Sensitivity of spatial structure of forecasts on model parameters

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In recent work it was shown that Numerical Weather Prediction (NWP) model parameters have a coherent and statistically significant effect on facets of forecasts that do not involve spatial information (e.g., domain average amount of precipitation). However, given the importance of spatial structure in forecast verification, it is important to assess the effect of model parameters on the spatial structure of forecasts. In this work clustering methods are employed to quantify the spatial structure of gridded forecasts and observations, and the sensitivity of the resulting structures is assessed via multivariate (i.e. multiple response) regression methods. The clustering methods include Gaussian Mixture Models (GMM), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), spectral clustering, etc. The statistical significance of the results is performed by tests developed for multivariate linear models.

Introduction

- NWP models have parameters whose values are often *ad hoc*.

- Question: How do model parameters affect the forecasts?

First piece:

- Previously we had developed a Sensitivity Analysis (SA) methodology.

– Variance-Based Sensitivity Analysis: An illustration on the Lorenz '63 Model

– Variance-Based Sensitivity Analysis: Preliminary Results in COAMPS

- In that work the forecasts were summarized by non-spatial quantities, e.g., mean (across domain).

Introduction ...

- BUT from a spatial verification perspective, a precip field is a set of objects.

Second Piece:

- Previously we had developed cluster-based spatial verification.

– Cluster Analysis for Verification of Precipitation Fields

– An Object-oriented Verification of Three NWP Model Formulations via Cluster Analysis: An objective and a subjective analysis

– Three Spatial Verification Techniques: Cluster Analysis, Variogram, and Optical Flow.

- New question: How do model parameters affect **object features**?

- Here, we apply several clustering methods to identify objects, and
- assess sensitivity of the objects to COAMPS model parameters.

