A Bayesian framework for postprocessing multi-ensemble weather forecasts

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Outline

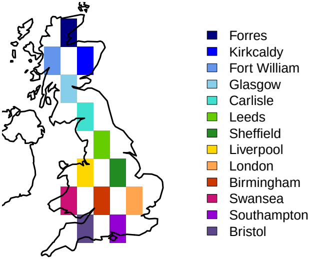
How can we combine forecasts from several models?

A new postprocessing framework

Summary

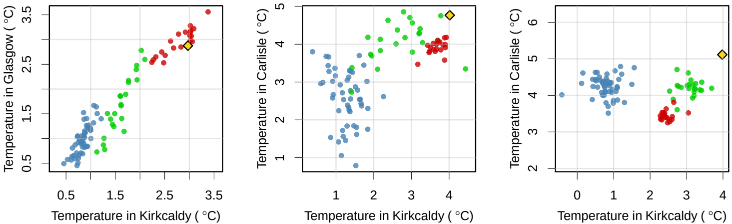
Data

- Forecasts from three operational centres
- Winter temperatures (DJF) 2007-2013 in the UK
- 13 regions postprocessed jointly
- Forecasts at 24h intervals, up to 15 days ahead
- Each day and leadtime is postprocessed independently



Multi-model ensemble predictions

Ensemble forecasts can sample the initial-condition uncertainty, but not uncertainty arising from the choice of model.
For that, we need to combine the output from several ensemble forecasts.



All of these forecasts may have systematic biases and dispersion errors, which also require correction.

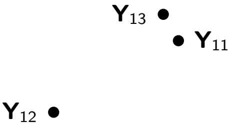
How can we combine multiple ensemble forecasts?

- Pool ensemble members into a single ‘superensemble’
    - improvement has been shown to be due to extra information, not just due to increased ensemble size
    - bias correction relies on error cancelling
    - less sharp - but more likely to contain the verifying observation?

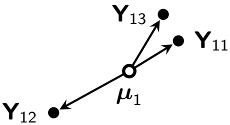
How can we combine multiple ensemble forecasts?

- Model output statistics: use regression to estimate the necessary correction
    - Univariate - dependence structure must be specified separately
    - Ensembles are often collinear - may only retain one
    - Only uses ensemble means - information from ensemble spread is lost
    - Computationally very costly - relies on numerical optimisation

A new postprocessing framework

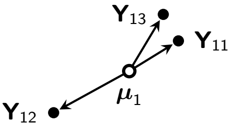


A new postprocessing framework



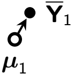
A new postprocessing framework

Ensemble members: $\mathbf{Y}_{ij}|\boldsymbol{\mu}_i \sim MVN(\boldsymbol{\mu}_i, \mathbf{C}_i)$



A new postprocessing framework

Ensemble means: $\overline{\mathbf{Y}}_i | \boldsymbol{\mu}_i \sim MVN(\boldsymbol{\mu}_i, n_i^{-1}\mathbf{C}_i)$



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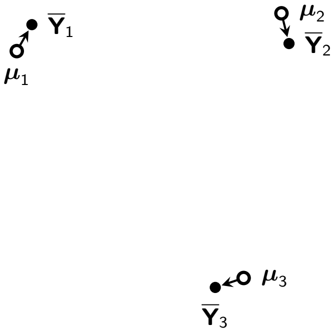

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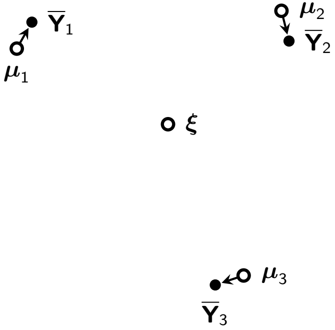
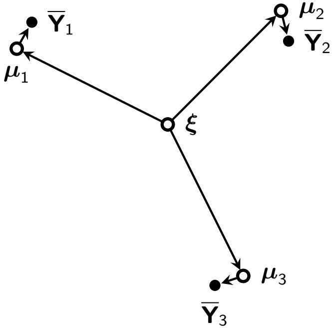


A new postprocessing framework

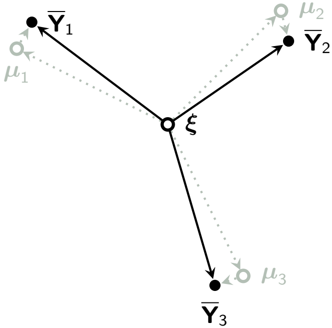
Ensemble means: $\overline{\mathbf{Y}}_i | \boldsymbol{\mu}_i \sim MVN(\boldsymbol{\mu}_i, n_i^{-1}\mathbf{C}_i)$

