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The use of regression for assessing a seasonal forecast model experiment

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Abstract. We demonstrate how factorial regression can be used to analyse numerical model experiments, testing the effect of different model settings. We analysed results from a coupled atmosphere-ocean model to explore how the different choices in the experimental set-up influence the seasonal predictions. These choices included a representation of the sea-ice and the choice of top of the atmosphere, and the results suggested that the simulated monthly mean temperatures poleward of the mid-latitudes are highly sensitivity to the specification of the top of the atmosphere, interpreted as the presence or absence of a stratosphere. The seasonal forecasts for the mid-to-high latitudes were also sensitive to whether the model set-up included a dynamic or non-dynamics sea-ice representation, although this effect was less important than the role of the stratosphere. The temperature in the tropics was insensitive to these choices.

1 Introduction

The question of whether seasonal forecasting has useful skill is getting increasingly relevant with the progress in climate modelling. Another question is how we can learn more about such skills, and one strategy is to examine the models used in seasonal forecasting. These include state-of-the-art coupled atmosphere-ocean-land-surface models, built on our knowledge of physical processes and formulated in terms of computer code (Palmer and Anderson, 1994; Stockdale et al., 1998; Palmer, 2004; George and Sutton, 2006). They can be used for seasonal forecasting if a correct initial state is provided, and from which the subsequent evolution can be simulated. Their skill depends on several factors, such as the quality of the initial states, the representation of all relevant processes, and whether the seasons ahead truly are predictable in the presence of non-linear chaos (Palmer, 1996). Thus, in order to address the initial question of useful skill for seasonal predictions, we need to understand what is important and what is irrelevant for the outcome of the predictions which includes choices about the model set-up. We know that the atmosphere in the high latitudes is subject to non-linear dynamics, and that the effect of different factors may interfere and amplify or dampen each other (Charney, 1947; Gill, 1982; Lindzen, 1990; Held, 1993; Feldstein, 2003).

1.1 Background

It is well-known that numerical weather prediction (NWP) has a limited forecast horizon because small initial errors will grow over time in a non-linear fashion (Lorenz, 1963). The case for seasonal forecasting is somewhat different, as it relies on slow changes in the ocean and cryosphere, which act as persistent boundary conditions. NWP and seasonal forecasting represent two types of predictability referred to as 'type 1' and 'type 2' (Palmer, 1996). Whereas NWP is more an initial value problem ('type 1'), the seasonal forecasts embeds a degree of the boundary value problem aspect ('type 2'). Furthermore, seasonal forecasts tend to present the statistics of the weather over a given interval, rather than the exact state at any instant. In other words, seasonal forecasts, can be compared with predicting a change in the statistics of a sample of measurements, whereas weather forecasting is more like predicting the details about one specific data point in that sample.

Models used for seasonal forecasting have traditionally involved a model for the atmosphere coupled to an ocean component, and were originally developed for the tropical region and the El Niño Southern Oscillation (Anderson, 1995; Stockdale, et al., 1998; Palmer and Anderson, 1994). Aspects such as sea-ice, the troposphere and snow cover were not emphasised as they were not believed to play an important role for the seasonal weather evolution. More recent studies have looked at the potential influence from sea-ice (Balmaseda et al., 2010; Petoukhov and Semenov, 2010; Overland and Wang, 2010; Francis et al. 2009; Deser et al, 2004; Magnusdottir et al., 2004; Seierstad and Bader, 2008; Benestad, et al. 2010; Orsolini et al. 2012), especially after the recent dramatic downward trends in the sea ice extent (Kumar et al. 2010; Boé, et al., 2010; Holland et al., 2008; Wilson, 2009; Kauker et al., 2009; Stroeve et al., 2007, 2008). Other studies have involved the effect of snow-cover on the atmospheric circulation (Cohen and Entekhabi, 1999; Ge and Gong, 2009; Ueda et al., 2003; Hawkins et al., 2002; Watanabe and Nitta, 1998; Orsolini et al, 2013) or the influence of stratospheric conditions on the lower troposphere (Baldwin et al., 2001, 2003; Thompson et al. 2002). Few of these studies, however, have looked at how these different factors in combination may interfere with each other. Nor has there been many sensitivity tests for investigating how the model set-up with different combinations of the components representing these different aspects affect the results. One question we would like to address is whether the response to these different factors add linearly or if the response is a non-linear function of these factors. Furthermore, it is interesting to find out which of these factors are more dominant than others. Moreover, our objective was to try to understand which *processes simulated by the model* are more important, rather than what real signals there are in nature. In this sense, this was a so-called *perfect model study* (Day et al., 2014). We present the combination of an experimental design (Williams, 1970; Kleijnen and Standridge, 1988) and analytical techniques that can address this question. The results were taken from a 'synthesis' experiment with a moderately high-resolution earth system model. Hence, these numerical experiments constitute a kind of sensitivity study (Bürger et al., 2013).

2 Method & Data

2.1 Model simulations

The model used in this study is the EC-Earth version 2.1 state-of-the-art earth system model (Hazeleger et. al, 2010), which has been developed by a consortium of meteorological Institutes/Universities across Europe. The atmospheric component of the EC-Earth model is based on ECMWF's Integrated Forecasting System (IFS) cycle 31R1 with a new convection scheme and a new land surface scheme. The ocean component is based on version 2 of the NEMO model (Madec, 2008), with a horizontal resolution of nominally 1x1 degrees and 42 vertical levels. The sea ice model is the LIM2 model (Fichefet and Maqueda, 1997). The ocean/ice model is coupled to the atmosphere/land model through the OASIS 3 coupler (Valcke, 2006).

The synthesis experiments consists of a set of 12 coupled model simulations. Six of these simulations used the L62 vertical resolution for the atmospheric component which extends up to 5 hPa, while the other six used the higher resolution L91 version, which extends up to 0.01 hPa. These two sets of experiments were designed to determine the sensitivity of model results to a better representation of the stratosphere. Further to evaluate the role of sensitivity to the representation of sea-ice, the LIM2 sea-ice model was implemented as a standard thermodynamic-dynamic model (DyIce) and as a thermodynamic only model (NoDyIce). Finally, sensitivity to initial conditions were tested by introducing perturbations to initial conditions corresponding to positive/negative NAO SST anomaly patterns over the North Atlantic (Melsom, 2010) All simulations started on 1 Jan 1990 and lasted 90 days. An overview of the model simulations are listed in Table 1.

