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Asymmetric responses of global grain production potential to future climate adaption

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Asymmetric responses of global grain production potential to future climate adaption

Abstract

Improving the future global grain production within existing cultivated land is a crucial issue to meet increasing food demand under future climate adaption. Yet, the potential may vary across different regions reflecting uncertainties about future climate changes. Here, we simulated the potential production and the yield gaps for rice, maize, wheat and soybean under SSP1-2.6, SSP3-7.0 and SSP5-8.5 in the near-term, mid-term and long-term future (2030s, 2050s and 2070s). We further decomposed future yield gaps into a historical gap, representing untapped potential from management optimization, and a future climate gap, isolating the net effect of climate change on production capacity. Our findings revealed moderate warming might provide a transient 'climate dividend' in 2030s, particularly in high-latitude regions, by narrowing both components of the yield gaps. However, exceedance of crop-specific thermal thresholds might constrains production and compress early climate gains under SSP5-8.5 in 2070s, especially in tropical and low-latitude zones. To ensure global food security, we advocated for a dual-track strategy: establishing resilient cross-border trade networks to buffer asymmetric production shocks, and implementing systemic local adaptations, such as shifting to heat-resilient alternative crops and upgrading climate-smart infrastructure, safeguarding the livelihoods of smallholder farmers to adapt future climate change.

Introduction

The global demand for food is continuing to increase as a result of population growth, greater diversification of consumer preferences, rapid urbanization and transformation of the agricultural industry. Achieving sustainable food production remains a longstanding and formidable challenge (Foley *et al.*, 2005; Steffen *et al.*, 2015; Webb *et al.*, 2020). In recent decades, the substantial expansion of cultivated land has been one of the primary pathways to achieve food security in the large-population countries, particularly in the Global South (Chaplin-Kramer *et al.*, 2015; Song *et al.*,

2018; Winkler *et al.*, 2021), but often at the expense of deforestation. For instance, the expansion of soybean planting areas has led to loss of tropical rainforest in the Brazilian Amazon (Barona *et al.*, 2010), and cultivated land expansion has contributed to nationwide forest loss in Indonesia (Austin *et al.*, 2019). Increasing the cultivated area is also unsustainable and places severe stress on global biodiversity (Rasmussen *et al.*, 2024; Zabel *et al.*, 2019). Therefore, increasing crop yield from existing cultivated land resources under the premise of adapting future climate change is a critical issue, especially for densely populated developing countries with limited agricultural resources (Mauser *et al.*, 2015; Yang *et al.*, 2024).

Food production systems, which are greatly dependent on the climatic regime, are at the forefront of climate change response and adaption (Liu *et al.*, 2021a; Piao *et al.*, 2010). Changes in climate resource elements drive the constant evolution of natural background conditions associated with crop growth. Various crops have disparate feedback to climate change in different regions and over varying time periods, contributing to the evolution of food production patterns (Liu *et al.*, 2022; Rezaei *et al.*, 2023; Sun *et al.*, 2024). Against the backdrop of significant climate warming and changing precipitation patterns, increasingly extreme weather events threaten crop yields and grain production in many breadbasket regions (Kornhuber *et al.*, 2023; Han *et al.*, 2024; Kim *et al.*, 2024). It is particularly important to adapt to future climate change, improving the utilization of future climate resources and increasing the grain production potential on the basis of existing cultivated land (Guo *et al.*, 2024; Liu *et al.*, 2023; Minoli *et al.*, 2022; Qiao *et al.*, 2023).

Closing yield gaps (i.e., the difference between the actual and potential attainable yields) under existing cultivated land resources is widely considered to be an effective way to increase grain potential production (Foley *et al.*, 2011; Hatfield and Beres, 2019; Suh *et al.*, 2020; Minoli *et al.*, 2022; Wang *et al.*, 2022). Previous studies have utilized various calculation methods to quantify regional and global yield gaps, i.e., to compare historical yields to a potential ceiling (Mueller *et al.*, 2012; Van Ittersum *et al.*, 2013; Grogan *et al.*, 2022). Based on historical statistics or survey data, previous studies generally concern the yield gaps covering multiple crops in different regions. Yet, these snapshot-in-time analyses seldom allow for the spatio-temporal uncertain impacts of climate change on agricultural production (Hatfield and Beres, 2019; Gerber *et al.*, 2024). Additionally, static yield gaps ignore yield gap trends over long periods and do not have consistent global coverage, resulting in limited policy implications (Fischer

and Connor, 2018; Gerber *et al.*, 2024; Grassini *et al.*, 2013). Furthermore, the bottom-up Global Yield Gap Atlas (GYGA) is a mainstream model to simulate yield gap. While GYGA offers high site-level precision, its heavy reliance on dense local datasets limits seamless global coverage and introduces upscaling uncertainties in data-poor regions (Chevuru *et al.*, 2023). Conversely, despite potential simplifications in local management, the GAEZ framework provides irreplaceable advantages in delivering globally consistent, spatially explicit data (Mao *et al.*, 2026).

Transfer learning models and semi-mechanistic models are newly emerging techniques to simulate crop yields and calculate yield gaps. The simulation process considers various climate factors and the simulation results show good performance (Dong *et al.*, 2020; Li *et al.*, 2020; Ji *et al.*, 2022; Zhao *et al.*, 2022). However, building these models over large regions is still challenging due to the need to prepare a reliable labeled dataset in advance (Zhang *et al.*, 2021; Zhao *et al.*, 2023). Furthermore, future climate models in combination with process-based crop models can be utilized to assess the impact of future climate change on grain production (Zhang *et al.*, 2019; Liu *et al.*, 2020), though the computation intensity of this approach is an issue that tends to be ignored when simulating large-area grain production (Zhao *et al.*, 2023). To bridge this knowledge gap, this study first validates crop yields as the primary factor driving the global production evolution of four staple crops in the historical period. It then quantifies the impact of future climate change on different crop yields and grain production potential within current cultivated areas under different future climate scenarios. Furthermore, we propose differentiated optimization strategies at the national scale based on future grain production potential.

Our work is mainly dedicated to addressing the following key questions: (1) Does unit yield dominate the change of rice, maize, wheat and soybean total production over recent decades? (2) How will future potential production and yield gaps of these four staple crops evolve under different climate scenarios and time periods? (3) How to fully release potential production of grain within the existing area of cultivated land under future climate change uncertainty to enhance global food security? To address these questions, we first delineated the global spatial production changes of rice, maize, wheat and soybean during 1980-2020. We quantified the contribution of yield and harvested area to the historical production increase for each crop, using the method of Logarithmic Mean Weight Division Index (LMDI). We then utilized the Global Agro-Ecological Zones (GAEZ) v5 model to simulate potential yield ceiling and future

potential production for these four staple crops within the current cropland area under three future climate scenarios (SSP1-2.6, SSP3-7.0 and SSP5-8.5) in the near-term, mid-term and long-term future (2030s, 2050s and 2070s), respectively. Furthermore, we calculated the future production gaps of different crops and classified them into three types, i.e., climate benefit type, climate fluctuation type and climate stress type. In this study, the future potential yield ceiling is defined as the agro-climatic potential attainable yield, and is the same as the definition in the GAEZ model (Fischer *et al.*, 2021). In addition, specific optimization strategies were provided for countries of different types.

