BAMS Article

Visual Communication of Probabilistic Information to Enhance Decision Support

Anne Heggli, Benjamin Hatchett, Zach Tolby, Kathryn Lambrecht, Meghan Collins, Lynda Olman, and Matthew Jeglum

KEYWORDS:
North America;
Probability forecasts/models/distribution;
Communications/decision making;
Decision making;
Decision support

ABSTRACT: When hazardous weather is forecast, communicating probabilistic information (PI) can improve trust, confidence, and understanding of forecast information, resulting in improved decision-making by emergency managers and public audiences. With probabilistic forecast tools modernizing forecast operations, the National Weather Service is calling on regional offices to increase the use of PI. However, communicating PI can be challenging since the information is intrinsically more complex than single-value deterministic forecasts that do not include a measure of uncertainty. We suggest that effective PI visualization not only includes the PI graphic but also communicates potential impacts and issues preventative guidance to limit exposure to weather-related hazards. Decision support tools like PI benefit from, if not require, effective visual communication that capitalizes on the efficiency of the visual system to extract information, decrease the time to interpret information, and increase the understanding of uncertainties. Furthermore, PI visuals need to be accessible to disabled and neurodivergent audiences. To enhance the visual communication of PI, we synthesize literature from graphic design and social science to identify guiding principles for effective visual communication and provide a one-page printout quick guide. To showcase how forecasters can incorporate guiding principles in the local context, we provide examples built from readily usable templates to demonstrate how probabilistic forecast information extracted from tools like the National Blend of Models can be used to enhance the visual communication of PI to support more informed decision-making.

https://doi.org/10.1175/BAMS-D-22-0220.1
Corresponding author: Anne Heggli, anne.heggli@dri.edu
In final form 18 July 2023
© 2023 American Meteorological Society. This published article is licensed under the terms of a Creative Commons Attribution 4.0 International (CC BY 4.0) License.

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

AFFILIATIONS: Heggli, Hatchett, and Collins—Desert Research Institute, Reno, Nevada; **Tolby**—National Weather Service, Reno, Nevada; **Lambrecht**—Arizona State University, Mesa, Arizona; **Olman**—University of Nevada, Reno, Reno, Nevada; **Jeglum**—National Weather Service Western Region Headquarters, Salt Lake City, Utah

Consistent with the World Meteorological Organization's (WMO) recommendations (WMO 2021), the U.S. National Weather Service (NWS) and its parent organization, the National Oceanic and Atmospheric Administration (NOAA), are transitioning toward probabilistic forecasts as a way to modernize forecast operations to maximize the decision-making value of Impact-Based Decision Support Systems (IDSS) (National Weather Service 2019a; National Weather Service 2022b; Uccellini and Ten Hoeve 2019). However, effectively communicating probabilistic information (PI) visually to emergency managers and general audiences alike remains a challenge (Grounds et al. 2017; Joslyn and LeClerc 2013; Juanchich and Sirota 2018). In a review of 327 studies, Ripberger et al. (2022) established the numerous benefits associated with PI but concluded these benefits hinge on the visuals being well designed (Franconeri et al. 2021; Padilla et al. 2021). Creating effective PI visualizations requires an interdisciplinary approach that respects the importance of scientific accuracy and leverages visual communication practices that have been proven to be effective.

Visual communication scholars have established that visualization is the best approach to communicate complex information like PI (Ash et al. 2014; Carr et al. 2016, 2021; Dallo et al. 2020; Franconeri et al. 2021; Kuller et al. 2021; Lipkus and Hollands 1999; Murchie and Diomede 2020). Visuals capitalize on the brain's visual system to extract complex information rapidly and accurately (Essen et al. 1992; Zacks and Franconeri 2020). At the same time, visuals such as graphs, charts, and maps enhance the comprehension of complex information by breaking down the information into smaller, more meaningful units (Malamed 2015). Visuals are essential aids to communicate PI to both core partners (e.g., emergency managers, school districts, government agencies) and public audiences.

With more accessible probabilistic forecast information, the NWS is transitioning toward improved PI visualizations to maximize the decision-making value in order to build a Weather-Ready Nation (Harrison et al. 2022; National Weather Service 2022b; Novak et al. 2023; Schumacher et al. 2021, 2022; Tripp et al. 2023). We define PI and discuss its relationship to impact-based decision support in the sidebar "Probabilistic information to advance Impact-Based Decision Support Systems." However, there remains a gap in the application of best practices from visual communication research to PI forecasting in the NWS. Tools like the public-facing experimental 1D Viewer or internal Whole Story Uncertainty and Probabilities (WSUP) Viewer and Probabilistic Graphics Generator are designed to visually convey probabilistic forecasts and thereby increase the capacity for agencies to disseminate PI when appropriate. However, these tools still require effective visual communication strategies to help improve the user's understanding of the forecast.

To support ongoing efforts of the NWS to communicate more PI to core partners and public audiences alike, we synthesize guidelines for visualizing PI from literature aimed specifically at visual communication for weather-related hazards and effective graphic design conventions. We summarize the findings in a one-page printout

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

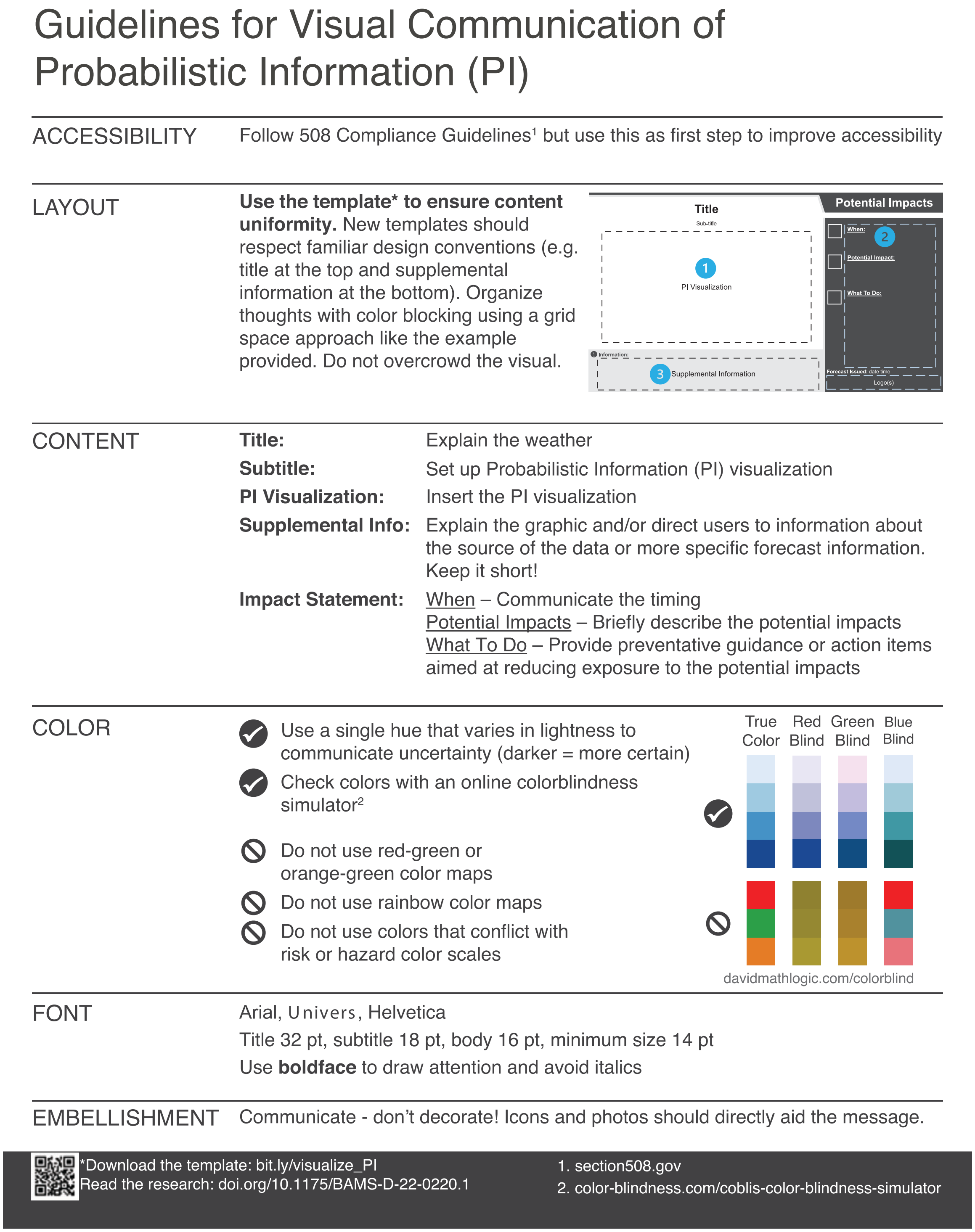

Fig. 1. A one-page printout of key visual communication guiding principles intended for forecasters tasked with disseminating PI visualizations.

(Fig. 1; https://doi.org/10.5281/zenodo.7600486). We then apply these guidelines to create "plug-and-play" templates (Heggli et al. 2023) to develop PI graphics in Excel and "plug" them into a PowerPoint template to "play" with colors and update text and icons accordingly. The templates incorporate the guiding principles identified in the literature as a way to demonstrate how PI extracted from probabilistic forecast tools can be visualized to support decision-making. To incorporate these methods into practice, we provide examples for primary weather conditions that commonly pose widespread and localized hazards in the western United States: snowfall, wind, temperature, and thunderstorms developed in collaboration with the NWS Office in Reno, Nevada. These tools are designed with an

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

emphasis on PI visualization for the NWS Western Region. Nonetheless, they are designed to be adaptable for other public-facing hazard communications in other NWS regions as well as by other government agencies and emergency managers for other hazards requiring early warning systems to encourage communities to prepare and/or take protective action (e.g., hurricanes, smoke, heat, and debris flows) (Hatchett et al. 2021; Lambrecht et al. 2021; Oakley et al. 2023; Rosen et al. 2023; VanderMolen et al. 2022).

Why communicate probabilistic forecast information

Though deterministic forecasts remain important to some users and are adequate for some situations (Carr et al. 2021; National Weather Service 2022b), communicating the full range of possibilities and their associated uncertainties becomes invaluable when a hazardous event is forecast (Hirschberg et al. 2011; Joslyn and LeClerc 2012; Miran et al. 2019). When a deterministic forecast is given, the uncertainty information is omitted, thus obscuring the complete forecast (National Research Council 2006). A single-valued deterministic forecast without a measure of uncertainty can be acceptable when the uncertainty in the forecast is very narrow or the weather will not impact routine operations or require any action (National Weather Service 2022b,c). For example, if the weather is expected to be 71.6°F (22°C) with a 10% chance of being 77.0°F (25°C), the addition of PI increases the cognitive load (the amount of visual information that can be processed mentally) to interpret the forecast with minimal additional benefit. However, it is ultimately up to the forecaster's judgment on whether there is a need for PI to be disseminated in certain weather situations based on their knowledge of their users.

