# Multiscale Forecasting of High-Impact Weather: Current Status and Future Challenges

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BAMS Article

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## Current Status and Future Challenges

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**ABSTRACT:** Improving the forecasting and communication of weather hazards such as urban floods and extreme winds has been recognized by the World Meteorological Organization (WMO) as a priority for international weather research. The WMO has established a 10-yr High-Impact Weather Project (HIWeather) to address global challenges and accelerate progress on scientific and social solutions. In this review, key challenges in hazard forecasting are first illustrated and summarized via four examples of high-impact weather events. Following this, a synthesis of the requirements, current status, and future research in observations, multiscale data assimilation, multiscale ensemble forecasting, and multiscale coupled hazard modeling is provided.

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Following the conclusion of the World Meteorological Organization (WMO)/World Weather Research Programme (WWRP) THORPEX project (Parsons et al. 2017), three new projects were launched with a view toward global collaboration on advancing prediction on multiple scales. One of these projects, the High-Impact Weather Project (HIWeather), was launched in 2015 and seeks to "promote co-operative international research to achieve a dramatic increase in resilience to high impact weather, worldwide, through improving forecasts for timescales of minutes to two weeks and enhancing their communication and utility in social, economic and environmental applications."[1] HIWeather emphasizes the relationships between key weather and societal drivers for (i) urban flooding, (ii) extreme local wind, (iii) urban heat waves and pollution, (iv) wildfires, and (v) disruptive winter weather. Decision-makers taking actions to mitigate against the impacts of these hazards need probabilistic impact-oriented forecast information across a variety of lead times (see Fig. 1 for the "ready, set, go"

[1] http://hiweather.net/

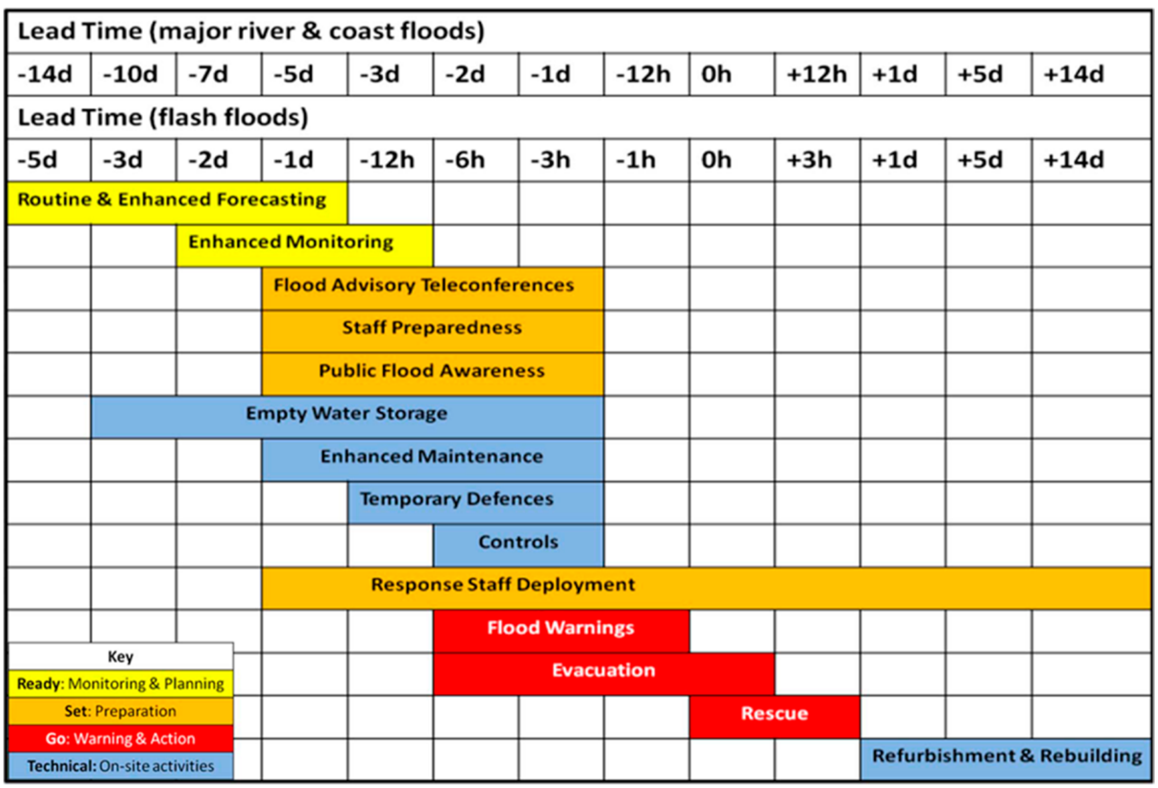


**Fig. 1. Action timelines for selected responses to urban flooding. The upper axis refers to actions in a major river or coastal flood, for which evacuation requires several days' notice and early warnings up to 2 weeks ahead may be available, while the lower axis refers to flash floods affecting smaller areas and for which less warning is possible. Response actions are categorized according to the risk threshold at which they are initiated (bearing in mind that risk encompasses both probability and impact), in a "ready, set, go" sequence represented by the colors yellow, orange, and red. Consistency of advice is important as the event approaches and the shortest-lead-time nowcasts are valuable in both scenarios for optimizing the rescue and recovery phase.**

timeline for the urban flooding hazard, designed by the HIWeather Task Team). To address the broad scope of the warning process, the HIWeather project has five research themes: Predictability and Processes; Multiscale Hazard Forecasting; Human Impacts, Vulnerability and Risk; Communication; and Evaluation, but much of the work is carried out in cross-cutting activities. Here we focus on the Multiscale Hazard Forecasting theme, to which the authors of this paper contribute. The purpose of this paper is to review the state of forecasting of high-impact weather events in the context of the warning chain described in Golding et al. (2019) so as to establish priorities and recommendations for future work.

We first set the scene with four cases from across the globe that focus on short-range forecasting of urban flooding, localized extreme wind, and wildfires. We then continue with a review of methodologies applicable to the forecasting of all hazards and their parent weather systems across multiple scales. We note that hazards may be interconnected; for example, extreme winds and flooding from tropical cyclones, or wildfires affected by localized extreme winds. Given these complexities, it is important to consider whether some of the challenges identified from these examples can be generalized, or if some are specific to a particular type of meteorological event, infrastructure or communication mechanism. For example, common global problems include the influence of terrain, the need for accurate real-time rainfall estimates for nowcasting, and the need to improve predictions of convective initiation. On the other hand, specific local challenges arise in observational infrastructure, forecasting, and communication due to cultural, economic, and political differences. In this paper, we restrict our attention to commonalities and disparities in the areas of observations, data assimilation, ensemble forecasting, and coupled hazard modeling.

## Examples of high-impact weather events

Every year there are numerous weather-related disasters around the world, resulting in many fatalities and injuries, the displacement of large populations, and substantial repair and recovery costs (CRED 2019). We present brief descriptions of four recent examples of weather-related disasters, including an outline of the weather, the resulting hazards and their impact, a summary of the warning timeline and resulting mitigation actions, and an assessment of the challenges and pointers for future development. While these examples were chosen to give a spread of geographical location and hazard, they are only a small sample of the challenges faced by countries across the world in forecasting and responding to high-impact weather. At the end, in Table 1, we summarize some features of these examples that appear to be generic and that highlight some challenges for the future development of forecasting and warning capabilities.

**Table 1. Common forecasting challenges for high-impact weather events.**

| | |
|---|---|
| **Challenge 1:** Early information to enable preparation. Information is needed by emergency managers and by those who will be affected. Early information is necessarily uncertain. The better the information is about the nature of that uncertainty, the more appropriate the preparation as the event approaches. Improving numerical modeling and multiscale ensemble prediction are the keys to meet this challenge. | **Challenge 2:** Early information to enable early action. To avert a major disaster, costly and time-consuming actions, including evacuation, may be needed. Information available at the time is critical to determine the scale of evacuation, safe evacuation routes and destinations, and to persuade reluctant people to move. This challenge requires improved numerical modeling, multiscale ensemble prediction, data assimilation, and coupled modeling. |
| **Challenge 3:** Precise information to enable targeted response. Emergency managers respond dynamically to the specific impacts of the hazard as it develops. In urban areas this detailed information is ultimately required at block level. Monitoring and very short-range forecasting of the hazard provides the situational awareness required for a fast and effective response. The key areas of improvement required to meet this challenge are hazard observations and nowcasting. | **Challenge 4:** Information on the nature of the threat. Decision-makers need to know what the hazard will be and what impact it will have. Aspects of the weather that create hazards are not those typically focused on by forecast verification. Coupling weather and hazard models can help the detection and correction of weaknesses in weather forecasts, such as biases in the extremes. Improvements in coupled data assimilation, modeling, and ensemble prediction are necessary for this challenge. |

***North America: Urban flooding from Tropical Storm Harvey (2017).*** Tropical Storm Harvey (Fig. 2) has to date been the most significant tropical rainfall event in U.S. history (Blake and Zelinsky 2018). It resulted in the loss of 68 lives and was the second-costliest tropical cyclone in U.S. history (adjusting for inflation). Rain was intense and widespread, some localities receiving approximately 60 in. (~1.5 m) of rain, producing major to catastrophic flash flooding and river flooding.

