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Editorial

Fog Decision Support Systems: A Review of the Current Perspectives

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1. Introduction

Accurate and timely fog forecasts are needed to support decision making for various activities which are critically affected by low visibility conditions. The societal impact of fog has significantly increased in recent decades, due to increasing air, marine, and road traffic, as well as the emergence of solar power as a source of renewable energy. In fact, the financial costs related to fog have become comparable to the losses from other weather events, such as storms [1]. Low visibility levels in fog lead to delays in air travel, hazardous navigation in crowded waterways and ports, and unsafe traffic conditions on roadways. More recently, information on fog is required for the applications of solar energy production and autonomous driving. Therefore, improved decision support systems tailored to a wide range of activities that are impacted by fog are needed more than ever. At the core of such systems, improved nowcasting (minutes to hours) and forecasting (hours to days) techniques for fog onset, severity, and dissipation are necessary. Further refinement of numerical weather prediction (NWP) models, new observation platforms and observational networks, and advanced analysis capabilities offered by artificial intelligence and machine learning algorithms all represent potential sources of improvement for next-generation fog predictions. Each of these approaches offer possibilities, but they also have their own limitations in providing forecasts with added value to decision makers. One aspect representing a significant challenge and requiring further attention is the capability of providing clear and reliable information on forecast uncertainty. Several aspects of these capabilities and challenges are discussed in this review.

This Special Issue, in particular, provides an overview of recent advances in the development of decision support systems, and their related components, for fog nowcasting and forecasting. The contributions highlight the use of different approaches (e.g., data-driven techniques, NWP models and ensemble forecasting systems, artificial intelligence and machine learning algorithms), either used individually or in combination (i.e., blending information from various sources), for generating improved fog predictions. We would like to thank all of the authors who contributed to this Special Issue for their hard work in creating the material contained within, as well as for considering the revisions based on the reviewers' comments. We also thank the reviewers for their constructive comments and suggestions. All of these contributions serve as key elements in this review to provide a fresh perspective on the state of the art of fog decision support systems and the remaining challenges to the production of useful fog predictions.

2. Why Is Fog Forecasting So Challenging?

Despite advances in atmospheric science research, fog forecasting remains challenging, as several physical and chemical processes are involved, along with many non-linear

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interactions. The consequence is difficulty in developing comprehensive and reliable forecast models. The main factors that make fog forecasting difficult are described below.

1. **Atmospheric stability:** The stability of the atmosphere can impact the onset and subsequent development of fog. For example, the onset phase of radiation fog is typically associated with a stable surface layer, while the mature phase is associated with unstable or neutral atmospheric conditions within the boundary layer. During the LANFEX fog field experiment in England, Price et al. (2018) [2] showed that approximately 50% of radiation fog cases developed into deep, optically thick layers (defined here as being opaque to thermal radiation in the 8–12 µm wavelength range). The other 50% remained shallow, optically thin, and often heterogeneous. Predicting these transitions between thin and deep fog layers can be challenging, due to the complex interactions involved between the temperature, humidity, and wind in the boundary layer. In addition, turbulence intensity, itself dependent on atmospheric stability, is a crucial factor that can affect the fog's development. For example, a fog layer may dissipate if the temperature inversion weakens or disappears, while the fog may deepen if the inversion becomes stronger under the influence of stronger or weaker turbulent exchanges of dry air at the top of the fog. The presence and strength of the inversion at the top of the fog layer modulates the turbulent interactions between the fog layer and the non-cloudy overlying atmosphere and, therefore, helps change the fog's properties during its life cycle;
2. **Radiation balance:** The balance between incoming and outgoing radiation can impact the transition from the onset to the dissipation of fog layers. During the onset phase, the balance is typically in favor of cooling while, during the mature phase, warming near the surface is favored, while cooling occurs at the top of the fog layer. Furthermore, solar radiation is one of the main factors that can cause fog to dissipate. However, the intensity of solar radiation can vary significantly, depending on the time of day and season but, more importantly, with the presence of aloft clouds and their microphysical properties. Thus, predicting changes in the radiation balance can be difficult, due to the complex interplay between clouds, solar radiation, and atmospheric stability;
3. **Moisture availability:** The availability of moisture is a critical factor that can impact not only the likelihood of fog formation, but also the transition from the onset to the mature phase of fog. The onset phase is typically associated with a high moisture content in the air, but the deposition of dew on surface elements can delay fog formation. During the mature phase, the deposition of fog water on the surface is dependent on turbulent and microphysical fog properties and, therefore, represents a highly (temporally and spatially) variable sink of water. The local processes driving this variability contribute to the difficulties with accurately predicting fog properties. The local processes responsible for this variability need to be better understood before more accurate predictions can be achieved. Another factor hindering fog predictions is the general lack of dense networks of humidity observations, limiting the details with which moisture distributions are described in the initial conditions in numerical weather forecasts;
4. **Aerosols and microphysics:** The presence and characteristics of aerosols in the atmosphere can impact the whole life cycle of the fog. Aerosols can act as nuclei for fog droplet formation, and can influence subsequent fog development. For example, results from the WIFEX field experiment in India [3] have demonstrated that a significant fraction of water-soluble inorganic aerosols (chloride, sulfate and nitrate, ammonium) exist during high aerosol loading. These aerosols grow exponentially in size once deliquescence occurs, and can remain in a hydrated state over a significant amount of time. Enhanced loading of hydrated aerosols can play a major role in visibility reductions in subsaturated conditions and, therefore, influence the radiation balance within the boundary layer. These results, and others from previous field campaigns, indicate that accurately predicting changes in aerosol concentrations and