2.2 The analysis

Here the experiments and analysis used an approach known as 'factorial design' (Yates and Mather, 1963; Fisher, 1926; Hill and Lewicki, 2005; Wilkinson and Rogers, 1973; Benestad et al., 2010), where a factorial regression was used to assess which influence each of the choices in the model set-up has on the forecasts. Factorial design is a technique that is well-suited for analysing a set of factors which are considered to have potential effects on the outcome in experiments, where an analysis of variance (ANOVA; Wilks, 1995) provides estimates for error bars and the level of statistical significance. Hence, the factorial regression offers an alternative to traditional ways for estimating statistical significance used in meteorology and climate sciences, such as difference tests between two ensembles. Factorial regression is especially handy when data is generated by a process which involves two or more factors (set-up options or categories) that are difficult to quantify due to their discrete nature (e.g. some factors may either present or absent), and has been used to analyse the effect of introducing different crop varieties in agriculture (e.g. Baril et al. 1995; Vargas et al. 1999; Vargas et al. 2006; Voltas et al. 2005). It is based on the concept "factorial experiment", or "factorial design", in statistics which involves two or more factors each of which can be assigned a category or a discrete value. The analysis takes into account all possible combinations of levels over all such factors including their interactions.

The model response to different initial conditions or different model set-up with different options for three configurations (SST perturbation, model top, and sea-ice model) was investigated, and a comparison was made between the different experiments in terms of vertical and horizontal cross sections of temperature anomalies. If the final response ΔT is a linear function of sea-ice, SST, and stratospheric effects, then it can be expressed as a sum of these different contributions $\Delta T = x_1 C(sea\text{-}ice) + x_2 C(SST) + x_3 C(stratosphere)$. The factorial regression provided an estimate of the coefficients x_i and their error estimates. In a non-linear case, this linear expression was unlikely to provide a good description, and the regression analysis will yield large errors and low statistical significance.

We do not know the relative strength of the different factors in terms of an input, however, the factorial regression quantifies the differences between output from different combinations of subsets. It was also used to estimate the probability that the response in the different combinations of these subsets would be due to chance. The results from the factorial regression were subsequently used to explore the combined effect of several factors.

The Walker test was used to assess the false discovery rate of the p-values found in the factorial regression (Wilks, 2006). The test involves comparing the minimum p-value p_n from the local tests with $p_W = 1 - (1 - \alpha)^{1/K}$ for K locations and the statistical significance level α. If $p_n < p_W$ then the expected fraction of local null hypothesis with incorrect rejections is smaller than the number of statistically significant local p-values.

3 Results

Figures 1-2 show the difference in the forecasts associated stratosphere, more specifically between the low (L62) and high (L91) top versions of the atmosphere for month 3. Figure 1 shows horizontal transects at 200 and 50 hPa levels respectively. They show the monthly mean temperature starting with a 2-month lead time, and the left panels show results with no initial perturbation (neutral NAO conditions), the middle panels show results from model simulation with initial conditions set at NAO, and the right panels results for which the initial conditions were the negative phase of the NAO. All the panels show that there were differences between the low and high top results, and the difference between the low and high-top model simulation is most pronounced at negative and positive NAO-type initial conditions (not shown). Hence, the forecasted air temperature is sensitive to the inclusion of the upper part of the atmosphere, and the effect can be seen extending throughout the entire vertical extent of the atmosphere (not shown). The difference between the upper and lower rows show the effect of dynamic versus non-dynamic sea-ice representation. With a non-dynamic sea-ice, the inclusion of a stratosphere resulted in stronger vertical dipole patterns at certain longitudes and for positive NAO initial conditions. For the negative NAO initial conditions, the dynamical sea-ice representation enhanced the differences between the L91 and L62 model simulations.

Figure 1 suggests that the effect of including the stratosphere and the representation of sea-ice matter for the mid-latitude to the polar regions, and the choice of the vertical levels had less impact in the tropics. The response suggests mid-latitude wave-like structures in the 200 hPa temperatures, albeit with a tendency of a coherent anomaly over the North Pole. The choice of the sea-ice representation had a pronounced impact on the simulation of the monthly mean temperature after 3 months. The horizontal picture at 50 hPa (Figure 1) suggests radically different wave structure for the negative NAO phase, however, whereas the ‘positive’ and ‘neutral’ NAO states differences are more in the details and magnitude. The exact geographical structure in these maps are not the important point here, as the longitude of action will depend on the initial condition. The important information here is the pronounced response in the mid-to-high latitudes.

In summary, it is apparent from Figures 1-2 that the effect of different model aspects such as the choice of model top and sea-ice representation influence the model forecasts. Furthermore, we see that the influence varies with the initial SST conditions, and that different sea-ice representation may introduce changes in the forecast of similar magnitude as the influence of the model top. It is difficult to compare these effects with that of the initial conditions merely from Figures 1-2, however, we can compare the effect from these different aspects through the means of a factorial regression. The analysis of variance for the factorial regression yields a set of coefficients β describing the association between the temperature and the model set-up choice, as well as the associated error bars ε and p-values p.

Figure 2 represents the coefficients and the error estimates from the factorial regression. The top panel shows the mean air temperature for the model forecasts with a model set-up of dynamical sea-ice component, no perturbation in the SST, and 62 vertical levels (low top). Panels b-f show difference in the forecasts due to different choices in the model set-up in terms of the regression coefficients β, and panels g-e show error estimates for these coefficients. Regions with large values estimated for the coefficients and large errors suggest a high sensitivity but also that the response cannot readily be attributed to the given factor. In other words, the level of both the signal and the noise is high. The magnitude of the error was mainly below 3K except for around 100ºE near the 100hPa level, and generally smaller than the influence of the variable. The results suggests that the results were sensitive to both the representation of the sea-ice and the inclusion of the stratosphere, as well as the initial conditions. The analysis also suggests that the magnitude of the effect of the sea-ice representation and the model top was similar to those of the different SST perturbation near 60ºN. Furthermore, the error estimates associated with the three factors (SST-perturbation, sea-ice representation and atmosphere top) exhibited similar magnitudes and spatial structure. A comparison between the different panels in Figure 2 suggests that the different choices for model set-up had similar magnitude on the predicted outcome for all these factors.

