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Supplementary information

Spatial frameworks for robust estimation of yield gaps

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Supplementary Material for "Spatial frameworks for robust estimation of yield gaps" by Rattalino Edreira *et al.*

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1. Sources of yield potential data derived from top-down and bottom-up approaches

1.1 GAEZ

The GAEZ was originally developed to provide a framework for the characterization of climate, soil, and terrain conditions relevant to agricultural production [1,2]. The GAEZ version 3.0, developed by FAO and IIASA, incorporates global assessments of maximum potential (*i.e.*, Yp and Yw) and agronomically attainable yield for several crops (http://www.fao.org/nr/gaez/en/). At the time of submission of this manuscript, GAEZ version 3.0 was the latest available source of yield potential estimations. Details about GAEZv3 can be found in IIASA/FAO [2]. Briefly, GAEZ methodology to estimate yield potential and attainable yield consists of a generic simulation model that combines weather, soil, terrain, and cropping system information **(Supplementary Table S1)**. Yield simulations are performed in cell-grids (*ca.* 5 arc-minute x 30 arc-second resolution near the equator) for different timeframes (based on historical, current, and future climate), input levels (high, intermediate, and low), and water regime (rainfed, rainfed with water conservation, and irrigation). To simulate different crops, the model uses specific crop parameters including length of growth cycle (days from emergence to full maturity), length of yield formation period, maximum rate of photosynthesis at prevailing temperatures, leaf area index at maximum growth rate, harvest index, crop adaptability group, sensitivity of crop growth cycle length to heat provision, development stage specific crop water requirements, and coefficients of crop yield response to water stress [3]. For each grid-cell, the starting and ending dates of the crop growth cycle are determined using an algorithm that computes the best possible crop yields. This algorithm does not consider the complexity of cropping system such as the co-existence of several crop sequences within the same geographic area and year. In irrigated conditions, the crop growth cycle length is 'optimized' so that the crop cycle coincides with the period of time when temperature allows crop growth. For rainfed conditions, a water-balance model is used to determine the beginning and duration of the period when water supply is sufficient to sustain crop growth. The methodology accounts for yield reduction due to limitations imposed by soil and terrain conditions based on the soil data contained in the Harmonized World Soil Database [4]. For our evaluation, we retrieve Yp (or Yw) estimations for maize, wheat, rice, and other crops available in the GAEZ "Agro-climatic yield" dataset that assumes the highest input level and uses the baseline climatic scenario, which includes the 1961-1990 period. Values of yield potential per site, climate zone, and country (or region) are shown in **Supplementary Tables S2-S3**.

1.2 AgMIP ensemble

The AgMIP initiative aims to improve agricultural systems data and models and to advance their use to support decision making from farm to national to global scales [5]. It follows a multi-model approach that uses harmonized datasets and protocols to evaluate and improve crop model performance **(Supplementary Table S1)**. The Global Gridded Crop Model Inter-comparison (GGCMI) component of AgMIP provides simulation results from 14 global crop modeling groups that contributed with simulations for maize, wheat, rice, and other crops following a common protocol [6-8]. Briefly, each of the crop modeling groups provided global simulations in cell-grids of 30 arc-minute resolution (~3,000 km^2 at equator), separately for (i) several gridded weather data sources (*e.g.*, WFDEI, GPCC, AgMERRA, and WATCH.GPCC), (ii) fertilizer assumptions (*default*, *fullharm*, and *harm-suffN*), and (iii) water regime (rainfed and irrigated). The *default* scenario used the standard assumption on growing seasons and fertilizer inputs the crop modelers typically use. In the fully harmonized configuration, *fullharm,* all modelers assumed the same fertilizer and growing season inputs (*i.e.*, sowing and harvest dates). Finally, in the *harm-suffN* scenario (also known as "*harmnon"*), modelers used the same growing season as in the *fullharm* scenario but in this case, assuming no nutrient limitations. Growing season data, including crop intensity, water regime, and sowing window, was compiled from two existing gridded global crop calendars, MIRCA2000 [9] and SAGE2 [10]. Each modeling group was asked to use the soil parameterization that they typically use. Some of the models included in the ensemble were developed for field-scale applications (*e.g.*, CGMS-WOFOST, EPIC-based models, pDSSAT, pAPSIM), while others were derived from global-scale models by incorporating field-scale processes (e.g., LPJ-GUESS, LPJmL, ORCHIDEE-crop, PEGASUS). Hence, model calibration was performed against actual yield reported at field and/or national scale (e.g., WOFOST, EPIC-BOKU, pAPSIM), with some exceptions where models were not calibrated (e.g., CLM-crop, LPJ-GUESS, ORCHIDE-crop) [6]. Similar to GAEZ, critical aspects of the model calibration that are needed to obtain accurate estimates of yield potential such as (i) the use of yield data from experiments that were explicitly managed to achieve yield potential, (ii) the source of climate and soil data used to perform the calibration, and/or (iii) information about the regions for which the models have been calibrated are generally poorly (or not) documented. Simulated yield potential provided by the modeling groups are then summarized, using either the mean or median of simulated values e.g., [11,12,13].

