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Sources of uncertainty for wheat yield projections under future climate are site-specific

Bin Wang[1,2,15] ✉, Puyu Feng[1,3,15], De Li Liu[1,4] ✉, Garry J. O'Leary[5], Ian Macadam[6], Cathy Waters[7], Senthold Asseng[8], Annette Cowie[9,10], Tengcong Jiang[2], Dengpan Xiao[11], Hongyan Ruan[12], Jianqiang He[2] and Qiang Yu[2,13,14] ✉

Understanding sources of uncertainty in climate–crop modelling is critical for informing adaptation strategies for cropping systems. An understanding of the major sources of uncertainty in yield change is needed to develop strategies to reduce the total uncertainty. Here, we simulated rain-fed wheat cropping at four representative locations in China and Australia using eight crop models, 32 global climate models (GCMs) and two climate downscaling methods, to investigate sources of uncertainty in yield response to climate change. We partitioned the total uncertainty into sources caused by GCMs, crop models, climate scenarios and the interactions between these three. Generally, the contributions to uncertainty were broadly similar in the two downscaling methods. The dominant source of uncertainty is GCMs in Australia, whereas in China it is crop models. This difference is largely due to uncertainty in GCM-projected future rainfall change across locations. Our findings highlight the site-specific sources of uncertainty, which should be one step towards understanding uncertainties for more robust climate–crop modelling.

Climate change, particularly increasingly variable rainfall and increased frequency and intensity of extreme temperatures, is anticipated to adversely affect crop production in many parts of the world[1–3].

A climate–crop modelling approach, in which process-based crop models are driven by climate data derived from global climate models (GCMs), has been applied extensively to quantify the magnitude of climate change impacts on crop yields[4,5]. The use of process-based crop models enables consideration of the complex and nonlinear physiological responses of crops to climate and soil conditions[6], and thereby supports the development of effective climate change adaptation strategies. For example, previous studies have used climate–crop modelling to optimize agronomic management[5,7] and design crop ideotypes with adaptive traits to cope with climate change[8].

Downscaling raw GCM climate data is an essential step in climate–crop modelling. The change factor (CF) method (also called the delta method) is a simple approach that is used widely in downscaling due to its ease of implementation and low computational cost[9]. This approach utilizes future monthly rainfall and temperature change from the GCMs to perturb historical daily data without changing the distribution of rainfall and temperature. At the other end of the spectrum, dynamical downscaling is a sophisticated approach that usually takes boundary conditions from GCMs to generate a physically consistent, high-resolution representation of the climate over the region of interest. However, dynamical downscaling is computationally expensive and therefore impractical to apply to large ensembles of GCM simulations. Statistical downscaling is a method of intermediate complexity that uses a statistical model built from observed relationships between local synoptic situations and the large-scale climate data. This is more realistic than the CF method but computationally less demanding than dynamical downscaling[10].

An understanding is needed of the major sources of uncertainty in yield change so as to develop strategies to reduce the total uncertainty. Uncertainty in crop yield projections from the climate–crop modelling approach is primarily reported in relation to imperfect models, input data, assumptions and representation of processes[11]. Of these, input datasets for both GCMs and crop models are important sources of uncertainty. The former relies on assumptions about future emissions of greenhouse gases, atmospheric aerosols and land-surface properties. These assumptions will affect the climate projections from GCMs modelling physical processes between the atmosphere, the land surface and the oceans based on different emission scenarios, resulting in uncertainty in the projected climate data. The latter includes daily climate data downscaled from different GCMs using

[1]New South Wales Department of Primary Industries, Wagga Wagga Agricultural Institute, Wagga Wagga, New South Wales, Australia. [2]State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Northwest A&F University, Yangling, Shaanxi, China. [3]College of Land Science and Technology, China Agricultural University, Beijing, China. [4]Climate Change Research Centre, UNSW Sydney, Sydney, New South Wales, Australia. [5]Agriculture Victoria, Department of Jobs, Precincts and Regions, Horsham, Victoria, Australia. [6]ARC Centre of Excellence for Climate Extremes and Climate Change Research Centre, UNSW Sydney, Sydney, New South Wales, Australia. [7]New South Wales Department of Primary Industries, Dubbo, New South Wales, Australia. [8]Agricultural & Biological Engineering Department, University of Florida, Gainesville, FL, USA. [9]New South Wales Department of Primary Industries, Armidale, New South Wales, Australia. [10]School of Environmental and Rural Science, University of New England, Armidale, New South Wales, Australia. [11]Engineering Technology Research Centre, Geographic Information Development and Application of Hebei, Institute of Geographical Sciences, Hebei Academy of Sciences, Shijiazhuang, Hebei, China. [12]Guangxi Geographical Indication Crops Research Center of Big Data Mining and Experimental Engineering Technology and Key Laboratory of Beibu Gulf Environment Change and Resources Use Utilization of Ministry of Education, Nanning Normal University, Nanning, Guangxi, China. [13]College of Resources and Environment, University of Chinese Academy of Science, Beijing, China. [14]School of Life Sciences, Faculty of Science, University of Technology Sydney, Sydney, New South Wales, Australia. [15]These authors contributed equally: Bin Wang, Puyu Feng. ✉e-mail: bin.a.wang@dpi.nsw.gov.au; de.li.liu@dpi.nsw.gov.au; yuq@nwafu.edu.cn

different downscaling methods and information describing agricultural management practices (for example, sowing time, crop rotation and fertilization rates). These inputs influence the performance of crop models, leading to uncertainty in simulated yields.

Uncertainty due to crop models can be a primary source of uncertainty in the assessment of climate change impacts for agricultural systems (https://agmip.org/). For example, research at four representative sites across wheat-growing regions worldwide found that uncertainty in the change in wheat yield estimated by 27 available crop models is greater than that estimated by the 17 GCMs[4]. Similarly, another study that used seven crop models forced with eight GCMs to quantify uncertainty in climate change impacts on barley yield in Europe[12] found that crop model structure (for example, the physiological processes included, and how they are modelled) provides a greater source of uncertainty in yield change than the GCMs. A common feature of these studies is that they applied a CF downscaling method to produce the future daily climate data that drove the crop models[4,12,13]. However, using a CF method may lead to a biased estimation of the contribution of uncertainty.