properties can be challenging, due to the complex interactions between atmospheric conditions, emissions, and transport. Once nucleated, the size distribution of fog droplets can evolve through a variety of mechanisms, including condensation, deposition, autoconversion, and collision-coalescence. The relative importance of each of these mechanisms can vary depending on overall environmental conditions, but also on the size and composition of the aerosols. Therefore, predicting the evolution of the size distribution of fog droplets, which influences the radiation balance and overall fog properties, is also a challenging objective;

5. **Turbulence:** The turbulent transport of heat, humidity, and droplets plays a very important role in the fog life cycle. However, turbulent transport has an ambiguous role, as it can both contribute to or prevent fog formation. At night, when the sky is clear, the atmosphere is stable due to surface cooling. The thermal (buoyant) production of turbulence is then negative. The production of turbulence, therefore, depends only on the intensity of the wind. If the wind is very weak or calm, the cooling of the surface will dominate, and saturation can be reached very quickly near the surface, depending on moisture availability. However, this surface cooling will not be able to propagate to the atmosphere, due to the lack of turbulent exchanges. The temperature inversion will be very strong and shallow (typically about ten degrees on a layer of about ten meters). Saturation will, therefore, not be able to propagate vertically, and will mainly result in a very thin layer of fog with the possibly of a significant deposition of dew. A stronger wind will reduce the cooling at the surface by increasing the turbulent exchanges on the vertical. However, once this is reached, it will allow the fog to develop vertically and, therefore, lead to a very dense fog. However, the existence of a well-defined turbulence threshold in radiation fog development remains an open question. As suggested by the discussion above, predicting the timing and intensity of turbulence is challenging, due to the complex nature of interactions involved, adding to the difficulty of accurately predicting fog occurrences and properties;
6. **Advection:** This is the transport of heat, moisture, aerosols, and clouds by the wind. It can influence the evolution of fog conditions by bringing in or removing moisture and altering the temperature and humidity profiles. The transport of aerosols can also modify fog properties. Mesoscale circulations and related advection patterns can be induced by contrasts in surface properties (e.g., land–water and urban–rural contrasts), and by topography (see the next item). Accurate modeling, and hence predicting, of changes in wind speed and direction can be challenging, particularly at small scales in complex terrain. The accurate representation of circulations and advection patterns affecting fog requires using a high-resolution NWP, in conjunction with high-density networks of observations and efficient data assimilation methods able to provide initial conditions representing the spatial variability in temperature, moisture, and wind at small scales;
7. **Topography and land use:** Topography plays an important role in fog occurrences and evolution by influencing circulations, as well as temperature and humidity profiles. For example, valleys and low-lying areas can experience deeper and more persistent fog layers, due to the high humidity levels and low wind speed conditions resulting from the pooling effects of drainage flows. On the other hand, urban areas tend to experience foggy conditions less frequently, due to their characteristic higher temperatures and lower humidity levels, in comparison with the adjacent rural areas. However, urban and industrial areas are generally characterized by increased concentrations of aerosols, which can affect the formation and dissipation of fog.