Figure 3 shows the ratio response to error for sea ice (upper), positive NAO SST perturbation (second from the top), negative NAO SST perturbation (third), and the stratosphere L91 (bottom). Only a small region had a response that was greater in magnitude than the error estimate for the sea ice, whereas for the SST perturbations and the stratosphere, the regions with response-to-error ratio has a magnitude greater to unity were more extensive. Note, both large negative and positive values indicate that the signal is stronger than the noise $|\beta/\varepsilon|>1$ as β may be both positive and negative whereas ε is positive.

The factorial regression gave highest number of low p-values for the stratosphere (L91), followed by the SST-perturbation (not shown). For most of the 60ºN vertical transect, the sea-ice representation did not yield a large response compared to the error term. Furthermore, for a global statistical significance level of $\alpha=0.05$ and $K=3840$, the threshold value for the Walker test was $p_W=1.3 \cdot 10^{-5}$. The minimum p-value for sea ice was 0.01, for SST-perturbation $p_n= 9.2\cdot 10^{-4}$ and the stratosphere $p_n=1.6\cdot 10^{-4}$. In other words, the 12-member experiment was not sufficient to resolve the response in the air temperature forecast at 60ºN for month 3 to the different set-up options, however, the results suggest that the model top had the greatest impact on the forecast. The lack of a clear dependency between the sea ice representation and the forecast was also found for the summer in Benestad et al. (2010), and the obscure links between the factors and the response may be explained by the presence of strong nonlinear dynamics, where one given factor may result in different forecasts depending on other influences.

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The question of degree of nonlinearity can be addressed by comparing the sum of the influence from the different factors with simulations with and without a set of factors combined. i.e, we check for the equivalency:

DyIce pNAO L91 - NoDyIce nNAO L62 = (DyIce - NoDyIce) nNAO L62 + …..... (1)

NoDyIce (pNAO - nNAO) L62 + NoDyIce nNAO (L91 - L62)

Here, the LHS of equation 1 (Figure 4a) shows the difference between the simulation with high top, dynamic sea ice, positive NAO perturbation (*DyIce pNAO L91*) and that with low top, non-dynamic sea ice, negative NAO (*NoDyIce nNAO L62*). Figure 4a is compared with sum of the differences from individual factors (RHS of equation 1, Figure 4b). The comparison shows that the non-linear model response is mainly confined to the mid- to high-latitudes especially in the northern Hemisphere (Figure 4c), e.g., along the 60ºN transect presented in Figures 3-5.

4 Discussion

The set of sensitivity experiments shows that seasonal forecasts at mid-to-high latitudes are sensitive to a number of factors concerning the model set-up, and that the choice of subjective and subtle options can have as strong effect on the monthly mean temperature poleward of the mid-latitudes as the initial conditions. A factorial design experiment allows us to assess the relative magnitudes of different model height with that of different sea-ice or different SST perturbations. We can also test the response in the model to see if they are close to being a linear superposition of the different single factors, or if the model response is highly non-linear. The statistical significance is estimated based on the factorial regression. The magnitude of the effect of the sea ice, SST-perturbations and the model top height were roughly similar, although the response to the sea ice was somewhat weaker than the others. The lower ratio of estimate-to-error also reflect the degree of nonlinearity, and the lower p-values associated with the sea-ice may be due to a greater degree of nonlinearity in the response to the sea-ice representation. The experiment nevertheless suggested that stratospheric conditions are important for mid-to-high-latitude seasonal forecasting. This experiment was only carried out for the northern hemisphere winter, and may change with season. The stratosphere decouples in the summer, and there is a hint of a weaker influence from the model top in the southern hemisphere where there was summer.

There is previous work where model sensitivity and uncertainty have been assessed (e.g. Rinke et al 2000; Wu, et al. 2005; Pope and Stratton, 2002; Jacob and Podzun 1997; Knutti et al. 2002; Dethloff et al. 2001), however, most of these assessments have been carried out for climate simulations as opposed to seasonal forecasts. In seasonal forecasting, the emphasis has been more on multi-model forecasts and their spread (Weisheimer et al. 2009), rather than the configuration of single models. However, Jung et al. (2012) discussed the effect of the spatial resolution on seasonal forecast based on an experimental design with a single model. The use of factorial regression has was also discussed by Rinke et al (2000) in conjunction with climate simulations, and Benestad et al. (2010) used it in a study of seasonal predictability and the effect of of boundary conditions associated with sea-ice and initial conditions. This study presented applied factorial regression to a new set of model configuration options, including the model top, the representation of sea-ice, and initial conditions. In this case, we emphasised the individual factors rather than their interaction because of the limited sample of model runs.

5 Conclusions

The sensitivity tests revealed that seasonal predictability of the temperature at the mid-to-high latitudes was as sensitive to subjective choices regarding the model set-up as the initial SST conditions. The forecasts for high-latitude regions were in particular sensitive to the model top, but also the representation of sea ice influenced the outcome. Hence, these results illustrate the difficulties associated with seasonal forecasting at the higher latitudes and has an effect of the forecast skill. The tropical temperatures were insensitive to these choices, and the sea-ice representation and the stratosphere do not have a visible effect on ENSO forecasts.

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References

Anderson, D. L. T. “The Legacy of TOGA: Seasonal Climate Prediction.” In *Predictability*, edited by ECMWF, Vol. 2. Seminar Proceedings. ECMWF, 1995.

Baldwin, M. P., and T. J. Dunkerton. “Stratospheric Harbingers of Anomalous Weather Regimes.” *Science* 294 (October 2001): 581–584.

Baldwin, M. P., D. B. Stephenson, D. W. J. Thompson, T. J. Dunkerton, A. J. Charlton, and A. O’Neil. “Stratospheric Memory and Skill of Extended-Range Weather Forecasts.” *Science* 301 (2003): 636–640.

