ARTICLE IN PRESS

International Journal of Forecasting xxx (xxxx) xxx

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

Epidemiological versus meteorological forecasts: Best practice for linking models to policymaking

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ARTICLE INFO

Keywords:
Forecasting
COVID-19
Weather
Climate
Disasters
Risk
Communication
Vulnerability
Uncertainty

ABSTRACT

Weather forecasts, climate change projections, and epidemiological predictions all represent domains that are using forecast data to take early action for risk management. However, the methods and applications of the modeling efforts in each of these three fields have been developed and applied with little cross-fertilization. This perspective identifies best practices in each domain that can be adopted by the others, which can be used to inform each field separately as well as to facilitate a more effective combined use for the management of compound and evolving risks. In light of increased attention to predictive modeling during the COVID-19 pandemic, we identify three major areas that all three of these modeling fields should prioritize for future investment and improvement: (1) decision support, (2) conveying uncertainty, and (3) capturing vulnerability.

From sporting events to stock market investments, predictive models are widely used by politicians and the public alike to inform decisions. Predictive epidemiological models of COVID-19 have been in the public eye since early 2020, forming the basis of major national and international public health and wider policy decisions (Rhodes & Lancaster, 2020). Weather forecasts are used for a range of public health and public safety actions, including mass evacuations (Climate Centre, 2020) and heatwave early action (Joy Shumake-Guillemot, WHO/WMO Joint Office for Climate and Health, 2020). In addition, climate change is increasingly recognized as a driver of more frequent and severe extreme weather events, and climate modeling

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https://doi.org/10.1016/j.ijforecast.2021.08.003
0169-2070/

informs policymaking on both greenhouse gas mitigation and adaptation to a changing climate. Given the challenge of managing compound risks of extreme weather events and outbreak response for COVID-19, decision support tools to anticipate their combined impact will also be required (Phillips et al., 2020).

While in some cases data from (i) weather forecasts, (ii) climate change projections, and (iii) epidemiological predictions are combined in specific decision-making arenas, for the most part, these three modeling communities operate in isolation, despite many similarities in terms of analysis and communication of model results. This perspective identifies best practices from each of these three domains that can be adopted by the others. These best practices are relevant to each domain separately but are also an essential building block toward more integrated early warning and risk management systems to mitigate compounding risks.

Based on recent events, we identify three major areas that all three of these modeling fields should prioritize for future investment and improvement: (1) decision support, (2) conveying uncertainty, and (3) capturing vulnerability.

1. Decision support

One of the most critical functions of modeling efforts is to inform policies and individual decisions; however, each field tends to focus on prediction as an end in itself. This includes both forecasting and scenario analysis. Forecasting tends to assign probabilities to possible future states; while scenario analysis is often an exploratory tool to test the outcomes of a set of conditions, independently of how likely they are to come to pass.

In the meteorology domain, weather forecasts traditionally focused on descriptive modeling of the physical atmosphere (e.g., 10 mm of rain). In recent years, weather forecasters have begun to provide impact-based forecasts, moving from predictions of what the weather will *be* into predictions of what the weather will *do*, enabling anticipatory actions (WMO, 2015). Weather forecasts are a tool for both the public sector and private sector, with private companies having long understood their value for industries such as insurance, transport, agriculture, and energy (Pirone, 2007; Spiegler, 2007).

When it comes to climate change projections, climate scientists use emissions scenarios to map out how the climate is likely to respond to societal changes over the coming decades. However, such modeling efforts are not generally directly linked to decision-making options (Sutton, 2019). Modeling work in support of the Intergovernmental Panel on Climate Change (IPCC) offers an example of good practice, in which projected risks are linked with scenarios and risk management options outlined in the United Nations Framework Convention on Climate Change. Some climate projection modeling analyses have been linked to interactive user interfaces, which allow users to test different policy options (e.g., http://tool.globalcalculator.org/).

