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SUPPLEMENTARY INFORMATION

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Similar estimates of temperature impacts on global wheat yield by three independent methods

Supplementary information

Author: Bing Liu[a,b], Senthold Asseng[b], Christoph Müller[c], Frank Ewert[d], Joshua Elliott[e,f], David B. Lobell[g], Pierre Martre[h,i], Alex C. Ruane[e,j], Daniel Wallach[k], James W. Jones[b], Cynthia Rosenzweig[e,j,†], Pramod K. Aggarwal[l], Phillip D. Alderman[m], Jakarat Anothai[n], Bruno Basso[o,p], Christian Biernath[q], Davide Cammarano[r], Andy Challinor[s,t], Delphine Deryng[e,f], Giacomo De Sanctis[u], Jordi Doltra[v], Elias Fereres[w], Christian Folberth[x], Margarita Garcia-Vila[w], Sebastian Gayler[y], Gerrit Hoogenboom[z], Leslie.A. Hunt[aa], Roberto C. Izaurralde[bb,cc], Mohamed Jabloun[dd], Curtis D. Jones[bb], Kurt C. Kersebaum[ee], Bruce A. Kimball[ff], Ann-Kristin Koehler[s], Soora Naresh Kumar[gg], Claas Nendel[ee], Gary O'Leary[hh], Jørgen E. Olesen[dd], Michael J. Ottman[ii], Taru Palosuo[jj], P.V. Vara Prasad[kk], Eckart Priesack[q], Thomas A. M. Pugh[ll], Matthew Reynolds[m], Ehsan E. Rezaei[d], Reimund P. Rötter[jj], Erwin Schmid[mm], Mikhail A. Semenov[nn], Iurii Shcherbak[o,p], Elke Stehfest[oo], Claudio O. Stöckle[pp], Pierre Stratonovitch[nn], Thilo Streck[y], Iwan Supit[qq], Fulu Tao[rr,jj], Peter Thorburn[ss], Katharina Waha[c], Gerard W. Wall[ff], Enli Wang[tt], Jeff W. White[ff], Joost Wolf[qq], Zhigan Zhao[uu,tt], and Yan Zhu[a,*]

Author affiliation:

[a] National Engineering and Technology Center for Information Agriculture, Jiangsu Key Laboratory for Information Agriculture, Jiangsu Collaborative Innovation Center for Modern Crop Production, Nanjing Agricultural University, Nanjing, Jiangsu 210095, China

[b] Agricultural & Biological Engineering Department, University of Florida, Gainesville, FL 32611, USA

[c] Potsdam Institute for Climate Impact Research, 14473 Potsdam, Germany

[d] Institute of Crop Science and Resource Conservation INRES, University of Bonn, 53115, Germany

[e] Columbia University Center for Climate Systems Research, New York, NY 10025, USA

[f] University of Chicago Computation Institute, Chicago, IL 60637, USA

[g] Department of Environmental Earth System Science and Center on Food Security and the Environment, Stanford University, Stanford, CA 94305, USA

[h] INRA, UMR759 Laboratoire d'Ecophysiologie des Plantes sous Stress Environnementaux, F-34 060 Montpellier, France

[i] Montpellier SupAgro, UMR759 Laboratoire d'Ecophysiologie des Plantes sous Stress Environnementaux, F-34 060 Montpellier, France

[j] National Aeronautics and Space Administration Goddard Institute for Space Studies, New York, NY 10025, USA

[k] INRA, UMR1248 Agrosystèmes et développement territorial (AGIR), 31326 Castanet-Tolosan Cedex, France

[l] CGIAR Research Program on Climate Change, Agriculture and Food Security, Borlaug Institute for South Asia. CIMMYT, New Delhi-110012, India

[m] CIMMYT Int. Adpo, D.F. Mexico 06600, Mexico

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[n] Department of Plant Science, Faculty of Natural Resources, Prince of Songkla University, Songkhla 90112, Thailand

[o] Department of Geological Sciences, Michigan State University East Lansing, Michigan 48823, USA

[p] W.K. Kellogg Biological Station, Michigan State University East Lansing, Michigan 48823, USA

[q] Institute of Biochemical Plant Pathology, Helmholtz Zentrum München – German Research Center for Environmental Health, Neuherberg, D-85764, Germany

[r] The James Hutton Institute Invergowrie, Dundee DD2 5DA, Scotland, UK

[s] Institute for Climate and Atmospheric Science, School of Earth and Environment, University of Leeds, Leeds LS29JT, UK

[t] CGIAR-ESSP Program on Climate Change, Agriculture and Food Security, International Centre for Tropical Agriculture (CIAT), A.A. 6713, Cali, Colombia.

[u] European Commission, Joint Research Centre, via Enrico Fermi, 2749 Ispra, 21027, Italy

[v] Cantabrian Agricultural Research and Training Centre (CIFA), 39600 Muriedas, Spain

[w] Dep. Agronomia, University of Cordoba, Apartado 3048, 14080 Cordoba, Spain

[x] Department of Geography, University of Munich, Germany

[y] Institute of Soil Science and Land Evaluation, University of Hohenheim, 70599 Stuttgart, Germany

[z] AgWeatherNet Program, Washington State University, Prosser, Washington 99350, USA

[aa] Department of Plant Agriculture, University of Guelph, Guelph, Ontario, N1G 2W1, Canada

[bb] Dept. of Geographical Sciences, Univ. of Maryland, College Park, MD 20742, USA

[cc] Texas A&M AgriLife Research and Extension Center, Texas A&M Univ., Temple, TX 76502, USA

[dd] Department of Agroecology, Aarhus University, 8830 Tjele, Denmark

[ee] Institute of Landscape Systems Analysis, Leibniz Centre for Agricultural Landscape Research, 15374 Müncheberg, Germany

[ff] USDA, Agricultural Research Service, U.S. Arid-Land Agricultural Research Center, Maricopa, AZ 85138, USA

[gg] Centre for Environment Science and Climate Resilient Agriculture, Indian Agricultural Research Institute, IARI PUSA, New Delhi 110 012, India

