Foundational Needs of Forecasters for Probabilistic Winter Forecasting

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ABSTRACT: This study explores forecaster perceptions of emerging needs for probabilistic forecasting of winter weather hazards through a nationwide survey disseminated to National Weather Service (NWS) forecasters. Questions addressed four relevant thematic areas: 1) messaging timelines for specific hazards, 2) modeling needs, 3) current preparedness to interpret and communicate probabilistic winter information, and 4) winter forecasting tools. The results suggest that winter hazards are messaged on varying time scales that sometimes do not match the needs of stakeholders. Most participants responded favorably to the idea of incorporating new hazard-specific regional ensemble guidance to fill gaps in the winter forecasting process. Forecasters provided recommendations for ensemble run length and output frequencies that would be needed to capture individual winter hazards. Qualitatively, forecasters expressed more difficulties communicating, rather than interpreting, probabilistic winter hazard information. Differences in training and the need for social-science-driven practices were identified as a few of the drivers limiting forecasters' ability to provide strategic winter messaging. In the future, forecasters are looking for new winter tools to address forecasting difficulties, enhance stakeholder partnerships, and also be useful to the local community. On the regional scale, an ensemble system could potentially accommodate these needs and provide specialized guidance on timing and sensitive/high-impact winter events.

SIGNIFICANCE STATEMENT: Probabilistic information gives forecasters the ability to see a range of potential outcomes so that they can know how much confidence to place in the forecast. In this study, we surveyed forecasters so that we can understand how the research community can support probabilistic forecasting in winter. We found that forecasters want new technologies that help them understand hard forecast situations, improve their communication skills, and that are useful to their local communities. Most forecasters feel comfortable interpreting probabilistic information, but sometimes are not sure how to communicate it to the public. We asked forecasters to share their recommendations for new weather models and tools and we provide an overview of how the research community can support probabilistic winter forecasting efforts.

KEYWORDS: Winter/cool season; Ensembles; Forecasting; Mesoscale forecasting; Numerical weather prediction/forecasting; Operational forecasting

1. Introduction

Ensemble modeling systems play a critical role within the NWS by allowing forecasters to see a range of solutions for a given event (Novak et al. 2008). Within the past decade, convection-allowing models/ensembles (hereafter CAM or CAE) have complemented global guidance by providing higher temporal and spatial detail in short-range forecasts (Benjamin et al. 2016; Schwartz et al. 2019; Roberts et al. 2019, 2020; Kalina et al. 2021). In recent years, advances in modeling include specialized guidance for hurricanes [Hurricane Analysis and Forecast System (HAFS); Dong et al. 2020] and warm-season hazards [wind, hail, and tornadoes in the Warn-On-Forecast System (WOFS); Stensrud et al. 2009; Wheatley et al. 2015; Jones et al. 2016; Gallo et al. 2022]. These efforts focus on tuning model parameterizations, data assimilation, grid spacing, run length, and output frequency to resolve each unique weather hazard within a specialized geographic domain. This work has received positive feedback from forecasters who find that the utility of specialized CAMs/CAEs generally improves their confidence and skill (Clark et al. 2021; Wilson et al. 2021). While this line of research has positively impacted warm-season forecasting, little effort beyond lake-effect snow (Fujisaki-Manome et al. 2020) has been devoted to innovating hazard-specific CAE guidance for winter hazards. Yet, many studies illuminate forecasting challenges for precipitation type and snow forecasts (Ralph et al. 2005; Wandishin et al. 2005; Thériault et al. 2010; Suarez et al. 2012; Reeves et al. 2014; Reeves 2016; Greybush et al. 2017; Ikeda et al. 2017; Radford et al. 2019). These studies point to several forecasting difficulties that could potentially be remedied by specialized CAE guidance.

In addition to modeling challenges, most winter hazards are derived from base-state model fields to provide information such as snow totals/rates (Baxter et al. 2005; Cobb and Waldstreicher 2005), precipitation type (Reeves et al. 2016; Birk et al. 2021; Reeves et al. 2022), visibility (Benjamin et al. 2021), etc. This has led to the development of several NWS software platforms and tools targeted at interrogating individual winter hazards or

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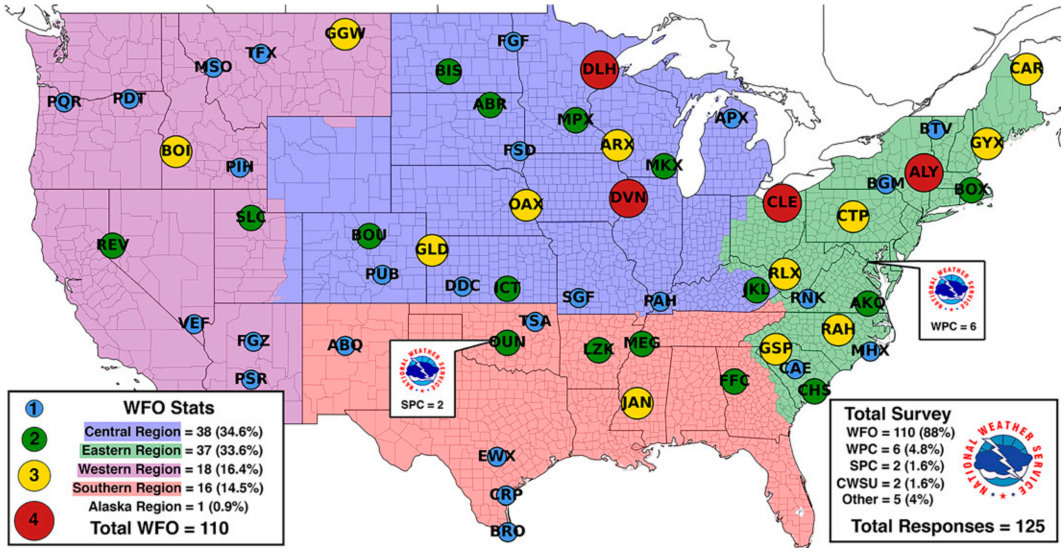

FIG. 1. Demographic summary of responses to the survey. Office response rate labeling scheme as follows: large/red = 4 responses, medium/yellow = 3 responses, small/green = 2 responses, and tiny/blue = 1 response. WFO = weather forecasting office; WPC = Weather Prediction Center; SPC = Storm Prediction Center; CWSU = Central Weather Service Unit.

