From MOS to eMOS

Generalising Model Output Statistics for Full Ensemble Forecasts

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- EPS raises another issue: The process generating the ensemble variation is not the same as the process underlying forecast uncertainty.
  - Our predictions may also benefit from a more sophisticated interpretation of the ensemble.
- We introduce the idea of "ensemble MOS" — a method of interpreting ensembles that conditions the forecast on the *joint* information present in the whole ensemble, rather than interpreting each ensemble member individually as a "scenario".

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Given: *only* the model-wet/dry event
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Forecast: probability of precip $>$ 0mm in an actual rain gauge.
(We use the one at WMO10015.)

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  2. Scenario MOS; a separate forecast probability is made for each ensemble member. These are then combined.

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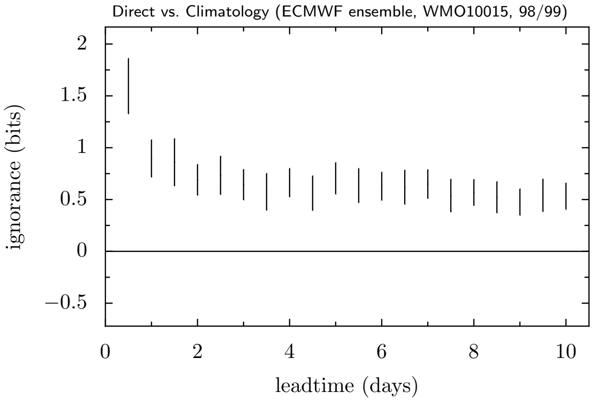
    1. Direct interpretation
    2. Scenario MOS
    3. Ensemble MOS (eMOS); the forecast is a function of the joint distribution of the *whole* ensemble.

Simplified Example: Direct Interpretation



- Ignorance is $-\log f(x)$, where $f(x)$ is the forecast probability of the outcome x. Smaller ignorance relative to climatology or another forecast is better.
- The confidence intervals are ± 1 bootstrap std. dev.

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   - model-wet could correspond to a 50% chance of precip (and, of course, 50% chance of no precip), while
   - model-dry corresponds to a 5% chance of precip (and 95% chance of no precip).

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3. The parameters are tuned to minimise the forecast's ignorance on a historical data-set.

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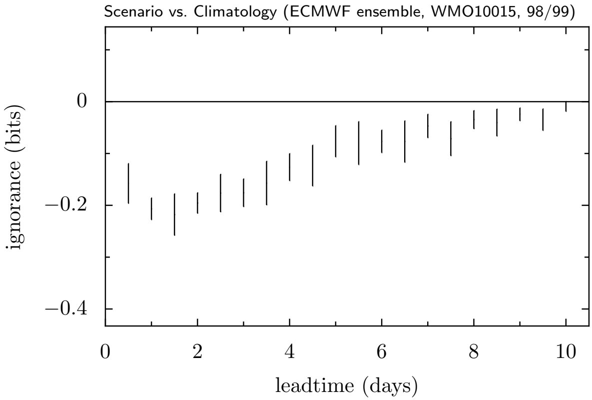

- In contrast to the direct interpretation, performance is now better than climatology.
- Skill generally improves with shorter lead times.

Idea: ensemble MOS

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- Going through the intermediate stage of a scenario forecast corresponding to each ensemble member can be a strong constraint on the types of forecast functions possible.

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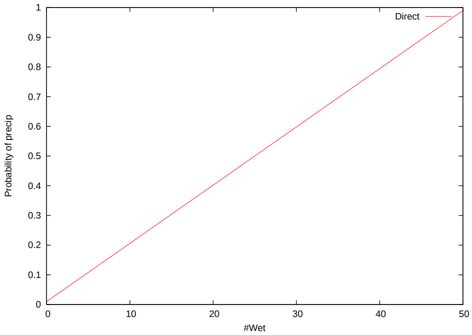

Direct interpretation is, essentially, the identity.

