

7

WEATHER FORECASTS

Up to one week in advance

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Home without boots, and in foul weather too!
How scapes he agues, in the devil's name?

Henry IV Part I by *William Shakespeare*

7.1 Introduction

A waiter at a dinner party once asked the Greek philosopher Socrates:

'Are you, Socrates, the one people consider the Expert?'
'Well, is that not better,' Socrates replied, 'than being considered the Idiot?'
'It would be were you not considered an expert meteorologist.'

(Xenophon, *Symposium* 6)

Of course, in Socrates's time, a 'meteorologist' was not quite the physics nerd that we may imagine today, but regardless of what 'meteorologists' are expert at, they have had bad reputations for centuries. Whereas Socrates was criticized for encouraging speculative and subversive thinking, today meteorologists are criticized from a sense that their weather forecasts are not as accurate as they should be.

Notwithstanding these negative public perceptions, weather forecasters have long been partners with public health practitioners involved in disaster management associated with extreme events. However, it is only relatively recently that weather forecasts have been considered as a public health tool. In recent years, National Meteorological and Hydrological Services (NMHSs) have helped develop tailored health forecasts designed for routine use by the public, hospital managers and general practitioners (GPs).¹ These forecasts provide early warning of increases in illnesses that may be linked to changes in the weather – such as heart attacks,

strokes, respiratory diseases, infectious diseases and broken bones. For example, the UK Met Office, in collaboration with the UK's National Health Service, has developed a weather-based alert system for Chronic Obstructive Pulmonary Disease (COPD), which has been shown to reduce hospital visits.² Such tailored forecasts can only be created in partnership with health specialists, meteorological agencies and health authorities. As another example, the Shanghai Meteorological Bureau has established co-operative agreements with many partners including: the Shanghai Food and Drug Supervision Administration for joint release of warnings of bacterial food poisoning; and the Shanghai Health Bureau and the Shanghai Municipal Center for Disease Control and Prevention for joint dissemination of heat wave information and human health monitoring and warning systems.³ Such partnerships are becoming more common, indicating a significant recent shift in the long history of public distrust of weather forecasters.

In this chapter, we examine how weather forecasts (see Box 7.1) are made and how they may be used by the health sector. We explore why, where and when we might obtain good forecasts and why sometimes the forecasts go wrong. We consider the theoretical and practical constraints on weather forecasts and why their accuracy declines rapidly after only a few days. Knowing the limitations of weather forecasts helps us to learn how to make best use of such information.

7.2 Why weather forecasts may be useful to the health community

Weather forecasts are particularly valuable in predicting *hazardous* weather conditions that put lives at risk, including the hydro-meteorological disasters outlined in Table 2.1 in Chapter 2. Forecasts of heavy rainfall may provide early warning of floods and landslides enabling early evacuation of at-risk households. They may also indicate relief to firefighters combatting wildfires. Storm warnings give time for individuals to seek shelter and authorities to prepare relief. For example, fishermen on Lake Victoria have long been vulnerable to localized storms; weather forecasts are now playing an increasing role in keeping them safe.⁴ Dust-storm warnings indicate reductions in visibility and air quality and encourage people (especially children) to stay indoors to avoid respiratory problems such as asthma or bacterial meningitis (see Case Study 7.1). Warnings of cyclones (including hurricanes, typhoons, and winter storms; § 4.2.8), which can have devastating effects over large areas, may result in the mass evacuation of populations or the shutdown of significant economic activity.

Forecasts of extreme and persistent temperatures (both heat waves and cold snaps) provide warnings of *inhospitable* weather conditions for which local populations are not adapted and where, without some form of protection, human survival will be compromised. Following the 2003 heat wave in Europe, which resulted in the deaths of over 70,000 people,¹⁰ Heat Early Warning Systems (HEWS) were established in many countries.¹¹ To be effective a HEWS must be based on locally determined critical meteorological thresholds, above which the adverse impacts of heat begin to escalate. Such thresholds vary from region to region according to

BOX 7.1 WEATHER AND CLIMATE FORECASTS

A *weather forecast* can be a statement of:

- What the atmosphere will be like at a specific time in the future (although the exact time of day may not be specified); for example, at the time of writing, the temperature tomorrow is predicted to drop to -1°C in New York, and snow is expected (with a probability of 80%).
- A specific atmospheric state at some uncertain time in the future; for example, at the time of writing (on a Thursday) a winter storm is expected to affect New York sometime around Monday or Tuesday next week.

A *climate forecast* is a statement about the general state of the atmosphere over a prolonged period, but makes no mention of what the weather will be like at any particular time during that period.

Weather and climate forecasts consist of:

- A *predictand*: the specific meteorological parameter (§ 4.2) that is being predicted, and that must be measured or estimated to test how accurate the forecast was. For a weather forecast, the meteorological parameter is often expressed as a maximum or minimum (in the case of temperature) or a total (in the case of precipitation); for a seasonal forecast, some aggregate (e.g., an average, an accumulation, a count) of the meteorological parameter is used. Sometimes the predictand is a specific weather phenomenon, usually hazardous, such as a tornado or storm, which must be described using multiple meteorological parameters.
- A *time- or target-period*: the period for which the forecast applies. A weather forecast typically refers to a specific date or time of day, whereas a seasonal forecast refers to a specific year and a three- or four-month period.
- A *lead-time*: the gap in time between the date the forecast is made and the start date of the period being forecast. The lead-time is how long you have to wait before the time the forecast is targeting begins. For example, if it is noon now, a weather forecast for tomorrow afternoon has a lead-time of 24-hours; if it is early March, a seasonal forecast for April–June will have a lead-time of about one month. Together, the lead-time and the time-period determine the *range* of the forecast. The range indicates how far into the future the forecast extends. The World Meteorological Organization (WMO) has set definitions of various forecast ranges (Table 7.1). According to these definitions, seasonal forecasts (Chapter 8) are examples of long-range forecasts, whereas sub-seasonal forecasts (Box 7.5) are examples of extended-range weather forecasts.
- An *indication of the uncertainty*: a forecast is most useful if it involves: a) a statement of what is expected to happen, as well as b) an indication of

how confident the forecaster is. There are different ways of communicating this degree of confidence (see Box 7.4).

TABLE 7.1 Definitions of meteorological forecasting ranges

<i>Range</i>	<i>Definition</i>
Nowcast	0–2 hours
Very short-range weather forecast	< 12 hours
Short-range weather forecast	12–72 hours
Medium-range weather forecast	72–240 hours
Extended-range weather forecast	11–30 days
Long-range forecast	30 days–2 years

Source: WMO³

CASE STUDY 7.1 DUST STORM IMPACTS ON HEALTH

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Dust storms are meteorological hazards that arise when strong winds blow loose sand and dust from a dry surface. They affect many arid and semi-arid regions of the world including North Africa and the Sahel, southern Europe, the Middle East, central and East Asia, Australia and the western United States. The airborne dust emitted from these regions is a key atmospheric constituent and represents an important natural source of atmospheric particulate matter. Dust impacts the climate, the weather, ecosystems and air quality (and consequently economic activities and human health). The Sand and Dust Storm initiative of the World Meteorological Organization⁵ brings together global researchers and operational meteorologists whose models of dust emission, transport and deposition are used to predict dust storms days before they occur; providing authorities with several days' lead-time to take mitigating actions.

