4.3

PREDICTABILITY OF COASTAL WEATHER AND ITS IMPLICATIONS TO ENSEMBLE FORECASTING

Darko Koracin*, Ramesh Vellore*, John Lewis*#, and Michael Kaplan*
*Desert Research Institute, Reno, Nevada
#NOAA, Severe Storms Laboratory, Norman, Oklahoma

1. INTRODUCTION

Modeling atmospheric processes on regional and mesoscale is a challenging task due to high resolution treatment of topography, vegetation, soil, land use, and other geothermal parameters, as well as thermodynamic and turbulence processes. As a consequence of these complexities, one can expect that any model will have spatially dependent success in the predictions. Prior to setting up a regional and mesoscale ensemble forecasting system, it is valuable to investigate model performance on spatial and temporal scales. These results could potentially provide guidance on adjusting ensemble forecasting schemes.

One of the important questions to be addressed is whether there are areas in which forecasts are persistently under- or over-performing. The knowledge of spatial distribution of a previous model's success and understanding the reasons for this inhomogeneity can be helpful information in improving future forecasts. These issues are more pronounced when forecasting severe weather phenomena on global and regional scales. We have selected 3 cases of flood events over a span of 20 years in the western and southwestern U.S. to examine characteristics of the spatial model's success using the Global Forecast System (GFS) on a global scale and the Weather and Research Forecasting (WRF) model on regional scale. Most of the studies investigate the capabilities of either global or regional models separately; however, our preliminary analysis showed that it is worthwhile to examine them in parallel. In particular, we investigate the propagation of the model's error as a function of a forecast lead time for air temperature, zonal and meridional wind components, and relative humidity at five pressure levels. These results could eventually provide better understanding of the model's capabilities and limitations and lead to possibly more efficient techniques for ensemble forecasting.

2. SPATIALLY INHOMOGENEOUS FORECAST ACCURACY

Our study focuses on weather forecasting of the western U.S. including the eastern Pacific. An obvious question is how well the models can reproduce atmospheric complexity in the vicinity of the coastline and how much coastal radiosoundings can improve model initial conditions and consequently prediction accuracy.

The first step in the study was to simulate weather conditions for three flood events in the western U.S.:

- 11-21 February 1986
- 25 December 1996 – 4 Jan 1997
- 24 December 2005 - 3 January 2006

We used the WRF model with a horizontal resolution of 36 km and 173 x 153 x 36 grid points. Initial and lateral boundary conditions were obtained from the North American Regional Reanalysis archive. The simulations consist of 16 runs with a forecast length of 84-hr on the coarsest grid. Each of these 16 runs has 7 forecast times (84/12) and consequently there are 112 sample points at each of the grid points on the coarsest domain. We computed a correlation between the modeled and objectively analyzed temperature fields at 500 hPa at each grid point. A shade grade of the spatial correlation values for the entire simulation period is shown in Fig. 1.

Notice that there is a significant spatial variability of the correlation coefficient when comparing the WRF and NARR objective analysis. Two areas are significantly pronounced: southwest and northwest. These areas are regions of moisture advection from the southwest and frontal passages from the northwest. The spatial correlation coefficients for temperature at 500 hPa for all three runs are shown in Fig. 1.

