCPs), GCMs or future time horizons (Cullen et al., 2009; Deryng et al., 2014; Tubiello et al., 2000; White et al., 2011).

There can be considerable uncertainties in GCM predictions of anthropogenic climate change (Murphy et al., 2004), to the extent that different models often disagree on the sign of the changes expected in particular regions (Giorgi and Francisco, 2000). It stands to reason that GCM skill in forecasting extreme events is less than that associated with gradual climate change (Meehl et al., 2000; Seneviratne et al., 2012; Thornton et al., 2014). The uncertainty associated with GCM ECE predictions can be due to the addressing of inter-annual and synoptic space-scales and modelling processes (Murphy et al., 2004), such as tropical cyclones, El Niño effects and extra-tropical storms (Meehl et al., 2000), parameter assumptions associated with climate distributions (Giorgi and Francisco, 2000; Smith et al., 2001), the irregularity of extreme event occurrence and the lack of access to high-quality, long-term climate data with the time resolution appropriate for parameterising models (Allan and Soden, 2008; Easterling et al., 2000; Easterling et al., 2016). Relatively large changes in the magnitude and frequency of extreme event forecasts can arise with small shifts in the mean or variance of a long-term distribution, because extremes lie in the tails of frequency distributions (Smith et al., 2001). Even among GCMs that forecast similar changes in temperature for a given region, predictions of regional precipitation may vary significantly due to the chaotic nature of climate, differences in modelling approaches to resolving local and regional atmospheric dynamics, and the coarse spatial resolution of many GCMs (Soussana et al., 2010).

The Australian dairy industry is a $13 billion farm, manufacturing and export industry and represents the third largest agricultural sector in Australia after grains and livestock meat (DA, 2016). The industry relies predominately on grazing of rainfed and irrigated pastures to feed dairy cows. Reports from Australian dairy farmers indicate that they have already experienced more heat waves, fewer frosts and less rainfall associated with climate change, and have already began adapting management by shifting calving times to make better use of changing seasonal pasture growth patterns and the threat of extreme heat events in summer, adjusting feedbase combinations of pasture and forage, cutting home-grown silage and developing water management plans to increase use-efficiency and reduce evaporative losses (DA, 2007). Despite this, there has been little previous research of climate change impacts on dairy farming systems in Australia, and notable exceptions have predominantly been conducted with gradual changes in climate from downscaled GCM data (Cullen et al., 2009; Phelan et al., 2015). Further, such research is typically reductionist, examining how changing a given factor (such as calving date or pasture species) impacts pasture grass production. In reality it is rare that a single factor can be changed in isolation; for example, shifting calving date would change milk payments received if prices differed intra-seasonally. There are few holistic studies that analyse how climatic events transition through the whole farm system, from pasture biomass production to milk yields, through to purchased fodder requirements and profit, though such research appears more than warranted (Nardone et al., 2010).

Here our goals were first to develop an approach for generating realistic future climate data in line with IPCC projections that contained greater variability in rainfall and temperature than data historically observed, and second to examine how such climate scenarios might impact on pasture-based dairy systems with regards to milk supply and profitability. Our focus was on ECEs and climate variability rather than mean climate change *per se*, since it is the events – not the trends – that have the greatest implications for biological systems (Soussana et al., 2010). To preserve historical climate characteristics of each site, we used actual data measured on a daily time-step, then perturbed these data with both Regional Climate Model (RCM) projections and monthly average projections from several GCMs. The climate sequences were produced on a daily time-step in line with IPCC climate change projections for each region, but with specific relevance to dynamically-downscaled extreme events (White et al., 2010). We then examined the extent with which climate variability influenced the long-term ranges of grazed pasture utilisation, purchased feed requirements and total return on assets for three dairy regions in Australia.

2. Methods

2.1. Overview

This study was part of a larger research program that examined the effects of ECEs and climate variability on Australian dairy businesses. The program was designed to identify the impacts of climate change on pasture production, and the influence of such drivers on the economic sustainability and social outcomes of farmers and the broader grazing industry. The present study documents the first part of this research; here we derive an approach for simulating future climate data that contains either gradual changes in climate or both gradual changes and increased variability. We contrast the outputs of the two methods by comparing several metrics and the effects of each approach under two different climate scenarios on pasture growth rates, milk production and farm profitability across the Australian dairy region. Our purpose in developing realistic future climate data with increased variability was to (1) increase the durations of dry-days (drought), the magnitudes of wet days (intense precipitation days), and the magnitudes and frequencies of very hot days (heat waves) relative to those observed historically, and (2) to generate climate-change data that were within the limits of projected climate change for each region.

2.2. Site locations and historical (baseline) climate data

Australian dairy farming occurs across diverse climatic zones but the bulk of milk production occurs in south-eastern temperate regions that experience wet winters and warm to hot dry summers (DA, 2016). We undertook case studies of three farms located in regions representing the breadth of climatic variation in south-eastern Australia and sourced historical weather data for each site from meteorological archives (http://www.longpaddock.qld.gov.au/silo). Historical climate data assumed as baselines were measured from 1 January 1975 to 31 December 2013 on a daily time-step and were used to produce future climate data for each region. Annual average rainfall (1975–2013) across sites was in the range 937–995 mm, with a winter-dominant pattern (Fig. 1). In winter, site averages of historical minimum and maximum daily temperatures range from 4 °C and 15 °C, respectively, and from 10 °C to 26 °C in summer. All simulations using historical data assumed a baseline atmospheric CO_2 concentration of 380 ppm. Further site characteristics are provided in Table 1 with historical climate details shown in Fig. 1.

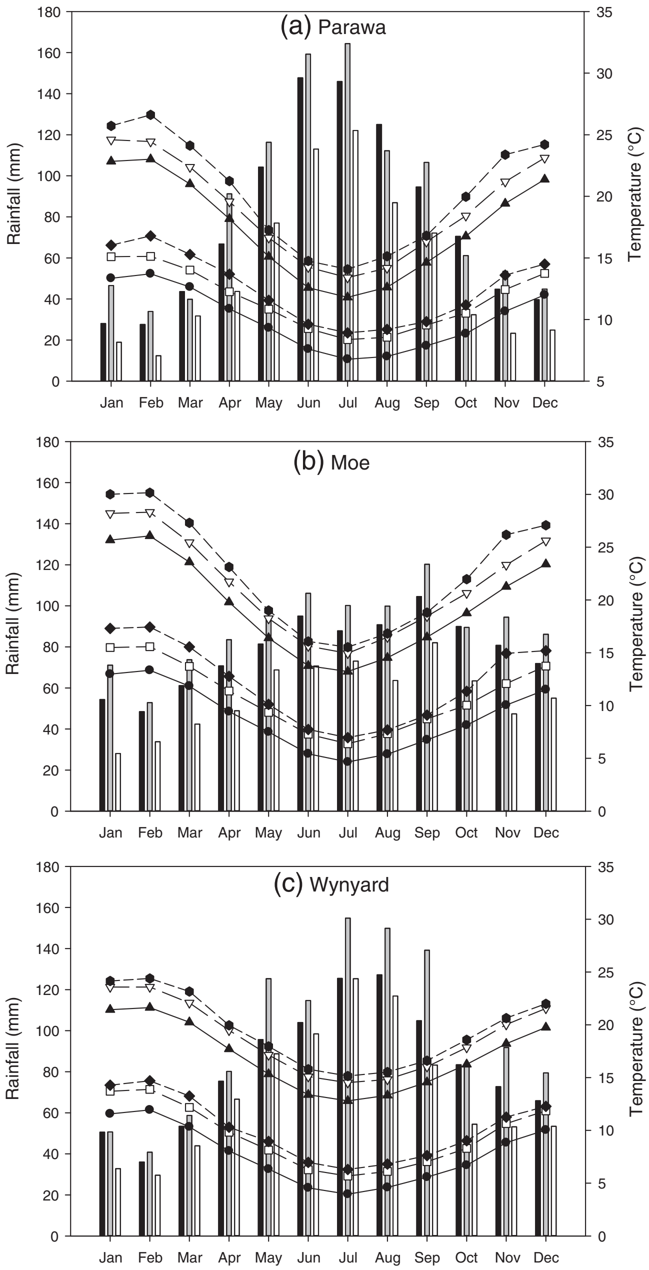

Fig. 1. Monthly average rainfall for the historical ( ), Low ( ) and High ( ) impact scenarios, minimum temperature for historical ( ), Low ( ) and High ( ) impact scenarios, and maximum temperature for historical ( ), Low ( ) and High ( ) impact scenarios at (a) Parawa, (b) Moe and (c) Wynyard.

2.3. Future climate data constraints

In the context of the larger research program described above there were several constraints in developing an approach for generating future climate data containing increased frequencies of ECEs. Against this background, this study used two different forms of the Delta-change or perturbation method (e.g. see Baynes et al. 2013) with the historical data from each site. Importantly, this allowed modification and replacement of climate indices from within the historical sequence, but at the same time retained the original time-series of the historical climate data. Following dynamically-downscaled RCM data (White et al. 2010), this approach allowed amplification of heat waves and extreme rainfall events, as well as increased dry-spell durations by modifying the magnitude (but not the order) of climate data historically measured at each site.

