Application of Spatial Verification Methods to Idealized and NWP-Gridded Precipitation Forecasts

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ABSTRACT

Several spatial forecast verification methods have been developed that are suited for high-resolution precipitation forecasts. They can account for the spatial coherence of precipitation and give credit to a forecast that does not necessarily match the observation at any particular grid point. The methods were grouped into four broad categories (neighborhood, scale separation, features based, and field deformation) for the Spatial Forecast Verification Methods Intercomparison Project (ICP). Participants were asked to apply their new methods to a set of artificial geometric and perturbed forecasts with prescribed errors, and a set of real forecasts of convective precipitation on a 4-km grid. This paper describes the intercomparison test cases, summarizes results from the geometric cases, and presents subjective scores and traditional scores from the real cases.

All the new methods could detect bias error, and the features-based and field deformation methods were also able to diagnose displacement errors of precipitation features. The best approach for capturing errors in aspect ratio was field deformation. When comparing model forecasts with real cases, the traditional verification scores did not agree with the subjective assessment of the forecasts.

1. Introduction

With advances in computing power, numerical guidance has become available on increasingly finer scales. Mesoscale phenomena such as squall lines and hurricane rainbands are routinely forecasted. While the simulated reflectivity field and precipitation distribution have more realistic spatial structure and can provide valuable guidance to forecasters on the mode of convective evolution (Weisman et al. 2008), the traditional verification scores often do not reflect improvement in performance over coarse-grid models. Small errors in the position or timing of small convective features result in false alarms and missed events that dominate traditional categorical verification scores (Wilks 2006). This problem is exacerbated by smaller grid spacing. Several traditional scores such as critical success index (CSI; or threat score) and Gilbert skill score (GSS; or equitable threat score) have been used for decades to track model performance, but their utility is limited when it comes to diagnosing model errors such as a displaced forecast feature or an incorrect mode of convective organization.

To meet the need for more informative forecast evaluation, novel spatial verification methods have been developed. An overarching effort to compare and contrast these new methods and coordinate their development is called the Spatial Forecast Verification Methods Intercomparison Project (ICP). The ICP stemmed from a verification workshop originally held in Boulder, Colorado, in 2007. A literature review by Gilleland et al. (2009a) defines four main categories of new methods: neighborhood, scale separation, features based, and field deformation, a convention that is also used here.

In the ICP, a common set of forecasts was evaluated by participants in the project using one or more of the new methods. In sections 2 and 3, we describe the
geometric and perturbed datasets that were analyzed by ICP participants. In section 4, we present nine real cases and offer examples of traditional scores and results of an informal subjective evaluation of the forecasts for the nine cases. Readers are encouraged to use this paper along with that of Gilleland et al. (2009a) to identify new methods that may be appropriate for their needs, and then delve into the more detailed papers on the individual methods. This set of papers makes up a special collection of *Weather and Forecasting* on the Spatial Verification Methods Intercomparison Project (Casati 2010; Brill and Mesinger 2009; Davis et al. 2009; Ebert 2009; Ebert and Gallus 2009; Gilleland et al. 2009b, manuscript submitted to *Wea. Forecasting*, hereafter GLL; Keil and Craig 2009; Lack et al. 2010; Marzban and Sandgathe 2009; Marzban et al. 2009; Mittermaier and Roberts 2010; Nachamkin 2009; Wernli et al. 2009).

### 2. Geometric cases

#### a. Definition

To explore the variety of the new methods, ICP participants were asked to apply their new methods to idealized elliptical patterns of precipitation with general forecast errors (Fig. 1). Called the geometric cases, they are labeled geom000–geom005 with geom000 representing the observation field and geom001–geom005 representing the forecast fields. These patterns portray simple storm cells or mesoscale convective systems with a high-intensity core embedded in a region of low precipitation. The high-intensity core is offset to the right of center within each feature.