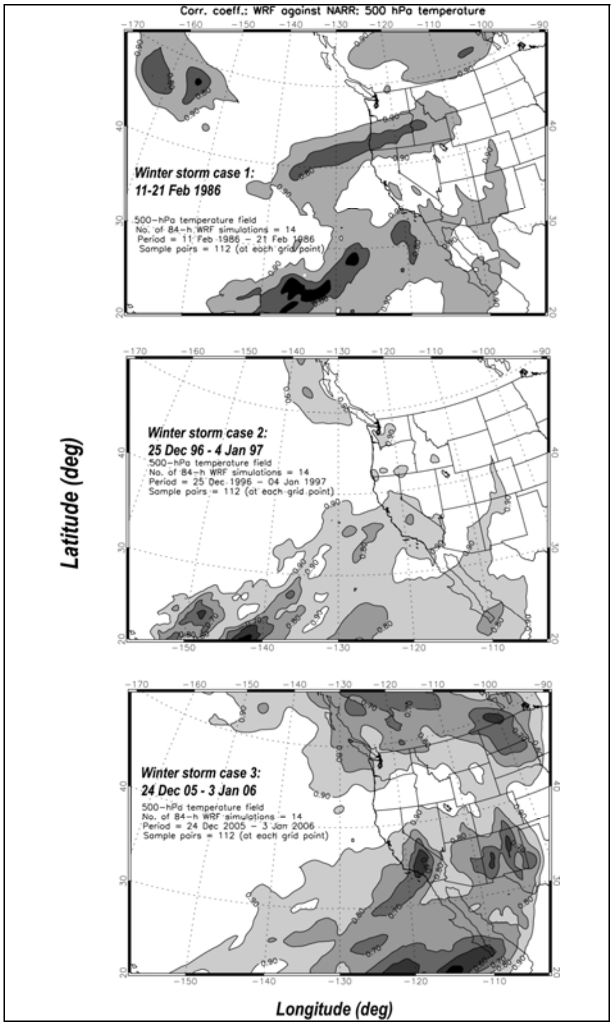

Fig. 1. Spatial distribution of the correlation coefficient for the temperature at 500 hPa between the sequential WRF 84-hr simulations for the periods: 11-21 February 1986 (upper panel); 25 December 1996 to 4 January 1997 (middle panel); and 24 December 2005 to 3 January 2006 (lower panel).

3. GROWTH OF ERRORS WITH THE FORECAST LEAD TIME

Although there are differences among these three cases distinctly separated in time, there are also similarities, especially in the southern part of the domain indicating the model's departure from the objective analysis. This brings up an interesting point of going back to the large scale model that was providing the initial and boundary conditions – in this case GFS – and examining the model's performance. To provide a sufficient statistical sample, we used GFS forecasts for two months: June and July 2008. GFS global forecasts archived at 1° × 1° grid resolution were obtained from the NOAA National Operational Model Archive & Distribution System (NOMADS; http://nomads.ncdc.noaa.gov). These forecasts from the global spherical grid were regridded to 36 km grid resolution on a Cartesian plane using a Lambert Conformal Projection centered at 39.417 N and 125 W. The forecasts were evaluated using data from 39 radiosonde stations in the western U.S. (Fig. 2).

The root-mean square errors (RMSE) were computed against the forecast lead time (Fig. 3) at each radiosonde location. Ideally there would be 26,325 pairs of model and radiosonde data (i.e., 39 stations × 45 forecast cycles × 15 forecasts within each 180 hr run) at five standard pressure levels (300, 500, 700, 850 and 925 hPa). Of the data pairs, after eliminating the missing data, there were 1050*15 pairs available for the 925 hPa, 1450*15 pairs for the 850 hPa, and 1700*15 pairs for the 700, 500, and 300 hPa pressure levels for the statistical verification. Figure 3 shows the RMSE as a function of the forecast lead time for June and July 2008.

There is noticeable similarity between the results for June and July with an almost linear increase of the RMSE with the lead time. Regarding the winds, larger magnitudes at higher levels cause larger RMSE (≈ 0.6 ms^{-1}/12 hr lead time). For the temperature the error growth is in a narrower band. The larger errors at the lower levels are due to a poor representation of the PBL (≈ 0.2 K/12hr lead time). Relative humidity shows the highest error at the highest level with a large initial condition error (35-45%). Other upper levels (500 and 700 hPa) show higher errors and somewhat higher error growth (1.3%/12hr lead time) in both months compared to lower levels (0.7%/12hr lead time).