We downloaded yield estimations based on the *harm-suffN* assumptions for rainfed and irrigated maize, rice, wheat, and other crops which is the dataset that gets closest to our definition of Yp and Yw (Data are available at https://zenodo.org/). Following Müller, et al. [7], we used simulations performed with the AgMIP climate forcing dataset AgMERRA, which was created based on the NASA Agriculture Modern-Era Retrospective Analysis for Research and Applications (MERRA) to provide consistent, daily time series over the 1980-2010 period with global coverage of climate variables required for agricultural models https://data.giss.nasa.gov/impacts/agmipcf/agmerra/; [14]. Following the typical procedure in crop model ensembles e.g., [11,12,13], we computed the median yield across the gridded models, obtaining one ensemble map for each combination of water regime and crop. Yield potential was not available for AgMERRA for some crop-water regime combinations **(Supplementary Table S4)**. Values of yield potential per site, climate zone, and country (or region) are shown in **Supplementary Table S2-S3**.

1.3 Global Yield Gap Atlas (GYGA)

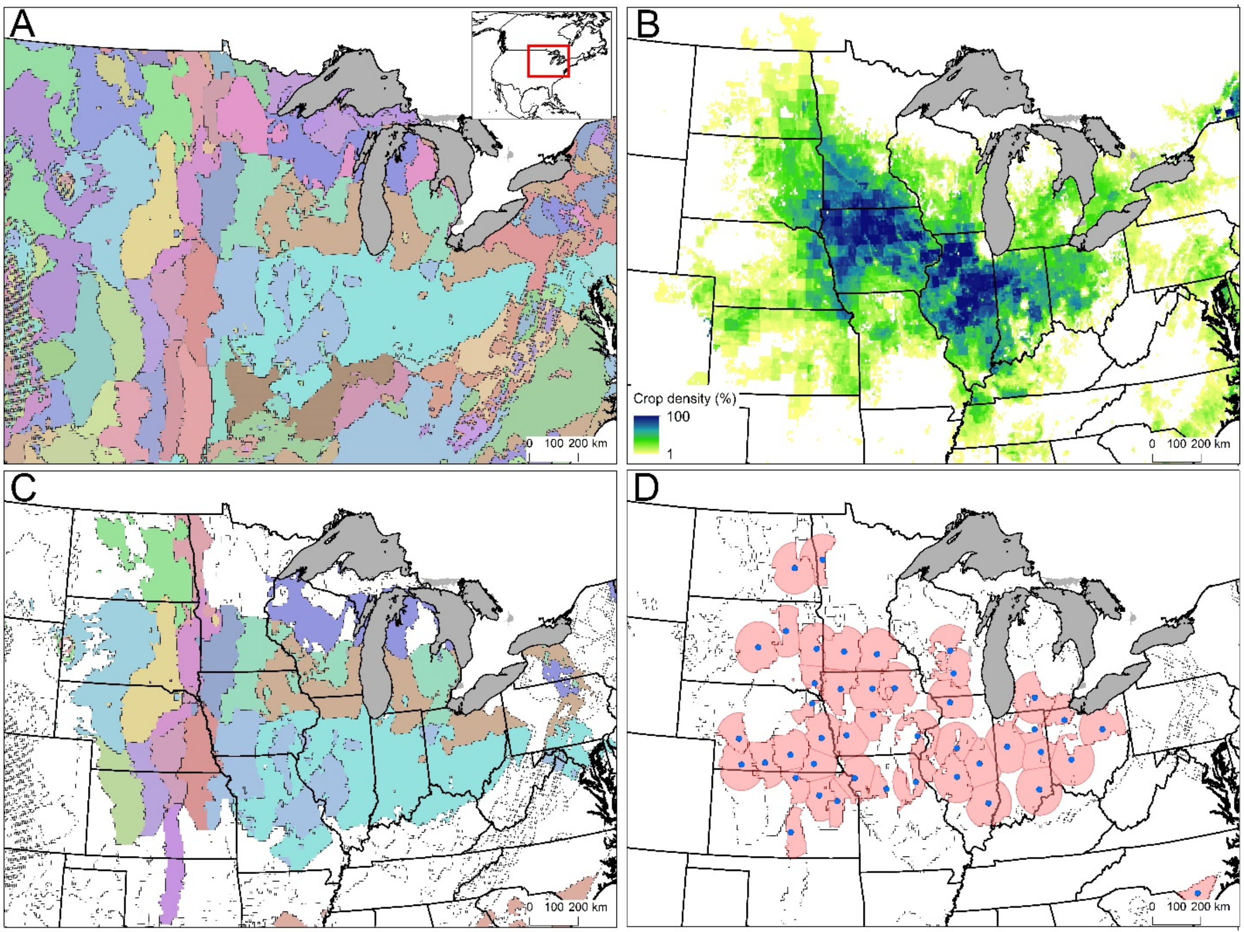
The GYGA provides estimates of untapped crop production potential on existing farmland based on current climate and available soil and water resources **(Supplementary Table S1)**. GYGA utilizes standard protocols for assessing Yp, Yw, and yield gap based on locally calibrated crop models and best available sources of weather, soil, and management data. A tiered approach is follow to give preference to high-quality data (e.g., measured weather data), moving gradually to other less reliable data sources (e.g. gridded weather data) when data are not available [15]. In the case of GYGA, less than 3% of the total buffers relied on gridded weather for model simulations.

Best sources of data and information on the cropping system context is provided by local experts [15]. GYGA protocols (Grassini et al., 2015; Van Bussel et al., 2015) have been applied consistently across crops and countries. In contrast to top-down approaches, GYGA simulates

