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Verification-Based Model Tuning – Part II

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LONG-TERM GOALS

Our long-term goal is to develop a methodology for modeling the relationship between model parameters (e.g., in NWP models) and features of the forecasts (e.g., the number of precipitation objects/events in the forecast domain). The relationship in question is modeled statistically, i.e. from data on both the model parameters and the forecast features. Given that data structure, we are able to develop a "forward model" which maps the model parameters to the forecast features, as well as an "inverse model" for mapping the forecast features to the model parameters. Both of these models can be used in "tuning" the model for the purpose of improving the forecasts when the verification metrics take into account spatial features of the forecasts (e.g., size and location of precipitation events).

OBJECTIVES

In the current phase of the project, the main objective has been to focus on COAMPS, and 11 of its parameters. In past work, we related these parameters to non-spatial features of the forecasts, e.g., overall precipitation amount across the entire forecast domain). The current objective is to focus on spatial features. Specifically, we have focused on the location of each precipitation event, amount of precipitation in each event, the size of each event, and the shape of each event.

APPROACH

We have adopted a multivariate regression framework; "Multivariate" refers to multiple **responses** (i.e., forecast quantities), in addition to multiple covariates (i.e., the 11 parameters). In this framework,

the regression coefficients corresponding to the 11 model parameters represent the sensitivity of the response with respect to that parameter. The response itself is taken to be a 3-dimensional vector corresponding to the minimum, median, and maximum of a forecast feature. This allows one to assess the effect of the parameters on the distribution of the forecast feature. To quantify the aforementioned forecast feature, 6 summary measures are computed **for each object/event** in the domain: Latitude and longitude (measures of location), amount of precipitation (measure of intensity), area (measure of size), and eccentricity and orientation of an elliptical fit to the event (measures of shape). The objects/events are identified using cluster analysis.

WORK COMPLETED

The completed work involves a large number of statistical tests each assessing the effect of a parameter on some summary measure of a forecast feature. Specifically, we have analyzed 36 days, 11 parameters, 6 forecast features, and 3 summary measures. In order to reduce the number of Type I errors resulting from multiple hypothesis testing, we have divided the task into two stages. (Type I error refers to falsely rejecting a true hypothesis, or finding someone guilty when in fact they are innocent). In stage I, we employ the above-mentioned multivariate regression model to perform omnibus tests (i.e., tests involving complex hypotheses). For example, we test whether **any** of the 11 parameters have an affect on **any** of the forecast features. Then, in the second stage, we focus on the effect of the individual parameters on the individual forecast summary measures, for each day.

RESULTS

We have shown that it is possible to control specific spatial features of precipitation events by manipulating model parameters in COAMPS. The following paragraphs present more specific conclusions.

The results of the first stage can be summarized into Figure 1, showing the histogram of all of the (36 x 6) p-values from the omnibus tests applied to 36 days and 6 forecast features. It can be seen that all of the p-values are extremely small. All, but two are smaller than 0.05. However, given that this is still a relatively large number of tests, one can apply a Bonferonni correction, which effectively reduces the significance level of 0.05 to 0.0002. Even at this severe significance level, most comparisons are significant. In other words, there is abundant evidence that some of the 11 parameters have an affect on some of the three summary measures (minimum, median, maximum across clusters).

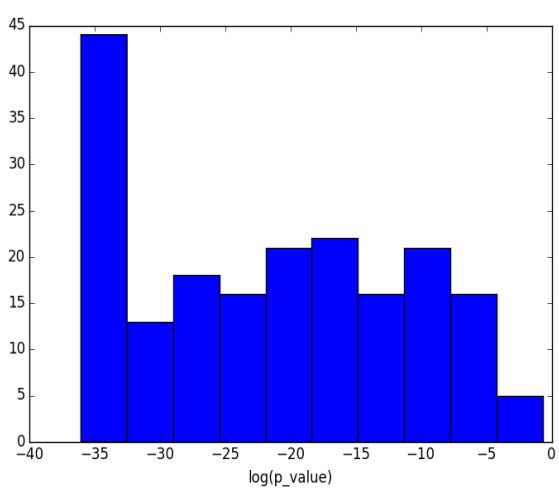

Figure 1. The histogram of 36 x 6 p-values resulting from testing whether any of the 11 parameters have an effect on any of the 3 summary measures.