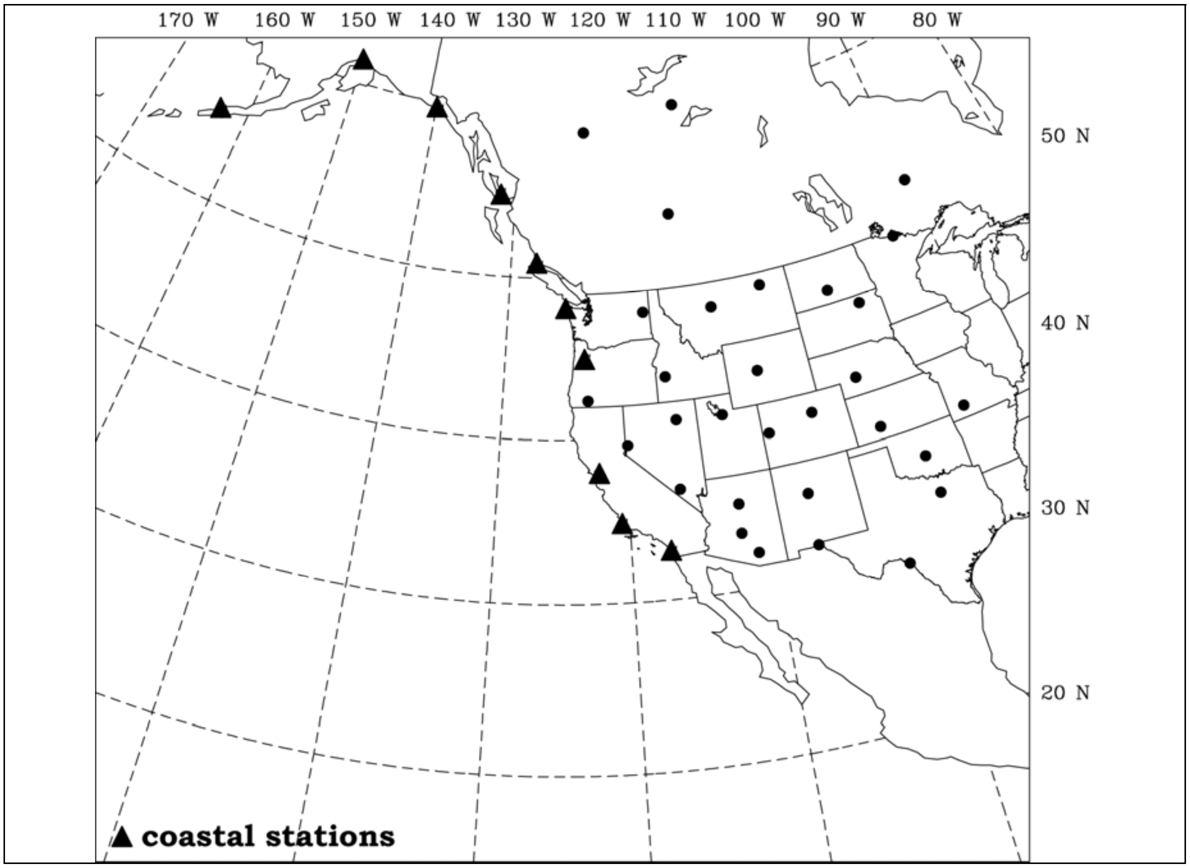

Fig. 2. Map with indicated radiosonde locations used in the analysis. Selected coastal stations are indicated by triangles.

