3.13 PROBABILISTIC FORECASTS OF PRECIPITATION TYPE

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1. INTRODUCTION

Precipitation-type forecasting is the determination of when and where particular types of precipitation (e.g., snow, rain, ice pellets, freezing rain) will occur during a forecast period. Although much is already known about the physical processes that determine the type of precipitation that reaches the ground, these forecasts are very challenging for most forecasters because of inadequate atmospheric data sampling and limited access to high resolution model data.

In this study, we examine the quality of six precipitation-type algorithms using Eta and RUC model data. We also analyze the quality of the probabilistic forecasts that were created from a combination of the algorithm outputs. Since a early examination of the algorithms using rawinsonde data showed that there was not one algorithm that accurately diagnosed the correct precipitation type for all types of precipitation, we combined the algorithms to provide a measure of forecast uncertainty. Data used in this study was created during the Precipitation-type Algorithm Experiment (PTAX), which occurred during the winter of 2000–2001 and involved meteorologists at the University of Oklahoma, the NOAA/Hydrometeorological Prediction Center, and the NOAA/Storm Prediction Center.

2. PRECIPITATION-TYPE ALGORITHMS

For this study, we tested six precipitation-type algorithms using only the thermodynamic data from the operational RUC and Eta models. (Only the Eta results will be shown in this paper.) All the algorithms used vertical thermodynamic data to identify warm and cold layers above a particular surface location (horizontal movement of the rawinsonde during ascent is not considered), where freezing and melting of a hydrometeor may occur. Most of these algorithms are described elsewhere (Baldwin et al. 1994; Bourgouin 2000; Czys et al. 1996; Ramer 1993), so the description of each algorithm in this paper will be limited. During this experiment, the algorithms were evaluated at locations where at least 0.1 mm of precipitation was forecasted in a one-hour period by the model.

2.1 *Thickness*

The thickness algorithm diagnoses precipitation type based upon the average virtual temperature, as determined by the hypsometric equation and the difference of the geopotential height of two pressure surfaces. We determined critical thickness values after examining the studies of Keeter and Cline (1991), and Zerr (1997) and identifying the values that were consistent among the studies. Using the geopotential height data from the model output, we determined the precipitation type near the ground. Snow was diagnosed if the 850–700 mb thickness was ≤1540 m. Rain was diagnosed if the 1000–850 mb thickness was > 1310 m or if the 850–700 mb thickness > 1560 m and the surface *Tw* > 0˚C; otherwise, if the surface *Tw* ≤ 0˚C, then the algorithm diagnoses freezing rain. If the 850–700 mb thickness > 1540 m and ≤ 1560 m, then ice pellets are diagnosed. The algorithm only diagnoses the precipitation type if the geopotential height data at all four mandatory levels are available (i.e., no extrapolated data).

2.2 *Ramer*

The Ramer algorithm (Ramer 1993) uses *p*, *T*, relative humidity, *RH*, and *Tw* to diagnosis snow, freezing rain, ice pellets, rain, and mixed precipitation. It, too, is based on the ice fraction of the precipitation at the ground. The algorithm begins by checking *Tw* at every available data level. If *Tw* at the lowest level is > 2˚C, then rain is diagnosed; if it is ≤ 2˚C and the *Tw* at every other level is < -6.6˚C, then snow if diagnosed. Other conditions require the algorithm to perform additional calculations to determine the precipitation type.

The algorithm begins by locating the precipitation generation level, the highest saturated layer (*RH* > 90%) with a depth of roughly 16 mb. *Tw* at that level determines the initial water phase of the precipitation: if the coldest *Tw* is < -6.6˚C, then the hydrometeor is entirely ice; otherwise, it is supercooled water.

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According to the algorithm, if *Tw* at the generation level is < -6.6˚C and the *Tw* at all the other levels is < 0˚C, then snow occurs.

