P3.8 APPLICATION OF SCALE-RECURSIVE ESTIMATION TO ENSEMBLE FORECASTS: A COMPARISON OF COARSE AND FINE RESOLUTION SIMULATIONS OF A DEEP CONVECTIVE STORM

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1. INTRODUCTION

Traditional quantitative precipitation forecasting (QPF) verification methods (e.g., threat score, equitable threat score and bias, as well as linear correlation coefficient and RMS error) are arguably limited owing to the tremendous scale-dependent variability of precipitation (Tustison et al. 2001), thus making the comparison of observations and model forecasts at different scales problematic. The challenge amplifies in the context of ensemble forecasting.

A new methodology, based upon statistical multi-scale analysis of precipitation and optimal estimation theory and called scale-recursive estimation (SRE) (Chou et al. 1994; Tustison et al. 2003), is proposed in this study to ensemble precipitation forecasts. The goals are twofold: 1) To evaluate the relative performance of multi-scale ensemble forecasts, and 2) to assess the usefulness of SRE in generating stochastic realizations of high-resolution precipitation forecasts from coarse-resolution ensembles, in conjunction with high resolution radar observations.

Ensemble forecasting has proven valuable in medium-range global model forecasts (6-10 days) and now is a foundation in major operational forecast centers around the world (Kalnay 2003). Short-range ensemble forecasting (SREF, ~40 km resolution, 1-3 days) with limited-area models has been underway for some time (Brooks et al. 1995; Du and Tracton 2001; Hamill et al. 2000; Hou et al. 2001), and interest now is growing in storm-scale ensemble forecasts (Sindic-Rancic et al. 1997; Elmore et al. 2003; Levit et al. 2004). Still, the effectiveness of the stochastic-dynamic approach on the storm-scale has yet to be fully explored, particularly the degree to which theories of error growth and initial condition specification at larger scales apply to smaller ones.

In this study, the Advanced Regional Prediction System (ARPS) is used to produce multiple-resolution ensemble forecasts of a tornadic thunderstorm complex that occurred in the vicinity of Fort Worth, TX on 28-29 March 2000. A five-member scaled lagged average forecasting (SLAF) ensemble (Ebisuzaki and Kalnay 1991) is generated for each resolution ranging from coarse (24 km) to fine (storm-scale, 3 km). A single forecast at fine resolution (3 km) also is generated. SRE is then applied to merge the model precipitation output by blending the coarse resolution ensembles with statistical information from the fine resolution forecast and/or high resolution NEXRAD Level-II radar data (remapped to 1.5 km grid-scale ARPS domain) to form a precipitation estimate with statistical information comparable to a more expensive fine-resolution ensemble forecast.

This extended abstract primarily presents the ARPS ensemble forecasting work. The SRE effort is still underway and findings from the study will be presented at the conference. Only the theory part is described in Section 5.

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2. STORM CASE DESCRIPTION

The 28-29 March 2000 Fort Worth, TX tornadic thunderstorm case was selected because it has been well documented and simulated successfully with the ARPS model (Xue et al. 2003). These storm complex produced two tornadoes between 0015 and 0045 UTC on 29 March with maximum winds over 115 mph. One tornado struck the downtown Fort Worth area for about 15 min, causing two deaths, many injuries and extensive damage to buildings. Torrential rain produced flooding, and softball-size hail caused several casualties. Figure 1 shows the lowest tilt of reflectivity from the Fort Worth WSR-88D (KFWS) at 0000 UTC on 29 March. A broken line of supercells is evident across the region.

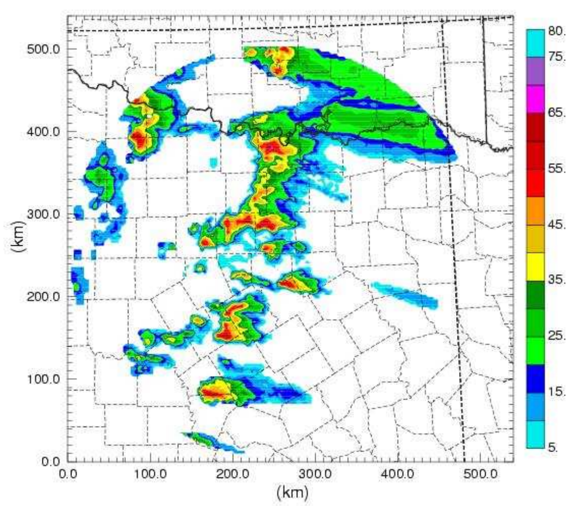

Figure 1. Fort Worth (KFWS) WSR-88D reflectivity at 0000 UTC on 29 March 2000.

