Using Ensemble Prediction Systems for Decision Support Activities

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1. INTRODUCTION

One of the primary purposes of weather forecasting is to reduce losses due to weather related events. Research on the economic value and cost-loss concepts associated with weather spans nearly 50 years (Murphy 1966, Murphy, 1977, Murphy 1978, Murphy 1985, and Murphy 1986). The more generalized concept of a decision support system (DSS)[1],a computer-based system emerged much later. Sage (1991) presented the components of a DSS. The main components included the user, a relational database system, and a modeling system. The critical concept is to facilitate cost-effective decision making.

Critical to any DSS is a realistic methodology to address risk assessment and to manage problems related to decision making (Haimes 2004). Though extremely important, it would be prohibitive to cover the components of designing a realistic DSS within this short paper. A simple example is provided in section 3 to illustrate this problem.

Developing cost-loss models requires probabilistic forecast information and knowledge of cost/loss (C/L) ratio (Mylne 1999). Relatively accurate ensemble forecast systems (EFS: Atger, 1999) can provide probabilistic forecast information with regard to a wide range of forecast parameters.
In addition to the probabilities, ensembles can provide information about uncertainty (Toth et al. 2001). A single deterministic model cannot readily provide information about uncertainty nor can it provide probabilistic information[2]. Current use of EFS data tends to separate uncertainty information from probabilistic information though the two are not independent. Therefore, it is difficult to use a single model in decision making activities as the forecasts are binary.

Ensemble prediction systems can provide important information which can be of value to decision-makers, including derived probabilistic and uncertainty products.. These data can reveal both the high probability of a significant event, such as heavy rain or snow, or the low probability event with potentially high impacts and costs, such as a land falling tropical storm. Decision makers need to be aware of the both event types.

The uncertainty information, based on the spread, can provide additional information to the forecaster as demonstrated by (Toth et al. 2001). Their study revealed that in general, when forecasts converged (low spread) they tended to be more accurate than when the forecasts diverged (high

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[1] The National Weather Service approaches this from a Decision Support Services aspect.

[2] Post processing of these data facilitates the use linear regression to derive probabilities.

spread). Thus, in addition probabilistic information, the spread in the EFS can be used to gage a measure of confidence in the forecast. Though relative measure of predictability (RMOP: Toth et al 2001) data are not provided here, the concept is useful in forecasting to gage the confidence in the forecast.

This paper will examine the use of an ensemble prediction system to aid in decision making. The focus is on how forecasters can leverage probabilistic and uncertainty information provided by ensemble prediction system to assist decision makers. Clearly, there is a need to establish cost-loss models for both a wide range of weather events and wide range decision makers. Decision makers are loosely defined as those who would make decisions based on meteorological forecasts or information.The goals include making forecasters more aware of the value of ensembles in the forecast process and of the value of understanding simple C/L models.

2. METHODS

Data from the NCEP NAM, GFS, and SREF are presented here. The data were available in GRIB format for use in this paper. The focus will be on SREF products related to forecasting quantitative precipitation amounts and types. At the conference, data related to the meteorological setting will also be presented.

For the NAM and GFS, the data is limited to a point near State College, PA for a December 2008 winter event. At this point, the instantaneous QPF is shown (Figs. 1 and 2) and the accumulated precipitation by model forecast precipitation type is also shown. A color key is included with each image, where snow is depicted as blue and rain as green.

For the SREF, a plume diagram is provided at the same point used to produce the NAM and GFS images (Fig. 3). The SREF has 21 members and thus there are 21 lines on each chart. Each SREF members' 3-hour QPF is shown (gray) and the accumulated precipitation color coded by precipitation type.

In addition to the plume diagrams, SREF probabilities of precipitation type are depicted in plan view (Figs. 4-7). These are raw uncalibrated probabilities based on the total number of members and the number that forecast rain, snow, ice pellets, or freezing rain respectively. These probabilities are plotted with the 3-hour ensemble mean QPF.

All times will be referred to as 12/0000 UTC for 12 December 2008. All the images were produced using NCEP gridded data and were displayed using GrADS (Doty and Kinter 1995).

3. CASE EXAMPLE

i. Overview of the problem

This case is taken from a true example. The basic problem was the potential for 7.5 to 12.5 cm (3-5 inches) of snow. This amount of snow would cause problems forcing an institution to close if the snow blocked roads and parking fields. Total costs of closing due to the snowfall were in excess of 1 million dollars (loss). The main cost to protect, if the snow were to fall overnight, which in this event was the case, was about 3 to 4 thousand dollars in overtime (cost to protect).