Sources of uncertainty seem to vary between studies. A growing number of studies have now reported downscaling as a major source of uncertainty in hydrological studies[14,15]. Gao et al.[16] showed that the selection of GCM is the dominant source of uncertainty, followed by downscaling data. However, Chen et al.[9] concluded that uncertainty due to downscaling is greater than uncertainty in the GCMs used in simulating extreme streamflow. Although their conclusions varied, these studies demonstrate the importance of recognizing uncertainty from downscaling/bias-correction methods in representing future climate scenarios in hydrologic simulations. Comparable studies of agricultural systems have examined the effect of different downscaling/bias-correction methods on the outputs of a single biophysical crop model in Australia[17,18]. However, we are not aware of any agricultural study so far that has assessed the direct and interactive effects of different downscaling data options on the cascade of uncertainty within the climate–crop modelling chain. Moreover, the dominant source of uncertainty in agricultural yield under future climate might differ depending on selected study sites.

In our study, we selected two major wheat-growing countries with contrasting growing conditions—China and Australia—to investigate the sources of uncertainty with different downscaling techniques when assessing the impacts of climate change on wheat yield. Future yield changes were simulated using eight crop models driven by 32 GCMs under four different atmospheric carbon dioxide (CO_2) concentrations (corresponding to the periods 2021–2060 and 2061–2100 under two Representative Concentration Pathways—RCP4.5 and RCP8.5) with two downscaling datasets, generated by statistical downscaling and the CF method. We quantified the contribution of different sources of uncertainty in the prediction of future yield change, as a step towards reducing the uncertainties, to enable robust climate–crop modelling to inform reliable climate change adaptation strategies.

Results

Projected climate change. We first explored the projected changes in climate variables resulting from the combination of the GCMs and downscaling methods. Figure 1 shows changes relative to the 1961–2000 baseline for growing season mean temperature, rainfall and solar radiation for the four study sites from the GCM ensemble for the different RCPs, future time periods and downscaling methods. Overall, the changes in each climate variable were similar for the change factor (CF) and statistical downscaling (SD) methods. Supplementary Table 1 shows that the results for individual GCM projections for all climate scenarios were highly correlated between the two methods.

All GCMs projected warmer temperatures for both RCPs for all four sites, with the most substantial warming occurring in the 2080s under RCP8.5 at Zhangbei, China (2.6–6.0 °C across all GCMs and both CF and SD, Fig. 1a). The CF and SD downscaling methods projected similar increases in growing season mean temperature at Balranald, Australia, but the SD method projected a slightly greater temperature difference than CF at Wagga, Australia. Some GCMs showed greater increases in temperature at Zhangbei and Changwu compared to the two Australian sites. The CF method generally projected greater temperature increases than SD at the two Chinese sites.

Unlike the results for temperature, the projected growing season rainfall changes differed between the Australian and Chinese sites (Fig. 1b). In the Australian sites, changes in projected growing season rainfall varied widely with GCM, with some GCMs simulating increases and some simulating decreases. The range of changes increased with climate forcing (that is, the projection under RCP8.5 was greater than with RCP4.5, and the 2080s projection was greater than the 2040s projection). Overall, the multi-GCM ensemble mean showed a decrease in rainfall of around 5% for both Australian sites, regardless of the RCP, time period or downscaling method. By contrast, almost all GCMs simulated a wetter future in Chinese sites, with ensemble mean rainfall increasing by around 10%, irrespective of climate forcing scenario or downscaling method. The multi-GCM ensemble mean changes indicated an increase in rainfall when increasing climate forcing for both downscaling methods. The difference between the 10th and 90th percentiles of rainfall projections for RCP8.5 in the 2080s was larger at Balranald (46%) and Wagga (42%) than at Zhangbei (24%) and Changwu (35%) (Fig. 1b).

Almost all GCMs projected an increase in growing season solar radiation, with ensemble means ranging from 1.5% to 3.6% over climate scenarios at Balranald and from 1.8% to 4.5% at Wagga. The magnitude of these changes increased with climate forcing (Fig. 1c). However, there were some differences in the direction of radiation change among the GCMs for the Chinese sites, which depended mainly on the time period. Specifically, at both sites and for both RCPs, radiation decreased in the 2040s and increased in the 2080s, except for Changwu by the 2080s under RCP8.5. The two downscaling methods gave similar changes in the multi-GCM ensemble mean for radiation.

Projected yield change. We next evaluated the influence of climate data on wheat yields derived from alternative crop models (a full list of the models is provided in Supplementary Table 2). Projected changes in the simulated wheat yield (%) at the four study sites under RCP4.5 and RCP8.5 relative to the baseline climate of 1961–2000 are shown in Fig. 2 for each crop model and crop model ensemble mean. The boxplots show the differences of projected yield changes across the 32 GCMs for each climate scenario (Fig. 2). At each location, simulated yield had bidirectional changes, depending on the combination of GCM and crop model used. An exception was Changwu, where almost all combinations of GCM and crop model showed yield increases. Generally, the trend of the yield changes across the GCM ensemble was the same between SD and CF, although there were exceptions (for example, APSIM and CropSyst for Balranald, CERES and WNMM for Zhangbei). Overall, the pattern of yield increases and decreases across the GCM ensemble was unaffected by climate forcing scenario, with the notable exception of OLC and STICS. In Australia, the range of the projected yield changes across the 32 GCMs was larger at Balranald, a dry site, than at Wagga, a relatively wet site, especially for APSIM, AquaCrop and Nwheat crop models. For example, the 10th to 90th percentile range in yield change under RCP8.5 in the 2080s for APSIM was 59% at Balranald and 31% at Wagga for SD. Similar patterns were found for the Chinese sites, with the drier site, Zhangbei, having larger variation in projected yield changes, except for with the CERES model.

To demonstrate the different responses of the crop models to climate change, we assessed the importance of changes in each of