[hh] Landscape & Water Sciences, Department of Environment and Primary Industries, Horsham 3400, Australia

[ii] The School of Plant Sciences, University of Arizona, Tucson, AZ 85721, USA

[jj] Environmental Impacts Group, Natural Resources Institute Finland (Luke), FI-03170 Vantaa, Finland.
[kk] Department of Agronomy, Kansas State University, Manhattan, KS 66506, USA
[ll] Institute of Meteorology and Climate Research, Atmospheric Environmental Research, Karlsruhe Institute of Technology, 82467 Garmisch-Partenkirchen, Germany
[mm] University of Natural Resources and Life Sciences, 1180 Vienna, Austria
[nn] Computational and Systems Biology Department, Rothamsted Research, Harpenden, Herts, AL5 2JQ, UK
[oo] PBL Netherlands Environmental Assessment Agency, 3720 AH, Bilthoven, The Netherlands
[pp] Department of Biological Systems Engineering, Washington State University, Pullman, Washington 99164, USA
[qq] Plant Production Systems & Earth System Science, Wageningen University, 6700AA Wageningen, The Netherlands
[rr] Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Science, Beijing 100101, China
[ss] CSIRO Ecosystem Sciences, Dutton Park QLD 4102, Australia
[tt] CSIRO Agriculture, Black Mountain ACT 2601, Australia
[uu] Department of Agronomy and Biotechnology, China Agricultural University, Yuanmingyuan West Road 2, Beijing 100193, China.
[†]Authors after C. Rosenzweig are listed in alphabetical order.

Section S1. Supplementary methods

Estimating temperature impacts on wheat yields in USA with county –level statistical regression

County-level wheat yield data from 1990 to 2010 were collected from the National Agricultural Statistics Service of United States Department of Agriculture (USDA)[1]. Yield data from 1174 and 262 counties in 18 major wheat production states, which produced more than 95% US total wheat production, were analyzed for winter wheat and spring wheat, respectively (Fig. S8, Regression_E). A linear mixed regression model was used to determine the temperature impacts on wheat yields (Eq. (S1)):

$$\text{Log(Yield)} = \beta_{Year} \times \text{Year} + \beta_{T} \times \text{T} + \beta_{P} \times \text{P} + \beta_{T \times P} \times \text{T} \times \text{P} + \beta_{County} + \varepsilon \qquad \text{(S1)}$$

In this model, the natural logarithm of reported yield was used (Log(Yield)), similar with previous statistical regression models [2, 3]. Year term was used to de-trend the wheat yield to exclude the no-climatic trends including improvements in cultivars,

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management, and increase in CO_2 concentration during the study period. T and P were the average temperature and precipitation during the 90 days period before maturity. Because wheat is dormant and insensitive to weather through most of the winter season, 90 days period prior to maturity were usually the most critical period for wheat growth. Also, the interaction between temperature and precipitation was taken into account with β_{TxP} . β_{County} was the county effect term on wheat yields, and the regression results were similar when β_{County} was treated either as fixed effects or random effects. ε was an error term. The temperature and precipitation data used in the regression came from the AgMERRA dataset [4], which is a global surface climate dataset with an resolution of 0.25*0.25^o from 1980-2010. The maturity data was the average maturity date during the last 10 years for each state, which were collected from the crop progress reports of USDA.

Two separate models were built for winter wheat and spring wheat. Sample size for each model were 22560 (winter wheat) and 5085 (spring wheat). Significant negative relationships between temperature and wheat yield were found in winter wheat and spring wheat (p<0.001), and R^2 for winter and spring wheat model were 0.64 and 0.73. The total temperature impact on wheat yields in the USA was the weighted sum of temperature impacts on winter and spring wheat yields.

Section S2: Supplementary tables and figures

Table S1. Details of different approaches used to estimate yield impacts with 1°C global temperature increase for global wheat and the top five wheat producing countries. Studies with +2°C where adjusted to +1°C by halving the impacts, assuming a linear change in impact with increasing temperature to +2°C (5). Note, estimates in which local temperature change were used were adjusted to the impact of global temperature change by a factor (ΔT) following the procedure described by Ref. 5.

Scale	Methods	Approaches	Spatial resolution	Period	Source	ΔT[a]
Global	Grid-based	7 global gridded models ensemble	0.5 x 0.5° grid size	Baseline (1980-2009), (2029-2058)[b]	Ref [6]	na
	Point-based	30 wheat models ensemble, including one statistical regression model	30 global representative high rainfall/irrigated locations	Baseline (1981-2010), Baseline+2°C	Ref [5]	na
	Regression_A	Statistical regression model	Country scale	1980-2008	Ref [2]	1.179
	Regression_B	Statistical regression model	Global scale	1961-2002	Ref [7]	1.179
China	Grid-based	7 global gridded models ensemble	0.5 x 0.5° grid size	Baseline (1980-2009), (2029-2058)[b]	Ref [6]	na
	Point-based	30 wheat models ensemble, including one statistical regression model	3 representative locations	Baseline (1981-2010), Baseline+2°C	Ref [5]	1.375
	Regression_A	Statistical regression model	Country scale	1980-2008	Ref [2]	1.375
	Regression_C[c]	Statistical regression model	0.5 x 0.5 grid size	1981-2006	Ref [8]	1.375
	Regression_D[d]	Statistical regression model	County scale	1980-2008	Ref [9]	1.375
India	Grid-based	7 global gridded models ensemble	0.5 x 0.5° grid size	Baseline (1980-2009), (2029-2058)[b]	Ref [6]	na
	Point-based	30 wheat models ensemble, including one statistical regression model	3 representative locations	Baseline (1981-2010), Baseline+2°C	Ref [5]	1.125
	Regression_A	Statistical regression model	Country scale	1980-2008	Ref [2]	1.125
Russia	Grid-based	7 global gridded models ensemble	0.5 x 0.5° grid size	Baseline (1980-2009), (2029-2058)[b]	Ref [6]	na
	Point-based	30 wheat models ensemble, including one statistical regression model	1 representative locations	Baseline (1981-2010), Baseline+2°C	Ref [5]	1.125
	Regression_A	Statistical regression model	Country scale	1980-2008	Ref [2]	1.125
USA	Grid-based	7 global gridded models ensemble	0.5 x 0.5° grid size	Baseline (1980-2009), (2029-2058)[b]	Ref [6]	na
	Point-based	30 wheat models ensemble, including one statistical regression model	3 representative locations	Baseline (1981-2010), Baseline+2°C	Ref [5]	1.375
	Regression_A	Statistical regression model	Country scale	1980-2008	Ref [2]	1.375
	Regression_E	Statistical regression model	County scale	1990-2010	Our own study	1.375
France	Grid-based	7 global gridded models ensemble	0.5 x 0.5° grid size	Baseline (1980-2009), (2029-2058)[b]	Ref [6]	na
	Point-based	30 wheat models ensemble, including one statistical regression model	2 representative locations	Baseline (1981-2010), Baseline+2°C	Ref [5]	1.125
	Regression_A	Statistical regression model	Country scale	1980-2008	Ref [2]	1.125