The cost-loss ratio (C/L) here was 0.004, suggesting that it was extremely cheap to protect ($3-4K) verse the loss of not protecting ($1M). Cleary, most decision makers, armed with this information would chose to protect with a very low

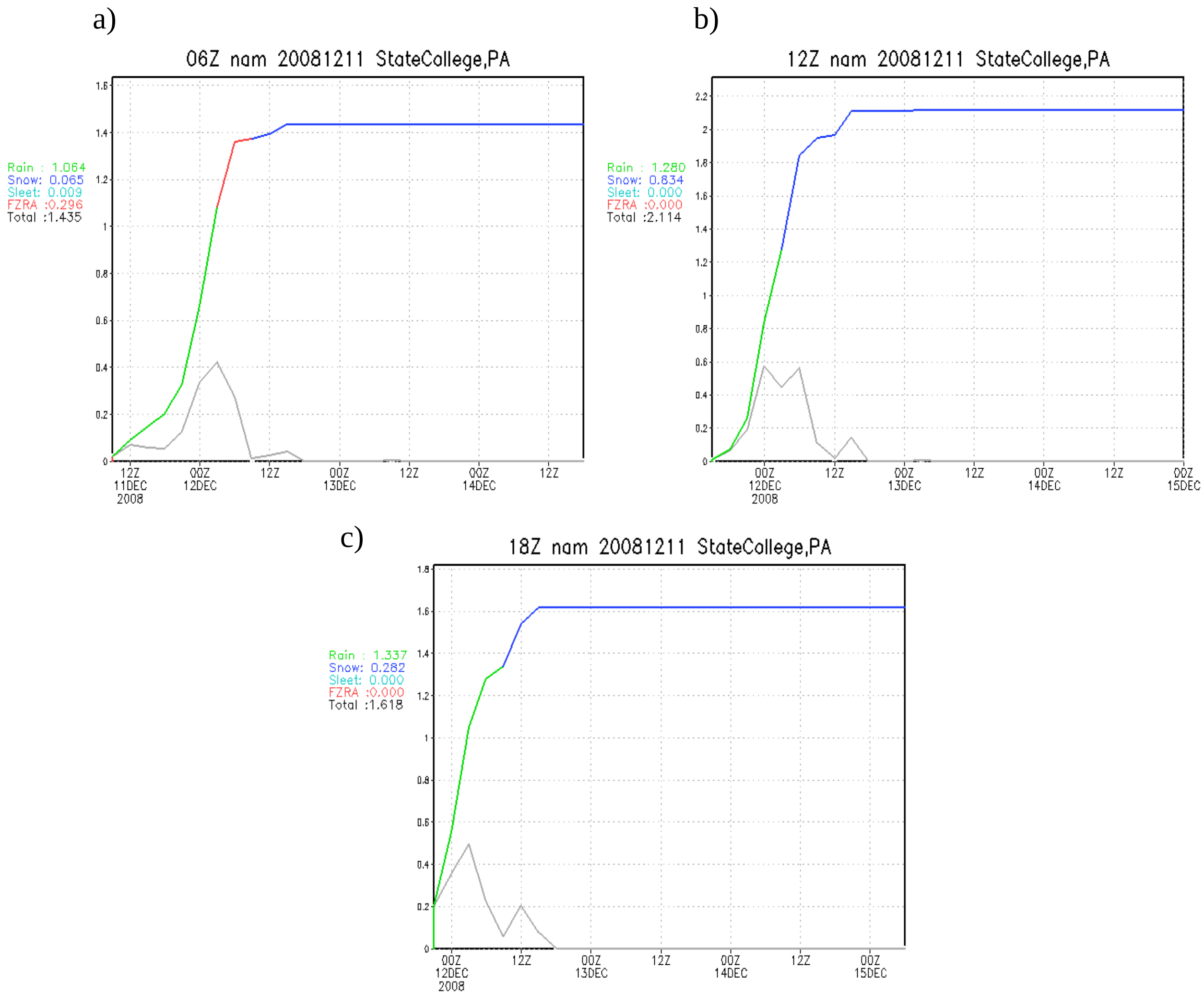

Figure 1 NAM forecasts of quantitative precipitation (inches) from forecasts initialized at ((a) 0600 UTC (b) 1200 UTC and (c) 1800 UTC 11 December 2008 The gray lines show the 3-hourly instantaneous precipitation (inches). The color coded lines show the accumulated precipitation color coded by the dominant precipitation type.

probability of 7.5 to 12.5 mm of snowfall. This situation is quite similar to why homeowners have an incentive to insure their homes; the relative cost of insurance is cheap compared to the replacement cost of a house.

Those in charge of budgets would of course desire to save the $3000-$4000 whenever possible and would like as accurate a forecast as possible to avoid spending any additional funds. Those providing the forecasts are likely unaware of the true cost verse the loss and want to provide as accurate a forecast as possible.

In this event, the forecast called for 7.5 to 12.5 cm of snow overnight which did not occur. The forecaster felt he had failed, however upon comparing the C/L and the forecasts it became clear this