Balmaseda, M.A., L. Ferranti, F. Molteni and T.N. Palmer (2010),’Impact of 2007 and 2008 Arctic ice anomalies on the atmospheric circulation: Implications for long-range predictions’, QJRMS, DOI: 10.1002/qj.661.

Baril, C. P., J. -B. Denis, R. Wustman, and F. A. van Eeuwijk. 1995. “Analysing Genotype by Environment Interaction in Dutch Potato Variety Trials Using Factorial Regression.” *Euphytica* 84 (1): 23–29. doi:10.1007/BF01677553.

Benestad, R.E., R. Senan, M. Balmaseda, L. Ferranti, Y. Orsolini, & A. Melsom (2010) 'Sensitivity of summer 2-m temperature to sea ice conditions', Tellus A, 63, 2, 324-337, doi: 10.1111/j.1600-0870.2010.00488.x

Boé, J., A. Hall, and X. Qu (2010),’Sources of spread in simulations of Arctic sea ice loss over the twenty-first century’, Clim. Change, 99, doi: 10.1007/s10584-010-9809-6, 637-645.

Bürger, G., S. R. Sobie, A. J. Cannon, A. T. Werner, and T. Q. Murdock. “Downscaling Extremes: An Intercomparison of Multiple Methods for Future Climate.” *Journal of Climate* 26, no. 10 (May 2013): 3429–49. doi:10.1175/JCLI-D-12-00249.1.

Charney, J. G. “The Dynamics of Long Waves in a Baroclinic Westerly Current.” *J.Meteorol.* 4 (1947): 135–63.

Cohen, J. and D. Entekhabi (1999), ‘Eurasian snow cover variability and northern hemisphere climate predictability’, GRL, 26, doi:10.1029/1998GL900321, 345-348.

Day, J. J., E. Hawkins, and S. Tietsche. “Will Arctic Sea Ice Thickness Initialization Improve Seasonal Forecast Skill?” *Geophysical Research Letters* 41, no. 21 (November 16, 2014): 7566–75. doi:10.1002/2014GL061694.

Deser, C., G. Magnusdottir, R. Saravanan and A. Phillips (2004), ‘The Effects of North Atlantic SST and Sea Ice Anomalies on the Winter Circulation in CCM3. Part II: Direct and Indirect Components of the Response’, J.Clim., 17, 877-889.

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Manuscript under review for journal Earth Syst. Dynam.
Published: 31 May 2016

Dethloff, K., C. Abegg, A. Rinke, I. Hebestadt, and V. F. Romanov. 2001. "Sensitivity of Arctic Climate Simulations to Different Boundary-Layer Parameterizations in a Regional Climate Model." *Tellus A* 53 (1): 1–26. doi:10.1034/j.1600-0870.2001.01073.x.

Feldstein, S. B. "The Dynamics of NAO Teleconnection Pattern Growth and Decay." *Quarterly Journal of the Royal Met. Society* 129, no. doi:10.1256/qj.02.76 (2003): 901–24.

Fichefet, T., and M. A. M. Maqueda, 1997 : Sensitivity of a global sea ice model to the treatment of ice thermodynamics and dynamics. Journal of Geophysical Research, 102, 12,609-12,646, doi:10.1029/97JC00480.

Fisher, R. (1926). "The Arrangement of Field Experiments". Journal of the Ministry of Agriculture of Great Britain 33: 503–513.

Francis, J.A., W. Chan, D.J. Leathers, J.R. Miller and D. E. Veron (2009), 'Winter Northern Hemisphere weather patterns remember summer Arctic sea- ice extent,GRL, 36, L07503, doi:10.1029/2009GL037274

Ge, Y. and G. Gong (2009), 'North American Snow Depth and Climate Teleconnection Pattern', J. Clim., 22, doi:19.1175/2008JCLI2124.1, 217-233

George, S. E., and R. T. Sutton. "Predictability and Skill of Boreal Winter Forecasts Made with the ECMWF Seasonal Forecast System II." *Quarterly Journal of the Royal Met. Society* 132 (2006): 2031–53.

Gill, A. E. *Atmosphere-Ocean Dynamics*. International Geophysics Series. San Diego, California: Academic Press, 1982.

Hawkins, T.W., A.W. Ellis, J.A. Skindlov and D. Reigle (2002), 'Inter-annual Analysis of the North American Snow Cover-Monsoon Teleconnection: Seasonal Forecasting Utility', J.Clim., 15,, 1743-1753

Hazeleger, Wilco, and Coauthors, 2010: EC-Earth: A Seamless Earth-System Prediction Approach in Action. *Bull. Amer. Meteor. Soc.*, 91, 1357–1363. doi: 10.1175/2010BAMS2877.1

Held, I. M. "Large-Scale Dynamics and Global Warming." *Bull. Amer. Meteor. Soc.* 74 (1993): 228–41.

Hill, T., and P. Lewicki. *Statistics: Methods and Applications : a Comprehensive Reference for Science, Industry, and Data Mining*. ISBN 1884233597. Tulsa, OK, USA: StatSoft, 2005.

Holland, M.M., M.C. Serreze and J. Stroeve (2008), The sea ice mass budget of the Arctic and its future change as simulated by coupled climate models, Clim. Dyn., DOI 10.1007/s00382-008-0493-4

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Manuscript under review for journal Earth Syst. Dynam.
Published: 31 May 2016

Jacob, D., and R. Podzun. 1997. "Sensitivity Studies with the Regional Climate Model REMO." *Meteorology and Atmospheric Physics* 63 (1–2): 119–29. doi:10.1007/BF01025368.

Jung, T., M. J. Miller, T. N. Palmer, P. Towers, N. Wedi, D. Achuthavarier, J. M. Adams, et al. 2012. "High-Resolution Global Climate Simulations with the ECMWF Model in Project Athena: Experimental Design, Model Climate, and Seasonal Forecast Skill." *Journal of Climate* 25 (9): 3155–72. doi:10.1175/JCLI-D-11-00265.1.