The region in the world most impacted by dust storms is the African Sahel. Much of the dust that forms the dry season storms originates in the ephemeral lake beds of the Bodélé Depression in Chad. Transported on the north-easterly Harmattan trade-wind (that blows from the Sahara into the Gulf of Guinea) these fine mineral particles are a risk factor for a wide range of health issues including cardiovascular disease and respiratory problems.

Dust has long been suspected as a risk factor for epidemic meningococcal meningitis, an infectious bacterial disease that is particularly common in the Sahel during the dry season. In 2007 the Meningitis Environmental Risk Information Technologies (MERIT) initiative, led by the World Health Organization, was established to identify opportunities for health and climate/dust scientists to work together to develop a meningitis epidemic early warning system for

the Sahel.⁶ The prediction of epidemics is challenged by the lack of spatially and temporally resolved near-real time information on the levels of carriage of the bacteria, population immunity and serogroup type and virulence. Although weather/climate and other environmental data contain uncertainties, they have shown the potential to improve meningitis forecasting. Several studies have established that statistical models including weather and dust aerosol data as inputs, could potentially forecast the risk of epidemics, saving lives and effectively allocating scarce vaccine resources.^{6–8} A study in Niger⁹ used a combination of epidemiological data and mechanistic studies in mouse infection models to investigate the link between climate and invasive bacterial disease. Disease surveillance and climate monitoring revealed that high temperatures and low visibility (a proxy for dusty air) were significant risk factors for bacterial meningitis and that the bacteria *Streptococcus pneumoniae* was more invasive in mice exposed to dust or heat. The dust effects were associated with a reduced ability of white blood cells to direct bacterial killing while high temperatures increased the release of damaging bacterial toxins.

the climate and the vulnerability of the local population and can be determined through research using local climate and health data,^{12,13} or through surveys and community consultations.¹⁴ Weather forecasts can then be tailored to indicate the likelihood of reaching these thresholds, and should be issued at lead-times appropriate to the local capacity to take action, within the limits imposed by forecast skill (see Box 7.2 and 7.3 and Case Study 7.2). A set of standard operating procedures outline the measures to be taken in response to the forecasts. These procedures vary depending on vulnerable population groups, the local capacity of stakeholders to respond, the available resources and the skill of the forecast.

BOX 7.2 SUB-SEASONAL FORECASTS

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A timescale of great interest is the sub-seasonal one, typically involving forecasts of weekly averages of variables like rainfall or temperature, a few weeks ahead. Sub-seasonal forecasts are particularly relevant to the prediction of heat waves – providing a potential bridge between seasonal risk assessments, seasonal forecasts and weather warnings (see Box 7.3).

Lead-times of sub-seasonal forecasts are long enough that much of the information in the initial conditions is lost, but at the same time are too short for other sources of predictability (such as sea-surface temperatures) to have a strong influence. Presently, sub-seasonal skill is limited, and in general sub-seasonal forecasts cannot yet be used to develop climate services. There are different physical processes that are sources of predictability at sub-seasonal-to-seasonal timescales. These processes include: interactions between the tropics and the extra-tropics that are related to tropical heating;

persistent weather patterns, like blocking; persistent oceanic conditions in the extra-tropics and the tropics; persistence of soil moisture anomalies affecting the overlying air; large-scale weather patterns like the Madden-Julian Oscillation (MJO, see Box 5.2); interactions between different weather and climate phenomena acting at multiple timescales, e.g., MJO and the El Niño – Southern Oscillation (ENSO, see Box 5.1), can enhance skill compared to when they are acting independently.¹⁵

BOX 7.3 POTENTIAL USE OF SUB-SEASONAL FORECASTS IN HEAT EARLY WARNING SYSTEMS

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Skilful forecasts are an essential building block of a HEWS, but for these forecasts to be actionable they must be tailored to the needs of decision-makers, focusing on critical thresholds, provided on appropriate lead-times, and calibrated for reliability so that forecast confidence can be easily interpreted.

Many risk reduction actions require more advanced warning than the few days provided by weather forecasts. Table 7.2 illustrates some of the measures that could be taken if heat wave forecasts could be made available on longer lead-times. In some ways, heat waves present a good test case for the use of sub-seasonal forecasts, which are currently only experimental, in early warning systems. Adaptation measures for hydro-meteorological hazards like flash floods tend to involve costly actions like evacuations and flood defence reinforcements. In contrast, there are many low-cost, no-regret adaptation options appropriate to cope with extreme heat, from training for health staff and social workers, to procuring emergency drinking water and contingency planning for outdoor sporting events. Furthermore, predictability of heat waves has been demonstrated on sub-seasonal timescales for several regions including Europe, South Asia and the United States.^{12,16,17}

At longer lead-times, reliable probabilistic forecasts (Box 7.4) become even more critical for an effective early warning system. Reliable forecasts are essential because they allow decision-makers to pair appropriate actions with forecast skill. Low-regret interventions such as recapping emergency response procedures or closely monitoring weather forecasts can be paired with weak probability forecasts. Actions that incur a higher cost, which might include rescheduling outdoor sporting events or setting up emergency drinking water stations, can be contingent on a higher probability trigger.

TABLE 7.2 Actions that could be taken in response to heat wave warnings at different timescales (sub-seasonal is in *italics* as it indicates potential only)

<i>Ready</i>	<i>Set</i>	<i>Go</i>
Seasonal risk	Higher risk in next month	Imminent risk
Actions to take every year before the at-risk season	Actions to be taken following sub-seasonal climate forecasts (if and when available)	Actions to be taken following a weather alert
Review average heat risk across season	<i>Monitor weather forecasts closely</i>	Prepare utilities for increased power demand
Access seasonal forecast	<i>Re-cap emergency action plan</i>	Prepare to open cooling centres
Update heat action plan	<i>Inform schools</i>	Begin mass media and public awareness campaign
Review communication strategies	<i>Inform cooling centres</i>	Distribute emergency drinking water
Refresh medical and media training	<i>Reinforce co-ordination with disaster management personnel</i>	Alert hospitals to increased demand
Prepare contingency plans for events	<i>Distribute appropriate advice through media</i>	Reschedule hospital staff shifts
Supply routes for backup water and generators	<i>Procure emergency drinking water</i>	Check in on elderly
Coordinate with utilities to ensure continued power supply		Reschedule sporting events

CASE STUDY 7.2 HEAT ACTION PLANS AND EARLY WARNING SYSTEMS HELP SAVE LIVES IN INDIA

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India currently faces a challenging array of climate-health threats, and among the most prominent are heat waves. Heat waves in 2010 and 2015 killed thousands of people in India. The Public Health Foundation of India (PHFI) and the Indian Institute of Public Health-Gandhinagar (IIPH-G), in partnership with the Natural Resources Defense Council (NRDC), and under the leadership of the Ahmedabad Municipal Corporation (AMC), have successfully developed a set of strategies to counter the health challenge of extreme heat. The first municipal Heat Action Plan (HAP) and heat early warning system in South Asia was launched by AMC with the help of NRDC, IIPH-G and partners in the western Indian city of Ahmedabad, in Gujarat state, in 2013.¹⁴

The heat early warning system initially produced probabilistic forecasts of maximum temperature, together with probabilities that the temperature

would reach specific mortality-determined temperature thresholds. The thresholds applied in the pilot plan were based on group consensus after analysis of the 2010 heat wave mortality and temperature data. Initially, probabilistic forecasts had a seven-day advance lead-time, which was identified during initial planning discussions with AMC as most useful to provide early warning and mount a coordinated public health and inter-agency response.

