More precise predictions of future polar winter warming estimated by multi-model ensemble regression

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Introduction

Here we introduce a simple robust statistical framework for providing more precise local (grid-box) projections from ensembles of climate models. Projections at grid-box spatial scales are important for impacts studies. The methodology builds on previous work in which inter-model relationships between simulated present-day and future Arctic-scale parameters are used to estimate future observations from present-day observations (e.g. snow-albedo feedback [Hall and Qu, 2006] and Arctic total sea ice extend [Boe *et al.*, 2009]).

- The main element of our framework involves inter-model relationships between present-day-mean bias and projected response (state dependence) in local near-surface winter temperature. Linear regression onto this state dependence is used to predict future observations at each grid point in turn (Fig. 1a).
- The second important element is identifying influential outlier climate models that have large leverage in the regression.
- The third element is determining the point at which errors stop decreasing with increasing ensemble size (or whether a larger ensemble is required).

Together these three elements provide a new framework for producing more precise (i.e. reduced variance in the statistical prediction) climate change projections at the grid-box scale. We refer to this statistical model-based approach as Ensemble Regression (ER). For locations where the multi-model climate change response is uncorrelated with present-day climate, the ER approach effectively reverts to an Ensemble Mean (EM) approach. In addition ER improves on and avoids difficulties associated with ad-hoc weighting of climate models (Giorgi and Mearns, 2002; Murphy et al., 2004; Connolley and Bracegirdle, 2007; Raisanen et al., 2010).

