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Thriving in an Age of Extremes

Climate change and property prices

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- Background
- Property price data
- Climate data

Section 2 - Modelling

- Postcode-level modelling
- Modelling the impact of climate variables on NSW property prices

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- Main findings
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Introduction

Issue to be investigated: does exposure to climate variability affect real estate prices?

Introduction

- **The ability for climate change to impact on prices of exposed assets is acknowledged by regulators and managers of financial assets:**
  - Climate change is a systemic risk that could have a material impact on the future financial position, performance or prospects of entities (ASIC, 2019)
  - Climate change is expected to impact on investment returns (Actuaries Institute 2019)
  - Climate change is a material, direct and current financial risk (Rest Super Fund, 2020)
  - Physical climate risks, including long-term changes in climate, can lower asset values(APRA 2021)

Introduction

- **A number of US studies have found links between climate change and property prices:**
  - Study of housing values on US Eastern seaboard from 2005 to 2017 found drop in prices from properties exposed to sea level rise (First Street Foundation, 2018)
  - US homes exposed to sea level rise sold for approximately 7% less than observably equivalent unexposed properties equidistant from the beach, with this discount having grown over time (Bernstein, Gustafson & Lewis, 2018)
  - Price impacts are correlated with the buyer's belief in climate change (University of British Columbia, 2019)

Introduction

Our study focusses on the link between climate change and property in Australia

Introduction

- **We have elected to investigate the link between movements in climate metrics and property prices over the long term**
- Another potential area of investigation is to look at impact of a natural peril event on property prices in an affected region (not covered by our paper)
  - CoreLogic previous studies on impact of Natural Hazard such as cyclone or bushfire have shown a strong resilience for the property market

Property price data

- **We utilised a CoreLogic hedonic regression index to measure the change in housing values over time.**

- Hedonic regression breaks down each property into its constituent parts (e.g., # of bedrooms, # of bathrooms, land area, location) and determines the contributory value of each attribute using observed transactions

$$\ln P_i^t = C_0^t + \sum_{k=1}^{K} C_k^t X_{ik}^t + \varepsilon_i^t$$

where:

P_i^t	= sale price (or listing price) of property *i* (*i*=1 to *M*) in period *t*
X_{ik}^t	= transformation of the hedonic variable *k* for property *i* in period *t*
$C_{0\ to\ k}^t$	= numerical coefficients to be estimated
ε_i^t	= (zero mean) residual error term for property *i* in period *t*

Property price data

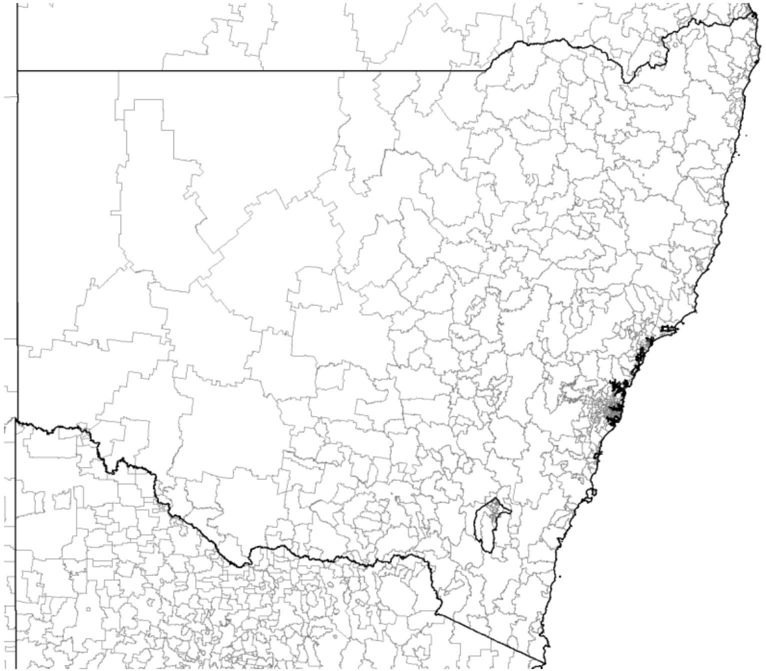
Difficulties measuring the property market (why hedonic index?)

1. **Compositional bias of underlying transactions**
   - We estimate the value of <u>every</u> property across the portfolio to ensure that even those that haven't transacted are factored into the indexation process
2. **Capital injections obscure organic growth**
   - By ensuring adjacent periods of an index use the same property attributes, we control for the impact of capital injections or changes to the underlying stock
3. **Majority of observed transactions aren't current**
   - We exclude sales with long settlement terms from the regression
   - We time weight the sales observations as part of the regression process

Property price data

What property data did we use in this analysis?

1. **Hedonic indices specific to New South Wales with a date range between January 1981 and December 2020**
2. **Geographically, indices across the following geographic boundaries were utilised:**
    1. 2016 ASGS: State, GCCSA and SA4
    2. Postcode



In case you didn't know…

The total value of residential housing across Australia is estimated to be worth $8.1 trillion*

The residential asset class is worth almost three times as much as all the superannuation funds combined and is three times the aggregate value of companies traded on the ASX!

