Science of the Total Environment 954 (2024) 176811

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Towards strategic interventions for global food security in 2050

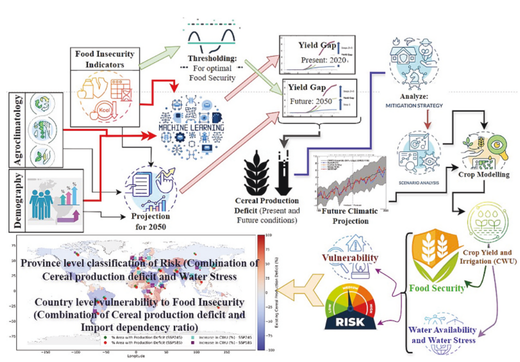
Adrija Roy [a,b,*], Hamid Moradkhani [a,b,*], Mesfin Mekonnen [a,b], Hamed Moftakhari [a,b], Nicholas Magliocca [a,c]

[a] Center for Complex Hydrosystems Research, The University of Alabama, United States of America
[b] Department of Civil, Construction and Environmental Engineering, The University of Alabama, United States of America
[c] Deparyment of Geography, The University of Alabama, United States of America

HIGHLIGHTS

- Prediction of Yield Gap (YG) based on agroclimatological classification.
- Projection of global cereal production at the province level under different Shared Socioeconomic Pathways (SSPs).
- Identification and classification of 'risk' with combined impacts of water stress and cereal production deficit.
- Conversion of rainfed areas to irrigated cannot resolve the gap in required and actual production in future scenarios.
- Import dependency to resolve food insecurity in 2050 identifies Iran, Saudi Arabia, Venezuela, Sub-Saharan Africa.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Jacopo Bacenetti

Keywords:
Cereal production deficit
Irrigation expansion
Agroecological Zones (AEZs)
Yield gap
Food security
Water stress
Shared socioeconomic pathways

ABSTRACT

This study aims to explore global food security, focusing on major cereal crops across different Agroecological Zones (AEZs). By projecting cereal production under different Shared Socioeconomic Pathways, insights into the challenges for achieving global food security by 2050 are drawn. The study identifies 'critical' risks in countries like Chad, Sudan, Algeria, Somalia, and Namibia in Africa, parts of Central Asia and the Middle East (Saudi Arabia), western USA, and Australia, due to high water stress combined with severe production deficits. However, implementing strategic interventions, like increasing harvested area, can significantly reduce these risks, potentially leading to surplus production in some regions. The regions still under cereal production deficit with such mitigation strategies are categorized in terms of risk to food security, considering water stress and import dependency. Iran, Venezuela, Sub-Saharan Africa, Saudi Arabia, parts of Southeastern Asia are projected to face persistent cereal production deficits and high import dependency by the mid-20th century. The study underlines the necessity for water-saving technologies and effective governance to balance crop production and water use, particularly in regions experiencing water scarcity.

* Corresponding authors at: Center for Complex Hydrosystems Research, The University of Alabama, United States of America.
E-mail addresses: aroy15@ua.edu (A. Roy), hmoradkhani@ua.edu (H. Moradkhani).

https://doi.org/10.1016/j.scitotenv.2024.176811
Received 1 July 2024; Received in revised form 20 August 2024; Accepted 6 October 2024
Available online 10 October 2024

1. Introduction

Global food security is a major concern due to population growth, changing climatic patterns, and alterations in cropping patterns. In 2022, 9 % of the global population was undernourished, while approximately 29.6 % experienced moderate to severe food insecurity (FAO et al., 2023). Projected changes in global climatic patterns potentially will affect conditions for crop growth influencing food security[2]. The global challenge lies in meeting the increasing food demand in a manner that is both environmentally sustainable and socially just (Foley et al., 2011a). With rising mean temperatures and unpredictable seasonal precipitation, crop production is expected to decrease (Araya et al., 2020; Prasad et al., 2006). Studies show that major cereal crops like wheat, maize, and paddy rice could see substantial decreases in yield (Challinor et al., 2014; Farooq et al., 2023; Rezaei et al., 2023; Sharma et al., 2022). Food insecurity is a multi-dimensional concept (FAO et al., 2021; Hameed et al., 2019a; Hameed et al., 2019b) and the ability of crop production to meet growing caloric demands is a key dimension particularly sensitive to climate change impacts. Crop productivity exhibits substantial variation worldwide, even in regions with similar climates (Ejike-Alieji and Ekpoh, 2021; Iizumi et al., 2017; Han et al., 2023; Han et al., 2024), due to genetic variability, agricultural and management practices, soil quality, etc. The difference between the actual and the maximum potential yield is the Yield Gap (YG) that is a critical parameter for assessing food security (Gerber et al., 2024; Godfray et al., 2010; Van Ittersum et al., 2013). Cereals are a major part of our diet, and their YG is influenced by agricultural practices, technology, and climate (Becker Pickson et al., 2023; Fatima et al., 2020). By 2050, the world will need to increase cereal supply by 70–100 % to adequately feed the projected global population of 9.8 billion people (FAO, 2009; Ranganathan et al., 2018; UN, 2013). Studies suggest that such an increase will translate to an additional cereal production of 1 billion metric tons per year (Alexandratos and Bruinsma, 2012; Tilman et al., 2011a). All else equal, closing YG could meet this demand by increasing crop calories by about 24 % and 80 % in the current irrigated and rainfed areas, respectively(Rosa et al., 2018).

A significant portion of the worldwide agricultural sector is irrigated (about 20 %), which produces a major fraction (40 %) of the total agricultural yield (FAO, 2021; Siebert and Döll, 2010a). Irrigation development must continue to be a top priority if food production is to be sustained against the impacts of climate change in the future (Burney et al., 2013; FAO, 2017). Intensification of agricultural inputs causes increased utilization of available resources and threatens sustainability. The Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production), emphasize the need for sustainable agricultural practices that increase productivity and food security while reducing environmental impact [49]. Studies have shown that there will be a significant mismatch between water demand (and subsequent withdrawal) and supply, in the future (Brown et al., 2013; Kirby and Mainuddin, 2022; Zhai et al., 2022). The agricultural sector is a substantial consumer, accounting for roughly 70 % of global water withdrawal (Molden, 2013; Pointet, 2022). Globally, approximately 24 % of cultivated land (around 310 million hectares) is irrigated, contributing to about 33 % of the total global crop production (Portmann et al., 2010). There is an evident need for addressing future food production demand and closing the yield gaps on a regional scale, with minimal impact on water security as a key dimension of environmental sustainability. It is found that additionally, 1.2 million square kilometers of land will be necessary to be converted by 2030 and another 5 % by 2050 with vast transformation in South America and Sub-Saharan Africa (Alexandratos and Bruinsma, 2012). Some studies predicted a 10–25 % increase in cropland by 2050 compared to 2005 for climate scenarios (Schmitz et al., 2014).

Here, we analyze the YG patterns for grain crops such as Maize, Wheat, and Rice, across various AEZs worldwide at sub-national level units (Level 1 administrative boundaries from the Global Administrative Areas (GADM) version 3.6). Impacts of climate change on YG will be uneven, with expectations of widening gaps in the most vulnerable AEZs, underscoring the importance of irrigation in such locations for closing the YG. The correlation of agroecology with YG and food safety has been evaluated and established qualitatively in few studies (Bezner Kerr et al., 2021; Ejike-Alieji and Ekpoh, 2021; Hatfield and Dold, 2018; O'Brien et al., 2021). This study quantifies the current and projected YGs for major cereal crops regionally and investigates the potential for two common strategies - increased irrigation or expanded cultivation areas - to meet future production needs. We aim to analyze food security of different AEZs under current and future climatic scenarios, an aspect not covered in earlier studies. GAEZ-based top-down gridded framework is found to be more reliable with less uncertainty, in foreseeing the global outlook of cereal self-sufficiency (Rattalino Edreira et al., 2021). We analyze some broad strategies to enhance crop production and estimate the impacts on water stress. We also analyze the risks in the multidimensional context of food security, water stress, and import dependency. The paper is arranged to answer the following questions:

- What is the existing YG for major cereal crops?
- How is food security projected to change in 2050 for different AEZs?
- How much additional yield is required for individual level 1 administrative units worldwide to ensure desired food safety in 2050?
- How will the crop yield improve if we use freshwater resources in the region to enhance agricultural productivity?
- What will be the projected additional "blue water" contribution towards the Crop Water Use (CWU), if the additional crop yield is required to achieve food security?

This study employs global agroecological classification based on temperature regimes, moisture regimes, soil quality, and terrain conditions as predictors of food security. A flowchart for the methodology adopted for the current analyses is shown in Fig. 1. The study considers AEZ classification, and other predictors such as population, cereal import dependency, calorific requirement met by cereals, and food security indicators to project YG at subnational level. Implications of these projections on zonal water and food security are assessed using relevant indicators.

We here did not analyze strategies like improving existing Water Use Efficiency (WUE) with proper land and water management, adopting high-yielding cultivars, or shifting dietary preferences. The study only considers major changes like expansion of agricultural land and conversion of rainfed to irrigated agriculture, to conceptualize the food security status in 2050. However, it is unequivocal that these are the choices that the policymakers need to act on as the intensification of agriculture will cause significant increase in GHG emissions. Studies show that it will be critically challenging to feed the world in the future with minimal impact on biodiversity(Delzeit et al., 2017; Foley et al., 2011b; Tilman et al., 2011b; Zabel et al., 2019). Database is developed identifying potentially cultivable land for future timespans until 2100, using a land suitability model with crop-specific characteristics linked with climate, soil, and topographic conditions(Schneider et al., 2022; Zabel et al., 2019). Potentially available cropland extent usually excludes impervious areas, strictly prohibited areas, forests, and wetlands, and we used datasets on the potential availability of land and Land Cover information to identify the justifiable thresholds in the present study.