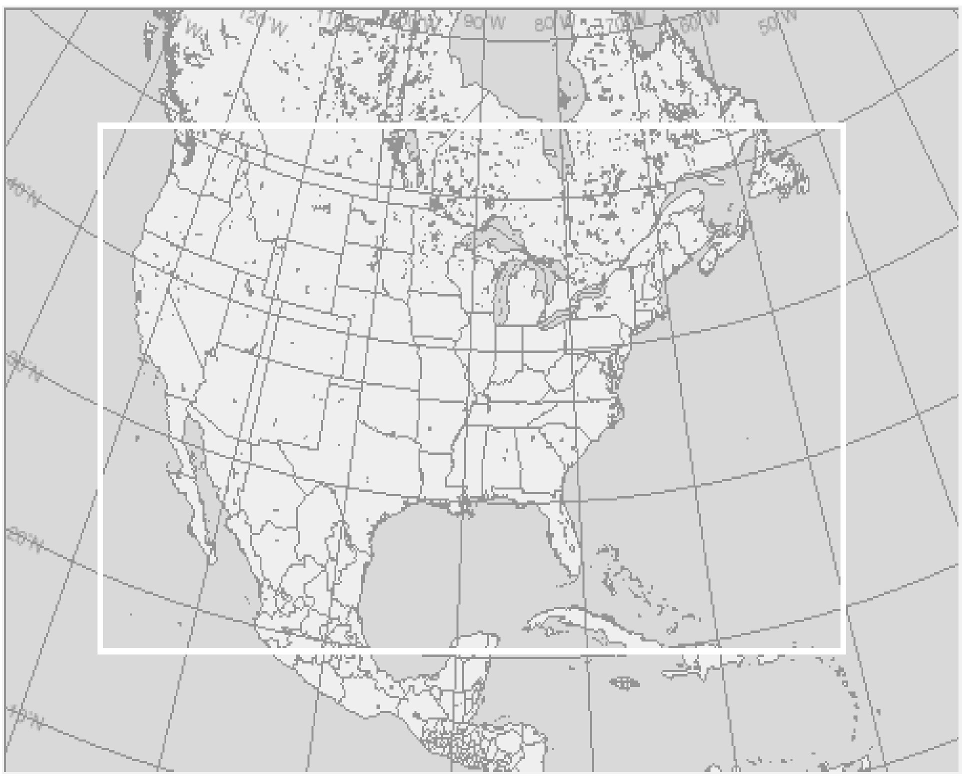
NWP Model Parameters

ID	Name (Unit)	Description	Default	Range
1	delt2KF ($°C$)	Temperature increment at the LCL for KF trigger	0	-2, 2
2	cloudrad (m)	Cloud radius factor in KF	1500	500, 3000
3	prcpfrac	Fraction of available precipitation in KF, fed back to the grid scale	0.5	0, 1
4	mixlen	Linear factor that multiplies the mixing length within the PBL	1.0	0.5, 1.5
5	sfcflx	Linear factor that modifies the surface fluxes	1.0	0.5, 1.5
6	wfctKF	Linear factor for the vertical velocity (grid scale) used by KF trigger	1.0	0.5, 1.5
7	delt1KF ($°C$)	Another method to perturb the temperature at the LCL in KF	0	-2, 2
8	autocon1 ($\frac{kg}{m^3 s}$)	Autoconversion factors for the microphysics	0.001	1e-4, 1e-2
9	autocon2 ($\frac{kg}{m^3 s}$)	Autoconversion factors for the microphysics	4e-4	4e-5, 4e-3
10	rainsi ($\frac{1}{m}$)	Microphysics slope intercept parameter for rain	8.0e6	8.0e5, 8.0e7
11	snowsi ($\frac{1}{m}$)	Microphsyics slope intercept parameter for snow	2.0e7	2.0e6, 2.0e8

KF = Kain-Fritsch
PBL = Planetary Boundary Layer
LCL = Lifted Condensation Level
Table 1. The 11 parameters studied in this paper. Also shown are the default values, and the range over which they are varied.

