Optimisation of a global climate model ensemble for prediction of extreme heat days

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Abstract

Adaptation-relevant predictions of climate change are often derived by combining climate models in a multi-model ensemble. Model evaluation methods used in performance-based ensemble weighting schemes have limitations in the context of high-impact extreme events. We introduce a locally time-invariant model evaluation method with focus on assessing the simulation of extremes. We explore the behaviour of the proposed method in predicting extreme heat days in Nairobi.

1 Introduction

Climate change is increasing the frequency and severity of extreme weather events, including high-temperature extremes [1]. The occurrence of heat extremes exceeding human heat stress thresholds is associated with increased mortality and morbidity, particularly in rapidly urbanising developing economies [2]. People particularly exposed and vulnerable to heat stress risk include the urban poor, those in informal housing, the elderly, those with chronic health conditions, and outdoor workers [3]. Reliable predictions of future changes in the frequency, intensity and distribution of high-temperature extremes are particularly critical for cities — impacts are amplified by urban heat island effects and high population density, but city-scale adaptation measures have been demonstrated to significantly reduce risk [4]. Here, we predict extreme heat days, defined as days on which average temperature exceeds the 90th percentile of local historically observed temperatures in accordance with several other analyses of changing extreme heat risk [5][6]. We introduce a method of evaluating the ability of climate models to simulate observed extreme heat days and derive a multi-model ensemble scheme with a focus on predicting these extremes.

Climate models

The latest General Circulation Models (GCMs) effectively reproduce observed large-scale trends and provide robust predictions of global average changes, but exhibit significant uncertainty in the local regime and for prediction of extremes [7]. The growing sector of climate services aims to bridge the gap between seasonal local weather forecasting and long-term mean climatology to provide decadal predictions for use in impact assessment and development of adaptation strategies [8]. Deriving decision-relevant information from GCMs typically involves combining predictions from several models in a multi-model ensemble. The multi-model approach aims to provide more skilful and robust predictions by utilising the various strengths of different models, as well as an estimate of structural model uncertainty [9].

Ensemble methods

The most straightforward and widely-used method of combining predictions from multiple models is to calculate a multi-model mean, which has been found to outperform any
individual model for a range of tasks \cite{10}. However, an equally-weighted ensemble does not take into account model skill in simulating the historically observed quantity of interest, and assumes each model is an independent estimate. Modelling groups often share assumptions and biases, leading to overconfident predictions \cite{11}. Alternative methods involving unequal independence-based or performance-based weighting of ensemble members include Reliability Ensemble Averaging \cite{12}, Independence-Weighted Mean \cite{13}, and Bayesian Model Averaging \cite{14}. In Section 3, we introduce a novel method for evaluation of ensemble members for performance-based weighting. Optimally combining simulations from multiple climate models for prediction of a specific quantity of interest is a task ideally suited to application of data-driven methods.

2 Data

Datasets  Daily mean surface temperature simulations from the historical experiment of five climate models from the latest phase of the Coupled Model Intercomparison Project (CMIP6) were used to demonstrate the method presented here: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL (see Appendix for variants used). These models were selected for the Inter-Sectoral Impacts Model Intercomparison Project (ISI-MIP), meeting criteria of structural independence, process representation, and historical simulation for a range of tasks. The subset was also found to span the range of climate sensitivity to atmospheric forcing exhibited in CMIP6 \cite{15}. ERA5, a high-resolution global gridded observational reanalysis, was used as a reference dataset \cite{16}. ERA5 hourly surface temperatures were resampled to provide daily mean temperatures.

Location  A daily mean temperature time-series for the grid-cell containing Nairobi, Kenya was selected from each model and the reference dataset. Studies have indicated increasing heat stress risk in East African cities in recent decades \cite{17}; persistent CMIP model biases in simulating climate features in the region have also been noted \cite{18}, making understanding of model uncertainty important. Data were split into a training period of 1979-01-01 to 1996-12-31 and testing period of 1997-01-01 to 2014-12-31. A bias correction was applied by calculating the mean bias of simulations relative to the training data and subtracting this bias from the simulations in the testing period.