Yp and Yw for a number of sites strategically selected for a given crop in a given country. Site selection is guided by a protocol that seeks to use the fewest number of sites to achieve crop coverage of at least 50% of the national cultivated area (van Bussel et al., 2015). Briefly, this protocol builds on the spatial framework developed by van Wart, et al. [16] and van Bussel, et al. [17], which delineates climate zones (CZs) with similar biophysical conditions. Each CZ corresponds to a geographic area with a unique combination of three biophysical attributes that govern crop yield and its inter-annual variability: (i) annual total growing degree-days, which determines the length of crop growing season (10 classes), (ii) aridity index, which largely defines the degree of water limitation in rainfed cropping systems (10 classes), and (iii) annual temperature seasonality, which differentiates between temperate and tropical climates (3 classes) **(Supplementary Figure S1A)**. Within the studied country, CZs with >5% of total national harvested area are selected **(Supplementary Figure S1B, C)**. Within each selected CZ, candidate sites with measured weather data are selected and buffer zones of 100-km radius (*ca.* 7800 km^2) are created around those sites to denote the inference area for weather data. The buffer zones are "clipped" by the CZ boundaries to ensure that each buffer is located within a unique CZ **(Supplementary Figure S1D)**. Buffers are sequentially selected based on their contribution to national crop harvested area until *ca.* 50% national crop area coverage is achieved. When measured weather data are missing in regions with high crop area density, additional buffers are created for these regions and NASA-POWER gridded weather data are used for model simulations. This approach for the selection of representative sites helps to reduce the number of locations for which site-specific data on weather, soils, and cropping systems are required, allowing to focus on quality of the underpinning data [18]. An example of site selection following the GYGA protocol is shown below for rainfed maize in the United States **(Supplementary Figure S1)**.

After site selection, yield potential is simulated for the dominant cropping systems and soil types within each buffer using a minimum of 10 (irrigated) or 20 years of daily weather data (rainfed) to obtain reliable estimates of Yp (irrigated) or Yw (rainfed) and their variability [15]. Cropping system information is provided by local agronomist and includes crop sequence, water regime, sowing window, and crop cycle duration. Separate simulations are performed for each crop cycle in those cropping systems with two or three crop cycles on the same piece of land during a 12-month period. We note that direct cross-validation of GYGA results with measured yields in research stations and/or highest yields in farmer fields is difficult because the latter may be obtained under the best combination of climate and soil in specific site-years within a region and/or with unusual crop sequences, providing an estimate of Yp that is not representative for the region [19]. In contrast, and as explained previously, GYGA uses well-validated models, coupled with long-term weather and information on dominant soils and crop sequences, to estimate yield potential and yield gaps that are relevant to the dominant biophysical and agronomic background in each region [15]. Contrarily to the top-down approaches, instead of using a single model globally, models are selected for each particular region based on their ability to reproduce locally measured yield in well-managed crops [19]. Crop models were calibrated using data sets from field studies where crops were grown without nutrient limitations and free of biotic adversities such as weeds, pests, and diseases e.g., [20,21-30]. **Supplementary Figure 1** shows the evaluation of the models used for simulating maize, rice, and wheat in GYGA based on measured yield data collected from well-managed irrigated and rainfed environments where nutrient limitations and incidence of biotic stresses were minimized. The evaluation includes for maize simulations using Hybrid-Maize model in USA, Brazil, Indonesia, and sub-Saharan Africa (SSA) [20,21,31,32], CERES-maize in Argentina and Uruguay [22,23,33-35], WOFOST in Europe [36-38], and SSM in Iran [32], (ii) wheat simulations using CERES-wheat in Argentina and Uruguay [22,35,39,40], APSIM in Australia [25,41,42], WOFOST in Europe and Middle East and North Africa [24], and SSM in USA[43] and Iran[32], and (iii) rice simulations using ORYZA in China, Indonesia, USA, SSA, and Brazil [27,28,32,44] and SSM in Iran[32]. Model coefficients related with crop development were calibrated to portray the observed phenology of the dominant cultivars grown in each region. To the extent it was possible, models were tested across a wide range of environments in each country or region, avoiding site-year calibration of internal model coefficients. Simulated yields reproduced well the range of measured yields across a wide range of environments and yield levels, ranging from near crop failure in harsh environments with severe water limitation to well-watered irrigated environments with high Yp. Evaluation of models on their ability to reproduce measure crop phenology, leaf area, biomass, and other agronomic traits have been published elsewhere (see aforementioned references).

Simulated Yp and Yw as well as shapefiles with buffers and CZs polygons for maize, rice, and wheat were downloaded from the GYGA website (www.yieldgap.org). Values of yield potential per site, climate zone, and country (or region) are shown in **Supplementary Tables S2-S3**.