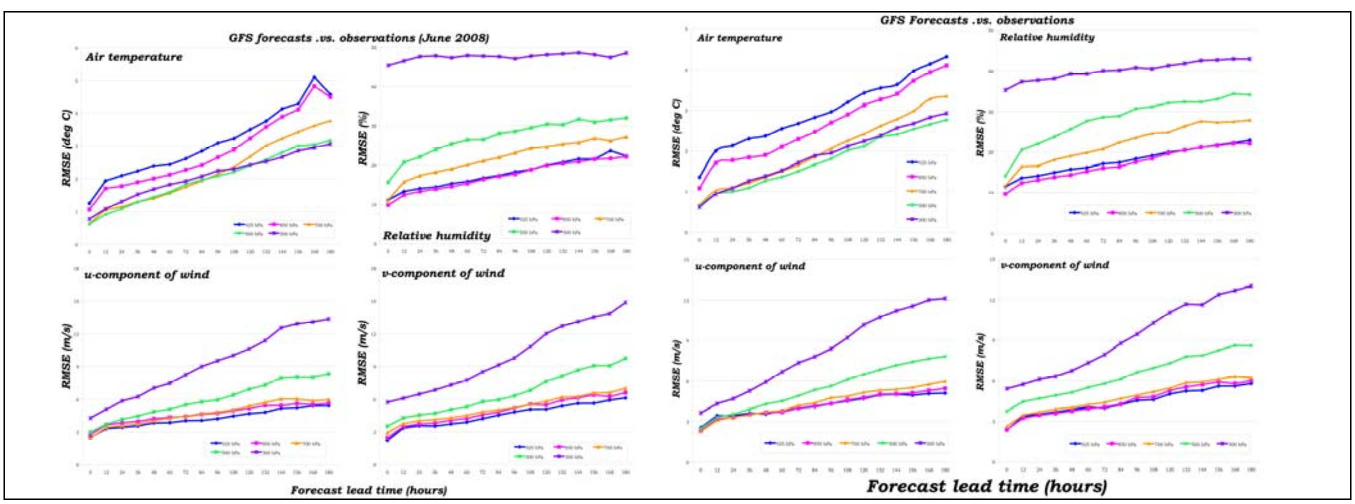

Fig. 3. Root-mean square error (RMSE) for the air temperature, zonal and meridional wind components, and relative humidity as a function of lead time for June (left panels) and July (right panels) 2008.

4. COASTAL EFFECTS

Figure 4 shows GFS-predicted temperature RMSE at 500 hPa as a function of the forecast lead time for July 2008. Results are given for using all radiosonde data (left panels) and only coastal stations (right panels).