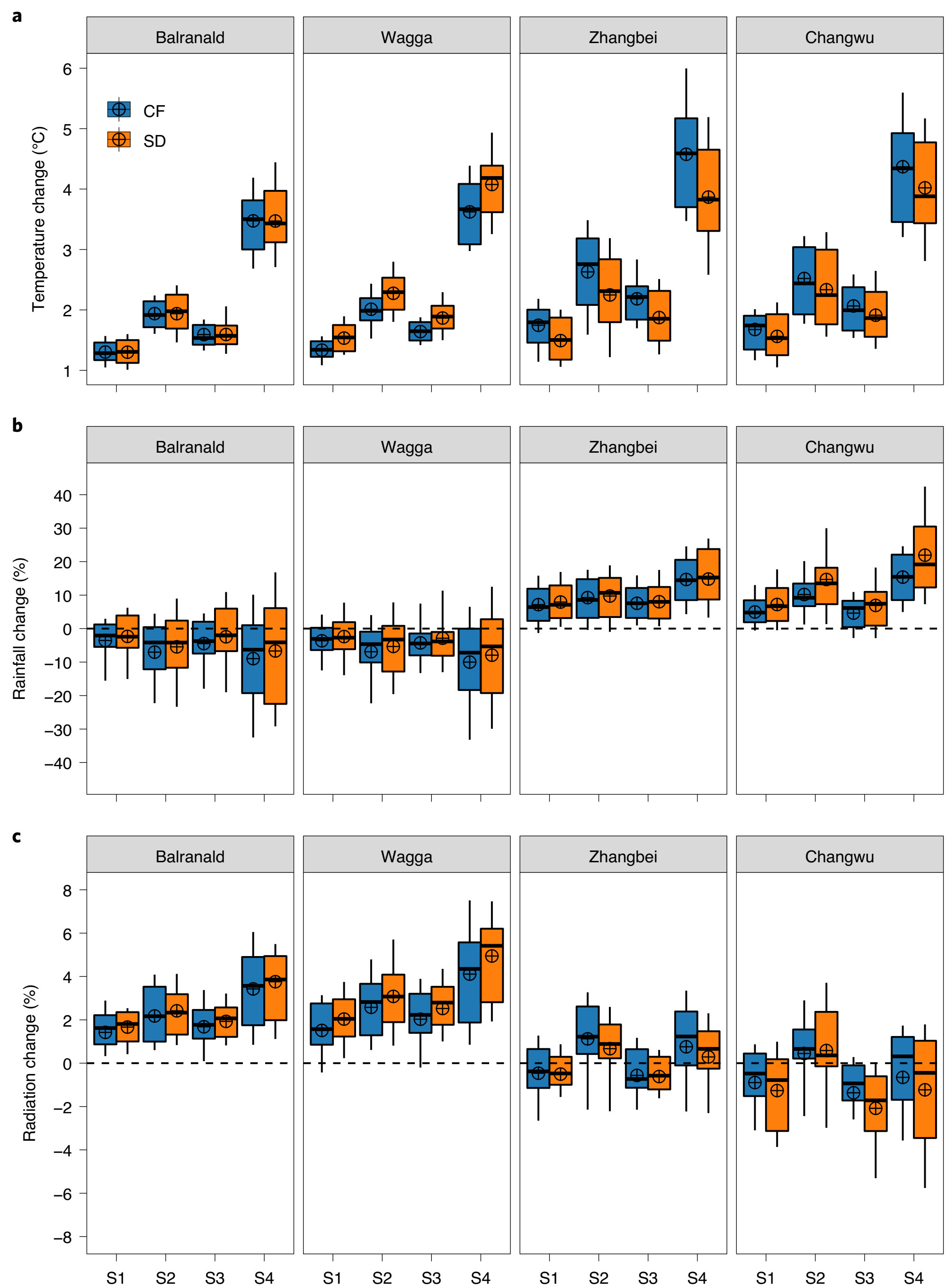

Fig. 1 | Projected climate change in wheat-growing season from 32 GCMs based on two downscaling methods at four study sites. a, Projected mean temperature (°C) change. **b**, Projected rainfall (%) change. **c**, Projected solar radiation (%) change. Projections are for the 2040s (2021–2060) and the 2080s (2061–2100) under RCP4.5 and RCP8.5 compared to the baseline (1961–2000). Box boundaries indicate the 25th and 75th percentiles across 32 GCMs, and whiskers below and above the box indicate the 10th and 90th percentiles, respectively. The black lines and crosshairs within each box indicate the multi-model median and mean, respectively. S1: RCP4.5_2040s, S2: RCP4.5_2080s, S3: RCP8.5_2040s and S4: RCP8.5_2080s. Balranald and Wagga are in southeastern Australia. Zhangbei and Changwu are in northern China. CF: change factor, SD: statistical downscaling.

the climatic variables (rainfall, radiation, temperature and CO_2 concentration) to wheat yield change using the random forest (RF) approach[19]. In contrast to methods such as multiple linear regression (Supplementary Fig. 1), RF accounts for nonlinear responses to the climate variables and untangles the influence of correlated variables. This was necessary, as a collinearity analysis showed notable covariance between mean temperature and CO_2 concentration (Supplementary Table 3). RF was applied to the change in yield for each crop model, site and downscaling method separately. The results were similar for both SD and CF, but varied between site and crop model, especially for the Chinese sites. Overall, growing season rainfall change was the most important factor in determining yield change for all eight crop models and all four sites except OLC at Balranald (Fig. 3a) and Wagga (Fig. 3b), regardless of downscaling method. At Zhangbei, the dominant variable was mean temperature for CropSyst, Nwheat, OLC, STICS and WNMM crop models,