3 Methodology

3.1 Model evaluation

Since GCMs simulate climate, they are not expected to provide synchronous simulations of weather at a specific location under future climate conditions, but it is assumed that they can yield informative statistics of future weather at some aggregate scale. Point-wise evaluation of daily simulations against historical observations requires a climate model to predict weather. Given sequences of $T$ daily simulations from a climate model $A$ and historical observations $B$ against which they are to be evaluated, we cannot expect the time-series to match under a daily point-wise error measure such as
the root mean squared error \( \text{rmse}(A, B) := \sqrt{\frac{1}{T} \sum_{t=0}^{T-1} (A_t - B_t)^2} \). We expect this error to be high even for GCMs that are skilled in reproducing large-scale patterns. RMSE implicitly assumes the two time-series to be aligned by comparing the predictions for individual days \( t \).

Summary statistics aim to avoid this issue by introducing some degree of time-invariance by binning data into monthly, seasonal or longer periods. Model error can then be calculated per bin, for instance by comparing the simulated and observed average or variance for each period, or by counting-based error measures such as comparing simulated and observed histograms to assess simulated variability. Within each bin, simulations could be permuted freely to yield the same measure of skill. This enables models to be evaluated without placing the expectation that they should simulate weather.

However, these summary statistics share two problems. First, they introduce artificial time boundaries by binning into periods to be evaluated independently. It is unclear how boundaries could be chosen objectively (e.g., on the first or fifteenth of each month) and in a way that minimises loss of accuracy introduced by rapidly changing weather conditions. Second, model precision is reduced. This method of introducing time-invariance blurs the model outputs to the resolution of the bins. This is problematic for localised extreme event prediction tasks, where retaining precision may be important.

We propose an evaluation method to reduce the inaccuracy introduced through summary statistics whilst conserving the time-invariance required to avoid the implicit requirement to predict weather. We assume a weather window size \( w \) of time steps within which we cannot expect simulated data-points to be aligned with observed data-points. To construct a metric that is locally time-invariant, we introduce a permutation \( \pi_w \), to the standard RMSE-measure before calculating differences in

\[
L_w^{\pi} (A, B) := \sqrt{\frac{1}{T} \sum_{t=0}^{T-1} (A_t - B_{\pi_w(t)})^2}. \tag{1}
\]

The permutation is constrained to locally reorder the time-series within the weather window - that is, every \( A_t \) can be compared to the values between \( B_{t-w} \) and \( B_{t+w} \). Note that this construction is symmetric with respect to \( A \) and \( B \). The final metric \( L^w \) is given by choosing the locally constrained permutation that minimises the RMSE in

\[
L^w (A, B) := \min_{\pi_w} L_w^{\pi} (A, B)
\]

with \( \pi_w^* \in \arg \min_{\pi_w} L_w^{\pi} (A, B) \). \tag{2}

Intuitively, we compare the simulations with observations under the assumption that the model was able to predict the weather as well as possible. See Figure 1 for a graphical representation of the algorithm. Since \( \pi_w \) is a permutation, the data-points in either time-series can only be used once, preventing the metric from inventing new data. Introducing local time-invariance through \( \pi_w \) solves a similar problem to calculating summary statistics by binning, but it is more precise: by design, there are no boundaries of bins since the whole time-series can be considered at once. As a consequence, the weather window size \( w \) can be chosen to be smaller than a bin width as no effects at the boundaries or due to bad placement of boundaries need to be considered.

We solve the minimisation problem via bipartite matching with the following cost matrix, here illustrating the case \( w = 1 \). Pairs at distance greater than \( w \) are assigned infinite cost to prevent matching (for details of the bipartite matching algorithm, see [19]):

\[
C^1(A, B) = \\
\begin{pmatrix}
(A_0 - B_0)^2 & (A_0 - B_1)^2 & \infty & \infty & \cdots \\
(A_1 - B_0)^2 & (A_1 - B_1)^2 & (A_1 - B_2)^2 & \infty & \cdots \\
\infty & (A_2 - B_1)^2 & (A_2 - B_2)^2 & (A_2 - B_3)^2 & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots & (A_{T-1} - B_{T-2})^2 & (A_{T-1} - B_{T-1})^2 \\
\end{pmatrix} \tag{3}
\]