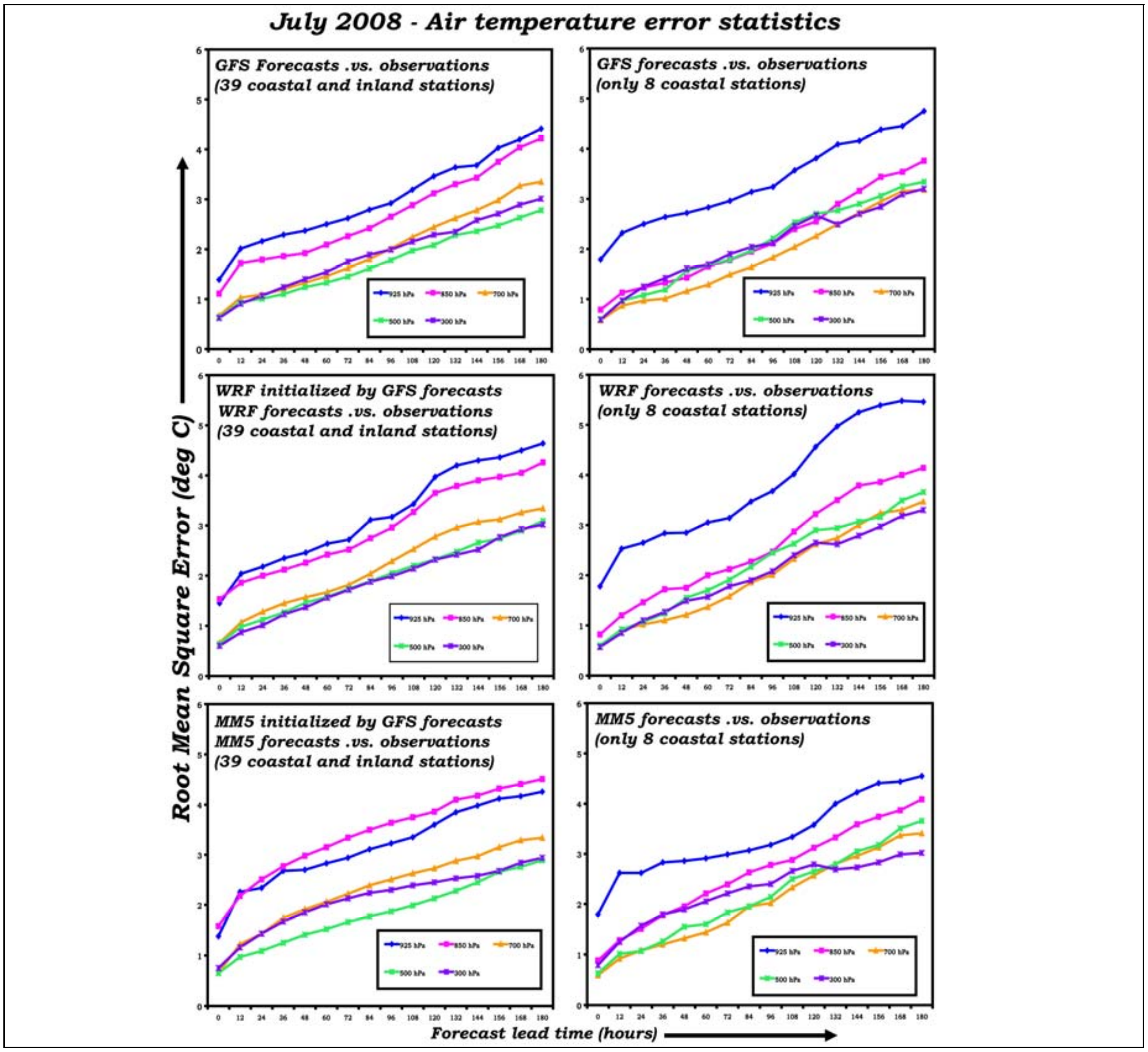

Fig. 4. The root-mean-square error of the temperature as a function of lead time for GFS (upper panels), MM5 (middle panels), and WRF (lower panels) using data from radiosondes in the western U.S. for July 2008. Left panels include the RMSE calculated using data from all considered radiosondes and right panels include only coastal and near-coastal radiosonde data (see Fig. 2 and the text).

Notice that the RMSE behavior for MM5 and WRF is similar to GFS. To a certain extent this is expected since MM5 and WRF were using GFS forecasts for initial and boundary conditions. However, the regional scale models generated very similar statistics. All three models have problems at lower elevations. This is more pronounced at the coastal station locations due to poor representation of the PBL and coastal complexity. Inland topographic complexity causes larger errors overall at 850 hPa for all stations compared to only coastal stations.

Figure 5 shows the RMSE statistics for the zonal wind component.