The geometric cases were defined on a 601 × 501 grid and were mapped to a 601 × 501 subsection of the National Centers for Environmental Prediction (NCEP) storage grid 240 (Dey 1998) for verification purposes. Because of the projection, the actual grid increment ranges from 3.7 to 4.3 km. Going from a Cartesian to a polar stereographic grid, the terms “to the right” and “to the east” are not strictly equivalent, but we use them interchangeably. The coordinates of the corners are (29.84°N, 109.98°W), (48.38°N, 112.60°W), (44.24°N, 78.23°W), and (27.44°N, 86.77°W) starting with the origin and moving clockwise.

The exact formulation of the forecast precipitation field is

\[
R(x, y) = \begin{cases} 
0.0 \text{ mm}, & \left(\frac{x - x_1}{a}\right)^2 + \left(\frac{y - y_1}{b}\right)^2 \geq 1 \\
12.7 \text{ mm}, & \left(\frac{x - x_1}{a}\right)^2 + \left(\frac{y - y_1}{b}\right)^2 < 1, \quad \left(\frac{x - x_2}{0.4a}\right)^2 + \left(\frac{y - y_1}{0.4b}\right)^2 < 1 \\
25.4 \text{ mm}, & \left(\frac{x - x_1}{a}\right)^2 + \left(\frac{y - y_1}{b}\right)^2 < 1 
\end{cases}
\]

\[y_1 = 250, \quad x_2 = x_1 + 0.4a,\]

where \(x\) and \(y\) are the grid indices of the 601 × 501 grid, \(a\) controls the width of the ellipse along the \(x\) axis, and \(b\) controls the width along the \(y\) axis; \((x_1, y_1)\) is the center of the low-intensity ellipse, and \((x_2, y_1)\) is the center of the high-intensity ellipse. The precipitation value, \(R\), is either zero outside the low-intensity ellipse (i.e., in the background), 12.7 mm inside the low-intensity ellipse but outside the high-intensity core, or 25.4 mm inside the high-intensity core. Note in Fig. 1 that

- all features are centered on the same \(y\) coordinate \((y_1 = 250)\)
- the area ratio of the high-intensity ellipse and low-intensity ellipse is constant
- the high-intensity ellipse is always right of center of the low-intensity ellipse

Other than location, the only differences among the geometric cases are forecast area and aspect ratio. The variables \(x_1, a,\) and \(b\) are defined in Table 1.

#### b. Analysis of geometric cases with traditional scores

The geometric cases illustrate three types of error: 1) displacement, 2) frequency bias, and 3) aspect ratio. Displacement and aspect ratio errors are especially difficult to discern with traditional verification methods. Knowledge of these errors could be useful for model development and improvement, and could be informative for users of the forecasts. When the forecasted precipitation does not overlap the observations at any precipitation threshold, traditional scores such as CSI, GSS, and Hanssen–Kuipers (H-K) are zero or less, indicating no (or negative) skill (Table 2). Even though geom001–geom004 share the characteristic of not overlapping the...
observation, geom003 has slightly higher probability of false detection and lower H-K, Heidke skill score (HSS), and GSS than the others because the larger forecast object increases the false alarm rate and decreases the correct forecasted null events.

The first two geometric cases, geom001 and geom002, illustrate pure displacement errors. The geom001 forecast feature shares a border with the observation, but the geom002 case is displaced much farther to the right. The geom001 case is clearly superior to geom002, but the traditional verification scores (column 2 of Table 2) suggest they are equally poor. Moreover, the geom004 forecast exhibits a very different kind of error from geom001 and 002, yet the traditional verification measures have equivalent values for all three of these cases. In contrast, some of the new spatial verification methods are able to distinguish the differences in performance for these three cases and quantify the displacement (and other) errors.

The geom003 and geom005 forecast areas are both stretched in the $x$ dimension, illustrating frequency bias. 

