Accounting for uncertainties in modeling the impact of climate change on agriculture

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1 Introduction

Impacts of climate change on future agricultural production and food security are a key concern because both climate risk and global demand for agricultural production are both expected to increase (Godfray et al., 2010). There have been many studies since the 1990s assessing the future impact of climate change on agricultural crop production using statistical and process-based crop modeling methods (e.g. Rötter and Van de Geijn, 1999; Lobell and Burke, 2008; White et al., 2011; Porter et al., 2014; Asseng et al., 2015). Statistical approaches have intrinsic limitations in predicting future climate change impacts since they are constrained by the historical data from which they were developed. Process-based crop models built on understanding processes and

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interlinkages in agroecosystems have been considered more promising and are routinely applied to simulate the potential impacts of climate change on crop growth and productivity from local to global scales (e.g. Asseng et al., 2015; Challinor, et al., 2009; Porter et al., 2014; Rosenzweig et al., 2014; Rötter et al., 2011; Tao et al., 2008, 2009; White et al., 2011). Simulations have been usually driven by climate projections from global climate models (GCMs) downscaled using statistical methods or regional climate models (RCMs) (White et al., 2011).

All climate change impact assessments include a degree of uncertainty due to the number and complexity of the physical, biological and socioeconomic processes involved (Asseng et al., 2013, 2015; Challinor et al., 2009; Lobell and Burke, 2008; Rötter et al., 2011, 2012; Tao et al., 2009a, 2009b, 2018; Wallach et al., 2016, 2017). Among other things, uncertainties can originate from (Fig. 1):

- variability in future development of greenhouse gas (GHG) emissions;
- variability in climate responses to global emissions;
- gaps or errors in input data;
- limitations in model structures and parameters; and
- human error.

Model uncertainty can be defined as the distribution of simulated values arising from these variables (Wallach, 2020). It is critical to understand and account for these uncertainties since they may substantially affect the accuracy of climate change impact assessments and resulting adaptation strategies.

There has been significant progress in dealing with uncertainties in models. One example is a study of future climate impacts on rice productivity

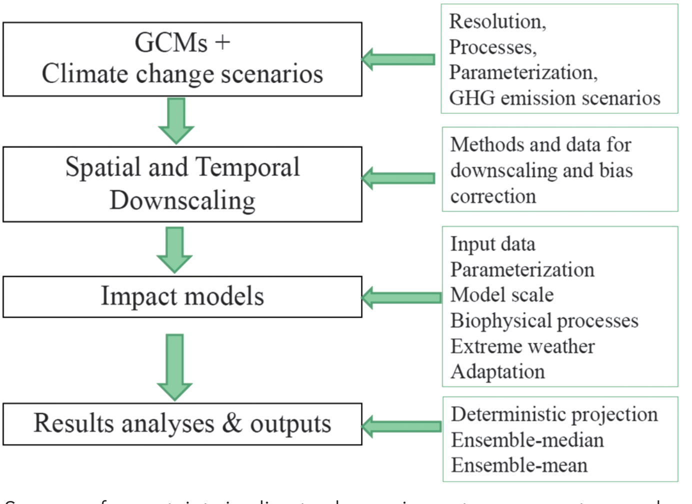

Figure 1 Sources of uncertainty in climate change impact assessment procedures.

and water use in China which used 20 climate change scenarios and a Monte Carlo simulation to test each scenario as a way of accounting for uncertainty in individual projections (Tao et al., 2008). Another approach has been to try to account for uncertainties associated with biophysical parameters used in a crop model, in this case simulating groundnut yield in India (Challinor et al., 2009). Probability distributions of biophysical parameter values in a crop model were inferred using Bayesian probability inversion and a Markov Chain Monte Carlo (MCMC) technique together with long-term data on crop phenology and yield (Iizumi et al., 2009; Tao et al., 2009b). Another study used double-ensemble probabilistic assessment to evaluate climate change impacts on maize productivity and water use in China (Tao et al., 2009b). Using a single crop model, 60 sets of crop model parameters and 10 climate scenarios, the study suggested that uncertainties in climate projection generally contributed more uncertainty to climate impact assessments than crop model parameters.