Results

Dynamics of global grain production pattern

The overall global production of the four staple crops showed a consistent increase from 1980 to 2020, with varying rates of increase for each of them. In 2020, the production of rice, maize, wheat and soybean were 767.66 Mt, 1152.57 Mt, 774.98 Mt and 357.10 Mt, respectively. This reflected individual increases of 374.91 Mt, 751.35 Mt, 317.71 Mt and 270.35 Mt (Tab.1) than that in 1980. From the perspective of continental scale (Tab.1), the increased production of rice (88.22%), maize (35.93%) and wheat (62.77%) was mainly concentrated in Asia over the past 40 years, while the increased production of soybean (61.82%) was mainly distributed in South America. Considering the top 10 countries with the fastest production growth of rice, maize, wheat and soybean, India (2.56 Mt/yr) and China (1.77 Mt/yr) stood out for their contributions in rice production growth, accounting for 27.31% and 18.87% of the global rice increased production respectively (Fig.1a and Supplementary Tab.1). In terms of maize, the United States (4.75 Mt/yr) and China (4.95 Mt/yr), with the largest production growth, accounted for 25.26% and 26.37% of the global maize production increase, respectively (Fig.1b and Supplementary Tab.2). For wheat, China (1.98 Mt/yr) and India (1.90 Mt/yr) contributed 24.88% and 23.93% respectively to the global wheat production increase (Fig.1c and Supplementary Tab.3), while Brazil (2.67 Mt/yr) and the United States (1.65 Mt/yr) accounted for 39.45% and 24.35% of the global soybean production increase (Fig.1d and Supplementary Tab.4). Overall, China and India showed significant contributions to the increased production of the four staple crops (20.97% and 12.51%, respectively) during 1980-2020.

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136 **Tab. 1 |** The production for rice, maize, wheat and soybean in different continents from 1980 to 2020.

Continent	Rice			Maize			Wheat			Soybean		
	1980 production (Mt)	2020 production (Mt)	Production change* (Mt)	1980 production (Mt)	2020 production (Mt)	Production change* (Mt)	1980 production (Mt)	2020 production (Mt)	Production change* (Mt)	1980 production (Mt)	2020 production(Mt)	Production change* (Mt)
Global	392.75	767.66	374.91	401.22	1152.57	751.35	406.89	774.98	368.08	86.74	357.10	270.35
Asia	357.87	688.63	330.77	85.71	355.68	269.97	139.84	346.80	206.97	10.06	33.73	23.67
Africa	7.92	35.89	27.97	27.57	92.80	65.23	13.04	24.97	11.93	0.35	4.59	4.24
Europe	3.28	5.05	1.76	68.18	123.40	55.22	143.73	254.83	111.10	6.84	10.74	3.90
Oceania	0.61	0.05	-0.56	0.31	0.47	0.16	11.16	32.38	21.21	0.08	0.02	-0.06
North America	8.74	13.11	4.37	189.25	403.90	214.65	86.88	88.18	1.30	49.94	121.42	71.49
South America	14.33	24.92	10.60	30.20	176.32	146.12	12.25	27.82	15.57	19.48	186.60	167.12

137 *The value of production change= The grain production in 2020 - The grain production in 1980.

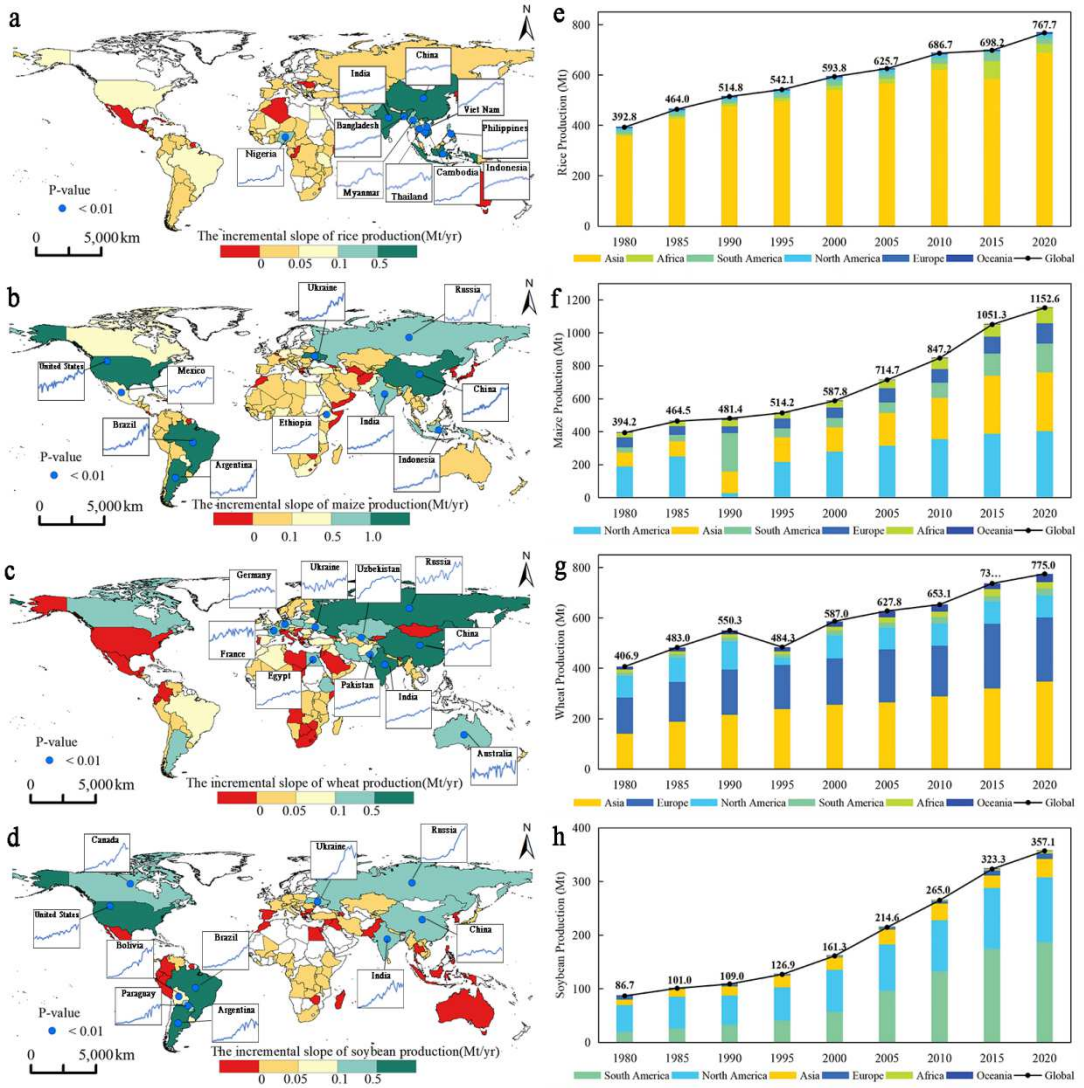


Fig. 1 | Global distribution of production growth rates and long-term trends for four staple crops (1980-2020). Panels (a)-(d) display the spatial patterns of production increment slopes for rice, maize, wheat and soybean, respectively. The inset line graphs in each panel highlight the top 10 countries with the fastest production growth for the corresponding crop. Panel (e)-(h) present the global production trends over the 40-year period for rice, maize, wheat and soybean, respectively.

The results of the Logarithmic Mean Weigh Division Index (LMDI) (details see the Methods) illustrate that the increase in global wheat and maize production was mainly attributable to the improvement of yield, while the increase in soybean production was mainly due to the increase in harvested area (Fig. 2). The increase in rice production was influenced by both yield improvement and expansion of the area harvested. Yield improvements were the major contributor to nearly two-thirds (65.91%) of the countries experiencing an increase in wheat production, 57.81% of the countries

experiencing an increase in maize production and 45.68% of the countries experiencing an increase in rice production. More than four-fifths (83.61%) of countries with increases in soybean production mainly attributed this to the expansion of harvested area. From a continental perspective, the increase of rice, wheat and maize production in Asia and North America was largely due to the improvement of yield, while the increase of soybean production was mainly driven primarily by increased harvested area. In Europe and South America, the increases in wheat and maize production were primarily attributed to the improvement of yield, while the increases in rice and soybean production were mainly due to the expansion of harvested area. Moreover, the increases in the production of the four staple crops in Africa were all attributed to the expansion of harvested area. When considering the national scale, major rice production-increasing countries such as India, China, Bangladesh, Vietnam, and Indonesia showed higher yield contribution rates of 86.29%, 128.42%, 89.46%, 80.44%, and 72.45%, respectively, compared with their harvested area contribution rates (Fig. 2a). Similarly, major maize production-increasing countries such as China, the United States, Brazil, Argentina, and Ukraine exhibited yield contribution rates of 84.00%, 60.77%, 50.39%, 71.39%, and 93.15%, respectively, all of which were higher than their contribution rates from the harvested area (Fig. 2b). In the case of the major wheat production-increasing countries, China, India, Russia, Canada, and Pakistan had higher yield contribution rates compared with their harvested area contribution rates (Fig. 2c). For the major soybean production-increasing countries, except for the United States and China, where the yield contribution rate surpassed the harvested area contribution rate, countries like Brazil, Argentina, and India had higher contribution rates from the harvested area than yield (Fig. 2d).