In Fig. S1 (supplementary information or SI), we show the percentage of the population suffering from moderate to severe food insecurity at a country scale, the distribution of agroecological zones based on climatology and the average length of the growing period, and Water Stress Score (WSS) report by AQUEDUCT. The data on food security indicators unequivocally demonstrate that SSA countries are the most affected, followed by Latin America and Western Asia. Looking from climatological perspective, such regions are mostly in tropical humid

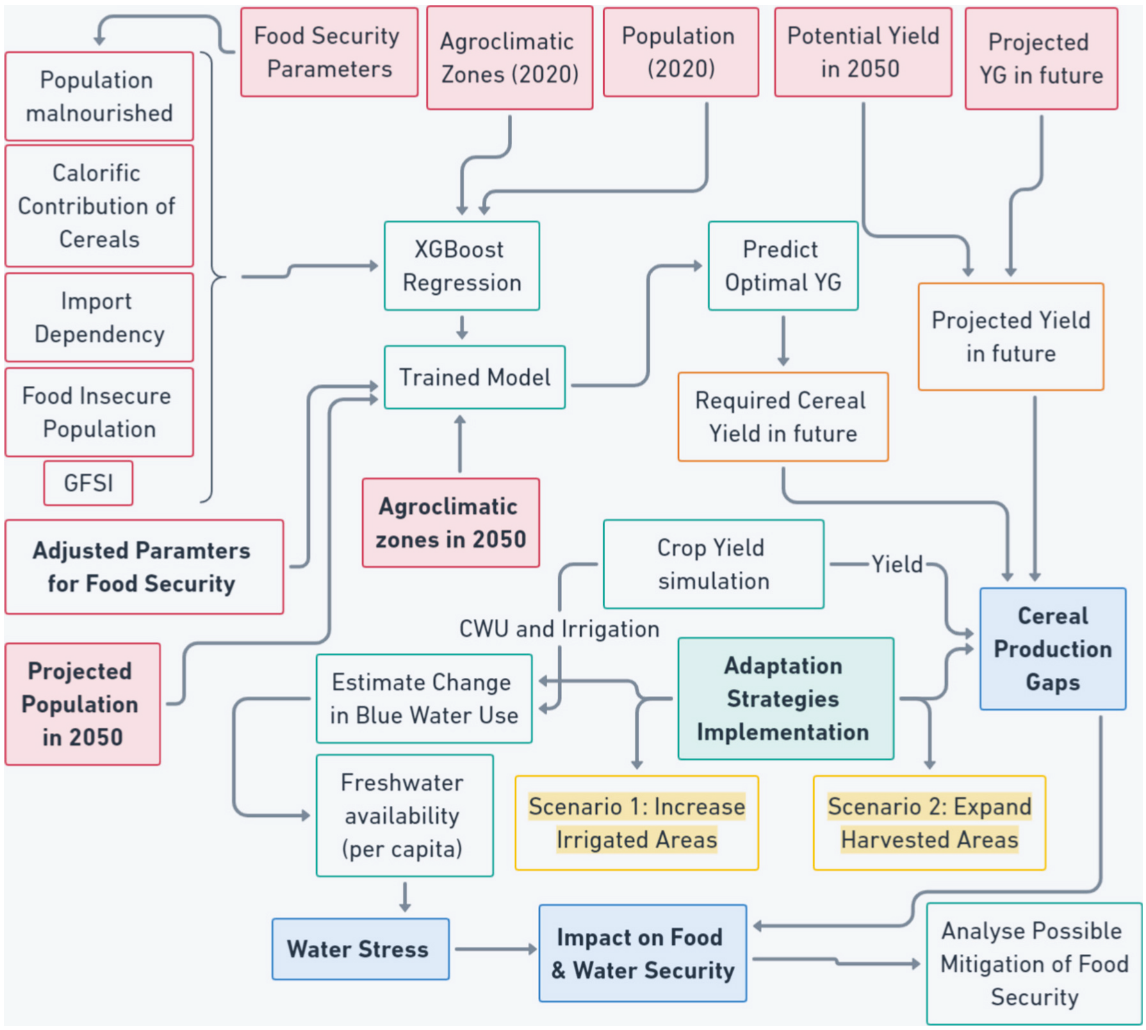


Fig. 1. Flowchart describing the process adopted to analyze the cereal production deficits under current situation and with mitigation strategies.

and sub-humid regions and arid desert. WSS indicates that the water stress is prevalent mostly in central-south Asia, northern Africa, and western Asia, specifically western Australia, and the west coasts of North and South America. The solution to improve cereal yields in food-insecure regions with less water stress is crucial, especially in Latin American countries (excluding Chile) and SSA regions (excluding Angola, Namibia, and Botswana).

2. Methods

2.1. Relationship between YG and food security

We aim to establish a relationship between subnational-level food insecurity and crop yield, more specifically, examining the yield gap (YG) for cereal crops across different countries. To determine the additional production of cereals required to mitigate food insecurity or attain a desired level of food safety, the calorific contribution of cereals was considered. According to the Food and Agriculture Organization (FAO), approximately 75 % of the food consumed by humans worldwide comes from only 12 plant and 5 animal sources (FAO, 2004). Out of these, three crops, namely wheat, rice, and corn, make up 51 % of the total calories included in the human diet (FAO, 2004). We focused on these three cereal crops intending to establish their current and projected production and contribution towards fulfilling dietary requirements.

2.2. Yield projection in 2050

Food security depends on various socioeconomic parameters, such as population density, population growth, Gross Domestic Product (GDP) of the region, crop potential yield achievement ratio, and Yield Gap (YG), and agroecological parameters such as climatic condition, soil condition, terrain limitation and length of growing period (LGP). Regression predictive modeling with the Extreme Gradient Boosting algorithm is found effective in crop yield simulation in past studies (Maheswari and Ramani, 2023; Mariadass et al., 2022; Pradeep et al., 2023), is used to ascertain the relationship or coefficients for each factor in defining the YG of Maize, Wheat, and Rice. The model is configured aiming to minimize squared errors. It builds 800 regression trees to make predictions and the maximum depth for each decision tree is set to 10. A subsampling rate of 0.6 for training each tree is used, to reduce overfitting. The learning rate is set to 0.01, indicating a slower, more careful approach to gradient descent, likely to improve model generalization by making more nuanced adjustments to the model weights during training. We employ a cross-validation strategy utilizing Repeated K-Fold with 5 splits and 3 repetitions to evaluate the model's performance, ensuring the robustness and reliability of the results. The Mean Squared Error, Mean Absolute Error, and R^2 values for the prediction of YG from the model are obtained as 0.33 t/ha, 0.24 t/ha, and 0.94, respectively.

YG of the cereal crops in 2050 under different Representative Concentration Pathways (RCPs) are subsequently predicted. We analyzed the food security status based on the current AEZ classification (year 2020) and predicted the AEZ classification for the year 2050, under three different RCPs: RCP2.6, RCP4.5, and RCP8.5. A description on the classification system of GAEZ dataset is given in Text S2 in the SI. The purpose of this analysis is to understand various scenarios ranging from 'significant efforts to mitigate climate change and limit warming' to 'continued high emissions causing significant warming'. The estimates of YG circa 2050 ultimately generated the estimates of Actual Yield (AY) under the RCPs considered, considering the Potential Yield remaining the same.

2.3. Threshold for food security

To achieve the desired level of food security, adjustments are required for various indicators including Global Food Security Index (GFSI), the population affected by moderate to severe food insecurity (%) or FI_{perc}, and the malnourished population (%) or MN_{perc}, average dietary energy supply adequacy (%) or Cal_{perc}, the share of dietary energy supply derived from cereals (%) or Cer_{perc} and import dependency (%) or ID_{perc}. We assumed 90th percentiles for the values of GFSI, Cal_{perc} and 10th percentile values for MN_{perc} and FI_{perc}. These thresholds are not standardized and are ascertained to aim for high standards in food security and nutritional availability. Meanwhile, the values for ID_{perc} and Cer_{perc} are kept the same. Using these adjusted values, we project the maximum allowable YG to achieve food security for cereal crops in 2050 under different RCPs. Subsequently, we obtain a set of adjusted AY values required in 2050, which correspond to the modified indicators. The estimated values of cereal crop yields, predicted under targeted food security indices are assumed to be optimal. To ascertain the cumulative cereal production required to achieve the hypothetical food security goal, it is necessary to multiply the optimal crop yield with the current area under cultivation and sum up the resulting estimates. The total required cereal crop production (in tons) for each state is used for comparison with the existing production (in 2020), and also with the projected actual cereal production, simulated using a crop simulation model (discussed in the next subsection).

2.4. Crop yield simulation

After we have the estimates of the desired amount of cereal production to achieve food security individually at each state, we now move to examine the actual projected cereal production values in 2050, without any alteration in the existing agricultural pattern. We used the AquaCrop model to obtain the yield and Crop Water Use (CWU). AquaCrop is a crop growth model by FAO that simulates the yield response of herbaceous crops to water, we selected AquaCrop due to its simplicity in terms of explicit parameter requirements. To simplify the process, we considered each state as a single entity and gathered meteorological and soil data. We also collected information on the area under each cereal crop (such as Maize, Wheat, and Paddy) for each unit, both for rainfed and irrigated conditions. The actual production of each crop type was calculated by multiplying the area under the crop with the simulated yield. To enable parallel execution of the simulations, an open-source version of the FAO AquaCrop model, is used in the present analysis (Foster et al., 2017).

