A WEATHER AND CLIMATE ENTERPRISE STRATEGIC IMPLEMENTATION PLAN FOR GENERATING AND COMMUNICATING FORECAST UNCERTAINTY INFORMATION

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The AMS Board on Enterprise Communication set goals and prepared a road map of tasks for enterprise sectors—led by the National Weather Service—to work on together to make uncertainty information integral to hydrometeorological forecasts.

Imagine it is a July afternoon and you are scheduled to take a flight from Washington, D.C., to Cleveland. You check in, go through security, and then head to your gate where a signboard says your flight is "on time." Meanwhile, thunderstorms start to develop along the middle of your route. In response, air traffic controllers try to reroute planes. A ground halt is declared for other planes preparing to fly through the thunderstorm zone. Delays develop, and the plane that you would have boarded is rerouted and becomes late. When it finally arrives at Ronald Reagan Washington National Airport (DCA), it is determined that the crew will exceed its legal flight length maximum if the flight to Cleveland goes forward. With no other crew immediately available, your flight is canceled. You try to rebook, all the while thinking there has to be a way of avoiding such cancellations. There is such a way being planned for the next generation of air travel, and it involves the use of weather forecast uncertainty information to

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anticipate future delays and minimize their impact (see sidebar and FAA 2011).

A great success of twentieth-century science and technology was developing the ability to forecast future weather conditions. The skill and accuracy of these forecasts have increased enough to improve decisions protecting life and property; health; national defense and homeland security; and socioeconomic, ecosystem, and individual well-being. Beyond the 1–2-week "weather regime," much progress has also been made in predicting expected conditions (e.g., above or below normal temperature, precipitation, drought, and storminess) associated with seasonal to interannual climate variability (e.g., El Niño) and even longer-term, scenario-based climate change. However, despite these successes, weather, water, and climate (hydrometeorological) forecasts are far from perfect. Errors in forecasts adversely affect not only decisions and outcomes but also decision makers' confidence in using the forecast information in the first place.

Forecast uncertainty depends on many factors. Generally, it increases as the forecast lead time (referred to here as forecast lead) increases. Forecast uncertainty also increases more quickly for smaller-scale (size and duration) phenomena, such as tornadoes and thunderstorms, than for larger-scale phenomena, such as a winter storm (Fig. 1). Additionally, forecast uncertainty grows more quickly in dynamically

EXAMPLES OF THE USE AND BENEFITS OF FORECAST UNCERTAINTY INFORMATION

Currently, weather impacts are associated with 70% of all air traffic delays within the National Airspace System, amounting to a cost of ~$28 billion per year, and about two-thirds of these delays could be avoided with better weather information (Abelman et al. 2009). These delays and costs are projected to escalate over the next 15 years as air traffic demand doubles or triples by 2025 (NRC 2008). A key goal of the Federal Aviation Administration's (FAA) Next Generation Air Transportation System (NextGen) is to reduce these delays by improving weather information and the use of weather information in air traffic management decision making (FAA 2011). Documented NextGen requirements (JPDO 2007) for improved weather information already include probabilistic weather forecasts. A study by Keith and Leyton (2007) showed that one airline alone could potentially save $50 million annually on domestic flights by relying on probabilistic terminal weather forecasts to save fuel and other associated costs. Another study (Steiner et al. 2008) showed how en-route weather probability information can be translated into anticipated airspace capacity reductions and consequently into shorter delay times and substantial cost savings, by enabling aircraft to fly shorter routes around weather hazards.

The military needs forecast uncertainty information to identify, assess, and mitigate risk resulting from hydrometeorological hazards during military operations. For example, atmospheric and oceanic hazards (e.g., strong winds and high seas) pose risks for ships at sea, and flood and high-water hazards impact ground-based operations. Forecast probabilities (obtained by using ensemble prediction systems and/or other techniques) of these and other hazards exceeding certain thresholds (with escalating impact on the mission) can be used in so-called Operational Risk Management (ORM) tools (OPNNAV 2010). The U.S. Navy is developing one such capability employing ORM to translate objective weather uncertainty guidance directly to piracy risk. In particular, the U.S. Department of Transportation Maritime Administration estimates that piracy around the Horn of Africa costs the U.S. maritime industry between $1 billion and $16 billion per year (Chalk 2009). Pirates operate in small vessels and therefore are particularly vulnerable to adverse wind and seas. The hypothesis is that pirate activity will likely be lower in areas of high meteorological risk compared to low risk. The Fleet Numerical Meteorology and Oceanography Center ensemble forecasts are used to identify the probability of various thresholds of surface winds and seas, enabling an assessment of piracy risk. Knowledge of the risk that pirates will assume by operating in a particular region at a particular time can be exploited to protect shipping through various forms of interdiction and avoidance efforts. In the example shown in Fig. S1, the meteorological risk to pirates operating in the Mogadishu area is much smaller than near the Gulf of Aden area at hour 84 (the pattern of risk changes with forecast lead). Therefore, based on this risk, pirate activity would be expected to be higher in the Mogadishu area. With this tool based on multivariate meteorological forecast uncertainty information, decision makers can take action, for example, by moving naval assets to areas that are favorable for piracy activity, providing divert recommendations to shipping, or other means.

The energy sector is one of the most weather- and climate-sensitive sectors of the economy, and a near-term challenge is establishing the smart energy grid. The current grid limitations and vulnerability to failure are reported to cost the nation $80 billion–$188 billion per year in losses due to power outages and power quality issues (Repower America 2010). To improve energy production and management, a probabilistic integrated renewable energy resource forecast of variability and thresholds, such as accumulated precipitation, wind, and solar radiance, could be utilized. The transformation of probabilistic climate forecasts into probabilistic energy demand, production, and operational risk scenarios is a high priority for predicting electricity consumption and peak load.

Probabilistic hydrometeorological forecasts could also be used to increase active regions around storms than in the middle of quiescent, fair-weather regimes. Typically by two weeks, uncertainty is large enough that forecast skill (predictability) is lost for nearly all types of weather (Simmons 2006; Tribbia and Baumhefner 2004) and the predictability/uncertainty of climate-scale anomalies becomes the question.

Uncertainties in hydrometeorological forecasts can be reduced through improved observations, data assimilation, and numerical modeling techniques. However, forecast uncertainty can never be completely eliminated no matter how much science and technology are applied to the problem because the atmosphere, oceans, and related Earth systems are inherently chaotic. According to chaos theory (Lorenz 1963), popularly known as the "butterfly effect," nearly perfect routine forecasts can never be achieved because of the exponential growth of unavoidable very small errors (perturbations) in forecast model initial conditions.

