Probabilistic Cloud Cover Forecasting from an Ensemble

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Summary

Background: Ensemble forecasts of cloud index (CI) are created through the advection of a satellite image with a wind field derived from NWP and optical flow combined through data assimilation [1].

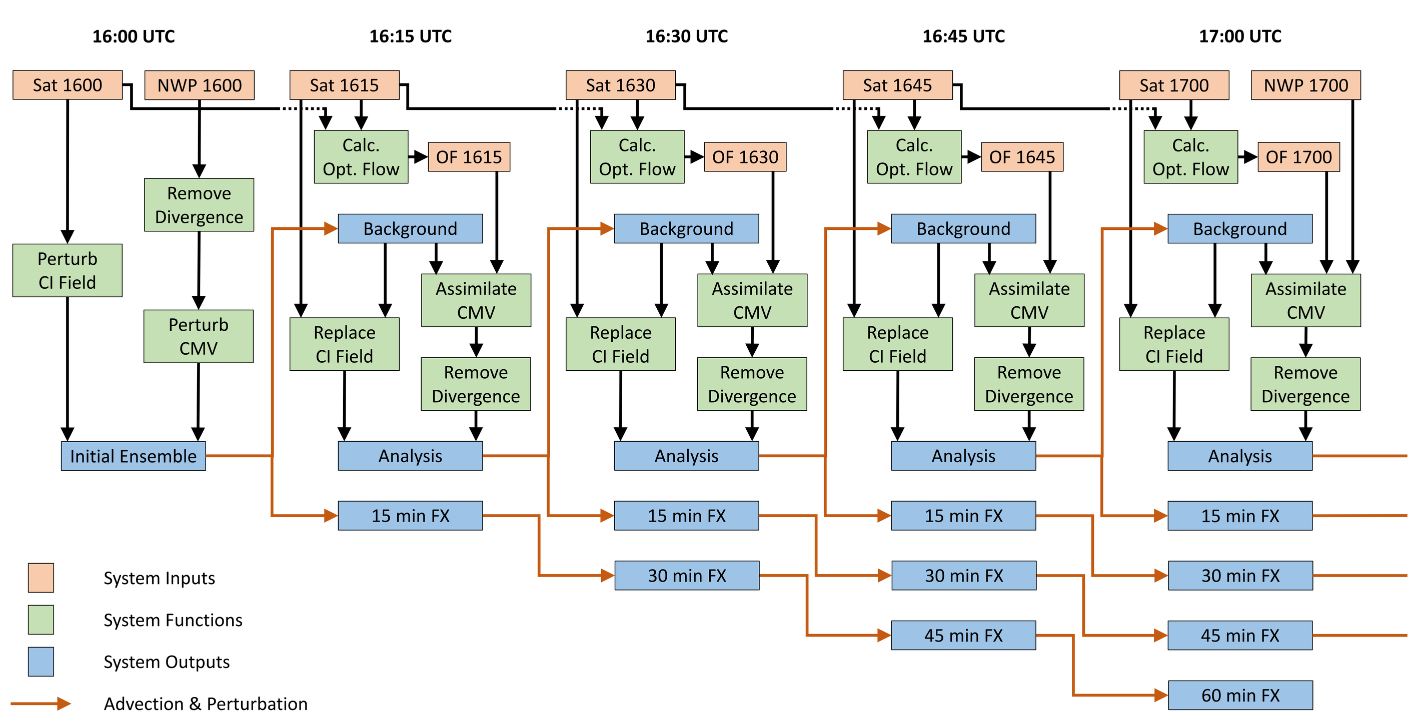
Motivation: A ensemble forecast can be used to create a probabilistic forecast, but must be calibrated to produce a reliable forecast.

Idea: Compare calibration using a calibration function [2] vs calibration using logistic regression [3].

Results: Both methods of calibration result in a probabilistic forecast with better reliability and modestly lower Brier score.

Introduction

- The ensemble (20 members) is generated by advecting CI fields derived from GOES-16 satellite images using an ensemble of cloud motion fields.
- Five months of data (March-July 2019) are used in this study. Only days which contain clouds over the Tucson region (40 km x 56 km area) are used.
- A schematic of the forecast system (showing 15 minute satellite resolution rather than 5 minute for simplicity) is shown below.
- When taking the ensemble mean, the forecast method presented here has a skill of 16% for 15 minute forecasts to 12% for 60 minute forecasts.



