Assessment of an Automatic, Object-oriented Approach to the Verification of Spatial Fields

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Introduction

The problem:

- Very high-resolution mesoscale models present a challenge to traditional verification methods, especially for discontinuous fields such as precipitation:
- The verification must consider "near misses."
    - If the forecast has the right structure, but is slightly wrong in space or time, it will be doubly penalized by traditional mean squared error methods.
- The method must be automated in order to assess many cases in a non-subjective manner.
    - Current mesoscale models produce very similar results. Often it requires 100s of cases to adequately identify the source of errors.
- The method must allow the user to define objects based on a selection of defining metrics or parameters.
    - It should be able to distinguish between rainfall from a thunderstorm and that from a warm front - even if "verifying" in the same location.

Introduction (2)

A Solution:

- **The use of object-oriented methods allows structures or "objects" to be identified in both the observed and forecast fields. This allows for "near-misses."**
- **The two fields can then be compared in terms of the placement of the "objects."**

Our Method:

- **Combinative Cluster Analysis**
  - **Creates clusters/objects in the combined observation and forecast field based on hierarchical agglomerative clustering.**
  - **Considers all "scales" - from one large cluster to N single point clusters.**

CCA Methodology

- Start with as many clusters as grid points, i.e., NC = N
- Identify “nearest” pair and join them into a new cluster, i.e. NC = NC – 1, Continue until 1 cluster remains, containing all grid points, i.e. NC = 1.
  - Note: Nearest can be x,y,p,T or any combination of parameters
  - Values are standardized so that the mean is 0, Stdev is 1
- If cluster is composed of 90% (or more) of obs points, call it a false alarm
- If cluster is composed of 10% (or less) of obs points, call it a miss
- Otherwise, call it a hit.
- Compute Critical Success Index (CSI), for every 1<NC<N

Most Recent Results

- Reflectivity forecasts were compared from the three NWP formulations: OU 2km WRF (ARW2), NCAR 4km WRF (ARW4), NCEP 4km NMM (NMM4) based on x,y clustering
- Results were compared to subjective (human) assessment
- Results:
  - ARW2 slightly better than NMM4 which is slightly better than ARW4 on most scales of interest (between 20 and 60 clusters)
  - Confirmed by independent human analysis

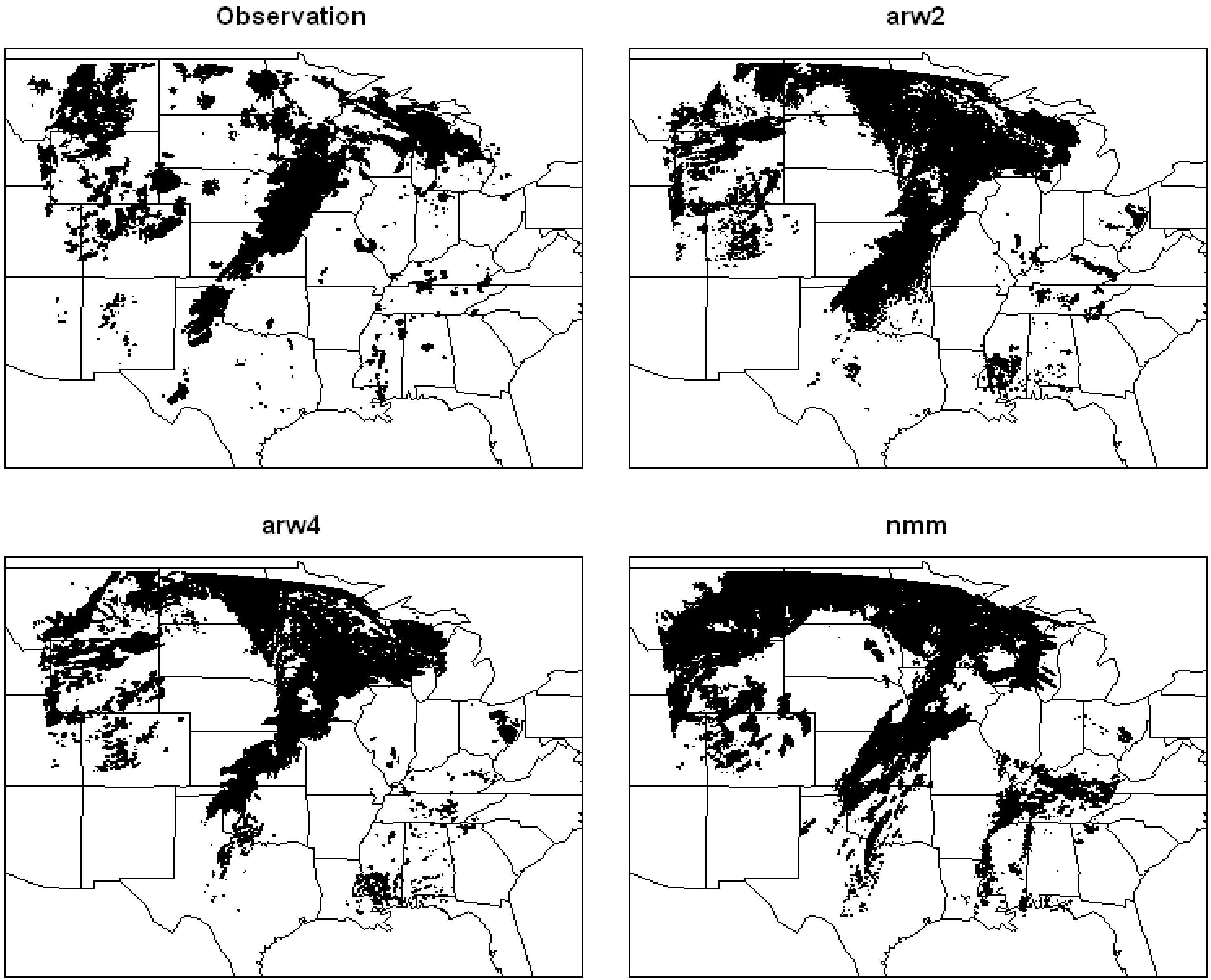
Current Effort

- Inclusion of meteorological variables in CA makes clusters more "meteorological".
- **Here** the analysis is in (x,y,z), where z = reflectivity.
- **Research question**:
- Does CA-based verification of arw2, arw4, and nmm4 reflectivity forecasts in (x,y,z) change the conclusions derived from the (x,y) analysis?
- **The answers depend on two parameters:**
- NC, the number of clusters, and g, the weight of z
  – Where $Distance^2 = (x2-x1)^2 + (y2-y1)^2 + g^2*(z2-z1)^2$

Data

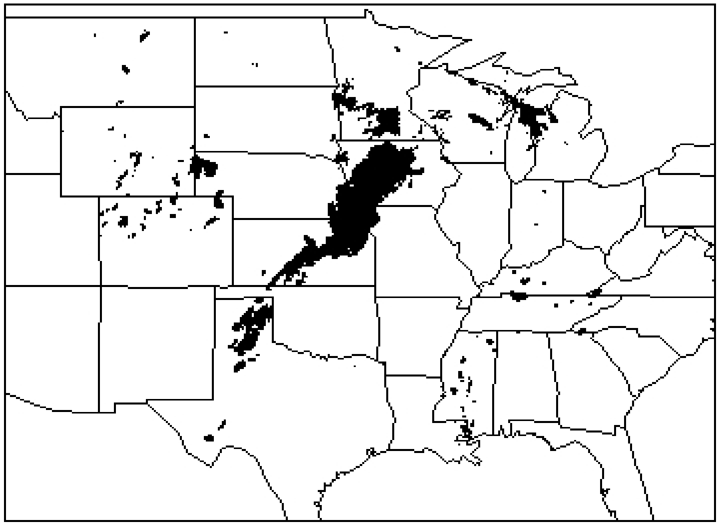
- US Spring mesoscale experiment
- 32 days from April 19 to June 4, 2005
- Observational grid 4.7625 km
- US east of Mississippi River
- Data divided into four quadrants (NW, NE, SW, SE) to simplify cases.
- Various fields available including precipitation and reflectivity courtesy of Michael Baldwin
- Models are OU 2km WRF (ARW2), NCAR 4km WRF (ARW4), NCEP 4km NMM (NMM4) all circa 2005.