The daily temperature forecasts were sent via e-mail alerts to the AMC's 'nodal officer' who served as point person on inter-agency notification and coordination. Besides daily maximum temperatures, a second panel on the forecasts provided a summary for the previous seven days, which was intended for decision-makers' use to show forecast consistency and highlight recent heat threat levels.

After a successful 2013 pilot phase, by 2016 another ten additional cities had adopted the Ahmedabad HAP developed by NRDC and partners to prepare for extreme heat, raising the numbers of people served by these HAPs from seven million to 15 million. By mid-2017, 17 cities and 11 states had adopted or were developing HAPs in India. At the national level, the Indian Meteorological Department (IMD) and the Indian Meteorological Society (IMS) have stepped up with five-day maximum temperature deterministic forecasts expanded to over 300 cities, enabling many more cities to build local HAP pilot projects, even without the probabilistic forecast features. The National Disaster Management Authority (NDMA) has issued new national guidelines and television advertisements in local languages focused on protecting communities from extreme heat.

The municipal framework for protecting communities from the health effects of extreme heat is also being adapted to the State level. Key components include developing an early warning system, building capacity among public health professionals in the state, building community and public awareness, and effective interagency coordination with support of the disaster management authorities. By helping partners in India to implement state-level HAPs, NRDC's goal is to help protect the health of hundreds of millions from heat-health threats. This work is enhancing climate resilience in India, reducing heat vulnerability today and for the future, and helping to save lives.

Forecasts of *unhealthy* weather (poor air quality) are now common in many cities around the world. Under certain circumstances, meteorological conditions promote ozone production and, combined with atmospheric pollutants and dust, create a toxic environment for plant, human and animal respiration. Forecasts of air quality are increasingly important in many urban environments.¹⁸

Finally, forecasts may be for weather conditions that are *suitable* for supporting a wide range of pathogens, pests and diseases that are important for crop production and/or human and animal health. When considering the development of a weather-driven health forecast system, it is important to consider exactly what weather parameter needs to be forecasted. It is also important to know exactly how good forecasts

are (Box 7.4) because weather forecasts may result in expensive and time consuming responses for individuals, communities, government agencies and private businesses.

Accurate weather forecasts can provide a timely warning of a weather event with potentially severe health consequences. The lead-time for action provided by the forecast is critical to its potential value. Tornado warnings may provide minutes of valuable time for individuals to shelter in their basement, while hurricane warnings provide several days for hospitals to move critical care patients away from the storm's likely path.

With a good climate monitoring system in place, confident early warnings of lagged health impacts (such as vector-borne disease epidemics) may be possible (see § 3.4). The added lead-time provided by weather forecasts in predicting the meteorological triggers of lagged health events may not be worthwhile. They often do not add much lead-time to the monitoring information and, of course, they are less certain than observing the weather event itself. Weather forecasts may, however, still be useful in predicting potential problems in the supply chain that is needed to respond to lagged events. For example, weather forecasts may be useful for anticipating possible damage to infrastructure (e.g., washed-away bridges) from rain-induced flooding, which may result in disrupted supply chains for commodities (drugs, drips, protective gloves, etc.) needed to counter an epidemic. Knowing the accuracy or reliability of the forecasts is a prerequisite to identifying the best ways of managing the risk (the distinction between accurate and reliable forecasts is explained in Box 7.4).

BOX 7.4 MEASURING HOW GOOD (OR BAD) FORECASTS ARE

The measurement of how well forecasts compare with the observed outcomes is called *forecast verification*.¹⁹ Measuring how good a forecast is (or a set of forecasts are) is a field of scientific research in its own right.²⁰ Here we provide only the briefest introduction to some of the most important terms and concepts.

How forecasts are verified depends on how the outcome is measured (is the outcome discrete, as with rainfall occurrence, or continuous, as with temperatures?) and on how the forecasts are presented (Box 7.5). For example, consider forecasts of whether there will be rain: the outcome is discrete – there will either be rain or no rain. A discrete deterministic forecast (it will rain or it will not rain) can be scored as correct or incorrect, but such a scoring cannot be applied to a probabilistic forecast (e.g., there is a 20% chance of rain) without making important assumptions. Here we discuss the verification of only the most common situations.

Verifying deterministic forecasts

Deterministic forecasts can be measured for *accuracy* if the outcome is continuous, or for *correctness* if the outcome is discrete. A forecast is *accurate* if

the forecast value is close to the observed value. *Precision* and *accuracy* are often confused or used synonymously. Precision is presumed accuracy: a precise forecast is one that gives an impression of being highly accurate, but may or may not be so. For example, a forecast of 20.1 °C implies that the temperature will be slightly more than 20.0 °C; whether that forecast is accurate is a separate question. Accuracy, correctness and precision are examples of *attributes* of forecast quality.

Inaccurate forecasts may be *biased*. Forecasts are biased if they more frequently overestimate or underestimate the actual weather. Bias is also indicated if the magnitude of errors of one sign are typically larger than those of the opposite. For example, forecasts of temperatures that are frequently too low have a cold bias. Similarly, deterministic forecasts of rain v no-rain are biased if rain is forecast too frequently or infrequently.

Accurate forecasts, or forecasts that are often correct, are not necessarily good forecasts.²¹ For example, it is easy enough to make accurate forecasts of rainfall in deserts simply by forecasting no-rain all the time. The same problem applies with forecasts of any rare event: if you always forecast that the event will not happen you will nearly always be correct. A second forecaster who does occasionally predict some rain, may have fewer correct forecasts or a lower accuracy, but could still be producing more useful forecasts than the person who always predicts no-rain. For similar reasons, comparing accuracy for different locations or times of year can be misleading. A comparison of the accuracy of rainfall forecasts for Arica, Chile (the driest city in the driest country on Earth), with those for Buenaventura, Colombia (the wettest city in the wettest country on Earth) tells us more about the different climatologies than it does about the quality of the forecasts.

Verifying interval forecasts

To represent forecast uncertainty one option is to use an interval forecast, which consists of an upper and a lower limit between which a future value is expected to lie with a prescribed probability. *Reliability* is a critical attribute of good interval forecasts – does the observed value fall within the interval the correct number of times? If a 70% prediction interval is used, 70% of the forecasts should capture the observed value, and the observed value should fall outside the interval for 30% of the forecasts. If the observed value does not fall above and below the interval an approximately equal number of times, the forecasts are biased (cf. the definition of bias for deterministic forecasts).

