Uncertainties in the impact assessments of climate anomalies and extremes on crop yields arise from the complexity and the limited knowledge of the involved biophysical processes, the variable accuracy of the meteorological and field data, and the limited information on the local agronomical practices.

A recent perspective paper (Siebert et al. 2017b) highlighted the complexity of this topic, the limitations of simplified statistical approaches such as the one proposed by Zampieri et al. (2017), and the need for systematic comparison with process-based crop growth models.

Here we provide a further perspective on the (dis-)advantages and main limitations of both approaches, especially for global scale applications, and explore how combining methods can improve our understanding of weather and climate impacts on yields in the diverse regions of the world.

Process-based crop models simulate crop growth and phenological stages, generally at daily time intervals as a response to daily meteorological inputs (e.g. air temperature, precipitation, radiation, wind and relative humidity). These models are used at both the field scale (e.g. Ceglar et al. 2011, Wallach et al. 2013) and the regional/global scale over gridded domains (e.g. Rosenzweig et al. 2014, Frieler et al. 2017).

Since the formulation of the involved biophysical processes cannot be derived from first principles, it is mostly based on empirical parameterizations that need to be calibrated with comprehensive sets of information and accurate observations of the driving variables. These variables are usually available only at the field scale and for a limited number of regions in the world (Levis 2014).

Among the most important adjustable parameters in crop models are the reference temperatures conducive to plant growth and the optimal range of temperatures determining the final yields (Wang et al. 2017). Wheat temperature-related critical physiological thresholds widely differ depending on the variety, even without considering the additional uncertainties related to the combined effect of water stress (e.g. Stone and Nicolas 1995a, Rana and Nagarajan 2004, Spierz et al. 2006, Farooq et al. 2011, Dias et al. 2011). Therefore, at the regional and global scales, several assumptions are necessary due to the lack of information on crop varieties, their spatial distribution and precise agro-management practices, such as irrigation and fertilization (Jones et al. 2017).

Several processes including the physiological effects of climate extremes, such as heat stress and drought and their non-linear combination, are still not reliably reproduced in crop models (Rosenzweig et al. 2014, Siebert et al. 2017b and references therein). Therefore, process-based models could underestimate the effect of heat stress compared to the statistical approaches (Roberts et al. 2017). Indeed, including the physiological effects of heat stress can alter significantly the model results (Lobell et al. 2015, Wang et al. 2017). The same issue arises more prominently for water excess (Rosenzweig et al. 2002) and other related factors such as pests and diseases, or leaching of nutrients in fertilizers. As a consequence, the reliability of process-based crop models highly depends on the region where they are applied, reducing the agreement with the observations (see e.g. Frieler et al. 2017).

Despite these limitations, process-based models of sufficient complexity can indeed be used to assess causality between yield and climate anomalies in particular regions (see for instance Lobell et al. 2013, 2015, Flohr et al. 2017, Jain et al. 2017).

Statistical approaches usually establish regression-like links between reported yield time series (e.g. FAOSTAT data) and the main climatic variables or more complex climatic indicators (e.g. Ray et al. 2015, Iizumi and Ramankutty 2016, Lesk et al. 2016, Matiu et al. 2017). Climate anomalies can be diagnosed based on a single indicator (Iizumi and Ramankutty 2016),
selection of multiple indicators (Ray et al 2015), or their combination (Zampieri et al 2017, Matiu et al 2017, Roberts et al 2017). Climate indicators are often integrated at the (sub-)national scales to allow the comparison with the available yield and production statistics (Iizumi and Ramankutty 2016, Lesk et al 2016, Zampieri et al 2017, Matiu et al 2017). These analyses do not explore causality, but they provide observed evidence in support of biophysical interpretation of the underlying processes.

