2.11 GEOSPATIAL UNCERTAINTY ANALYSIS AND GRIDDED FORECAST VERIFICATION

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1. INTRODUCTION

The availability of gridded forecasts from National Weather Service (NWS) Weather Forecast Offices (WFOs) allows for quantitative evaluation of forecast performance. Gridded objective analyses of meteorological variables can be used to verify such forecast products. The NWS Western Region currently is provided with hourly gridded analyses from the University of Utah referred to as Utah ADAS, a modified version of the ARPS Data Analysis System; Lazarus et al. (2002). ADAS uses an analysis technique which converges to optimal interpolation. Utah ADAS analysis grids can be used to evaluated forecast grids from the WFOs such as those provided as part of the NDFD system (at 5km resolution).

Use of a gridded analyses for forecast validation assumes some level of certainty in the analysis product. However, evaluation of the analysis error is rarely provided and is generally not incorporated into skill scores used to evaluate forecasts. Kriging, an optimum interpolation technique with a theoretical basis similar to the approach used in ADAS, can provide an estimate of the analysis error. This error estimate is used as a proxy for an estimate of the error in Utah ADAS and is then used in a modified skill score which accounts for analysis error.

2. KRIGING: THE SEMIVARIOGRAM

Kriging is an optimum interpolation approach originally developed by D.G. Krige in the 1950s and used frequently in geostatistics. Kriging can be formally related to Gandin's optimum interpolation scheme (Herzfeld, 1996) which is used more predominantly in the meteorological community and from which the Bratseth technique used in Utah ADAS is based. Both variants of optimum interpolation can be cast in the context of analyzing departures from a background field. In this study we will be using the 20km Rapid Update Cycle (RUC) as the background field and will use MesoWest (Horel, et al, 2002) surface observations to determine departures from the background field. In kriging, spatial analysis of the departure from the background field is used to tune the analysis. The semivariance function, γ, is defined as:

$$\gamma(h) = 0.5 \, \mathrm{Var}\{Z(x+h)-Z(x)\}$$

where h is the lag. In this case we assess the temperature departure between the observations and the background field as a function of horizontal lag. RUC surface temperature was interpolated to MesoWest station locations prior to calculating temperature departures. These departures were then used to generate a semivariogram, which is simply a plot of the semivariance as a function of the lag. Figure 1 is the semivariogram for temperature during AUG 2003 as a function of UTC hour.

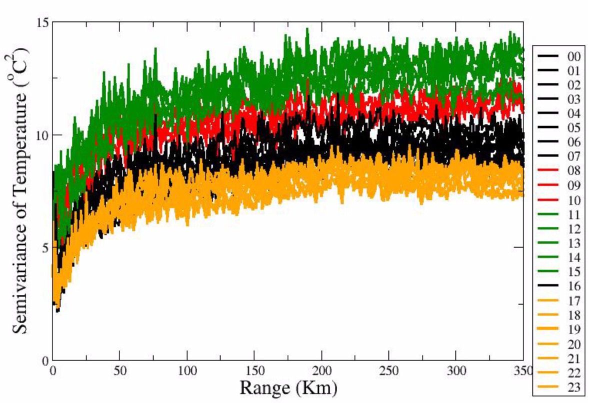

Fig. 1. Semivariance of temperature observations from MesoWest minus interpolated RUC values at the station locations as a function of UTC hour.

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The semivariance in Fig. 1 appears to asymptote at by about 200 km for all times, this distance is defined as the range in geostatistics. The estimated semivariance at lag equal to 0 km is referred to as the nugget, while the value at the range is referred to as the sill. The diurnal variation indicates the best match between the RUC and MesoWest observations occurs during the well mixed portions of the day. Care should be taken in interpreting the results as background error due to the uncertainty of observations and due to error introduced by interpolation to station locations, etc.

The value of the nugget is influenced by more than standard observational error. In this application it likely reflects effects ranging from the representativeness of station locations to sensor characteristics and siting. Localized land use and vegetation impact the surface meteorological quantities, though are not often incorporated into gridded forecasts or analysis schemes, and are assumed to be included in the nugget.

An analytic function describing the semivariance is required for the kriging analysis. The AUG 2003 data were fitted to a gaussian function. A gaussian function was chosen versus the traditional exponential function since ADAS uses a gaussian weighting scheme. Figure 2 displays the best fit values for the semivariogram parameters to a gaussian model. Diurnal effects for the individual parameters are noted with the range varying from 20 km to 60 km. It is apparent that a single semivariogram model could not be used for the kriging technique.