Though deterministic forecasts do not include uncertainty information, research indicates that people do infer some uncertainty from them (Joslyn and Savelli 2010; Morss et al. 2008, 2010; Savelli and Joslyn 2012; Zabini et al. 2014). However, during high-uncertainty and high-risk events, deterministic forecasts are problematic (Hirschberg et al. 2011; Todhunter 2011). People often incorrectly estimate the level of uncertainty in deterministic forecasts, resulting in the perception of too much uncertainty when it is not warranted or not enough certainty when the forecast is highly uncertain (Fleischhut et al. 2020). Furthermore, when a hazard is presented in the deterministic forecast but the hazard does not occur, it results in a false alarm. Continued exposure to false alarms can lead to poor decision-making from the messaging fatigue effect ("crying wolf") when people no longer trust the forecast (Breznitz 2013; LeClerc and Joslyn 2015; Oakley et al. 2023). On the other hand, weather resulting in a greater impact due to an underprediction from the deterministic forecast can be more costly than false alarms since protective action may not have been taken to reduce losses to life and property. Balancing the cost–benefit between false alarms and costly misses can make it difficult to trust a forecast, and trust is a strong predictor of the likelihood of people taking preparatory action (Losee and Joslyn 2018). Visually communicating PI offers a more effective way to improve compliance with preventative guidance and decision quality than efforts to improve deterministic forecast accuracy aimed at reducing false alarms and costly misses alone (LeClerc and Joslyn 2015).

Research shows PI is valuable in building trust, increasing confidence and understanding of the forecast, and improving decision-making (Carr et al. 2021; Grounds and Joslyn 2018; Howe et al. 2019; Joslyn and LeClerc 2012; Joslyn and Grounds 2015; Joslyn and Demnitz 2019; Morss et al. 2008; Ripberger et al. 2022). Communicating uncertainty demonstrates a commitment to transparency that increases credibility and trust (Joslyn and LeClerc 2012, 2013; van der Bles et al. 2020). When users trust the forecast they are more motivated to take preventative action, thereby decreasing the impact of the hazard (Grounds et al. 2017; LeClerc and Joslyn 2012, 2015; Miran et al. 2019). However, making the forecast is only beneficial if it motivates action (Murphy 1993).

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

Guidelines for visual communication of probabilistic weather information

Through an interdisciplinary review of visual communication research, we identify common guidelines that improve infographic-style PI visuals. Our review attempts to cover the spectrum of literature from graphic design to social science as they relate to the visual communication of public messaging using an infographic format for hazard communication. This spectrum includes many topics ranging from the visual aesthetic to scientifically proven communication methods building off of the work done by Ripberger et al. (2022). We focus on six components of effective visual communication: 1) accessibility, 2) layout, 3) content, 4) color, 5) font, and 6) embellishments to apply to probabilistic weather information (Samara 2020). These key findings are summarized in a one-page printout (Fig. 1).

Accessibility. Inclusivity through accessibility is an important aspect of communication to increase the reach of information and improve user experience. Accessibility compliance is legally required by federal agencies in the United States (U.S. Congress 1973). Making documents accessible for disabled populations is an important consideration for anyone who creates or publishes documents; this is especially true for PI visualizations. For example, it is important to consider color vision deficiencies. Red–green color blindness (protanopia and deuteranopia) is the most common, occurring in around 8% of males though less frequently in females (0.5%) (Deeb 2005; Motulsky and Deeb 2001; Sharpe et al. 1999). Beyond color vision deficiencies, the use of alternative text ("alt text") promotes inclusivity for people who are visually impaired or have difficulty seeing images by providing equal access to information. Alt text ensures individuals using screen readers or assistive technologies can understand the context and content of images shared on social media platforms (Chiarella et al. 2020; Huntsman 2022). It is also important to consider neurodivergent characteristics (dyslexia, ADHD, autism, etc.) (McGee 2012). Between 10% and 15% of the U.S. population is estimated to have symptoms of dyslexia, and simple design changes can improve readability for some individuals (Eden and Moats 2002; Fletcher et al. 2018).

Accessibility standards help ensure the information and resources are available and usable for as many people as possible, especially those with disabilities. Since this is an overarching consideration, we provide specific examples throughout the following sections. We integrate considerations for colorblind-safe color pallets, design the layout to guide the viewer's focus, and select fonts with sufficient contrast between font color and background to improve readability. Each of these is an important visualization consideration. While alt text is not a part of the visual communication design, we urge anyone posting images to social media to include a summary as the alt text when posting the image.

Layout. The term "layout" encompasses the organization and placement of text, color, and images. Layout influences how readers navigate the visualization by implementing effective use of 1) hierarchy to highlight the most important message, 2) alignment to create a visual connection between elements, 3) repetition to build familiarity, and 4) negative space to help create a sense of simplicity to reduce cognitive load (Poulin 2018; Samara 2020; Tondreau 2019). Reducing cognitive load is especially important for probabilistic weather information, and arguably even more important for public audiences that may not have the motivation to look further into the forecast (Palmer 2002). The layout for PI visualizations should respect familiar design conventions, like titles at the top of the layout with supplemental material at the bottom, as this reduces cognitive load (Andry et al. 2021; Gordon et al. 2022; Franconeri et al. 2021). This top-down approach is further advantageous as visualizations are read cyclically between the title, legend, and the data before reasoning (Andry et al. 2021).

Lowering cognitive load is especially helpful for neurodivergent audiences such as individuals with autism or dyslexia (Eraslan et al. 2020). A simple and effective layout

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

technique is to apply a grid system to organize visual content (Ambrose et al. 2019; Hilligoss and Howard 2002; Poulin 2018; Samara 2020). Within each grid, there should be sufficient negative (empty) space to frame active spaces and call attention to content (Hilligoss and Howard 2002; Samara 2020). Color-blocking major grid sections can also be an effective tool to separate thoughts within the visualizations (Poulin 2018).

Content. PI visuals should include a combination of graphics and writing: graphics provide the visual overview and the text provides the key details since the ability to understand graphics alone is related to numeracy levels (having the ability to understand numbers and do math) (Dallo et al. 2020). Effective visual communication benefits from content uniformity (Gordon et al. 2022). PI visualizations should include three core components: 1) the PI visualization of where and what the weather is forecast to be with an expression of likelihood, 2) an impact statement, and 3) supplemental material as we demonstrate in Fig. 2, which is consistent with the findings and work of Bean et al. (2015), Grounds and Joslyn (2018), Gordon et al. (2022), Kuller et al. (2021), and Sutton and Kuligowski (2019).

It is beneficial to build on what is familiar, especially if the intended audience has limited exposure to PI (Fundel et al. 2019). Familiar graphs to populate with PI include axis-aligned bar charts, data-filled tables, and maps (Andry et al. 2021; Dallo et al. 2020; Franconeri et al. 2021; Fundel et al. 2019). However, less familiar designs like boxplots, which communicate the full range of scenarios and most likely scenario in a single figure for a location, may be more useful to communicate PI if properly introduced (European Food Safety Authority 2019; Carr et al. 2021). Therefore, when introducing graphics, we suggest the addition of a supplemental material section (Fig. 2) to consistently assist existing users gain familiarity and help new viewers to interpret the visualization. Over time, increased familiarity helps users interpret the graphic quickly and provides space to seek more information, a common request from users analyzing PI (Carr et al. 2021; Fundel et al. 2019; Flynn and Lide 2023).

In any PI visualization, it is recommended to provide numerical and verbal expressions of uncertainty (e.g., 40% moderate chance) and if only one must be selected, numerical expressions of uncertainty are more effective than verbal expressions in reducing subjective

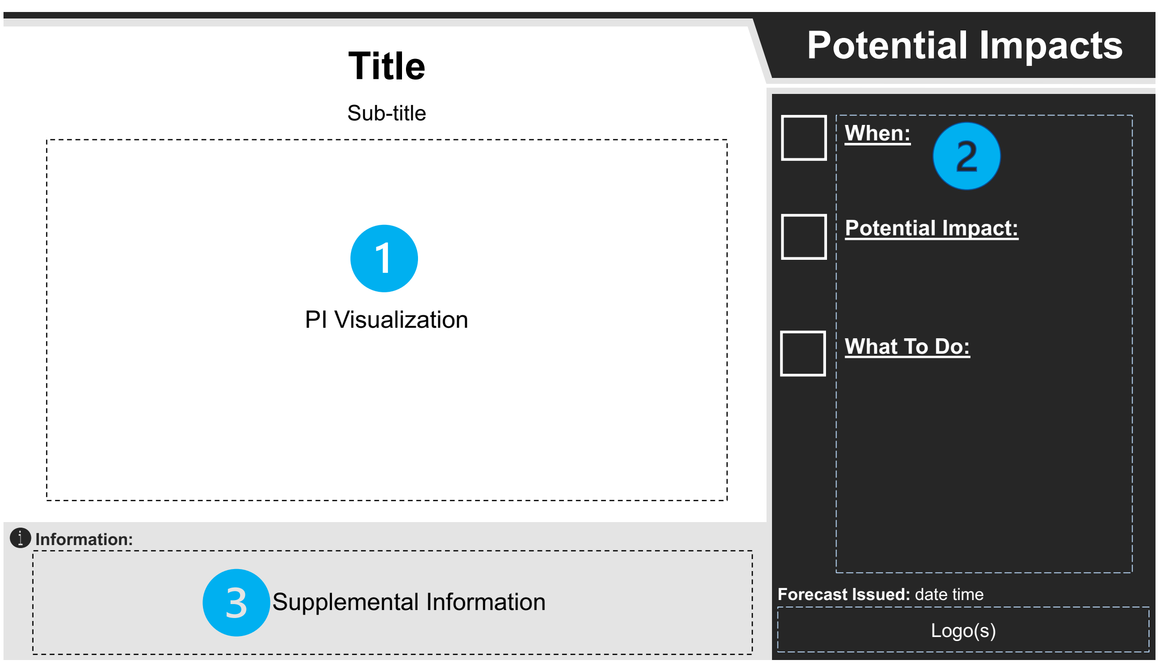

Fig. 2. Example layout for PI visualizations following recommended guiding principles with three areas for key content: 1) the PI graphic, 2) an impact statement, and 3) supplemental material.

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

interpretations (Jenkins et al. 2018, 2019; Joslyn and LeClerc 2012; Lenhardt et al. 2020; Nadav-Greenberg and Joslyn 2009; Rosen et al. 2021; Windschitl et al. 2017). Finally, the PI visualization should include a standard impact statement summarizing when the weather is expected, the potential impacts, and preventative guidance to reduce exposure (Bean et al. 2015; Gordon et al. 2022; Grounds and Joslyn 2018; Kuller et al. 2021; Sutton and Kuligowski 2019).

Color. Color is more than a decorative choice. Color is one of the most important and powerful selections in visual communication (Stone et al. 2008). Color attracts attention, conveys meaning, and visually organizes information (Stone et al. 2008; van Gorp and Adams 2012). There is a growing consensus regarding the rank order of colors to communicate impact or hazard: green, yellow, orange, red, and violet (Gordon et al. 2022; National Weather Service 2022c). Therefore, any color-coded uncertainty should not conflict with the hazard level since the probability is not necessarily proportional to the impact. If color is required to communicate uncertainty, the color values should be assigned on a continuum of lightness, hue, or both, if the data benefits from a diverging pallet (Crameri et al. 2020; Dasgupta et al. 2020; Franconeri et al. 2021; Wong 2010, 2011). It is also best for the highest saturated hue to communicate the greatest certainty with the lightest hues representing lower certainty since saturation levels have an effect on cognitive arousal (van Gorp and Adams 2012; Wilms and Oberfeld 2017). If data are best represented with multiple hues, they must be visible to those with color vision deficiencies. Red–green color combinations are the most problematic, but any colors with red or green components (e.g., brown and green) can make it difficult to decipher (Basak and Roy 2022; Crameri et al. 2020; Wong 2011). We suggest using red–blue in lieu of red–green and verifying any color selection with an online color-blindness simulator (e.g., www.color-blindness.com/coblis-color-blindness-simulator/ or davidmathlogic.com/colorblind/). An example of effective color mapping of probabilities is the NOAA Climate Prediction Center's Temperature and Precipitation Outlooks, which communicate the probability of temperature above normal or below normal (red to blue) (https://www.cpc.ncep.noaa.gov/).