The observed value should fall outside of the interval sometimes. If the observed value falls outside of the interval too frequently then the forecasts are overconfident – the interval is too narrow. Conversely, if the observed value falls outside of the interval too infrequently then the forecasts are

under-confident – the interval is too wide. Because of the way reliability is measured, it is not possible to verify a single interval forecast: the one observation will either fall within the interval or outside it, and we cannot assess whether the proportion of intervals that contain the observation is correct.

It is possible to guarantee reliability by always issuing the same forecast and using knowledge of the climatology (§ 4.3.1), or even by cheating (issuing 70% of the forecasts with ridiculously wide intervals, and 30% with impossibly narrow or with unrealistic extremes). Therefore reliability is only one important attribute. However, there has been surprisingly little research on measuring other important attributes of interval forecasts.

Verifying probabilistic forecasts

As for interval forecasts, *reliability* is a critical attribute of good probabilistic forecasts. Similar problems apply – reliability can also be achieved from unhelpful forecasts, and individual probabilistic forecasts cannot be meaningfully verified – but there is at least a wealth of research on what additional attributes are important for probabilistic forecasts. Imagine that we are predicting rainfall occurrence. If rainfall occurs more frequently when the probability is high compared to when it is low, then the forecasts have *resolution* (not to be confused with spatial or temporal resolution). Alternatively, if the forecasts indicate higher probabilities when rain occurs compared to when it is dry, then the forecasts have *discrimination*.

How can I distinguish good from bad forecasts, or identify the best forecasts?

Skill is an attribute that can be applied to all types of forecasts. Forecasts are *skilful* when they outscore an alternative (usually, but not necessarily simple) set of forecasts. For deterministic forecasts, the alternative forecasts may be persistence (the assumption that the latest observation, or possibly the latest observed anomaly, will remain unchanged), the climatological average (§ 4.3), some other unchanging value (such as always forecasting no-rain in a desert) or random values (but with a realistic climatology). Forecasts may be skilful against one of these alternative forecasts, but not against another of them. It is important to examine the validity of the alternative forecasts carefully, since there are many ways of making forecasts look more skilful than they are useful. For probabilistic forecasts, the alternative forecasts are usually climatological probabilities, and the assumption is that if forecasts cannot outscore the climatology then it is best not to use the forecasts. Depending on the score that is used, that assumption is not always valid.²²

BOX 7.5 FORECAST FORMATS

Weather and climate forecasts generally take one of various formats:

- *Deterministic*: a forecast with no accompanying information about the associated uncertainty. For example: the maximum temperature tomorrow will be 27 °C. This forecast indicates the expected temperature, but provides no information regarding the expected accuracy; it is not possible to calculate the chance of exceeding 30 °C, for example. Deterministic formats are commonly used for temperature forecasts at short- and medium-range weather timescales. The level of accuracy usually has to be learned by experience.
- *Ranges and prediction intervals*: an upper and a lower value between which the observed value is expected to occur. For example: rainfall accumulations of between 25 and 40 mm overnight. The range could be the maximum and minimum possible values, or, more likely, may be a prediction interval. For a prediction interval there is an implied probability that the observed value will lie within the interval. That probability is often 70%, but alternative probabilities are used. Prediction intervals are commonly used for rainfall forecasts at short- and medium-range weather timescales.
- *Probabilistic*: a forecast of the probability of occurrence of one or more discrete events. For example: there is a 60% chance of rain tomorrow. Probabilities are used frequently in short-range weather forecasting to indicate the chance that some rainfall will occur (so-called *probability of precipitation*, PoP, forecasts). Probabilities are also used extensively in seasonal forecasting (see Box 8.3). Occasionally, the probabilities may be expressed as *odds*. Odds are used in preference to probabilities in contexts such as risk assessments and sporting events. Odds are defined as the probability of a specific outcome occurring divided by the probability of it not occurring.
- *Multiple alternatives*: a forecast that shows all, or a selection of, the individual predictions. This option is applied when showing a collection of forecasts of El Niño / La Niña (see Box 5.1) from various models (Chapter 8). It is less often applied for weather forecasts, but the individual trajectories of storm tracks may be shown as an alternative to an idealized plume.
- *Full probability distributions* (typically shown as a probability of exceedance curve): a forecast that shows the probability of exceeding (or not exceeding) all possible thresholds across a range of values. Exceedance probability curves are used in flood forecasting,²³ and have had some limited application in seasonal forecasts.²⁴

7.3 Why is it so hard to predict the weather beyond a few days?

Weather forecasts are made by trying to predict how the weather that is occurring now (the *initial conditions*) will change over the next few hours to days. Anticipating how the weather will change is actually the easier part of the problem; the more difficult problem is to know exactly what the weather is like now. The primary reason why weather forecasts sometimes fail is that the forecasters do not always have an adequate estimate of what the current weather is like.

The difficulty with forecasting the weather is that it is chaotic.²⁵ A chaotic system is one in which future states are highly sensitive to small differences in current states²⁶ – i.e., the smallest of difference now can evolve into substantial differences in the future. If two virtually indistinguishable starting values can give different outcomes, in effect there are different solutions to the governing equations; and, if there is more than one solution, we cannot be certain what the actual outcome will be.²⁷ The implication is that it is impossible to make accurate weather predictions in practice because even a slightly inaccurate estimate of the current weather will translate into a large error in the forecast at some stage in the future. Lorenz first articulated chaos theory when he observed that his meteorological model gave completely different results if he ran it using three decimal places instead of six. He called this extreme sensitivity the ‘butterfly effect’ because, taking the argument to its limit, it may be possible for the flapping of butterfly wings to cause a tornado half way around the world.²⁸

The Earth’s weather is chaotic, and therefore impossible to predict perfectly, but there are additional reasons why weather forecasts are inexact. We do not know perfectly all the equations that govern our weather, and the ones that we do know we cannot model exactly because of computer limitations. Weather forecasts are time-sensitive and so have to be made as quickly as possible, which means that the forecasters have to simplify their models. Even if the current weather were measured exactly, the forecasts would fail because of these simplifications. Having access to immensely powerful computers would still not be enough: there are random effects, such as volcanoes and various human activities, which again make perfect forecasting impossible. Despite all these theoretical and practical difficulties in forecasting the weather, a chaotic system may be predicted with reasonable accuracy, as long as we do not try to predict too far into the future. Useful forecasts of a chaotic system can also be made by indicating how sensitive the forecasts are, perhaps by communicating a set of possible outcomes rather than predicting one specific outcome.

