1 Supplementary Material

2 Significance tests

3	We test for significance by computing the probability that any particular statistic (e.g.
4	skill measure, RPC or difference in skill) could be accounted for by uncertainties
5	arising from a finite ensemble size (M) and a finite number of validation points (T) .
6	This is achieved using a non-parametric block boot-strap approach [Wilks, 2006;
7	Goddard et al., 2012; Smith et al., 2013], in which an additional 1000 hindcasts (or
8	pairs of hindcasts when testing differences, for example before and after RPC
9	correction) are created as follows:
10	1. Randomly sample with replacement T validation cases (over time). In order to take
11	autocorrelation into account this is done in blocks of five consecutive cases (years) for
12	the decadal hindcasts.
13	2. For each of these, randomly sample without replacement M -3 ensemble members.
14	Replacement is not used over ensemble members because repeatedly resampling the
15	same members reduces the number of independent data points in the ensemble mean,
16	and so reduces the correlation unfairly. We use M -3 members to retain a large enough
17	ensemble size to maintain representative estimates of the skill measure.
18	3. Compute the required statistic (e.g. skill measure, RPC or difference in skill) for the
19	ensemble mean of the bootstrapped sample (or samples if testing differences).
20	4. Repeat from step (1) 1000 times to create a probability distribution (PDF) of the
21	required statistic.
22	5. Obtain the significance level based on a two-tailed test against the null hypothesis.
23	For example, the null hypothesis 'RPC is not different to one' is rejected at the 90%
24	level if the 5 to 95% confidence interval obtained from the bootstrapped pdf
25	distribution does not span one.

For RPC, MSSS and correlation this method is performed on individual time-series of
grid points or area averages separately, while for the reliability diagram in Figure 2 it
is performed by re-sampling entire fields (for the regions of interest). For example, for
the correlation of the NAO in Figure 3a, this method leads to a 99% confidence
interval of [0.20, 0.91] such that the null hypothesis that the correlation is not different
to zero is rejected.

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Variable	Dataset	References
SAT	Average from:	
	HadCRUT4	Morice et al. [2012]
	NASA	Hansen et al. [2010]
	NCDC	Smith and Reynolds [2005]
MSLP	HadSLP2	Allan and Ansell [2006]
PREC	GPCP ^b	<i>Adler et al.</i> [2003]
PREC	GPCC ^c	Schneider et al. [2011]

36 Table S1 Gridded observation datasets^a

^a Details of gridded observation datasets used.

38 ^b For assessing seasonal hindcasts.

^c For assessing decadal hindcasts which precede the coverage of GPCP (noting that

40	GPCC observations only cover land).
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Model	Ensemble Size;	References
	start dates	
GloSea5	24 members;	MacLachlan et al.
	around 1 st Nov	[2014]
	1992 to 2011	
DePreSys,	37 members; 1 st	Smith et al. [2010;
HadCM3	Nov 1960 to 2005	2013]
DePreSys2,	4 members; 1 st Nov	Knight et al.,
HadGEM3	1960 to 2005	submitted ^c [2014]
CanCM4	10 members; 1 st	Merryfield et al.
	Jan 1961 to 2006	[2013]
GFDL-	10 members; 1 st	Delworth et al.
CM2.1	Jan 1961 to 2006	[2006]
MIROC5	6 members; 1 st Jan	Watanabe et al.
	1961 to 2006	[2010]
MPI-ESM-	3 members; 1 st Jan	Jungclaus et al.
LR	1961 to 2006	[2006]
	GloSea5 DePreSys, HadCM3 DePreSys2, HadGEM3 CanCM4 GFDL- CM2.1 MIROC5	start datesGloSea524 members;around 1 st Nov1992 to 2011DePreSys37 members; 1 st HadCM3Nov 1960 to 2005DePreSys2,4 members; 1 st NovHadGEM31960 to 2005CanCM410 members; 1 st GFDL-Jan 1961 to 2006MIROC56 members; 1 st Jan1961 to 20061961 to 2006

46 **Table S2. General Circulation Models**^a

^a Details of General Circulation Models used (decadal systems except for GloSea5).

^b Model output from the Coupled Model Intercomparison Project Phase 5 (CMIP5)

49 [*Taylor et al.*, 2012].

50 ^c *Knight et al.*, Predictions of climate several years ahead using an improved decadal

51 prediction system, submitted to J. Clim., 2014.

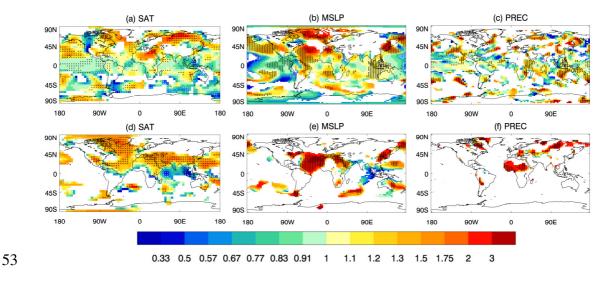


Figure S1: As Figure 1 but with the additional constraint that regions of correlation not *significantly* greater than zero are masked out, leading to the masking of regions with RPC below one that correspond to regions of insignificant skill.