displaying a composite of threats from multiple hazards [snow squall parameter and winter storm severity index (WSSI); Banacos et al. 2014; WPC 2020]. Advancements over the past decade have introduced probabilistic snow products [probabilistic winter precipitation forecast (PWPF); Novak et al. 2014; Waldstreicher and Radell 2018], subfreezing road guidance (Handler et al. 2020), a new probabilistic WSSI (in development), and several probability/threshold fields from the High-Resolution Ensemble Forecast (HREF; Roberts et al. 2019) and the National Blend of Models (NBM; Craven et al. 2020). As the NWS continues the transition to probabilistic forecasting within the Unified Forecast System (UFS; Jacobs 2021), this new era comes with the need to support forecasters with the appropriate tools, models and training for probabilistic winter forecasting and impact-based decision support services (IDSS). A large movement in this direction has been driven under the Forecasting a Continuum of Environmental Threats (FACETs; Rothfusz et al. 2018) framework which emphasizes the utility of probabilistic hazard information (PHI; Karstens et al. 2015, 2018). More recent work on CAEs/PHI by Demuth et al. (2020) has found that forecasters need hybrid deterministic/probabilistic products, map-based guidance on hazard timing and support for IDSS. To ensure new technology leads to appropriate stakeholder actions, Ripberger et al. (2022) and other ongoing projects are developing guidance on how to best communicate probabilistic information. These efforts have outlined specialized techniques for different warm-season hazards (Karstens et al. 2015, 2018; Roberts et al. 2019, 2020), created a general baseline of forecaster needs from CAEs (Demuth et al. 2020), and provided guidance on communicating probabilistic information (Ripberger et al. 2022). In this study we follow a similar methodology to Demuth et al. (2020), but specifically focus on winter hazards and seek to quantify hazard-specific problems to provide a baseline for the NWS winter weather suite of models and tools to be improved upon.

Through an NWS survey, this study aims to report the current challenges and successes forecasters embrace in probabilistic winter forecasting and to provide insight for improvements to winter weather products. The survey was distributed to NWS forecasters asking hazard-specific questions focused on 1) timelines of how forecasters message individual winter hazards, 2) forecasters' current winter toolbox and new tools they need, 3) modeling needs to predict winter hazards, and 4) current preparedness to interpret and communicate probabilistic winter information. Open-ended questions were also included in the survey to generate qualitative feedback about probabilistic information and technology. The survey metadata and qualitative methodology are laid out in section 2 with specific survey questions provided in the appendix. Section 3 presents the quantitative data and section 4 contains the qualitative analysis of the survey data.

2. Survey metadata and methodology

The survey was created as a Google form and disseminated through e-mail to every Science and Operations Officer (SOO) within the NWS. This process was conducted in coordination with the NWS Office of Programming, Planning and Service Delivery. SOOs were permitted to share survey access with other forecasters, which was available between 26 October and 18 December 2020. A total of 125 NWS employees responded with the majority of responses coming from the NWS Central and Eastern regions (Fig. 1). All respondents were guaranteed anonymity unless they voluntarily opted to provide demographic information (96% reported; Fig. 1). Forecasters were asked to provide an average estimate of the number of years of experience for their office. Results show a wide range of experience

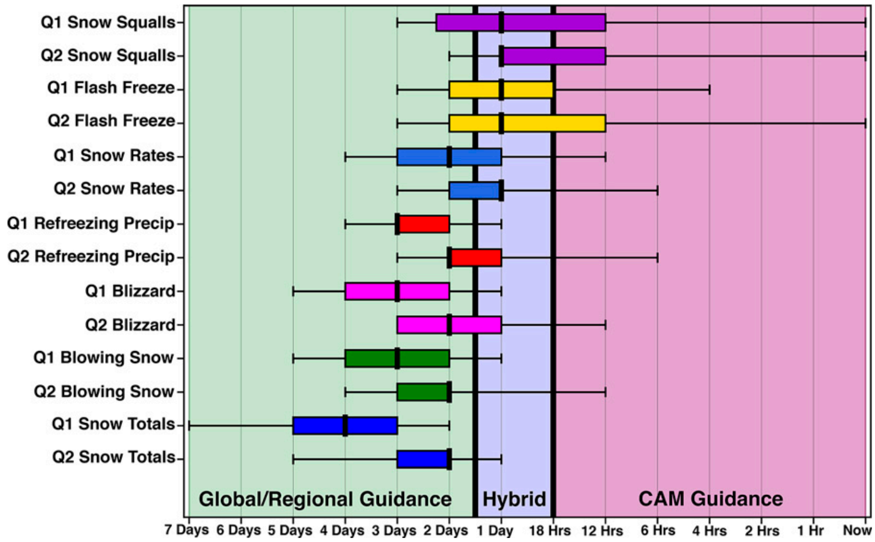

FIG. 2. Box-and-whisker plot of responses to questions 1 (Q1) and 2 (Q2). The median response is the thick black line on each box. Whiskers extend out to the 5th and 95th percentile.

within individual offices and thus it is likely that the data represent diverse viewpoints from forecasters who have had longer/shorter tenures forecasting within the NWS.

The survey had four sections consisting of 18 questions that included a mix of checkbox, multiple choice, and short answer (see the appendix). Herein, a quantitative analysis of the responses is provided, in addition to a qualitative thematic analysis of the open-ended questions in the survey. Qualitative research methods can provide in-depth insights on how individuals perceive and give meaning to concepts, experiences, and interests (Braun and Clarke 2006; Tracy 2019). Qualitative perspectives are useful in uncovering ideas that may not have been considered previously and can help advance the decision-making process, but the data are not meant to be generalizable and quantified. The detailed steps for the qualitative analysis, consistent with Braun and Clarke (2006), are outlined in the following list.

1) The authors read and reread through the open-ended responses to gain understanding and awareness of the data they were interested in analyzing. They took initial notes and highlighted portions that resonated with them.
2) The team identified open-ended questions with meaningful data and developed codes in the form of phrases. These codes highlight various factors that forecasters noted as important to them to integrate into winter weather operations and technology.
3) The codes were collated to themes, or descriptive labels, that encapsulated NWS forecaster's reactions and recommendations to PHI technology.
4) These themes were reviewed thoroughly by the researchers to guarantee there was mutual agreement.
5) The team carefully reviewed each other's analyses, ensured the themes thoroughly represented the responses of the participants, and binned them into categories.