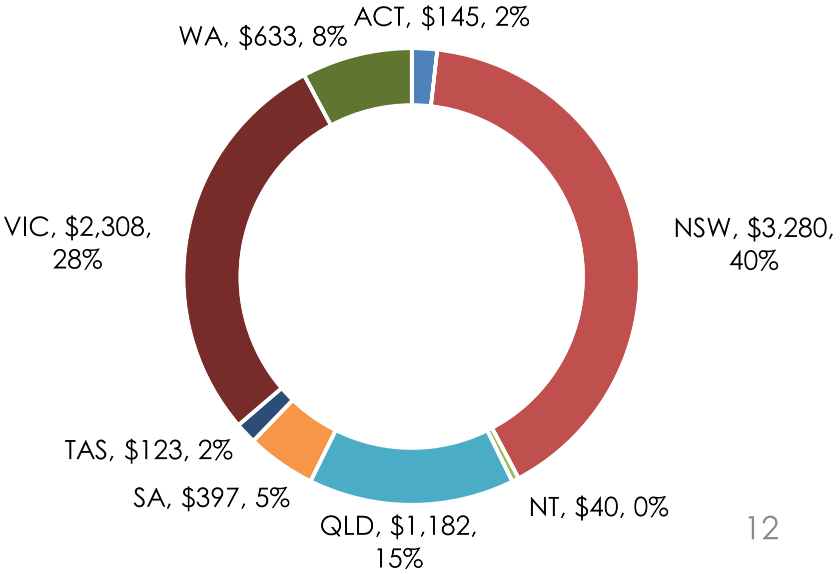
RESIDENTIAL REAL ESTATE
$8.1 Trillion

AUSTRALIAN SUPERANNUATION
$3.0 Trillion

AUSTRALIAN LISTED STOCKS
$2.7 Trillion

COMMERCIAL REAL ESTATE
$964 Billion

Estimated value of dwellings by state ($ billion) as at April 2021

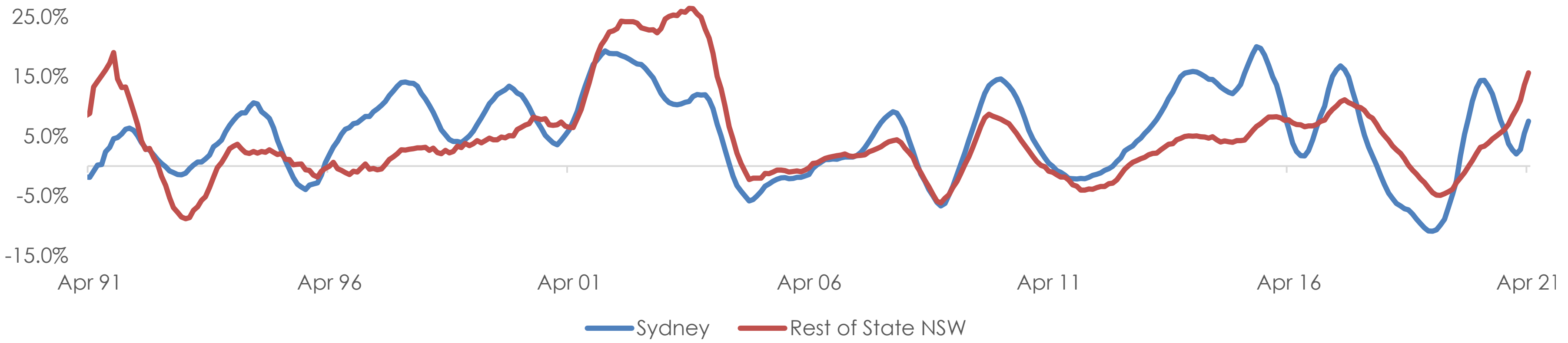


* Source: CoreLogic estimate

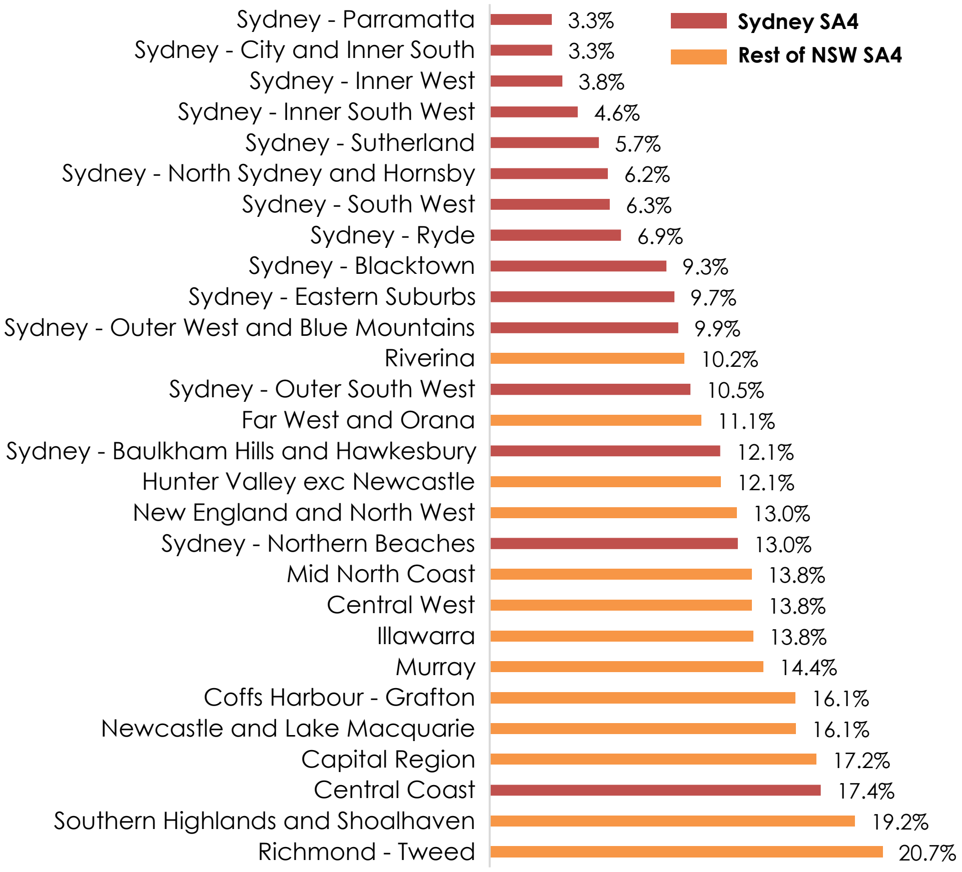
A broad overview of housing markets across NSW

- **Housing values are in the midst of a geographically broad-based upswing, although regional areas of NSW have generally seen values rising at a faster pace relative to Sydney**

