Weather and Climate Predictions for the Energy Sector

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WEATHER AND CLIMATE PREDICTIONS FOR THE ENERGY SECTOR

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Abstract. Weather and climate forecasts are potentially valuable sources of information for use in risk management tools. It is important however to be aware of their limitations (several approximations go into a forecasting model) as well as of opportunities to enhance their information content (e.g. through understanding the underlying physical processes which lead to a given forecast). This chapter explores, at a rather high level, the physical basis of forecasts, the tools used for producing them and the importance of assessing their skill. An interesting case of a seasonal forecast and its impact on the energy market is also discussed.

Keywords: Weather; climate information; climate predictions; forecast skill; energy management

1. Introduction

Weather and climate predictions are worthwhile scientific endeavors in their own right. What makes them really useful however is the application or transfer of this information to specific sectoral activities of societal relevance. There are numerous sectors for which this information is critical, prominent amongst which is energy. Energy exploration, extraction, transportation, refining, generation, transmission and demand are all critically exposed to weather and climate events in one way or another. Energy generation, to pick one, is sensitive to wind, rain, hail, ice, cloudiness, radiation, storms, droughts, water in rivers, unseasonable demands, amongst others. The potential for improving these energy operations by using quality weather and climate information is therefore apparent.

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Clearly to say that forecasts are valuable tools for a certain sector is just the beginning of a long path. One needs to assess which aspects of the predictions are really useful for energy applications – numerical models used for predictions churn out millions of variables and therefore one needs to be clear on what aspects of the forecasts are the most relevant for the problem at hand. Then there is the "presentational" aspect of the prediction. Getting the message across to recipients is what really matters: there is little benefit, apart from leaving scientists a feeling of accomplishment, to achieving the 'perfect' forecast if it is not used. Even when the useful variables have been identified and the message effectively communicated the road ahead is still rough. How does well-communicated weather/climate information get considered in the mix of information by the decision taker in the energy sector? In other words, how can you convey the fact that there is a high probability that a temperature anomaly of 2 degrees may occur for the next season over a certain region and such anomaly may affect the way gas is stored, for instance?

After an overview of the types of predictions available (Section 2), a discussion of how these forecasts are actually produced is given (Section 3). It is also important to acquire confidence in these forecasts and thus a discussion on the quality of these forecasts is provided (Section 4). The chapter concludes with a case study of the way a seasonal forecast was communicated in the UK for the European winter of 2005/06 (Section 5). Complementary discussion on weather and climate predictions can be found in Dutton (2009) and Buontempo et al. (2009) in this volume.

2. Rationale for Weather and Climate Forecasting

Weather forecasting has been around for many decades. Beginning from the first hand written charts of the 1940s the technology has expanded enormously. Forecasts are now performed using the most powerful supercomputers available that churn out millions of pieces of information coming from a combination of measurements of the earth system and the mathematical representation of the atmosphere, ocean, land and ice. These forecasts, available on horizontal grids of as low as 20 km on the global scale, have reached such a high quality that people can now consider sensibly, say, the predicted probability distribution of temperatures for a specific location at a 10-day lead time. Precipitation forecasts are not of the same quality as those for temperature as yet since, by its very nature, rainfall is highly variable both spatially and temporally and this makes it more difficult to predict. Overall, the chaotic nature of the climate system is such that we will always be limited in our ability to predict weather beyond a theoretical threshold (currently thought to be about 2 weeks but dependent on numerical model features, including resolution, used to test the predictability assumptions).

However, there are parts of the geophysical system, like the oceans, which evolve more slowly than the atmosphere and this slower motion allows us to extend the time horizon of predictions to well beyond this theoretical limit. That is why we can talk about seasonal to interannual forecasts, though the way in which results are looked at has to be modified (see discussion later). The ocean has a large heat capacity and slow adjustment times relative to the atmosphere. In addition, ocean variability can give rise to enhanced atmospheric predictability in the case of processes that depend on both media interacting. The coupling between the atmosphere and ocean is known to be relatively strong in the equatorial region, viz. El Niño/Southern Oscillation (ENSO). By including other external (to the natural earth system) factors such as human-induced gas concentrations in the atmosphere and oceans we can extend the prediction time horizon, also called *lead time*, even further and therefore produce climate change scenarios.