2.5. Assumptions

The food security indicators used here are based on conditions and behaviors reported by adults through the Food Insecurity Experience Scale (FIES) survey module. These indicators are given as percentages, determined to ensure adherence to Development Goals (SDGs), in particular Goal 2 on eradicating hunger and all forms of malnutrition. Ideally, to completely eradicate food insecurity, 100th percentiles for the values for Global Food Security Index (GFSI) and average dietary energy supply adequacy (%), and 10th percentiles for by moderate to severe food insecurity (%) and the malnourished population (%), should be considered. Here, we assume that 90th and 10th percentiles for these will be 'sufficient enough'.

In our study, we did not apply bias correction to the CMIP6 model outputs. The application of bias correction on a global scale presents significant challenges due to the diverse climatic conditions across different regions. Instead, we addressed the potential biases by using an ensemble approach, where inputs from five different CMIP6 models were selected for each region based on data availability. The models used include CESM2, BCC-CSM2-MR, MPI-ESM1–2-LR, CNRM-CM6–1, GFDL-ESM4, CanESM5, MIROC6, HadGEM3-GC31-LL, and ACCESS-CM2. By averaging the outputs (Crop Water Requirement and Yield) of the AquaCrop model from these five different climate projections, we aim to reduce the impact of any individual model's biases and provide a more robust projection of future climate conditions. This ensemble mean approach helps to mitigate the uncertainties associated with using a single model.

It is worth mentioning that the AquaCROP model is rather uncalibrated and for the individual unit (or the administrative level 2); we focused on comparative analyses between the present and the future. With the logical assumption of transpiration being proportional to the crop yield, we calculated the actual transpiration from the actual yield (AY) estimates we already obtained from GAEZ data portal. The multiplication factors for obtaining AY from the simulated yield with present climatic data are obtained. The same factors are applied to obtain the AY from the yield estimates simulated for future climate projections. This ensemble mean approach helps to mitigate the uncertainties associated with using a single model. However, future studies can benefit from postprocessing or bias correction (Khajehei and Moradkhani, 2017; Khajehei et al., 2017) or using a Bayesian model averaging of different climate models to more formally address the model uncertainty (Madadgar and Moradkhani, 2014; Abbaszadeh et al., 2022).

The AquaCrop model, which we employed to simulate crop yields and water use, explicitly accounts for both rainfed and irrigated agricultural conditions. In our model, irrigation management is governed by a soil moisture-based approach, designed to optimize water use while ensuring crop water requirements are met throughout the growing season. The model dynamically monitors soil moisture levels within the root zone, and irrigation is triggered when soil moisture falls below a predefined threshold, expressed as a percentage of Total Available Water (TAW). Specifically, the threshold is set at 60 % of TAW for each growth stage of the crop, ensuring that irrigation is applied when soil moisture depletion indicates a significant need for water. Once the need for irrigation is identified, the model calculates the required irrigation depth to restore soil moisture to the target level. This calculation considers the irrigation application efficiency, set at 70 %, which adjusts for potential water losses due to factors such as evaporation and runoff. The irrigation depth is further constrained by a maximum allowable limit of 25 mm per day to prevent over-irrigation.

The most recent BWU data for irrigated Maize, Wheat, and Rice for the year 2002, the latest available data from the Global Crop Water Model (GCWM), has been procured and serves as a benchmark for comparison against simulated irrigation amounts generated by AquaCrop. This data enables the assessment of simulated irrigation amounts. By applying multiplication factors to future simulation results, specific to each state, and derived from the comparison between actual and simulated irrigation amounts, adjustments are made. These adjustments ensure that future irrigation estimates from the simulations are more precise and closely aligned with observed patterns, providing accurate projections.

2.6. Hypothetical strategies for balancing cereal production gaps

Once the estimates of individual crop yield in the present (year 2020) and future (year 2050) scenarios are obtained from the crop growth simulations, we move into estimating the gaps in cereal production. The areas under rainfed and irrigated cereal crops are extracted from GAEZ v4 data. The total production for each of the 6 types of crops (rainfed maize, rainfed wheat, rainfed rice, irrigated maize, irrigated wheat, and irrigated rice) is computed by multiplying the area under that crop with the estimated yield. Finally, we obtain the deficit in the production of cereal crops by subtracting the actual crop production (sum of individual crop production) from the optimal cereal production. In total, four sets of comparisons are made, each for 3 SSPs considered in 2050 (SSP126, SSP245, SSP585) and for the present condition (in 2020). The analyses for these comparisons are discussed in the Results section. The areas for conversion from rainfed to irrigated cropland in Strategy 1, and non-cropped to agricultural land in Strategy 2, are increased sequentially, starting from 10 % to 50 %. The increase in rainfed and irrigated areas are capped by a threshold of a maximum of 25 % of total potentially available cropland, available at the sub-national level. The spatial dataset of the "potentially available cropland" is obtained from the dataset generated by Schneider et al. (2022). A brief explanation of the "potentially available cropland" in the future as per the dataset is given in Text S1 in the SI. We again cross-checked the possible maximum increase in harvested area, as in strategy 2, with an upper limit based on the land cover distribution of the state. We used Consensus 1-km land cover data (Tuanmu and Jetz, 2014a) and took 10 % of the total land under shrubs, fallow, herbaceous, and flooded vegetation to be the other upper limit to expand the harvested area. The increase in the percentage of the irrigated area (Strategy 1) was not increased failing to produce much improvement in mitigating the production gap. The deficit in production in 2050 for the existing trend and with the incremental adaptation in both the proposed strategies are shown in Figs. S1, S2, and S3 (SI) for SSP126, SSP245, and SSP585 respectively. In these figures (Fig. S1, S2, and S3), total 5 hypothetical adaptation cases are represented: 25 % and 50 % rainfed to irrigated area conversion (Strategy 1), and 10 %, 25 % and 50 % increment in total harvested area (Strategy 2). For the subsequent analyses, we only report Strategy 1 with up to 50 % of the rainfed area being converted to irrigated and up to 50 % increase in the overall area harvested.

The Results section also elaborates on the strategies and findings from our investigation into agricultural pattern modifications aimed at mitigating food insecurity. To assess cereal production gaps to actionable strategies, we explored two distinct methodologies aimed at addressing the deficiencies in agricultural patterns. The initial strategy, termed as Strategy 1, involves a phased enhancement of the irrigated areas, facilitating the adoption of irrigation practices within regions predominantly reliant on rainfed agriculture, up to 50 % at maximum. The alternative strategy proposes a simultaneous expansion of both irrigated and rainfed agricultural areas, maintaining their existing proportional distribution. This strategy is termed as Strategy 2 in the Results and Discussions. The fundamental distinction between these approaches lies in the changes in the total harvested area. The first approach maintains the current extent of harvested land, while the second advocates for an overall increase in the land area dedicated to crop cultivation. These strategies are critically analyzed for their potential to address the pressing challenge of food insecurity, exacerbated by climate change and other socio-economic factors. The analysis considers the impact of these strategies on the total harvested area, crop yield, and the broader implications for water security and sustainability for the specific regions.

2.7. Data

The datasets used have been described in the following sections. A table showing the sources and description of the datasets are given in

Table 1
The datasets used in the study: Sources, Parameters and Description.

Category	Indicator/parameter	Source	Description
Food Security Indicators	Global Food Security Index	Economist Impact (https://impact.economist.com/sustainability/project/food-security-index)	Assesses the food security status of 113 countries based on affordability, availability, quality and safety, and sustainability and adaptation.
	Population affected by food insecurity	FAOSTAT (https://www.fao.org/faostat/en/ - data/FS)	Percentage of population affected by moderate to severe food insecurity.
	Malnourished population	FAOSTAT (https://www.fao.org/faostat/en/ - data/FS)	Percentage of population that is malnourished.
	Average dietary energy supply adequacy	FAOSTAT (https://www.fao.org/faostat/en/ - data/FS)	Percentage of average dietary energy supply adequacy.
	Share of dietary energy from cereals	FAOSTAT (https://www.fao.org/faostat/en/ - data/FS)	Percentage of dietary energy supply derived from cereals.
	Import dependency	FAOSTAT (https://www.fao.org/faostat/en/ - data/FS)	Percentage of import dependency for food.
Yield Gap (YG)	YG data for rice, maize, wheat	Global Agroecological Zones v4 (GAEZ v4) (http://www.fao.org/nr/gaez/en/)	Used to identify the correlation with food security, based on data from 2010.
Agroecologic Characteristics	Agroecological Zoning (AEZ)	Global Agroecological Zones v4 (GAEZ v4) (http://www.fao.org/nr/gaez/en/)	Framework assessing natural resources for agricultural purposes, categorizing land based on climate, soil, and terrain.
Population Information	Present and estimated population in 2050	World Population Projection, United Nations (http://population.un.org/wpp/)	Data on current and projected population by country and state, using medium variant estimation for 2050.
Potentially available cropland	Gridded Potentially available cropland data at 30 arcseconds	Global inventory of potentially cultivable land and potentially available cropland under different scenarios and policies (2022)) (doi:https://doi.org/10.5281/zenodo.5993934)	Data on Potentially available cropland for future time periods under RCP2.6 and RCP8.5, under rainfed and irrigated conditions
Land Use Land Cover Data	12 classes of lad cover	Consensus 1-km LULC data (https://www.earthenv.org/landcover)	Data on possible extension of cropland from Fallow, Shrubland and Herbaceous vegetation cover information
Datasets in AquaCrop Simulation	Historical Climate Data	Precipitation, minimum and maximum temperatures: AgMERRA PET data: ERA-5 Land (https://data.bris.ac.uk/data/dataset/qb8ujazzda0s2aykkv0oq0ctp)	Daily data of climate variables, such as precipitation, temperatures, and solar radiation, are used for AquaCrop simulation inputs.
	Future Climate Projections	CMIP6 (https://esgf.llnl.gov/)	
	Soil Information	Harmonized World Soil Database v2.0 (https://data.apps.fao.org/catalog/dataset/ff5c613c-75bb-46a9-a162-bc728059b465) Curve Number: GCN250	Provides soil texture and depth information for AquaCrop simulation.
	Crop Parameters	Default in AquaCrop model	Includes planting data, harvesting date, plant density, etc., for crop growth simulation.
	Blue and Green Water Use for Crops	Global Crop Water Model Data https://springernature.figshare.com/collections/Global_Gridded_Dataset_of_Crop-specific_Green_and_Blue_Water_Requirements/4893084	Information on Crop Water Use (CWU) for different crops at the state level, derived from spatial average values of water use data.