Rolling annual change in dwelling values
Sydney v Rest of State NSW



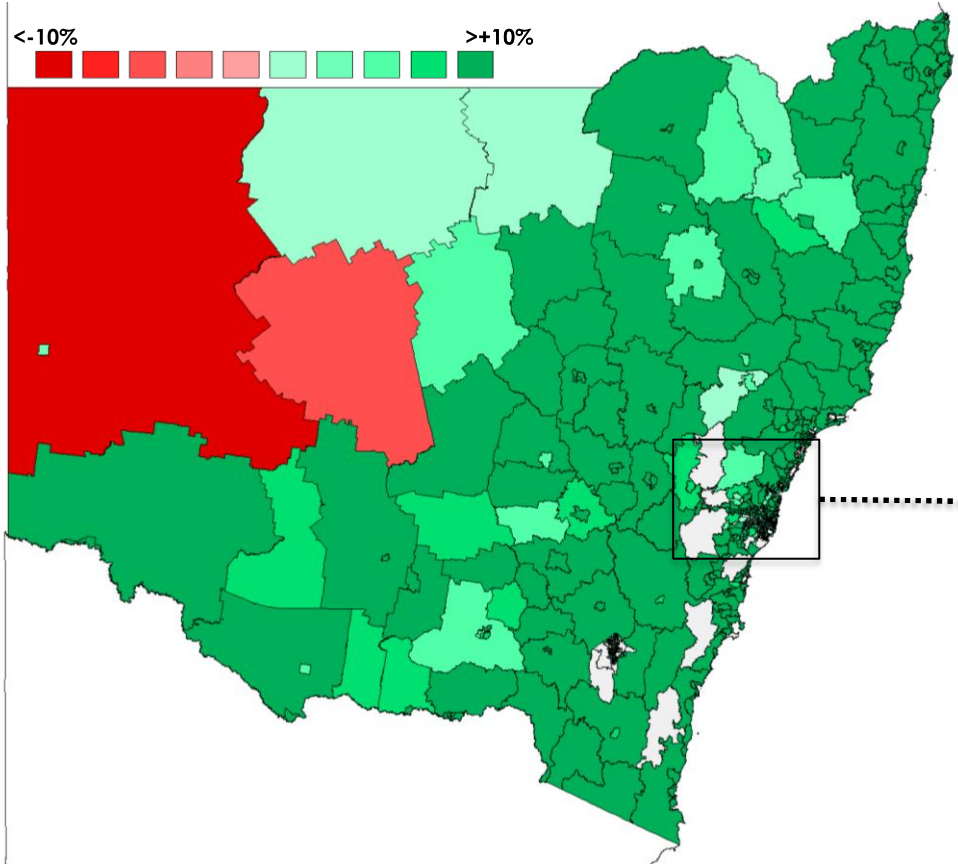
Annual change in dwelling values
NSW SA4 regions

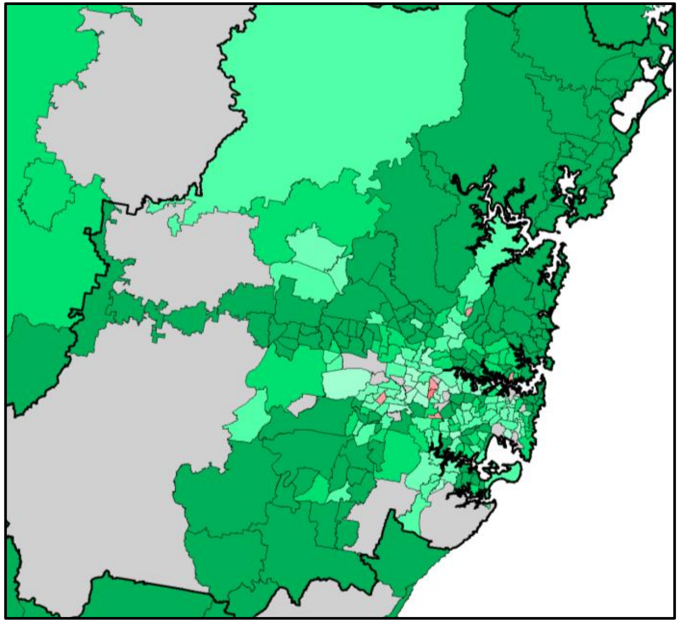


Each of the SA4 sub-regions across New South Wales have recorded a lift in dwelling values over the past year…

but regional areas of the state have dominated the strongest capital gain positions.

Annual change in dwelling values (twelve months to to April 2021)
Thematic map is plotted across SA2 geographies



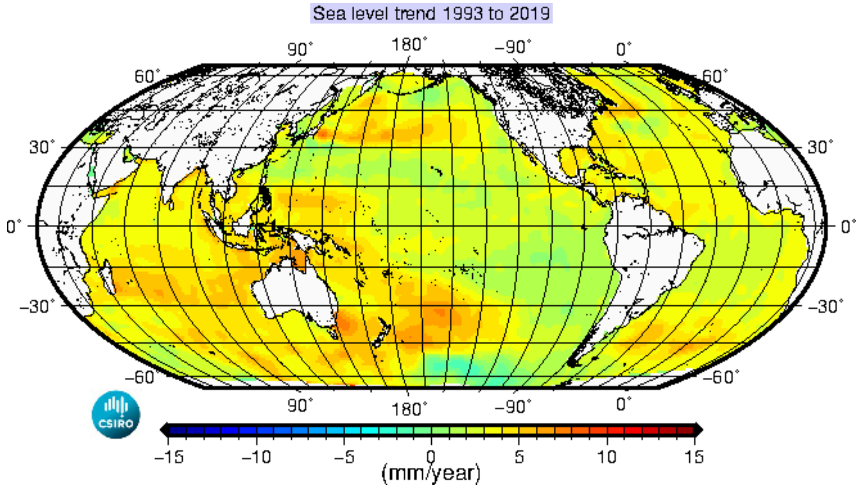


Climate data (1)

- Climate metrics were sourced from the BOM and the CSIRO focusing on the three metrics used in the composite Australian Actuaries Climate Index (AACI): high temperature, rainfall and sea level height.
- Data was extracted Jan-1981 to Dec-2020 for monthly rainfall and monthly average maximum temperature, and Jan-1993 to Jul-2020 for sea level height.
- Did not take extreme values or threshold exceedance measures as done in the AACI. Focus is on changes in the absolute level of measures.