The operational Eta model (not shown) predicted no precipitation south of Red River in the 12 hours prior to 0000 UTC on 29 March, presumably due to its coarse grid spacing and other limitations. Readers are referred to Xue et al. (2003) and Levit et al. (2004) for more information regarding the storm environment.

3. EXPERIMENT CONFIGURATION

Because storm-scale forecasting generally requires very fine horizontal grid spacing (1-3 km), nested grids must be used. In this study, we employ triple nesting (Figure 2). Owing to the preference by SRE of a factor of 2 differences in spacing between adjacent grids, we use 24-km, 6-km, and 3-km spacing for the coarse, medium, and fine resolution domains, respectively. The fine 3-km domain is centered over Fort Worth with sufficient coverage for the features of interest. The numbers of horizontal grid points are shown in parentheses in Figure 2. All use 53 terrain-following vertical layers, with nonlinear stretching from 20 m at the ground to approximately 800 m at the top.

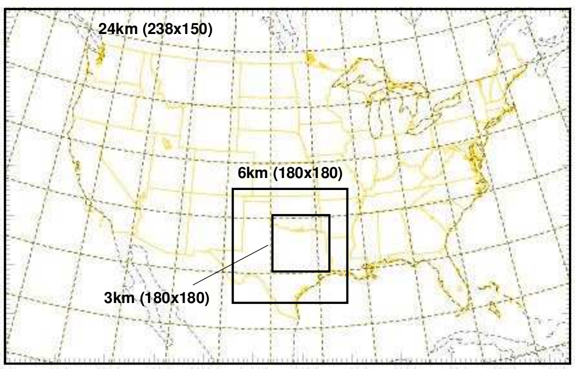

Figure 2. Domain configuration, with horizontal grid spacing and array dimension shown for each nested grid.

Several approaches are available for creating ensemble initial conditions, e.g., Monte-Carlo (random perturbations), breeding of growing modes, lagged average forecasting, singular vector, and physics perturbation (Hamill et al. 2000; Kalnay 2003). Similar to the work reported by Levit et al. (2004) in this volume, we employ SLAF (Ebisuzaki and Kalnay 1991).

For each nested domain, a 5-member SLAF ensemble (one control forecast plus 4 perturbed members) is generated. To construct the latter, the perturbation between a previous ARPS forecast and the current analysis is scaled based upon time (error growth) and then added to and subtracted from the analysis to form two (paired) members. A 5-member SLAF requires two successive previous ARPS forecasts.

Figure 3 shows how the 24-km SLAF ensemble is constructed. P1 and P2 represent two previous forecasts initiated using the NCEP Eta analysis at 0600 UTC and 0000 UTC 28 March, respectively. P0 is initiated at 1200 UTC the same way and serves as the control run. The ARPS Data Assimilation System (ADAS) (Brewster 1996) is used to produce gridded initial conditions for P0, P1, and P3. Observations analyzed include surface reports, wind profiler and rawinsonde data, ACARS commercial aircraft wind and temperature data, GOES visible and IR data, and Oklahoma Mesonet data. No radar data are used for 24-km domain.

Forecast members s1 and s2 are generated using perturbations between P1 and P0; while s3 and s4 are do the same from P2 and P0. The 5 members (P0, s1, s2, s3, and s4) are integrated under the same conditions, each generating 18 h forecasts. Lateral boundaries are always perturbed in a manner consistent with the initial conditions.