Table 1.

2.8. Data for production deficit projection

(i) Food Security Indicators

Selecting relevant indicators is critical for projecting the required yield and ensuring food security. The indicators that have been selected for this purpose include the Global Food Security Index (GFSI), the population affected by moderate to severe food insecurity (%) or FI_{perc}, and the malnourished population (%) or MN_{perc}, average dietary energy supply adequacy (%) or Cal_{perc}, the share of dietary energy supply derived from cereals (%) or Cer_{perc} and import dependency (%) or ID_{perc}. These are fundamental indicators that provide crucial information regarding the food security situation in each region or country. Therefore, it is imperative to carefully analyze and interpret the data provided by these indicators to make informed decisions regarding food security. The data from the GFSI index is widely considered to be the most reliable source for understanding the factors that impact global food security. Economist Impact created the index, which received support from Corteva Agriscience. The GFSI index assesses the food security status of 113 countries based on four main criteria: affordability, availability, quality and safety, and sustainability and adaptation. The remaining indicators are sourced from FAOSTAT.

(ii) Yield Gap

Information on YG is obtained from Global Agroecological Zones v4 (GAEZ v4), developed by the collaborative effort of the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA) (Fischer et al., 2021). The YG data for rice, maize, and wheat from 2010 was utilized as a representative sample of the extant YG. State-level data was extracted and analyzed to identify its correlation with food security.

(iii) Agro-climatological Classification

Agro-climatological characteristics of the states are derived from GAEZ v4 data. Agroecological Zoning (AEZ) is an exceptional framework for assessing natural resources for agricultural purposes (Fischer et al., 2021; Wing et al., 2021). By considering established principles of land evaluation, plant characteristics, climate, and soil requirements, AEZ evaluates the suitability of each crop type individually. The GAEZ v4 employs a uniform structure to categorize land based on the combination of climate, soil, and terrain features. This system is a useful resource for evaluating the agricultural capacity of land and providing guidance for land use planning, policy formulation, and food security initiatives (Van Wart et al., 2013; Wing et al., 2021). The data portal provides access to the required AEZ classifications such as moisture regime classification, simplified AEZ classification, LGP classification, and climate data for historical and future scenarios.

To draw conceivable analyses at a regional level, we selected a few groups of countries (most of these are defined by SDG Country groups). Apart from that, the 57 AEZ classes are also aggregated in terms of climatology (considering thermal climate, temperature regimes, and moisture regimes), and average length of growing period (LGP) in days. The country groups considered are: USA, Northern America excluding USA, Central and South Asia, Europe, North Africa and Western Asia, Latin America and Caribbean region, Sub-Saharan Africa, Oceania and Eastern and Southeast Asia. On the other hand, the climatic zones defined here, are: Subtropical Cool Arid, Subtropical Cool Humid, Subtropic Moderate Arid, Subtropic Moderate Humid, Subtropic Warm Arid, Subtropic Warm Humid, Tropical Arid, Tropical Humid, Temperate Cool Arid, Temperate Cool Humid, Temperate Moderate Arid and Temperate Moderate Humid.

(iv) Population Information

The data on the present and estimated population in 2050 has been procured from the United Nations Population Division at the country level. To derive the projection, we have used the medium variant estimation from the same source. Moreover, subnational-level disintegration was performed by assuming uniform population density for both present and future scenarios, ensuring accurate results.

2.9. Datasets used in aquacrop simulation

(i) Historical Climate Data

A consistent, daily time series over the 1980–2010 period is obtained using the Agricultural Model Intercomparison and Improvement Project (AgMIP) climate forcing dataset, AgMERRA, which provides global coverage of climate variables required for agricultural models (Rosenzweig et al., 2013; Ruane et al., 2015); we used precipitation, minimum and maximum temperatures to create inputs to the AquaCrop model. AgMERRA incorporates MERRA-Land product for improved daily precipitation distribution and precipitation extremes, utilizing NASA/GEWEX Solar Radiation Budget data for better solar radiation values (Ruane et al., 2015). Potential ET data is obtained from daily-PET or dPET dataset, derived using 7 variables from ERA-5 Land. This dataset encompasses the world's entire land area at a 0.1° spatial resolution, spanning from 1981 through 2022 (Singer et al., 2020).

(ii) Future Climate Projection

The same climatic variables for the year 2050 are obtained from the outputs of Phase 6 of the Climate Model Intercomparison Project (CMIP6). Inputs from five models are selected for each state from CMIP6 (Any 5 from CESM2, BCC-CSM2-MR, MPI-ESM1–2-LR, CNRM-CM6–1, GFDL-ESM4, CanESM5, MIROC6, HadGEM3-GC31-LL and ACCESS-CM2) for generating yield simulations individually. The mean of the five individual simulations is taken for deriving yield, evaporation, transpiration, and irrigation, at each unit. The selection of 5 models was based on data availability for that region.

(iii) Soil Information

Soil texture and depth information required for AquaCrop simulation was obtained from the Harmonized World Soil Database version 2.0 or HWSD v2.0. We assume 2 soil layers in the crop model, and the volumetric percentage of sand, clay, organic matter, and depth of each soil layer are extracted as the spatial average values for the mentioned variables for each state. Apart from that, AquaCrop needs Curve Number data for each unit, which was obtained from GCN250, global curve number datasets for hydrologic modeling and design (Jaafar et al., 2019).

(iv) Crop Parameters

AquaCrop model has an in-built set of parameters for parameters required for simulation of the final crop yield in the four steps: (i) Simulation of green canopy cover, (ii) Simulation of crop transpiration and root water uptake, (iii) Simulation of above-ground biomass production, (iv) Simulation of final crop yield. These default sets of crop parameters in AquaCrop model were used. Some required adjustments were made on parameters like planting data, harvesting date, plant density, maximum canopy cover, time to crop emergence, flowering, start of canopy senescence and to maturity, and maximum effective root depth, for enabling the crop growth simulation.

2.10. Global crop water model data

The Crop Water Use (CWU) information for the crops is obtained from the Global Crop Water Model (GCWM), designed for 26 different crop classes for water use (Siebert and Döll, 2010b). We obtained the actual crop water use (CWU) and irrigation amounts by taking the spatial average values of Blue Water Use (BWU) and Green Water Use (GWU) from GCWM for the cereal crops at the state level for the current situation. (Chiarelli et al., 2020).

2.11. Data for potentially cultivable land and potentially available cropland

A global dataset is available that provides information on potentially cultivable land (pcl) and potentially available cropland (pac) for both historic and future periods. The data is presented for two different climate scenarios, RCP2.6 and RCP8.5, and includes information on current irrigation patterns as well as rainfed and irrigated conditions separately. The information is available at both 30 arc-seconds and 30