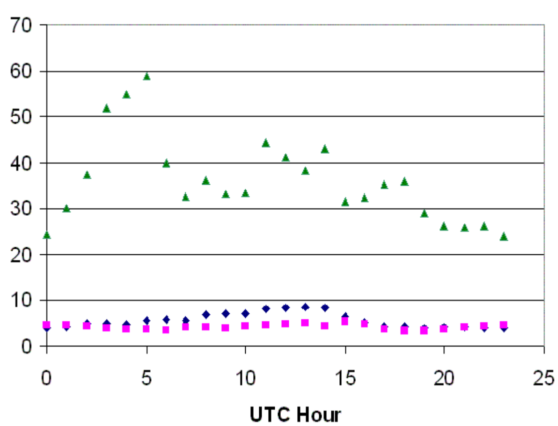

Fig. 2. A gaussian best fit to the semivariogram parameters from AUG 2003 data including the range (green triangle, km), sill (blue diamonds, deg^2), and nugget (pink squares, deg^2).

3) KRIGING: ERROR VARIANCE

Once an acceptable semivariogram has been chosen (a non-trivial step), the kriging analysis can be conducted using the departures at the observation locations. The reader is referred elsewhere for a thorough discussion of kriging (e.g. Issaks and Srivastava, 1989). Kriging relies on the semivariance function to optimize weights that are used to determine analysis values at grid points. The equation for kriging error variance for a grid point location is as follows:

$$S_e^{\,2} = \sum_{n=1}^{N} w_n \gamma(h_{np}) + \lambda$$

where N is the number of observation locations with temperature anomaly values, and the lag h is the horizontal distance between an observation point (n) and the analysis grid point (p). λ is a lagrange multiplier required due to the constraint that the estimator be unbiased. A modified version of a commercial software kriging analysis program was used to compute the kriging error variance at grid points. MesoWest station locations with the exact same horizontal location were removed from the analysis as this causes ill conditioning of the solution matrices for the kriging system. This constraint only caused a few data points to be excluded from the kriging error calculation.

An estimate of the Utah ADAS analysis temperature error for the MSO WFO region for 10 OCT 2003 1200 UTC is depicted in Figure 3. The estimated error variance in temperature anomaly ranges from the semivariogram nugget (4 deg^2) and the sill (12 deg^2) which were used for the model semivariogram for this realization.The kriging error is a function of station geometry, especially station density and the choice of semivariogram. The kriging error program can be run in a mode to use a sample variance rather than that specified by the semivariogram. In addition, a semivariogram could be calculated using only the data used in the kriging analysis, but there is a trade-off in terms of quality of the semivariogram when using fewer observation points to estimate this function. The appropriateness of the semivariogram will impact the reliability of the error estimates. The best approach might require diurnally varying semivariograms as a function of time of year, perhaps with monthly resolution. All temperature data were treated the same, though uncertainty likely varies some between networks.

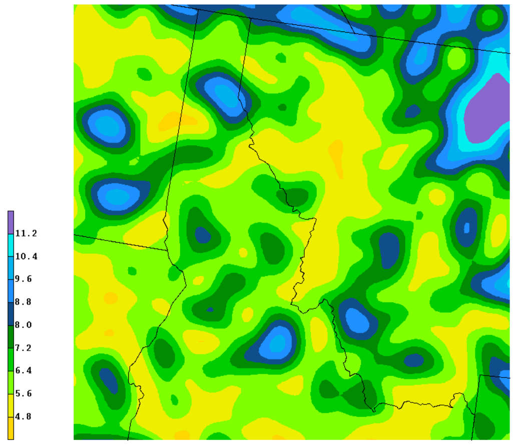

Fig. 3. Kriging error variance estimate for 10 OCT 2003 1200 UTC.

4) NORMALIZING THE SKILL SCORE

The analysis error estimate obtained via the kriging optimum interpolation method can be used to modify skill scores for the evaluation of forecast performance. The rational being that the penalty ought to be reflective of the observational uncertainty. Figure 4 depicts the difference between the NDFD (Glahn and Ruth, 2003) 12 hour forecast grid valid 10 OCT 2003 1200 UTC and the Utah ADAS analysis also valid at that time (subsampled to equal the 5 km resolution of the NDFD grid). The impact of complex terrain is quite obvious in this region with errors highly correlated along topographic features.