Analysis of ensemble

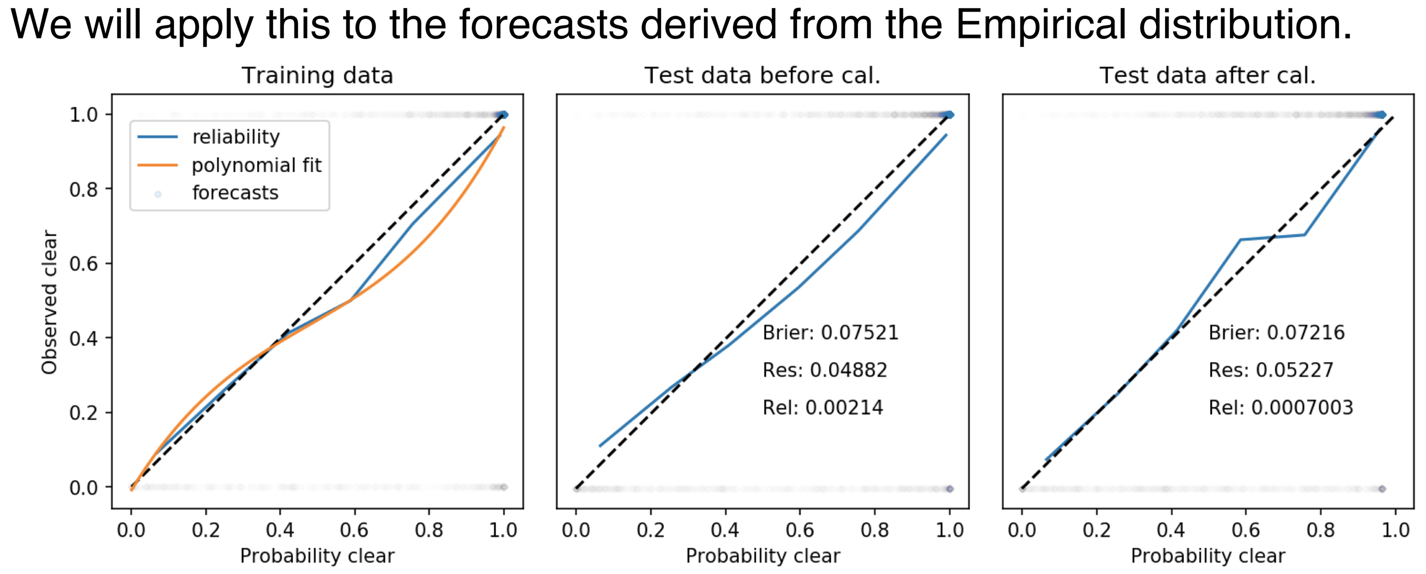
- In this study we generate a probabilistic forecast of the form $P(X < b)$ for a single location (over the University of Arizona) with b equal to 0.2.
- We use two ways of generating a probability distribution directly from the ensemble:
  - 1) an empirical distribution in which $P(X < b)$ is determined by the number of ensemble members less than b.
  - 2) A Gaussian distribution with mean and standard deviation defined by the forecasted ensemble.
- We calculate the above quantities by convolving the forecasted fields with a truncated 2-D gaussian with a standard deviation of 2 km in order to avoid under dispersion and account for positional uncertainty.
- We assess our forecasts using the Brier score, the reliability, the resolution, and the uncertainty:

$$BS = \frac{1}{N}\sum_{i=1}^{N}(y_i - o_i)^2 = \underbrace{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{o}_i)^2}_{\text{reliability}} - \underbrace{\frac{1}{N}\sum_{i=1}^{N}(\bar{o}_i - \bar{o})^2}_{\text{resolution}} - \underbrace{\bar{o}(1-\bar{o})}_{\text{uncertainty}}$$

- where y_i is the forecasted probability, o_i is the observation, $\bar{o}$ is the average observation, and $\bar{o}_i$ is the average observation conditioned on y_i.

