Developments and applications of CBaM for post-processing seasonal climate forecasts

Andrew Schepen, QJ Wang, David Robertson, James Bennett
Talk outline

• Seasonal climate forecasting in Australia
• Introducing CBaM
• Applications and results
• Future development
Official seasonal climate forecasting in Australia is now GCM based

Climate outlooks – monthly and seasonal

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Rainfall - Summary

<table>
<thead>
<tr>
<th>Chance of above median</th>
<th>Outlook scenarios</th>
<th>Chance of at least</th>
</tr>
</thead>
</table>

Wetter in the west and centre

- There is an increased chance of a wetter-than-average season over much of southern and central WA, the southern NT, SA and extending into parts of western NSW Victoria and Queensland. In far north Queensland, spring is likely to be drier than average. Most of eastern Australia has a roughly equal chance of a wetter or drier season.

- The current outlook reflects the record warm sea surface temperatures in the Indian Ocean, and a strengthening El Niño in the Pacific.

- Historical outlook accuracy for spring is moderate to high over most of Australia.
Water management and agriculture continue to use statistical forecasts.
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Overcoming the disconnect - Introducing CBaM

• CBaM is a statistical post-processing method
  • Corrects biased and/or unreliable GCM forecasts and upskills
• Produces ensemble time series forecasts
• Adoption can benefit water management, agriculture, energy, mining
How does CBaM work?

- **Calibration**
  - Eliminates bias and improves reliability

- **Bridging**
  - Recovers skill through teleconnections
  - Extends forecast lead times

- **Merging**
  - Maximises skill for each location and time period
  - Links ensemble members into time series

- Matches spatial scales
  - Downscaling
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Calibration

Raw GCM output

Calibration forecast
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Bridging

GCM SSTs

Bridging forecast

Predictors: Ensemble means of GCM climate indices

(e.g. NINO3, NINO3.4, NINO4, EMI, DMI, II)
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\[ \text{CBaM} = \text{BJP} + \text{BMA} + \text{Schaake Shuffle} \]
Recent applications

- POAMA, CFS2, System4
- Seasonal Rainfall, Tmin, Tmax
- 1983 – 2010 Cross-validation
- 2.5 degree grid across Australia
Improvement to reliability (e.g. POAMA2)

Rainfall

Raw

mean-corrected

CBaM

post-processed

Tmin

Tmax
Skill of calibration (e.g. POAMA2 rainfall)

Mean-corrected (Raw)

Calibration (CBaM)
Skill improvement through bridging (e.g. POAMA2 rainfall)
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Contribution of bridging to improving skill (e.g. POAMA2)
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Bridging improves skill for multiple GCMs

![Improvement due to bridging (All models)](chart.png)
Bridging improves skill for multiple GCMs

Improvement due to bridging (All models)

<table>
<thead>
<tr>
<th></th>
<th>Proportion of grid cells (%)</th>
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<tbody>
<tr>
<td>POAMA2</td>
<td>15</td>
</tr>
<tr>
<td>CFS2</td>
<td>20</td>
</tr>
<tr>
<td>System4</td>
<td>10</td>
</tr>
</tbody>
</table>

- Rainfall
- Tmin
- Tmax
Bridging improves skill for multiple GCMs

![Improvement due to bridging (All models)]
Summary of results

• CBaM produces reliable ensemble forecasts
• Bridging produces additional skilful forecasts in many locations and time periods
• CBaM is effective for maximising skill across multiple GCMs
Much work to be done

• Transition to ACCESS-S
• Catering for different ensemble generation methods
• Linking to user models (e.g. crop)
• Quantifying the benefit of using GCM forecasts
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Questions?
Thank you.

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