Disentangling the interplay of heat and drought stress is not straightforward (Barnabas et al 2008). High temperatures affect crops both directly and indirectly (Lobell and Gourdji 2012). Direct effects involve shortening of the growing season, damage in the plant cells, but also reduced photosynthesis rate (Lobell and Gourdji 2012, Lobell et al 2013, Webber et al 2017, Liu et al 2017). Indirect effects are associated with a cascading mechanism where water vapour deficit reduces water use efficiency and increases demand for soil water, followed by a reduction of future soil water supply (due to the increased transpiration), and lower heat tolerance when the crop closes its stomata (Lobell and Gourdji 2012, Lobell et al 2013). Water stress being clearly a key factor, is often associated to high temperatures. In addition, higher temperatures can also favour the development of some pests and diseases disturbing the crop growth (Ziska et al 2011).

Therefore, in correlative analysis high temperatures often represent the prevailing factor influencing crop growth and yields. Indeed, all the aforementioned statistical studies have generally found similar or larger detrimental effect of heat stress on the final wheat yield, when compared to drought effect. Interestingly, a modelling study by Lobell (2013) for the USA, also demonstrated large impact of heat stress for maize, despite the relatively larger heat stress resistance of maize compared to wheat.

Zampieri et al (2017) have identified regions where drought is the most important yield anomaly predictor consistently with the multi-model analysis of Frieler et al (2017), who compared simulation results under actual rainfed/irrigation fraction and fully irrigated conditions. The full irrigation experiment results in a complete decoupling of the simulated yields from the observed ones in some of the models analysed by Frieler et al (2017). Indeed, the spatio-temporal variability of freshwater available for irrigation, often assumed to be not limiting, represents a further important source of uncertainty for the crop models (Elliott et al 2014, Schewe et al 2014), and for the statistical approaches as well (because the drought indicators neglect irrigation).

The global scale analysis of Zampieri et al (2017) and Matiu et al (2017) also identified the detrimental role of water excess on yields in some regions. These regions include large wheat producers, such as China, India and France, where model simulations show limited skill (van der Velde et al 2012, Frieler et al 2017). Negative correlation between precipitation and yield in the Punjab region, which is the most productive wheat-growing region of India, is also found by Jain et al (2017). Additional observations of events related to water excess are needed to shed light upon the underlying processes for developing the new parameterizations to be included in the models.

At the current stage, it is therefore evident that both approaches (the statistical one and the process-based models) suffer from different advantages and shortcomings. An important issue raised by Siebert et al (2017b) is how to combine them more effectively in a climate change context in an optimal and consistent way. Notably, a recent study points to this direction by including crop model output as additional regression parameter in a statistical model (Roberts et al 2017). In general, statistical analyses can aid the identification of crop models’ weaknesses, suggesting the processes to be included or improved.

A further fundamental aspect of Zampieri et al (2017) statistical approach, also discussed by Siebert et al (2017a), is worth to be discussed in detail: the use of statistically determined thresholds with respect to the standard fixed thresholds to diagnose the impacts of temperature extremes based on 2 metres temperature data. All following factors should be considered:

– the uncertainty in gridded temperature data used in most regional and global studies due to the spatial extrapolation of station observations, which are sparser in developing countries (Moricc et al 2012);
– the difference between mean grid temperature and local temperature that is actually perceived by the crop in the field due to the local orography (i.e. lapse rate, slope orientation and shading), the local atmospheric processes (e.g. precipitation, clouds, etc.), the local micro-climatic regimes (e.g. thermally driven winds, surface and boundary layer properties, etc.), the local alteration of the surface energy balance (i.e. land cover, land use, Bowen ratio anomalies due to irrigation and other agro-management practices, etc.), and the interaction between them (see e.g. Troy et al 2015, Siebert et al 2014, Mueller et al 2016, Siebert et al 2017a);
– the lack of knowledge on crop varieties spatial distribution, of their resistance to high temperatures, and their endogenous adaptation to climate change (Mäkinen et al 2017);
– the lack of precise knowledge of agro-management practices influencing the effects of heat stress (Jones et al 2017);
– the temperature threshold characterizing wheat heat tolerance at flowering and the subsequent evolution during the grain-filling period (Stone and Nicolas 1995a, 1995b, Farooq et al 2011, Siebert et al 2017b).

Because of these biases and uncertainties, which are presumably quite different around the world, the ambitious use of a unique global absolute temperature threshold to estimate heat stress from 2 metres
temperature data is likely to represent a sub-optimal simplification and arbitrary temperature thresholds are often used instead of the standard physiological ones (e.g. 27°C instead of 31°C, Rezaei et al 2015).