Madec, G. 2008: "NEMO ocean engine". Note du Pole de modélisation, Institut Pierre-Simon Laplace (IPSL), France, No 27 ISSN No 1288-1619.

Magnusdottir, G., C. Deser and R. Saravanan (2004), 'The Effects of North Atlantic SST and Sea Ice Anomalies on the Winter Circulation in CCM3. Part I:Main Features and Storm Track Characteristics of the Response', J.Clim., 17, 857--875.

Melsom, A. (2010), Perturbing the ocean initial state from NAO regression, Met.no report, 1/2010,

Kauker, F., T. Kaminski, M. Karcher, R. Giering, R. Gerdes, and M. Voßbeck (2009), 'Adjoint analysis of the 2007 all time Arctic sea-ice minimum', GRL, 36, doi:10.1029/2008GL036323, L03707

Kleijnen, Jack P.C., and Charles R. Standridge. "Experimental Design and Regression Analysis in Simulation: An FMS Case Study." *European Journal of Operational Research* 33, no. 3 (February 1988): 257–61. doi:10.1016/0377-2217(88)90168-3.

Knutti, Reto, Thomas F. Stocker, Fortunat Joos, and Gian-Kasper Plattner. 2002. "Constraints on Radiative Forcing and Future Climate Change from Observations and Climate Model Ensembles." *Nature* 416 (6882): 719–23. doi:10.1038/416719a.

Kumar, A., J. Perlwitz, J. Eischeid, X. Quan, T. Xu, T. Zhang, M. Hoerling, B. Jha and W. Wang (2010), Contribution of sea ice loss to Arctic amplification, GRL, 37, L21701, doi:10.1029/2010GL045022

Lindzen, Richard S. *Dynamics in Atmospheric Physics*. Cambridge, U.K.: Cambridge University Press, 1990.

Lorenz, E. "Deterministic Nonperiodic Flow." *Journal of the Atmospheric Sciences* 20 (1963): 130–41.

Orsolini, Y.J., R. Senan, R.E. Benestad, and A. Melsom (2012) 'Autumn atmospheric response to the 2007 low Arctic sea ice extent in coupled ocean-atmosphere hindcasts', Climate Dynamics, 38, 2437-2448, doi:10.1007/s00382-011-1169-z.

Orsolini, Y.J., Senan, R., Carrasco, A., Balsamo, G., Doblas-Reyes, F.J., Vitart, F., Weisheimer, A., and R.E. Benestad (2013) 'Impact of snow initialization on sub-seasonal forecasts', Climate Dynamics, doi:10.1007/s00382-013-1782-0.

Overland, J.E. and M. Wang (2010),'Large-scale atmospheric circulation changes are associated with the recent loss of Arctic sea ice', Tellus A, DOI: 10.1111/j.1600-0870.2009.00421.x

Palmer, T.N. (1996) 'Predictability of the Atmosphere and Oceans: from Days to Decades', in 'Decadal Variability' edited by D.L.T. Anderson and J. Willebrand, Springer, NATO ASI series, volume 44

Palmer, T.N. "Progress towards Reliable and Useful Seasonal and Interannual Climate Predicition." *WMO Bulletin* 53 (2004): 325–33.

Palmer, T.N., and D.L.T Anderson. "The Prospect for Seasonal Forecasting - A Review Paper." *Q.J.R.M.S.* 120 (1994): 755–93.

Petoukhov, V. and V.A. Semenov (2010), A link between reduced Barents-Kara sea ice and cold winter extremes over northern continents, JGR, 115, D21111, doi:10.1029/2009JD013568

Pope, V., and Stratton R. 2002. "The Processes Governing Horizontal Resolution Sensitivity in a Climate Model." *Climate Dynamics* 19 (3–4): 211–36. doi:10.1007/s00382-001-0222-8.

Rinke, Annette, Amanda H. Lynch, and Klaus Dethloff. 2000. "Intercomparison of Arctic Regional Climate Simulations: Case Studies of January and June 1990." *Journal of Geophysical Research: Atmospheres* 105 (D24): 29669–83. doi:10.1029/2000JD900325.

Seierstad, I.A. and J. Bader (2008), 'Impact of a projected future Arctic Sea Ice reduction on extratropical storminess and the NAO', Clim. Dyn., 33, 937-943, DOI 10.1007/s00382-008-0463-x

Stockdale, T. N., D. L. T. Anderson, J. O. S. Alves, and M. A. Balmaseda. "Global Seasonal Rainfall Forecasts Using a Coupled Ocean-Atmosphere Model." *Nature* 392 (1998): 370–73.

Stroeve, J., M. Serreze, S. Drobot, S. Gearheard, M. Holland, J. Maslanik, W. Meier and T. Scambos (2008), 'Arctic Sea Ice Extent Plummets in 2007',Eos, 89 (2), 13-14

Stroeve, J.. M.M. Holland. W. Meier. T. Scambos and M. Serreze (2007), 'Arctic sea ice decline: Faster than forecast', GRL, 34, doi:10.1029/3007GL029703, L09501

Thompson, D. W. J., M. P. Baldwin, and J. M. Wallace. "Stratospheric Connection to Northern Hemisphere Wintertime Weather: Implications for Prediction." *Journal of Climate* 15 (2002): 1421–1428.

Earth Syst. Dynam. Discuss., doi:10.5194/esd-2016-14, 2016
Manuscript under review for journal Earth Syst. Dynam.
Published: 31 May 2016

Valcke, S. , 2006: OASIS3 User Guide (prism_2-5). PRISM Support Initiative Report No 3, 64 pp.

Vargas, Mateo, José Crossa, Fred A. van Eeuwijk, Martha E. Ramírez, and Ken Sayre. 1999. "Using Partial Least Squares Regression, Factorial Regression, and AMMI Models for Interpreting Genotype × Environment Interaction." *Crop Science* 39 (4): 955. doi:10.2135/cropsci1999.0011183X003900040002x.

Vargas, Mateo, Fred A. van Eeuwijk, Jose Crossa, and Jean-Marcel Ribaut. 2006. "Mapping QTLs and QTL × Environment Interaction for CIMMYT Maize Drought Stress Program Using Factorial Regression and Partial Least Squares Methods." *Theoretical and Applied Genetics* 112 (6): 1009–23. doi:10.1007/s00122-005-0204-z.

