Real-Time Forecasting of Snowfall Using a Neural Network

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ABSTRACT
A set of 53 snowfall reports was collected in real time from the 2004/05 and 2005/06 cold seasons (November–March). Three snowfall-amount forecast methods were tested: neural network, surface-temperature-based lookup table, and climatological snow ratio. Standard verification methods (mean, median, bias, and root-mean-square error) and a new method that places the forecasts in the context of municipal snow removal, and introduces the concept of forecast credibility, are used. Results suggest that the neural network method performs best for individual events, owing in part to the inverse relationship between melted liquid equivalent and snow ratio; hence, the ongoing difficulty of producing accurate forecasts of melted equivalent precipitation (a problem in all seasons) is compensated for rather than amplified when converting to snowfall amounts. This analysis should be extended to a larger selection of reports, which is anticipated in conjunction with efforts currently ongoing at the National Oceanic and Atmospheric Administration’s Hydrometeorological Prediction Center.

1. Introduction
Recently, there have been attempts to provide improved guidance to forecasters concerning forecasts of snowfall (Roebber et al. 2003; Dubé 2006; Cobb and Waldstreicher 2005; Baxter et al. 2005; Ware et al. 2006). Roebber et al. (2003) conducted a principal component analysis of radiosonde and surface data and identified seven factors that influence the diagnosis of snow ratio: solar radiation per month, low- to midlevel temperature, mid- to upper-level temperature, low- to midlevel relative humidity, midlevel relative humidity, upper-level relative humidity, and external compaction, as measured by surface wind speed and liquid equivalent precipitation amount. They then constructed 10-member ensembles of artificial neural networks\(^1\) that substantially improved the diagnosis of snow-ratio class compared with the then-existing techniques [10:1 ratio, sample climatology, and National Weather Service (NWS) new-snowfall-to-estimated-meltwater conversion table, also known as Table 4-9 of U.S. Department of Commerce (1996) and hereafter called “lookup”]. In fall 2004, this ensemble system was made available online (http://sanders.math.uwm.edu/cgi-bin-snowratio/sr_intro.pl), using soundings derived from the National Centers for Environmental Prediction (NCEP) operational forecast models.

In this note, we report on preliminary tests of this

\(^1\) A neural network can be thought of as a system that maps inputs to outputs. In this application, conditions that have an influence on snow ratio (temperatures, liquid equivalent precipitation, surface winds, etc.) are mapped to snow ratios obtained from a large sample of cases. This “trained” network can thereafter be used to predict the snow ratio for any new case based upon the mapping derived from the original data.
2. Data and methods

The dataset comprises a collection of 53 reports from the 2004/05 and 2005/06 cold seasons (November–March) across the contiguous United States (CONUS) east of the Rocky Mountains (Fig. 1). Although many of the sites are collocated with a radiosonde launch, the only criterion for these events was that the observed new snow be at least 2.5 cm (1 in.; hereafter, English units will be used to reflect the operational orientation of this work). The small number of cases reflects the preliminary nature of this study—case selection was governed by author time constraints and real-time data availability. A larger sample, consisting of more sites over more events, is presently being generated from archival data and will be studied in a future paper. Additionally, the Hydrometeorological Prediction Center (HPC) is conducting its own data collection and verification of snowfall forecasts in winter 2006/07 (K. Brill 2006, personal communication). The mean and median snowfalls (liquid equivalent) for the 53 cases reported herein were 5.4 (0.35) and 3.1 (0.18) in., respectively (Table 1), whereas the maximum observed event featured a snowfall of 24 in. The mean and median snow ratios for the dataset were 20:1 and 18:1, respectively (Table 1).