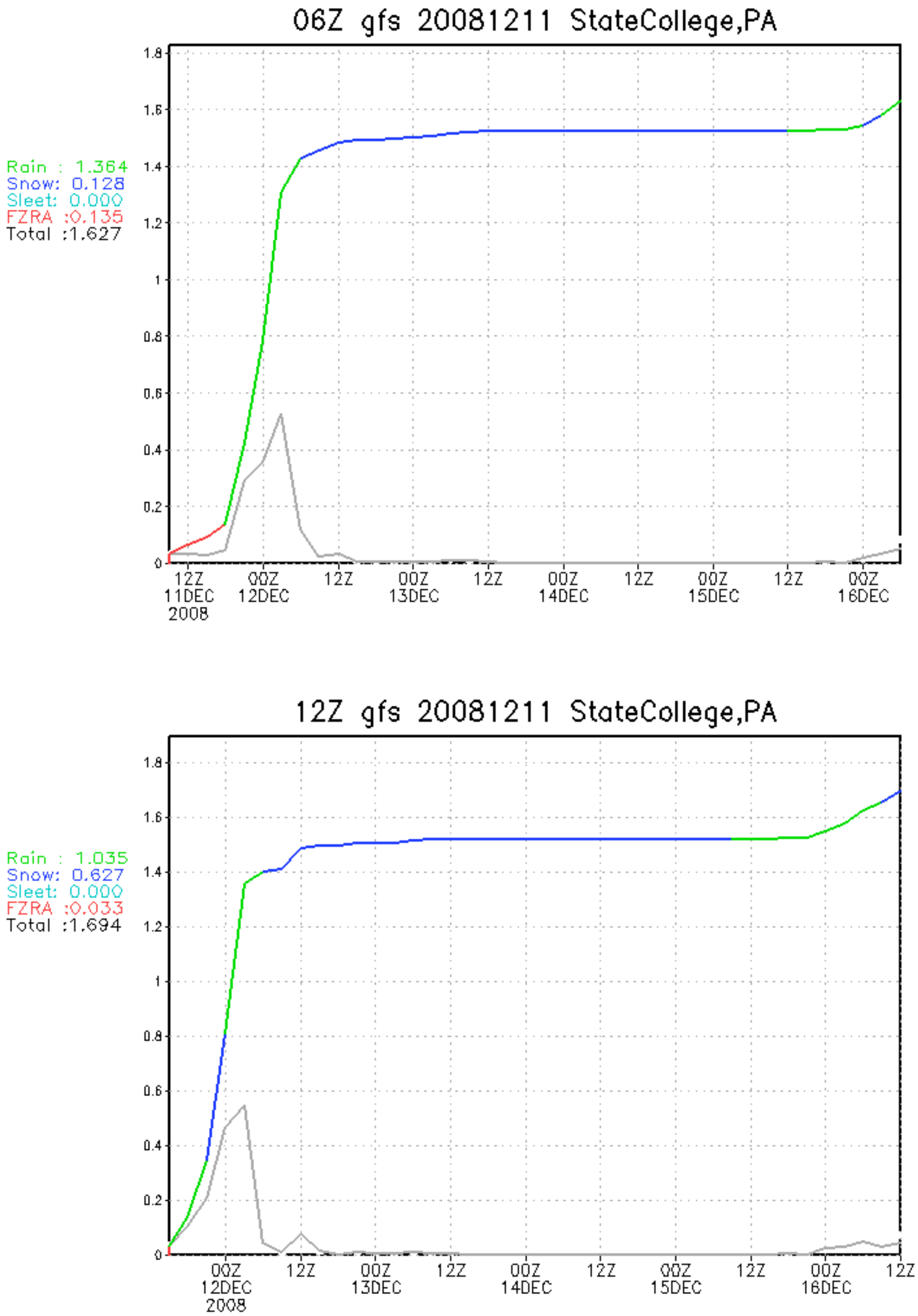

Figure 2. As in Figure 1 except showing the GFS forecasts of 6-hourly precipitation and accumulated precipitation by precipitation type for (a) 0600 UTC and (b) 1200 UTC.

was likely a very cost-effective forecast.

The forecasts are addressed in the following section.