Calibration function

- If the reliability of a forecast is perfect, then $y_i = \bar{o}_i$ for all forecasts and reliability will be equal to zero. We therefore estimate a calibration function $f(y_i) = \bar{o}_i$ and apply this to our forecasted probabilities to calibrate our forecasts [2].
- The figures below show this calibration process. We use a training set of observations (20% of our observations) and fit a 3rd order polynomial from our probability forecasts to our observations. We then apply this to our testing data to determine the calibrated forecasts.
- We will apply this to the forecasts derived from the Empirical distribution.

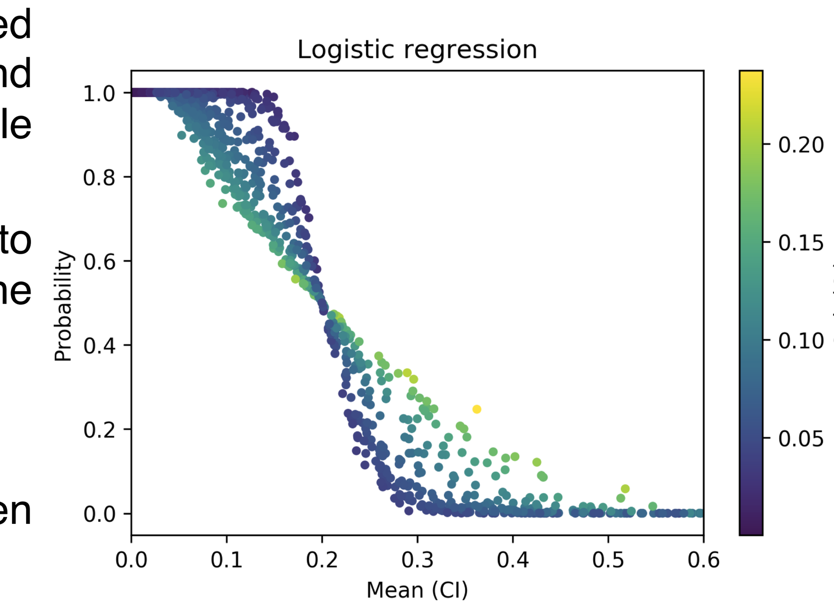


Logistic regression

- Alternatively, we forecast calibrated probabilities directly from the mean and standard deviation of our ensemble using logistic regression [3].
- We will do this by fitting our test data to a logistic curve that is a function of the mean and standard deviation,