A recent focus has been uncertainty deriving from the structures and parameters of different models (Asseng et al., 2013, 2015; Bassu et al., 2014; Li et al., 2015; Martre et al., 2015; Palosuo et al., 2011; Pirttioja et al., 2015; Rötter et al., 2011, 2012; Wang et al., 2017; Tao et al., 2018, 2020). As an example, Palosuo et al. (2011) estimated uncertainty from model structure by comparing eight widely used crop models for winter wheat under current climatic conditions across Europe. A similar study has been carried out for barley using nine crop models (Rötter et al., 2012). International initiatives have included the Modelling European Agriculture with Climate Change for Food Security (MACSUR) project (Ewert et al., 2015) and the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2014). Both MACSUR and AgMIP have made great progresses in quantifying and reducing uncertainty from model structure in simulating the response of crop yields to climate change, through ensemble modeling approaches and suggested improvements to individual models (e.g. Asseng et al., 2013, 2015; Bassu et al., 2014; Li et al., 2015; Martre et al., 2015; Pirttioja et al., 2015; Maiorano et al., 2017; Wallach et al., 2016; Wang et al., 2017; Tao et al., 2018, 2020). The results showed that simulated climate change impacts on crop yield varied significantly across models due to differences in crop model structure and parameters. One study of 26 wheat simulation models found that degrees of uncertainty in these models were larger than those from downscaled GCMs (Asseng et al., 2013).

Previous attempts to account for uncertainty have tended to focus on one or two key sources of variability such as:

- climate projections (e.g. Tao et al., 2008);
- crop model parameters (e.g. Challinor et al., 2009; Iizumi et al., 2009; Tao et al., 2009a);

- crop model parameters and climate projections combined (Tao et al., 2009b);
- crop model structure (Palosuo et al., 2011; Rötter et al., 2012);
- crop model structure and climate projections combined (Asseng et al., 2013, 2015; Bassu et al., 2014; Li et al., 2015);

Building on this, Tao et al. (2018) developed a triple-ensemble probabilistic assessment to account for uncertainties in seven crop models from three sources: crop model structure, crop model parameters and climate change projections. The results showed that the contribution of crop model structure to the total variance of ensemble output was larger than that from downscaled climate projections and model parameters. The relative contribution of crop model parameters and downscaled climate projections to the total variance of ensemble output varied greatly between the seven crop models. The contribution of downscaled climate projections was on average larger than that of crop model parameters.

This information on degrees of uncertainty from different sources is essential for model users to decide where to put the most effort when developing or improving models for impact analyses. The study concluded that triple-ensemble probabilistic approach incorporating uncertainties from multiple sources provides more comprehensive information for quantifying uncertainties than studies that only account for uncertainties from one or two sources. The following sections review each of the major sources of uncertainty in model-based climate impact studies for crop production and how levels of uncertainty can be reduced.

2 Managing uncertainties from greenhouse gas emission and climate change scenarios

Future climate impacts will depend on the future development of GHG emissions and the climate response to rising GHG concentrations. Socioeconomic and emission scenarios have been used to provide plausible descriptions of how the future may evolve. These scenarios involve assumptions about changes in socioeconomic conditions, technologies, energy requirements, land use as well as related emissions. Various scenarios have been developed, starting with the IS92 scenarios published in the 1992 Supplementary Report to the IPCC Assessment (Leggett et al., 1992), the Special Report on Emissions Scenarios (SRES) scenarios (Nakicenovic et al., 2000), the Representative Concentration Pathways (RCPs) (Van Vuuren et al., 2011) and, more recently, a framework (incorporating Shared Socioeconomic Pathways (SSPs) as discussed in O’Neill et al., 2014) to facilitate production of integrated scenarios based on combinations of climate model projections, socioeconomic conditions and assumptions about climate policies (Van Vuuren et al., 2011; O'Neill et al., 2020). Since completion of the IPCC's Fifth Assessment Report (AR5) in 2014, concentration pathways have been considered together with SSPs (Riahi et al., 2017). RCPs are greenhouse gas concentration (rather than emission) trajectories adopted by the IPCC. Four pathways were created to describe different climate scenarios, depending on the future volume of GHGs emitted. The RCPs – originally RCP2.6, RCP4.5, RCP6 and RCP8.5 – set total radiative forcing targets (the difference between incoming and radiation in the upper atmosphere, measured in watts per square meter) to the year 2100 (2.6, 4.5, 6 and 8.5 W/m^2, respectively).