The extension of the predictions/scenarios lead time from a few days to decades needs careful consideration however. It is entirely reasonable that a prediction for a specific date 10 years from now may not be of the same quality as a prediction for the day after tomorrow, say. In other words, what is considered a meaningful feature, according to some metric, varies considerably according to lead time. So, looking at the predicted temperature probability distribution at a specific location for a certain day several months in the future, although do-able, has limited scientific validity. A practical approach to interpret predictions at different lead times is to increase the averaging spatial and temporal intervals with increasing lead times[1]. What this means is that instead of trying to extract information from a probability distribution at a specific location (e.g. Lecce) and a specific date several months from now it is more useful to consider how the climate is going to differ from a certain reference period for the Mediterranean region over the period of a month, say. More simply, the trick is in the averaging. By taking a larger area and a longer averaging period, the signal from the forecasts starts to emerge (whether it is the correct signal or not is a different matter: more on this in Section 4). Going even further into the future in terms of lead times (decades and beyond), one needs to consider even larger regions (e.g. North America) and longer averaging time periods (typically 20–30 years).

[1]Mathematically, this equates to saying $\bar{x} = \bar{x}(leadtime)$ and $\bar{t} = \bar{t}(leadtime)$.

In summary, in order to be able to extract potentially useful information, the longer the lead time the larger the averaging time and the larger the spatial area need to be. The schematic in Figure 1 shows how this can be done in practice for the time averaging case. Therefore the extent to which one can define medium-range, seasonal and decadal predictions/scenarios – along with the levels of their skill – will depend on the time and space scales considered. Note that the level of skill is an important qualifier because users would like to know about the quality of the forecasts before using them. An implication is that the longer the lead time the longer the observed record needs to be in order to assess the quality of a forecast/scenario. This is why, for instance, it is essentially impossible, at present, to define the level of skill of climate change scenarios.

It is worth noting that while the focus here is on weather and climate predictions, these are just a subset of all the available weather and climate information. For example direct observations and re-analyses (i.e. the 'best' reconstruction of the past) also provide extremely useful information for the decision making process (see Harrison and Troccoli, 2009, Chapter 9, this volume).

3. How Are Weather and Climate Forecasts Produced?

Different components or attributes of the earth system affect in specific ways physical processes relevant to weather and climate. By isolating certain aspects of the earth system predictions of weather and climate at different lead times become a more tractable problem. Generally speaking physical processes can be divided into fast ones (e.g. atmospheric convection) and slow ones (e.g. circulation of the deep ocean), with an essentially continuous spectrum of processes in between. Given the presence of this wide spectrum, choices about which process is more relevant for a particular purpose have to be made. Thus for instance it would be of little use to run a complex sea ice component to produce forecasts for tomorrow's weather as the sea ice response is much longer than a day. Likewise for a climate forecast several years hence, the precise details of today's weather are less relevant than for forecasts for the next few days/weeks. So, although in principle a single system for all lead times would be desirable (and this is what some prediction centres are attempting to achieve), in practice predictions are made with built-for-purpose model configurations.

As a rule of thumb, atmospheric initial conditions are essential for weather forecasts on lead times up to a few weeks, land surface initial conditions are important on lead times up to a few months, ocean initial conditions are critical for climate predictions on lead times from months to decades, and sea ice is relevant on time scales from years to centuries (unless it disappears in the meantime!). This time scale classification indirectly tells us also which component of the earth system needs the most attention by modellers at the various lead times. Typical current configurations of forecasting systems are illustrated in the schematic of Figure 2.

There are three essential elements in a forecasting system:

1. A numerical model for which various complexities are available (e.g. an atmospheric model)
2. Observations of the earth system (e.g. sea surface temperatures, greenhouse gas concentrations)
3. A strategy for combining numerical models with observations in a consistent way (e.g. using a variational assimilation approach)

These elements are discussed in more detail in the following subsections.