Our aim was to derive a method for producing future climate sequences that

1. Retained historical climate characteristics, including the long-term average annual rainfall and average monthly minimum and maximum temperature;
2. Was sufficiently flexible to allow addition and modification of temperature and precipitation extremes in historical climate sequences. This requirement precluded use of downscaled climate forecasts from GCMs because such outputs do not allow manipulation of the extent or frequency of climate extremes;
3. Produced future climate data in line with relevant forecasts of global climate change for each region. We used projections of Representative Concentration Pathways (RCPs) from the IPCC and changes forecast in future ECEs (White et al., 2010) to meet this constraint (see below);
4. Allowed random manipulation of historically measured data but preserved the observed sequence of precipitation and temperature, and
5. Accounted for the autocorrelation within the time series of each climate metric (i.e. the correlation between the value on day i with that on day $i-1$), as well as the covariance within daily climate metrics (such as the association between minimum and maximum daily temperatures).

2.4. Future climate data: 'Gradual' and 'Variable' approaches

Two approaches were used to generate future climate data. The first contained only gradual changes in climate and was computed by uniformly scaling daily climate indices according to monthly average GCM forecasts (hereafter, the 'Gradual' approach). The second approach contained both monthly average trends in gradual climate change but also increased magnitudes and frequencies of ECEs based on forecasts from RCMs (White et al., 2010), such that climate data were more variable compared with historical climate observations (hereafter, the 'Variable' approach). For each site, both approaches used the same historical climates as a template for modification, and all modifications were made on a daily time-step. Identical changes in average monthly rainfall and temperature were applied

Table 1
Locations, climate and soil characteristics of the case study farms used in the simulations.

Site (State)	Lat., Lon. (°S, °E)	Altitude (m ASL[a])	Climate[b]	Soil type[c]	PAW (mm)[d]	KSat (mm/d)[e]
Parawa (SA)	35.55, 138.34	361	Temperate; dry, warm summer	Grey Dermosol	80	150
Moe (Vic.)	38.20, 146.26	150	Temperate; no dry season, warm summer	Grey Dermosol	80	150
Wynyard (Tas.)	41.00, 145.73	12	Temperate; no dry season, mild summer	Red Mesotrophic Haplic Ferrosol	32	7200

[a] Above sea level.
[b] Based on a modified Koeppen classification system of the Australian Bureau of Meteorology (Manins, 2001).
[c] According to Isbell (2002).
[d] PAW, plant available water to a root depth of 400 mm.
[e] KSat, saturated hydraulic conductivity; depth-weighted average values.

in both approaches for all years in each climate dataset, such that climates did not change inter-annually within each 39-year simulation. This ensured that both the Gradual and Variable approaches generated the same long-term average monthly rainfall, maximum or minimum temperature over each 39 year dataset, whereas the standard deviation of each metric computed under the Variable approach was greater. The Gradual approach uniformly applied a constant factor to rainfall for all days in each month, whereas the Variable approach increased and decreased the magnitude of wet-day events falling above the 70th percentile or below the 30th percentile historically observed for that month, respectively. Rainfall events between this range were scaled up or down, depending on the magnitude of change in average monthly rainfall required to match that applied in the Gradual approach. The same method for scaling maximum and minimum daily temperature as for rainfall was applied for the Gradual approach, and both approaches used a uniform monthly scaling factor for each temperature metric. For the Variable approach, only 50% of values below the median monthly maximum daily temperature were scaled; all values above the median were upscaled. Minimum daily temperatures for the Variable approach were set equal to those of the historical data and were added to the corresponding difference between daily maximum temperatures of the Variable and historical data. Further descriptions and associated formulae of both approaches are detailed below.

Future climate scenarios were based on projections for the year 2080 under the RCP8.5 (where 8.5 relates to radiative forcing values in the year 2100 relative to pre-industrial values in W/m^2 and represents the most intensive emissions pathway; Riahi et al., 2011). The atmospheric CO_2 concentration for RCP8.5 at 2080 is 758 ppm (Riahi et al., 2011); this value was applied as a constant in all years used to simulate future climate scenarios. Monthly temperature and rainfall change projections (C_{mTmax}, C_{mTmin} and C_{mR} described below) for RCP8.5 at 2080 were obtained from an ensemble of the top quartile of GCMs used in the IPCC Assessment Report 5 (Flato et al., 2013) ranked on their skill score for predicting climate in southern Australia (Watterson et al., 2013). The GCMs in the ensemble were ACCESS1.0, MPI-ESM-LR, HadGEM2-ES, CRRM-CM5, CanESM2 and HadGEM2-CC. Monthly temperature and rainfall change projections were extracted from the three sites using the SimCLIM software package (Yin et al., 2013). To account for the variation in climate projections between the GCMs in the ensemble, Low and High change scenarios were developed. The Low change scenario combined the lowest projected temperature change for each month (i.e. smallest increase, using the 10th percentile of temperature change from the GCM ensemble) with the highest rainfall (i.e. largest increase or smallest decrease, using the 90th percentile of rainfall change from the GCM ensemble), while the High change scenario combined projections for the highest monthly temperature change (i.e. largest increase, using the 90th percentile of the ensemble) with the lowest monthly rainfall (i.e. largest decrease, using the 10th percentile of ensemble). The general approach to creating the Low and High change 2080 scenarios was to multiply the daily historical climate data for each site by the relevant temperature and rainfall change factors for the month. The timing of extreme climatic events in both the Gradual and Variable approaches was not altered from that recorded in the historical data. Thus, drought, heat waves and extreme rainfall events etc. in the future climate data occurred in the same time series as in the historical data, but were amplified upon occurrence; for example, drought periods became longer and heat waves became hotter. This allowed extreme events to occur more frequently in the future climate data. The extent with which extremes were perturbed from historical data in both approaches is documented in the results, thereby allowing direct comparison of climate metrics generated under the Gradual and Variable approaches. Further distinctions between climate scenarios and approaches are now described.

Future rainfall scenarios were generated using the Gradual and Variable approaches by computing daily factors (F_{dR}) to modify historical daily rainfall:

1. Gradual: daily rainfall events were multiplied by the projected rainfall change for the month (monthly change, C_{mR}), similar to methods developed in previous climate change analyses (Cullen et al., 2009). C_{mR} values were imposed for all rainfall events in each month.

$$F_{dR} = C_{mR} \tag{1}$$

2. Variable: small, medium and large rainfall events were separately manipulated to achieve more dry days, greater contiguous dry-day durations and more intense rainfall events. The same value of C_{mR} as that in the Gradual approach was obtained but rainfall events were modified according to monthly rainfall percentiles:
   a. For each month, rainfall deciles were computed using historical data (1975–2013).
   b. To introduce stochasticity associated with natural climate variability and the difficulty in predicting future rainfall events at the local scale, 80% of events were randomly selected for manipulation and the remaining 20% were set equal to historical rainfall.
   c. Small, medium and large historical rainfall events measured on a daily time-step (R_d) were multiplied by different factors (F_{dR}) to achieve the required overall monthly change in rainfall:

$$FdR = \left\{ \begin{array}{lr} \max(0.1, C_{mR} - 0.2) & Rd < 30^{\text{th}}\ \text{percentile} \\ C_{mR} \pm 0.2 & 30^{\text{th}}\ \text{percentile} \le Rd \le 70^{\text{th}}\ \text{percentile} \\ C_{mR} \pm 0.2 & Rd > 70^{\text{th}}\ \text{percentile} \end{array} \right\} \tag{2}$$

The Solver routine in Microsoft Excel was used to optimise F_{dR} across years y and percentiles p in Eq. (3) such that

$$\frac{\sum_{y=1}^{39} \sum_{p=1}^{3} F_{dR} R_d}{\sum_{y=1}^{39} \sum_{p=1}^{3} R_d} = C_{mR} \tag{3}$$

using initial F_{dR} values of 0.5, 0.8 and 1.2 for the small, medium and large rainfall percentile bins in the optimisation process.

The approach above generated a single realisation of future rainfall data (all F_{dR} values are shown in Table S1). Multiple realisations of rainfall or temperature data were beyond the scope of this study.

Future temperature scenarios were also generated using the Gradual and Variable approaches by computing daily factors (F_{dTx}) that were used to modify historical daily minimum or maximum temperatures (x = minimum or maximum daily temperature):

1. Gradual: minimum and maximum daily temperatures were multiplied by factors F_{dTx} reflecting the projected monthly change in temperature (C_{mTmin}, C_{mTmax}, Eq. (4)) from the ensemble of GCMs (Taylor et al., 2015). C_{mTx} values were imposed for every day of the historical climate data using Eq. (4).

$$F_{dTx} = C_{mTx} \tag{4}$$

2. Variable: this approach was designed to incorporate regional climate projections for more hot days and heatwaves (CSIRO, 2015; White et al., 2010) into the climate change scenario while maintaining

Table 2
Summary of the data used to parameterise the case study dairy farms at Parawa, Moe and Wynyard. These details were used in all simulations, including historical and future climate data.