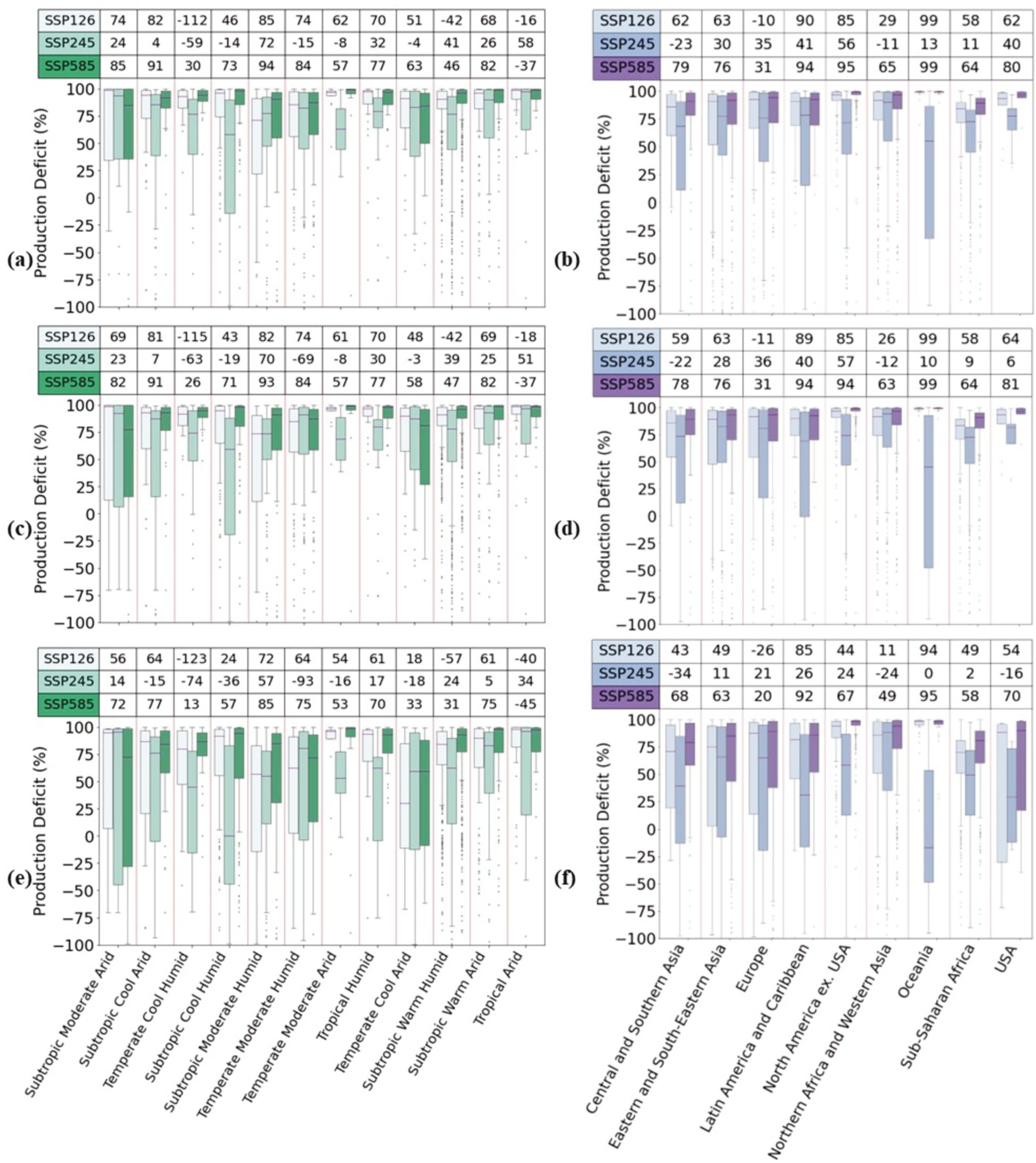


Fig. 2. Projected Cereal Production Deficit in 2050 under different Shared Socioeconomic Pathways (SSP126, SSP245, and SSP585)– Classified into SDG Regions and Climatic Zones. Subplots (a) and (b) show the cereal production deficit in 2050 without any mitigation strategy, classified across Climatic zones and country groups, respectively. The subplots (c) and (e) show the remaining cereal production deficit with Strategy 1 and 2, respectively, for varied climatic zones. Similarly, the subplots (d) and (f) show the remaining cereal production deficit with Strategy 1 and 2, respectively, for different country groups. The values in the tables on top of each chart represent the mean production deficit percentages.

arc-minutes spatial resolution and has been aggregated at the country level (Schneider et al., 2022).

2.12. Land cover data

We use Consensus 1-km Land Use Land Cover (LULC) data with 12 classes of land cover, to cross-check the threshold for possible extension of harvested area, as per the strategy 2 (Tuanmu and Jetz, 2014b).

3. Results

3.1. Projections of cereal production deficits in 2050

Fig. 2 gives an estimate of the cereal production shortages projected by 2050, based on different Shared Socioeconomic Pathways (SSPs) such as SSP126, SSP245, and SSP585, among different climatic zones (left panels) and country groups (right panels). Subplots (a) and (b) illustrate the potential future cereal deficits that could happen without any intervention, highlighting the differences in production shortages across climatic zones and country groups. Some regions are consistently projected to have higher deficits for all SSPs, indicating a potential vulnerability to future food insecurity. Country groups with high import dependency and significant food insecure populations could face compounded risks due to their projected production deficits, as they may have less capacity to buffer against global cereal shortages. The difference in deficit percentages across the SSP126, SSP245, and SSP585 for the same country groups suggests that socioeconomic factors will have a significant influence on future cereal production. SSP585, which is often associated with high greenhouse gas emissions and limited adoption of environmental policies, shows greater deficits in some country groups, hinting at a correlation between less sustainable practices and increased food production challenges.

A negative value of the mean of the cereal production deficit symbolizes surplus production while a positive value denotes deficit in production. SSP585 shows substantial crop production deficits across all regions except subtropical cool arid. Significant vulnerability to cereal production gaps can be observed in subtropical warm arid, tropical arid and humid, temperate cool, and moderately humid regions. Certain regions, such as central-south Asia and SSA, show significant projected deficits. Developed regions, like the USA and Europe, display relatively lower deficits, which reflect better adaptive capacities, technological advancements, and more resilient agricultural infrastructures. There is considerable uncertainty in the projections, arising from reasons that are difficult to predict.

3.2. Possible mitigation of cereal production deficits

We examine two strategies to address the gaps in cereal production. Strategy 1 focuses on increasing irrigated areas, promoting irrigation practices in rainfed regions, up to a maximum of 50 %. Strategy 2 suggests expanding irrigated and rainfed agricultural areas while maintaining their current proportional distribution. Investigating spatial patterns of future expansion of cropland is essential in determining the trade-offs between food security, climate protection, and biodiversity (Delzeit et al., 2017; Hosonuma et al., 2012; Kehoe et al., 2017; Zabel et al., 2019). Minimum of two estimates, one the 1/4th of the estimated land potential to be suitable, cultivable, and available for agricultural use(Schneider et al., 2022), extracted from 30 arc-seconds spatial resolution global dataset, and the other from 10 % of the total land under shrubs, fallow, herbaceous, and flooded vegetation, has been used to threshold the expansion of cropland in the current study.

In Fig. 2, subplots (c) and (d), the impact of Strategy 1 is shown for different climatic regions and country groups. The production deficit is not mitigated under this strategy, and maximum improvement is seen in tropical and subtropical arid regions, essentially because of the lower seasonal rainfall and suitable soil and climatic condition. In most classes, both in country groups and climatic zones, the average reduction in deficit is limited to 3–5 %. Alternatively, with strategy 2, significant decrease in production deficits is observed (∼ 30 %) for all regions (Fig. 2 (e) and (f)). The sample data for all the boxplots exclude the regions with surplus of 100 % or more. The highest improvement in crop production is observed in the SSP245 projection. It is possible that the positive changes in the temperature and increased CO_2 concentration can lead to better conditions for agriculture(Shanker et al., 2022; Xu et al., 2016). A high-emission scenario could have a detrimental effect on agriculture, which cannot be rectified by implementing irrigation methods(Asseng et al., 2014; Iizumi et al., 2017). Thus, minimal improvement in SSP585 scenario is observed except for higher threshold for expansion of cropland. In Europe and Central-southern Asia, comparatively lower production deficit is projected by 2050.

We show the prevalence of food insecurity, the caloric contribution from the cereals, and import dependency in Fig. 2 for each class. The graphs indicate that most country groups with high import dependency are facing larger cereal production deficits (except for Canada). This underscores the potential risk of increased cereal prices and highlights the importance of developing domestic agricultural capabilities and diversifying import sources. East and Southeast Asia have potential to mitigate food insecurity with enabling irrigation in the rainfed lands, conforming to the observation from Fig. 2(c), lying in tropical and subtropical regions. Countries with a higher percentage of food-insecure populations and a greater reliance on cereals for calorie intake are projected to have larger deficits. This emphasizes the urgency for targeted interventions to enhance food security through improved agricultural yields and food distribution policies.

3.3. Changes in CWU

The regions with higher Water Stress Score (WSS) and significant production deficits are of particular concern. In these regions, the additional water required for crop production could lead to over-extraction of water resources, affecting not only the environment but also other sectors. Fig. 3 illustrates changes in CWU with the expansion of irrigated areas and increased harvested areas, per the suggested hypothetical strategies. The presence of WSS alongside the CWU changes indicates that such increases in CWU could exacerbate existing water stress conditions. The current study has noted that the CWU increase varies significantly across different regions. For instance, in subplot (a), Central and Southern Asia, as well as North America and Europe, exhibit a higher increase in CWU under SSP585. Additionally, different climatic zones demonstrate distinct responses to the adaptation strategies. For example, in subplot (b), subtropical regions exhibit a more substantial increase in CWU than temperate regions under SSP585. SSP126, a more sustainable pathway, displays a lower increase in CWU, indicating that sustainable development can result in more efficient water use in agriculture. The adaptation strategies considered in the current study can lead to an increase in CWU. However, analyzing only the modifications in CWU cannot identify water stress for the regions. To have a better understanding of the impacts of such aggressive strategies to ensure food self-sufficiency at the subnational level, the changes in available renewable Blue Water (BW) resources.