Broadly, the themes were culled down to include three categories related to 1) ability to interpret probabilistic guidance, 2) skillfulness to communicate probabilistic winter weather guidance, and 3) components that make forecasting technology useful. The following research questions were considered:

- RQ1: How skillful do forecasters feel about *interpreting* probabilistic guidance?
- RQ2: How skillful do forecasters feel about *communicating* probabilistic guidance?
- RQ3: What makes a mesoscale ensemble forecasting tool useful?

These are presented in section 4 by narratives and quotes that support the perspectives of NWS forecasters.

3. Quantitative results

a. Messaging timelines

Forecasters message winter hazards on a range of temporal scales. Some of the factors that contribute to this are forecast uncertainty, geography, societal impacts, and stakeholder needs. To quantify the range of hazard-specific nuances in these messaging timelines, question 1 (Q1; hereafter questions are referred to as QX where "X" denotes the question number) asks forecasters to select a memorable event and record the time in which they began to message a general threat of its associated hazard. Q2 expands upon this by asking when they felt comfortable messaging spatial and temporal detail of the hazards. Responses to these questions primarily show that forecasters message winter hazards in the day 1–3 time frame (Fig. 2). A common practice evident in Fig. 2 is that forecasters generally message spatial and temporal detail roughly 24 h after messaging a general threat. This pattern appears to be more frequently breached with hazards that have shorter lead

TABLE 1. Percentages of responses to question 3 for individual hazards.

	Yes	No
Snow totals	82.9%	17.1%
Refreezing precipitation	63.6%	36.4%
Blizzards	58.5%	41.5%
Snow rates	43.4%	56.6%
Blowing snow	29.1%	70.9%
Flash freeze	26.7%	73.3%
Snow squalls	21.6%	78.4%

times in the 24-h range (e.g., flash freeze and snow squalls). It was also noted that if forecast agreement among models is low, the timelines in Fig. 2 typically shift to the right to await better agreement or high-resolution CAM guidance before providing spatial and temporal detail. Q3 dives further into this topic asking forecasters if stakeholders typically seek detailed information before the earliest forecast window. In the responses, three winter hazards (snow totals, blizzards, and refreezing precipitation) had the majority of forecasters stating these specific phenomena usually come with premature stakeholder inquiries (Table 1). This is likely a result of a larger media buzz about ice storms and snowstorms due to their widespread impacts, thus resulting in forecasters feeling pressure to provide details.

b. Modeling needs

It is not entirely known what model/ensemble configurations (parameterization schemes, data assimilation, grid spacing, run length, and output frequency) work best for individual winter hazards. To establish a baseline for future modeling efforts, Q8 and Q9 focus on collecting information about forecaster preference on run length and output frequency for a hypothetical hazard-specific ensemble. Most responses center on a run length out to day 1–4 (Fig. 3a) which aligns with the general timeline that forecasters message winter hazards (Fig. 2). With regard to hazard-specific timelines, a similar trend exists (as in Fig. 2) pointing to a preference for longer lead times for snow totals and shorter lead times for snow squalls (Fig. 3a). The next question in the survey focused on how often this hypothetical ensemble should output data (Q9). Snow totals and blizzards trended toward lower output frequency (3-hourly median response) while the others centered more around hourly output (Fig. 3b). These responses align with current operational output frequencies of several modeling systems. It is important to note that some forecasters expressed interest in subhourly output which is rarely available in operations. Future efforts exploring subhourly output are likely to be most beneficial focusing on snow squalls and other rapidly evolving hazards (Fig. 3b).

The last quantitative modeling question (Q11) looks at a forecaster's attitude toward the specialized ensemble system described in previous questions (Q8 and Q9). Forecasters almost unanimously voted positively (extremely or somewhat useful) for specialized ensemble guidance for snow totals, rates, and refreezing precipitation (Figs. 4a–c). The other hazards were also viewed in a positive light by the majority (Figs. 4d–g), but the neutral or dissenting viewpoint (rarely or not useful) was a bit larger. These results complement Table 1 pointing to forecasters wanting more detailed information from a mesoscale ensemble tool that could assist their communication strategies with stakeholders.

4. Qualitative results

a. Interpreting winter weather probabilistic guidance

While the majority of participants felt confident in their ability to interpret winter weather probabilistic guidance, they noted various factors that affect their forecasting process. Figure 5 outlines both bridges and barriers to skill.

First, participants unanimously agreed that previous scientific experience positively impacts their probabilistic forecasting process (Fig. 5; "scientific experience"). When it came to statistical knowledge, however, NWS forecasters expressed varying degrees of confidence (Fig. 5, "statistical knowledge and training"). While some felt prepared due to previous education and experience, others lacked training opportunities to

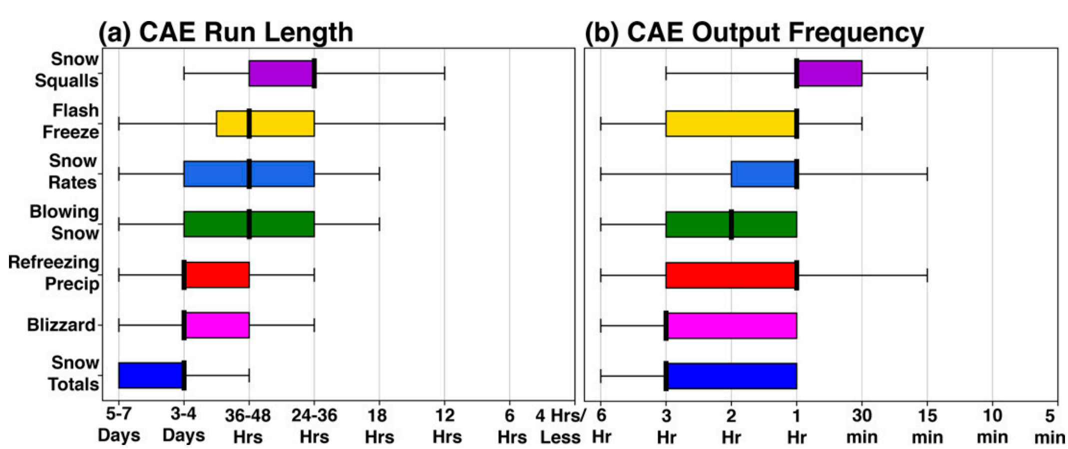

FIG. 3. Box-and-whisker plots of responses to questions (a) 8 and (b) 9. The median response is the thick black line on each box. Whiskers extend out to the 5th and 95th percentile.