FIG. 1. (a)–(f) Five simple geometric cases derived to illustrate specific forecast errors. The forecasted feature (red) is positioned to the right of the observed feature (green). Note, in (f) (geom005), the forecast and observation features overlap. One grid box is approximately 4 km on a side.
Traditional bias scores do pick up the frequency bias, and the RMSE is largest for geom005, but the behavior of some other traditional scores is troubling. In particular, geom005 has an extremely high-frequency bias, but its false alarm ratio, H-K, GSS, and CSI scores are superior to all other geometric cases (Table 2). Those scores only give credit if the forecast event overlaps the observation. To be fair, a hydrologist might actually prefer geom005, even if it is considered to be extremely poor by modelers and other users. Nevertheless, a larger CSI value does not necessarily indicate that the forecast is better overall, which is why these traditional scores can be misleading when used in isolation.

The final type of error in the geometric forecasts is aspect ratio. Although the geom004 forecast resembles a simple rotation of the observed feature, geom004 actually illustrates an error in aspect ratio. In particular, the zonal width is 4 times too large, and the meridional extent is too narrow.

In the following analysis of the spatial verification methods, we address three questions pertaining to the geometric cases:

1) Does geom001 score better than geom002 and is the error correctly attributed to displacement?
2) Is the method sensitive to the increasing frequency bias in geom003 and geom005?
3) Can the method diagnose the aspect ratio error in geom004?

Table 3 summarizes the answers to these questions, which are discussed in greater detail below. Note that the paper of Gilleland et al. (2009a) answers a different set of questions that addresses the nature of the information provided by the various spatial verification methods.

c. Neighborhood methods applied to geometric cases

The neighborhood methods (Ebert 2009; Mittermaier and Roberts 2010) look in progressively larger space–time neighborhoods about each grid square and compare the sets of probabilistic, continuous, or categorical values from the forecast to the observation. These methods are sensitive to the greater displacement error in geom002 versus geom001, but because they are not based on features, they do not provide direct information on the feature displacement. Instead, the neighborhood methods show that larger neighborhoods are necessary for geom002 to reach the same performance as geom001. For example, Mittermaier and Roberts (2010) show that...
geom001 exhibits Fractions skill score (FSS) above zero with neighborhoods larger than 200 km, but geom002 has no skill with any reasonably sized neighborhood. Aply, according to FSS, the skillful neighborhood size for geom001 (200 km) corresponds exactly to the prescribed displacement error of 200 km.

The neighborhood methods do detect the frequency bias of forecast geom003 and geom005, but the grossly overforecasted geom005 has better skill scores at small scales because it overlaps the observations. This holds true for FSS (Mittermaier and Roberts 2010), conditional bias difference (Nachamkin 2009), the multievent contingency table (Atger 2001; Ebert 2009), and practically perfect hindcast (Brooks et al. 1998; Ebert 2009). As the size of the neighborhood approaches the grid scale, the neighborhood method scores match the scores from traditional methods.

The neighborhood methods do not explicitly measure displacement or structure error, so the aspect ratio error in geom004 is difficult to diagnose.

d. Scale separation applied to geometric cases

The intensity-scale separation (IS) method of Casati (2010) and the variogram approach of Marzban and Sandgathe (2009) and Marzban et al. (2009) are sensitive to the displacement errors in geom001 and geom002, but they do not quantify them. The IS method (Casati 2010) uses wavelets to decompose the difference field between the observed binary field and the forecast binary field. For geom001, there is a sharp minimum in the IS skill score at the spatial scale of 128 km and a rapid rebound to $IS > 0$ for scales of 512 and 1024 km (Fig. 7a of Casati 2010; 12.7-mm threshold). For geom002, the IS skill scores are much lower at scales of 512 and 1024 km relative to geom001 (Fig. 7b of Casati 2010). The variogram approach compares the texture of the forecasted field to the observations at different spatial scales. Similar to the IS method, the variogram of Marzban and Sandgathe (2009) and Marzban et al. (2009) is sensitive to displacement error, but does not isolate the magnitude of the displacement.