Reflectivity (z) for 13 May 2005

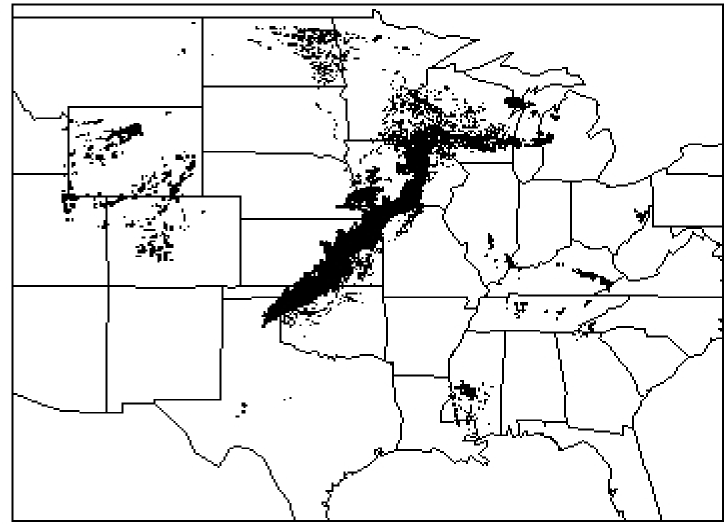


Reflectivity > 20 dBz for 13 May 2005

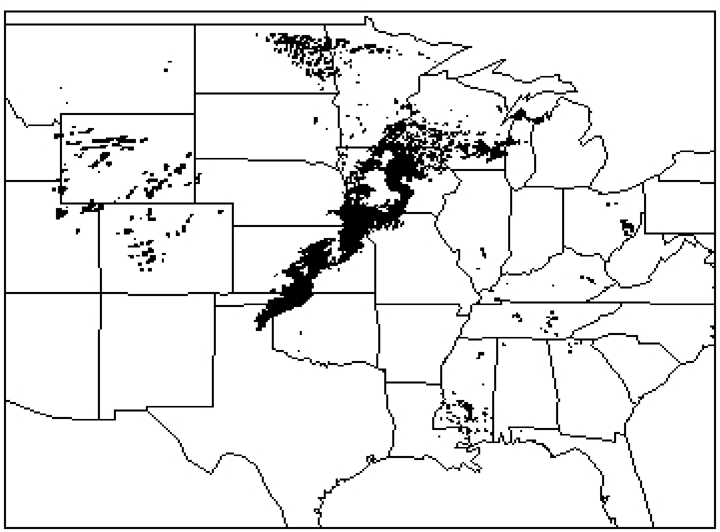
Observation > 20dbz



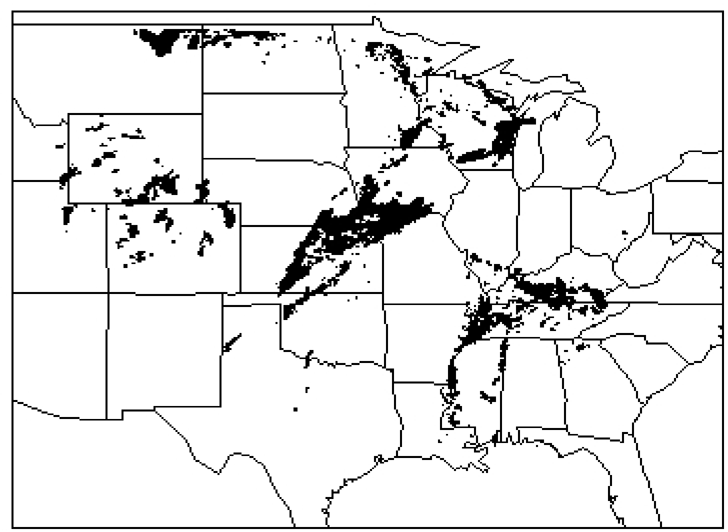
arw2 > 20dbz



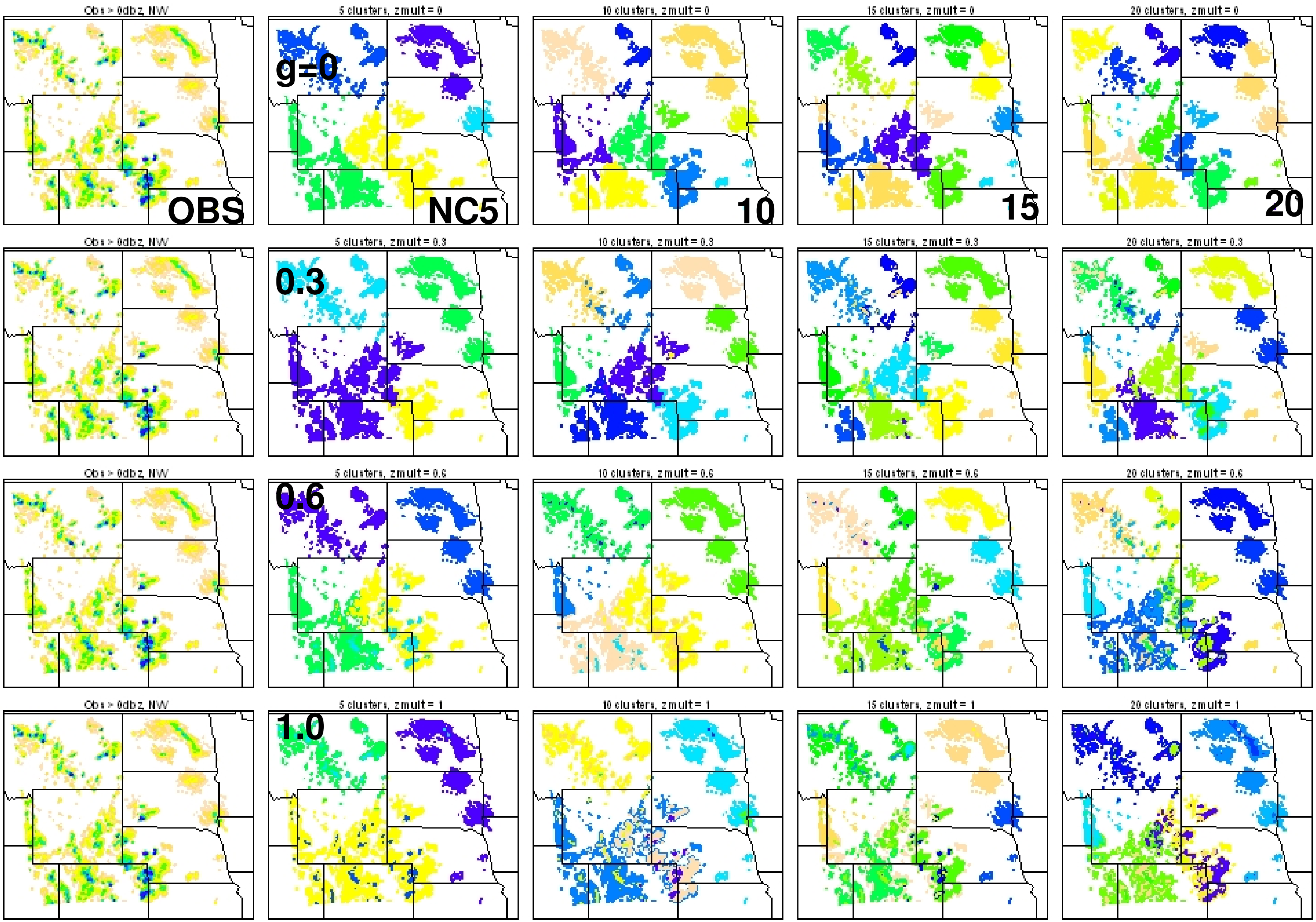
arw4 > 20dbz