The procedure used to make a snowfall amount forecast is as follows. First, 12–36-h forecasts (NAM/Eta Model, if available; otherwise, GFS) of surface wind speed, liquid equivalent precipitation, and the vertical profiles of temperature and humidity were used as inputs to the ensemble of neural networks of Roebber et al. (2003) to obtain multiple forecast snow-ratio class probabilities. The final class, composed of the ensemble average of the individual forecasts, was then assigned according to the highest ensemble class probability (e.g., with ensemble probabilities of 0.10, 0.30, and 0.60 for “heavy,” “average,” and “light,” respectively; the assigned class would be light). Second, a numerical snow ratio was assigned based on a representative value for that class. Specifically, for the heavy designation, a snow ratio of 8:1 was assumed; for average, a snow ratio of 13:1 was assumed; and for light, if the probability in that class was less than 0.67, 18:1 was assumed; otherwise, 25:1 was assumed. This differentiation for the light class is based on the observation, documented in the dataset collected by Roebber et al. (2003), that higher snow ratios are correlated with higher network probabilities for the light class. The selection of representative values for each class as described above is somewhat ad hoc; more research is needed to determine optimal values.

Third, the snow depth for each 6-h period of the event was then computed based on the product of the snow ratio obtained for that period and the model QPF. Hence, for a snow ratio of average with a 0.40-in. QPF, the forecast snow amount in that 6-h period would be 13 times 0.40 or 5.2 in. Analysis of the results from the two datasets relative to the lookup [a baseline standard as shown in Roebber et al. (2003)] is reported in section 3. Concluding remarks are provided in section 4.

3. Results

Table 1 shows that both QPFs and snow-ratio errors contribute to the overall snowfall depth errors. For this
sample of 53 reports, the model QPF reveals an overforecast bias. For the lookup, this QPF overforecast combines with a high bias in the snow ratio (the result of a number of reports with cold surface temperatures but warm air aloft) to produce a substantial overforecast bias of the snowfall amount. In contrast, a distinct feature of the network methodology is that there are compensating errors that result from the physical process of compaction associated with high liquid equivalents (see Roebber et al. 2003; Ware et al. 2006, their Fig. 4). Specifically, when the QPF is too high, the forecast snow ratio will be too low, and their product will remain relatively bounded compared with the unconstrained lookup result. The reverse is also true: underforecasts of liquid equivalent will lead to an overestimation of snow ratio, and their product will remain bounded.

This can be quantified in these data by defining an overforecast (underforecast) as a QPF that exceeds (is less than) the observed amount by more than 0.05 in. The mean network snow-ratio errors are -6.6 (too low) and +0.9 (too high) in the QPF overforecast and underforecast categories, respectively. The Kruskal–Wallis test is a nonparametric test of the null hypothesis that groups come from the same distribution [it is similar to the analysis of variance (ANOVA) method, but is resistant to outliers in the data]. Using this test, one finds that there is indeed a statistically significant ($p = 0.029$) dependence of the network snow-ratio error on the QPF error, in the directions indicated above.

Overall, the network shows only a slight overforecast bias in snow amount and the lowest overall root-mean-square error (RMSE; Table 1). This strongly suggests that the network approach can add significant utility to snowfall forecasts, relative to the lookup baseline. It should be noted that in the winter of 2005/06, HPC began a preliminary evaluation of a variety of snowfall forecast techniques (K. Brill 2005, personal communication). Although complete data are unavailable at this time, these data indicate that the climatological snow-ratio approach [the product of the climatological snow ratio of a particular site as obtained from Baxter et al. (2005) times the QPF] provides useful guidance. Consistent with this, for the 2004/05 and 2005/06 dataset reported herein, the climatological approach provides the smallest mean and median snowfall errors (Table 1). Also notable, however, is the considerably larger RMSE, suggesting that for key events, the effectiveness of this approach may be reduced by large forecast errors.

### Application to municipal snow removal

To examine these impacts in an operational context, we place the dataset results in the evaluative framework of the municipal snow-removal problem. Although this is only one aspect of the overall impact of snowstorms, it is a useful context in which to examine several operationally important issues that are not completely addressed by the usual statistics.

The municipal snow-removal problem is a key and largely quantifiable aspect of the overall impact of snowstorms. Two controlling principles exist. First, there are costs associated with snow removal. Second, the core mission of municipal snow removal is to ensure that the roadways are cleared and safe for travel, and funds are expended as needed to achieve this mission. Risk aversion is a prominent characteristic of this activity (e.g., Stewart et al. 2004). City commissioners cite inaccurate forecasts as the biggest challenge to these services, since, if the operation is resourced at an inappropriately low level, extending the operation for a longer time and finding the equipment and personnel to manage the storm becomes difficult.