[a]. To adjust local or country temperature changes to global temperature change, temperature factors (ΔT) were calculated (weighted by the production represented by each location) of the 30 locations in the point-based simulations, "na" indicates that data were already presented at global temperature change. The temperature factor for the global regression_A and regression_B was calculated with the average temperature factor (weighted by the production represented by each location) of the 30 locations in point-based simulations. For grid-based simulations global temperature was already applied in this study.

[b] The future period represent Baseline (1980-2009) +2°C.

[c] We translated the absolute national yield reduction number from the national level regression in this study into yield impacts per degree local warming with an average national wheat yield from 1981-2006 (from FAO reports). The local warming impact was then corrected to global temperature change.

[d]. Two different regression methods were applied to same datasets in this study. We used the average value of these two methods here.

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Table S2 Regression parameters of simulated wheat yields and estimated yield impacts with 1^{o}C global temperature increase between grid-based simulations (0.5 x 0.5^{o}) with cells centered around the locations of the point-based method (from Ref. 6) and the 30 locations of the point-based simulations (from Ref. 5).

Model ensemble	Category	Period	Slope	Intercept	R^2
Median	Absolute yield	Baseline	0.69±0.14	-1.07±0.99	0.46***
		Baseline+1^{o}C	0.70±0.12	-1.03±0.84	0.52***
	Temperature impacts	Baseline+1^{o}C	1.74±0.23	0.04±0.02	0.66***
Mean	Absolute yield	Baseline	0.75±0.11	-1.22±0.79	0.62***
		Baseline+1^{o}C	0.75±0.10	-1.10±0.69	0.64***
	Temperature impacts	Baseline+1^{o}C	1.69±0.18	0.04±0.02	0.75***

*** indicates significance at p<0.001

Table S3 Comparison of model inputs of point-based simulations (Ref. 5) and grid-based simulations (Ref. 6).

Category	Point-based simulation	Grid-based simulation
Model	LPJmL, CERES-Wheat, EPIC, and other 27 models, including one statistical model after Lobell et al. (2011)	EPIC, GEPIC, IMAGE, LPJmL, LPJ-GUESS, CERES-Wheat (pDSSAT), PEGASUS
Climate	Baseline: AgCFSR climate dataset Baseline+2ºC: Temperature: Baseline+2ºC Radiation: no change Precipitation: no change	HadGEM2-ES RCP8.5 (bias corrected, see ref. [10])
CO_2 concentration	No CO_2 effects	No CO_2 effects
Cultivar	Region-specific, same cultivar during two periods	Model-specific, region-specific, static in time for all except LPJ-GUESS and PEGASUS
Sowing date	Fixed for each location	Model-specific, pixel-specific, fixed for all except PEGASUS and GEPIC
Soil condition	Type characteristics, initialization every year (no impact as water stress and N stress were switched off)	Model-specific, pixel-specific
Water management	Fully irrigation and high rainfall, no water stress	Fully irrigated
Nitrogen management	No nitrogen stress	Actual (national) fertilizer data for those that account for N stress. National intensity calibration for LPJmL, no calibration for LPJ-GUESS, national management factors for IMAGE
Adaptation	No adaptation	Adaptation through cultivars in LPJ-GUESS and PEGASUS and sowing dates in GEPIC, and PEGASUS; IMAGE is based on the length of the growing season (T and soil water limited) and thus explicitly assumes perfect adaptation.

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Table S4 Baseline and baseline+2°C period for the 30 grids where the 30 global locations in point-based simulations centered in grid-based simulations and temperature differences (T_{diff}) between point-based and grid-based simulations.

