Paper:
Supporting material for:

Challinor, AJ, Simelton, ES, Fraser, EDG, Hemming, D and Collins, M (2010) *Increased crop failure due to climate change: assessing adaptation options using models and socio-economic data for wheat in China.* Environmental Research Letters, 5 (3). 034012.

http://dx.doi.org/10.1088/1748-9326/5/3/034012

SUPPLEMENTARY DATA

Increased crop failure due to climate change: assessing adaptation options using models and socio-economic data for wheat in China

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Section S1

It is known that different climate models produce different projections of climate change even under the same forcing scenario (see, e.g., [1]). Such projection uncertainties arise because of assumptions which are made in the formulation of climate models (resulting from the representation of processes which cannot be fully resolved due to limitations in computing power) and because of natural fluctuations in climate such as El Niño which cannot be predicted many decades into the future. Here, climate model outputs are taken from an ensemble of climate model simulations with perturbations to parameters which control climate processes and feedbacks. Such perturbed physics ensembles (PPEs) have been developed to systematically sample uncertainties in processes and to feed into projections of climate change, which are expressed in terms of probability density functions [2–4]. By construction, PPEs sample projection uncertainties resulting from uncertain parameters in climate models but cannot sample the ‘full’ range of uncertainty associated with the myriad different choices that are made in determining the structure of different models. Issues of use of climate model ensembles are discussed in an IPCC Good Practice Guidance Paper [5].

We used output from a 17-member PPE in which parameters are perturbed in the atmosphere component (ensemble AO-PPE-A of [4]). Perturbing parameters in the atmosphere component of the model allows us to sample the leading-order uncertainties associated with changes in global mean climate sensitivity. The simulations were started in 1860, run through the 19th and 20th centuries using observed and reconstructed estimates of anthropogenic and natural forcing factors (greenhouse gases, sulphate aerosols, ozone, solar and volcanic) and then are run into the future using SRES A1B emissions.

Section S2

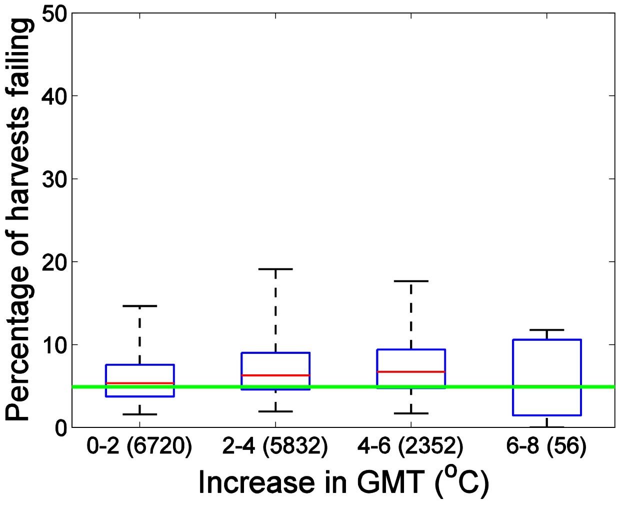
The GLAM crop model was designed to operate on spatial scales commensurate with climate model grids, thus enabling time series of daily weather to be used to project crop yield. It is a process-based model that has a large number of observable parameters, such as transpiration efficiency and maximum rate of change of leaf area index. It has a single calibration parameter to account for spatial heterogeneity in the non-climatic determinants of yield. Since GLAM is calibrated and evaluated using simulations on the climate model grid, it has no genotype-specific parameters, and does not attempt to resolve sub-regional differences in yield due to different soils, management practices or weather. Rather, it simulates the impact of weather on crop growth and development over large areas. In this way, it combines regional scale applicability, and relatively low input data requirement, of empirical studies (e.g. [6]) with the strengths of field-scale process-based models; namely the plant growth and development mechanisms needed to simulate a range of environments, including climate change.