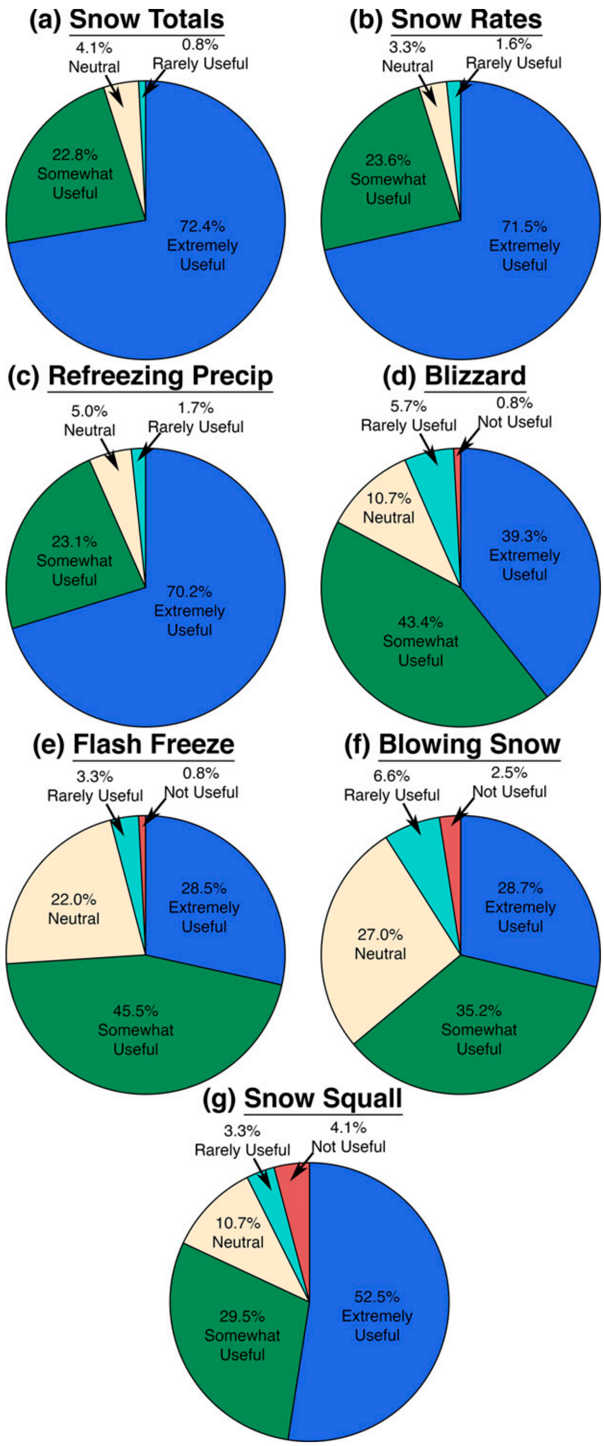

FIG. 4. (a)–(g) Percentages of responses to question 11 for individual hazards.

become more familiar with probabilistic information. Participants agreed that, in order for there to be increased consensus with scientific and probabilistic knowledge, additional resources need to be provided going forward:

> "We do not get to use this guidance very often, but we train with probabilities so I believe we can use this guidance effectively."

> "We're getting better but we still have a long way to go. We have been promoting the use of probabilistic guidance for the last couple of years and forecasters are gradually becoming more comfortable with it. However, training is primarily on-the-job training because no formal probabilistic training currently exists[1] in the NWS. Forecasters were not trained to forecast this way in college so it's new for most, and formal training that is desperately needed is currently severely lacking."

Depending on their location or their organizational structure, forecasters also expressed various degrees of familiarity with probabilistic winter weather guidance and tools (Fig. 5; "familiarity, repetition, and emphasis"). Generally, offices that experience winter weather year-round were more familiar with products. These participants also stated that they are provided with repeated opportunities to expand their knowledge throughout the year:

> "Everyone has seen cases with probabilistic tools and many of the staff have taken advantage of 1-on-1 help with the tools. The tools are regularly used in office briefings."

Forecasters from offices that rarely experience winter weather expressed more unfamiliarity, citing mainly the lack of repetition. To overcome lack of real-world experience, some of these offices provided opportunities to become more involved with probabilistic tools through increased training opportunities and by incorporating it as part of their everyday practice. This had a positive impact, as forecasters from these offices expressed increased understanding of winter probabilistic guidance:

> "We are improving. We have been attempting to look at ensemble systems over the past several winter seasons, and in fact a list of ensembles to check each forecast shift is part of our shift log… With that said this is a process, and the ability to efficiently and effectively interpret probabilistic guidance does not come overnight… it requires a lot of practice and doing."

Differences in the understanding of probabilistic information among forecasters were identified, where some forecasters had an advantage due to their offices and/or educational background (Fig. 5; "experience working with tools"). In addition, some forecasters acknowledged that some of their colleagues may not be interested in probabilistic solutions, as they mostly see forecasting in a deterministic lens:

> "Overall, [we] likely [have an] above average [skill of interpreting probabilistic products], but with a very wide range among individuals. Some folks find it extremely difficult to wrap their minds around a probabilistic answer, while others believe it is our job to give a deterministic forecast."

[1] At the time of the survey, no formal or foundational probabilistic training existed for NWS forecasters. However, as of June 2022, the Cooperative Program for Operational Meteorology, Education, and Training (COMET) has developed three lessons. These trainings are not required for NWS meteorologists; however, they are strongly recommended for most WFOs across the country.