	Parawa, SA	Moe, Vic.	Wynyard, Tas.
Milking area (ha)	208	110	150
Area irrigated (ha)	0	0	100
Irrigation applied (ML/ha)	0	0	3.0
Pasture species	Perennial ryegrass[a]	Perennial ryegrass	Perennial ryegrass
Nitrogen fertiliser application (kg N/ha)	110	189	251
Milking cows	350	352	450
Stocking rate (cows/ha of milking area)	1.7	3.2	3.0
Calving time	May–Jun	Aug–Sep	Aug–Sep
Mature cow liveweight (kg)	600	475	500
Replacements reared per year	93	100	115
Grain consumed (t DM/cow)	1.6	1.1	1.1
Max. allowable fodder intake (kg DM/cow day)	13	10	5
Min. pasture grazing threshold (t DM/ha)	1.2	1.3	1.5
Max. pasture threshold required for cutting (t DM/ha)	4.0	3.8	4.5
Wastage of hay/silage (%)	10	15	20
Milk price (A$/kg fat and protein)	5.40	5.25	5.25
Grain cost (A$ t/DM)	290	335	335
Hay/silage cost (A$ t/DM)	210	265	265
Total costs excluding feed cost (×A$1000)	452	311	550
Farm asset value (A$ million)	5.35	4.47	5.92

[a] *Lolium perenne*.

the same monthly average temperature increase as the Gradual approach.

a. Fifty percent of days within each month having maximum temperatures less than the median value for the month were randomly selected and excluded from modification. Maximum daily temperatures on these days were set equal to historical values.
b. For all other days within each month, the Solver routine in Microsoft Excel was used to determine F_{dTmax} across years y such that

$$\frac{\sum_{y=1}^{39} F_{dT\max} T\max}{\sum_{y=1}^{39} T\max} = C_{mT\max} \qquad (F_{dT\max} > C_{mT\max}) \tag{5}$$

where F_{dTmax} and C_{mTmax} represent the factor applied to historical maximum daily temperature and the monthly change in maximum daily temperature from the GCM ensemble, respectively, and *Tmax* represents historical maximum daily temperature. For each optimisation F_{dTmax} was initialised using the corresponding C_{mTmax} value.

c. Minimum daily temperatures were computed as the sum of the historical minimum daily temperature and the difference between the Variable maximum daily temperature and the historical maximum daily temperature.

The monthly temperature scalars used for each site are provided in Table S2. Actual vapour pressure in all future climate scenarios was not modified from the historical values, since the effect of higher temperature on saturated vapour pressure was internally calculated by the biophysical model used to conduct the simulations (see below). This computation is conducted using Teten's formula (Campbell and Norman, 1998) by adjusting daily minimum and maximum relative humidity and thereby vapour pressure deficit, following Cullen et al. (2012).

2.5. Simulation of dairy farm systems

The study sites shown in Table 1 are located in temperate regions in the south-eastern corner of Australia, where the majority of dairy farming is conducted. A whole farm model (DairyMod; Johnson et al., 2008) was used to simulate the farm system for each site and climate scenario. The model simulates leaf- and canopy photosynthetic rates, sward growth and composition, soil biophysics including water balance, organic carbon and nitrogen pools, grazing animal pasture intake as well intake from supplementary feed sources, milk production, and feedbacks between plant growth and pasture management; all variables are simulated on a daily-time-step. The ability of DairyMod to realistically simulate the effects of climate variability and management on pasture growth rates (Bell et al. 2013; Chapman et al., 2009; Cullen et al., 2008) and milk production (Johnson, 2016) in the study region has been well established. DairyMod has also been used to assess the impacts of climate change on pasture production patterns (Cullen and Eckard, 2011; Cullen et al., 2012; Cullen et al., 2009; Perring et al., 2010). The model does not account for plant death *per se*. However, the pasture submodel in DairyMod has well validated functions for describing the senescence of root and shoot tissues, as described in Johnson (2016). The subject of plant death is dealt with further in the discussion. For each site, we modelled pasture-based dairy systems designed using representative case study farms (Tables 1 and 2). Pasture management, stocking rates, calving times and grain feeding were typical of the range of practices used in south eastern Australia (AusVet, 2005). The farms at Parawa and Moe did not have any irrigation, while 66% of the farm area at Wynyard was irrigated. Nitrogen fertiliser in the simulations was applied to pastures at historical rates documented by each case study farmer (Table 2). Cows were fed according to their energy demands, first with grain, second with available pasture and third with conserved or purchased fodder when their energy demands were not met by the grain and available pasture. Total grain consumed per animal per annum was constant at all sites (Table 2). In response to low pasture availability and inadequate energy supply, DairyMod increases supplementary feeding of silage or purchased feed and attempts to maintain milk production; however, since lactation is a function of metabolisable energy, milk production may decrease if total energy released from the daily ration is suboptimal. Further details of animal metabolism and lactation are provided in Johnson (2016). All values shown in Table 2 except for nitrogen fertiliser and irrigation were fixed inputs and were used both in historical and future climate scenarios. Nitrogen fertiliser and irrigation vary as a function of soil and pasture status on a daily time-step in DairyMod. In seasons with suboptimal pasture availability, herd feed supply was increased in response to total demand via silage and purchased fodder, rather than manipulating herd numbers or target production. Pasture intake was calculated as pasture intake per animal, while pasture utilisation was

Table 3
Historical and future rainfall indices for each site and climate scenario. Statistics are expressed from computations using 39 years of climate data (avg. = average, st. dev. = standard deviation).

Variable	Unit	Historical	Low impact		High impact	
			Gradual	Variable	Gradual	Variable
Parawa, SA						
Avg. total rain	mm/yr	939	1030	1030	659	659
St. dev. total annual rain	mm/yr	157	168	230	110	136
Avg. no. dry days	d/yr	242	242	265	259	286
Avg. no. wet days	d/yr	123	123	100	106	79
Avg. max contiguous duration of dry days	d/yr	25.0	26.2	35.5	32.7	46.4
Avg. max contiguous duration of wet days	d/yr	9.2	9.0	7.7	8.1	6.5
Avg. max wet day event	mm/d	53	62	102	37	50
Avg. wet day rain (R_d)	mm/d	7	8	10	5	7
St. dev. of R_d	mm/d	0.9	1.0	1.8	0.7	1.1
10^{th} percentile of R_d	mm/d	1.3	1.4	1.2	1.3	1.4
50^{th} percentile of R_d	mm/d	4.4	4.7	3.6	3.7	4.4
90^{th} percentile of R_d	mm/d	17.4	18.7	22.6	13.3	20.4
95^{th} percentile of R_d	mm/d	24.4	26.6	43.0	18.8	27.6
99^{th} percentile of R_d	mm/d	42.0	46.1	78.7	30.3	46.6
Moe, VIC						
Avg. total rain	mm/yr	937	1073	1073	678	678
St. dev. total annual rain	mm/yr	177	202	247	128	150
Avg. no. dry days	d/yr	243	243	263	257	279
Avg. no. wet days	d/yr	122	122	102	109	86
Avg. max contiguous duration of dry days	d/yr	18.7	18.7	22.1	21.4	33.8
Avg. max contiguous duration of wet days	d/yr	7.7	7.6	6.6	6.8	6.2
Avg. max wet day event	mm/d	47	55	89	34	47
Avg. wet day rain (R_d)	mm/d	7	8	10	6	7
St. dev. of R_d	mm/d	0.8	1.0	1.6	0.7	1.1
10^{th} percentile of R_d	mm/d	1.4	1.5	1.2	1.4	1.3
50^{th} percentile of R_d	mm/d	4.6	5.3	3.6	4.0	4.4
90^{th} percentile of R_d	mm/d	17.4	20.0	24.0	13.7	19.6
95^{th} percentile of R_d	mm/d	24.0	27.1	44.4	17.4	26.1
99^{th} percentile of R_d	mm/d	37.2	42.4	74.4	28.2	41.2
Wynyard, TAS						
Avg. total rain	mm/yr	995	1169	1169	846	846
St. dev. total annual rain	mm/yr	188	221	299	159	195
Avg. no. dry days	d/yr	245	244	264	254	270
Avg. no. wet days	d/yr	120	121	101	112	95
Avg. max contiguous duration of dry days	d/yr	19.7	20.0	24.4	22.1	28.8
Avg. max contiguous duration of wet days	d/yr	8.7	8.9	7.3	8.3	7.4
Avg. max wet day event	mm/d	56	65	104	48	64
Avg. wet day rain (R_d)	mm/d	8	9	11	7	8
St. dev. of R_d	mm/d	1.1	1.3	2.1	0.9	1.3
10^{th} percentile of R_d	mm/d	1.4	1.5	1.3	1.4	1.3
50^{th} percentile of R_d	mm/d	5.0	5.8	3.7	4.7	4.4
90^{th} percentile of R_d	mm/d	18.2	21.5	23.2	16.4	19.0
95^{th} percentile of R_d	mm/d	25.0	29.2	49.7	22.0	32.6
99^{th} percentile of R_d	mm/d	44.6	52.9	89.4	39.8	55.4

calculated as total herd pasture intake per farm area. Since this study was about examining the impacts of extreme events on farm systems and the differences between approaches used to generate climate data, we did not explore how adapting farm systems to climate change would influence production or profitability (such analyses are separately documented in Harrison et al. (2016) and Armstrong et al. (2016)).