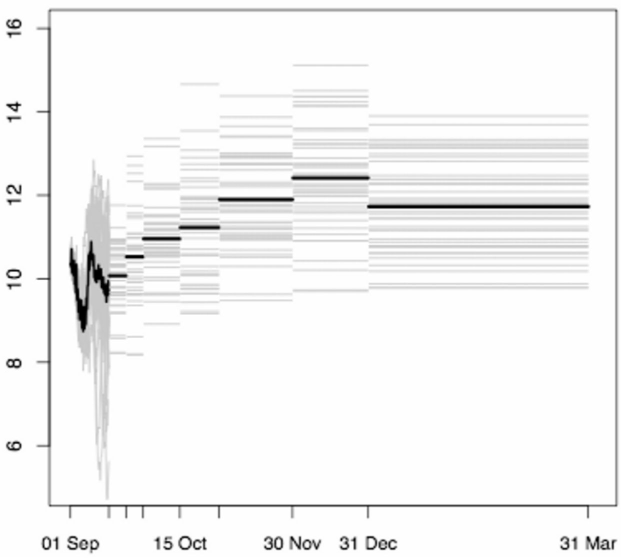

Figure 1. Example of time averaging for a generic forecast started on a 1st September. The time averaging has been applied here to an ensemble of forecasts (i.e. different representations of the same event) but the approach is valid even with one model realization only. The grey lines represent individual ensemble members and the black line is their mean. No time averaging is carried out for the first 2 weeks (the direct model output is plotted). This first period is followed by increasing time-window averages: two weekly averages, two bi-weekly averages, two monthly averages and a 3-month average. A similar approach can be applied to spatial averages. Plot adapted from Rodwell and Doblas-Reyes (2006).

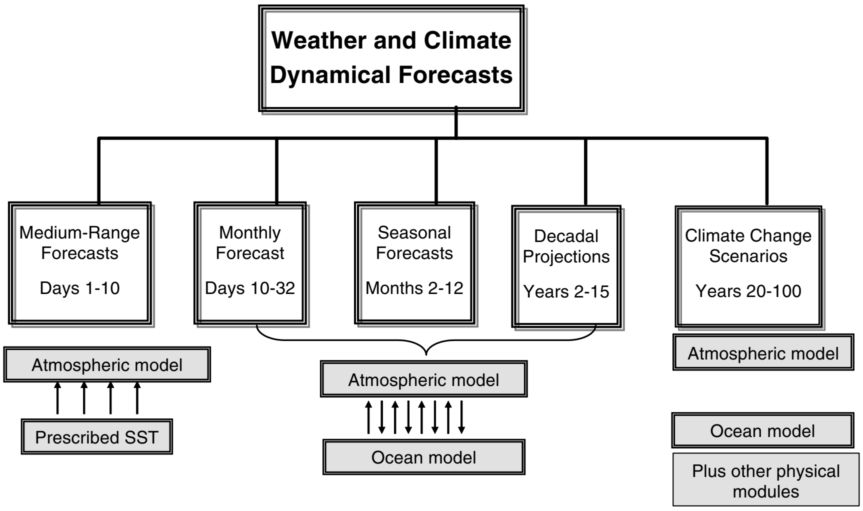

Figure 2. Schematic of lead time classification (from Medium-Range Forecasts on the left to Climate Change scenarios on the right) based on the forecast systems currently in use. For instance, Medium-Range Forecasts are carried out with an atmospheric model whereas at longer lead times an ocean model, possibly with a sea-ice component, needs to be used. Atmospheric models normally include a land surface model too.

3.1. NUMERICAL MODELS

A numerical model is a computerized version of mathematical relationships that describe the earth system. The earth system in these models is typically subdivided into cells of sizes varying by model (e.g. 100 by 100 km in the horizontal and 50 m in the vertical for the atmosphere). Dynamic and thermodynamic relationships are solved for each cell as well as for the interactions amongst cells.

All components of the earth systems could in principle be included in forecasting systems for each lead time. Practical considerations, however, limit the complexity of such systems. For instance, a weather forecasting system is normally constituted of an atmospheric model with a land surface component (left-hand-side in Figure 2). In such a system, the ocean model is often replaced by best estimates of sea surface temperatures at the start of the forecast. However, at longer lead times, say from several days onward, an ocean model becomes essential, even if its impact will differ according to which part of the earth system is considered. Thus, an ocean model is clearly more useful in places where ocean dynamics evolves faster. For instance tropical cyclones, phenomena which show a strong interaction between the atmosphere and ocean on timescales of hours/days may be better predicted when an ocean model is used (see Troccoli et al., 2008, for a case study of the impact of an ocean model on predictions of a tropical cyclone). It is also to be expected that deeper parts of the oceans become increasingly relevant at longer lead times. The details of the north-south deep ocean circulation in the North Atlantic, for instance, are unnecessary for weather forecasts but are important if a prediction a decade hence is attempted. Analogous considerations apply to ice models, biological models, carbon cycle models, and so on.

