CLIMATE PREDICTIONS FOR AGRICULTURE

A frequently-used approach to estimate near-future climatic conditions consists of taking the historical average (i.e. average of observations of the last 20-30 years) for a specific climate variable, place and time of interest. For example, we would assume that the mean temperature for next summer in Seville (Spain) would be equal to the average temperature experienced during summer in Seville in the past years. However, many farming decisions, in reality, are not even based on this historical average. Instead, they use what we call the 'climate memory', which refers to the average climate conditions of the most recent years (what we can remember). Both approaches (the historical average and the climate memory average) assume that future conditions will be similar to past conditions, which has two main shortcomings. First, past conditions can be highly variable, meaning that one year can be dramatically different from the previous one. Secondly, these approaches cannot predict events that have not occurred before, such as extreme events, which are becoming more frequent under the context of climate change.

Climate predictions provide information on how likely it is that the coming months (or seasons, years or decades) **will be more, equal or less warm** (or wet or windy, etc.) **than normal**. In this case, 'normal' refers to the historical average for a particular location and time. To be useful for the agriculture sector, climate predictions need to be tailored to the requirements of users (see **Fig.1**).

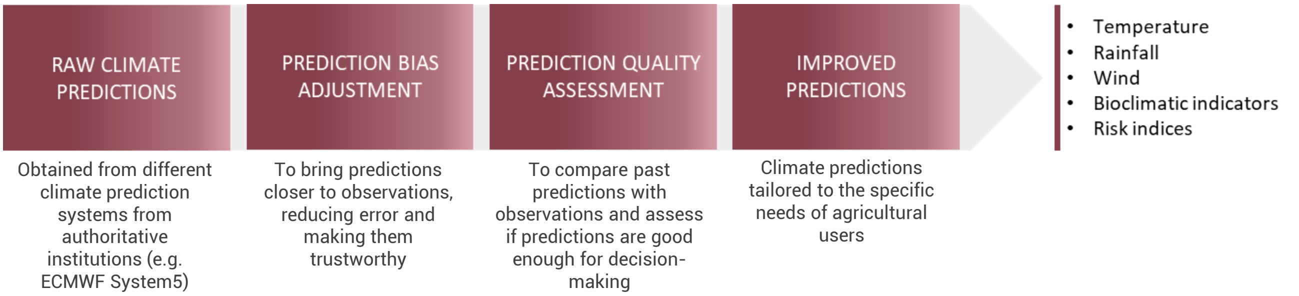


Figure 1. Tailoring climate predictions to user requirements. Source: BSC-CNS

HOW TO INTERPRET CLIMATE PREDICTIONS

Climate predictions are probabilistic. They give information on the probability of certain outcomes to occur. Imagine that we are interested in the temperature of the next month (e.g. May) at a region in the South of Spain. The climate prediction will give us information on the probability for the temperature to be **lower than normal**, **normal** and **higher than normal**. 'Normal' referring to the average temperature of the past years in this region in May.

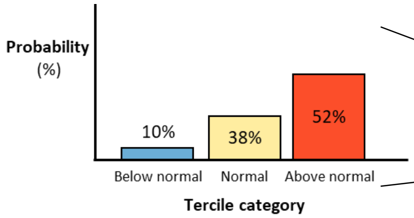
Probabilities for each of these categories are calculated by running 25 computer simulations of how climate might evolve, each using slightly different initial conditions for climate variables such as wind, temperature, pressure or soil moisture. These conditions must be plausible, i.e. they need to be consistent with current and past climate observations. Because of differences in initial conditions, the result of each simulation will differ from the others and this variation is a measure of the prediction's uncertainty. The more similar results are, the more confident we can be in the prediction.

For the location selected on the map in **Fig.2**, 3 out of the 25 simulations predicted the lower than normal category, 9 the normal category and 13 the higher than normal category. This corresponds to 10% predicted probability of having below normal temperature in May 2016, 38% probability of having normal temperature, and 52% probability of having above normal temperature.

The map in **Fig.2** indicates the most likely category of temperature (i.e. category with the highest predicted probability at each location) and its probability of occurrence (in %). As in this case the 'above normal' category received the highest predicted probability, the selected location is displayed in red on the map. Coloured categories show locations where the model improves upon using the historical average. White areas correspond to locations where either the probability predicted for the three categories is too similar to identify the most likely category OR the quality of the prediction is not good enough to be used for decision-making (skill score below zero, *see reverse for information on skill*).

In white areas, it is better to assume that the temperature in May 2016 will be normal, i.e. equal to the average temperature observed in the last years in May.