Despite a growing theoretical understanding of forecast uncertainty and an increasing ability to quantify it with ensemble prediction techniques, "deterministic" forecasting is still standard for most hydrometeorological applications. As the name implies, the goal of deterministic forecasting is to determine and communicate a single, most accurate value for a future hydrometeorological element, such as tomor-

business productivity and competitiveness as well as enhance public well-being, especially with respect to public health. For example, it has been estimated that in the United States poor air quality causes as many as 60,000 premature deaths each year, and the cost associated with air pollution–related illness alone ranges from $100 billion to $150 billion per year (NOAA 2010). Probabilistic forecasts could provide earlier notice about the risk for poor air quality to individuals and communities and help them limit exposure and reduce asthma attacks; eye, nose, and throat irritation; and other respiratory and cardiovascular problems and therefore save lives. Although it is difficult to estimate how many lives and costs could be saved with accurate and reliable air quality predictions, assuming that such predictions reduce by 1% the premature deaths and the costs listed above, about 600 lives and more than $1 billion (NOAA 2009) could be saved each year.

Two other examples that could benefit from probabilistic information are ocean-state and ecosystem forecasts.[1] A forecast of the ocean state would include probabilistic sea surface temperature forecasts but also, as the need arises, probabilistic forecasts of elements such as oil concentration. The spring 2010 Deepwater Horizon oil spill in the Gulf of Mexico provided a general illustration of the difficulties in quantifying uncertainty as well as the potential benefits. Uncertainty estimates for the amount of oil leaking changed dramatically in the weeks and months after the spill. A more precise quantification of the uncertainty of oil flows from the wellhead may have changed the actions of both governmental and industrial officials. During future oil spills, ensemble prediction techniques applied to the ocean would provide a range of estimates of oil concentrations and how they would evolve with time. These oil concentration estimates could then be used as inputs to models of affected ecosystems (e.g., along the Gulf Coast), yielding probabilistic estimates of the range of impacts. This impact information could be used to prioritize and appropriately target cleanup resources and marshal solutions more quickly. For example, perhaps resources would be targeted to the most vulnerable ecosystems at highest risk.

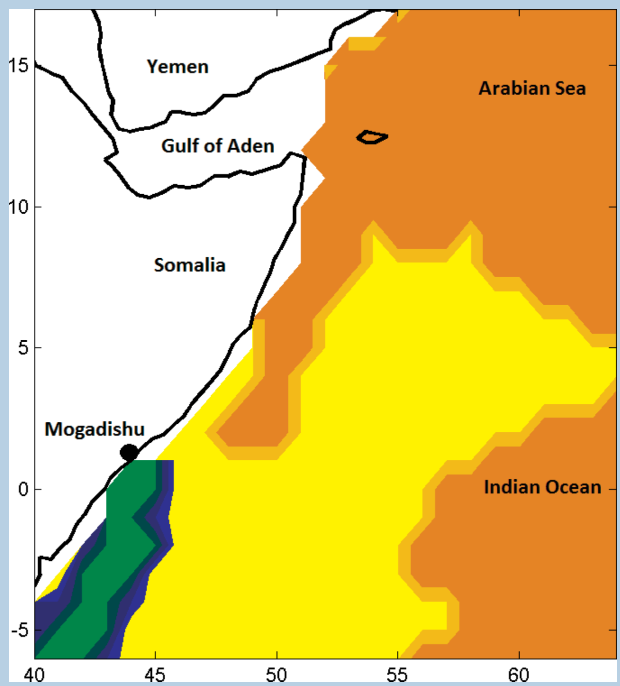

Fig. S1. Example 84-h forecast of the meteorological risk to pirates operating around the Horn of Africa (i.e., the risk to pirates operating in an area due to meteorological conditions) scaled from high risk (orange) to low risk (green).

[1] Here, ecosystem forecasts refer to the prediction of the impacts of physical, chemical, biological, and human-induced change on ecosystems and their components (Valette-Silver and Scavia 2003).

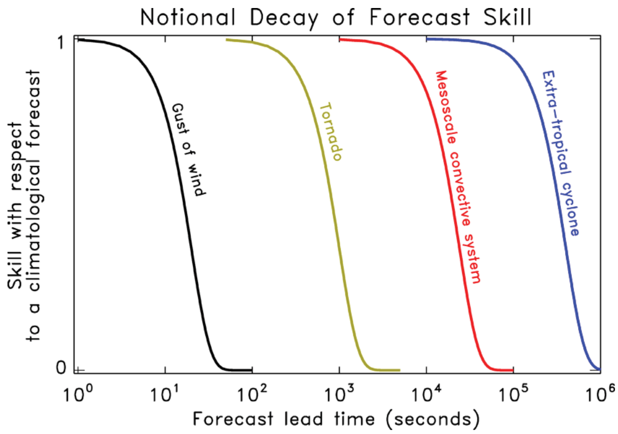

Fig. 1. Notional decay of forecast skill (0 is no skill compared to climatology and 1 is perfect skill, i.e., agrees perfectly with observations) as a function of lead time in seconds. Theoretically, a perfect forecast can be produced with a perfect model and perfect initial conditions. However, the initial state cannot be known perfectly and even exceedingly small errors will grow rapidly during the forecast, eventually making even a perfect-model ensemble forecast no more skillful than a climatological forecast. The time scale when zero skill is reached generally depends on the scale of the phenomenon. This time scale is determined by the phenomenon, not the model. For most of these phenomena, the skill of current forecasts decreases much more rapidly than these curves with a perfect model and may end up below zero because of model imperfections.

row's high temperature. Although there are notable exceptions, such as hurricane track, wind and storm surge forecasts, and precipitation forecasts, most current operational forecast products and services are based on single-value predictions with little or no accompanying forecast error or uncertainty information. In part, deterministic forecasts likely have been the format of choice because the public desires easy-to-understand, unambiguous predictions. In some cases, communication time and format restrictions have also played a significant role in the choice of presentation formats. For example, broadcasters may only have minutes or even seconds to deliver a weather forecast and have no time to explain vagaries in the forecast. Moreover, determining what forecast uncertainty information users actually need and can benefit from and how to communicate the information (e.g., forecaster confidence, alternate scenarios, probabilities) effectively is a challenging task requiring the application of social, behavioral, and economic science, outreach, and education. Nevertheless, the consequence of conveying only single-value information is that poorer decisions may be made by users because they do not have the benefit of knowing and accounting for the forecast uncertainties and risks upon which their decisions are based.

After reviewing the societal needs and potential benefits of forecast uncertainty information, the National Research Council (NRC; NRC 2006) and the American Meteorological Society (AMS; AMS 2008) conclude that there are compelling reasons for the U.S. weather, water, and climate enterprise (referred to here as the Enterprise) to consider uncertainty as an integral and essential component of all hydrometeorological forecasts. These reports recommend that quantifying and communicating forecast uncertainty based on the probability of possible outcomes should be emphasized in addition to the current practice of determining and communicating the single most probable forecast.

