Agricultural Water Management 269 (2022) 107693

Contents lists available at ScienceDirect

Agricultural Water Management

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

Understanding implications of climate change and socio-economic development for the water-energy-food nexus: A meta-regression analysis

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ARTICLE INFO

Handling editor - Dr R Thompson

Keywords:
Water-energy-food nexus
Meta-analysis
Future prediction
Water withdrawals
Food yield

ABSTRACT

In recent years, the impacts of climate change and socio-economic development on the water-energy-food nexus have been a hot topic. Forecasting future food and energy production and water withdrawal trends under a range of climate and socio-economic scenarios is a critical step for formulating agricultural, industrial, and environmental policy. However, published studies are imprecise due to the complexity of the changeable environment and nexus system. Here we conducted a systematic review and meta-analysis based on 97 studies (1253 observations) published before September 2021 to evaluate the effects of climate change factors on food yield and irrigation water, as well as the influence of socioeconomic development on energy production and water withdrawal. The study shows that the most serious impact of climate change on food yield occurred under the RCP8.5 scenario, with an average decrease of 1.73%, 4.17% and 4.56% in the 2020s, 2050s, and 2080s, respectively. Similar to the prediction of food yield, the irrigation water requirement of food production under the influence of climate change in the RCP8.5 scenario (12.22–18.01%) is higher than that in RCP4.5 and RCP2.6. Under the five socio-economic future scenarios, the average energy generation is projected to increase from 77.41 EJ (2010) to 334.11 EJ (2100). Water withdrawals for electricity generation range from 347 km^3 (SSP1) to 1263 km^3 (SSP5). Population and GDP were significantly and positively correlated with power generation and water withdrawal ($P < 0.001$). To some extent, increases in CO_2 concentration and precipitation could compensate for the negative impact of rising temperatures on food yield. Climate change, as well as economic and social growth, will provide substantial challenges to the future water-energy-food nexus. In particular, the water resource risk at its core will create significant uncertainty in the future water-energy-food nexus. To ensure the security and stability of the nexus, we advocate for quick adoption of innovative technologies as well as a multi-sectoral, coordinated strategy for adaptation. We believe that the findings of this paper will provide effective and reliable data support for future policy formulation.

1. Introduction

Global water, energy, and nexus (WEFN) are highly interconnected (Wichelns, 2017). Nexus is driven and constrained by both climate change and socio-economic development (Bhaduri et al., 2015; Biggs et al., 2015). Population growth, urbanization and economic development have aggravated the shortage of global nexus resources. It is expected that by 2050, the global demand for food and energy will increase by 60% and 80%, respectively (Ferroukhi et al., 2015). More critically, Stockholm Environment Institute (SEI, 2015) pointed out that "available water" was the core element of the "nexus". Climate change has greatly affected the availability of water resources, which has become a critical constraint for food and energy production. It is estimated that climate change and water shortages will leave 120 million people undernourished (Schmidhuber and Tubiello, 2007). In addition to water constraints, the energy system is also driven by population,

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https://doi.org/10.1016/j.agwat.2022.107693
Received 5 February 2022; Received in revised form 11 April 2022; Accepted 2 May 2022
Available online 13 May 2022

economic growth and structural change. Therefore, to ensure WEFN security and mitigate the impact of uncertainties such as climate change and population expansion, we need to further explore the following three questions: (1) How will climate change affect food yields and irrigation water in the future? (2) What is the response of energy production and water withdrawal to economic society? (3) What are the key drivers the WEFN faces in a changing environment?

Studies have quantified the impact of future climate change on food yields and irrigation water, and a variety of methods have been applied. Among them, crop models were the most widely used (Araya et al., 2015; Chenu et al., 2017). Compared with other methods, crop models can effectively simulate the physiological process of crop production at each development stage and evaluate the changing trend of crops under climate change scenarios. But in fact, discrepancies in scenarios, study areas and methods contributed to the variability of the existing research findings. The distinction is not only numerical but also in opposite directions. A global assessment has found that food yields will increase in the future (Tian et al., 2021). However, Deryng et al. (2011) stated that future climate change might diminish yields. Some studies in North America anticipated that yields would fall in Mexico (Kai, 2018), Oklahoma (Rasoulzadeh Gharibdousti et al., 2019) and Canada (Brassard and Singh, 2007). But several other studies in Mexico (Murray--Tortarolo et al., 2018), the United States (Johnston et al., 2015) and Canada (Qian et al., 2016) have forecast an increase in food yields. Food irrigation water use is expected to grow in China (Zhao et al., 2014) and Iran (Ahmadi et al., 2021) as a result of climate change, while another study in the United States predicted a decrease in water use (Johnston et al., 2015). The same is true for energy production projections. Taking electricity generation as an example, while scholars predict that electricity generation and water withdrawal will increase under various SSPs scenarios, the values of different studies fluctuate significantly. For example, Graham et al. (2018) anticipated 950 km^3 of water withdrawal for electricity generation under the SSP5 scenario by 2100, while another study predicted 1942 km^3 (Ando et al., 2017).

Despite the fact that studies have predicted the effects of climate change and socio-economic factors on the WEFN or the nexus subsystem, the disparities in prediction results create challenges for decision-makers to pick a choice. Given the increasing concerns about the security of the WEFN. This study intends to standardize the impacts of uncertain elements (climate change and socio-economic factors) on prediction results by constructing a meta-regression model, as well as explain the causes for the disparities in prediction results. Meta-regression analysis (MRA) is a valuable method for summarizing results and assessing consensus in the literature (Stanley and Jarrell, 2005; Thompson and Higgins, 2002). It emerged from meta-analysis and remains primarily a regression analysis method, but its strength is in its capacity to systematically explain a complex set of underlying factors that may influence dependent variables (Loomis and White, 1996). Therefore, MRA can recount the results of multiple studies on the same research topic and identify the sources of heterogeneity (Baker et al., 2009; Gurevitch et al., 2018). Meanwhile, the application of MRA can avoid some of the deviations in the original literature. While similar studies are being conducted to assess the impact of climate change on crop yield (Wilcox and Makowski, 2014), food demand (van Dijk et al., 2021), crop water efficiency (Fan et al., 2018) and energy demand (Menegaki, 2014). There have been few studies on MRA from the perspective of WEFN, especially the comprehensive influence of climate change and socioeconomic factors on WEFN.

In the framework of MRA, this study attempts to synthesize peer-reviewed findings. Food yields, irrigation water, energy production, and water withdrawal were forecasted under changing environmental conditions. The implications of climate change and socio-economic development were also considered. In this paper, potential future WEFN challenges and corresponding countermeasures are proposed to provide support for ensuring WEFN collaboration security.

2. Materials and methods

2.1. Literature identifying and screening

To select relevant studies on future global food (grain), energy (electricity) production and water use projections, we identify review questions, search strategies and inclusion/exclusion criteria following the systematic review guidelines developed by EPI-Centre. We asked: What are the global trends in food and energy production, as well as water use, up to the year 2100? What are the driving elements influencing their evolution? Based on the above questions, this study combined two search engines: Web of Science and Google Scholar. A systematic search strategy for identifying peer-reviewed and gray literature was devised. In searching the peer-reviewed literature, the keywords used in various combinations were "wheat, rice, corn, maize, electricity, electric power, yield, generation, climate change, economic development, future population, water demand, irrigation water requirement, water withdrawal, etc."; details are given in Appendix A1. No time period was set for this search so all relevant publications through September 27, 2021, were selected. 35,142 papers were retrieved from Web of Science and 86,201 papers from Google Scholar. We extracted the top 500 relevant results from Google Scholar for screening. After removing duplicates, 35,485 related references were selected.

We used the following criteria for screening: (1) Exclude publications that are unrelated to wheat, corn, rice, electricity and water requirements, i.e., articles that focus on other crops or energy products. (2) Only quantitative evaluation was included. (3) Articles that restrict the quantitative study to specific historical years should be excluded. (4) For electricity generation studies, the focus of this review is on global studies and therefore country and regional studies will be excluded. However, for the studies of food production, the statistics in this paper are not limited to worldwide data, thus there is no need to exclude them. (5) Relevant data can be extracted or calculated from the publication, and the data contains at least one variable, such as temperature, precipitation and population. Specific data screening principles can be found in Appendix A2. If there are multiple climate scenarios, time scales or crop varieties in the same study, these results are extracted as independent samples.

In the literature screening, the first reviewer will screen the entire text of the studies that have been identified as relevant after initially reviewing the titles and abstracts. The studies under review will be assessed by a second reviewer if there is any doubt during the screening process. If needed, the research teams will discuss the details of the studies. After screening, 97 research studies (1253 observations) met the selection criteria (Fig. 1), with detailed information summarized in Appendix A3.