As outlined in the discussion above, fog formation, development, and dissipation is determined by a large number of physical processes and subtle interactions, which are difficult to accurately represent in numerical models. On the other hand, the lack of widely available comprehensive sets of observations, taken in a wide range of environments, represent a limitation for the development of observation-driven forecast algorithms.

The fact that fog occurs in a variety of environments and weather conditions makes the development of comprehensive forecast models a difficult task. The highly heterogeneous nature of fog at very small scales, as revealed through high-density visibility observations around Charles de Gaulle airport, Paris, for example (see [4]), further adds to the difficulty. Our current knowledge on fog, as outlined above, has been acquired through the analysis of observations from field campaigns and carefully designed numerical modeling experiments. Despite the progress achieved, it is also recognized that the insights gained from such observations have limits. The highly heterogeneous character of fog at small scales limits the usefulness of local observations for informing on conditions over wider areas. Furthermore, the presence of gravity waves can affect the evolution of fog characteristics, as revealed by Large Eddy Simulations (LES) (e.g., [5]), are generally not detected from typical surface-based observations that can be more easily deployed as networks. Therefore, progress in fog forecasting is hindered by persisting incomplete understandings of and capabilities for modeling the multi-scale interactions involved. A lack of high-density networks of routine observations monitoring the wide arrays of conditions relevant to fog forecasting is also an important limiting factor. Our current fog prediction capabilities and related issues are discussed in more detail in the following sections.

3. Contributions and Limitations of NWP Models

Accurately forecasting the occurrence of fog constitutes a crucial meteorological service, providing important information on atmospheric conditions that can affect public safety and disrupt a wide array of operations. While NWP models have greatly improved our ability to forecast severe weather, they still face several challenges when it comes to predicting fog (see, e.g., [6]). NWP models often fail to correctly predict events predominantly driven by sub-grid scale processes such as fog. The main challenges of NWP models for fog forecasting include:

(1) **Resolution:** The current NWP models lack sufficient resolution, both vertically and horizontally, to accurately simulate the fog's life cycle. Some research efforts have been undertaken using LES, but generating operational forecasts using LES remain out of reach, due to computational expenses and difficulties in accurately representing initial conditions at small scales. Moreover, fog layers exhibit a significant spatial variability at the metric scale, and their vertical development is strongly determined by turbulent motions occurring at very fine scales. Accurate representations of these small scales remains out of the reach of current NWP models;

(2) **Boundary layer:** The fog life cycle is strongly influenced by conditions within the lower atmosphere under stable conditions. However, the stable boundary layer (SBL) is often poorly represented in NWP models, which limits the accuracy of fog predictions. Therefore, more efforts should be undertaken to improve parameterizations of the SBL, particularly for scenarios where surfaces are characterized by small-scale heterogeneities. Particular attention should be placed on understanding and parameterizing the interactions driving the variability of the boundary layer across scales (from mesoscale to microscale);

(3) **Microphysics:** Fog formation, and the subsequent evolution of its characteristics, are strongly determined by the ambient aerosol properties and related microphysical processes. Accurate representations of aerosol and cloud droplet spectra are necessary for accurate fog predictions, particularly for accurate predictions of visibility. However, the complexity of these processes makes it challenging to model them accurately, and the current NWP models fail to represent the different microphysical stages of aerosols and fog evolution. Deficiencies in the relevant parameterizations (microphysics, radiation, and turbulence), and the interactions between them, limit models' abilities to predict reductions in visibility. As such, Ref. [7] describes the limitations associated with the use of fixed parameters in microphysical parameterizations that do not take the regional variability in aerosol conditions properly into account. The authors highlight the fact that use of existing parameterizations and their parameters to

predict fog in contrasting environments is a flawed approach. The optimization of microphysical parameters to better predict fog in one region can lead to less accurate forecasts in another. NWP models are, in essence, complex ecosystems of interacting components, each with a number of tuneable parameters. The global optimization of these parameters is an extremely difficult, if not impossible, task to achieve, creating a scenario where significant compromises have to be made. The development and implementation of appropriate parameterizations in NWP models able to predict fog everywhere and in all scenarios remains an open question. More research is needed for more comprehensive representations of the relationships between key microphysical properties within fog (e.g., the shape parameters describing particle size distributions) and the local environmental conditions. Striking the right balance between sophistication (often associated with sizable increases in computational costs) and accuracy poses a significant barrier to achieving this. Recognizing this difficulty, research should include a greater emphasis on the development of stochastic parameterizations, which aim to represent the inherent uncertainties in the representation of key processes, rather than seek to develop more and more complex and expensive parameterization schemes. A strategy which combines both approaches appears to be the most promising way forward at this time;