Number	Location	Baseline		Baseline+2°C	
		Period	T_{diff}	Period	T_{diff}
1	Maricopa, USA	1980-2009	-0.14	2017-2046	0.00
2	Obregon, Mexico	2021-2050	0.00	2052-2081	-0.01
3*	Toluca, Mexico	1980-2009	-2.88	1980-2009	-0.88
4	Londrina, Brazil	1980-2009	-0.44	2017-2046	-0.01
5	Aswan, Egypt	1992-2021	0.00	2030-2059	0.02
6	Wad Medani, Sudan	1981-2010	-0.01	2012-2041	0.00
7	Dharwar, India	1980-2009	-0.54	2021-2050	0.00
8	Dinajpur, Bangladesh	2029-2058	0.01	2063-2092	-0.03
9	Wageningen, The Netherlands	1990-2019	0.02	2034-2063	-0.04
10	Balcarce , Argentina	2007-2036	-0.01	2059-2088	-0.01
11	Ludhiana, India	2000-2029	0.03	2036-2065	0.01
12	Indore, India	2002-2031	-0.02	2034-2063	0.00
13	Madison, USA	2053-2082	0.07	2070-2099	0.57
14	Manhattan, USA	2009-2038	-0.02	2032-2061	0.03
15	Rothamsted, UK	1982-2011	-0.03	2030-2059	-0.02
16	Estrées-Mons, France	1988-2017	-0.02	2030-2059	-0.03
17	Orleans, France	1985-2014	-0.01	2024-2053	-0.02
18	Schleswig, Germany	1985-2014	-0.03	2030-2059	0.03
19	Nanjing, China	1998-2027	0.00	2032-2061	0.00
20	Luancheng, China	2003-2032	-0.03	2033-2062	-0.02
21	Harbin, China	2001-2030	0.01	2034-2063	0.02
22	Kojonup, Australia	1980-2009	-0.06	2040-2069	0.02
23	Griffith, Australia	2003-2032	0.00	2043-2072	-0.01
24	Karaj, Iran	2047-2076	-0.02	2070-2099	0.34
25	Faisalabad, Pakistan	2008-2037	0.00	2038-2067	0.00
26*	Karagandy, Kazakhstan	1980-2009	-4.11	1980-2009	-2.11
27	Krasnodar, Russia	1981-2010	0.00	2017-2046	0.01
28	Poltava, Ukraine	1980-2009	-0.12	2011-2040	-0.03
29	Izmir, Turkey	1990-2019	0.03	2033-2062	0.01
30	Lethbridge, Canada	2008-2037	0.04	2034-2063	0.05

* In these locations, large temperature differences occurred due to temperature in point-based simulations was much higher than that in grid-based simulations.

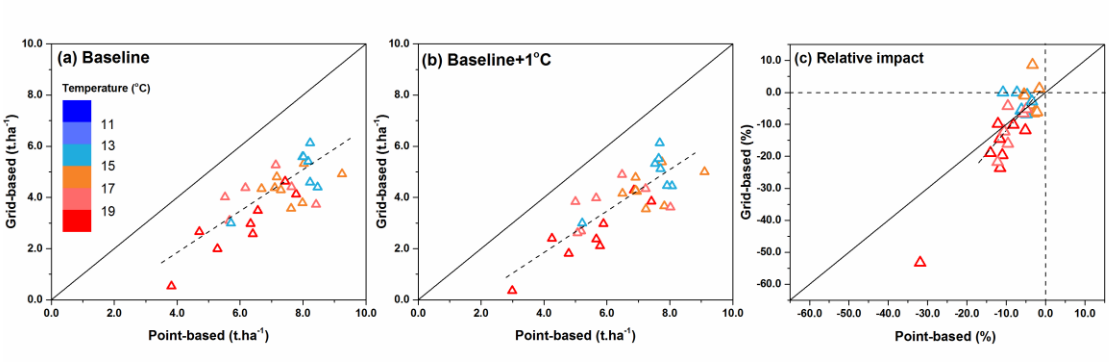

Figure S1. Comparison of simulated multi-model mean yields and yield changes during (a) baseline, (b) baseline+1°C, and (c) relative yield change with 1°C global temperature increase for grid-based simulations (0.5° x 0.5°) (from Ref. 6) with cells centered around the locations from the point-based study versus the 30 locations of the point-based simulations (from Ref. 5). Note in (c), regression line is drawn without outlier (location in Sudan)

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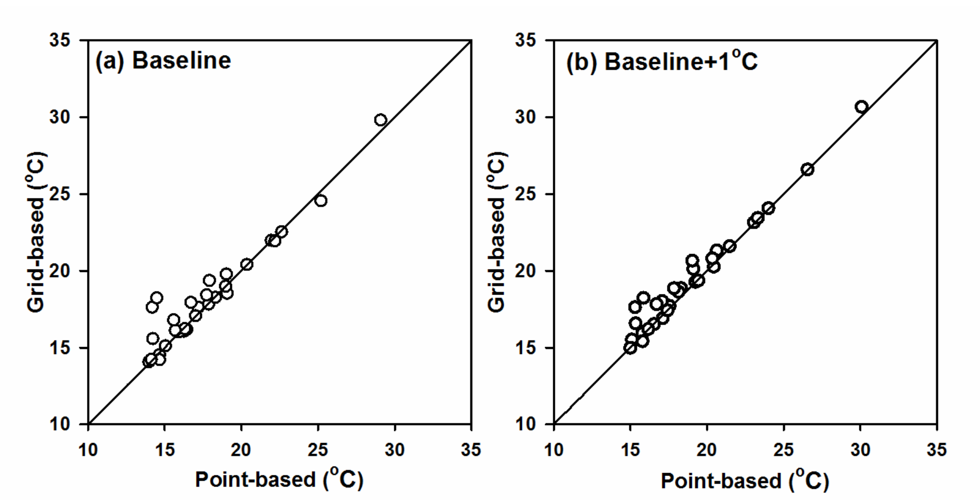

Figure S2. Comparison of average temperature (^{o}C) during 90 days period before the maturity day for 30 locations from the grid-based simulations (from Ref. 6) versus the data from the point-based simulations (from Ref. 5) during baseline (a) and baseline+1^{o}C (b) period. Each symbol is average over 30 years.

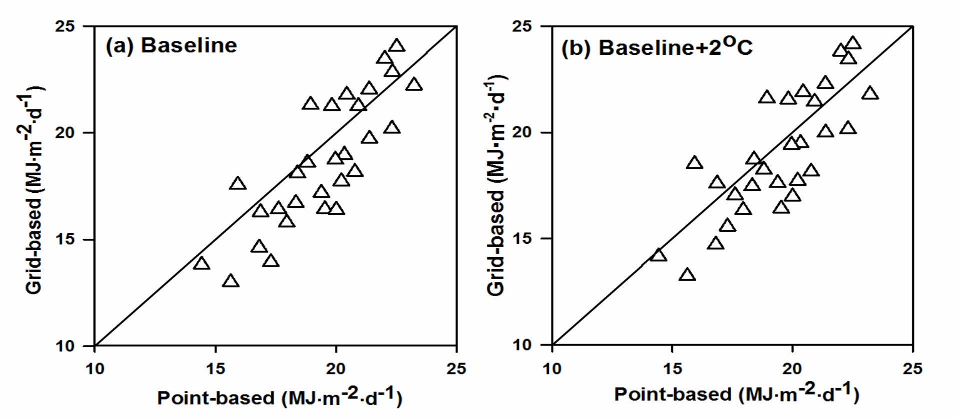

Figure S3. Comparison of average daily radiation (MJ.m^{-2}.d^{-1}) during the 90 days period before the maturity day for 30 locations from the grid-based simulations (from Ref. 6) versus data used in the point-based simulations (from Ref. 5) during baseline (a) and baseline+2^{o}C (b) period. Each symbol is average over 30 years.