As the hydrometeor descends from the generation level, the algorithm assumes that the particle will begin to melt or freeze depending on the *Tw* of the hydrometeor's environment. The ice fraction of the hydrometeor is determined by the formula

$$DI / d \ln (p) = (0^\circ C - Tw) / E, \qquad (1)$$

where $E = E' RH$. Ramer empirically derived the constant, $E'=0.045^\circ C$, by examining 2084 observations of precipitation that occurred near rawinsonde stations. The range of *I* is from 0 (liquid) to 1 (solid). The final determination of the precipitation type is made by the value of *I* and *Tw* at the lowest level. If *I* > 0.85, and partial melting has occurred, then the algorithm diagnoses ice pellets. If no melting has occurred, then snow is diagnosed. If *I* < 0.04 and the *Tw* near the ground is < 0˚C, then freezing rain is diagnosed; otherwise, if the *Tw* near the ground is ≥ 0˚C, then rain is diagnosed. If 0.04 ≤ *I* ≤ 0.85 and the surface *Tw* < 0˚C, then a freezing mix (one precipitation type is freezing rain) is diagnosed; otherwise, a frozen mix (no freezing precipitation) is diagnosed.

2.3 *BTC*

The algorithm developed by Baldwin et al. (1994), hereafter referred to as the BTC algorithm, diagnoses a single precipitation type (e.g., rain, snow, freezing rain, ice pellets) from an observed thermodynamic vertical profile and currently is used by the U.S. Weather Service. Although this algorithm uses various empirically-derived constants, other algorithm variables are based upon their importance in the melting and freezing of hydrometeors. The basic procedure used by the algorithm is to examine the vertical thermal structure that a falling hydrometeor encounters as it descends to the ground to determine the potential for freezing or melting. It identifies warm (> 0˚C) and cold (≤ 0˚C) layers above a particular location by computing the area between 0˚C and the wet-bulb temperature, *Tw,* on a skew-*T*-log*p* diagram. The area is computed separately for warm and cold layers and is used, along with the surface temperature, *To*, to determine precipitation type.

The algorithm begins by determining if precipitation initially begins as supercooled water or ice. The precipitation generation level is assumed to exist at the highest saturated layer ($T - Td < 6^\circ C$). Next, it computes the area between –4˚C and *Tw* up to 500 mb, and the area between 0˚C and *Tw* of the surface-based warm or cold layer. The algorithm diagnoses snow if the coldest temperature at any level with a pressure, *p*, of 500 mb or greater is ≤ -4˚C, and the area of the sounding between –4˚C and *Tw* is not large (< 3000 deg. m.)

The algorithm diagnoses freezing rain when the coldest temperature in a saturated layer is > -4˚C and *To* is < 0˚C. Freezing rain also is diagnosed if the net area, with respect to 0˚C, of the surface-based layer is > -3000 deg. m, the area between –4˚C and *Tw* > 3000 deg. m, and *To* is ≤ 0˚C.

If the coldest *Tw* in a saturated layer is ≤ -4˚C, and the area between -4˚C and *Tw* is > 3000 deg. m, then ice pellets are diagnosed when the surface-based cold layer is ≤ -3000 deg. m, or the net area between 0˚C and *Tw* within the lowest 150 mb is ≤ -3000 deg. m and the surface-based warm layer is < 50 deg. m.

Rain is diagnosed when the coldest *Tw* in a saturated layer is > -4˚C and *To* is > 0˚C. Rain is diagnosed also when *To* > 0˚C and the area between -4˚C and *Tw* is > 3000 deg. m, and the net area between 0˚C and *Tw* within the lowest 150 mb is > -3000 deg. m, or the surface-based warm layer is > 50 deg. m.

2.4 *Bourgouin*

The algorithm developed by Bourgouin (2000) is similar to the BTC algorithm and determines if enough energy is available in the environment to melt or freeze hydrometeors. It computes the areas bounded by 0˚C and the observed temperature > 0˚C (melting energy) and the observed temperature < 0˚C (freezing energy) on a standard tephigram. The Bourgouin algorithm determines precipitation type by examining the magnitude of the melting and freezing energies: Snow occurs when the melting energy of a surface-based layer is ≤ 5.6 J kg^{-1} or the melting energy available in a mid-level warm layer (a warm layer above a surface-based cold layer) is < 2 J kg^{-1} when no surface-based warm layer is present. If the surface-based melting energy is between 5.6 and 13.2 J kg^{-1}, Bourgouin notes that frozen and melted precipitation are equally likely, so we randomly choose either snow or rain. Rain will also occur if the elevated layer of melting energy is < 2 J kg^{-1} and the surface-based melting energy is > 13.2 J kg^{-1}.