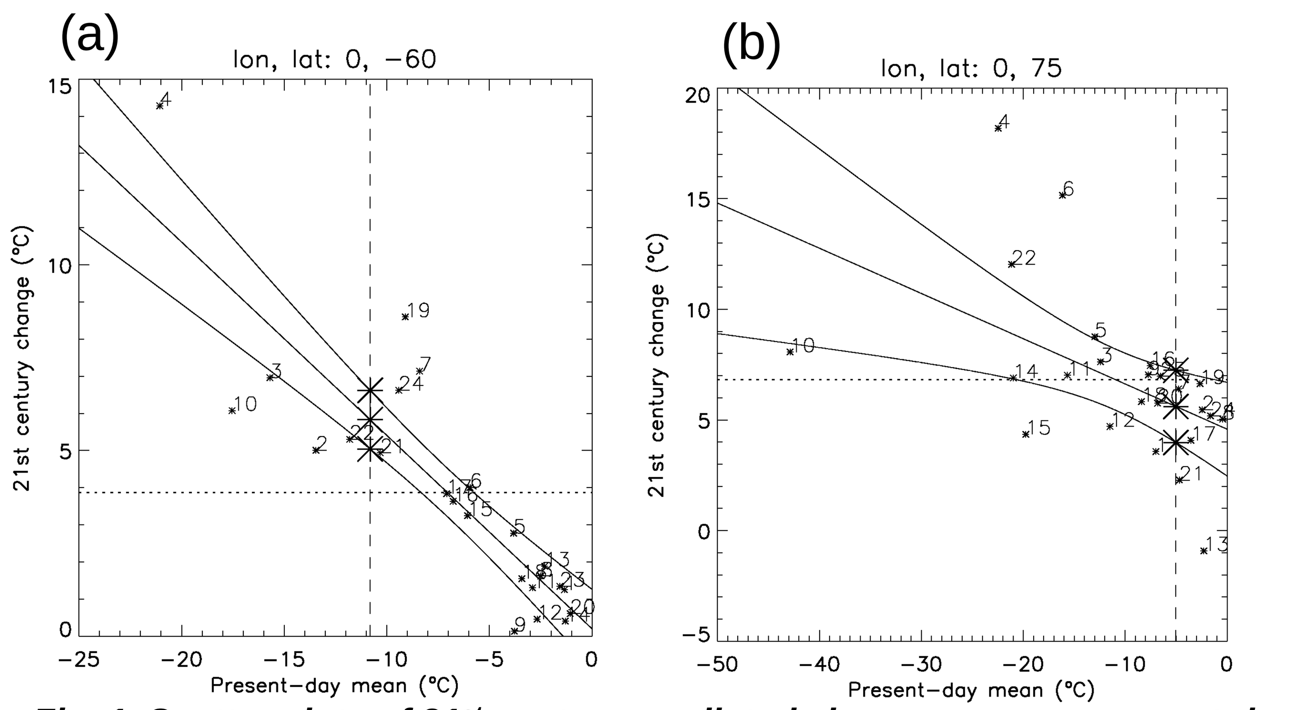


Fig. 1. Scatter plots of 21st century predicted changes versus present-day means in wintertime near-surface temperatures at (a) 65S, 0E in July and (b) 75N, 0E in January. Each small asterisk represents one CMIP3 climate model, which are annotated by the numbers used as identifiers in Table 1. The straight lines fits are from linear regression and the solid curves show the 95% confidence intervals. The vertical dashed lines show the present-day observations (ERA-40 data) with large asterisks showing the associated mean response and confidence interval from linear regression. The horizontal dotted line shows the simple equal-weight multi-model average of 21st century change. Present-day mean is the period 1970-1999 from all 20c3m runs and 21st century change is the difference between the period 2069-2098 from all sresa1b runs and present-day mean.

Table 1. CMIP3 models

Model ID	Model name
1	BCCR BCM2.0
2	CCSM3
3	CGCM3.1(T47)
4	CGCM3.1(T63)
5	CNRM-CM3
6	CSIRO-Mk3.0
7	CSIRO-Mk3.5
8	ECHAM5/MPI-OM
9	ECHO-G
10	FGOALS-g1.0
11	GFDL-CM2.0
12	GFDL-CM2.1
13	GISS-AOM
14	GISS-EH
15	GISS-ER
16	INGV-SXG
17	INM-CM3.0
18	IPSL-CM4
19	MIROC3.2(hires)
20	MIROC3.2(medres)
21	MRI-CGCM2.3.2
22	PCM
23	UKMO-HadCM3
24	UKMO-HadGEM1

Method

The ensemble regression model gives the following prediction of the expected observable mean climate change response ($\hat{y}_0$) based on observed present-day mean (x_0).

$$\hat{y}_o = \bar{y} + \hat{\beta}(x_0 - \bar{x})$$

Because of the small number of climate models, it is also important to test how much influence each model has on the mean response. We investigate this by calculating the leverage for each CMIP3 model, which identifies model 10 as overly influential (Fig. 2). For details see Bracegirdle and Stephenson [in review].