The model was calibrated and run according to standard procedures that account for uncertainty in the simulation of both baseline and projected yields (e.g. [7]). The spring wheat version of the model was developed and tested using data for China, resulting in the parameter ranges used in the current study [8]. Following previous studies, GLAM was calibrated using the yield gap parameter (YGP). This parameter acts to reduce the maximum rate of change of leaf area index from the maximum observed value for the crop in question to an effective value. For each grid cell and each ensemble member, YGP was varied in increments of 0.01, between a minimum of 0.01 and a maximum of 1.00. The value that minimised error in mean yield was chosen as the calibrated value. As with any model calibration, the results are sensitive to the methods and data used for this process. To account for this uncertainty, two different time periods were used to determine YGP. Due to the relatively short baseline period, the calibration periods were chosen to be of four years, centred at the start and end of the baseline period (i.e. 1978–1982 and 1987-–1991). As with many previous studies, the model was calibrated on mean yields, not interannual variations. Accounting for uncertainty in the value of YGP is particularly important for the chosen baseline period, since the Household Responsibility System was introduced across China in the early part of the time period, resulting in significant year-on-year increases in yield during the early 1980s.

Planting in the baseline and future climate scenarios is simulated on the first day after the start of the planting window in which the soil moisture exceeds a threshold value, or after 30 days, whichever is soonest. Thus the choice of first date in the planting window can have an impact on the simulated yields. Two values were used in this study: (i) 1March for the whole region (which resulted in planting on 17 March on average, with a standard deviation of nine days); (ii) the spatially-explicit planting dates of [9], which resulted in planting on 21 March on average, with a standard deviation of 21 days. For the future climate simulations, transpiration efficiency (TE) was determined by linear interpolation over time between two values: baseline and double-CO_2. In order to quantify uncertainty due to elevated CO_2, two pairs of values of TE, both taken from [7], were used.

Section S3

Crop model. Simulated crop durations across all four baseline simulations, and across all grid cells and years, averaged 136 days, with a standard deviation of 17 days. Thus the crop commonly matured in 4–5 months, in accordance with observed harvest dates [10]. Observed yield data were aggregated to the grid of the climate model, in order to enable comparison with simulated values. Whilst simulated mean yields were less than 4% from observed values, some coefficients of variability are outside the observed ranges. The observed ranges of coefficient of variation (CV), across the four provinces, of the linearly detrended time series were 0.14 to 0.29 for the period used for model calibration (1978 to 1991); and 0.44 to 0.85 for the full period of data availability (1978 to 2001). Simulated ranges of CV, across grid cells and four baseline simulations, were 0.12 to 0.71. The coarse model simulation grid is likely to introduce errors in the comparison of CV, since the observed variability at this scale masks heterogeneity due to differences in management and in the availability of soil water; whereas the simulated variability is the result of a single climate variability time series. In the case of mean yields, averaging over time is likely to make observations and simulations more directly comparable. Underlying this issue is the question of whether regional-scale estimates of crop yield based on climate model output are truly representative of grid-scale variability, or whether aggregation errors prohibits such a direct comparison [11]. It is also possible that the high values of CV resulting from the model reflect the fact that the model does not account for socio-economic influences on adaptation. This would be consistent with the results presented in the main paper, and in supplementary figure 1, which suggest that there is significant current ability to buffer crop yields from drought.



Supplementary figure 1. The percentage of harvests failing under temperature adaptation as a function of increase in global mean temperature (GMT). The numbers in brackets indicate the number of data points (note that the 6–8 degrees bin has a low population compared to the other three bins). GMT increase is defined using January-December data referenced to the average GMT over the full baseline period. Crop failure is defined as yields less than two standard deviations below the corresponding baseline mean. Each box and whiskers shows the median, inter-quartile range and maximum and minimum values. The horizontal line shows the baseline failure rate, which is the average of the failure rates in the four baseline simulations.

Vulnerability analysis. Natural hazards data [12] were used as an independent test of the vulnerability modelling. These data were only available for 1995–2001 and do not describe specific crops. However, they indicate qualitative agreement with the vulnerability index modelling . Based on previous analyses, the vulnerability index was successful in identifying a number of historic cases where relatively small meteorological droughts caused widespread food production problems. For example the VI for Ethiopia in the mid 1980s was very high which coincides with the 1984 famine that was triggered by an extremely small drought when measured in meteorological terms [13].

The time series of historical VI were tested for temporal trends, in order to test the viability of any conclusions drawn on the basis of the three VI scenarios. The correlation coefficients for the four provinces were 0.47, 0.28, 0.28 and 0.00 with only the latter of these being significant at the 10% level. Thus no statistically significant trends were found.

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