Supplementary Figure S1: Selection of locations, buffers, and climate zone*. Example of strategic selection of climate zones, locations, and buffers followed by Global Yield Gap Atlas (GYGA; www.yieldgap.org) to estimate yield potential on a relatively small number of sites that represent major crop producing regions. (A) Climate zones with fairly similar weather conditions, (B) maize harvested area, (C) selected climate zones with >5% of national harvested area, and (D) locations and buffers inside the selected climate zones.*

Supplementary Table S1. Summary of most relevant features of the databases used in this study to compare top-down *versus* bottom-up approaches.

Features	Global Agro-Ecological Zones (GAEZ)	Agricultural Model Intercomparison and Improvement Project (AgMIP)	Global Yield Gap Atlas (GYGA)
Approach	Top-down	Top-down	Bottom-up
Crop model	Single, generic model based on monthly weather data that uses generic crop parameters to simulate different crops (Kassam, 1977). The model is not locally calibrated.	Combination of (i) generic and crop-specific, (ii) site-based process and ecosystem, and (iii) calibrated and non-calibrated models (Table S3).	Crop-specific model, simulates crop growth on a daily step. To the extent it is possible, models are calibrated for each study region.
Data source			
Weather	Gridded weather (Climate Research Unit and GPCC)	Gridded weather data (including, but not limited, to AgMERRA, WFDEI, and GPCC)	Tier selection approach: weather station data (1^{st} option), corrected measured data (2^{nd} option) & NASA gridded data (3^{rd} option).
Soil	Global gridded soil database (Harmonized World Soil Database, FAO/IIASA/ISRIC, 2009).	Different models use different soil databases and, in some cases, soil was ignored or not documented	Tier selection approach: high-quality national soil maps (1^{st} option), global soil databases (2^{nd} option) & expert opinion (3^{rd} option).
Cropping system	Crop cycle length is determined *in silico* by optimizing crop cycle with the length of growing season. Cropping system is incorrect or oversimplified in many cases.	Coarse global crop calendars, *e.g.*, MIRCA2000 (Portmann et al., 2010) and SAGE (Sacks et al., 2010). Cropping system is incorrect of oversimplified in many cases.	Cropping system data provided by local experts, including crop sequence, sowing date, crop cycle duration, and water regime.
Time period	30 years (1961-1990)	31 years (1980-2010)	Minimum of 10 (irrigated) and 20 years (rainfed), using the most updated data that is available after 1980.
Finest level of spatial resolution	Grids of *ca.* 100 km^2 near the equator	Grids of *ca.* 3,000 km^2 at equator	Buffers around weather stations, with border clipped by climate zones, and size varying from 200 to 31,000 km^2.
Upscaling method	No upscaling is needed as yield potential is simulated for each grid	No upscaling is needed as yield potential is simulated for each grid	Uses a climate zone scheme for upscaling yield from buffer to climate zone, and then from climate zone to country or continental levels.
References	http://www.fao.org/nr/gaez/en/; Fischer et al., 2002, IIASA/FAO, 2012	https://agmip.org/; Elliot et al., 2015; Muller et al., 2017, 2019	http://www.yieldgap.org/; Grassini et al., 2015; van Bussel et al., 2015.

Supplementary Table S2. Agreement in yield potential estimations between top-down and bottom-up approaches. Comparison between yield potential estimations derived from the Global Yield Gap Atlas (GYGA) and the Global Agro-Ecological Zones (GAEZ) or the Agricultural Model Intercomparison and Improvement Project (AgMIP) frameworks. Agreement between yield potential data sources was evaluated by calculating the absolute mean error (ME) and the root mean square error (RMSE), in t ha^{-1}.