From the time when the U.S. NOAA/National Weather Service (NWS)/National Hurricane Center (NHC) started reissuing advisories for a regenerated Harvey in the Gulf of Mexico on 23 August 2017, 3 days before the most intensive flooding began, they included key

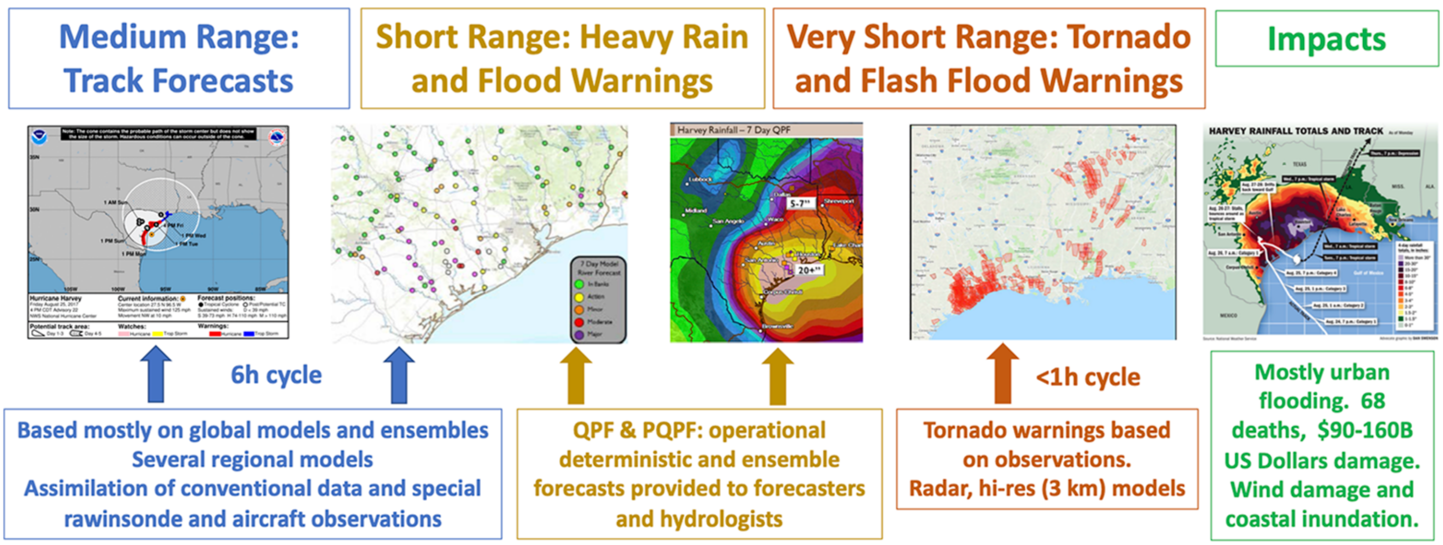


**Fig. 2. Timeline leading to the impacts from Tropical Storm Harvey (2017).**

messages stating that "several days of heavy rainfall" were likely over regions that included the Houston area, and that the rainfall "could cause life-threatening flooding." The track and stall of Harvey's center were captured accurately in NHC's forecasts, based on a consensus of operational global and regional forecast models, and the rainfall threat was consistently well communicated. NWS offices in the affected areas in Texas issued 372 tornado, flash flood, and severe thunderstorm warnings during 25–30 August (NOAA 2018). Many of these warnings were based on rapidly updated radar imagery and were credited as a major motivator for public action and the saving of lives. Operational deterministic forecasts including the High-Resolution Rapid Refresh (HRRR; Benjamin et al. 2016), hydrologic ensemble forecasts, and probabilistic quantitative precipitation forecasts, which are complementary products provided by different NWS centers, were used.

**Challenges.** The main forecasting challenges cited by NOAA included (i) the evolution of Harvey's rainbands; (ii) the duration and trajectory of precipitation near the center; (iii) a dry bias to the east and northeast of the storm center; (iv) the timing and location of locally extreme rainfall; (v) the bursting of banks of rivers and reservoirs; (vi) the lack of products to communicate the impacts of an unprecedented amount of rain; and (vii) the need for probabilistic information, especially rainfall, at least 2 days in advance (NOAA 2018). A key lesson was the critical importance of mutual understanding and messaging of precipitation and flooding. A complication was the presence of tornadoes in the rainbands, with simultaneous tornado and flash flood warnings producing conflicting public guidance (previously documented by Nielsen et al. 2015).

***Europe: Large-scale flooding (2016).*** Following a wet winter and spring, intense rainstorms on 28 May 2016 were followed by heavy precipitation from a frontal disturbance giving 4-day totals of 80–120 mm in central France (Fig. 3). The Loing River rose rapidly at Montargis, 110 km southwest of Paris, with maximum water levels exceeding the century record set in 1910. Supplemented by additional rain (~20 mm) in northeastern France, the flooding reached Paris on 3 June, with the Seine River level reaching 6.10 m in Paris-Austerlitz. A total of 1,400 French municipalities were placed in a "natural disaster" status for the events that occurred from 27 May to 3 June and 15,000 people were evacuated (van Oldenborgh et al. 2016; Perrin et al. 2017).

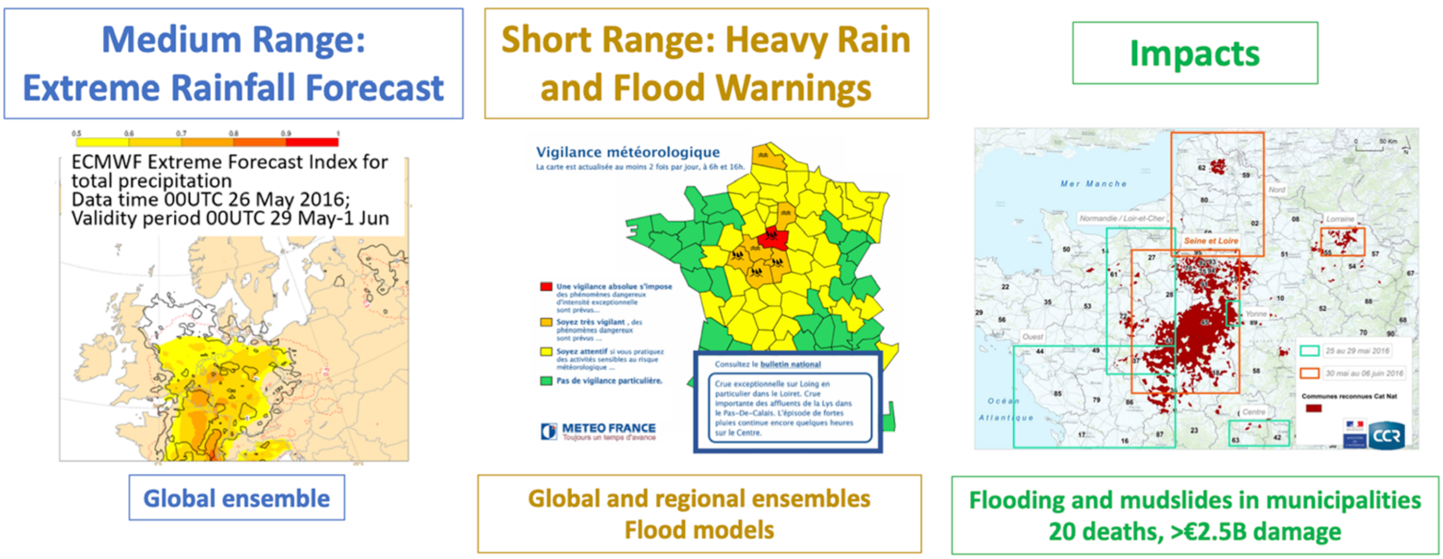


**Fig. 3. Timeline leading to the flooding impacts in France (2016).**

The rainy episode of 29–30 May was predicted from 28 May with uncertainty in the location and total expected amounts. The first weather watches were issued on 30 May, recommending extreme vigilance in the center and north of France. On 27 May, the European Flood Awareness System began to disseminate information for 1–3 June to the Vigicrues national flood forecasting service about significant river level peaks. The SIM hydrological model driven by the ECMWF ensemble also predicted alert thresholds at about this time (Ramos et al. 2017). Flood watches issued by the Vigicrues national flood forecasting network reached maximum alert level (red) for the first time on some rivers on 31 May. Red watch levels remained in force up to 2 June.

**Challenges.** While the rainfall amounts were well forecasted 2–3 days ahead, the location, timing, and spatial extent of the extremes were less well predicted. Hydrological monitoring worked well except when gauges were lost due to flooding. However, there were shortcomings in the flood forecasts and better hydrological data assimilation is needed. More effective communication of these forecasts and their associated uncertainty to civil protection would have allowed more timely responses. A need for improved coordination between meteorological and hydrological watch messages was identified. The role of human interpretation remains crucial.

***East Asia: Wind and storm surge impacts from Typhoon Hato (2017).*** Super Typhoon Hato made landfall in Zhuhai, China, on 23 August 2017 (Fig. 4). It brought destructive wind and record-breaking storm surge to the city and other parts of the highly populated Pearl River Delta (Liu et al. 2018). Many buildings and public facilities were damaged, including transport, communication, the electrical grid, and trees.