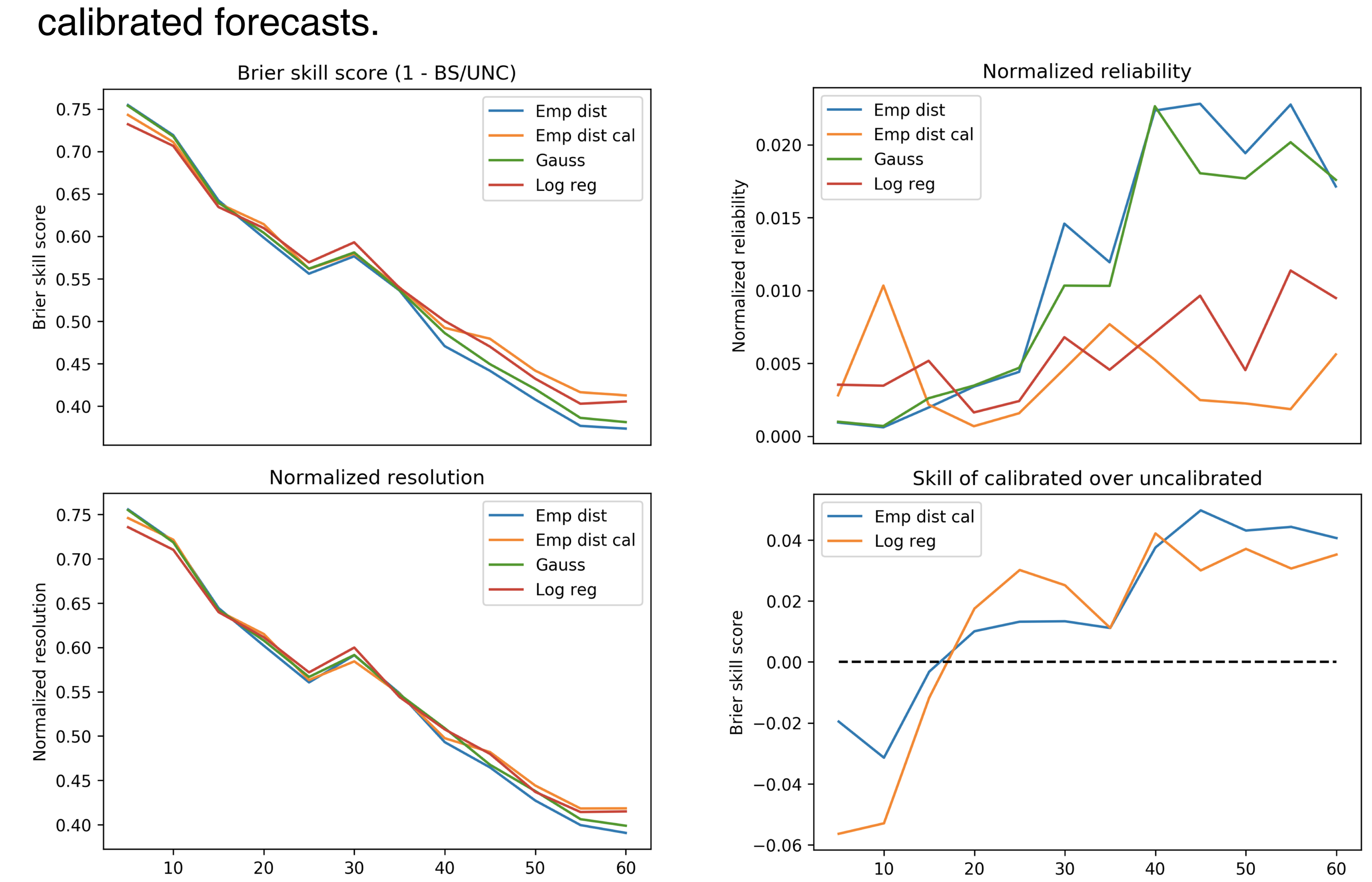
$$P(X < b) = \frac{\exp(1 + a_1\tilde{\mu} + a_2\tilde{\sigma})}{1 + \exp(1 + a_1\tilde{\mu} + a_2\tilde{\sigma})}$$

- The result of such a fitting can be seen to the right.