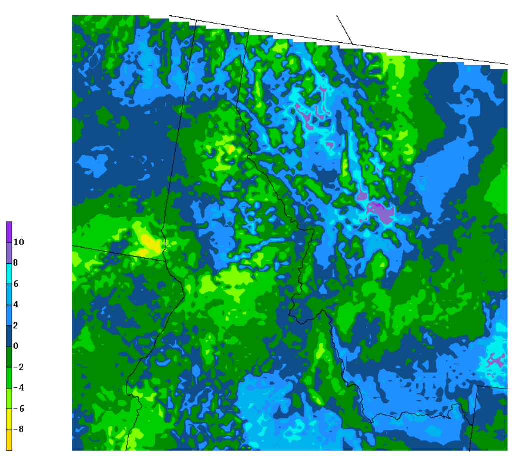

Fig. 4. Temperature difference between 12 hour forecast of temperature (from NDFD 5km grid) and ADAS analysis at 10 OCT 2003 1200 UTC.

Using the temperature difference between the two grids as a simple skill score for the quality of the temperature forecast, a modified skill score is generated by multiplying the temperature difference by a factor that weights the error more heavily if there is a lower observational error. The following normalizing factor was chosen to equal 2 when the observational for a grid point was equal to the nugget value (or the minimum possible analysis error) and equal to 1 when the equal to the sill (or the maximum possible analysis error).

$$Factor = 2 - (S_e^2 - nugget)/(sill)$$

Other approaches to modifying the skill score certainly could be used, this is just one possible approach used for the purpose of discussion.

Figure 5 depicts a modified skill score using this normalizing factor. Visual inspection may not reveal significant impact, though the complex terrain effects in this region add significant noise to the graphic. Ultimately, it is the culmination of longer time series of these type of statistics that are expected to provide insightful views on forecast validation rather than case by case examples. Interesting cases, though, can reveal limitations of the analysis schemes in extreme situations (e.g. strong frontal zones, etc.). The underlying statistical assumptions of the optimum interpolation approach used in this example may be violated in such situations, and this would include the application of the kriging error variance as a method to estimate the uncertainty in the gridded analysis.

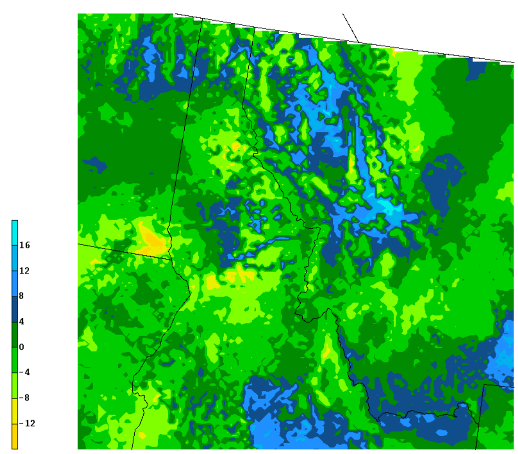

Fig. 5. A modified evaluation of forecast error based on the kriging error variance.

5) DISCUSSION

A method to incorporate observational error estimates in gridded forecast verification has been developed making use of the kriging error variance which is used as a proxy for estimating the error in the Utah ADAS gridded surface analyses. Only results for temperature were shown, but the approach is applicable to other surface meteorological variables. The semivariogram analysis provides insightful information that may be helpful in it's own right for tuning analysis parameters in ADAS (i.e., the weighting function). Since the surface analysis from the Utah ADAS incorporates 3 dimensional weighting and other factors such as proximity to water and an anisotropy factor, the Kriging error would only be a rough estimate of the actual analysis error. Cross validation methods could be used to estimate error, but are computationally expensive compared to the kriging approach and are also not perfect estimators of analysis uncertainty. Some level of cross validation would probably be beneficial to compare with Kriging estimates.

The kriging method used essentially accounts for data density and it is understood that the application of the kriging error variance has limitations that may make use of this approach problematic, but perhaps no more so than the use of optimum interpolation as an analysis and verification tool. The strong point of this approach is that grid point analysis values and observations are treated as quantities with a level of uncertainty, and this uncertainty is visibly quantifiable in the semivariogram. Other approaches to validation often use methods that fit an analysis exactly to observation values; essentially assuming no observational error and perfect certainty of analysis at grid point.

Skill scores based on observational error will be utilized over longer time records to evaluate if such error can impact forecast evaluation. It is possible that areas considered poorest in terms of forecast skill could change as a result of accounting for observational error. Testing of this approach in complex terrain may be the most severe test, and it is probable that the method may be more easily adapted or evaluated in areas with less severe topographical variations.

6) REFERENCES

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