AGRICULTURAL IMPACTS

# Robust uncertainty

An up-to-date synthesis of climate change impacts on crop yields shows that the bounds of uncertainty are increasing. So why do estimates of the effect of climate change on crop productivity differ so much?

Reimund P. Rötter

The challenge of feeding a global population expected to reach 9 to 10 billion by mid-century, while at the same time coping with a changing climate, calls for estimates of how much climate change might affect global food production[1]. However, attempts to understand and help prepare for the future, such as the assessment of climate change impacts on crop productivity, are inherently uncertain[2]. In his essay 'On Modern Uncertainty', Bertrand Russell[3] emphasized the importance of being aware of the limitations of our knowledge while communicating clearly what we do know, so that informed action can be taken. As they describe in *Nature Climate Change*, Challinor and colleagues[4] follow this advice for crop yields under the impacts of climate change.

Challinor *et al.* use meta-analysis to summarize climate change impacts on the productivity of three major food crops (wheat, maize and rice) and their adaptation potential as a function of temperature — similar to that reported in the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC)[5]. The database was extended from 2007 to 2012, more than doubling the number of studies and the number of data points. This is the largest pool of data from diverse modelling studies ever used for a global synthesis of this kind. The work contributes to the food security and food production systems chapter of the Fifth Assessment Report (AR5) of the IPCC, due to be released on 31 March 2014 in Yokohama, Japan.

Although there are similarities between the results of Challinor *et al.* and those of the earlier AR4 meta-analyses, there are also distinct differences. For example, wheat grown in mid to high latitudes does not only show a positive yield response to local warming (up to 3 °C), as was the case in AR4, but also negative responses. Furthermore, in temperate regions all three crops show a higher risk of yield loss at moderate levels of local warming than was suggested in the earlier AR4 analysis. The considerably larger number of entries used by Challinor and colleagues show a greater spread, or uncertainty range, than AR4 (schematically depicted in Fig. 1) and, without adaptation, significant losses in the aggregate production of wheat, rice and maize are already projected when local warming exceeds 2 °C, both for temperate and tropical regions. This is different from AR4, which suggested such yield loss would occur only when exceeding 3–4 °C local warming.

Building on previous analysis[5], Challinor and colleagues explicitly address uncertainty, establish confidence intervals for aggregate production, carry out extensive quality control and apply a transparent database and more comprehensive methods for statistical analysis of future trends in aggregate production. They also investigate the development of yield impacts over time and the effectiveness of different adaptation measures.

When looking at this update of the AR4 meta-analysis of climate impacts on crop yields, the reader cannot but wonder: what might have caused the increase in the range of uncertainty? The authors partly answer this by pointing at the spatial sampling that now covers a larger and more diverse population of crop cultivation environments. Furthermore, enlarging the suite of modelling approaches, the number of crop models and the scenario spread inevitably adds to this and increases the range of quantifiable uncertainty[6] as compared with AR4 (Fig. 1). Spatial sampling and model uncertainty factors (see, for example, ref. 7) constitute what can be coined quantifiable uncertainty, as distinguished from unquantifiable uncertainty, which goes beyond the projected range[6] (Fig. 1). For example, we do not know what technological breakthroughs we can expect, or how human behaviour and skills will change.

In the first instance Challinor *et al.* were interested in establishing robust estimates of the aggregate effects of climate change on crop yields, not in analysing how much spread is caused by different sources of uncertainty. The latter was made impossible by the heterogeneity of the database, but the authors were able to assess, for example, whether there are differences in yield response from simulation-based (mechanistic) versus statistical studies (see Supplementary Information in ref. 4). They found that statistical models predict a greater negative impact of climate on crop yields. An additional explanation for generally

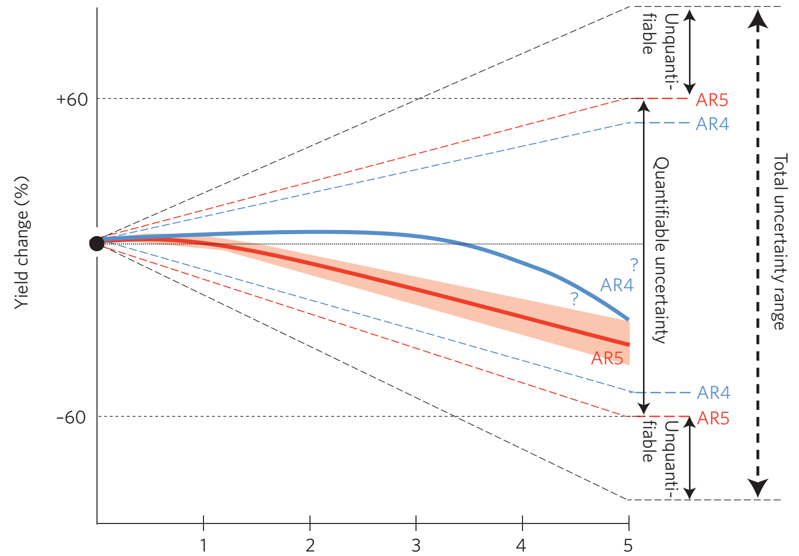


**Figure 1 |** Schematic illustration of the relationship between total uncertainty, projected ranges of relative yield changes and best fits of aggregate yield changes. The figure refers to model-based results from AR4 (ref. 5) and AR5 (WGII chapter 'Food security and food production systems') and indicatively depicts the main message and novelties of this study[4]. Figure modified from ref. 6.



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more negative yield impacts projected by recent studies is a tendency towards reduced optimism about the yield benefits of enhanced atmospheric $CO_2$ concentration, an issue still under much debate[8,9].

The consideration of adaptation effectiveness by Challinor *et al.* is a first attempt to differentiate between various adaptation measures. This is an important step but the resultant estimates of the aggregate impact of adaptation should be treated with caution. This is because only a few measures of adaptation are considered — reflecting the limited capability of crop models[8] — and the number of paired data points is also small. More fundamentally, analysis of adaptation that does not take farm-level socio-economic context into account — the level on which most decisions on adaptation are taken — is not very meaningful. Consideration of shifts in yield reliability is also very limited, owing to data availability and deficiencies in most crop models in adequately capturing variability and extremes[7–9].

Being aware of these limitations and considering that the current database originates from inherently uncoordinated studies, how can this situation be improved in the future? One avenue towards more robust global results has already been taken by the Agricultural Model Intercomparison and Improvement Project[10] and in Europe by Modelling European Agriculture with Climate Change for Food Security[11], a project launched by the Joint Research Programming Initiative on Agriculture, Food Security and Climate Change. These projects coordinate efforts to improve agricultural models and develop common protocols to systematize modelling for the assessment of climate change impacts on crop production. They also go beyond crop modelling and emphasize the importance of integrating biophysical and socio-economic analysis from farm to global scale[9], to generate information that can guide decisions on feasible adaptation strategies.

Although Challinor *et al.* compiled a large database, they certainly missed many studies, as would have happened to any other author team, which in the IPCC assessment cycle usually changes every five to seven years. To avoid the negative effects of such discontinuities, a continuous monitoring of the 'state of knowledge' was proposed at a recent symposium in Oslo[11]. If this was carried out on a rolling basis, certain key results generated for one assessment could be updated and made available for subsequent IPCC and other international assessments. Such an effort could possibly be coordinated by the Agricultural Model Intercomparison and Improvement Project[10]. ❐

*Reimund P. Rötter is at MTT Agrifood Research Finland, Lönnrotinkatu 5, FI-50100 Mikkeli, Finland. e-mail: reimund.rotter@mtt.fi*

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