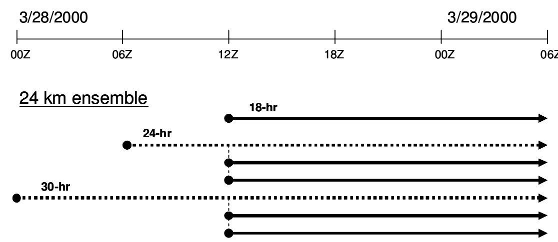

Figure 3. Diagram showing 24-km SLAF construction.

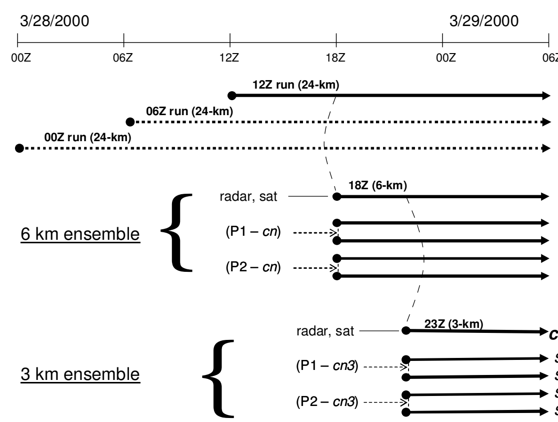

Figure 4. Construction of the 6-km and 3-km ensembles.

Nested grids complicate the construction of ensemble forecasts because no unique strategy exists to link the grids. Thorough experiments are underway to address this issue, and we employ here a very a simple approach (Figure 4). Only the control runs of the 6-km ensemble (cn) and 3-km ensemble (cn3) are nested successively from the coarser grids, as indicated with the curved dotted arrow. WSR-88D Level III reflectivity data are included in the ADAS analysis in addition to other observation data.

The perturbed members are constructed directly for the two previous 24-km ARPS forecasts (interpolated onto 6-km and 3-km grids, respectively) and the current analyses on the finer grids (cn and cn3). For both the 24-km and 6-km ensembles, the Kain-Fritsch (Kain and Fritsch 1993) cumulus parameterization scheme and explicit ice-phase microphysics are used. For the 3-km ensemble, only the explicit microphysics scheme is applied.

4. ENSEMBLE RESULTS

In this section we present results from the 24-km ensemble and 3-km ensemble forecasts.