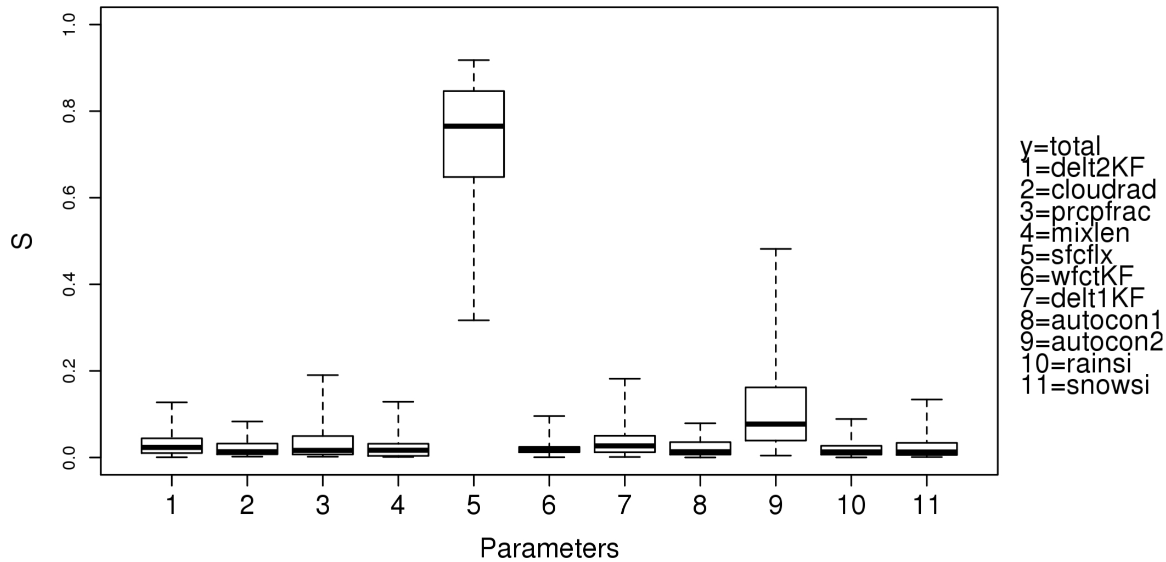
Data

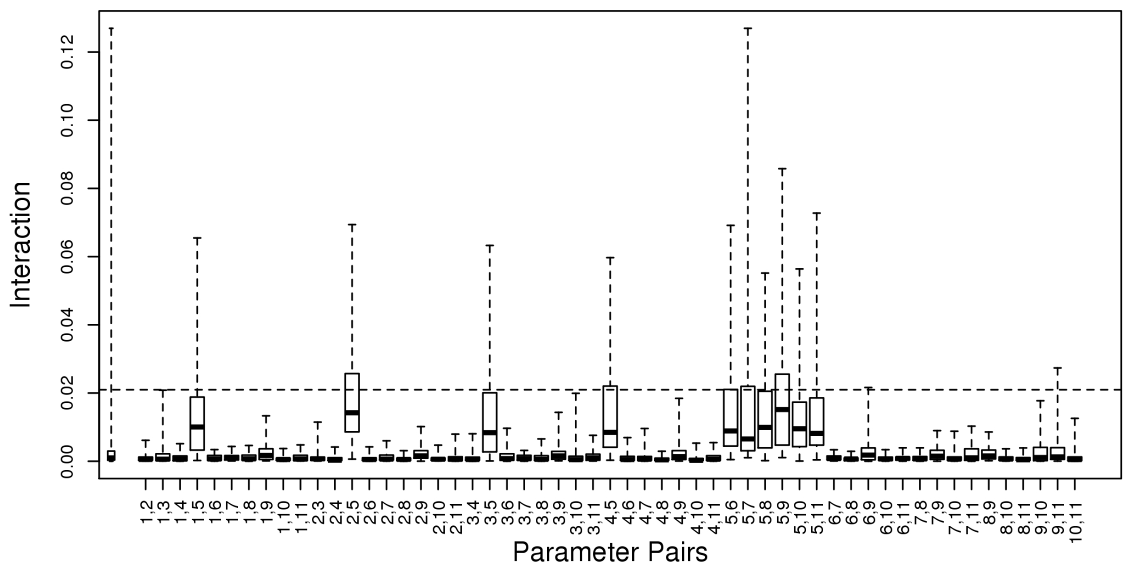
- 36 days between Jan. 1 and July 4, 2009
- 11 parameters
- 100 (99) parameter values, selected via Latin Hypercube Sampling (LHS).
LHS is no-less precise than simple random sampling.
- Domain:



Previous SA Results

Measure of Sensitivity:
S = Conditional variance explained by parameter.





Sensitivity of spatial-mean precip w.r.t. model param (top), and their interactions (bottom).
Horizontal line: Critical value corresponding to 0.05 significance level.

New Method

Sensitivity $\sim$ **multivariate** regression coefficients :

$$\begin{array}{ccccccc} Y & = & X & \cdot & B & + & E \\ (99 \times 3) & = & (99 \times 11) & & (11 \times 3) & + & (99 \times 3) \end{array}$$

X = standardized (mean=0, stddev=1) model parameters
Y = (minimum, median, maximum) across clusters in precip field

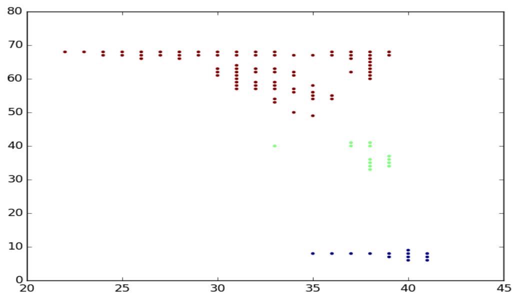
For each object, 6 object features:
latitude, longitude, intensity, size, eccentricity, and orientation.

Specific question: What is the effect of the 11 model parameters on the minimum, median, and maximum (across clusters) of precip for each of the 6 cluster features?

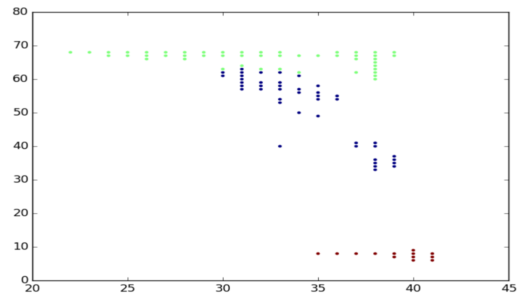
precip = 90^{th} percentile across domain, i.e., "heavy precip."