2.2. Data extraction

In this study, the percentage change of grain yield and irrigation water requirement, electricity generation and water withdrawal during power generation were selected as indicators to explore the trend of WEFN in the future changing environment. The following information is systematically extracted from the screening results: basic information of the article (author, institution, and published year), study area, forecast year and baseline, model method, forecast scenario (such as SRES, RCP, SSP, or others), percentage change in grain yield and irrigation water requirement, global electricity generation and water withdrawal during power generation. This database will be the foundation for descriptive analysis. Temperature, precipitation, and CO_2 concentration all have an impact on grain yield and irrigation requirements in a changing climate. Global electricity generation will be influenced by GDP and population increase. In order to find explanatory variables that might influence the response of food and energy to changing environment, this study extracted driving variables corresponding to each observation sample

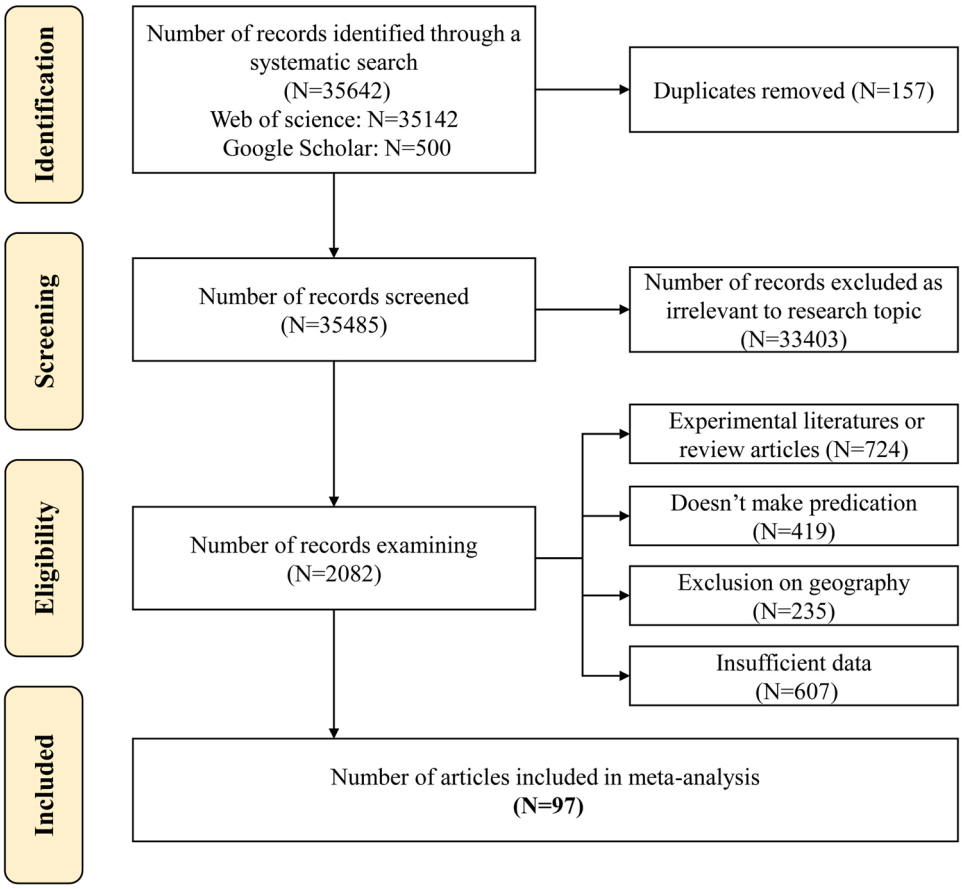

Fig. 1. Flow diagram of the literature search and study selection process.

from the collected studies. However, at least one of these variables was missing in many studies, so the full sample observation value (restricted dataset) corresponding to these variables was 598 (Table 1). We used the restricted dataset to establish a meta-regression model.

Note* : Many studies contain more than one variable; thus, the sum of the literature is 97 rather than 110.

2.3. Meta-regression analysis

A mixed-effects model is one in which the independent variables have both fixed and random effects (Fox and Weisberg, 2018). Fixed effects are essentially predictor variables. This is the effect of interest after considering random variability. And random effects are described as noise in the data. These are effects caused by uncontrolled variability within the sample. In this study, based on the lmerTest (Kuznetsova et al., 2017) and lme4 (Bates et al., 2014) packages of R (v.4.1.2), a linear mixed-effect model was constructed to identify the driving factors of food, energy production and water requirement trends. The mathematical formulation of its model is

$$Y_i = \beta_0 + \beta_1 X_{1i} \cdots + \beta_p X_{pi} + \alpha_0 z_{1i} \cdots + \alpha_p z_{pi} + \varepsilon$$

where Y_i denotes the dependent variable; β_0 is the intercept; $\beta_1 \cdots \beta_p$ are the fixed-effect coefficients; and $X_{1i} \cdots X_{pi}$ are the fixed-effect regressors. $\alpha_0 \cdots \alpha_p$ are the random effect, and $z_{1i} \cdots z_{pi}$ are the random-effect regressors, and ε is residual error random term.

We estimated separate linear mixed models for each of the four indicators. For electricity generation and water withdrawal, the fixed effects in the model are population and GDP, while the random effects comprise prediction models and future SSP scenarios. The fixed effects for food production and irrigation water requirements include average temperature change, precipitation change and carbon dioxide concentration change. Random effects include prediction models, study sites, climate scenarios and crop categories.

Table 1
Summary of the database for meta-regression analysis.

	Number of publications	Number of observations	Number of restricted datasets
Food yield	80	746	406
Water requirement for food yield	16	324	65
Electricity generation	5	70	52
Water withdrawal for electricity generation	9	113	75
Total	97	1253	598

3. Results

3.1. Overview of studies

We ultimately selected 97 publications for meta-analysis. The number of studies has increased dramatically during the last 20 years, and related research has been expanded (Fig. S1). Especially after 2014, the issues of "food security", "energy security" and "water shortage" have attracted people's attention, triggering academics to debate future food yields, energy production and water use (Fig. 2). Most studies used models to simulate the future water-energy-food change trend, and the DSSAT model is the most widely used (n = 37, Fig. S2). This model has been utilized in more than 100 countries around the world for over 20 years and has been applied to the simulation of the crop growth process

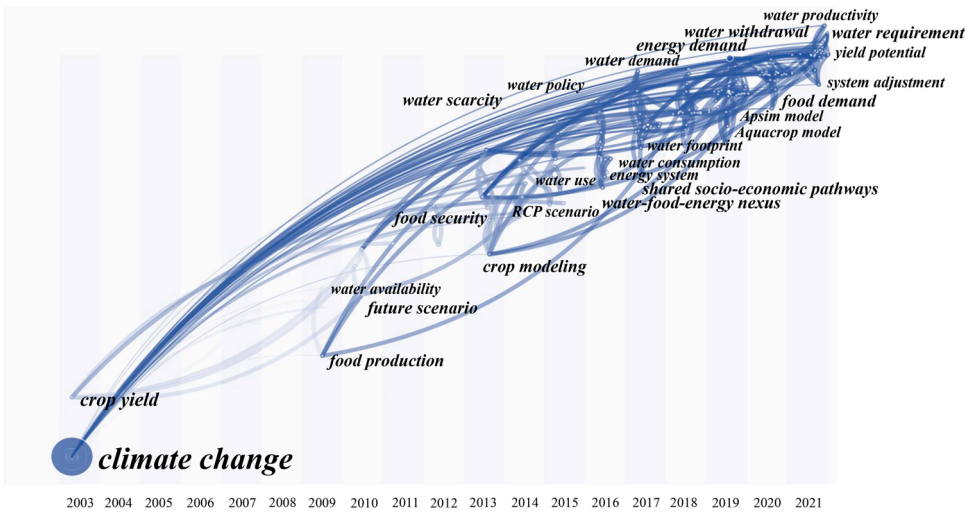

Fig. 2. Time zone chart of From 2003–2021. From 2003 to 2021 the color of keyword links becomes darker. And node size is correlated with the keyword occurrence frequency.

for a long time (Patel et al., 2017). As a sub-module of the DSSAT model, CERES series models have been updated and widely used to evaluate the influence of climate change on crop yield (Timsina and Humphreys, 2006;). In addition to the DSSAT model, it also includes the APSIM, AquaCrop, ORYZA, AIM/CGE model and PRECIS models. Thereinto, the AIM/CGE model is mainly applied to forecast the future production of energy.

To further explore the change characteristics of the selected literature research topics, this study obtained the time zone map of keywords based on Citespace5.7. R2 software (Chen, 2014). Its development can be summed up in two stages. The first period lasted from 2003 to 2014. Related research was in the preliminary stage, and there were few publications and keywords. This stage primarily forecasts the trend of crop yield change in the context of climate change. The concept of water, energy, and food nexus was formally proposed at the Bonn conference in 2011, and FAO expanded on it in terms of food security in 2014, raising concerns regarding related issues. Subsequently, relevant studies entered the development stage from 2015 to 2021. In the second stage from 2015 to 2021, the number and content of keywords are more abundant than in the previous stage. With the proposal of the concept of WEFN, scholars no longer focus only on the development trend of food yields, but gradually launch research directions such as "water demand" and "energy demand". Meanwhile, as future scenarios, the terms "RCP scenario" and "common socio-economic routes" were frequently employed. Comprehensive analysis shows that its research scope and methods have been enriched, and the WEFN has become a research hotspot. However, as this study only conducts keyword analysis on the 97 studies obtained in the final screening, the results are more targeted at the relevant studies that meet the screening conditions of this study.