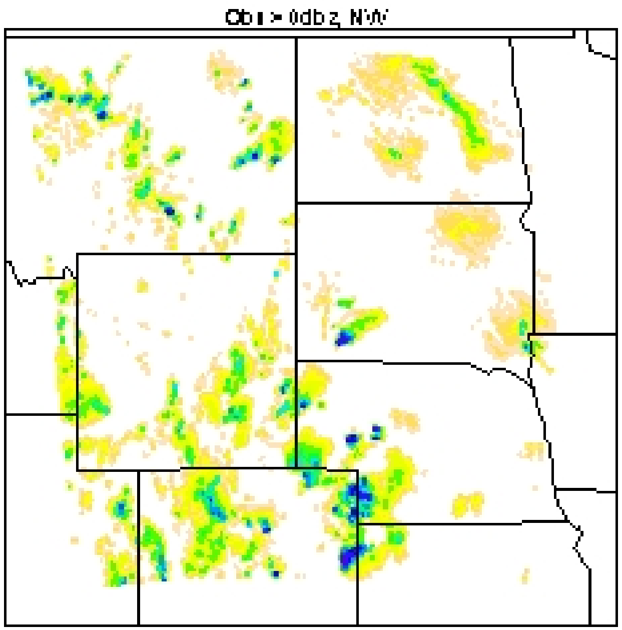
nmm > 20dbz

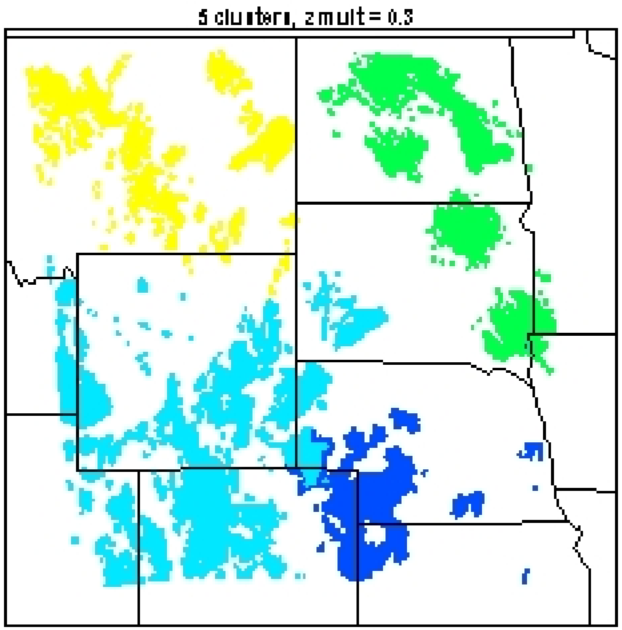


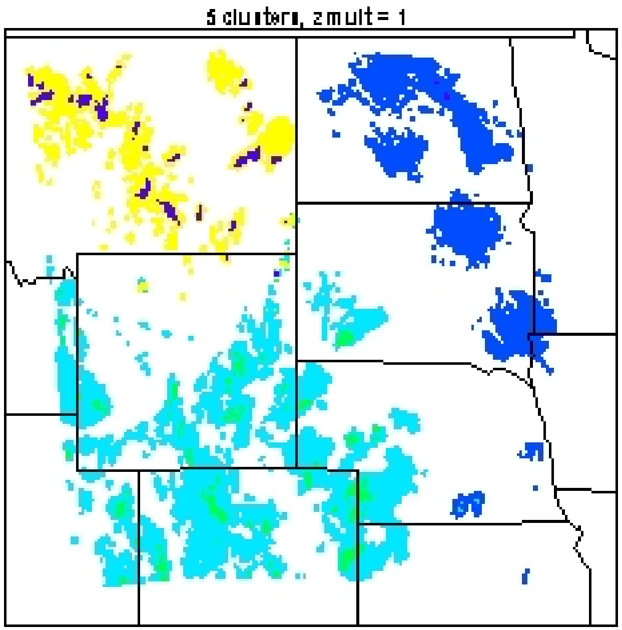
CCA observations as a function of NC and g
7 May 2005 NW quadrant



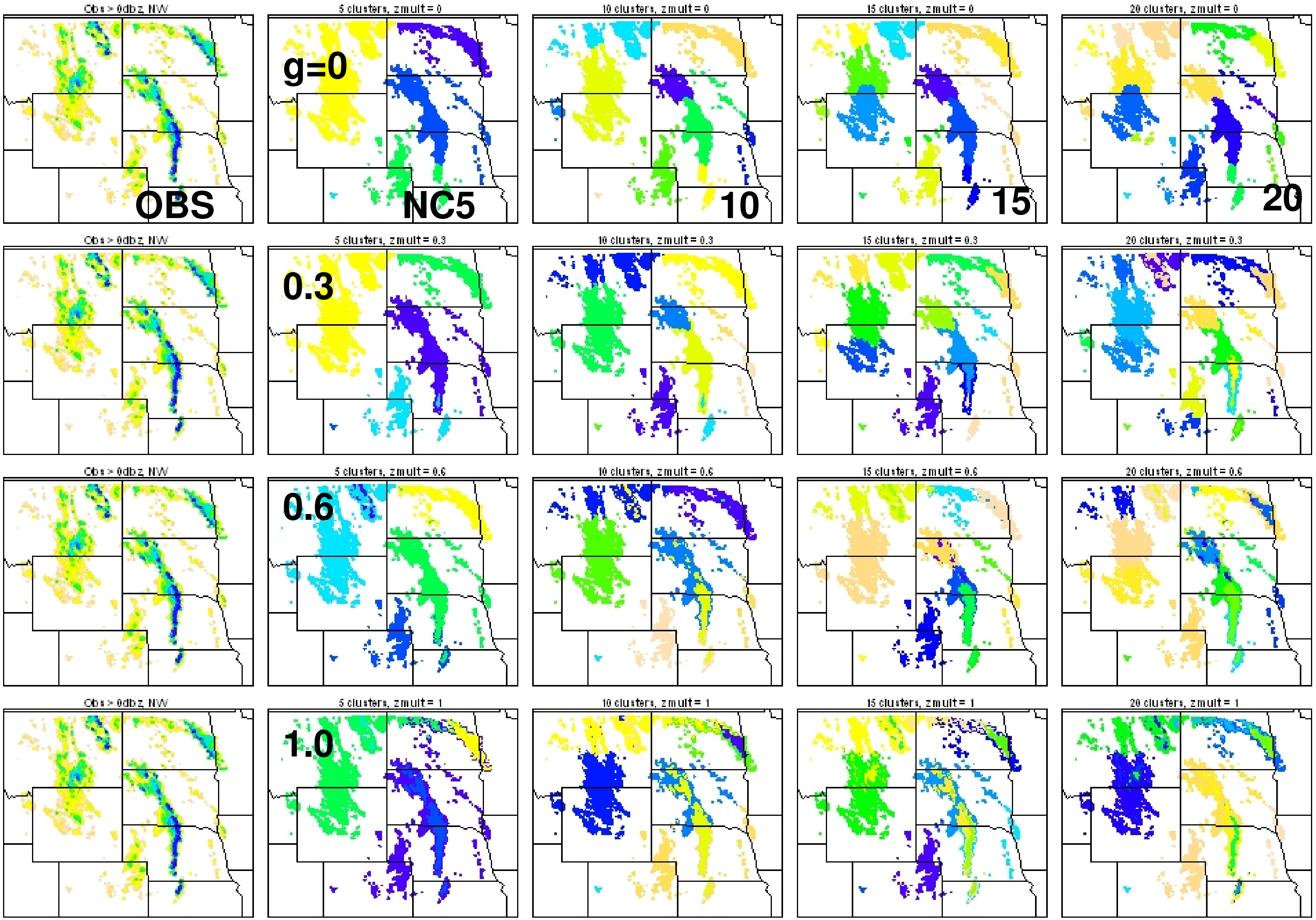
CCA observations as a function of NC and g
7 May 2005 NW quadrant