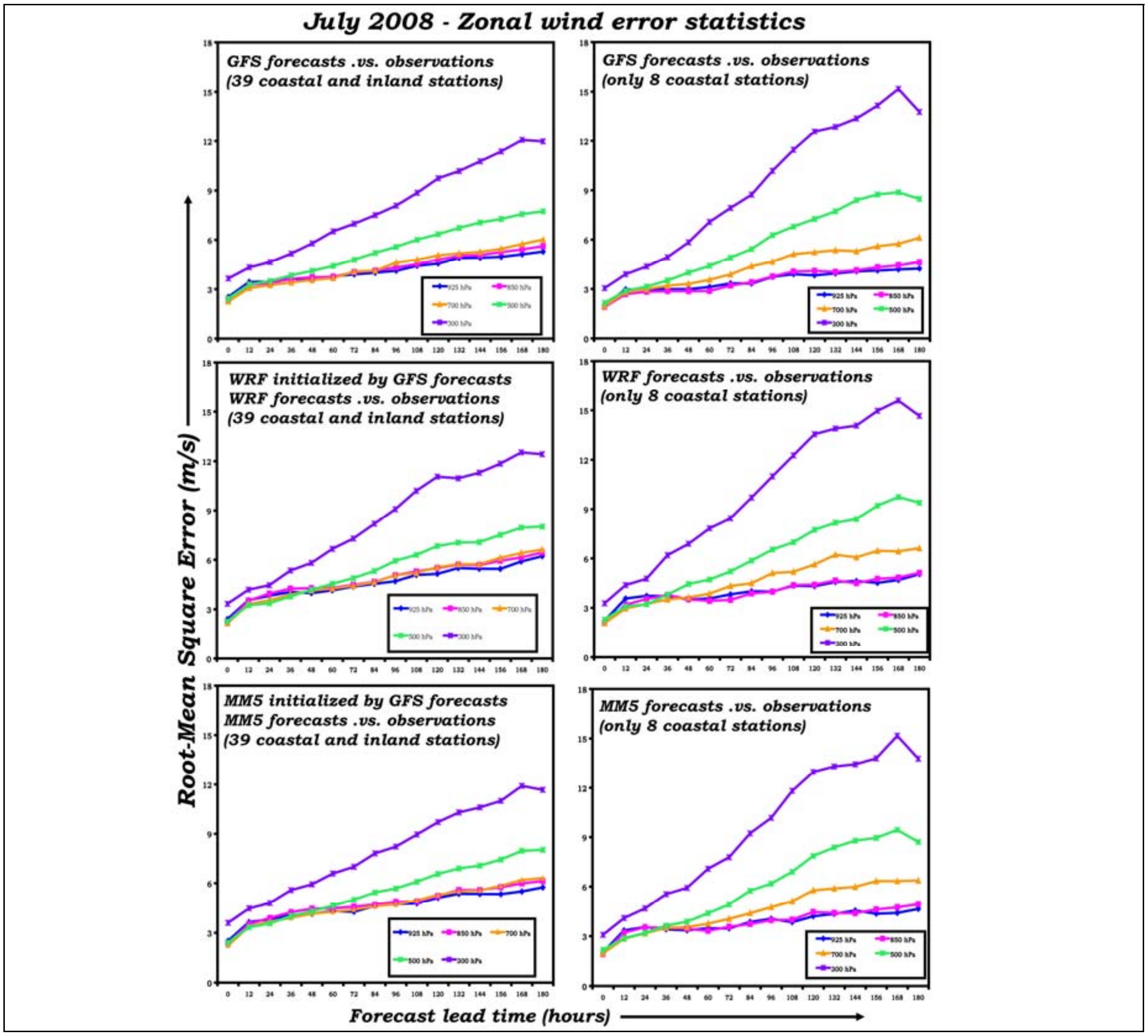

Fig. 5. The root-mean-square error for the zonal wind component as a function of lead time for GFS (upper panels), MM5 (middle panels), and WRF (lower panels) using data from radiosondes in the western U.S. for July 2008. Left panels include the RMSE calculated using data from all considered radiosondes and right panels include only coastal and near-coastal radiosonde data (see Fig. 2 and the text).

At these resolutions the monthly error statistics appears to be similar for all models. Error magnitude and growth is reversed with respect to height compared to air temperature (the greatest errors and growth are at the highest elevations due to the large magnitude of the winds at higher elevations). Errors are somewhat more pronounced at the coastal stations at mid levels due to the complexity of flow adjustment approaching the coastline. At the lower levels, all models tend to keep RMSE around 3 ms^{-1} with a very slow growth trend.

5. SEASONAL MODEL SUCCESS

Figure 6 shows the GFS RMSE as a function of lead time for the winter (December 2007-February 2008) and the summer (June – August 2008) using data from 39 radiosonde stations.