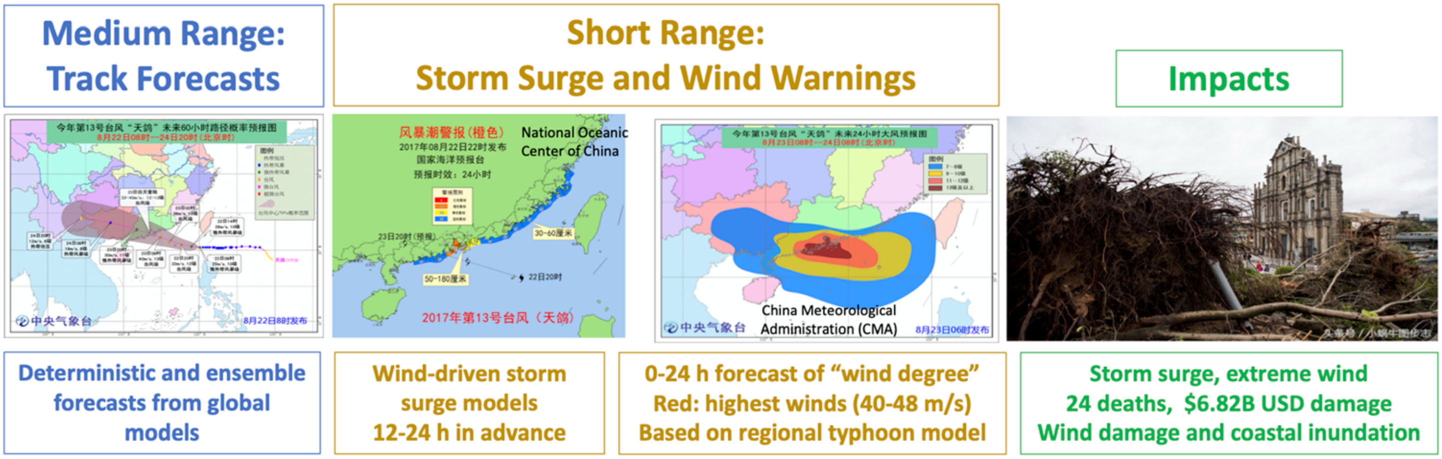


**Fig. 4. Timeline leading to the impacts from Typhoon Hato (2017).**

Two days before Hato's landfall, the China Meteorological Administration issued the blue typhoon warning signal (the lowest level), with forecasts of landfall location, time, wind and rainfall, and corresponding defensive notices. One day later, the warning was upgraded to brown with increased forecast wind intensity (35–42 m $s^{-1}$). Seven hours before the center of Hato made landfall, the warning was changed to the highest level (red) with forecast winds of 40–48 m $s^{-1}$.

**Challenges.** Although the track of Hato was predicted reasonably well in the 48 h before landfall, the intensity was underpredicted by models and by both central and regional weather offices until a very short lead time (<8 h). The complex challenges for Hato were (i) to forecast the rapid intensification (−45 hPa in 24 h and +15 m $s^{-1}$ in 12 h) observed near the coast during the 24 h before landfall (Zhang et al. 2018); (ii) to predict the cumulative impacts of strong wind and the astronomical tide on storm surge in the cities; and (iii) to identify and nowcast accompanying tornado events. Other lessons include the need for timely public warnings and close cooperation between forecasters and decision-makers, not only to help understand the risks and impacts of the typhoon but also to take the right actions for quick rescue and recovery.

***Australia: Wildfires (2013).*** Following a wet spring and hot start to summer, an outbreak of severe wildfires in the Australian state of Tasmania occurred on 3–4 January 2013 (Fig. 5).

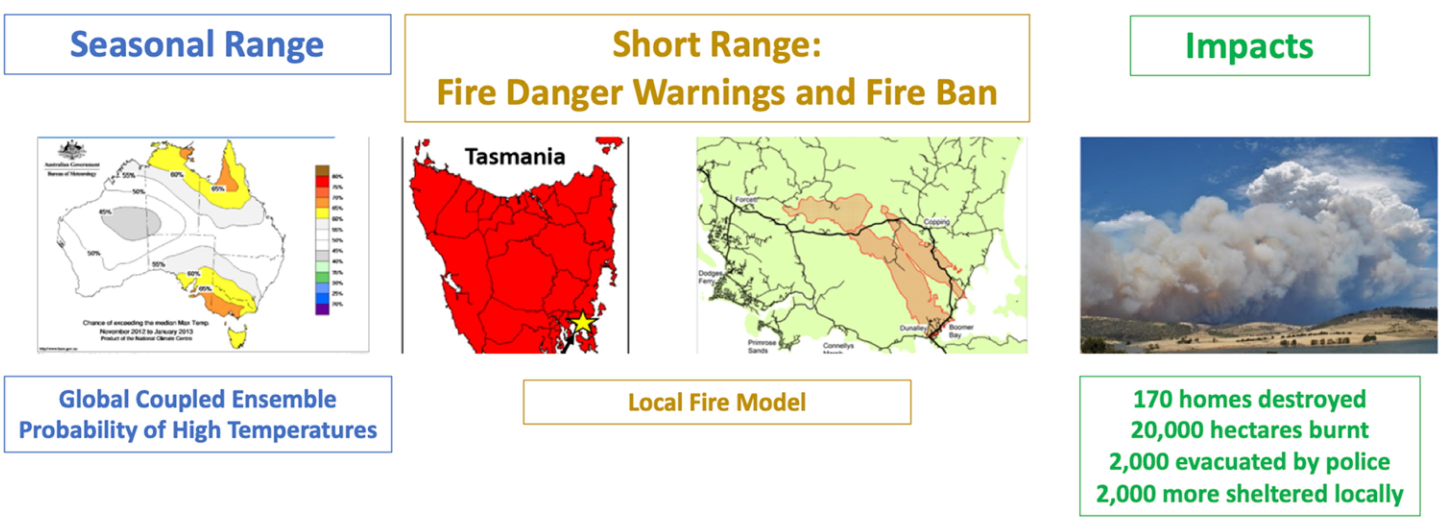


**Fig. 5. Timeline leading to the impacts from the Australian wildfires (2013).**

Some of the fires were in tourist areas during the peak holiday season, and record high temperatures were recorded at several observing sites. The rugged terrain limited access to settlements in the worst affected area. Since these fires occurred only 4 years after Australia's worst bush fire disaster up to that time (the "Black Saturday" fires), the level of community preparedness was perhaps heightened.

Seasonal outlooks from the Australian Bureau of Meteorology (2012) predicted raised probabilities of a dry and hot summer associated with neutral El Niño and Indian Ocean dipole indices and a warm Indian Ocean. The heat wave in southeastern Australia was associated with a large high pressure system and was well predicted by global models at medium range time scales. The Australian Forest Fire Danger Index, derived from these model runs and incorporating vegetation information, gave very high to extreme fire danger levels in the days leading up to the fires.

**Challenges.** The subsequent inquiry highlighted the value of experimental modeling of fire behavior and its interaction with the atmosphere (Tasmanian Government 2013). Once the fires had broken out, the PHOENIX RapidFire model (Tolhurst et al. 2008) was used to predict fire behavior given wind forecasts. The effect of atmospheric stability on fire behavior was emphasized, particularly the feedback between convection, fire ventilation and increasing wind speed/decreasing humidity, and the lofting of embers creating further spot fires. This in turn affected visibility (from smoke/debris) and low-level turbulence, influencing the use of aircraft to assist in fire control. Making these modeling systems operational is an important future development that will assist in making better decisions for safe evacuation of residents and protection of firefighters.

The above four examples illustrate some common features of high-impact weather events that challenge our forecasting capabilities on multiple scales. These are summarized in Table 1. One important theme that exists at all stages of the forecast and warning process is the *communication* of the information. Even when skillful forecasts are made, effective communication at all stages is essential for hazard avoidance or mitigation. While communication is a central research theme of the HIWeather project, a detailed synthesis of communication of high-impact weather warnings and decision-making processes is beyond the scope of this paper. Instead, the interested reader is referred to activities conducted by the HIWeather task team in Communication, and Taylor et al. (2018) and accompanying papers in a special issue of the *International Journal of Disaster Risk Reduction*. Their key points include the need for timely and accessible information, varying needs of different user groups, and communication of the hazards instead of the meteorological variables. Additionally, challenges remain in the messaging and communication of forecast uncertainty, and these are additional central topics in HIWeather. One example of how the messaging challenge is being addressed is the NHC's annual training of meteorologists in WMO Regional Association RA-IV and emergency managers on probabilistic forecasts of tropical cyclones.

The remainder of this paper provides a review of the primary elements of the multiscale forecasting process, mindful of the fact that this is only one section of the full warning chain (Golding et al. 2019). The elements of the forecasting process are introduced sequentially, beginning with the collection of observations and nowcasting that is sometimes employed based on these observations. A central component is data assimilation, through which observations are blended with numerical models to provide a gridded analysis (or ensemble of analyses). The review concludes with probabilistic predictions created from these analyses, and recent progress in coupled hazard forecasting.

## Observations

Observations and monitoring networks evolve over time in quantity, quality, and diversity with technological advances. Accurate observations on all scales are required for many facets of the forecasting and warning process, including scientific understanding, hazard monitoring, nowcasting, data assimilation, and forecast evaluation and verification. In this section we emphasize hazard monitoring and nowcasting, with a section on data assimilation to follow.

***Hazard monitoring: Requirements and current status.*** In a hazardous weather situation, it is necessary to maintain both situational awareness of the evolving meteorological environment on the medium-to-large scales in space and time, and a focus on the specific hazardous weather elements on the smaller scales for strategic and tactical decisions and actions. An accurate representation of the environment that may alter (and be altered by) the hazardous weather system is critical to the prediction of small-scale hazardous weather, and the issuance of weather watches. Hence, continuous, multiscale observations are required. In addition to the environment, the evolution of the location and nature of the hazard itself needs to be known accurately at all times, in order to enable hazard warnings to be initiated, updated, or discontinued, and for response and recovery operations to be managed effectively (e.g., Fig. 1). Hazard observations are also required for verification of early warnings and to enable research into improving hazard prediction. The discussion in this section focuses mostly on observations of hazards on smaller scales.

Many hazards have highly heterogeneous distributions and are difficult to observe. Examples include snow in undulating terrain that is alternately above and below the freezing level and fire risk in partially wooded country. The accurate spatial and temporal monitoring of such hazards may require a combination of observing systems, integrated using statistical and/or process modeling methods. Most importantly, hazard observations must meet the needs of the decision-makers. Some parameters need to be quantitative and highly accurate, whereas for others, a qualitative or binary indication may be sufficient. When observations are made for multiple uses, trade-offs have to be made, but this should not be at the expense of providing timely information for key decisions.