(4) **Model biases:** NWP models are imperfect tools, characterized by systematic errors that affect the accuracy of fog predictions. These biases can be difficult to correct, due to the interactions between the different sources of errors, such as those related to deficient model physics and lack of accurate initialization of the smaller scales. Traditionally, Model Output Statistics (MOSs) have been used to post-process NWP outputs to produce more accurate forecasts of variables related to the ceiling and visibility (see, e.g., [8]). Recognizing the limitations of corrections based on multilinear regressions, as is the case with MOSs, more advanced bias correction methods are being developed and tested, such as the analog method (e.g., [9]) to correct model biases and provide more reliable fog forecasts. Recent efforts on the development of other forecast correction methods involving Artificial Intelligence (AI) and Machine Learning (ML) concepts have also shown promising results (see, e.g., [10]);

(5) **Initialization:** NWP models require accurate initial conditions to produce accurate forecasts. These initial conditions are obtained by combining the information provided by a wide array of observations and prior short-term model forecasts using sophisticated data assimilation (DA) schemes. Significant challenges remain related to DA and initial conditions, with respect to fog forecasting. Generating accurate initial conditions of critical parameters involved in fog formation and evolution remains difficult, particularly in areas with complex terrain or limited observations. Standard meteorological observations do not always inform on the complex processes occurring at small scales, such as turbulent mixing in the SBL, whereas local measurements are not always efficiently incorporated into NWP analyses. The accurate depiction of conditions within the boundary layer remains a challenge, particularly with respect to SBL characteristics and humidity conditions prior to fog formation. Once fog has formed, the representation of important fog characteristics, such as water content, the depth of the fog layer, etc., are difficult to obtain using standard observations. The assimilation of data from new observing systems could help overcome these deficiencies. For example, more widespread use of cloud-affected radiances from latest-generation satellites would help fill gaps with needed information about cloud presence and properties. The assimilation of observations from Doppler and differential absorption lidars (DIALs), would help refine analyses of boundary layer properties with high-resolution information on wind, turbulence, and water vapor profiles. Such information has the potential to help improve forecasts of the boundary layer structure prior to fog formation, timing, location of fog onset, and its subsequent development. The assimilation of observations from ground-based microwave radiometers (see, e.g., [11]) provides the needed high temporal resolution information

on bulk fog properties, despite the low vertical resolution characterizing observations from these instruments. The use of imagery from IR cameras (see, e.g., [12]) could also help overcome the poor coverage of observations on fog presence and characteristics. A challenge here is the availability of suitable forward operators, particularly with respect to the use of camera imagery, needed for effective assimilation of such observations;

(6) **Variability time-scale:** Conditions favorable to fog formation and the evolution of fog itself can change rapidly. Therefore, timely forecasts initialized with the latest information available are needed by end users. Predicting fog formation and dissipation at local scales requires frequent and locally adapted forecasts (i.e., rapid cycling using local observations). However, NWP models are typically initialized on time-scales between one and a few hours, which can limit their ability to generate up-to-date predictions of rapid changes in fog conditions. The use of single-column models with rapid cycling in a local nowcasting framework have been shown to produce useful forecasts of local fog conditions (see, e.g., [13]), overcoming this deficiency to some extent. The remaining challenge here is how to properly take into account the influences of heterogeneities at the mesoscale on the evolution of local conditions.

In general, the output from NWP models remain a crucial source of forecast information for end users. Consequently, a complete and thorough analysis of the shortcomings of these models and possible avenues of refinement remains a priority. As suggested by the papers submitted to this Special Issue, there appears to be very little direct use of NWP data in decision support systems. Current efforts rather focus on developing the post-processing of existing NWP systems via, e.g., AI/ML methods, or developing ways of representing elements of fog predictability via ensemble forecasting methods.