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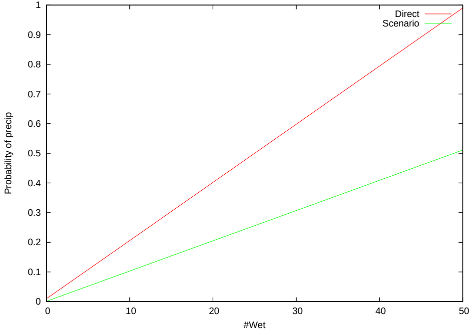

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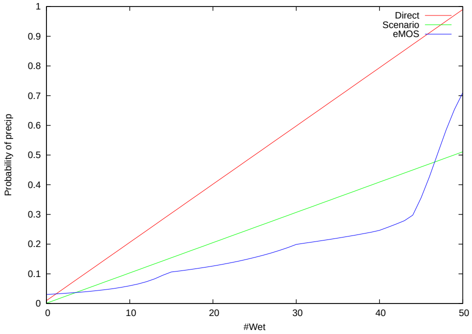

An eMOS method can choose a *non-linear* predictor.

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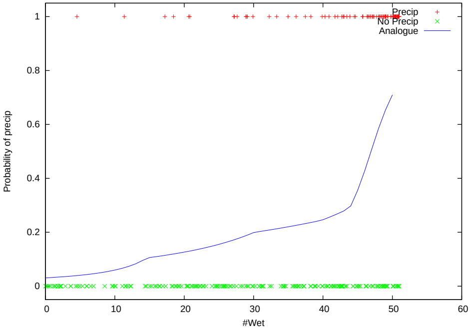
- The method of analogues can be used to fit the eMOS function:



Predicted probability of precip is the proportion of historical cases with precip at nearby #wet values.

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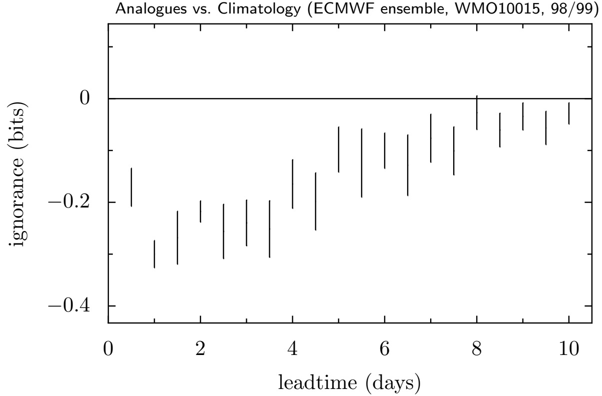

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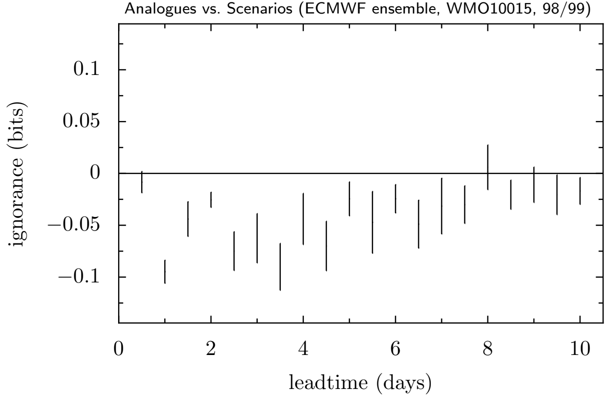

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- This is clearly seen by comparing the two models directly rather than to climatology.