The collected data related to energy in this study is global scale, so the study area is not analyzed. However, food yield forecasts are often affected by temperature and precipitation. The assessment scales are smaller. In this study, the number of food yield datasets in different regions of the final selected literature was counted. Fig. 3 shows that the

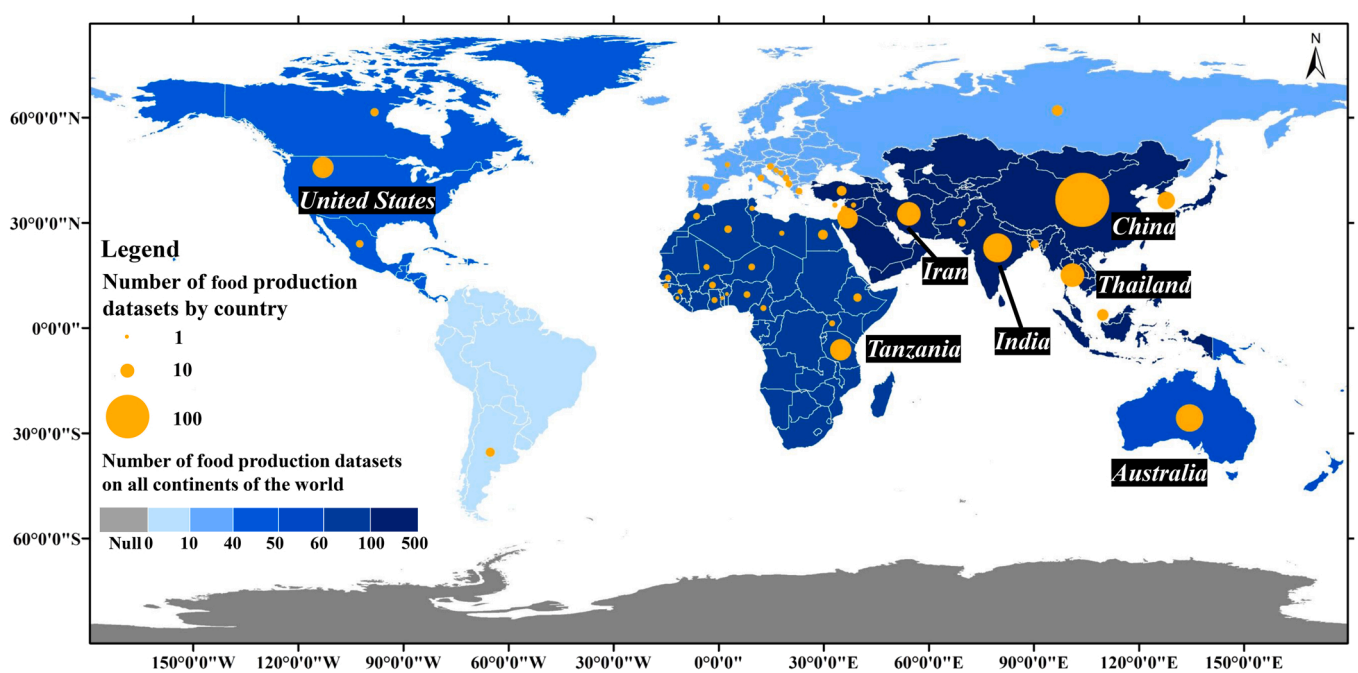

Fig. 3. Map of the number of country scale food production datasets.

datasets are mainly concentrated in Asian countries, especially China (234 observations, 31.79%) and India (66 observations, 8.96%). The number of datasets was much higher than those of other regions. One of the main reasons is that as China and India are the most populous countries in the world, changes in food production will have a significant impact on local food security. Secondly, from the perspective of data collection, the data of Chinese and Indian literature are more comprehensive and easier to obtain. Aside from Asia, Africa's unique geographical location makes its food production vulnerable to drought and extreme weather. Furthermore, as one of the most food-insecure states in the world, Africa has attracted the interest of academics. The number of datasets in this region is second only to that of Asia, accounting for 13.17% of the total. The United States, as the world's largest food producer, produces 40% of the world's corn (Karlen et al., 2012). Scholars are concerned about the future food production capacity of the United States. We finally extracted 44 observations from the United States datasets. It can be found that hot spots are areas with prominent food security or significant contribution to food production.

3.2. Projections of global food yield and irrigation water use

Considering all RCPs scenarios, future food yield declines by 1.82%, with confidence intervals ranging from − 0.81% to − 2.83%. The magnitude of the yield change generally increases with time: − 2.28% and − 2.62% of average yield change in the 2050 s and 2080 s, compared with − 0.27% for the 2020s (Table 2). For the second half of the century, more systematic and aggressive adaptation to climate change impacts may be required to avoid food security risks caused by significant declines in average food yields.

Note* : n is the number of observations; 95% CI stands for 95% confidence intervals.

Given that different crops respond depending on various climate scenarios, we extracted yield change trends of different crops (wheat, maize and rice) under various climate change scenarios over multiple periods (2020 s, 2050 s and 2080 s) (Fig. 4). The declining trend of maize (−3.89 ± 3.25%) was greater than that of wheat (−0.93 ± 4.41%) and rice (−1.05 ± 4.81%). This is mainly due to the higher water demand of maize and its tendency to grow without irrigation, making it more sensitive to climate patterns. Heavy irrigation of wheat in countries such as China and India explains the milder effects of weather patterns. Unlike wheat, rice yields are less affected by climate change than maize yields because rice is typically grown in water-rich areas, so precipitation is less limiting to rice production than maize. Anderson et al. (2019) also discovered that maize is the crop most vulnerable to failure due to climate change. 18% of the annual change in maize yield is the result of climate variation, while the wheat yield reduction caused by climate variation only accounts for 6% of the global total yield change. This conclusion also confirms our findings.

Variability in yield changes under different climate scenarios due to variable levels of projected climate change. According to ur Rahman et al. (2018), the RCP8.5 scenario has more effect on climate than other RCPs. Our research also found that the RCP8.5 scenario had the most serious impact on food yield, with an average decrease of 1.73%, 4.17% and 4.56% for the 2020s, 2050s and 2080s, respectively. In RCP 4.5, climate change would increase food yield by 1.23%, 0.23% and 0.07% in the 2020s, 2050s and 2080s, respectively. This result is due to the greater degree of warming under the RCP8.5, with higher temperatures negatively impacting food production. Baek et al. (2013) showed that compared to 1986–2005, the temperature increased by 4.6 ℃ in the RCP 8.5 scenario at the end of the 21st century (2081–2100), while the temperature only increased by 1.4 ℃ and 2.6 ℃ in RCP 2.6 and RCP 4.5 scenarios, respectively. Especially under the RCP 2.6 scenario, global temperature changes tend to be flat at the end of the 21st century. The disparity in results between the RCP4.5 and RCP8.5 scenarios emphasizes the importance of developing feasible GHG emission policies.

Table 2
Model predictions of food yield change.

Forecast type	n	Mean	95% CI
Food yield change	746	-1.82%	-0.81% to − 2.83%
2020 s	203	-0.27%	1.33% to − 1.88%
2050 s	354	-2.28%	-0.76% to − 3.80%
2080 s	189	-2.62%	-0.42% to − 4.82%

Globally, agriculture is a major user of water. According to statistics, water withdrawal for food has increased 7.3 times in the past century (FAO, 2014). The future increase in irrigation water requirements for food production, combined with the effects of climate change, will exacerbate global water scarcity. Fig. 5 depicts the evolution of crop irrigation water requirements with time (ranging from the 2020 s to the 2080 s) and different RCPs. It can be found that the irrigation water requirements will become prominent over time. The effect of climate change on irrigation water requirements for food production under the RCP8.5 scenario (12.22–18.01%) is higher than that under the RCP4.5 (9.43–17.02%) and RCP2.6 scenarios (6.65–15.54%). This is also consistent with the forecasts for food production.

3.3. Projections of global energy generation and water withdrawal

SSPs describe five plausible future worlds that are defined by narrative storylines and quantitative information and can be characterized by two indices, socio-economic challenges for adaptation and mitigation (Riahi et al., 2017). For example, SSP1 is characterized by low levels of socioeconomic challenges in both mitigation and adaptation, implying a reasonably optimistic perspective of future climate change conditions. Smaller populations, faster economic growth, more advanced energy technologies, and a variety of other variables all support this viewpoint. SSP3, on the other hand, is marked by a high level of mitigation and adaptation challenges. Therefore, SSP1 has the lowest population, with an estimated 7 billion people by 2100, and SSP3 has the largest population, with 12.6 billion people. In SSP4, there is strong income inequality and high adaptation challenges. SSP5 has the fastest economic growth, with global GDP expected to reach 1014 trillion US $2005 in 2100, whereas SSP2 is in the middle of the other four scenarios.

