The COMET Outreach Program
Final Report

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Title: “Use of Mesoscale Ensemble Weather Predictions to Improve Short-Term Precipitation and Hydrological Forecasts”

Collaborative Project: UCAR Award No: S07-66814

Date: March 28, 2010

1. Summary of Project Objectives

The primary objective of this project was to develop tools and approaches that will improve short-term (< 48 hour) hydrologic watches, warnings and forecasts issued by NOAA’s National Weather Service (NWS). This project utilized a multi-model short-range atmospheric ensemble system with operational hydrologic models. We hypothesized that the skill of the atmospheric ensemble system can be increased through using a multi-model ensemble, bias correction, and weighting selected members based on previous performance. Our experimental basin was the Passaic River Basin in northern New Jersey during the warm season using NCEP’s short range ensemble forecast (SREF) system (21 members) and Stony Brook University (SBU) WRF and MM5 SREF (13 members).

2. Project Accomplishments/Findings

a. Post-processing of multi-model ensemble precipitation forecasts

<u>1. Short-range ensemble datasets and approach</u>

A common problem with predicted ensemble state variables is their consistent underdispersion and vulnerability to systematic and conditional biases. Combining ensembles from different operational centers has been shown to somewhat offset this problem and improve ensemble probabilistic scores (Ebert 2001). This study created a multi-model ensemble (34 members) by combining the 13 Stony Brook University (SUNY-SB) members run at 12 km grid spacing over the Northeast U.S. with the 21-member NCEP SREF run between 32 and 45 km grid spacing. The SUNY-SB ensemble consists of seven MM5 and six WRF members with a variety of model physics parameterizations (planetary boundary later, cloud microphysics and convection) and initial conditions (GFS, NAM, CMC, and NOGAPS) The NCEP SREF contains four different model cores (RSM, WRF NMM, WRF ARW, and ETA), with additional members created through perturbing the initial conditions. The SREF ensemble has not been combined and studied with other ensembles, making this multi-model ensemble unique.

Despite the added benefit of including additional ensemble members to the NCEP SREF, as will be shown below, this multi-model ensemble is still largely underdispersed and conditionally biased for many variables. Bayesian model averaging (BMA) has been shown to correct dispersion and reliability issues common to ensembles. BMA creates a probability density function (PDF) for each ensemble member centered on individual bias corrected forecasts and weights each member based on its uniqueness and accuracy in the recent past. Stony Brook implemented a statistical approach to post-process ensemble forecasts based on BMA to the MM5 and WRF members as well as SREF during the 2007-2009 warm seasons (May to August). BMA was applied to the 18-42 h accumulated precipitation of the multi-model ensemble in a manner similar to Sloughter et al. (2007). A training period of 30 days was selected for all parameter estimations based on the experimentation with the different training periods in Sloughter et al (2007). This study makes use of the Stage IV precipitation data for the verifying observations rather than rain gauges. Stage IV rain data consists of a blend of rain gauge and radar estimates to create a high resolution (~4 km) grid of precipitation estimates (Fulton et al. 1998). Before BMA was applied, the model and stage IV rain data were interpolated to a 0.5^o latitude by 0.5^o longitude grid. The full Northeast U.S. domain was used in the verification in order to obtain a large enough sample over the two warm seasons.

Quantative precipitation forecast (QPF) distributions are more difficult to fit for the BMA calculations than normally distributed variables like temperature, since QPF is strongly skewed to the right with many zero value events. As in Sloughter et al. (2007), QPF data was fit using a logistic regression to determine the probability of zero values, with positive probabilities assigned using a gamma distribution. The data was power transformed prior to model fitting in order to make the data appear more normally distributed. As in Sloughter et al. (2007), a power transformation of 1/3 was found suitable for this purpose. The logistic regression for the probability of zero precipitation was fit for each model individually over the training period,

$$\text{logit}\, P(y=0 \mid f_k) = a_{0k} + a_{1k} f_k^{1/3} + a_{2k}\delta_k \tag{1}$$

where y is the cube root of the observed precipitation and f is the forecasted precipitation for each k ensemble member. δ is a binomial variable that is equal to 1 if f = 0, otherwise it is zero.

The probability of precipitation greater than zero was fit using a gamma distribution:

$$f(y) = \frac{1}{\beta_k^{\alpha_k}\Gamma(\alpha_k)} y^{\alpha_k - 1} \exp(-y/\beta_k) \tag{2}$$

with mean:

$$\mu_k = b_{0k} f_k^{1/3} \tag{3}$$

and variance:

$$\sigma_k^2 = c_{0k} + c_{1k} f_k \tag{4}$$

Note that this differs from Sloughter et al. (2007) definition of the mean, which was:

$$\mu_k = b_{0k} + b_{1k} f_k^{1/3} \tag{5}$$

We decided on the former approach since the latter greatly reduced the variance of the data, due to a very small b_{1k} term and large compensating b_{0k} term.

The parameters a_0, a_1, and a_2 are fit with a logistic regression using the entire dataset from the calibration period. Only days with observed precipitation values greater than zero are used in the linear regression to calculate b_0 and the corresponding gamma fit. Meanwhile, c_0, c_1 and the weights for each member are estimated with an iterative procedure that will be described below. The final BMA posterior PDF is thus,

$$p(y \mid f_1,\dots,f_k) = \sum_{k=1}^{K} w_k [P(y=0 \mid f_k) + P(y>0 \mid f_k) g_k(y \mid f_k)] \tag{6}$$

and corresponding log-likelihood is

$$l(w_1,...w_k,c_0,c_1)=\sum_{s,t}\log p(y_{st}\mid f_{1st},...,f_{Kst}) \tag{7}$$

The iterative procedure within BMA can be tuned to solve for a variety of unknown parameters, but to avoid overfitting only the variance (model uncertainty) and weights for each ensemble member were estimated. Since these parameters cannot be solved analytically, the iterative procedure was necessary to maximize the log-likelihood as a function of the parameters. Raftery et al. (2005) used the Expectation-Maximization (EM) algorithm to estimate the parameters, but convergence to a global maximum likelihood estimate cannot be guaranteed. Therefore, BMA parameters were solved using the DiffeRential Evolution Adaptive Metropolis (DREAM) Markov Chain Monte Carlo (MCMC) algorithm developed by Vrugt et al. (2008), which samples a larger area of the parameter space and is more likely to find the global maximum likelihood estimate. Additionally, DREAM MCMC does not require algebraic modifications for different conditional probability distributions and creates a PDF of the estimated parameters (Vrugt et al. 2008; Vrugt et al. 2009). Since DREAM MCMC can estimate the PDF of the parameters, it is able to quantify the uncertainty of the parameter estimates while sampling the parameter space after the algorithm converged.

The bias correction, logistic regression and BMA algorithm were implemented using an iterative sliding window approach with a training period of 30 days. The parameters estimated from the training period were used to verify the following day before the calibration window was advanced one day and the process was repeated. In order for the verifying day to be considered, at least 30 out of 34 members must run that day with corresponding observations. In the calibration window, the data set length and dates used for each model must be identical; otherwise the variance parameter was underestimated in the iterative MCMC algorithm. Therefore only dates where all models ran were used in the calibration window. Locations with an unusually large amount of missing observational data were removed to avoid missing data issues prior to BMA. In order for the verification period to be considered, 50% of the calibration period must have days where all models ran.

It should be noted that the above BMA algorithm is flexible, and we can adjust it to match the work ongoing at the MARFC. Specifically, we can set BMA or the standard verification code to only work with the SUNY-SB, SREF, or both ensembles. In addition, we can adjust the number of members needed in the verification period, the number of acceptable days where all models ran in the calibration period, and the length of the training window in the calibration period. The start and end dates can be adjusted by changing just one variable, and the same applies for switching from the warm to the cool season. The size and resolution of the rectangular grid where verification and post-processing takes place can be adjusted easily to consider the Northeastern US as a whole or just a small subsection of the domain. This code can also verify and train on specific dates.

b. Verification and post-processing results

Figures 1 and 2 show the bias and equitable threat scores for the various MM5, WRF, and NCEP SREF members for the 2007-2009 warm seasons using the stage IV data and the contingency table approach. The SBU MM5 and WRF ensemble has a general wet bias for the heavy precipitation events, while the SREF has a weak dry bias for many members. The ensemble mean has a high (low) bias for the small and large thresholds given the smoothing effect of averaging precipitation from all members. The various members also have different deterministic QPF accuracy. In particular, the NCEP SREF “control” members tend to be more accurate than the SREF perturbed members for all precipitation events. This suggests that the perturbations are hurting model performance on average. The MM5 Mellor-Yamada PBL members also have less skill than other members. The SBU ensemble has slightly better ETS scores than the NCEP SREF and there is little increase in ETS when combining the SBU and SREF ensembles.

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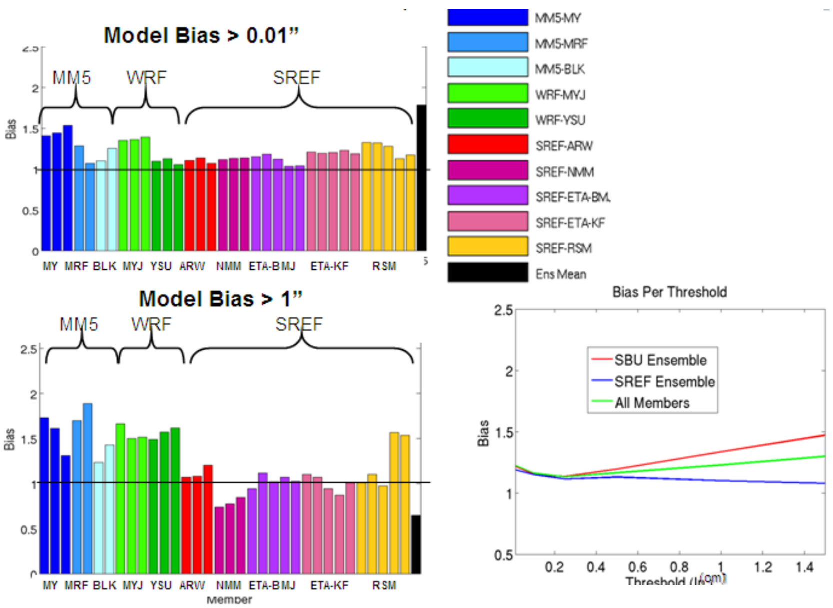

Figure 1. Bias for >0.01" and 1.0" thresholds for the various SBU and NCEP SREF members over the Northeast U.S. for the 18-42 h forecast (21-45 for SREF), and the domain average bias for the various thresholds.