Weather forecasts and hazard maps are repeat offenders of the misuse of color (e.g., commonly applied NWS weather radar, temperature, and wind speed graphics). This is due in part to the precedence of such color scales in early versions of weather products likely due to ease of access to flawed color scales (e.g., rainbow) from visualization programs (Borland and Ii 2007; Dasgupta et al. 2020). Using color scales that vary indiscriminately in hue and brightness, such as rainbow-type color scales, are well known to poorly represent data and should be avoided at all costs (Borland and Ii 2007; Crameri et al. 2020; Dasgupta et al. 2020; Rogowitz and Treinish 1998; Stauffer et al. 2015). Since PI visualizations lie at the intersection between science and society with a potentially large impact on decision-making, they should specifically apply effective color use. This includes avoiding red–green color pallets and rainbow-type color maps (Carr et al. 2021; Morss et al. 2008). In general, it is advised to use two or three colors and apply a contrasting color sparingly if the graphic needs something extra to "pop" (Samara 2020).

Font. Fonts frame the tone of what is being communicated. Selecting the proper font creates trust and confidence as well as improves the overall perception of a visualization's impact (Hyndman 2016; Nersesian et al. 2020). When selecting a typeface, readability and legibility are critical considerations. Sans serif fonts such as Helvetica, Arial, and Verdana are more effective than serif (embellished) fonts not only for people with dyslexia (Rello and Baeza-Yates 2013) but all populations (Bernard et al. 2001; Chaparro et al. 2010). Later, Rello et al. (2016) found an increase in font size above 14 pt, but no larger than 22 pt,

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

improves readability. When communicating hazard information, selecting familiar fonts is especially important since the message needs to be trusted (Hyndman 2016). Familiar sans serif fonts (without embellishment), such as Helvetica, Arial, and Univers, are preferred for warning messages and scientific illustrations over serif fonts like Times New Roman, Garamond, and Courier New (Nersesian et al. 2020; Sattler et al. 1997).

Though most readers can engage with two or three fonts, these should be selected as an organizational aid to establish hierarchy if needed (Poulin 2017). Variation in contrast (boldface) and font size also effectively establish hierarchy, indicating where the attention of the reader should go first, second, and third (i.e., heading, subheading, informational body) (Poulin 2017). We recommend avoiding italics to improve readability for all populations (Rello and Baeza-Yates 2013).

Embellishments. Embellishments such as icons, color gradients, shadows, shapes, and background images (sometimes referred to as "chart junk") decrease clarity as they are not essential to understanding the data (Tufte 1997). It is a good practice to remove noncritical design elements as this reduces the cognitive load requirement that is necessary for more complex PI visualizations (Franconeri et al. 2021; Sweller 2011; Tufte 1997). However, relevant embellishments can be effective for catching the attention of busy viewers, help readers distinguish the purpose of the visualization, and anchor the detail in the viewer's memory (Andry et al. 2021; Bateman et al. 2010). An effective rule for developing visualizations is "communicate, don't decorate" (Samara 2020). For example, the use of snowflakes for snow-related PI quickly signals the reader what the graphic is about, potentially increasing engagement (Andry et al. 2021).

Examples

To show what these principles look like in practice, we provide examples of PI visualization by coupling PI with the previously discussed guiding principles from graphic design and social science-informed visual communication. Grounding these examples in the NWS Western Region, which covers Arizona, California, Nevada, Idaho, Montana, Oregon, Utah, and Washington, we focus on primary weather conditions that pose widespread and localized hazards including snowfall, temperature, wind, and thunderstorms. Each example has unique probabilistic visualization requirements.

Data and methods. Following the graphic design of weather impact and hazard statements by Gordon et al. (2022), we developed a template (Heggli et al. 2023; https://doi.org/10.5281/zenodo.7600486) to facilitate consistent formatting to promote familiarity through repetition. Repetition indirectly reduces the cognitive load to interpret the data each time it is provided (Franconeri et al. 2021; Fundel et al. 2019).

Figure 2 employs the best practices identified in the previous section:

- A grid system approach to create three color-blocked sections to distinguish each core content component: 1) PI visualization, 2) impact statement, and 3) supplemental material (Ambrose et al. 2019; Hilligoss and Howard 2002; Poulin 2018; Samara 2020).
- Gridded layout with color blocking to create a visual connection between elements (Hilligoss and Howard 2002; Poulin 2018; Ambrose et al. 2019; Samara 2020).
- Appropriate negative space to aid in simplicity (Hilligoss and Howard 2002; Samara 2020).
- Variation in font size and weight to establish a hierarchy of information (Poulin 2017).
- Arial font (a minimum font size of 14 pt) for readability (Bernard et al. 2001; Chaparro et al. 2010; Nersesian et al. 2020; Rello et al. 2016; Sattler et al. 1997).
- Space for communication-driven embellishments to act as topical cues (Samara 2020).

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

The template provided is designed with a color theme based on http://www.ColorBrewer.org (Harrower and Brewer 2003). The deepest single hue color (with five data classes) was used as the base color option providing five template colors (blue, green, orange, red, and purple) in addition to standard black and white colors. Each color should be established to represent one weather parameter to 1) build familiarity of that color to the weather being communicated (Dasgupta et al. 2020) and 2) limit the graphic use to just two or three hues (Samara 2020). We selected a blue template for precipitation/snowfall due to blue being a cool color and the association with water, green for thunderstorms to build on the familiarity of existing thunderstorm potential products issued by the NWS Reno Office, orange for wind as a warmer color often associated with drying vegetation, and the black/white template for ad hoc weather concerns like a hard freeze (Stone et al. 2008).

The templates were designed to establish content uniformity while providing options and space to customize the PI visualization for the community. Our approach allows forecasters to "color within the lines," i.e., to add content that connects with their communities but is restricted by visual communication guidelines aimed to communicate the message effectively. The dashed boxes within each section delineate the area reserved for content and demonstrate the use of negative space (Hilligoss and Howard 2002; Samara 2020). The icons for the impact statement can be customized; we selected a clock icon to communicate the "When" section and a light bulb icon for the "What To Do" section. An appropriate icon should be selected to visually represent the potential impact. Each template uses an information icon to cue the supplemental material section where forecasters can provide instructions to familiarize users with new graphics or provide links to additional resources (Carr et al. 2021). Finally, there is a space for the forecast issue time stamp and a logo.

Our template uses Arial font throughout the entire visualization. The title is 32 pt, the subtitle is 18 pt, and the other body text is 16 pt with boldface to distinguish the headers. The minimum font size is 14 pt, used in the forecast date and on some labels given space limitations. These templates assume the platforms have zooming capabilities. All of the graphics were verified for readability and display with cellphone use.

We used the National Blend of Models (NBM) to extract probabilistic forecast information. The NBM is a blend of NWS and non-NWS models that creates probabilistic gridded forecast guidance (Craven et al. 2020; National Weather Service 2022a). Following the recommendation of NWS forecasters, the PI graphics were developed in PowerPoint and Excel since these tools are readily available in NWS offices. The PI visualization PowerPoint and Excel templates are available online (Heggli et al. 2023; https://zenodo.org/record/7999820). Data extracted from the NBM 1D Viewer and WSUP Viewer were used to develop graphics in Excel. The map is exported directly from GraphiDSS, an internal NWS program, to create public-facing weather map graphics.

Snowfall. Snowfall does not have a universal impact threshold; a dusting of snow on cold roads before rush hour may be more impactful than heavy snow on a holiday. For decision-making, the regional Department of Transportation traction (chain) control threshold is typically different from school districts' snow-day policies. A range of risk tolerances likely exists for community members driving in the snow. Some will have more experience and snow-capable vehicles while others avoid driving if any snow accumulates on roads. The objective of the snowfall example (Fig. 3) is to communicate a range of potential scenarios so users can make a decision based on their personal risk threshold.

A boxplot is a data visualization tool currently used in NWS visual communications to express a range of possible outcomes with an associated expression of likelihood. Since users may not be familiar with how boxplots are constructed (Frigge et al. 1989) and because boxplots can be challenging to correctly interpret (Bakker et al. 2004; Edwards et al. 2017),

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

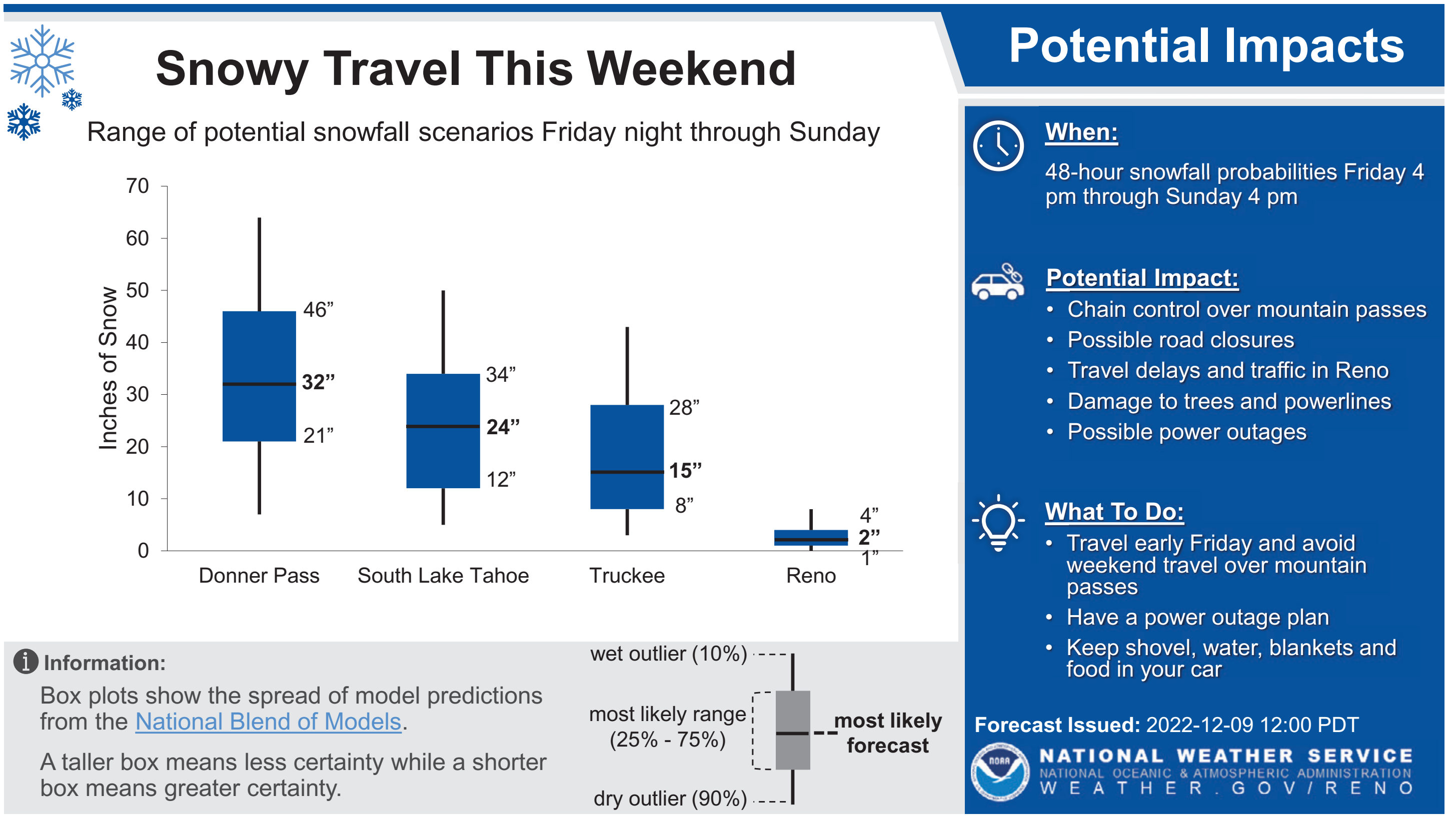

Fig. 3. An example of using a boxplot to communicate a range of possible snowfall scenarios.

we utilize the supplemental material section to teach users how to interpret a boxplot. We recommend boxplots to present information that needs to communicate the high- and low-end scenarios for parameters like snowfall or rainfall. Boxplots are not recommended for temperature, as showing a range of potential temperatures can cause deterministic construal error where a user misinterprets the probabilistic forecast as being deterministic (Joslyn and Savelli 2021). We also give both numerical and simple verbal expressions of uncertainty (Nadav-Greenberg and Joslyn 2009; Lenhardt et al. 2020; Rosen et al. 2021). The impact statement communicates timing, potential impacts, and preventative guidance. To emphasize the potential for traction control, a car and chain icon illustrates the impact. Last, the statement includes guidance to reduce exposure or impacts by suggesting protective actions. The blue color theme is a “cool” color often associated with cold and water. Embellishments were limited to snowflake icons to reinforce the graphic’s focus on snowfall.