Accordingly, the measure that we employ incorporates costs, but does so in the context of what we introduce as a measure of the forecast “credibility.” A definition of credibility is the quality, capability, or power to elicit belief. Social science research on the dimensions of credibility (e.g., Berlo et al. 1969) frequently cite two core components: competence (ability) and trustworthiness (benevolence and integrity).
Where information is obtained from model guidance rather than a human source, competence might be measured by forecast skill for the phenomena in question and trustworthiness by a measure of the consistency between the forecast and observations such as the type I conditional bias or reliability. Hence, one might consider estimating credibility from a decomposition of a skill score (e.g., Murphy 1997). For hazard assessment and decision making, however, serious past errors substantially reduce source credibility (Covello 1989). In these situations, users are often risk averse and the overall skill and its decomposition becomes less useful.

Here, a different approach is attempted. The first step is to compute an estimate of the cost to remove the observed snow [note that it is the depth of the snow rather than its weight which is of interest (R. Holmes, GuaranteedWeather LLC, 2006, personal communication)]:

\[ \text{Removal} \left( \$ \right) = 15,865 \times \text{snowdepth}^{1.307} \times \frac{\text{population}}{323,000}. \]

(1)

Equation (1) is derived from data collected by GuaranteedWeather LLC for Ann Arbor, Michigan (population 323,000) for snowfall totals from 2 to >7 in. Because removal costs are proportional to road mileage, it is expected that costs will scale linearly with population for urban areas. We can test this equation for other urban populations and snow amounts using some widely reported cases. On 11–12 February 2006, New York City, New York, received a record snowfall of 27 in. Snow-removal costs were reported in news accounts to be about $27 million. Using a city population of 8.1 million as reported by the U.S. Census, (1) produces a cost estimate of $29.5 million. On 1–3 January 1999, up to 22 in. of snow fell in northern Illinois. Reported snow-removal costs were $250,000 for locations with populations of 100,000, compared with the estimate of $279,000 obtained from (1). Hence, (1) appears to provide reasonable estimates across a range of community sizes and snowfall amounts.

Next, the expected snow-removal costs are estimated from (1) for the forecast of interest (in this study, the neural network, lookup, and climatological snow-ratio methods). Third, the costs of accidents associated with poor forecasts (defined here as underforecasts of ≥3 in., because most plowing efforts begin once the depth reaches this level) are estimated. These costs are based on Blincoe et al. (2002), who analyze motor vehicle crash costs in the United States for the year 2000, based on a present value estimation of the lifetime comprehensive costs (economic costs and values for intangible consequences based on quality-adjusted life years lost) across a range of accident severity (property damage only up to fatal). For example, a fatality is estimated at $977,208 for economic components (medical, emergency services, market and household productivity, administrative and legal costs, travel delays, and property damage), and $2,389,179 for quality-adjusted life years lost, for a total cost of $3.4 million. Fortunately, these data also show that 82.5% of all crashes are at the lowest level (property damage only), with only 0.1% fatal crashes in urban areas. Hence, the statistical expectation of the cost of a given crash is $14,340.

To complete this calculation, the accident rate in “snow” weather is needed. Based on data collected by the U.S. Department of Transportation (2001, 2006a,b), we estimate this accident rate to be 2.72 per million vehicle miles. Further, the U.S. Department of Transportation estimates daily travel to be approximately 40 miles per person. Thus, the costs of accidents are estimated as

\[ \text{accident cost} \left( \$ \right) = \text{population (millions)} \times 40 \times 2.72 \times 14,340. \]

(2)

A credibility score \( C \), which ranges from zero up to 1.00 for a perfect set of forecasts, can then be defined as

\[ C = \frac{\sum N \min(\text{forecast cost, observed cost})}{\sum N \max(\text{forecast cost, observed cost}) + \sum N \text{accident cost}} \]

(3)

for \( N \) forecasts.