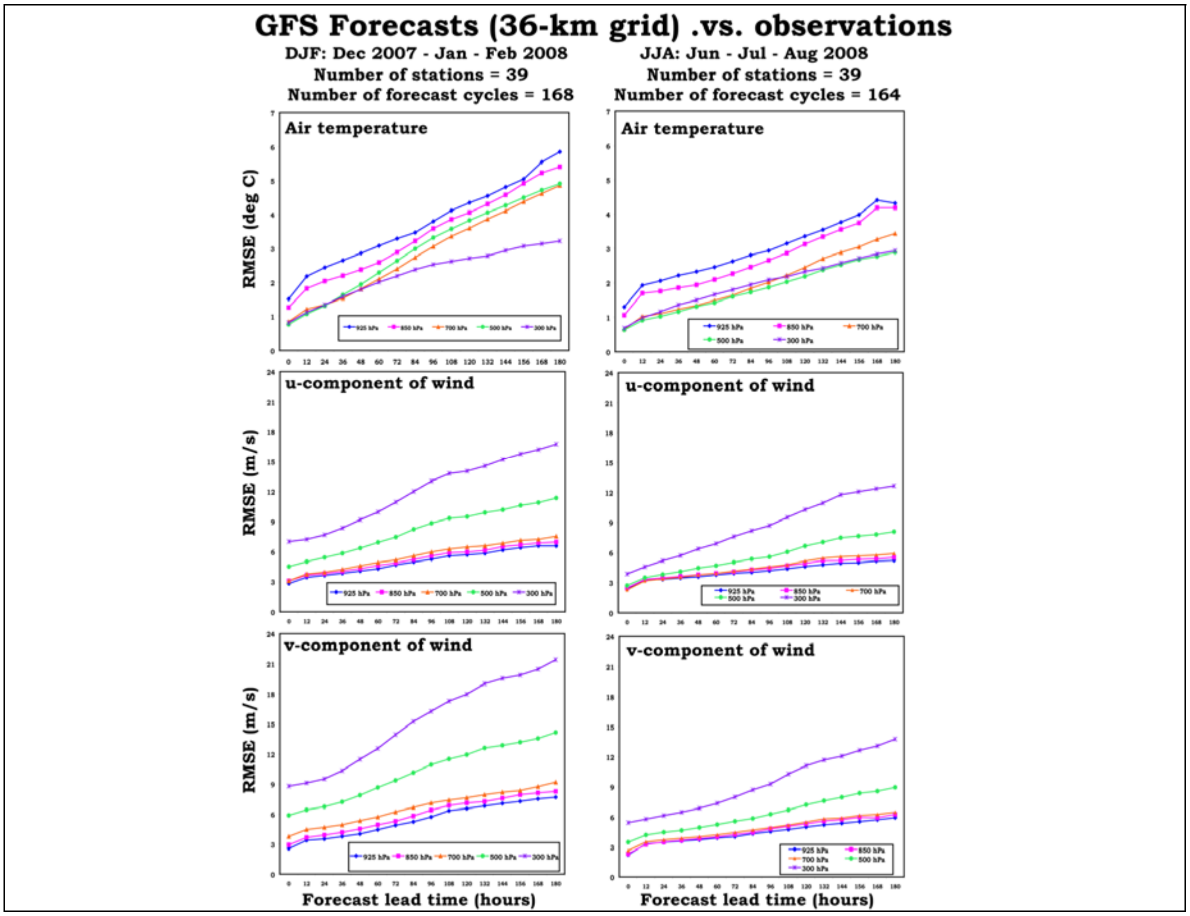

Fig. 6. The root-mean-square error for the air temperature as a function of lead time for GFS for winter (left panels) and summer (right panels) months of 2008 using data from radiosondes in the western U.S. (see Fig. 2 and the text).

For each 3-month period there are 3650*15 pairs of observations and model results at 925 hPa, 5000*15 pairs at 850 hPa, and 5950*15 pairs at 700, 500, and 300 hPa. As expected, the model success is much better in the summer, with usually slow developing and stagnant weather patterns, while in the winter the success is lower due to transient pressure systems and frontal passages. The same reverse picture is shown in Fig. 6 as in the case of the monthly statistics (Fig. 3) with the temperature having higher errors at lower elevations (PBL complexity and higher magnitudes) while the winds are having higher errors at higher elevations (larger magnitude of the winds aloft).

Figure 7 shows the error analysis differences among the three model results for the winter (December 2008) and the summer (July 2008). The analysis includes 1050*15 pairs of observations and forecasts for the 925 hPa level, 1450*15 pairs for the 850 hPa level, and 1700*15 pairs for the 700, 500, and 300 hPa levels.