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- Can summarise the distribution by (say) its 10%, 50%, and 90% quantiles (p_{10}, p_{50}, and p_{90}).
  And fit a function from this information into the probability of real precipitation:

$$(p_{10}, p_{50}, p_{90}) \mapsto \text{probability of real precip}$$

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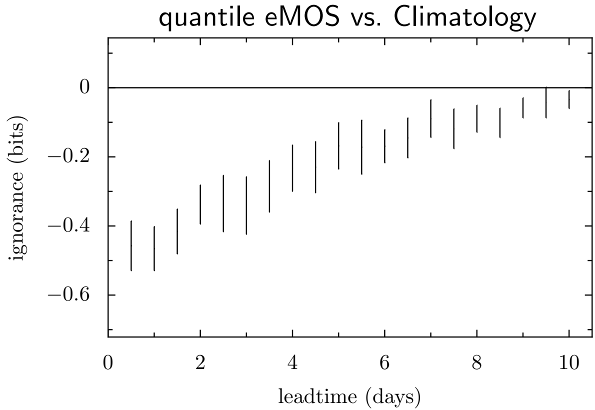

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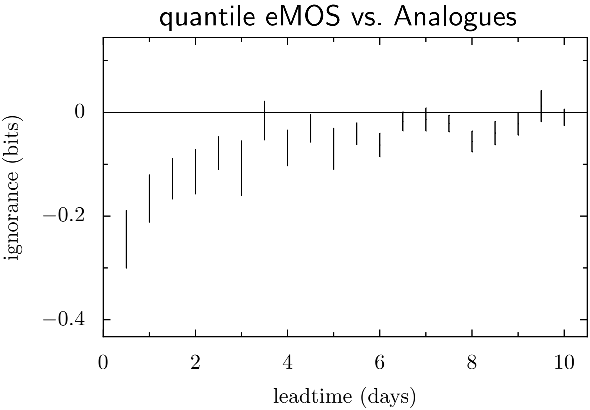

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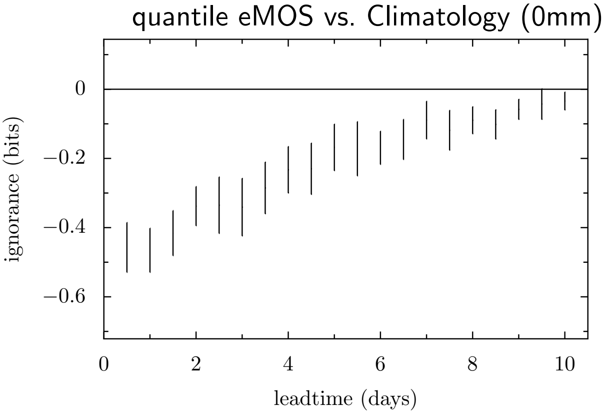

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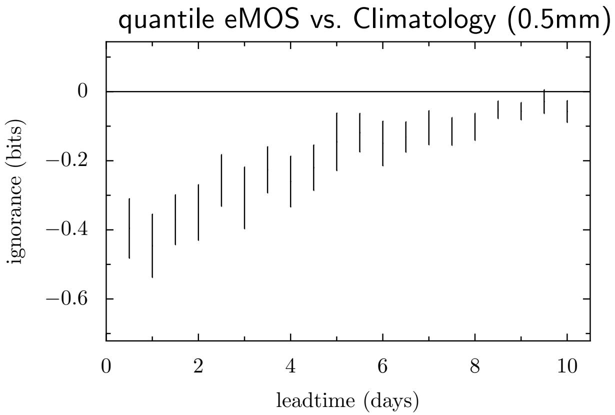

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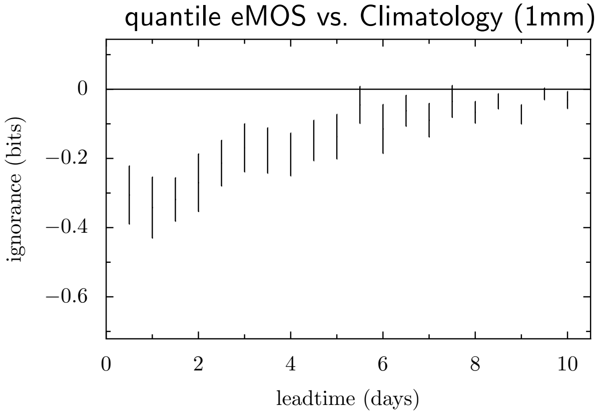