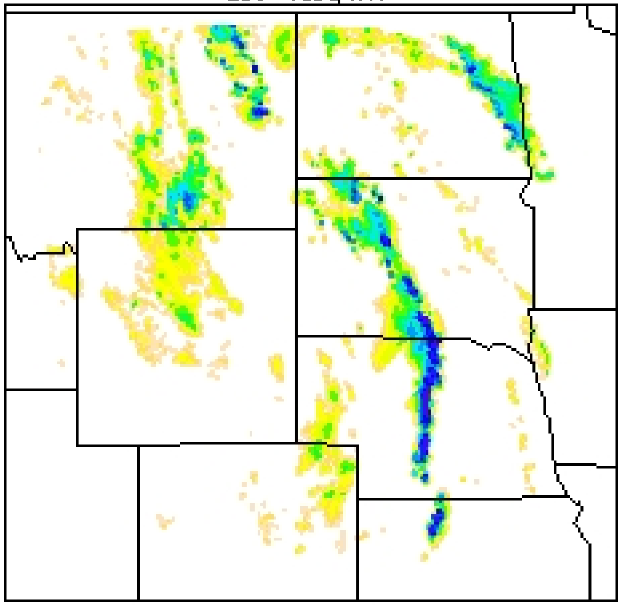
CCA observations as a function of NC and g
18 May 2005 NW quadrant



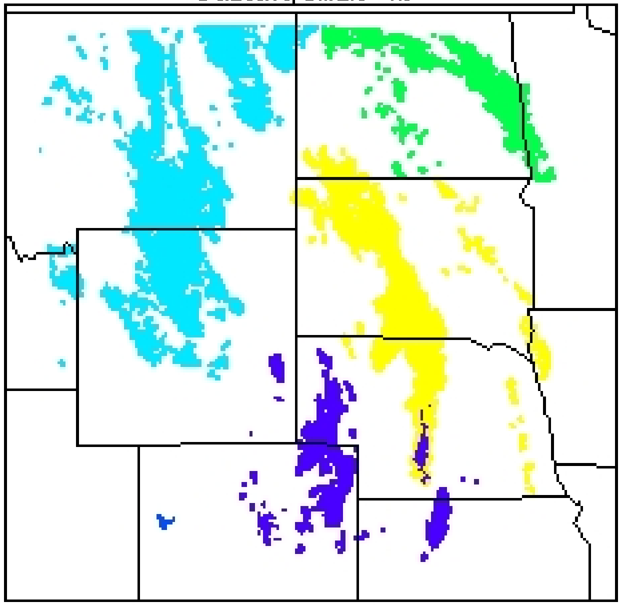
CCA observations as a function of NC and g