In response to these and other studies and reports recognizing the scientific, socioeconomic, and ethical value of quantifying and effectively communicating forecast uncertainty information, the AMS Commission on the Weather and Climate Enterprise (CWCE) Board on Enterprise Communication commissioned the Ad Hoc Committee on Uncertainty in Forecasts (ACUF) to formulate a cross-Enterprise plan to provide forecast uncertainty information to the nation. The resulting Weather and Climate Enterprise Strategic Implementation Plan for Generating and Communicating Forecast Uncertainty (Hirschberg and Abrams 2011; referred to here as the Plan) is now available on the AMS website (at www.ametsoc.org/boardpges/cwce/docs/BEC/ACUF/2011-02-20-ACUF-Final-Report.pdf) and is summarized here.

The Plan defines a vision, strategic goals, roles and responsibilities, and an implementation road map that will guide the Enterprise toward routinely providing the nation with comprehensive, skillful, reliable, sharp, and useful information about the uncertainty of hydrometeorological forecasts. As an overview of the use and benefits of forecast uncertainty information, the Plan offers several scenarios of how hydrometeorological forecast uncertainty information can improve decisions and outcomes in various socioeconomic areas (see sidebar). For example, shifting to a warning capability, which incorporates probabilistic forecasts and thresholds into the warning criteria, a "warn on forecast" (WOF; Stensrud et al. 2009) or "warn on probability" (WOP) capability could increase warning lead times[1] (see Fig. 2) and

[1] Any new warning capability based on probabilities will need to be developed in conjunction with social science research to elicit needs for content, format, and channels of communication.

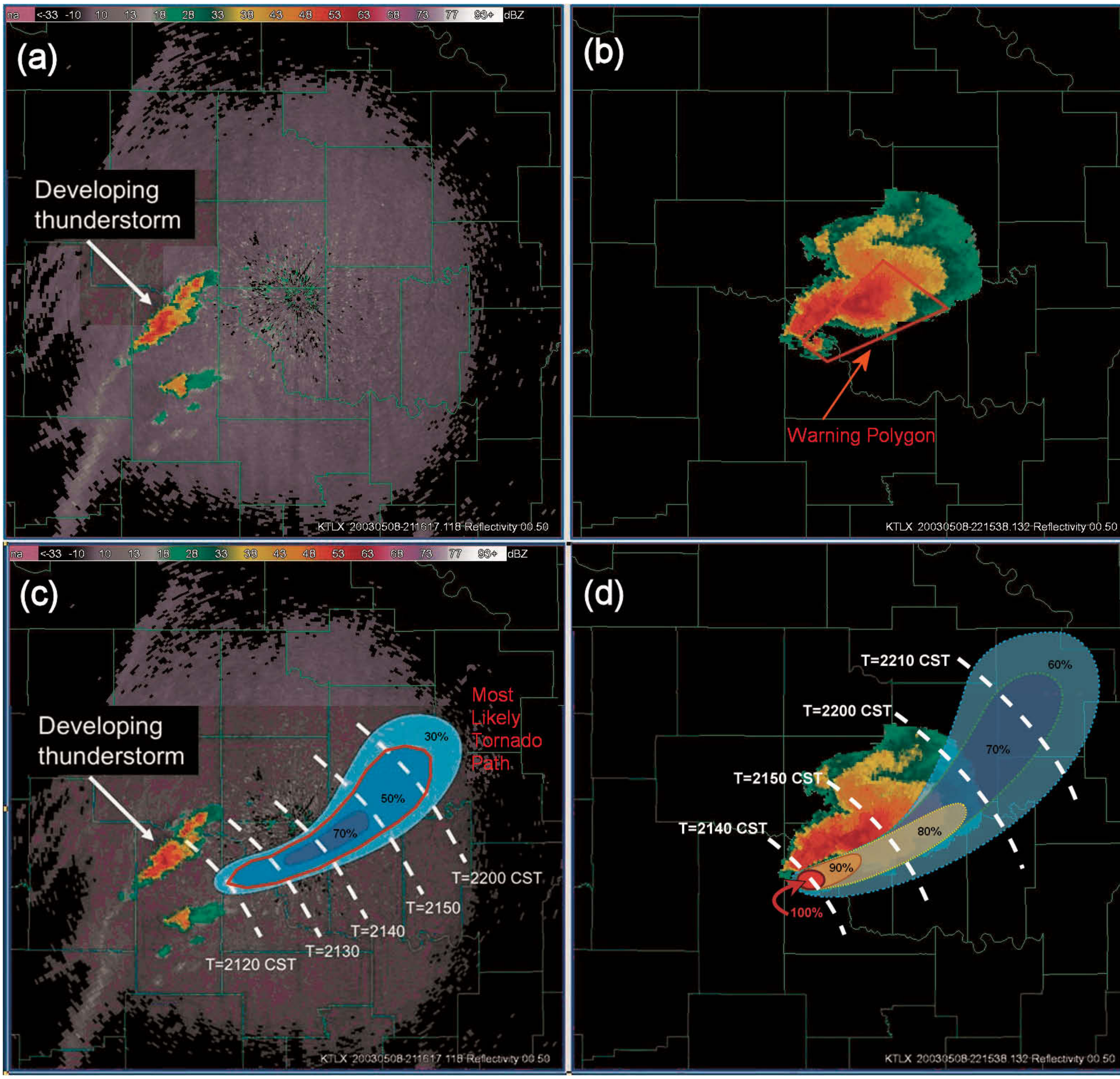

Fig. 2. Comparison of a tornadic thunderstorm evolution and the issuance of tornado warnings under the currently operational warn on detection (WOD) paradigm and a hypothetical warning application under a WOF or WOP paradigm. (a) Radar reflectivity of a developing thunderstorm. The radar reflectivity does not yet indicate the presence or formation of a tornado. (b) Radar reflectivity of the same thunderstorm after it has developed a mature mesocyclone radar signature (hook echo); a warning polygon (red box) indicates the geographic area under a tornado warning. Under the WOD paradigm, the warning polygon can only be issued when a mesocyclone signature [such as indicated in (b)] is detected by the radar or there is an actual observation (e.g., by a trained spotter indicating the formation of a tornado). (c) As in (a), but with a conceptual 1-h lead time probabilistic tornado path superimposed. (d) As in (b), but with an updated conceptual 1-h probabilistic tornado path instead of a warning polygon. Under a WOF/WOP paradigm, a tornado warning using appropriate probabilistic thresholds may be able to be issued when thunderstorms are in their incipient stages [as in (a)], providing more lead time. Adapted from Stensrud et al. (2009).

provide emergency managers, other decision makers, and the public additional valuable information by which to save lives and property.