### 3.2 Bayesian Model Averaging

Given an ensemble of \( K \) plausible models \( M_1,...,M_K \) predicting a quantity \( y \), and training data \( y_{yr} \), Bayesian Model Averaging (BMA) provides a method of conditioning on the entire ensemble
of models rather than selecting a single ‘best’ model [14]. The BMA predictive distribution for \( y \) is given by \( p(\hat{y}) = \sum_{k=1}^{K} p(\hat{y}|M_k)p(M_k|y_T) \), where \( p(\hat{y}|M_k) \) is the predictive distribution of an individual model \( M_k \), and \( p(M_k|y_T) \) is the posterior probability of \( M_k \) given the training data \( y_T \). The BMA prediction is a weighted average of individual model predictions with weights given by the posterior probability of each model, since \( \sum_{k=1}^{K} p(M_k|y_T) = 1 \).

4 Results

The multi-model mean (MMM) was used as a baseline approach for combining ensemble simulations. A standard Bayesian Model Averaging approach (BMA) was also implemented, along with a modified BMA where only days exceeding the 90th percentile temperature threshold were considered when calculating model weights. The method introduced in Section 3 was then tested by applying three different matchings \( \pi_3, \pi_{15} \) and \( \pi_{30} \) (corresponding to matching intervals of 7, 31 and 61 days) to the training data before using BMA to derive model weights. Evaluation of the predictions given by each of these methods relative to the ERA5 reference dataset, including number of extreme heat days exceeding the 90th percentile temperature threshold, root mean squared error and the locally time invariant skill metric \( L_{15} \) for these days, are shown in Table 1. Figure 2a shows a short sample time-series from the test dataset, showing the five simulations from the ensemble, the multi-model mean prediction, and the BMA (\( \pi_{15} \)) prediction with a \( \pm 1 \) standard deviation region shaded. Figure 2b shows a cross-section for a single day from this time-series indicating the BMA (\( \pi_{15} \)) predictive distribution as a combination of the weighted ensemble members. Further results for other geographical locations are provided in the Appendix.

Table 1: Results for ensemble methods, showing number of extreme heat days \( n \), root mean square error \( rmse \) and locally time-invariant skill \( L_{15} \) for predicting extreme heat days.

| Ensemble method   | \( n \) (train) | \( n \) (test) | \( rmse \) (train) | \( rmse \) (test) | \( L_{15} \) (test) |
|-------------------|----------------|---------------|-------------------|-----------------|-------------------|
| MMM               | 535           | 813           | 1.40              | 1.36            | 0.69              |
| BMA               | 618           | 762           | 1.28              | 1.33            | 0.72              |
| BMA (threshold)   | 720           | 876           | 1.23              | 1.32            | 0.70              |
| BMA (\( \pi_3 \))| 707           | 871           | 1.14              | 1.32            | 0.70              |
| BMA (\( \pi_{15} \)) | 689           | 906           | 1.11              | 1.29            | 0.66              |
| BMA (\( \pi_{30} \)) | 670           | 860           | 1.09              | 1.30            | 0.67              |
| ERA5              | 641           | 1095          |                   |                 |                   |

Figure 2: Left: Sample time series, showing ensemble members, ERA5 reference, multi-model mean (MMM), and BMA (\( \pi_{15} \)) prediction. Dotted line indicates date of cross-section shown right. Right: Cross-section of BMA (\( \pi_{15} \)) predictive distribution and weighted ensemble members for one day.
5  Discussion

In this work, we present a novel approach to climate model evaluation that introduces local time-invariance without reducing the temporal precision of models. This method is then applied before combining models in a multi-model ensemble by BMA to produce a probabilistic prediction of daily surface temperatures in Nairobi. Initial results suggest that this method improved prediction of the number of extreme heat days and RMSE for these days compared to standard BMA. However, further investigation is required to draw definite conclusions on the time-invariance hypothesis proposed in this paper. The metric proposed in this paper could also be combined with other model averaging techniques, or as a separate tool for ranking the performance of individual models within the ensemble, which we will explore in future work.