It is projected that by 2050, 68% of the world's population will be concentrated in urban centers (United Nations 2018). As the focus on urban areas increases, the nature of weather-related hazard monitoring will evolve, particularly for those hazards that threaten the infrastructure services that maintain urban life. Since these hazards, particularly winds, lightning, floods, and heat, are strongly influenced by the urban fabric, the traditional nature of monitoring that is largely independent of human structures will need to change.

Observations of weather hazards are conventionally made by human observers, in situ instrumentation, and remote sensing platforms (Fig. 6, left panel). To accompany the discussion

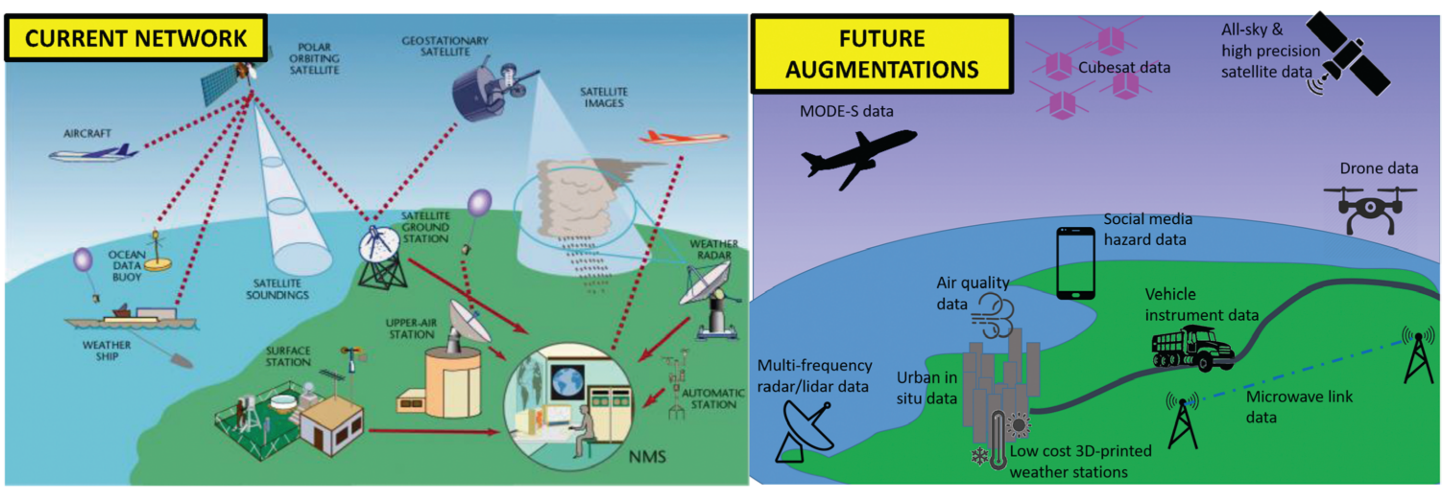


**Fig. 6. (left) The current global observing network provides in situ and remotely sensed data for hazard monitoring, nowcasting, and data assimilation. Observing methods are standardized to ensure that results are compatible for use in specifying the climate and the initial state for global weather prediction. (right) Potential future sources of weather and hazard observations that may need to be accommodated in hazard monitoring and forecasting systems (source: World Meteorological Organization).**

below, some examples of recent advances in hazard monitoring and key references are provided in Table 2.

Human observations include variables that require visual classification. Although reproducible results require skilled professionals, some requirements may be met with

**Table 2. Summary of recent advances in hazard monitoring by ground-based, airborne, and space-based sensors, with key references.**

| Recent Advances: Hazard Monitoring | | |
|---|---|---|
| **Instrumentation** | **Capability** | **Key References** |
| **Ground-based sensors** | | |
| **Centimeter radar** | Doppler wind and reflectivity of precipitation cloud; Doppler wind of boundary layer; precipitation type (with dual polarization); refractivity; quantitative precipitation estimate | Ryzhkov and Zrnić (2019); McLaughlin et al. (2009) |
| **Millimeter radar** | Doppler wind and reflectivity for fog, cloud, and light precipitation | Kollias et al. (2007) |
| **Lidar** | Doppler measurements of boundary layer wind and turbulence profiles; aerosols and air quality; temperature and water vapor profiles | Wulfmeyer et al. (2015) |
| **Lightning detection network** | Remotely sensed electromagnetic emissions (ground and spaced based) that directly observe lightning; proxy for rainfall | Orville (2008) |
| **Radiosondes** | Vertical profiles of temperature, water vapor, wind, used in satellite calibration and data assimilation | Ingleby et al. (2016) |
| **Radiometers** | Temperature and water vapor profiles; liquid water path | Westwater et al. (2005) |
| **Cell phones** | Pressure and temperature sensors | Mass and Madaus (2014); Droste et al. (2017) |
| **Ground transportation** | Precipitation type and rate, temperature, and other observations from mobile sensors on vehicles | Mahoney and O'Sullivan (2013) |
| **Social media** | Visual reports of hazards and impacts | Elmore et al. (2014) |
| **Low-cost, compact weather stations** | Meteorological measurements with low-cost infrastructure in both rural and urban environments | van de Giesen et al. (2014) |
| **Air quality sensors** | Small, low-cost sensors measuring air quality | Jiao et al. (2016) |
| **Airborne sensors** | | |
| **Dropwindsondes** | Temperature, pressure, relative humidity, vertical wind profiles | Wang et al. (2015) |
| **Radar** | Precipitation, wind | Vivekanandan et al. (2014) |
| **Lidar** | Vertical profiles of wind and humidity | Lux et al. (2018) |
| **AMDAR** | Temperature, pressure, relative humidity, and wind profiles during ascent, descent, and en route, by commercial aircraft | Petersen (2016) |
| **Mode-Selective Enhanced Surveillance (Mode-S)** | Temperature and wind retrievals from routine messages broadcast by commercial aircraft | Stone and Pearce (2016) |
| **Unmanned aircraft** | In situ and remote sensing platforms mounted aboard small and large unmanned aircraft systems | Cione et al. (2020) |
| **Space-based sensors** | | |
| **Cloud sensors** | Routine monitoring from geostationary satellites and polar orbiters, plus new continental, mesoscale, and "flex" modes aboard geostationary satellites | Stephens et al. (2018) |
| **Precipitation sensors** | Constellation of sensors aboard multiple polar-orbiting satellites | Skofronick-Jackson et al. (2017) |
| **Optical and infrared sensors** | Increased resolution of hazard monitoring under clear skies | Schmit et al. (2017) |
| **Radar sensors** | Additional data in cloudy and rainy regions, including severe storms | Goodman et al. (2013); Hou et al. (2014) |
| **Lightning sensors** | Total lightning detection from geostationary satellites | Goodman et al. (2013) |
| **Lidar; aerosol sensors** | Vertical wind profiles; aerosol direct detection | Lux et al. (2020) |
| **Global navigation satellite system/ global positioning system** | Zenith Total Delay to estimate precipitable water; Delay Doppler Mapping to estimate soil moisture, water, and wind; refractivity measurement of water vapor | Guerova et al. (2016); Ruf et al. (2016) |
| **CubeSats** | Constellation of small sensors | Blackwell et al. (2018) |

simple binary observations made by nonprofessionals. Such observations may include rain, snow, hail, fog, flood, mudslides, wind damage, fire, and tornadoes (e.g., mPING; Elmore et al. 2014).

Ground-based in situ observations are well suited to monitoring the parent synoptic-scale weather systems within which hazardous weather may develop. However, they are mostly too coarse to capture the full details of the hazards themselves, though relatively high-density mesonets have been implemented in a few countries. Ground-based remote sensing observations are available in some countries. Radars provide the foundation for high-resolution precipitation mapping, and the detection of the parent structure of extreme local winds including microbursts and tornadoes. Polarization diversity enables the detection of large hail and rain–snow discrimination. However, radars are expensive to install and maintain, and they need to be close enough together to sample rainfall everywhere at altitudes that correlate well with the surface rainfall. Aircraft observations provide an additional capability, but commercial flights are limited by fixed paths, and special missions targeted at hazardous weather are compromised by range limitations and safety considerations.

Satellite remote sensing forms the core of observations for numerical weather analysis and prediction. Traditional passive sensors detect radiation emitted or reflected from the atmosphere and its constituents at multiple wavelengths, yielding retrievals of temperature and moisture. More recent advances include cloud sensors, lightning sensors, atmospheric motion vectors (AMVs) based on cloud tracking, and global positioning system (GPS) radio occultation. Active sensors emit radiation and detect the amount that is reflected or backscattered from targets, with recent developments including precipitation radars and active wind lidars. A detailed review of satellite observations including the hydrological cycle, weather analysis and prediction, and atmospheric composition is provided by Ackerman et al. (2018). Over several decades, radiances and derived quantities such as AMVs from geostationary and polar-orbiting satellites have formed the basis for model initialization on the synoptic scales, especially over the oceans. Moreover, recent increases in horizontal resolution together with the new ability for geostationary satellite sensors to adaptively scan mesoscale sectors now allow for the sampling of high-impact weather systems down to the convective scales. The increase in scanning frequency in geostationary satellites, now of order 1–10 min, allows for the timely capture of the rapid evolution of convective systems. The leading numerical models and data assimilation schemes therefore face a challenge to fully exploit the vast volume of satellite data at these advanced temporal and horizontal spatial resolutions. On the other hand, several limitations, which vary depending on the type of sensor, include the restricted vertical resolution, the limited ability to sample below cloud tops, and the attenuation of radiation in precipitating systems. Low-Earth-orbiting satellites provide very few passes each day over any particular region. These deficiencies are exacerbated in hazardous convective weather systems.