The Plan is intended for a wide audience, including senior decision makers, program managers, service providers, and physical and social scientists. It is based on and is intended to provide a foundation for implementing recent recommendations in NRC (2006), AMS (2008), WMO (2008), and others, and it leverages emerging results from scientific and socioeconomic studies and the best practices of hydrometeorological services and industry from around the world.

VISION, STRATEGIC GOALS, AND IMPLEMENTATION ROAD MAP.

The vision described in the Plan is of a future where societal benefits of forecast uncertainty information are fully realized, a vision in which the use of forecast uncertainty information in decision making helps to

- protect lives and property;
- improve national airspace, marine, and surface transportation efficiency;
- strengthen national defense and homeland security;
- improve water resources management;
- sustain ecosystem health;
- improve energy production, safety, and management;
- increase business and agricultural productivity and competitiveness;
- provide a basis for sound, risk-informed planning; and
- enhance public well-being.

In order to reach this vision, the Plan defines four interrelated strategic goals and supporting objectives (Table 1) to meet the scientific and cultural challenges associated with a greater focus on probabilistic forecasts. Summary discussions of these strategic goals and objectives are presented later in this section. In the full version of the Plan, each objective has tabulated background information; the need for the objective; current capabilities and gaps; performance measures and targets; a proposed solution strategy; and specific tasks (with suggested Enterprise partner leads) that must be accomplished to meet the objective.

The Enterprise consists of four primary sectors: 1) the government sector, which includes local, state, and federal governments; 2) America's weather and climate industry, which includes consulting/service companies and media; 3) academia, which includes associated research institutions; and 4) nongovernment organizations (NGOs), which includes organizations like the AMS and National Weather Association. In order for the Plan to be successful, the Enterprise will need to leverage the expertise and resources of each sector to mainstream quantitative forecast uncertainty information (by using, e.g., probabilistic forecasts) into decision making. Increasingly, the missions, strengths, and capabilities among these sectors can overlap, making distinct delineations difficult. Nevertheless, there are leadership roles each partner group needs to fill to generate and communicate comprehensive forecast uncertainty information that can be used effectively by all decision makers, from the public and emergency management to agencies and corporations.

Strategic goal 1. Understand forecast uncertainty. Strategic goal 1 is to understand the hydrometeorological forecast uncertainty needs of society, including how humans can most effectively interpret and apply uncertainty information in their decision making; the natural predictability of the coupled atmosphere, oceans, and related Earth systems; and the optimal design of ensemble prediction systems. Meeting this goal will increase the Enterprise's understanding and knowledge about hydrometeorological forecast uncertainty, so that the Enterprise can communicate this information more effectively to users (strategic goal 2) and improve operational probabilistic prediction systems (strategic goal 3). First, understanding in several areas (objective 1.1) is needed to determine and provide uncertainty information that is most beneficial and to effectively communicate and assist users in using the information in their decision making under strategic goal 2. These areas include understanding how various types of users currently perceive, synthesize, and use uncertainty information to make decisions; how uncertainty information combines with other factors to influence decision making; what types of uncertainty information are needed; how needs for uncertainty information vary by hydrometeorological event; what formats will most effectively improve decision making; and how the needs for content and format vary by communication channel. At best, if this need is not met, the forecast uncertainty information the Enterprise provides will continue to go largely unused. At worst, uncertainty information will be misinterpreted or misused, leading to poor decisions and negative outcomes. A few preliminary studies exist on effective ways for communicating probabilistic information (Kuhlman et al. 2009). However, there is limited knowledge specific to the effective communication of hydrometeorological forecast uncertainty and risk to various customer and user groups. Although communicating uncertainty and risk has been studied in other fields and contexts, it is not apparent how this knowledge applies to communicating hydrometeorological forecast uncertainty.

Second, to improve operational probabilistic prediction systems (which produce the uncertainty information), an increased understanding of the nature of atmospheric predictability is needed (objective 1.2) to set reasonable forecast accuracy and reliability goals and to help prioritize the development of forecast uncertainty products and services. A more complete understanding of predictability will also provide insights about forecast model errors and help assess and improve data assimilation and other techniques to quantify forecast uncertainty. Although some rough quantification exists (e.g., predictability usually increases with the scale of motion), knowledge about the predictability of specific phenomena is lacking. For example, is a 3-day tornado outlook at the county scale more or less predictable than a 10-day hurricane track and intensity forecast? Current understanding does not allow quantification of the relative gap between the ability to forecast a phenomenon and the phenomenon's intrinsic predictability. Quantifying how this gap changes for various phenomena may help determine which aspects of forecast models are in greatest need of improvement.

Table 1. Strategic goals and supporting objectives.

Strategic goal 1 **Understand forecast uncertainty**	Strategic goal 2 **Communicate forecast uncertainty information effectively, and collaborate with users to assist them in interpreting and applying the information in their decision making**	Strategic goal 3 **Generate forecast uncertainty data, products, services, and information**	Strategic goal 4 **Enable forecast uncertainty research, development, operations, and communications with supporting infrastructure**
Objective 1.1: Identify societal needs and best methods for communicating forecast uncertainty.	Objective 2.1: Reach out, inform, educate, and learn from users.	Objective 3.1: Improve the initialization of ensemble prediction systems.	Objective 4.1: Acquire necessary high-performance computing.
Objective 1.2: Understand and quantify predictability.	Objective 2.2: Prepare the next generation for using uncertainty forecasts through enhanced K–12 education.	Objective 3.2: Improve forecasts from operational ensemble prediction systems.	Objective 4.2: Establish a comprehensive archive.
Objective 1.3: Develop the theoretical basis for and optimal design of uncertainty prediction systems.	Objective 2.3: Revise undergraduate and graduate education to include uncertainty training.	Objective 3.3: Develop probabilistic nowcasting systems.	Objective 4.3: Ensure easy data access.
	Objective 2.4: Improve the presentation of government-supplied uncertainty forecast products and services.	Objective 3.4: Improve statistical postprocessing techniques.	Objective 4.4: Establish forecast uncertainty test bed(s).
	Objective 2.5: Tailor data, products, services, and information for private-sector customers.	Objective 3.5: Develop nonstatistical postprocessing techniques.	Objective 4.5: Work with users to define their infrastructure needs.
	Objective 2.6: Develop and provide decision-support tools and services.	Objective 3.6: Develop probabilistic forecast preparation and management systems.	
		Objective 3.7: Train forecasters.	
		Objective 3.8: Develop probabilistic verification systems.	
		Objective 3.9: Include digital probabilistic forecasts in the weather information database.	

