



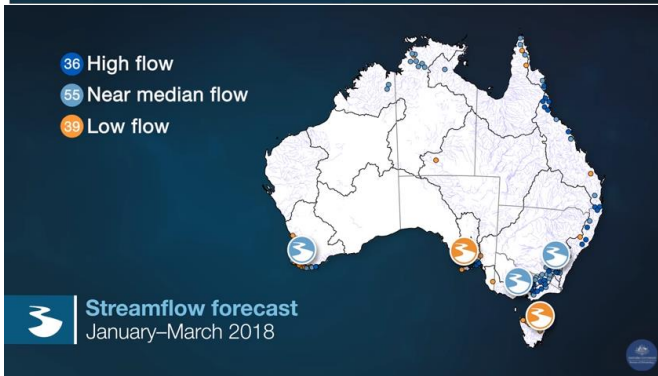
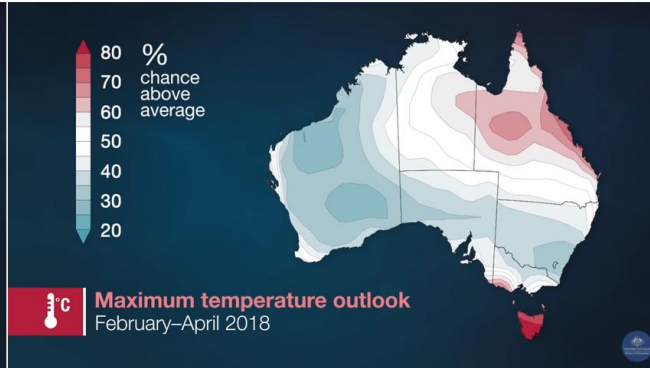
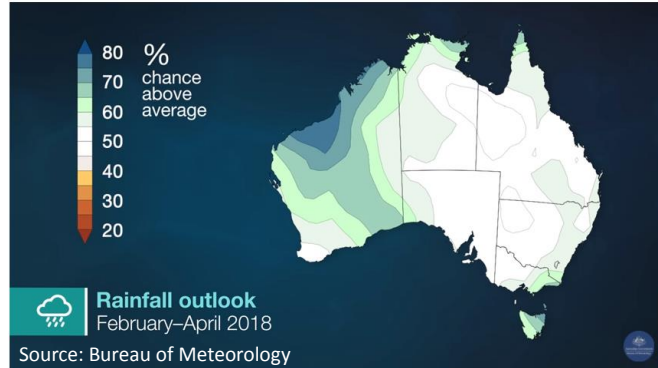
Is it better to post-process GCM rainfall and temperature forecasts at daily or monthly time steps?

Andrew Schepen, Q.J. Wang and Yvette Everingham
7 February 2018

Talk outline

- Seasonal forecasting in Australia
- Methods for daily and monthly post-processing
- Experiments and results
- Future directions

Seasonal forecasting in Australia

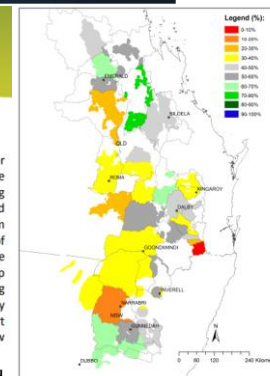


SEASONAL CROP OUTLOOK Sorghum – January 2018

SUMMARY

The outlook is for a close to average yielding sorghum crop for the 2017/18 summer growing season in north-eastern Australia (NEAUS). However, some variation in the outlook among local regions exists. More specifically, some areas in CQ are showing slightly above average crop yield expectations, while most areas in southern QLD and NSW are having sorghum yield outcomes close to or below the long-term expectation. It should be noted, this is still early in the growing season and the range of likely sorghum yield outcomes remains wide. Widespread average to above average rainfall is needed, during the next couple of months to improve the current crop outlook across all areas of the north-eastern Australian (NEAUS) summer cropping region. *It should be noted*, this is still early in the growing season and the range of likely sorghum yield outcomes remains wide. This crop outlook is based on a crop-free (short fallow) practice through the winter season and therefore areas with longer fallow practices are likely to have better yield prospects for the coming season.

Source: Queensland Alliance for Agriculture and Food



Linking climate, streamflow & Ag forecasts

- Raw forecasts unsuitable for use in hydrological/crop models
- Downscaling / post-processing required
- Need:
 - Daily ensemble time-series (e.g. GR4J, APSIM)
 - Skilful, reliable and “coherent” forecasts
 - Known deficiencies in analogue downscaling, QQ-mapping [Use BJP*](#)
- Efficiency important for large scale operational services

*Poster: Song, Yong - A Gibbs Sampler Bayesian Joint Probability Model

Daily or monthly post-processing for best forecasts?

