BAYESIAN STATISTICAL MODELS FOR QUANTITATIVE SYNTHESIS OF CLIMATE CHANGE IMPACT STUDIES

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ABSTRACT

The amount of experimental and simulated data produced by scientists working on climate change impact assessment has grown exponentially during the last two decades. The growth of the literature on climate change was faster than the growth in other areas of research. Scientists are now facing a 'data synthesis challenge' making increasingly difficult the conduct of rigorous and comprehensive assessments. Quantitative research synthesis methods are needed to maintain a high level of credibility in the scientific assessments of climate change impacts and in the evaluation of mitigation strategies in agriculture. Here, I show that simple and efficient statistical tools could help climate and crop scientists to synthetize large sets of studies in order to provide the decision makers with reliable conclusions. More specifically, I demonstrate that Bayesian hierarchical statistical models constitute powerful tools for analyzing ensembles of experimental data. Through several examples, I illustrate how this type of statistical models can be fitted to large sets of studies for estimating the global effects of climate change on crop productions accounting for the relative accuracy of each individual study. Once fitted to data, these models can be easily run to explore a diversity of scenarios and analyze uncertainties in projections of crop responses to climate change. They can also be implemented to derive more plausible estimations of climate change impacts by constraining ensembles of process-based crop model outputs using experimental data. I advocate for the inclusion of this type of statistical model in the tool boxes of scientists working on climate change impact assessment. More rigorous quantitative syntheses could help scientists to promote evidence-based decision making.

Keywords: Bayesian, climate change, crop yield, meta-analysis, meta-model, hierarchical model

INTRODUCTION

The number of papers published on climate change is increasing exponentially. In this area of science, the annual growth rate of the number of published papers is about equal to 16%, i.e., much larger than the rate of 4% measured over all scientific domains (Minx *et al*. 2017). Scientists and decision makers are now facing a « data synthesis challenge »; as more and more data become available, how to conduct rigorous and comprehensive assessments on climate change?

This challenge is made difficult by the explosion of the number of papers published on climate change. At the time of the first assessment report (AR) cycle of the Intergovernmental Panel on Climate Change (IPCC) (1986-1990), 1697 studies on climate change were referenced in ISI Web of knowledge while 108277 were available at the time of the fifth AR cycle (2008-2013) (Minx *et al*., 2017). Only a fraction of these published studies was cited in the reports of IPCC. Although 63% of the published literature was cited in the first report (AR1) of IPCC, only 23% of the available studies was cited in the 5th assessment report (Minx *et al*., 2017). This result reveals that scientists are now overwhelmed by the number of publications and have difficulties to conduct rigorous and comprehensive literature synthesis.

Reliable methods are required to help scientists delivering high quality syntheses to decision makers. Meta-analysis is one of most powerful method for quantitative synthesis. Meta-analysis consists in analyzing a large collection of results from individual studies for the purpose of integrating the findings (Albert and Makowski, 2018; Borenstein *et al*., 2009; Makowski *et al*., 2018). It includes a systematic review of existing studies and a statistical analysis of the data extracted from these studies. The first step of a meta-analysis is to conduct a systematic review and to select relevant studies. The systematic review produces a set of studies dealing with a specific topic. Here, I will consider a specific problem related to climate change impact on crop yield, i.e., the estimation of the percentage of yield loss resulting from an increase of the temperature during the growing season. In this specific case, each study corresponds to one paper reporting the results of a specific experiment conducted to measure the effect of a temperature increase on crop yield. At the second step, the extracted data are used to compute the effect size for each individual study separately (here, the yield loss or yield grain resulting from +1°C), and the result is a set of individual effect sizes covering the set of selected studies. The third step is to estimate the mean effect size, i.e., the weigthed average of all individual effect sizes. The mean effect size (MES) summarized the results across all studies. A confidence interval is computed to show the level of uncertainty in the estimated MES. The MES is a single number summarizing the whole dataset, but the individual effect sizes may vary a lot between studies and take values well below or above the MES depending on the study characteristics. In such case, it is sometimes possible to explain part of the between-study variability of the individual effect sizes using one or several covariates.

In this paper, I show how simple hierarchical Bayesian statistical models can help scientists to estimate the effect of temperature increase on crop yield from large sets of field warming experiments. I advocate for the inclusion of this type of statistical model in the tool boxes of scientists working on climate change impact assessment.

DATA

In order to illustrate the flexibility of the proposed approach, I consider here two datasets successively, one on rice and one on wheat.