***Hazard monitoring: Challenges and suggested foci.*** The design and implementation of hydrometeorological, climate, and environmental observational networks at fine resolution is expected to focus on urban and specialized environments (e.g., nuclear power stations, dams; WMO 2019). Some examples of new augmentations are illustrated on the right panel in Fig. 6. Key questions for future network design include: What needs to be observed: the phenomenon, its environment, and/or its precursors? Where and when do the target area and/or upstream regions need to be observed? Are multiple applications supported? Several technical challenges remain, including the integration of multiple sources of measurements and sharing of data and metadata. Three major challenges and suggested foci are described here.

**Surface in situ monitoring.** Crowdsourcing, professional networks, vehicles, and social media contain vast amounts of information on the weather and its impacts, at a much higher density than a decade ago, but their effective use depends on overcoming challenges in accessibility, selection, quality control, and integration. High density is particularly needed in urban areas, where observations are influenced by the urban fabric, and so are only representative of the immediate surroundings. The use of such unrepresentative data poses many challenges, but urban models are now being designed to capture the characteristics of urban canyons, green and blue spaces, and the built environment (Schoetter et al. 2017; Ching et al. 2018). Unmanned aerial vehicles and cell phones have sensors that could be of value for monitoring and forecasting. For winter weather, the observation of multiple precipitation types remains a challenge.

**Surface remote sensing.** While ground-based radar can potentially provide information on humidity via refraction of fixed returns, complex processing is required. Microwave attenuation using commercial cell phone links is an alternative or complement to radar rain measurement, but data are proprietary and access is an issue. New services can benefit from higher wavelength radars and lidars. Networks of cameras also offer the potential for analyzing clouds, fog, and wind.

**Satellite remote sensing.** Challenges include the interpretation of data from heterogeneous scenes, such as cloud-contaminated infrared. To augment the conventional satellite network, relatively low-cost satellites such as CubeSats are increasingly being proposed for the observation and forecasting of high-impact weather events, potentially leading to a more comprehensive but less integrated and long-term space-based observing capability.

***Observation-based nowcasting: Requirements and current status.*** While the WMO definition of nowcasting (WMO 2017) has evolved over the years from lead times from 2 to 6 h by any method, it is generally viewed as primarily "observation-driven forecasting" (as opposed to model-driven forecasting). Originally, nowcasting was synonymous with warnings of thunderstorm hazards, whose small-scale details were unable to be captured by numerical models. Forecasters would first issue hazardous weather "watches" that used large-scale observations and models to predict the environmental conditions conducive to the imminent development of thunderstorms. Forecasters would then issue hazard "warnings" based, for example, on radar pattern recognition and science-based conceptual models. Nowcasting has been extended to precipitation predictions through the computer extrapolation of radar images. These are limited to predictions of less than 2 h, as the small hazardous elements of most precipitating systems such as tornadoes, hail, and heavy rain cores have very short life cycles (an exception being supercell thunderstorms). In contrast, the larger and less hazardous synoptic-scale precipitating systems can be extrapolated for much longer periods of time, beyond 6 h. Also, nowcasting systems have been developed to blend radar with model precipitation fields to attempt to extend the lead time, with a goal to achieve the skill levels appropriate for issuing warnings.

At these very short ranges, forecasters and emergency managers are looking for definitive information that enables fast and accurate decision-making. Due to the nature of hazardous weather, the relevance of an observation to future events falls off rapidly with time, making predictions highly perishable. This type of nowcasting has particularly focused on rapidly developing hazardous weather such as convective storms, heavy rain, and strong winds including tornadoes and downbursts, hail, and lightning. Specialized services for events (e.g., conventions, sports, terrorism) and applications (e.g., oil rig operations, concrete pouring, port operations) use nowcasting methods that are often developed by the private sector to address niche requirements.

***Observation-based nowcasting: Challenges and suggested foci.*** Numerical weather prediction (NWP) on the synoptic and mesoscales is often capable of providing the information required for issuing watches for precautionary and preparatory actions. Increased attention is therefore now being directed toward the gaps in the capabilities to issue hazard warnings, and to inform response and recovery actions. With a maturing capability of NWP to predict convection, the key challenges and suggested foci in nowcasting are directed increasingly toward rapidly developing storms and their hazardous weather elements.

Scale remains a major challenge. For example, damaging floods can be produced by intense rain from a single stationary subkilometer storm. Detecting and highlighting that possibility demands advanced observation processing and human interfaces to access the relevant information quickly. Furthermore, the relationship between what can be observed and the hazard that may result depends on a detailed knowledge of local topography, land use, vegetation, and potential projectiles (parked cars, fallen trees, trash, temporary sediment accumulations, etc.). Obtaining up-to-date information and integrating it into the NWP and forecasting process at a sufficiently finescale is a major challenge. Process modeling is limited in this area, which is a major opportunity for application of machine learning techniques.

The rapid development or intensification of high-impact weather and related hazards is generally associated with nonlinear processes, characterized by rapidly growing uncertainty. Another missing link is the physical mechanism to initiate convection. However, case-study analyses have shown that there are often signals in the data (e.g., "fine lines" in the boundary layer) that provide indications of future initiation that taps into the larger-scale environment for development. Progress to date has largely depended on using these analyses to develop empirical rules-based forecasting methods. Moving beyond this empirical approach will require observation systems that can effectively observe these signals (e.g., highly sensitive radars, lidar and radar networks that can detect the lowest levels of the atmosphere over broad areas), assembly of multisensor datasets, and the use of data assimilation and new approaches such as machine learning.

## Multiscale data assimilation, ensemble prediction, and coupled hazard modeling

Forecast products from NWP systems have been routinely used in the preparation of high-impact weather warnings, through providing information on the evolving large-scale situation prior to the warning being issued. For example, warnings based on NWP have been in effect for winter storms and tropical cyclones over several decades. More recently, warnings based on NWP have been extended to include convective-scale weather (Stensrud et al. 2009). Much of this progress has been enabled through successive improvements to the spatial resolution of NWP models, with regional convection-permitting models now operating at a horizontal grid spacing of 1–2 km. These models allow for the representation of (i) convective storms and their associated hazards, (ii) the underlying topography and its interaction with near-surface weather, (iii) smaller predictable spatial scales for very short-range forecasts, and (iv) interaction with small-scale ocean and land surface hazard processes. However, a considerable gap remains between the practical predictability and intrinsic predictability for high-impact weather systems. To close this gap and realize the benefits of improved model representations, focused efforts are required particularly in data assimilation, ensemble prediction, and coupled modeling of the hazards.

***Multiscale data assimilation: Requirements and current status.*** Data assimilation (DA) blends together observational data with a "first guess" field, normally a short-range forecast from a numerical model or ensemble, to provide the initial conditions for NWP. DA technique development and applications have received considerable attention in recent years, especially for convective and smaller scales, and new challenges are emerging.

Advances in producing accurate initial conditions down to the convective and even smaller scales are necessary to address the challenges outlined in Table 1. Following initial efforts by Lilly (1990), research into techniques to initialize convection-permitting models has produced encouraging results (Sun et al. 2014; Gustafsson et al. 2018). In parallel, the number of observations available for assimilation on all scales is increasing, due in part to the growing number of platforms and sensors, and also to continuous gains in computational power. Earlier efforts in convective-scale DA needed to focus on reducing the model spinup, by producing convective-scale analyses and through diabatic initialization. More recently, attention has evolved to address the problem of multiscale DA, in recognition that the convective-scale information can be quickly lost during the subsequent forecast without an accurate analysis across the scales. Major operational centers throughout the world are now assimilating multiscale data in convection-permitting regional NWP systems with 1–3-hourly rapid update cycles. The ingredients of the data flow in such modern NWP and DA systems are summarized in Fig. 7. Some recent advances are described in the next two paragraphs, with specific details and references provided in Table 3.

Over the past two decades, there has been substantial progress in DA technique development and applications on all scales. The 4DVar technique has demonstrated its capability in global models, and more recently in convection-permitting models. In parallel, the ensemble Kalman filter (EnKF) has come to the fore in research and operational NWP, again at all scales. Recent research and operational DA development has centered on hybrid ensemble–variational (EnVar) approaches that combine the benefits of the variational and ensemble approaches. Several variants have been proposed using different blends of the climatological background error covariance with the flow-dependent error covariance. The benefits have been demonstrated for global models and coarse-resolution regional applications, and more recently for convective-scale DA, although challenges remain. However, the variational, EnKF, and hybrid techniques are usually reliable only when the dynamics are quasi-linear. When the convective-scale physical processes are resolved with a kilometer-scale model, the model prediction may manifest rapid nonlinear error growth,

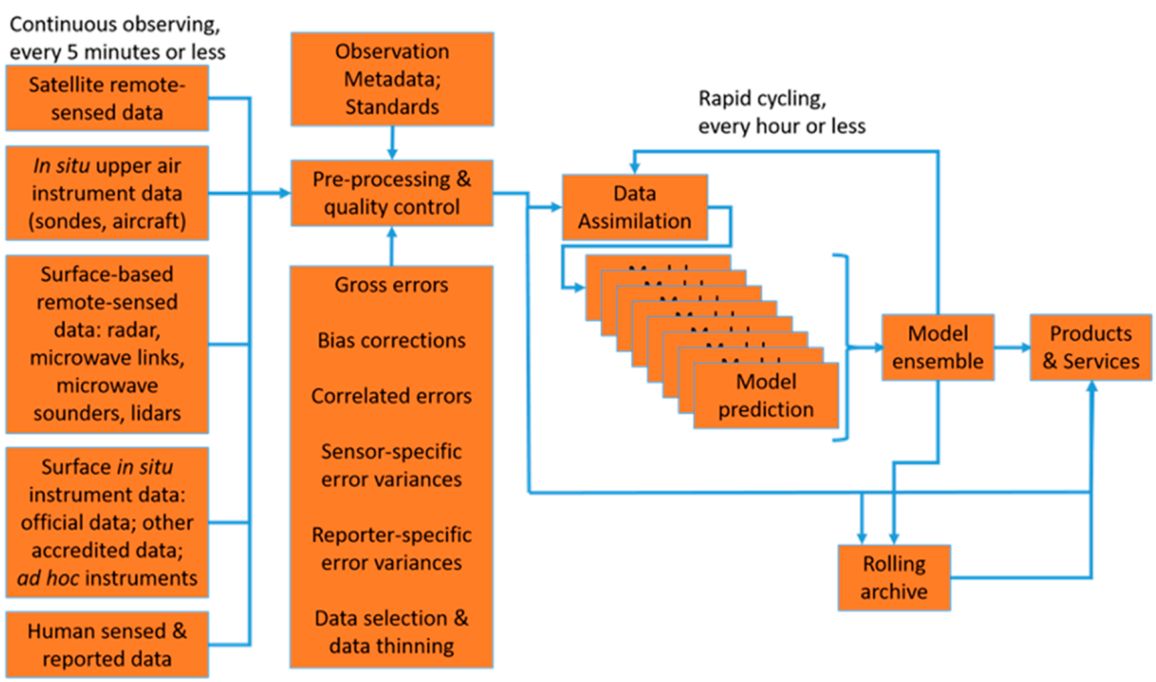


**Fig. 7. Outline of the data flow in a kilometer-scale rapid update prediction system. Very short-range forecasts will be based on the latest observations or on the most recent NWP cycle. Longer forecasts may use multiple NWP cycles to optimize ensemble spread.**