In contrast, epidemiological models can be linked more directly with decision support to assess the impact of interventions or their removal (Davies et al., 2020). Many models being used in the COVID-19 crisis were developed for decision support, and some of them have incorporated graphical user interfaces to enable decision-makers to better understand the consequences of different policy choices and other influences that are likely to affect the pandemic's trajectory. The EPIFORGE guidelines include a requirement to comment on implications for public health action. These models involve scenario-based methods to enable the user to examine different trajectories and possible outcomes, without explicitly providing forecasts, or any quantification of how likely different scenarios are to become reality. Some examples include:

- Imperial College London's COVID-19 Scenario Analysis Tool
- University of Washington Institute for Health Metrics and Evaluation's Projections Scenarios
- Centre for Mathematical Modelling of Infectious Diseases at the London School of Hygiene and Tropical Medicine's COVID-19 Transmission Model

Epidemiological forecasts, on the other hand, aim to explicitly quantify the probability of different future trajectories of a pandemic. Because of inherent uncertainties in policy, individual behavior, and the many other factors influencing transmission, they are usually focused on the very short term, considering a few weeks into the future. Because these forecasts are meant to be interpreted as genuine predictions, they can later be confronted with the true events to assess their accuracy (Held, Meyer, & Bracher, 2017, Funk, Camacho, Kucharski, Lowe, Eggo, & Edmunds, 2019) (see Table 1).

In many cases, decision support models allow for additional insight into and learning about complex socio-ecological systems (Sterman, 2010). Models can allow for the ongoing integration of new observations about the systems being modeled and their responses to various stimuli, including efforts at systems management. This process, which has been relatively well developed in the management of certain socio-ecological systems, is commonly referred to as adaptive management (McLain & Lee, 1996), and the framework has been extended to a range of domains, including water (Pahl-Wostl, 2007), fishery management (Wilson, Ahmed, Siar, & Kanagaratnam, 2006), health (Hess, McDowell, & Luber, 2012; Ebi, 2011), and among others.

Because decision-support models are critical for public benefit, we argue that such models and related adaptive management practices should be further developed with attention to operational mandates and design procedures.

An important challenge for each of these fields in the context of data for decision support is there are no clear mandates about who should build and run decision models operationally and how models should be updated and maintained. For example, while there are clear mandates for meteorological services to predict weather variables (e.g., temperature/rain), the leading crop models are run by private enterprises, and cutting-edge COVID-19 modeling is housed at several universities. There are no clear guidelines for how experts or citizens should contribute to the development of these models (Kleinschmit,

Table 1
Example of forecasting initiatives and scenario analyses in meteorology and for COVID-19.

	Meteorology/climatology	Epidemiology
Forecasting initiatives/models	European centre for medium-range weather forecasts	COVID-19 forecasting hub
Scenarios/projections	Coupled Model Intercomparison Project (CMIP)	COVID-19 international modelling consortium (CoMo consortium) COVID-19 scenario modeling hub

Pülzl, Secco, Sergent, & Wallin, 2018). Model development should be transparent, reproducible, and easy to interpret. Several sets of principles have been offered to guide this, including the FAIR principles (findability, accessibility, interoperability, and reusability) (Wilkinson et al., 2016) or the principles of salience, credibility, and legitimacy (Cash et al., 2002).

The choice of policy options included in these models is entirely at the discretion of the researcher or designer, who include possibilities they deem feasible and worth exploring (Chowdhury, Kabir, & Tanimoto, 2020); though in many cases, decision models are considered public goods to some degree, and thus designers solicit and are to some degree beholden to stakeholder input. While models are often expensive to run, having a small set of experts determine all possible societal decisions that should be modeled can unnecessarily constrain the policy space and limit the possibilities for learning about complex systems and their management. In the design of these models, the diversity of model developers and stakeholders with management interests is critical, and model developers need to be properly advised by subject matter experts and end-users. In epidemiological modeling for decision-support models, modelers should consider not only biases embedded in the algorithms, but also the appropriateness of the non-pharmaceutical interventions and uncertainties associated with assumptions related to human behavior.