For all climate scenarios, paddocks modelled were rotationally grazed until pasture reached a minimum biomass threshold. Pasture biomass was cut to a residual of 1.0 t DM/ha and conserved as silage if biomass reached a maximum threshold (Table 2). Conserved silage was fed as fodder in accord with maximum allowable intakes and wastage rates at each site, and silage/hay was purchased for fodder in years when there were insufficient pasture and fodder reserves on the farm. Wastage rates were estimated based on the conditions and infrastructure when the fodder was being fed out. Silage fed at Parawa was predominantly in summer onto very dry ground. Silage fed at Moe was conducted in summer and autumn onto dry ground with a small amount fed out in winter and early spring. Silage at Wynyard was in winter and early spring on wet ground. These values are within the range of measurements for wastage recorded on Australian farms and were based on input from the expert/farmer panel we used to validate the case-study farm designs.

Detailed information on recent income from milk sales and costs of the case study farms was collected from the farm managers through farm visits and interviews. Total costs (excluding feed) shown in Table 2 include annual expenses for herds, sheds, cash overheads, depreciation and imputed labour. Annual whole farm budgets were developed according to Malcolm et al. (2005) using average return on total assets to compare profitability across systems, since this measure allows comparisons between businesses with different amounts of assets invested.

3. Results

3.1. Rainfall data generated using the Gradual and Variable approaches

In the Low impact scenarios annual rainfall increased by 10%, 15% and 18% at Parawa, Moe and Wynyard respectively, but in the High impact scenarios rainfall decreased by 30%, 28% and 15% (Fig. 1). For each climate scenario the Gradual and Variable approaches had the same overall impact on the change in total annual and monthly rainfall relative to the baseline, but the Variable approach increased the standard deviation of total annual and daily rainfall by increasing the magnitude of wet day events (Table 3). Relative to the Gradual approach, the Variable approach increased the average number of annual dry days (24 h rainfall < 1 mm) by 6–10% and reduced the number of annual wet days by 15–25%, with the greatest differences between the two approaches occurring under the High impact scenario. Of particular relevance to pasture-based production systems and the progressive development of soil water stress, the average maximum number of contiguous dry days of the climate generated using the Variable approach was 18–58% greater than that of the Gradual approach. The Variable approach increased the intensity of extreme rainfall events such that the average magnitude, standard deviation and 99th percentile of wet days were up to 34%, 80% and 75% greater than those of the Gradual approach, respectively (Table 3).

The effect of each climate approach on daily rainfall event size is illustrated for Moe in Fig. 2, which shows distributions of the probability of exceeding a rainfall event with any given size. Relative to historical rainfall events, the Gradual approach applied uniform scaling to all wet days and maintained the shape of the historical distribution, with the High and Low impact scenarios reducing or increasing rainfall event sizes, respectively. In contrast, the Variable approach altered the shape of the rainfall size frequency distribution such that extreme events were more common. For example, the likelihood of a wet day with less than ~7 mm was greater under the historical climate compared with the Low Variable approach, whereas the likelihood of an extremely large rainfall event under the Low Variable approach was greater than that observed historically. Compared with the Low Gradual approach, the Low Variable approach also resulted in greater frequencies of wet days receiving >20 mm.

Under the Low impact scenario, average annual rainfall at Moe was predicted to increase by 15% by 2080 (Table 3). While both the Gradual and Variable approaches produced data adhering to this constraint, the former did so by small, consistent increases in the magnitude of all rain events, uniformly shifting the frequency distribution to the right of the historical distribution. Conversely, the Low Variable approach increased average annual rainfall by 15% by reducing the frequency of small rainfall events and increasing the frequency of large events (Table 3, Fig. 2).

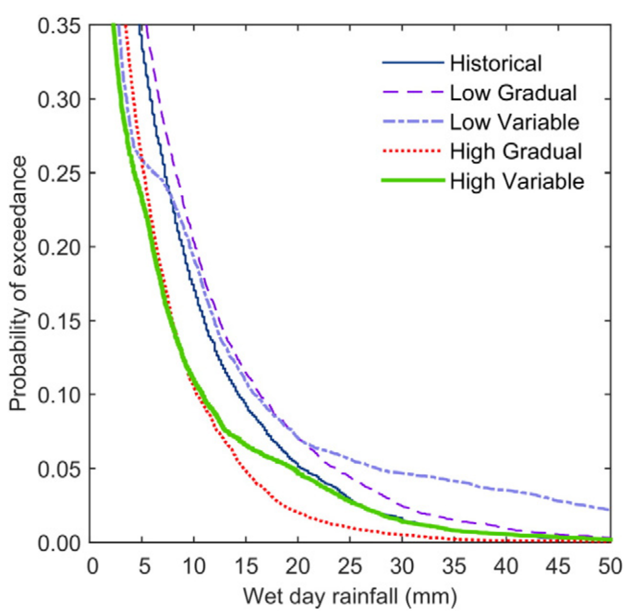

Fig. 2. Probability of exceeding a rainfall event size for wet-day distributions measured historically and for the High and Low impact climate change scenarios under the Gradual and Variable approaches at Moe.

3.2. Maximum and minimum daily temperatures generated using the Gradual and Variable approaches

In the Low impact scenarios minimum and maximum temperatures increased by 1.6 °C, 2.0 °C and 1.8 °C at Parawa, Moe and Wynyard respectively, with increases of 2.8 °C, 3.2 °C and 2.5 °C in the High impact scenario (Fig. 1, Table 4). While changes in maximum daily temperatures averaged across years or months under the Gradual and Variable approaches were identical, there were large differences in maximum temperature distributions produced by each method (Fig. 3). The average number of consecutive days with maximum daily temperatures greater than the 90th percentile of the historical maximum temperature (90histmax) increased by between 43% and 191% across sites and climate scenarios, with the largest changes occurring under the High Variable scenario at Wynyard. Both the Gradual and Variable approaches resulted in large increases in the maximum number of consecutive days above 90histmax, in line with our aim of increasing the frequency of heat waves in future climate data (Table 4). The Variable approach generated greater variability in maximum daily temperatures compared with the Gradual approach. Relative to the annual average standard deviation of historical maximum daily temperature, the Gradual and Variable approaches increased variability across sites by 5–17% and 11–30%, respectively (Table 4).

An example of the effect of the Variable and Gradual approaches on the long-term frequencies of maximum and minimum daily temperatures is illustrated in Fig. 3. For the High impact scenario, both approaches shifted the frequency distribution of maximum temperature to the right of the historical distribution and reduced the maximum height of the distribution such that days with maximum temperatures less than ~13 °C were less frequent (Fig. 3a). However, whereas the Gradual approach had a greater effect on maximum temperatures that were common (>10 d/year), the Variable approach resulted in more frequent extreme events associated with heat waves. The frequencies of warm and hot nights (i.e. minimum daily temperatures) above 20 °C were also greater under the Variable approach (Fig. 3b).

3.3. Impacts of climate scenario on soil water content, pasture growth rates, biomass accumulation, evapotranspiration, deep drainage, feed intake and milk production

Fig. 4 shows daily time-series of average volumetric soil water content to root depth over each 39-year simulation. Soil water content increased in winter (June–August) and was lowest during summer (December–February). The Low-Gradual approach resulted in soil water content that was often the same as or greater than that observed historically. Both Gradual and Variable approaches under the High change scenario reduced soil water content relative to historical values. For both climate scenarios, the Variable approach mostly resulted in lower long-term average soil water content, particularly for the Low-change scenario (Fig. 4).

For a given year at Moe, Fig. 5 illustrates how climate data containing more extreme events impacts on processes occurring at the soil, pasture and animal-levels compared with gradual climate change and historical data. Soil water content in the surface under the High Variable was consistently less than that of the High Gradual approach, despite the fact that long-term average monthly rainfall computed under both approaches was identical (Fig. 5a). Although evapotranspiration (ET) simulated using both future climates was greater than that historically observed in late autumn, winter and

Table 4
Historical and future temperature indices for each site, climate scenario and climate methodology. Statistics are expressed from computations using 39 years of climate data (avg. = average, st. dev. = standard deviation, hist. = historical, grad. = gradual approach, var. = variable approach).