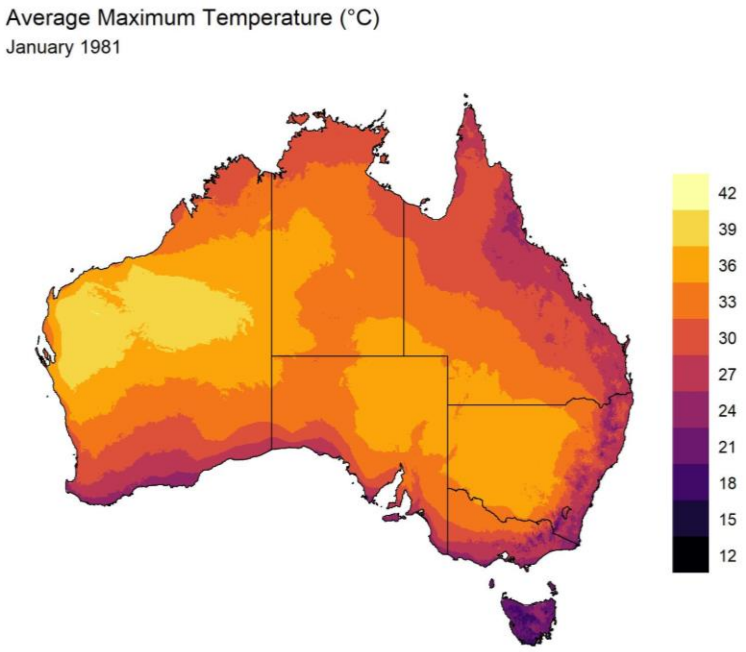
Climate data (2)

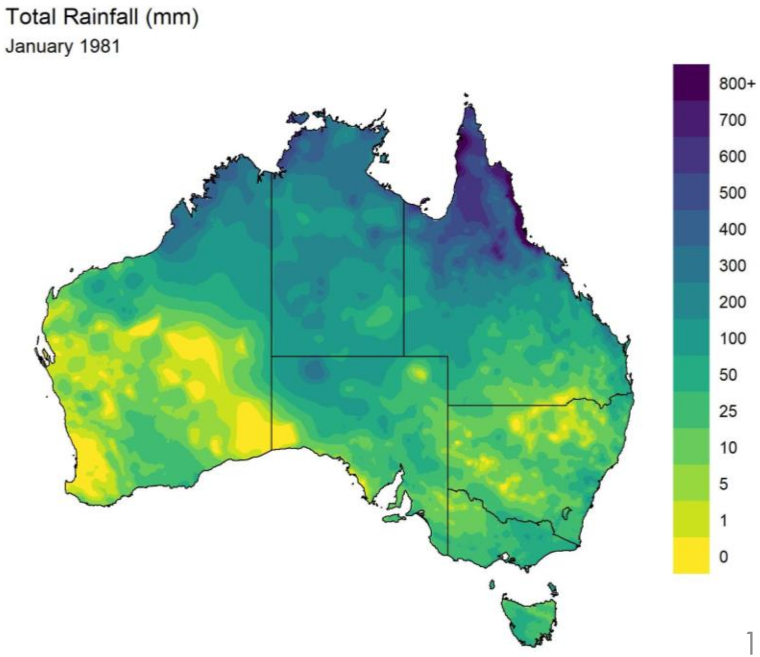
- **Sea level height** does not rise or fall uniformly over the oceans. It also reflects patterns of ocean heat storage. CSIRO data on monthly maximum observed sea level is used. The measures were smoothed along the coast-line and corrected for seasonal, tidal and other factors.
- **Rainfall and temperature** data are available as gridded files from the BOM, containing spatially interpolated station-based temperature and rainfall measurements across all available measurements from ~700 stations.



Climate data – geographic variation

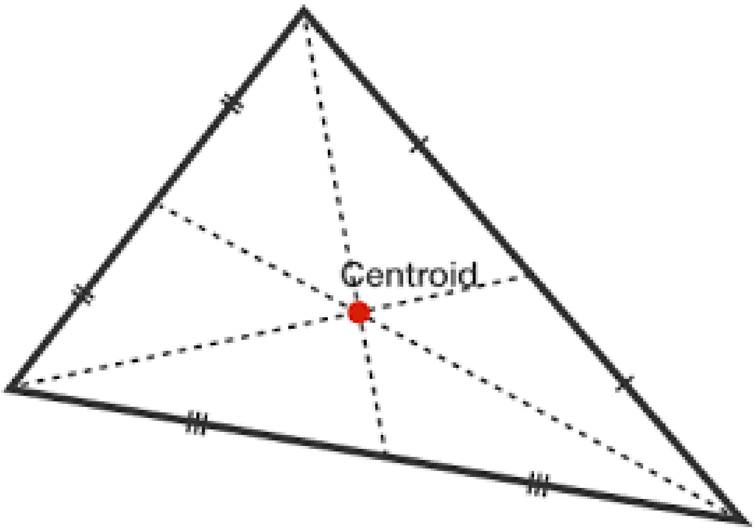
- In a single month, temperature and rainfall vary significantly across NSW





Climate data – centroids

- As climate measures can vary across a single postcode, to set values for climate factors in postcode 'i' at time 't' we tested two alternative methods:
  - Climate variables at the centroid of each postcode
  - Climate variables at population-weighted centroid of each postcode (the average of mesh block centroids, weighted by mesh block population)
- In postcodes outside of Greater Sydney these two locations can be far apart.
- For property price modelling, using the population-weighted centroid improved model goodness of fit.