Crop	Water regime	Country or sub-continental region	Location					Climate zone					Country or sub-continental			
				GYGA-GAEZ		GYGA-AgMIP			GYGA-GAEZ		GYGA-AgMIP		GYGA-GAEZ		GYGA-AgMIP	
			n †	ME	RMSE	ME	RMSE	n	ME	RMSE	ME	RMSE	ME	RMSE	ME	RMSE
Maize	Irrigated	Asia ɣ	47	0.7	3.3	6.0	6.3	32	1.3	3.7	5.6	5.8	-0.4	0.4	5.9	5.9
		Eastern Europe	6	-2.0	3.5	2.7	3.6	6	-2.1	3.5	2.8	3.6	-2.6	2.6	2.5	2.5
		MENA ǂ	22	0.1	2.4	12.2	12.5	13	0.1	2.1	11.2	11.6	-0.5	0.5	11.1	11.1
		USA	21	-1.9	2.7	3.5	3.8	13	-2.0	2.8	3.5	3.7	-1.8	1.8	3.9	3.9
		Western Europe	64	-0.1	3.1	3.0	3.3	51	-0.2	3.1	2.9	3.2	0.1	0.1	3.2	3.2
	Rainfed	Asia	69	1.2	4.1	5.4	6.0	31	0.9	3.7	5.7	6.0	1.1	1.1	5.4	5.4
		Eastern Europe	101	0.6	3.5	3.8	4.4	73	0.6	3.5	3.8	4.4	-0.7	0.7	3.1	3.1
		USA	45	0.8	2.4	4.4	4.7	18	1.2	2.5	4.4	4.5	1.4	1.4	5.1	5.1
		South America	43	-0.7	4.9	1.9	2.7	22	-2.2	4.7	1.7	2.2	0.5	0.5	3.0	3.0
		SSA	105	-2.5	5.3	0.6	3.4	62	-2.1	5.0	0.8	3.4	-2.4	2.4	1.3	1.3
		Western Europe	40	3.9	5.5	4.6	5.1	28	4.3	5.4	5.1	5.6	2.5	2.5	3.5	3.5
Wheat	Irrigated	Asia	7	1.2	1.2	1.3	1.4	4	1.1	1.1	1.2	1.2	0.9	0.9	1.0	1.0
		MENA	41	-1.7	2.2	1.8	2.7	23	-1.6	2.1	1.7	2.5	-1.4	1.4	2.4	2.4
		USA and Mexico	11	2.6	2.9	2.8	3.0	8	2.5	2.7	2.4	2.6	2.3	2.3	3.2	3.2
	Rainfed	Australia	22	0.8	1.4	2.4	2.5	6	0.6	0.8	2.4	2.5	-0.1	0.1	2.0	2.0
		Eastern Europe	137	-2.3	2.7	2.9	3.3	101	-2.3	2.7	2.8	3.1	-2.0	2.0	3.2	3.2
		MENA	51	-2.4	3.3	0.2	1.6	29	-2.2	3.1	0.3	1.5	-3.3	3.3	-0.1	0.1
		South America	20	-1.6	2.0	1.5	1.8	11	-1.7	2.1	1.4	1.8	-1.0	1.0	1.8	1.8
		SSA	23	-0.6	1.9	0.6	1.5	18	-0.2	2.1	1.1	2.4	-0.7	0.7	0.8	0.8
		Western Europe	136	-0.8	2.4	2.9	3.3	92	-0.8	2.3	3.0	3.4	-0.8	0.8	3.0	3.0
Rice	Irrigated	Asia	88	-0.8	1.7	4.6	4.8	36	-0.4	1.7	4.7	5.0	-0.5	0.5	5.0	5.0
		MENA	21	-4.4	4.6	2.8	3.1	15	-4.1	4.2	3.1	3.3	-3.1	3.1	3.7	3.7
		USA	14	-0.7	1.0	6.3	6.4	9	-0.7	1.0	6.2	6.3	-0.7	0.7	6.4	6.4
		South America	20	2.7	2.9	8.7	8.7	10	2.6	2.8	8.6	8.6	3.0	3.0	9.0	9.0
		SSA	50	-0.2	2.9	3.7	4.0	32	-1.1	2.5	3.3	3.6	-1.2	1.2	2.8	2.8
	Rainfed	Asia	31	3.2	3.5	2.7	3.0	16	3.3	3.8	2.6	2.8	3.0	3.0	2.6	2.6
		South America	8	3.6	3.6	3.6	3.7	6	3.6	3.7	3.4	3.5	4.7	4.7	3.6	3.6
		SSA	40	1.7	2.9	1.0	2.9	32	2.2	3.0	1.6	2.9	1.8	1.8	1.5	1.5