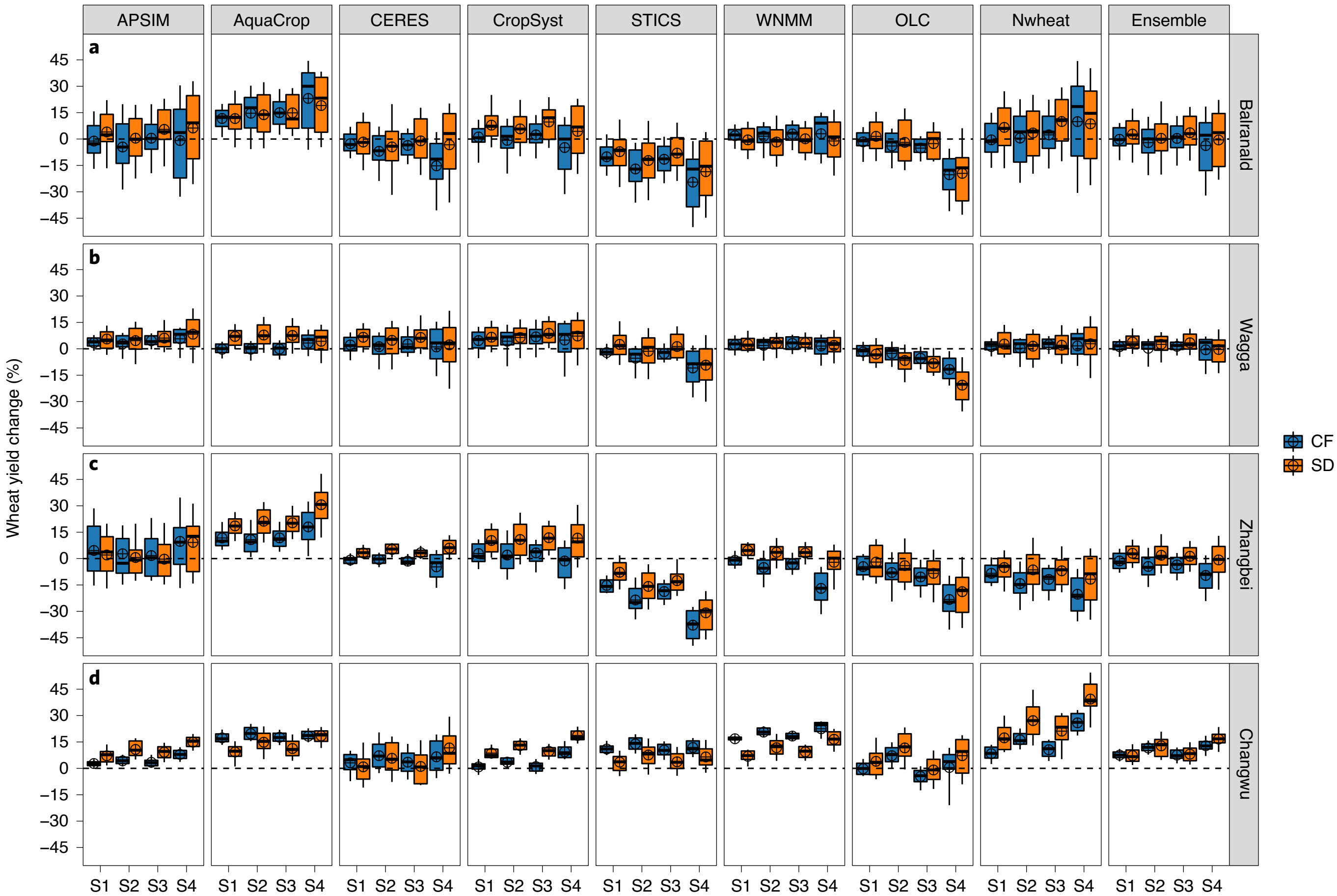

Fig. 2 | Projected wheat yield change and crop model ensemble means in response to climate change at four study sites. a–d, Projected wheat yield changes and crop model ensemble means for Balranald (**a**), Wagga (**b**), Zhangbei (**c**) and Changwu (**d**). The yield projections included eight crop models (APSIM, AquaCrop, CERES, CropSyst, Nwheat, OLC, STICS, WNMM) and crop model ensemble means based on 32 GCMs downscaled using two methods (CF, change factor; SD, statistical downscaling) in the 2040s (2021–2060) and the 2080s (2061–2100) under RCP4.5 and RCP8.5, compared to the baseline (1961–2000). Box boundaries indicate the 25th and 75th percentiles across 32 GCMs, and whiskers below and above the box indicate the 10th and 90th percentiles. The black lines and crosshairs within each box indicate the multi-model median and mean, respectively. S1, RCP4.5_2040s; S2, RCP4.5_2080s; S3, RCP8.5_2040s; S4, RCP8.5_2080s.

and all four variables had similar importance for APSIM for both SD and CF (Fig. 3c). The most important variable was either mean temperature or CO_2 concentration for AquaCrop and CERES models. By contrast, at Changwu, rainfall and CO_2 concentration were each leading factors for approximately half of the eight crop models, while mean temperature was the most important variable for one model for each downscaling method (AquaCrop for SD, OLC for CF; Fig. 3d).

The contribution of uncertainty to yield change. We analysed the different contributions to the total uncertainty of future yield change for each downscaling technique. At each of the four study locations, we partitioned the total uncertainty of projected yield into seven sources of uncertainty caused by GCM, crop model, climate scenario and the interactions between these three factors (Methods and Fig. 4). GCM was the largest source of uncertainty in yield changes at the Australian sites, regardless of downscaling method. At Wagga, GCM downscaled with SD and CF respectively contributed to 50% and 44% of the total uncertainty at Balranald, 32% and 37% for SD and CF, respectively. The uncertainty from the interaction of GCM and climate scenario (GCM × Scen) was also large for both sites. The second largest source of uncertainty at the two Australian sites was the crop model. Crop models further contributed to uncertainty by their interactions with GCM uncertainty (GCM × Model), especially at Wagga. In contrast to the Australian sites, crop model was the most important source of uncertainty at the two Chinese sites, regardless of downscaling method (Fig. 4c,d). At Changwu, the second largest share of total uncertainty was the interactions of GCM and crop model (16% for SD and 12% for CF). Overall, the uncertainty introduced by climate scenario was minor for all four locations except Changwu, where it contributed 12% for SD and 7% for CF.

Generally, the contributions to uncertainty were broadly similar between the SD and CF downscaling methods at all locations. A notable exception to this was at Changwu, where crop models contributed to 53% of the total uncertainty when CF was used and only 34% when SD was used (Fig. 4d). This is probably due to differences in the behaviour of WNMM and OLC between the two downscaling methods for Changwu. Supplementary Table 4 shows that the correlations between the yield changes for the two downscaling methods were relatively low for these models for Changwu.

The contribution to uncertainty from individual crop models was evaluated by consecutively removing each of eight crop models, then comparing the difference of projected yield changes between the full crop model set and that without the particular model