3.2. OBSERVATIONS OF THE EARTH SYSTEM

Observations are essential to ensure the model starts from a point as close as possible to reality. Observations can be segregated into two types:

1. *In situ* measurements, which require sensors to be collocated with the quantity to be measured
2. Remotely sensed measurements, which rely on inferring physical variables from afar through the inversion of a radiated signal

Radiosonde temperature measurements and satellite temperature retrievals are prototypical examples of in situ and remotely sensed data respectively. Prior to the advent of satellites in the 1980s, the majority of data were collected through in situ measurements. Since then an exponential growth in volumes of remotely sensed data from satellites has been achieved. To give an idea of this growth, about 100,000 observations were used for weather forecasting in the early 1990s. Now, about 15 years later, this number is about ten million, i.e. 100 times larger. The spatial data coverage has also become more uniform. Whereas before satellites the southern hemisphere was relatively poorly observed, now the quality of forecasts for the north and south hemispheres is basically the same mainly as a reflection of the more uniform global data coverage.

3.3. STRATEGIES FOR COMBINING MODELS WITH OBSERVATIONS

In order for a model to be able to produce reasonable forecasts, appropriate knowledge of the real world must be inserted into the model. The merging of observations and models is achieved through an approach called data assimilation. Data assimilation is therefore a combination of observations and model data, performed with the aim of achieving the ‘best’ initial state for the model. Ideally all available information should be used for this purpose. However practical considerations such as the inter-dependency of different observations, the need for models to be ‘in balance’ with observations (a technical requirement to ensure the model moves forward smoothly, rather than jumps, from its initial state) and many others put constraints in the way data assimilation is actually implemented.

We will not discuss the details of data assimilation, but it is worth noting that data assimilation is not a specific technique for the earth system only. Rather, it is utilized in a wide variety of disciplines, e.g. in satellite orbit determination, in any application that requires an optimal way to combine a model with observations. For a more detailed discussion see e.g. Tribbia and Troccoli (2008).

4. How Trustworthy Are Weather and Climate Forecasts?

A valid skill assessment of forecasts may only be carried out on past performance. As mentioned above, the longer the lead time the longer the period of assessment must be. This is perfectly understandable since skill assessment requires a minimum number of cases in order for its statistics to become robust. Weather forecasts are typically assessed over a few seasons, assuming the forecasts are run every day, i.e. the sample is of order of hundreds of cases. Seasonal forecasts are normally assessed over 2–3 decades, with the system run every month, i.e. again of order hundreds of cases. Very different is the case for climate change scenarios for which no assessment can be made except by using the model to 'predict' over a past known period.

By carrying out these assessments one finds that skill varies markedly depending on the region considered, on the state of the earth system components when the prediction starts and on the lead time. So for instance it is easier to predict when an El Niño is likely to occur than to predict its termination once it has started. This is because we understand relatively well the dynamics of the ocean-atmosphere interaction subsequent to the start of an El Niño (e.g. see Anderson, 2008). Moreover, location dependent skill is easily explained if one takes into account local features (e.g. a mountainous region versus a desert) or the presence of remote atmospheric connections (also known as tele-connections) during, for example, an El Niño. More specifically, because of the relatively large climate anomalies accompanying an El Niño, several global tele-connections are manifest, for instance, over North America. Thus, although predictions are generally more skillful in tropical areas than at higher latitudes during an El Niño, predictable features can be seen at higher latitudes. A map of skill for near surface temperature of a seasonal forecasting system as given by the anomaly correlation for forecasts started in February is shown in Figure 3. This plot confirms that the tropics display a higher degree of skill but higher latitudes also have some potentially useful skill, where correlations are larger than 0.4. Somewhat different considerations apply to another important physical variable, precipitation. Although the analogous map for precipitation displays also a maximum in the equatorial Pacific, though with lower values, elsewhere correlation values are close to zero (not shown).