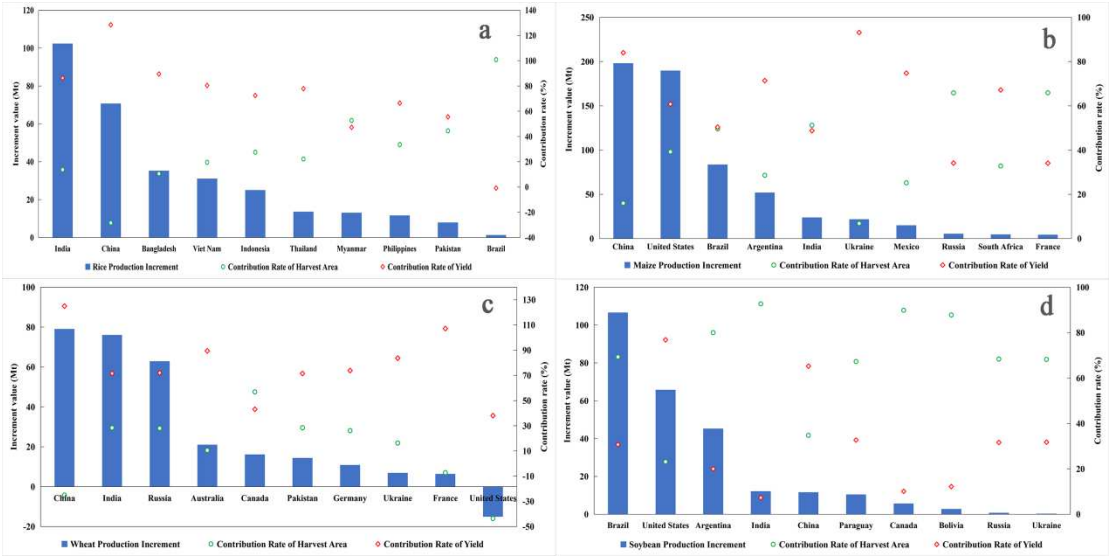


Fig. 2 | The contribution rate of harvested area and yield to the production increment. The contribution rate to historical production increment of rice **(a)**, maize **(b)**, wheat **(c)** and soybean **(d)** in the top 10 countries with the fastest production growth during 1980-2020.

Climate change and future crop production

Global crop potential production generally increases under future climate scenarios, although prolonged warming under SSP5-8.5 diminishes early climate dividends, most major food-producing countries retain a positive climate gap. Specifically, maize and rice exhibit early potential gains across scenarios, while 2070s potential production under SSP5-8.5 constrained to approximately 1,508 Mt and 819.47 Mt, respectively, indicating a diminished yet positive climate-induced gain (Fig. 3 and Supplementary Tab.5-6). Soybean potential follows a similar trajectory, expanding initially to ~370 Mt before prolonged warming compresses totals to ~352 Mt (Fig. 3a and Supplementary Tab.8). Wheat experiences an initial surge exceeding 1,060 Mt, though high emissions potential drops to roughly 931 Mt under SSP5-8.5 in 2070s (Fig. 3b and Supplementary Tab.7).

Global crop potential production presents a distinct spatial divergence, with temperate zones driving capacity growth while tropical regions experience more constrained physical boundaries. Maize potential production in temperate zones expands substantially, ranging from ~1117.69 Mt to 1133.93 Mt in 2030s, and capacity is sustains at approximately 1,113 Mt under SSP5-8.5 in 2070s; nearly triple the stagnant tropical potential, which plateaus at roughly 400 Mt across all scenarios. The

regional polarization is even more pronounced in wheat production. In the temperate zone, wheat capacity in 2030s experiences a massive expansion to between ~1041.77 Mt and 1057.47 Mt, and maintains a robust production of ~917.86 Mt under SSP5-8.5 in 2070s. Conversely, tropical wheat potential remains critically marginalized, plateauing between ~13.09 Mt and 18.76 Mt across all future scenarios.

This comparison indicates temperate zones sustain their early climate gains, but tropical zones approach environmental thresholds that limit further production improvements.

