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Choosing the RCMs to perform the downscaling

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Choosing the RCMs to perform the downscaling

The RCMs to be used will be based on the Weather Research and Forecasting (WRF) modelling system [*Skamarock et al.*, 2008]. This system facilitates the use of many RCMs by allowing all model components to be changed and hence many structurally different RCMs can be built. The aim of this methodology is to choose three RCMs from a large ensemble of adequately performing RCMs, such that they retain as much independent information as possible while spanning the uncertainty range found in the full ensemble. Due to computational limitations, the RCM performance and independence will be evaluated based on a series of event simulations rather than using multi-year simulations.

1. Method

1.1. Evaluate RCM performance for a series of important precipitation events

By limiting the evaluation period to a series of representative events for NSW, a much larger set of RCMs can be tested. In this case an ensemble of 36 RCMs will be created by using various parametrizations for the Cumulus convection scheme, the cloud microphysics scheme, the radiation schemes and the Planetary Boundary Layer (PBL) scheme. Each of these RCMs will be used to simulate a set of 7 representative storms that cover the various NSW storm types discussed in the literature [*Shand et al.*, 2010; *Speer et al.*, 2009]. An eighth event focused on a period of extreme fire weather will also be analysed. In each case a two week period is simulated centred around the peak of the event. Subsequent analysis then includes pre and post-event climate as well as the event itself.

Evaluation will be performed against daily precipitation, minimum and maximum temperature from the Bureau of Meteorology's (BoMs) Australian Water Availability Project [*Jones et al.*, 2009]. Evaluation will also be performed against the mean sea level pressure and the 10m winds obtained from BoMs MesoLAPS analysis [*Puri et al.*, 1998]. Any RCMs that perform consistently poorly will be removed from further analysis. The overall spread in these results provides a measure of the uncertainty due to the choice of RCM.

1.2. Determine RCM independence

Using the method of *Abramowitz and Bishop* [2010] the level of independence between the RCMs will be quantified. This method uses the correlation of model errors as an indicator of model independence. In combination, more independent models provide more robust estimates of the climate. Quantification of the model independence provides an indicator of which models contribute the most independent information and hence should be retained in the three chosen RCMs.

1.3. *Choose the RCMs*

The ensemble subset of adequately performing models, which is anticipated to be most of the 36 member ensemble, is identified in section 1.1 This ensemble subset is then evaluated for model independence (section 1.2). The most independent RCMs in this ensemble will be chosen.

2. Results

2.1. *RCM performance*

The RCMs are evaluated in terms of simulating temperature, MSLP, wind speed and rain, various metrics were calculated and combined using four different methods. The metrics used for the ranking are RMSE, MAE and R for Tmin, Tmax, MSLP and wind speed. The FSS score was used for the rainfall totals. These metrics are calculated for all 8 events and combined as described in Evans et al. (2011). Two overall metrics are calculated. One metric characterizes the climatology (clim) and the other is dominated by the most extreme events (impact).

Figure 1 & 2 below show that the overall performance metrics increase gradually from the best to the worst model. This gradual increase rises sharply at the 6th worst performing model. Since these 6 worst performing models show a rapid decrease in performance they are excluded from further analysis.

These models are

Ensemble member	Planetary Boundary layer physics / Surface layer physics	cumulus physics	Micro-physics	Shortwave / Longwave radiation physics
3	YSU / MM5 similarity	KF	WSM 3 class	RRTMG / RRTMG
4	YSU / MM5 similarity	KF	WSM 5 class	Dudhia / RRTM
6	YSU / MM5 similarity	KF	WSM 5 class	RRTMG / RRTMG
9	YSU / MM5 similarity	KF	WDM 5 class	RRTMG / RRTMG
19	MYJ / Eta similarity	KF	WSM 3 class	Dudhia / RRTM
28	MYJ / Eta similarity	BMJ	WSM 3 class	Dudhia / RRTM