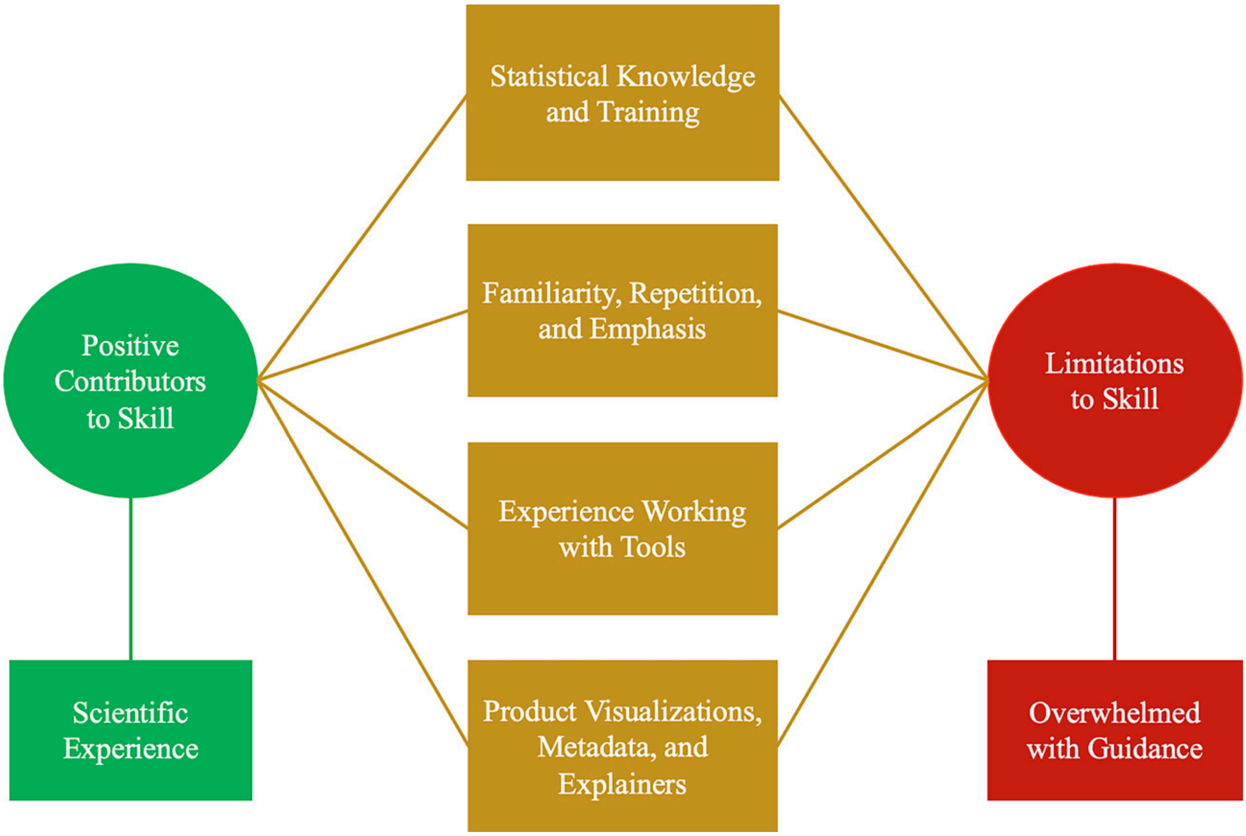

FIG. 5. How skillful do forecasters feel about interpreting probabilistic guidance? Gold-shaded themes were mentioned as both positive and limiting factors to skill.

Forecasters experienced both strengths and challenges when handling probabilistic tools and technology. Similar to the previous theme, participants felt a divide among who is actually incorporating probabilistic tools in their guidance. It is important to acknowledge that some forecasters have been using deterministic guidance for years, and introducing probabilistic guidance will require additional resources, training, and repetition:

> "[Winter probabilistic guidance] has been gaining traction over the past year or two, but some forecasters are more comfortable with it than others at this point."

> "The office is ok, but still needs to build their confidence and understanding of the information. With the forecast being deterministic and forecasters being used to only looking at a few models, it's a big change to change from a deterministic to probabilistic mindset."

Regarding forecast tools, participants expressed curiosity in learning more about the products they use (Fig. 5; "product visualizations, metadata, and explainers"). Some forecasters noted that they wanted to learn more about the metadata and background of each tool that they use. Some forecasters felt that internal technology does not fully provide them the capabilities they need to interrogate probabilistic information. This led them to depend on tools not provided by the NWS to effectively interpret winter weather probabilistic guidance. While there is no singular tool that forecasters rely on, many described the variety of options that can be used:

> "Within AWIPS, the ability to interpret ensembles is woefully inadequate to be almost useless. However, there are a number of web-based tools both within and outside of the NWS that allow for effective interpretation of winter probabilistic guidance."

Due to a plethora of internal and external tools, participants agreed that it can be overwhelming to navigate the winter forecasting process (Fig. 5; "overwhelmed with guidance"). With different forecasters using different products to interpret the same scenario, participants felt confused painting the broader picture of the forecast in a team setting. Knowing which product to use in specific situations is critical in ensuring higher confidence among forecasters in the future:

> "There is a large variety of options from a lot of different web sites. Sometimes it's hard to correlate the different information into a coherent picture."

b. *Communicating winter weather probabilistic guidance*

Considering winter weather probabilistic guidance, three contributing factors and three limitations were identified. Experience communicating uncertainty information was identified as both positive and negative. Figure 6 summarizes the resounding themes.

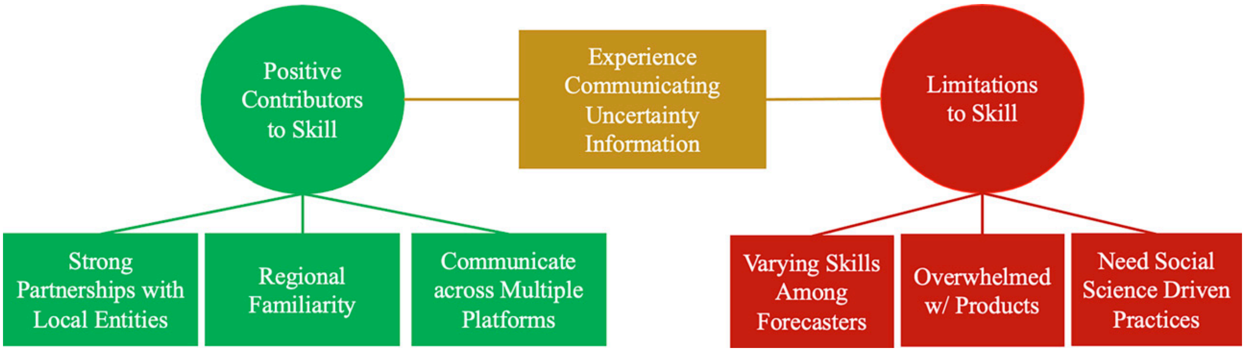

FIG. 6. How skillful do forecasters feel about communicating probabilistic guidance?