2. Estimating and communicating uncertainty

In meteorology, climate science, and epidemiology, modelers face the challenge of appropriately assessing and communicating uncertainties around their predictions, which is especially challenging for events that have not been experienced in human memory, such as novel strains of virus or a category 5-hurricane hitting New York.

While weather forecasts originally provided deterministic predictions (e.g., it will rain 10 mm tomorrow), they have moved gradually to focus on probabilistic information (e.g., 80% chance of at least 10 mm of rain tomorrow). Longer-term climate projections take the form of scenarios. The decision science and welfare economic literature provide a strong basis for drawing best practice in how uncertainty is characterized and managed; as an example, such best practice was used to design hurricane scenarios for the USA and the Thames Barrier in the UK (Ranger & Niehoerster, 2012; Ranger, Reeder, & Lowe, 2013).

Here, we offer several best practices in estimating uncertainty and communicating uncertainty in a transparent way for decision-making.

Meteorologists have developed some of the most advanced techniques for quantifying uncertainty in their forecasts of physical variables: ensemble forecasting. This is where multiple plausible iterations ('members') of each model are run with slightly different initial conditions to produce an 'ensemble' or range of different possible future outcomes from which statements about the uncertainty in the forecast (e.g., of the chance of rain) can be derived (Gneiting & Raftery, 2005; Zhu, 2005). This ensemble approach is used to represent the state of knowledge or uncertainty in aspects such as the initial observed state of the atmosphere or in the model structure. A calibrated weather forecast ensemble can be relied upon to provide a robust probability distribution, although for extreme weather events this is more challenging (Stephenson, Casati, Ferro, & Wilson, 2008).

However, for long-term climate change projections (e.g., for the coming decades, or even until the end of the century), it is difficult to verify how well models perform, because there is only one future that has not yet happened. To estimate uncertainty, modelers use a set of different climate models, comparing their projections to each other's and to the past (Stephens, Edwards, & Demeritt, 2012). Climate modeling experiments such as the Coupled Model Intercomparison Project have been used for this purpose. However, multi-model ensembles such as CMIP have a poor experimental design, since the choice of model is not random or systematic, or independent from the others (Knutti, 2010). One way of dealing with this is to quantify the uncertainty in the model design choices themselves, which has been proposed as a method for hydrological model intercomparisons (e.g., Clark et al., 2015).

For both weather forecasts and climate change projections, the techniques applied to quantify uncertainty focus on the predictions of physical variables. However, including climate impact estimates adds substantial uncertainty (e.g., Li et al., 2015). In COVID-19 and other epidemiological modeling, input uncertainties (e.g., case numbers and associated delays between symptom onset and reporting) are compounded by uncertainties about human behavior (e.g., compliance with restrictions) and underlying socio-economic vulnerabilities, which are difficult to test (Currie et al., 2020).

Multi-model comparison and ensemble modeling were traditionally rare in the epidemiological world but have recently seen increased use (Johansson et al., 2019). Many insurance products, such as the Pandemic Emergency Financing Facility (PEF), are based entirely on a single model. Individual epidemiological models can struggle with basic calibration of their input parameters and appropriate quantification of uncertainty (Punyacharoensin et al. 2011, McGowan, Grantz, & Murray, 2021). In many cases, the results that are communicated to the public are single-outcome results for any given decision choice, without showing the range of possible outcomes. This can cause misunderstandings and frustration among those making decisions using these models.