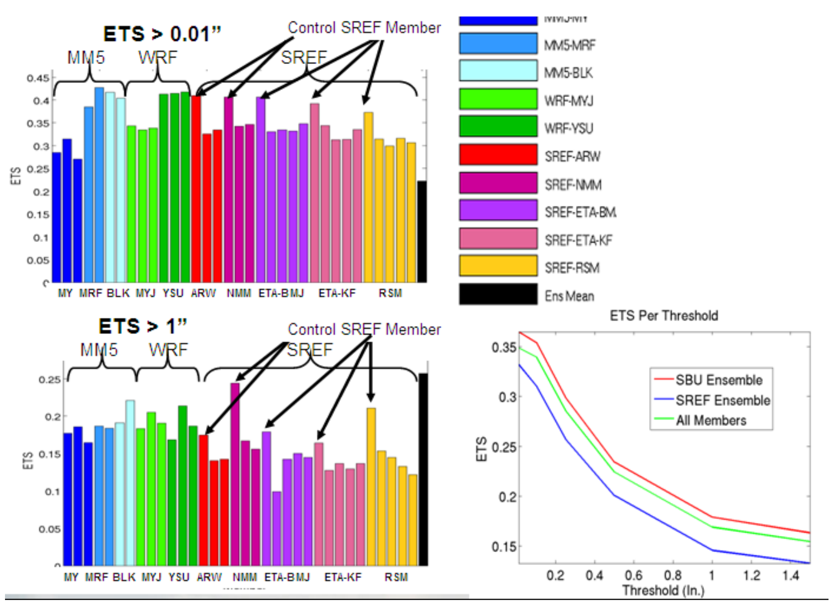

Figure 2. Same as Figure 1 except for equitable threat score (ETS).

The ensemble members also have different diurnal variations of precipitation averaged across the Northeast U.S (Fig. 3). All the SBU members overestimate the convective cycle during its peak. Two of the MY members are a few hours too early with the diurnal peak, while the Betts-Miller MY is slightly late and predicts more than twice as much precipitation as observed. Some of the SREF members do not have a diurnal cycle of precipitation (NMM and ETA-BMJ), while others have characteristics similar to the SBU ensemble.

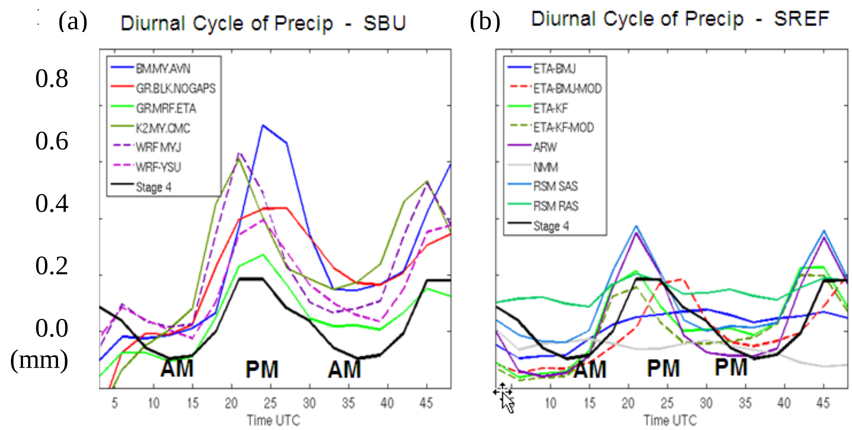

Figure 3. Diurnal cycle of average preciptiation (in mm) for the SBU and SREF ensemble showing average for select members and the observed stage 4 (black).

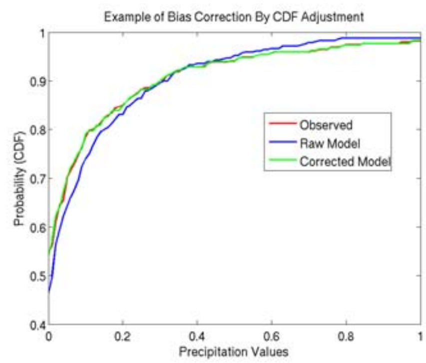

Figure 4. Example bias correction by the CDF adjustment approach.

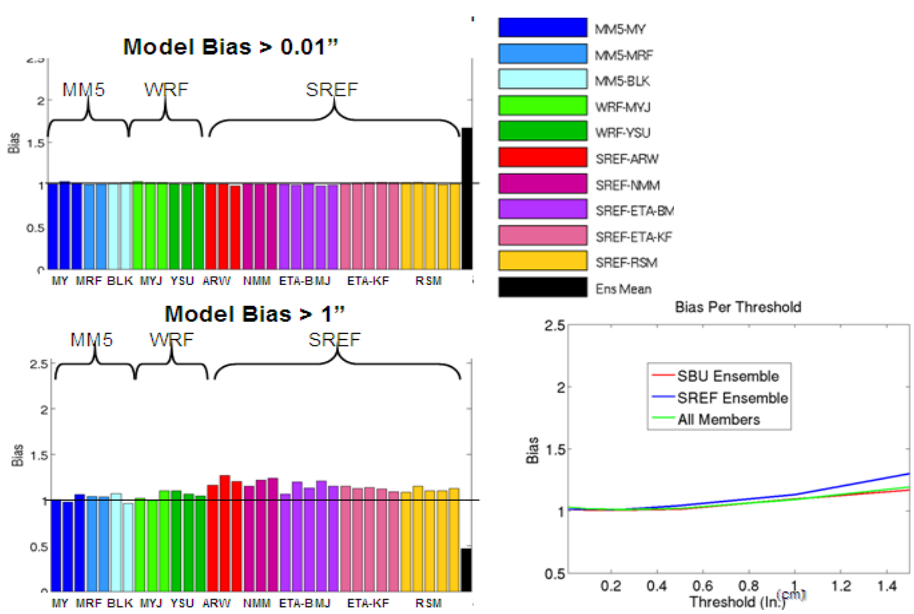

Figure 5. Same as Fig. 1 except for the bias of each member.

A bias correction was also tested for precipitation using the cumulative distribution function (CDF) method (Hamill and Whitaker 2006). Basically, one determines the CDF of the observation and model, then adjusts the model CDF to the observed for all precipitation amounts (Fig. 4). The 2007-2009 warm seasons (April – Sept) were tested over the NE US, and the previous 30 days was used to train the data (1 May 2007 used 1-30 April 2007 to train). The bias correction is member dependent (different for each member), but the same correction is used for each point in the domain. Future work can break up the correction into regions. The bias correction removes the most of the bias from all SBU and SREF members (Fig. 5), while maintaining most of the precipitation variance (not shown). However, a bias correction can not remove the ensemble mean bias using the contingency verification approach given the smoothing (averaging) of precipitation associated with displacement errors. Without bias correction, the SREF adds more probabilistic (Brier) skill to the total (SBU+ SREF) ensemble than the SBU ensemble (Fig. 6a); however, after bias correction, the SBU ensemble provides more skill to the total ensemble. These bias correction results are encouraging and the approach will soon be expanded to include with the BMA. The below BMA results do not use the CDF bias correction, rather a variation of the Sloughter et al. (2007) approach.

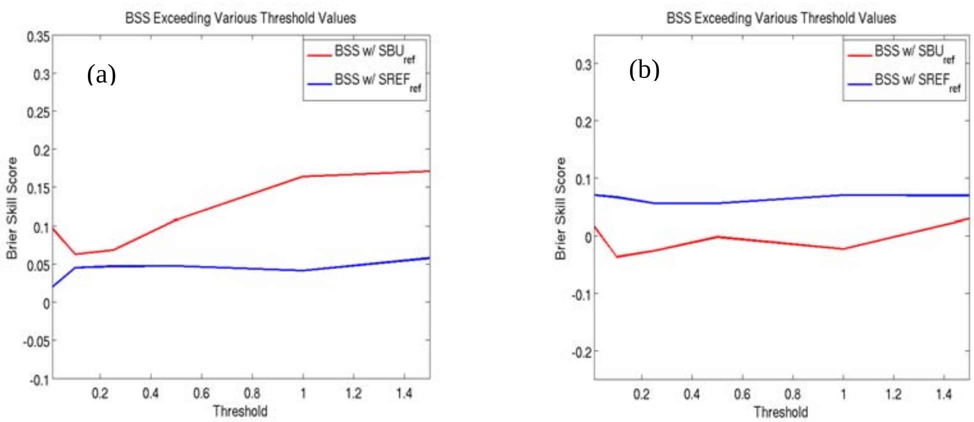

Figure 6. (a) Brier skill score (BSS) increase by adding the SREF (red) and SBU (blue) to the total ensemble (SREF + SBU). In other words, the red line shows the added benefit on including the SREF rather than just using the SBU ensemble. (b) Same as (a) except for after CDF bias correction.

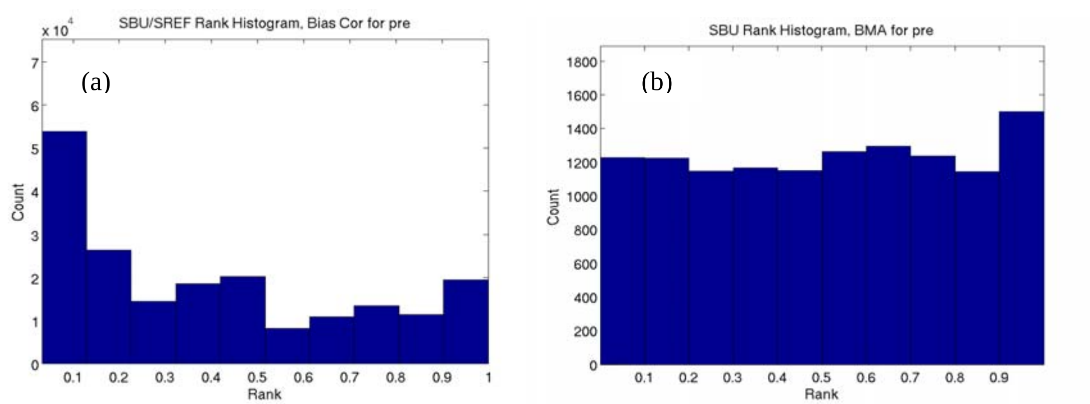

Figure 7. Rank histogram for the (a) raw and (b) BMA weighted SBU and SREF ensemble. The rank of the 34 members is scaled evenly from 0 to 1.