In order to better identify the individual parameters, and forecast measures, we examine the boxplot of the regression coefficients for each parameter, and for each forecast feature. Figure 2 shows the results.

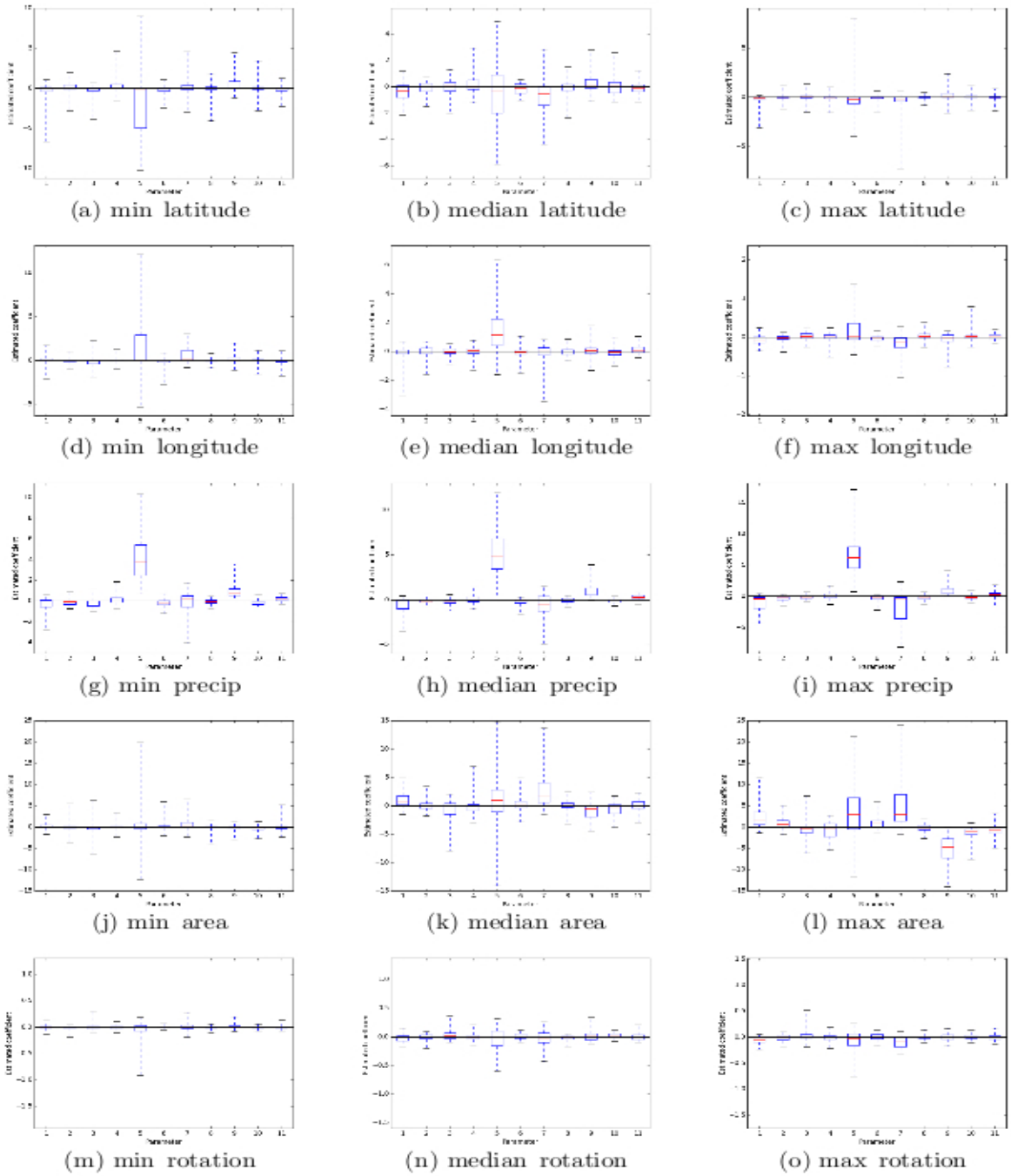

Figure 2. The sensitivity of the forecast features (rows), and each forecast summary measure (columns), with respect to the 11 parameters (x-axis in each panel).

Many of the 11 parameters have no effect on the forecast features, but the most obvious exception is parameter 5 (i.e., a linear factor that modifies the surface fluxes) which, by virtue of having mostly positive values for its regression coefficient, is positively associated with median precipitation. Parameter 9 (i.e., an autoconversion factor for the microphysics) has a similar effect but to a lesser degree. Parameter 1, i.e., temperature increment at the Lifted Condensation Level (LCL) for the Kain-Fritsch (KF) trigger, and parameter 7, i.e., another method to perturb the temperature at the LCL in KF, not only have a weaker effect (because their center is closer to zero), they are also not as statistically significant (because the number zero appears well within the span of the boxplots). Moreover, these two parameters are negatively associated with precipitation intensity in the typical (median) cluster.

It appears that the latitude of the clusters is not affected by any of the 11 model parameters. The second row of figures suggests that parameter 5 may have a weak, positive effect on the longitude of the clusters. In fact, only the minimum and median longitude (i.e., most easterly and midfield) clusters appear to be affected. However, this effect is weak both statistically and in magnitude, and so, will not be further examined.

Based on the ``area row'' (panels j, k, l), there is no evidence that any of the 11 parameters have an effect on the smallest clusters (panel j), while there is some weak evidence that parameters 1 and 7 have a weak effect on the typical area (panel k) and the largest cluster (panel l). There is also some indication from panel (l) that parameter 9 has a negative effect on the largest cluster; in other words, increasing this parameter is likely to shrink the largest cluster in the domain, without significantly affecting the size of the other clusters.