Daily-PP

- Apply BJP to daily data
- Schaake Shuffle (SS-clim)

Schepen et al. (2018) *Hydrology and Earth System Sciences*

Monthly-PP

- Apply BJP to monthly data
- Schaake Shuffle (SS-clim)

Schepen et al. (2014) *Journal of Hydrology*

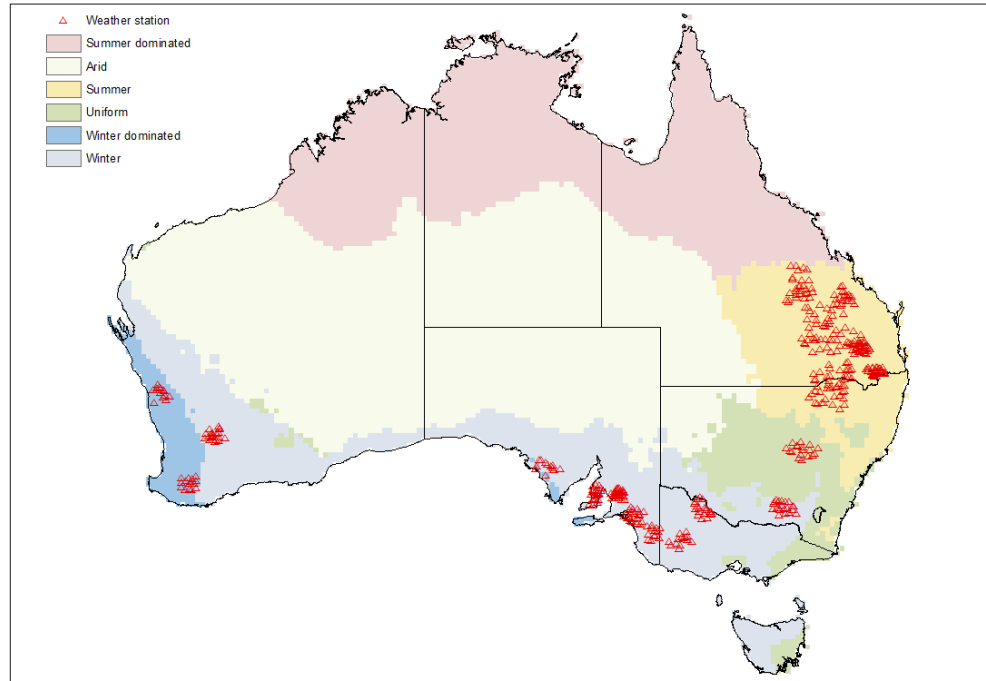
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Bennet et al. (2017) *Hydrology and Earth System Sciences*

- Disaggregate
 - Obs data template

Experimental set up

- ECMWF System4 forecasts
 - 1981-2016
 - Daily rainfall and temperature
 - 90 days ahead
- 435 met stations
 - OzWheat network
 - Infilled observation records



Verification:

- Separate models for each month
- Leave 1-year-out cross-validation

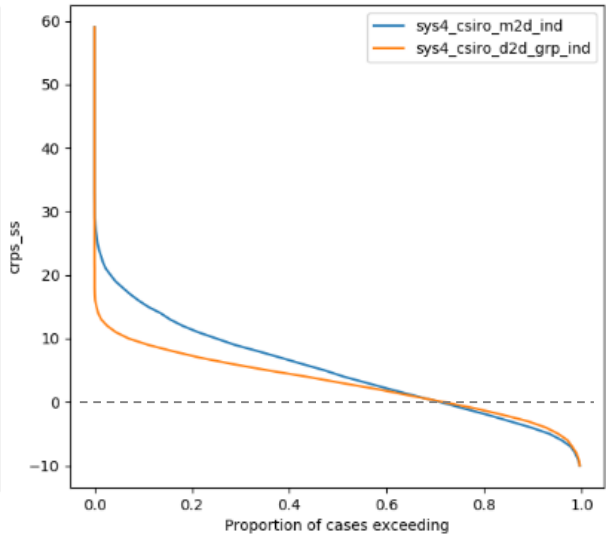
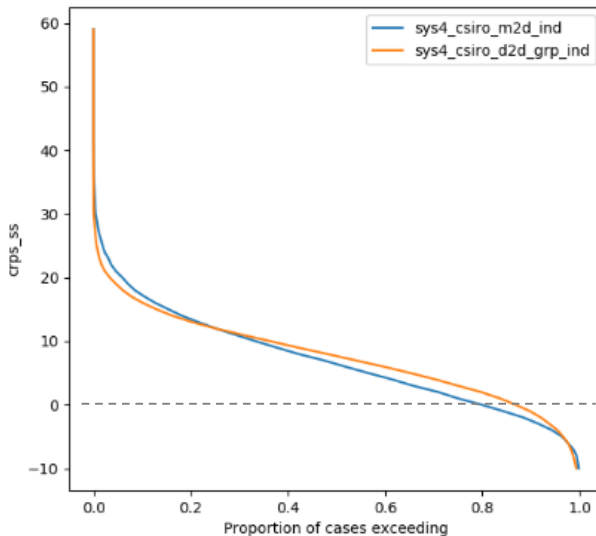
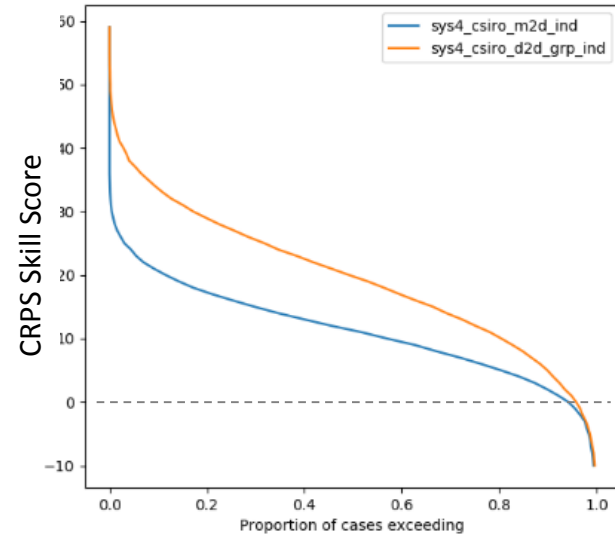
- Skill (CRPS skill scores)
- Reliability (PIT reliability score)
- Temporal structure (lag-1 autocorrelation)