The frequency bias of geom003 and geom005 results in a large drop in IS skill score at the largest spatial scales (2048 km; Casati 2010). Variograms also have the potential to detect the frequency bias in geom003 and geom005, but only if zero pixels are included (Marzban et al. 2009).

As with the neighborhood methods, neither of these scale-separation methods is designed to detect the aspect-ratio error in geom004.

e. Features-based methods applied to geometric cases

Features-based methods (Gilleland et al. 2009a) divide a gridded field into objects by grouping clusters of similar points. For the geometric cases, the low-intensity or high-intensity ellipses could represent the objects. If the forecast object is matched to the observed object, attributes such as position and size can be compared. If they are too distant, no match occurs and no diagnostic information about displacement or area bias is derived.

Several features-based methods were able to quantify the displacement errors in geom001 and geom002. The structure, amplitude, and location (SAL) quality measure (Wernli et al. 2008) does not provide an actual distance, but it provides a normalized location error ($L$) with higher values associated with more displacement error. For geom001, $L = 0.11$, and for geom002, $L = 0.39$ (Wernli et al. 2009). The Method for Object-Based
FIG. 3. (top left) Observation field and (other panels) seven perturbed cases for the ICP. The observation field is the 1-h accumulated precipitation valid at 0000 UTC 1 Jun 2005 from the CAPS model. Perturbed forecasts are identical to the observation field, except they have been displaced southward and rightward by prescribed amounts listed in Table 4. The final two perturbed forecasts have a displacement error and a global intensity error, as described in Table 4.
Diagnostic Evaluation (MODE; Davis et al. 2009) quantifies the displacement error perfectly because it matches the forecasted and observed precipitation features and uses centroid distance as one of the matching criteria. The Procrustes object-oriented verification scheme also matches objects based on their centroid distance. Lack et al. (2010) show that the Procrustes method measures the right amount of displacement (200 and 800 km) in geom001 and geom002, as was also the case for the contiguous rain area (CRA) method (Ebert and Gallus 2009). Most of the features-based methods diagnose the frequency bias of geom003 and geom005. In the SAL approach (Wernli et al. 2009), the structure (S) and amplitude (A) terms indicated the forecast objects are too large (S = 1.19 for geom003 and S = 1.55 for geom005, with S = 0 being perfect) and the domain-average precipitation amounts are too high (A = 1.19 for geom003 and A = 1.55 for geom005, with 0 being perfect). The contiguous rain area (Ebert and Gallus 2009), MODE (Davis et al. 2009), and Procrustes methods (Lack et al. 2010) are also sensitive to the frequency bias with a greater proportion of error attributed to frequency bias in geom005 than in geom003.

The features-based methods diagnose the aspect ratio error of geom004 as an orientation angle error [MODE (Davis et al. 2009); Procrustes (Lack et al. 2010)] or generic “pattern” error (Ebert and Gallus 2009), or they are insensitive to this type of error (SAL; Wernli et al. 2009).

f. Field deformation methods applied to geometric cases

Field deformation methods attempt to morph the forecast and/or observation fields to look like each other, minimizing a score such as RMSE. As long as the search radius exceeds the displacement error, the displacement errors of geom001 and geom002 can be quantified. Keil and Craig (2009) use a pyramidal matching algorithm to derive displacement vector fields and compute a score based on displacement and amplitude (DAS). For geom001 the displacement component dominates the DAS as expected, but for geom002 the amplitude component dominates the DAS because the features are farther apart than the search radius. Optical flow techniques behave similarly. A small displacement error such as in geom001 has a trivial optical flow field that simply shifts the object from one location to another. However, when the forecast object is beyond the optical flow search radius, the optical flow vectors converge on the forecast object and attempt to “shrink” the apparent false alarm (C. Marzban 2009, personal communication). The Forecast Quality Index (FQI; Venugopal et al. 2005) utilizes the partial Hausdorff distance (PHD) to characterize the global distance between binary images. The PHDs for geom001 and geom002 are 41 and 191 grid points, respectively, which are slightly less than the actual displacements (50 and 200 grid points).