4. Machine Learning

Artificial Intelligence (AI) has been applied to fog forecasting using various techniques, including machine learning, deep learning, and fuzzy logic (see, e.g., [14]). Machine learning algorithms, such as random forest, decision tree, and support vector machines, have been used to predict fog formation using observations of atmospheric parameters. Deep learning techniques, such as convolutional neural networks (CNN), have also been used to predict fog occurrences using satellite images, meteorological data, and NWP output. Recently, machine learning has emerged as a powerful tool for predicting fog occurrences, due to its ability to learn complex relationships between meteorological variables and the occurrence of fog.

AI applications aiming to predict fog generally focus on enhancing NWP models, either by emulating sub grid-scale parameterizations [15,16], or by emulating the numerical models altogether [17]. In some cases, numerical model outputs remain an essential component in the training of a ML-based model while, in other applications, the ML model is driven by observational data alone [18]. In other applications, the ML model is based on a combination of the two data sources (NWP model and observations) (see, e.g., [19]).

The application of AI for fog forecasting has shown promising results, with high accuracy rates in predicting fog occurrences. The use of AI for fog forecasting can provide several benefits, including:

(1) **Improved accuracy and faster predictions:** AI algorithms, such as machine learning, neural networks, fuzzy logic, and expert systems, can analyze vast amounts of meteorological data in real-time and identify patterns and relationships that may be difficult for human analysts to detect. This can result in more accurate fog forecasting, and allows for faster predictions of fog formation and dissipation;

(2) **Cost-effectiveness:** AI algorithms can be trained to analyze meteorological data, resulting in integrated systems that best meet users' needs. This can result in cost savings for national meteorological services and a wide community of other end users. Additionally, AI-based fog forecasting systems can also be automated, reducing the workload of forecasters, improving the efficiency of forecasting operations, and

best meeting users' needs. Additionally, AI-based systems can be trained to adapt to changing weather patterns, improving the accuracy of forecasts over time. Therefore, the use of AI offers several benefits over traditional forecasting methods, including increased accuracy, efficiency, and adaptability.

However, there are several challenges associated with the application of AI and machine learning for fog forecasting:

(1) **Availability of high-quality data**: This is critical for training and validating machine learning models [20]. However, fog observations remain sparse, and often come from different sources, such as meteorological stations, satellite imagery, and remote sensing. These data sources may have different spatial and temporal resolutions, which can affect the accuracy of AI models. Additionally, fog is a complex phenomenon influenced by various factors, some difficult to measure directly and accurately (e.g., turbulence, slight changes in humidity levels, etc.). Obtaining a comprehensive and reliable dataset that captures all these factors can be challenging. Beyond the standard meteorological variables as predictors, Bartok et al. [21] developed a ML forecast model that uses visibility information obtained through remote camera observations. The authors found that camera-based observations help overcome some of the drawbacks associated with the use of automated sensors (predominantly point-based measurements) and human observers (more comprehensive observations, but taken at lower frequencies), and offer a viable solution in certain situations, such as during the recent COVID-19 pandemic;

(2) **Model complexity and interpretability:** The need for interpretable models that can provide insights into the physical mechanisms underlying the occurrence of fog. Although AI models can provide accurate predictions, they often lack interpretability, making it challenging to identify the critical variables driving the occurrence of fog. Peláez-Rodríguez et al. [22] propose different explainable forecasting approaches, based on inductive and evolutionary decision rules, for extreme low-visibility event predictions. The explainability of the processes derived from the rules generated by their system is one of the core objective of this work. The authors proposed a combination of the individual rules into a fuzzy-based controller to refine the final results obtained, or testing functional regression methods as final outcomes for the system to overcome the limitations in the interpretability of the proposed approach. A lack of interpretability can be problematic in critical applications, such as in aviation forecasting, where understanding the reasons for fog formation is a desirable outcome. This is not always achievable, as most AI models used in fog forecasting are complex, such as with deep learning models which can have millions of parameters. Such models are challenging to train, require significant computing resources, and the results are often difficult to interpret. The inability to interpret rapidly varying results from a series of consecutive forecasts can represent a significant barrier to gaining confidence in the results;