Voltas, J., H. López-Córcoles, and G. Borrás. 2005. "Use of Biplot Analysis and Factorial Regression for the Investigation of Superior Genotypes in Multi-Environment Trials." *European Journal of Agronomy* 22 (3): 309–24. doi:10.1016/j.eja.2004.04.005.

Ueda, H, M. Shinoda and H. Kamahori (2003), 'Spring northward retreat of Eurasian snow cover relevant to seasonal and interannual variations of atmospheric circulation', Int.J. Clim., 23, 615-629

Watanabe, M. and T. Nitta (1998), 'Relative Impacts of Snow and Sea Surface Temperature Anomalies on an Extreme Phase in Winter Atmospheric Circulation', J.Clim., 11, 2837-2857

Weisheimer, A., F. J. Doblas-Reyes, T. N. Palmer, A. Alessandri, A. Arribas, M. Déqué, N. Keenlyside, M. MacVean, A. Navarra, and P. Rogel. 2009. "ENSEMBLES: A New Multi-Model Ensemble for Seasonal-to-Annual predictions—Skill and Progress beyond DEMETER in Forecasting Tropical Pacific SSTs." *Geophysical Research Letters* 36 (21). doi:10.1029/2009GL040896.

Wilkinson, G. N., and C. E. Rogers. "Symbolic Description of Factorial Models for Analysis of Variance." *Applied Statistics* 22 (1973): 392–399.

Wilks, D. S. *Statistical Methods in the Atmospheric Sciences*. Orlando, Florida, USA: Academic Press, 1995.

Wilks, D. S. "On 'Field Significance' and the False Discovery Rate." *Journal of Applied Meteorology and Climatology* 45, no. DOI: 10.1175/JAM2404.1 (2006): 1181–1189.

Williams, John D. "A Regression Approach to Experimental Design." *The Journal of Experimental Education* 39, no. 2 (1970): 83–90.

Earth Syst. Dynam. Discuss., doi:10.5194/esd-2016-14, 2016
Manuscript under review for journal Earth Syst. Dynam.
Published: 31 May 2016

Wilson, M. (2009) ‘Satellite altimetry quantifies the alarming thinning of Arctic sea ice’, Physics Today, September, 19-21

Wu, Wanli, Amanda H. Lynch, and Aaron Rivers. 2005. “Estimating the Uncertainty in a Regional Climate Model Related to Initial and Lateral Boundary Conditions.” *Journal of Climate* 18 (7): 917–33. doi:10.1175/JCLI-3293.1.

Yates, F., and K. Mather. “Ronald Aylmer Fisher. 1890-1962.” Biographical Memoirs of Fellows of the Royal Society 9, no. 0 (November 1, 1963): 91–129. doi:10.1098/rsbm.1963.0006.

Earth Syst. Dynam. Discuss., doi:10.5194/esd-2016-14, 2016
Manuscript under review for journal Earth Syst. Dynam.
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Figure captions.

Figure 1: Map of monthly mean air temperature difference at 200 hPa between the high-top and low-top experiments for the third month.

Figure 2: Coefficients and error estimates from the factorial regression of air temperature at 60ºN. These results describe the systematic differences associated between the different choices in the model set-up.

Figure 3: The ratio of the factorial regression coefficients to the error estimate for different factors: (a) sea ice representation, (b) positive NAO SST perturbation, (c) negative NAO SST perturbation and (d) the model top L91/stratosphere (bottom).

Figure 4: Monthly mean air temperaure at 60ºN. (a) Difference between *DyIce pNAO L91* and *NoDyIce nNAO L62* (b) Sum of the differences: *NoDyIce (pNAO - nNAO) L62*, *(DyIce - NoDyIce) nNAO L62* and *NoDyIce nNAO (L91 - L62)* (c) Difference (a) - (b).

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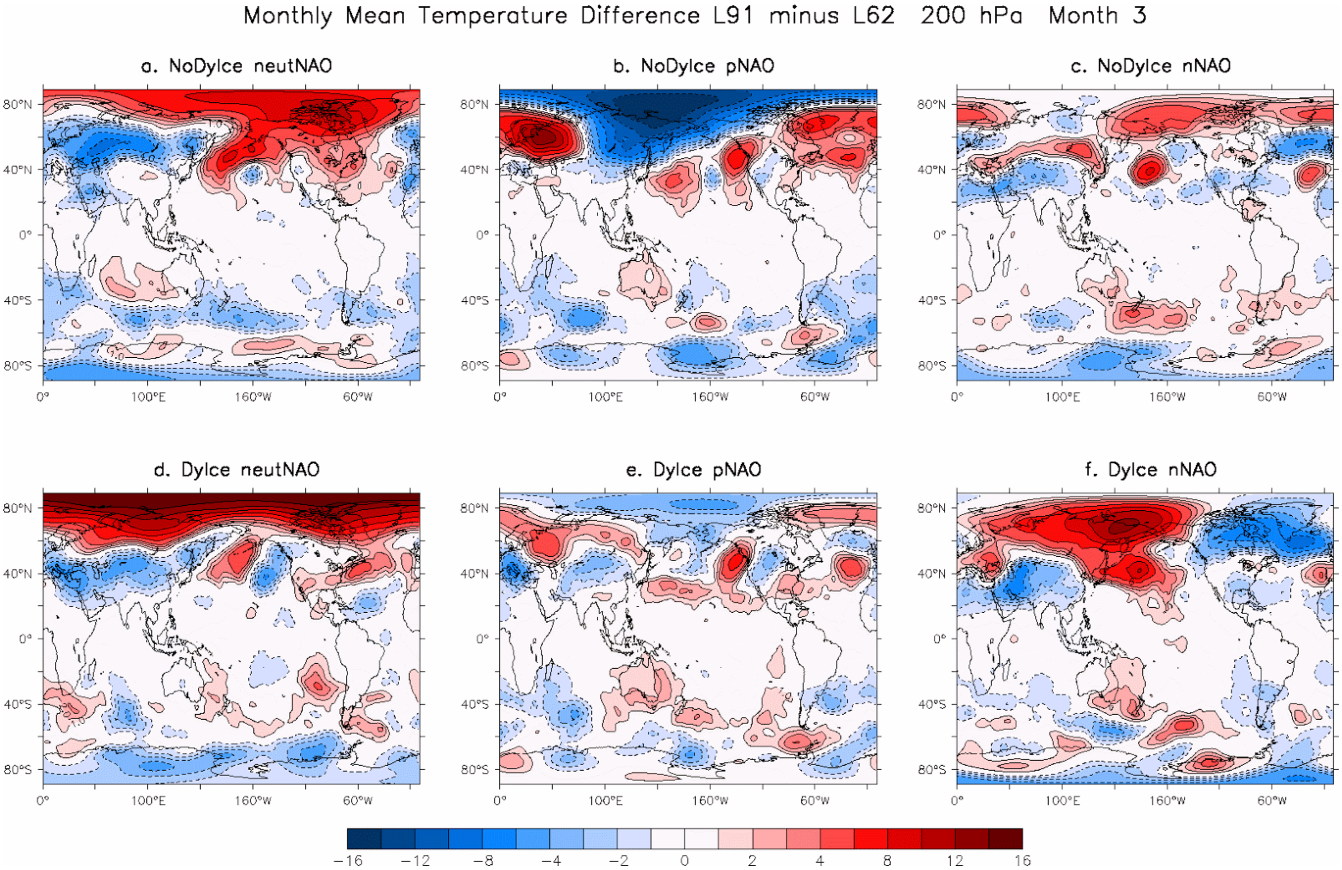