Forecasts and the C/L associated with them must be understood by users and to

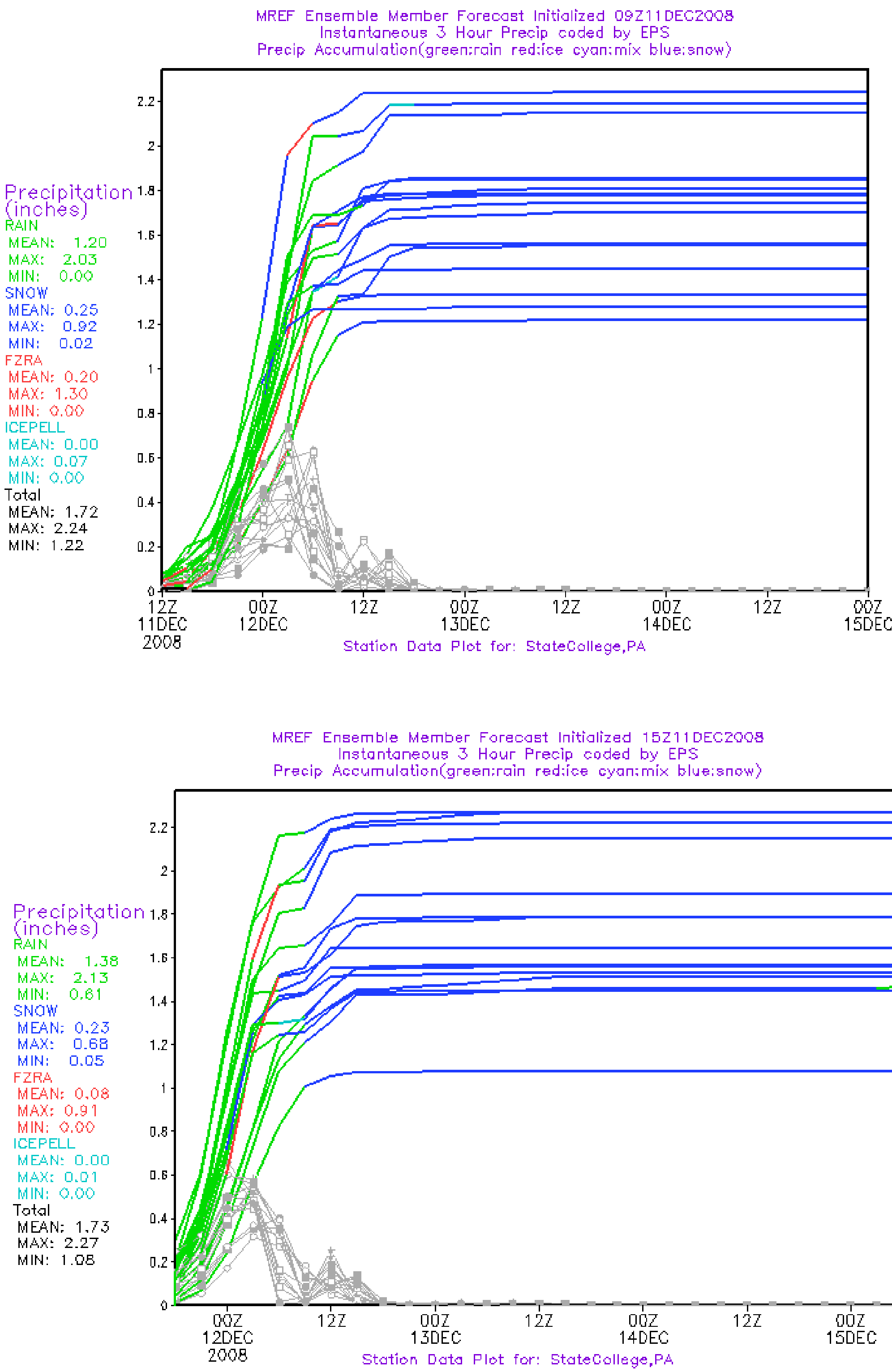

Figure 3. As in Figure 1 except SREF forecasts initialized at (a) 0900 UTC and (b) 1500 UTC11 December 2008. Data are shown for each of the 21 SREF members.

some degree, by forecasters. Clearly, every user has unique requirements and their own unique C/L models. Thus, as outlined by Haimes (2004), there is a requirement to systematically address risk and manage decision making. The DSS concepts outlined by Sage (1991) could help users determine C/L ratios.

Continuing with the snow example, a wide range of users must take action to prepare for the potential snowfall. Airport managers may need to pre-position crews to clear runways and de-ice planes. Municipalities may be required to get trucks and crews ready to plow and treat roads. School systems must decide whether to close or remain open. All of these activities have associated cost-loss ratios. Each users C/L ratio may require action at a different threshold probability.

National Weather Service (NWS) forecasts of snow amounts for advisories and warnings are tied to discrete amounts and probabilities of occurrence. In general, a longer fused watch is a 50% outcome event while a shorter-fused advisory or warning is expected to verify at about 80%. There is slight disconnect here as the user probabilities are nearly a continuous spectrum while the NWS forecasts are discrete. Private companies that can fill the gap in this area are for higher end users with significant C/L issues and knowledge.