Table 3. Summary of recent advances in multiscale data assimilation, with key references.

| Recent Advances: Multiscale Data Assimilation | | |
|---|---|---|
| **Technique** | **Capability** | **Key References** |
| **Methodologies** | | |
| Multistep DA | Observations that sample different scales of motion are assimilated using different cost functions and localization radii | Tong et al. (2016) |
| Multiscale DA | Systematic approaches via sophisticated localization related to observation density, physical correlation length, model resolution, etc. | Buehner and Shlyaeva (2015); Li et al. (2015) |
| EnKF convective-scale DA | Applications of EnKF to convection-permitting models | Tong and Xue (2005); Bick et al. (2016) |
| 4D variational (4DVar) DA | 4DVar systems for synoptic-scale and convective-scale applications | Rabier et al. (2000); Li et al. (2018) |
| Ensemble–variational (EnVar) DA | Blends of the climatology background error covariance (variational) with the flow dependent error covariance (ensemble-based) and applications to both synoptic scale and convective scale | Clayton et al. (2013); Lu et al. (2017) |
| Particle filter | Simulated radar observations assimilated within a local particle filter demonstrated the potential for producing probabilistic analyses of non-Gaussian variables, such as hydrometeor mixing ratios | Poterjoy et al. (2017) |
| **DA of ground-based sensors** | | |
| Ground-based radar | Convective-scale assimilation of radar radial velocity and reflectivity assimilation for high-impact weather prediction | Ballard et al. (2012); Sun and Wang (2013) |
| Dual-polarization radar | Research on the potential of assimilating dual-polarization data to improve high-impact weather prediction | Li and Mecikalski (2012); Augros et al. (2018) |
| Lightning | Assimilation of lightning flash rate on convection-permitting grids | Fierro et al. (2012); Dixon et al. (2016) |
| **DA of airborne sensors** | | |
| Aircraft radar | Improved tropical cyclone intensity prediction by assimilating airborne radar observations into a convection-permitting model using the 4DVar or EnKF DA method | Zhang and Weng (2015) |
| Mode-S | High-density wind and temperature data during takeoff and landing enabled improved initialization of atmospheric structure | Strajnar et al. (2015) |
| **Convective-scale DA of space-based sensors** | | |
| All-sky (cloudy) radiance DA | Assimilation of 5–15 min all-sky radiances from geostationary satellites to improve tropical cyclone and severe storm predictions | Honda et al. (2018); Zhang et al. (2019a) |
| **Convective-scale DA of combined remote sensors** | | |
| Satellite and radar | Assimilation of combined observations proved beneficial to severe storm prediction compared with assimilation of a single type | Zhang et al. (2019b) |
| Radar and lightning | Assimilation of both observations in a 4DVar system significantly improved the structure and intensity of a local-scale convective system | Xiao et al. (2021) |

and there are likely to be spurious model adjustments when a forecast is integrated from the analysis created by an imperfect DA technique. An example of a nonlinear DA technique is the particle filter, which uses ensemble members or "particles" to produce probabilistic analyses of non-Gaussian variables such as hydrometeor mixing ratios. No assumptions are made about the prior or posterior error distributions. While particle filters are computationally expensive, new approaches to improve their efficiency are being developed. A localized particle filter (Poterjoy et al. 2017) assumes the dynamical system to be a set of loosely coupled systems, which allows for the localization of the effect of observations and therefore the number of required particles. A localized particle filter may produce more physically consistent posterior members than the EnKF, leading to fewer spurious model adjustments during forecasts.

In parallel with technique development, applications of DA on multiple scales have proliferated in recent years. The most common research applications on convective scales involve radar DA for high-impact weather prediction. In addition to ground-based radar measurements of radial velocity and precipitation, airborne radar and dual-polarization Doppler radar observations have demonstrated promise in improving predictions of tropical cyclones and severe weather. Research has also expanded to other types of observations, such as geostationary satellite data. Historically, most satellite channels have been used only in clear-sky conditions. Recent developments have led to the use of such data also in cloudy conditions, again with applications to individual severe storms and tropical cyclones. Several studies using different DA techniques and convection-permitting grids have also provided encouraging results on the assimilation of lightning data. In addition to covering data-sparse regions between radar networks, lightning data can detect rapidly growing cells within a convective system. Another recent area of success is the use of mode-selective enhanced surveillance (Mode-S) wind and temperature data from aircraft. The high density of these data during takeoff and landing enables improved initialization of atmospheric structure over that available from conventional observations only.

***Multiscale data assimilation: Challenges and suggested foci.*** Creating high-resolution analyses at $O(1)$ km that contain multiscale information is a key challenge for the future success of improved NWP for high-impact weather warning. For tropical cyclones, accurate rainfall forecasts require the eyewall and rainband structures to be accurately initialized in combination with the overall vortex dynamics. For severe convective storms, the three-dimensional cloud structure must be initialized consistently with the dynamics of the cloud and its environment. For topographically driven systems, the local response must be initialized in balance with larger-scale forcing and the resolved topography. The challenge is not just to produce an initial state that gives an accurate forecast, but one that evolves smoothly, with minimal noise or spinup, so that very short-range forecasts can be used as input for hourly cycling, for instance. Below we suggest four foci that can potentially lead to meeting the challenge.

**Integrated assimilation of multiple types of observations.** Monitoring systems that are deployed for different purposes, with different sensors, characteristics, and scales of motion, need to be integrated to meet the needs of high-impact weather forecasting. For example, operational radar networks sample wind and precipitation with less than 1 km horizontal resolution and 5–10 min temporal resolution, whereas radiosondes provide observations that are typically hundreds of kilometers apart every 6 or 12 h, but with a very fine vertical resolution. Merging these and other disparate datasets will require sophisticated DA systems at high resolution that account for error characteristics of each technology, each sensor type, and each scale of motion. The design of the monitoring network needs to take account of how this will be achieved. Since most DA studies on the convection-permitting scale have evaluated the impact of a single type of unconventional observation, new methods are needed to optimally merge the high-resolution observations along with conventional observations. New types of data include crowdsourced observations from professional observing sites with nonstandard exposures and pressure observations from smart phones. The challenges of quality control and of estimating observation errors are substantial, and much work remains to be done before integrating these into routine operational application.

**Quantifying observation, model, and DA uncertainties.** Diagnosing and understanding the uncertainties in observations, convection-permitting model forecasts, and DA systems, especially those related to atmospheric convection, are necessary for future development of multiscale DA. To optimally extract multiscale information from a mix of observation types, not only their measurement errors but also their correlations, representativeness characteristics, and information content must be understood and quantified. Furthermore, diagnosis, understanding, and correction of multiscale forecast bias and noise is important in a rapidly cycled system such that a true continuously cycled system can be built without requiring periodical restarts.

**Developing approaches for multiscale DA at *O*(1) km.** The rapid nonlinear development of convective storms and other kilometer-scale disturbances requires frequent updating (typically hourly) of the model forecast with assimilation of the latest observations. This requires a smooth transition from initial state to forecast, with minimal noise or spinup bias. Methods of addressing initialization noise in larger-scale models have included filters, penalty terms in variational DA, and forms of diabatic initialization. Application to kilometer-scale prediction is more challenging as the required balances are implicit in the local atmospheric structure, rather than universally defined by geostrophic constraints. Whereas it is important to produce an initial analysis with small-scale balance to minimize spinup, the underlying large-scale balance must not be compromised. Localization schemes capable of taking account of multiple-scaled observation types, observation density, ensemble size, and flow-dependent correlation length of the modeled flow need to be explored. The multistep DA approach, in which observations with different spatial resolutions and temporal frequencies are assimilated at different steps, also deserves further study. Since warning is a cascading process, from longer lead times and larger regions to shorter lead times and specific locations, the multistep approach offers flexibility in the use of DA techniques, selections of observation types, grid resolution, and cycling frequency in each step depending on the desired application. Nevertheless, experimental and theoretical studies are required to design such systems.

**Development of advanced DA techniques for convective scale.** The benefits of hybrid DA have been demonstrated for global systems and implemented operationally. However, its application in convection-permitting regional DA systems lags behind. More research is required to deal with several issues pertaining to the convective scale in a hybrid system. Among them are the selection of ensembles that can represent multiscale uncertainty of high-impact weather, optimal design of rapid update cycles, multiscale covariance localization, improving estimation of static background error covariance, and dealing with nonlinearity and non-Gaussianity of clouds and precipitation. The utility of 4DVar multiscale DA should be further explored. In addition to further examination of its role in hybrid EnVar DA, one of the key scientific questions deserving exploration is how to assimilate multiscale observations with varied lengths of assimilation windows for different nonlinear outer loops. The encouraging recent results of nonlinear filters such as the local particle filter for high-impact weather warrant further studies for convective-scale DA.