18 May 2005 NW quadrant

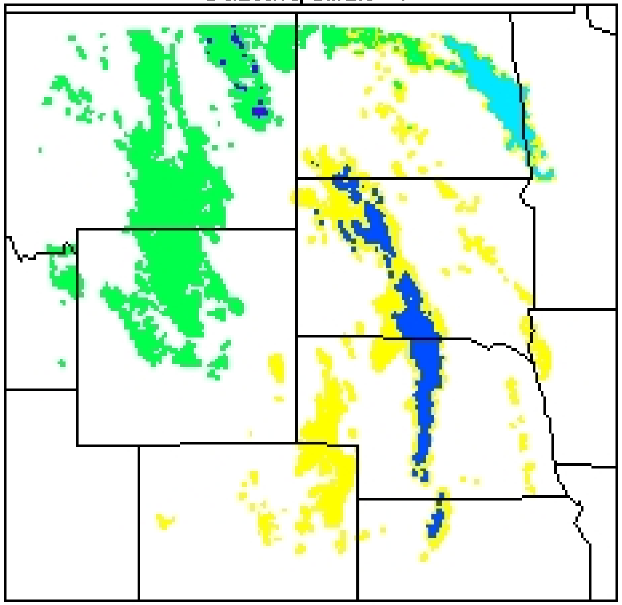
Obs > 0dbz, NW



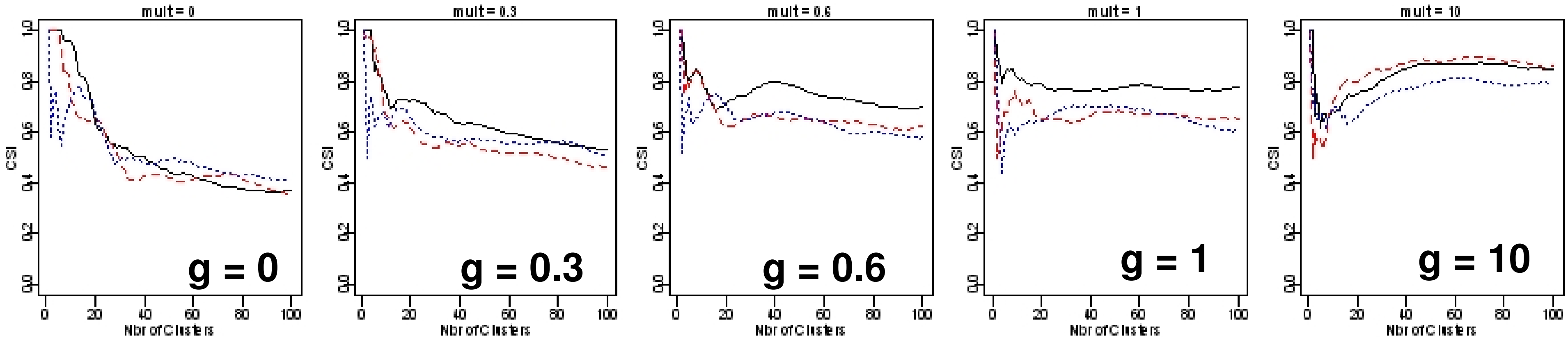
5 clusters, zmult = 0.3



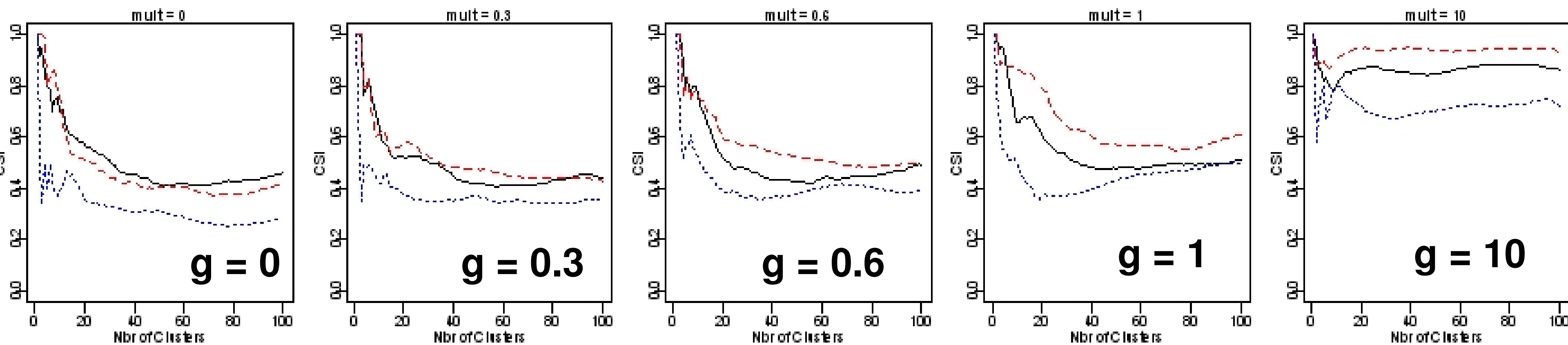
5 clusters, zmult = 1



CSI – ARW2 (B), ARW4(R), NMM4(B)