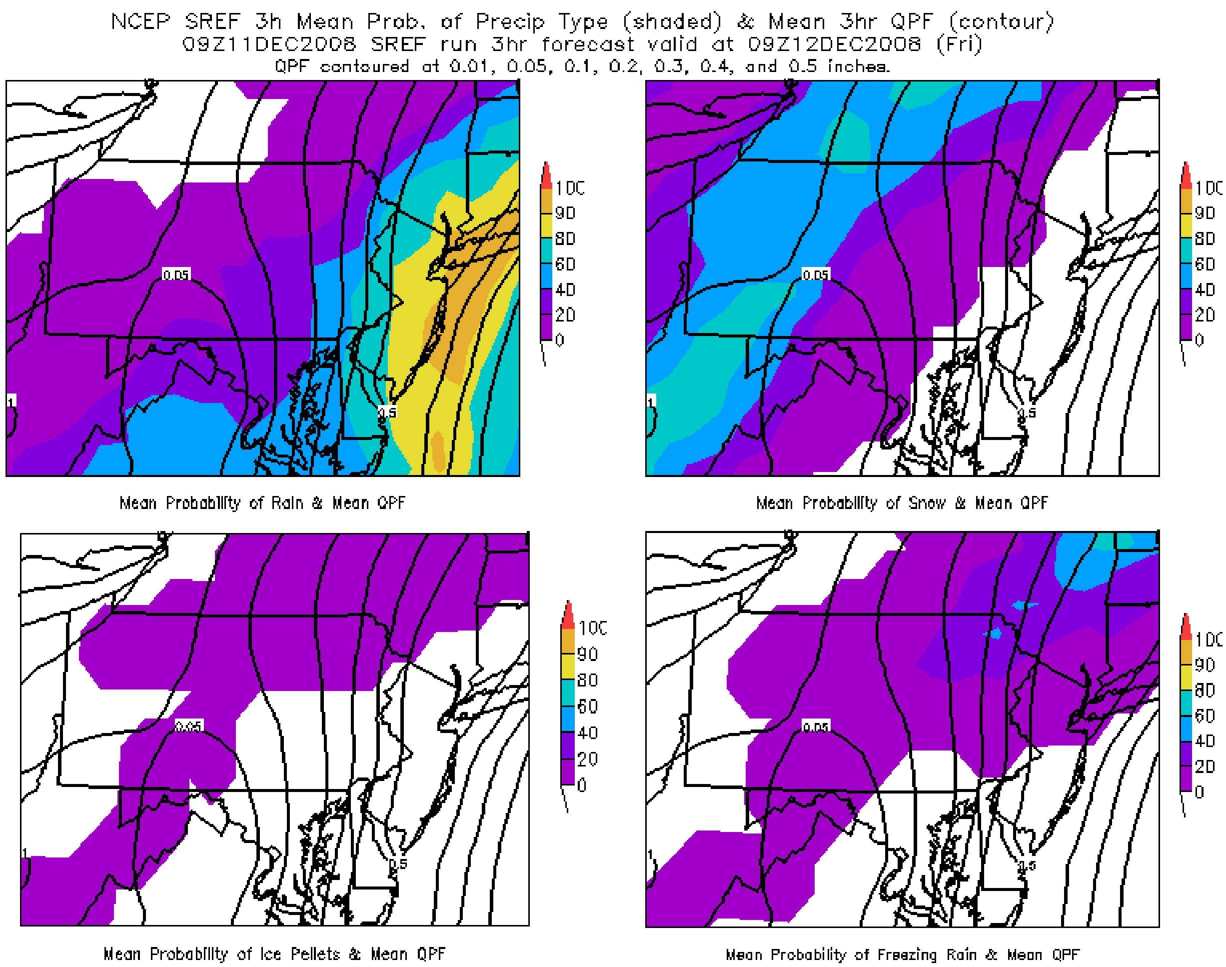

Figure 4. SREF forecasts initialized at 0900 UTC 11 December showing the ensemble mean precipitation (black contours:inches) and clockwise from upper left, the probability of the precipitation type being rain, snow, ice pellets, or freezing rain. Probabilities are in percent as noted at the right of each image. Precipitation contours are black showing 0.05, 0.10, 0.20, 0.30,0.40 and 0.50 inch contours.

A critical point in this process is how to arrive at probabilities and information about uncertainty from forecast guidance. Single forecasts, from the NAM or GFS, provide no probabilistic or uncertainty information. This type of information, however, can be derived from an ensemble of models or from an EFS.

The next section shows how ensembles can be used toward this means. This approach, though presented simplistically is similar to the concepts presented by Mylne (1999 and 2001) and Toth et al. (2001).

ii. Deterministic Forecasts

The evolution of the snow potential with the 12/2008 event was slow. Initially, the precipitation amounts, falling as snow, were quite low. The 11/0600 UTC NAM (Fig. 1a) showed about 0.06 inches of QPF falling as snow by 12/1800 UTC. The model initialized 12-hours (Fig 1b.) later showed about 0.60 inches of QPF falling as snow. The NAM initialized at 11/1800 UTC (Fig. 1c) showed less QPF than the more aggressive 11/1200 UTC run (Fig. 1b) with about 0.30 inches of QPF to be in the form of snow.

The lower resolution GFS forecast initialized at 11/0600 UTC (Fig. 2a) showed just over 0.10 inches of QPF falling as snow. Similar to the NAM, the 11/1200 UTC run (Fig. 2b) was more aggressive, showing 0.60 inches of the QPF falling as snow, though it showed some rain and snow issues.

iii. SREF forecasts

The SREF plumes (Fig. 3) showed the complex nature of the event with regard to precipitation type, amounts, and timing. The SREF initialized at 11/0900 UTC (Fig. 3a) showed the potential for rain, freezing rain, or snow during most of the event, with the precipitation ending as a brief period of snow. Most of the members showed little significant snowfall. One member did show as much as 0.92 inches of the QPF falling as snow. The mean was around 0.25 inches of the QPF falling as snow.

The SREF initialized at 11/1500 UTC (Fig. 3b) showed a similar scenario, with the precipitation possibly ending as snow. The overall snow fall was slightly less than depicted in the previous forecast cycle and the maximum snowfall QPF amount was nearly 0.30 inches lower.

Plan view images from the 11/0900 UTC SREF showing probability of precipitation by precipitation types are shown in Figures 4-7. These data show that prior to 12/0900 UTC fewer than 40 percent of the members predicted the QPF to fall as snow. This increased to 60-80% of the members showing snow by 12/1200 UTC. The probabilities dropped off after this time due to the number of members forecasting any QPF. Thus, snow was only briefly the primary precipitation type.