The rice dataset includes 83 values of yield sensitivity calculated from the results of field warming experiments located in different sites in several countries (Zhao *et al.* 2016a). Data were extracted from each published study in turn. On each site, yield data were collected during several years. For each site-year, yield was measured in a field control (under ambient temperature) and in an adjoined field with an increased temperature ΔT. For each site-year, the two yield observations were used to compute the following relative yield difference

$$\Delta Y = \frac{Yield\ with\ increased\ temperature - Yield\ in\ control}{Yield\ in\ control}$$

and, then, the yield sensitivity equal to $S = 100 * \Delta Y/\Delta \mathrm{T}$. The yield sensitivity S measures the yield change in % resulting from +1°C.

The wheat dataset (Zhao *et al.*, 2016b) includes the same type of data for wheat. Yield data were collected in field warming experiments located in 14 sites in China. Several years of data are available in each site, and a yield sensitivity was calculated for each site-year as explained above. The total number of sensitivity values available for wheat is equal to 45.

STATISTICAL MODEL

The model is a Bayesian version of a random-effect model including two levels, namely the within-study level and the between-study level. The within-study level describes the within-study variability of the data and is defined by:

$$S_{ij} = \mu + b_i + \varepsilon_{ij} \tag{1}$$

where S_{ij} is the yield sensitivity in the ith study (site) and the jth year, μ is the mean sensitivity value over all studies, $b_i \sim N(0, \sigma_b^2)$ is a random study effect, $\varepsilon_{ij} \sim N(0, \sigma_{\varepsilon i}^2)$ is a random term describing the within-study variability (i.e., here, the between year variability). The two variances σ_b^2 and $\sigma_{\varepsilon i}^2$ correspond to the between-study variance and to the within-study variance, respectively. Here, the within-study variance is indexed by i because this variance is assumed variable across studies, depending on the level of variability of S_{ij} between years within a given study (the higher the between-year variability in study i, the higher the value of $\sigma_{\varepsilon i}^2$). Each study is thus characterized by a specific value of $\sigma_{\varepsilon i}^2$.

This model includes three types of parameters, namely μ, σ_b^2, and $\sigma_{\varepsilon i}^2$, i=1, …, N. As these parameters are estimated here using a Bayesian method, it is necessary to define prior distributions for all the unknown parameters of the model. Here, non-informative priors are defined, specifically $\mu \sim N(0, 10^6)$, σ_b^2, $\sigma_{\varepsilon i}^2 \sim InvGamma\left(\frac{k}{2}, \frac{k}{2}\right)$. Several values were tested for k in order to analyze the sensitivity of the results to the prior, i.e., k=1, 0.2, 0.02, and 0.002.

The model described above can be expanded in order to explain part of the between-study variability using one or several covariates. This approach is illustrated here for the wheat dataset where the average temperature measured during the growing season is used to explain part of the variability of the wheat yield sensitivity to temperature increase. The model is expanded as follows:

$$S_{ij} = \mu_0 + \mu_1 X_{ij} + b_i + \varepsilon_{ij} \tag{2}$$

where X_{ij} is the average temperature in the site i for year j, and μ_1 is an additional parameter to be estimated from the data.

In some meta-analyses, the model (1) is simplified and the random term b_i is omitted. This simplified version of the model is often named “fixed effect model”. This model assumes that all studies share the same effect size and that the heterogeneity among studies is negligible. This assumption is often unrealistic and the use of a fixed-model in case of strong between-study variability can lead to underestimation of the level of uncertainty of the estimated values. Here, I illustrate the consequence of the inappropriate use of a fixed-model by comparing the results obtained with this model to those obtained with the random-effect model (1).

All models are fitted using a Markov chain Monte Carlo algorithm implemented using the R package MCMCglmm (Hadfield, 2010). The posterior distributions are computed with 100,000 or 1,000,000 iterations and a burnin period of size 10,000. An example of chain and of posterior distribution is shown in Fig. 1.