If snow is not diagnosed, the algorithm diagnoses freezing rain if the freezing energy < 46 + 0.66 X melting energy. Although not suggested by Bourgouin, we also require *To* < 0˚C; otherwise, if *To* ≥ 0, then rain is diagnosed. Ice pellets occur when the freezing energy > 66 + 0.66 X melting energy and the surface-based melting energy is ≤ 5.6 J kg^{-1}. As in the snow diagnosis, if the surface-based melting energy is between 5.6 and 13.2 J kg^{-1}, Bourgouin notes that both types are equally likely, so we choose randomly either ice pellets or rain. Also, Bourgouin notes that for any freezing energy between 46 + 0.66 X melting energy and 66 + .66 X melting energy, there is an equally probable chance of freezing rain or ice pellets. In these cases, we randomly choose either type, subject to the proper *To* or surface-based melting energy test described previously. The various constants used in this algorithm were empirically chosen by Bourgouin (2000) after examining cases during the 1989-1990 and 1990-1991 cold seasons.

2.5 *CSTPS*

The algorithm developed by Czys et al. (1996), hereafter referred to as CSTPS, was developed to distinguish primarily between ice pellets and freezing rain environments by predicting the ice portion of a single ice sphere as it descends to the ground through a given thermodynamic profile. We made minor modifications to this algorithm to also predict snow and rain as well.

Precipitation type is determined primarily by computing the ratio, τ, of the time that an ice sphere remains in the warm layer (the residence time), and the time necessary to completely melt the sphere: If $\tau = 0$, then no melting occurs; If $0 < \tau < 1$, then partial melting occurs; If $\tau \geq 1$, then complete melting occurs. The algorithm determines the residence time by dividing the warm layer depth by the terminal velocity of the hydrometeor (assuming the vertical velocity of the air is zero). We used an initial ice sphere radius of 400 microns, as determined by Czys et al. (1996) using radar reflectivity data during a U.S. ice storm. The algorithm estimates the time that is needed to completely melt the particle from a balance between the release of latent heat from melting and the rate of heat transfer through its liquid water shell. It uses three characteristics of the elevated warm layer: average depth, average pressure, and average *Tw*, to determine the melting time. In this study we do not require an elevated melting layer in order to use this algorithm since we believe that the physical processes upon which the algorithm is based also occur in surface-based melting layers.

According to the CSTPS algorithm, ice pellets occur if $0 < \tau < 1$ for any value of *To*. Freezing rain occurs if $\tau > 1$ and $To \leq 0$˚C; if *To* > 0˚C, then rain occurs. Snow occurs if there is no melting layer, $\tau = 0$.

2.6 *Cortinas*

The Cortinas algorithm, like CSTPS, attempts to determine if a single frozen hydrometeor melts completely as it descends through any melting layer. Although there are some minor differences between some of the equations used in the Cortinas algorithm and those used in the CSTPS algorithm, the major difference is that the Cortinas algorithm does not use the characteristics of the warm layer (i.e., depth and average temperature); instead, the entire thermodynamic profile below 500 mb is used to compute the melting rate of the ice sphere that is the same size as the one used in CSTPS. The algorithm determines the precipitation type based upon the size of the ice sphere at the ground. (The large processing time required for this algorithm prohibited its use during PTAX; however, it was modified to diagnosis only rain, if no warm layers existed above the surface and *To > 0˚C.*

3. PROBABALISTIC FORECASTS

In addition to producing algorithm output during PTAX, we generated probabilistic output to provide an estimate of the forecast uncertainty. A probabilistic forecast for each type of precipitation was computed using all available algorithm output. (Recall that algorithms 1 and 6 would not always produce output given particular conditions described in the previous section.) During this experiment, hourly model soundings were available every hour at roughly 600 Eta forecast points across the United States. Using these data, each algorithm produced a precipitation type forecast. Probabilities were assigned to each type by using a weighted sum of the algorithm output. For each algorithm, *A(i)*, that produces a particular precipitation type, *x*, the probability of that precipitation type, *P(x)*, is

$$P(x)= \{\sum[w_x(i) * A_x(i)]\} / \sum w_x(i) ,$$

where $w_x(i)$ is the weight assigned to algorithm *A(i)* for type, *x*. The value of *A* is 1 or 0, depending on whether *A(i)* diagnosed the precipitation type *x* or another precipitation type. Only algorithms that produced output were used in the *P(x)* calculation. The weights were based upon a preliminary evaluation of these algorithms using observed soundings across North American from 1976 to 1990 (Table 1) and may not represent the most optimal weights.