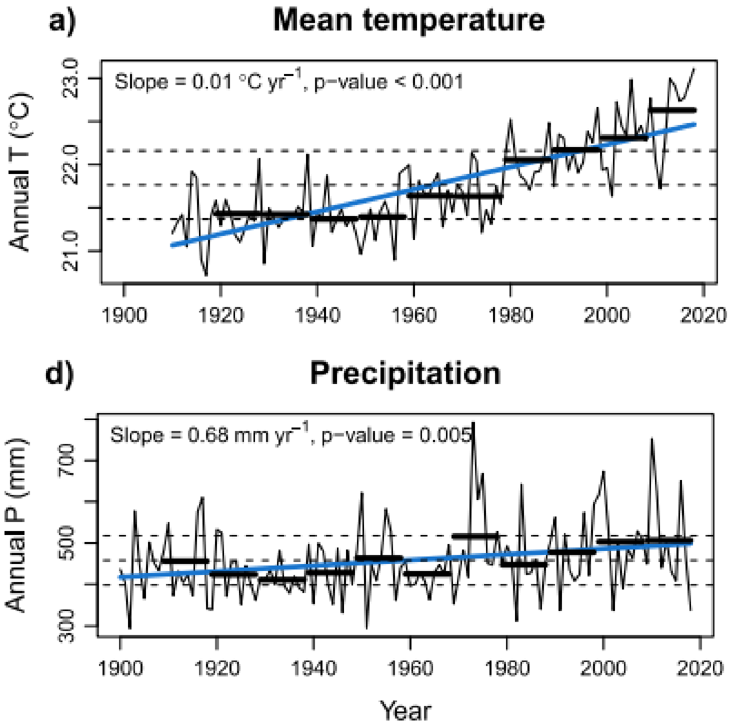


Climate data – variation over time

Ukkola et al. 2019 find:

- **Temperature -** there have been highly significant increases in temperature that are non-stationary over time
- **Precipitation –** Seasonal and annual precipitation over the last century is found to be stationary in most (but not all) regions.

Since stationarity is an assumption underlying time series models, we transform non-stationary temperature data to be stationary by taking first differences.



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Modelling approach (1)

- To model postcode level hedonic indices we use the framework developed in Hanewald and Sherris (2013)
- CAPM style approach

$$ln(\frac{P_i^t}{P_i^{t-1}}) = \boldsymbol{\alpha} + \boldsymbol{\beta} ln(\frac{P_{Market}^t}{P_{Market}^{t-1}}) + \boldsymbol{\varepsilon}_i^t$$

- Response is log growth in hedonic price index for each postcode $ln(\frac{P_i^t}{P_i^{t-1}})$
- We extend to test whether local climate factors ($\boldsymbol{x}_i^t$)are significant in addition to the market index

$$ln(\frac{P_i^t}{P_i^{t-1}}) = \boldsymbol{\alpha} + \boldsymbol{\beta} ln(\frac{P_{Market}^t}{P_{Market}^{t-1}}) + \boldsymbol{\theta x}_i^t + \boldsymbol{\varepsilon}_i^t$$

Modelling approach (2)

- Hanewald and Sherris (2013) find variable slope parameters across postcodes (β_i) improve goodness of fit, implying house prices in different postcodes have different sensitivity to the market index.
- We test variables slopes for market and climate variables using linear mixed models. LMMs can allow for both fixed and random effects:
- **Fixed effects**
  – Models with fixed effects account for the within group variation, i.e., change in price within a single postcode over time.
- **Random effects**
  – Models with variable parameters and random effects effectively capture the cross-sectional heterogeneity observed in house prices at the postcode level.

Modelling approach (3)

- Focus is not on forecasting or predicting, rather on testing whether climate variables have historically influenced property prices.

- To test the significance of climate variables and fixed vs. random effects we focus on using the Likelihood Ratio (LR) test statistic:

$$LR = -2ln\left(\frac{L(m_1)}{L(m_2)}\right)$$

- Where $L(m_*)$ denotes the likelihood of the respective model (either Model 1 or Model 2), m_1 is the more restrictive model, and m_2 is the less restrictive model.

Model (1) – Simple panel with temperature, rainfall and sea level height variables

- Response was log price growth on a monthly time scale:

$$ln\left(\frac{P_i^t}{P_i^{t-1}}\right) = \alpha + \beta ln\left(\frac{P_{Market}^t}{P_{Market}^{t-1}}\right) + \theta \boldsymbol{x}_i^t + \boldsymbol{\varepsilon}_i^t$$

- $\boldsymbol{x}_i^t$ is matrix of observations across postcodes (i) and time (t) of:
  - Monthly sea level height
  - Total rainfall
  - Mean maximum temperature

Climate variable	Measures (monthly)
Temperature	Average maximum daily temperature
Precipitation	Total rainfall
Sea level height	Average sea level height

Model (1) – Results

- Three models fit:
  - [1] Fixed slopes model (β and θ are fixed effects)
  - [2] Variable slope for market index only (fixed and random effects)
  - [3] Variable slope for all variables (fixed and random effects)
- In models [2] and [3], β and θ have fixed and random components and vary across postcodes.
- In all models, only the relationship between postcode level prices and the market index was significant.
- Temperature, rainfall and sea level metrics did not significantly affect property price growth i.e. θ coefficients were roughly equal to 0.

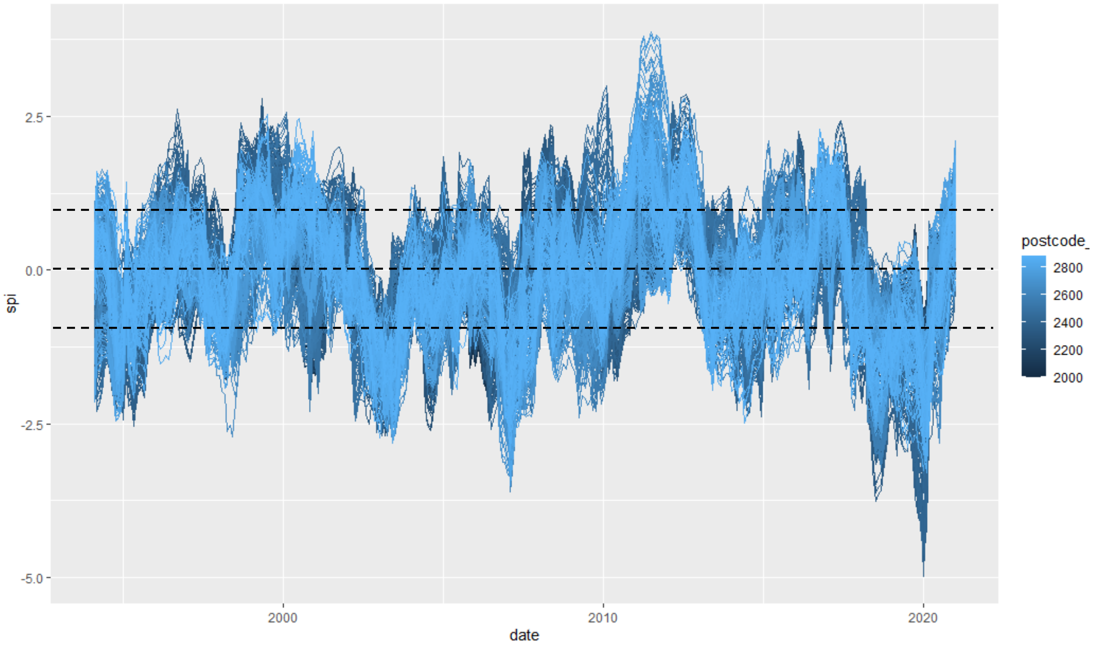
Model (2) – Alternative transforms of rainfall