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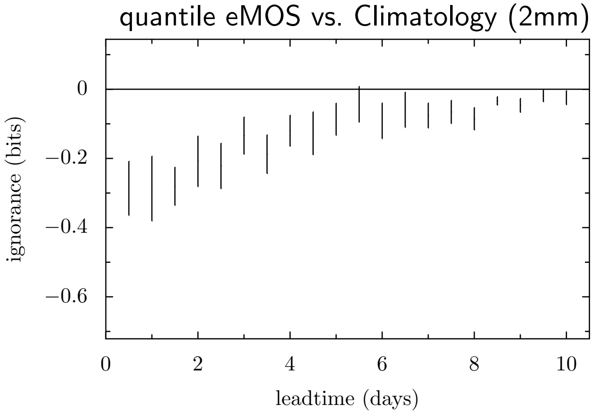

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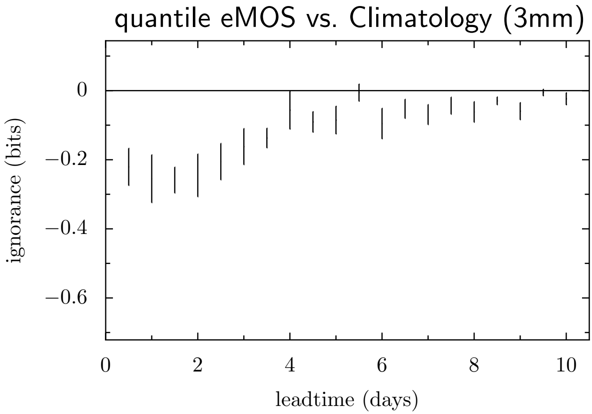

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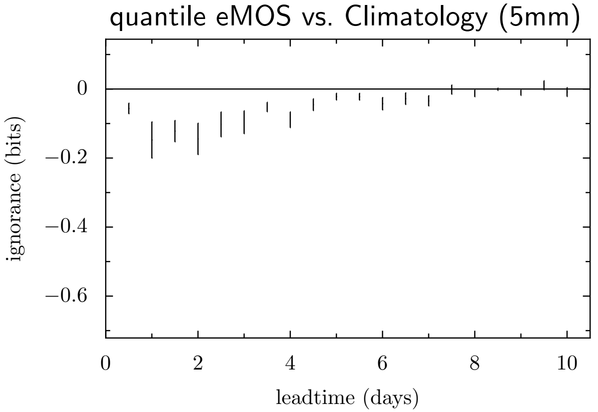

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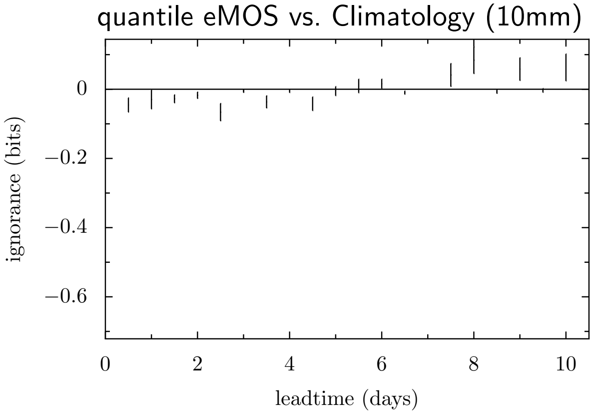

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- This might be due to the small number of examples of > 10 mm precip in the training period — only about 6 occur.

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- Forecast-verification archives of sufficient size are essential.
- eMOS makes no strong assumptions about the “meaning” of the information it uses — it can be easily extended to combine information from different sources.