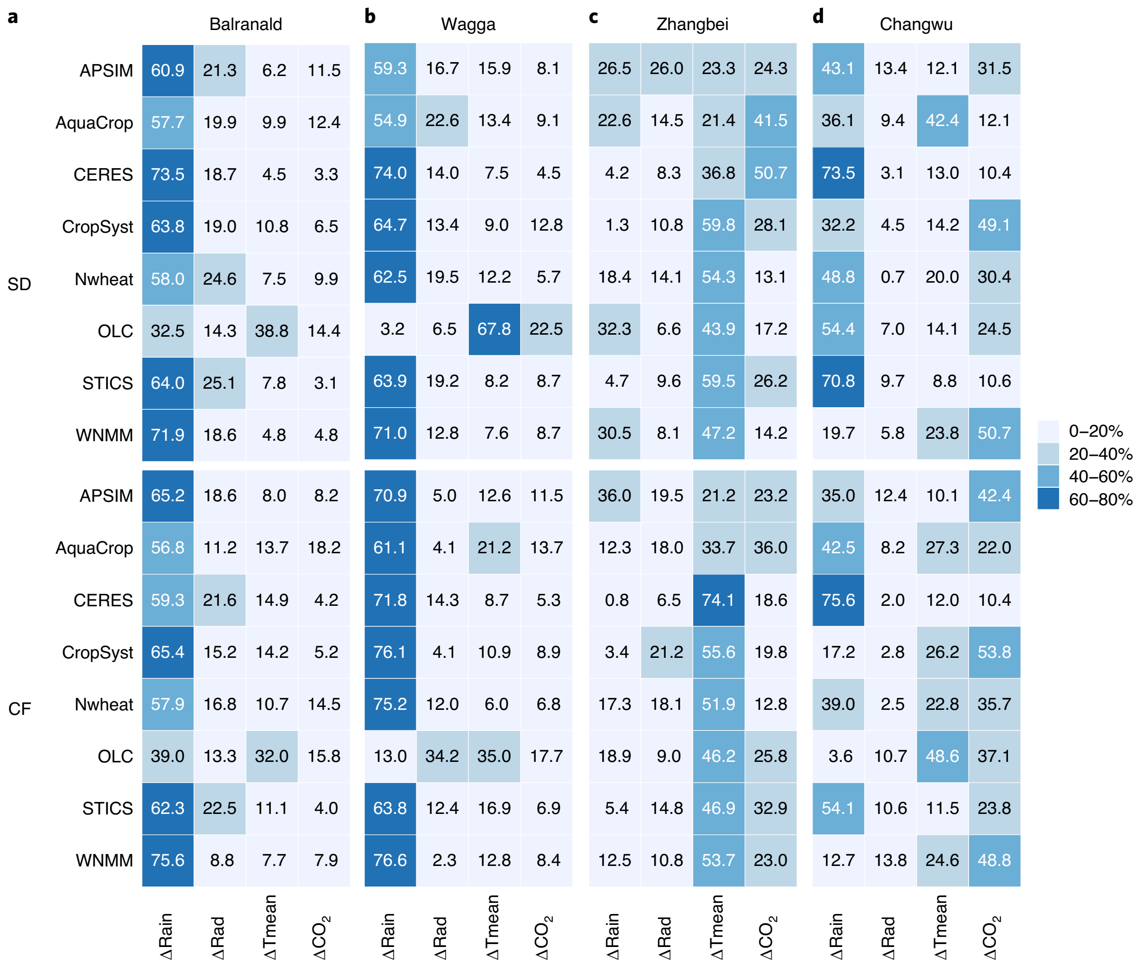

Fig. 3 | The relative importance of variables influencing future yield change. a–d, The relative importance of the variables influencing future yield change for each crop model and downscaling method for Balranald (**a**), Wagga (**b**), Zhangbei (**c**) and Changwu (**d**). We included 32 GCMs × 4 climate scenarios to produce 128 data points for each analysis. The importance of each variable is expressed as the mean increase in prediction error (that is, the increase in mean square error, %IncMSE) with predictor omitted, scaled to sum to 100% for each analysis. ΔRain, changes in growing season rainfall; ΔRad, solar radiation; ΔTmean, mean temperature; ΔCO_2, atmospheric CO_2 concentration.

(Fig. 5). Positive differences indicate that the model will increase degrees of uncertainty. AquaCrop, OLC and STICS each added a large degree of uncertainty at multiple sites for both downscaling methods. Adding APSIM, CERES or CropSyst made a small change for either downscaling method. However, the largest changes for SD, from Nwheat at Changwu (+19%) and from OLC at Wagga (+14%), were not replicated for CF.

We assessed the contribution to uncertainty from individual GCMs using the same method as used for crop models. The results show that the influence of each GCM on total uncertainty was always less than 5% (Supplementary Fig. 2).

Discussion

In this study, we have assessed the relative contribution to uncertainty of crop yield response to climate change from biophysical crop models, GCMs and climate scenarios with two downscaling techniques. We found that the relative contributions to uncertainty depend on locations, but not on the downscaling methods used. In contrast to previous studies, we found that crop models are not always the dominant source of uncertainty; the relative contribution to uncertainty from crop models and GCMs varies with location, and for some locations, GCM uncertainty is more important than crop models uncertainty.

The projections for future climate changes indicated increased growing season rainfall at the two Chinese sites (Fig. 1b). By contrast, at the Australian sites, changes in projected growing season rainfall were inconsistent in direction and showed larger differences between the GCMs, especially by the 2080s under RCP8.5. This is consistent with results from CSIRO and BoM[20], which show large uncertainty in projected rainfall for Australia, while rainfall in China is expected to increase by 8–12% by the end of the twenty-first century based on Coupled Model Intercomparison Project Phase 5 (CMIP5) climate model projections[21]. We note that, although the Australian sites showed a negative correlation between rainfall and radiation, presumably due to cloud cover, this was not seen in Zhangbei in the 2080s. Similar projections to the results at Zhangbei in the 2080s have been reported for other sites in China[22,23] and may be due to an increase in large rainfall events.

We found that differences in yield change uncertainty are largely due to uncertainty in GCM-projected future rainfall change across locations. Regions with high natural variability (as in Australia) tend to be regions where projected rainfall is uncertain because the models vary more when describing the natural variability. The GCMs contribute larger uncertainty to future yield changes in these regions. There is also a stronger influence of growing season rainfall in the Mediterranean climate at the Australian sites than the