† Total number of locations or climate zones for which yield potential is compared between bottom-up and top-down approaches.

ɣ Asia region excluding Middle East. ǂ Middle East and North Africa.

Supplementary Table S3. Actual yield and yield potential estimations. Actual yield and yield potential estimations derived from the Global Yield Gap Atlas (GYGA) and the Global Agro-Ecological Zones (GAEZ) or the Agricultural Model Intercomparison and Improvement Project (AgMIP) frameworks at three different spatial scale. Yield levels are expressed in t per harvested ha.

Crop	Water regime	Country or sub-continental region	Location					Climate zone					Country or sub-continental			
			n[†]	Actual yield	Yield potential			n	Actual yield	Yield potential			Actual yield	Yield potential		
					GYGA	GAEZ	AgMIP			GYGA	GAEZ	AgMIP		GYGA	GAEZ	AgMIP
Maize	Irrigated	Asia [ɣ]	47	7.3	13.6	12.9	7.6	32	7.1	13.4	12.2	7.8	6.0	12.5	15.1	10.0
		Eastern Europe	6	6.0	12.7	14.7	10.0	6	6.0	12.7	14.8	9.9	6.6	16.5	17.1	5.4
		MENA [ƚ]	22	6.7	17.5	17.4	5.3	13	6.9	17.5	17.4	6.3	11.8	14.0	15.9	10.1
		USA	21	11.5	13.6	15.5	10.1	13	11.5	13.6	15.6	10.1	8.1	13.9	14.3	7.9
		Western Europe	64	9.8	14.7	14.8	11.7	51	9.6	14.7	14.9	11.9	10.6	14.3	14.2	11.2
	Rainfed	Asia	69	5.9	10.8	9.6	5.4	31	6.1	10.9	10.0	5.2	4.9	8.8	9.5	5.7
		Eastern Europe	101	5.3	9.4	8.8	5.6	73	5.3	9.4	8.9	5.6	9.7	12.4	11.0	7.4
		USA	45	8.5	11.2	10.3	6.7	18	7.6	9.9	8.8	5.5	6.9	10.9	9.8	5.5
		South America	43	5.9	10.8	11.5	8.9	22	5.6	10.0	12.2	8.3	6.1	10.9	10.4	7.9
		SSA	105	1.8	9.1	11.6	8.5	62	1.8	9.2	11.3	8.4	1.7	9.1	11.5	7.8
		Western Europe	40	9.3	11.1	7.2	6.5	28	9.5	11.5	7.2	6.4	8.9	10.2	7.7	6.7
Wheat	Irrigated	Asia	7	2.1	4.9	3.8	3.6	4	2.1	5.0	3.9	3.8	3.3	8.6	10.0	6.2
		MENA	41	3.2	8.3	10.0	6.5	23	3.2	8.1	9.7	6.4	5.9	9.3	7.0	6.2
		USA and Mexico	11	5.7	9.1	6.5	6.3	8	5.6	9.2	6.7	6.8	2.2	4.9	4.0	4.0
	Rainfed	Australia	22	1.7	3.6	2.8	1.3	6	1.8	3.9	3.3	1.5	1.7	3.6	3.7	1.7
		Eastern Europe	137	3.8	8.6	11.0	5.7	101	3.8	8.6	10.9	5.8	3.6	8.5	10.4	5.2
		MENA	51	1.1	2.9	5.3	2.7	29	1.1	3.2	5.3	2.9	1.0	2.6	5.8	2.7
		South America	20	2.9	5.3	6.9	3.8	11	2.7	5.1	6.8	3.6	3.0	5.3	6.3	3.5
		SSA	23	1.9	6.7	7.3	6.1	18	2.1	6.8	7.1	5.7	2.2	7.9	8.6	7.1
		Western Europe	136	5.4	8.3	9.2	5.4	92	5.3	8.3	9.2	5.3	6.3	9.0	9.8	6.1
Rice	Irrigated	Asia	88	6.2	9.7	10.4	5.1	36	6.2	10.0	10.5	5.3	6.8	9.4	12.5	5.8
		MENA	21	4.6	7.7	12.1	4.8	15	4.7	7.9	12.0	4.8	8.1	12.4	13.1	6.0
		USA	14	8.3	12.5	13.2	6.2	9	8.3	12.3	13.0	6.1	6.3	9.8	10.3	4.8
		South America	20	7.9	14.5	11.8	5.9	10	7.9	14.5	11.9	5.9	7.6	14.7	11.7	5.8
		SSA	50	3.7	9.6	9.8	6.0	32	3.4	9.3	10.4	6.0	3.2	9.7	10.9	7.0
	Rainfed	Asia	31	4.4	8.5	5.4	5.8	16	4.3	8.3	5.0	5.7	4.0	8.1	5.0	5.4
		South America	8	2.5	8.9	5.4	5.3	6	2.4	9.0	5.4	5.6	2.6	9.0	4.3	5.4
		SSA	40	1.7	6.4	4.7	5.4	32	1.7	6.7	4.5	5.0	1.8	6.1	4.3	4.6