When it comes to communicating probabilities, participants first reported their strengths. Forecasters were most proud of the partnerships they have established over the years (Fig. 6; "strong partnerships with local entities"). While all acknowledged that communication is difficult during high-impact events, forecasters emphasized that their continued collaboration and communication with stakeholders and practitioners got them through even the toughest events. This foundation is especially important when introducing probabilistic guidance into the broader decision-making process.

> "[We are] very well equipped [to communicate uncertainty] and willing to do it routinely with partners in our briefings."

In addition to their well-established collaborations, forecasters stated that another strength for them involved their familiarity with their county warning areas' (CWAs') weather conditions and population (Fig. 6; "regional familiarity"). Their expertise could be valuable in personalizing information and making it more accessible to the populations they served. For example, one participant spoke favorably of their team's skill and experience in communicating threats and developing local expertise:

> "We have a number of forecasters that are experienced in communicating threats, and a number of forecasters that have years of experience in this area and have good relationships with our partners."

With strong partnerships, forecasters prioritized exploring ways to communicate and personalize their information to their partners, relying on multiple platforms to ensure their messaging is effective (Fig. 6, "communicate across multiple platforms"):

> "Communicating uncertainty can be tricky, but we try our best utilizing briefing graphics with explanations, conference calls, and more technical aspects of probabilistic forecasts in the AFD."

When asked about their overall experience communicating uncertainty information, forecasters had mixed responses (Fig. 6; "experience communicating uncertainty information"). Though they were not the majority, some participants expressed their confidence in communicating uncertainty information. These forecasters often experienced winter weather more routinely in their CWAs and had abundant opportunities for training and collective learning:

> "We are improving. We have been taking probabilistic information and testing messaging based on the probabilistic information over the past 4 winter seasons. We have learned what our customers understand and what they do not understand, and we are way more comfortable now than 4 years ago. This is a process, and the ability to do this is something that needs to be practiced and done consistently."

On the other hand, most participants conveyed their inexperience with communicating probabilistic information. Forecasters expressed the need for tools that help them develop probabilistic messaging as most products that they use to forecast are purely deterministic. In addition, though they may be familiar with probabilities, forecasters indicated that it is still being integrated in broader communication practices, like briefings.

> "I think we have longer to go here [in communicating uncertainty]. Any map-based product that drops out of the Graphical Forecast Editor (GFE) is mostly deterministic, so first we need tools to create probabilistic messaging graphics … Our IDSS briefings have moved slowly in the probabilistic direction, but there is much more that can be done."

Participants described their offices having a mix of forecasters that either do or do not communicate uncertainty. Forecasters explained that these differences in skill may be caused by differing education, experience, forecasting philosophy, and the lack of consistent tools when it comes to communicating uncertainty (Fig. 6; "varying skills among forecasters"). Forecasters also echoed sentiments of feeling overwhelmed with tools (Fig. 6; "overwhelmed with products"). Even those that are familiar with communicating uncertainty had no idea how to do it in a consistent manner, recognizing that many of their colleagues all used different tools to communicate probability. On a broader scale, participants recognized that this further complicates efforts to communicate uncertainty on a consistent basis.

> "Again, a wide range among individuals, mostly predicated on the individual understanding/acceptance of the probability space."

> "We're overwhelmed. There's a ton of guidance, but little way to communicate which is good and which is bad."

Addressing all of these challenges, forecasters also proposed solutions to standardize and improve their communication skills (Fig. 6, "need social science driven practices"). Since there were several useful recommendations, we further elaborated each suggestion in Table 2. While participants had various approaches to

TABLE 2. "Social-science-driven practices" subthemes.

Subthemes	Representative quotes
Tools and templates	"We need to be more innovative in how we display uncertainty in graphics. I am not a good (creative) weather story creator and some canned programs for displaying information would be useful."
Distillation of information	"We're still working on an ideal way to take the large amount of numerical information and distill it down to a format partners can understand. We've communicated such information in graphics and Facebook Live videos, etc."
Needs of end users	"I think we are decently well-equipped, although I do have some concerns about knowing what kind of probabilistic information to communicate to whom, such as with partners vs. public."
Standardization and training	"Formal training in this is desperately needed NWS-wide. Currently, new probabilistic tools are thrown out and forecasters are largely left to figure out on their own how to use them in the forecast and messaging process. If this is truly going to be a primary focus for the agency going forward (which it needs to be), then considerable resources need to be directed at training forecasters how to effectively utilize probabilistic tools to message uncertainty."
Better wording for low-probability, high-consequence outcomes	"High probabilities of high mountain storm in mid-winter is normal and not often worthy of mention to many customers - low probability of valley storm at unusual time of day in early/late season - but which is much more likely than climatological probability - is MUCH more important to many customers."
Better data visualizations	"For those able and willing, our graphical tools are improving, but still not great. We also don't have a lot of great ways to visualize data, since GFE and AWIPS are extremely limited in what they can do."

communicating probabilistic information in a winter weather context, all recognized that social-science-driven strategies need to be implemented across the entire NWS for their messaging to be most effective. Tools and templates developed in consultation with social scientists can establish consistency across the agency. Improved data visualizations would assist forecasters in communicating a comprehensive picture of uncertainty across various time scales. Recommendations for wording during low-probability, high-consequence outcomes can provide forecasters with clarity on how to navigate even the most difficult communication scenarios. Distillation of complex information can open accessibility for partners that may not be as familiar with probabilistic information. Last, an increased understanding of the needs of partners and essential stakeholders can provide insight into what information is most important to communicate. Overall, forecasters acknowledged that both physical and social scientists need to work closer together to best communicate uncertainty in winter weather events.

c. *What makes a winter mesoscale ensemble tool useful?*

After analyzing forecaster responses about interpretation and communication of winter probabilistic information, the team identified several comments about forecaster needs from mesoscale ensemble tools. When forecasters reflected on aspects of the ensemble systems they utilized, several different aspects of usefulness were identified in their responses. Participants' responses were divided into three themes, highlighting that a useful forecasting tool would 1) address winter forecasting difficulties, 2) enhance partnerships and communication among stakeholders, and 3) be useful to the local community (Fig. 7). From there, several subthemes emerged (presented in the following tables) that are of particular interest to future developers and researchers seeking to improve technology.

The most common attribute of usefulness identified by forecasters was a tool that could help address a winter weather forecasting difficulty. This theme consisted of several subthemes, including particular kinds of winter weather forecasting challenges: nowcasting (and difficulties associated with features involved in nowcasting) and situations characterized by rapid development. Tools that are more consistent, consumable, address sensitive forecast scenarios, increase forecast confidence, provide more continuous information, better determine the potential array of outcomes, and match the spatiotemporal scale of forecasted phenomena were characterized as useful by forecast participants. Table 3 includes a set of quotes representing various aspects of each subtheme.