The rationale for this scoring is as follows. The municipality has a responsibility to ensure that the roads are properly cleared and safe for travel and thus needs to know the level of resources required to accomplish that. An overforecast of snowfall is undesirable because too many resources are identified relative to the need (e.g., crews on call; sanding, salting, and chemical treatments; public awareness). A loss of credibility results. An underforecast is undesirable because sufficient resources will initially be unavailable and roads will not be adequately cleared during the storm, with deterio-
Table 2. Estimated snowfall-removal costs and snowfall forecast impact for a climatologically normal and a heavy snow season for three large urban areas. Populations are based on the Combined Statistical Area (CSA) from 2005 U.S. Census data and the Census Metropolitan Area (CMA) from 2005 Statistics Canada data, and are 9.6, 21.9, and 3.6 million for Chicago, New York City, and Montreal, respectively. Snowfall (in inches) for Chicago, New York, and Montreal, respectively, are <2 in. (24.0, 4.1, and 46.3), 2–5 in. (5.0, 5.3, and 9.3), 5–10 in. (0.9, 1.0, and 5.0), and >10 in. (0.1, 0.3, and 0.5). The heavy snow season is defined as above, except with two extra storms greater than 10 in. Climatologically normal (record) snow season amounts for Chicago, New York, and Montreal are 35.9 (83.7), 24.6 (69.9), and 85.6 (122.2) in., respectively. Dollar amounts are in millions. Snow amounts are in in. Shown are simulated seasonal snowfall (Sim snow), seasonal snow-removal cost (Rem cost), minimum and maximum of snow-removal and vehicle accident costs [Eq. (2)], and credibility score [Eq. (3)] from the neural network, lookup, and climatological snow-ratio methods (Net Min, Lkup Min; Net Max, Lkup Max; Net Acc, Lkup Acc; Clim Min, Clim Max; Net Acc, Lkup Acc, Clim Acc).

<table>
<thead>
<tr>
<th>Site</th>
<th>Sim snow (in.)</th>
<th>Rem cost ($)</th>
<th>Net min ($)</th>
<th>Net max ($)</th>
<th>Net acc ($)</th>
<th>Net C</th>
<th>Lkup min ($)</th>
<th>Lkup max ($)</th>
<th>Lkup acc ($)</th>
<th>Lkup C</th>
<th>Clim min ($)</th>
<th>Clim max ($)</th>
<th>Clim acc ($)</th>
<th>Clim C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chicago</td>
<td>33.6</td>
<td>23.09</td>
<td>21.31</td>
<td>37.12</td>
<td>0.30</td>
<td>0.574</td>
<td>21.88</td>
<td>54.54</td>
<td>0.30</td>
<td>0.401</td>
<td>19.49</td>
<td>35.77</td>
<td>1.81</td>
<td>0.545</td>
</tr>
<tr>
<td>New York</td>
<td>30.4</td>
<td>53.67</td>
<td>48.88</td>
<td>90.38</td>
<td>1.39</td>
<td>0.541</td>
<td>51.21</td>
<td>140.41</td>
<td>0.66</td>
<td>0.365</td>
<td>45.41</td>
<td>94.82</td>
<td>10.94</td>
<td>0.479</td>
</tr>
<tr>
<td>Montreal</td>
<td>91.1</td>
<td>25.86</td>
<td>23.57</td>
<td>40.75</td>
<td>0.73</td>
<td>0.578</td>
<td>24.79</td>
<td>62.03</td>
<td>0.36</td>
<td>0.400</td>
<td>21.86</td>
<td>41.98</td>
<td>4.53</td>
<td>0.521</td>
</tr>
<tr>
<td>Chicago</td>
<td>61.3</td>
<td>52.48</td>
<td>45.07</td>
<td>77.25</td>
<td>4.65</td>
<td>0.583</td>
<td>50.10</td>
<td>120.58</td>
<td>2.24</td>
<td>0.416</td>
<td>40.31</td>
<td>91.91</td>
<td>23.51</td>
<td>0.439</td>
</tr>
<tr>
<td>New York</td>
<td>59.2</td>
<td>125.25</td>
<td>105.97</td>
<td>187.76</td>
<td>18.50</td>
<td>0.564</td>
<td>119.40</td>
<td>289.29</td>
<td>6.53</td>
<td>0.413</td>
<td>99.01</td>
<td>212.31</td>
<td>53.74</td>
<td>0.466</td>
</tr>
<tr>
<td>Montreal</td>
<td>119.5</td>
<td>37.45</td>
<td>32.80</td>
<td>55.75</td>
<td>3.08</td>
<td>0.588</td>
<td>35.93</td>
<td>86.14</td>
<td>1.33</td>
<td>0.417</td>
<td>30.10</td>
<td>62.56</td>
<td>13.06</td>
<td>0.481</td>
</tr>
</tbody>
</table>