The field deformation methods are sensitive to frequency bias. Since the forecast objects in geom003 and geom005 are too big, the field deformation methods shrink the forecasted precipitation area (e.g., GLL). The frequency biases of geom003 and geom005 may not affect the amplitude component of the FQI (Venugopal et al. 2005), but they do affect the PHD. Using the formulation in Venugopal et al. (2005), the PHDs of geom003, geom004, and geom005 were 145, 141, and 186 grid points, respectively. This accounts for the 125 gridpoint shift to the right and the stretching in the x dimension.

The field deformation method is the only one to truly capture the aspect ratio error in geom004. Figure 2 illustrates the image warping technique of GLL. As seen in Fig. 2, the field deformation vectors change the aspect ratio and do not rotate the object.

3. Perturbed cases

In addition to the geometric shapes, some ICP participants evaluated a set of perturbed precipitation forecasts from a high-resolution numerical weather prediction model. The verification field was actually a 24-h forecast of 1-h accumulated precipitation provided by the Center for Analysis and Prediction of Storms (CAPS) valid at 0000 UTC 1 June 2005 (Fig. 3). Perturbed forecasts were made by shifting the entire field to the right and southward by different amounts (Table 4). The fields were provided on
FIG. 4. One-hour accumulated precipitation and three corresponding model forecasts for nine real cases. The observations and forecasts are valid at 0000 UTC on the date indicated. The upper left quadrant is the stage II observation, and quadrants A–C contain the 24-h forecasts from the wrf2caps, wrf4ncar, and wrf4ncep models, respectively. For the subjective evaluation, the model forecasts were not labeled and were randomly ordered.
the same 4-km grid used in the geometric cases. Additional details about the model are provided in Kain et al. (2008). Pixels that shifted out of the domain were discarded and pixels that shifted into the domain were set to zero. In the last two perturbed cases, the displacement error was held constant, but the precipitation field in pert006 was multiplied by 1.5 and the field in pert007 had 1.27 mm subtracted from it. Values less than zero were set to zero in pert007. This paper does not describe the verification results for the perturbed cases, but interested readers can consult the papers describing the individual spatial verification methods for more detailed discussion of these cases.

4. Real cases

a. Model description

For the real precipitation examples, we use nine cases from the 2005 Spring Program. These cases were presented to a panel of 26 scientists attending a workshop on spatial verification methods to obtain their subjective assessments of forecast performance (Fig. 4). The three forecast models were run for the 2005 Spring Program sponsored by the Storm Prediction Center (SPC) and the National Severe Storms Laboratory (NSSL) (http://www.nssl.noaa.gov/projects/hwt/sp2005.html). Two of the three numerical models [provided by the National Center for Atmospheric Research (NCAR) and NCEP Environmental Modeling Center (EMC)] were run on a 4-km grid, while one (CAPS) was run on a 2-km grid and mapped to a 4-km grid. The models are denoted wrf4ncar, wrf4ncep, and wrf2caps, respectively. Additional information on the model configurations can be found in Kain et al. (2008). All forecasts and observations were remapped onto the same (~4 km) grid used for the geometric cases. This remapping method maintains, to a desired accuracy, the total precipitation on the original
grid and is part of the NCEP iplib interpolation library that is routinely used and distributed by NCEP as part of the Weather Research and Forecasting (WRF) post-processing system. This interpolation performs a nearest-neighbor interpolation from the original grid to a $5 \times 5$ set of subgrid boxes on the output grid centered on each output grid point. A simple average of the $5 \times 5$ subgrid boxes results in the interpolated value (M. Baldwin 2009, personal communication).