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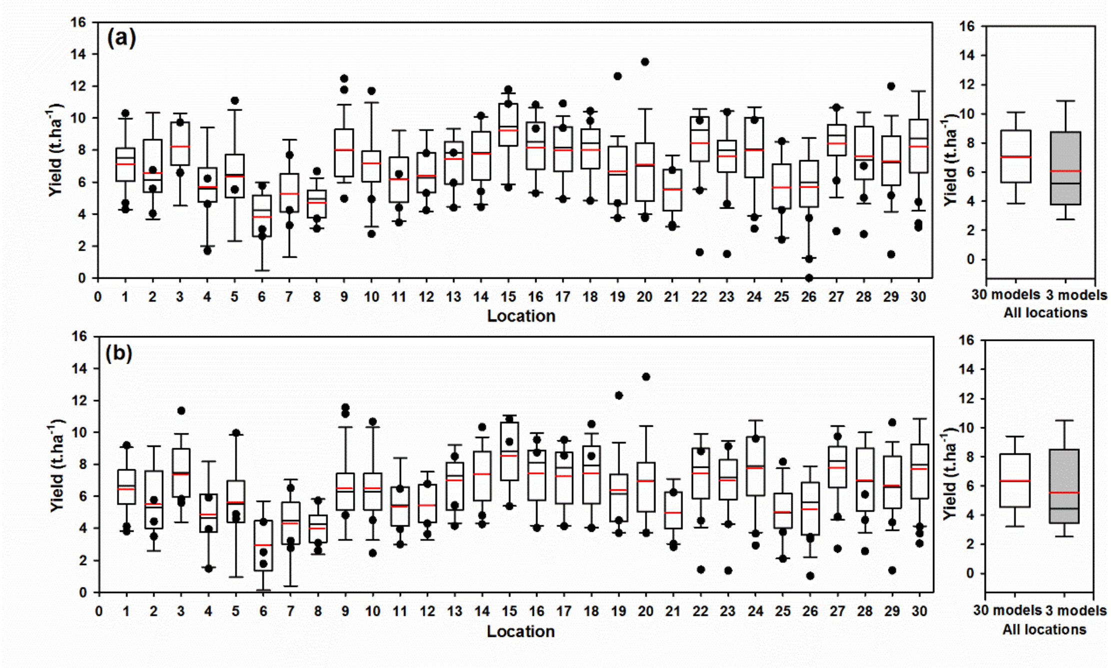

Figure S4. Simulated yields (mean of 30 years) for baseline (a) and baseline+2°C (b) period from point-based simulations with all 30 models (whisker plots) (Ref. 5) and the 3 models (CERES-Wheat, EPIC, LPJmL) (black symbols) from the Ref. 5 which were also used in the grid-based simulations (in the study of Ref. 6) for each high rainfall/irrigated location (1-30). Summary of 30 models (open whisker plots) and three models (grey whisker plots) for all 30 locations is shown in panels on right. Horizontal red line in each box shows ensemble mean, horizontal black line in the box indicates ensemble median. Edges of box are 75 and 25 %-tiles, the whiskers of box indicate 90 and 10 %-tiles.

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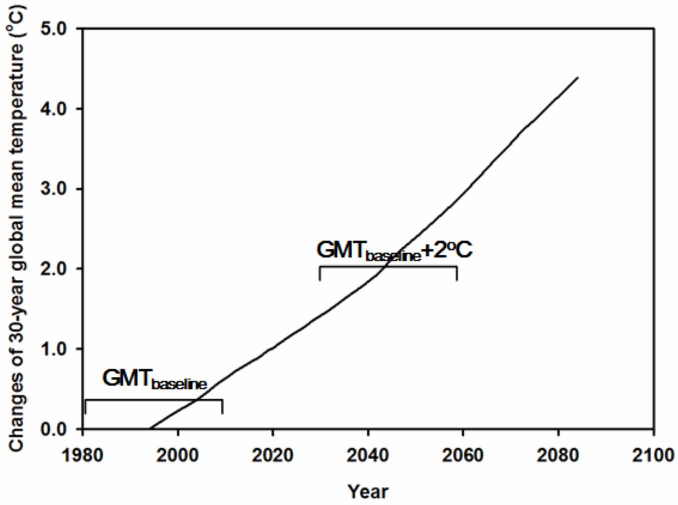

Figure S5. Change of 30-years global mean temperature (GMT) during 1980-2099 in grid-based simulations.