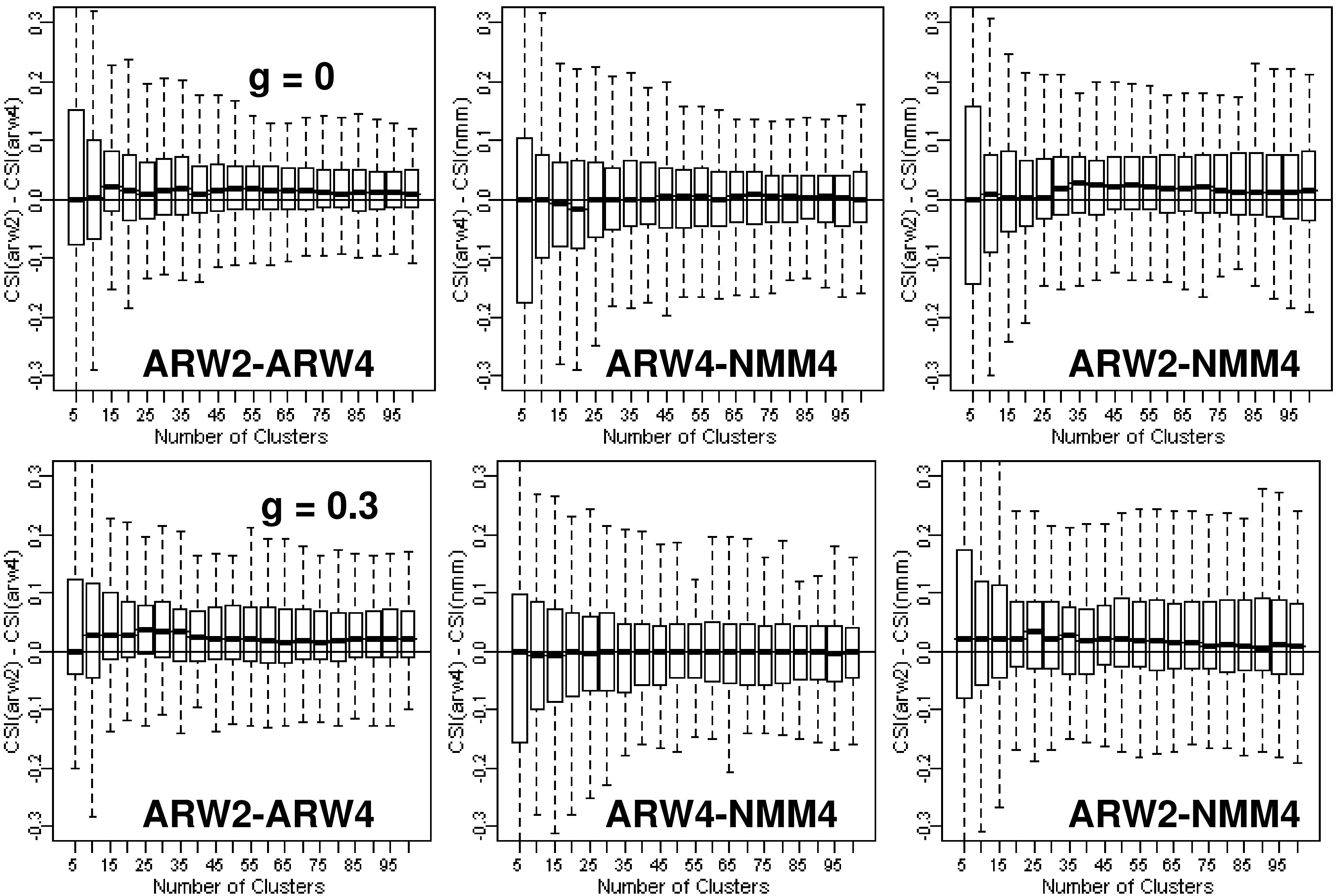


7 May 2005 NW

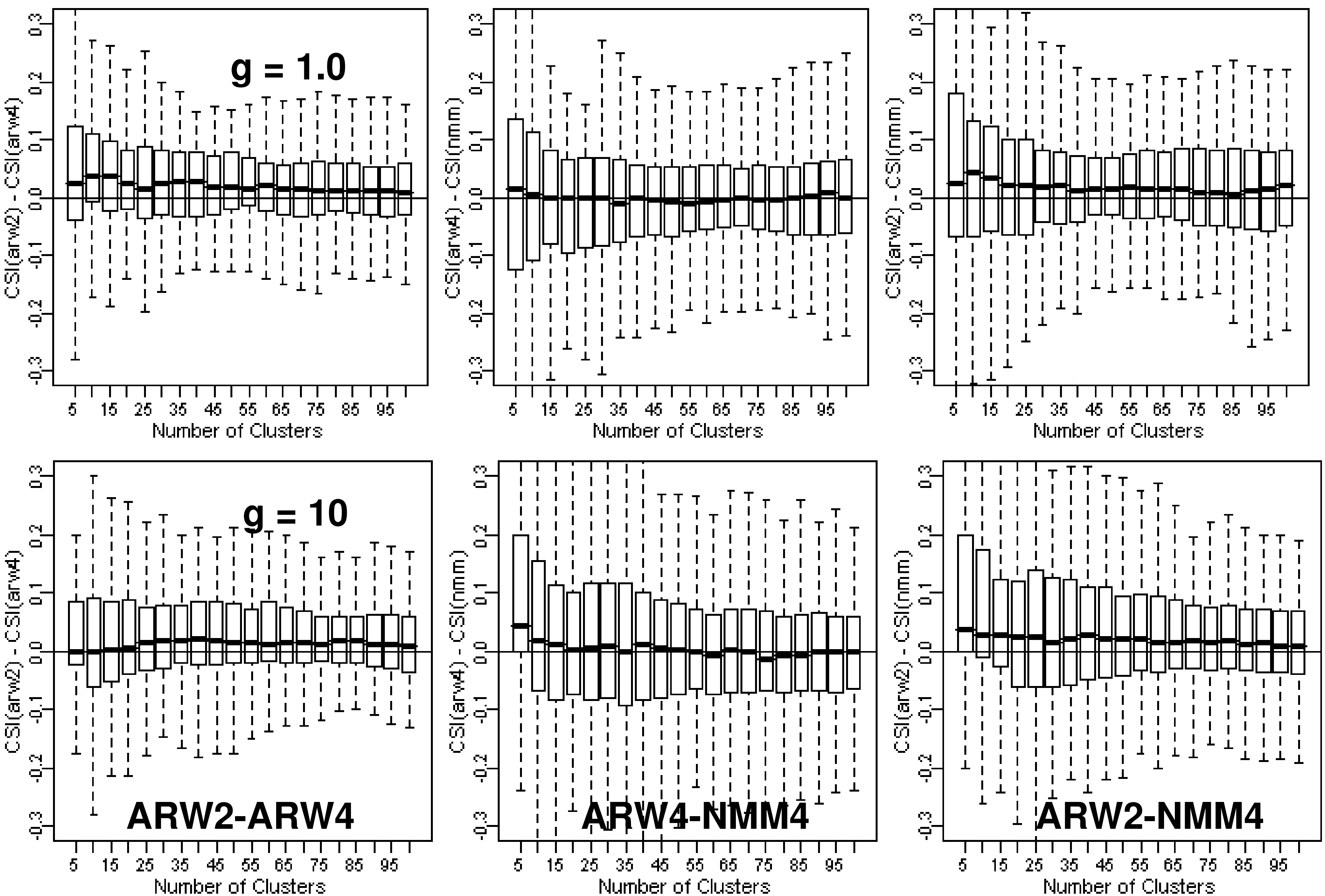


18 May 2005 NW

CSI Differences (g = 0, g = 0.3)



CSI Differences (g = 1.0, g = 10)



Conclusions

- Inclusion of reflectivity (z) into clustering does not significantly change results (for our 128 cases).
- We were able to demonstrate that CCA can be expanded to include meteorological variables (in addition to spatial x,y).
- Incorporating additional clustering variables is not a significant computational burden.
- Weighting of “other” variables is subjective; however, except for appearance, it doesn’t seem to change the relative assessment of the performance of the three models.
- Future: (x,y, z, $\mathbf{V} \cdot \mathbf{grad}$ T) or other suggestions??

Questions?

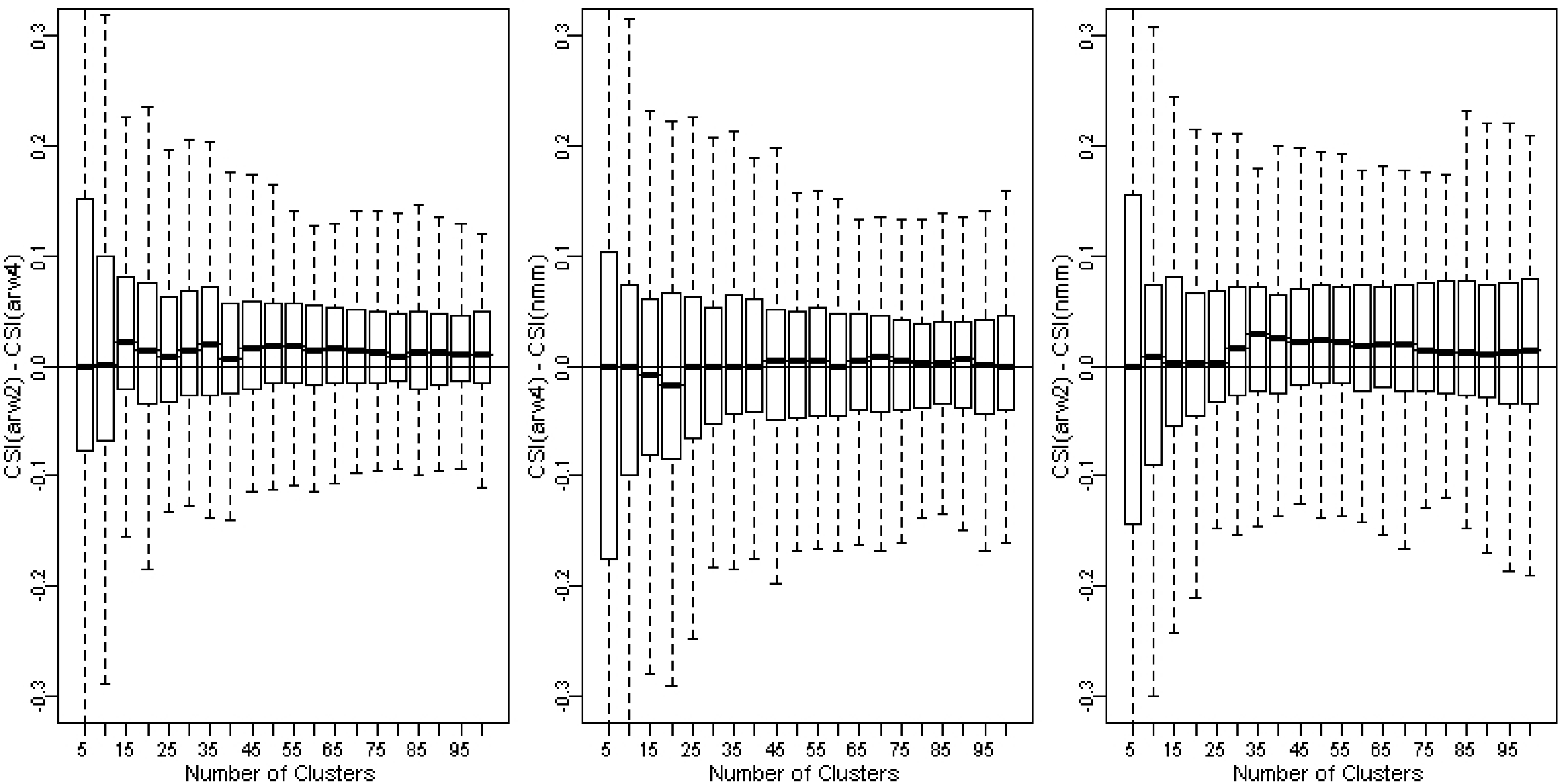
Abstract

The statistical technique of cluster analysis has been employed to perform object-oriented verification of high-resolution mesoscale numerical predictions. The technique was designed to provide fully automated, non-subjective verification of complex discontinuous fields such as precipitation. Initially, the method was used to identify clusters in the forecast and observed fields separately. This initial methodology proved to be computationally intensive and difficult to interpret. In this presentation, the authors describe the results of an improvement on the cluster analysis technique in which the cluster analysis is performed on the combined set of forecasts and observations rather than on the individual fields separately. The method is also expanded to beyond x,y clustering to include precipitation rate or reflectivity in defining clusters. The improved method is tested on a set of 32 predictions and verifying reflectivity fields for 32 days during the spring 2005 high-resolution mesoscale experiment over the eastern United States. Predictions from two high resolution versions of the Weather Research and Forecast model (WRF) and the NOAA Mesoscale Model (NMM) are verified and compared.

