A Climate Index Weighting Method for Ensemble Forecasts Based on a Bayesian Resampling Approach

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This presentation introduces a new climate index weighting method for ensembles.

A Bayesian resampling method for climate index weighting.

An application of the method for Blue Nile ensemble forecasts.

Some properties of the Bayesian climate index weighting method.

\[ \rho = 0.75 \]

\[ \rho = 0 \]

\[ \rho = 0 \]
CLIMATE INDEX WEIGHTING IN ENSEMBLE FORECASTING

Climate Index Weighting Using a Bayesian Resampling Method
Historical weather or streamflow is often used to make seasonal ensemble forecasts.

Seasonal Ensemble Forecast

Forecast Issued on 1 September

Each ensemble trace associated with a historical year

Climate Index Weighting

Each ensemble member is selectively weighted to reflect the climate conditions at the time of the forecast.
Bayes Theorem uses new information to update the prior ensemble distribution.

Bayes Theorem

\[
f(y | \theta) = \frac{f_\theta(\theta | y) f(y)}{f_\theta(\theta)}
\]

Climate index \( \theta \) at time of forecast

Bayesian Updating

Direct evaluation of the updated distribution can be very challenging.
Bayesian updating is more easily done with a sample drawn from the prior distribution.

Original Ensemble Forecast

\[ y_i, i = 1, \ldots, N \]
\[ w_i = \frac{1}{N} \]

Climate-Weighted Ensemble Forecast

\[ y_i, i = 1, \ldots, N \]
\[ w_i = \frac{f_\theta(\theta | y_i)}{N} \sum_{i=1}^{N} f_\theta(\theta | y_i) \]

Reference: Smith and Gelfand (1992)
APPLICATION TO BLUE NILE
ENSEMBLE FLOOD FORECASTS

Climate Index Weighting Using a Bayesian Resampling Method
Blue Nile flood volume is correlated with the El Niño-Southern Oscillation (ENSO). Interannual variability in the Blue Nile flood is related to ENSO. Floods tend to be larger (smaller) during La Niña (El Niño) years.
Nile Forecast System (NFS) flood volume forecasts issued in June will be examined.

Initial conditions on forecast date

Pre-processing
Flow data assimilation

Historical weather available from 1952

Multiple years of historical weather sequences

Nile Forecast System

We used the Nile Forecast System to generate retrospective forecasts from 1992-2009

Post-processing
Climate index weighting

Post-processing
Bias correction

Enssemble forecast of Blue Nile Flood Volume

ENSO Index (NINO4.0)
The ensemble forecast has the information needed to define the likelihood function.

2001 Ensemble Forecast (Issued in June) for the Blue Nile Flood Volume

The ensemble forecast flood volume $y_i$ is plotted along with the NINO4.0 Index $\theta_i$ for its historical year.
The ensemble forecast has the information needed to define the likelihood function.

**2001 Ensemble Forecast (Issued in June) for the Blue Nile Flood Volume**

The ensemble forecast flood volume $y_i$ is plotted along with the NINO4.0 Index $\theta_i$ for its historical year.

The forecast likelihood function $f_{\theta}(\theta|y)$ is estimated directly by a regression model (LOWESS).
The ensemble forecast has the information needed to define the likelihood function.

2001 Ensemble Forecast (Issued in June) for the Blue Nile Flood Volume

The ensemble forecast flood volume $y_i$ is plotted along with the NINO4.0 Index $\theta_i$ for its historical year.

**Climate Index $\theta_{2001}$**

The forecast likelihood function $f_{\theta}(\theta | y)$ is estimated directly by a regression model (LOWESS).
The Bayesian method weights more heavily ensemble members with an *expected* climate index (regression line) close to the observed index $\theta$.
The Bayesian method weights more heavily ensemble members with an expected climate index (regression line) close to the observed index $\theta$.

The kernel method weights more heavily ensemble members with a historical climate index close to the observed index $\theta$.

The Bayesian method weights more heavily ensemble members with an expected climate index (regression line) close to the observed index $\theta$. 
Bayesian and Kernel methods can assign very different weights.

A Subset of Ensemble Forecasts for the Blue Nile Flood Volume

The two climate index weighting methods do not always produce similar shifts in response to the climate conditions.
Forecast skill is higher for Bayesian climate weighting for most thresholds.

The Kernel bandwidth parameter was found to maximizes $SS$ for the hindcasts.

Still, the average skill is higher for the Bayesian method (which requires no hindcast calibration).
SOME PROPERTIES OF THE BAYESIAN CLIMATE WEIGHTING METHOD

Climate Index Weighting Using a Bayesian Resampling Method

Bayesian Climate Index Weights

\[ \rho = 0.75 \]

\[ \rho = 0 \]
Bayesian weights adapt to the strength of the relation with the climate index

Hypothetical bivariate normal likelihood function

\[ \rho = 0.75 \]

Bayesian weights depend on the strength of the relationship
Bayesian weights adapt to the strength of the relation with the climate index

Hypothetical bivariate normal likelihood function

Bayesian weights depend on the strength of the relationship

Weights strongly discriminate if the relationship is strong ($\rho = 0.75$)
Bayesian weights adapt to the strength of the relation with the climate index

Hypothetical bivariate normal likelihood function

Bayesian weights depend on the strength of the relationship

Weights discriminate less as the strength of the relationship weakens ($\rho = 0.5$)
Bayesian weights adapt to the strength of the relation with the climate index

Hypothetical bivariate normal likelihood function

Bayesian weights depend on the strength of the relationship

Weights discriminate less as the strength of the relationship weakens ($\rho = 0.25$)
Bayesian weights adapt to the strength of the relation with the climate index

Hypothetical bivariate normal likelihood function

Bayesian weights depend on the strength of the relationship

Equal weights are applied if there is no relation with the climate index ($\rho = 0$)
Weights can be applied to ensemble traces that do not have a historical climate index.

Mismatching Historical Periods

Ensemble forecast is created using a long historical record.

Climate index is unavailable for a portion of the ensemble members.

Bayesian climate index weights can still be applied to all ensemble members.

Example Ensemble Forecast

The forecast likelihood function $f_\theta(\theta | y)$ can be estimated for the overlapping historical period.
Weights can be applied to ensemble traces that do not have a historical climate index.

Mismatching Historical Periods

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Example Ensemble Forecast

The forecast likelihood function $f_{\theta}(\theta | y)$ can be estimated for the overlapping historical period.
Weights can be applied to ensemble traces that do not have a historical climate index.

Weights can be assigned for the non-overlapping period because $f_{\theta}(\theta|y_i)$ is defined for all ensemble members.

The forecast likelihood function $f_{\theta}(\theta|y)$ can be estimated for the overlapping historical period.
SUMMARY AND CONCLUSIONS

Climate Index Weighting Using a Bayesian Resampling Method

\[ \rho = 0.75 \]

\[ \rho = 0 \]
Bayesian climate index weighting is a simple, self-calibrating, self-adjusting method. The method only uses the ensemble members from the forecast to estimate of climate index weights. The method can be applied to any ensemble forecast directly (no hindcasts are needed for calibration).

The weighting adjusts to the strength of the relationship with the climate index. If no relationship exists, the method defaults to equal weighting.

Applications are not limited to ensemble traces that have historical climate index values. The likelihood function defines how all available traces are weighted.