3.4. Impact on water security

To draw focused analyses on water security, we estimate the available renewable freshwater resources, considering the implementation of two mitigation strategies, Strategies 1 and 2. The comparison of these strategies in terms of remaining freshwater availability (in 10^9 cu.m.) by changes in irrigation intensity is presented in Fig. 4. Subplots (a) – (f) show the distribution of residual availability of freshwater after implementation of both the strategies with three different SSPs ((a) and (b) for SSP126, (c) and (d) for SSP245, and (e) and (f) for SSP585). The paired box plots for different groups of countries ((a), (c) and (e)), and different

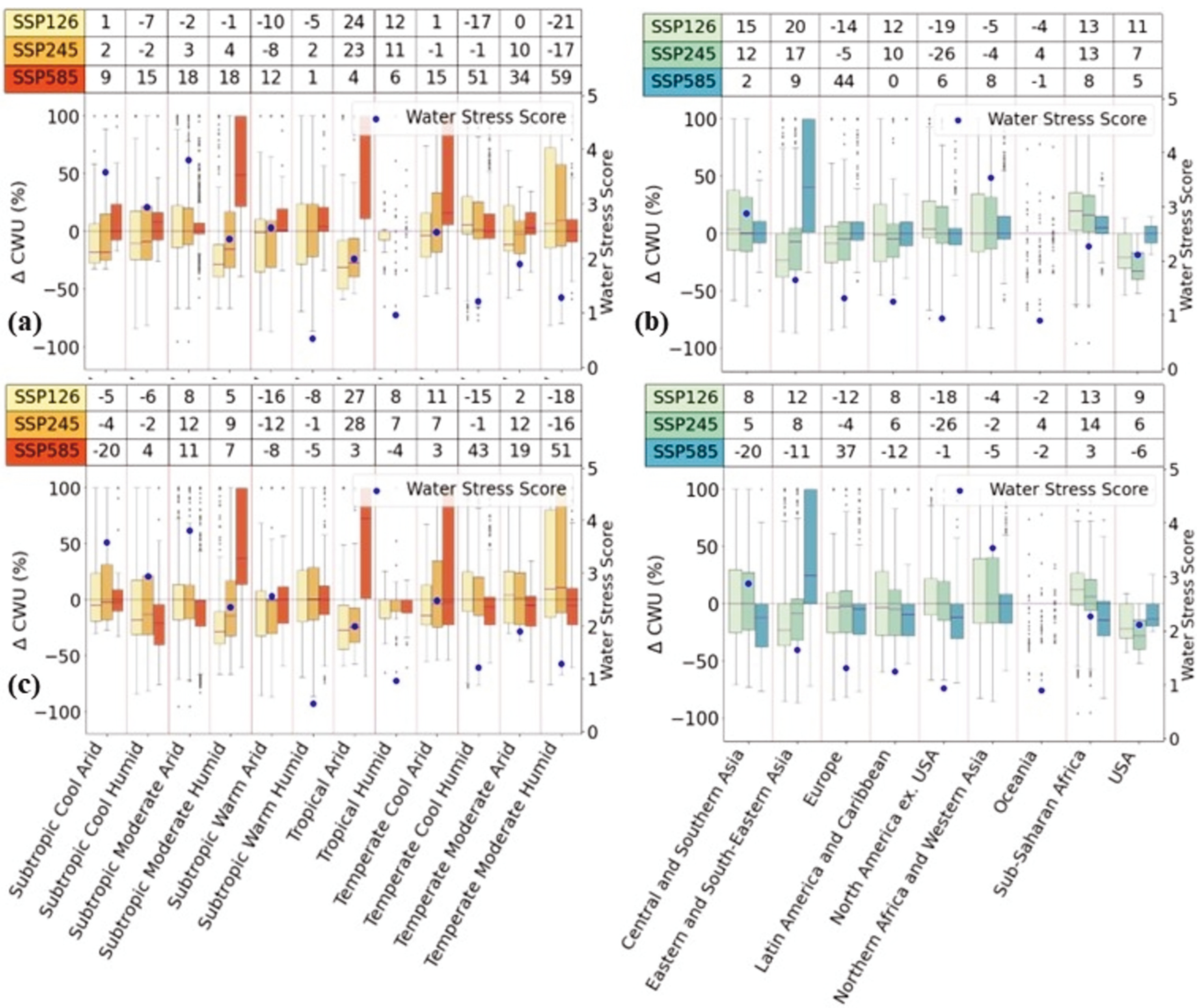


Fig. 3. Projected increase in Crop Water Use (CWU) in 2050 under different Shared Socioeconomic Pathways (SSP126, SSP245, and SSP585)– Classified into SDG Regions and Climatic Zones.
The subplots (a) and (c) shows the increase in CWU with Strategy 1 and 2 respectively, for different country groups. Similarly, the subplots (b) and (d) shows the increase in CWU with Strategy 1 and 2 respectively, for varied climatic zones.

climatic regimes ((b), (d) and (f)), are shown. The blue markers in each class indicate the WSS, which assesses the level of competition for and depletion of water resources.

Based on the plots (a) – (f) in Fig. 4, there is no significant visible variability in renewable freshwater availability for different emission scenarios. The analyses show that USA is in a relatively secure position concerning water stress. A national overview may not fully represent the localized challenges in these agriculturally intensive regions as significant regional disparities do exist that pose serious challenges to water sustainability, particularly in major agricultural zones. Regions with higher water stress, such as SSA and Central and South Asia, may encounter difficulties enhancing crop production due to the projected decrease in freshwater availability. Notably, subtropical and humid regions in temperate and tropical zones exhibit higher water stress. Nevertheless, tropical humid regions are projected to have sufficient freshwater in both strategies, enabling increased irrigation application sustainably. Subtropical moderate and cool arid, subtropical and temperate cool humid and subtropical moderate humid regions may face pressing challenges from freshwater scarcity. These regions are at risk of food insecurity by 2050.

4. Discussion

The regions have been classified based on the risk of insufficient availability of renewable blue water to mitigate cereal production deficit with altered practices. Subplots (a) and (b) in Fig. 5 show the Low and High Emission scenarios for the classification based on the percentage of deficit in cereal production (projected in 2050) and WSS, without any adaptation. After implementing the strategies, the WSS is projected by assuming a linear relationship with the remaining available per capita freshwater. The WSS and production deficit are classified in quantiles based on SSP126 projection (Table 2), and are also mapped on SSP585 scenario. Classification for the variables are: 0–25 %: 'low', 25–50 %: 'moderate', 50–75 %: 'high', 75–100 %: 'very high'. The intensity of risk is color-coded as follows: Red: 'critical', Orange: 'severe', Yellow: 'very high', Beige: 'moderate', Sky blue: 'low', Blue: 'very low', Dark blue: negligible. The tables below each subplot represent the area-weighted average of cereal production deficit for each class.

Algeria, Chad, Niger, Namibia, Sudan, South Sudan, and Somalia will be at 'critical' risk, with both WSS and cereal production deficit 'very high'. Apart from that, the western part of the USA (California, Utah), Western Australia, and Saudi Arabia will also be at 'critical' risk. Central Asian desert regions (Kazakhstan, Uzbekistan, Tajikistan, Kyrgyzstan)