Seasonal prediction of temperature for May 2016



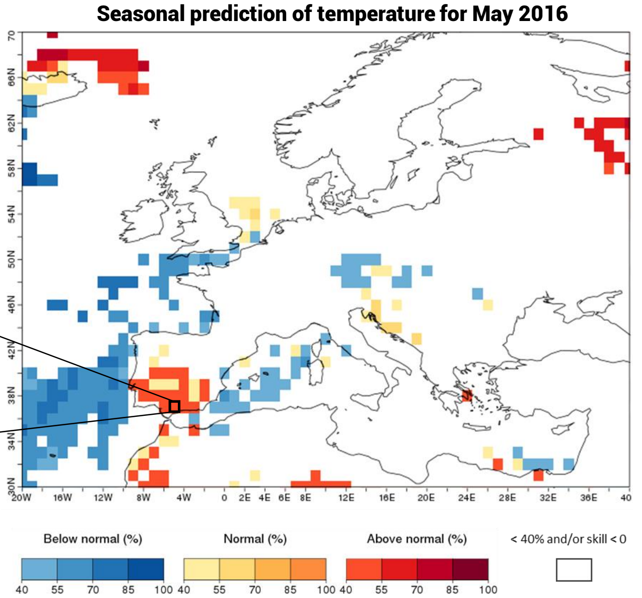


Figure 2. Seasonal prediction of temperature in May 2016 in Europe and percentage of probability predicted at a selected location. Prediction issued one month in advance (April 2016). Colours on the map show the most likely category at each location for Europe. The prediction at the selected location shows the percentage probability for each category. Source: BSC-CNS.

THE QUALITY OF CLIMATE PREDICTIONS

Climate predictions are of little use without information on their quality (skill). The quality of climate predictions is assessed by systematically comparing predictions of the past with observations (i.e. what actually happened) and deriving statistical measures from this comparison. Such measures are called *skill scores* and assess the performance of a climate prediction in relation to a standard (i.e. the alternative to using the prediction). Often, the historical average is used as the standard.

In general, we say that **a prediction has skill** (skill scores greater than zero) **when the number of times that the prediction matches the observation is higher than the number of times that the historical average matches the observation**. In these cases, using the climate prediction for making decisions is better than using the historical average. Conversely, when skill scores are less than zero, the prediction does not have skill, which means that it is better not to use it for decision-making.

Fig.2 (see previous page) was showing a prediction of temperature for May 2016 at a location in the South of Spain. When a farmer gets this prediction, the logical question would be whether (s)he should use it or not. For that, it is crucial to know how the prediction has performed in previous years. **Fig.3** shows the predicted most likely category of temperature for the past years (squares in red, yellow or blue colour) as well as the category in which real-life observations actually fell (black dots) at the mentioned location.

The prediction shown in **Fig.3** has skill. As we can see, the number of years where the prediction matches the observation (9 years, number of black dots in the red, yellow or blue squares) is higher than the number of years where the historical average matches the observation (7 years, number of black dots in the normal category). This means that in this case the prediction provides a better estimate of future climate than the historical average. Using the prediction, is therefore recommended when it has skill. In situations when the prediction has no skill, then the historical average provides a better estimate of future climate.

Figure 3. Example of climate prediction with skill. For each year, from 1993 to 2015, the prediction of the temperature for May (issued 1 month in advance) is shown by a coloured square: red indicates that the most likely category for temperature in May is the above normal category, yellow indicates it is the normal category, and blue the below normal category. Years with no colour (such as year 2009) mean that the probability of the different categories is <40%, so a most likely category cannot be clearly distinguished. Note that the normal category, highlighted with a grey shadow, corresponds to the historical average. Black dots indicate the category in which the observation falls. When the black dot falls in a red, yellow or blue square, it means that the prediction matches the observation. Source: BSC-CNS.

It is key to understand that the skill score is obtained by comparing the performance of climate predictions against a benchmark. In the example provided in **Fig. 3**, data for 23 past years are displayed. In this case, the prediction matched the observation in 9 of the years whereas the historical average matched it in only 7 of the years. This leaves 7 additional years for which neither using the prediction nor the historical average would have been useful to know what it actually was going to occur. Despite that, for this example, using the climate prediction has a better outcome than using the historical average and may provide, overall, an added value for making specific decisions.

Single years vs long range

When assessing the added value of climate predictions, we need to move from a short- to a long-term approach, since **the benefits from adopting climate predictions can only be perceived in the long term**. Agricultural users often remember a particular year of the past because it was extremely good or extremely bad in terms of crop production and revenues. Therefore, they would be tempted to look for that particular year in **Figure 3**, to see if the climate conditions for that year were correctly predicted. However, this might provide a wrong impression about how useful climate predictions can be, especially if that year had been 2015, for instance, when normal temperature conditions were predicted but above normal temperatures were observed.

When it comes to climate predictions, we cannot base their performance on individual years. We simply need to accept that the prediction can miss the observation in some particular years. However, one thing is certain: **in areas where the prediction has skill, using it will always be better than using the historical average**.

Final remarks

It is important to be aware that the skill of climate predictions will vary according to the **climate variable of interest** (e.g. temperature, precipitation, etc.), **geographical location** (e.g. tropics, higher latitudes, etc.), **predicted period** (e.g. month of April, summer season, etc.) as well as **how far in advance** the prediction is issued (e.g. one, two, three months before the predicted period, etc.). Windows of opportunity for the use of climate predictions can be found according to each situation.

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