The 11/1500 UTC SREF was less aggressive with the snow as seen in the plume diagrams and as displayed in Figures 7 & 8. These data show about a 40% chance that snow is the main precipitation type by 12/0900 UTC and a 90% chance of snow by 12/1200 UTC. By the time the precipitation was mainly snow, the mean QPF was around 0.10

inches. Due to a decrease in the number of members predicting any QPF, by 12/1500 UTC the probability of snow was around 40% (not shown).

4. SUMMARY AND CONCLUSIONS

The forecast of 3 to 5 inches of snow predicted over central Pennsylvania, to include State College, was not observed. Observations suggest that about 1 inch of snow was observed in and around State College on the morning of 12 December 2008. A minor ice storm was observed on the 11th.

With the notable exception of run-to-run inconsistencies, the data presented here suggest that neither the NAM nor the GFS presented any information with regard to uncertainty. It is also evident that forecasts of 3 to 5 inches of snowfall were biased toward the 11/1200 UTC forecast cycle and the deterministic models. The 11/0900 UTC SREF indicated that snow was not a high probability forecast until the very end of the event and the mean snowfall was under 0.20 of QPF.

The NAM and GFS snowfall forecasts decreased after 11/1200 UTC. The 11/1500 UTC SREF showed the same trend, with decreased overall snowfall and a decrease in the ensemble mean amount of QPF falling as snow.

From a traditional forecast perspective the forecasts of 3 to 5 inches of snow were biased toward QPF produced by the deterministic operational models. The SREF forecasts clearly indicated snow, and accumulations over 1 to 2 inches were low probability outcomes.

This case clearly shows some of the limitations of plume diagrams. It is difficult to get at the probabilities. Thus, the plumes are good for some generalized statistics and they clearly convey information about uncertainty, but they lack good probabilistic data. Thus the precipitation plumes are good for timing, amounts, maximum amounts, and uncertainty information. However, a new plume concept needs to be developed to exploit the probabilistic nature of these data.

It is also evident, comparing Figures 1 and 2 that neither the NAM nor the GFS can convey any uncertainty information. The uncertainty information from these single models was derived from the run-to-run inconsistencies.

From a decision support perspective the forecasts of 3-5 inches of snow were good forecasts. Despite being a low probability outcome event, the chance of over 3 inches of snow was approximately 40%. This is a conditional probability given all the precipitation falls as snow. However, for a user with a cheap cost to protect (3-4K) and a large potential loss if no action was taken (1M) it pays to protect if the event is a low probability outcome.

To some forecasters this might not sound correct, but for a user with a small C/L ratio it was a good forecast. Both the forecaster and the user require some level of knowledge of the C/L ratios. Budgetary concerns might have leaned toward the fact that a 40% outcome cost about 3K to protect and thus 3K was lost. However, one event where 1M is lost quickly mitigates the few losses of 3K when 3 to 5 inches of snow is low probability forecast.

