CLIMATE-SHOCK RESILIENCE AND ADAPTATION FOR NORTH CANTERBURY FARMS

Matt Dumont(ne Hanson),[1] Laura Bunning,[2] Bryn Gibson,[3]
Alex Schuddeboom,[3,4] Greg Bodeker,[3] Zeb Etheridge,[1] Andrew Curtis[2]
1 Kowmanawa Solutions Ltd.; 2 Water Strategies; 3 Bodeker Scientific; 4 University of Canterbury

Project Overview

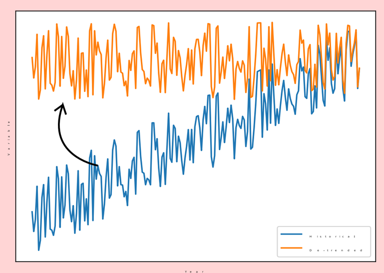
Farming is vulnerable to financial shocks associated with extreme weather events. The likelihood of multiple extreme events occurring within a compressed period is increasing, but the impact of these events on the primary sector under current climate conditions has not been investigated.

This poster summarises the methodology and findings of the first year of work on our two-year, multi-disciplinary, **Sustainable Land Management and Climate Change (SLMACC)** research project: a North Canterbury case study which aims to better understand the risk and impact of adverse weather and water availability sequences under current climate conditions.

During this project we have engaged with a number of interested parties including local North Canterbury farmers to help develop our understanding and definitions of adverse events. The feedback we have received from farmers is that the current state of climate research, which focuses on mean impacts from long term changes (e.g., at 2050 and 2100), is not as important as the near-term climate shock events. The consensus from our farmers panel was that their planning window was often only up to 3 years ahead of present. 10–20 year changes in climate states were difficult to weigh up in comparison with other factors e.g., economic, environmental, and global demand. Therefore, we believe that our work can help farmers make good decisions within their planning time frame.

Methods

1. De-trend Climate & Restriction Data



Remove the non-stationary impacts of climate change and adjust the data to 'present' based on t' southern hemisphere land.

2. Define Climate States

Define the climate states for each month in a way that can be passed to weather@home without incurring bias.

Temperature			Precipitation		
Measure: Monthly mean temperature percentile			Measure: Monthly mean soil moisture anomaly percentile		
Cold	Average	Hot	Wet	Average	Dry
x <= 25th	25th < x < 75th	x >= 75th	x <= 25th	25th < x < 75	x >= 75th

3. Classify De-trended Data

Year	Month	Sma	Tmean	T-class	P-class
...	...	...	...	...	...
2019	Jan	-7.2	18.5	H	A
2019	Feb	-17.0	17.2	A	D
...	...	...	...	...	...

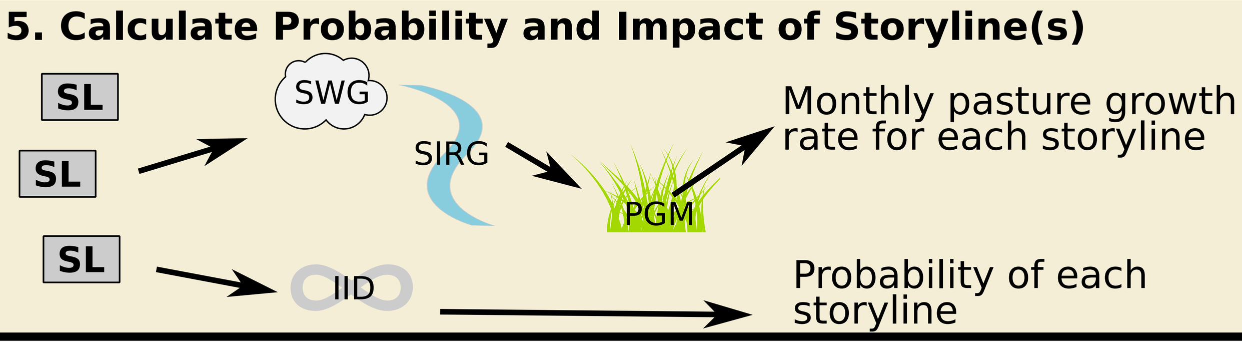
Classify each month of the detrended data into: Temperature Classes (Cold, Average, Hot) and Precipitation Classes (Wet, Average, Dry) based on the climate states (2).