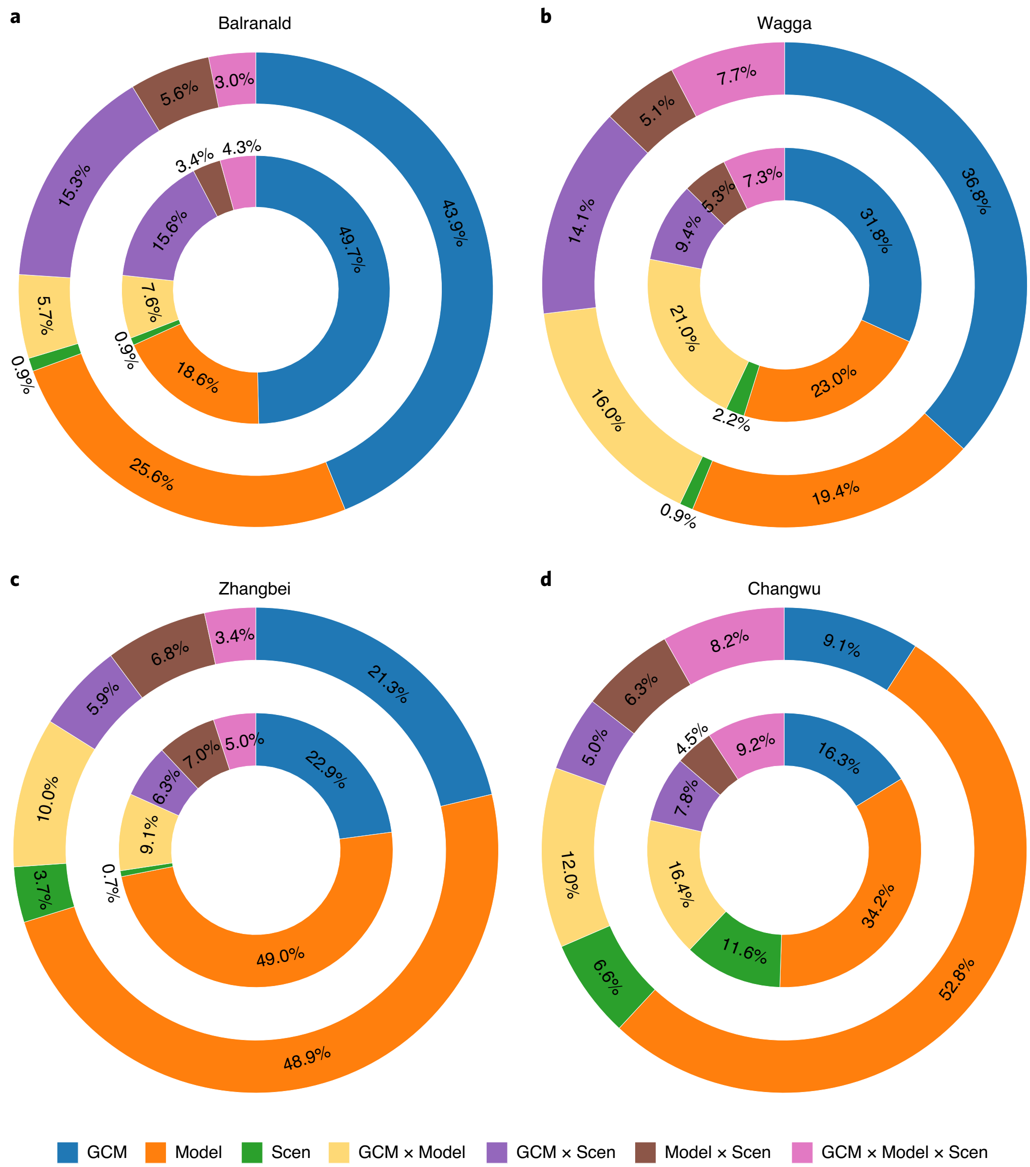

Fig. 4 | Proportion of uncertainty in simulated wheat yield changes. a–d, Sources of uncertainty at Balranald (**a**), Wagga (**b**), Zhangbei (**c**) and Changwu (**d**). The sources of uncertainty were dissected into GCM, crop model (Model), climate scenario (Scen) and their interactions. The outer ring represents the uncertainty share based on CF data and the inner circle represents the uncertainty share based on SD data.

more temperate climate at the Chinese sites. This was supported by our variable importance analysis (Fig. 3), which showed that rainfall change was the most important variable in determining yield in the Mediterranean climate of the Australian sites for almost all crop models.

The uncertainty from crop models in predicted yield response demonstrates the importance of using multiple crop models to inform climate change adaptation, rather than relying on a single model that performs well in a specific region under particular agro-ecological conditions. In our study, although the crop models were calibrated to reproduce historical average yields, we found substantial differences between the yield responses to climate changes simulated by the models, including an inconsistent direction of change in some cases (for example, between AquaCrop and STICS at Balranald and Zhangbei, Fig. 2a,c). In addition, the relative importance of different climate variables can vary between crop models (for example at Changwu, Fig. 3d). We found that inconsistencies between crop models relate to divergence in the interactions between temperature, atmospheric CO_2 content and seasonal rainfall. Across the crop models, processes related to water use and energy balance are simulated differently, adding additional uncertainty from the model structure and parameters[12,24,25]. Moreover, our approach of sequentially removing each individual model from the ensemble clearly revealed differences between models (Fig. 5). For a model to be included in the ensemble, it must be suitable for the local conditions. Models may need to be calibrated to meet this criterion. However, despite calibrating the models to give similar performance for the baseline period, we found crop models giving divergent results under climate change scenarios. The inconsistency among crop models mainly lies in the discrepancy between the interactions of increased temperature and CO_2 fertilization and variable seasonal rainfall[24]. Further work is needed to validate and refine the physiological responses to climate change of different models.

Improvements are clearly needed in crop models. For example, multiple linear regression found that the lowest R^2 occurred in OLC

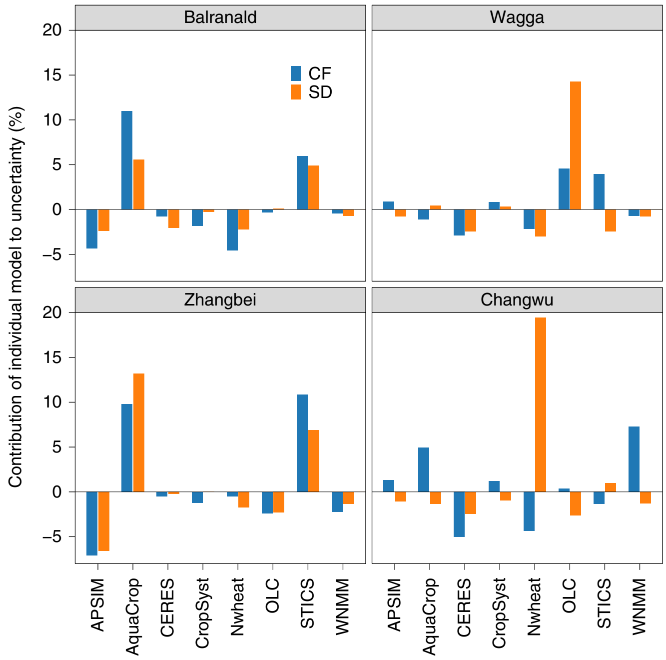

Fig. 5 | The contribution to crop model uncertainty made by individual crop models. The contribution was determined by sequentially removing each of eight crop models from the ensemble of crop models at four sites for both SD and CF downscaling methods. The percentage contributions are changes in crop model uncertainty when the model under consideration was added to an ensemble of the other seven models. Positive contributions mean a model has increased the uncertainty. Negative contributions show a model has reduced the uncertainty.

for CF at Changwu (Supplementary Fig. 1). The OLC model was sensitive to temperature change (Fig. 3d), but it does not include a vernalization response. Therefore, future warming projected by CF (Fig. 1a) resulted in early flowering in winter, and low temperature caused the failure of seed formation, which led to increased uncertainty. The challenge is to identify the improvements needed in the model to simulate an accurate response to a changing climate. In addition, we need a deeper understanding of how model structure affects uncertainty, especially with respect to the components of crop models that are sensitive to changes in climate and atmospheric CO_2 concentrations. This recommendation is consistent with other recent studies. For example, Ahmed et al.[26] identified that different process-based crop models vary in the simulation of crop response to CO_2 concentration, with greater difference under water-stressed conditions. They recommend the use of ensembles to improve the accuracy in modelled responses to CO_2. More experimental work is needed to investigate the interacting effects of increased temperature and water deficit with elevated CO_2 concentration[27].