CCA Methodology

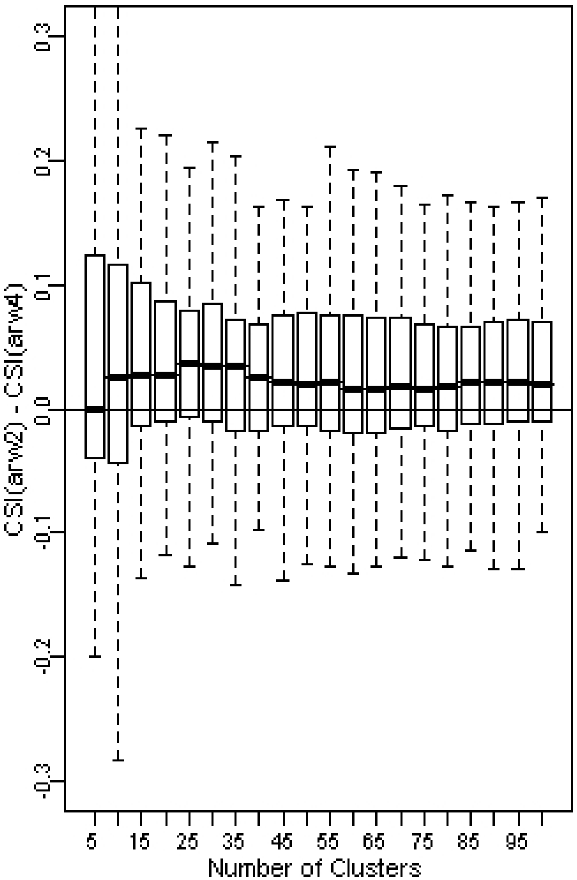
- Marzban, C., and S. Sandgathe, 2006: Cluster analysis for verification of precipitation fields. *Wea. Forecasting*, **21**, **5**, 824-838.
  - **Developed the CA methodology clustering the observed and forecast fields separately, then comparing clusters.**
- Marzban, C., and S. Sandgathe, 2007: Cluster Analysis for Object-Oriented Verification of Fields: A Variation. Accepted Monthly Weather Review.
  - **Developed the concept of Combinative Cluster Analysis on the combined observed and forecast fields.**
- Marzban, C., S. Sandgathe and Hilary Lyons, 2007: An Object-oriented Verification of Three NWP Model Formulations via Cluster Analysis: An objective and subjective analysis. Submitted Monthly Weather Review.
  - Available at http://faculty.washington.edu/marzban/cluster3.pdf)
  - **Compared reflectivity forecasts from three NWP formulations: arw2, arw4, nmm4; clustering in x,y.**
  - **Compared them with a human forecaster assessment.**

CSI Differences (g = 0)

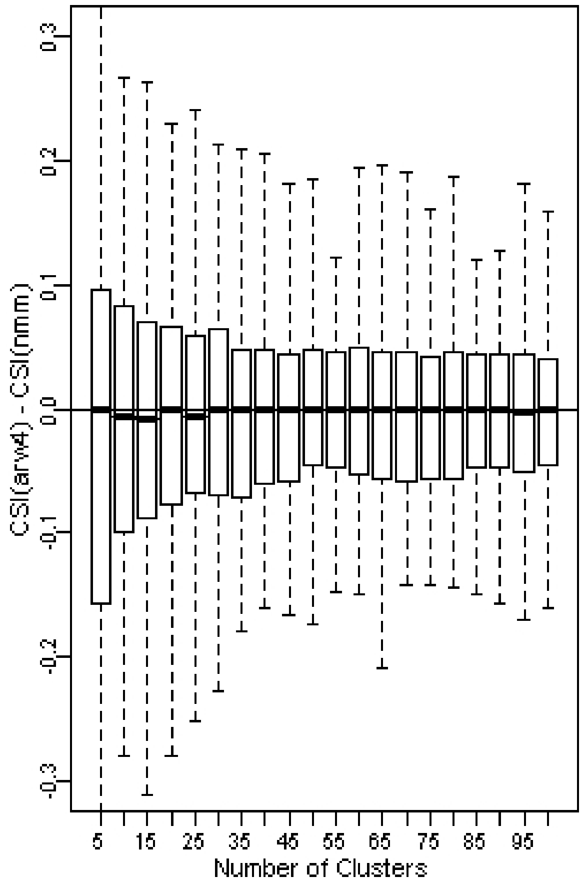


ARW2-ARW4 **ARW4-NMM4** **ARW2-NMM4**

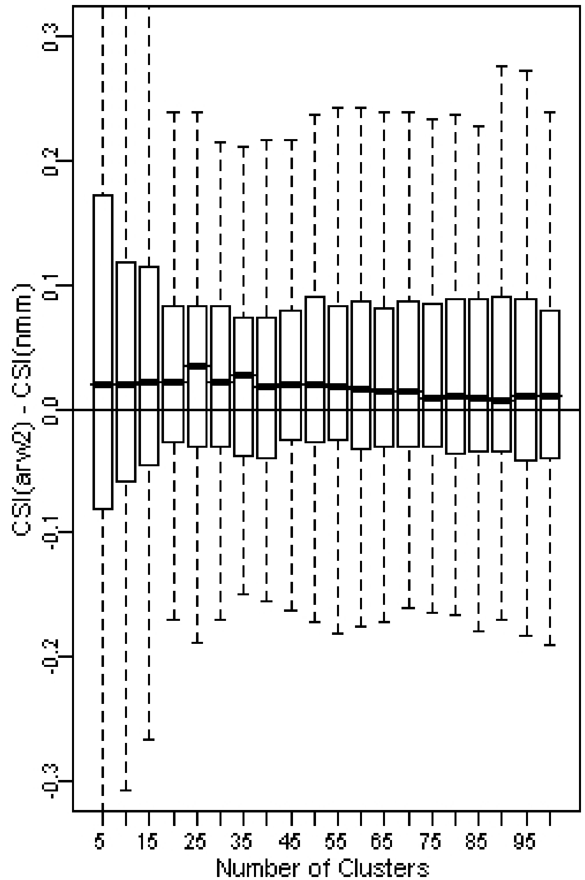
CSI Differences (g = 0.3)