The panel compared the three aforementioned models to the stage II precipitation analysis (Lin and Mitchell 2005) for a lead time of 24 h and an accumulation interval of one hour. Panelists rated the models’ performance on a scale from 1 to 5, ranging from poor to excellent. For fairness, the models were ordered randomly and not labeled.

b. Traditional scores and subjective evaluation

The panel’s subjective scores are alternative viewpoints, not definitive assessments of forecast performance. The evaluators were not asked to consider the usefulness of the forecasts from the standpoint of any particular user (e.g., water manager, farmer, SPC forecaster) or to focus on a particular region, but to subjectively evaluate the forecast as a whole. Afterward, several of the panel members indicated that more guidance was needed in these areas, because the usefulness of a forecast depends greatly on the perceived needs of the user and the geographical area of concern; sometimes a model performed well in one region and poorly in another. But in order to keep the study simple, participants were asked to simply give an overall impression of the models’ skill and were left to themselves to decide what mattered most.

Although the evaluation was performed twice in order to increase the stability of the overall responses and to assess the natural variability from one trial to the next, several aspects of the survey added uncertainty to the results. First, the panel members had varying professional backgrounds, including meteorologists, statisticians, and software engineers. Meteorologists were more likely to consider realistic depictions of mesoscale structure (such as in the stratiform precipitation area of a mesoscale convective system) as an important criterion defining a “good” forecast, and may have focused on different features than scientists with a pure mathematical background. Examples of a good forecast were not provided.

As expected with convective precipitation forecasts on a fine grid, the traditional scores are quite poor. In Fig. 5 we focus on the wrf4ncep model just to illustrate this point. The scores do depend on our choice of 6 mm as an intensity threshold. Higher thresholds correspond to intense precipitation cores, which typically result in even lower scores. Grid-scale prediction of convective precipitation is not yet feasible 24 h in advance and the GSS < 0.1 reflects that difficulty. Ideally, the frequency bias (top left panel) would be 1, but the model consistently overforecasts precipitation above 6 mm.

The slightly negative GSS for 1 and 4 June suggests that these two forecasts are uniformly poor, however their subjective scores tell a different story (Fig. 6). Out of the 24 participants, 18 gave a higher score to the 1 June forecast from wrf4ncep, 4 scored them equally, and only 2 scored 4 June higher. The panel members were not asked to explain why they rated the 1 June wrf4ncep forecast better than the 4 June forecast, but there are some positive aspects of the 1 June forecast that could play a role. Although slightly displaced, the 1 June forecast captured the overall shape of the long band of convective precipitation curling from North Dakota to Texas (Fig. 4). The forecasted heavy precipitation cores in the Texas Panhandle were also close to the observed precipitation cores. On the other hand, for 4 June, there is a prominent false alarm in the strong north–south band of forecasted precipitation in Missouri and Arkansas.

To have some objective comparison of the subjective scores with the traditional verification scores, the subjective and traditional scores are ranked in order of best score (where one is best and nine is worst), based on their point estimates (not including uncertainty information) for each day for the wrf4ncep model. Such a day-to-day comparison does not account for differing climatologies, so this is not standard practice for evaluating a forecast model’s performance, but it does provide information about how traditional scores agree (or disagree) with subjective assessments on a case-by-case basis. The resulting ranks are displayed in Fig. 7.

It can be seen from Fig. 7 that in many cases the subjective evaluations agree remarkably well with the RMSE, but tend to disagree with the other scores. The 19 May wrf4ncep case stands out in that there is good agreement between the subjective scores and the frequency bias and GSS; however, with such a high bias, the GSS is not very interpretable for this case (indeed, only the 25 May case is nearly unbiased). Another case that stands out is that of 3 June where all of the scores are in good agreement about the rank. For this day, the model scored reasonably well for all of the summary scores, but had a few better scores for each type of statistic on a few other days; these other days differed depending on the type of statistic. Similarly, the 4 June case has good agreement for all methods that this case is regarded as one of the worst days among these cases for this forecast model. Finally, the subjective scores differed strongly regarding rank from all of the other scores (except
frequency bias) for the 1 June case; both the subjective scores and frequency bias rank this case somewhere in the middle, while the other scores have it as the worst or nearly the worst case.