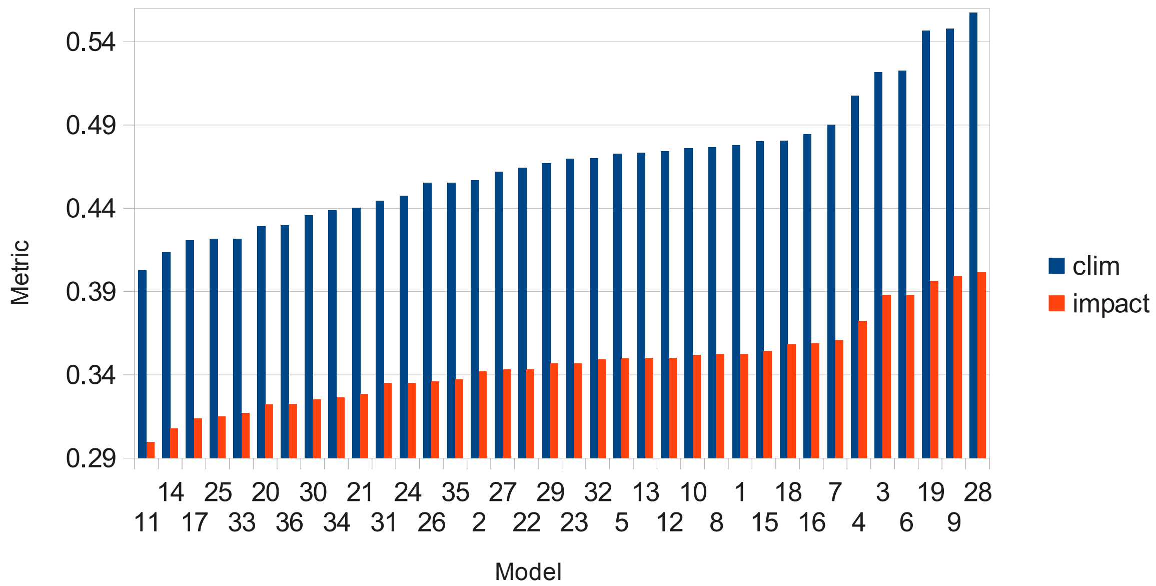

Figure 1: Overall metrics for models ordered from best (left) to worst (right).

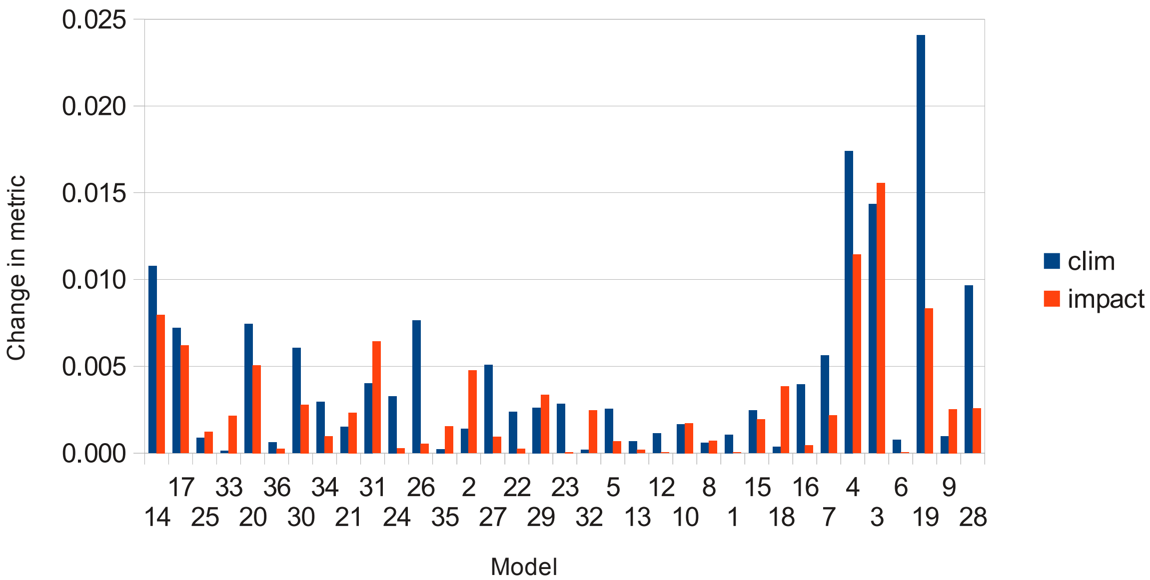

Figure 2: Change in the overall metrics between neighbouring models ordered from the best model (left) to the worst model (right).