Based on the meta-analysis method, this study integrated and compared the predicted ranges of energy production and water withdrawal by scholars, and mapped them to SSPs for further analysis. The results show that if all SSPs are considered, average electricity generation is expected to increase to 334.11 EJ by 2100. Furthermore, all SSPs project an increase in electricity generation in comparison with the 2010 levels, but the magnitudes of these increases vary (Fig. 6). Under the fossil-fueled rapid growth scenario (SSP5), electricity generation will peak at 482.67 EJ in 2100, a 5.24-fold increase over the base year. Following that is the future world characterized by inequality (SSP4) and business-as-usual development (SSP2), with electricity generation reaching 320.44 EJ and 318.51 EJ in 2100, respectively. However, under the regional rivalry (SSP3) and sustainability scenarios (SSP1), the increase of electricity generation is low. Especially under the SSP1 scenario, the increase tends to moderate after 2075.

Water withdrawal of electricity generation in 2100 ranged from 347 km^3 (SSP1) to 1263 km^3 (SSP5). In the SSP1 scenario, advancements in water withdrawal technology mitigate the increasing trend of water withdrawal for electricity generation, with water withdrawal for electricity generation declining from 2010 to 2100. Furthermore, by comparing generation withdrawals under two scenarios with no and maximum water use efficiency improvements, Bijl et al. (2016) found that improving water use efficiency can reduce water withdrawal by 40%. In addition, a study by Graham et al. (2018) showed that, in the same scenario, technological advancements would significantly reduce water withdrawal. However, for the SSP5 scenario, although the improvement of WUE restrains the increase in water withdrawal, it remains the largest due to the rapid growth of GDP and power generation.

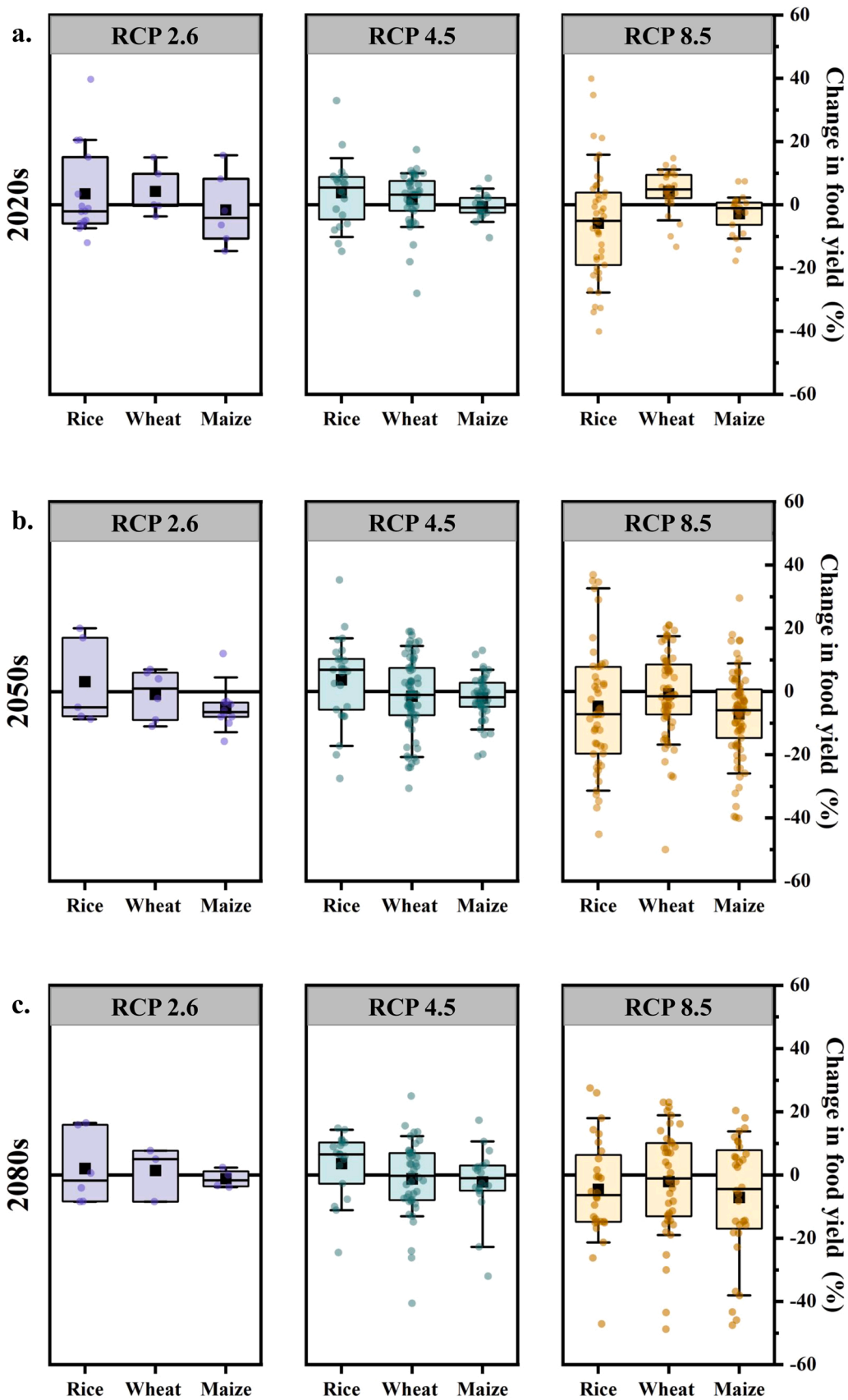

Fig. 4. Boxplots of yield change in 2020s (a), 2050s (b) and 2080s (c). The colored box in the figure indicates the center 50% of the group data distribution interval, the middle line is the median, and the upper and lower ends of the box are the upper and lower quartiles. The upper and lower whiskers are the maximum and minimum values after removing all outliers. ■ in the figure indicates the mean value.

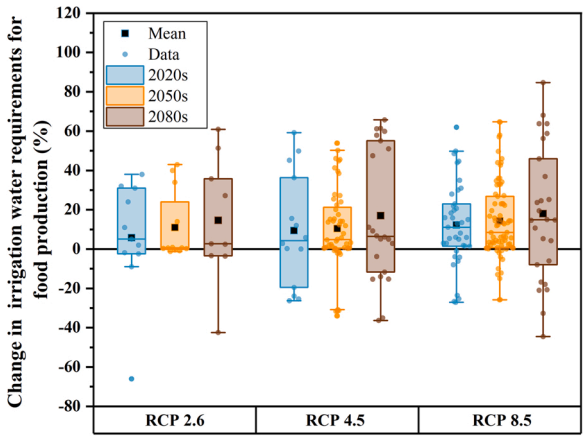

Fig. 5. Boxplots of the changes in irrigation water for food production in 2020s, 2050s and 2080s. The colored box in the figure indicates the center 50% of the group data distribution interval, the middle line is the median, and the upper and lower ends of the box are the upper and lower quartiles. The upper and lower whiskers are the maximum and minimum values after removing all outliers.

The power generation of SSP4 and SSP2 scenarios is similar. Nevertheless, due to the high reliance of SSP4 power generation on renewable energy, the water withdrawal of SSP4 (627 km^3) is expected to be lower than SSP2 (763 km^3). SSP3 is considered to be a world of slow technological progress, with water withdrawal reaching 724 km^3 by 2100. Overall, the results of electricity generation and water withdrawal results are consistent with the SSPs narrative.

3.4. Regression analysis

In addition to the water efficiency discussed in the previous section, the rate of economic and social development has a significant impact on electricity generation and water withdrawal. Based on the mixed effect model, this study constructed regression models of power generation and water withdrawal with economic and social development factors (population, GDP), future scenarios, method models, etc. (Tables 3 and 4). Power generation and water withdrawal are positively correlated with population and GDP growth ($P < 0.001$). Electricity generation and water withdrawal will increase by 0.02 EJ and 0.11 km^3, respectively, for every million-population increase. When GDP increases by 1 trillion US$/2005, electricity generation and water withdrawal will increase by 0.41 EJ and 1.21 km^3 respectively. It has been discovered that both have a clear driving effect.

Previous studies have used various methodological models to set up a variety of potential future scenarios to predict global electricity generation and water withdrawal. Our simulation results show that there are significant differences in generation capacity and water withdrawal between different SSPs scenarios and models. The differences caused by SSPs scenarios are mainly affected by the speed of future social development and relevant policies. For example, in the SSP1 scenario, the focus of global economic growth shifts to human well-being, consumption is oriented towards low energy intensity, the increase in global electricity generation is effectively alleviated, and water withdrawal decreases. In contrast to the SSP3 scenario, consumption at this stage tends to be resource-intensive, and water efficiency improvement is a low priority. This successfully explains why the SSP3 and SSP1 scenarios have similar electricity generation in 2100, but double the amount of water withdrawal. Energy forecasting models such as GCAM and AIM/CGE are widely used. The characteristics of the model drive the diversity in results. To be specific, GCAM is distinguished by its comprehensiveness, especially the detailed descriptions of the agricultural and land-use sectors, whereas AIM/CGE is characterized by its full consideration of the interaction among production factors.