GCMs contain large uncertainties in projecting future climate due to limited understanding of various earth processes, temporal and spatial resolution, and various biophysical parameters (Knutti et al., 2013). The Coupled Model Intercomparison Project, which began in 1995, is now in its sixth phase (CMIP6). CMIP6 coordinates independent GCM intercomparison activities and experiments and has established a common infrastructure for collecting, organizing and distributing output from climate models based on common sets of experiments (https://esgf-node.llnl.gov/projects/cmip6/). Multi-model results provide insights into errors and uncertainty in individual climate model simulations (Collins et al., 2011). GCMs have been continuously improved to reflect the latest developments in climate science. An example is refinement of estimates of equilibrium climate sensitivity, an important measure of long-term temperature rise due to a doubling of atmospheric CO_2. The current AR6 estimate is 3°C with a likely range of 2.5–4°C, compared to 1.5–4.5°C assessed in AR5. According to IPCC AR6 (2021), compared to 1850–1900, global surface temperature averaged over 2081–2100 is projected to range from 1.0°C to 1.8°C under the very low GHG emissions scenario (SSP1-1.9) to 3.3–5.7°C under the very high GHG emissions scenario (SSP5-8.5).

Since spatial resolution of GCMs is generally too coarse, spatial downscaling and bias correction are necessary before using the data for impact assessments (Laux et al., 2021). Different approaches for spatial downscaling and bias correction have been developed to facilitate regional climate projections (Semenov and Stratonovitch, 2015). It should be noted that climate change not only affects mean climate variables but also overall climate variability (IPCC, 2012). Robust climate change impacts studies need to consider climate variability as well. Unfortunately, uncertainties in projections of extreme events are largely unknown (IPCC, 2021).

One way to quantify uncertainties in predicting climate change is to use multiple GCMs with different emissions scenarios (e.g. Tao et al., 2008, Liu et al., 2019, Palosuo et al., 2021, Webber et al., 2018). This reduces uncertainty though some unquantifiable uncertainty will always remain (Rötter, 2014). An alternative approach is to use probabilistic impact estimation using impact response surfaces. This technique combines impact modeling with probabilistic climate projections that can be applied to any climate scenario (Pirttioja et al., 2015, 2019).

3 Managing uncertainties from crop model input data

The quality of crop model input data, e.g. related to weather, soil and agricultural management, including issues such as how data is obtained and data resolution, is critical for robust model. At a site scale, high-quality field experiment data on soil properties, environmental conditions, agricultural managements, as well as crop development, growth, biomass and yield, are essential for model calibration and validation (Kersebaum et al., 2015). At a regional scale, crop simulations frequently use low-resolution input data. Climate and soil data are often generated via averaging or sampling data. This may bias simulated yields at large scales (Angulo et al., 2013).

Research quantifying the aggregation effect found that the relative mean absolute error of most models using aggregated soil data was similar to or larger than inter-annual or inter-model variability in yields. This error increased further when both climate and soil data were aggregated (Hoffmann et al., 2015). Similarly, weather data and management data resolution also affect results. Quality of soil and management data can cause significant uncertainty where a model developed from conditions in one area is applied to a new area. Soil type-related yield variability generally outweighs inter-annual variability in yield due to weather variables (Folberth, et al., 2016). Due to nonlinear responses within models, input data should be as accurate as possible to reduce uncertainties in climate change impact assessment. Although good agricultural management data is critical for modeling climate change impacts, it is notoriously difficult to obtain. An alternative approach is to derive agricultural management information from high-resolution remote sensing data, e.g., relating to leaf area index (LAI) or soil moisture status and incorporate it into crop models to improve simulation performance (Chen and Tao, et al., 2022).