7.4 Given that it is hard, how do forecasters make predictions?

To predict the weather, forecasters need to know: a) as much as possible about the current weather – all over the globe, and not just at the surface; b) how the weather patterns will change; and c) what those changes mean for the weather where people need forecasts. To predict the movement of storms over the next few minutes or hours, for example, forecasters can use simple extrapolation procedures, known as nowcasting techniques (Box 7.1), if good observations (perhaps from weather

radars) are available. However, to predict accurately beyond about two hours, it becomes necessary to model how those observed weather systems will change. To make such predictions the following steps are taken:

- *Observation*: take measurements of the current state of the weather.
- *Analysis*: estimate the current state of the atmosphere over the whole globe and from the surface up to at least about 10 km, including where we do not have any measurements.
- *Initialization*: input these measurements and estimates into a computer model.
- *Integration*: use the model to predict how the current state of the atmosphere will evolve.
- *Post-processing*: determine how that future state will affect the weather at the locations and times of interest.

These steps are described in more detail in the following sub-sections. Case Study 7.3 illustrates how such techniques can be used in disease forecasting.

CASE STUDY 7.3 WEATHER FORECASTING TECHNIQUES FOR FLU FORECASTING

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As for the atmosphere, the processes describing the propagation of infectious agents within a human or animal population, or between vectors of disease and hosts, are nonlinear and can be modelled mathematically. Indeed, to simulate an outbreak of a novel or recurrent infection such dynamical representation of the infectious disease system is imperative. Although the system is nonlinear, the methods used for numerical weather prediction can similarly be brought to bear to construct accurate, calibrated infectious disease forecasting systems.

Three principal 'ingredients' are needed to develop a dynamic infectious disease forecasting system. The first is a mathematical model describing the transmission of a particular pathogen through a population. Numerous model constructs exist for simulating disease transmission and range from simple, low-dimension compartmental models, which bin individuals by infection status, to higher dimension network model structures and agent-based forms, which represent individuals in the system. The second required ingredient is observation of the system itself. Observations are vital for optimizing the model prior to forecast – in essence, for training the model to represent conditions and transmission activity as thus far observed. For infectious disease systems, observations are typically near real-time estimates of infection incidence, which are derived from sentinel clinical networks. The third required ingredient is a Bayesian inference algorithm, or data assimilation method, which is used to carry out the model optimization in the presence of observations.

For the purposes of forecast, a low dimension model construct is often preferred as this enables better model optimization given limited observations. As an example, early forecasts of influenza and influenza-like illness were developed using a simple compartmental model, observations of incidence and a data assimilation method.^{29–31} These efforts have generated accurate prediction of outbreak onset (the week at which influenza incidence rises above some baseline level), outbreak peak timing and magnitude, and total cases. Due to the weaker nonlinear dynamics governing disease transmission, accurate forecasting of influenza is possible two to three months in advance of an outcome. These long lead-times suggest that influenza forecasts will have considerable utility as they become integrated into real-time public health and medical decision-making. It should be noted that, as for weather, prediction of an infectious disease event prior to any observed activity is presently not feasible. That is, much as the specific landfall location and timing of a hurricane cannot be accurately forecast before a nascent tropical disturbance has been observed, specific local influenza outbreak outcomes cannot be predicted before incipient influenza activity has been observed. As a consequence, prediction of the emergence of a novel pathogen is not suited for the methods described here.

Infectious disease forecasts, like weather forecasts, are probabilistic and provide a distribution of potential future outcomes, which can be calibrated to provide the end-user still greater information. For example, a weather forecast does not merely indicate that rainfall will or will not occur; rather, predictions are provided as calibrated probabilities. With this calibration, precipitation occurs on roughly 80% of days for which an 80% chance of precipitation tomorrow has been predicted and on 20% of days for which a 20% chance of precipitation tomorrow has been predicted (see Box 7.4). Similar calibrated probabilities can be developed for infectious disease forecasts. Such discrimination of *expected* forecast accuracy provides end users with richer information. For example, a calibrated forecast of a 70% chance that influenza incidence will peak in five weeks has much more urgency than a forecast of a 10% chance that influenza incidence will peak in five weeks. Both forecasts predict the same outcome, but the former ascribes a much higher probability to the event occurring and may be actionable. In contrast, the latter indicates the best estimate is a peak in five weeks, but the likelihood of this event is low and the uncertainty high.

In the last five years, the field of influenza and infectious disease forecasting has advanced considerably. Influenza forecasts have been operationalized and delivered in real-time,^{32,33} purely statistical forecasting approaches have been developed,³⁴ and ensemble forecasts have been generated.³⁵ The field is still in its infancy; however, with continued investment, one can expect to witness improved accuracy and application of infectious disease forecasts in ways not yet anticipated.

7.4.1 Observation

Observations of the weather are drawn from many sources:

- Surface observations of temperature, rainfall, winds, humidity, air pressure, etc. (§ 4.2). These observations are taken at weather stations over the land, and from ships and buoys in the sea. There are many formally designated weather stations that take measurements at set times of the day that are coordinated across the whole globe. The measurements are distributed electronically by international agreement between National Meteorological Services via the Global Telecommunications System (GTS) of the WMO (§ 6.2).
- Observations of temperature, air pressure, winds, and humidity, at different altitudes above the weather stations. These *upper-air soundings* are obtained by fastening an automatic weather instrument to a balloon, and transmitting the measurements by radio waves back to the weather station. The instruments are called *radiosondes* or *rawinsondes*.
- Observations from aircraft to supplement the upper-air soundings. These observations may be taken directly from the aircraft, or an instrument similar to the radiosonde, called a *dropsonde*, may be dropped and the observations transmitted back to the aircraft. Observations are taken routinely by air traffic, but special reconnaissance flights may be sent into major storms to take more detailed observations that assist with predicting the storms evolution. These reconnaissance observations have made important contributions to improvements in the accuracy of forecasts of tropical cyclones, for example.
- Remotely-sensed observations, such as satellite and radar measurements, can provide more complete spatial coverage than is possible from direct measurement (see § 6.3.2).

7.4.2 Analysis

The various observations are checked for likely errors based, in part, on consistency with nearby and preceding observations and with other parameters (for example, is the relative humidity physically consistent with the air temperature?). This quality-checking involves comparisons of the observations with the prediction made a few (typically six) hours earlier using a numerical weather prediction (NWP) model (see § 7.4.4 for further details on NWP models). The new observations that are accepted as reasonable are used to correct the previous forecast, and thus provide an estimate of the current state of the atmosphere. This estimate is called the *analysis*.

The upper-air data from the balloons and aircraft, and especially from the satellites, are by far the most important data used in the analysis. Only limited use is made of the surface observations, in part because observations near the ground can change substantially over just a few metres or within a few seconds, and so are often

insufficiently representative of the surrounding area. However, the movement and evolution of storms and other weather systems are most strongly affected by winds a few kilometres above the surface, including the jet streams (§ 5.3.2); thus, upper-air soundings may be more important than surface observations.

The analysis is a very complex and computationally intensive step, and is performed only by those forecasting centres with the most powerful computers (§ 6.3.3). These analyses are made available to other centres, which, in turn, use them to initialize their own weather prediction models.