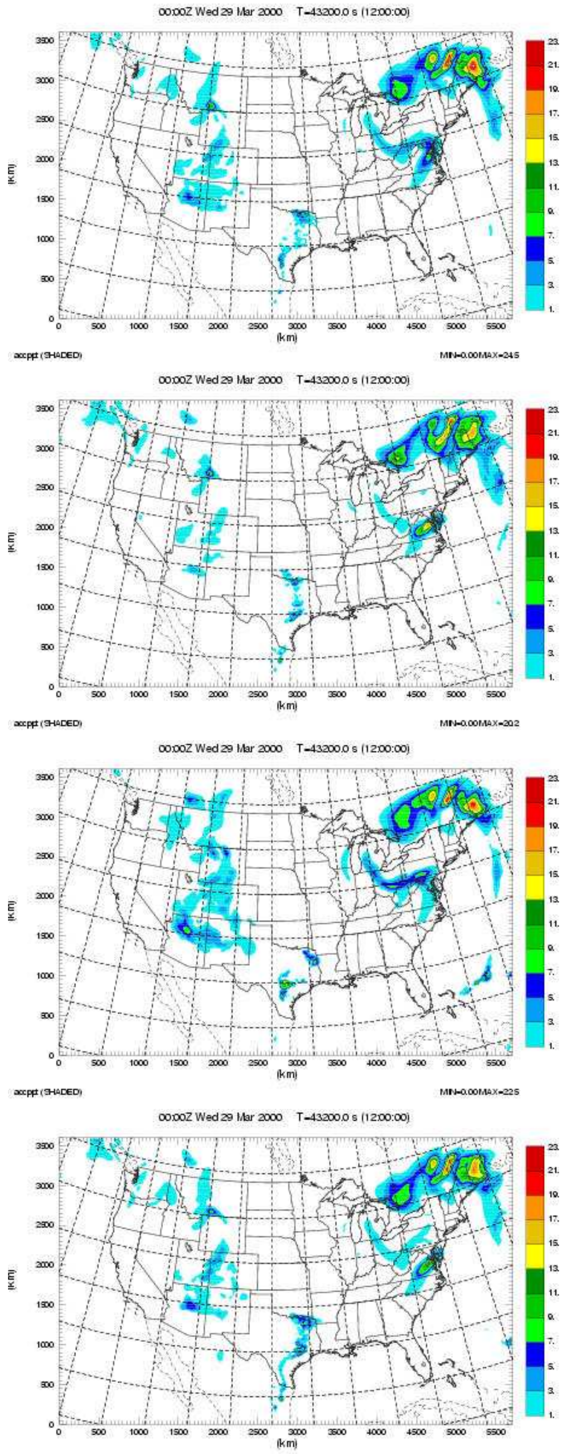

Figure 5. (continued)

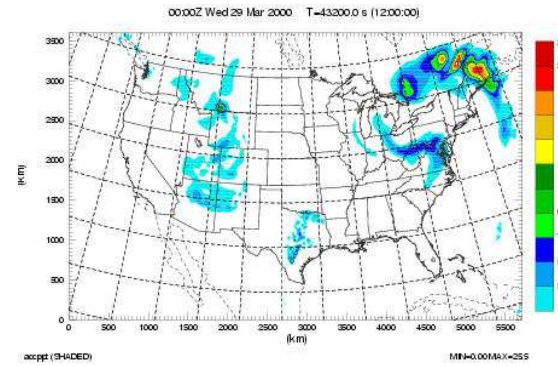

Figure 5. 3-h accumulated rainfall valid at 0000 UTC on 29 March 2000 from individual 24-km ensemble members (from top to bottom: P0 (cntl), s1, s2, s3, and s4).

The predicted 3-h accumulated rainfall from the five ensemble members at 24-km grid spacing is shown in Figure 5. Each member exhibits diversity and captures the major precipitation systems.

Figure 6 shows the conditional probability of precipitation based upon the five ensemble members shown above. It compares reasonably well with the Stage IV rainfall map, especially over the Fort Worth region (Figure 9), though with notable disagreement over far northeast and southeast Texas.

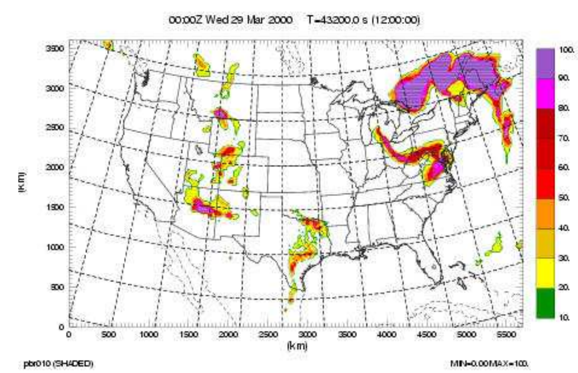

Figure 6. Probability of 3-h rainfall exceeding 0.1 inch based upon the 24-km ensemble forecast valid at 0000 UTC 29 March 2000.

The hourly rainfall predicted from each 3-km ensemble member is presented in Figure 7, along with the ensemble mean. Not surprisingly, the 3-km ensemble contains significantly greater detail compared to its 24-km counterpart, and generally agrees more closely with reality (cf. Figures 1 and 9).

Figure 8 presents the 3-km ensemble conditional probabilities of rainfall exceeding 0.1 and 0.5 inches for the 1-hour forecast. The maxima in probability are reasonably well aligned with the rainfall cores in the Stage IV rainfall map in Figure 9, and with the reflectivity shown in Figure 1.