Clustering Results

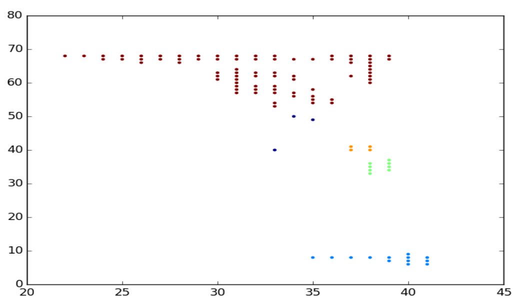
Here two Clustering methods:
1) Density-Based Spatial Clustering of Applications with Noise (DBSCAN), with parameters ϵ and min_n .
2) Gaussian Mixture Model (GMM), with parameter NC = No. of Clusters.



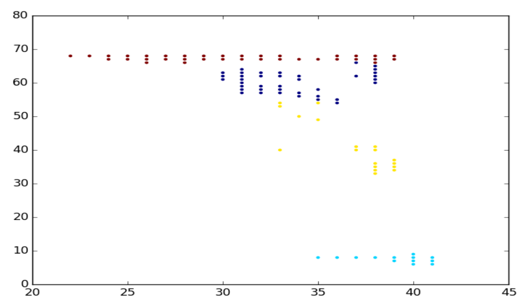
(a) DBSCAN, $\epsilon = 3\sqrt{2}$, min samples=3



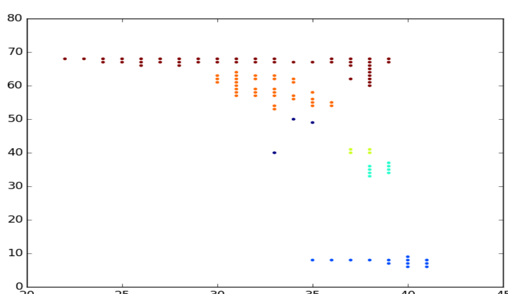
(b) GMM, num clusters=3



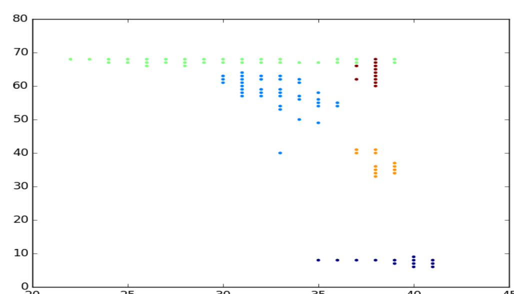
(c) DBSCAN, $\epsilon = 3$, min samples=3



(d) GMM, num clusters=4



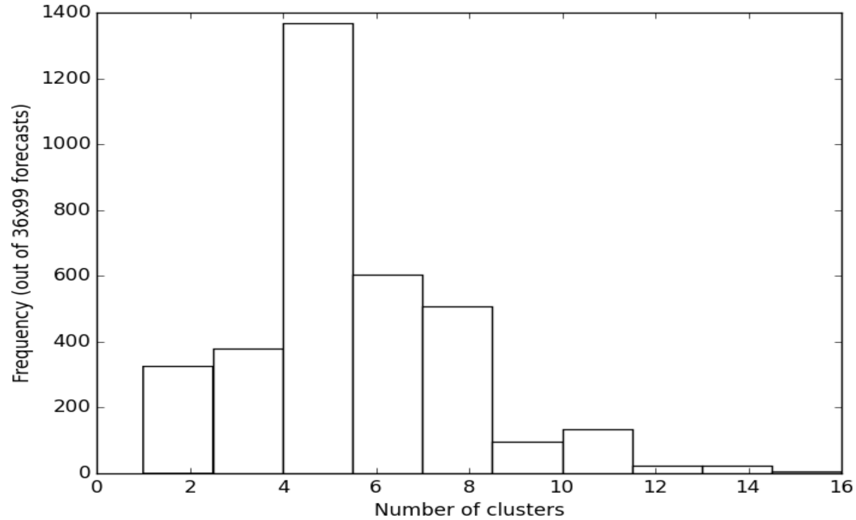
(e) DBSCAN, $\epsilon = 2\sqrt{2}$, min samples=3