Third, a fuller understanding of the sources of forecast uncertainty as well as efficient numerical methods for estimating uncertainty in prediction systems (objective 1.3) are also needed. The two primary contributions to uncertainty in a forecast are uncertainty in the model initial conditions and forecast model error (i.e., model uncertainty). Progress in understanding and estimating the former source of uncertainty is relatively more mature than the latter. Ensemble Kalman filtering and other optimal estimation techniques are being developed to improve initial condition uncertainty estimates and ensemble initialization. Ongoing challenges include improvement of analysis uncertainty estimates, especially for nonnormally distributed variables such as cloud liquid water. In comparison, efforts to better understand and develop techniques to quantify model uncertainty are only in their relative infancy. Although some model errors can be reduced through the regular model development process (i.e., improving model dynamics and traditional parameterizations, increasing resolution, etc.), there will always be errors associated with hydrometeorological processes occurring below the resolution (the "grid scale") of the model. For example, the common assumption in meteorological models has been that the effects of subgrid-scale processes could be "parameterized." That is, given the grid-scale conditions, the average effects of subgrid-scale motions could be estimated deterministically (i.e., every time grid-scale condition X occurs, the feedback from subgrid-scale effects is exactly Y). As the grid resolution is refined, this deterministic assumption is increasingly invalid; a wider and wider range of subgrid-scale effects Y are all plausible given the same forcing X (Plant and Craig 2008). If a range of effects Y is plausible but a single Y is consistently used, this may contribute to a lack of spread in ensemble forecasts. The implication for ensemble prediction is the need to better understand the random (stochastic) nature of parameterized hydrometeorological processes in models and to reformulate them to be stochastic.

Strategic goal 2. Communicate and collaborate with users. Strategic goal 2 is to communicate forecast uncertainty information effectively and collaborate with users to assist them in interpreting and applying the information in their decision making. Simply generating forecast uncertainty information (strategic goal 3) is not enough. Users must see the value of the information, collaborate with developers to determine what information is needed, and learn to use the information to help them make decisions. Objectives supporting strategic goal 2 apply existing and emerging understanding from the research community under strategic goal 1 to reach out to, educate, and work with users about uncertainty information and probability; sensitize and educate students (including hydrometeorological students) about the underlying physical theory and social science aspects of uncertainty; improve the general presentation of forecast uncertainty information and tailor it for users based on social science and user feedback; and provide decision-support tools and services to help users interpret and apply forecast uncertainty information in their decision making.

Generations of hydrometeorological users and the general public have grown accustomed to single-value deterministic forecasts. Inaccurate weather forecasts are disparaged and often satirized. New information and products that include forecast uncertainty could be viewed as a hedge against poor science and forecasts, although some social scientists argue that acknowledging uncertainties and unknowns builds credibility (Morrow 2009). Perhaps the negative connotation associated with the terminology "forecast uncertainty" argues that it should be replaced with "forecast certainty" to help put the information and its use in a more positive light. Nevertheless, outreach, education, and public information campaigns are needed to inform users and the public that forecast uncertainty is an inherent component of hydrometeorological prediction, and that comprehending and using uncertainty information can improve their decision making (objective 2.1). Moreover, users will also need ongoing collaboration with the hydrometeorological and social science community to determine what data and products they want and need and the proper format for optimal use.

More exposure to the basic concepts of probability and statistics in K–12 (especially with salient weather examples) will help children grow into adults who are more sensitized about uncertainty and the advantage of probabilistic forecasts and more likely to use the information in their decision making. Currently, the topic of uncertainty and use of probabilities in weather information only arises if math students happen to be given a probability example that has to do with weather. A more structured, systematic, and reinforcing approach is needed (objective 2.2) to illustrate and embed the concepts of probability and statistics in hydrometeorology in our nation's youth.

Undergraduate and graduate students in hydrometeorological science need a better basic understanding of chaos theory, the fundamentals of ensemble predication, probabilistic forecasting, and the use of uncertainty guidance for decision making. They also need a broad understanding of the social sciences and effective communication techniques (objective 2.3).

Improving the effectiveness of the day-to-day communication of forecast uncertainty information will involve both improving the presentation (e.g., formats) of government-supplied uncertainty forecast products and services (objective 2.4) and tailoring uncertainty information by the commercial sector for specific customers (objective 2.5). Many, if not most, users of forecast uncertainty information will not encounter it in a purely digital form from such sources as a weather information database (see objective 3.9) but rather through regularly available products. By leveraging social science research results and user feedback (see objectives 1.1, 2.1, and 4.4), these products will need to be formatted to best convey the breadth of uncertainty information iconically, graphically, textually, and/or numerically (e.g., Joslyn et al. 2009). Although there are no established Enterprise standards for graphical uncertainty products, there are examples of ways of displaying data (Fig. 3). NRC (2006) and WMO (2008) also provide some ideas about how probabilistic information could be conveyed effectively and are good starting points for the complex process of designing appealing and useful new web pages and web services for uncertainty products.

Finally, decision-support tools and services are needed (objective 2.6) to link forecast uncertainty information and direct user impacts and risk tolerance. Single-value deterministic forecasts severely limit the utility of weather, water, and climate forecast information because they do not allow users to apply probabilities to their own thresholds (i.e., risk assessment) when making decisions. In contrast, the multiple possible forecast outcomes produced by ensembles can support decisions of various levels of sophistication depending on a user's cost/loss considerations. Automated decision-support systems can ingest probabilistic forecasts into preset user threshold/risk tolerance algorithms that generate a recommended decision based on optimizing the cost/benefit. To be successful, the Enterprise will need to collaborate with users to understand their decision framework. In the end, many decisions are deterministic: go or no go, do it or do not do it. However, in some cases, the timing, venue, methodology, etc., may be changeable, perhaps depending on various hydrometeorological outcomes. All of these decisions could be helped if uncertainty information were presented in a way the decision maker could understand and use to her or his best advantage.

Strategic goal 3. Generate forecast uncertainty data, products, services, and information. Strategic goal 3 is to generate reliable, high-resolution weather, water, and climate probabilistic and other forecast uncertainty data, products, services, and information that meet users' emerging needs for uncertainty information. Currently, the National Weather Service (NWS), and other parallel organizations, such as the U.S. Navy and Air Force, operationally generate mostly deterministic hydrometeorological forecast data and information by employing the following forecast process:

- Collect observations.
- Apply data assimilation techniques to synthesize the observations together with prior forecasts to produce initial conditions for numerical prediction models.
- Run the models to produce numerical prediction forecasts.
- Postprocess the raw model output statistically and otherwise to reduce errors.
- Produce objective and human forecaster–modified guidance, forecast, and warning data and information.