7.4.3 Initialization

Initializing a model involves specifying the starting values in the various equations in the model; thus, the equations in the NWP model need to be initialized with estimates of the current weather – the *initial conditions*. The NWP models' initial values cannot always be taken directly from the analysis because the NWP model may have a different grid or use different equations than the analysis model (see § 7.4.2). In these cases the analysis has to be interpolated to the NWP model grid, and possibly adjusted. Even if the same model is used, initialization is a distinct step when generating alternative initial conditions as a means of producing a set (an *ensemble*) of forecasts (as discussed in the following sub-section on Integration).

7.4.4 Integration

NWP models involve a set of equations, known as *primitive equations*, which are based on the physics of how air behaves. These equations describe what is happening at a specific location, and are calculated at many points, vertically and horizontally, over a region of interest or over the whole globe. Since 2016, the most complex NWP model has almost one billion gridpoints (about 6.5 million spread across the globe at each of 137 vertical layers). The equations are used to predict the values of various meteorological parameters from current values.

The primitive equations cannot be used to make an immediate prediction for 24 hours hence; instead they predict only a few minutes into the future. The equations are then updated using these new values to predict the subsequent few minutes ahead, and the process is repeated until the predictions extend as far into the future as desired. For example, if the equations are set to predict ten minutes ahead, then to predict one day ahead requires that the calculations are repeated 144 (6 per hour × 24 hours) times. The smaller this time step is, the more precise the equations are, but the longer the forecast will take to compute. Similarly, the equations work best if the distances between the gridpoints are small, but the forecast will again take a long time to compute if there are many gridpoints. Compromises have to be made on the model time step and the grid resolution (i.e., the number of gridpoints) to minimize computation time. The compromises are one set of reasons why forecasts are not always accurate.

A further complication is that some of the important processes cannot be represented by primitive equations, perhaps because they occur at spatial scales that are too small for the model to capture. Many clouds, for example, are much smaller than the grid-spacing of the model, and so many of the important mechanisms in the formation of rain cannot be modelled properly. These processes have to be simplified or approximated using alternative equations called *parameterizations*. Parameterizations are another reason why forecasts are not always accurate.

We have discussed three main sources of error in weather forecasts: 1) the initial conditions are imperfect; 2) the model is imperfect; and 3) the weather is inherently chaotic (making the first two imperfections real problems!). Given that forecasters know these sources, different strategies are available to try to address the problems:

- *Minimise the imperfections* by generating the best analysis possible, and using the best-possible NWP model to produce a single best-possible forecast. This forecast is known as a *deterministic* forecast. A good example of this approach is the European Centre for Medium Range Weather Forecasts (ECMWF), which is widely acknowledged to have one of the best weather forecasting systems in the world. However, since ECMWF produces only medium- and longer-range forecasts (Box 7.1), it is able to take more time than other centres to produce its analysis (waiting for additional observations to become available, and taking longer to perform a more careful analysis), and to run a more complex model.
- *Assess how much the imperfections matter* by generating multiple forecasts using slightly different estimates of the current weather, and/or by using different models (Box 7.6). If the individual forecasts in this *ensemble* do not differ much then we can presumably be confident that the imperfections do not matter very much, but if they do differ then the likely outcome is unclear. Ensemble forecasting has become standard for forecasts beyond about three days, and has enabled us to predict weather about 50% further into the future. Further details of how the ensemble is generated, and how the multiple predictions can be combined to produce a meaningful forecast are provided in Box 7.6.

BOX 7.6 ENSEMBLES

For all weather and climate forecasts beyond about three days, it is standard practice to generate multiple predictions. The collection of predictions for the same target period is called an 'ensemble'. The objective when generating an ensemble is to produce alternative predictions that account for different sources of uncertainty: the initial conditions and the model imperfections in the case of weather forecasts. Alternative ways of generating an ensemble of

predictions are described here; some of these options are more suitable for weather forecasting, others for climate forecasting, as indicated.

Generating an ensemble from different initial conditions

Recognizing that the initial conditions in our NWP model are inexact, we could produce additional predictions using alternative (and ideally equally reasonable) initial conditions.

Perhaps the simplest way to generate an ensemble of predictions from different initial conditions is to use recent predictions as well as the latest one(s). For example, when predicting the weather for Tuesday, say, we could consider both the forecast for Tuesday that was made today as well as the forecast for Tuesday that was made yesterday. This combination of current predictions with slightly out-of-date predictions is known as *lagged-averaging*. The procedure is not generally used in weather forecasting because forecast accuracy decreases rapidly with increasing lead-time: yesterday's forecast for Tuesday is likely to be less accurate than today's forecast for Tuesday. However, lagged-averaging is used in long-range (e.g., seasonal) forecasting (Table 7.1) where the initial conditions are no longer the primary basis for prediction (see § 8.2.2).

For extended- and shorter-range forecasts, the older predictions are too inaccurate. An alternative option is to take the most recent prediction, called the control run, and to make additional predictions by perturbing the initial conditions from the analysis. The perturbations need to be introduced in ways that organize into alternative weather patterns. Defining these *dynamically constrained perturbations* involves complex statistical procedures that identify where past errors in the forecasts have grown most rapidly. There are various ways of identifying such perturbations, and one or more of these options is the preferred approach for generating ensembles by the leading weather forecasting centres around the world.

An additional possible option is to use alternative analyses in the model initialization. This procedure is widely used with regional NWP models, but it is less often used in global models. The analysis produced by one global NWP model may result in an initialization that is numerically unstable in a second global model. The effect is that the second model quickly predicts highly unrealistic weather conditions, or the model may even crash.

Generating an ensemble from different or modified models

A conceptually simple way of generating an ensemble is to use forecasts from different NWP models. This approach is used widely for extended and long-

range forecasts; forecasts produced by different centres are combined into a *multi-model ensemble*.^{36,37} For shorter-range forecasts, there may be practical and other reasons why an ensemble might need to be developed in-house, but maintaining the computer code for different models in an operational setting is expensive. A cheaper option is to modify a single NWP model's simplified equations – the parameterizations (§ 7.4.4). These parameterizations can be modified in two ways: by adding random errors at each calculation to represent the uncertainty in the parameterizations (so-called *stochastic physics*); or by using an alternative parameterization across every calculation (so-called *perturbed parameterization*). These methods have become standard for medium-range forecasting.

7.4.5 Post-processing

The outputs from the NWP model(s) may be inadequate as a forecast for various reasons:

- The model produces predictions at its gridpoints, which may not be in the locations that forecasts are needed.
- The model outputs represent area-averages, which can be misleading, especially in the case of rainfall. Rainfall is often highly localized (§ 5.2.5.2), but the model cannot produce rainfall events smaller than its grids, and so localized downpours will instead be represented as widespread drizzle over the whole grid. As a result, the frequency of rainfall is likely to be overestimated, but the intensity underestimated. Similarly, the area-average temperature may not be representative of the location of interest, especially in mountainous areas.
- The models can have large systematic errors, such that temperature forecasts, for example,³⁸ may be consistently too high or too low.

Each of these problems can be addressed by applying a statistical correction to the NWP model output. The statistical correction is applied by comparing past forecasts with observations. A forecast that is derived from NWP output and then corrected using a statistical model is called *model output statistics* (MOS) guidance. The MOS techniques can range from simple linear regression to highly complex procedures using ensembles of forecasts from more than one NWP model.