Although previous studies have focused on uncertainties arising from crop models and GCMs, downscaling uncertainty has been ignored in most assessments of climate change impact on agriculture[4,24]. In this study, we have explored two statistical downscaling approaches (CF and SD) to translate coarse-resolution monthly data from GCMs to site-specific daily data. Although the magnitude of future multi-year change of rainfall, temperature and radiation was comparable between CF and SD (Fig. 1 and Supplementary Table 1), the SD method had greater future changes in the distribution and temporal sequencing of daily values of the climate variables. The simulated yields were sensitive to this difference in some cases, especially at the two Chinese sites (Fig. 2c,d). Despite this, overall, differences in downscaled climate inputs did not add much uncertainty to yield change (Figs. 2 and 4). Only two downscaling techniques were included in this study. If more downscaling types, such as dynamical downscaling or statistical methods that use daily GCM data, were to be considered, we would expect greater downscaling uncertainty and greater impacts of the downscaling method on the relative magnitude of GCM, crop modelling and climate scenario uncertainties.

A previous study on uncertainties in future wheat yield changes found that a greater proportion of the uncertainty was due to the crop models than the GCMs at all four sites (located in Argentina, India, Australia and the Netherlands)[4]. Mismatch in the size of crop and climate ensembles is normally a practical limitation that applies in all climate–crop modelling studies. However, in our study, the difference in the size of crop and climate model ensembles is not the dominant source of variation. The contribution depends on the location (reflecting natural variability). We found that the relative contribution of the uncertainties due to GCMs and crop models was not consistent across the four study sites. The differences could be partly explained by downscaling methods, Asseng et al.[4] kept radiation constant in their CF method, as they assumed that uncertainties with projecting radiation change are too large among GCMs from CMIP3 in their study regions. More importantly, their southwest Australian site is in a region with less uncertain rainfall projections than our sites in southeast Australia[20].

An important limitation of our study, and other climate–crop modelling studies, relates to how well the variance in climate and yield change results based on the ensembles of GCM and crop model simulations reflects how uncertainty in climate and yields will change in reality. Our consideration of downscaling uncertainty was limited to two downscaling methods. We used RCP4.5 and RCP8.5 to consider uncertainties in forcing of the climate system, but these are unlikely to sample all the uncertainty related to climate forcing, especially regional forcing due to atmospheric aerosols and changing land-surface properties. There are other potentially important sources of uncertainty that we have not addressed in our simulations. For example, we did not address the interannual variation of climate variables and yield. Furthermore, agricultural management practices (such as sowing time, crop rotation and fertilization rates) influence yields and are potential sources of uncertainty that were not examined in this study, where we used one management regime for each location. Different approaches for deriving required climate data (for example, sunshine hours translating to solar radiation) can also introduce uncertainty. In addition, all simulations for each location were based on one soil type, representative of each location. Folberth et al.[28] found that estimated climate change effects on yield vary between soil types as soil characteristics can either buffer or amplify climate impacts. Wang et al.[29] quantified contributions of GCMs, RCPs, soil types and nitrogen application rates to uncertainty in wheat yield change in southeastern Australia and found that soil properties have large impacts on yield change, especially in the locations with summer-dominant rainfall. In addition, the choice of calibration methods could have some impacts on parameter optimization[30]. Tao et al.[12] found that model parameterization uncertainty can play an important role in yield projections. More subtly, in common with other climate–crop modelling studies[6,31], we have assessed variability across our model ensembles by weighting each model equally, yet the interdependence in multi-model ensembles could be addressed further by other approaches[32,33].

Studies of climate change impacts on agricultural productivity should be interpreted with caution if they are based on a single crop model forced with data from a limited number of GCMs. Given the response of current crop models to climate, our study supports the use of an ensemble of multiple crop models and GCMs, and highlights the need for further work to validate and refine the responses to changing climate of different crop models. The use of locally validated climate and crop models to ensure sound projections is critical to inform the development of climate change adaptation strategies for cropping systems.

Methods

The study sites. Four sites representing important climatic zones of rain-fed wheat production in Australia and China were selected for inter-continental comparison (Supplementary Fig. 3 and Supplementary Table 5). In southeastern Australia, Balranald and Wagga Wagga (abbreviated here as 'Wagga') have a Mediterranean-type climate with a hot and dry summer and a cooler winter. Spring wheat is grown from April to November. The mean annual rainfall (1961–2000) in Balranald is 346 mm, of which 71% falls between April and November. Wagga has an annual mean rainfall of 595 mm, 71% of which falls in the growing season. Changwu in northwestern China and Zhangbei in northern China have a continental monsoon climate. In Changwu, winter wheat is grown during the September to June growing season. The annual rainfall in Changwu is 582 mm, with 64% falling in the growing season. In Zhangbei, spring wheat is grown during the April to August season. The annual rainfall in Zhangbei is 388 mm, with 80% falling in the growing season.

Historical climate data and observed yield data. Daily maximum temperature (Tmax), minimum temperature (Tmin), rainfall and solar radiation (Rad) are required as climate inputs to the crop models. Some models also use wind and humidity data, but these were not available from our downscaled GCM datasets. Directly observed daily Tmax, Tmin and rainfall data for the period 1961–2000 were obtained from China's Meteorological Administration (CMA; http://www.cma.gov.cn/en2014/). Daily Rad data were also obtained from CMA, calculated from observed sunshine hours using the method of Angstrom[34]. Daily data for Balranald and Wagga for 1961–2000 were downloaded from a database of historical climate records for Australia, the Scientific Information for Land Owners (SILO; https://legacy.longpaddock.qld.gov.au/silo/about.html)[35]. CMA and SILO are both observation-based climate datasets. We conducted a homogeneity test[36] for historical climate data and found that rainfall, solar radiation and maximum and minimum temperature in the wheat-growing season for all four sites were considered homogeneous and could be used for driving crop models.

Observed average wheat yields for specific cultivars at Changwu (3.8 t ha^{-1}) and Zhangbei (1.6 t ha^{-1}) were obtained from local agro-meteorological experiment stations that are maintained by the Chinese Meteorological Agency. Australian wheat yields were obtained from national variety trials (https://www.nvtonline.com.au/) for Wagga (3.0 t ha^{-1}) and Balranald (1.8 t ha^{-1}) (Supplementary Table 5). These yields were used as references to adjust each crop model to acquire cultivar parameter values.

Future climate projection. *Change factor method.* The CF method has been widely used in many climate change impact-related uncertainty studies to downscale GCMs[4,12,13]. To apply the CF method, we first obtained the GCM historical (1961–2000) and future monthly temperature, rainfall and solar radiation data for a specific site using an inverse distance-weighted (IDW) interpolation method based on its distance from the geographic centre of the four nearest GCM grid cells[37]. Change factors for temperature were then calculated for calendar months by subtracting the model means of the historical period from the future temperatures. For solar radiation and rainfall, change factors were derived from the ratio of future means to historical means. These change factors were then added (temperature) or multiplied (rainfall and radiation) in relation to observed daily climate series to derive daily climate projections for each site. A major disadvantage of this method is that downscaled and observed climate series differ only with regard to their respective absolute values. Other features of the data, such as the frequency of rainfall events in a given month, remain unchanged.