Hard freeze. A hard freeze, unlike snowfall, has a defined risk threshold of 28°F (−2°C) (National Weather Service 2019b). Temperatures dropping below this threshold for multiple hours present a hazard for ornamental and agricultural vegetation, exposed or poorly insulated water pipes or irrigation systems, and drivers. The example in Fig. 4 demonstrates how PI can be applied to show the chance of a hard freeze threshold being exceeded.

We selected a familiar axis-aligned bar chart (Andry et al. 2021) and labeled the *x* axis with the percent chance of exceeding the threshold to communicate the uncertainty numerically with an adjacent verbal expression of uncertainty. This chart style could also be employed to communicate record-breaking or critical thresholds of temperatures, snowfall, or rainfall totals. The supplemental material section provides information and a link to learn more about the NBM, a common request from users (Carr et al. 2021; Kuller et al. 2021). It also includes a sentence to help users understand the numerical information. The impact statement gives consistently formatted information about when the hard freeze is expected to occur, the

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

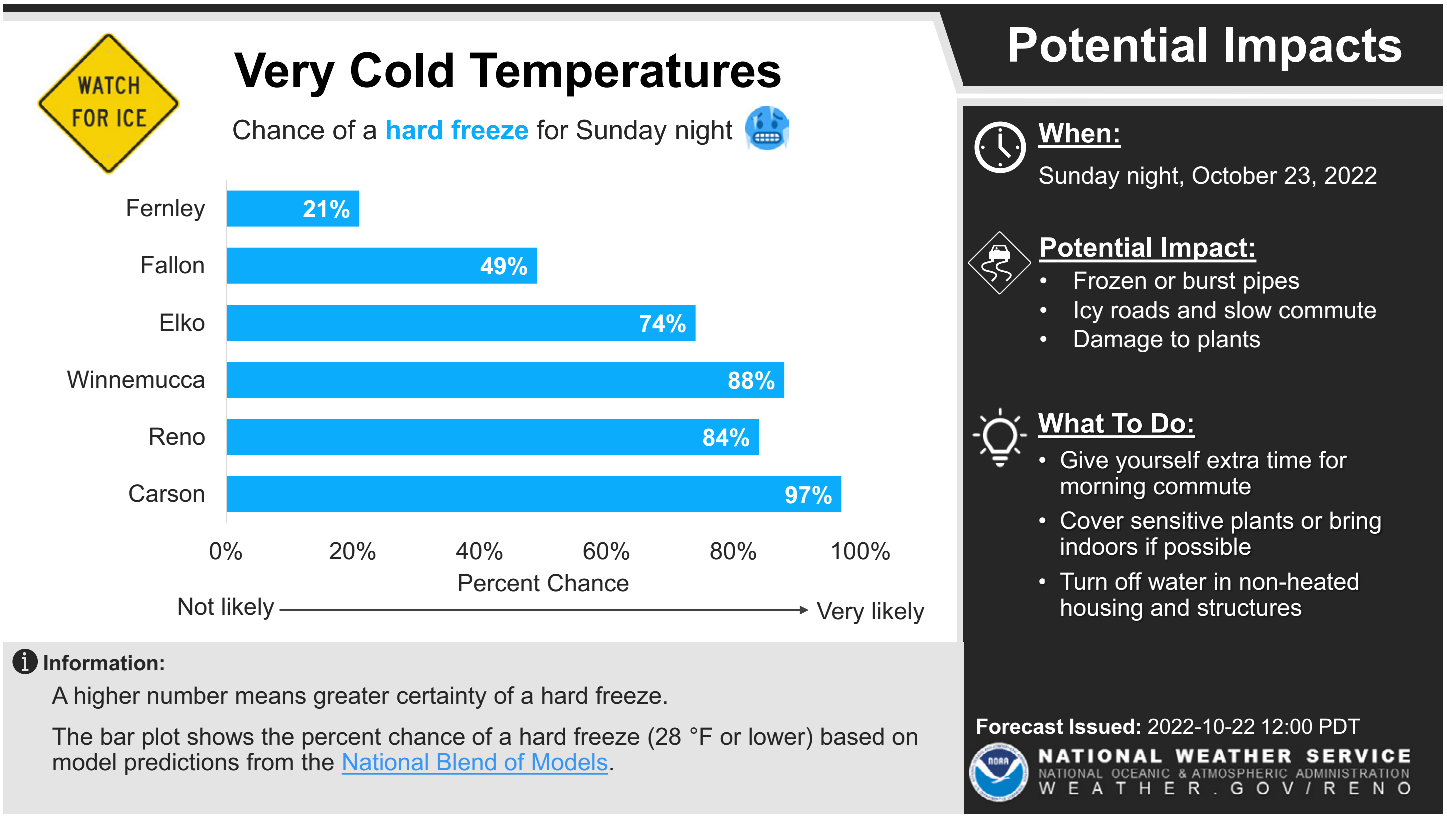

Fig. 4. Example of a horizontal bar chart to communicate the probability of exceeding the hard freeze threshold of 28°C.

potential impacts of a hard freeze with a slippery road icon, and provides preventative guidance to minimize these impacts. A black and white theme was selected as we consider this type of PI visualization to be an ad hoc advisory and not a standard event like precipitation, wind, or thunderstorm that benefits from a consistent color theme. We used a cooler blue tone to illustrate the chart and a contrasting color embellishment in yellow to attract the viewer's attention and communicate that the visualization is about the potential for ice (Samara 2020). Emojis can have a positive impact on interpersonal communication (Elder 2018) and can be useful for nonverbal communication (Bai et al. 2019). In this PI visualization, we included a cold face emoji.

Damaging wind. Similar to a hard freeze, wind speed has a specific hazard threshold for damaging winds, classified when sustained winds exceed 40 mph (≈64 km h^{-1}) for at least 1 h or gusts greater than 58 mph for any duration (≈93 km h^{-1}) (National Weather Service 2019b). However, wind speed impacts can vary depending on timing and duration. The wind example aims to communicate the likelihood of damaging winds in different regions and the expected timing and duration by using a table.

We extracted the exceedance probability of wind gusts greater than 58 mph and color-coded the probability of damaging winds over a 72-h period. Since color-coded PI can improve the understanding of likelihood (Ash et al. 2014; Miran et al. 2019), we use a single hue of orange that increases in lightness as the probability of damaging winds decreases (van Gorp and Adams 2012; Wilms and Oberfeld 2017). The color-coded uncertainty is labeled using a numerical expression of uncertainty. A legend with color-coded verbal and numerical expressions is provided (Lenhardt et al. 2020; Nadav-Greenberg and Joslyn 2009). In this example, we use the supplemental material section to develop weather literacy by explaining the impact of 58 mph winds and coupling this with a fallen tree icon (Fleischhut et al. 2020). Embellishments to communicate a warning about wind were included by adding a warning

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

icon coupled with a wind icon. A dark theme background was selected to add contrast and intensity to the orange theme color. A similar design approach could communicate the timing and probability of precipitation or snowfall.

Thunderstorm. Thunderstorms in the western United States are often isolated and have different likelihoods of occurring regionally and locally. Thunderstorms produce lightning hazards for life and property (Holle 2014), wildfire ignitions from dry lightning (Nauslar and Hatchett 2018), gusty outflow and downdraft winds (Peterson 2000), and localized rainfall and flooding (Changnon 2001). This example aims to demonstrate how PI can be communicated spatially with a map to show the probability of occurrence both regionally and locally.

Since current thunderstorm probability graphics already use a green color scale, we chose to use green for this example to retain a sense of familiarity while improving accessibility by having categorical colors rather than a gradient scale. Similar to the damaging wind example, we used a single hue that varies in lightness with the uncertainty level (van Gorp and Adams 2012; Wilms and Oberfeld 2017). The color-coded legend provides both numerical and verbal expressions of uncertainty. If terms such as "slight," "moderate," or "high" are used in PI communications as expressions of uncertainty, but do not correspond to the Storm Prediction Center's (SPC; https://www.spc.noaa.gov/) Severe Thunderstorm Outlook Categories or other products, it is necessary to explicitly define these terms (i.e., "high *chances*") and provide the quantitative ranges associated with them (50%–75%) to avoid any confusion with SPC products or definitions. For forecast maps with areas of less than low chances (i.e., 0%–10%), we recommend defining the base map color in the legend if a monochromic color is used to avoid potential confusion about an undefined color on the map. We leverage the supplemental material section to clarify that this graphic only provides the probability of a thunderstorm occurring "over your head" but regionally the chances of seeing a thunderstorm is typically higher. In this impact statement, we issue the standard information to communicate when, the possible impacts, and preventative guidance if a thunderstorm does occur. To make the graphic "pop" we selected a dark background with a green theme using thunderstorm and wind icons with a bright green outline to improve the aesthetic (Samara 2020).

Discussion

Building a Weather-Ready Nation benefits from a customer-centric approach to forecasting for core partners and general audiences that does not sacrifice the scientific accuracy of a product (Uccellini and Ten Hoeve 2019). To support a customer-centric approach, we provided an adaptable tool with a "plug-and-play" approach by developing Excel and PowerPoint templates (Heggli et al. 2023; https://doi.org/10.5281/zenodo.7600486) through an iterative design process with NWS forecasters. These templates incorporate guiding principles based on a review of graphic design and social science literature as a step toward producing more effective and accessible PI visualizations. We designed these templates to facilitate consistent messaging between NWS offices and to reduce the time required to develop PI visualizations. Reducing time investments could allow forecasters to focus time on creating multiple visualizations targeted at individual regions within their forecast area of responsibility. Many NWS forecast offices have found daily weather briefing packages to be effective tools for providing context about upcoming weather events to core partners (Carr et al. 2021). However, social media remains a common place for NWS offices to disseminate forecast information (National Weather Service 2017). Carefully designed visual explanations will likely improve regional weather literacy among both core partners and public audiences. This will help users leverage the power of probabilistic weather forecasts to improve decision-making (Fleischhut et al. 2020; Fundel et al. 2019).