(3) **Generalizability:** Fog can occur in different regions and under various meteorological conditions. Therefore, AI models need to be trained on diverse datasets to be able to generalize to new scenarios. However, collecting such datasets can be challenging, due to the general sparsity of fog data, particularly in regions lacking dense observations;

(4) **Real-time processing:** Fog forecasting is a time-critical task, and AI models need to process data in real-time to provide accurate predictions. However, deep learning models, which are commonly used in fog forecasting, can be computationally intensive, making real-time processing challenging. Bari et al. [23] applied optical flow (sparse and dense) and deep learning techniques (CNN, ConvLSTM, and Unet) to geostationary satellite images for fog/low-stratus (FLS) nowcasting. Although quantitative and qualitative comparisons indicate the superiority and greater effectiveness of DL techniques over nowcasts based on extrapolation of satellite RGB products, some limitations remain. These include the limited availability of training data, owing to the typical infrequent occurrences of FLS conditions (e.g., limited spatial coverage,

occurrences, and duration). This lack of data hinders the development of robust models, and can ultimately lead to under-performing forecasts. One strategy which can overcome these limitations consists of combining the optical flow with deep learning, leveraging the strengths of both techniques while mitigating their individual limitations (see FlowNet [24,25] and DeepFlow [26]). From a practical perspective, it is important to note the large costs associated with the download and storage of large amounts of satellite data. This represents a significant barrier to the use of this valuable source of weather information.

5. Predictability

Despite an overall improvement in weather forecasts in recent decades, errors in forecasts of fog occurrences and characteristics remain large. As outlined in the previous sections, multiple factors contribute to imposing significant limits to the predictability of fog. Among the main remaining challenges are:

(1) **The complexity of physical processes driving the fog life cycle:** Fog formation and evolution depend on a variety of factors that interact in complex ways over multiple scales, making it difficult to accurately predict occurrences and duration of foggy conditions. Furthermore, fog events can be highly localized, with only subtle contrasts delineating the presence or absence of fog. Therefore, providing accurate fog forecasts for specific locations is very challenging;

(2) **The lack of observations, particularly of small-scale atmospheric features that affect the fog life cycle:** Fog forecasting requires data from multiple sources of observations, including weather stations, satellites, and radars. In some regions, such as rural areas or developing countries, availability of this data may be limited or outright unavailable. In addition, current weather observation networks typically do not capture the variability in temperature and humidity conditions at smaller scales, such as in urban areas and mountainous regions. Furthermore, limited observations of other important features, such as water vapor distribution in the boundary layer, structure of the stable boundary layer, or properties of low clouds in the case of stratus-lowering fog events, all contribute significant uncertainties in initial NWP conditions, as well as the development of more comprehensive observation-based ML forecast models. All of these issues impose limits on our ability to forecast fog.

Recognizing these limits on fog predictability, having access to information on how much confidence can be placed on a fog forecast becomes essential for decision makers involved in ensuring safety and productivity in many socio-economic activities. Ensemble prediction systems (EPSs) have emerged as powerful tools for estimating uncertainties in NWP forecasts. By producing multiple forecasts (members of an ensemble), the dispersion characterizing the ensemble can be directly related to the uncertainty in the forecast. Another advantage of EPSs consists of having direct access to probabilistic information on the occurrence, duration, and intensity of fog events, which can help end-users make more informed decisions. For example, a local ensemble prediction system has shown significant improvement over traditional deterministic forecasts of fog in the context of a single-model forecasting system [27]. Furthermore, using a combination of multiple models, and/or perturbations of model parameterizations, and/or perturbations of initial conditions, and/or perturbations of lateral boundary conditions, EPSs can reduce the uncertainty and increase the reliability of fog forecasts. Parde et al. [28] found that their EPS produces forecasts with substantially reduced errors in predicting fog onset and dissipation (mean onset and dissipation errors of 1 h) compared to control (deterministic) forecasts.

One of the main limitations of EPSs are **the high computational requirements and data storage needs**. Ensemble systems require significant computational power and storage space to process and store large amounts of ensemble data. Such requirements represent barriers for smaller organizations to implement ensemble forecasting systems. However, the analog ensemble method is considered one of the most low-cost and intuitive ensemble methods [9]. Typically, the selection of analogs is performed from historical data only for each grid point in the study domain closest to the observation sites. Here, the authors suggest extending the search space by considering neighboring grid points to enhance the chances of finding the best analogs.