4 Managing uncertainties from model parameters and human error

Model parameters affect model simulation results and related uncertainties substantially. Model parameters need to be calibrated, i.e. adapted to the target cultivar and environment using empirical data, so that model performance is consistent with what is known about the behavior and management of a particular crop (Iizumi et al., 2009; Seidel et al., 2018;

Tao et al., 2009a, b; Gao et al., 2020, 2021; Wallach et al., 2021a). Currently, there is no standard way of undertaking calibration and calibration practices among the crop models vary (Seidel et al., 2018). Practices vary from ad hoc, i.e. typically trial and error approaches, to least squares and Bayesian parameter estimation. For example, biophysical parameter values in a crop model were optimized using Bayesian probability inversion and MCMC by Iizumi et al. (2009) and Tao et al. (2009a). Gao et al. (2020) compared three calibration methods including Ordinary Least Square (OLS), MCMC and Generalized Likelihood Uncertainty Estimation (GLUE) and found that MCMC for model calibration, coupled with estimation of model error variance, is a promising method for quantifying prediction uncertainty. Where goodness-of-fit was the main criterion, OLS was the fastest and most effective method. More generally, the process of model calibration underlines the importance of the (skills of) the modeler or model user. Model comparison studies have shown variability in results from the same model when applied by different users (e.g. Confalonieri et al., 2016; Salo et al., 2016) and that much of the variability comes from the calibration process (Wallach et al., 2021a, 2021b). Based on an analysis of approaches to calibration by multiple modeling groups, Wallach et al. (2021b) have proposed a standardized approach to calibration of the phenology component of crop models to reduce model uncertainty due to calibration.

Another source of uncertainty is human error which can affect all aspects of model design, collection and input of data and model use. Quantifying uncertainties due to human error is challenging. It is possible to reduce likelihood of error by, e.g., training, creating modeling protocols, routines for checking key stages, visualization and plausibility tests.

5 Managing uncertainties from model structures

Recent studies have consistently shown that uncertainty from issues relating to crop model structure is greater than that from variability in climate projections and crop model parameters (Asseng et al., 2013, 2015; Bassu et al., 2014; Li et al., 2015; Tao et al., 2018). A key area in reducing uncertainty is improving crop model structure (Wang et al., 2017; Challinor et al., 2018; Tao et al., 2018; Rötter et al., 2018). A recent analysis found that differing assumptions about temperature and CO_2 relationships in models caused large discrepancies in climate impact projections between models (Tao et al., 2020). In particular, the impacts of increases in temperature and CO_2 on leaf area development were identified as the major causes of uncertainty in simulating changes in evapotranspiration (ET), above-ground biomass and grain yield.

5.1 Model improvements to better simulate impacts of extreme temperature

Most of the main crop simulation models for predicting wheat grain yield are highly uncertain in simulating crop responses to extreme temperatures. Asseng et al. (2015) tested 30 different wheat crop models against field experiments in which growing season mean temperatures ranged from 15°C to 32°C. Many models simulated yields well at conventional temperatures but were less accurate at higher temperatures. Schewe et al. (2019), using the 2003 European heat wave and drought as a historical analogue for comparable events in the future, found that a majority of models underestimate the scale of impacts. Crop models can be improved, e.g., through re-parameterization and/or incorporating or modifying heat stress effects on phenology, leaf growth and senescence, biomass growth, and grain number and size in the light of field experimental data (Maiorano et al., 2017).

Wang et al. (2017) showed that the variations in the mathematical functions currently used to simulate temperature responses of physiological processes account for >50% of uncertainty in simulated grain yields for mean growing season temperatures ranging from 14°C to 33°C. Improving temperature response functions can improve modeling of crops under increasing temperatures, leading to improved crop yield projections.

5.2 Model improvements to improve simulation of crop responses to elevated CO_2

Elevated CO_2 concentrations have positive effects on the productivity of C3 crops, such as wheat and rice, by increasing photosynthesis, biomass and grain yield and by reducing crop transpiration and increasing crop water use efficiency (Leakey et al., 2009). They can partially offset the negative impacts of increasing temperature (Rosenzweig et al., 2014).

Current crop models differ in simulating major crop processes including LAI development, photosynthesis, ET and biomass production, as well as effects of elevated CO_2 (Asseng et al., 2013; Tao et al., 2020). Commonly used methods for modeling these processes include (Farquhar et al., 1980; Hasegawa et al., 2017):

1. the coarse-grained concept of radiation use efficiency (RUE);
2. the light response curve (LRC) of instantaneous leaf photosynthesis scaled to hourly or daily canopy photosynthesis and crop respiration; and
3. the Farquhar, von Caemmerer & Berry (FvCB) biochemical model of C3 photosynthesis.