The raw SBU and NCEP SREF ensembles are underdispersed even after bias correction (Fig. 7). However, after post-processing with BMA, the rank histogram is nearly flat, thus illustrating good dispersion of the ensemble. Reliability diagrams were constructed for the SBU and SREF ensembles. Figure 8 shows the impact of BMA for the SBU ensemble. The reliability of the raw SBU ensemble is overconfident, but after BMA the ensemble is much better (along 1:1 line).

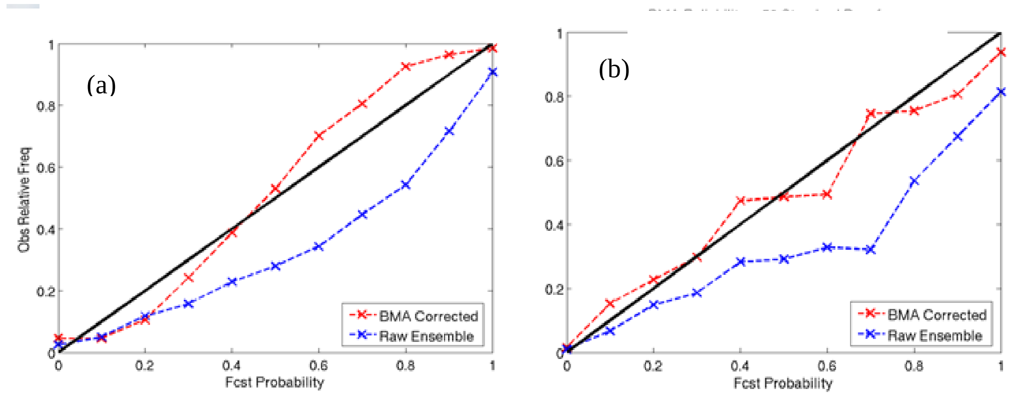

Figure 8. Reliability diagrams for the (a) > 0 inch and (b) 0.50 inch threshold for the raw ensemble (raw) and BMA corrected (red).

The increase in probabilistic skill using the BMA was also assessed. The Brier Skill score increases by 0.1 to 0.2 for many 24-h precipitation thresholds using BMA for the SBU ensemble (Fig. 9), which is a 30-40% increase in skill. A similar benefit was noted for the SREF ensemble (not shown). However, a combined SREF and SBU ensemble does not improve the probabilistic skill after BMA over any one of these ensemble systems (not shown).

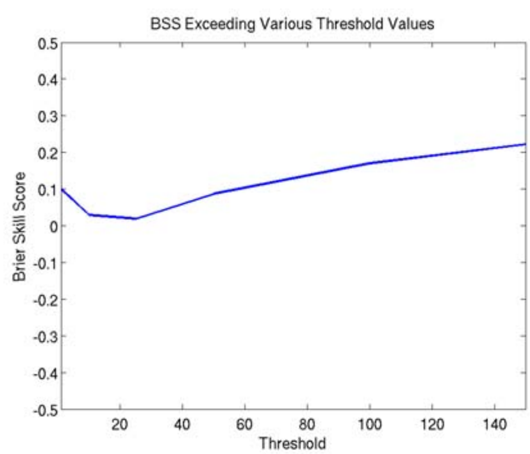

Figure 9. Difference in Brier Skill Score (BSS) between the SBU ensemble and running BMA and the raw SBU ensemble.

c. Ensemble streamflow prediction (MARFC)

MARFC's objectives in this project were to view the ensembles on AWIPS and to prepare probabilistic hydrologic forecasts utilizing the 48-hour precipitation ensembles. They also provided Site Specific model information for selected locations in PHI and OKX service areas, including unit hydrograph and routine headwater guidance.

The MARFC utilized basin-averaged precipitation generated from the SBU-provided grids as input to a process known as Ensemble Streamflow Processing (ESP), a component of the NWS' River Forecast System (NWSRFS). ESP ingests basin-averaged precipitation constructed from each precipitation ensemble into a hydrologic model to produce a trace of streamflows. Each precipitation field is considered to have an equally likely chance of occurring and the resulting streamflow traces are treated the same. SBU and MARFC are still collaborating to explore the impact of BMA weighted precipitation on the ensemble streamflow predictions.

For the streamflow simulations, basin-averaged precipitation fields were constructed from the SBU and NCEP SREF provided precipitation grids (Fig. 10). To this end, the MARFC adapted a package provided by the NERFC for processing GFS ensemble grids to work with the SUNY and SREF QPF grids. This package utilizes the open-source GIS package GRASS to first downscale the grids to the specified GRASS grid resolution using a numerical interpolation and then to average the resulting rasters over each basin. The initial 12 km resolution of the SUNY grids minimizes the amount of downscaling required.

The SUNY ensemble grid files were retrieved once per day (at 1400Z). The files then were processed via the GRASS-based downscaling and basin-averaging methodology and fed to ESP. An internal-to-MARFC web site provided MARFC forecasters with a view of the ESP-derived graphics for all MARFC forecast basins (samples below in Fig. 11).

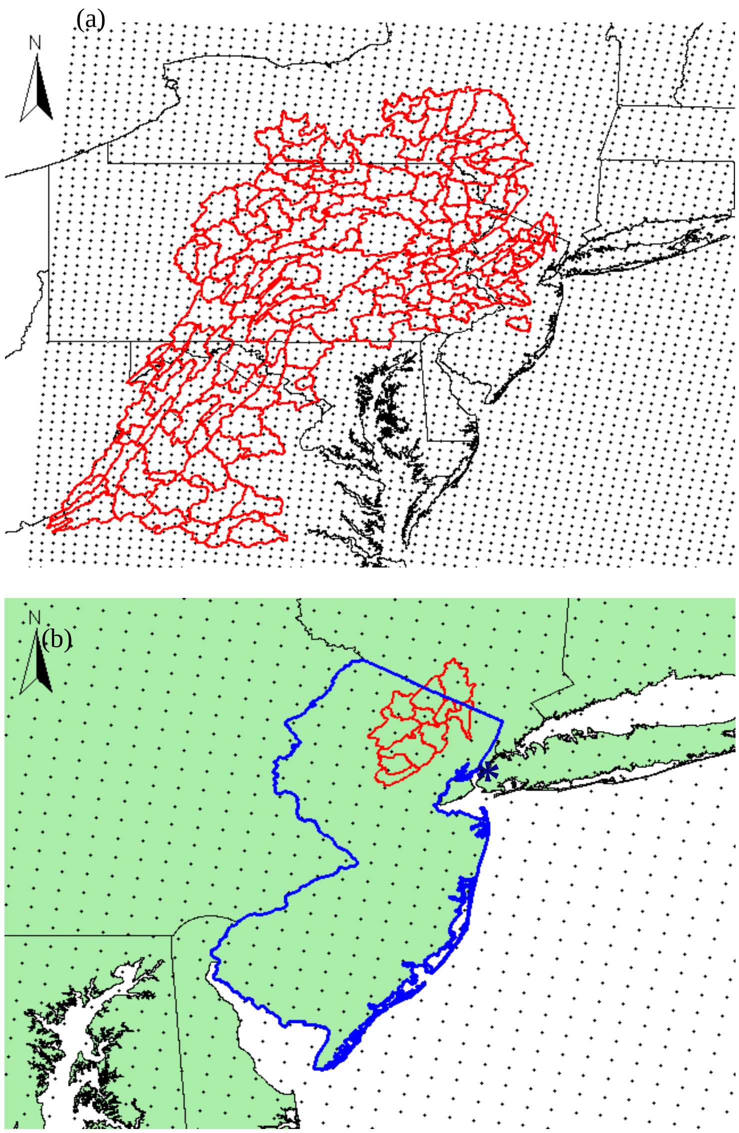

Figure 10. (a) MARFC area overlaid on a portion of the 12-km SUNY grid. (b) Passaic sub-basin on a portion of the 12-km SUNY grid.

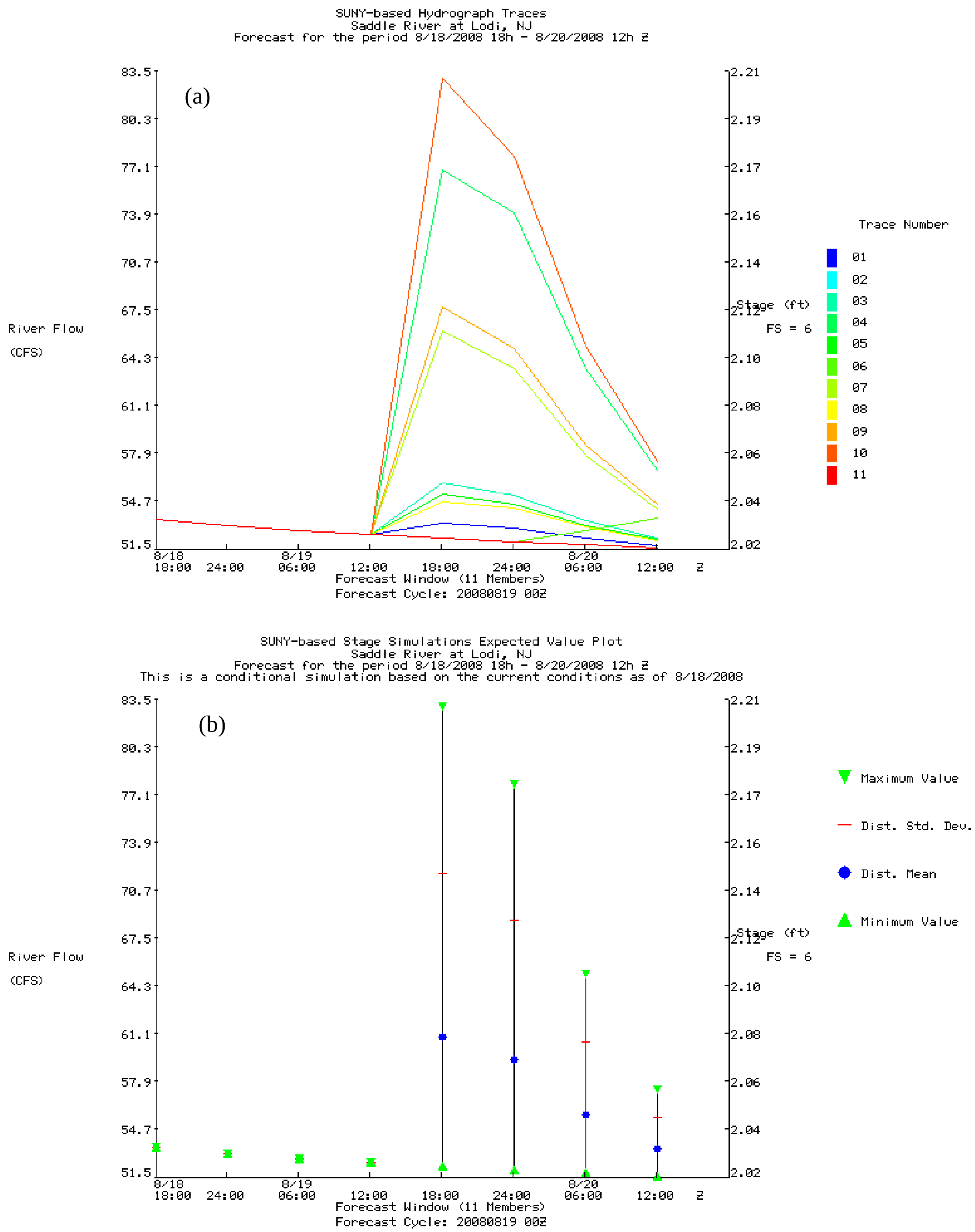

Figure 11. (a) Plot of individual traces resulting from hydrologic simulations using basin-averaged precipitation generated from SBU-provided grids and (b) expected value plot analysis of the traces.