- Second phase of modelling focussed on alternative measures of precipitation.
- Precipitation has a direct channel to influence property prices in some areas through flood risk
- In the second set of models, we focussed on using three alternative transforms of precipitation (shown on the right)

Climate variable	Measures
Precipitation [4]	Total rainfall (year to date)
Precipitation [5]	Consecutive dry months
Precipitation [6]	Standardised Precipitation index

Model (2) – Alternative transforms of rainfall

- SPI is a widely used index to characterize drought on a range of timescales
- SPI values below -1 indicate a condition of drought
- SPI values higher than +1 indicate wetter conditions compared to a normal situation.
- SPI values between -1 and +1 indicate the situation is identified as "normal"



Model (2) – Property price increase vs. alternative measures of precipitation

- We also moved from monthly to 12-mthly rolling price growth and explanatory variables (as SPI is a rolling measure)
- Response was log price annual growth on a monthly time scale:

$$ln\left(\frac{P_i^t}{P_i^{t-12}}\right)=\boldsymbol{\alpha}+\boldsymbol{\beta}\,ln\left(\frac{P_{Market}^t}{P_{Market}^{t-12}}\right)+\boldsymbol{\theta}\boldsymbol{x}_i^t+\ \boldsymbol{\varepsilon}_i^t$$

- Where $\boldsymbol{x}_i^t$ is matrix of observations across postcodes (i) and time (t) of one of three alternative measures of precipitation (total rainfall, consecutive dry months or SPI) in postcode ‘i’ at time ‘t’

Model (2) – Results

- The models using Total Rainfall over the last 12 months and SPI showed significant fixed effects
- Consecutive dry months was not significantly related to postcode level property prices

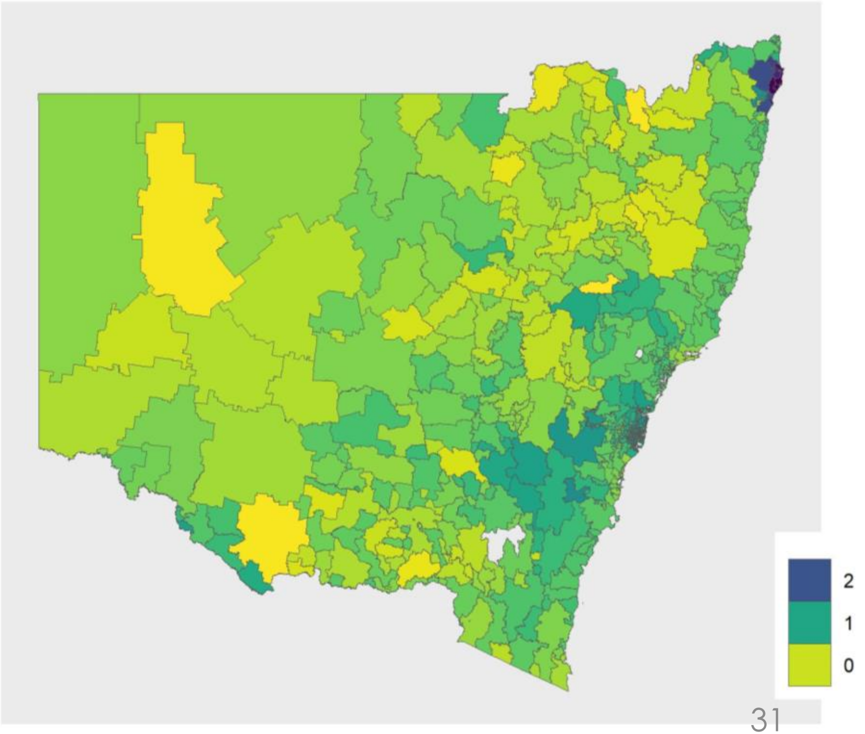
			Fixed effect coefficients and significance			
Model		AIC	Intercept	Market index	Rainfall	
[4] Total rainfall	-	406,081	0.0015	0.8092	0.0000	***
[5] Consec. dry months	-	404,439	0.0016	0.8079	-0.0002	
[6] SPI	-	406,588	0.0019	0.8027	-0.0014	**

- We proceed with the model using SPI because SPI values are in units of standard deviation from the long-term mean, so is a better way to compare precipitation anomalies across geographic areas than total rainfall.

Model (3) – Sensitivity to market index

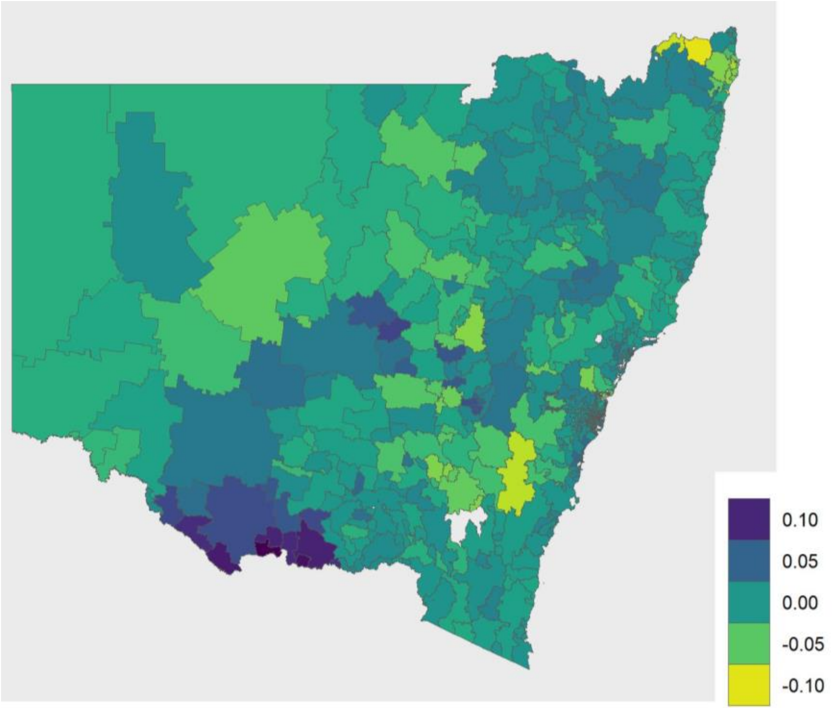
- A higher slope parameter estimated for a postcode area indicates that a higher proportion of house price risk is explained by the market-wide index
- In Greater Sydney, like Hanewald and Sherris (2013) we find house prices in postcodes closer to Sydney CBD are more sensitive to the market index
- In Rest of NSW, we find house prices in postcodes closer to Byron are most sensitive to the market index for "Rest of NSW"