Table 1. Weights used in current study

		Algorithms					
		1	**2**	**3**	**4**	**5**	**6**
PrecipitationType	Rain	1	2	1	1	1	1
	Snow	1	1	1	1	2	1
	Ice Pellets	1	1	2	1	1	1
	Freezing Rain	1	2	1	1	1	1
	Undeter-mined	1	2	1	1	1	1
	Mixed	1	2	1	1	1	1

In addition to the probabilistic output by precipitation type, the most probable type at a particular location and model valid time was obtained by identifying the type associated with the highest *P(x)*. If *P(x)* for one type was equal to the *P(x)* for another type, then a hierarchical ordering of snow, rain, freezing rain, ice pellets was used to determine the most probable type.

4. EVALUATION PROCEDURE

The forecast quality of the algorithms and the most probable precipitation type were assessed by constructing a standard contingency table for each type of precipitation using model data every three hours. Algorithm output using Eta forecast soundings from November 2000 to March 2001 were compared to surface observations of precipitation type at +/- 1 hour of the model valid time. Only those locations where precipitation was observed and forecasted were verified since the algorithms were originally developed to be used at locations where precipitation is occurring. Additionally, the rain forecasts were only verified against observations of rain where $To \leq 5^{\circ}C$, since forecasting rain at these temperatures can be most difficult.

For the evaluation period, numerous verification statistics were computed, namely, probability of detection (POD), false alarm rate (FAR), bias, threat score, Heidke skill score, and Kuipers skill score. Only POD and FAR will be discussed in this paper.

5. RESULTS

An analysis of the POD (Fig. 1) and FAR (Fig. 2) for algorithms 2-5 and each precipitation type shows that there is no algorithm that has the highest (lowest) POD (FAR) for all times and all precipitation types. Results for the thickness algorithm are not included in the plots since it was only applicable to roughly 10% of the forecasts of algorithms 2-5; however, the median POD (FAR) values for snow, ice pellets, freezing rain, and rain were 0.39 (0.18), 0.6 (0.95), 0.0 (1.0), and 0.88 (0.11) respectively. Also recall that the Cortinas algorithm only was used in this experiment to discriminate between rain and no rain. The plots indicate that the forecast accuracy for rain is relatively good, whereas, the accuracy of the ice pellet forecasts is poor. Generally, the forecast accuracy decreases as the forecast hour increases, as expected.

Despite the fact that the accuracy of one algorithm is not consistently superior to the others, it is important to note that the most probable type forecast ranks in the upper-half of the algorithms for all types, except ice pellets. This provides some evidence that ensemble, or consensus, forecast techniques may be useful when forecasting precipitation type, as suggested by Brooks et al. (1996).

An examination of the probabilistic forecasts using Eq. (1) reveals that snow, rain, and freezing rain forecasts are usually reliable, whereas ice pellet forecasts are not (Fig. 3). These results also show that this forecast system overforecasts snow and rain, and underforecasts freezing rain and ice pellets.

An alternate method of combining model output to provide a probabilistic forecast was also used to evaluate the effect of different methodologies of generating probabilistic output. Using only algorithms 2-5, a probability of precipitation type was created by using the forecast relative frequency for that particular precipitation type, similar to a linear combination of these algorithms with all the coefficients equal to one (hereafter referred to as the unweighted combination). The plot of these two types of combinations shows that the weighted combination did not generate probabilistic forecasts that were more reliable than a linear combination of algorithms 2-5 with all the coefficients set to one, particularly for snow and rain at midrange probability values. The reasons for this effect are currently under investigation.