For the most part, all of this forecast information is made available to Enterprise partners. The Enterprise partners, including the NWS and similar government operational organizations, in turn use this

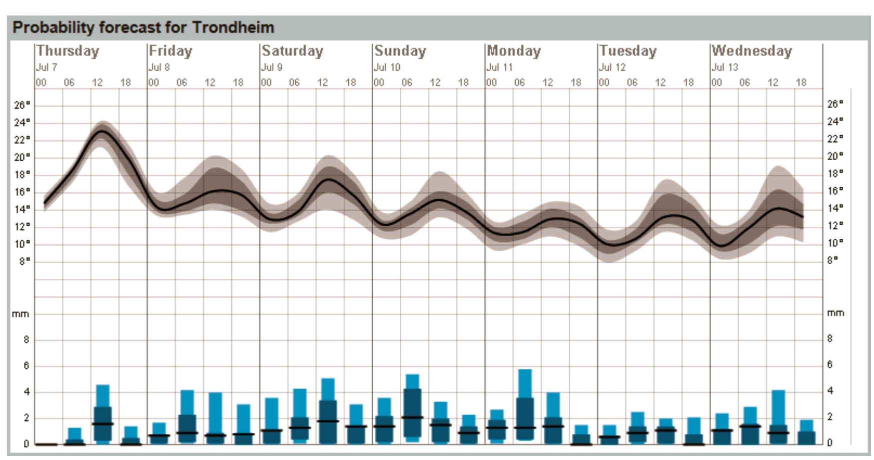

Fig. 3. A weather forecast graphic for Trondheim, Norway, indicating numerical probabilities for different possible temperature and precipitation occurrences as a function of time. (Image from www.yr.no, a website by the Norwegian Meteorological Institute and the Norwegian Broadcasting Corp.)

information as a foundation for generating products, services, and other value-added information that they communicate to their customers and users.

A key to meeting strategic goal 3 is to enhance and establish a similar capability to generate and make available routinely to Enterprise partners a "foundational" set of forecast uncertainty data and information for a range of variables and forecast leads, which the Enterprise partners can use to meet their mission and customer needs. For the most part, the routine generation of this foundational set of forecast uncertainty information should remain primarily the responsibility of the government sector because of the resources and infrastructure required to support this activity. However, all Enterprise partners will be communicating this information to their users and customers either in its raw form or through value-added products, services, and information.

It will be necessary to continue to collaborate with users, social scientists, and partners by using ongoing strategic goals 1 and 2 outcomes to define what this foundational forecast uncertainty dataset should be and how it will evolve. This dataset likely will include observation and analysis uncertainty information, raw and postprocessed ensemble model output, and human value–added information for forecast leads out to several weeks (see Table 2 for examples). Uncertainty information will be stored in ways both compact and informative; this may include the data to estimate the full probability density functions (PDFs).

Generating and making available this foundational set of forecast uncertainty data and information will require changes in the forecast process. The needed changes are reflected in the objectives listed under strategic goal 3 in Table 1. These objectives will leverage the new understanding about forecast uncertainty gained under strategic goal 1, and user and customer feedback that is part of strategic goal 2. Enhancements to information technology (IT) and other infrastructure improvements will also be

Table 2. A sample of the types of forecast uncertainty information that should be generated operationally and made freely available as part of a foundational set.

1) Continuous variables

- Temperature and dew point
  - Hourly, daytime maximum, and nighttime minimum temperatures mean and range of uncertainty (e.g., 10th/50th/90th percentile of forecast distribution)
  - Extreme temperature probability of exceedance
  - User-specific probability of exceedance (e.g., subfreezing thresholds for crop growers, materials applications thresholds for concrete pourers)
- Wind speed
  - Exceedance values for predefined thresholds (e.g., gale, hurricane force)
  - User-specific probability of exceedance (e.g., wind-energy industry)
- River level and flow
  - Exceedance values for predefined thresholds (e.g., minor, moderate, major flood stage)
  - Volume of water into reservoirs for optimal water management

2) Quasi-continuous variables

- Wind direction and wind gust PDFs (critical for aviation, wind energy industry, and temperature forecasts)
- Sky cover and cloud optical depth PDFs (critical for solar energy industry and aviation/transportation sector)
- Ceiling height PDFs (critical for aviation)
- Visibility PDFs (critical for aviation)
- Precipitation [probabilistic quantitative precipitation forecast (PQPF), timing, and precipitation type]
  - PQPF probability of exceedance values such as 0.1", 0.25", 0.5", 1", 2", etc., including flooding exceedance values
  - Probability of precipitation shortfalls (e.g., drought and water availability)
  - Precipitation timing (onset/cessation), including timing of any changeover in precipitation type (e.g., 60% chance of snow will arrive in Boulder between 4 and 6 pm, 20% chance between 2 and 4 pm, and 20% chance between 6 and 8 pm)

3) Discrete weather elements

- Severe weather

necessary to achieve these objectives; such supporting improvements are covered under strategic goal 4.

Objectives 3.1–3.9 focus on improving the steps by which forecasts are produced and uncertainty data and information are generated and made available to Enterprise partners. Note that, although the observations that are used to initialize the forecast process are also uncertain, no observation uncertainty objective is included here because it is judged that observation uncertainty is already handled adequately by instrument designers and data assimilation scientists.

New and improved data assimilation techniques are needed (objective 3.1) that can produce an ensemble of initial conditions that is accurate, can sample the range of possible true analyses, and can project upon growing forecast structures so that differences between member forecasts grow (appropriately) quickly. Existing techniques are typically designed to produce sets of initial conditions that primarily grow quickly but, in doing so, do not necessarily reflect flow-dependent analysis uncertainty accurately. As forecast spatial and temporal resolution increases, these techniques must be able to estimate uncertainty at the mesoscale as well as the synoptic and planetary scales.

Improved ensemble prediction methods (objective 3.2) are needed that can propagate the initial conditions forward in time and provide reasonably sharp and reliable probabilistic forecasts, correctly accounting for the uncertainty due to model error. Current-generation ensemble prediction systems produce uncertainty forecasts that are biased and underestimate the forecast uncertainty (i.e., underdispersion of the ensemble members collectively). This is partly because of the low resolution of the forecast models, partly because of improper initial conditions, and partly because the ensemble prediction systems do not include effective treatments for the error introduced by model deficiencies.

Often, the accuracy of the first few forecast hours of numerical weather prediction (NWP) model

Table 2. Continued.