7.5 How accurate are weather forecasts?

There is a common tendency to see weather forecasts as less accurate than they really are because of implicit expectations that forecasters should be able to predict exactly *when* a *specific* weather event will occur. Imagine that on a Friday a

meteorologist predicts that there will be a storm bringing heavy rain early the following week. The forecaster is not sure precisely when the storm will arrive but the best estimate is Monday afternoon. The storm approaches more slowly than anticipated and only arrives Tuesday morning. As a result, Monday is sunny when it was forecast to be wet, while Tuesday is wet when it was forecast to be sunny, and so the forecast looks to be wrong twice. If a health worker postpones a visit to an isolated village on Monday afternoon to Tuesday morning to avoid the storm she may be justifiably annoyed. However, it does seem unfair to blame the forecaster who correctly predicted that a storm was approaching. If the health worker had known that the exact timing of the storm was uncertain, she may have been able to postpone her visit until the Wednesday or Thursday, well after the storm should have passed by.

The forecaster, while correct in predicting a storm, could have provided more useful information by indicating the uncertainty in the timing of the storm (Box 7.1). Of course, it would be wonderful to know exactly when the next storm will occur; just as it would be helpful for a midwife to know exactly when an expectant mother will go into labour. But neither are perfectly predictable. However, it is still possible to plan for a storm, or a birth, with only a rough sense of when it will occur – anytime in the next three to five days, perhaps. As the storm becomes more imminent, it may be possible to get a more precise forecast of where it will hit when, and how intensely.

One further complication is that measurements of the quality of forecasts need to be targeted at forecasts of the specific weather conditions of interest. For example, knowing that temperature forecasts for your city are, on average, accurate to within 0.5 °C, may be misleading if the most accurate forecasts are for all the days when temperature is close to average but one is only interested in the forecasts of extreme temperatures.

Accounting for all such intricacies, and many others besides, makes evaluating forecasts in a scientifically rigorous, but intuitive, way an almost impossible task (Box 7.4). Given that describing how good (or bad) weather forecasts are is a far more complex question than it may at first appear, it is possible here to provide only some crude generalizations. Perhaps the simplest place to start is with how weather forecasts have been improving with time. A simple rule of thumb is that since at least the 1970s, the lead-time of a forecast for a given level of accuracy has improved by about one day each decade. In other words, three-day forecasts that are available now are as accurate as the two-day forecasts that were available ten years ago. As a second simple rule of thumb, one week is about the limit for usable deterministic forecasts of individual weather systems; that limit extends to about ten days for probabilistic forecasts. There are attempts to predict weather conditions beyond this ten-day limit, in so-called sub-seasonal forecasts (Box 7.4), but forecast products remain primarily research initiatives. Forecasts at such long lead-times may be available from some commercial centres, but many commercial weather forecasts do not provide adequate estimates of skill and can be misleading.

7.5.1 Temperature

Temperature is generally easier to predict than rainfall, largely because of the highly localized nature of rainfall (§ 5.2.5). Figure 7.1 shows a measure of our ability to predict hot and cold spells three days in advance. The two main features are:

- Cold spells are predicted more successfully than hot spells. The cold spells are easier to predict because they are generally associated with large-scale wind patterns, possibly in conjunction with cold fronts (§ 4.2.8.2). Hot spells, in contrast, can be sensitive to small differences in cloudiness and to surface conditions for which observational data may be limited. However, although cold spells can generally be predicted more successfully than hot spells, summer temperatures (in the mid-latitudes) are typically more accurate than winter temperatures simply because summer temperatures are less variable (§ 5.3). This apparent paradox is partly an effect of the distinction between accurate and skilful forecasts (Box 7.4).
- Forecasts are better in the mid-latitudes than in the tropics. Mid-latitude temperature forecasts are relatively easy for similar reasons to the cold / hot spell contrast: they are determined by large-scale wind patterns (§ 5.2.5). In the tropics temperatures are more uniform and unvarying, and days that qualify as part of a hot spell can be highly localized depending on small differences in cloudiness or surface heating.

7.5.2 Rainfall

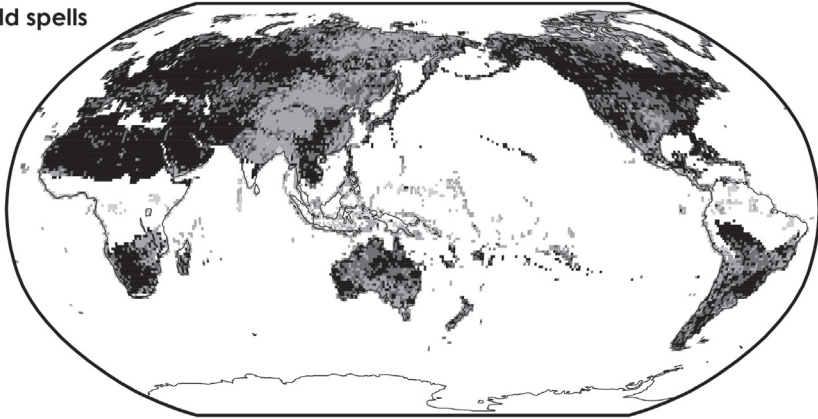
Forecast probabilities of rainfall occurrence are generally reliable (Box 7.4) for all weather timescales if the NWP model outputs are post-processed (§ 7.4.5). What changes with the increasing lead-time is that fewer probabilities of close to 0% or 100% are issued. If forecast probabilities are reliable, the quality of the forecasts is essentially built in to the forecast itself, and there may be no need for further verification information. When the forecast says there is a 60% chance of rain, the probability indicates how often the warning is a correct alarm if the forecast is interpreted as a warning of rain.

Predicting rainfall amounts is difficult, especially for convective rainfall (§ 4.2.2) because it is so localized (which makes predicting its occurrence difficult too). The smallest useful scale for 24-hour forecasts of rainfall is about 85 km.⁴⁰ Largely because convective rainfall is harder to predict than large-scale rainfall, forecasts in the tropics are not as good as forecasts in the extra-tropics. For the same reason, summer rainfall is harder to predict than winter rainfall.