6. ACKNOWLEDGEMENTS

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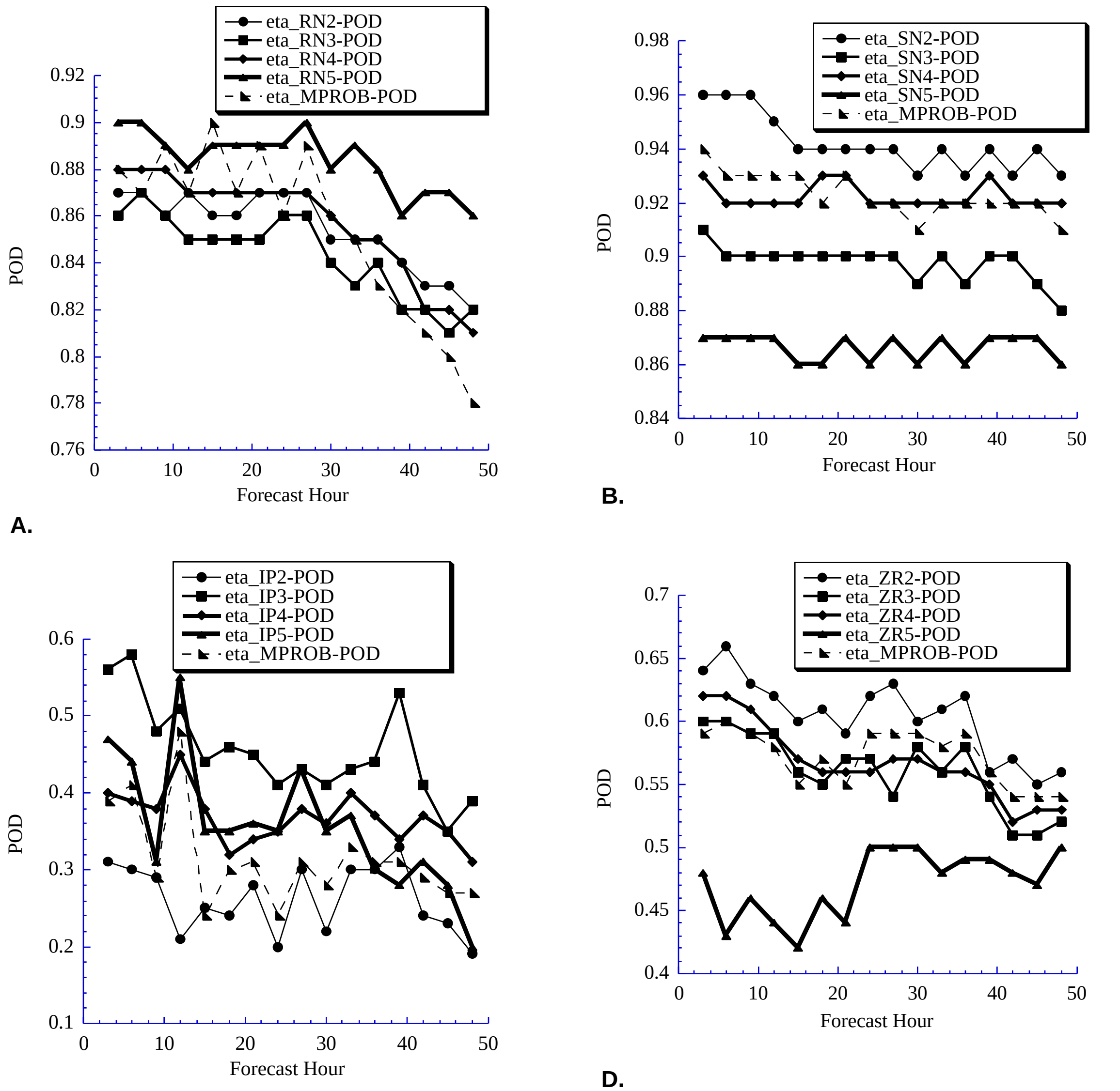

Fig. 1. POD scores for (a) rain, (b) snow, (c) ice pellets, and (d) freezing rain, using 3-hrly Eta model output from all 0 and 12 UTC runs between November 2000 and March 2001 (roughly 190,000 forecast points). The algorithm number is indicated in each plot as well as the most probable (MPROB) output.