The diversity in model algorithms, combined with inconsistency in model parameterization procedures, can produce significant uncertainties in model projections (Asseng et al., 2013, 2015; Bassu et al., 2014; Li et al., 2015; Tao et al., 2020).

The performance of 21 maize models in assessing the impact of elevated CO_2 levels on maize yield and water use has been assessed using a 2-year free-air carbon dioxide enrichment (FACE) experiment (Durand et al., 2018). The models matched experimental results in predicting yield responses to elevated CO_2 under well-watered conditions, as well as to the impact of water deficit at ambient CO_2. However, the models captured only 30% of the impact of exceptionally high CO_2 levels on observed yields under water deficit conditions. Models were unable to simulate low soil water content at anthesis and the increase of soil water and grain number brought about by the elevated CO_2 under dry conditions. Models incorporating stomatal control of transpiration tended to perform better, highlighting the need for model improvement in simulating transpiration water use and its impact on water status during the kernel-set phase (Durand et al., 2018).

The performance of 16 rice models in predicting yield under elevated CO_2 was investigated using FACE and chamber experiments by Hasegawa et al. (2017). The model ensemble reproduced experimental results well. However, yield prediction in response to elevated CO_2 varied significantly among models. The variation was not associated with model structure or magnitude of photosynthetic response to elevated CO_2 but was significantly associated with simulated morphological development, primarily leaf area, under elevated CO_2. Cammarano et al. (2016) compared 16 crop models for wheat water use and found that uncertainties in simulated water use and transpiration were greater with increased temperatures and elevated atmospheric CO_2, which were associated with different approaches to simulating transpiration.

Leaf area development is fundamental to biomass accumulation and yield formation, directly affecting canopy intercepted radiation, photosynthesis rate, ET and the balance of evaporation and transpiration. The impacts of temperature and CO_2 on LAI development are major causes of uncertainty in simulating above-ground biomass and grain yield of crops (Tao et al., 2020).

Many crop models use a biomass-dependent approach to simulate LAI development (Bannyayan et al., 2005; Ratjen et al., 2018). While this biomass-dependent approach has been shown to simulate leaf area development fairly well in normal conditions, it may greatly overestimate leaf area development under elevated CO_2 (Bannyayan et al., 2005). The approach depends on simulating biomass, leaf-stem partitioning processes and specific leaf area (SLA). Most importantly, it does not account for the uncoupling of leaf expansion and photosynthesis under water deficit (Muller et al., 2011) and elevated CO_2 (Ainsworth and Long, 2005) and the very different temperature sensitivities of these two processes (Asseng et al., 2013, 2015; Wang et al., 2017). Assumptions about developmental stages may not capture the allometric relationship between LAI and biomass (Ratjen et al., 2018). Leaf-stem partitioning and SLA are not independent given the allometric relationship between LAI and biomass, and LAI may explain canopy SLA better than developmental traits (Ratjen et al., 2018). However, these mechanisms are rarely represented in current crop models.

As a possible solution, leaf-stem partitioning and SLA could be simulated based on LAI dynamics instead of developmental stage or thermal time (Ratjen et al., 2018). Alternatively, leaf area development could be simulated based on the availability of nitrogen rather than biomass (Jamieson and Semenov, 2000; Sinclair et al., 2003; Martre and Dambreville, 2018), which could improve the simulations of CO_2 responses and capture their secondary processes (Vanuytrecht and Thorburn, 2017). Temperature impact functions and cardinal temperatures in simulating crop phenological development, LAI development, photosynthesis rate, ET and yield formation need to be further validated based on data from free-air temperature-increase experiments (Wang et al., 2017). Advances in understanding and simulating the basic processes and thresholds by which increases in temperature and elevated CO_2 will affect leaf area development, crop ET, photosynthesis and grain formation in contrasting environments should be incorporated to improve model performance. An alternative suggested approach is the use of fundamental biology and mathematical principles to develop simpler equations that can better model crop growth (Yin et al., 2021).

6 Managing uncertainties from adaptations in agricultural practices

Projected climate change impacts on crop growth and yields need to take account of adaptation strategies in modeling (IPCC, 2022). The adaptation settings in models to account for variations in sowing dates, cultivars, fertilization and irrigation regimes will affect projected climate impacts on crop growth and yields. A fixed set of model parameters fails, e.g., to take into account factors such as crop genotypic variability (Tao et al., 2009b). Since it can be challenging to obtain information on genotypes when models are applied to new situations, ensemble simulations using multiple sets of model parameters provide a sound solution (Tao et al., 2017). This is true for other adaptation options such as sowing dates, fertilization and irrigation.