7.5.3 Tropical storms (cyclones, hurricanes and typhoons)

Storm-track forecasts have steadily improved over the last few decades as a result of the ever-increasing quantity and accuracy of atmospheric observations,

Cold spells



Weak

Moderate

Good

Excellent

Hot spells

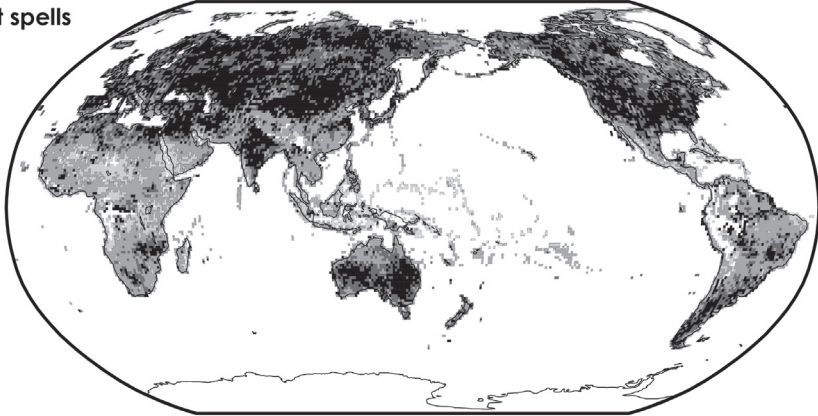


FIGURE 7.1 How well can we forecast severe heat or cold? Ability to discriminate (see Box 7.2) cold (top) and hot (bottom) spells from all other days. The spells are defined as temperatures beyond the 5th and 95th percentiles, respectively, on at least two consecutive days. The forecasts are derived from ECMWF's ensemble prediction system (see § 7.4.4), and are verified against the ECMWF analysis (which means that the quality of the forecasts are over-estimated). The score is classified as 'excellent' (> 95%), 'good' (90–95%), 'moderate' (67–90%) or 'weak' (< 67%), and guessing would score 50%. Some areas show no score because of insufficient numbers of spells. (Data source: adapted from Coughlan de Perez et al.³⁹)

improvements in the way those observations are used to initialize NWP models, improvements in the models themselves and the benefits of access to more powerful computers. The tracks of tropical cyclones are predicted most accurately in the North Atlantic because these storms are monitored carefully and so the prediction models can be initialized most accurately. A sample of average errors for the 2016 storms is shown in Table 7.3, together with previous errors to show

TABLE 7.3 Approximate average errors (in km) in predicting North Atlantic tropical storm tracks

<i>Lead-time</i>	<i>2016</i>	<i>1996</i>	<i>1976</i>
24 hours (1 day)	50	135	240
48 hours (2 days)	100	240	530
72 hours (3 days)	155	350	750
96 hours (4 days)	240	N/A	N/A
120 hours (5 days)	330	N/A	N/A

Source: National Hurricane Center Forecast Verification Official error trendsⁱⁱ

improvements over the last 40 years. Average errors do fluctuate from year-to-year by about 20–50%, and errors in other ocean basins are generally no more than about 20% larger than those shown in the table. Most tropical cyclones are less than about 1000 km in diameter (§ 4.2.8), so the errors for five-day forecasts are about one-third the size of a large hurricane. Whether such errors are considered large or small depends on one’s perspective. Failing to act and acting in vain have to be weighed carefully by decision-makers (§ 7.3).

7.6 What weather forecasts are available?

7.6.1 Watches and warnings of hazardous and inhospitable conditions

When there is a risk of severe weather conditions, most countries provide official alerts. For many reasons, it is important to work with alerts from mandated government authorities (typically the NMHS), even if there is a perception that higher quality information may be available elsewhere. There are two levels of alert:

- *Watches*: indicate that hazardous conditions are *possible*. During a watch the appropriate response is to prepare for action should the hazardous weather strike, and to keep a look out for updated information.
- *Warnings*: indicate that hazardous conditions are *expected*. During a warning the appropriate response is to take action immediately.

In the event of a watch or a warning, some countries may have standard procedures that relevant government agencies are expected to follow. However, sometimes it is useful to receive notification of hazardous weather that does not meet the criteria for an alert. The NMHS may then issue an *advisory*, which does not have the official status of an alert, but which may still warrant action. Each country has its own criteria for issuing advisories and alerts, and its own protocols to follow for disseminating the information, so there may be some apparent inconsistencies across borders. The WMO collates the various active official alerts in its Severe Weather Information Centre.ⁱⁱⁱ MeteoAlarm^{iv} is a more detailed site specifically for Europe.

As part of the World Weather Watch (§ 6.2), the NMHSs are supported by a set of Regional Specialized Meteorological Centres, which are responsible for monitoring specific hazards. There are centres to monitor tropical cyclones, nuclear accidents, volcanic ash, wildfires, floods and droughts.

Many NMHSs are now developing as multi-hazard warning centres because they already provide a 24/7 service and are mandated authorities for weather warnings.⁴¹ As an example, heat health early warning systems are being established in many countries through collaboration between NMHSs and public health departments. As a measure of heat-related health risk, temperature alone is inadequate: it is the combination of unusually high temperatures with high humidity that constitutes a health threat (see Box 4.2). Defining a heat index that is applicable everywhere is problematic, and even for a given location, the health impacts of heat stress vary through the year. In the mid-latitudes, for example, humans are more sensitive to heat stress in early summer even though the heat index typically reaches peak values a few weeks or even months later. Similarly, for cold spells, it is the combination of unusually low temperatures with windy conditions, rather than temperatures alone, that pose the greatest threat. Because of these compounding effects of humidity and wind and of human adaptability to location and time of year, heat wave and cold spell monitoring and early warning systems have to be adapted to the local environment.

7.6.2 Forecasts of unhealthy weather

In some cases it may be important to include air quality measurements in the heat health early warnings. For example, increased near-surface ozone concentrations are often a problem in heat waves, while in winter certain weather conditions can be conducive to both extremely cold conditions and increased air pollution (§ 5.2.4; see also § 6.4.2.2 on air quality monitoring). The Regional Specialized Meteorological Centres (§ 7.6.1) are responsible for providing forecasts and information on additional transboundary unhealthy weather conditions, such as dust and radioactive material.

7.6.3 Forecasts of suitable weather

Weather forecasts that indicate the timing of a seasonal window for disease occurrence may also be useful in health decision-making. While weather forecasts may only give a few days' indication of the start of the normal transmission window for a seasonal respiratory disease, the prediction that the season is nearing its end allows health decision-makers to scale back their response and re-focus their attention elsewhere. For example, meningococcal meningitis epidemics occur during the hot and dusty dry season in the African Sahel when relative humidity is low (see Case Study 7.1). A weekly average humidity below 40% is predictive of epidemic occurrence. Weather forecasts that predict a rise in relative humidity above 40% and the end of the seasonal epidemic window have been developed to help health practitioners plan the end of their seasonal vaccination activities.⁷

7.7 Conclusions

Weather forecasts are more accurate than many people suppose them to be, but predicting rainfall accurately is notoriously difficult, especially in the tropics. Despite their accuracy, weather forecasts may not add much value to a health early warning system if there is a long lead-time between the observed weather and the health outcome; e.g., for vector-borne diseases. However, weather forecasts can be useful for other purposes, such as for prediction of hazardous conditions. If weather alerts of hazardous conditions are to be used, it is important to work with alerts from officially mandated sources. Weather forecasts can provide at most a few days' advanced notice; for informing preparedness actions weeks or months in advance, it may be possible to use seasonal forecasts – the topic of the following chapter.

Notes

- i www.wmo.int/pages/prog/www/DPS/GDPS-Supplement5-AppI-4.html.
- ii <https://www.nhc.noaa.gov/verification/verify5.shtml>.
- iii <http://severe.worldweather.org/>.
- iv www.meteoalarm.eu/.

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