4. Develop Storylines SL

Month	P	T	Irr
Jan	D	H	50%
Feb	A	H	60%
Mar	D	A	40%
Apr	A	A	30%
...	...	...	...

A storyline is a user prescribed 1+ year record of classified climate states (precipitation state and temperature state) and mean monthly irrigation restriction percentile for the given climate state (e.g. Hot-Dry-60th percentile restrictions). These storylines can be either user developed to investigate impacts of specific bespoke climate states (e.g., for impact analysis), or can be generated statistically (Markov chain Monte Carlo) to assess the cumulative impact probabilities of the current climate.

5. Calculate Probability and Impact of Storyline(s)



Tool Development

A major component of the project was developing a series of tools to produce synthetic weather and river flow data, to translate those data into pasture growth data, and to assess the probability of a given story-line. These tools have been tuned to North Canterbury Farms, but could be re-tuned to other locations.

Infinite Improbability Drive (IID)

The Infinite Improbability Drive calculates the probability of a user specified set of monthly climate states and irrigation restrictions (i.e. a story line) occurring in any given year.

1. Calculate transition probabilities

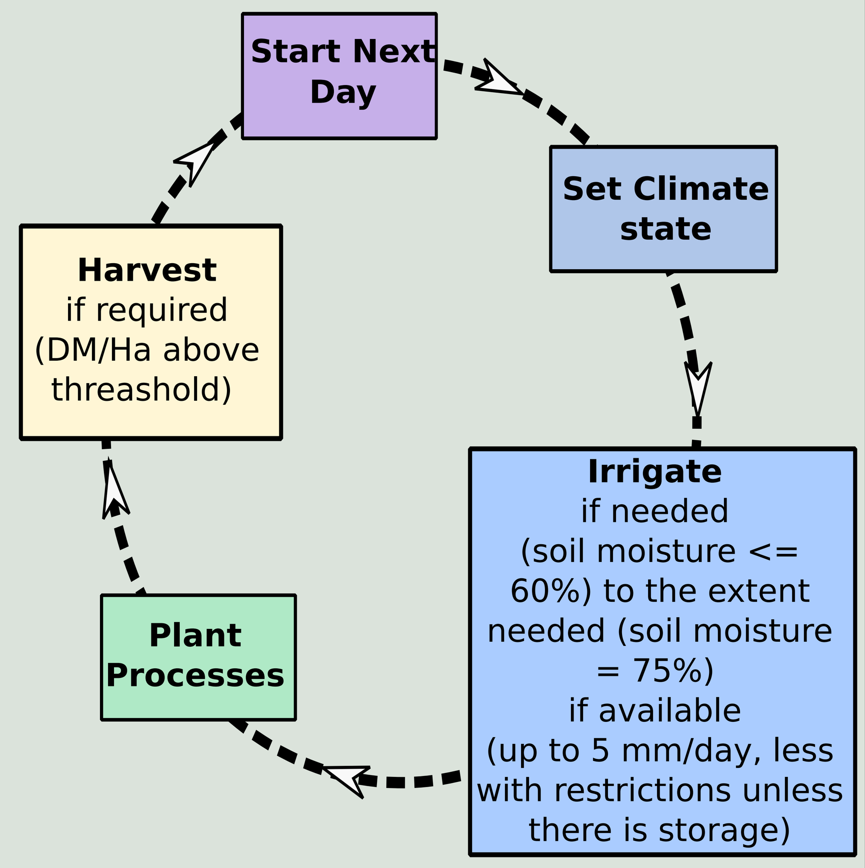
Weather@home contains many realisations of different weather under the same climate. This means there are enough realisations to adequately calculate the probability of any transition between monthly climate states. These transition probabilities can then be used to calculate the probability of any given story line.

2. Calculate storyline probability

1. Calculate the probability of the first state of the storyline which is the product of:
   1.1. the probability of the climate state
   1.2. the probability of restrictions being more extreme than the storyline level (0-0.5).
2. Calculate the probability of the next month which is the product of:
   2.1. the transition probability from the previous month's state to the current month's state.
   2.2. the probability of restrictions being more extreme than the prescribed restrictions
3. Repeat step 2 for every month in the storyline
4. Calculate the final probability; the product of the probabilities calculated in steps 1-3.