rating travel conditions and increased accidents, a failure of the core mission. Hence, poor forecasts for both large and small events can diminish overall credibility in different ways, an experience all too familiar to operational forecasters.

Consider these examples. As noted above, on 11–12 February 2006, a 27-in. snowfall occurred in New York City. If the forecast had been perfect, C = 1.00 for that event and is weighted by the large cleanup cost. A forecast like this combined with less successful forecasts from a number of minor events would still produce a relatively high C for a winter season. On the other hand, if this event had been “missed” (say, a forecast of 3 in.), approximately $30 million would still have been required to clear the roads but only $2 million would have been initially allocated. Further, as the snow accumulated, approximately $1.3 million in accident costs would occur. Credibility for this forecast is 0.05 and is weighted by the size of the event, so a number of good forecasts for high impact events would be needed to recover from this over the season. If the event were overforecast (say, a forecast of 36 in.), an extra $21 million is initially allocated [based on (1)]. The snow is cleared in a timely fashion, but the additional situational awareness is wasted. Nonetheless, credibility is moderately high (0.59, with a $51 million weight). Although some customers might express some dissatisfaction with the forecast, this would be muted by the fact that 2 ft of snow fell without causing major problems.

In the case where a small amount of snow falls, the conclusions are different. The weight for a perfect forecast is $2 million, so the overall credibility of a set of forecasts is relatively unaffected by this particular event, except in the instance of a substantial overforecast. The false alarm in that case would be heavily weighted by the expected large cost, and credibility would need to be established by better forecasts in subsequent events. Table 2 presents the results of such an analysis for three urban sites subject to significant snowfall. Because the cost of a winter season is better correlated with the sum of the individual events rather than the total snow amount (R. Holmes, Guaranteed-Weather LLC, 2006, personal communication), the climatology of daily snowfalls of various amounts was used to sample from the 53 reports summarized in Table 1. Two scenarios for each urban site are presented: a climatological average and a heavy snow season, composed of the normal daily snowfall climatology in the first scenario and the normal climatology plus two additional events with snow greater than 10 in. in the second scenario, respectively. Sampling with replacement from the original 53 reports is conducted for 100 such snow seasons, and the results are averaged.

Several important points emerge. First, the frequent overforecasts from the use of the lookup result in the poorest overall credibility by a substantial margin (e.g., 0.365 compared with 0.541 for the network for a climatological average snow season at New York; 0.413 vs 0.564 for a heavy snow season), despite the fact that this risk-averse procedure maximizes effective clearing and minimizes accident rates (e.g., $0.66 million versus $1.39 million). Second, the climatological snow-ratio method results in some underforecasts of large events, yielding the largest accident costs (e.g., $10.94 million for a normal snow season at New York). This feature has the greatest impact in a heavy snow season, where the credibility score falls markedly (e.g., from 0.545 to...
0.439 at Chicago). Third, the network method reduces the frequency and impact of these underforecasts, yet maintains the reliability of the climatological method in the less extreme events, producing the highest overall credibility for the simulated forecasts (e.g., 0.564 for a heavy snow season at New York). The relative performance of a climatological approach can be improved by considering a snow ratio conditional upon QPF, because there is a strong relationship between the liquid equivalent precipitation and the snow ratio. Median climatological snow ratios for melted equivalent precipitation values in increments of 0.2 in. were obtained from the dataset of Roebber et al. (2003): 19.7:1 (0.20–0.40 in.), 13.1:1 (0.40–0.60 in.), 9.9:1 (0.60–0.80 in.), and 5.9:1 (>0.80 in.). Credibility scores in the heavy snow season using this method are 0.504, 0.485, and 0.553 for Chicago, Illinois, New York City, and Montreal, Quebec, respectively, which is better than the “standard” climatology and about halfway between the lookup scores and those of the network method.