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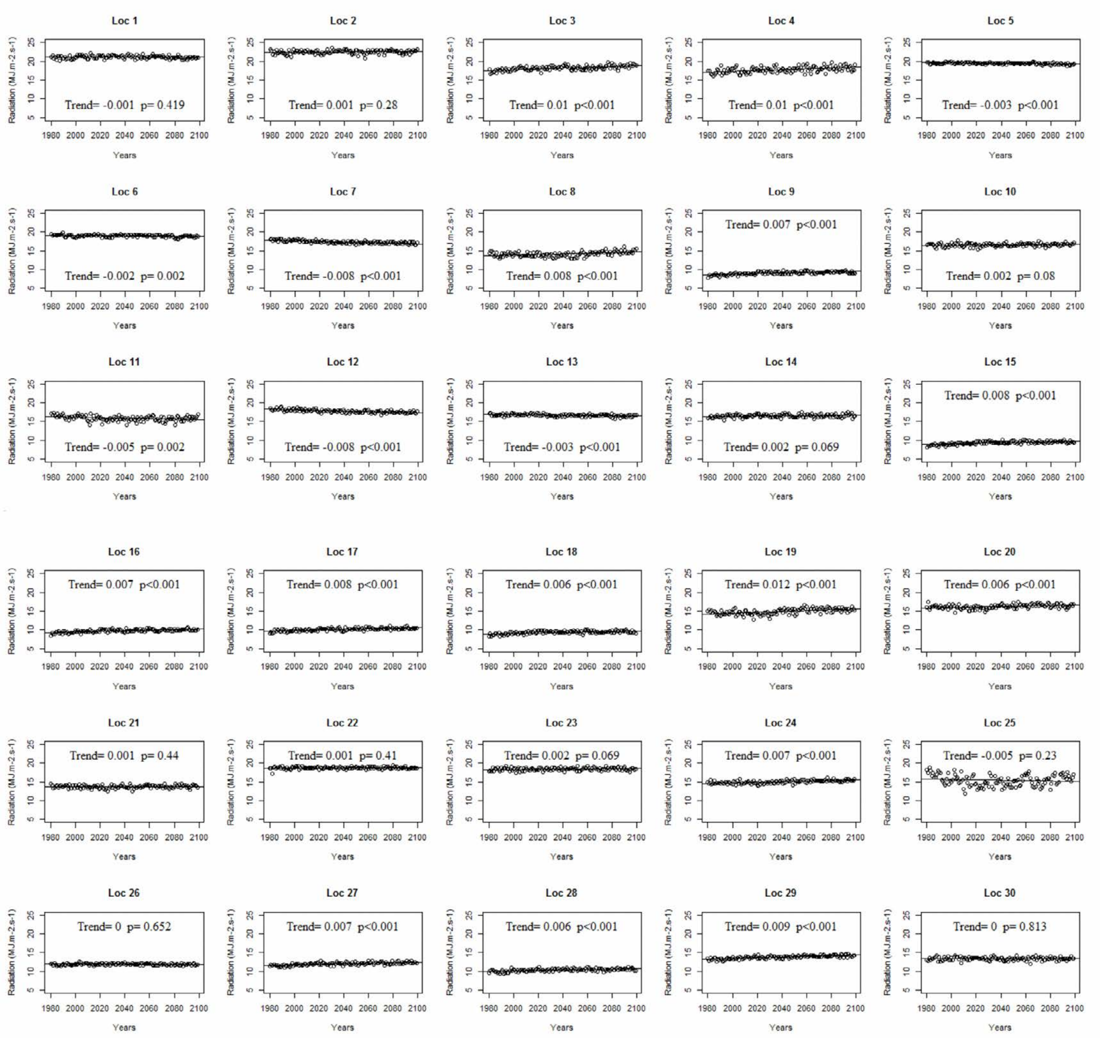

Figure S6. The annual radiation for the 30 grids centered around the 30 global representative locations from the point-based method during 1980-2099 under RCP8.5 scenario with HadGEM2-ES in grid-based simulations. The trends were the slopes of simple linear regression between radiation and year.