Ensembles: $\boldsymbol{\mu}_i | \boldsymbol{\xi} \sim MVN(\boldsymbol{\xi}, \boldsymbol{\Sigma})$



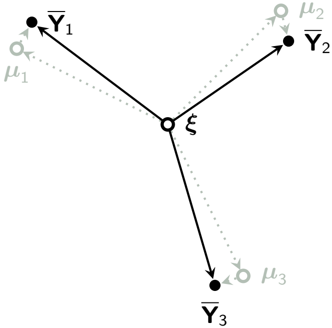
A new postprocessing framework

Ensemble means: $\overline{\mathbf{Y}}_i | \boldsymbol{\xi} \sim MVN(\boldsymbol{\xi}, \boldsymbol{\Sigma} + n_i^{-1}\mathbf{C}_i)$



A new postprocessing framework

Ensemble means: $\overline{\mathbf{Y}}_i | \boldsymbol{\xi} \sim MVN(\boldsymbol{\xi}, \mathbf{D}_i)$



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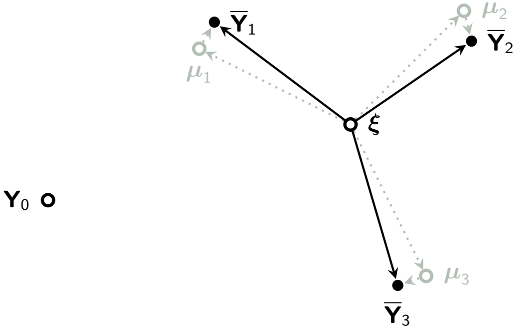

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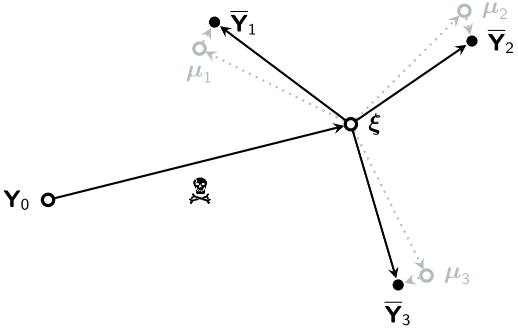
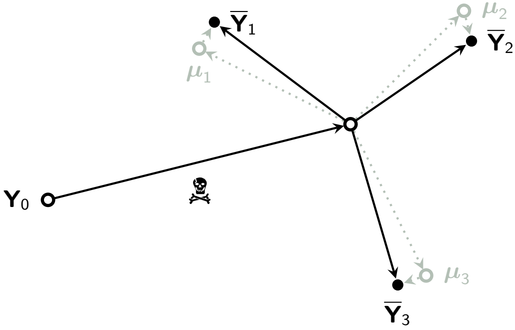


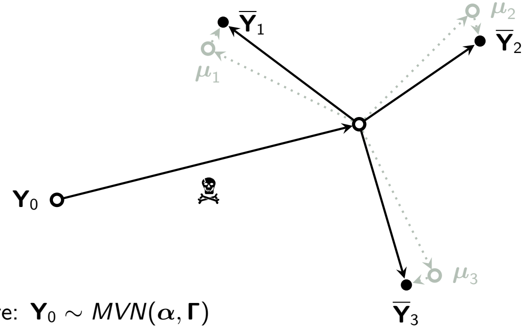
A new postprocessing framework

Ensemble means: $\overline{\mathbf{Y}}_i | \mathbf{Y}_0 + ☠ \sim MVN(\mathbf{Y}_0 + ☠, \mathbf{D}_i)$



A new postprocessing framework

Ensemble means: $\overline{\mathbf{Y}}_i | \mathbf{Y}_0 + \text{☠} \sim MVN(\mathbf{Y}_0 + \text{☠}, \mathbf{D}_i)$



Actual temperature: $\mathbf{Y}_0 \sim MVN(\boldsymbol{\alpha}, \boldsymbol{\Gamma})$

Discrepancy: $\text{☠} \sim MVN(\boldsymbol{\eta}, \boldsymbol{\Lambda})$

Posterior form

It can be shown that the posterior distribution of Y_0 is:

$$\mathbf{Y}_0 | \mathbf{Y}_{ij}, \text{☠} \sim MVN(\boldsymbol{\tau}, \mathbf{S})$$