Participants also expressed that a future tool could enhance partnerships and communication among stakeholders. Participants most frequently mentioned partners in the emergency management, public safety, utilities, media, transportation, and aviation sectors (Table 4). Many acknowledged that probabilistic information already plays a significant role into their communication plan. An expansion of several services to various spatiotemporal scales would improve the way forecasters communicate uncertainty and impacts. Forecasters agreed that incorporating probabilistic information into their messaging would assist practitioners in more confidently making sensitive decisions, such as road closures, school cancellations, and concerts.

The last set of characteristics that forecasters identified as desired in future winter weather forecasting tools involved the benefits it can provide to the local community (Table 5). First, participants emphasized the need for future technology to better identify areas of high impact or severity. When crafting

FIG. 7. What makes a winter mesoscale ensemble tool useful?

their messages to the public, more precise technology can lead to better communicating events that may be hard to predict but have large impact potential. Second, forecasters also noted the importance of including timing information (e.g., time of arrival and event duration), as it is frequently requested by community partners and the public. Third, forecasters expressed their preference for future tools to address regional forecasting concerns that are important to the local community. Some hazards, such as lake effect snow and flash freezes, are not always captured in ensembles and can present confusion when communicated.

5. Summary and discussion

Tool and ensemble development for probabilistic winter forecasting is a burgeoning area of research with the potential to improve forecaster confidence and skill. However, these improvements need to be driven by end-user needs in the NWS community. A survey was distributed to NWS forecasters to collect this information. It was found that forecasters message winter threats on various temporal scales (nowcasting to 7-day lead times). These temporal variations in messaging are likely a result of model capabilities (forecast skill and resolution), socioeconomic impacts caused by the hazard, and availability/accuracy of postprocessing algorithms. Survey participants expressed that forecasting snow totals, refreezing precipitation and blizzards are challenging because stakeholders typically request detailed information before they are comfortable providing it. These results provide insight into the time windows that stakeholders need information in order to prepare. This also provides a baseline of hazard-specific time frames that forecasters typically operate on. *Therefore, our recommendation is that new or improved technology embodies these time frames (Fig. 2) in order to satisfy the needs of both forecasters and their stakeholders.*

Forecasters also provided their recommendations for future regional ensemble systems that could be tuned for specific hazards. Most participants held a favorable view of this type of guidance and requested that the ensemble run length at least capture their current forecast time frames. The majority of forecasters noted that an ensemble output frequency of hourly or 3-hourly is sufficient for most winter hazards. However, some participants viewed subhourly output as beneficial for rapidly evolving hazards such as snow squalls, snow rates, flash freezes and refreezing precipitation. These requests

TABLE 3. How future forecasting tools can better address winter weather forecasting difficulties. Subthemes as seen in Fig. 7.

Addresses winter forecasting difficulties	Representative quotes
Nowcasting/difficult to forecast	"Snow squall would be useful to have an updated forecast for more frequently than an hour. This would help with situational awareness about where intense, localized but difficult to predict bands of snowfall might form, and could help with frequent forecast updates on social media. This could give more lead time to people that there could be very heavy snowfall in the next hour, even before issuing the warning."
Rapid development	"Sub hourly snowfall rates, snow squalls and freezing rain are critical impacts that fluctuate significantly, requiring sub hourly output. Would use for IDSS, social media, etc."
Consistent and consumable	"Quite simply - we have no true hi-res or regional ensemble for this that currently exists. We have the HREF, but that is not a true ensemble - so having a true ensemble that is well-calibrated for all of the above hazards selected as 'extremely useful' would be exactly that - extremely useful."
Addresses sensitive forecast scenario	"A high-resolution, reliable ensemble would be very useful in snowfall totals, snowfall rates, snow squalls, and refreezing precipitation. ...For refreezing precipitation, this would help because precipitation type can be inaccurate if there are small errors in the forecast temperature profile or surface temperature, which ... affects messaging significantly."
Increases forecast confidence	"Regular updating helps promote messaging and gives confidence to both the forecasters and to partners that the forecast is on track, shifting, etc. The gaps in information are a killer to forecast operations efficiency and productivity. If partners (or even the public) can see the forecast is always current (or has just been updated), that heads off a lot of questions we currently end up answering repeatedly in partner briefings."
Better determination of array of potential outcomes	"Snowfall totals, snowfall rates, and refreezing precipitation probabilistic information would be useful as it would allow a better understanding of the forecast envelope and allow forecasters to better identify low probability, high impact events."
Matches spatiotemporal scale of phenomenon	"Snowfall rates, snow squalls, refreezing precipitation all had sub-hourly output request. It is these high impact events that are of brief duration that do not get captured well by the lower resolution output. All of these would be used for tactical decision making."

were typically associated with the need to provide precise timing information (such as time-of-arrival) and to have high temporal resolution of forecast trends to communicate to stakeholders. Forecasters who held unfavorable views of sub-hourly output expressed concerns of data overload and not having time to analyze the weather or message on these time scales. *We recommend that future modeling efforts prioritize hazard-specific guidance that is tailored to the appropriate run length and output frequencies to meet the operational needs presented in Fig. 3.*

A thematic analysis of the survey introduced a broad landscape of the challenges and successes of winter probabilistic

TABLE 4. How future forecasting tools can better enhance partnerships. Subthemes as seen in Fig. 7.

Enhances stakeholder partnerships and communication	Representative quotes
Emergency management and public safety	"Probabilistic information on snowfall totals is already a critical part of our messaging plan and our partners really like it. So seeing this extended to precipitation type, blowing snow, and blizzards is very easy to envision and would allow us another way to message these phenomena which we currently lack the tools to do. For snowfall rate, I could see that being powerful (when explained) for schools and Department of Transportation (DOTs) since they would know when snow would rapidly accumulate on roads making traveling more difficult."
Utilities	"[I] believe this is needed to maintain safety of travel and maintenance of travel corridors as well as the power industry"
Media and social media	"The data would be used to inform partners (DOTs, Emergency Managers, Media) and Social Media users of short term threats. Perhaps help the forecaster better determine if a snow squall is going to maintain itself for the next 30 min or couple of hours."
Transportation and aviation	"Temporally detailed snowfall rate information could be hugely beneficial to those making plans for road maintenance and other travel considerations (think aviation). Snow squalls are often a small-spatiotemporal scale event and having high detail can make for optimal predictions and warnings."