	Unit	Hist.	Low impact		High impact	
			Grad	Var	Grad	Var
Parawa, SA						
Avg. max daily T	°C	17.4	19.0	19.0	20.2	20.2
Avg. min daily T	°C	10.0	11.6	11.6	12.5	12.9
Avg. daily T range	°C	7.4	7.4	7.4	7.7	7.4
Avg. no. days max T > 90histmax[a]	d/yr	36.6	52.2	56.7	66.4	76.9
Avg. no. consecutive days max T > 90histmax	d/yr	2.9	3.0	3.1	3.2	3.3
Avg. max no. consecutive days max T > 90histmax	d/yr	5.3	6.6	6.8	7.5	8.7
Avg. no. days min T < 10histmin[b]	d/yr	31.3	15.6	15.6	13.0	13.0
Avg. no. consecutive days min T < 10histmin	d/yr	2.8	2.3	2.3	2.3	2.3
Avg. max no. consecutive days min T < 10histmin	d/yr	4.5	2.7	2.8	2.6	2.4
St. dev. of max daily T	°C	5.8	6.0	6.4	6.5	7.2
St. dev. min daily T	°C	3.5	3.8	3.9	4.2	4.7
10^{th} percentile of max daily T	°C	11.5	12.8	12.0	13.2	12.5
50^{th} percentile of max daily T	°C	16.0	17.6	17.5	18.7	18.5
90^{th} percentile of max daily T	°C	25.5	27.8	28.4	29.8	30.9
95^{th} percentile of max daily T	°C	29.5	31.6	32.3	33.9	35.2
99^{th} percentile of max daily T	°C	34.5	37.2	37.8	39.9	41.4
10^{th} percentile of min daily T	°C	6.0	7.1	7.0	7.6	7.5
50^{th} percentile of min daily T	°C	9.5	11.2	11.3	12.1	12.2
90^{th} percentile of min daily T	°C	14.5	16.3	16.6	17.8	18.9
95^{th} percentile of min daily T	°C	16.0	18.4	18.8	19.9	21.6
99^{th} percentile of min daily T	°C	20.5	23.1	23.5	25.1	26.6
Moe, VIC						
Avg. max daily T	°C	19.4	21.4	21.4	22.6	22.7
Avg. min daily T	°C	8.9	10.7	10.9	11.7	12.2
Avg. daily T range	°C	10.5	10.7	10.5	11.0	10.5
Avg. no. days max T > 90histmax[a]	d/yr	34.5	58.7	65.9	78.9	87.9
Avg. no. consecutive days max T > 90histmax	d/yr	2.9	3.3	3.4	3.7	3.8
Avg. max no. consecutive days max T > 90histmax	d/yr	5.2	7.1	7.7	9.6	10.0
Avg. no. days min T < 10histmin[b]	d/yr	29.6	22.9	13.2	18.8	11.1
Avg. no. consecutive days min T < 10histmin	d/yr	2.9	2.8	2.7	2.8	2.7
Avg. max no. consecutive days min T < 10histmin	d/yr	4.9	4.4	3.5	3.8	3.1
St. dev. of max daily T	°C	6.0	6.4	6.9	7.1	7.8
St. dev. min daily T	°C	4.0	4.6	4.5	5.0	5.3
10^{th} percentile of max daily T	°C	12.5	14.2	13.5	14.7	13.5
50^{th} percentile of max daily T	°C	18.0	20.2	20.0	21.4	21.0
90^{th} percentile of max daily T	°C	28.0	30.7	31.4	32.7	34.1
95^{th} percentile of max daily T	°C	31.0	34.0	34.8	36.4	37.9
99^{th} percentile of max daily T	°C	36.0	39.5	40.4	42.2	43.9
10^{th} percentile of min daily T	°C	3.5	4.7	5.4	5.1	5.6
50^{th} percentile of min daily T	°C	8.5	10.6	10.6	11.7	11.6
90^{th} percentile of min daily T	°C	14.5	16.8	17.0	18.2	19.7
95^{th} percentile of min daily T	°C	15.5	18.4	18.7	20.0	21.6
99^{th} percentile of min daily T	°C	18.0	21.2	21.5	23.0	24.6
Wynyard, TAS						
Avg. max daily T	°C	17.0	18.8	18.8	19.5	19.5
Avg. min daily T	°C	7.7	9.4	9.4	10.1	10.2
Avg. daily T range	°C	9.3	9.4	9.3	9.4	9.3
Avg. no. days max T > 90histmax[a]	d/yr	36.0	79.1	87.6	98.6	106.9
Avg. no. consecutive days max T > 90histmax	d/yr	3.1	5.0	4.4	5.6	4.6
Avg. max no. consecutive days max T > 90histmax	d/yr	5.7	16.2	12.7	20.6	14.6
Avg. no. days min T < 10histmin[b]	d/yr	35.6	28.2	20.2	26.9	17.1
Avg. no. consecutive days min T < 10histmin	d/yr	2.9	2.7	2.6	2.8	2.5
Avg. max no. consecutive days min T < 10histmin	d/yr	4.7	4.0	3.2	3.9	2.8
St. dev. of max daily T	°C	3.8	4.0	4.4	4.1	4.7
St. dev. min daily T	°C	4.4	5.2	4.8	5.5	5.0
10^{th} percentile of max daily T	°C	12.5	14.0	13.2	14.6	13.5
50^{th} percentile of max daily T	°C	16.5	18.3	18.4	19.0	19.1
90^{th} percentile of max daily T	°C	22.0	24.2	24.8	24.9	25.9
95^{th} percentile of max daily T	°C	23.5	25.6	26.4	26.5	27.4
99^{th} percentile of max daily T	°C	26.5	29.1	29.9	29.9	31.1
10^{th} percentile of min daily T	°C	1.9	2.5	3.2	2.7	3.5
50^{th} percentile of min daily T	°C	7.6	9.5	9.4	10.3	10.1
90^{th} percentile of min daily T	°C	13.5	16.2	15.9	17.2	16.9
95^{th} percentile of min daily T	°C	15.1	17.8	17.7	18.9	18.7
99^{th} percentile of min daily T	°C	17.5	20.5	20.3	21.6	21.5

[a] 90histmax = 90^{th} percentile of historical maximum daily temperature.
[b] 10histmin = 10^{th} percentile of historical daily minimum temperature.

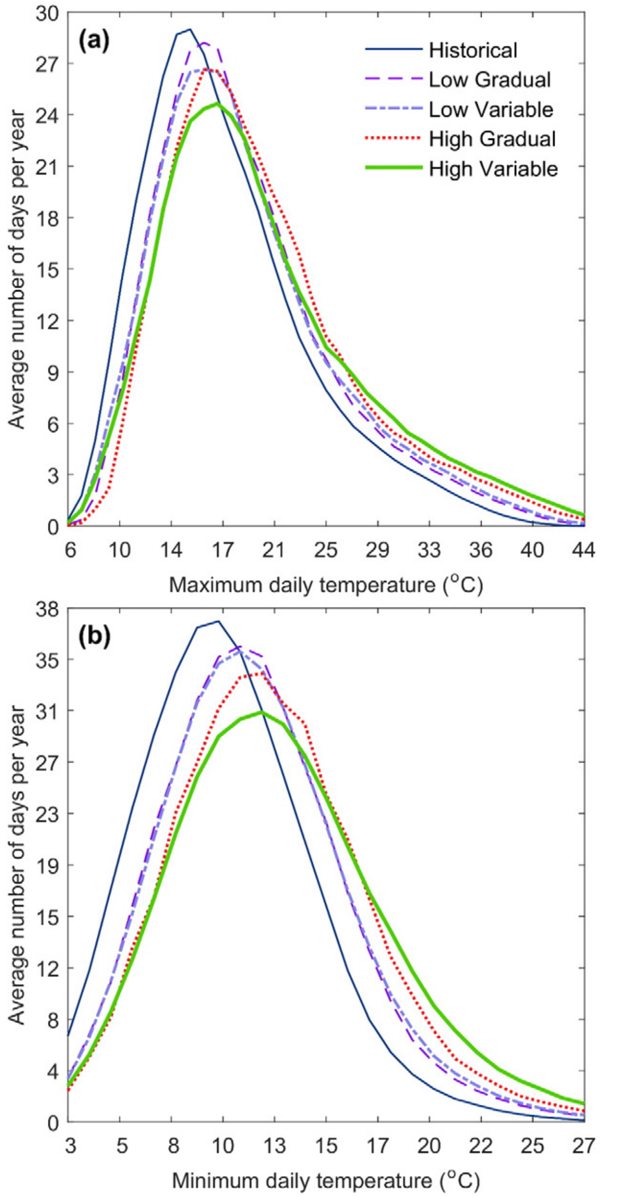

Fig. 3. Frequency histograms showing the average number of days per year for (a) daily maximum and (b) daily minimum temperatures measured historically and generated using the Gradual and Variable approaches for the Low and High impact climate change scenarios at Parawa.

spring due to higher pasture growth rates (Figs 5b, d), ET determined using the High Variable approach was less than that of the High Gradual approach in summer. Larger rainfall events simulated using the High Variable approach resulted in greater loss of soil moisture from the soil profile relative to High Gradual climates (both future climates had lower deep drainage than historical drainage due to the long-term drying trend; Fig. 5c). Trends in pasture growth rates and total dry matter predominantly reflected those in ET, with growth rates and total dry matter in 2080 being greater in winter due to warmer temperatures, and lower in other seasons due to increased temperatures, higher vapour-pressure deficit and lower rainfall (Figs 5d, e). It is also worth noting that growth rates and total dry matter determined using High Variable climate data were consistently less than those of the High Gradual approach (Figs 5d, e). Less dry matter accumulation due to more extreme events reduced pasture intake and increased requirement for supplementary forage in late November and December (cf. High Variable with High Gradual in Figs 5f, g), reducing average daily herd milk production (Fig. 5h).

Daily pasture growth rates averaged per month for each of the 39 years simulated in the future climate scenarios were higher than the baseline climate from June to September at each site, but lower from December to March due to lower and more variable rainfall and temperature in the future climate scenarios (Fig. 6). At the rainfed sites of Parawa and Moe, pasture growth rates were lower and more variable in the months of October–November, but the difference was less marked at Wynyard due to irrigation, such that seasonal growth rates were more consistent through the year (Fig. 6c). For both the Low and High climate scenarios, median monthly pasture growth rates of the Variable approach were lower than those of the Gradual approach, and yearly dispersion under the Variable approach was greater.