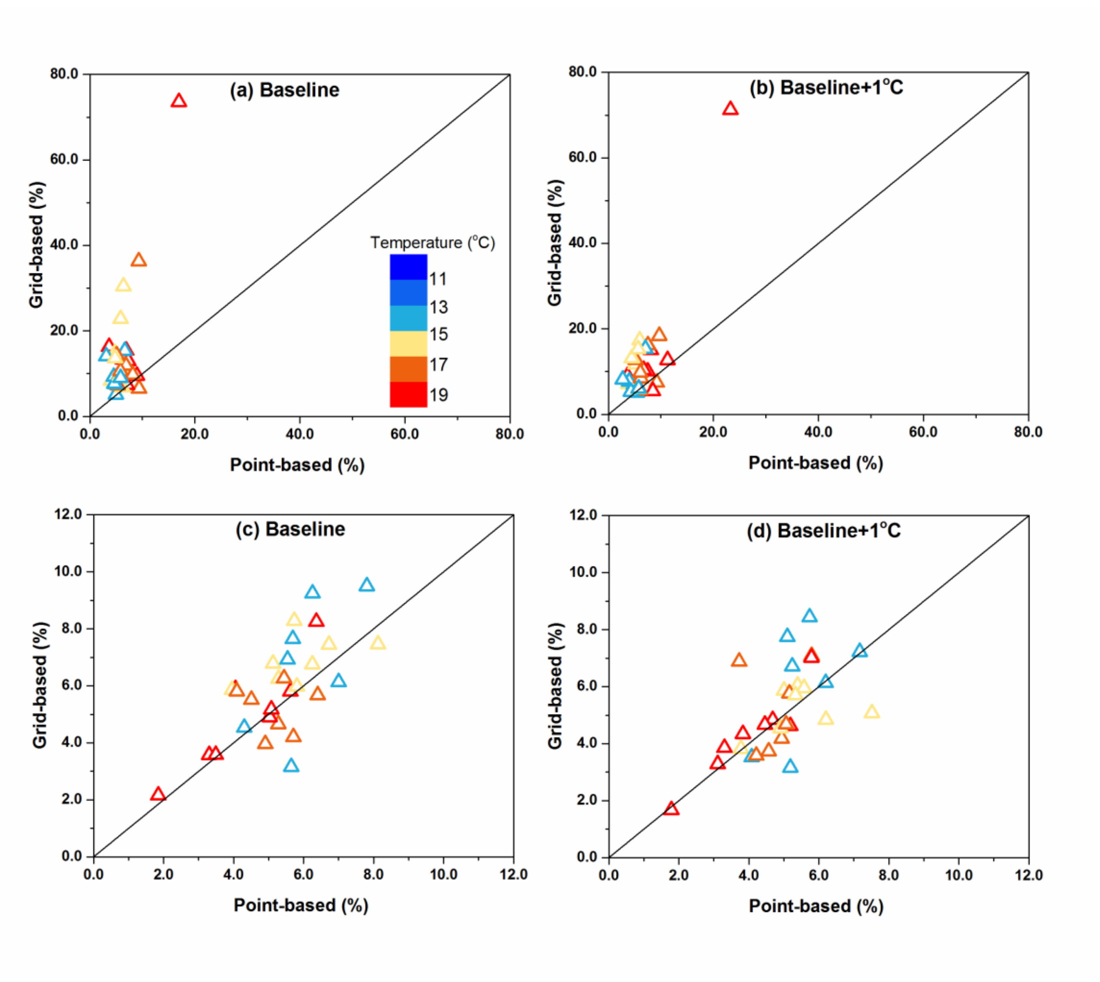

Figure. S7 Comparison of temporal variability for simulated yield and average temperature (°C) during 90 days period before the maturity day for the 30 locations between grid-based and point-based simulations. Coefficient of variation (%) for simulated grain yields according to year variability for baseline period (a) and baseline+1°C (b). Coefficient of variation (%) for average temperature (°C) during 90 days period before the maturity day according to year variability for baseline period (c) and baseline+1°C (d).

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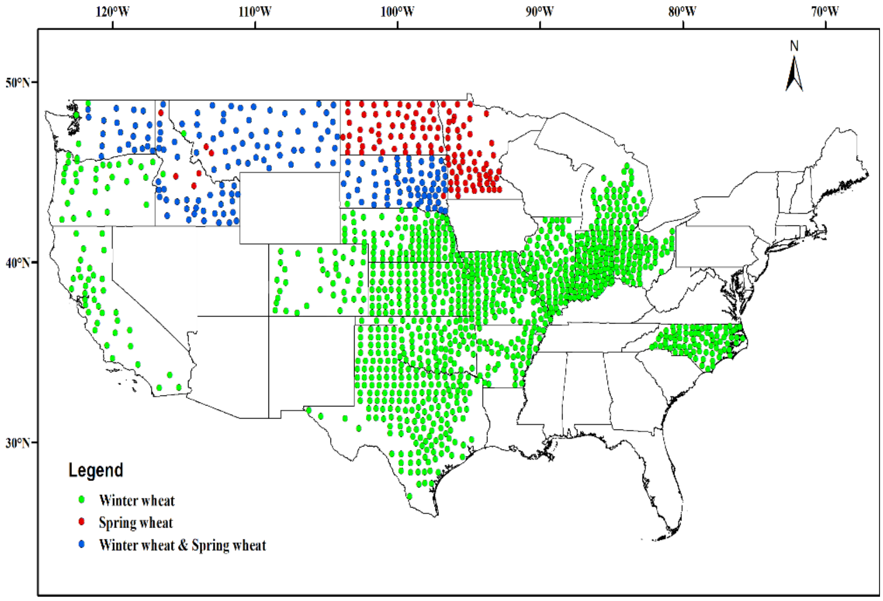

Figure S8. Map of counties used in the county-level statistical regression between temperature and wheat yields for US wheat. Color of circle indicates the wheat type. Green: winter wheat, red: spring wheat, blue: winter wheat and spring wheat

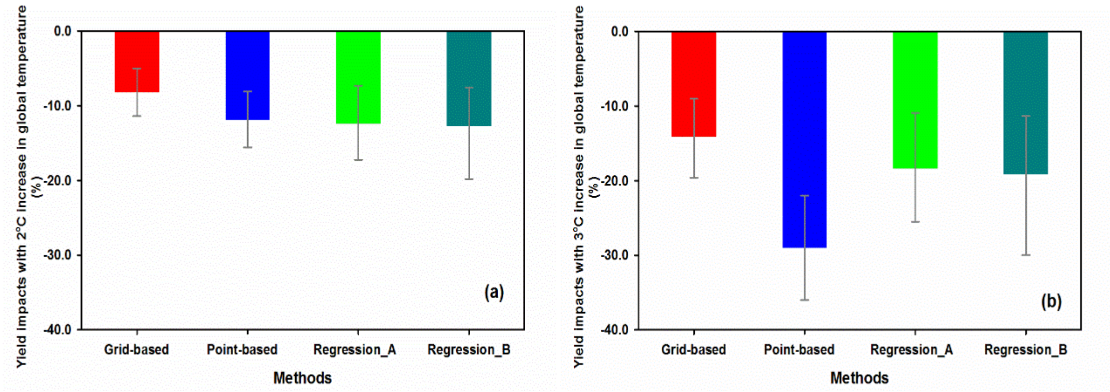

Figure. S9. Comparison of impacts of (a) 2^{o}C and (b) 3^{o}C global temperature increase on global wheat yield estimated by different assessment methods.

Note: The original point-based and grid-based simulations were done for a 2°C warming compared to baseline. The effect of 1°C warming in the main text was obtained by halving the simulated effect of 2°C. The grid-based simulation study included the effect of baseline+3^{o}C (attained in the period 2047-2076). The point-based simulation study included baseline+4^{o}C. The impact at +4°C was multiplied by ¾ to estimate the effect of 3^{o}C global warming.

Since Regression_B is a linear regression model, yield impact is simply proportional to temperature increase. As country temperature was used in Regression_A, we applied the regression model for 2°C and 3°C increase in country temperature, and then adjusted the impacts by a global temperature factor in Table S1.