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

Successful efforts to visualize probabilistic weather information have focused on the probability of precipitation (PoP) (Lowry and Glahn 1976), hurricane forecasts (Broad et al. 2007; Rosen et al. 2021), and severe weather (Rothfusz et al. 2014). Currently, other efforts are being carried out across the NWS with the Central Region Probabilistic Messaging Testbed (Schumacher et al. 2021, 2022), High-Resolution Ensemble Forecast system (HREF) for thunderstorm guidance (Harrison et al. 2022), and probabilistic hazard information and decision support services for winter storms (Novak et al. 2023; Tripp et al. 2023). Continued engagement and co-production are critical to improving the utility of PI tools through transparency and communication, which further develops trust between forecasters, core partners, and the general public (Carr et al. 2021; Fundel et al. 2019; Pappenberger et al. 2012; Sivle et al. 2014). However, it is important to reiterate that the numerous benefits associated with PI hinge on the visuals being well designed (Franconeri et al. 2021; Padilla et al. 2021). Layout, color selection, font, and embellishments are more than a decorative choice with PI visualization as they impact the users' ability to efficiently and accurately extract information.

There are limitations associated with the use of PI that can be counterproductive, but identifying these limitations can lead to solutions that can improve user understanding. Unfamiliar visualizations can cause deterministic construal error when users do not understand forecast information is probabilistic, so the visualization must expressly communicate that the information is probabilistic. (Fleischhut et al. 2020; Grounds et al. 2017; Joslyn and LeClerc 2013; Joslyn and Savelli 2021; Savelli and Joslyn 2013). To reduce the chances of deterministic construal error, we attempt to cue the users to the presence of uncertain information by using words like "could," "chance," and "probability" as well as expressing the impact statement as "potential impacts." PI can also lead to biased or subjective decision-making (Wernstedt et al. 2018). However, bias in decision-making is hard to quantify as it relates to people's past experiences, predisposition to certainty, and avoiding loss (Grounds and Joslyn 2018). Even when considering the limitations, probabilistic forecasts are generally considered to be better than deterministic forecasts because they provide a more accurate and realistic representation of uncertainty, and can help to reduce the risk of overconfidence and bias (Ripberger et al. 2022). Our work attempts to address these limitations by encouraging consistent messaging, transparency of information, and familiarity with PI.

In parallel with ongoing development of technical products (Harrison et al. 2022; Novak et al. 2023; Schumacher et al. 2021; Tripp et al. 2023), the communication and perception of these products by users should be systematically examined (Dallo et al. 2020; Lambrecht et al. 2019). While our visualization examples were developed collaboratively with NWS forecasters, further research should analyze the impact and perception of probabilistic visualizations more broadly with emergency managers and the general public across a diversity of environments, demographics, and hazards.

Summary

PI can improve credibility, strengthen understanding of the forecast, support decision-making, and help build trust by enabling targeted messaging and demonstrating a commitment to transparency by communicating forecast uncertainty (Grounds and Joslyn 2018; Joslyn and LeClerc 2012; Morss et al. 2008; National Weather Service 2022b; Ripberger et al. 2022). Our work leverages social science and graphic communication literature to develop a ready-to-use template (Heggli et al. 2023) aimed at improving the usability and comprehension of probabilistic forecast information. The templates provide a "plug-and-play" tool to develop PI visualizations to reduce the forecaster's time, increase consistency, and ensure design principles are followed when developing graphics. While these templates were designed focused on advancing the NWS with improved PI visualizations, the principles can be

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

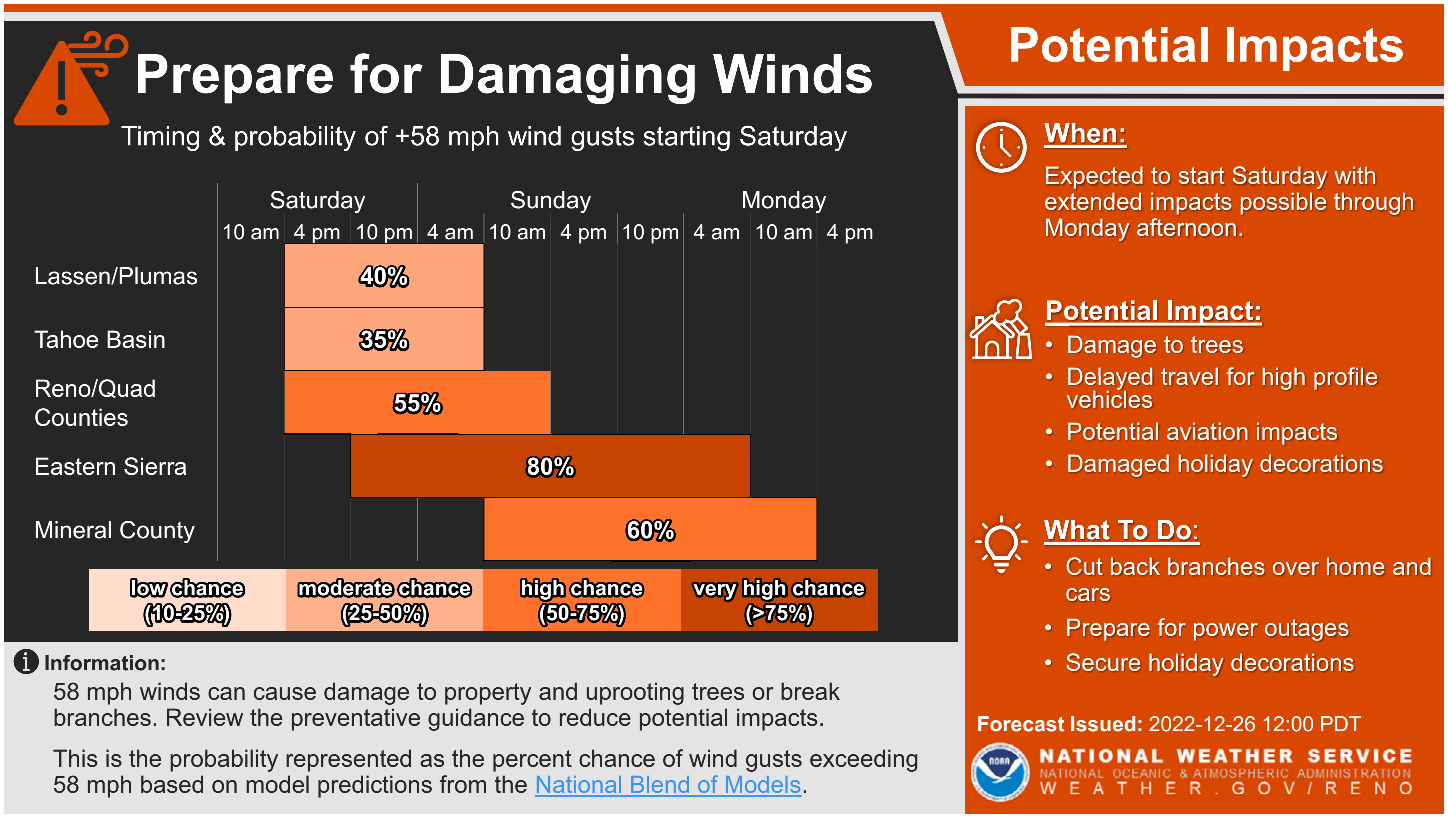

Fig. 5. **Example using a table to communicate timing and probability of damaging winds.**

applied to other weather information graphic designs. The value of PI is not that it provides the decision. Rather, PI provides information useful for the binary decision-making process for user-specific thresholds (Pappenberger et al. 2012). PI can inform any weather-related decision, but single-value deterministic information with no expression of uncertainty leaves decision-makers less well equipped to make the best possible decision(s). The continued integration and improved visual communication of PI into NWS forecasts will help NOAA reach its goal: to continuously transform weather, water, and climate information service delivery to better support evolving societal needs (National Oceanic and Atmospheric Administration 2022).

Acknowledgments. The authors thank Chris Johnston at NWS Reno for his time, input, and creative collaboration on Figs. 2, 5, and 6. We also appreciate Chris Smallcomb at NWS Reno and Chad Gravelle from the NWS Southern Region for their discussions and Lori Fulton for her constructive feedback on Fig. 2. We thank the anonymous reviewers for their diligent and thoughtful comments that directly improved this paper. Additionally, we thank Maureen McBride for her comments and constructive critiques of the paper. This project was funded by the National Oceanic and Atmospheric Association Weather Program Office Social Sciences Program under Grant NA21OAR4590208.

Data availability statement. No datasets were generated or analyzed during the current study. Data used to populate the visualizations is publicly available through the experimental 1D Viewer but originated from the National Blend of Models (National Weather Service 2022a). PowerPoint and Excel templates are available on a Zenodo repository: https://zenodo.org/record/7600486.

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

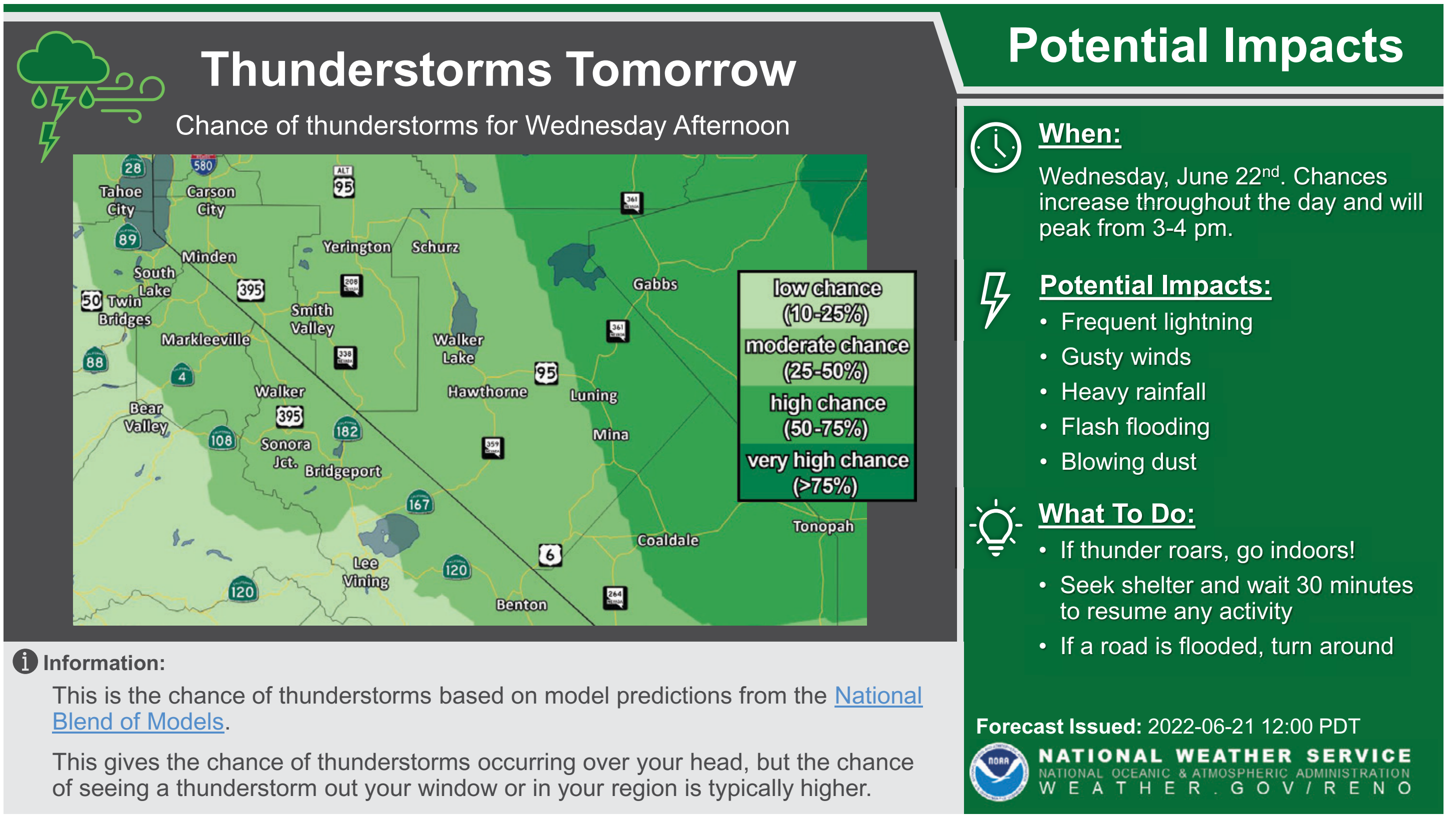

Fig. 6. Example of a map to communicate the probability of thunderstorms in a region. If less than low chances (0%–10%) are required, a lighter green can be used. For areas of no chances (0%) we recommend defining the base map color in the legend if a monochromic base map is used.