Statistical downscaling technique. Statistical downscaling has been widely used to provide daily climate data to drive crop models in the assessment of climate change impacts on agricultural yield. We used the SD model NWAI-WG, developed by Liu and Zuo[10], to downscale GCM monthly gridded data to daily climate data for each of our four study sites. SD consists of three major components: spatial downscaling, bias correction and temporal downscaling. Spatial downscaling used IDW interpolation as described above for the CF method, and then applied bias correction to result in bias-corrected monthly data using a relationship derived from observations and GCM data for a historical training period, in this case 1961–2000. Finally, daily maximum and minimum temperature, rainfall and radiation sequences for each site were downscaled from the bias-corrected monthly GCM projections using a modified version of the stochastic weather generator[38]. Liu and Zuo[10] provide a detailed description of SD. The method has been widely used and evaluated in China and Australia[5,22,23,39–41]. The SD method of Liu and Zuo[10] uses only GCM monthly climate data and historical observed data for the variables of interest. The major advantage of this SD method, particularly in comparison with more computationally demanding dynamical downscaling, is that it can be easily applied to any location for which a long-term daily historical climate record is available[42]. Unlike CF, SD reproduces changed daily patterns in all climate variables.

The main structural difference in bias correction between SD and CF is that SD uses quantile mapping to correct the biases in the distribution of monthly GCM data. The technique not only corrects the mean biases, but also corrects bias in the magnitude of interannual variations to some extent[17]. It retains the temporal sequencing of the monthly GCM data and has temporal sequencing of daily data defined by a weather generator. CF has no biases relative to the observations and retains their temporal sequencing, but future changes in climate are limited to changes in the mean climate.

Crop model simulations. Eight wheat simulation models—APSIM, AquaCrop, CropSyst, DSSAT-CERES, DSSAT-Nwheat, OLC, STICS and WNMM (the New South Wales Department of Primary Industry version)—and the resultant eight-model ensemble were used in this study (Supplementary Table 2). These models were considered appropriate for our study because they have been tested in many regions of the world where dryland wheat is grown. Specifically, they all respond in daily time steps to the major climate variables of rainfall (water supply), solar radiation, temperature and atmospheric CO_2 concentration. The models differ in terms of several key physiological processes, such as leaf area/light interception, light utilization, phenology, biomass accumulation and partitioning, grain formation and response to water, nitrogen and temperature stress (Supplementary Table 6).

Cultivar selection, crop management (including sowing window and nitrogen application rates) and soil properties were site-specific, based on local conditions and experimental records (details are provided in Supplementary Methods and Supplementary Tables 7 and 8). The crop models were calibrated using the site-specific observed yield. We first calibrated for wheat phenology, especially for flowering dates (Supplementary Table 5). We then adjusted each cultivar's other parameters based on local cultivar knowledge to simulate historical average yield comparable to the observed yield (error range within 0.1 t ha^{-1}) for all crop models (Supplementary Fig. 4). This allowed future changes in yield simulated by different crop models to be compared. The adjusted parameters of each cultivar are listed for each model in Supplementary Tables 9–16.

Crop model simulations were run for the historical baseline period 1961–2000 and future periods 2021–2060 (abbreviated as 2040s) and 2061–2100 (2080s). The initial soil conditions were reset each year to exclude any 'carry-over' effects from previous seasons. Soil characteristics, genetic coefficients and crop management settings were kept constant for all three periods. For the future periods, simulations were run for two RCPs (RCP4.5 and RCP8.5). The RCPs describe future trajectories for the energy imbalance of the climate system due to change in atmospheric greenhouse gas concentrations and other anthropogenic climate forcers[43]. RCP8.5 is consistent with rapidly increasing CO_2 concentrations throughout the 21st century, whereas RCP4.5 is consistent with more moderate increases in CO_2 concentrations. For both RCPs, simulations were performed with climate data downscaled from 32 GCMs of CMIP5 (Supplementary Table 17)[44]. Representative annual atmospheric CO_2 concentrations were estimated for each RCP for each year (Supplementary Methods).

Analyses and partitioning uncertainty. Our analysis used an approach analogous to the Morim et al.[45] analysis of uncertainties in wind–wave projections due to GCMs, wave models and RCPs. We assessed uncertainties in wheat yield changes due to the eight crop models, 32 GCMs, four climate forcing/CO_2 concentration scenarios (RCP4.5 for the 2040s, RCP8.5 for the 2040s, RCP4.5 for the 2080s and RCP8.5 for the 2080s) and associated interactions among them for each downscaling method and site using a three-way analysis of variance (ANOVA). We did not quantify uncertainty from the downscaling method. Note that, in this analysis, for simplicity in notation, we refer to the climate forcing/CO_2 concentration scenarios as 'climate scenarios' or 'Scen'. The ANOVA model allows the total sum of the squares (SST), a measure of the total uncertainty in yield changes across all simulations for each downscaling method and site, to be split into sums of squares due to three main factors (SS_{GCM}, SS_{Scen} and SS_{Model}) and their four interactions ($SSI_{GCM\times Model}$, $SSI_{GCM\times Scen}$, $SSI_{Model\times Scen}$ and $SSI_{GCM\times Model\times Scen}$) as

$$SST = SS_{GCM} + SS_{Model} + SS_{Scen} + SSI_{GCM\times Model} + SSI_{GCM\times Scen} + SSI_{Model\times Scen} + SSI_{GCM\times Model\times Scen}$$

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this Article.

Data availability

The wheat data and parameters for each crop model used in this study are available in Supplementary Tables 5 and 9–16. The detailed downscaling climate data and yield data simulated by each crop model that support the findings of this study are available from the corresponding author upon request.

Code availability

The detailed R code for data processing and illustration is available from the corresponding author upon reasonable request. The executable source code and pseudo-code of the crop models used in this study are available from their respective owners, as listed in Supplementary Table 2.

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Author contributions

B.W. and D.L.L. designed the research. B.W., T.J. and D.X. collected crop data. P.F. and D.L.L. generated change factor and statistical downscaling climate data, respectively. P.F., B.W., D.L.L., G.J.O. and T.J. ran crop models. B.W. and P.F. drew the figures. B.W. wrote the draft manuscript. P.F., D.L.L., I.M., G.J.O., S.A., C.W., A.C., H.R., J.H. and Q.Y. contributed to writing the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to B.W., D.L.L. or Q.Y.

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