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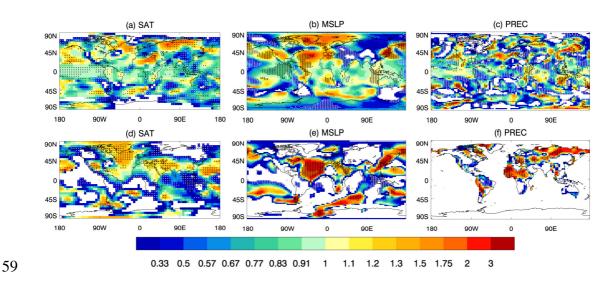


Figure S2: As Figure 1 but with all bias corrections applied in cross-validation mode
(ignoring current year and, for decadal hindcasts the four years either side), leading to
similar conclusions but with a slight reduction in the strength of the high RPC values
as cross-validation is known to underestimate correlation [*Smith et al.*, 2013; *Gangsto et al.*, 2013].

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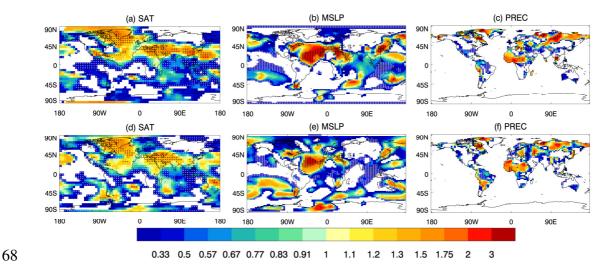


Figure S3: As Figure 1 but for HadCM3 only (row 1, 37 members) and for the four non-Met Office Hadley Centre CMIP5 (row 2, 29 members) to see the results for a single model versus that for the remaining models. This splitting of the models leads to the same conclusions, but with a slight reduction in the strength of the high RPC value, likely due to the reduced ensemble size.

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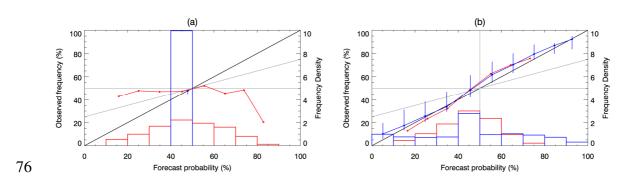
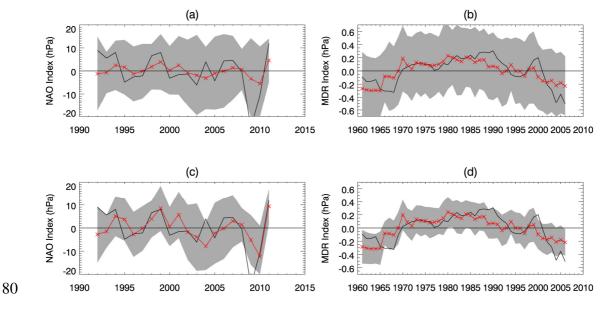
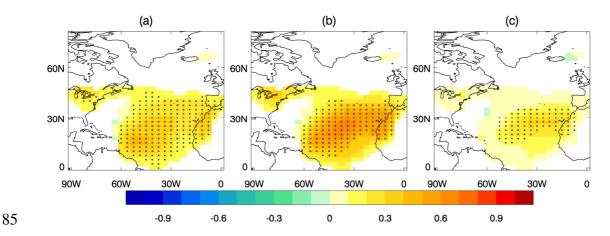


Figure S4: As Figure 2 but with all bias corrections applied in cross-validation mode(ignoring current year and four years either side).

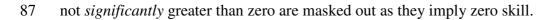


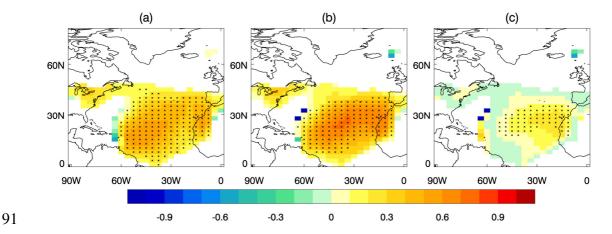
81 Figure S5: As Figure 3 but with all bias corrections applied in cross-validation mode

82 (ignoring current year, and for decadal hindcasts the four years either side).



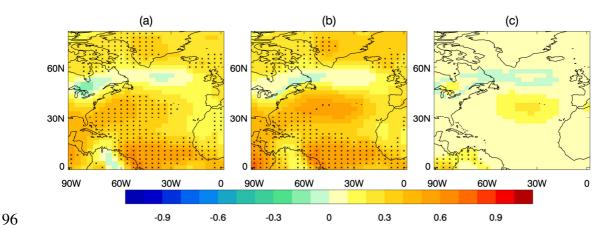
86 Figure S6: As Figure 4 but with the additional constraint that regions of correlation





92 Figure S7: As Figure S6 but with all bias and variance corrections applied in cross-

93 validation mode (ignoring current year and four years either side).



97 Figure S8: As Figure 4 but from the Met Office Hadley Centre seasonal forecasting
98 system for DJF seasonal mean, showing a slight improvement after the variance
99 correction but not significant (noting that there are only 20 years of model output
100 from this system, while 46 years are analysed from the decadal systems).

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