A specific event captured in the study period will help to illustrate these performance issues. During 21–23 January 2005, a cyclone developed and moved east and north across the midwestern states to New England (Fig. 2). This storm, popularly referred to as the “Blizzard of 2005,” produced snowfall accumulations of up to 3 ft across a wide area. From west to east, snowfall forecasts were archived for the following sites during this period: International Falls, Minnesota (INL); Davenport, Iowa (DVN); Milwaukee, Wisconsin (MKE); Detroit–Wayne, Michigan (DTW); Pittsburgh, Pennsylvania (PIT); Albany, New York (ALB); New York City/Laguardia Airport International, New York (LGA); Gray–Portland, Maine (GYX); and Chatham, Massachusetts (CHH). Mean snowfall for the sampled periods across these nine sites was 11.5 in., while the mean forecasts from the neural network, lookup, and climatological snow-ratio methods were 11.2, 18.8, and 9.8 in., respectively. Based on the procedure detailed above, and accounting for the urban populations surrounding each of these sites, the total snow-removal cost for the nine locations for this event was approximately $35.3 million. Corresponding C scores for the neural network, lookup, and climatological snow-ratio methods were 0.73, 0.38, and 0.56, respectively. We examine this event at three sites in more detail: DTW, ALB, and GYX. The soundings (Fig. 3; ALB not shown) indicate near saturation and warm-air advection in a deep, cold layer, along with strong boundary layer winds and larger melted equivalent precipitation (approximately 0.5 in. at each site; Table 3). The deep, moist layer within the dendritic growth zone is consistent with high snow ratios, as expected based on the lookup. The strong winds and larger melted equivalent precipitation argue for greater surface compaction and lower ratios (Roebber et al. 2003). Observed snow ratios were higher than the climatological average of about 10:1 for precipitation amounts of 0.50 in., but considerably less than the 40:1 estimate based on surface temperature for ALB and GYX. Observed snowfalls as a consequence were about 1 ft at each of the three sites. In contrast, the model QPFs were substantially overforecast at ALB and GYX, which combined with the higher-than-observed snow ratios using the lookup, yielded expected snowfalls of 2–3 ft at those locations using that method (Table 3).

Despite the overforecasts of the QPFs, the climatological method produced underforecasts at these locations as a result of the lower-than-observed snow densities. At DTW, where the QPF was not substantially overforecast, the climatological snow ratio of 10.8:1 led to an underforecast of 6.3 in. of snow (Table 3). Owing to the inverse linkage between the liquid equivalent precipitation and snow ratio in the neural network method, however, the QPF overforecasts are partially compensated by underforecasts of the snow ratio, leading to snowfall values close to the observed amounts for that method (9.9 in. forecast vs 12.2 in. observed at DTW, 12.7 in. forecast vs 11.5 in. observed at ALB, and 15.5 in. forecast vs 12.8 in. observed at GYX; Table 3). Although the best forecasts from the network will result given the best input information, the operational reality is that QPF errors will occur, and thus the linkage between QPF and snow ratio built into the neural network methodology is a significant advantage relative to the other methods. It should be noted that the network would also have outperformed a conditional climatological forecast based on the QPF. In that case, the forecast snow ratios at DTW, ALB, and GYX would be 10.2:1, 9.9:1, and 5.9:1, respectively, with resultant snowfall forecasts of 5.6, 6.9, and 5.4 in. at those locations.

