

Seasonal forecasts are constructed using either complex climate simulators, which encode the laws of physics as they apply to the climate system, or empirical relations between a selection of climate indicators, or both. Forecasts provide estimates of seasonal averages of weather conditions, typically up to three months ahead, and so provide an idea of how likely a forthcoming season will be wetter, drier, warmer, or colder than normal, see also [SPECS fact sheet #1 “What is a seasonal prediction?”](#).

The chaotic nature of the climate system, with its strong sensitivity to initial conditions (also known as the “butterfly effect”) makes precise long-term forecasts impossible. So, seasonal forecasts have to be probabilistic, i.e. they provide the odds of certain outcomes, rather than a single yes-no prediction. Inevitably, the approximate nature of all weather and climate simulators introduces an additional degree of inaccuracy. For example, the physical processes that occur in the formulation of clouds at micrometer scales cannot be directly represented by our climate simulations, which are typically constructed of millions of grid boxes, or nodes, of approximately 100 km length.

Seasonal forecasts are increasingly used for forward planning purposes, such as by the government, emergency agencies, the water industry and agriculture. For example, information about seasonal average rainfall and temperature for the growing season can inform a farmer’s decision about which type of crop to plant ahead of time. But this information can only be useful if it is reliable. Here the word “reliable” does not just describe the generic confidence or trustworthiness in forecasts but has a specific statistical meaning attached to it. Broadly speaking, a forecasting system is said to be reliable if the forecast probabilities for an event are in agreement with the probabilities of that outcome occurring.

While it is impossible to generate an idea of reliability from a single forecast, the **reliability of a series of forecasts can indeed be quantified in a meaningful way**. For example, consider a set of predictions over 30 years or so. The forecasting system is said to be reliable if predictions of an 80% probability of a warm season correspond to observed warm seasons 80% of the time (and do not correspond – i.e. an average or cold season occurs, 20% of the time). If a forecasting system is unreliable in this sense, the forecast users can be misled – perhaps into making unfortunate decisions.

To illustrate the concept, we can also use the familiar story of the shepherd boy who repeatedly tricks the villagers into thinking a wolf is attacking their flock. When a wolf actually does appear and the boy again calls for help, the villagers believe that it is another false alarm but the sheep are eaten by the wolf. The probability of the boy crying “Wolf!” is high. However, wolves seldom actually appear on such occasions. The boy becomes increasingly unreliable because he cries “Wolf!” too often, and his warnings become useless. Improving the reliability of forecasts with a view on consequences for decision making is one of the big challenges in weather and climate forecasting.

Reliability can be quantified in a so-called reliability diagram. Here the reliability curve describes the statistical relationship between the forecast probabilities and the statistical frequency with which these events actually happened. For a perfectly reliable forecasting system the reliability curve (within some margin of error) would indicate a linear relationship between the forecast and observed probabilities (see Fig 1a). In contrast, a flat reliability curve, demonstrating little relation between forecast probabilities and observations, implies that the forecasts are irrelevant for the seasonal climate conditions (see Fig 1b). Note that simple climatological forecasts would show in the reliability diagram as one data point on the diagonal at the climatological frequency for both forecast and observed probabilities. While such a forecast is perfectly reliable and thus not misleading, it has no skill and may not be of additional value to the users.