Eccentricity is not shown here, because like the last row (i.e. rotation), none of the parameters appear to have an effect on any of the forecast features. This conclusion, however, is tentative, and therefore will be further examined.

The clustering algorithm used in all of the above is developed in another related project (See related projects).

All of this work was done in collaboration with graduate students Ning Li and Natalia Hryniw. Although Natalia is still enrolled in the Atmospheric Sciences Ph.D. Program, Ning has left this project to join a Ph.D program in a different field. For the Summer quarter, another Ph.D student in the Statistics Department (Corinne Jones) took over Ning's responsibilities; Corinne was able to make tremendous progress, alas she too, has decided to move on to other topics. All of these students have been funded at 50% from this grant and 50% from another grant (again, see Related Projects).

IMPACT/APPLICATIONS

All of these results can be used to better set model parameters for the purpose of affecting forecasts. This may be for the purpose of improving forecasts (as compared with observations), or for the purpose of correcting one forecast feature (e.g. precipitation area) without negatively impacting other features.

RELATED PROJECTS

Two of the PIs (Marzban and Sandgathe) have received NSF funding on a related project. Sensitivity Analysis (SA) is common to both projects. However, the NSF project aims to develop a verification method, based on cluster analysis (CA), for automatic identification of "objects," their locations, and their orientation, in both forecast and analysis fields. Progress in the NSF project will aid this project in better assessing how the model parameters affect the number of clusters in the forecast field.

The two projects have been mutually beneficial. In fact, the clustering algorithm used to perform the analysis here was developed jointly as part of both projects.

PUBLICATIONS

Marzban, C., C. Jones, N. Li, S. Sandgathe 2015: Sensitivity of Forecast Spatial Features to Model Parameters: COAMPS . To be submitted to *Monthly Weather Review.*