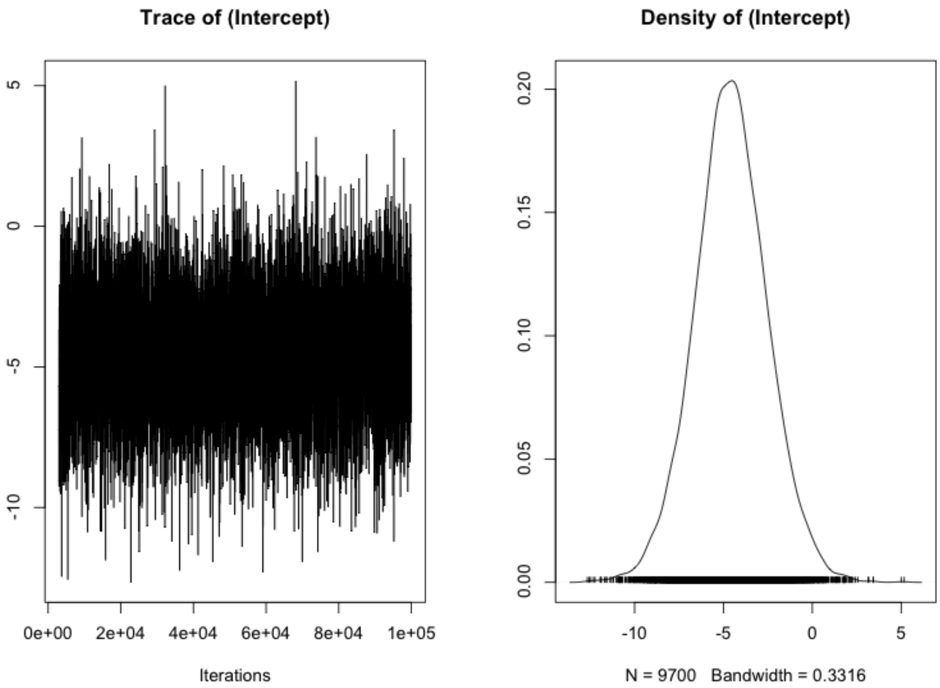

Fig. 1. Chain of values of μ obtained with MCMC (left) and corresponding posterior distribution (right).

RESULTS

The results obtained with the random-effect model (1) for rice (dataset 1) are summarized in Fig. 2 and Table 1. The mean effect-size ranges from -4.87% to -5.09% depending on the prior chosen for the variance parameters of the model. The influence of the prior on the results is thus relatively weak. The individual effect sizes estimated site-by-site show contrasted values; some are smaller than 9% or even 10% while others are not different from zero. However, the results reveal that the effect size is never positive; no positive effect of +1°C on yield is estimated for the sites included in the dataset.

For wheat in China (dataset 2), the estimated effects of an increase of +1°C on yield are quite different (Fig. 3) compared to rice (Fig. 2). The MES is not significantly different from zero for wheat and this result reveals that, in average over the experimental sites, an increase of +1°C has no substantial effect on wheat yield. However, the effect of +1°C on wheat yield strongly varies across sites. Some sites show a positive effect while the effect on yield is negative in other sites. The range of yield sensitivity values is very large, from +10% to -10%, depending on the sites.

A model including a covariate was fitted to the wheat data in order to explain part of the strong variability of wheat yield sensitivity. The selected covariate is the mean temperature recorded during the growing season. This covariate is reported in the x-axis of Fig. 4. The y-axis of this figure shows yield sensitivities site-by-site. The fitted model reveals a decreasing trend; the yield sensitivity values tend to be positive in cold areas (on the left) and to be negative in warm areas (on the right). But the uncertainty remains high and a substantial part of the variability is not explained by this covariate.

Finally, Fig. 2 and Fig. 3 show that, although the MES estimated by the fixed-effect model are similar to those obtained with the random-effect model, the level of uncertainty is strongly underestimated by the fixed-effect model; the use of a fixed-effect model gives an over-optimistic view of the level of accuracy of the estimated values.

Table 1. Mean effect size (MES=mean yield sensitivity to +1°C) estimated with model (1) for different parameter values (k) of the prior distribution (Inverse Gamma), and lower and upper bounds of the associated 95% credibility intervals of MES

k	*MES*	*Q2.5*	*Q97.5*
1	-4.57	-8.44	-0.29
0.2	-5.02	-9.02	-0.66
0.02	-5.10	-9.26	-0.88
0.002	-5.09	-9.87	-0.64

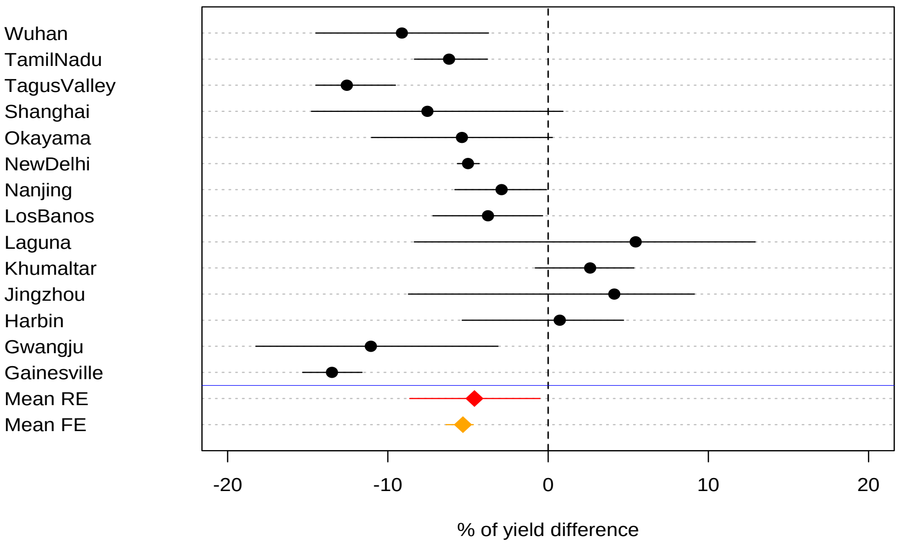

Fig. 2. Meta-analysis of field warming experiments: Rice yield sensitivity to +1°C (ambient [CO_2]). The black points correspond to the yield sensitivity estimated for each site. The red point corresponds to the mean effect size estimated with the random-effect model (RE) and the orange point corresponds to the mean effect size estimated with the fixed-effect model (FE). The bars correspond to the 95% credibility intervals. Results were obtained with k=1 (see text).