Probabilistic information to advance Impact-Based Decision Support Systems

We define probabilistic information (PI) as messaging that conveys the likelihood of one or more specific outcomes. Therefore, probabilistic weather information includes the forecast scenario and the associated uncertainty. PI is developed with an ensemble forecast, defined as "a set of different forecasts all valid at the same forecast time(s)" (American Meteorological Society 2020). From there, forecasters may adjust the model-derived probabilistic information based on external information and/or experience (i.e., local knowledge).

While it is not always necessary to communicate multiple scenarios, in certain situations, it may be imperative to communicate the full range of possible scenarios with the associated uncertainties so decision-makers can prepare accordingly. For example, precipitation falling as either rain or snow benefits from communicating the wet and dry scenarios to inform people about 1) the potential worst-case scenario, 2) the most likely scenario, and 3) the likelihood of the worst-case scenario.

To create an effective PI visualization, it is important to communicate the potential impact as a way to build weather literacy since people cannot easily infer the impact from a weather forecast alone (Fleischhut et al. 2020; WMO 2015). For example, Fleischhut et al. (2020) found people overestimate severe wind speeds that cause damage. Therefore, communicating what the weather "can do" (uproot trees and knock down power lines) versus what it "would be" (56 mph/90 km h^{-1}) can improve weather literacy needed to understand weather impacts. In this way, PI can be coupled with hazard or individual risk thresholds with their associated potential impacts to create Impact-Based Decision Support.

When PI is used for a specific hazard threshold, PI evolves into probabilistic hazard information (PHI), but there are many benefits of communicating probabilistic weather information when there is little to no hazard present. Creating more opportunities for core partners to access and learn how to use PI helps build familiarity with PI so when PHI is disseminated, partners will be familiar with the products and it could help them extract uncertainty information for their decision threshold and associated risk tolerance.

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

References

Ambrose, G., P. Harris, and N. Ball, 2019: *The Fundamentals of Graphic Design.* Bloomsbury Publishing, 192 pp.

American Meteorological Society, 2020: Climatology. Glossary of Meteorology, http://glossary.ametsoc.org/wiki/climatology.

Andry, T., C. Hurter, F. Lambotte, P. Fastrez, and A. Telea, 2021: Interpreting the effect of embellishment on chart visualizations. *CHI'21: Proc. 2021 CHI Conf. on Human Factors in Computing Systems*, Yokohama, Japan, Association for Computing Machinery, 1–15, https://doi.org/10.1145/3411764.3445739.

Ash, K. D., R. L. Schumann, and G. C. Bowser, 2014: Tornado warning trade-offs: Evaluating choices for visually communicating risk. *Wea. Climate Soc.*, **6**, 104–118, https://doi.org/10.1175/WCAS-D-13-00021.1.

Bai, Q., Q. Dan, Z. Mu, and M. Yang, 2019: A systematic review of emoji: Current research and future perspectives. *Front. Psychol.*, **10**, 2221, https://doi.org/10.3389/fpsyg.2019.02221.

Bakker, A., R. Biehler, and C. Konold, 2004: Should young students learn about box plots. *Curricular Development in Statistics Education: International Association for Statistical Education Roundtable*, International Statistical Institute, 163–173, https://iase-web.org/documents/papers/rt2004/4.2_Bakker_etal.pdf.

Basak, A., and S. T. Roy, 2022: Visual ergonomics for colourblindness: Applying universal design principles in graphical user interface to provide affordance to the colourblind users. *Proc. Des. Soc.*, **2**, 2055–2066, https://doi.org/10.1017/pds.2022.208.

Bateman, S., R. L. Mandryk, C. Gutwin, A. Genest, D. McDine, and C. Brooks, 2010: Useful junk? The effects of visual embellishment on comprehension and memorability of charts. *CHI'10: Proc. SIGCHI Conf. on Human Factors in Computing Systems*, Atlanta, GA, Association for Computing Machinery, 2573–2582, https://dl.acm.org/doi/abs/10.1145/1753326.1753716.

Bean, H., J. Sutton, B. F. Liu, S. Madden, M. M. Wood, and D. S. Mileti, 2015: The study of mobile public warning messages: A research review and agenda. *Rev. Commun.*, **15**, 60–80, https://doi.org/10.1080/15358593.2015.1014402.

Bernard, M., C. H. Liao, and M. Mills, 2001: The effects of font type and size on the legibility and reading time of online text by older adults. *CHI EA'01: CHI'01 Extended Abstracts on Human Factors in Computing Systems*, Seattle, WA, Association for Computing Machinery, 175–176, https://doi.org/10.1145/634067.634173.

Borland, D., and R. M. T. Ii, 2007: Rainbow color map (still) considered harmful. *IEEE Comput. Graphics Appl.*, **27**, 14–17, https://doi.org/10.1109/MCG.2007.323435.

Breznitz, S., 2013: *Cry Wolf: The Psychology of False Alarms.* Psychology Press, 280 pp.

Broad, K., A. Leiserowitz, J. Weinkle, and M. Steketee, 2007: Misinterpretations of the "cone of uncertainty" in Florida during the 2004 hurricane season. *Bull. Amer. Meteor. Soc.*, **88**, 651–668, https://doi.org/10.1175/BAMS-88-5-651.

Carr, R. H., B. Montz, K. Maxfield, S. Hoekstra, K. Semmens, and E. Goldman, 2016: Effectively communicating risk and uncertainty to the public: Assessing the National Weather Service's flood forecast and warning tools. *Bull. Amer. Meteor. Soc.*, **97**, 1649–1665, https://doi.org/10.1175/BAMS-D-14-00248.1.

——, K. Semmens, B. Montz, and K. Maxfield, 2021: Improving the use of hydrologic probabilistic and deterministic information in decision-making. *Bull. Amer. Meteor. Soc.*, **102**, E1878–E1896, https://doi.org/10.1175/BAMS-D-21-0019.1.

Changnon, S. A., 2001: Thunderstorm rainfall in the conterminous United States. *Bull. Amer. Meteor. Soc.*, **82**, 1925–1940, https://doi.org/10.1175/1520-0477(2001)082<1925:TRITCU>2.3.CO;2.

Chaparro, B. S., A. D. Shaikh, A. Chaparro, and E. C. Merkle, 2010: Comparing the legibility of six ClearType typefaces to Verdana and times new roman. *Inf. Des. J.*, **18**, 36–49, https://doi.org/10.1075/idj.18.1.04cha.

Chiarella, D., J. Yarbrough, and C. A.-L. Jackson, 2020: Using alt text to make science twitter more accessible for people with visual impairments. *Nat. Commun.*, **11**, 5803, https://doi.org/10.1038/s41467-020-19640-w.

Crameri, F., G. E. Shephard, and P. J. Heron, 2020: The misuse of colour in science communication. *Nat. Commun.*, **11**, 5444, https://doi.org/10.1038/s41467-020-19160-7.

Craven, J. P., D. E. Rudack, and P. E. Shafer, 2020: National blend of models: A statistically post-processed multi-model ensemble. *J. Oper. Meteor.*, **8** (1), 1–14, https://doi.org/10.15191/nwajom.2020.0801.

Dallo, I., M. Stauffacher, and M. Marti, 2020: What defines the success of maps and additional information on a multi-hazard platform? *Int. J. Disaster Risk Reduct.*, **49**, 101761, https://doi.org/10.1016/j.ijdrr.2020.101761.

Dasgupta, A., J. Poco, B. Rogowitz, K. Han, E. Bertini, and C. T. Silva, 2020: The effect of color scales on climate scientists' objective and subjective performance in spatial data analysis tasks. *IEEE Trans. Visualization Comput. Graphics*, **26**, 1577–1591, https://doi.org/10.1109/TVCG.2018.2876539.

Deeb, S., 2005: The molecular basis of variation in human color vision. *Clin. Genet.*, **67**, 369–377, https://doi.org/10.1111/j.1399-0004.2004.00343.x.

Eden, G. F., and L. Moats, 2002: The role of neuroscience in the remediation of students with dyslexia. *Nat. Neurosci.*, **5**, 1080–1084, https://doi.org/10.1038/nn946.

Edwards, T. G., A. Özgün Koca, and J. Barr, 2017: Interpretations of boxplots: Helping middle school students to think outside the box. *J. Stat. Educ.*, **25**, 21–28, https://doi.org/10.1080/10691898.2017.1288556.

Elder, A. M., 2018: What words can't say. *J. Inf. Commun. Ethics Soc.*, **16**, 2–15, https://doi.org/10.1108/JICES-08-2017-0050.

Eraslan, S., Y. Yesilada, V. Yaneva, and L. A. Ha, 2020: "Keep it simple!": An eye-tracking study for exploring complexity and distinguishability of web pages for people with autism. *Univers. Access Inf. Soc.*, **20**, 69–84, https://doi.org/10.1007/s10209-020-00708-9.

Essen, D. C. V., C. H. Anderson, and D. J. Felleman, 1992: Information processing in the primate visual system: An integrated systems perspective. *Science*, **255**, 419–423, https://doi.org/10.1126/science.1734518.

European Food Safety Authority, 2019: Guidance on communication of uncertainty in scientific assessments. *EFSA J.*, **17**, e05520, https://doi.org/10.2903/j.efsa.2019.5520.

Fleischhut, N., S. M. Herzog, and R. Hertwig, 2020: Weather literacy in times of climate change. *Wea. Climate Soc.*, **12**, 435–452, https://doi.org/10.1175/WCAS-D-19-0043.1.

Fletcher, J. M., G. R. Lyon, L. S. Fuchs, and M. A. Barnes, 2018: *Learning Disabilities: From Identification to Intervention.* The Guilford Press, 418 pp.

Flynn, F. J., and C. R. Lide, 2023: Communication miscalibration: The price leaders pay for not sharing enough. *Acad. Manage. J.*, **66**, 1102–1122, https://doi.org/10.5465/amj.2021.0245.

Franconeri, S. L., L. M. Padilla, P. Shah, J. M. Zacks, and J. Hullman, 2021: The science of visual data communication: What works. *Psychol. Sci. Public Interest*, **22**, 110–161, https://doi.org/10.1177/15291006211051956.