Pasture Growth Model (PGM)

The pasture growth model used here is BASGRA_NZ_PY. Full details on the pasture growth model is available in the GitHub repo (https://github.com/Komanawa-Solutions-Ltd/BASGRA_NZ_PY).



Stochastic Weather Generator (SWG)

The SWG produces daily climate variables for a storyline based on the detrended climate data at one or more sites while maintaining the intersite correlation. It also preserves the intra-monthly auto-correlation.

1. Data generation

1. Initialize the SWG (day 1) with a day picked randomly from the binned data at each site
2. Calculate the next day's (day n+1) climate data for site 1
   2.1. Determine whether the day is dry or wet
   2.2. If wet determine precipitation amount
   2.3. Calculate other climate variables
3. Calculate the next day's climate data for site m+1 based on site 1
4. Repeat steps 2 and 3 for day in the month
5. Repeat steps 1-4 for each month in the storyline

2. Check data matches criterion

The SWG can produce data that does not match the storyline due to its random nature. Any such instances must be recalculated.

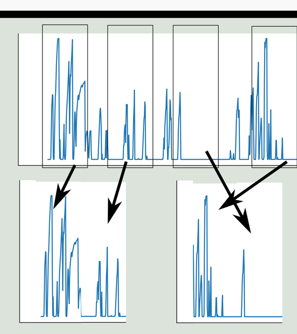
3. Repeat steps 1 & 2 to create many realisations

Many realisations are needed as any single realisation may be an extreme example of the storyline.

Stochastic Irrigation Restriction Generator (SIRG)

The SIRG produces daily irrigation restrictions (0-100%) for a storyline with a moving block bootstrapping of the detrended restriction record. This method preserves the distribution of restrictions across a month and the intra-monthly autocorrelation.

2. Data generation

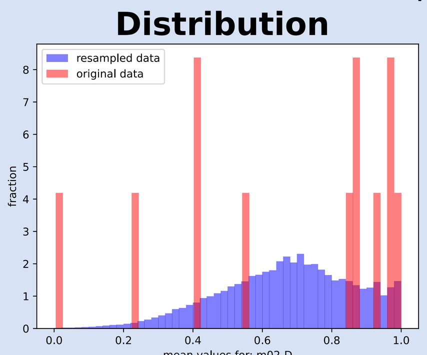


Produce a very large suite of data for each bin: 1. make a set of data blocks 2. randomly group the blocks 3. clip the grouped data to the lenght of the month 4. calculate the mean restriction level 5. redo 1-4 many times with different sized blocks

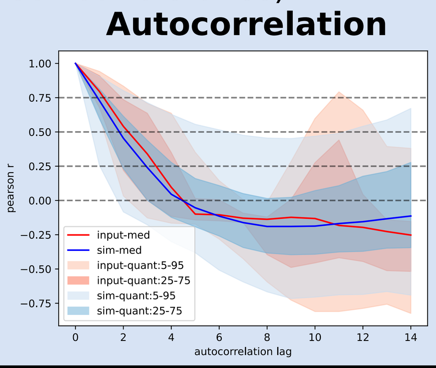
3. Data selection

Select n timeseries which match the specified mean restrictions (within user specified tolerance)