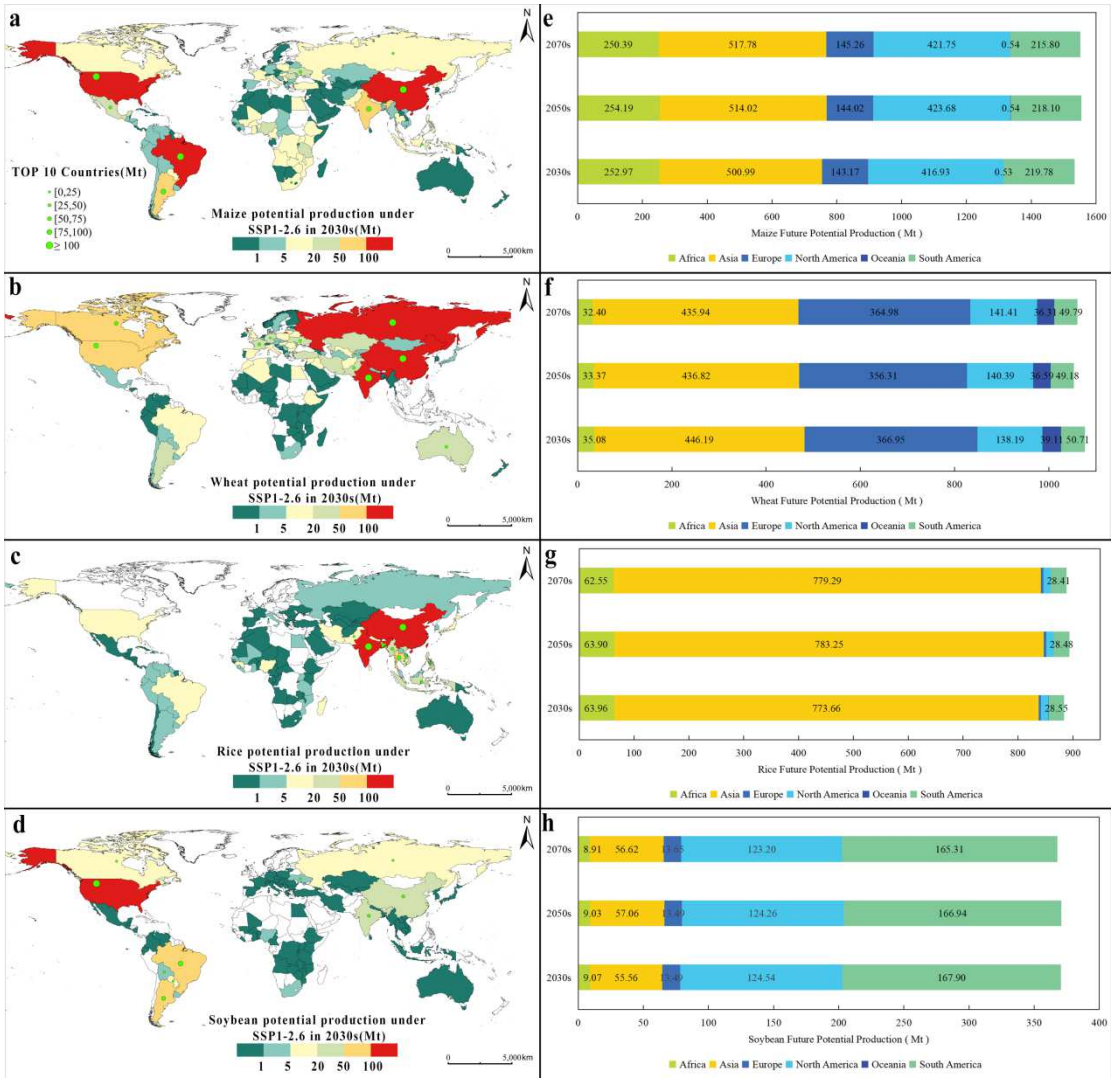


Fig. 3 | Global distribution of future potential production for four staple crops under SSP1-2.6 in 2030s. Panels (a)-(d) display the spatial patterns of future potential production for maize, wheat, rice and soybean under SSP1-2.6. The green points in each panel highlight the top 10 countries with the highest potential production for the corresponding crop. Panels (e)-(h) present the future potential production of each continent for each crop under SSP1-2.6 in 2030s, 2050s and 2070s, respectively.

Future warming drives a geographical redistribution of agricultural capacity, increasing potential in high latitudes while attenuating climate dividends in historical production centers. Wheat possesses strict thermal physiological thresholds, its extensive cultivation spans high latitudes and traditional agricultural zones. In Europe, future potential production increases significantly. Near term (2030s) European wheat potential ranges from 364.46 Mt to 366.95 Mt across all scenarios (Fig. 3f). The long term (2070s) low emissions (SSP1-2.6) pathway maintains this regional potential near 364.98 Mt (Supplementary Tab.7). Although moderate (SSP3-7.0) and high-emission (SSP5-8.5) scenarios constrain the long-term capacity to 341.79 Mt and 320.10 Mt, respectively, these pathways still reflect a narrowed but positive climate-induced gain. In contrast, historical production centers experience a future capacities compression. Asia potential reaches over 437.54 Mt in 2030s. However, prolonged warming in long term (2070s) under SSP3-7.0 and SSP5-8.5 limits the Asia potential to 395.79 Mt and 377.48 Mt, respectively, demonstrating a squeezed but existent positive margin. Africa shows a persistent downward trajectory. Its long term (2070s) potential drops below 14.89 Mt under high emissions (SSP5-8.5) (Supplementary Tab.7). Furthermore, regions like Africa might face more frequent climate disasters, their inadequate infrastructure results in insufficient capacity against climate risks.

The gains observed at the continental level contrast with internal disparities among major food-producing nations. China and India consistently rank in the top tier across the four major crops, emerging as crucial global producers whose trajectories heavily influence global food security. In China, maize potential demonstrates consistent expansion. Its near term (2030s) capacity ranges from ~342.74 Mt to 353.08 Mt. Interestingly, this capacity further increases to roughly 369.21 Mt under long-term (2070s) high-emission (SSP5-8.5) scenarios, indicating a robust resilience to prolonged warming. Conversely, the climate dividend for Chinese wheat capacity declines continuously under high emissions (SSP5-8.5). Although near-term potential remains robust at over 141.34 Mt, this capacity is compressed to under 129.34 Mt at SSP5-8.5 in 2070s. This trend reflects an attenuation of the positive climate gap rather than an absolute production loss. India experiences a more pronounced squeeze on its future climate dividends. Its near term (2030s) rice potential exceeds 254.71 Mt. However, prolonged warming under high emissions (SSP5-8.5) suppresses this capacity to under 235.79 Mt. Indian wheat potential similarly undergoes a notable compression, shifting from over 121.46 Mt in 2030s to roughly 88.65 Mt under high emissions (SSP5-8.5) in

2070s, whereas moderate emissions (SSP3-7.0) project 97.00 Mt. The United States exhibits a similar moderation of climate benefits in response to long term (2070s) warming. Its future maize potential initially expands to over 350.55 Mt. It later falls to 343.35 Mt under high emissions (SSP5-8.5). Other dominant producers show heterogeneous trends. Russia benefits from early warming. Its near term (2030s) wheat potential approaches 158.88 Mt. Yet, long term (2070s) high emissions (SSP5-8.5) compress this capacity to under 136.64 Mt. Argentina maintains a near term (2030s) soybean potential of approximately 60.56 Mt to 61.23 Mt. This capacity is eventually constrained to roughly 56.15 Mt under moderate emissions (SSP3-7.0) and 56.04 Mt under high emissions (SSP5-8.5).

Spatiotemporal divergence of future crop yield gaps

Since our experimental hypothesis assumes that the cultivated land area remains constant, all variations in future production potential are fundamentally driven by changes in future potential attainable yields. Future crop yield gaps is shaped by two parts: the historical gap represents potential gains from management optimization, and the future climate gap isolates the net impact of future climate change. Maize and wheat exhibit substantial near-term (2030s) potential expansion, driven by positive future climate gaps of approximately 202.73~222.68 Mt and 264.23~280.39 Mt, respectively, compared to historical gaps of 318.84 Mt and 172.75 Mt (Fig. 4). Under long-term moderate emissions (SSP3-7.0), these gaps narrow to roughly 193.66 Mt for maize and 181.06 Mt for wheat, confirming that climate dividends persist despite attenuation (Supplementary Fig. 2b and Supplementary Tab.7). Rice and soybean display greater sensitivity to prolonged warming. Near-term climate gains for rice add future climate gaps approximately 71.97~81.08 Mt (Fig. 4), yet under SSP5-8.5 this increment compresses sharply to roughly 25.67 Mt by the 2070s. Similarly, the soybean future climate gap provides a near-term boost of 24.73~30.08 Mt contracting to approximately 11 Mt under SSP5-8.5 in 2070s, limiting total soybean potential to roughly 352.25 Mt.

Agro-ecological temperature zones determine the asymmetric impact of climate change on global crop production, with temperate regions experiencing robust climate-driven potential attainable yield increases while tropical zones face more constrained physical limitations. In the temperate zone, wheat potential production receives a dual contribution, as favorable climate shifts supplement agricultural management improvements. The historical gap for temperate wheat is ~171.80 Mt. The wheat future climate gap provides a substantial boost in 2030s, which adds over 253.03 Mt across

all scenarios (Fig. 4b). However, this climate-induced contribution attenuates under long term (2070s) warming pathways. By the long term (2070s), the future climate gap remains robust at 254.81 Mt under SSP1-2.6 , while this positive gap is narrowed to 173.55 Mt and 129.12 Mt under SSP3-7.0 and SSP5-8.5, respectively. In contrast, the tropical zone shows a more restricted capacity for expansion. The tropical wheat sector shows a minimal historical gap. It also faces a constrained future climate gap. Climate shifts contribute from ~11.20 Mt to 11.66 Mt in the near term (2030s). By the long term (2070s), this gap is compressed to ~5.99 Mt under SSP5-8.5. This diminished climate margin limits realizable production increases through environmental shiftsin low-latitude regions.