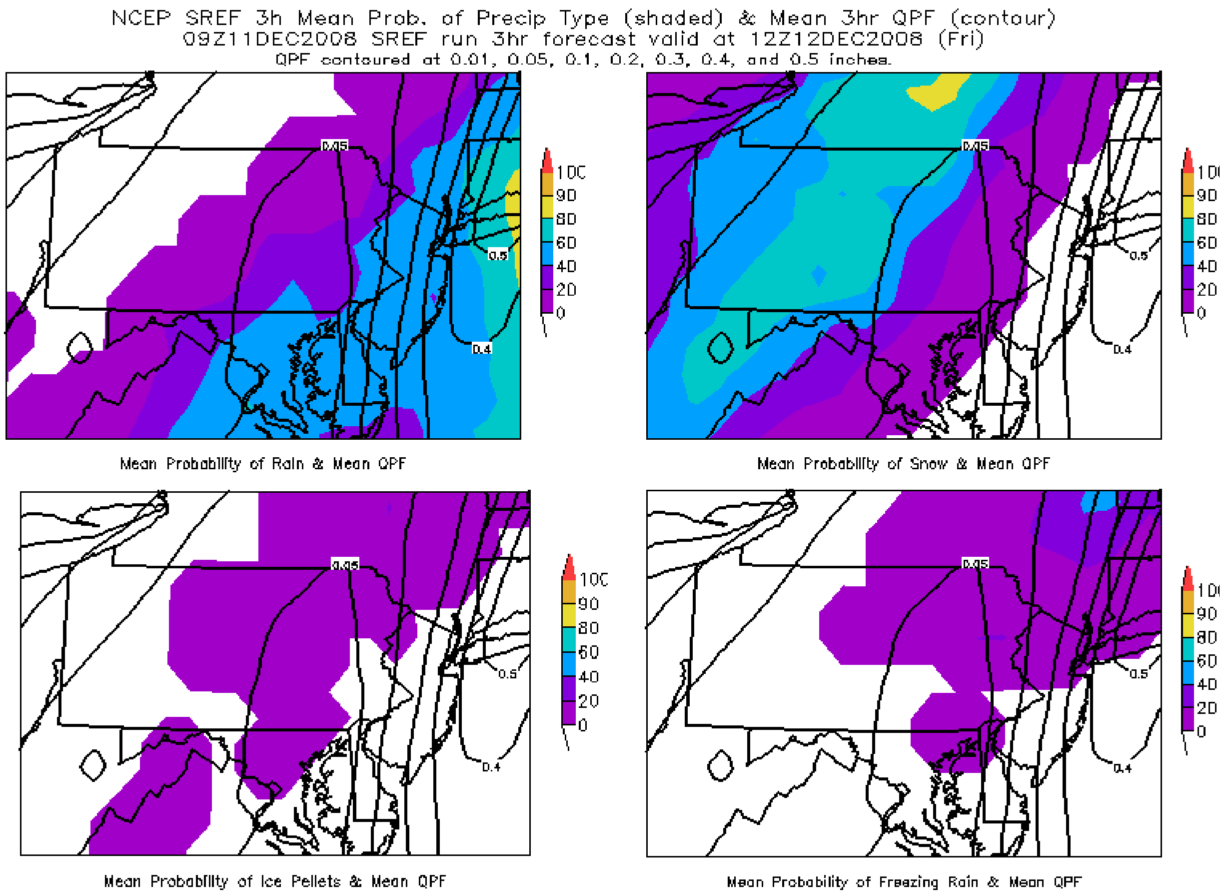

Figure 5. As in Figure 4 except valid at 1200 UTC 12 December 2008.

A continuous set of probabilities of an event needs to be produced. Users need to know their C/L so they can exploit the probabilities to make good decisions. This simple illustrates this point making the connection between the user and the forecaster.

It should be noted that each user has unique C/L ratios. In our simple snow example, a ski lift operation may make decisions related snow production based on the forecasts for of 3-5 inches of new snow. In this case, the ski resort could reduce or cease snow making to save some money on energy costs related to snow making. Thus some organizations, in particular those with potentially large risk, require specific forecasts from forecast services while others could use forecasts based on continuous probabilities and their known C/L ratios. The latter group could use forecasts where the forecaster only needs to convey information about uncertainty and the probability of an outcome. However, the former group requires that the forecaster and the user know information about the specific users C/L ratio.

5. ACKNOWLEGEMENTS

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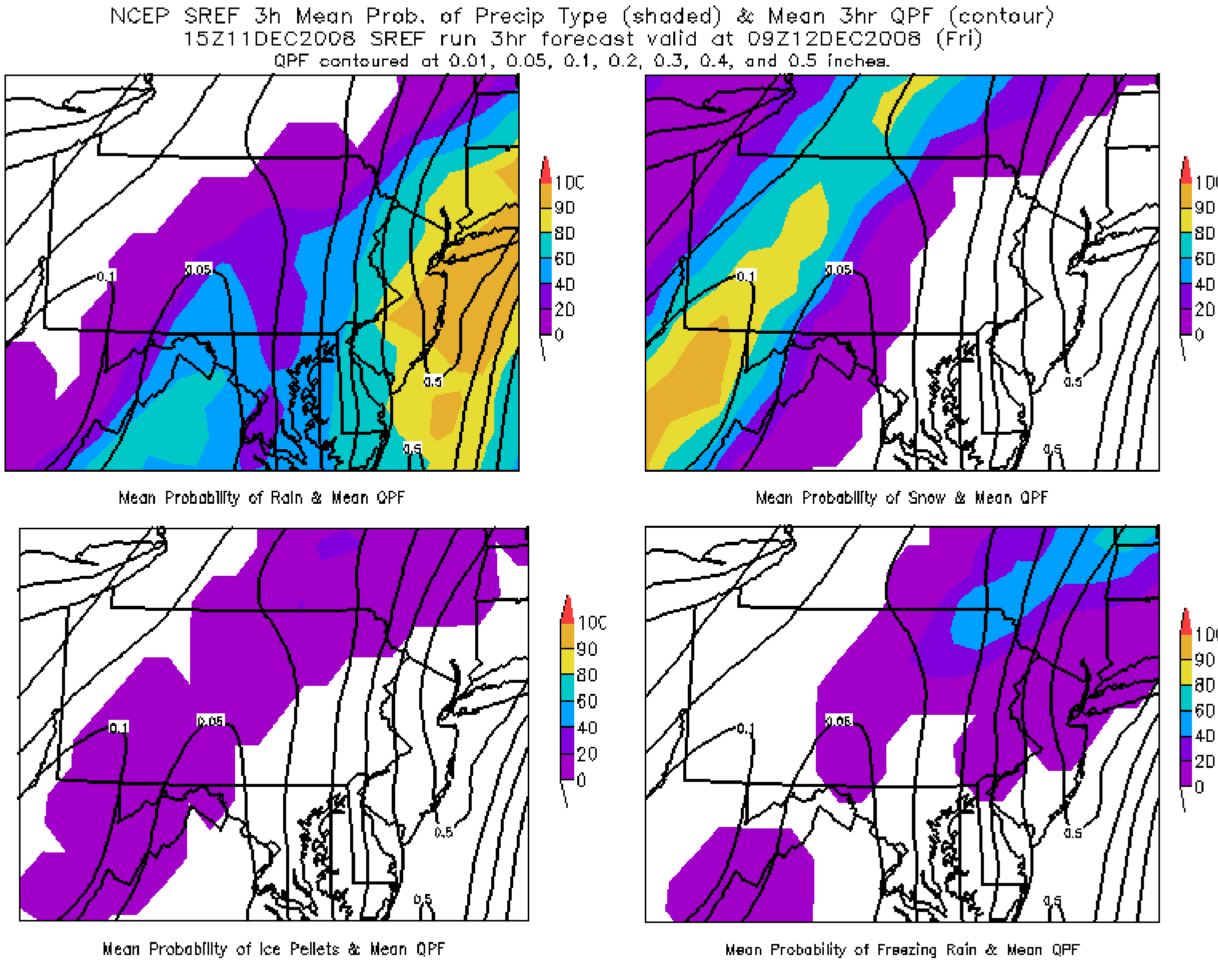