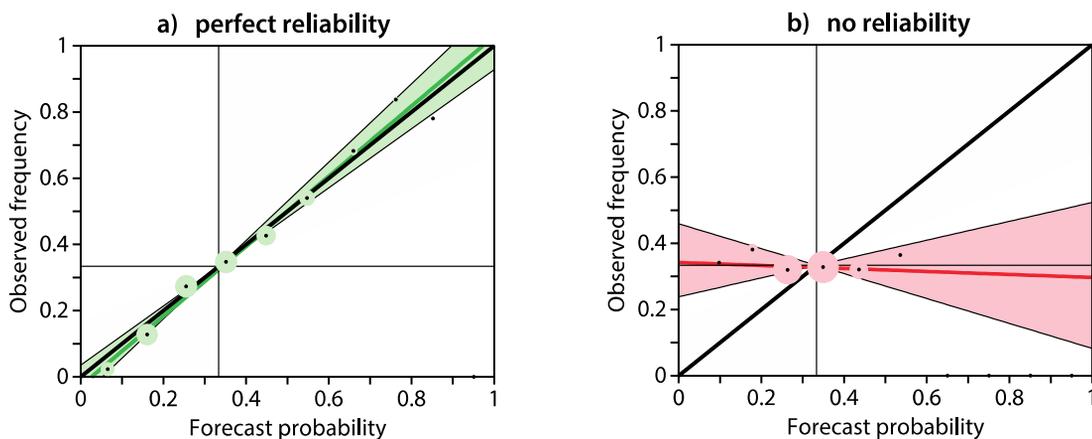


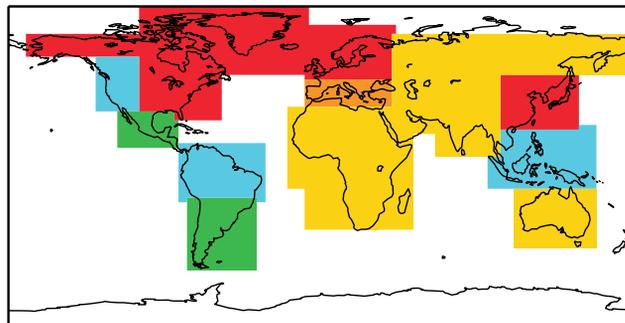
Fig 1: Example reliability diagrams for a) perfect and b) no reliability. *Figures after Weisheimer and Palmer (2014)*

Unreliability of model forecasts typically arises from a lack of [ensemble spread](#) where the observations can fall outside the [ensemble](#) range. The resulting forecast probabilities are overly confident with higher probabilities for a specific outcome than observed. In the reliability diagram such a forecasting system would have a reliability curve that has a slope smaller than the perfect diagonal slope. Similarly, forecasts that have a very large spread are not very confident about the outcome (underconfident). In the reliability diagram such a system would be characterized by a reliability curve being steeper than the perfect diagonal.

How reliable are seasonal forecasts currently? There is no simple answer – they fall into a wide range of reliability rankings, depending on the region, season, and meteorological variable of interest. Fig 2 shows an example of the reliability of a state-of-the-art seasonal forecasting system for predicting dry June-July-August (JJA) seasons over 21 standard land regions of the world. Here the colours indicate the degree of

reliability on a scale of 5 (perfectly reliable) to 1 (dangerously useless). For this particular example one can see predicting European summers is especially unreliable while forecasts for some other parts of the world are more reliable.

Reliability of dry JJA



5 Perfect 4 Still useful 3 Marginally useful 2 Not useful 1 Dangerous

Fig 2: Reliability of the ECMWF seasonal forecasts of dry JJA. *Figure taken from Weisheimer and Palmer (2014).*

We still have some way to go before we can provide reliable seasonal forecasts everywhere. The key to improve reliability will be our ability to understand and represent physical processes more accurately. One way to improve the forecasts is to run the model at finer resolution, thus allowing important cloud systems and ocean currents to be represented explicitly in the models. This will require much more powerful supercomputers that are currently available. Another approach is to represent the inherent uncertainties within the model's equations themselves by incorporating randomness for small-scale processes. While it may seem paradoxical that adding uncertainty to a climate model can actually lead to more accurate and reliable forecasts, increasingly this is what research is telling us. Furthermore, accurate and comprehensive observations of the climate system, especially in the ocean, are important to provide good-quality initial conditions for the forecasts. In addition, forecast reliability can also be improved by applying statistical post-processing techniques to the unreliable climate model forecasts.

While producing increasingly skilful climate information is clearly important, providing reliable inputs from weather and climate forecast models are absolutely essential to users for any forecast-based decision making.

Further reading

Weisheimer, A. and T.N. Palmer (2014), On the reliability of seasonal climate forecasts. *J.R.Soc. Interface*, **11**, 20131162.