At the continental level, the future climate gap drives an asymmetric redistribution of agricultural potential, supplementing management gains in high-latitude regions with robust production bonuse, while providing a constrained climate dividend in historically vulnerable areas. In North America and Europe, the maize potential production increment is driven by a synergistic effect, where favorable climate shifts compound ongoing improvements in agricultural management. The historical gap for North American maize is ~14.62 Mt. The future climate gap provides a substantial boost in 2030s, adding above 53 Mt across different scenarios. Even under long term (2070s), this gap remains highly positive, reaching 42.92 Mt under SSP3-7.0 and 50.70 Mt under SSP5-8.5. This sustained gap provides continuous support to technological gains rather than a reversal of benefits. In contrast, Africa experiences a more compressed climate dividend. The African maize production holds a historical gap of ~133.13 Mt. Near term (2030s) climate shifts contribute over 39.67 Mt to potential production increment (Supplementary Tab.6). However, this climate-driven effect is gradually attenuated over time. Under long-term (2070s) scenarios, Africa's future climate gap is narrowed to roughly 36.09 Mt under SSP3-7.0 and 35.24 Mt under SSP5-8.5. This provides limited support to existing management requirements. Similarly, the near-term (2030s) future climate gap for Asian maize expands significantly, ranging from 70.56 Mt to 81.99 Mt. Yet, prolonged warming under long term (2070s) pathways maintains this robust gain at 82.81 Mt under SSP3-7.0 and 95.15 Mt under SSP5-8.5. Future climate change shifts eventually constrain agricultural potential in historical production centers.

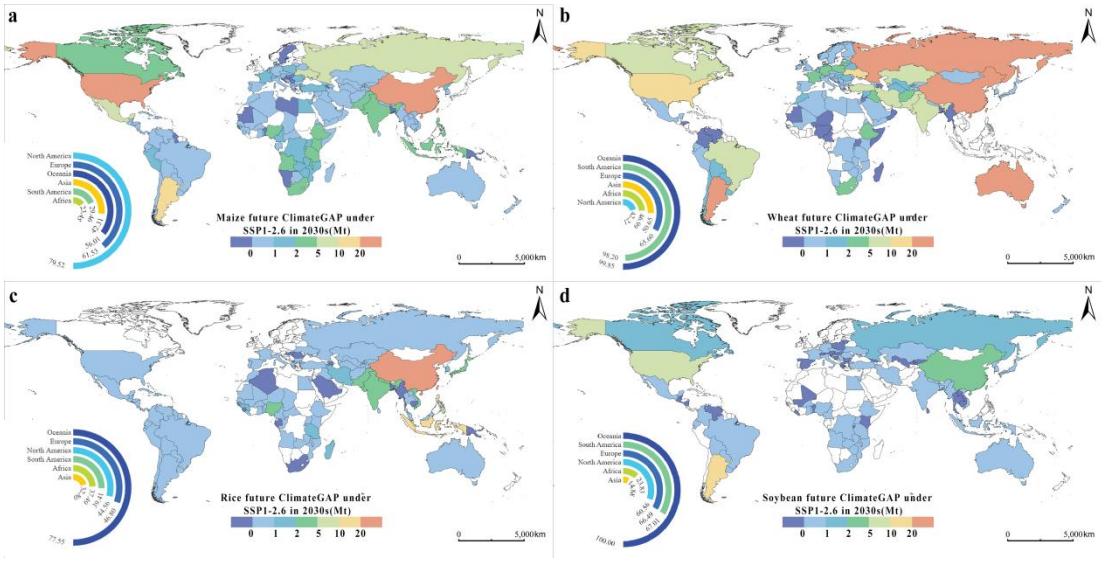


Fig. 4 | Global distribution of future climate gap for four staple crops under SSP1-2.6 in 2030s. Panels (a)-(d) display the spatial patterns of future climate gap for maize, wheat, rice and soybean under SSP1-2.6. The green points in each panel highlight the top 10 countries with the highest potential production for the corresponding crop. The ring graphs in each panel represent the contributions of the future climate gap on future crop yield gap in each continent.

The global redistribution of future climate gaps drives a distinct polarization among major food-producing nations, separating long-term beneficiaries from those facing severely constrained capacities. China represents a primary beneficiary group in the maize production. The historical gap for Chinese maize is ~51.70 Mt. The future climate gap adds 54.46~64.80 Mt in 2030s, and expands to 71.36 Mt under moderate emissions (SSP3-7.0) and 80.93 Mt under high-emission (SSP5-8.5) scenarios in 2070s. The continuous climate advantage significantly reinforces localized agronomic interventions. Russia exhibits a similar early-stage benefit for wheat. Its wheat future climate gap provides a boost of 41.69~ 46.66 Mt in 2030s. Although the climate dividend remains positive in 2070s, this benefit is compressed to 24.42 Mt under SSP5-8.5, and it is narrowed to 35.71 Mt under SSP3-7.0. In contrast, certain traditional agricultural powerhouses face severe compression or even net capacity losses. India exemplifies this vulnerability in wheat production. Its historical gap stands at approximately 13.82 Mt. Prolonged warming under high emissions (SSP5-8.5) imposes a climate penalty of roughly 25.40 Mt. This absolute reduction completely offsets potential management gains, representing a rare instance of a net negative climate

impact. The United States shows a transition from positive to constrained impacts for maize.The near-term (2030s) maize future climate gap in the U.S. adds roughly 38.66~39.02 Mt. Long-term (2070s) warming pathways compress this bonus to 25.27 Mt under moderate emissions (SSP3-7.0) and 31.81 Mt under high emissions (SSP5-8.5). Nevertheless, this constrained gap continues to provide a positive yield bonus, climate-driven capacity is squeezed rather than entirely lost in these key regions.

Potential grain productivity types relevant to food security

The potential grain productivity of maize, rice, wheat and soybean can be divided into three types by calculating the future climate gap under each scenario in different future periods (see Methods). This gap is defined as the difference between the future potential production and historical potential production. Based on the calculation, producing nations are classified into the climate benefit type (consistently positive gaps), the climate fluctuation type (both positive and negative gaps), and the climate stress type (strictly negative gaps).

Global crop production are overwhelmingly skewed toward a climate benefit type, with an astonishingly small fraction of nations (under 5% across four staples) facing absolute 'climate stress' (Fig. 5). This steady increase in capacity reveals distinct geographical clustering. Maize and rice lead the climate benefit type, encompassing 83.45% and 81.31% of their respective producing nations, largely driven by Africa and Asia. Specifically, maize benefits are concentrated in Africa (31.03%), Asia (28.45%), and Europe (18.10%), generating a massive potential increase of 199.13 ~237.31 Mt. Rice benefits are distributed across Africa (34.48%), Asia (22.99%), and North America (14.94%), adding 62.46~84.18 Mt. Conversely, wheat and soybean demonstrate slightly lower benefit proportions but strong Eurasian concentrations. For wheat, 73.87% of growing countries — primarily in Europe (37.80%), Asia (23.17%), and Africa (18.29%)—drive an expected surge of 168.42~256.98 Mt. Soybean sees 69.66% of its producing nations benefiting (scattered across Asia at 29.03%, Africa at 25.81% and Europe at 19.35%), projecting a 17.02~28.26 Mt increase. Furthermore, the remaining countries largely fall into the uncertain climate fluctuation type (ranging from 12.95% for maize to 25.84% for soybean), while the climate stress type is statistically marginal, peaking at merely 4.49% for soybean and dropping as low as 0.93% for rice.