Verification was also completed for the Passaic River basin (Fig. 10b) using the MARFC ensemble streamflow forecasts from April to September 2006-2009. There were about 400 days in which all the SBU/SREF ensemble and observed streamflow data was available (only raw data was used, not biased corrected, etc…). The river model was run using an ensemble of 6-hourly precipitation inputs starting at 1200 UTC. However, since the SBU ensemble started at 0000 UTC, the first two 6-h periods used the observed precipitation for the basin. As a result, hour 12 for the SBU ensemble (15 h for 21 UTC SREF) corresponds to hour 24 in the streamflow forecast.

The Ensemble Verification System (EVS) is an experimental prototype that verifies ensemble forecasts of hydrologic and atmospheric variables, such as precipitation, temperature, streamflow and stage, given at points/areas (Brown et al., 2008; Brown et al. 2010). It is intended for use by forecasters at the RFCs, researchers and developers at OHD, and collaborators elsewhere. It was implemented at the MARFC at the end of 2009 and used in this project to verify the SBU and SREF ensemble precipitation and streamflow forecasts for the Passaic basin. EVS is programmed in Java and can be run on any operating system for which a Java Virtual Machine is available (Linux, Unix, Windows etc.). EVS can be used as a command-line tool or through a Graphical User Interface. EVS includes multiple verification statistics: 1) for deterministic verification using the ensemble means, correlation coefficient, mean error, and root mean squared error; 2) for probabilistic verification, box-and-whisker plots of forecast errors, Brier Score, Mean Continuous Ranked Probability Score (CRPS) and its decomposition, bias-spread plots (similar to cumulative Talagrand diagram), Reliability diagram, Relative Operating Characteristic (ROC) and ROC Score (Wilks 2006).

The SBU ensemble precipitation forecasts had a larger spread and higher ensemble mean than the SREF forecasts (Fig. 1), leading to less underestimation of higher rainfall events in the SBU (less conditional bias). These translated to larger spread and higher ensemble mean in the streamflow forecasts as well. In streamflow, the raw SBU ensemble also had slightly less RMSEs for streamflow at Lodi, NJ (see * for location on Fig. 10b) than the raw SREF (Fig. 12). Both ensemble systems have the largest errors at hours 30 and 54, which is when convective development frequently occurs during the early afternoon (1800 UTC). There is little difference in the ROC (Rank Operating Curve) between the SREF and SBU for day 1 for the 90th percentile flow (~1/10 of flood flow) (not shown), but by day two of the forecast, SUNY has a slightly higher POD (probability of detection) and POFD (probability of false detection) than the SREF, due to SBU's slightly larger spread and higher ensemble mean.

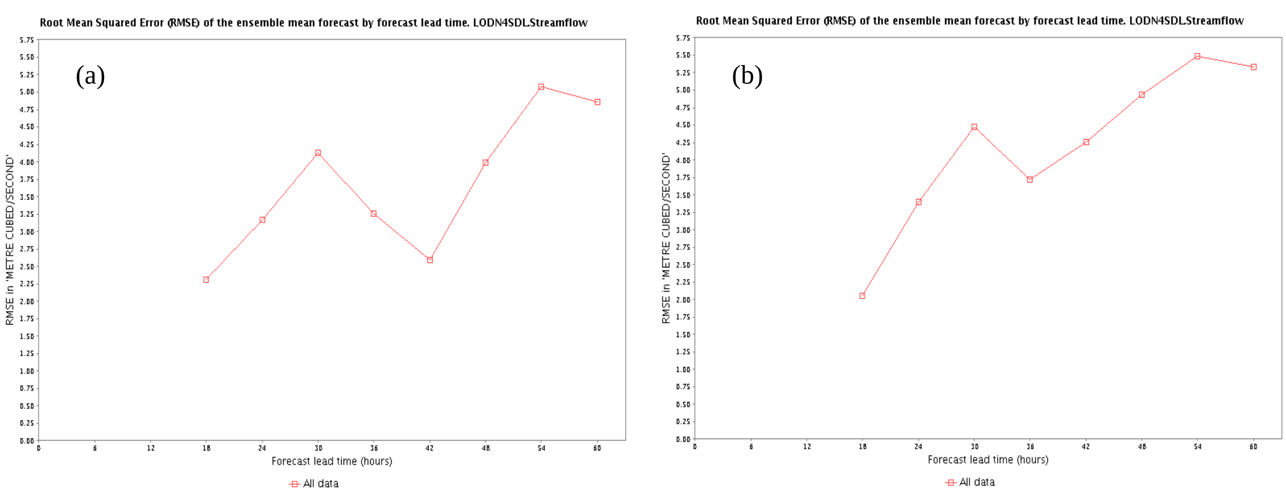

Figure 12. Root mean square error (m^3 s^{-1}) of the ensemble mean streamflow forecast using the (a) SBU and (b) NCEP SREF ensemble members as input into the MARFC ensemble prediction system. Hours 24-60 of the streamflow forecast corresponds to hours 12-48 of the SUNY ensemble (15-51 of SREF). See text for details.

Spread-bias diagrams show what percentage of the time the observation fall at or below various percentiles of the ensemble forecast that are paired with it. Spread-bias calculations for the 36-42 h streamflow forecast at Lodi, NJ suggest that for probabilities < 25% there are more observations falling within the forecast distribution than expected, while greater than these probabilities, there are too few observations falling within the probability range (Fig. 13a). Thus, for most probabilities, the streamflow ensemble is overconfident (underdispersed). The results are very similar for the streamflow forecasts using SUNY precipitation data (not shown), as well as other streamflow gauge locations within the basin. It is hypothesized that these results will improve after applying BMA to the precipitation and the streamflow forecasts.

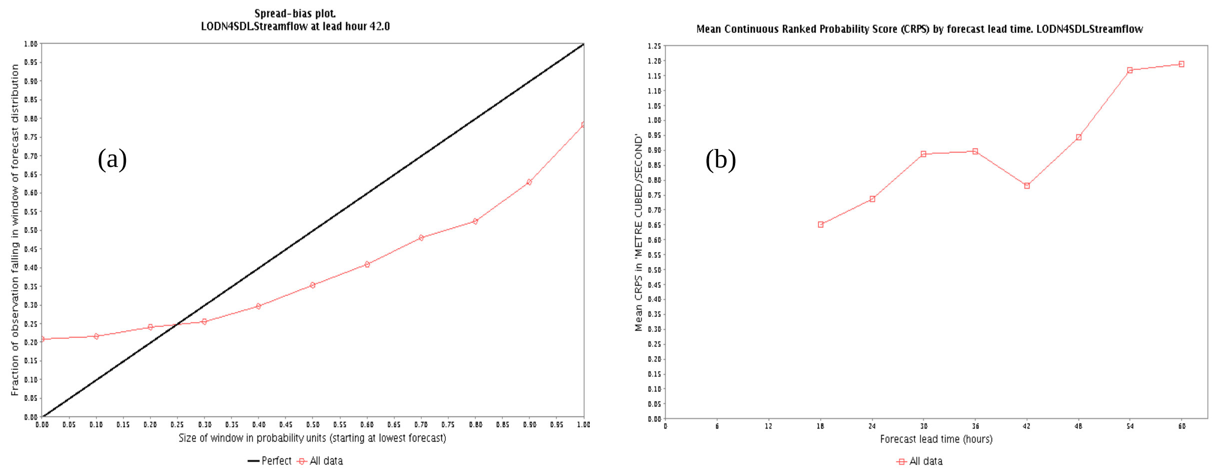

Figure 13. (a) Spread-bias plot for streamflow forecasts (36-42 h) using SREF showing the fraction of observed falling within the ensemble (y-axis) and the probability window (x-axis) at Lodi, NJ. A perfect spread-bias is along the 1:1 line. (b) The continuous ranked probability score (CRPS) versus forecast hour for the streamflow forecasts at Lodi, NJs using SREF precipitation.

The Continuous Ranked Probability Score (CRPS) measures the average error in the cumulative distribution of forecasts, and hence it is a summary metric similar to the RMSE for single valued forecasts (CRPS = CRPSRel – CRPSRes+CRPSUnc). As expeccted, the CRPS for the streamflow forecasts increases (greater probabilistic error) with increasing lead time (Fig. 13b). Early in the forecast, the reliability is poor (underdispersed), but there is resolution (sharpness). However, later in the forecast, the reliability only improves slightly, while there is little or no resolution (not shown). The uncertainity term does not change much throughout the simulation. The results are not different statistically using the SBU ensemble. Future work needs to combine both ensembles as well as use post-processed weighting to the streamflow forecasts.

d. Site Specific Hydrologic Predictor (SSHP) at Mount Holly, NWS

The Site Specific Hydrologic Predictor (SSHP) program is an important part of hydrology and flood prediction operations at NWS Mount Holly. This program is designed to provide a forecasting tool for fast-responding streams, based on estimated rainfall up to the current time, and/or forecast rainfall, for their associated drainage basins. SSHP provides stage forecasts at 1-hour intervals, compared to the 6-hour interval typically provided by an RFC.