In all cases, we recommend that the use of multi-model comparisons and ensemble modeling become standard practice to estimate uncertainty. For example, the US Centers for Disease Control and Prevention (CDC) provides multi-model estimates for COVID-19 deaths, which are made available to the public. There has been a focus on multi-model collaborative forecasting efforts set up in a range of countries (e.g., Bracher et al., 2020; Faggio & Peracchi, 2020; Ray et al., 2020; Bicher et al., 2021), based on the insight from other diseases and other fields including meteorology that creating an ensemble from multiple models usually improves the quality of forecasts (Palmer, 2002; McGowan et al., 2019; Reich et al., 2019). The recently formed COVID-19 scenario hub aims to use insights to improve long-term scenario modeling (Shea et al., 2020). Monitoring systems need to be set up ahead of time to collect relevant data for forecast verification and calibration of these uncertainty estimates. When there is model disagreement, mechanisms should be in place to facilitate dialogue among experts, to uncover the sources of uncertainty, and to facilitate communication of uncertainties to the public (Beebe, Baghramian, Drury, & Dellsen, 2019).

Once uncertainty is estimated, this needs to be communicated clearly and transparently to the public. There is a common perception that communicating uncertainty in projections can confuse decision-makers and the public. However, several stakeholder engagement studies led by the weather forecasting community have shown this not to be true (e.g., Stephens, Spiegelhalter, Mylne, & Harrison, 2019). In fact, the EPIFORGE guidelines for epidemic forecasting include a requirement to present and explain uncertainty in forecasting results. Robust decision-making techniques have been developed in the field of climate change to enable people to make choices when there is a wide range of possible scenarios of how the future might evolve. For example, Shi, Hobbs, and Jiang (2019) evaluate decision models for 12 adaptation options in the Chesapeake Bay, Hallegatte and Lempert (2012) offer deep uncertainty methods for World Bank investments, and Haasnoot, van't Klooster, and van Alphen (2018) describe a Dynamic Adaptive Policy Pathway for the Delta Program of the Netherlands. These techniques emphasize what could realistically happen in the future, and help people make choices today that are robust to the aspects that might vary across possible future outcomes. These approaches are also consistent with an adaptive management framework that emphasizes and supports ongoing learning about system dynamics and the impact of management decisions. Such techniques can be applied more widely in the use of meteorological and epidemiological models.

Within weather, climate, and epidemiological modeling, the presentation of predictive analytics and model results for societal decision-making should acknowledge what we do and do not know and be transparent about what is included and not included in the model itself. Estimating and communicating this uncertainty would allow for experts to clearly express and acknowledge sources of disagreement, leaving the onus of decision-making on the policymakers.

3. Capturing vulnerability

While minimizing overall damages or maximizing benefits is a common goal of most modeling efforts, protecting specific vulnerable populations is often a high priority for policymakers. One of the most critical elements of modeling societal outcomes is capturing the differential outcomes for different groups in society. For example, many epidemiological models are constructed to allow for different outcomes for groups with different vulnerability characteristics such as the age bracket, which accounts for outcomes that can be radically different depending on people's underlying age-related vulnerability.

Greater attention needs to be paid to this type of differentiation, both in model design and in the communication of model results to society. Several multi-model collaborative forecasting efforts have been set up in a range of countries (e.g., Bracher et al., 2020; Faggio & Peracchi, 2020; Ray et al., 2020; Bicher et al., 2021), based on the insight that creating an ensemble from multiple models usually improves the quality of forecasts (Palmer, 2002; McGowan et al., 2019; Reich et al., 2019). Forecasters can identify risk management priorities at the outset, and incorporating updated priorities as modeling efforts continue. This can greatly facilitate communication of model results. For COVID-19, most model results were communicated as a single rate of transmission per country or region, without distinguishing between neighborhoods or different demographic groups. Certain populations might also have a higher case fatality rate (CFR), and projections of caseload or deaths over large geographical areas mask these variations among vulnerable populations and obscure opportunities not only to reduce morbidity and mortality through focused testing and early treatment but also to intervene and reduce transmission in hotspot populations.