Maps such as that in Figure 3 provide useful indications about the quality of predictions. As one can imagine, a much more extensive assessment than just correlation maps is normally carried out in operational forecasting centres in order to examine how a forecasting system is performing. This is because (a) there are many ways skill can be measured, correlation being just one of them (see e.g. Mason and Stephenson, 2008); (b) skill depends on time and location and (c) several other physical variables need to be assessed aside from the most common two, surface temperature and precipitation (e.g. pressure, wind). As a result of such evaluations a wealth of statistics is usually produced which can then be used to calibrate subsequent specific forecasts either objectively or subjectively.

Statistics are fundamental to gaining confidence on the quality of a forecasting system: clearly it is desirable to learn as much as possible about past performance before diving into the unexplored territories of the future. However, one needs to be careful about over-interpreting statistics. By definition, statistics provide a summary of behavior of a system and as a consequence they may gloss over important details.

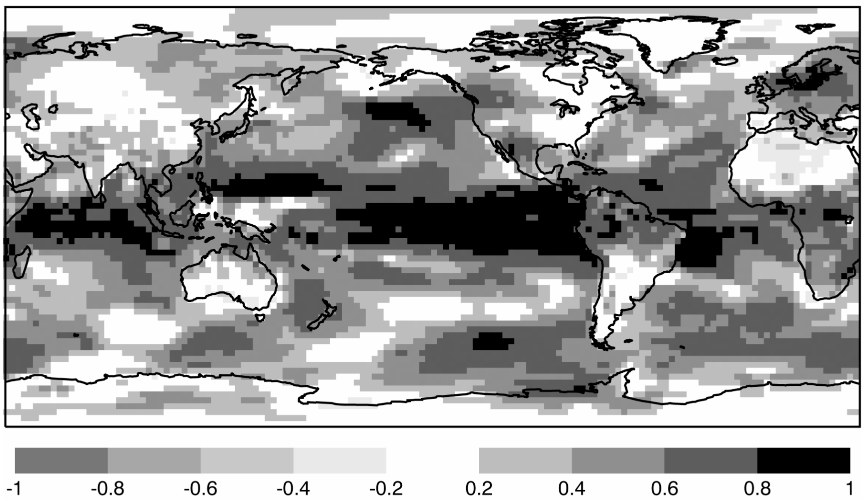

Figure 3. Skill of a seasonal forecasting skill as measured by anomaly correlation for near surface temperature. Results will vary depending on the season being predicted. In general skill is higher in the tropics than at higher latitudes and for this particular season (March-April-May) the temperature signal over northern Europe is real (From Anderson, 2008).

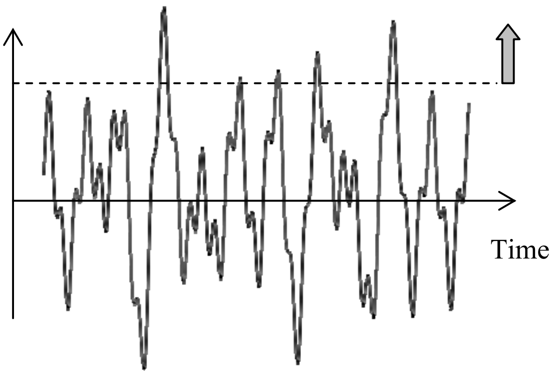

Figure 4. Schematic of temporal evolution of a generic skill measure with zero mean. Values above a chosen threshold (dashed line) may provide potentially useful predictions (the so-called "Windows of Opportunity").

Imagine a particular skill measure that behaved like the curve in Figure 4 with periods of both negative and positive values, but with a zero mean (this could be a white area within Figure 3). It is apparent that, based on this skill measure, there are instances on which this forecasting system performed particularly well. This may be the case, for instance, for forecasts produced while an El Niño is underway: models are often sensitive to stronger anomalies such as those provided by an El Niño and hence their response may emerge from the noise during such events and may then provide a good forecast. Periods of higher positive skill in such circumstances are normally referred to as "windows of opportunity" as potentially beneficial forecasts may be attainable during such periods.

Being able to exploit windows of opportunity would therefore equate to achieving a higher skill than that yielded by assessing the system purely from a statistical basis. Critical to the exploitation of these windows is the understanding of how the physical system works. The forecast provided by the model then becomes just one, though an important, piece in the jigsaw of the final forecast. This was the case with the seasonal forecast issued by the UK Met Office in the winter 2005–2006 discussed in the next section.