[†] Total number of locations or climate zones for which yield potential is compared between bottom-up and top-down approaches.
[ɣ] Asia region excluding Middle East. [ƚ] Middle East and North Africa.

Supplementary Table S4. Ensemble global gridded model. Models from the Global Gridded Crop Model Intercomparison (GGCMI) project of AgMIP that were combined to obtain ensemble maps for different combinations of water regime (irrigated and rainfed) and crops (maize, rice, and wheat).

Models	Maize	Rice	Wheat	Key reference(s)
WOFOST	●	●	●	Boogaard, et al. [37],van Diepen, et al. [38]
CLM	●	●	●	Drewniak, et al. [45]
EPIC-BOKU	●	●	●	Izaurralde, et al. [46],Kiniry, et al. [47],Williams, et al. [48]
EPIC-IIASA	●	●	●	Izaurralde, et al. [46],Kiniry, et al. [47],Williams, et al. [48]
EPIC-TAMU	●	x	●	Kiniry, et al. [47],Izaurralde, et al. [49]
GEPIC	●	●	x	Izaurralde, et al. [46],Williams, et al. [48],Liu, et al. [50]
LPJ-GUESS	●	●	●	Smith, et al. [51]
LPJmL	●	●	●	Bondeau, et al. [52],Schaphoff, et al. [53],von Bloh, et al. [54]
ORCHIDEE	●	●	●	Wu, et al. [55]
pAPSIM	●	x	x	Keating, et al. [42],McCown, et al. [56],Elliott, et al. [57]
pDSSAT	●	●	●	Ritchie and Otter [39],Elliott, et al. [57]
PEGASUS	●	x	x	Deryng, et al. [58],Deryng, et al. [59]
PEPIC	●	●	●	Liu, et al. [60]
PRYSBI2	xx	xx	xx	Sakurai, et al. [61],Okada, et al. [62]

●: Simulations combined to obtain ensemble maps. x: Simulations for AgMERRA not available; xx: Simulations based on a harmonized growing season and absence of nutrient limitation (so-called “harm-suffN” scenario) not available.

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