The SSHP application produces stream-flow forecasts for headwater forecast points and can use either the Antecedent Precipitation Index-Missouri River Basin Forecast Center (API-MKC) or the Sacramento Soil Moisture Accounting (SAC-SMA) rainfall-runoff models, configurable by forecast point. Each forecast point must also have a unit hydrograph and a rating curve. At NWS Mount Holly, SSHP has been set up for 15 forecast points within the office Hydrologic Service area (see Fig. 14), and is configured to use the API-MKC model for all points. For six of these 15 points (APAP1, CHBD1, CHSP1, DWNP1, RCCD1, and DWNP1), the local NWS Office is required to produce forecasts of maximum stage height (crest) whenever flooding conditions are expected. The last forecast point in the table (WHIN4) was set up specifically for this COMET project.

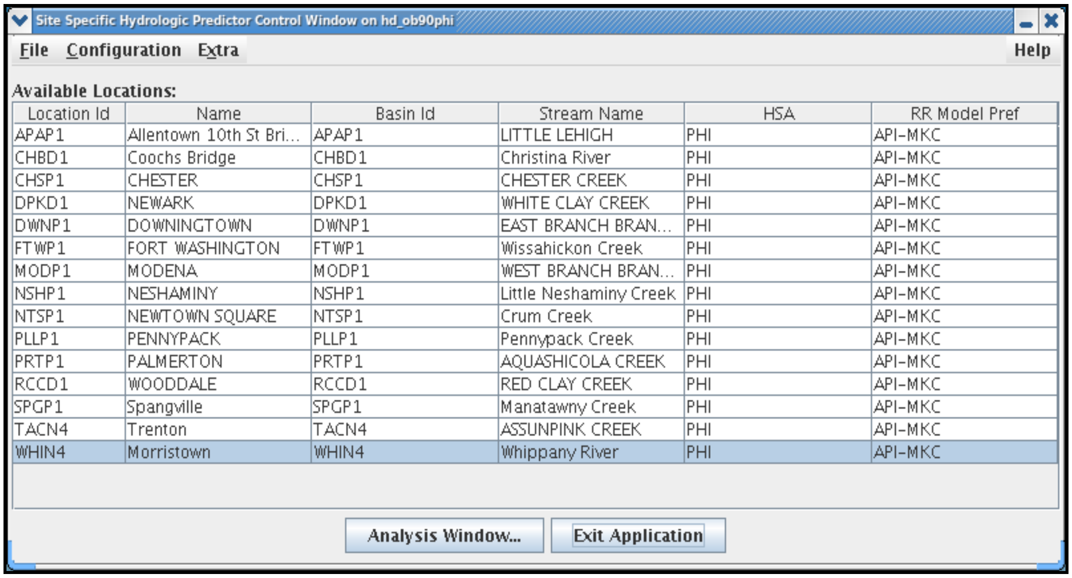

Figure 14. Main control window for the SSHP program, showing available forecast points in the NWS Mount Holly hydrologic service area.

SSHP is designed to produce one deterministic river-stage forecast at a time, as shown in Fig. 15 below. For this project, the goal was to produce multiple river forecasts based on different forecasts for the amount and timing of expected rainfall (QPF). To accomplish this, the SSHP forecast hydrograph was created by entering the houly Mean Areal Precipitation (average QPF for the drainage basin) from each SUNY-SB ensemble member, one at a time. The resulting hydrograph for each member, consisting of hourly forecast stages, was saved off as a table. The forecast tables for all members were imported into a spreadsheet, from which an ensemble plot of hydrographs was created.

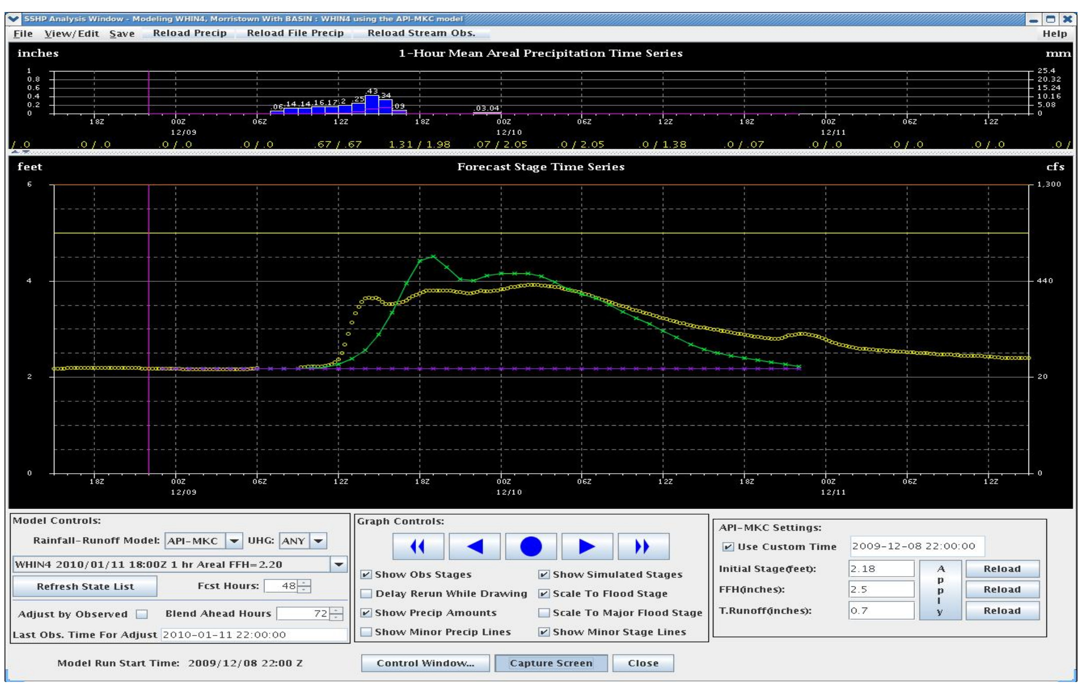

Figure 15. Example of the SSHP Analysis window for forecast point WHIN4. The green line represents the forecast hydrograph, while the yellow circles show the observed hydrograph. In this case, the hydrograph is based on forecast rainfall represented by the blue bar graph at the top.

An example of such an ensemble plot is shown in Fig. 16 below. The hydrographs are based on QPFs from 13 members of the SBU mesoscale ensemble, initialized at 0000 UTC 9 December 2009. The forecasts for maximum stage (crest) range from 3.7 ft to 5.3 ft approximately, while the timing of the crest varies from around 1800 to 2200 UTC. The actual observed hydrograph in this case is mostly well within the forecast envelope, except the intial rise occurred more quickly than any of the ensemble members. For this case, the two main API-MKC model parameters, FFH (flash flood headwater guidance) and T.Runoff (runoff threshold) were chosen so that the hydrograph resulting from the ensemble mean QPF would have a similar crest to the actual observed hydrograph. This means of chosing parameter values would not be possible in real time, but the resulting ensemble of hydrographs gives perhaps a more realistic range of possibilities. In practice, the T.Runoff parameter could perhaps be "tuned" by looking at previous events.

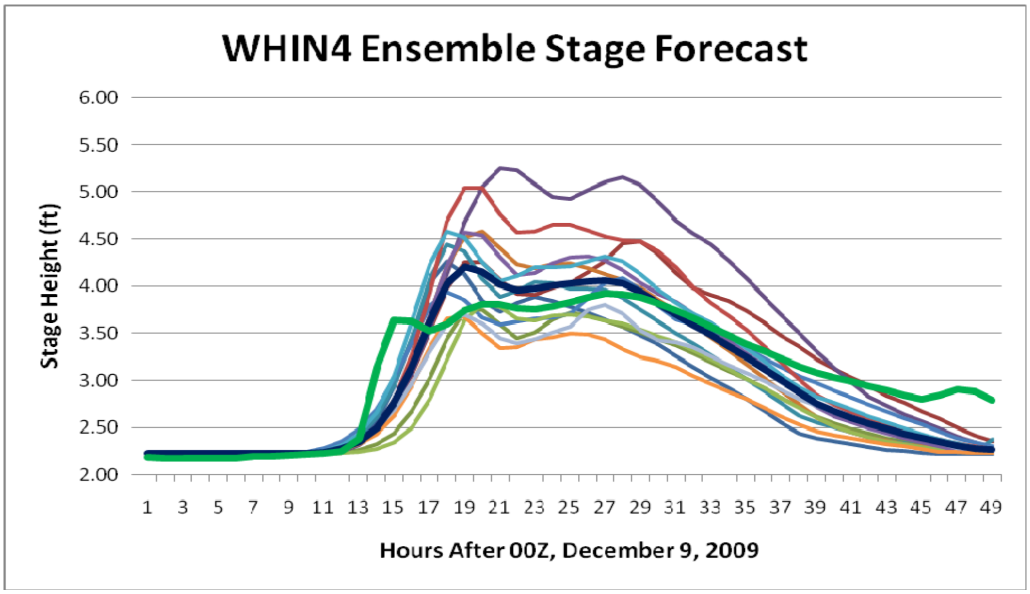

Figure 16. Ensemble forecast hydrographs for the Whippany River at Morristown, NJ, (WHIN4)based on QPFs from 13 NWP model runs, initialized at 00 UTC, December 9, 2009. Heavier black line is the mean of all hydrographs; heavier green line is the observed hydrograph. Flood stage is six feet.

e. SSHP and case studies at OKX

The SSHP was also implemented at the OKX forecast office. Case studies were completed, such as the 9 November 2006 flooding event for the Saddle River in northern New Jersey when East Coast cyclogenesis along the North Carolina coast early on 8 November 2006 and tracked northeast to the Gulf of Maine by the morning of 9 November 2006 as it gradually intensified. The storm produced several inches of rain in northern New Jersey that resulted in moderate flash flooding along small streams and rivers including the Saddle River at Lodi, NJ. Precipitation from the storm totaled 2-4 inches with an estimated 3 inches in the Saddle River basin. The Saddle River, a small fast responding river that flows through highly populated northeastern New Jersey, is examined in this case. The Saddle River is termed "flashy" due to its relatively small drainage basin and quick response to rainfall/runoff. The NWS forecast point located on the river is in Lodi, NJ.

Ensemble Quantitative Precipitation Forecasts (QPF) from two mesoscale ensemble prediction systems (EPS) are examined. The SBU SREF initialized at 00 UTC 8 November 2006 and the NCEP SREF initialized at 21 UTC 7 November 2006 were used. QPF provided by the NWS River Forecast Center (RFC) was considered the deterministic operational forecast for this analysis. In addition, the arithmetic mean for each EPS along with a worst case, defined as the maximum accumulated QPF by any EPS member for each forecast period, 1 or 3 hour, were computed. The accumulated precipitation from the SBU EPS consists of 11 12 km WRF and Eta members with varied physics and initial conditions. These are depicted in figure 17 as accumulated plumes. All members of the

SBU EPS underestimated the precipitation with ensemble mean falling about an inch (or a third) below the observed. The RFC QPF was a slight improvement upon the ensemble mean.