***Multiscale ensemble prediction: Requirements and current status.*** Several days ahead of a high-impact weather event, NWP provides guidance on the potential for local weather in a region. Examples include winter storm or tropical cyclone tracks, or whether heat waves or pollution episodes will begin or continue. Less than 2 days ahead, the guidance ranges from more deterministic for larger-scale weather systems (e.g., heat waves, fronts) to more probabilistic for smaller scale short-lived systems (e.g., severe storms), while midlatitude and tropical cyclones are intermediate in the sense of deterministically knowing that there is a swath of large risk, but not its exact structure or impacts. While the forecaster is able to use experience to judge the uncertainty qualitatively, high-impact weather forecasting requires a quantitative uncertainty assessment, tying risks to specific locations (e.g., urban areas) and times. This requirement motivates the use of ensemble prediction systems (EPSs), which are expected to improve on the practice of a forecaster judging deterministic forecasts for their uncertainties. Features with sharp boundaries between hazardous and nonhazardous weather, such as severe storms and precipitating systems, are particularly challenging in this regard.

An EPS produces a range of forecast scenarios that, taken together, can be used to predict the likelihood of a hazardous weather situation occurring or of a hazardous threshold being surpassed. Global EPSs were initially designed to capture uncertainties of synoptic-scale motions, and the more recently introduced stochastic parameterizations (Berner et al. 2017) can capture uncertainties on all resolvable scales including the mesoscale. Other ensemble perturbation methods continue to be designed and implemented. Global EPSs can also exploit reforecasts, which can be used to diagnose model bias and statistically correct forecasts (Hamill et al. 2006). Convective-scale EPSs currently comprise regional models that capture phenomena including short-lived severe storms, bands of intense snow, or wind and rainfall distributions in tropical cyclones. Examples of some challenges are described below.

Nonhydrostatic models run at convection-permitting scales (<4 km) with state-of-the-art physics parameterizations (surface, planetary boundary layer, microphysics, radiation) are able to represent the general characteristics of storm development and evolution, although not necessarily the exact location, structure, and timing. Many operational NWP centers now have nonhydrostatic national-scale models with grid sizes of one to a few kilometers that resolve not only large convective cores but also the major features of complex terrain and associated flows that may impact local weather.

Requirements for tackling uncertainty in short-range forecasts of convective cloud systems are different from those that formed the basis of medium-range EPSs. Bowler et al. (2008) outlined the differences: in resolution, initial perturbations effective at short lead times, and representation of model uncertainties that influence surface variables. High resolution implies nesting, which introduces the complication of matching boundary perturbations. With the implementation of convection-allowing models (CAMs), research has turned to configuring EPSs at this scale. The processes involved in convective cloud systems are a challenge to initial perturbation specification with much greater growth rates anticipated, while many more model processes need to be explored as potential sources of uncertainty. It remains important to recognize that the large scales continue to provide the environment for convective development, and therefore remain important sources of uncertainty.

Experimentation with CAMs began at NOAA's Hazardous Weather Testbed in 2004 (Kain et al. 2017). This allowed forecasters to be exposed to CAMs where diagnostics such as simulated reflectivity and updraft helicity have proven to be valuable, given the ability of CAMs to resolve storm cells. With coordinated efforts from different groups, a single ensemble framework called the Community Leveraged Unified Ensemble (CLUE; Clark et al. 2018) with a common set of model specifications (e.g., grid spacing, vertical levels, domain size) was developed with the goal of identifying optimal design and configuration strategies for CAM-based ensembles for near-future operational systems. Experience in ensemble storm-scale real-time forecasting is further exemplified by Schwartz et al. (2015) using 10 members at 3 km from a 15 km EnKF DA system where probabilities are derived including proxies for hail and tornadic risks. More recently, several operational centers have begun to run convection-permitting ensembles, e.g., MOGREPS-UK at 2.2 km, AROME-EPS (France) at 2.5 km, and COSMO-DE-EPS (Germany) at 2.8 km, while in the United States the HRRR Ensemble (HRRRE) at 3 km is being evaluated. MOGREPS-UK has recently been upgraded to an hourly cycle, using a moving 6 h window to create an 18-member combined perturbed and lagged ensemble (Hagelin et al. 2017). An example of a probabilistic product computed directly from such ensembles is the probability of exceeding an extreme rainfall threshold within 50 km of a location. The calibration of raw ensemble probabilities to remove biases remains a challenge and relies on experience with the model. Reforecasts may be applied to CAM-based ensembles if the locations of extreme weather features are accounted for, which will likely require alternative methods to point verifications. Reforecasts are also used in the training of bias-corrected analog ensembles (Alessandrini et al. 2019).

Ensemble forecasts of tropical cyclones are increasingly being used operationally, with new ensemble-based techniques and products under development. The probabilistic skill of ensemble-based track forecasts is improving (Titley et al. 2020), which is expected since the track is largely determined by the synoptic-scale flow. Although the progress in ensemble predictions of structure and intensity are lagging, several centers are now using downscaling on demand in high-resolution prediction, where a single refined convection-permitting grid follows a tropical cyclone nested within a coarser model. For example, NOAA's Hurricane Weather Research and Forecasting (HWRF) model employs moving 6 and 2 km grids around the world. Other similar examples include the U.S. Navy's COAMPS-TC, China's GRAPES-TC, and the Taiwan Central Weather Bureau's TWRF. Recent research with a fixed regional convection-permitting model by Short and Petch (2018) has also demonstrated improved intensity forecasting, especially in periods of rapid intensification.

Finally, even when ensemble predictions are available, the utilization and presentation of probabilistic forecasts by forecasters is varied. Possible reasons include a lack of availability of ensemble data or time to synthesize them under an operational timeline, or the unfamiliarity that some forecasters, officials, and emergency managers may possess in communicating and/or interpreting probabilistic output.

### *Multiscale ensemble prediction: Challenges and suggested foci*

**Surface interactions.** While models at kilometer-scale have sufficient resolution, dynamics, and physics to represent much hazardous weather, further work is needed to adequately model the interaction between the surface (marine and land) and the internal cloud dynamics and physics, particularly those aspects that remain unresolved. Computing advances are making it possible to have focused grids in the 100–300 m scale over small regions of interest, such as urban areas. For example, the United Kingdom's Met Office is using a 100 m grid domain over London (Lean et al. 2019), and Environment and Climate Change Canada has tested 250 m over Vancouver (Leroyer et al. 2014). However, such models remain in the gray zone where large turbulent eddies are resolved but smaller ones are not, and where the heterogeneity and complexities of the surface topography and the urban built surface are at scales comparable to the grid scale. Alternative approaches to downscaling include the use of surface urban models instead of full atmospheric models, statistical downscaling (e.g., for local heat islands or wind-prone urban canyons), and offline precomputation of scenarios indexed to the larger-scale forcing (Speight et al. 2018).

**Uncertainty quantification on kilometer scales.** For weather features that are resolved by the model, the uncertainty of the initial state and of the small-scale processes requires that any prediction is accompanied by a quantitative estimate of uncertainty. While kilometer-scale EPS can provide probabilities and give a better chance of capturing risks of extreme events, obtaining an ensemble that spans the range of likely weather without excessive spread remains a challenge. Interactions of storms with each other and with complex terrain (e.g., for streamflow) is highly stochastic, regardless of the accuracy of initial conditions, and the challenge is to have enough ensemble members to represent the sources of uncertainty. Ensemble spread is generated by perturbing the initial conditions, the lower boundary state, and the model processes, within realistic ranges, but more research is needed to do this effectively at kilometer-scale and to calibrate the resulting ensemble probabilities. A particular challenge at kilometer-scale is to interpret an ensemble in which single members may contain forecasts of apparently unrelated extreme events. Upscaling (aggregating to a coarser resolution) provides one solution, but at the cost of losing the additional information at small scales.

**Initiation and maintenance of convective processes.** While nowcasting addresses preexisting storms out to about an hour, NWP needs to play a crucial role in forecasting features such as short-lived storms or hazards that may not be in the initial state but are favored by large-scale conditions. A suggested focus is the accurate probabilistic representation of convective initiation, which is expected to improve as the above two priority areas (surface interactions and kilometer-scale uncertainty quantification) mature. For forecasts with convective features present at the initial time, the DA and ensemble challenges are to include them in such a way that the model can forecast them seamlessly and consistently with the larger-scale processes, capturing uncertainty evolution in order to meet the needs of decision-makers for information on probability and impact.

**Tropical cyclones.** As is also the case for extratropical cyclones, the challenge of predicting tropical cyclone structure (including size) and related hazards is intrinsically multiscale, depending on complex physical processes over a wide range of temporal and spatial scales. Using a combination of observations, idealized modeling, and case simulations, many authors have provided insights into the large-scale control of structure and intensity through vertical wind shear and air–sea interactions, and also the roles of internal dynamics and physics. A logical next step is to use these recent advances in process understanding to address related issues in predictability. While the intrinsic predictability of different tropical cyclone hazards depends in large part on the tropical cyclone track, the individual processes (e.g., rapid intensification) and hazards (e.g., extreme rainfall) possess varying levels of predictability, and the predictability may change from storm to storm. By developing an improved understanding of multiscale interactions and their predictability, the priorities of accurate DA and quantification of uncertainty of multiscale hazards in tropical cyclones can be addressed in operational-quality ensembles.