Frigge, M., D. C. Hoaglin, and B. Iglewicz, 1989: Some implementations of the boxplot. *Amer. Stat.*, **43**, 50–54, https://doi.org/10.2307/2685173.

Fundel, V. J., N. Fleischhut, S. M. Herzog, M. Göber, and R. Hagedorn, 2019: Promoting the use of probabilistic weather forecasts through a dialogue between scientists, developers and end-users. *Quart. J. Roy. Meteor. Soc.*, **145**, 210–231, https://doi.org/10.1002/qj.3482.

Gordon, A., E. Chimenti, R. Amirazizi, S. Busalacchi, M. Buhler, P. Goedderz, C. Grevin, and S. Kashani, 2022: Crafting effective public safety messages for wildfire and subsequent debris flow risks. Chapman University, 40 pp., https://www.chapman.edu/wilkinson/research-centers/babbie-center/_files/nws_effective_messaging_design_final-1.pdf.

Grounds, M. A., and S. L. Joslyn, 2018: Communicating weather forecast uncertainty: Do individual differences matter? *J. Exp. Psychol.*, **24**, 18–33, https://doi.org/10.1037/xap0000165.

——, S. Joslyn, and K. Otsuka, 2017: Probabilistic interval forecasts: An individual differences approach to understanding forecast communication. *Adv. Meteor.*, **2017**, 1–18, https://doi.org/10.1155/2017/3932565.

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

Harrison, D. R., M. S. Elliott, I. L. Jirak, and P. T. Marsh, 2022: Utilizing the high-resolution ensemble forecast system to produce calibrated probabilistic thunderstorm guidance. *Wea. Forecasting*, **37**, 1103–1115, https://doi.org/10.1175/WAF-D-22-0001.1.

Harrower, M., and C. Brewer, 2003: ColorBrewer.org: An online tool for selecting color schemes for maps. *Cartogr. J.*, **40**, 27–37, https://doi.org/10.1179/000870403235002042.

Hatchett, B. J., and Coauthors, 2021: Mobility data to aid assessment of human responses to extreme environmental conditions. *Lancet Planet. Health*, **5**, e665–e667, https://doi.org/10.1016/S2542-5196(21)00261-8.

Heggli, A., B. Hatchett, Z. Tolby, K. Lambrecht, M. Collins, L. Olman, and M. Jeglum, 2023: Visual communication of probabilistic information to enhance decision support. Zenodo, https://zenodo.org/record/7600486.

Hilligoss, S., and T. Howard, 2002: *Visual Communication: A Writer's Guide.* Longman Publishers, 159 pp.

Hirschberg, P. A., and Coauthors, 2011: A weather and climate enterprise strategic implementation plan for generating and communicating forecast uncertainty information. *Bull. Amer. Meteor. Soc.*, **92**, 1651–1666, https://doi.org/10.1175/bams-d-11-00073.1.

Holle, R. L., 2014: Some aspects of global lightning impacts. *2014 Int. Conf. on Lightning Protection (ICLP)*, Shanghai, China, Institute of Electrical and Electronics Engineers, 1390–1395, https://doi.org/10.1109/ICLP.2014.6973348.

Howe, L. C., B. MacInnis, J. A. Krosnick, E. M. Markowitz, and R. Socolow, 2019: Acknowledging uncertainty impacts public acceptance of climate scientists' predictions. *Nat. Climate Change*, **9**, 863–867, https://doi.org/10.1038/s41558-019-0587-5.

Huntsman, S., 2022: An image for all: The rhetoric for writing alt-text. *2022 IEEE Int. Professional Communication Conf. (ProComm*), Limerick, Ireland, Institute of Electrical and Electronics Engineers, 49–52, https://doi.org/10.1109/ProComm53155.2022.00012.

Hyndman, S., 2016: *Why Fonts Matter.* Virgin Books, 144 pp.

Jenkins, S. C., A. J. Harris, and R. Lark, 2018: Understanding 'unlikely (20% likelihood)' or '20% likelihood (unlikely)' outcomes: The robustness of the extremity effect. *J. Behav. Decis. Making*, **31**, 572–586, https://doi.org/10.1002/bdm.2072.

——, A. J. L. Harris, and R. M. Lark, 2019: When unlikely outcomes occur: The role of communication format in maintaining communicator credibility. *J. Risk Res.*, **22**, 537–554, https://doi.org/10.1080/13669877.2018.1440415.

Joslyn, S., and S. Savelli, 2010: Communicating forecast uncertainty: Public perception of weather forecast uncertainty. *Meteor. Appl.*, **17**, 180–195, https://doi.org/10.1002/met.190.

——, and J. LeClerc, 2013: Decisions with uncertainty: The glass half full. *Curr. Dir. Psychol. Sci.*, **22**, 308–315, https://doi.org/10.1177/0963721413481473.

——, and R. Demnitz, 2019: Communicating climate change: Probabilistic expressions and concrete events. *Wea. Climate Soc.*, **11**, 651–664, https://doi.org/10.1175/WCAS-D-18-0126.1.

——, and S. Savelli, 2021: Visualizing uncertainty for non-expert end users: The challenge of the deterministic construal error. *Front. Comput. Sci.*, **2**, 590232, https://doi.org/10.3389/fcomp.2020.590232.

Joslyn, S. L., and J. E. LeClerc, 2012: Uncertainty forecasts improve weather-related decisions and attenuate the effects of forecast error. *J. Exp. Psychol.*, **18**, 126–140, https://doi.org/10.1037/a0025185.

——, and M. A. Grounds, 2015: The use of uncertainty forecasts in complex decision tasks and various weather conditions. *J. Exp. Psychol.*, **21**, 407–417, https://doi.org/10.1037/xap0000064.

Juanchich, M., and M. Sirota, 2018: Not as gloomy as we thought: Reassessing how the public understands probability of precipitation forecasts. *J. Cognit. Psychol.*, **31**, 116–129, https://doi.org/10.1080/20445911.2018.1553884.

Kuller, M., K. Schoenholzer, and J. Lienert, 2021: Creating effective flood warnings: A framework from a critical review. *J. Hydrol.*, **602**, 126708, https://doi.org/10.1016/j.jhydrol.2021.126708.

Lambrecht, K., B. J. Hatchett, K. VanderMolen, and B. Feldkircher, 2021: Identifying community values related to heat: Recommendations for forecast and health risk communication. *Geosci. Commun.*, **4**, 517–525, https://doi.org/10.5194/gc-4-517-2021.

Lambrecht, K. M., B. J. Hatchett, L. C. Walsh, M. Collins, and Z. Tolby, 2019: Improving visual communication of weather forecasts with rhetoric. *Bull. Amer. Meteor. Soc.*, **100**, 557–563, https://doi.org/10.1175/BAMS-D-18-0186.1.

LeClerc, J., and S. Joslyn, 2012: Odds ratio forecasts increase precautionary action for extreme weather events. *Wea. Climate Soc.*, **4**, 263–270, https://doi.org/10.1175/WCAS-D-12-00013.1.

——, and ——, 2015: The cry wolf effect and weather-related decision making. *Risk Anal.*, **35**, 385–395, https://doi.org/10.1111/risa.12336.

Lenhardt, E. D., R. N. Cross, M. J. Krocak, J. T. Ripberger, S. R. Ernst, C. L. Silva, and H. C. Jenkins, 2020: How likely is that chance of thunderstorms? A study of how National Weather Service forecast offices use words of estimative probability and what they mean to the public. *J. Oper. Meteor.*, 64–78, https://doi.org/10.15191/nwajom.2020.0805.

Lipkus, I. M., and J. G. Hollands, 1999: The visual communication of risk. *J. Natl. Cancer Inst. Monogr.*, **1999**, 149–163, https://doi.org/10.1093/oxfordjournals.jncimonographs.a024191.

Losee, J. E., and S. Joslyn, 2018: The need to trust: How features of the forecasted weather influence forecast trust. *Int. J. Disaster Risk Reduct.*, **30**, 95–104, https://doi.org/10.1016/j.ijdrr.2018.02.032.

Lowry, D. A., and H. R. Glahn, 1976: An operational model for forecasting probability of precipitation—PEATMOS PoP. *Mon. Wea. Rev.*, **104**, 221–232, https://doi.org/10.1175/1520-0493(1976)104<0221:AOMFFP>2.0.CO;2.

Malamed, C., 2015: *Visual Design Solutions: Principles and Creative Inspiration for Learning Professionals.* John Wiley and Sons, 384 pp.

McGee, M., 2012: Neurodiversity. *Contexts*, **11**, 12–13, https://doi.org/10.1177/1536504212456175.

Miran, S. M., C. Ling, A. Gerard, and L. Rothfusz, 2019: Effect of providing the uncertainty information about a tornado occurrence on the weather recipients' cognition and protective action: Probabilistic hazard information versus deterministic warnings. *Risk Anal.*, **39**, 1533–1545, https://doi.org/10.1111/risa.13289.

Morss, R. E., J. L. Demuth, and J. K. Lazo, 2008: Communicating uncertainty in weather forecasts: A survey of the U.S. public. *Wea. Forecasting*, **23**, 974–991, https://doi.org/10.1175/2008WAF2007088.1.

——, J. K. Lazo, and J. L. Demuth, 2010: Examining the use of weather forecasts in decision scenarios: Results from a US survey with implications for uncertainty communication. *Meteor. Appl.*, **17**, 149–162, https://doi.org/10.1002/met.196.

Motulsky, A. G., and S. S. Deeb, 2001: Color vision and its genetic defects. *The Metabolic and Molecular Bases of Inherited Disease*, Vol. 4, C. Scriver et al., Eds., McGraw-Hill, 5955–5976.

Murchie, K. J., and D. Diomede, 2020: Fundamentals of graphic design—Essential tools for effective visual science communication. *FACETS*, **5**, 409–422, https://doi.org/10.1139/facets-2018-0049.

Murphy, A. H., 1993: What is a good forecast? An essay on the nature of goodness in weather forecasting. *Wea. Forecasting*, **8**, 281–293, https://doi.org/10.1175/1520-0434(1993)008<0281:WIAGFA>2.0.CO;2.

Nadav-Greenberg, L., and S. L. Joslyn, 2009: Uncertainty forecasts improve decision making among nonexperts. *J. Cognit. Eng. Decis. Making*, **3**, 209–227, https://doi.org/10.1518/155534309X474460.

National Oceanic and Atmospheric Administration, 2022: Weather, water, and climate strategy. Tech. Rep. FY 2023-2027, 66 pp., https://www.noaa.gov/sites/default/files/2022-12/NOAA-FY23-27-Weather-Water-and-Climate-Strategy-12092022.pdf.

National Research Council, 2006: *Completing the Forecast: Characterizing and Communicating Uncertainty for Better Decisions Using Weather and Climate Forecasts.* The National Academies Press, 124 pp., https://doi.org/10.17226/11699.

National Weather Service, 2017: How the national weather service leverages social media for severe weather. NOAA/NWS, https://www.weather.gov/wrn/summer-article-how-the-NWS-leverages-social-media.

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

——, 2019a: Building a Weather-Ready Nation: 2019–2022 strategic plan. NOAA Tech. Rep., 28 pp., https://www.weather.gov/media/wrn/NWS_Weather-Ready-Nation_Strategic_Plan_2019-2022.pdf.

——, 2019b: WFO non-precipitation weather products specification. NWSI Tech Rep. 10-515, 25 pp., https://www.nws.noaa.gov/directives/sym/pd01005015curr.pdf.

——, 2022a: National Blend of Models. Meteorological Development Laboratory, NOAA, https://vlab.noaa.gov/web/mdl/nbm.