Distribution

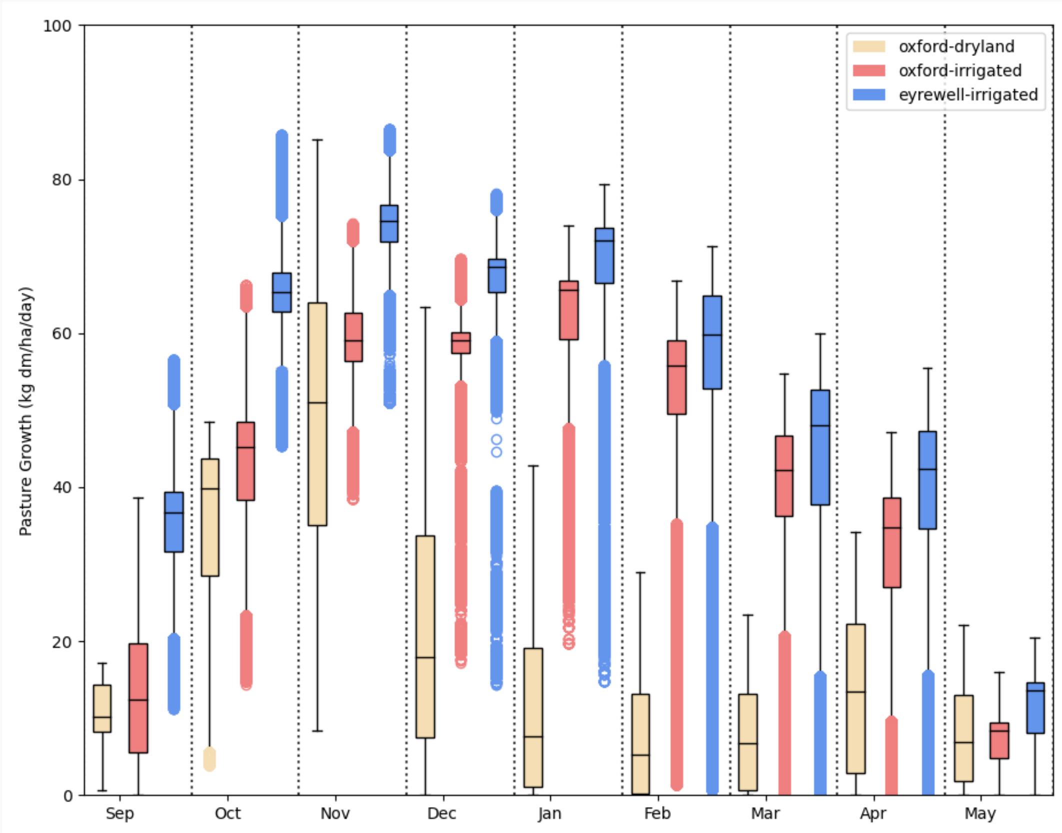


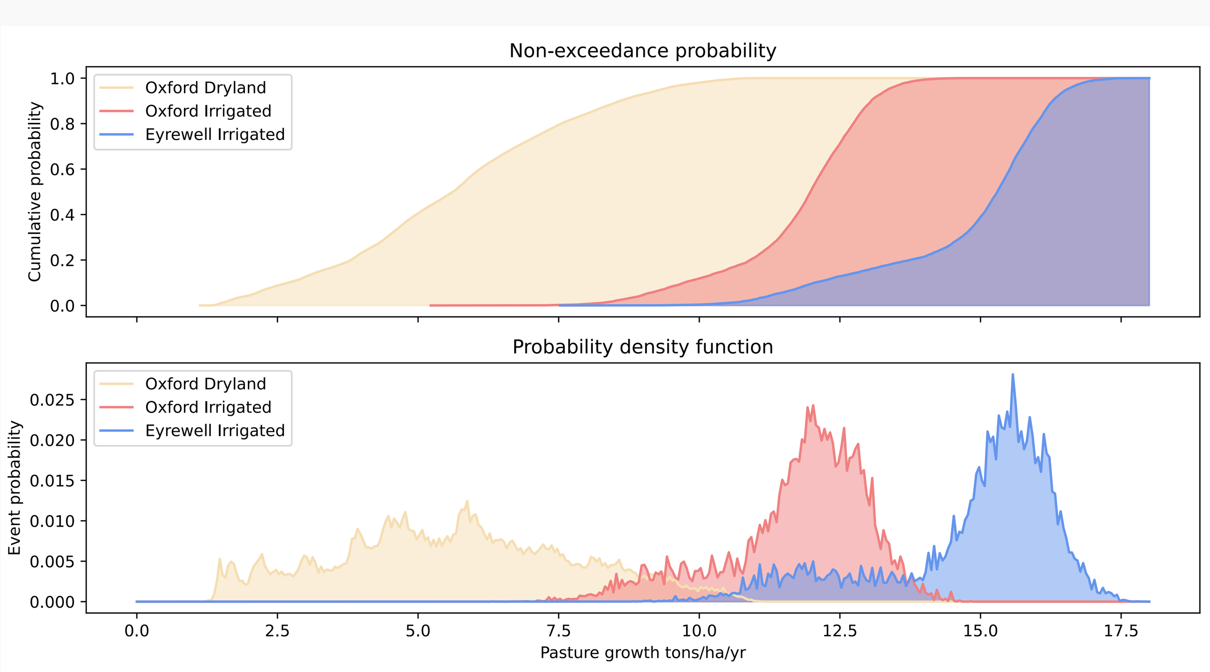
Autocorrelation



Results / Current Climate State

The distribution of monthly pasture growth (right) provides insight into the range of possible monthly impacts. Dryland farms show significant variation, particularly in Nov. and Dec. This suggests that increased monitoring on farms during Nov. and Dec. could provide farmers with an early warning of annual deficits. Irrigated farms on the other hand have the most variability associated with the later summer irrigation period (Feb. to Apr.). Note that the dryland and irrigated farms use different model parametrisations and are therefore may show different biases, which is why dryland farms may show a higher production in Nov. than irrigated farms at the same location. The BASGRA model does not do a good job of predicting the winter (Jun. - Aug.) pasture growth. The pasture growth variability is minimal at this time, so we simply set monthly average values.

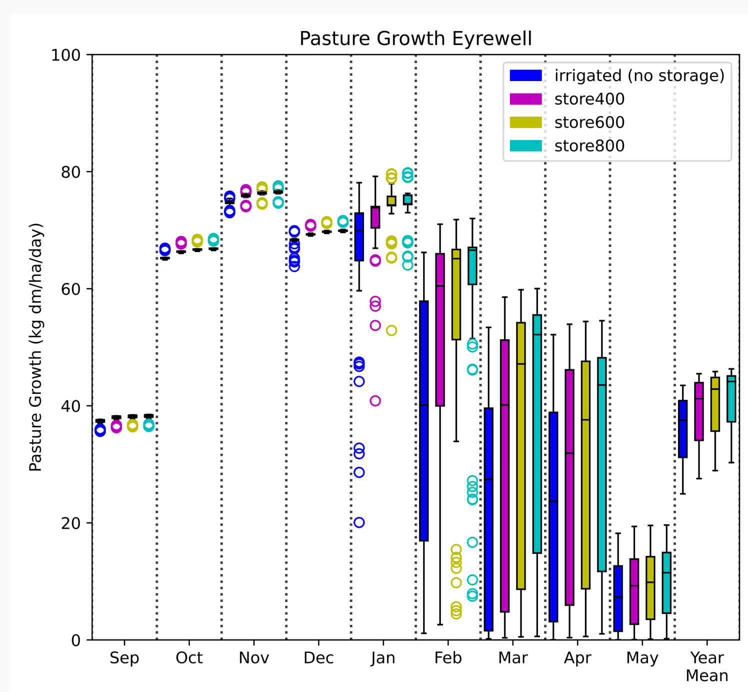




The non-exceedence probability and probability density function of annual pasture growth (left) provides an overview of the annual variance farmers can expect under the current climate state (2020-2030). Dryland farm production is far more variable than the irrigated sites (as expected) but are largely Gaussian. Irrigated sites have a main Gaussian peak with a long, low productivity, tail. Farm systems are likely less well optimised for pasture growths that fall in this tail. We can expect events in this tail on average every 1 in 5 years.

Storage Mitigations

One of the most discussed on farm mitigation to climate extremes for irrigated farms is the inclusion of on farm storage. We modelled the impacts of on farm storage for 3 different storage scenarios (400, 600, & 800 m^3/ha) on a range of different climate scenarios. The figure (right) shows the impact of storage at an Eyrewell farm on 100 storylines, which are, on average, a 1 in 5 year low pasture production event (for a farm without storage). On farm storage may allow novel water allocation regimes (e.g., short term take secession to allow fish passage), but may raise other ecological challenges (e.g., winter takes to fill storage).



Next Steps

1. Incorporate our pasture growth and on farm results into regional macro economic modelling.
2. Investigate alternative and adaptive flow restrictions on a generic braided alpine river to assess the economic, ecological, and cultural impacts.
3. Communicate these results with interested parties including the farmer panel.