ARW2-ARW4

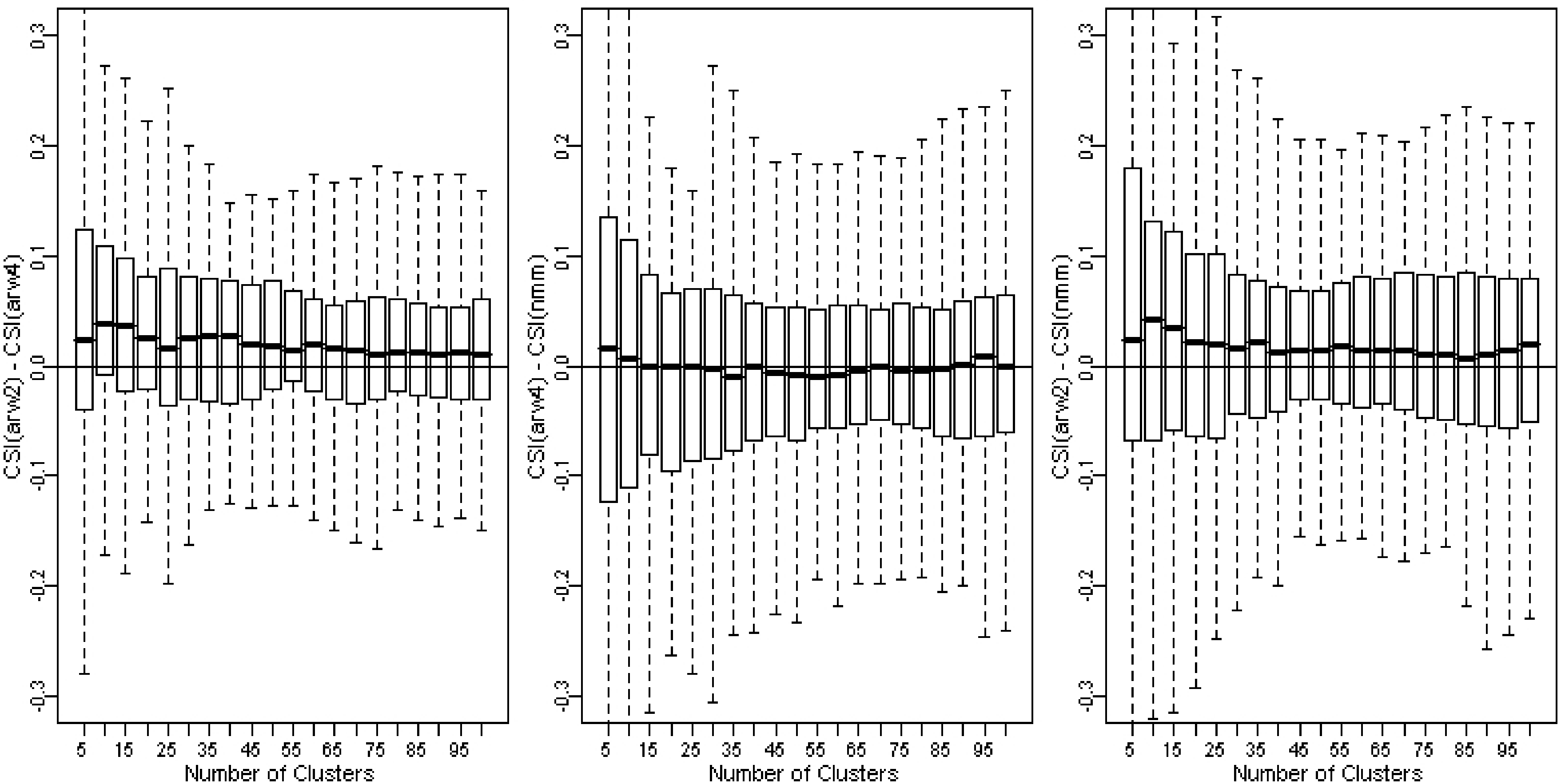


ARW4-NMM4



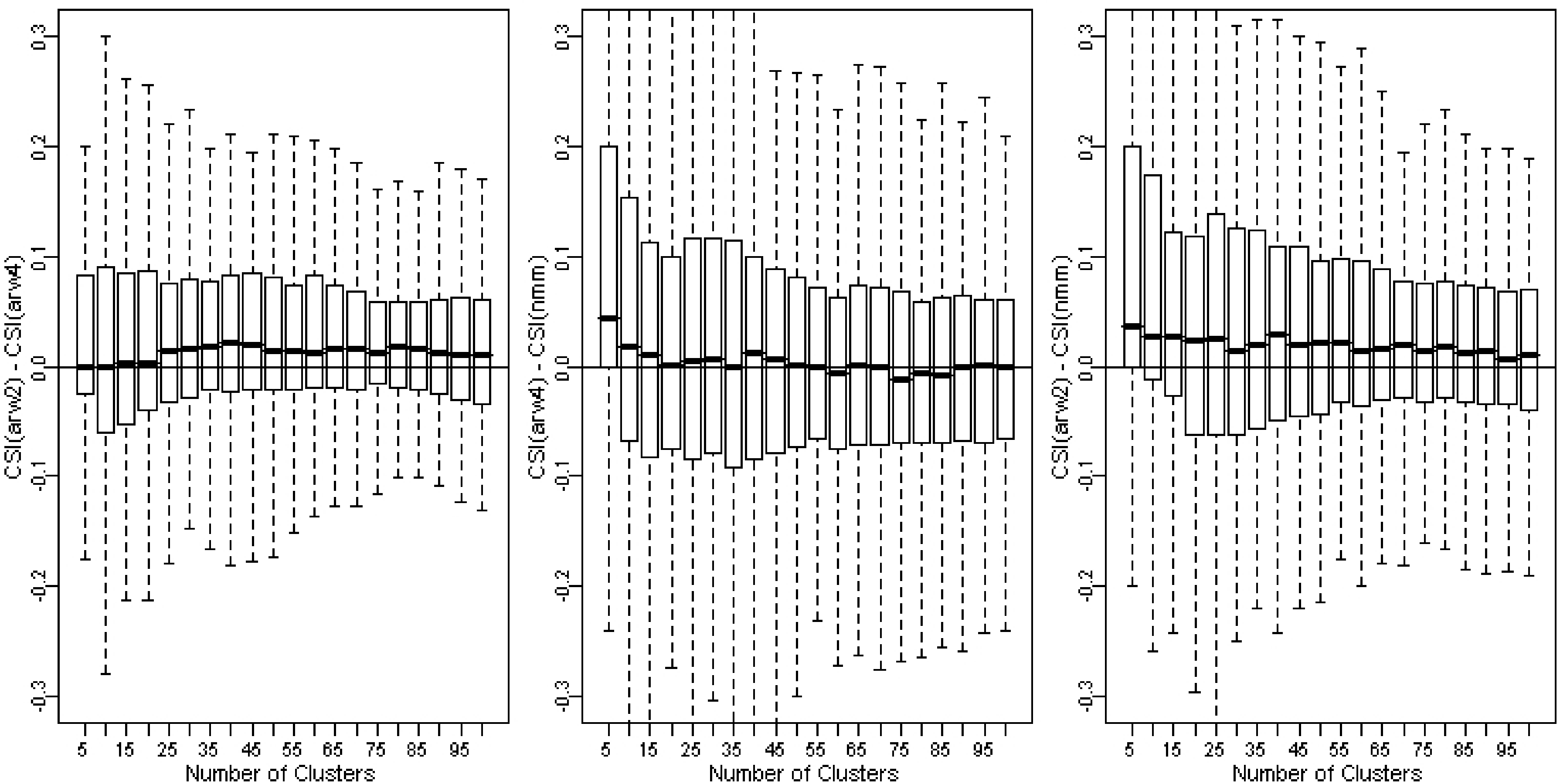
ARW2-NMM4

CSI Differences (g = 1)



ARW2-ARW4 **ARW4-NMM4** **ARW2-NMM4**

CSI Differences (g = 10)



ARW2-ARW4 **ARW4-NMM4** **ARW2-NMM4**