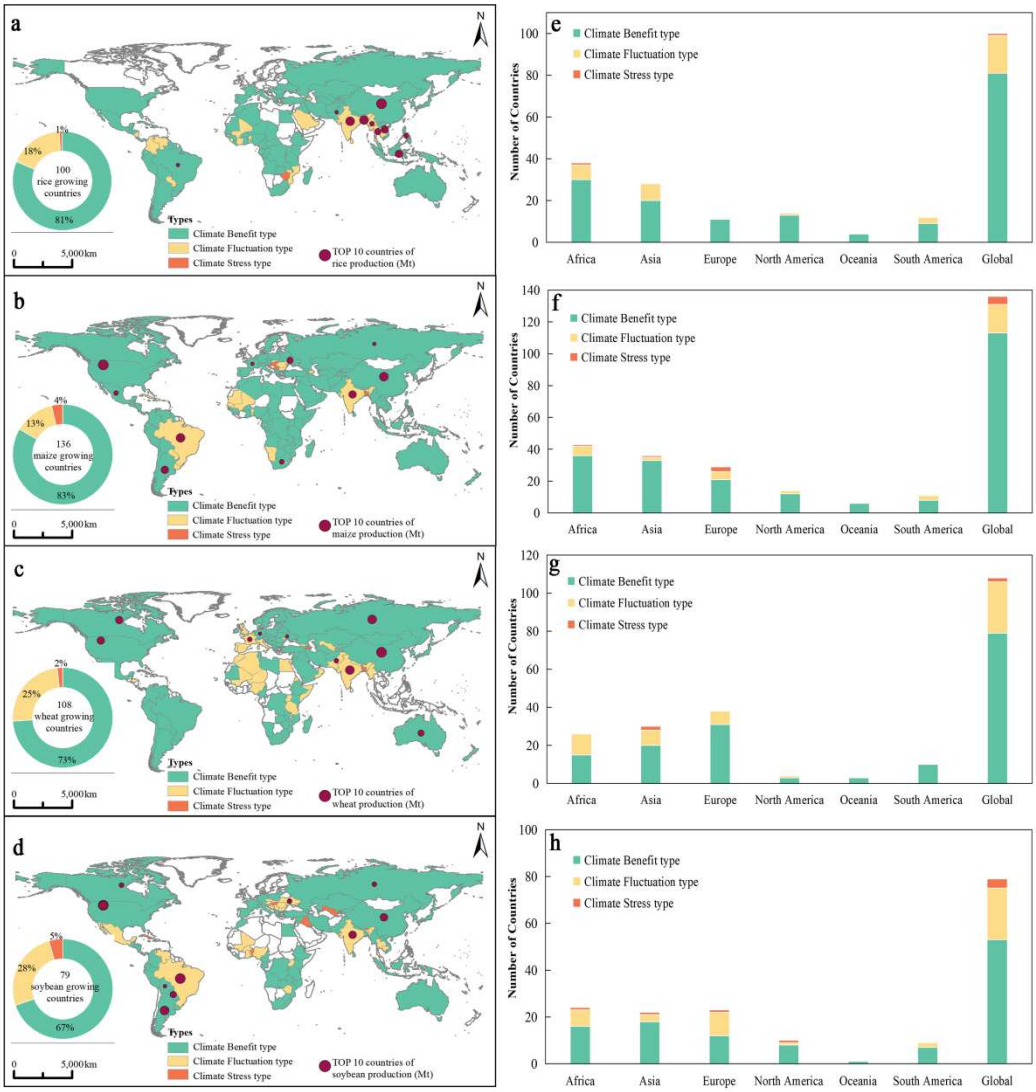


Fig. 5 | The future spatial distribution of potential grain productivity types for four staple crops. The spatial distribution of potential grain productivity types for rice (a), maize (b), wheat (c) and soybean (d) in the future. The inset pies in (a)-(d) represent the proportion of different types for corresponding crops.The inset dots in (a)-(d) represent the production of the top 10 countries in historical production for corresponding crops. Countries of different continents belong to different potential grain productivity types for rice (e), maize (f), wheat (g) and soybean (h).

From the perspective of the top twenty grain-production countries, the major producers of rice, wheat, and soybeans would mainly be the climate benefit type in the future. Specifically, fourteen major producers among the top twenty rice-producing countries, including China, Indonesia and Vietnam, are expected to be the climate benefit type. Meanwhile, nations like India and Bangladesh face greater climatic

uncertainties, falling into the climate fluctuation type. For wheat, thirteen major producers, including China, Russia, and the United States, are likely to be the climate benefit type. Moreover, thirteen major soybean producers, such as the United States, Argentina and China, are all expected to be the climate benefit type. Furthermore, fifteen major maize producers are anticipated to be the climate benefit type. These countries include the United States, China and Argentina. However, this positive global trend involves distinct regional vulnerabilities. Traditional agricultural powerhouses like Brazil and India frequently exhibit the climate fluctuation type across multiple crops. Some European nations like Hungary and Serbia face the climate stress type in maize production. Global crop capacity largely benefits from future climate shifts. Therefore, localized environmental variations will still impose significant constraints on specific key producers.

Discussion

A fundamental insight from our simulation is the highly non-linear, time-dependent nature of climate-driven agricultural gains. Our results reveal that near-term (2030s) potential attainable yield expansions act as a transient climate dividend rather than a permanent shift. This early-century surge, driven by moderate warming and extended growing seasons in high latitudes (Rashid *et al.*, 2019; Liu *et al.*, 2022), brings global wheat capacity above 1,060 Mt. However, it creates a 'climate illusion' that temporarily masks severe future physiological limitations. Mechanistically, the long-term (2070s) potential attainable yield reversal under extreme emissions (SSP5-8.5) is driven by the breaching of crop-specific thermal thresholds. As warming intensifies, initial agro-ecological benefits are overwhelmed by severe heat stress, which inherently inhibits photosynthesis, accelerates maintenance respiration, and shortens the grain-filling period (Feng *et al.*, 2021; Kang *et al*., 2022). Consequently, late-century global wheat potential plummets to 930.95 Mt under SSP5-8.5, whereas strict mitigation (SSP1-2.6) sustains production. By explicitly decoupling the future climate gap from historical management potentials, our findings demonstrate that relying on severe warming for agricultural expansion is physiologically untenable (Gerten *et al.*, 2020; Melesse, 2025; Xu et al., 2025). Without stringent emission controls (SSP1-2.6), early-century dividends will be entirely neutralized, driving an irreversible long-term contraction in global yield potential.

Beyond temporal variations, our findings reveal a significant spatial asymmetry driven by agro-ecological boundaries. High-latitude and temperate regions benefit from

418 a ‘dual contribution’ of agricultural management improvements (the historical gap) and
419 favorable environmental shifts(the future climate gap) (Hassan *et al.*, 2022; Liu *et al.*,
420 2021b). For instance, the temperate wheat, which possesses a 171.80 Mt historical gap,
421 receives a above 250 Mt in near-term (2030s) climate boost that remains substantial at
422 ~130 Mt even under long-term (2070s) high emissions (SSP5-8.5). Similarly, North
423 American maize maintains a positive future climate gap that continuously supplements
424 its 2.32 Mt Historical Gap, creating a buffered environment where technological gains
425 are fully realized. Previous studies reported China’s Loess Plateau had large potential
426 for supporting a double cropping system to increase regional grain production against
427 the background of climate warming (Liu *et al.*, 2019; Liu *et al.*, 2021a). Conversely,
428 tropical and historically vulnerable zones face an absolute environmental ceiling that
429 management interventions cannot independently overcome (Choi & Eltahir, 2023;
430 Zhao et al., 2017). The tropical wheat exhibits a constrained future climate gap that
431 collapses to a negligible 5.99 Mt under long-term SSP5-8.5 conditions. This physical
432 limitation is starkly evident in African wheat: despite a massive historical gap
433 exceeding 9 Mt, representing substantial theoretical room for management-driven
434 growth, its long-term future climate gap shrinks to -1.60 Mt under SSP5-8.5. As severe
435 warming imposes hard physical deficits in low-latitude regions, the fundamental
436 environmental capacity to support crop physiology deteriorates. Consequently,
437 conventional strategies focused purely on closing the historical gap, such as optimizing
438 fertilizer or irrigation, will eventually hit a rigid physical boundary in the tropics (Xu
439 *et al.*, 2024; Sun *et al.*, 2024). This drastic reduction in the realizable future climate gap
440 neutralizes potential technological dividends, signaling that vulnerable low-latitude
441 regions are rapidly approaching the absolute limits of *in situ* agricultural adaptation
442 (Schaeffer *et al.*, 2025; Taiwo *et al.*, 2025) .