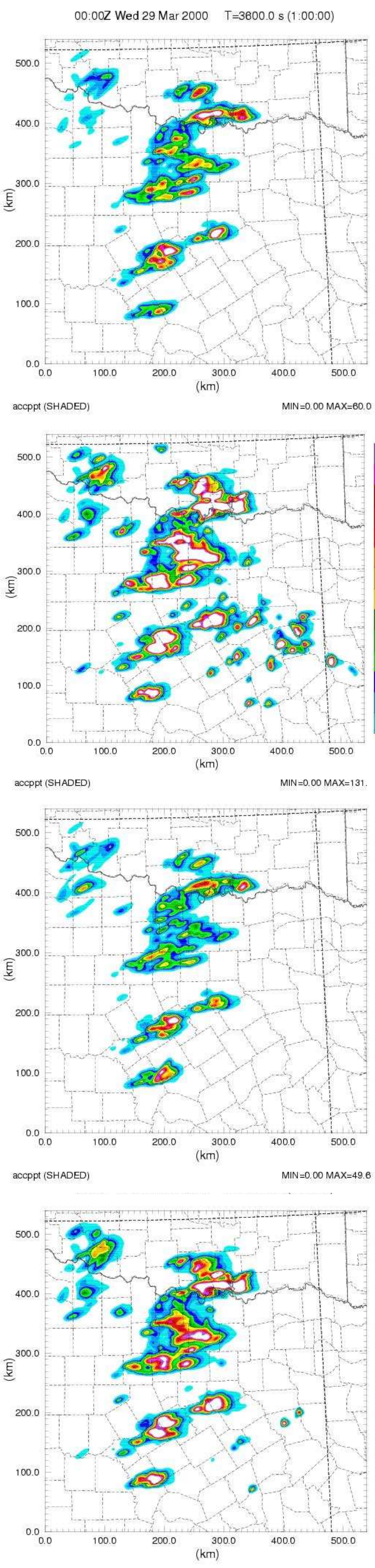

Figure 7. (continued)

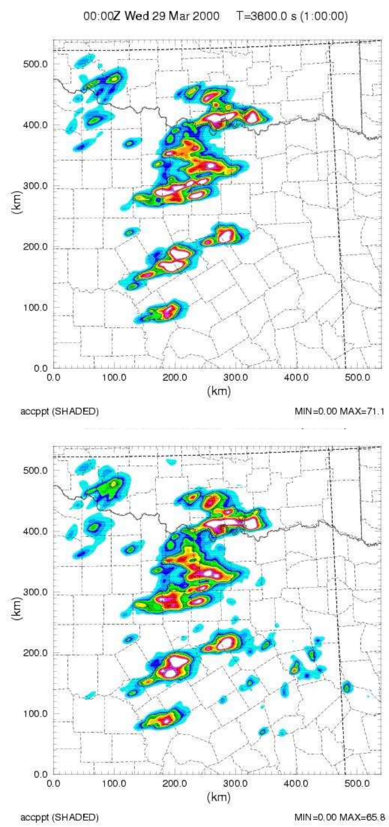

Figure 7. Hourly accumulated rainfall valid at 0000 UTC 29 March 2000 from individual 3-km ensemble forecasts (from top down: cn3, s1, s2, s3, and s4), along with the ensemble mean (the bottom plot).

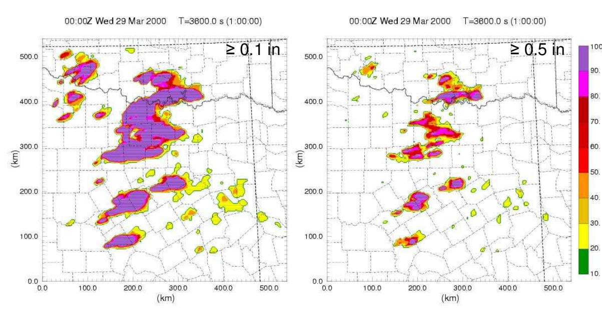

Figure 8. Conditional probabilities of accumulated rainfall exceeding 0.1 and 0.5 inches from the 1-hour, 3-km ensemble forecast.

At 3-km grid spacing, convection is explicitly resolved by the microphysics scheme, though this grid spacing is toward the upper limit of that deemed practicable for application to deep convection. Owing to the spatially intermittent nature of deep convection, the ensemble mean reflectivity forecast covers a much broader area than any of the individual forecasts, and each storm tends to be much weaker. For this reason, only conditional probabilities of surface reflectivity exceeding 35 dBZ and 45 dBZ are shown in Figure 10. They compare very favorably with the WSR-88D (KFWS) reflectivity in Figure 1. The low probability echoes over the southeastern portion of the domain are not shown in KFWS radar.