5. Prediction for a Cold Winter: Impact on the Energy Sector

In August 2005 and in updates during the subsequent autumn, the UK Met Office issued a forecast for the UK and the rest of Europe for the boreal winter 2005–2006. Public seasonal forecasts had routinely been issued for about a decade, but this was the first time the forecast was specifically targeted to a high latitude region such as UK/Europe. Judging by the overall skill of the UK Met Office (and others) dynamical seasonal forecasting system this forecast looked hazardous: the skill of temperature predictions over the region was in fact negative on average. However, the dynamical forecast constituted only part of the forecast preparation process. The final forecast was prepared by considering also information from a statistical model, from observed subsurface ocean conditions and their evolution, as well as from interpretation by operational forecasters (Graham et al., 2006). Based on these various inputs the issued forecast read:

> Our predictions continue to indicate a colder than average winter for much of Europe. The balance of probability is for a winter colder than those experienced since 1995/6. There is also an indication for a drier-than-average winter over much of the UK.

In spite of the impossibility to state after the event whether an individual probabilistic forecast of this type was correct, most of Europe did experience the colder-than-average temperatures stated as a 66% probability in the forecast (Folland et al., 2006). Southern regions of the UK were indeed affected, though northern UK had a relatively mild winter. The UK also had a drier-than-normal winter, as suggested as more probable by the forecast – as did much of the European region. Thus, on this occasion, the observed European conditions for winter 2005/06 matched very closely the most likely outcome that had been predicted.

5.1. IMPACT OF WINTER FORECAST ON ENERGY MARKETS

As it may be expected in a colder-than-normal winters, energy markets have to be prepared to face marked changes in offer-demand balances. Especially when energy availability is low, cold spells, and therefore increased demand for energy, may trigger disproportionate market reactions. As it turned out, towards the end of 2005 the UK was turning from a net exporter of gas to a net importer. Moreover, there was a high demand for energy in other parts of Europe too. Ahead of the winter 2005/06, there was no impact on the markets at the time of the Met Office winter forecast press release in September. The markets did however react significantly when the first anomalously cold weather hit London in November (e.g. Oil & Gas UK, 2007), so it is possible that the winter forecast primed the markets and made them more sensitive (Troccoli and Huddleston, 2006). Overall wholesale gas prices for the UK remained well above the long term average for the whole winter 2005/06, reaching another peak in mid-March 2006, reflecting the fact that demand was anomalously high.

A question often asked by stakeholders when they were told about the prediction for a cold winter was: “How cold is cold? You’re the experts - what’s your best guess?” Indeed many people naturally needed context for their planning: was it going to be another 1962–1963 British winter, the coldest over England and Wales for more than two centuries? Not properly quantifying the context led to a lot of invention about how extreme it would be in 2005/06. And although climate information, as often is the case, was only one of the components in the decision making process (e.g. Harrison et al., 2008), better communication could have possibly avoided over-reactions by the energy markets.

All in all, important lessons were learned by the scientific community in the UK following the 2005/06 winter forecast exposed, as it was, to public reaction to a long-range (seasonal) forecast. One such lesson was that it is crucial to engage with a wide range of stakeholders to ensure they understand the forecast and that they do not base their decisions on, say, newspaper headlines, as happened in some cases. It is probably fair to say that one critical aspect of communicating forecasts, deterministic and probabilistic, yet to be resolved adequately is the proper communication of uncertainty to all. For less specialised audiences “likely” might be more readily understood than “a 60% chance”, yet might lead readily to misinterpretation. Precise communication (e.g. a 60% chance) unfortunately might confuse, or even repel, some. Answers on a postcard, please.

6. Conclusion

In this chapter the different types of predictions available have been presented along with a discussion of how these forecasts are produced and assessed. A case study of the prediction of the European winter of 2005/06 and its impact on the energy market in the UK has also been presented. The main messages are: (1) the quality of forecasts is dependent on the time and space scales considered; (2) although average skill may be low, there may still be windows of opportunity to be exploited: it is important to get to know the system and not to consider just overall statistics (forecasting, especially at time scales longer than 2 weeks, is a recent endeavor and as such is still a mixture of science and art: the role of the forecasters, the people who understand the physical aspects of the system being forecasted, is therefore vital); (3) when communicating forecast it is important to quantify the context e.g. by referring to recent periods or major events.

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