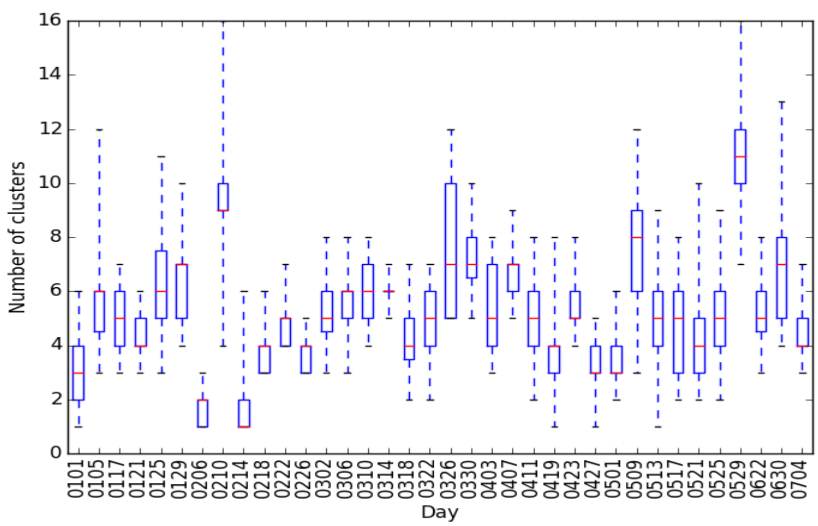
(f) GMM, num clusters=5

Default-parameter values, Jan. 25, 2009.
Dark blue points in (c), (e) = "outliers" (unassigned to cluster).

Clustering Results ...

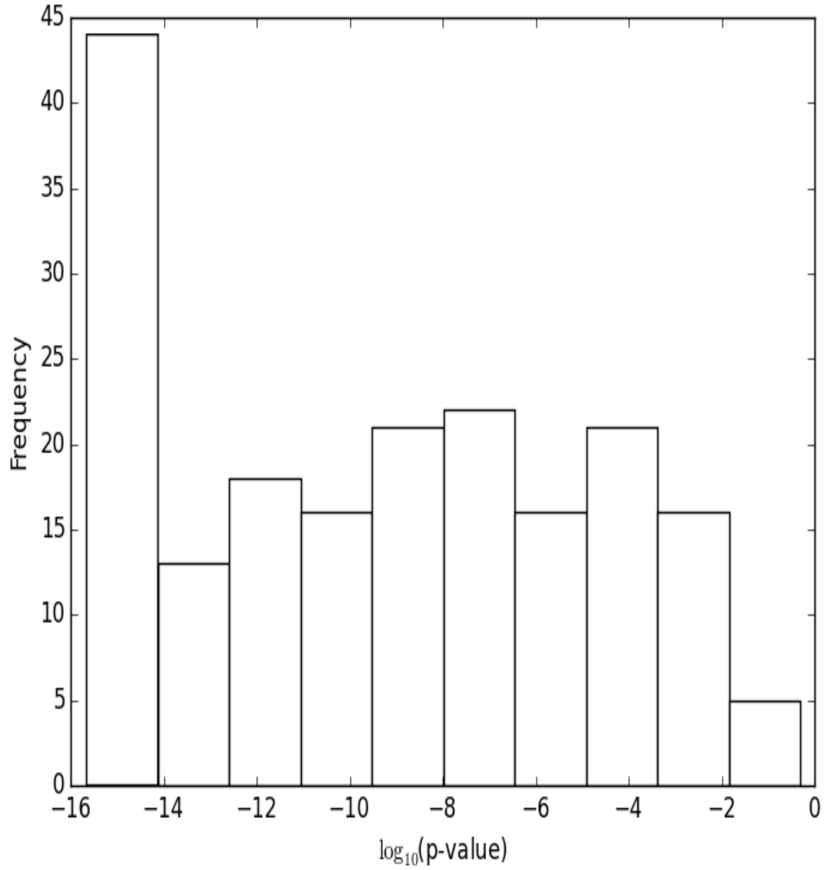


NC Histogram (36 days, 99 param values); DBSCAN($\epsilon = 2$, min_$n = 3$).