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A  Models

Table 2: CMIP6 models and realisations

| Model name        | Realisations | Experiment |
|-------------------|--------------|------------|
| GFDL-ESM4         | r1i1p1f1     | Historical |
| IPSL-CM6A-LR      | r1i1p1f1     | Historical |
| MPI-ESM1-2-HR     | r1i1p1f1     | Historical |
| MRI-ESM2-0        | r1i1p1f1     | Historical |
| UKESM1-0-LL       | r1i1p1f2     | Historical |

B  Additional results for other geographic locations

Fig. 3 and Fig. 4 provide additional results of applying the proposed methodology in a variety of urban geographic locations, primarily in Africa and the Indian subcontinent: Nairobi, Kampala, Lagos, Abidjan, Karachi, Mogadishu, Cairo, Freetown, Addis Ababa, Dakar, Mombasa, Aleppo, London, Algiers, Accra, Dar es Salaam, Chicago, Lome, Kinshasa, Timbuktu, Kolkata, Khartoum, Dhaka, Bamako, Abuja. The results correspond to the metrics provided in Table 1 in the main part of the paper.

C  Joint comparison of different methods on other geographic locations

Fig. 5 provides quantitative comparison of the proposed and the baseline methods. It summarises the average rank (where 1 is the best performing method) of each method on the dataset of 25 locations.

D  Weights of ensemble members at different models

Fig. 6 shows the weights assigned to the 5 members of the ensemble by Bayesian model averaging methods with and without permutations. Note that for most locations the assignment of weights varies substantially from the equal weights assigned by multi-model mean, as well as the weights assigned by Bayesian model averaging without permutations (see, for example, Freetown and Dar es Salaam). Meanwhile, the results for BMA with permutation show a lot of consistency irrespective of the window size. These initial results show that further investigation is required to draw conclusions related to the effect of different ensemble members are different geographical locations.
| City          | RMSE          | City          | RMSE          | City          | RMSE          |
|--------------|---------------|--------------|---------------|--------------|---------------|
| Mombasa      | 0.680         | Mogadishu    | 0.690         | Nairobi      | 0.695         |
| Kolkata      | 2.38          | Dar es Salaam| 2.40          | Lagos        | 2.42          |
| Kampala      | 1.120         | Shanghai     | 2.44          | Jakarta      | 2.46          |
| Cairo        | 2.72          | Karachi      | 2.48          | Accra        | 2.50          |
| Algiers      | 2.76          | Timbuktu     | 2.52          | Dakar        | 2.54          |
| Addis Ababa  | 2.78          | Kinshasa     | 2.56          | Lagos        | 2.60          |
| Bamako       | 2.80          | Lome         | 2.62          | Abidjan      | 2.64          |
| Accra        | 2.82          | Accra        | 2.66          | Lagos        | 2.68          |
| Accra        | 2.84          | Accra        | 2.70          | Lagos        | 2.72          |

Figure 3: RMSE for 25 cities comparing Bayesian model averaging with varying window sizes (BMA w7, BMA w15, BMA w31, BMA w45, BMA w55) as well as standard Bayesian model averaging (BMA lp), Bayesian model averaging with threshold (BMA thr) and multi-model mean (MMM).
Figure 4: RMSE 90th quantile for 25 cities. comparing Bayesian model averaging with varying window sizes (BMA w7, BMA w15, BMA w31, BMA w45, BMA w55) as well as standard Bayesian model averaging (BMA 1p), Bayesian model averaging with threshold (BMA thr) and multi-model mean (MMM).
Figure 5: Summary plot showing how each of the methods rank in the experiment with data from 25 geographic locations (best performing method is rank 1). The bars show the average rank across geographic locations and the black error bars show the standard deviation.
Figure 6: Weights assigned to 5 climate models for 25 cities comparing Bayesian model averaging with varying window sizes (BMA w7, BMA w15, BMA w31, BMA w45, BMA w55) as well as standard Bayesian model averaging (BMA lp), Bayesian model averaging with threshold (BMA thr).