Figure 6. As in Figure 4 except for SREF initialized at 1500 UTC 11 December 2008 valid at 0900 UTC 12 December 2008.

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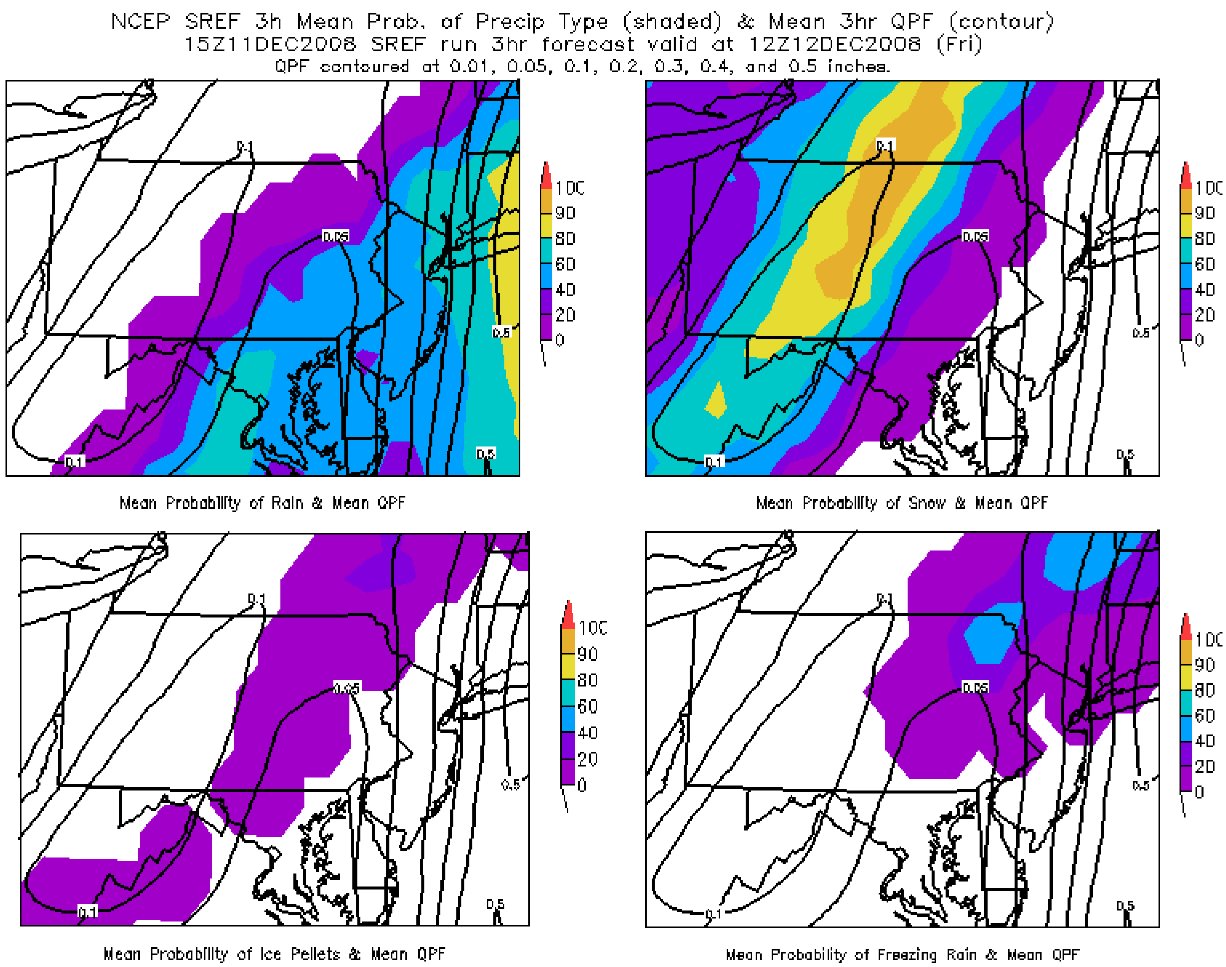

Figure 7. As in Figure 8 except initialized at 1500 UTC 11 December and valid at 1200 UTC 12 December 2008.

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