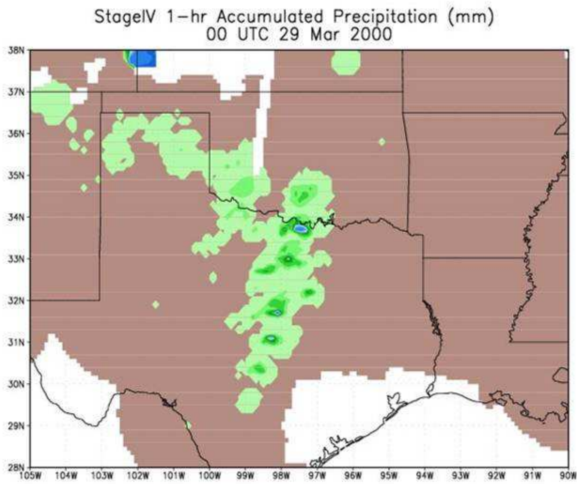

Figure 9. Stage IV hourly rainfall valid at 0000 UTC 29 March 2000.

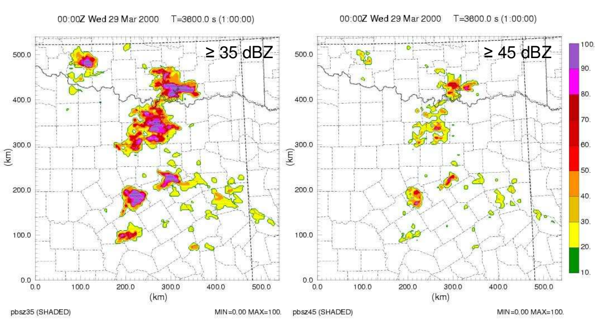

Figure 10. Probability of surface reflectivity greater than 35 dBZ (left) and 45 dBZ (right) from the 3-km ensemble valid at 0000 UTC 29 March 2000.

5. SCALED-RECURSIVE ESTIMATION - THEORY

The proposed methodology utilizes stochastic scale-recursive estimation (SRE) technique introduced by Chou et al. (1994). This technique, whose essence is derived from (similar to) Kalman filtering, can optimally merge observations of a process at different scales while explicitly accounting for their uncertainties and variability at all scales. It requires the specification of a model (called multiscale model) describing how the process variability changes with scale. A multi-scale process can be represented via an inverted tree structure, as illustrated schematically in Figure 11. This tree can essentially be viewed as a way of connecting information about the process at different scales. Each node on the tree corresponds to a unique combination of scale and spatial location, and is given a location index λ. The quantity $\gamma\lambda$ is used to specify the value falling directly above that node on the next coarser spatial scale of the tree (called the parent node).

The representation of a multi-scale process on the inverted tree is achieved via a governing **state-space equation** that specifies how the state at one scale relates to the state at other scales, i.e., the state-space recursive equation specifies how the multi-scale process evolves from coarse $\gamma\lambda$ to fine (λ) scale. Along with the estimate of the state, we are also interested in the **scale-to-scale propagation of its variance** in order to determine the uncertainty of the estimates.

In order to incorporate the measurements of a process at different scales into this framework, it is necessary to form a **measurement model** that relates the measurements and the state of the system at a given location. The measurement model incorporates the measurement uncertainty that may change with sensor and scale, as, for example, would be the case for rain gauges, radars, and satellites. The state-space equation, variance propagation equation, and measurement model equation form the basic framework of SRE.

The SRE algorithm consists of two steps: filtering and smoothing. The filtering step (upward sweep) consists of initialization, measurement update, variance propagation and merging. The second step (downward sweep) consists of smoothing, which allows the exchange of information between nodes of spatial proximity. Figure 11 illustrates the inverted tree, the methodology by which measurements are placed on the tree for inclusion in the multi-scale estimation, and the upward and downward sweeps. The details of the SRE algorithm can be found in the original work of Chou et al. (1994), and also in Kumar (1999), Primus (1996) and Tustison et al. (2003).