4. Concluding discussion

A neural network approach to snowfall forecasting, using only forecast information available on a real-time basis, shows substantial gains relative to the lookup and climatological snow-ratio methods. In particular, in addition to reducing errors in the snow ratio, the network approach compensates for errors in QPFs, helping to constrain the overall error in forecast snow amount. Although the procedure employed in this study has proven effective based on a small sample collected over the course of two cold seasons (November–March),
several elements could be further refined. First, the assignment of a snow-ratio number to the predicted class is somewhat ad hoc; it may be possible to make improvements by relating the specific within-class ratio to the forecast class probability, as was informally done for the light class (e.g., a high probability of a heavy snow ratio might indicate a lower snow ratio than a lower probability within that same class). Second, refinements based upon the relationship between the forecast vertical motion and the details of the sounding profile might allow for further refinement, particularly in the light class when maximum vertical motions may align with temperature conditions most conducive for dendritic growth. Such ideas have been explored by Cobb and Waldstreicher (2005). Finally, it would be useful to extend the verification to a wider selection of reports, to increase the confidence in the results. Now that HPC is developing a verification system to study snowfall forecasts, it is expected that such data will soon become available for further study. The authors are also in the process of developing such a dataset from archived information from recent winters.

Fig. 2. Sea level pressure analysis for (top) 1200 UTC 22 Jan 2005 (obtained from the Daily Weather Map series produced by the NOAA/Central Library Data Imaging Project) and (bottom) 1200 UTC 23 Jan 2005. Shown are isobars (interval 4 hPa), frontal analysis (standard meteorological convention), positions of the cyclone (LOW) and anticyclone (HIGH) centers, precipitation (shaded), and the positions of the 32° and 0°F surface isotherms (dashed).
Acknowledgments. We thank Richard Hozak of NOAA/NWS Grand Forks, North Dakota, for implementing the snow-ratio Web site; Keith Brill, Pete Manousos, and Dan Peterson of HPC for their continuing interest in improving snowfall forecasts; Robert Holmes of GuaranteedWeather LLC for clarifying a number of details concerning municipal snow removal; and Dr. David Schultz of NOAA/NSSL and the two anonymous reviewers for their helpful comments on an earlier version of this paper.

Fig. 3. Skew T plot (standard meteorological convention; data obtained from the NOAA/Forecast Systems Laboratory real-time archive: available online at http://raob.fsl.noaa.gov/) for (top) Detroit–Wayne, MI, at 1200 UTC 22 Jan 2005 and (bottom) Gray, ME, at 1200 UTC 23 Jan 2005.
Table 3. Station reports and forecasts for three sites (DTW, ALB, and GYX) during the Blizzard of 2005. Precipitation is in inches. Shown are observed liquid equivalent precipitation, snow ratio, and snow amount; model QPF; snow ratio; and amounts from the neural network, lookup, and climatological snow ratio methods (network, lookup, and climo, respectively). The forecasts using a conditional climatological value based on QPFs are shown in parentheses.

<table>
<thead>
<tr>
<th>Site</th>
<th>Melted equivalent</th>
<th>Snow ratio</th>
<th>Snow amount</th>
<th>Model QPF</th>
<th>Network ratio</th>
<th>Lookup ratio</th>
<th>Climato ratio</th>
<th>Network amount</th>
<th>Lookup amount</th>
<th>Climato amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTW</td>
<td>0.51</td>
<td>23.9</td>
<td>12.2</td>
<td>0.55</td>
<td>18.0</td>
<td>24.7</td>
<td>10.8</td>
<td>9.9</td>
<td>13.6</td>
<td>5.9 (5.6)</td>
</tr>
<tr>
<td>ALB</td>
<td>0.53</td>
<td>21.7</td>
<td>11.5</td>
<td>0.70</td>
<td>18.2</td>
<td>40.0</td>
<td>11.0</td>
<td>12.7</td>
<td>28.0</td>
<td>7.7 (6.9)</td>
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<tr>
<td>GYX</td>
<td>0.44</td>
<td>29.1</td>
<td>12.8</td>
<td>0.91</td>
<td>17.0</td>
<td>40.0</td>
<td>10.6</td>
<td>15.5</td>
<td>36.4</td>
<td>9.6 (5.4)</td>
</tr>
</tbody>
</table>

REFERENCES


Dubé, I., cited 2006: From mm to cm . . . : Study of snow/liquid water ratios in Quebec. Meteorological Service of Canada, Quebec, QC, Canada. [Available online at http://www.meted.ucar.edu/norlat/snowdensity/from_mm_to_cm.pdf.]