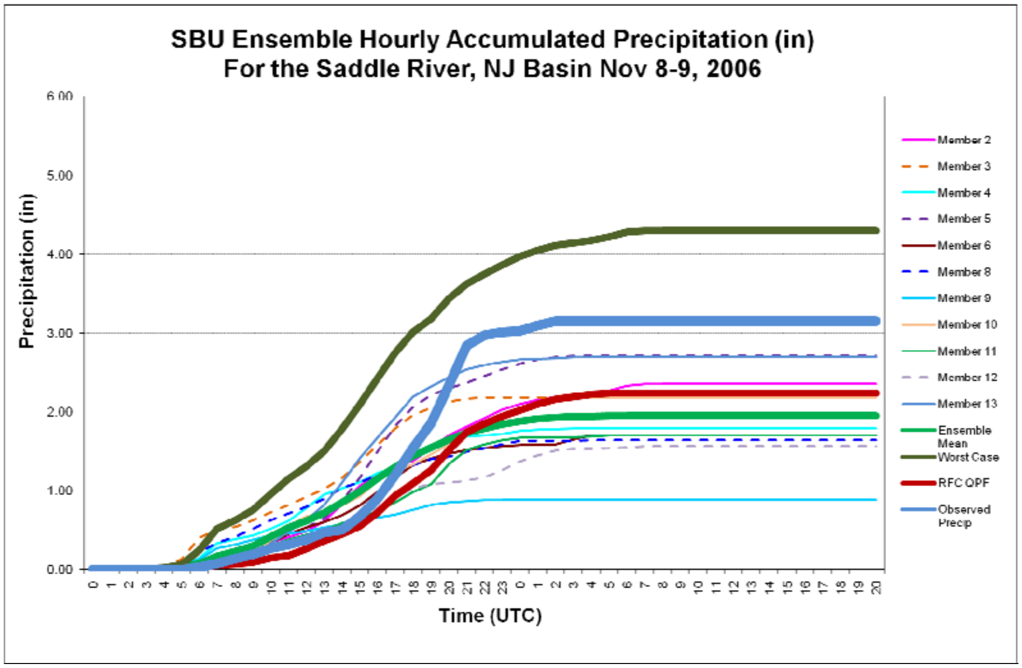

Figure 17. SBU SREF hourly accumulated precipitation for each member and the ensemble mean (green), worse case (dark green), RFC QPF (red) and Observed (blue).

The accumulated precipitation from the NCEP SREF consists of 16 32 and 45 km RSM and eta members with varied initial conditions. These are depicted in figure 18 as accumulated precipitation plumes. Note that the NCEP SREF ensemble mean is very similar to that of the SBU SREF.

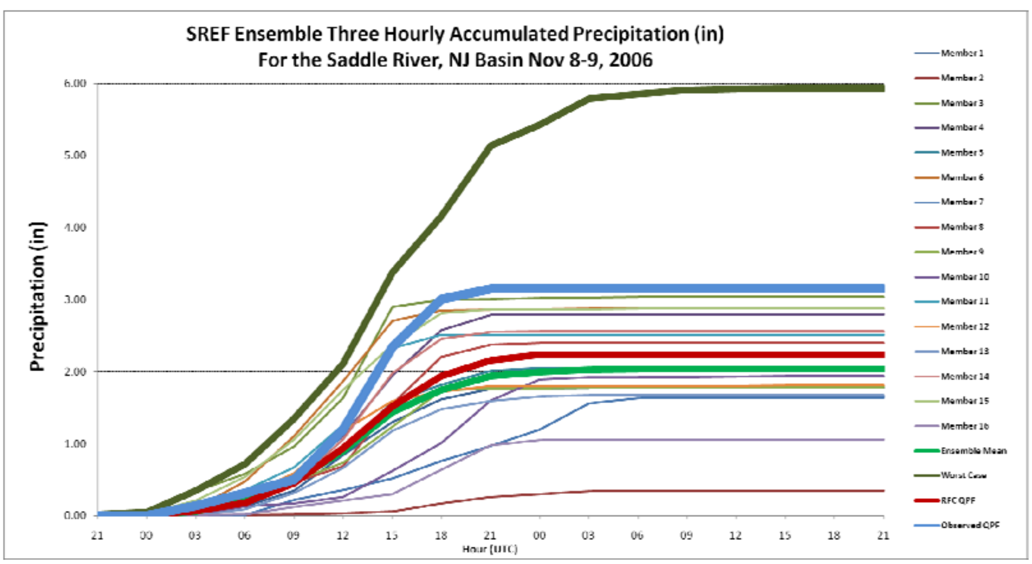

Figure 18. SREF SREF three hourly accumulated precipitation for each member. The heavy solid lines are the ensemble mean (green), the RFC QPF (red), the worst cast (dark green) and the observed rainfall (blue).

The AWIPS application Site Specific Hydrologic Predictor (SSHP) was used to evaluate ensemble QPF affect on the stage height on the Saddle River at Lodi, NJ. SSHP forecasts river stage height using two possible hydrologic models and a single QPF. The objective is to evaluate and eventually have the SSHP modified to accept an ensemble of QPF.

Since SSHP cannot currently plot multiple hydrographs based on various QPF inputs, the SSHP output had to be composited using Microsoft Excel. SSHP outputs from the two EPS's are shown in Figs. 19 and 20. In general, the SSHP show based on the EFS QPF that the hydrographs were under forecast and offset in time by several hours. In addition, the SSHP did poorly handling runoff from the heavy precipitation. This phenomena is seen with the observed precipitation trace in addition to all EPS members.

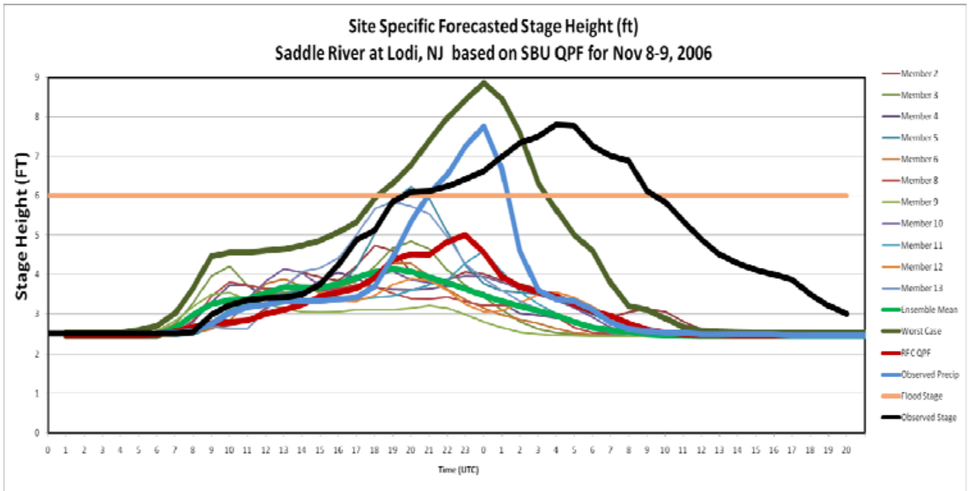

Figure 19. Site Specific Forecast Based on SBU QPF

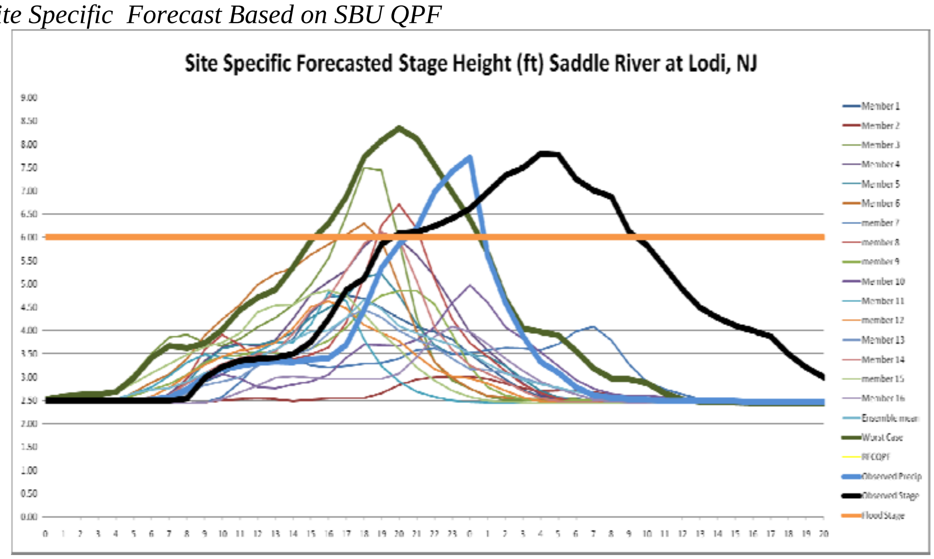

Figure 20. Site Specific Forecast Based on SREF QPF

Hydrologic prediction is extremely difficult. It is extremely sensitive to small variation in precipitation intensity. It is simply not sufficient for forecasters to predict the amount of rainfall accurately, but to forecast its distribution temporally. QPF from EPS's provide very valuable insight to hydrologic possibilities. Hydrologic prediction also requires a "tuned" hydrologic site specific model. As this case demonstrated the SSHP was not accurately calibrated.

3. Benefits and Lessons Learned: Operational Partner Perspective

a. *MARFC perspective*

Collaborating with SUNY-Stony Brook (SBU) fit in perfectly with the NWS River Forecast Centers' (RFCs') desire to integrate probabilistic information into their daily forecast operations and to do so in a quantitative fashion. A national RFC project, "Experimental Ensemble Forecast System" (XEFS), currently is underway to address effective means for producing traces of the hydrologic forcings of precipitation and temperature, for evaluating the uncertainty associated with hydrologic forecasting, and for displaying pertinent information both to NWS RFC forecasters and to the user community outside the NWS. A corollary effort, initiated by the NWS Eastern Region (ER) RFCs and entitled "Meteorological Model-based Ensemble Forecast System" (MMEFS), allows meteorological ensemble outputs to be used as inputs to hydrologic models, an approach outside of the methods being developed for XEFS, within the NWS River Forecast System (NWSRFS) Ensemble Streamflow Prediction (ESP) component. The MMEFS system design is flexible enough to accept gridded fields from many meteorological ensemble sources, one of which is from SBU.