443 The Future Climate Gap redistribution precipitates a distinct geopolitical
444 polarization among major food-producing nations, driving a structural shift in global
445 production dominance and trade dynamics. China emerges as a primary beneficiary in
446 maize; its near-term (2030s) climate gap expands potential production by 54.46~64.80
447 Mt, escalating to 71.36~79.45 Mt under long-term (2070s) scenarios. This continuous
448 climatic bonus partly alleviates pressure on agricultural management improvements
449 (which face a ~51 Mt historical Gap). Conversely, traditional agricultural powerhouses
450 in lower latitudes face starkly different structural constraints. Brazil, a cornerstone of
451 global agricultural exports, exemplifies this dynamic. Unlike high-latitude beneficiaries,

Brazil's maize future climate gap (-4.04~6.86 Mt) is significantly dwarfed by its massive historical gap (17.02 Mt). This stark contrast dictates that future production improvement in Brazil might rely almost entirely on capital-intensive management improvements to close existing yield gap, rather than benefiting from a natural "climate dividend." As long-term SSP1-2.6 further compresses its already limited climate capacity, Brazil's ability to expand exports and buffer global food shocks might become strained. Furthermore, even nations with advanced infrastructure are not immune. The United States (maize) and Russia (wheat) transition from early-stage beneficiaries (securing near-term boosts of 38.66~41.93 Mt and 41.69~46.66 Mt future climate gap, respectively) to long-term plateauing, as intense SSP5-8.5 warming compresses these bonuses below 26 Mt and 24 Mt. The policy implications are unequivocal: relying on a few traditional 'breadbasket' nations to stabilize the global food market is precarious (Mäkinen *et al.*, 2018; Xie *et al.*, 2023).The international community must urgently pivot away from localized self-sufficiency toward highly resilient, adaptive cross-border agricultural trade networks capable of offsetting asymmetric climate gap redistribution (Arneth *et al.*, 2020; Hu *et al.*, 2020; Qu *et al.*, 2026).

The empirical evidence presented in this study underscores the critical need to broaden international food security policies, complementing traditional frameworks that primarily focus on closing the 'Historical Gap' through incremental technological interventions like fertilizers and irrigation (Villamayor-Tomas *et al*., 2024; Liu *et al.*, 2026). While these strategies remain vital in the near term, our projections decisively demonstrate that under unmitigated warming (SSP5-8.5), severe environmental degradation will ultimately dictate the physical boundaries of global crop production, rendering management-based adaptations insufficient in vulnerable, low-latitude regions (Jat *et al.*, 2020; Qiao *et al.*, 2023; Xiao *et al.*, 2024). For climate-benefited zones, such as high-latitude regions, strategic priorities should focus on upgrading agricultural infrastructure, expanding storage and optimizing logistics to absorb surplus production for global export markets (Galli *et al.*, 2023; Liu *et al.*, 2020). Conversely, for climate-threaten regions, such as the African maize and Indian wheat sectors, must recognize that progressive technological improvements might bring limited potential improvement (Sloat *et al.*, 2020; Kraklow *et al.*, 2026).These vulnerable zones urgently require systemic climate adaptations, including large-scale crop substitution toward heat-resilient alternatives like sorghum or millet, and the strategic relocation of agricultural hubs (Minoli *et al.*, 2022; Springmann *et al.*, 2018). Moreover, farmers in

these regions generally lack strong risk awareness, and are relatively deficient in disaster resistance and sustainable production management technologies, posing a risk of future grain production reduction (Cui *et al.*, 2018; Adolph *et al.*, 2021; Keshavarz and Moqadas, 2021). For instance, densely populated low-latitude developing countries such as Benin, Mali, Senegal and Kenya, are at risk of production reduction from extreme weather events, which may pose a challenge for most countries of Africa to achieve SDG2 (zero hunger) in the future (Sun *et al.*, 2024).

Our study illustrates that improvement of future crop yields will be the major contributor to global production increments for rice (45.68%), maize (57.81%) and wheat (65.91%) against the background of global climate warming. This finding demonstrates closing future yield gaps by adapting to climate change based on existing cultivated land is an effective way to increase future grain production potential. In the near term (2030s), moderate warming provides a transient 'climate illusion', boosting potential production particularly in temperate and high-latitude regions through a synergistic effect of the future climate gap and the historical gap. However, under long-term (2070s) unmitigated warming (SSP5-8.5), the breaching of crop-specific thermal thresholds will impose rigid physical boundaries, compressing early future climate gains, especially in tropical and low-latitude zones. This spatial redistribution of agricultural capacity will trigger geopolitical polarization, rendering the global food market's reliance on a few traditional 'breadbaskets' precarious. Furthermore, we divide three potential grain productivity types (i.e., climate benefit type, climate fluctuation type and the climate stress type) based on future climate gaps, and propose differentiated strategies to release grain production potential within current cultivated areas while adapting to the uncertainty of future climate change. Climate-benefited high-latitude regions should prioritize infrastructure upgrades to absorb export surpluses, climate-threatened developing nations urgently require systemic adaptations, including the strategic relocation of agricultural hubs and large-scale substitution toward heat-resilient crops.

Despite the comprehensive assessment of global grain potential production and crop yield gaps, several limitations must be acknowledged. First, while we utilized multi-model ensembles under diverse future climate scenarios, the inherent structural uncertainties of Global Climate Models (GCMs) and crop models, particularly regarding the magnitudes of the CO_2 fertilization effect and extreme weather frequency, may influence the precision of long-term yield simulation. Second, our analysis

primarily focused on thermal and radiative drivers, potentially underestimating the localized impacts of water scarcity and soil degradation pressures under shifting climatic zones. Third, the grain harvested area served as the control variables in our study; however, future land-use changes driven by urbanization or deforestation could significantly alter the actual realized production. Furthermore, while we categorized countries into three productivity types, the socio-economic barriers to adopting advanced technologies, such as high capital costs for smallholder farmers or geopolitical instability, were not fully parameterized in our biophysical modeling framework. Future research should integrate high-resolution multi-source data and agent-based models to better simulate the dynamic feedback between human adaptation behaviors and environmental constraints.

Methods

Contributions of grain production change factors

The direct factors contributing to grain production change included the increase of harvested area and the rise in yields per unit (Guilpart *et al.*, 2022). The Logarithmic Mean Weight Division Index (LMDI) is employed to calculate the contribution rate of these two factors (Harold et al., 2021). For a specific region, the total grain production increase can be divided into the production increase caused by harvested area expansion and the production increase caused by the yields per unit rising, expressed as:

$$\Delta P_i = \Delta \mathrm{P}_{\mathrm{HA_i}} + \Delta \mathrm{P}_{\mathrm{YpU_i}} \tag{1}$$

where ΔP_i represents the increased production of a crop in country i. $\Delta \mathrm{P}_{\mathrm{HA_i}}$ represents the increased production of a crop in country i resulting from the harvested area expansion. $\Delta \mathrm{P}_{\mathrm{YpU_i}}$ represents the increased production of a crop in country i resulting from yields per unit. $\Delta \mathrm{P}_{\mathrm{HA_i}}$ and $\Delta \mathrm{P}_{\mathrm{YpU_i}}$ can be further decomposed to obtain specific contribution values by the following equations:

$$\Delta P_{HA_i} = \frac{P_{ti} - P_{0i}}{\ln P_{ti} - \ln P_{0i}} \times \ln \frac{HA_{ti}}{HA_{0i}} \tag{2}$$

$$\Delta P_{YpU_i} = \frac{P_{ti} - P_{0i}}{\ln P_{ti} - \ln P_{0i}} \times \ln \frac{YpU_{ti}}{YpU_{0i}} \tag{3}$$

where P_{0i} and P_{ti} represent the grain production of a certain crop in country i

at the initial and final time, respectively. HA_{ti} and HA_{0i} represent the harvested area of a certain crop in country i at the initial and final time, respectively. YpU_{ti} and YpU_{0i} represent the yields per unit of a certain crop in country i at the initial and final time, respectively. The contribution rate of harvested area and yields per unit to grain production increase can be obtained by dividing the calculated contribution value of harvested area and yields per unit by the total grain production increase separately.