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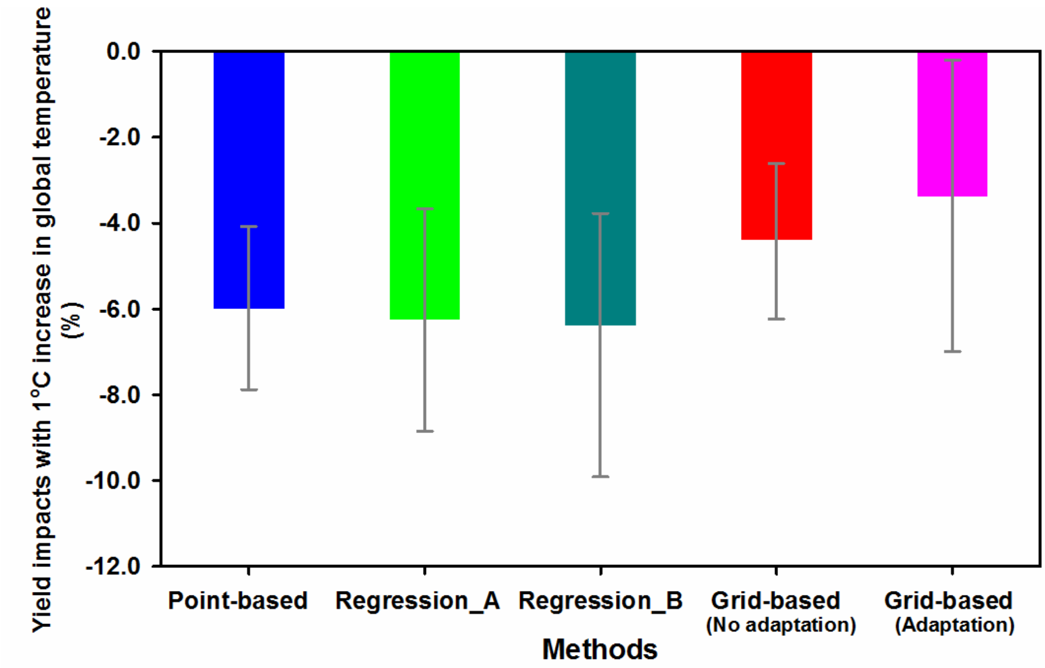

Figure. S10. Impacts of 1°C global temperature increase on global wheat yield estimated by different assessment methods. Same as Figure 1 except for the results from grid-based method. Temperature impacts from two kinds of models (with or without adaptation, see in Table S3) in the grid-based method were aggregated separately. Models with adaptation were: GEPIC, IMAGE, LPJ-GUESS, and PEGASUS, and models without adaptation were EPIC, LPJmL, and CERES-Wheat (pDSSAT). The error bars indicate the 95% confidence intervals based on multi-model ensembles in the simulations.

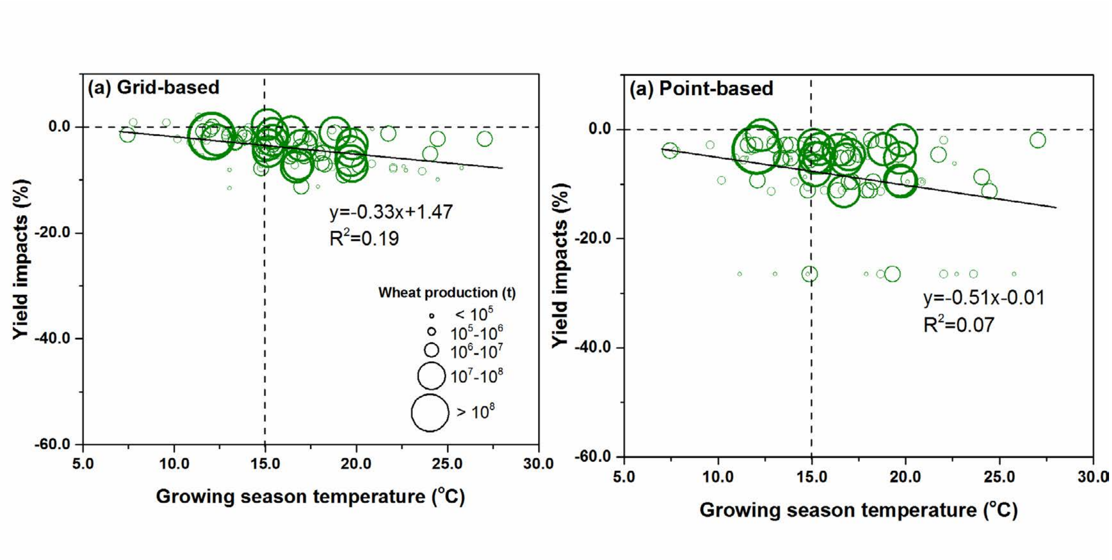

Figure.S11. Relationship between yield changes with 1°C global temperature increase for 97 wheat producing countries and wheat growing season temperature. Yield impacts were estimated with (a) Median simulations of a grid-based (0.5° × 0.5°) ensemble of seven models (after Ref. 6) and (b) Median simulations of a point-based (30 locations over 30 years) ensemble of 30 models (after Ref. 5) The wheat growing season temperature for 97 countries came from Ref. 2.

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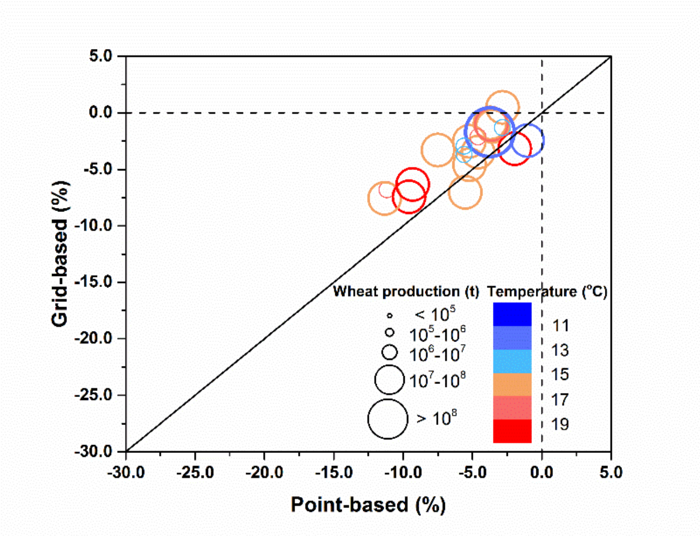

Figure.S12 Same as Figure 2a, except results for the top 20 wheat producing countries are shown only.

Supplementary references

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