Based on the mixed-effects model with limited data sets, we found that the negative effects of warming on grain yield could be compensated for by increasing CO_2 concentration and precipitation. Precipitation is the main environmental factor affecting crop production. For every 1% increase in precipitation, grain yield will increase by 0.12%. Certainly, heavy rainfall can cause disasters such as floods and landslides, which may hamper food yields. Temperature is negatively correlated with grain yield. Under a high-temperature environment, the growth period of crops is shorter, and the quality and yield of crops are decreased. For every 1 ℃ increase in average temperature, grain yield will decrease by 1.60%. Carbon dioxide has a positive impact on crop yields. Carbon dioxide can increase crop yield by enhancing photosynthesis and decreasing stomatal conductance (Deryng et al., 2016). Although carbon dioxide will increase crop yield to some extent, in this study, it is simulated that every 1 ppm increase in CO_2 concentration will increase grain yield by 0.01%. It should also be mentioned that when the carbon dioxide concentration exceeds a certain critical value, it no longer benefits crop growth, and if the temperature keeps climbing, food yield will decrease (Challinor et al., 2014).

In addition to the above-mentioned climate parameters influencing food yield, various research models, study areas, climate scenarios and crop types all affect the degree of yield change (Table 5). The variance in random effects research models, study areas and climate scenarios were 560.84, 180.12 and 12.27, respectively, with statistical significance ($P < 0.001$). Crop models and study areas are the main sources of uncertainty about the impact of climate change on crop yield. The selection of crop models by scholars is diverse. DSSAT, AquaCrop and other complex models are widely used. Different model principles or parameter settings in crop models will lead to inconsistent results. For the study areas, the study shows that climate change (increasing temperatures or decreasing precipitation) will have a greater negative influence on crop yields in arid or semi-arid regions than in other regions (Babel and Turyatunga, 2015). Poor countries that are less resilient to climate change also face larger food security challenges.

Under climate change, crop irrigation water will increase by 13.10% compared to the baseline scenario. This indicates that climate change has a significant impact on global irrigation water requirements. Crop irrigation water is proportional to temperature increase. Higher temperatures will increase irrigation water by increasing crop photorespiration and reducing water use efficiency. For every 1 ℃ increase in temperature, irrigation water will increase by 9.77%. Furthermore, the decrease in precipitation will directly lead to an increase in irrigation water (Winter et al., 2017). It is predicted that for every 1% decrease in precipitation in the future, irrigation water use will increase by 0.28%. The variability of water for food production between different models and RCP scenarios is large, but the variability between study areas is small (Table 6).

4. Discussion

4.1. Challenges of water, food, and energy security

Climate change, economic and social pressures on WEFN are compounding. Food production is often constrained by climate change, natural disasters, soil and water. According to the IPCC (2007), the impact of climate change on food production will worsen in the coming decades. Our study also found that food yield is declining as a result of climate change. At the demand level, population increase, urbanization, changes in dietary structure and consumption levels can all contribute to food insecurity. Ortiz-Bobea et al. (2021) even cautioned that food supply would face unprecedented strain as the world's population reaches 10 billion by 2050 and food demand approaches the limitations of modern agricultural development. According to Tian et al. (2021), the food gap will increase to 1.26 billion tons in 2050, making it challenging to achieve the balance between global food supply and demand. Therefore, strategies to reduce food demand and adapt to climate

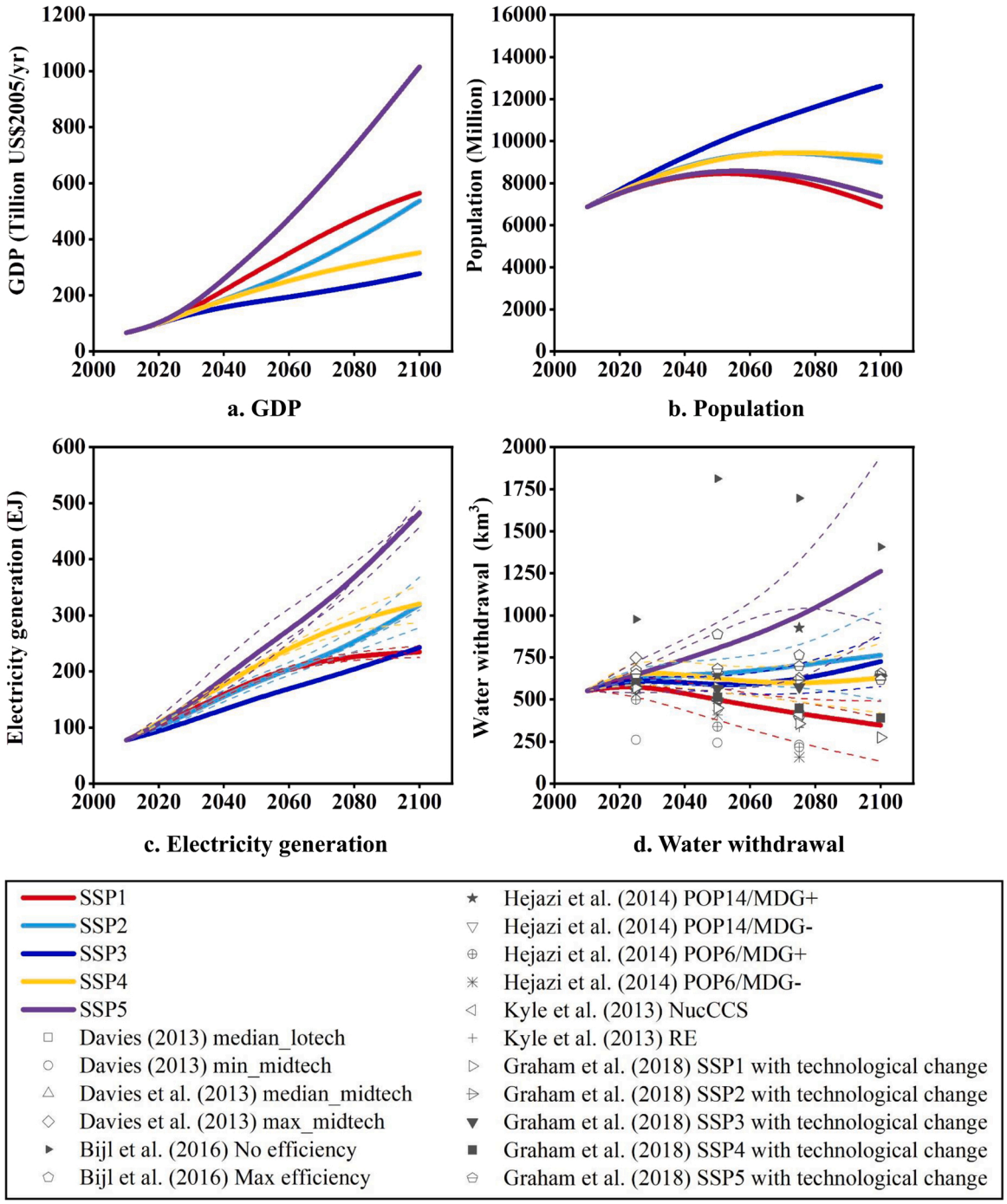

Fig. 6. Global (a) GDP (Trillion US$/2005) (Dellink et al., 2017), (b) population (Million) (Samir and Lutz, 2017), (c) electricity generation (EJ) and (d) water withdrawal (km^3) under the SSPs.

change are urgently needed.

We also need to recognize that food is both water - and energy-intensive. Agricultural irrigation accounts for approximately 70% of global human freshwater consumption (Hoekstra and Mekonnen, 2012). Farm machinery and irrigation consume energy in the food production process. Statistics show that irrigation accounts for 23–48% of the energy consumption from agriculture (Singh et al., 2002). Shortages of energy and water in production will also limit food production.

There is also a supply-demand imbalance in the energy system. According to our findings, electricity generation will increase. However, due to population and economic expansion, energy demand will increase by 50% in 2030 (Marien, 2013). Energy production will be unable to keep pace with population growth, leaving about 3 billion people without access to safe and reliable energy. Furthermore, water scarcity will jeopardize global energy security. Especially in electricity production, water withdrawal for electricity generation accounts for 88% of that from the energy industry (OECD, 2016). Aside from the water withdrawal of thermal power generation, uranium mining and processing, steam cooling and other links in nuclear power production all consume a significant quantity of water. With the rapid increase in food and energy demand, competition for limited water resources will intensify, and the unpredictability of water supply will become the primary risk source of energy production. It is necessary to adjust the energy structure and reduce the water demand.

Table 3
The estimated meta-regression coefficient values for energy generation.