- ° Probability of tornado occurrence within 25 mi (40 km) of a point
- ° Probability of extreme tornado
- ° Probability of any severe weather (tornado, winds, and hail)
- • Tropical cyclones
  - ° Probabilistic intensity values (e.g., 50% chance of category 1 at landfall)
  - ° Probabilistic storm surge values with inundation mapping of each probability
  - ° Probabilistic storm track (e.g., probabilistic information within "cone of uncertainty")
- • Flooding
  - ° Probability of exceeding streamflow heights (e.g., location-specific levee heights, inundation mapping)
  - ° Probability of time until exceeding river heights and duration above threshold

4) Earth- and near-terrestrial-system elements

- • Avalanche probability for a given area
- • Mudslides/debris flows probability for a given area
- • Tsunamis
- • Space weather (e.g., solar storms)

5) Multivariable probabilities

- • Heat index (e.g., combining temperature and dewpoint)
- • Wind chill (e.g., combining temperature and wind speed)
- • Fire weather [e.g., combining temperature, dewpoint, wind speeds, and probability of preceipitation (POP)]

6) Multiple weather and water climate scenarios

- • Aviation applications (individual gridded scenarios from an ensemble input into flight-routing software)
- • Hydrologic forecast chains on weather and climate time scales (individual time series of possible rainfall/temperature and other hydrologic forcing scenarios fed into ensemble of hydrologic forecast models to produce ensemble of streamflow estimates)
- • Probabilistic drought outlooks

guidance, including ensemble guidance, is poor because the NWP models need several model hours to "spin up" (i.e., develop internally consistent vertical motions) (Roberts and Lean 2008). Because of this, new probabilistic nowcasting techniques (objective 3.3) are needed to generate reliable probabilistic forecast information for forecast leads of zero to several hours. Most current nowcasting techniques are deterministically based and have their roots in extrapolation techniques used on existing features, which may not properly account for stochastic aspects, especially new feature development or dissipation of existing features.

The need for statistical postprocessing (objective 3.4) of raw ensemble model output to ameliorate bias and other deficiencies will likely never be completely eliminated despite improvements in ensemble prediction methods (objectives 3.1 and 3.2). Additionally, statistical postprocessing can "downscale" (Cui et al. 2009) relatively coarse-resolution model output to finer detail and also be used to derive quantities not directly predicted by the model that may be required by users (Hamill et al. 2006). Most current statistical postprocessing techniques (e.g., model output statistics; Glahn and Lowry 1972) are based on deterministic model output. A variety of new ensemble model–based calibration techniques (e.g., ensemble kernel density model output statistics; Glahn et al. 2009) appear to perform relatively well for normally occurring weather and relatively short forecast leads. However, for rare events and long-lead forecasts, longer training datasets of "reforecasts" and new statistical techniques may be needed (Hamill et al. 2006); for example, in order to correct biases in the position of a hurricane in the Gulf of Mexico, observed and forecast tracks from many similar storms in the Gulf of Mexico will be needed. With limited computational resources, the requirement to generate these computationally expensive reforecast training datasets with a stable modeling system often conflicts with the desire to rapidly implement improvements in operational ensemble forecast systems.

Nonstatistical postprocessing techniques (objective 3.5) are also needed to produce reliable and skillful forecast uncertainty information about forecast variables of interest that are not directly predicted by numerical models or derived from statistical relationships (using statistical postprocessing techniques discussed under objective 3.4). Considering aviation as an example, a variety of groups [e.g., National Center for Atmospheric Research (NCAR) Research Applications Laboratory, Massachusetts Institute of Technology Lincoln Laboratory] have developed algorithms for estimating aviation-related parameters, such as icing, turbulence, and ceiling, from weather model output (NCAR 2011). Many of these algorithms have been implemented for deterministic forecasts in the NWS at the Aviation Weather Center in Kansas City, Missouri. However, little has been done to develop, test, and verify algorithms that produce skillful and reliable probabilistic forecasts of these variables that are not normally observed.

The specific role of human forecasters in the day-to-day generation of probabilistic forecasts will depend on their ability to add value to raw and/or postprocessed ensemble model output. In general, the role of human forecasters likely will expand from the current routine preparation of single-value (deterministic) forecasts to monitoring, quality controlling, and interpreting probabilistic forecast guidance; identifying and assigning confidence to alternate forecast scenarios; and when appropriate (e.g., during high-impact events) manually modifying automated model guidance (Stuart et al. 2006, 2007; Novak et al. 2008; Sills 2009). Although most current forecast preparation systems and tools aiding human forecasters are focused on generating single-value forecasts, these new functions will require probabilistic forecast preparation systems (objective 3.6) and tools that allow humans to interpret and manipulate entire ensemble distributions.

Regardless of the specific role that human forecasters eventually assume in the operational generation of forecast uncertainty information, they will need training (objective 3.7). Although some basic training on the theoretical basis for ensemble prediction systems has been developed, more is needed to provide knowledge of the general underlying theory behind and the performance of ensemble prediction and other probabilistic systems, the weaknesses in current operational systems, and what can and cannot be corrected with statistical postprocessing. Forecasters will also need to be trained in the new uncertainty forecast preparation tools they will use in addition to how to collaborate with and assist users in interpreting and using uncertainty information in their decision processes (strategic goal 2).

The Enterprise also needs a comprehensive, agreed-upon set of standards and software algorithms for uncertainty verification (objective 3.8). Currently, forecast verification methods focus on verifying the best single-value forecast estimate. Probabilistic forecast verification techniques must be developed and/or applied that will assess the characteristics of uncertainty forecasts and provide quantitative feedback to ensemble developers, forecasters, service providers, and end users to aid in interpretation and decision making. Statistics generated from these techniques are needed to serve as a reference for user expectations, guide future improvements, and assess the value added during each step of the forecast process.

The final objective under strategic goal 3 (objective 3.9) is to make all of this forecast uncertainty information available to Enterprise partners, who can then communicate it to their users and customers either in its raw form or through value-added products, services, and information. Currently, hydrometeorological observations and forecast products and information flow, in various formats and via numerous push–pull technologies, from their originating sources to partners, customers, and other users inside and outside of the Enterprise. This direct-from-source-to-user information flow will not necessarily diminish in the future. However, more powerful computational and telecommunications technologies now are enabling "one stop" repositories of archived and real-time data and information. The NWS, for example, is already providing gridded mosaics of sensible surface weather elements in its National Digital Forecast Database (NDFD) (Glahn and Ruth 2003). This concept is expected to expand to include more parameters and four dimensions (three space dimensions and one time dimension). Moreover, the FAA, National Oceanic and Atmospheric Administration (NOAA), and other federal agency partners are envisioning using this weather information storage approach to support NextGen. This "four-dimensional weather information database" will contain real-time observation and forecast data. Initial NextGen requirements already state that all forecast products must have probabilistic attributes. The ultimate vision is for a four-dimensional environmental information database that includes comprehensive hydrometeorological as well as other Earth system observations, predictions, and related information for users to access. Comprehensive forecast uncertainty data and information will need to be included in the planning, deployment, and access of these database systems as they evolve.