A key challenge for models is that farming practices continue to evolve and improve, a process that will only accelerate in response to climate change (Hampf et al., 2020). However, there have been relatively few studies comparing the performance of different cropping systems to account for developments in agricultural practices (Xin and Tao, 2020). And an approach for forecasting technology-driven yield increases based on biophysical yield maxima has been developed to account for improvements in breeding and crop management (Hampf et al., 2020). The design and use of Representative Agricultural Pathways (RAPs) in regional integrated assessments of climate impacts provides one way to account for broader socioeconomic developments (Antle et al., 2017). There is also a need for integrated biophysical and economic modeling of agricultural production systems (Antle and Stöckle, 2017).

7 Reducing model uncertainties

Probabilistic approaches combining multiple climate change scenarios (Tao et al., 2008), multiple sets of model parameters (Iizumi et al., 2009; Tao et al., 2009a, b) and ensembles of crop models (Palosuo et al., 2011; Rötter et al., 2011; Asseng et al., 2013, 2015; Bassu et al., 2014; Li et al., 2015; Pirttioja et al., 2015; Tao et al., 2017) have become well-established approaches in model-based climate change impact assessments. These have been combined into super-ensemble-based probabilistic assessments (Tao et al., 2009b; Tao et al., 2020). These approaches help to account for uncertainty in model predictions (Tao et al., 2018) and produce more robust predictions, e.g. using an ensemble mean or median (Martre et al., 2015; Wallach et al., 2018). Some studies, e.g., suggest that the median value of a multi-model ensemble is more accurate in simulating the crop temperature response and yields than any single model (Asseng et al., 2013; Martre et al., 2015).

In working with crop multi-model ensembles, several key questions should be considered. These include defining criteria for acceptance of models in a crop multi-model ensembles, the influence of ensemble size and composition on model outcomes, and possible differential weighting of models in an ensemble (Wallach et al., 2016, 2018; Rodríguez et al., 2019). The predictive values of an ensemble mean (e-mean) and median (e-median) have also been investigated (Wallach et al., 2018). They found mean squared error of the e-mean decreases monotonically with the size of the ensemble if models are added at random but has a minimum with 2–6 models if best-fit models are added first (Wallach et al., 2018). An Ensemble Outcome Agreement (EOA) index developed by Rodríguez et al. (2019) has analyzed the effect of changes in composition and size of a multi-model ensemble (MME). Typically, each individual model in an ensemble is assigned an equal weight by simply averaging the predictions over all the models. Use of Bayesian model averaging (BMA), which assigns different weights to individual models according to their performance in reproducing historical data, has been shown to achieve better results (Gao et al., 2021).

8 Conclusion and future trends

Model-based climate change impact assessments involve uncertainties given the many physical, biological and socioeconomic processes involved. Among other things, uncertainties arise from unknown future development of GHG scenarios and uncertainties in climate change scenarios, input data, model structures and parameters and human error. Recent developments with crop models have helped to quantify or reduce these uncertainties.

Since uncertainty due to crop model structure is a particular problem, improvements to the model structure are key to reducing uncertainty. Advances in understanding the basic processes through which increasing temperatures and CO_2 may affect leaf area development, crop ET, photosynthesis and grain formation in contrasting environments will improve model accuracy. The impacts of different levels of temperature and CO_2 changes on many physiological and developmental phenomena need to be studied in contrasting environments. The three-way or four-way interactions of multiple climate change factors on crop development, growth, water use and yield formation need to be investigated experimentally. Advanced biological insights and mathematical methods should be combined to derive simple but theoretically sound equations that apply to different processes of crop growth. Another area of improvement is improving calibration techniques, e.g. to reduce human error. RAPs in regional integrated assessments can help to take account of socioeconomic factors.

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10 Where to look for further information

Further information is available from:

- https://www.macsur.eu/;
- https://agmip.org/;
- https://www.ipcc.ch/assessment-report/ar6/; and
- https://www.researchgate.net/profile/Fulu-Tao.

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