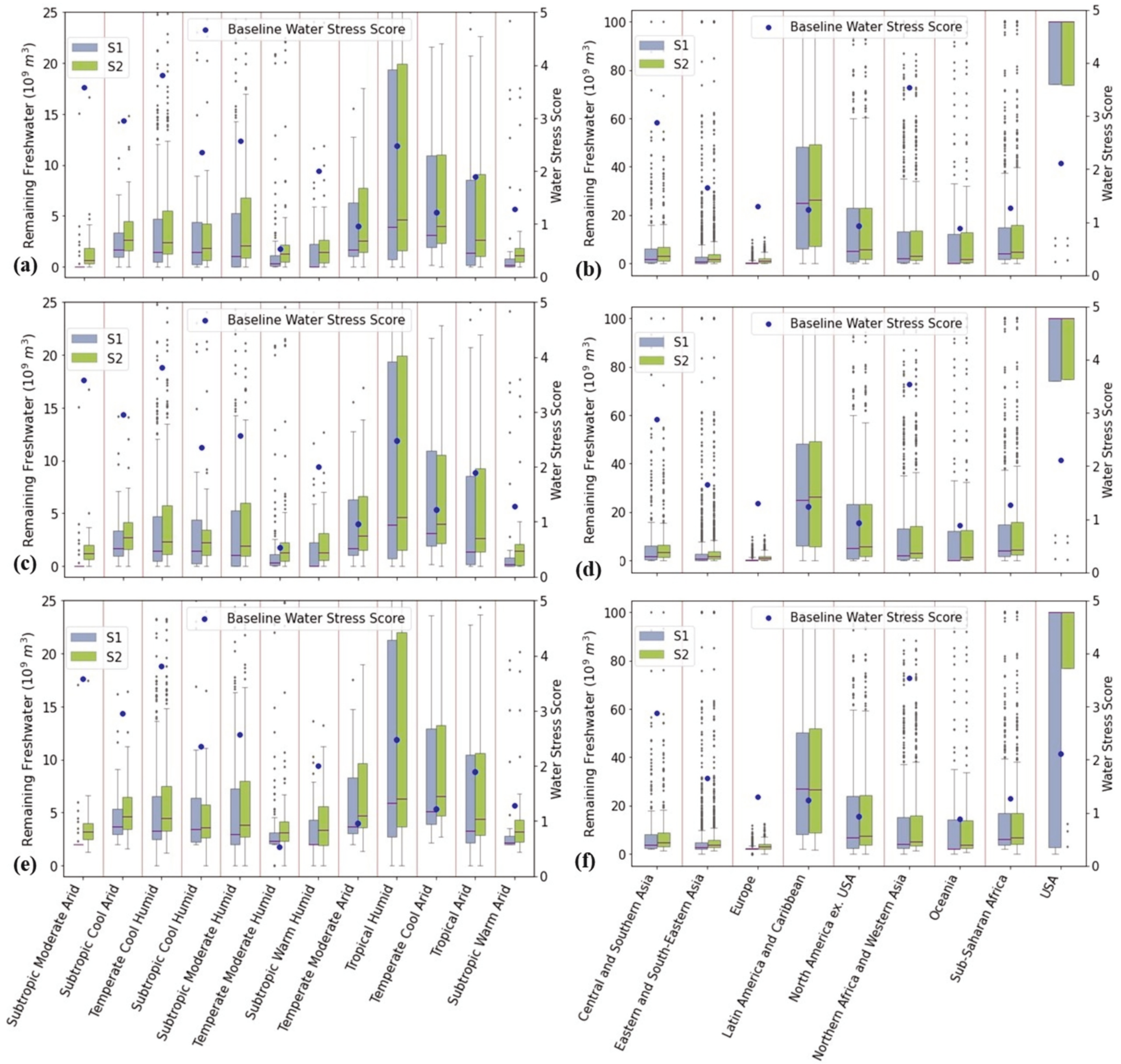


Fig. 4. Available renewable freshwater after irrigation enhancement under the hypothetical strategies, S1 and S2. (a) and (b): SSP126, (c) and (d): SSP245, (e) and (f): SSP585. (a), (c) and (e): classified as per SDG country groups. (b), (d) and (f): classified as per climate regimes.

and Southern Asia will be at 'severe' risk. Central India is also under this category, even in low-emission scenarios. Under SSP585 scenario, more parts of the world will be under high and very high risks of food insecurity (Fig. 5b). However, the proposed mitigation strategy in S2 can reduce the percentage of regions with 'critical' and 'severe' risk zones (Fig. 5c and d). Some regions in SSA, will still be under 'critical' risk. There is a substantial increase in the area with surplus production, even in SSP585. In SSP126, about 15 % of the world is projected to have surplus cereal production. Most areas with 'severe'-'very high' risk in existing situations are transformed into 'moderate'-'low' risk categories. The classification in the adoption of Strategy 1 is shown in Fig. S5 in SI.

We further extend the analyses on the percentage of area in each country to be under production deficit, not resolved even with strategic adaptation implementation. Figs. 6 and 7 display two maps each, that illustrate the projected area under production deficit and cereal import dependency ratios under SSP126 (Figs. 6(a)) and 7(a)) and SSP585 (Figs. 6(b) and 7(b)) for 2050, hypothetically implementing Strategy 1 and 2, respectively. The color coding indicates the percentage of area under production deficit, while the tables provide the area-weighted average of production deficit across different classes. The classes in import dependency and area under deficit are identified based on quantiles in SSP126 projection, (Table 3). The classification of zones is based on vulnerability to food insecurity (color-coded similar to Fig. 5). Regions with higher cereal import dependency and higher fraction of area under production deficit, tend to be more vulnerable to adverse impacts of climate change. Policymakers in regions with 'critical' or 'severe' vulnerability, need to diversify sources, improve agricultural practices, and invest in technology for adaptation.

Venezuela, South and North Korea, Laos, Vietnam, and Iran are most vulnerable with a higher percentage of area under production deficit

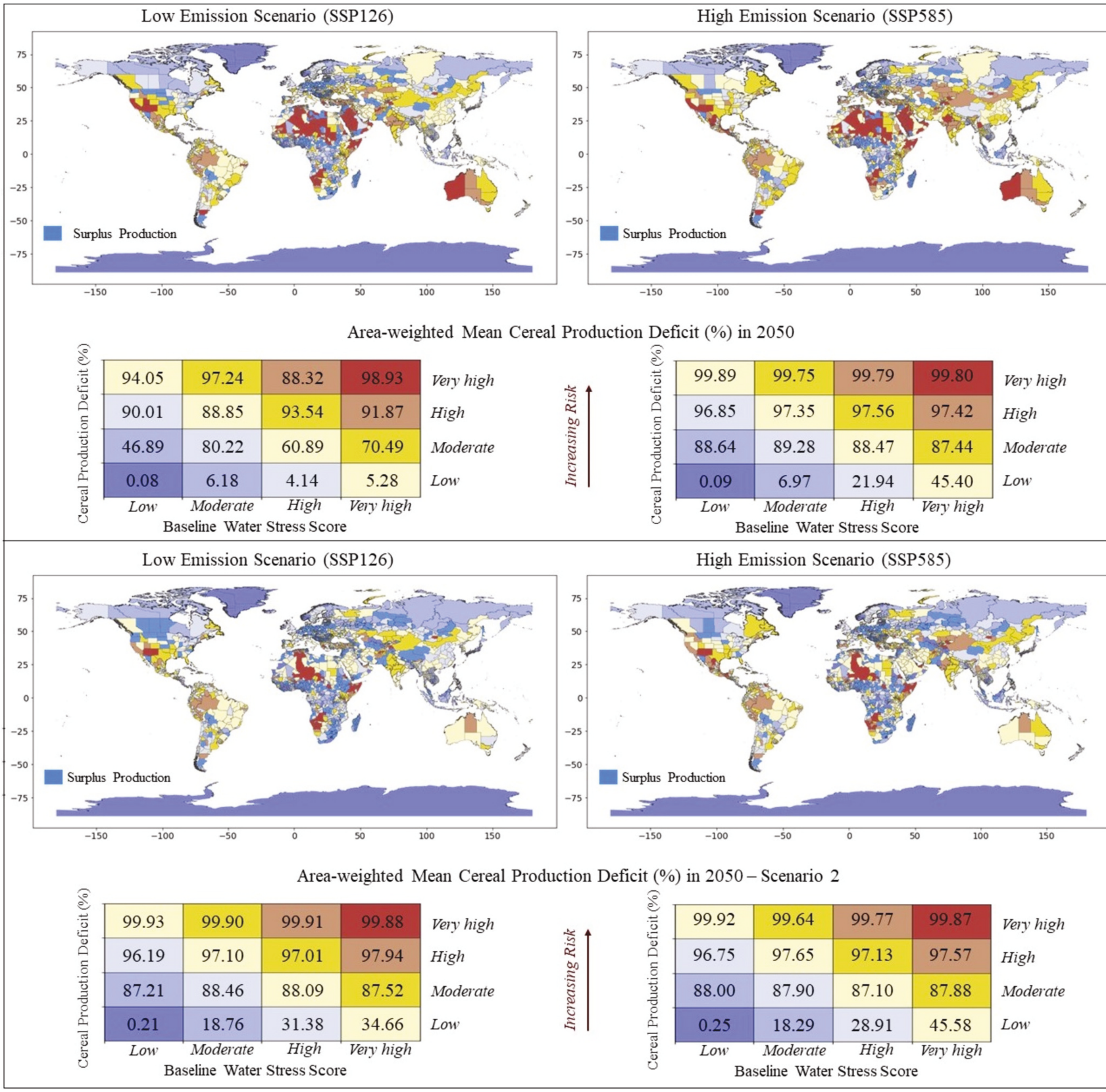


Fig. 5. Classification of subnational units based on Percentage of deficit in cereal production (projected in 2050) and Baseline Water Stress Score. The tables below the plots give the area-weighted average values for the Cereal Production Deficit for each class.
The classification for projection without any adaptation strategy for Low Emission Scenario (SSP126) and High Emission Scenario (SSP585) are shown in (a) and (b) respectively. Similarly, the same is represented in (c) and (d) plots with the implementation of Strategy 2 for Low Emission Scenario (SSP126) and High Emission Scenario (SSP585), respectively.

Table 2
Quantile values for classification based on Production Deficit and Water Stress Score (WSS).

Percentiles	Cereal production deficit (%)	WSS
0.25	80.55	0.33
0.50	93.65	1.27
0.75	99.22	2.81

and higher import dependency. Saudi Arabia, Bolivia, and parts of SSA may also face challenges in feeding the population with high import dependency and deficit in production. In SSP585, the mean production deficit in several classes is less, but the percentage of areas with higher vulnerability is more worldwide. The situation is more severe in SSP585, with a larger number of countries in Africa and central Asia falling into 'high' to 'very high' vulnerable categories. In countries with less area under production deficit, the surplus (negative values in the tables) production also is reduced in SSP585. Notably, most of Europe and North America are safe in terms of being vulnerable to food and water security (even without increasing harvested area: Fig. 6).