Hedonic Home Value Index - NSW



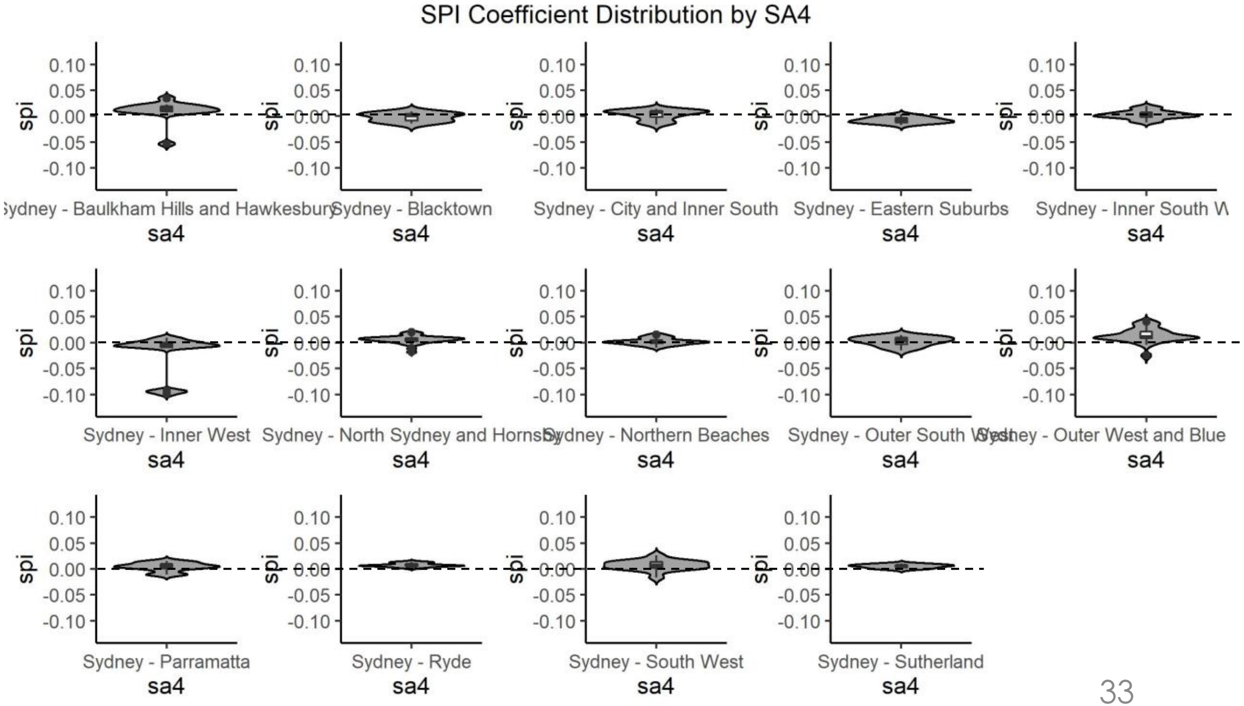
Model (3) – SPI coefficients

- Positive SPI indicates wetter than normal conditions, so a positive coefficient (blue/dark blue) indicates property prices respond negatively to drought/positively to excessive rainfall
- Vice versa, negative SPI coefficients (green/yellow) indicate that property prices respond positively to drought/negatively to excessive rainfall
- The LR test shows the coefficients are significant, and they are spatially "smooth" across postcodes
- Broad correspondence between
  - Postcodes with negative SPI coefficients and flood regions
  - Postcodes with positive SPI coefficients and drought-sensitive regions



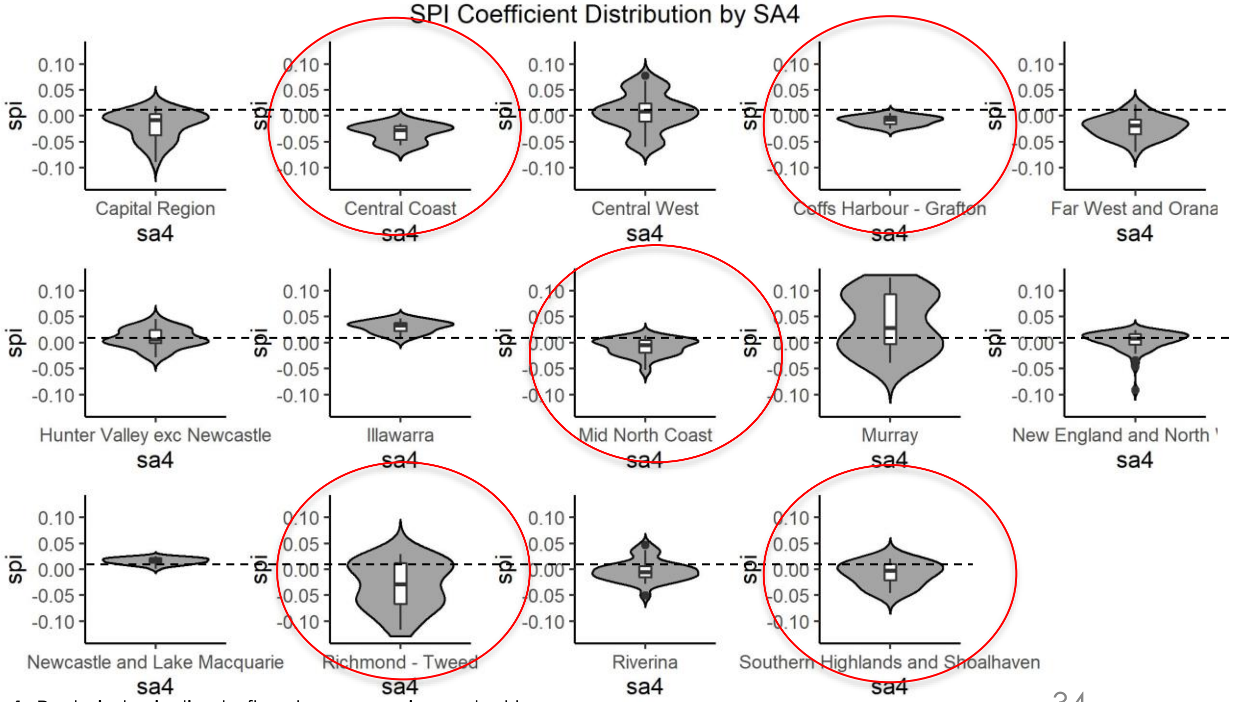
Model (3) – SPI coefficients Greater Sydney