Another challenge of EPSs are **their need for constant and regular updating and maintenance of the system** to ensure that forecasts remain accurate and reliable. This can be time-consuming and costly, and requires a skilled team of meteorologists and data scientists to maintain the system.

Despite the challenges and limitations, the outlook for use of ensemble systems adapted to fog forecasting is encouraging. Advances in computing technology, including increased computational power and development of more easily accessible cloud-based computing, make ensemble forecasting systems more accessible and cost-effective. Additionally, the development of machine learning algorithms and artificial intelligence can help automate updates to and maintenance of the system, reducing the workload for meteorologists and data scientists.

6. Perspectives for Fog Decision Support Systems

6.1. Design Features of Decision Support Systems

To improve the accuracy of fog forecasting, decision support systems (DSSs) are being developed that incorporate a wide range of data sources and analytical techniques. Future fog DSSs should provide frequently updated, highly accurate, timely forecasts. DSS output should be easily accessible, as well as customizable to meet the needs of different industries and stakeholders. Incorporating machine learning and real-time data collection is believed to be key to achieving these goals. Here are some potential design features of future fog-forecasting DSSs:

(1) **Integration of Machine Learning:** DSSs could incorporate machine learning algorithms to analyze large volumes of historical and real-time data, complementing other, more traditional, algorithms, such as calculating fog indices (see, e.g., [29]). This could enhance the identification of patterns and relationships between weather conditions and the likelihood of fog formation;

(2) **Improved data collection:** The accuracy of fog forecasting can be improved by collecting more comprehensive data. This should include more precise and numerous "classical meteorological" measurements of temperature, humidity, wind speed, and direction, as well as real-time monitoring of atmospheric conditions, particularly in the atmospheric boundary layer (ABL), using more advanced sensing platforms such as ground-based remote sensing instruments (e.g., radiometers, lidars) and instrumented drones;

(3) **Improved NWP products:** Despite their limitations with respect to fog, NWP systems can provide valuable weather forecast information, which should be used as additional input in DSSs. NWP systems are continuously being improved through increased resolution, implementations of enhanced parameterization schemes, improvements to data assimilation systems, and the use of new sources of key observations. Updating DSSs to ingest the most up-to-date NWP products should prioritized;

(4) **Cloud-based architecture:** To facilitate data integration and analysis, a cloud-based architecture could be adopted. This would enable data to be more easily shared and accessed by different stakeholders, as well as providing a more scalable development environment;

(5) **User-friendly interface:** DSSs should have a user-friendly interface that provides easy access to weather data and forecast information. This would enable decision-makers to quickly and accurately assess the risk of fog formation and take appropriate actions;

(6) **Customizable alerts:** DSS should be able to generate customizable alerts that are tailored to the specific needs of different the industries and stakeholders. For example, airlines may require more detailed information on fog formation and duration, to ensure safety and efficiency of their operations.

6.2. Types of Needed Fog Forecast Information

Operational meteorologists and industry end-users may require different types of information to effectively utilize fog forecast guidance. Here are some examples of the information that could be provided to each group:

For operational meteorologists:

(1) **Model output data:** NWP models can provide information on the atmospheric conditions conducive to fog formation, including the main thermodynamic atmospheric parameters and more elaborate parameters, such as fog water content and fog index. Any changes in fog forecast should be communicated as soon as new information becomes available. In addition, providing information on the probability of fog occurrences in specific locations or over specific regions, along with the level of confidence in the forecast, could help meteorologists assess the likelihood of fog formation and provide the most useful forecast information;

(2) **Observational data and satellite imagery:** Observational data from surface and upper-air weather stations, as well as satellite imagery, can provide the most up-to-date insights into current weather conditions (e.g., information on cloud cover, occurrence of precipitation and type, and temperature gradients) and, hence, the likelihood of fog formation and evolution. The availability of historical fog climatological data can also assist meteorologists in understanding the typical frequency, intensity, and duration of fog events, providing valuable context for the current forecast;

(3) **NWP model guidance and ensemble forecasts:** Information about the various NWP models and ensembles used to generate fog forecasts should be made available, including details on their performance and skill over previous fog events, to help meteorologists evaluate their reliability. Any biases and specific performance issues should be highlighted for each of the models. Access to verification statistics, including metrics tailored to rare threshold events such as fog, should help meteorologists assess the accuracy and reliability of forecasts from the different models and, therefore, provide further guidance into their task of producing an integrated final forecast product.