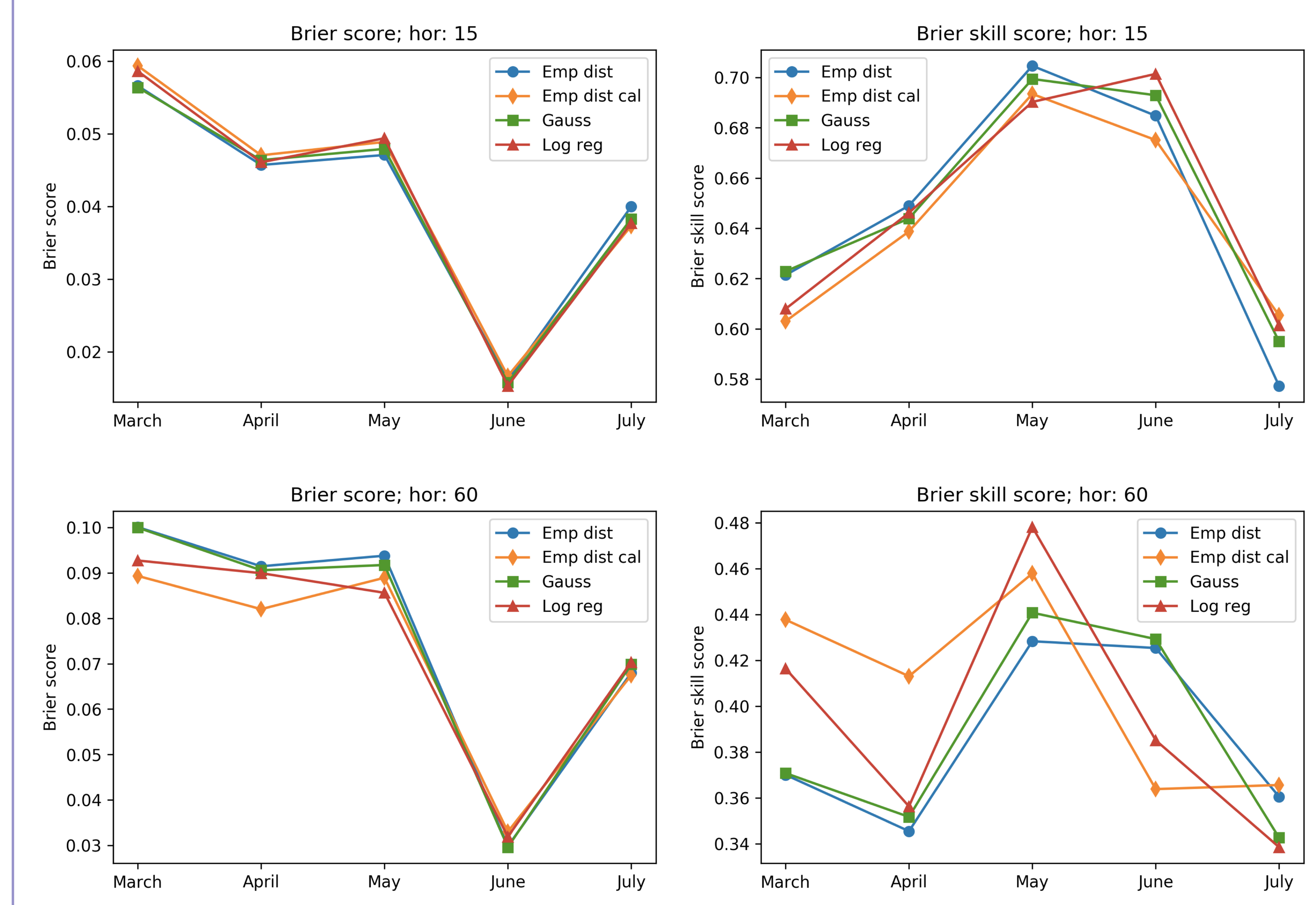
Results

- Below are the Brier score, reliability, and resolution normalized by uncertainty and the skill of the calibrated vs uncalibrated forecasts.
- Resolution is relatively unaffected by the calibration process, reliability is improved (decreased) for longer horizons and harmed (increased) for shorter horizons. This results in a corresponding change in the skill of the calibrated forecasts.



Results (continued)

- Below are the Brier skill and Brier skill score (based on the persistence ensemble) of the forecasts by month for 15 and 60 minute horizons.
- The persistence ensemble are generated using the past 20 days for a given time and location. The empirical distribution for this ensemble is then used to create a probabilistic forecast.
- All methods presented here show skill for all months and forecast horizons (up to 1 hour) when compared to the persistent ensemble.



- The Brier score and skill of our forecasts, both calibrated and uncalibrated, are affected by month.
- A significant amount of the change in Brier score from one month to the next is caused by the uncertainty of the days in question (Junes uncertainty is less than half that of May).
- Monthly dependency has not been taken into account for this calibration method. This is due to having too little data by month.

Conclusions

- All forecasts presented here show a significant improvement over the persistence ensemble.
- Calibration results in greater improvement over longer forecast horizons.
- The calibration function performed similarly to logistic regression.
- Separate calibration by month would likely result in improved forecasts if more data were available.
- Should increase resolution of forecast possibly by decreasing std. of convolved gaussian.

References

1. Harty, T., Holmgren, W., Lorenzo A., Morzfeld M. (2019). Intra-hour cloud index forecasting with data assimilation. *Solar Energy*.
2. Bröcker, J. (2008). Some Remarks on the Reliability of Categorical Probability Forecasts. *Monthly Weather Review*.
3. Wilks, D. (2011). *Statistical Methods in the Atmospheric Sciences.* Academic press.

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