Calculation of future potential grain production

In this study, future potential grain production was calculated by combining future attainable yields with historical harvested areas for each crop, accounting for both irrigated and rainfed cultivated land. Future potential yields were simulated using the GAEZ v5 model, which comprehensively considered various factors such as future climate, soil attributes, terrain, land cover, protected areas, biodiversity areas and water resources (Grogan *et al.*, 2022; Li *et al.*, 2020). To reduce the uncertainty inherent in climate projections, a multi-model ensemble approach was utilized. For each of the three Shared Socioeconomic Pathways (SSP1-2.6, SSP3-7.0, and SSP5-8.5), we averaged the climate data across five Earth System Models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL), and then calculated 20-year averages for each climate attribute to represent near-term (2030s), mid-term (2050s) and long-term (2070s) future climate conditions. Using these ensemble climate variables as inputs, the GAEZ v5 model was used to simulate the future attainable yields of four major crops (rice, wheat, maize, and soybean) under both rainfed and irrigated conditions across the three future periods (Supplementary GAEZ)

To evaluate the reliability of the GAEZ simulations, we validated our simulated results against the gold-standard Global Yield Gap Atlas (GYGA) results. Firstly, we simulated the potential attainable yields for the four major crops at a 1-km spatial resolution in the 2010s baseline period (2001-2020). We then compared these raster outputs with the station-based potential attainable yield derived from GYGA for the same period. For each crop, we obtained potential attainable yields of sites for the top 10 countries within the GYGA database and paired them with the corresponding pixel values from our GAEZ historical simulations. This cross-validation was conducted separately for both rainfed and irrigated conditions. The results demonstrate a high degree of consistency, with the coefficient of determination (R^2) exceeding 85% across

all crops (Supplementary Fig. 3). This strong correlation confirms the high credibility of the GAEZ framework in capturing spatial yield variabilities, thereby justifying its application for projecting future potential attainable yields under changing climatic regimes.

In this study, the grain harvested area serves as the control variable. To ensure spatial consistency, all historical and future potential yield rasters were first resampled to a uniform spatial resolution and extent. The harvested area for each crop remains constant during the prediction of future grain production, with only future yields changes taken into consideration. The future grain production is calculated using the following formula:

$$PoPRD_{ij}^{t,s} = a_{ij_irri}^{t,s} \times S_{ij_irri} + a_{ij_rain}^{t,s} \times S_{ij_rain} \quad (4)$$

where $PoPRD_{ij}^{t,s}$ represents the future grain production of crop j for country i at period t and scenario s, $a^{t,s}$ denotes the future potential attainable yield under period t and scenario s. S_{ij_irri} and S_{ij_rain} represent the constant harvested areas under irrigated and rain-fed conditions.

Calculation of historical and future climate gaps

The calculation of historical potential production ($HisPoPRD_{ij}$) is similar to $PoPRD_{ij}^{t,s}$, integrating the historical potential yield (a^{his}) and the constant harvested areas (S):

$$HisPoPRD_{ij} = a_{ij_irri}^{his} \times S_{ij_irri} + a_{ij_rain}^{his} \times S_{ij_rain} \quad (5)$$

The historical actual production ($HisPRD_{ij}$) is derived symmetrically using the historical actual yield (Y^{his}):

$$HisPRD_{ij} = Y_{ij_irri}^{his} \times S_{ij_irri} + Y_{ij_rain}^{his} \times S_{ij_rain} \quad (6)$$

Model uncertainties may cause simulated potential yields to fall below actual observations. Therefore, we establish an adjusted historical potential production ($HisPoPRD'_{ij}$). We apply a zero-truncation mechanism. The adjusted potential is the maximum between the calculated historical potential and the actual historical production:

$$HisPoPRD'_{ij} = \max(HisPoPRD_{ij}, HisPRD_{ij})$$

(7)

This forces the historical gap ($HistoricalGAP_{ij}$) to be strictly non-negative. It represents realistic unfulfilled management potential:

$$HistoricalGAP_{ij} = HisPoPRD'_{ij} - HisPRD_{ij} \quad (8)$$

The future climate gap ($ClimateGAP_{ij}^{t,s}$) isolates the physical impact of climate change on grain production. It is defined as the difference between the future climate production potential and the historical potential:

$$ClimateGAP_{ij}^{t,s} = PoPRD_{ij}^{t,s} - HisPoPRDij \quad (9)$$

Equations (4) through (9) are expressed at the national level (i) for conceptual clarity. However, the actual computational workflow was fundamentally based on grid-cell operations. All yield-area multiplications and zero-truncations were executed at the high-resolution grid scale. We subsequently derived the national-level variables ($HisPoPRD$, $PoPRD$, $HistoricalGAP$ and $ClimateGAP$) by aggregating these pixel values using ArcGIS 10.8.2 zonal statistics function. This grid-based approach preserves local spatial details. It also prevents calculation errors caused by subtracting national totals directly.

Classification of potential grain productivity types

In the face of future climate uncertainty, assessing the potential of each country's grain production, particularly relative to historical potential yields, is of great significance for optimizing global grain production patterns and increasing grain production. The future climate gaps, i.e. the difference between future potential production and historical potential production, intuitively reflect the national grain-producing potential under climate warming in the future. By calculating the differences between the future production of a certain crop and its historical potential production in different countries under three climatic scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5) and three time periods (2030s, 2050s and 2070s), we classified the future climate gaps of crop growing countries into three types. The formula is as follows:

$$Country_type_{ij} = \begin{cases} Climate\ benefit\ type, & if\ ClimateGAP_{ij}^{t,s} \geq 0, \forall t \in T, s \in S \\ Climate\ fluctuation\ type, & Otherwise \\ Climate\ stress\ type, & if\ ClimateGAP_{ij}^{t,s} < 0, \forall t \in T, s \in S \end{cases}$$

(10)

where $Country_type_{ij}$ denotes the climate response classification of country i for crop j. T represents the set of three future time periods (2030s, 2050s, and 2070s). S represents the set of three climate scenarios (SSP1-2.6, SSP3-7.0, and SSP5-8.5). Specifically, a country is classified as the climate benefit type if its climate gap remains non-negative across all nine combinations of periods and scenarios. It falls into the climate stress type if the gap is strictly negative under all conditions. If the climate gap exhibits both positive and negative values across different combinations, the country is categorized as the climate fluctuation type.

Data availability

The global yield data of four crops (rice, wheat, maize and soybean), thre e future time periods (near-term, mid-term and long-term future), three scenario s (SSP21-.6, SSP3-7.0 and SSPP5-8.5) and two irrigation modes (rain-fed and i rrigation) in this study have been deposited in the Zenodo database. The FAO national-scale statistics of crop production, harvested area, yield, import quantit y, and export quantity from 1980 to 2020 are available at https://www.fao.org/f aostat/en/#data/QCL. Historical potential yield of four crops generated by GYG A data are available at https://www.yieldgap.org/web/guest/coverage-and-data-dow nload. The software used to draw maps charts in this paper mainly included A rcGIS10.8.2, Origin 2025 and Microsoft office 2021.

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Author contributions

Yansui Liu conceived the idea, designed the study, and revised the manuscript; Xueqi Liu and Zongfeng Chen performed the study, processed data and wrote the original draft; Guy Robinson revised the manuscript. All authors read the manuscript and approved the submission.

Competing interests

The authors declare no competing interests.

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