The differences in annual pasture utilisation (with utilisation defined as total pasture intake per farm area) between the Low and High climate change scenarios were greater than the differences between the Gradual and Variable approaches, but utilisation was consistently lower with the Variable approach (Fig. 7). For instance, at the Moe site, average annual pasture utilisation was 3% higher than the historical climate in the Low-Gradual scenario but 5% lower in the Low-Variable scenario, whereas it was 23% and 33% lower than the historical climate in the High-Gradual and High-Variable scenarios, respectively. The inter-annual variation in pasture utilisation was also higher in the Variable compared to the Gradual scenarios, particularly at Parawa and Wynyard.

As the majority of the pasture utilised was grazed rather than conserved and fed back to cows, the changes in pasture intake per cow showed similar patterns to the annual pasture utilisation with the lowest pasture intakes, together with highest within-year variability, predicted under the High-Variable scenario at all sites (Table 5). To meet cow energy demand, both conserved fodder intake and purchased hay increased as pasture intake decreased for the Variable approach and for the High impact scenarios. A larger proportion of the milking area pasture utilisation was derived from conserved silage in the future climate scenario. Milk production per cow also declined to its lowest level in the High-Variable scenario, although the magnitude of the differences varied between sites.

Average operating profit and return on total assets (ROTA) was highest at all sites in the baseline climate (Table 6). In the Low impact scenarios the differences in ROTA between the Variable and Gradual approaches were small. In contrast, average ROTA declined substantially in the High-Gradual scenario and declined further under the Variable approach. This was due to higher costs (especially feed) in the Variable approach at Parawa and Moe, and a combination of lower income and higher costs at Wynyard. As for most other metrics, the standard deviation of operating profit and ROTA was greater for the Variable approach compared with the Gradual approach, and greater under the High impact scenario.

4. Discussion

In the coming decades the IPCC has forecast a *virtually certain reduction in the frequency and magnitude of unusually cold days and nights*, a *very likely increase in the length, frequency and/or intensity of heat waves*, a *likely increase in the frequency of heavy precipitation events*, and *medium confidence in projected increases in the duration and intensity of droughts* (IPCC, 2012; Thornton et al., 2014). Paradoxically, the vast majority of previous work examining the impacts of climate change on grassland and livestock systems has dealt with gradual climate change rather than extreme events (Smith et al., 2001; Thornton et al., 2014; White et al., 2011), even though extreme events are more likely to have exponentially greater impacts upon food production and security (Thornton et al., 2014; Tubiello et al., 2007).

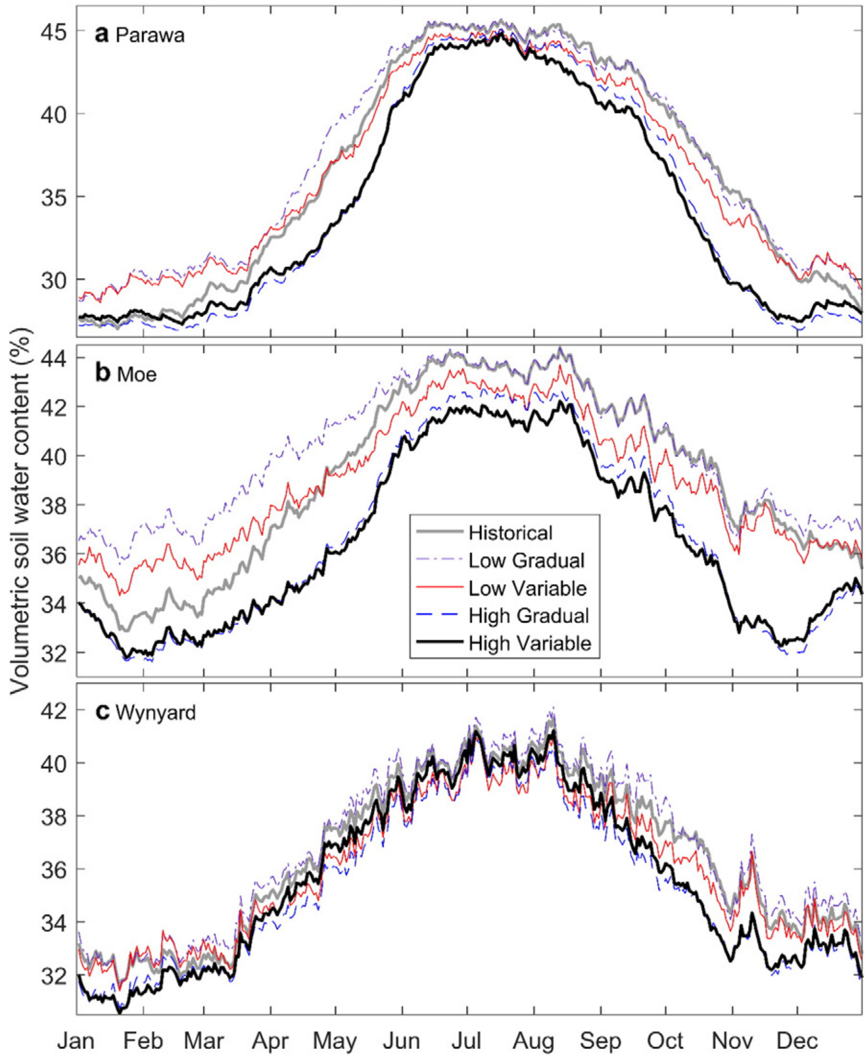

Fig. 4. Daily time-series of average soil water content to root depth for (a) Parawa, (b) Moe and (c) Wynyard over 39-years.

Against this background, we developed an approach for direct comparison of the effects of ECEs with those of gradual climate change on pasture-based dairy production systems. Since GCM data can underestimate natural climate variability (Hulme et al., 1999) due to the addressing of inter-annual and synoptic space-scales (Murphy et al., 2004), parameter assumptions (Giorgi and Francisco, 2000; Smith et al., 2001), and the lack of access to high-quality data with the time resolution appropriate for parameterisation (Allan and Soden, 2008; Easterling et al., 2000; Easterling et al., 2016), we based our methods on historical and RCM data to retain regionally-relevant characteristics while ensuring that future climate data were consistent with changes in precipitation and temperature forecast by the IPCC. We then perturbed the historical data on monthly intervals according to GCM forecasts and dynamically-downscaled RCM data to increase the frequency of extreme climatic events occurring in the tails of the distribution. For example, higher rainfall intensity was captured in the Variable scenarios with rainfall on the wettest day of the year comprising 7–10% of annual rainfall, compared with the wettest days in the baseline and gradual scenarios of 5–6% of annual rainfall.

Our results revealed that any modelling of agricultural systems which only accounts for gradual climate change (e.g. Cullen et al., 2009; Hulme et al., 1999) risks underestimation of climate change impacts. We showed that the combination of more extreme rainfall events, increased drought severity and more intense heatwaves translated into lower soil water availability, higher ET and deep drainage, which together not only reduced mean pasture growth rates and annual yields, but also further increased the variability in growth rates and soil water stress within and across seasons, as well as the inter-annual variation in grazed pasture utilisation and milk production. These results have implications for studies that propose using biophysical model simulation to examine (1) the impacts of climate change on agricultural systems, (2) grassland productivity, forage availability, livestock production and farm profitability, and (3) natural resource management, such as surface runoff, soil erosion and flash flooding.

The majority of past modelling research that examines climate change impacts on agricultural production systems (Cullen et al., 2009; Harrison et al., 2014; Phelan et al., 2015) uses data directly output or scaled from GCMs, and examines the effect of gradual climate change rather than extremes. This is likely because most biophysical models are not designed to account for extreme events. However, research including stakeholder interviews highlights the importance of analysing extreme event impacts in livestock systems. Malatinszky (2016) outline farmer challenges relating to conflicting management objectives and perverse incentives arising from policy-level issues (such as regulatory structures and implementation). Interviewees noted that years with high precipitation caused late mowing due to inaccessible pastures, poor quality of hay, undergrazing and compaction damage. Years with very low rainfall had decreased quantity and quality of hay, loss of