Fixed effect			
Variable	Coefficient	*t* value	P-value
Population	0.02237	6.197	$1.27e^{-07}$ ***
GDP	0.40787	26.230	$< 2e^{-16}$ ***
Intercept	105.43201	-2.878	0.00699**
Random effect			
	Variance	Standard deviation	P-value
SSP scenarios	866.3	29.43	$4.022e^{-07}$ ***
Models	236.6	15.38	0.02786*
Residual	500.6	22.37	
R^2	0.95		

Note: When the original hypothesis is true, P-value is the probability that a consequence more extreme than the obtained sample observation will occur. The smaller the P-value, the more significant the outcome. Significant codes: P < 0.001 ' ** ', P < 0.01 '* *', P < 0.05 '* ', P < 0.1 '·'

Table 4
The estimated meta-regression coefficient values of water withdrawal for energy generation.

Fixed effect			
Variable	Coefficient	*t* value	P-value
Population	0.10794	4.026	0.000223***
GDP	1.21455	6.218	$1.03e^{-07}$ ***
Intercept	-698.76832	-2.155	0.038888[a]
Random effect			
	Variance	Standard deviation	P-value
SSP scenarios	4816	69.4	0.0136036[a]
Models	22,465	149.9	$7.913e^{-08}$***
Year	69,401	263.4	0.0009251***
Residual	19,091	138.2	
R^2	0.90		

[a] Note: When the original hypothesis is true, P-value is the probability that a consequence more extreme than the obtained sample observation will occur. The smaller the P-value, the more significant the outcome. Significant codes: P < 0.001 '* ** ', P < 0.01 '* *', P < 0.05 '* ', P < 0.1 '·'

Table 5
The estimated meta-regression coefficient values of food yield.

Fixed effect			
Variable	Coefficient	*t* value	P-value
ΔP	0.121732	4.218	$3.06e^{-05}$ ***
ΔT_{av}	-1.602504	-3.165	0.00167**
CO_2	0.013399	1.891	0.05991 ·
Intercept	7.973835	0.690	0.50296
Random effect			
	Variance	Standard deviation	P-value
Models	180.12	13.421	$< 2.2e^{-16}$ ***
Study areas	560.84	23.682	$< 2.2e^{-16}$ ***
Crop species	71.52	8.457	0.003694**
RCP scenarios	12.27	3.503	$3.063e^{-15}$ ***
Residual	127.95	11.312	
R^2	0.87		

Note: When the original hypothesis is true, P-value is the probability that a consequence more extreme than the obtained sample observation will occur. The smaller the P-value, the more significant the outcome. Significant codes: P < 0.001 ' ** ', P < 0.01 '* *', P < 0.05 '* ', P < 0.1 '·'

Water is a key constraint to food and energy production. Population increase, urbanization, and economic development will alter the original demand pattern for water supplies. The underlying difficulty is not merely fluctuations in water demand. Climate change's influence on water resources will be superimposed on population growth, urbanization and globalization (Falkenmark, 2013). Extreme weather and unpredictable precipitation intensity will exacerbate the insecurity and vulnerability of water resources.

Taken together, the relevance and complexity of the nexus,

Table 6
The estimated meta-regression coefficient values of water use for food yield.

Fixed effect			
Variable	Coefficient	*t* value	P-value
ΔP	-0.2751	-1.241	0.21978
ΔT_{av}	9.7677	3.541	0.00117**
Intercept	-12.4411	-0.593	0.58651
Random effect			
	Variance	Standard deviation	P-value
Models	194.82	13.958	0.01839[a]
Study areas	1198.98	34.626	0.27178
RCP scenarios	106.11	10.301	0.08454 ·
Year	93.47	9.668	0.16318
Residual	215.00	14.663	
R^2	0.89		

[a] Note: When the original hypothesis is true, P-value is the probability that a consequence more extreme than the obtained sample observation will occur. The smaller the P-value, the more significant the outcome. Significant codes: P < 0.001 '* ** ', P < 0.01 '* *', P < 0.05 '* ', P < 0.1 '·'

particularly the water resource risk at its core, provide significant uncertainty to the future security of WEFN. Scholars and policymakers should think about how to balance the nexus relationship.

4.2. A way forward for water-energy-food nexus: adaptation strategies and technologies

Climate change, economic and social development pose greater challenges to WEFN. Developing adaptation strategies and new technological breakthroughs are the way forward for WEFN (Fig. 7). The way forward for the WEFN is to develop adaptation strategies and new technologies. First, the application of efficient technologies can help to reduce the negative impacts of climate change and economic society on water, energy and food. Drought-resistant crops, no-till crops, water-saving irrigation technologies, and the development of sustainable energy can cut energy and water usage while increasing yields. Furthermore, altering the planting period and selecting the correct crop types can help to mitigate the effects of climate change. Early seeding, for example, resulted in stronger root development and less stress from heat and drought in some locations (Kirkegaard et al., 2014; Zeleke, 2021).

In addition to agriculture, technical advancements are critical for the generation of power and the usage of water. Especially under the condition of water scarcity, promoting water-saving and recycling technology, as well as striving for zero wastewater discharge, will reduce water consumption in the energy production process, alleviate the competition degree between food and energy for water, and reduce the environmental impact. Certainly, we must not only enhance water efficiency, but also accelerate the replacement of fossil fuels at the source. To achieve structural transformation of the electricity industry, the principles of safety, cleanliness, and efficiency must be followed. However, fossil fuels, especially coal, will continue to dominate electricity production in the short term. This will eventually result in tremendous carbon dioxide emissions. Carbon capture and storage (CCS) could alleviate the problem. The International Energy Agency said CCS contributes 14% of the global decrease in CO_2 emissions (Bui et al., 2018). Therefore, "green coal power" technologies based on CCS and integrated gasification combined cycle (IGCC) will play a key role in the gradual transition of the energy mix to renewables.

Not only new technologies, but also adaptation strategies, are required to deal with the changing environment and assure WEFN security. In particular, there is a dynamic relationship between water, energy and food. The behavior of one system frequently has an effect on one or both other systems. For example, biomass fuels, while relieving energy pressures, will compete with food for available farmland and irrigation water, which may threaten food security. Large-scale bioenergy production must be built on the synergy of food and energy security policy (Scott et al., 2015). Therefore, we need to start by

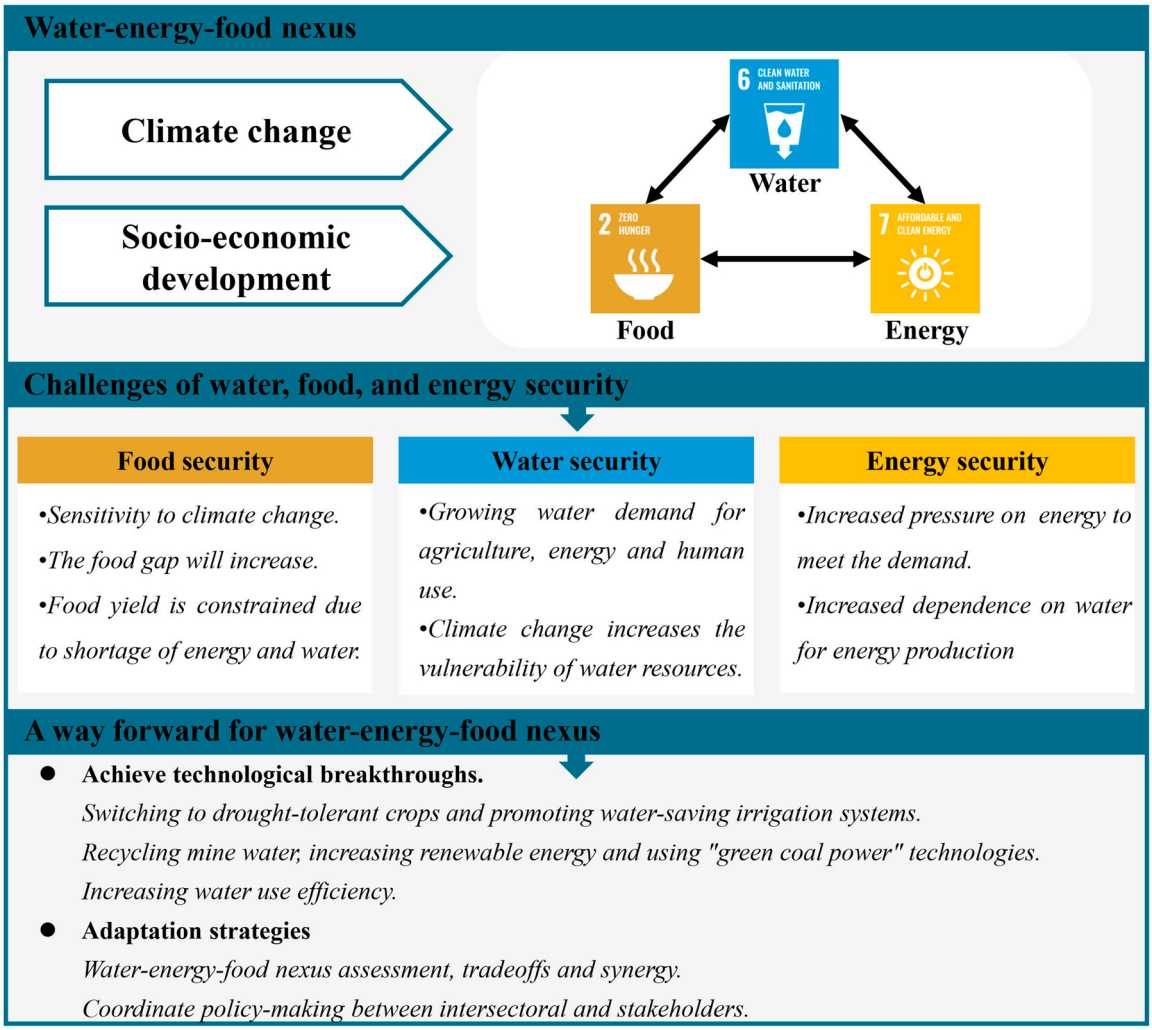

Fig. 7. Challenges and adaptation framework for WEFN.