For end-users:

Industry end-users are generally weather savvy, but not as highly trained as weather forecasters. Therefore, information derived from raw forecast data and tailored to be more closely related to the specific operational needs should be provided. For example:

(1) **Forecast information:** End-users require information on the timing of the onset, intensity, and duration of fog events. Information on the likelihood of visibility and/or ceiling height conditions reaching meaningful thresholds specific to operational needs is also required to assess safety risks and make informed decisions about operations in transportation, aviation, and other outdoor activities impacted by the presence of fog;

(2) **Impact assessments:** End-users may require information on the potential impacts of fog events on their operations, including transportation delays, flight cancellations, and other disruptions to industry activities. A tailored analysis of relevant cost–benefit parameters derived from weather forecast data can help end-users in their decision making process;

(3) **Recommended actions:** End-users may also require specific guidance on recommended actions to take during fog events, such as reducing driving speed, using fog lights, or altering flight plans.

Providing information on fog uncertainties in a clear and concise manner is of utmost importance for end-users, so that informed decisions are made and the societal impacts of fog events are minimized. Here are some ways to provide information on fog uncertainties:

(1) **Visual display:** End-users are more likely to understand the information when it is presented in a visual format, such as graphs, charts, and maps. Displaying information in a clear and visually appealing way help end-users interpret the data and act accordingly in a more effective manner;
(2) **Probabilistic forecast information:** Providing probabilistic information on fog parameters can help end-users make more effective and informed decisions. For example, providing information on the probability of fog occurrence, or the range of possible visibility conditions, can help end-users take necessary precautionary decisions;
(3) **Collaboration with stakeholders:** Collaborating with stakeholders, such as transportation companies or aviation authorities, can help tailor the information to their specific needs. A complete understanding of the operational needs helps determine which forecast products should be provided, and how forecast information is presented (e.g., which forecast metrics are provided). This can improve the usefulness of the information provided, and help minimize the impact of fog events on the specific activities that the various stakeholders are concerned with.

7. Concluding Remarks

A wide variety of socio-economic activities are affected by the presence of low visibility conditions. Accurate fog nowcasts and forecasts are, therefore, required by a number of stakeholders. Decision support systems (DSSs), providing the most accurate and concise information on the likelihood of fog formation, the physical characteristics (e.g., minimum visibility), and the dissipation, are emerging tools of choice by end-users. DSSs are tasked with integrating a vast amount of information from numerous observational platforms and forecast data, and produce timely fog products tailored to the specific user needs.

Recent developments, including the ones reported in this Special Issue, have highlighted the importance and limitations of key components of any DSS. Despite the limitations, related to fog in particular, due to the resolution, deficient physical parameterizations, and initial conditions, forecast data from NWP systems remain a primary source of forecast information. The continuous improvement in NWP models and data assimilation systems, including the input of new sets of observations, is greatly encouraged. However, additional efforts beyond this traditional approach are strongly recommended. For instance, in recognition of the severe limits of fog predictability, the further development and greater exploitation of ensemble forecast systems should be considered, including their application at the mesoscale and beyond. The availability of probabilistic forecasts, and the ability to integrate the estimated confidence levels in fog forecasts into the decision-making processes, should be central parts of any DSS. Furthermore, the integration of AI/ML algorithms should be considered for fine-tuning NWP forecast outputs, and also for the production of additional observation-based local fog nowcasts. These can complement the existing NWP guidance by providing fast, up-to-date nowcasts. However, in order for this to be successful, issues related to the training and validation of algorithms in the case of rare events, such as fog, should be addressed to ensure more robust forecast results. Furthermore, the formal identification of which observations are critically needed to enhance fog nowcasts and forecasts should be undertaken, and the potential deployment of additional observations, and possible development of new observational platforms, should be considered. Finally, the design of DSS code infrastructure and interfaces should be carefully considered, for (1) efficient integration of large volumes of data, (2) for ease of access and analysis of forecast guidance and algorithm performance, (3) to effectively translate forecast data into estimates of operational impacts and action recommendations, and (4) for adaptability to the various needs of end-users.

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