Results: Skill* - rainfall

10 days**

30 days**

90 days**

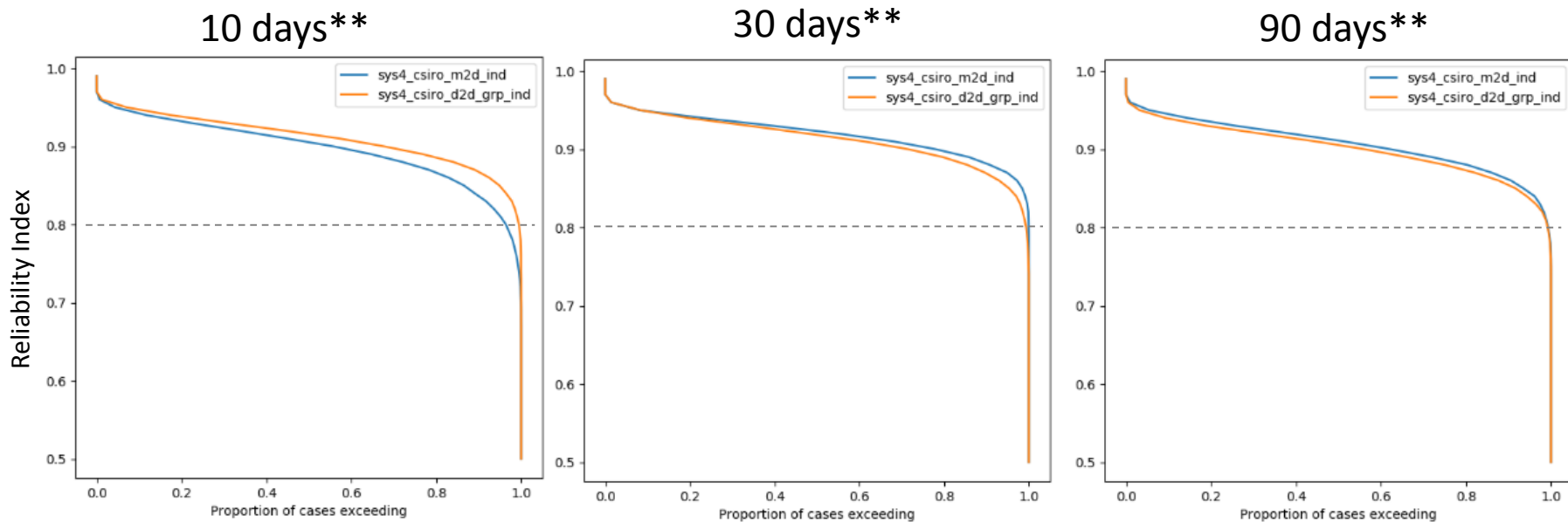


*CRPS skill scores relative to climatology

**Aggregated forecasts

Measuring skill over all stations and initialisation months

Results: Reliability* - rainfall



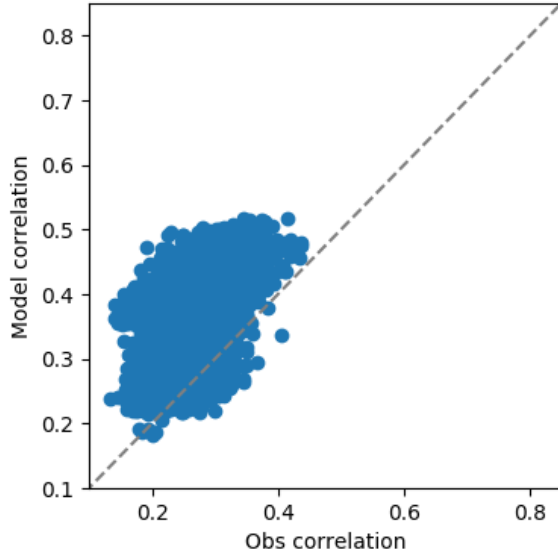
*PIT-alpha reliability index
(Renard et al. 2010, WRR)

**Aggregated forecasts

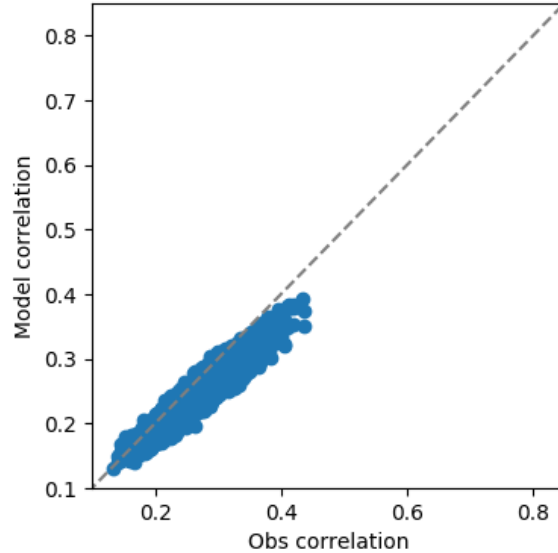
Measuring reliability over all stations
and initialisation months

Results: Lag-1 temporal correlation* - rainfall

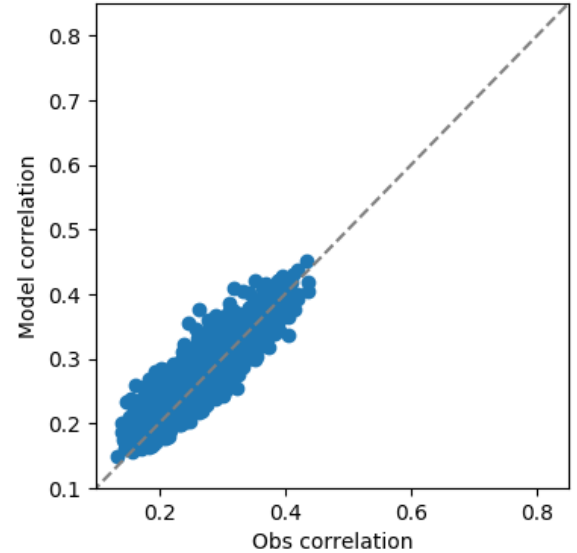
Raw



Daily-PP



Monthly-PP



*Kendall correlation averaged over ensemble members and lead times

One dot per station and month

Results: Temperature

- Forecasts are more skilful and reliable overall
- Monthly-PP skill is higher for 30 and 90 days
- Forecast lag-1 correlations better match observations

Results: Main findings

- Skill:
 - Daily-PP is most skilful for 10 day forecasts
 - Monthly-PP yields more skilful 30 day and 90 day forecasts
- Reliability:
 - Daily-PP and monthly-PP produce reliable forecasts
 - Daily-PP and monthly-PP forecasts have realistic temporal correlation

Future directions

- Improve skill
 - Blend daily- and monthly- PP forecasts
 - Blend forecasts from NWP, sub-seasonal and seasonal models
 - Use multi-level post-processing models (e.g. Bayesian hierarchical models)
- Evaluate streamflow forecasts and crop yields

Thanks. Questions?

Andrew Schepen

Hydro-climate modeller

Andrew.Schepen@csiro.au

0411 156 213

LAND AND WATER

www.csiro.au



Bayesian joint probability (BJP) modelling

- GCM ensemble mean → observations
- Issues
 - Heteroscedasticity
 - Zero value
- The BJP solution
 - Transformations
 - Censored data
- Full calibration tool for post-processing

Wang, Robertson and Chiew (2009) *Water Resources Research*

Wang and Robertson (2011) *Water Resources Research*

Wang, Shrestha, Robertson and Pokhrel (2012) *Water Resources Research*

Robertson and Wang (2013) *Water Resources Management*