- Average magnitude of SPI coefficients is close to zero in many Greater Sydney postcodes indicating low sensitivity of price to SPI
- Average magnitude of SPI coefficients is larger in rural NSW (ex. Greater Sydney)



Model (3) – SPI coefficients NSW ex. Greater Sydney

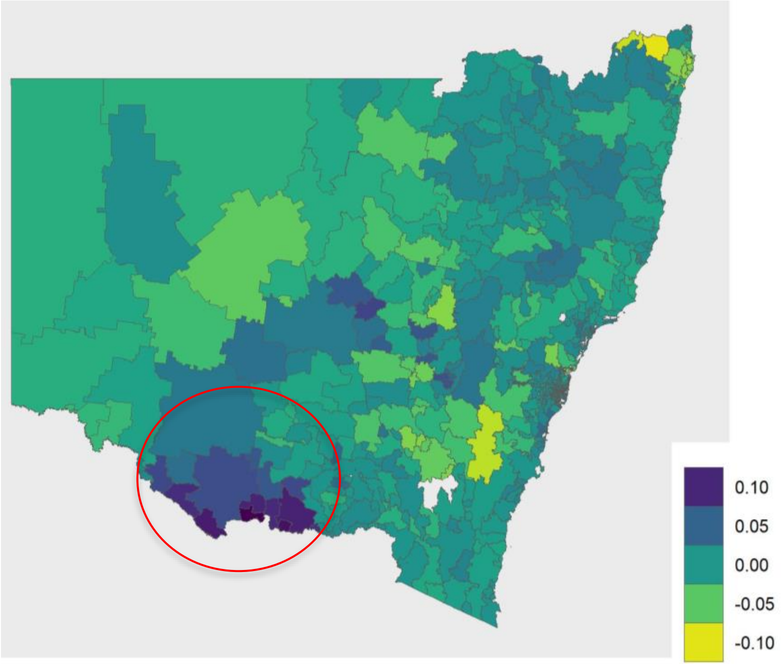
- SA4 areas where SPI coefficients are negative for all or most postcodes correspond to high flood risk regions noted by IAG[1] including Central Coast, Clarence Valley (Coffs Harbour Grafton), Shoalhaven, Tweed, Kempsey (Mid North Coast)



1. Red circles indicate flood prone region noted here: www.iag.com.au/sites/default/files/Documents/Climate%20action/IAG-Flood-Fact-Sheet.pdf

Model (3) – SPI coefficients

- Highest positive sensitivity to SPI found in the Riverina region of South-West NSW. Riverina is an agricultural region and one of the most productive and agriculturally diverse areas of Australia.
- Results suggest property prices in this region are sensitive to drought as measured by SPI.
- The correlation between postcode-level SPI coefficients and the proportion of agriculture, forestry and fishing workers living in a postcode (from the census) is very low (-0.02) for inland regions of NSW.
- Low correlation could be because seasonal farm worker populations pose several census challenges.
- More testing required.



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Model findings

- Could not detect a significant relationship between property prices and historic maximum daily temperatures or sea level height.
- In parts of NSW, we found a significant link between property price and rainfall, but the choice of metric was important.
- For modelling sea level rise and flooding impacts, postcode is not optimal geographic unit (as risk can vary at address level within a postcode e.g. due to elevation).
- Need to be mindful of the trade-off between property price data availability and geographic granularity.

Further research

1. Different climate variables e.g. SPEI (evaporation/temperature)
2. Forward looking vs backward looking climate risk measures
3. Mean vs. extreme climate metrics (Investigate impact of natural peril events on property prices as well as trends)
4. Expand research to other states and climate metrics
5. Improve modelling of economic variables (we found a weak link)

Conclusions

- This study may be the first to demonstrate a link between climate variability and property prices in Australia
- For NSW, lack of rainfall - i.e. drought - was revealed to be the most demonstrable climate metric impacting on property price, particularly in rural areas
- Australia's urban property markets are very dynamic and are ruled by greater factors such as demographic and strong economic rules (supply and demand), so it is not surprising that those factors supersede climate indices
- CoreLogic previous studies on impact of Natural Hazard such as cyclone or bushfire have shown a strong resilience for the property market
- BUT **this study shows that in some rural areas of NSW, rainfall is correlated to property price**

Questions

Appendix

References

- Hanewald, K., Sherris, M. (2013). *Postcode-Level House Price Models for Banking and Insurance Applications*. Economic Record, Vol. 89, Issue 286, pp. 411-425, 2013
- Ukkola, A.M., Roderick, M.L., Barker, A., Pitman, A.J. (2019). *Exploring the stationarity of Australian temperature, precipitation and pan evaporation records over the last century*. Environ. Res. Lett. 14 124035. Available at: https://doi.org/10.1088/1748-9326/ab545c