Figure 1

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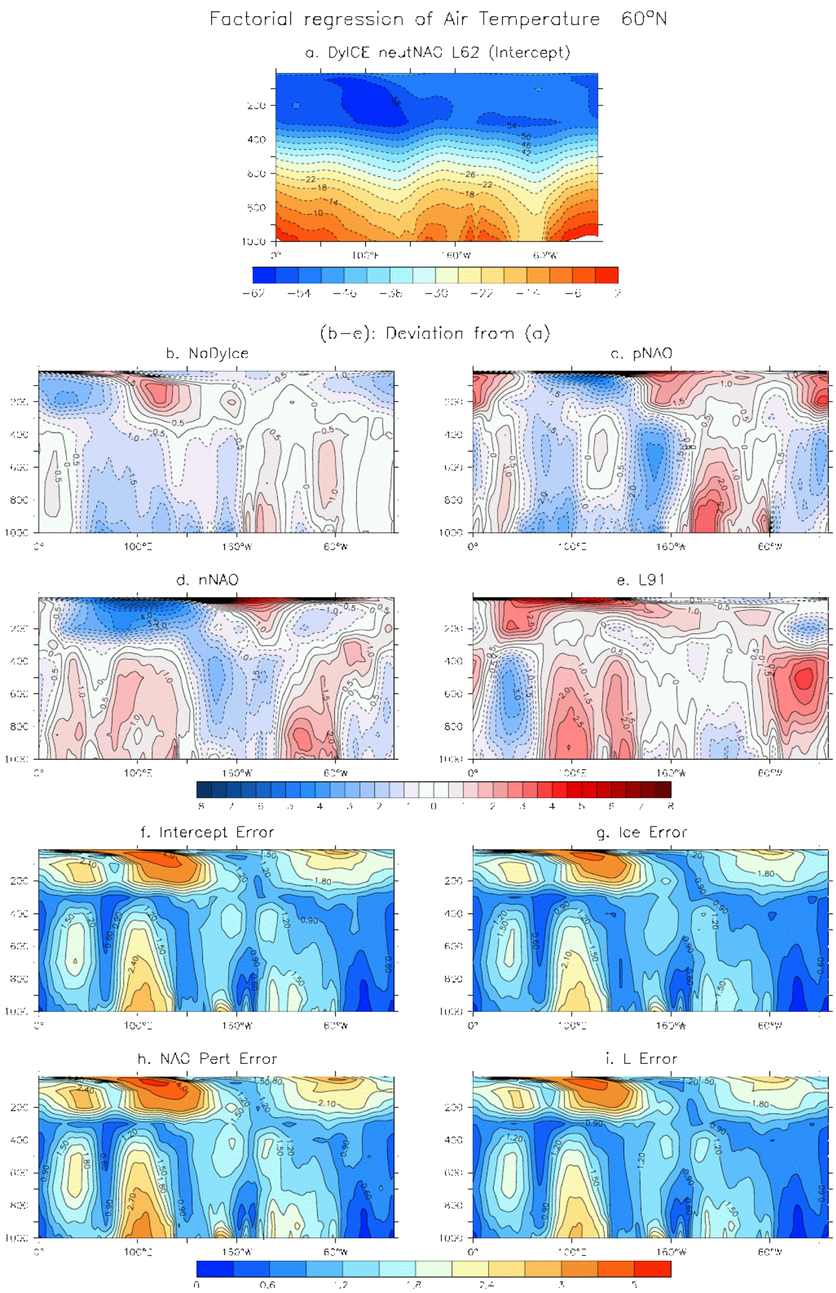

