

Forecasting the number of extreme daily events on seasonal timescales

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[Hamilton et al., 2012]

Questions addressed

- 1) Is it possible to skilfully predict the **number of daily temperature extremes** within a 3 month **season** using the new Met Office Global Prediction System, **GloSea4**? [Arribas et al., 2011]?
- 2) How much of the skill in predicting extremes can we explain with the forecasted seasonal mean alone?
- 3) Is the skill all a result of **ENSO** and **climate change**?

Extreme daily temperatures mean different things to different people

- Temperature related mortality studies, including those by *Curriero et al.* [2002] and *Gosling et al.* [2007], show that temperature-related mortality rates can start to increase at fairly **modest** temperature anomalies of either sign. They also show that, due to **acclimatisation**, people living in warm climates have a higher heat-related mortality threshold than those living in cool climates.
- To orange farmers in Florida 'extreme cold' means temperatures less than -4 °C; below this long term damage to citrus trees can occur [Rogers and Rohli, 1991]. Whereas cattle can be reared in harsh Canadian winters; they can survive temperatures as low as -35 °C [Young, 1981].

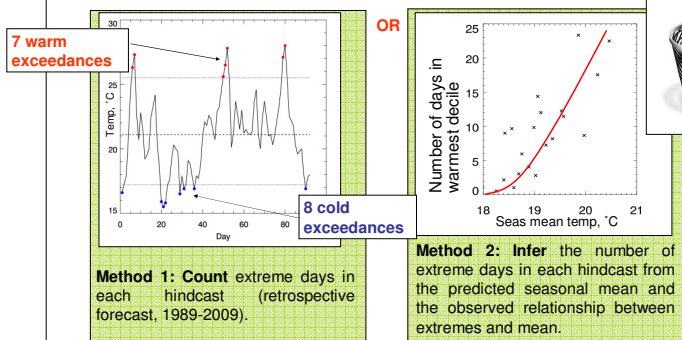
Around the world the temperature that people are susceptible to varies – we therefore use a **percentile based approach**.

What is a daily temperature extreme in this study?

Here an extreme daily temperature is defined as one in either the **upper or lower decile** of the daily temperature distribution from the relevant three month **season** (Dec-Feb, Mar-May, Jun-Aug, Sep-Nov). We consider minimum and maximum daily near surface temperatures (**Tmin** and **Tmax**). There are therefore $2 \times 4 \times 2 = 16$ different **types of extreme temperature**.

Methodology

- Count** the number of extreme days in observations (HadGHCND dataset, [Caesar et al., 2006]). See left-hand plot below.
- Calculate** the ensemble mean number of extreme days in the model by either method 1 or method 2:

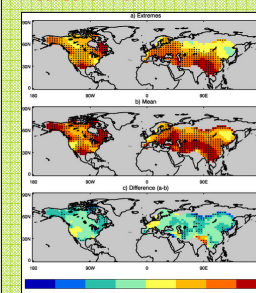


- Smooth** the resulting observations and hindcasts using a 17.5° (lat) by 18.75° (lon) box.
- Compute** skill as the Spearman's rank correlation coefficient between the smoothed observations and smoothed hindcasts for method 1 or method 2.
- Average** the correlation of all 16 types of extreme.
- Plot** the mean correlation (skill) at each grid-point (see figures opposite).

References

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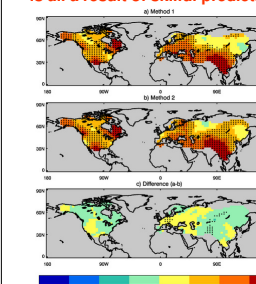
1) Is it possible to skilfully predict the number of daily temperature extremes within a 3 month season using the new Met Office Global Prediction System, GloSea4? Answer: Yes! Assessment using a GloSea4 hindcast (1989-2009) shows that skill is not vastly less than that for predicting the seasonal mean.



The **top plot** shows the skill in forecasting daily temperature extremes on a seasonal timescale (using method 1). The stippling shows where skill is locally significantly greater than zero. Grey indicates missing data. The area-weighted average (global) skill is significantly greater than zero and significantly greater than a persistence forecast (plot not shown).

The **central plot** shows the skill in forecasting the seasonal mean temperature. Forecasts of seasonal mean temperature are issued routinely by many forecasting centres. The **bottom plot** shows difference in skill between forecasting extremes and the seasonal mean. Skill is of a comparable magnitude (global mean skills of 0.20 and 0.27 respectively). However the global difference in skill is statistically significant.

2) How much of the skill in predicting extremes can we explain with the forecasted seasonal mean alone? Answer: All of it – the skill of the model is all a result of skilful predictions of shifts in the seasonal mean.



Compare the relative skills in predicting the number of daily temperature extremes using method 1 (**top**) with that of method 2 (**middle**). One might expect to lose some predictive capability by replacing all of the daily data with an inference based solely on the predicted seasonal mean. However, the global skills are almost identical (0.20 and 0.22 respectively). The difference in skill between the methods (**bottom**) is not statistically significant. This implies that all of the skill in predicting the number of extremes comes from being able to predict shifts in the seasonal mean. This result follows from the strong relationship between extremes and the mean in observations, and the inability of the model to predict seasons in which the distribution of daily data is skewed in an unusual way.

3) Is the skill all a result of ENSO and climate change (CC)? Answer: No, in fact only a moderate amount of the skill can be attributed to these phenomena.

ENSO and the CC signal are well known sources of skill in seasonal forecast systems. To assess the extent to which these factors contribute to skill in extreme prediction in **GloSea4** the contributions played by the representation of ENSO and CC are removed from the hindcast.

Defining ENSO and climate change

ENSO and CC indices were calculated in the GloSea4 hindcast: The ENSO index was taken to be sea surface temperatures (SSTs) in the Niño 3.4 region. The CC index was the global average of SSTs with the ENSO index regressed out. SST was chosen rather than land surface temperature for its smoothness and relative independence to the number of land-based extremes. See **above** for an example time series of each index (the Dec-Jan average of indices for an ensemble member). Over the hindcast period the correlation between the seasonal ensemble mean ENSO index and an equivalent index in observations is 0.89, similarly for the CC index, correlation with observations is 0.77. So the indices are predicted very well.

Removing ENSO or climate change effects

In the hindcast the relationship between each index and the seasonal mean temperature at each grid-point was found through linear regression. This response was removed from all the daily data for each season. The number of extreme days was then recalculated using method 1. The resulting skill (**left**) and the change in skill (**right**) are plotted **below** (for change plots blue indicates that, as expected, skill is lost by the removal of either response).

For ENSO the global average loss of skill is 0.02. Most of this occurs in Alaska and southern states of USA – regions with known strong ENSO teleconnections. For CC the global average loss of skill is 0.05. Most of this occurs in north-east Canada and southern Eurasia. This is where strong responses in model and observations coincide, but not necessarily where the **strongest response** in the observations is seen.