2.2. RCM independence

In the method of *Abramowitz and Bishop* [2010] the model independence is defined based on the correlation of model errors. For precipitation, minimum and maximum temperature, the daily time series for each event is bias corrected using the BAWAP observations, to produce an anomaly time series. This anomaly time series for all events is joined together to produce a single long time series for each variable. These time series are then used to create the model error covariance matrix. *Abramowitz and Bishop* [2010] are able to show that the coefficients of a linear combination of the models that optimally minimizes the mean square error depends on both model performance and model dependence. The solution of this minimization problem can be written in terms of the covariance matrix already constructed. The size of the coefficients assigned to each model reflects a combination of model performance and independence. That is, the models with the largest coefficients are the best performing/most independent models in the ensemble.

These coefficients are calculated for each variable and then averaged to give the overall performance/independence of each model (Table 1).

Table 1: Magnitude of performance/independence coefficients for each model

model	Tmax coefficient	Tmin coefficient	Rain coefficient	Average coefficient
N34	0.01469795	0.2209294	0.1352511	0.12362615
N25	0.08731876	0.1627385	0.1140634	0.1213735533
N8	0.08207202	0.1056273	0.1313051	0.1063348067
N16	0.09282326	0.06290033	0.1031864	0.08630333
N32	0.04916942	0.1301999	0.06887183	0.08274705
N21	0.1242759	0.03612048	0.07676102	0.0790524667
N36	0.140581	0.05059778	0.03693159	0.07603679
N30	0.1383406	0.03729973	0.03645576	0.0706986967
N2	0.0708931	0.02839982	0.1088712	0.06938804
N23	0.08196212	0.1045801	0.01099404	0.06584542
N11	0.007608448	0.04882414	0.1402673	0.0655666293
N10	0.01927792	0.06793443	0.1056475	0.0642866167
N12	0.08037093	0.1064822	0.005134887	0.0639960057
N13	0.04323415	0.05732841	0.0770985	0.0592203533
N35	0.1379583	0.001707422	0.02854035	0.0560686907

N26	0.08641391	0.04594476	0.03469255	0.05568374
N27	0.14701	0.008586845	0.009002835	0.05486656
N1	0.03344357	0.06230814	0.05866471	0.05147214
N14	0.09695464	0.04197799	0.006428991	0.0484538737
N33	0.09339102	0.01378837	0.03475221	0.0473105333
N20	0.02490285	0.03309715	0.07767075	0.0452235833
N22	0.0001778862	0.02392053	0.109115	0.0444044721
N5	0.07685906	0.001091265	0.04673374	0.041561355
N31	0.03873078	0.03593164	0.02980383	0.0348220833
N24	0.009470238	0.03574339	0.05262557	0.032613066
N18	0.03222973	0.05254753	0.01095403	0.03191043
N17	0.03348057	0.03824754	0.0216635	0.0311305367
N29	0.02739154	0.03276426	0.01132241	0.02382607
N7	0.00129288	0.04051392	0.02537299	0.0223932633
N15	0.02214795	0.007922001	0.004026355	0.0113654353

2.3. The RCM choice

The three most independent/best performing models of the 30 model ensemble are:

NARCliM Ensemble member	ESCCI Ensemble member	Planetary Boundary layer physics / Surface layer physics	cumulus physics	Micro-physics	Shortwave / Longwave radiation physics
R1	**N25**	MYJ / Eta similarity	KF	WDM 5 class	Dudhia / RRTM
R2	**N34**	MYJ / Eta similarity	BMJ	WDM 5 class	Dudhia / RRTM
R3	**N8**	YSU / MM5 similarity	KF	WDM 5 class	CAM / CAM

3. Publications

This evaluation methodology has been presented at a national conference and accepted for publication in an international journal.

Ji, F., J.P. Evans and M. Ekstrom (2011) Using dynamical downscaling to simulate rainfall for East Coast Low events, MODSIM2011 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand and International, Perth, Australia, 12 -16 December 2011.

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4. References

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Jones, D. A., W. Wang, and R. Fawcett, 2009: High-quality spatial climate data-sets for Australia. *Australian Meteorological Magazine*, **58**, 233–248.

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