The relevance of the SRE technique to QPF verification is that SRE can optimally combine the observations to a single product at any desired scale, and, in addition, provide an estimate of the uncertainty of this product. By choosing the desired scale to be the scale (grid size) of the forecast model, one reduces the problem of QPF verification from multiple sensors to an easier problem of comparing two fields (merged observation product and model output) at the same scale. Moreover, this comparison can be made in a more meaningful way since the uncertainty of the merged product is also known (probabilistic comparison).

The effort to apply SRE technique to merge the precipitation forecasts data from the ARPS multiple resolution ensembles presented in previous sections and the high resolution WSR-88D radar observations is currently underway. The findings from this application will be presented at the conference.

6. SUMMARY

The Advanced Regional Prediction System (ARPS) was used to produce multiple resolution ensemble forecasts for the Fort Worth, Texas tornadic thunderstorm case. A five-member ensemble was generated using the SLAF technique at grid spacings ranging from coarse (24 and 6 km) to fine (3 km). Though very simple, the SLAF ensembles do show very promising storm scale forecasting skill.

The suitability of scale-recursive estimation (SRE) for generating statistical realizations of fine-scale forecasts from coarse resolution forecasts and fine-scale radar observations will be examined and presented at the conference. The proposed approach is to apply SRE method to merge model precipitation output by blending the coarse resolution ensembles with statistical information from the fine resolution forecast and/or high resolution NEXRAD Level-II radar data (remapped to 1.5 km grid-scale ARPS domain) to form a precipitation estimate with statistical information comparable to a more expensive fine resolution ensemble forecast.

7. ACKNOWLEDGMENTS

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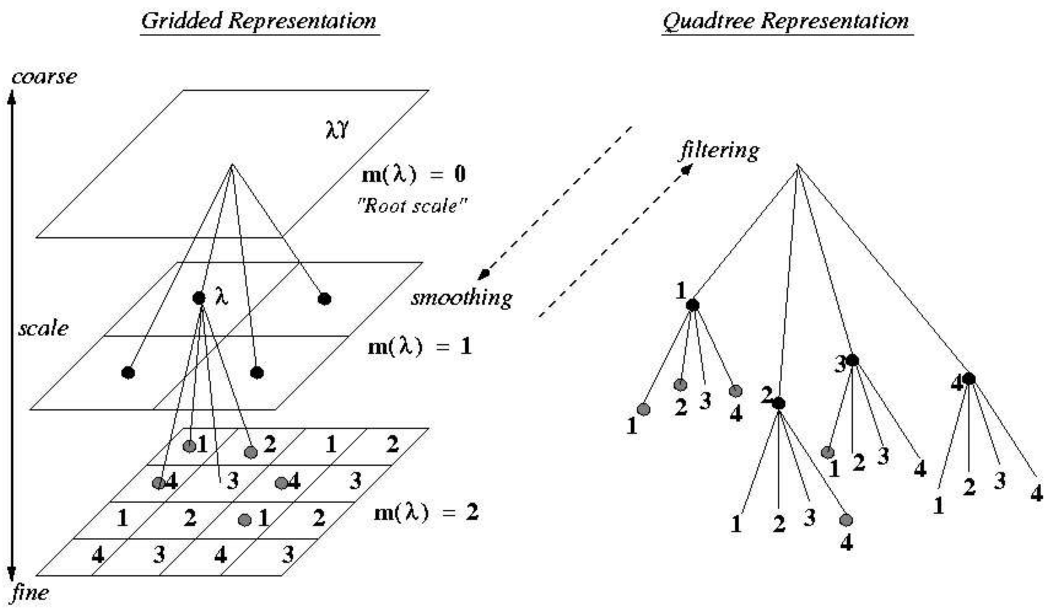

Figure 11. Illustration of the scale-recursive estimation technique applied to precipitation measurements. Sparsely-distributed measurements at one scale (gray dots), and measurements at a coarser scale (solid dots), are placed on an inverted quad-tree and merged via filtering and smoothing to obtain estimates at multiple scales (adapted from Tustison et al., 2003).

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