However, we recognize that detailed breakdowns are hindered by a lack of data in many regions, and qualitative commentary on vulnerability might be the only option when it is not possible to quantify differential transmission rates among groups of people. Lack of data is a particular handicap in epidemiological forecasting, in which data collection and observing systems are nonexistent in many areas, and forecasting needs to happen in real-time during a crisis. In comparison, the weather and climate fields have benefitted from satellite data, for example, to complement gaps in on-the-ground data collection.

Applying the same principle in weather forecasting, a transition is taking place from only forecasting atmospheric variables, such as temperature, wind, and precipitation, to so-called impact-based forecasting. For such impact-based forecasts, understanding differential vulnerabilities are critical (Harrowsmith et al., 2020). For instance, in the case of storm warnings, it is important to know that wind speed above a certain threshold might destroy thatched-roof homes but might not destroy brick homes. The expected impact, which does not just depend on the hazard itself, dramatically changes the type of warnings that need to be given in different places and for different groups.

Collaboration with societal partners is critical to identify these differential vulnerabilities and determine the levels at which warning information should be communicated to different groups. This will also be impacted by the error tolerance that different groups have for false alarms or false negatives (Lopez et al., 2020); for example, in both the weather warning community and in outbreak preparedness, decision-makers often prefer to have more false alarms than missed events (Lowe et al., 2016). Policymakers and societal representatives should dialogue with modelers about how model results can directly inform appropriate choices in different vulnerability contexts, from evacuations to non-pharmaceutical interventions for COVID-19 (Faye, 2020). Rostami-Tabar et al. (2020) include several recommendations to ensure that forecasting is driven by social and environmental goals and priorities.

4. Conclusions

The COVID-19 pandemic has generated a surge in interest in epidemiology, which has been elevated from a niche technical field into the mainstream. Epidemiology, at its core, is a way to forecast disease progression and predict the impact of interventions in order to support policymaking. In this sense, it is very similar in purpose to meteorological or climate modeling, in that it aims to support government preparedness in order to mitigate the effects of disasters. Both fields of research also have a high tolerance for false positives, in that policymakers prefer to err on the side of preparedness. However, these two fields have developed forecasting methodologies somewhat independently of each other, even though they share similar objectives. This proposes that each field can borrow methods from the other, in order to enhance their robustness and usefulness during crises.

With increasing investments in weather forecasts and disease prediction, we urge researchers and practitioners to adopt these three areas of best practice: (1) decision support, (2) conveying uncertainty, and (3) capturing vulnerability. To ensure the best outcomes for vulnerable groups, investment priorities should include decision-support tools, multi-model approaches, data gathering to verify and calibrate models, robust decision-making approaches, and regular vulnerability assessments. We also need to invest in collaborative decision-making and intentional learning about complex systems to more quickly gain and apply insights from modeling efforts. Research is needed to test outcomes of cross-disciplinary collaboration on model development and communication; we hypothesize that collaboration among forecasters from these different disciplines would improve outcomes in each field.

Technically competent modeling is sometimes considered the end goal, but this is a shortsighted aim. Better models do not automatically translate to better outcomes. Even with the most sophisticated cholera models, for example, forecast-based interventions cannot eliminate cholera. Long-term investments are needed to improve environmental hygiene, health systems and governance. Improvements to modeling need to be coupled with investments in infrastructure, governance, and incentives to take appropriate action. Co-design and participation of policymakers and vulnerable groups can help highlight these critical areas for investment, so that forecast-based action can help people avoid unnecessary devastation, loss, and suffering.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

E Stephens and E Coughlan de Perez acknowledge support from the UK's Natural Environment Research Council (NERC) and Foreign, Commonwealth and Development Office through the FATHUM (Forecasts for AnTicipatory HUManitarian action, grant number NE/P000525/1) project, part of the Science for Humanitarian Emergencies and Resilience (SHEAR) research programme. R Lowe was supported by a Royal Society Dorothy Hodgkin Fellowship. S Funk is funded by the Wellcome Trust (210758/Z/18/Z).

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