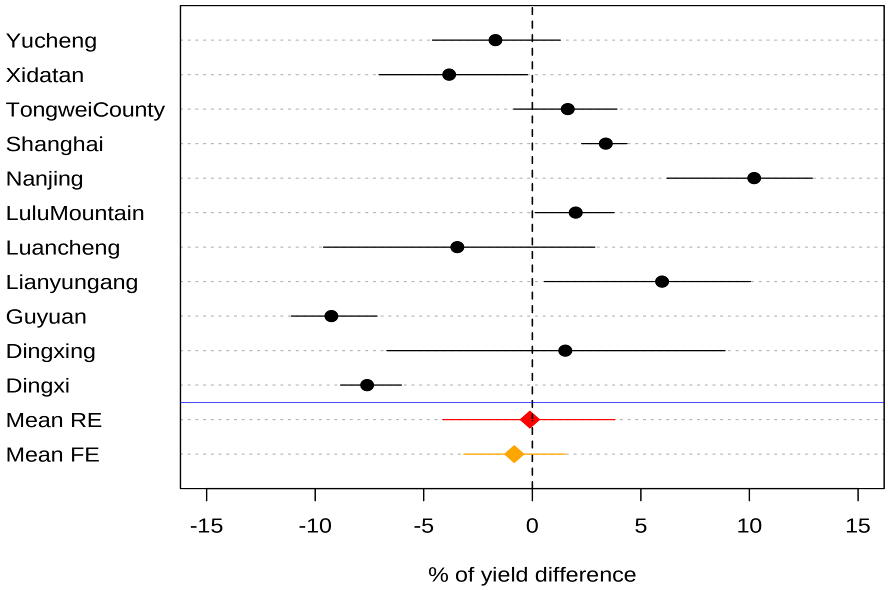

Fig. 3. Meta-analysis of field warming experiments: Wheat yield sensitivity to +1°C (ambient [CO_2]) in China. The black points correspond to the yield sensitivity estimated for each site. The red point corresponds to the mean effect size estimated with the random-effect model (RE) and the orange point corresponds to the mean effect size estimated with the fixed-effect model (FE). The bars correspond to the 95% credibility intervals. Results were obtained with k=1 (see text).

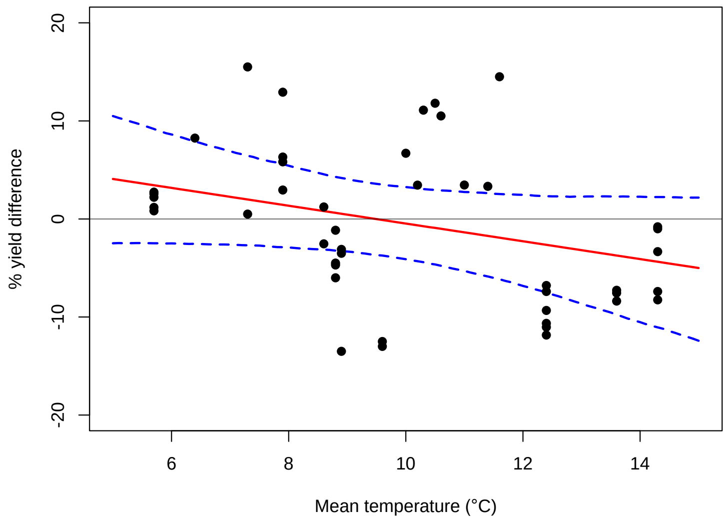

Fig. 4. Meta-regression: Wheat yield sensitivity vs. Mean temperature.

CONCLUSION

Bayesian hierarchical statistical models are powerful tools for analyzing the effect of climate change on crop yields from large sets of experimental studies. Here, I showed how this type of statistical models can be used to estimate the global effects of climate change on crop productions accounting for the relative accuracy of each individual study. Once fitted to data, these models can be easily run to explore a diversity of scenarios and analyze uncertainties in projections of crop responses to climate change. I advocate for the inclusion of this type of statistical model in the tool boxes of scientists working on climate change impact assessment. More rigorous quantitative syntheses could help scientists to promote evidence-based decision making.

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