NC Boxplot (99 param values) for each of 36 days.
Daily variability is comparable to that across 99 param values.

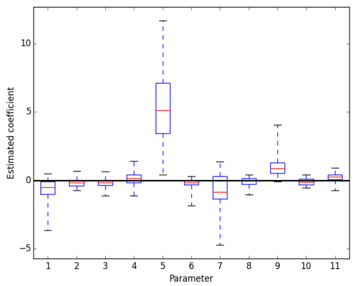
Sensitivity Results



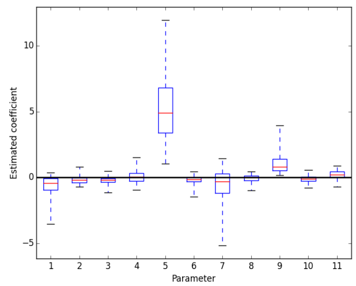
Histogram (36 days and 3 $Y's$) of p-values from multivariate tests.
Many effects are statistically significant (i.e., sample is large enough).
Physical significance is better assessed with boxplots:

Sensitivity Results ...

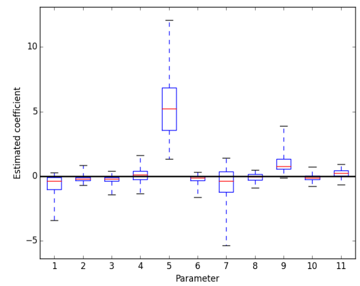
Sensitivity of the model parameters.
Response = median (across clusters) precipitation.



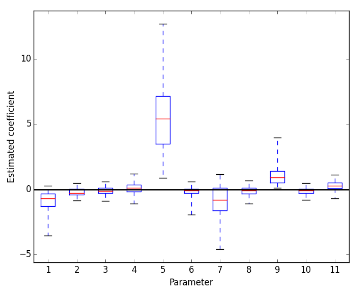
(a) ϵ =2, min samples = 3



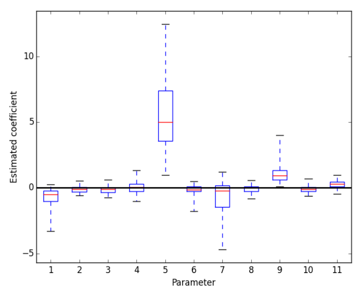
(b) ϵ =3, min samples = 3



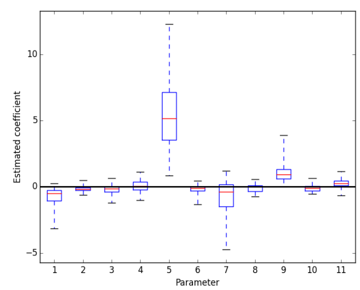
(c) ϵ =4, min samples = 3



(d) ϵ =2, min samples = 5



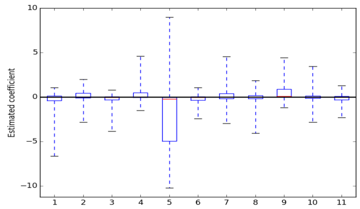
(e) ϵ =3, min samples = 5

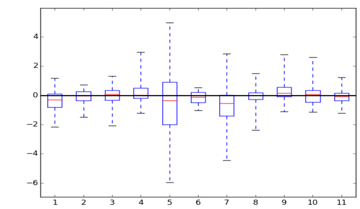


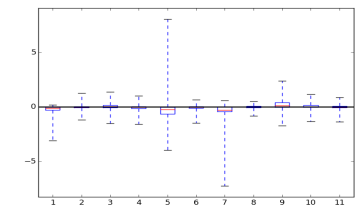
(f) ϵ =4, min samples = 5

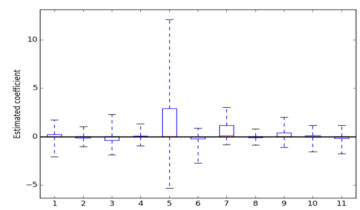
Sensitivity Results ...