The work SBU is performing as part of this project, that is the error correction and member weighting, also ties in the MMEFS project. Biases and under-dispersion are known characteristics of the meteorological ensemble outputs and that behavior has a direct input on the hydrologic simulation results using those as inputs. A project is being spun up at NWS Headquarters to look at various approaches to reduce biases, both for inputs to hydrologic simulations and on the hydrologic simulations themselves. The MARFC is willing to work with SBU further to utilize/incorporate their error-correcting techniques to improve hydrologic simulations.

During this project, MMEFS at MARFC utilized forcings from 3 different meteorological ensemble sources: the 12 member GEFS as provided via AWIPS (GEFSA), the 21 member SREF as accessed directly from NCEP, and the 13 member SSB system. Key differences among these sources are the grid coarseness and the frequency of updates from these sources. The met ensemble availability is:

- GEFSA: 00 and 12Z initialization cycles, available approximately H+6; 168 forecast hours processed
- SREF: 03, 09, 15, and 21Z initialization cycles; available approximately H+4:30; 87 forecast hours processed
- SBU: 00Z initialization cycle; available approximately H+14; 48 forecast hours processed

The effect of finer grid resolution (finer resolution results in less dependence on numerical interpolation or other downscaling measures for calculating basin average precipitation and temperatures, instead incorporating detailed meteorological influences, such as topography, in the modeling) is shorter forecast horizons, due to the increased computing resources (time and hardware) required to generate the fields.

Also, the time elapsed between the SBU forecast cycle initialization and file retrieval made the information available well into MARFC's morning operations, typically too late for consideration for the short term (less than one day) hydrologic forecast. By the time MARFC received SBU information, only 30 hours of forecast information (out of 48 totally produced) was available for forecaster review. (Note that late in the project MARFC discovered a "spin-up" effect of the SBU approach that usually took 12 hours to overcome, so the earlier periods of information were deemed (by SBU) as less reliable than the later hours. That information will affect our view of the data SBU provides.)

SBU did not provide temperature fields so the hydrologic results in the cold season were generated from climatological temperature values which did not adequately reflect the current weather. Therefore hydrologic results in the snow season were disregarded in this project.

Both MARFC and SBU are in the midst of evaluations of the basin average values generated compared to those calculated on precipitation observations and the stages calculated via the hydrologic models and observed values. These analyses are being performed both for the SBU ensembles and the SREF ones, with preliminary results indicating better performance by the SBU method versus the SREF.

The hydrologic results derived from SBU ensembles were reviewed in a qualitative fashion together with those from the GEFSA and the SREF. At this time, the subjective evaluation in comparing one method to another is inconclusive, but the important factor to consider is all the probabilistic information generated by the 3 ensemble sources were reviewed and evaluated by the RFC forecasters in making their judgments on the single-valued forecasts needed every day.

Also, the problems reported by Mt. Holly and Upton, about easily ingesting ensemble precipitation data into the SSHP, may be addressed using MMEFS technology at the RFC. MARFC will work to learn more about the SSHP difficulties and work to help the WFOs overcome them.

In conclusion, the results from the SBU-NWS collaboration were not incorporated directly into MARFC's daily operations as the effectiveness of doing so is still under design and development. However, the SBU project, together with the other meteorological ensemble sources, heightened the interest of and showed the value of considering an ensemble approach both to precipitation and hydrologic forecasting.

b. Mt. Holly (PHI) perspective

The biggest operational benefit for our office has been the development of an ensemble river forecasting system (MMEFS) by the MARFC. This system is officially "experimental", but the forecasts have been very reliable. Our office began using them during the 2009 convective season when they were available via FTP, and we continue to do so now that they are posted to the web. These ensemble river forecasts cover numerous forecast points within our hydrologic service area, and they have become an important part of our local flood watch/warning decision process. Joe Ostrowski and Patti Wnek of MARFC both provided training to our office on the use of MMEFS.

Also as a result of this project, our office has gained a better understanding of the Site Specific Hydrologic Prediction (SSHP) program. (SSHP is part of the suite of hydrologic applications programs in AWIPS.) We went through the instructive process of adding a new forecast point into SSHP (WHIN4, the Whippany River at Morristown, NJ), and we also observed the behavior of the SSHP stage forecast for a variety of QPF scenarios. We learned how to use SSHP in a retrospective mode as well as for real-time forecasts.

Finally, our office benefited generally from many useful discussions with WFO-OKX, the MARFC, and the faculty/staff of SUNY-Stony Brook School of Marine and Atmospheric Sciences.

We had hoped to automate the process of creating ensemble forecast hydrographs using SSHP, but this would apparently require significant modification of the program for which we lacked expertise. If these ensembles were routinely available in near-real time for heavy rain events, they could provide useful information for hydrologic operations at the local forecast office in three ways. First, when possible flooding is anticipated but has not yet begun, the ensemble hydrograph could provide an estimate of the probablility of exceeding flood stage, at any forecast point for which SSHP was configured and for which the SBU ensemble could provide MAP forecasts for the associated drainage basin. This information would help in the decision of whether or not to issue a flood "watch". Second, when heavy rain has begun and flooding seems likely, the ensemble mean hydrograph could provide a "best estimate" of the time when flood stage would first be reached, when the maximum stage (crest) would occur and its height, and when the water would fall below flood stage. Finally, the ensemble envelope could provide an estimate of the "worst case" or maximum possible crest; however it is also important to know the QPF associated with that case in order to make intelligent use of it.

c. Upton, NY (OKX) perspective

The Use of Mesoscale Ensemble Weather Predictions to Improve Short-Term Precipitation and Hydrological Forecasts COMET Collaborative Project has positively affected the integration of ensemble forecast systems into National Weather Service operations. This was not only influential in the hydrologic area, but throughout the entire spectrum of WFO applications. Part of this project required integrating the SBU ensemble data into the AWIPS environment (see Appendix). While a great deal of effort was required to make this happen, it was accomplished and this information has been shared with surrounding NWS offices. Having these data in the AWIPS environment is key for WFO forecasters to integrate and interogate the data set. As a result, the use of SBU ensemble data along with SREF and GEFS have become commonplace in the WFO's forecast process.

The biggest achivement of this project at WFO OKX was the use of the Site Specific Hydrologic Predictor (SSHP). Prior to this project, SSHP was not used or even configured for use at the WFO. It is now being used and as recently as 13 March 2010 provided valuable insight into hydrologic watch and warning decisions.

WFO OKX has worked with the developers of SSHP at WSH HSD and will continue to do so such that SSHP can integrate and display multiple precipitation possibilities on a single hydrograph – a feature deemed critical by WFO forecasters.

WFO OKX will also work with the developers of SSHP and MARFC to develop a simpler method to ingest EPS QPF into SSHP via ASCII text files rather than SHEF coded data.

WFO OKX will continue to streamline local processing of SBU EPS QPF for use in its SSHP.

Ultimately, while this projected has greatly increased the knowledge of hydrologic prediction within WFO OKX, the hope is that EPS QPF can be used in real-time within SSHP by operational forecasters. The WFO OKX will continue to work with SBU and the SSHP developers to make this happen.

4. Benefits and Lessons Learned: University Partner Perspective

The KOKX and KPHI offices are running the workstation WRF (NMM version) in their offices down to 4-km grid spacing around southern New England and NYC area. For example, KOKX has a web page (http://www.erh.noaa.gov/okx/wseta.shtml), which allowed the university to compare forecasts with its WRF members on a daily basis.

This research has allowed a graduate student (Michael Erickson) working on the project to better understand operational forecasting needs and constraints. The student has interacted with the forecast partners to help ingest data into the office as well as the interpretation of the ensemble products.

The COMET support for this ensemble system in this project has initiated other projects at Stony Brook supported by NOAA Seagrant on ensemble storm surge prediction, NOAA CSTAR on predictability (starting 1 May 2010), and NSF on convective weather evolution around New York City.

Other benefits to this project for the university are as follows:

- The ensemble web page receives nearly 5,000 hits from the NWS offices across the region during active weather months. Two-thirds of the hits were from offices not directly associated with this COMET project, thus suggesting that this effort is having a broader impact.
- Stony Brook participated in the Northeast Operational Workshop in Albany in early November 2007-2009. This provided an opportunity to discuss with some of the forecast partners on this project and introduce the project to other forecasts.
- This project has helped develop a long term verification and post-processing for ensembles. This will help with additional predictability studies in the future.
- This project is supporting and training a Ph.D. student on developing new ways for ensemble prediction and post-processing.
- The data for this project was used in classroom instruction and Friday weather discussions within the department.

5. Presentations and Publications

a. Presentations

- Tri State Weather Conference, Danbury, CT (April 2009)

  The Tri-State Nor'Easter of April 15, 2007 - Application of a Mesoscale Ensemble Forecast System to a Major Flood Event

  Jeffrey Tongue, Nancy Furbush, Adrienne Leptich (NOAA/NWS New York, NY)
  Alan Cope, Raymond Kruzdlo (NOAA/NWS Mt Holly, NJ)
  Joseph Ostrowski (NOAA/NWS State College, PA)
  Brian Colle, Michael Erickson (School of Marine & Atmospheric Sciences, Stony Brook University, NY)

- Eastern Region Flash Flood Conference, Wilkes-Barre, PA (June 2010)

  Ensemble River Stage Forecasts From the Site Specific Hydrologic Predictor

  Alan M. Cope (NOAA/NWS Mt Holly, NJ)
  Nancy Furbush, Jeffrey Tongue (NOAA/NWS New York, NY)
  Michael Erickson (School of Marine & Atmospheric Sciences, Stony Brook University, NY)

- 23rd Conference on Weather Analysis and Forecasting/19th Conference on Numerical Weather Prediction, Omaha, NE (June 2009)

  Integration of a real time high resolution ensemble system into National Weather Service hydrometeorological operations

  Jeffrey Tongue, Nancy Furbush, Adrienne Leptich (NOAA/NWS New York, NY)
  Alan Cope, Raymond Kruzdlo (NOAA/NWS Mt Holly, NJ)
  Joseph Ostrowski (NOAA/NWS State College, PA)
  Brian Colle, Michael Erickson (School of Marine & Atmospheric Sciences, Stony Brook University, NY)

- 23rd Conference on Weather Analysis and Forecasting/19th Conference on Numerical Weather Prediction, Omaha, NE (June 2009)

  Using a Calibrated Mesoscale Ensemble to Improve Precipitation and Hydrological Forecasts over the Northeast U.S

  Michael J. Erickson, Brian Colle, (School of Marine & Atmospheric Sciences, Stony Brook University, NY)
  Jeffrey Tongue (NOAA/NWS New York, NY)
  Alan Cope (NOAA/NWS Mt Holly, NJ)
  Joseph Ostrowski (NOAA/NWS State College, PA)

b. Publications

Charles, M., and B. A. Colle, 2009: Verification of extratropical cyclones within cyclones within NCEP forecast models using an automated tracking algorithm: Part 1: Comparison of the GFS and NAM models., *Wea. Forecasting*, **24**, 1173-1190.