5. Conclusion

Conversion to agricultural land (Strategy 2), though beneficial in solving food insecurity, leads to significantly higher water stress in

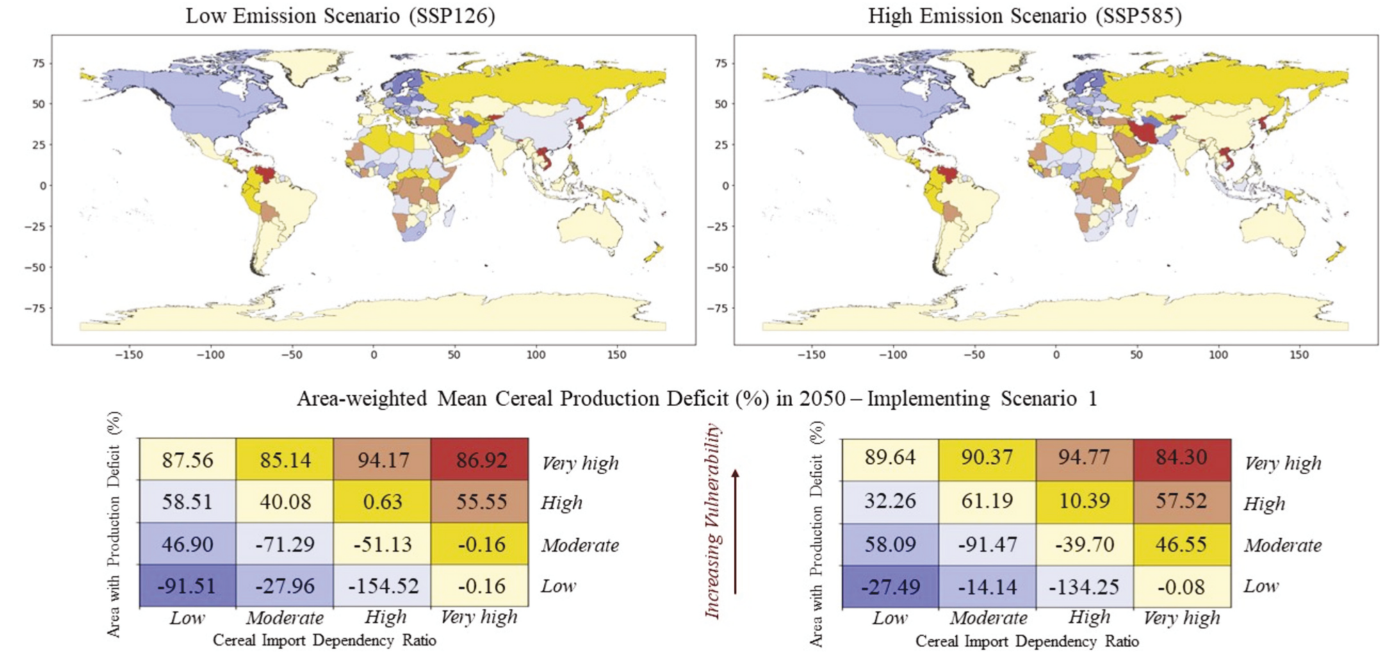


Fig. 6. Classification of countries based on the percentage of area still under cereal production deficit with the implementation of Strategy 1 (projected in 2050) and the Cereal Import Dependency Ratio (%). The tables below the plots give the area-weighted average values for the Cereal Production Deficit for each class. The classification for projection for Low Emission Scenario (SSP126) and High Emission Scenario (SSP585) are shown.

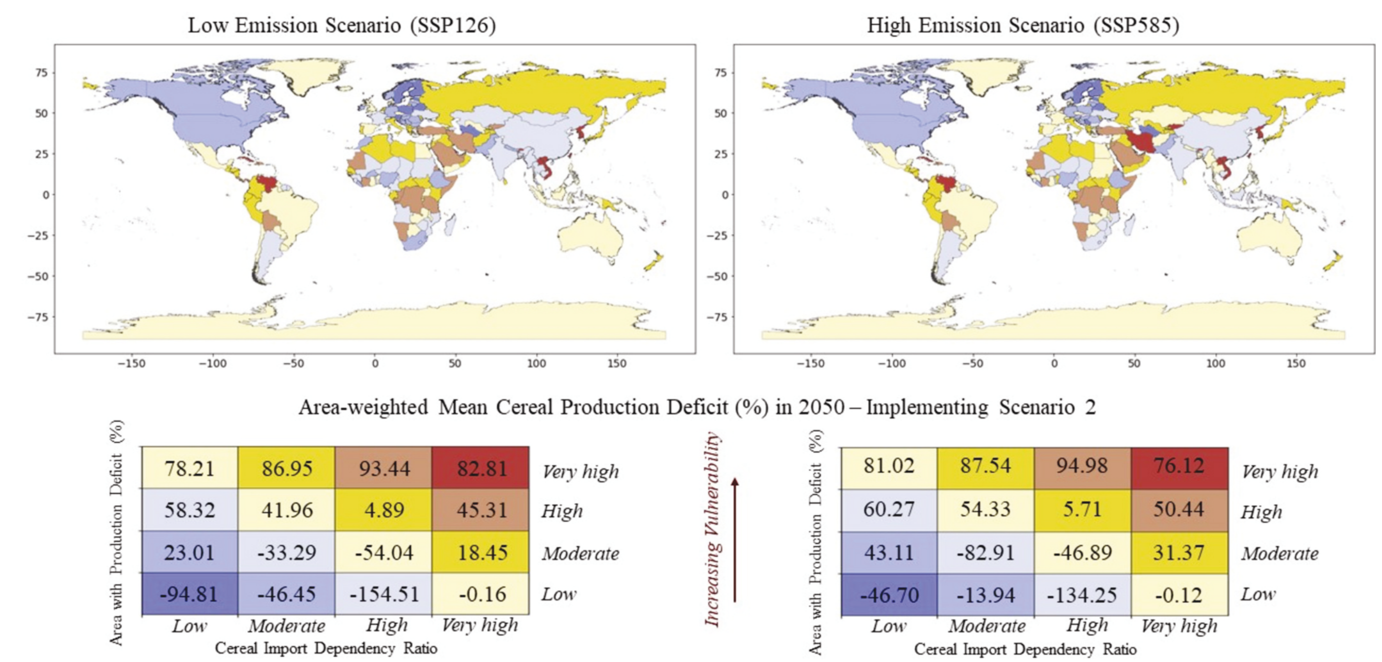


Fig. 7. Classification of countries based on the percentage of area still under cereal production deficit with the implementation of Strategy 2 (projected in 2050) and the Cereal Import Dependency Ratio (%). The tables below the plots give the area-weighted average values for the Cereal Production Deficit for each class. The classification for projection for Low Emission Scenario (SSP126) and High Emission Scenario (SSP585) are shown.

Table 3
Quantile values for classification based on Area under Production Deficit after implementing S2 and Import Dependency.

Percentiles	Area with cereal production deficit (%)	Import dependency ratio (%)
0.25	2.59	18.68
0.50	63.06	64.45
0.75	96.80	100

certain regions. Regions with already high WSS may not be able to support further water-intensive practices sustainably. The analyses indicate that by 2050, regions with high to very high cereal import dependency ratios are likely to experience significant cereal production deficits under both low (SSP126) and high emission scenarios (SSP585). Implicitly these regions may face increased food insecurity and potential socioeconomic impacts. Even regions with low import dependency are not immune to the effects of climate change on cereal production.

Reducing emissions could mitigate the severity of cereal production deficits and, consequently, the vulnerability of dependent regions. However, intensified agriculture, needed to meet food demand, will likely lead to biodiversity loss and increased carbon emissions. Despite these challenges, cropland expansion is projected to continue globally to meet the food demand of a growing population(Ray et al., 2022; Wise, 2013). Strategic policies are crucial for addressing food production and import dependency challenges, especially in the identified vulnerable areas. Adopting sustainable agricultural practices, improving water management, and increasing investments in agricultural infrastructure to achieve higher yields with minimal cropland expansion are necessary steps. Diversifying food sources, enhancing agricultural practices, and investing in adaptive technologies are key priorities. Switching to less water-intensive crops is one among several promising strategies for enhancing agricultural sustainability, particularly in regions experiencing significant water stress. While this study focused on major cereal crops due to their pivotal role in global food security, transitioning to crops that require less water could significantly reduce agricultural water consumption and alleviate the pressures of water scarcity. However, the success of crop switching depends on a range of factors, including local agronomic conditions, market demand, and socioeconomic contexts. Less water-intensive crops may not always match the nutritional value or economic return of staple crops, and thus, their adoption must be supported by agricultural policies, market infrastructure, and farmer education to prevent unintended negative consequences, such as reduced food availability or economic instability.

In addition to crop switching, other sustainable yield-enhancing methods deserve attention. For instance, precision agriculture can optimize resource use, improve crop management, and increase yields while minimizing environmental impact. Conservation agriculture, which emphasizes minimal soil disturbance, permanent soil cover, and crop rotations, can enhance soil health, reduce erosion, and improve water retention, leading to more resilient agricultural systems. Additionally, integrating agroforestry practices, where trees and shrubs are grown alongside crops, can provide multiple benefits, including enhanced biodiversity, improved soil fertility, and better water management. While these methods offer significant potential, region-specific research is essential to fully understand their viability across different climates, soils, and cropping systems. Such research is crucial to tailoring these approaches to local conditions, ensuring they contribute effectively to sustainability goals. Investigating these approaches, alongside crop switching, as part of an integrated strategy is essential for advancing agricultural sustainability and food security in the face of climate change and growing global demands. In regions with high water stress levels, it is critical to balance the sustainability of water resources with agricultural output to ensure long-term food security. Another limitation of our study is the absence of bias-corrected climate model datasets, which could have provided more precise projections. Future studies can benefit from postprocessing or bias correction (Khajehei and Moradkhani, 2017; Khajehei et al., 2017) or using a Bayesian model averaging of different climate models to more formally address the model uncertainty (Madadgar and Moradkhani, 2014; Abbaszadeh et al., 2022).

CRediT authorship contribution statement

Adrija Roy: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Mesfin Mekonnen:** Writing – review & editing, Visualization. **Hamed Moftakhari:** Writing – review & editing, Supervision, Funding acquisition. **Nicholas Magliocca:** Writing – review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known conflict/competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors acknowledge the financial support provided by the National Science Foundation (NSF-INFEWS) (Grant EAR-1856054).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.176811.

Data availability

Data will be made available on request.

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