While the use of self-adapting temperature thresholds in statistical analyses indeed ignores some plant-physiological knowledge, it also has several advantages. In the study of Zampieri et al (2017), the critical values are defined as the 90th percentile of daily temperature maxima, centred in a two week window, computed from 1980–2010. This approach implicitly assumes that wheat varieties and agronomical practices are adapted to the local climatological conditions and are most sensitive to the temperature anomalies with respect to the local climate variability.

Figure 1 summarises the global distribution of diverse climatic conditions as given by critical temperatures values at harvest and their evolution observed during the previous three months. (see also figures S4 and S5 in Zampieri et al 2017). This period is chosen to ensure that the flowering stage is accounted for in all world regions, especially the relatively cooler ones characterised by longer growing seasons (Lobell and Tebaldi 2014).

The thresholds characterising heat stress for rainfed winter sown wheat (RWW) varieties at harvest range between 30°C and 38°C in most regions (35.2°C ± 3.8°C). This result is consistent with the critical temperatures range identified by Porter and Gawith (1999) and Porter and Semenov (2005), indeed providing evidence that the 90th percentile maximum daily temperatures are related to the actual physiological critical temperatures of wheat.

It is relevant to also inspect the difference of the maximum and minimum values of the 90th percentile daily maximum temperatures recorded during the three months preceding harvest over different wheat growing regions (figure 1, dashed lines). These differences correspond to increasing resistance of wheat to heat stress as the maturity approaches.

For RWW, two distinct peaks (red dashed lines) are found for the three month maximum temperature 90th percentile differences. The first peak centred on 5°C is associated with production in Central-Northern Europe, while the second broader peak of about 8°C–13°C is found for the wheat grown in Central-Southern Europe and in the rest of the world. This indicates that winter wheat varieties grown in these regions are likely to be better suited to deal with a large seasonal temperature cycle.

The mono-modal signal characterising the temperature envelope of rainfed spring wheat (RSW) varieties from flowering to maturity (green dashed line, peak centred around 6°C) is dominated by the climatic conditions found mainly in Spain and Canada—i.e.
much more limited in spatial extent than RWW varieties. In these regions, the 90th percentile of maximum temperature at harvest is more frequently between 30 °C and 37 °C (33.4 °C ± 2.9 °C).

Irrigated winter sown wheat (IWW) varieties are located in regions characterised by diverse climatic conditions. We note a wide range of temperature thresholds at harvest, ranging with no preferential value between 23 °C and 41 °C (32.2 °C ± 6.1 °C). Among these critical temperature thresholds, the higher values are consistent with cultivars such as HD 2189 specifically developed for India (Rane and Nagarajan 2004), while the lower values are likely more representative of sub-optimal conditions than actual heat stress (Spiertz et al. 2006, Farooq et al. 2011). Interestingly, the 90th temperature threshold increases by about 14 °C during the sensitive period over most IWW cropping regions (blue dashed lines). Such extreme temperature envelopes are seldom found for rainfed winter varieties.

The difference of 90th percentile of daily maximum temperatures at harvest and around flowering (figure 1, dashed lines) integrates the dynamic temperature dependent processes discussed by Siebert et al. (2017b) (cf. their figures 1 and 2).

This analysis highlights the need of collecting more precise information about agronomical practices, especially over Southern and Southeastern Asia, where wheat is mostly irrigated. Shifting of existing and developing new varieties, altogether with implementing sustainable irrigation strategies could provide an effective method to cope with the effects of climate change (Hasegawa et al. 2014, Semenov et al. 2014, Elliott et al. 2014). Preserving genetic diversity in varieties along the selection process will become a challenge, also to maximise the variety of available breeding traits to meet the adaptation strategies to cope with increasing decadal scale variability (Goncharov et al. 2009). Crop model simulations combined with information on new breeding methods and genetic quantitative trait loci (QTL) mapping approaches could help the development of future cereal cultivars for different environments (Rotter et al. 2015, Mäkinen et al. 2017).

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