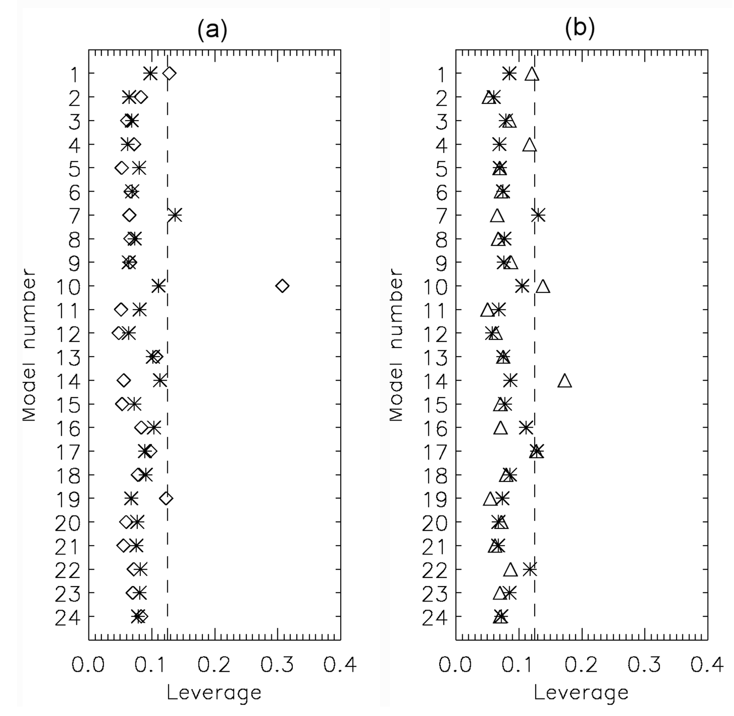
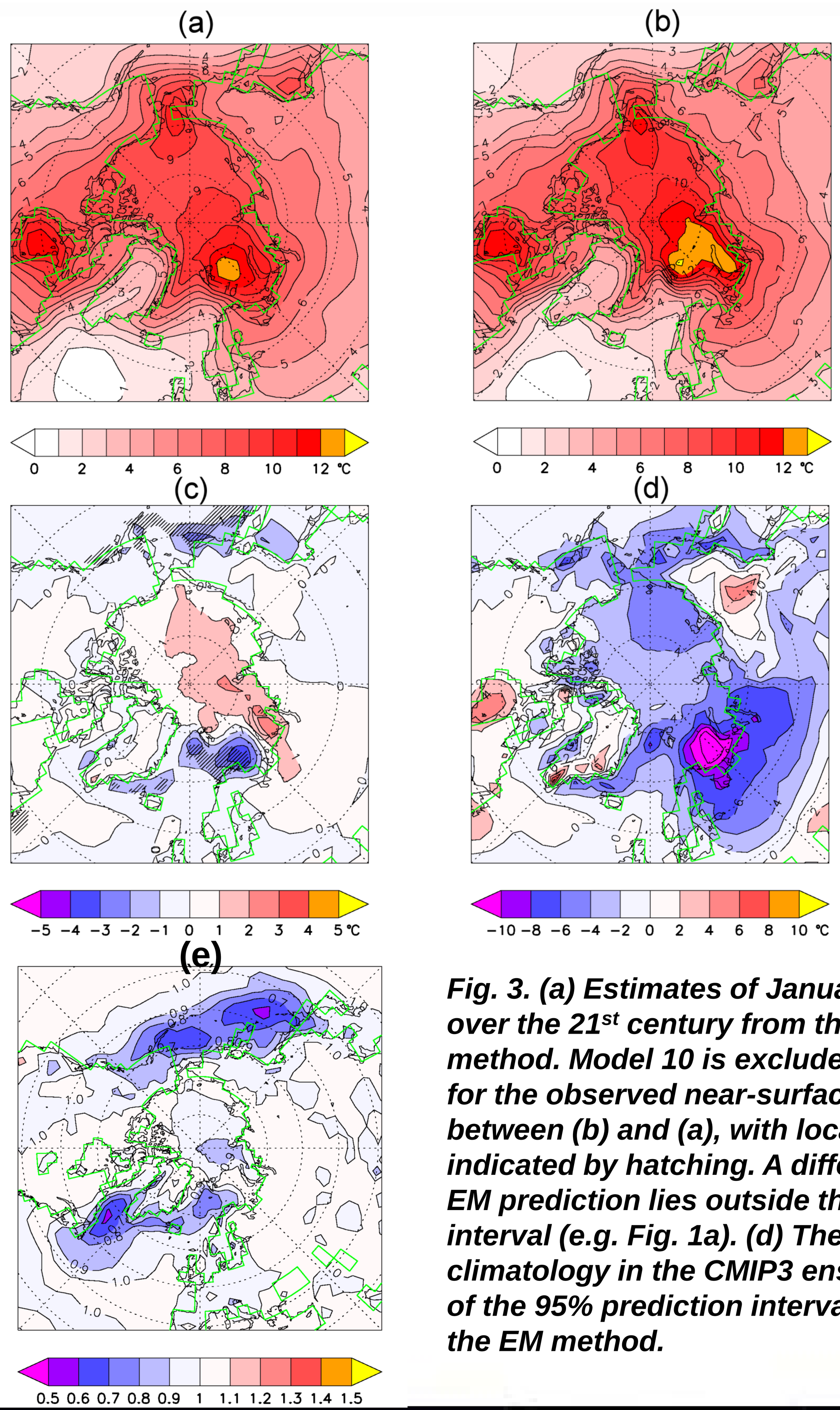


Fig. 2. Leverage in (a) January and (b) July. Global mean (asterisks), Arctic mean (diamonds) and Antarctic mean (triangles) leverage. Vertical dashed lines show the rule of thumb value for labelling cases as high leverage.