——, 2022b: Advancing IDSS through probabilities: FY22 western region goals & guidance. NWS Western Regional Headquarters Tech. Rep.

——, 2022c: Risky business – Supplement for advancing IDSS through probabilities. NWS Western Regional Headquarters Tech. Rep.

Nauslar, N. J., and B. J. Hatchett, 2018: Dry thunderstorms. *Encyclopedia of Wildfires and Wildland-Urban Interface (WUI) Fires*, Springer International Publishing, 1–10, https://doi.org/10.1007/978-3-319-51727-8_176-1.

Nersesian, S., N. Vitkin, S. Grantham, and S. Bourgaize, 2020: Illustrating your research: Design basics for junior clinicians and scientists. *BMJ*, **370**, m2254, https://doi.org/10.1136/bmj.m2254.

Novak, D. R., and Coauthors, 2023: Innovations in winter storm forecasting and decision support services. *Bull. Amer. Meteor. Soc.*, **104**, E715–E735, https://doi.org/10.1175/BAMS-D-22-0065.1.

Oakley, N. S., and Coauthors, 2023: Toward probabilistic post-fire debris-flow hazard decision support. *Bull. Amer. Meteor. Soc.*, https://doi.org/10.1175/BAMS-D-22-0188.1, in press.

Padilla, L., S. Dryhurst, H. Hosseinpour, and A. Kruczkiewicz, 2021: Multiple hazard uncertainty visualization challenges and paths forward. *Front. Psychol.*, **12**, 579207, https://doi.org/10.3389/fpsyg.2021.579207.

Palmer, T. N., 2002: The economic value of ensemble forecasts as a tool for risk assessment: From days to decades. *Quart. J. Roy. Meteor. Soc.*, **128**, 747–774, https://doi.org/10.1256/0035900021643593.

Pappenberger, F., E. Stephens, J. Thielen, P. Salamon, D. Demeritt, S. J. van Andel, F. Wetterhall, and L. Alfieri, 2012: Visualizing probabilistic flood forecast information: Expert preferences and perceptions of best practice in uncertainty communication. *Hydrol. Processes*, **27**, 132–146, https://doi.org/10.1002/hyp.9253.

Peterson, C. J., 2000: Catastrophic wind damage to North American forests and the potential impact of climate change. *Sci. Total Environ.*, **262**, 287–311, https://doi.org/10.1016/S0048-9697(00)00529-5.

Poulin, R., 2017: *Design School: Type: A Practical Guide for Students and Designers.* Rockport Publishers, 240 pp.

——, 2018: *Design School: Layout: A Practical Guide for Students and Designers.* Rockport Publishers, 232 pp.

Rello, L., and R. Baeza-Yates, 2013: Good fonts for dyslexia. *ASSETS'13: Proc. 15th Int. ACM SIGACCESS Conf. on Computers and Accessibility*, Bellevue, WA, Association for Computing Machinery, 1–8, https://doi.org/10.1145/2513383.2513447.

——, M. Pielot, and M.-C. Marcos, 2016: Make it big! *CHI'16: Proc. 2016 CHI Conf. on Human Factors in Computing Systems*, San Jose, CA, Association for Computing Machinery, 3637–3648, https://doi.org/10.1145/2858036.2858204.

Ripberger, J., A. Bell, A. Fox, A. Forney, W. Livingston, C. Gaddie, C. Silva, and H. Jenkins-Smith, 2022: Communicating probability information in weather forecasts: Findings and recommendations from a living systematic review of the research literature. *Wea Climate Soc.*, **14**, 481–498, https://doi.org/10.1175/WCAS-D-21-0034.1.

Rogowitz, B., and L. Treinish, 1998: Data visualization: The end of the rainbow. *IEEE Spectrum*, **35**, 52–59, https://doi.org/10.1109/6.736450.

Rosen, Z., M. J. Krocak, J. T. Ripberger, R. Cross, E. Lenhardt, C. L. Silva, and H. C. Jenkins-Smith, 2021: Communicating probability information in hurricane forecasts: Assessing statements that forecasters use on social media and implications for public assessments of reliability. *J. Oper. Meteor.*, 89–101, https://doi.org/10.15191/nwajom.2021.0907.

——, G. Henery, K. D. Slater, O. Sablan, B. Ford, J. R. Pierce, E. V. Fischer, and S. L. Magzamen, 2023: A culture of fire: Identifying community risk perceptions surrounding prescribed burning in the Flint Hills, Kansas. *J. Appl. Commun.*, **106**, https://doi.org/10.4148/1051-0834.2455.

Rothfusz, L. P., C. Karstens, and D. Hilderband, 2014: Next-generation severe weather forecasting and communication. *Eos*, **95**, 325–326, https://doi.org/10.1002/2014EO360001.

Samara, T., 2020: *Design Elements: Understanding the Rules and Knowing When to Break Them – A Visual Communication Manual.* Rockport Publishers, 320 pp.

Sattler, B., B. Lippy, and T. Jordan, 1997: Hazard communication: A review of the science underpinning the art of communication for health and safety. US-DOL OSHA Rep., 34 pp., https://repository.usfca.edu/cgi/viewcontent.cgi?article=1073&context=nursing_fac.

Savelli, S., and S. Joslyn, 2012: Boater safety: Communicating weather forecast information to high-stakes end users. *Wea. Climate Soc.*, **4**, 7–19, https://doi.org/10.1175/WCAS-D-11-00025.1.

——, and ——, 2013: The advantages of predictive interval forecasts for non-expert users and the impact of visualizations. *Appl. Cognit. Psychol.*, **27**, 527–541, https://doi.org/10.1002/acp.2932.

Schumacher, P. N., and Coauthors, 2021: Incorporating probabilistic information into winter storm services. *16th Symp. on Societal Applications*, Online, Amer. Meteor. Soc., 8.4, https://ams.confex.com/ams/101ANNUAL/meetingapp.cgi/Paper/381654.

——, and Coauthors, 2022: Using ensembles and probabilities to message winter weather hazards. *12th Conf. on Transition of Research to Operations*, Houston, TX, Amer. Meteor. Soc., 5B.5, https://ams.confex.com/ams/102ANNUAL/meetingapp.cgi/Paper/394274.

Sharpe, L. T., A. Stockman, H. Jägle, and J. Nathans, 1999: Opsin genes, cone photopigments, color vision, and color blindness. *Color Vision: From Genes to Perception*, Cambridge University Press, 4–22.

Sivle, A. D., S. D. Kolstø, P. J. K. Hansen, and J. Kristiansen, 2014: How do laypeople evaluate the degree of certainty in a weather report? A case study of the use of the web service yr.no. *Wea. Climate Soc.*, **6**, 399–412, https://doi.org/10.1175/WCAS-D-12-00054.1.

Stauffer, R., G. J. Mayr, M. Dabernig, and A. Zeileis, 2015: Somewhere over the rainbow: How to make effective use of colors in meteorological visualizations. *Bull. Amer. Meteor. Soc.*, **96**, 203–216, https://doi.org/10.1175/BAMS-D-13-00155.1.

Stone, T., S. Adams, and N. Morioka, 2008: *Color Design Workbook: A Real-World Guide to Using Color in Graphic Design.* Rockport Publishers, 240 pp.

Sutton, J., and E. D. Kuligowski, 2019: Alerts and warnings on short messaging channels: Guidance from an expert panel process. *Nat. Hazards Rev.*, **20**, 04019002, https://doi.org/10.1061/(asce)nh.1527-6996.0000324.

Sweller, J., 2011: Cognitive load theory. *Psychology of Learning and Motivation*, Vol. 55, Elsevier, 37–76.

Todhunter, P. E., 2011: Caveant admonitus ("let the forewarned beware"): The 1997 Grand Forks (USA) flood disaster. *Disaster Prev. Manage.*, **20**, 125–139, https://doi.org/10.1108/09653561111126076.

Tondreau, B., 2019: *Layout Essentials Revised and Updated: 100 Design Principles for Using Grids.* Rockport Publishers, 208 pp.

Tripp, D. D., J. E. Trujillo-Falcón, K. E. Klockow-McClain, H. D. Reeves, K. L. Berry, J. S. Waldstreicher, and J. A. Nelson, 2023: Foundational needs of forecasters for probabilistic winter forecasting. *Wea. Forecasting*, **38**, 3–15, https://doi.org/10.1175/WAF-D-22-0116.1.

Tufte, E., 1997: *The Visual Display of Quantitative Information.* Graphics Press, 197 pp.

Uccellini, L. W., and J. E. Ten Hoeve, 2019: Evolving the national weather service to build a weather-ready nation. *Bull. Amer. Meteor. Soc.*, **100**, 1923–1942, https://doi.org/10.1175/BAMS-D-18-0159.1.

U.S. Congress, 1973: Section 508 of the rehabilitation act of 1973. 29 U.S.C. section 794d, https://www.section508.gov/manage/laws-and-policies/.

van der Bles, A. M., S. van der Linden, A. L. J. Freeman, and D. J. Spiegelhalter, 2020: The effects of communicating uncertainty on public trust in facts and numbers. *Proc. Natl. Acad. Sci.*, **117**, 7672–7683, https://doi.org/10.1073/pnas.1913678117.

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC

VanderMolen, K., N. Kimutis, and B. J. Hatchett, 2022: Recommendations for increasing the reach and effectiveness of heat risk education and warning messaging. *Int. J. Disaster Risk Reduct.*, **82**, 103288, https://doi.org/10.1016/j.ijdrr.2022.103288.

van Gorp, T., and E. Adams, 2012: *Design for Emotion.* Elsevier Science, 256 pp.

Wernstedt, K., P. S. Roberts, J. Arvai, and K. Redmond, 2018: How emergency managers (mis?)interpret forecasts. *Disasters*, **43**, 88–109, https://doi.org/10.1111/disa.12293.

Wilms, L., and D. Oberfeld, 2017: Color and emotion: Effects of hue, saturation, and brightness. *Psychol. Res.*, **82**, 896–914, https://doi.org/10.1007/s00426-017-0880-8.

Windschitl, P. D., A. R. Smith, A. M. Scherer, and J. Suls, 2017: Risk it? Direct and collateral impacts of peers' verbal expressions about hazard likelihoods. *Thinking Reasoning*, **23**, 259–291, https://doi.org/10.1080/13546783.2017.1307785.

WMO, 2015: WMO guidelines on multi-hazard impact-based forecast and warning services. WMO 1150, 34 pp., https://library.wmo.int/doc_num.php?explnum_id=7901.

——, 2021: WMO guidelines on multi-hazard impact-based forecast and warning services. Part II: Putting multi-hazard IBFWS into practice. WMO-1150, 48 pp., https://library.wmo.int/doc_num.php?explnum_id=10965.

Wong, B., 2010: Points of view: Color coding. *Nat. Methods*, **7**, 573, https://doi.org/10.1038/nmeth0810-573.

——, 2011: Color blindness. *Nat. Methods*, **8**, 441, https://doi.org/10.1038/nmeth.1618.

Zabini, F., V. Grasso, R. Magno, F. Meneguzzo, and B. Gozzini, 2014: Communication and interpretation of regional weather forecasts: A survey of the Italian public. *Meteor. Appl.*, **22**, 495–504, https://doi.org/10.1002/met.1480.

Zacks, J. M., and S. L. Franconeri, 2020: Designing graphs for decision-makers. *Policy Insights Behav. Brain Sci.*, **7**, 52–63, https://doi.org/10.1177/2372732219893712.

Brought to you by Desert Research Institute | Unauthenticated | Downloaded 12/05/23 10:04 PM UTC