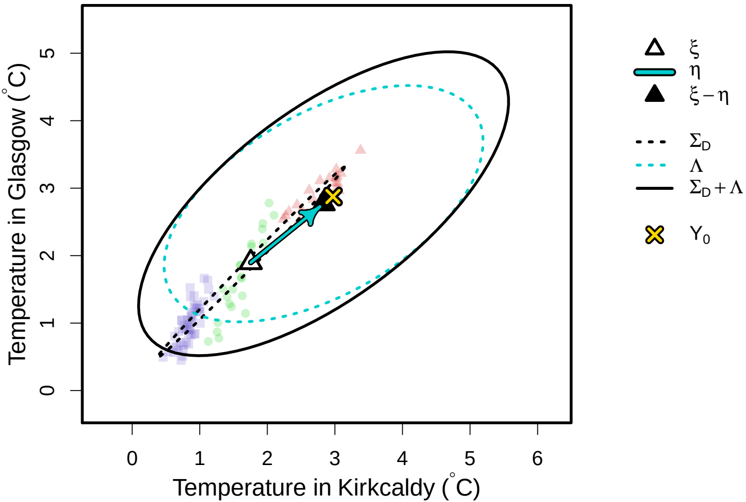
with

$$\mathbf{S}^{-1} = \boldsymbol{\Gamma}^{-1} + [\boldsymbol{\Lambda} + \boldsymbol{\Sigma}_{\boldsymbol{D}}]^{-1}$$

$$\boldsymbol{\tau} = \mathbf{S} \left\{ \boldsymbol{\Gamma}^{-1} \alpha + [\boldsymbol{\Lambda} + \boldsymbol{\Sigma}_{\boldsymbol{D}}]^{-1} \left[\underbrace{\boldsymbol{\Sigma}_{\boldsymbol{D}} \sum_{i=1}^{m} \mathbf{D}_i^{-1} \overline{\mathbf{y}}_i}_{\xi} - \eta \right] \right\}$$

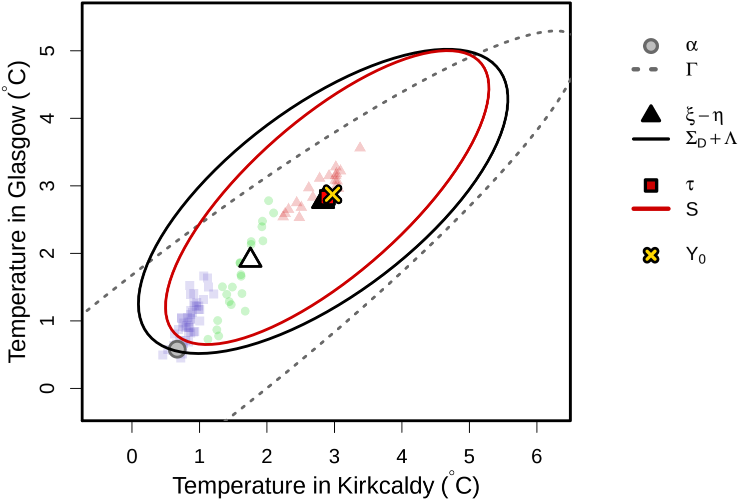
where $\boldsymbol{\Sigma}_{\boldsymbol{D}} = \left(\sum_{i=1}^{m} \mathbf{D}_i^{-1} \right)^{-1}$

Discrepancy-adjusted consensus: $MVN\left(\xi - \eta, \boldsymbol{\Sigma_D} + \boldsymbol{\Lambda}\right)$



Posterior forecast:

$$\mathbf{Y}_0 \sim MVN(\boldsymbol{\tau}, \mathbf{S})$$



The proposed framework has theoretical advantages...

- Flexible framework - each element can be estimated/specified as user sees fit, and extension to multiple weather quantities/sequential forecasting is (relatively) straightforward.
- Bayesian analysis follows from graphical representation of the data structure
- No 'black box' computations - all sources of uncertainty in the postprocessed forecast are identifiable

... as well as practical advantages

- Substantial improvement over raw superensemble - although marginally not as well calibrated as state of the art (NR)
- Representation of joint spatial structure than either ensembles (ECC) or observations (Schaake Shuffle) alone
- Much less costly than NR which takes around 30 times as long to run even in this toy example
- Careful choice of training set based on synoptic weather conditions can further improve performance

Key references

- A paper on this work is currently under review for the Quarterly Journal of the Royal Meteorological Society

- Chandler, R. E. (2013). Exploiting strength, discounting weakness: combining information from multiple climate simulators. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences,* (1991):20120388.

- Demetriou, M. (2015). A Bayesian approach to the interpretation of climate model ensembles. *PhD thesis, University College London*