Results and Conclusions: Arctic



For the CMIP3 ensemble results from the ER approach show a broadly similar pattern to those from EM (Fig. 3a,b), but with key differences (Fig. 3c):

- Less warming over the Barents Sea by approximately 3°C.
- Less warming over parts of the northern boundary of the Pacific
- Fig. 3d shows that differences shown in Fig. 3c are associated with biases in the CMIP3 ensemble mean present-day climatology.
- The ER method gives more precise predictions near the sea ice edge (Fig. 3e); with approximately 30% reductions in prediction interval over the Sea of Okhostk, Bering Sea and Labrador Sea.

Fig. 3. (a) Estimates of January near surface temperature change over the 21st century from the EM method and (b) from the ER method. Model 10 is excluded and ECMWF ERA-40 data is used for the observed near-surface temperature. (c) The difference between (b) and (a), with locations of significant difference indicated by hatching. A difference is considered significant if the EM prediction lies outside the 95% confidence interval of the ER interval (e.g. Fig. 1a). (d) The difference between the present-day climatology in the CMIP3 ensemble mean and ERA-40. (e) Ratio of the 95% prediction interval from the ER method to that from the EM method.

Results and Conclusions: Antarctic

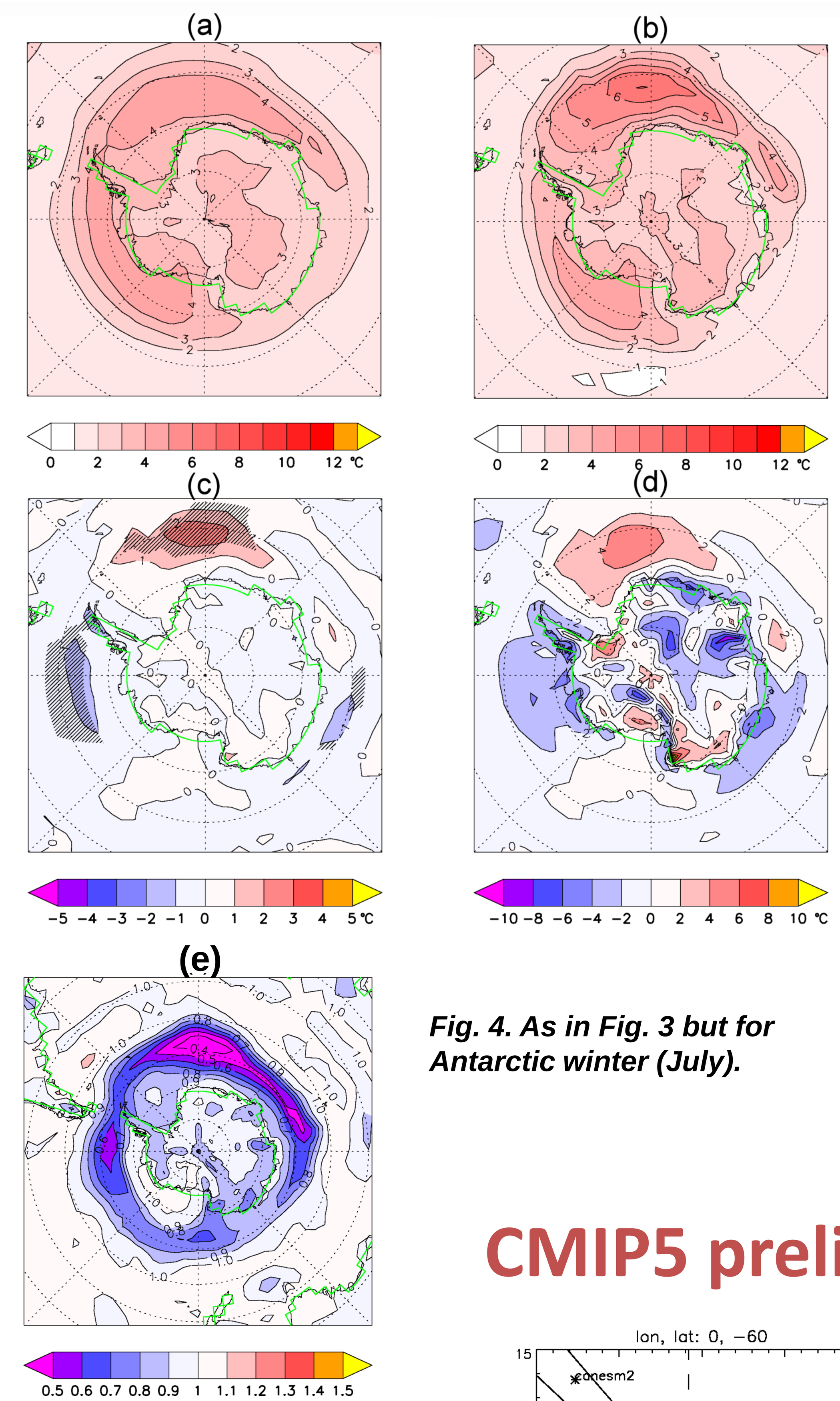


Fig. 4. As in Fig. 3 but for Antarctic winter (July).

For Antarctic winter (July), key differences between ER and EM predictions are:

- The ER method gives warming of approximately 2°C more than estimates based on the EM method northwest of the Weddell Sea at approximately 62°S, 5°W (Fig. 4c).
- There is a large region of significantly less warming extending westwards from the tip of the Antarctic Peninsula, centred on ~60°S, ~90°W (Fig. 4c).
- . As was found in the Arctic winter these differences coincide with regions of large bias in the present-day climatology of the CMIP3 ensemble average (Fig. 4d).
- Reductions in prediction interval of 50% extend across a sector of the Southern Ocean between 0° and 90°E (Fig. 4e).

CMIP5 preliminary results

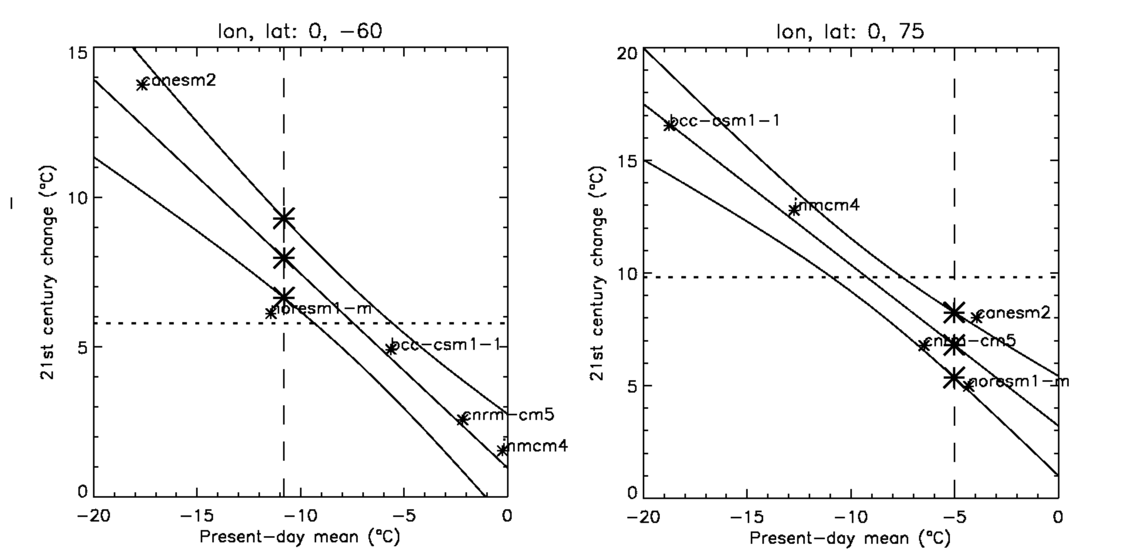


Fig. 5. As in Fig. 1, but for CMIP5 models. Present-day mean is the period 1976-2004 from all available 'historical' runs and 21st century change is the difference between the period 2069-2098 from all 'RCP4.5' runs and present-day mean.

From a preliminary analysis of the CMIP5 dataset (Fig. 5), a state-dependence similar to that seen in the CMIP3 models (Fig. 1) appears occur.

References

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