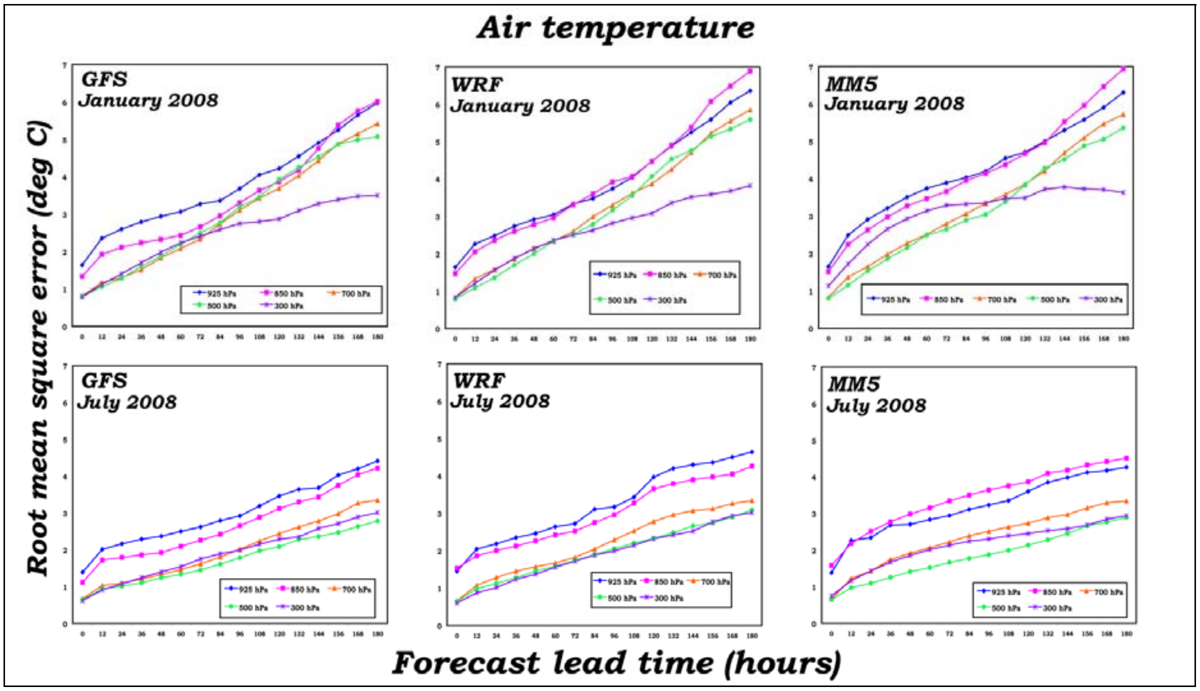

Fig. 7. The root-mean-square error for the air temperature as a function of the forecast lead time for a winter month (upper panels) and a summer month (lower panel) 2008 for: GFS (left panels), WRF (middle panels), and MM5 (right panels). The data from radiosondes in the western U.S. were used for the analysis (see Fig. 2 and the text).

The regional models show the same behavior as the global model with significantly higher RMSE in the winter month compared to the summer month. It is interesting that WRF and MM5 show somewhat larger errors in the winter compared to GFS, which should be investigated further.

6. CONCLUDING REMARKS

Root-mean-square-error statistics for the GFS, WRF, and MM5 models was performed for flood event, monthly, and seasonal samples using data from 39 radiosonde stations and the North American Regional Reanalysis (NARR) archive as a baseline.

WRF simulations of the three flood events and evaluation using the NARR results indicated in all cases spatially inhomogeneous correlations with some areas prone to a lower model success. Advection from the NW and W-SW show systematically lower correlation compared to the rest of the area. However, this could be partially an artifact of the re-analysis fields, since they are not purely measurements and would require further analysis and complementary evaluation.

Monthly comparison between the global model (GFS, 1^0 x 1^0 resolution) and two regional models (WRF and MM5, 36 km resolution) showed that the regional models are not superior to GFS at these resolutions. A question remains what resolution is needed of the regional/mesoscale models to provide significantly better results than the global models.

Seasonal statistics confirms the conclusions from the monthly statistics and indicates that the differences among the seasons are larger than the differences among the models for each season. Both seasonal and monthly statistics shows that the temperature RMSE is persistently larger at lower levels and the winds RMSE is larger at higher levels.

Coastal effects appear to not be dominant in the overall error statistics. Major error generation in the coastal zone is at the lowest level due to problems in resolving the marine boundary layer and the air-sea interaction. The complexity of inland topography makes the strongest impact on the overall error growth.