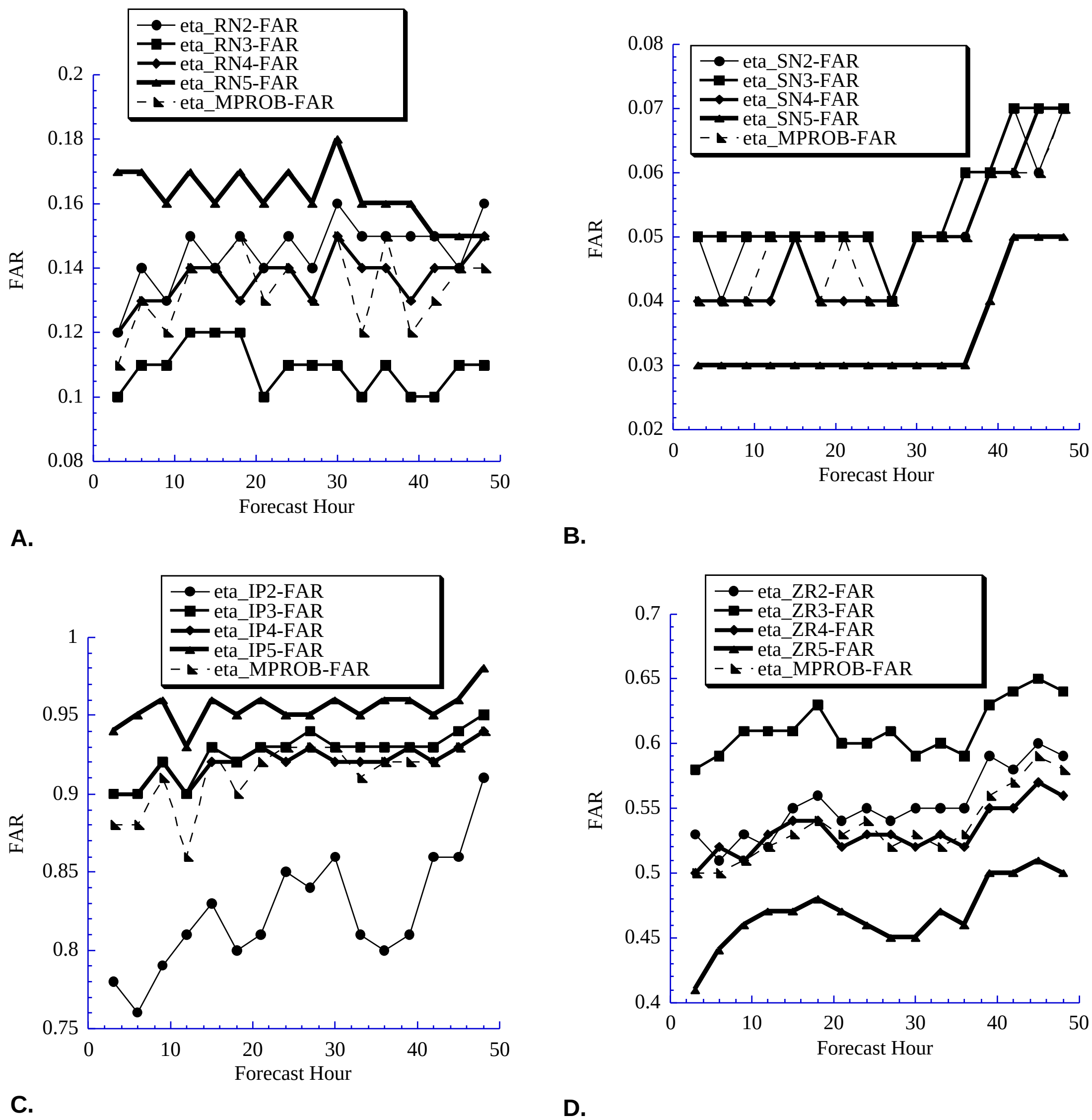

Fig. 2. FAR scores for (a) rain, (b) snow, (c) ice pellets, and (d) freezing rain for same data in Fig. 1.

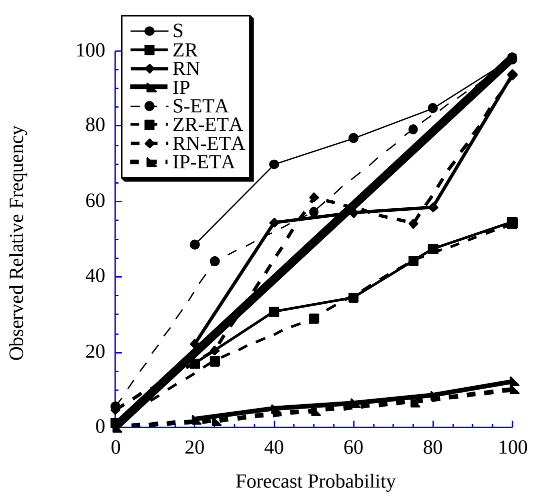

Fig 3. Reliability diagram combining all algorithms with weights (S, ZR, RN, IP) and without weights (-ETA). Dashed lines indicate unweighted forecasts. Thick solid line indicates perfect reliability.