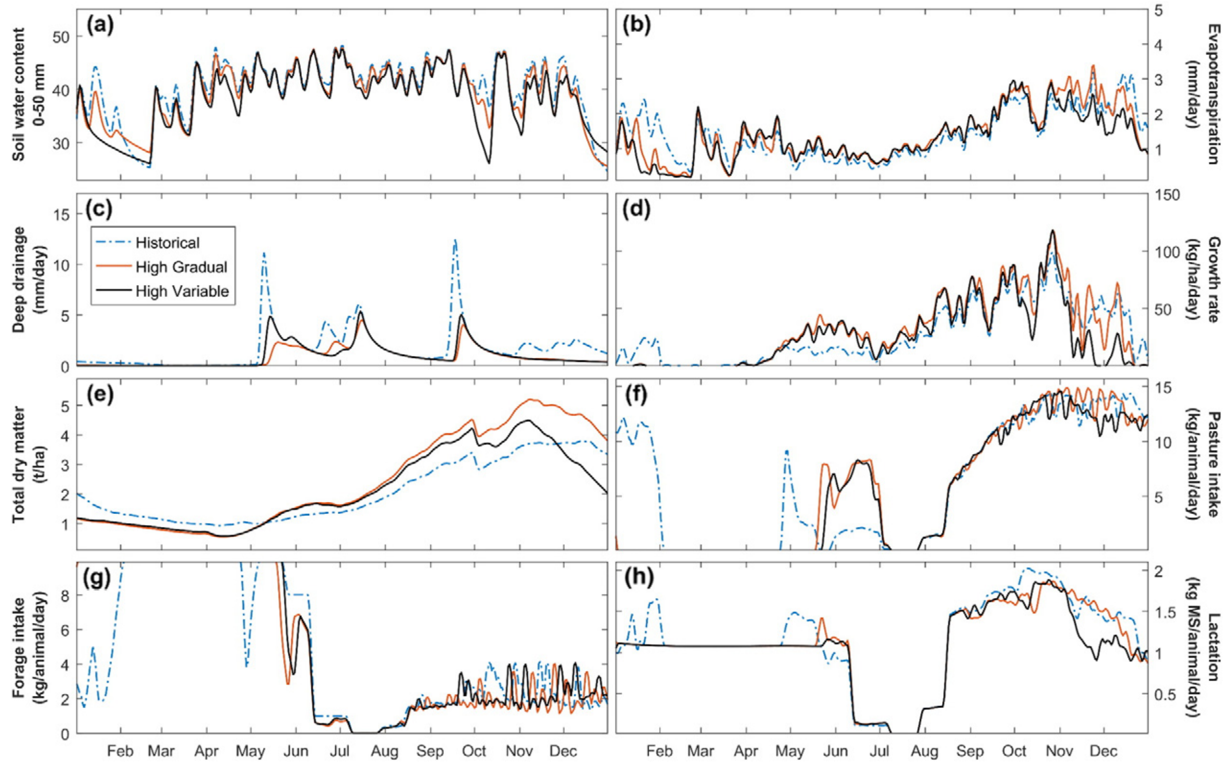

Fig. 5. Impacts of gradual climate change (High Gradual), historical climates and climate change data containing more extreme events (High Variable) on (a) volumetric soil water content in the soil surface, (b) evapotranspiration rate, (c) drainage below the deepest root layer, (d) pasture growth rate, (e) total dry matter, (f) pasture intake, (g) forage intake and (h) milk production (MS = milk solids). Curves represent seven-day moving averages for one year at Moe.

forage, winter shortage of green fodder, land degradation, increased water demand, shifting grazing seasons, decreased carrying capacity, overgrazing, heat stress, expansion of invasive plant species, and conflicts between economic interests and nature conservation objectives. In only a few cases was the awareness of these issues converted into practical adaptation or mitigation activities (Malatinszky, 2016).

While GCMs provide realistic predictions of mean changes in climate over longer time scales, their skill in forecasting extreme events is low (Smith et al., 2001; Soussana et al., 2010). This means that disentangling the impacts of extreme events from those of gradual climate change is error prone. This is important because agricultural systems are exponentially sensitive to increasing frequencies of

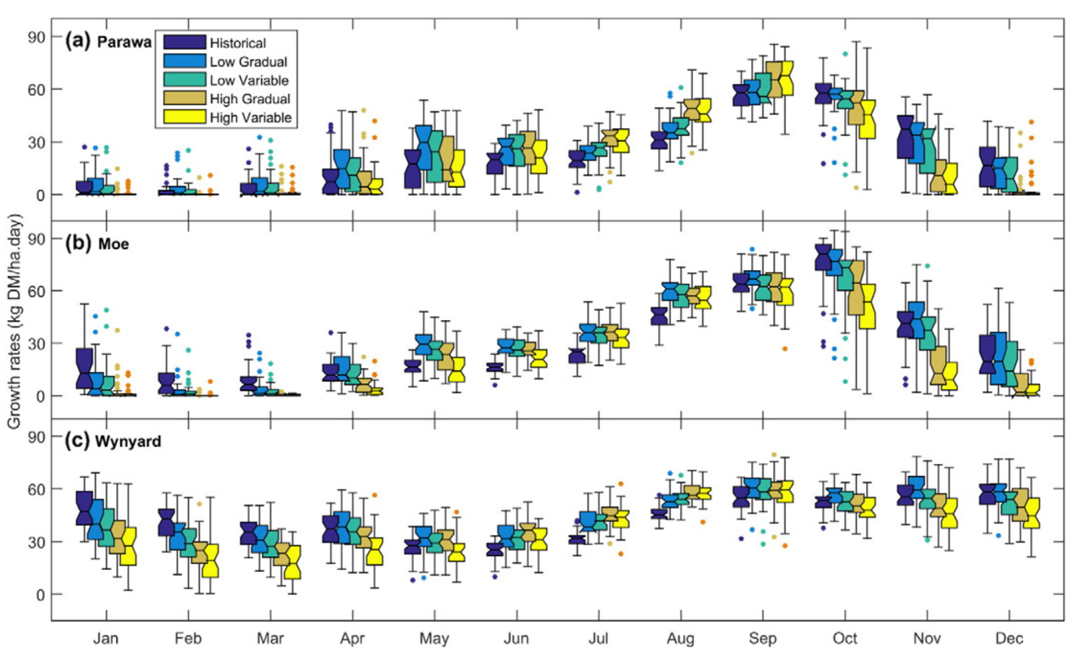

Fig. 6. Boxplots of pasture growth rates at (a) Parawa, (b) Moe and (c) Wynyard. Plots show the median, 25th and 75th percentiles in the box, with the 10th and 90th percentiles in the whiskers and dots showing values beyond the 5th and 95th percentiles. Each boxplot represents 39 years of simulations, with each point showing an average of daily pasture growth rate for that month (e.g. each of the 39 points for the Low Gradual approach in January represents the daily growth rate averaged over 31 days).

ECEs. For example, in a study of corn crops in the US, Katz and Brown (1992) found that the relative sensitivity of standard deviation to extreme high temperatures was exponential, whereas the relative sensitivity of the mean with increasing temperatures was linear. Put another way, the probability of corn crops being exposed to extreme temperature events was much more sensitive to changes in the standard deviation rather than the mean of the temperature distribution. Katz and Brown (1992) concluded that variability was more important than averages and that any analysis using climate models should not rely on scenarios of future climate involving only changes in means. In accord with this finding and suggestions by White et al. (2011), we present both means and variability of results, as well as probability density functions.

We revealed that analyses including only the effects of gradual climate change tend to underestimate variability in pasture growth rates, grazed pasture utilisation, milk production and profitability. Averaged across all sites and climate scenarios, the monthly average coefficient of dispersion of pasture growth rates under the Variable approach increased by 3% (range 0–8%) relative to the dispersion of the Gradual approach (dispersion coefficient was computed as $(Q_3 - Q_1) / (Q_3 + Q_1)$, where Q_3 and Q_1 represent the third and first quartile of monthly pasture growth rates, respectively). This observation concords with past work showing that crop yields in Africa were underestimated when only changes in climatic means were taken into account and variability was ignored (Rowhani et al., 2011). Greater variability in pasture growth rates resulted in +9 to −16% grazed pasture intake, 4–14% lower pasture utilisation and (in most cases) lower milk production, despite the fact that the requirement to purchase hay/silage increased by 29–100%. Further, the coefficient of variation in grazed pasture intake and grazed pasture utilisation generally increased under the Variable approach, despite the reduced average values under climate change. The combination of these factors meant that the average return on total assets of the Variable approach was +10% to −57% lower than that of the Gradual approach, even though the mean monthly climate changes applied in both methods were identical. These results demonstrate that increased climate variability cascades through the soil-plant-animal continuum to impact on whole farm production and profitability.

As with any study, the present paper had limitations. The model used to conduct the biophysical part of this analysis does not account for plant death, so even though exposure to higher temperatures and increased water stress drives faster senescence rates and transfer of live tissue to standing dead material and litter, extreme heat waves or extended dry spells does not kill plants. Pasture persistence and ground cover were not accounted for here because they are complex phenomena that are governed by several factors, including grazing intensity/frequency (Cousins et al., 2003; Harris and Brougham, 1970), weed ingression (Tozer et al., 2011), insect attack (Popay and Hume, 2011), botanical composition and competition with other pasture species (Tozer et al., 2011), and endophyte infection (West et al., 1993), among others. We feel that independent modelling of either plant persistence (e.g. as in Hill et al., 1989) or the aforementioned biotic factors as inputs or outputs to the DairyMod simulations would introduce more uncertainty to the results than rigour. Another limitation was that although stochasticity was accounted for in the Gradual and Variable methodologies, we applied only one realisation of climates generated using each method. A more comprehensive study could examine how multiple realisations from each climate methodology impacted on pasture growth and how this was realised in the farm system, particularly with respect to the sensitivity of variability within and across years.