TABLE 5. How future forecasting tools can resonate with the local community. Subthemes as seen in Fig. 7.

Usefulness to the local community	Representative quotes
Strong/highest impacts or severity	"...in high impact events, these hazards are critical in aggregate to understand an event, the ways in which it might unfold and should or could be capable of providing needed context and perspective for crafting a story that can be conveyed in winter weather messaging."
Time of arrival and event duration	"Snow totals are always useful for stakeholders, though snowfall rates and when they occur may actually be more important than the totals themselves."
Regional concerns	"All of these hazards can produce high impacts. Working in a WFO with very complex terrain, a regional hi-res ensemble would be a tremendous help in resolving complex terrain influences that greatly impact the development and evolution of these hazards."

forecasting. While these results are not meant to be generalizable, it does introduce potential blockades and bridges to future probabilistic forecasting and communication. In general, NWS forecasters acknowledged both forecasting and social-science obstacles in their decision-making process. Participants expressed more difficulties in *communicating* rather than *interpreting* probabilistic winter weather forecasts. Inconsistent standards of training and a lack of social-science-driven practices across the broader weather enterprise limited forecasters' ability to provide consistent, strategic winter messaging. A standardization of forecasting products can enable forecasters to communicate consistent, unified forecasts and messages to the public.

In the future, forecasters look for winter mesoscale ensemble tools to address forecasting difficulties, enhance stakeholder partnerships, and be useful to their local community. Some of the forecasting difficulties discussed were rapidly developing hazards, inconsistent guidance, sensitive forecast scenarios, and inadequate spatiotemporal scales to resolve winter hazards. When it comes to improving partnerships, participants want future tools to provide better support to their local partners (emergency management, utilities, social media, and transportation/aviation) and to have utility in their local CWAs. This means that information must not only be more easily consumed by forecasters, but also have products that can help communicate complex information to critical partners that may not be familiar with analyzing probabilistic information. Historically, technology has generally focused on supporting the entire CONUS (Schwartz et al. 2019; Kalina et al. 2021). But a regional ensemble, akin to the WOFS/HAFS concept, provides an opportunity for hazard-specific guidance to account for regional influences and also provide specialized guidance on timing (Demuth et al. 2020) and sensitive/high-impact winter events. As noted by Rothfusz et al. (2018), social, behavioral, and economic sciences are included in the FACETs forecasting process at each stage, from development to dissemination. In order for NWS operations to transition to a probabilistic future, Trujillo-Falcón et al. (2022) emphasized the importance of modernizing partnerships, forecast practices, and communication strategies simultaneously. *Applying this into a winter weather context, our recommendation is that new postprocessing tools are developed with social scientists to improve forecaster communication strategies, fill data gaps in winter forecasting, and provide a broader societal impact to local communities.*

Previous studies have demonstrated the benefit and utility of general purpose (e.g., full CONUS) CAEs for NWS forecasters (Schwartz et al. 2019; Demuth et al. 2020). In the future, an extension of these efforts can potentially provide insight into the creation of a new ensemble system that targets winter hazards on the regional scale (similar to WOFS/HAFS) based on the general guidelines presented in this study. Postprocessing for these ensemble systems is another critical aspect to ensuring forecasters can provide effective IDSS. Since most winter hazards are derived from base-state model fields, postprocessing algorithms have the potential to bias a well-calibrated winter ensemble system. These sources of error need to be quantified in future studies to understand if improvements need to be made in modeling, tool development, or both. Uccellini and Hoeve (2019) notes that as algorithms and modeling systems become more advanced, this must be met with a well-trained workforce that is prepared to disseminate weather information that meets stakeholder needs. More resources are being developed on public perception and stakeholder needs to provide insight into messaging strategies (Ripberger et al. 2022). This study provides a starting point for developers to understand how new technology can meet the needs of forecasters and highlights the important role of social science to ensure new winter technology is effective.

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Data availability statement. All non-identifiable survey data are available upon request from the CIWRO/NSSL authors.

APPENDIX

Survey Questions

a. Messaging a forecast

1) All winter events are unique, but pick an event you remember well for each of the following hazards. At what point did you begin to message a general threat for the following hazards?

2) Again, pick an event you remember well for each hazard. When did you feel comfortable messaging temporal and spatial detail for each of the following hazards?
3) For each of the hazards listed, do stakeholders typically seek information about spatial and temporal details before the typical earliest forecast window listed above? You can use the forecast windows from the previous question for reference.
4) Are there any winter hazards not mentioned above you feel need to be included in our analysis? If so, list the hazard(s) here along with the information collected above.

b. Hazard prioritization

5) What winter hazards are important to your office? List in order of importance for your office.
6) What probabilistic tools is your office currently using for messaging winter hazards? (For example, probabilistic snow totals or probabilistic freezing rain)
7) What new probabilistic tools would be helpful to you in messaging winter hazards? (Example: probabilistic time of arrival, max intensity, threshold probabilities)

c. Mesoscale ensembles

8) If you could create your own regional on-demand ensemble for winter hazard prediction (tuned for specific hazards), how far out should the ensemble run for the following hazards? (To infinity would be great … but let's be realistic here.)
9) Following from the previous question, how often should the regional on-demand winter ensemble output data for the following hazards?
10) If you selected subhourly output for any hazard in the previous question, please explain how you would use that data in an operational setting? Specify which hazard(s) you are talking about in your response.
11) How useful would you find a regional on-demand winter ensemble for the following hazards? (Assuming it is good/reliable)
12) If you marked" Extremely Useful" on any of the boxes in the previous question, please explain why. State which hazard(s) you are talking about in your response.
13) Are there any winter hazards not mentioned above you feel need to be included in our analysis? If so, list the hazard(s) here along with the information collected above.

d. Probabilistic training

14) How well equipped is your office to interpret winter probabilistic guidance?
15) How well equipped is your office to communicate uncertainty in probabilistic winter forecasting?
16) What are some of the strengths of forecasters at your office in forecasting winter threats?
17) What topics need to be addressed in training to prepare your office for probabilistic winter forecasting?
18) Since this is the last content question, do you have any other concerns/thoughts regarding winter weather hazard prediction? If so, what are they?

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