Clearly, there is no ardent consistency between traditional verification scores and subjective human evaluation. It has long been realized that no one traditional verification score can give meaningful information alone. However, it is not clear, as demonstrated by this ranking exercise, how to go about combining the traditional scores to create a score that would consistently concur with subjective evaluation. It is beyond the scope of this paper to create such a score, and certainly beyond the scope of this example. Nevertheless, this exercise sheds light on one of the difficulties in trying to interpret traditional verification scores for spatially dense forecasts.

Although it is beyond the scope of this paper to compare the results from all of the spatial methods to the results of the subjective assessment, a few comments can be made. In the case of 1 June, some of the spatial methods (e.g., object-based approach) would have been able to capture the displacement error that characterized the major part of the error and that led to a relatively good rating through the subjective assessment and a poor rating by the traditional scores. However, in general it appears that scores from some of the spatial methods are not able to mimic the subjective scores better than the traditional scores. For example, the verification results for the CRA method did not agree with the subjective results any better than traditional results (Ebert and Gallus 2009). In contrast, the results for the Keil and Craig approach show greater consistency with the subjective results regarding the relative performance on individual days (Keil and Craig 2009).

Additional model comparisons are found in accompanying papers in the ICP special collection (Casati 2010; Brill and Mesinger 2009; Davis et al. 2009; Ebert 2009; Ebert and Gallus 2009; GLL; Keil and Craig 2009; Lack et al. 2010; Marzban and Sandgathe 2009; Marzban...
et al. 2009; Mittermaier and Roberts 2010; Nachamkin 2009; Wernli et al. 2009). Lack et al. (2010) specifically apply the Procrustes approach to consider the reasoning that may have been associated with the subjective evaluations.

5. Summary

We constructed simple precipitation forecasts to which traditional verification scores and some of the recently developed spatial verification methods were applied. These simple geometric cases illustrated potential problems with traditional scoring metrics. Displacement error was easily diagnosed by the features-based and field deformation methods, but the signal was not as clear cut in the neighborhood and scale separation methods, sometimes getting mixed with frequency bias error. Errors in aspect ratio affected some of the scores for neighborhood and scale separation approaches, but the aspect ratio error itself was diagnosed by only a couple of specialized configurations of the features methods. Typically, the features-based methods treat aspect ratio error as rotation and/or displacement. The field deformation methods seemed to have the best ability to directly measure errors in aspect ratio.

For the more realistic cases that we tested, each method provided different aspects of forecast quality. Compared to the subjective scores, the traditional approaches were particularly insensitive to changes in perceived forecast quality at high-precipitation thresholds ($\geq 6$ mm h$^{-1}$). In these cases, the newer features-based, scale-separation, neighborhood, and field deformation methods have the ability to give credit for close forecasts of precipitation features or resemblance of overall texture to the observations.

It should be pointed out that the four general categories into which we have classified the various methods are only used to give a general idea of how a method describes forecast performance. Some methods fall only loosely into a specific category (e.g., cluster analysis, variograms, FQI). Further, it is conceivable to combine the categories to provide even more robust measures of forecast quality. This has been done, for example, in Lack et al. (2010), who apply a scale separation method as part of a features-based approach. Results shown here should not only assist a user in choosing which methods to use, but might also point out potentially useful combinations of approaches to method developers and users.

Upon examining the results from the subjective evaluation, it became clear that a more rigorous experiment with more controlled parameters would be preferred. A more robust evaluation with a panel of experts would undoubtedly require pinning down the region of interest, isolating the potential users’ needs, and providing a concrete definition of a good forecast. This type of exercise, which would be best done in collaboration with social scientists and survey experts, is left for future work.

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