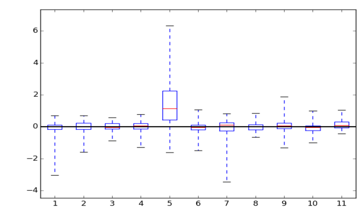
Sensitivity of the model parameters.
Response (columns) = (minimum, median, maximum)
6 cluster features (rows): lat, lon, inten, area, orient, eccent (not shown).
DBSCAN($\epsilon = 2$, min_$n = 3$).

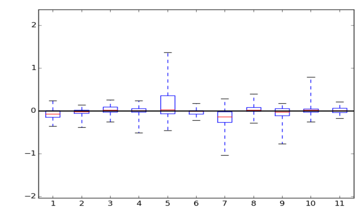

(a) min latitude

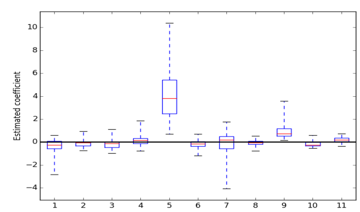

(b) median latitude

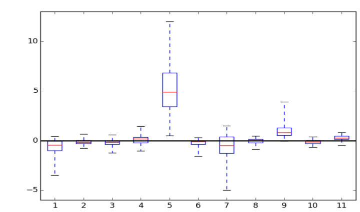

(c) max latitude

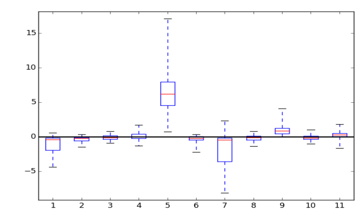

(d) min longitude

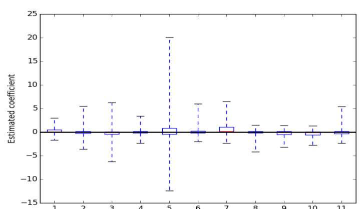

(e) median longitude

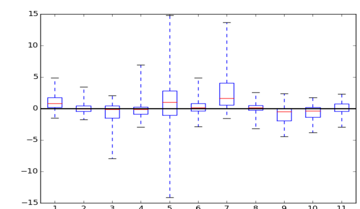

(f) max longitude

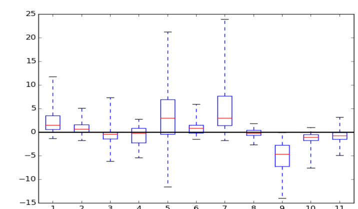

(g) min precip

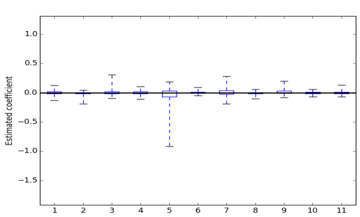

(h) median precip

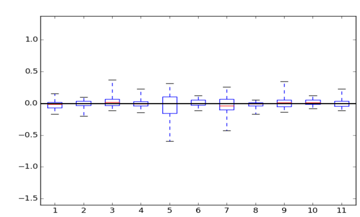

(i) max precip

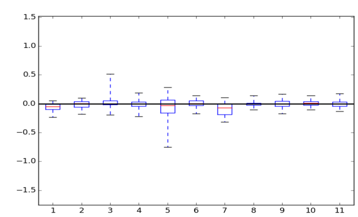

(j) min area


(k) median area


(l) max area


(m) min orientation


(n) median orientation


(o) max orientation

Summary and Conclusion

- sfcflx affects amount of prcp in all objects.
- autocon2 that affects the size of the largest object.
- Some of the params affect shape (right tail) of the distribution.
- Many of the params **appear** to have no effect; still useful.

It appears that the proposed methodology for assessing the effect of model parameters on forecast object features may be useful for improving forecast quality within a spatial verification framework.