Other areas where this study might be improved include the effects of high temperatures on plant death and consideration of limiting factors which interact with elevated CO_2, such as soil nutrients, pests and weeds, though it should be noted that these factors are neither fully understood nor well implemented in leading models (Soussana et al., 2010). Targeted model developments will be required based on experimental data concerning (i) the role of extreme climatic events, (ii) the interactions between abiotic factors and elevated CO_2, (iii) the genetic variability in plant CO_2 and temperature responses, (iv) the interactions with biotic factors, and (v) the effects on harvest quality (Soussana et al., 2010). To help make better use of the available knowledge, it is envisioned that

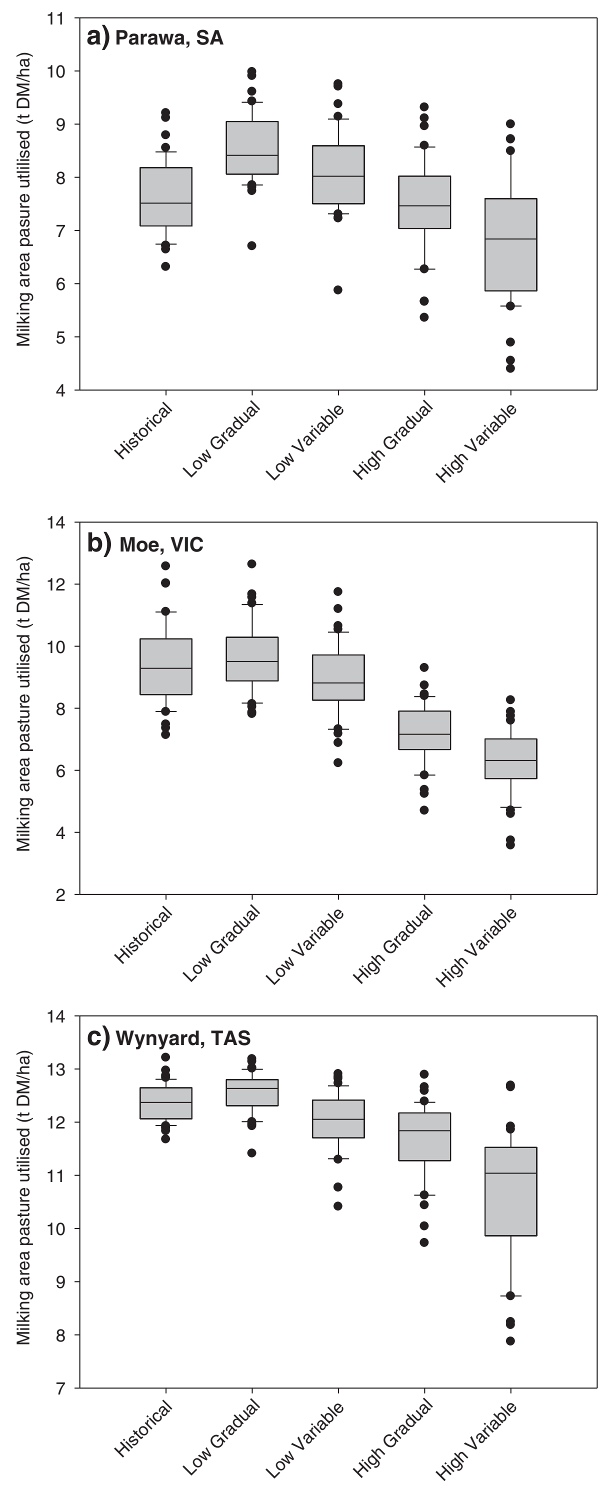

Fig. 7. Boxplots of annual milking area pasture utilised at (a) Parawa, (b) Moe and (c) Wynyard for the historical climate and future climate scenarios at each site. Plots show the median, 25th and 75th percentiles in the box, with the 10th and 90th percentiles in the whiskers and dots showing values beyond the 10th and 90th percentiles.

Table 5
Long-term average annual milk yield, pasture and conserved fodder intake, purchased hay/silage, pasture utilised and return on total assets for each case study site for the historical baseline and 2080 scenarios. Standard deviation and percentage coefficient of variation are shown in parentheses, respectively (Grad = gradual approach, Var = variable approach).

	Milk yield (kg fat & protein/cow)	Grazed pasture intake (kg DM/cow)	Conserved fodder intake (kg DM/cow)	Purchased hay/silage (t DM/farm)	Proportion of milking area pasture utilised for silage (%)	Total milking area pasture utilised (t DM/ha)
Parawa, SA						
Baseline	526 (18/3)	3345 (420/13)	1971 (350/18)	352 (13/4)	23.7 (3.8/16)	7.6 (0.7/9)
Low Grad	506 (17/3)	3655 (366/10)	1706 (286/17)	167 (139/83)	27.7 (5/18)	8.6 (0.7/8)
Low Var	511 (16/3)	3386 (434/13)	1912 (334/17)	220 (145/66)	29.4 (5.7/19)	8.1 (0.8/10)
High Grad	509 (12/2)	2385 (446/19)	2282 (340/15)	227 (152/67)	37 (8.4/23)	7.4 (0.9/12)
High Var	508 (14/3)	2600 (536/21)	2455 (387/16)	455 (218/48)	39.4 (10.5/27)	6.8 (1.1/16)
Moe, VIC						
Baseline	411 (18/4)	2648 (428/16)	1344 (338/25)	247 (131/53)	9.6 (0.2/2)	9.4 (1.3/14)
Low Grad	396 (14/4)	2653 (372/14)	1335 (266/20)	136 (96/71)	12.3 (3.3/27)	9.7 (1.1/11)
Low Var	396 (16/4)	2416 (375/16)	1500 (247/16)	219 (111/51)	13.2 (2.7/20)	8.9 (1.2/13)
High Grad	381 (12/3)	1997 (318/16)	1733 (207/12)	354 (88/25)	11.2 (2.3/21)	7.2 (1/14)
High Var	378 (12/3)	1673 (321/19)	1918 (200/10)	456 (96/21)	14.6 (5.3/36)	6.2 (1.1/18)
Wynyard, TAS						
Baseline	496 (15/3)	3572 (62/2)	790 (42/5)	240 (52/22)	13.4 (1.7/13)	12.4 (0.4/3)
Low Grad	459 (11/2)	3535 (93/3)	754 (53/7)	179 (51/28)	15.4 (1.5/10)	12.5 (0.4/3)
Low Var	471 (16/3)	3447 (145/4)	836 (76/9)	265 (70/26)	13.8 (1.8/13)	12 (0.6/5)
High Grad	459 (18/4)	3351 (181/5)	873 (81/9)	291 (77/26)	13.8 (1.9/14)	11.7 (0.7/6)
High Var	444 (38/9)	3073 (369/12)	969 (106/11)	376 (88/23)	13.2 (2.1/16)	10.6 (1.2/11)

future crop and pasture modelling studies will need to use a risk assessment approach by combining an ensemble of results from historical data, GCM scenarios and regional climate models, using both crop and pasture models (Soussana et al., 2010).

5. Conclusions

The current state of the art in forecasting extreme climatic events (ECEs) using global circulation models is in its infancy, which makes application of (and uncertainties in) such data in climate change studies error prone. We developed a new approach for simulating and partitioning the effects of ECEs from those of gradual climate change using historical site data. We presented case studies illustrating the differences between simulations using climates with only gradual climate change ('Gradual' approach) or both gradual change and more frequent extreme events ('Variable' approach). We revealed that simulations accounting only for the effects of gradual climate change and omitting future increases in the frequencies of ECEs underestimated the consequences of greater variability in extreme rainfall events, drought and heat waves. Despite identical changes in monthly mean temperature and rainfall as predicted by an ensemble of GCMs, increased climate variability introduced through RCMs was translated into more variable plant growth and biomass production in pasture-based dairy systems. This resulted in lower grazed pasture utilisation, greater reliance on purchased feeds and lower average profitability, with the magnitude of these impacts increasing under high impact (warmer and drier) climate scenarios. These results underscore the need for improved global- and regional-scale predictions of future changes in ECEs, as well as the need for more advanced methods of implementing such data within agricultural modelling studies.

Table 6
Long-term average gross income (×A$1000), total costs (including feed costs, ×A$1000), operating profit (×A$1000) and return on total assets (ROTA) for each case study site for the historical baseline and 2080 scenarios. Standard deviation and coefficient of variation (%) are shown in parentheses, respectively (Grad = gradual approach, Var = variable approach).

	Gross income (×A$1000)	Total costs (×A$1000)	Operating profit (×A$1000)	Return on total assets (%)
Parawa, SA				
Baseline	1050 (34/3)	898 (29/3)	151 (39/26)	2.8 (0.7/25)
Low Grad	1015 (29/3)	877 (25/3)	138 (28/20)	2.6 (0.5/19)
Low Var	1020 (32/3)	885 (27/3)	136 (36/26)	2.5 (0.6/24)
High Grad	1013 (25/2)	890 (28/3)	123 (30/24)	2.3 (0.7/30)
High Var	1016 (27/3)	932 (36/4)	84 (52/62)	1.6 (1/63)
Moe, VIC				
Baseline	789 (33/4)	647 (38/6)	142 (44/31)	3.2 (1/31)
Low Grad	761 (27/4)	630 (24/4)	131 (40/31)	2.9 (0.9/31)
Low Var	763 (30/4)	648 (27/4)	114 (42/37)	2.6 (0.9/35)
High Grad	734 (22/3)	671 (22/3)	64 (32/50)	1.4 (0.7/50)
High Var	729 (22/3)	702 (24/3)	27 (35/129)	0.6 (0.8/133)
Wynyard, TAS				
Baseline	1227 (36/3)	970 (9/1)	257 (31/12)	4.3 (0.5/12)
Low Grad	1139 (26/2)	959 (8/1)	180 (24/13)	3 (0.4/13)
Low Var	1167 (38/3)	973 (10/1)	194 (37/19)	3.3 (0.6/18)
High Grad	1140 (43/4)	976 (11/1)	164 (45/27)	2.8 (0.8/29)
High Var	1103 (90/8)	990 (13/1)	114 (95/114)	1.9 (1.6/84)

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.agsy.2016.07.006.

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