Charles, M., and B. A. Colle, 2009: Verification of extratropical cyclones within cyclones within NCEP forecast models using an automated tracking algorithm: Part 2: Evaluation of the Short-Range Ensemble Forecast (SREF) system, In press to *Wea. Forecasting*, **24**, 1191-1214.

Colle, B. A., and M. Charles, 2010: Flow-dependent extratropical cyclone errors over North America and adjacent oceans in the NCEP Global Forecast System model. Submitted to *Wea. Forecasting.*

Erickson, M., B. A. Colle, J. Ostrowski., 2010: Multi-model ensemble precipitation predictions over the Northeast U.S., Part I: Impact of post-processing. In preparation to *Wea. Forecasting.*

Erickson, M., J. Ostrowski., and B. Colle, 2010: Multi-model ensemble precipitation predictions over the Northeast U.S., Part 2: Impact on ensemble streamflow predictions. In preparation to *Wea. Forecasting.*

6. Summary of University/Operational Partner Interaction and Roles

Each of the collaborative partners played an active role in the progress and results of this study:

<u>Stony Brook University</u>: Validated the SREF and SBU ensemble preciptitation forecasts over the Northeast U.S. from 2006-2009 and completed the post-processing and weighting of the various ensemble members. Stony Brook processed all the SUNY and SREF data to be used in the MARFC and WFO operations. Programs were written to convert the data into the formats needed for these streamflow prediction systems, and the data was put on a real-time ftp server for the operational partners to obtain.

The student volunteer program has continued in which 2-3 undergraduate students spend 5-15 hours per week at the Upton, NY forecast office. These students learn about the forecast process and NWS operations, and assist with a variety of tasks. For example, two students helped to ingest the AWS school network data to get real-time precipitation rates on the mesoscale around the NYC area.

Active and animated interactions have occurred between the KOKX office and Stony Brook using phone and email during important local forecasting situations.

<u>Mid-Atlantic River Forecast Center (MARFC)</u>: Used the SREF and SUNY ensemble precipitation forecasts in their ensemble streamflow prediction system over the Northeast, and validated that system for the Passaic River basin for nearly two warm seasons of forecasts.

<u>Upton, NY (OKX) and Mt. Holly WFOs (PHI)</u>: Used the ensemble precipitation forecasts for their in-house (site specific) hydrologic models and tested for several case studies.

Eastern Region (ER) assisted KOKX in developing computer protocols and software to ingest MM5 and WRF grib data into AWIPS. A detailed instruction manual was also written (see Appendix below), which allowed other offices across ER to do this easily as well. This is a major accomplishment, and this effort will help foster research and educational exchanges between NWS offices and universities running mesoscale models, especially during storm events.

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Appendix:
Adding SUNY Stony Brook Ensemble Data to AWIPS
Joshua Watson: NWS-Eastern Region 5/22/2008

LDM Modifications

As user 'ldm' on ls1 (ok, really its ls2):

1. Edit ~/etc/ldmd.conf add the lines:

```
<tab> is the actual tab key

# Request sunysbENS
request<tab>EXP<tab>"(gribfile|GrbF)"<tab>198.206.32.99
```

2. Edit ~/etc/pqact.conf add the lines:

<tab> is the actual tab key. The spaces between -overwrite -close /data/Incoming/\1\2\3.GribF are single spaces.

```
# Process sunysbENS data
EXP<tab>(.*)/(gribfile_d[1-3].)...........(f[0-9][0-9]).ALL
<tab>FILE<tab>-overwrite -close /data/Incoming/\1\2\3.GribF
EXP<tab>(.*)/(WRF_d[1-3].)Grb(F[0-9][0-9])
<tab>FILE<tab>-overwrite -close /data/Incoming/\1\2\3.GribF
```

3. Restart LDM

```
ldmadmin restart
```

4. If the restart works without errors, copy the new ldmd.conf and pqact.conf to ls3

```
scp ~/etc/ldmd.conf ls3:/user/local/ldm/etc/
scp ~/etc/pqact.conf ls3:/user/local/ldm/etc/
```

AWIPS Modifications

As user 'fxa' on dx3:

1. Put sunysbENS.tar.gz in /data/fxa/customFiles/ and unpack it. It will create a sunysbENS subdirectory.

```
cd /data/fxa/customFiles/
```

```
tar -xzvf sunysbENS.tar.gz
```

2. IMPORTANT! Backup the following files in /data/fxa/customFiles:

```
activeGridSources.txt
browserFieldMenu.txt
gridPlaneTable.txt
localGridSourceTable.txt
localPurgeInfo.txt
makeDataSups.patch
virtualFieldTable.txt
```

3. Create or edit activeGridSources.txt

```
sunysbENS36
sunysbENS12 4,5
sunysbENS4 4,5
```

4. browserFieldMenu.sunysbENS contains a set of submenus that hold lots of ensemble elements. If you have a customized browserFieldMenu.txt file, you can put these entries where your offices deems appropriate. This file can be highly customized at sites. If you have no customized browserFieldMenu.txt file, you can use browserFieldMenu.sunysbENS, rename it to browserFieldMenu.txt and uncomment the first line so a new main entry will show up in your Volume Browser field area.You can edit that entry to say something other than More Ensemble. As a side note, these entries will work for the GFSEnsemble as well as the sunysbENS data.

5. Copy the two *ATHENS* files to /data/fxa/customFiles/

```
cp sunysbENS/*ATHENS* .
```

The post-processing code for the MM5 has "ATHENS" as the default modeling center. This works to our advantage such that we can define any models we want and we will not impact the NCEP models.

6. Append the contents of sunysbENS/gribTableInfo.sunysbENS to /data/fxa/customFiles/gribTableInfo.txt

```
cat sunysbENS/gribTableInfo.sunysbENS >> gribTableInfo.txt
```

If /data/fxa/customFiles/gribTableInfo.txt does not exist, then:

```
cp sunysbENS/gribTableInfo.sunysbENS gribTableInfo.txt
```

7. Create or edit gridPlaneTable.txt, add the line:

```
     | standard | 0,FHAG | SFC
```

8. Append the contents of sunysbENS/localGridSourceTable.sunysbENS to /data/fxa/customFiles/localGridSourceTable.txt

```
cat sunysbENS/localGridSourceTable.sunysbENS >>
localGridSourceTable.txt
```

9. Append the contents of sunysbENS/makeDataSups.sunysbENS to /data/fxa/customFiles/makeDataSups.patch

```
cat sunysbENS/makeDataSups.sunysbENS >> makeDataSups.patch
```

If /data/fxa/customFiles/makeDataSups.patch does not exist, then:

```
cp sunysbENS/makeDataSups.sunysbENS makeDataSups.patch
```

10. Copy sunysbENS/*.cdl files to /data/fxa/customFiles/

```
cp sunysbENS/*.cdl .
```

11. Edit customFiles/virtualFieldTable.txt The first section of sunysbENS/virtualFieldTable.sunysbENS labled 'under "New" variable list, before any replacements' all the way to just before the label 'Replacement Variables' should be inserted at the end of your 'new' variable list in customFiles/virtualFieldTable.txt If that location is not noted in virtualFieldTable.txt, email your customFiles/virtualFieldTable.txt file to Joshua.Watson@noaa.gov, along with what your AWIPS Build ID is.

The second section of section of sunysbENS/virtualFieldTable.sunysbENS labled 'Replacement Variables' should be appended to the end of customFiles/virtualFieldTable.txt

12. Run -grids -dirs -dataSups -clipSups localization on dx3

```
cd /awips/fxa/data/localization/scripts/
./mainScript.csh -grids -dirs -dataSups -clipSups
```

If you observed 'field indexing' errors during localization, email customFiles/virtualFieldTable.txt and dx3 localization.log to Joshua.Watson@noaa.gov for assistance. These errors need to be corrected to keep notification working correctly.

13. If no field indexing errors are observed, run -grids -dataSups -clipSups localization on dx4

```
ssh dx4 /awips/fxa/data/localization/scripts/mainScript.csh
-grids -dirs -dataSups -clipSups
```

14. Run sunysbENS/createENSlookup.csh This script builds the necessary entries to modify /awips/fxa/data/master_grib1_lookup.txt so that each of the model elements from sunysb are remapped to be a perturbation in AWIPS. Its full of comments to help decipher its actions. You will need to rerun this script if master_grib1_lookup.txt is overwritten in an upgrade. There is no way to customize the lookup file, all we can do is add our changes back.

At the end of the script, GribDecoder will be restarted.

```
sunysbENS/createENSlookup.csh
```

15. Add entries to customFiles/localPurgeInfo.txt to keep sunysbENS data purged:

```
grep sunysbENS
$FXA_LOCALIZATION_ROOT/$FXA_INGEST_SITE/gridNetcdfKeys.txt
```

You should get something similar to the following, but the numbers in the first column will be different. You need those numbers!:

```
1070000094 | | | | | | | Grid/LOCAL/netCDF/sunysbENS36 | | | raw
sunysbENS36 grids
1070000095 | | | | | | | Grid/LOCAL/netCDF/sunysbENS12 | | | raw
sunysbENS12 grids
1070000096 | | | | | | | Grid/LOCAL/netCDF/sunysbENS4 | | | raw
sunysbENS4 grids
```

Add the following to customFiles/localPurgeInfo.txt, but USE THE NUMBERS ON YOUR SYSTEM, NOT THESE ONES!!!

```
1070000094 |  |  | 2- | 2 // 36km sunysbENS36
1070000095 |  |  | 2- | 2 // 36km sunysbENS12
1070000096 |  |  | 2- | 2 // 36km sunysbENS4
```

This will keep two versions of the ensemble data for each domain

16. Run -grids -dirs -dataSups -clipSups -purge localization on dx1 and dx2

```
ssh dx1 /awips/fxa/data/localization/scripts/mainScript.csh
-grids -dirs -dataSups -clipSups -purge
ssh dx2 /awips/fxa/data/localization/scripts/mainScript.csh
-grids -dirs -dataSups -clipSups -purge
```

17. Restart notification and purge processes on dx1

```
ssh dx1 restartNotificationServer; stopPurgeProcess;
startPurgeProcess
```