recognizing the interdependence of water, energy, and food, and then weigh and coordinate appropriate responses to a changing environment. Secondly, inter-sector and stakeholder synergies should be brought into play (Rasul and Sharma, 2016). In order to attain single sector (agricultural sector, energy sector or water sector) goals, current policy-making frequently disregards inter-departmental cooperation. The resource risks and challenges posed by environmental, economic, and social development, on the other hand, demonstrate that management of a single sector leads to the separation of regulatory measures. Furthermore, the concept of resource management centered on a single sector makes it impossible to achieve sustainable goals. As a result, the nexus-based collaborative management theory is critical for improving the present single system management mode and adequately protecting and managing the security of multi-resource nexus systems. To maximize mutual advantages, policymakers should strengthen synergies across the water, energy, and food sectors, as well as establish comprehensive multi-sectoral adaptation strategies.

4.3. Uncertainty and consistency in projections

Due to uncertainties in climate scenarios, social development scenarios, scenario setting, model selection, parameter setting and other aspects, the reliability of studies on the impact of climate change and socio-economic development on WEFN will be greatly affected by specific objects and regions. The meta-analysis of this study quantified the trends of food and energy production, as well as water withdrawal, in a changing environment, identified the main driving forces, and proposed adaptation strategies for future climate change and socio-economic development.

The meta-analysis method was applied to comprehensively analyze existing research results in this study, which can significantly increase the universality and reliability of research results. However, we accept that there is still some uncertainty in forecasts. This is due to two factors. One is due to data collection restrictions. For example, not all regions of the world have access to the food production data predicted by academics. Furthermore, our data only included peer-reviewed articles before the retrieval period, and additional studies produced by experts may be published in the future. Even though a new study may not significantly alter the conclusions, it can further complement the existing statistics. Gray literature such as reports or books are also useful to support our findings, but were not included due to data collecting limitations. Therefore, we suggest that subsequent studies can continue to enrich and complement our foundation. Relevant publications, or peer-reviewed articles published in languages other than English, can also be included in subsequent studies.

Another source of uncertainty is the disparity between models and data sources that predict production and water withdrawal. Food and energy production projections, as well as water withdrawal forecasts, all depend on future climate change, economic and population estimates. For the prediction of food yield under climate change, many studies have used multiple GCM climate models based on Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). Other

studies have opted for individual climate models. Different choices may lead to different results. Furthermore, multiple climate scenarios such as IPCC SRES and RCPs are widely used. Although multiple climate change scenarios can be mapped to RCP scenarios, changes in input data may still cause findings to deviate. Similarly, energy predictions for SSPs scenarios are inevitably influenced by data sources. For example, many studies use projections from the World Bank or the OECD, while some scholars prefer to use their own calculated demographic projections. The results of all of these data will be biased in different ways.

Despite these limitations, as Challinor et al. (2007) asserted, it is extremely challenging to directly compare the impacts of climate change, social, economic, and other factors on agricultural and other industries. Although the data are limited, the results are valid for the geographic area covered. Furthermore, since high-quality quantitative studies are primarily published in peer-reviewed journals, the inclusion of reports or other language studies may not dramatically alter the conclusions of this study. Therefore, the conclusion based on the existing research results has certain credibility. However, more accurate and comprehensive research on WEFN projections in changing environments is still needed in the future.

5. Conclusions

Based on meta-regression approaches, this study quantifies the changes in food, energy production and water withdrawal under climate change and socio-economic development scenarios, as well as the implications of climate, socio-economic, and other uncertainties. The findings are indicative and illustrative for the future. This can indicate the direction and magnitude of the impact of climate change and economic development on the WEFN and improve the accuracy of decision-makers in formulating adaptation strategies. For instance, the findings reveal that future food production will decline, while global food demand will continue to rise consistently, exacerbating the supply-demand conflict. Considering maize is more strongly affected by climate than other crops, optimizing planting structure may be able to alleviate the existing issue of conflicting food supply and demand to some extent. Similarly, energy production and generation show a stronger dependence on energy mix, water use efficiency and the degree of economic and social development. This also serves as a reference point for policymakers.

Using meta-analysis, this study primarily explores the effects of climate and economic factors on the WEFN at the production level and provides an effective basis for policy formation. A consumer-based meta-analysis, on the other hand, will be required in the future, examining how population growth and economic development influence food and energy demand, for instance. Government authorities may be more interested in comparing performance on the production and consumption sides. We also consider that tackling complex WEFN concerns with multidisciplinary methodologies like meta-analysis is critical in solving climate change, supply-demand conflicts, and water scarcity.

CRediT authorship contribution statement

Xinxueqi Han: Conceptualization, Data curation, Methodology, Formal analysis, Visualization, Writing – original draft. **En Hua:** Data curation, Formal analysis, Visualization. **Bernie A Engel:** Writing – review & editing, Data curation. **Jiajie Guan:** Formal analysis, Visualization. **Jieling Yin:** Methodology, Formal analysis. **Nan Wu:** Methodology. **Shikun Sun:** Writing – review & editing. **Yubao Wang:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

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

Acknowledgments

This work was jointly supported by the National Natural Science Foundation of China (41871207, 41961124006) and the 111 Project (No. B12007).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2022.107693.

References

Ahmadi, M., Etedali, H.R., Elbeltagi, A., 2021. Evaluation of the effect of climate change on maize water footprint under RCPs scenarios in Qazvin plain, Iran. Agr. Water Manag. 254, 106969 https://doi.org/10.1016/j.agwat.2021.106969.

Anderson, W., Seager, R., Baethgen, W., Cane, M., You, L., 2019. Synchronous crop failures and climate-forced production variability. Sci. Adv. 5 (7), 1976. https://doi.org/10.1126/sciadv.aaw1976.

Ando, N., Yoshikawa, S., Fujimori, S., Kanae, S., 2017. Long-term projections of global water use for electricity generation under the shared socioeconomic pathways and climate mitigation scenarios. Hydrol. Earth Syst. Sci. Discuss. 1–25. https://doi.org/10.5194/hess-2017-27.

Araya, A., Hoogenboom, G., Luedeling, E., Hadgu, K.M., Kisekka, I., Martorano, L.G., 2015. Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia. Agr. For. Meteorol. 214, 252–265. https://doi.org/10.1016/j.agrformet.2015.08.259.

Babel, M.S., Turyatunga, E., 2015. Evaluation of climate change impacts and adaptation measures for maize cultivation in the western Uganda agro-ecological zone. Theor. Appl. Climatol. 119 (1), 239–254. https://doi.org/10.1007/s00704-014-1097-z.

Baek, H.J., Lee, J., Lee, H.S., Hyun, Y.K., Cho, C., Kwon, W.T., Byun, Y.H., 2013. Climate change in the 21st century simulated by HadGEM2-AO under representative concentration pathways. Asia Pac. J. Atmos. Sci. 49 (5), 603–618. https://doi.org/10.1007/s13143-013-0053-7.

Baker, W.L., Michael White, C., Cappelleri, J.C., Kluger, J., Coleman, C.I., From the Health Outcomes, Policy, and Economics (HOPE) Collaborative Group, 2009. Understanding heterogeneity in meta-analysis: the role of meta-regression. Int. J. Clin. Pr. 63 (10), 1426–1434. https://doi.org/10.1111/j.1742-1241.2009.02168.x.

Bates, D., Mächler, M., Bolker, B., Walker, S., 2014. Fitting linear mixed-effects models using lme4. J. Stat. Softw. 67 (1), 1–48. https://doi.org/10.18637/jss.v067.i01.

Bhaduri, A., Ringler, C., Dombrowski, I., Mohtar, R., Scheumann, W., 2015. Sustainability in the water–energy–food nexus. Water Int. 40 (5–6), 723–732. https://doi.org/10.1080/02508060.2015.1096110.

Biggs, E.M., Bruce, E., Boruff, B., Duncan, J.M., Horsley, J., Pauli, N., Imanari, Y., 2015. Sustainable development and the water–energy–food nexus: A perspective on livelihoods. Environ. Sci. Policy 54, 389–397. https://doi.org/10.1016/j.envsci.2015.08.002.

Bijl, D.L., Bogaart, P.W., Kram, T., de Vries, B.J., van Vuuren, D.P., 2016. Long-term water demand for electricity, industry and households. Environ. Sci. Policy 55, 75–86. https://doi.org/10.1016/j.envsci.2015.09.005.