Strategic goal 4. Enable forecast uncertainty research, development, and operations with supporting infrastructure. The purpose of strategic goal 4 is to provide the infrastructure that will be necessary to carry out the objectives under the other three strategic goals. Specifically, many of the objectives under strategic goals 1 and 2, such as predictability studies (objective 1.2), ensemble design (objective 1.3), operational ensemble initialization and prediction (objectives 3.1 and 3.2), and statistical postprocessing (objective 3.4), will require increases in high-performance computing (objective 4.1). Despite advances that may be possible by sharing multimodel ensemble forecast data among U.S. and international centers, the production of skillful and reliable probability products cannot be achieved fully without a large increase in computational resources dedicated to the production of improved uncertainty forecasts. Currently, the U.S. Enterprise does not focus as much high-performance computing on ensemble prediction systems as some other international hydrometeorological organizations. For example, the European Centre for Medium-Range Weather Forecasts (ECMWF) currently runs a larger global ensemble (51 members) compared to the NWS's National Centers for Environmental Predication (NCEP) global ensemble (21 members), at approximately 3 times higher resolution,[2] and includes the regular production of real-time reforecasts that can be used for calibration. Although NCEP runs its ensemble system 4 times daily to ECMWF's twice daily, it may take currently as much as 40 times[3] more computational resources for NCEP to fully match the ECMWF system.

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[2] Currently, the ECMWF global ensemble runs at T639 resolution for the first 10 days of its forecast and T319 thereafter. The NCEP global ensemble runs at T190 for its full 16-day forecast.

[3] The 40 times multiple is estimated based on the following: ECMWF's ensemble resolution is currently T639L62 and NCEP's ensemble resolution is T190L28—that is 3.36 times greater resolution for ECMWF in the horizontal and 2.14 times greater in the vertical. Neglecting differences in advection approach (discussed below), this means that ECMWF's ensemble is based on $3.36^3 \times 2.14 \cong 81$ times more calculations, including the proportionally reduced time step for ECMWF. ECMWF also generates 100 real-time members per day, whereas NCEP generates 84 real-time members per day. However, ECMWF also generates 90 reforecast members (5 members × 18 yr) each week, or an extra ~13 per day. So, ECMWF produces a factor of $(100 + 13)/ 84 = 1.34$ times more members. The total extra computational burden is thus $81 \times 1.34 \cong 109$ times more. Assuming roughly that ECMWF's semi-Lagrangian scheme allows a time step 3 times longer, this then indicates a ~36 times greater computational burden. There are many other factors neglected here: the sophistication and computational expense of different parameterization methods, the different computational expense of the Legendre transforms to grids, different data assimilation approaches, and so on. Nevertheless, we think 40 times greater is a reasonable rough estimate of the overall computational difference.

A readily accessible public archive of past operational ensemble forecasts and verification statistics is also needed (objective 4.2) to facilitate research (objectives 1.2 and 1.3), the calibration (statistical adjustment) of ensemble forecasts (objective 3.4), the ensemble technique development process, product development, and forecaster training. Currently, the NOAA Operational Model Archive and Distribution System (NOMADS; Rutledge et al. 2006) is an emerging Enterprise-wide resource for storing numerical forecast guidance. NOAA has a cooperative agreement with the Meteorological Service of Canada to share ensemble forecast information in NOMADS and is developing similar agreements to share forecasts with the U.S. Navy and Air Force. The Observing System Research and Predictability Experiment (THORPEX) Interactive Grand Global Ensemble (TIGGE; Bougeault et al. 2010) archives a base set of global medium-range ensemble forecast and analysis information from nine different forecast centers worldwide. However, more data storage is required.

Data access systems are needed (objective 4.3) that are capable of transferring very large amounts of data from forecast uncertainty providers to clients and/or that allow these data to be parsed into subsets, transformed, and reformatted prior to transfer to the client. A number of current projects are exploring facets of ensemble data access, including NOMADS, Unidata, and the Global Interactive Forecasting System.

A test bed is needed (objective 4.4) where developers, forecasters, and users can interact with and test forecast uncertainty products, services, and information prior to implementation. Although there is a nascent ensemble test bed within the Developmental Testbed Center (Toth et al. 2011), which focuses on testing and evaluating ensemble-related techniques, there is currently no facility that permits users (e.g., operational NWS and industry forecasters, emergency managers, other officials responsible for public safety, utility companies and other sectors, general public) to conveniently evaluate and critique experimental uncertainty products. Such a test bed would avoid the challenges of testing in a live production environment and provide a forum for feedback among providers and users before operational implementation.

Finally, users will need assistance (objective 4.5) defining the infrastructure they will need to use new forecast uncertainty information. Universities, industry, and consumers all have made significant and continuing investments in infrastructure. Technological advances keep increasing capabilities without increasing the cost. However, current user software systems are mostly oriented toward single deterministic forecasts. Software systems and decision aids that deal with a single-value forecast and no probabilistic information will need to be upgraded and optimized in a manner that most easily allows later improvement.

NEXT STEPS. Likely, the most important next step for this Plan is to identify a lead to implement it. The ACUF believes strong leadership in organizing and motivating Enterprise resources and expertise will be necessary to reach the Plan's vision and goals and shift the nation successfully to a greater understanding and use of forecast uncertainty information. To this end, the committee endorses the recommendation in NRC (2006) for NOAA and, in particular, the NWS as the nation's public weather service to take on this leadership role. Furthermore, the ACUF recommends that the AMS Commission Steering Committee (CSC) as part of the CWCE monitor progress and provide executive oversight for this Plan because the CSC is a body of senior representatives from the entire Enterprise.

Another important next step is to develop an overarching strategy of how the Enterprise will resource and implement the proposed tasks. Examples of such a strategy would be 1) to attempt to establish a single large program, 2) to use the Plan to guide various independent but nevertheless connected projects, or 3) some combination of 1 and 2.

Activities under the second option are occurring already and have informed and are leveraging this Plan. For example, the National Unified Operational Prediction Capability (NUOPC) program (see www.weather.gov/nuopc/) is using the Plan to help build a national research and development (R&D) agenda that will be used to improve a tri-agency (NOAA, Navy, and Air Force) unified ensemble system. Another example is the national workshop on mesoscale probabilistic prediction, which was held in September 2009 and sponsored by NCAR and the NWS. The recommendations from this workshop support and extend modeling and enabling infrastructure objectives and tasks under strategic goals 3 and 4 in this Plan. Moreover, the workshop recommended the formation of working groups, lead by a national advisory committee, to perform the needed R&D effort and to use the Plan to help guide their activities.

Finally, although the implementation road map suggests sector roles and responsibilities and sector leadership for the various tasks in the Plan, the Plan itself is not programmatic in the sense of defining specific program/project plans with accompanying cost, schedule, and performance information. Defining these important programmatic details is also among the next steps in implementing the Plan and should be the purview and responsibility of Enterprise decision makers throughout the partnership.

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