Can we attribute Australia's record 2010-2012 rainfall to a particular cause?

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1. Overview

During 2010-2012, Australia experienced heavy rainfall in association with strong and extended La Niña conditions. To investigate the relative contributions of anthropogenic climate change and natural climatic variability to the probability of heavy rainfall occurring, we use multiple, detection and attribution model datasets (CMIP5 fully coupled models and C20C experiments driven by prescribed SSTs). Using fraction of attributable risk (FAR), we compare the likelihood of above average, heavy and extreme Australian rainfall between anthropogenic and natural-only experiments.

What were the dominant causes of the seasonal record rainfall and to what extent does this assessment depend on the model datasets utilised?

2. Observations

6. Anthropogenic influences

 $FAR = 1 - \frac{P_{NAT}}{P_{ALL}}$

[Stone and Allen, 2005]

• Compare the likelihood of rainfall between natural forcings only, and anthropogenic and natural forcings

• Calculate FAR values based on the exceedance of series of thresholds - precipitation mean ("average"), 1σ above normal ("heavy") and 2 σ above normal ("extreme")











Fig. 1 Observed rainfall anomalies for southeastern Australia (SEA).

2010-2012 wettest two-year period on record

• Heavy Australian rainfall during this period was associated with extended La Niña conditions

• Warm sea surface temperatures (SST) observed to the north of Australia and in the eastern Indian ocean



Fig. 2 Observed rainfall-NINO3.4 relationship for SEA.

3. Model datasets and experiments

Observations	CMIP5 (fully coupled models)					Models FGOALS-g2
Australian Water Availability Project	Experiment	Description	Model years	Number of simulations	Ensemble type	CCSM4
(AWAP) gridded precipitation dataset [Jones et al., 2009]	historicalNat	Solar, volcanics	1850- 2005	29	16 models	CESM1-FASTCHEN
	historical	Anthropogenic (greenhouse gases,aerosols, ozone) and natural (solar, volcanics)	1976- 2005	65	16 models	HadCM3 NorESM1-M
HadCRU14 gridded surface air temperatures dataset [Morice et al., 2012]	RCP8.5	Anthropogenic (greenhouse gases, aerosols, ozone scenarios) and natural (solar)	2006- 2020	45	16 models	CNRM-CM5 HadGEM2-AO CSIRO-Mk3-6-0
	piControl	Non-evolving pre-industrial forcings	All	16	16 models	HadGEM2-CC HadGEM2-ES
	[Taylor et al., 20	012]				IPSL-CM5A-LR IPSL-CM5A-MR

Fig. 5 All forcings (red) and natural only (blue) SEA Fig. All forcings (red) and natural only rainfall for CAM5.1 for 2010-2011 and 2011-2012. (blue) SEA rainfall for CMIP5 (La Niña years only).

Fig. 6 All forcings (red) and natural only (blue) for HadGEM3-A for different model anthropogenic SST estimates.

• FAR values sensitive to model dataset, season, region and threshold used

• Different FAR values for different model estimates of anthropogenic SST contributions

7. La Niña influences

- P_{El Niño/Neutral} FAR = 1P_{La Niña}
- Investigate changes in the probability of rainfall associated with La Niña and El Niño/neutral conditions
- La Niña events defined when NINO3.4 SAT anomalies less than 0.5 K for at least six consecutive months from April to March. Model years not categorised as La Niña conditions designated as El Niño/neutral

CAM5.1 (prescribed SSTs)

Experiment	Description	Model years	Number of simulations	Ensemble type
All-Hist	Evolving ocean surface temperatures, greenhouse gas concentrations, and aerosol concentrations over the last 50 years	2010,2011, 2012	50	Perturbed initial conditions
NonGHG-Hist	Greenhouse gas and aerosol concentrations maintained at pre- industrial levels, with estimates of anthropogenic SST warming	2010,2011, 2012	50	Perturbed initial conditions

4. Model evaluation



HadGEM3-A (prescribed SSTs)

Experiment	Description	Model	Number of	Ensemble	Models	
		years	simulations	type	HadGEM3-A	
All-Hist	Evolving ocean surface temperatures, greenhouse gas concentrations, and aerosol concentrations over the last 50	2010,2011, 2012	99 (2010,2011) and 594 (2012)	Perturbed physics and initial	HadCM3 HadGEM1	
NonGHG-Hist	years Greenhouse gas and aerosol concentrations maintained at pre- industrial levels, with estimates of anthropogenic SST warming	2010,2011, 2012	396 (2010,2011) and 1584 (2012)	conditions Perturbed physics and initial conditions	HadGEM2 CSIRO-MK3-6L CanESM2 HadGEM2	

[Christidis et al., 2013]

on:

• Evaluate the models utilised and determine whether models adequately represent natural internal variability of Australian rainfall and ENSO conditions

• CMIP5 models selected for inclusion in this study based

- representation of monthly temperature variability in the NINO3.4 region

- simulated mean and standard deviation of seasonal areal-average precipitation amounts

- simulated La Niña–Australian rainfall relationship

CMIP5 (fully coupled models)



Fig. 7 PDFs of La Niña (blue) and El Niño (red) SEA rainfall for CMIP5

Standardised precipitation anomalies





• Shift in PDF to wetter conditions for La Niña compared with El Niño/neutral conditions

• Best estimate 5x risk of April-May extreme SEA rainfall attributable to La Niña conditions

• FAR value robust for different regions and seasons

• Relationship between NINO3.4 SEA rainfall variability and insensitive to forcings (Fig. 8)

10. What influenced Australia's 2010-2012 rainfall?

We use fraction of attributable risk (FAR) to compare the likelihood of above average, heavy and extreme rainfall between experiments with and without anthropogenic forcings.

We find that attribution statements are sensitive to the attribution framework employed. Changes in the probability of rainfall depend on the seasons, region and rainfall thresholds and models used [King et al., 2013; Christidis et al, 2013b.] Comparing the likelihood of heavy rainfall during simulated La Niña years with rainfall occurring during El Niño/neutral years shows a substantial La Niña influence on heavy Australian rainfall that is robust to changes in the attribution framework. This study demonstrates that the attribution of seasonal-scale heavy rainfall events to a particular cause is likely more complicated than for temperature extremes. It is useful to consider outputs from several model datasets and employ various estimates of counterfactual surface conditions.

• 16 models included thatare realistic compared to observations for all criteria

Fig. 3 Observed and simulated NINO3.4 temperature variability (σ), SEA standardised DJF mean precipitation and σ . The mean observational value is shown by a cross and the 5-95th percentile range indicated by horizontal dashed lines, as determined by bootstrap resampling observed values. Individual model realisations are shown by black squares and model mean by red circles.

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