Figure 2

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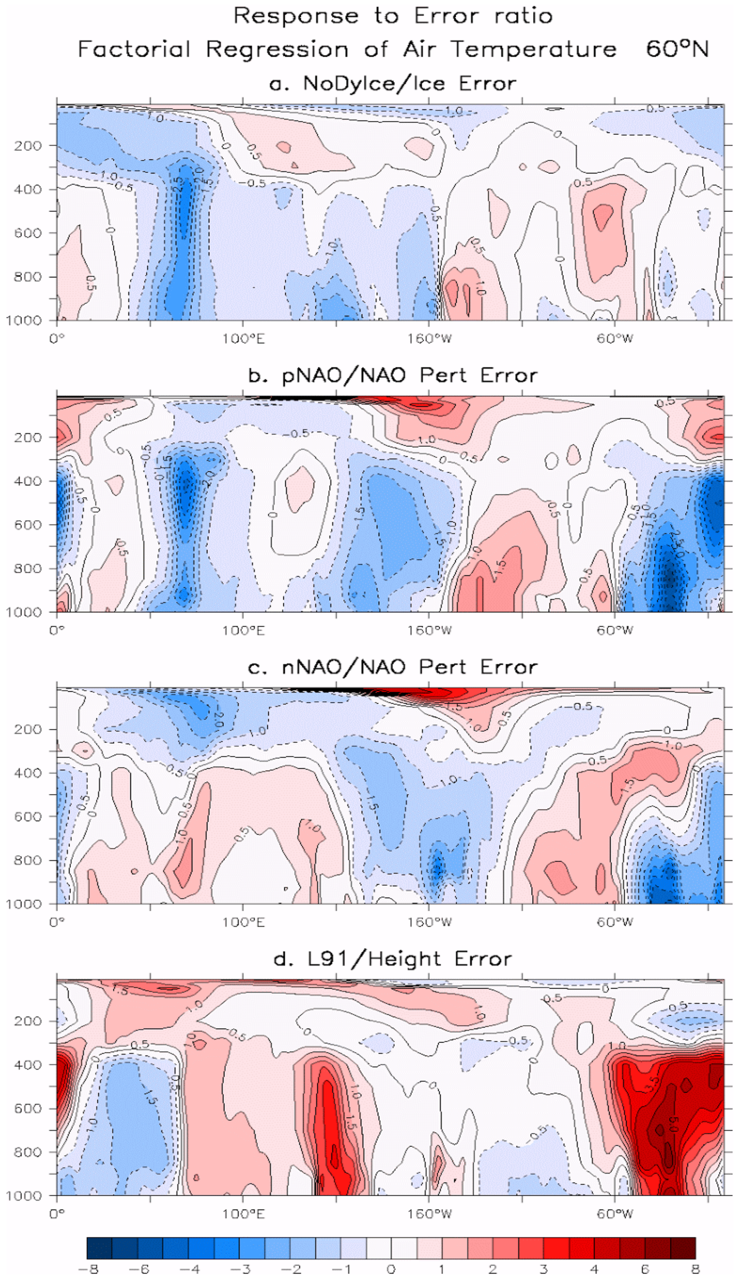

363 Figure 3

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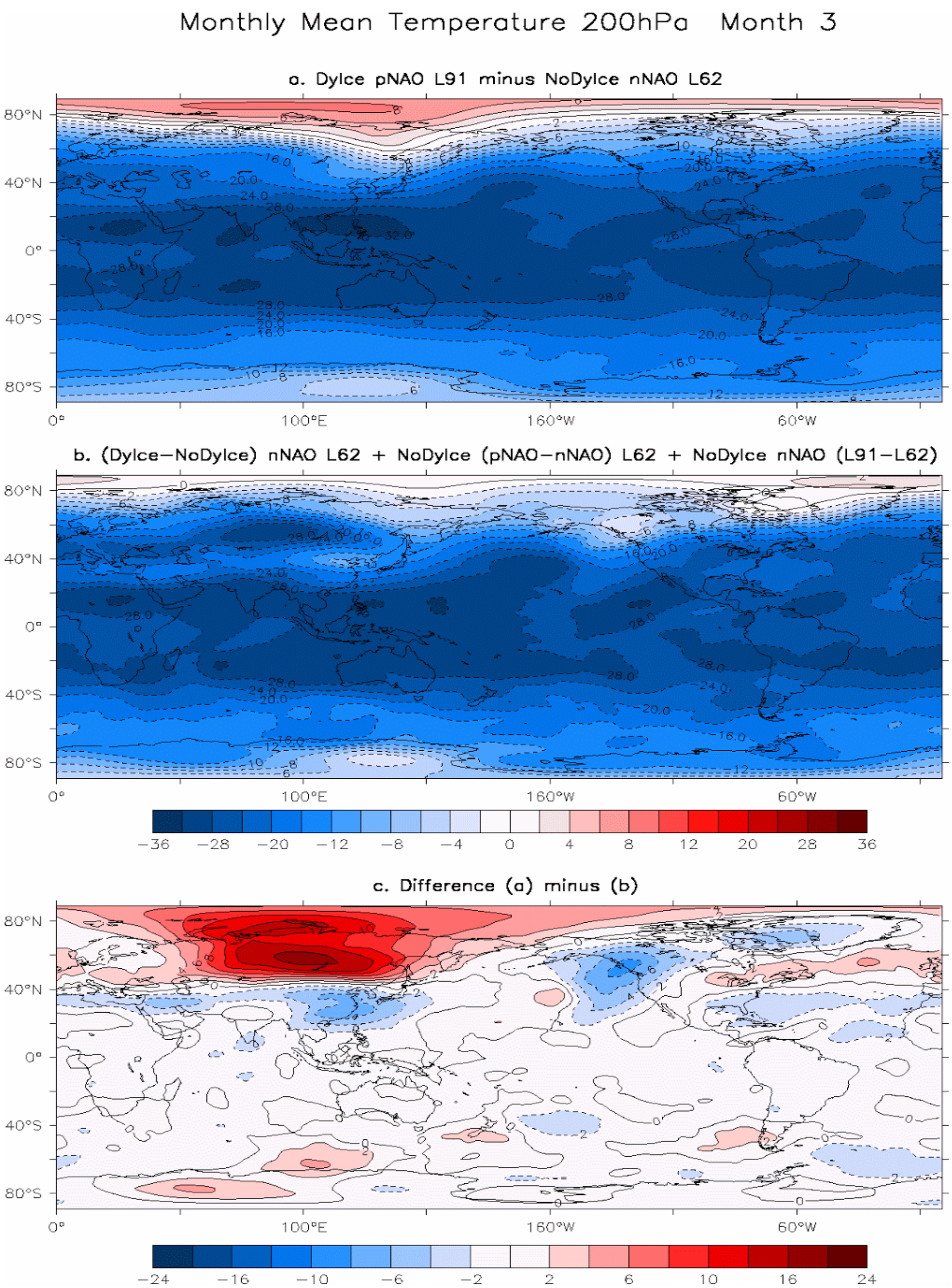

Figure 4

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Published: 31 May 2016

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