***Multiscale coupled hazard modeling: Requirements and current status.*** While some weather impacts such as wind damage, snow, and ice storms are direct, many other weather impacts largely occur indirectly. Prediction of these hazards is achieved using flood, storm surge, ocean wave, and fire models, among others. Coupling of the oceans and land surface hydrology with the atmosphere in Earth system models has a long history in climate modeling, where the fluxes among these different parts of the environment are key to modeling climate variability. However, such integration has been slow to develop in operational weather forecasting, partly for practical reasons of speed and computer capacity, and partly because the dominant processes occurring on these short time scales are in the atmosphere. Instead, hazard models are generally run separately using meteorological inputs from NWP.

There is now a growing movement toward closer integration, partly to provide better hazard warnings, and partly because of the recognition of sensitivities to the feedbacks between different parts of the environment, such as in the vicinity of strong gradients of moisture, temperature, or friction. Modeling the coupled environment is challenging, not least because the natural spatial and temporal scales of the processes are so different. For instance, river modeling at 1 km scale is considered coarse, while inundation models need 10 m resolution or finer, especially in urban areas. The major sources of uncertainty are also different. For storm surges, the neglect of a recent change in the seabed, coastal development, or accurate representation of ocean waves could outweigh any benefit from better modeling of the interaction of the atmosphere and ocean. Coupled models are more complex than NWP models, requiring more sophisticated DA and ensemble prediction methods. If the result is a delayed transfer of research into operations due to testing complexity or a delayed forecast time due to a more complex model, the result may be a less effective warning, despite the benefits of coupling.

Several advances have been made in coupled global and mesoscale weather prediction. First, importance of soil moisture gradients has long been recognized and is represented to some degree in most models. Second, coupled ocean waves were recently introduced by ECMWF to represent the effect of wave age on atmospheric drag. The ECMWF coupled atmosphere–wave–ocean model, which has been operational since 2013, has been investigated in tropical cyclone prediction (Mogensen et al. 2017). The model was found to realistically reproduce the air–sea interaction in the presence of passing typhoons. It was also concluded that a strong coupled feedback is evident when the heat content of the upper-ocean layer is low, while a very weak coupled feedback is found when the ocean has a thick warm mixed layer. Finally, aerosol modeling has advanced substantially. Simplifications of full chemistry have proven to be effective. An example is the incorporation of aerosols into models such as the HRRR without greatly increasing the computational expense. Recent research into the interactions of aerosols with radiation and clouds has led to a move from using prescribed aerosols in NWP toward modeling the distribution based on emissions, transport and chemistry (Benedetti and Vitart 2018).

Most of the above activities are oriented toward medium-range forecasting, where the interaction terms have time to grow to a size that can significantly influence the weather. By contrast, the U.K. Environmental Prediction project (Fig. 8) and the Great Lakes Water Cycle project in Canada (Durnford et al. 2018) have been focused on much shorter ranges where details of the air–sea–land interactions can lead to specific hazards, particularly fog and ice fog over the sea and storms over land. An example of the impact of air–sea coupling on heavy-precipitation events in coastal Mediterranean regions is given by Rainaud et al. (2017).

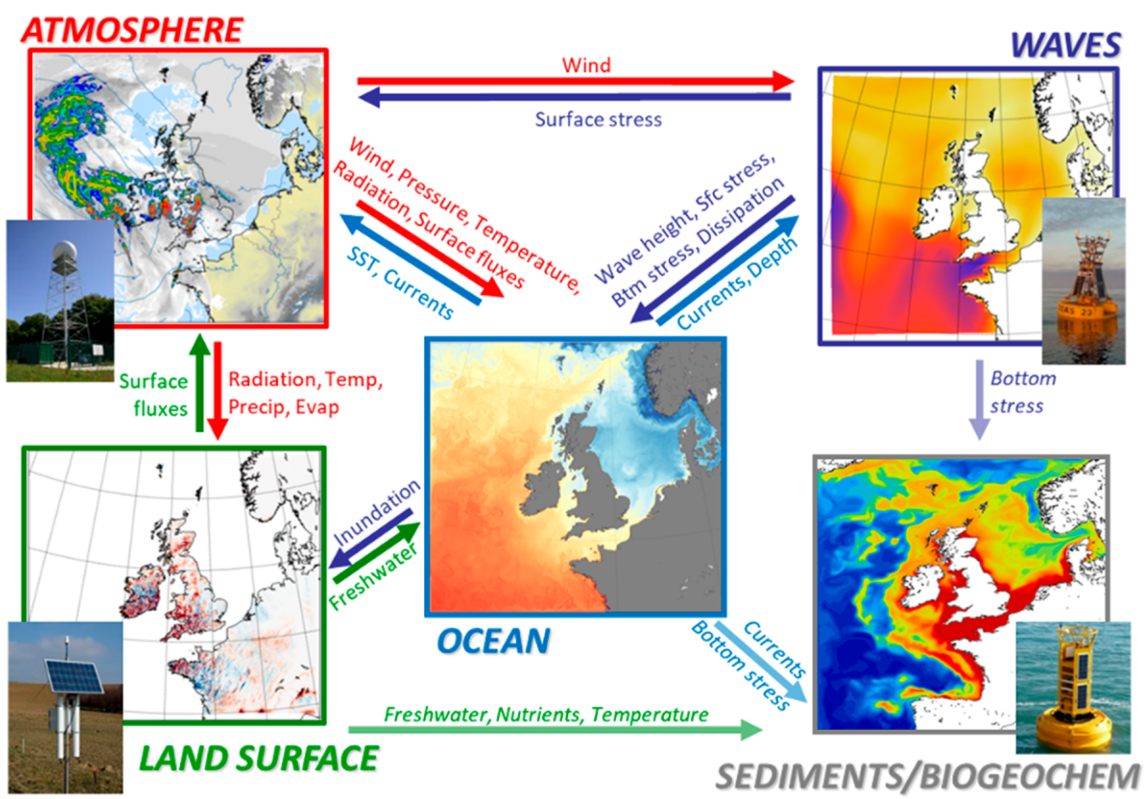


**Fig. 8. Concept diagram of the U.K. Environmental Prediction (UKEP) coupled modeling project (H. W. Lewis 2018, personal communication). Progress to date is described in Lewis et al. (2018).**

### *Multiscale coupled hazard modeling: Challenges and suggested foci*

**Observations.** Coupled hazard modeling imposes challenges on all aspects of the forecasting process. Observations of all parts of the environment are required, but only atmospheric and oceanographic in situ observations are widely exchanged. There is an urgent need for exchange of more atmospheric composition and land surface hydrology information, particularly for variables for which remote sensing by satellites has limited capability.

**Coupled data assimilation.** DA methods have been developed separately for each component of the coupled system, but achieving a consistent initial state remains a major challenge and is an area of active research. Magnusson et al. (2019) identified the key challenge of initializing the ECMWF coupled ocean–atmosphere model simultaneously by using "outer loop" coupling in the analysis, where the 4DVar nonlinear integrations use the coupled model, but the minimizations are performed separately for the atmospheric and oceanic states. This improvement should lead to more consistent oceanic and atmospheric states with reduced initialization shock; more timely sea surface temperature (SST) analysis including the diurnal cycle; and use of in situ ocean observations to provide atmospheric increments, particularly under cloudy conditions. Improved assimilation of ocean surface data (e.g., from scatterometers) is further expected to improve representations of ocean surface exchanges and coupling with the wave and ocean models. A consistent representation of initial and model uncertainty in coupled EPS is also crucial.

**Coupled modeling techniques.** The coupling procedure itself is an outstanding challenge that depends on the consistency of the different components, especially where different resolutions are used. A key test of completeness and consistency of the coupling will be to achieve balanced heat and water budgets through the complete coupled system. Probabilistic prediction for hydrological and ocean models has traditionally been based on deterministic modeling from an ensemble of atmospheric inputs, ignoring further uncertainty, but future coupled systems will need a consistent application of appropriate perturbation methods for each component of the system [e.g., Édouard et al. (2018) for hydrological EPSs]. Finally, where the coupled system is being used to directly predict a hazard, the resulting predictions need to be competitive with those from uncoupled systems, requiring appropriate postprocessing and verification. While several aspects of coupling will gradually appear in NWP systems in the next few years, achievement of the full benefits of coupling is a long-term challenge. This will require significant investment in diverse scientific approaches to provide opportunities for cross-fertilization of ideas (Theurich et al. 2016).

## Concluding remarks

In the context of the Multiscale Hazard Forecasting theme of the WMO HIWeather project, this paper provides a summary of the current status and future challenges in monitoring and predicting high-impact weather. Over the past decade, there have been substantial advances in this capability and the provision of information required by emergency managers and the public to enable more effective preparation, response, and recovery from weather-related hazards. Earlier and more reliable indications of the location and severity of probable hazards from convection-permitting NWP systems have enabled better preparation for high-impact weather. Greater variety and accuracy in remotely sensed observations, coupled with access to crowdsourced data, have improved the situational awareness of those managing the response during an emergency. While these advances have contributed to the continued reduction in fatalities from high-impact weather, changes in society and climate are increasing its economic cost. Further improvement is therefore needed to continue to reduce fatalities and socio-economic impact. Technological and scientific progress will enable further advances in coming years, particularly in the areas of

1) advanced urban observation monitoring, ubiquitous sensing and social media analysis for better situational awareness, and reporting of severe weather and related hazards;
2) novel application of techniques including machine learning to identify the conditions that precede severe weather development;
3) achievement of physically consistent multiscale initial states and ensemble forecast distributions for kilometer-scale models;
4) closer coupling of hazard prediction models with NWP models;
5) more effective communication and use of probabilistic forecast information in the formulation of warnings and decision support products; and
6) greater research and development focus on the specific requirements of emergency responders and of societal behavior to hazard warnings.

The HIWeather project brings together groups focusing on each of these areas as well as on the structure and effectiveness of the overall warning chain. The project co-chairs and theme leaders welcome approaches from researchers and practitioners who are engaged in addressing these challenges.

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