Brassard, J., Singh, B., 2007. Effects of climate change and CO_2 increase on potential agricultural production in Southern Québec, Canada. Clim. Res. 34 (2), 105–117. https://doi.org/10.3354/cr034105.

Bui, M., Adjiman, C.S., Bardow, A., Anthony, E.J., Boston, A., Brown, S., Mac Dowell, N., 2018. Carbon capture and storage (CCS): the way forward. Energy Environ. Sci. 11 (5), 1062–1176. https://doi.org/10.1039/c7ee02342a.

Challinor, A., Wheeler, T., Garforth, C., Craufurd, P., Kassam, A., 2007. Assessing the vulnerability of food crop systems in Africa to climate change. Clim. Change 83 (3), 381–399. https://doi.org/10.1007/s10584-007-9249-0.

Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A meta-analysis of crop yield under climate change and adaptation. Nat. Clim. Change 4 (4), 287–291. https://doi.org/10.1038/nclimate2153.

Chen, C., 2014. The citespace manual. http://www.doczj.com/doc/0dfa7560aeaad1f346933fb2.html/~cchen/citespace/CiteSpaceManual.pdf (accessed 9 November 2021).

Chenu, K., Porter, J.R., Martre, P., Basso, B., Chapman, S.C., Ewert, F., Asseng, S., 2017. Contribution of crop models to adaptation in wheat. Trends Plant Sci. 22 (6), 472–490. https://doi.org/10.1016/j.tplants.2017.02.003.

Dellink, R., Chateau, J., Lanzi, E., Magné, B., 2017. Long-term economic growth projections in the Shared Socioeconomic Pathways. Glob. Environ. Change 42, 200–214. https://doi.org/10.1016/j.gloenvcha.2015.06.004.

Deryng, D., Sacks, W., Barford, C., Ramankutty, N., 2011. Simulating the effects of climate and agricultural management practices on global crop yield. Glob. Biogeochem. Cycle 25 (2). https://doi.org/10.1029/2009GB003765.

Deryng, D., Elliott, J., Folberth, C., Müller, C., Pugh, T.A., Boote, K.J., Rosenzweig, C., 2016. Regional disparities in the beneficial effects of rising CO 2 concentrations on crop water productivity. Nat. Clim. Change 6 (8), 786–790. https://doi.org/10.1038/nclimate2995.

Falkenmark, M., 2013. Adapting to climate change: towards societal water security in dry-climate countries. Int. J. Water Resour. Dev. 29 (2), 123–136. https://doi.org/10.1080/07900627.2012.721714.

Fan, Y., Wang, C., Nan, Z., 2018. Determining water use efficiency of wheat and cotton: a meta-regression analysis. Agr. Water Manag. 199, 48–60. https://doi.org/10.1016/j.agwat.2017.12.006.

FAO, 2014. The water–energy–food nexus: a new approach in support of food security and sustainable agriculture. Food and Agriculture Organization of the United Nation, Rome.

Ferroukhi, R., Nagpal, D., Lopez-Peña, A., Hodges, T., Mohtar, R.H., Daher, B. and Keulertz, M., 2015. Renewable energy in the water, energy & food nexus. IRENA, Abu Dhabi.

Fox, J., Weisberg, S., 2018. An R Companion to Applied Regression. SAGE Publications, London.

Graham, N.T., Davies, E.G., Hejazi, M.I., Calvin, K., Kim, S.H., Helinski, L., Vernon, C.R., 2018. Water sector assumptions for the Shared Socioeconomic Pathways in an integrated modeling framework. Water Resour. Res. 54 (9), 6423–6440. https://doi.org/10.1029/2018WR023452.

Gurevitch, J., Koricheva, J., Nakagawa, S., Stewart, G., 2018. Meta-analysis and the science of research synthesis. Nature 555 (7695), 175–182. https://doi.org/10.1038/nature25753.

Hoekstra, A.Y., Mekonnen, M.M., 2012. The water footprint of humanity. Proc. Natl. Acad. Sci. 109 (9), 3232–3237. https://doi.org/10.1073/pnas.1109936109.

Johnston, R.Z., Sandefur, H.N., Bandekar, P., Matlock, M.D., Haggard, B.E., Thoma, G., 2015. Predicting changes in yield and water use in the production of corn in the United States under climate change scenarios. Ecol. Eng. 82, 555–565. https://doi.org/10.1016/j.ecoleng.2015.05.021.

Kai, S., 2018. Climate change impact on Mexico wheat production. Agr. For. Meteorol. 263, 373–387. https://doi.org/10.1016/j.agrformet.2018.09.008.

Karlen, D.L., Archer, D., Liska, A. , Meyer, S., 2012. Energy issues affecting corn/soybean systems: challenges for sustainable production. Issue Paper 48. CAST, Ames, Iowa. http://digitalcommons.unl.edu/bseliska/12.

Kirkegaard, J.A., Hunt, J.R., McBeath, T.M., Lilley, J.M., Moore, A., Verburg, K., Whitbread, A.M., 2014. Improving water productivity in the Australian Grains industry—a nationally coordinated approach. Crop Pasture Sci. 65 (7), 583–601. https://doi.org/10.1071/cp14019.

Kuznetsova, A., Brockhoff, P.B., Christensen, R.H., 2017. lmerTest package: tests in linear mixed effects models. J. Stat. Softw. 82 (1), 1–26. https://doi.org/10.18637/jss.v082.i13.

Loomis, J.B., White, D.S., 1996. Economic benefits of rare and endangered species: summary and meta-analysis. Ecol. Econ. 18 (3), 197–206. https://doi.org/10.1016/0921-8009(96)00029-8.

Marien, M., 2013. Global Trends 2030: Alternative Worlds. A Publication of the National Intelligence Council, Washington, DC, USA.

Menegaki, A.N., 2014. On energy consumption and GDP studies; a meta-analysis of the last two decades. Renew. Sust. Energ. Rev. 29, 31–36. https://doi.org/10.1016/j.rser.2013.08.081.

Murray-Tortarolo, G.N., Jaramillo, V.J., Larsen, J., 2018. Food security and climate change: the case of rainfed maize production in Mexico. Agr. For. Meteorol. 253, 124–131. https://doi.org/10.1016/j.agrformet.2018.02.011.

OECD, 2016. World energy outlook 2016. International Energy Agency, Paris.

Ortiz-Bobea, A., Ault, T.R., Carrillo, C.M., Chambers, R.G., Lobell, D.B., 2021. Anthropogenic climate change has slowed global agricultural productivity growth. Nat. Clim. Change 11 (4), 306–312. https://doi.org/10.1038/s41558-021-01000-1.

Patel, C., Nema, A.K., Singh, R.S., Yadav, M.K., Singh, S.K., SINGH, M., 2017. Evaluation of DSSAT-CERES model for irrigation scheduling of wheat crop in Varanasi region of Uttar Pradesh. J. Agrometeorol. 19 (2), 120–124.

Qian, B., Wang, H., He, Y., Liu, J., De Jong, R., 2016. Projecting spring wheat yield changes on the Canadian Prairies: effects of resolutions of a regional climate model and statistical processing. Int. J. Climatol. 36 (10), 3492–3506. https://doi.org/10.1002/joc.4571.

Rasoulzadeh Gharibdousti, S., Kharel, G., Miller, R.B., Linde, E., Stoecker, A., 2019. Projected climate could increase water yield and cotton yield but decrease winter wheat and sorghum yield in an agricultural watershed in Oklahoma. Water 11 (1), 105. https://doi.org/10.3390/w11010105.

Rasul, G., Sharma, B., 2016. The nexus approach to water–energy–food security: an option for adaptation to climate change. Clim. Policy 16 (6), 682–702. https://doi.org/10.1080/14693062.2015.1029865.

Riahi, K., Van Vuuren, D.P., Kriegler, E., Edmonds, J., O'neill, B.C., Fujimori, S., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Glob. Environ. Chang 42, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009.

Samir, K., Lutz, W., 2017. The human core of the shared socioeconomic pathways: population scenarios by age, sex and level of education for all countries to 2100. Glob. Environ. Chang 42, 181–192. https://doi.org/10.1016/j.gloenvcha.2014.06.004.

Schmidhuber, J., Tubiello, F.N., 2007. Global food security under climate change. Proc. Natl. Acad. Sci. 104 (50), 19703–19708. https://doi.org/10.1073/pnas.0701976104.

Scott, C.A., Kurian, M., Wescoat, J.L., 2015. The Water-energy-food Nexus: Enhancing Adaptive Capacity to Complex Global Challenges. Springer International Publishing, Switzerland.

SEI, 2015. The SEI Initiative on the Water, Energy and Food Nexus. https://www.sei.org/publications/the-sei-initiative-on-the-water-energy-and-food-nexus/ (accessed 13 December 2021).

Singh, H., Mishra, D., Nahar, N., 2002. Energy use pattern in production agriculture of a typical village in arid zone, India—part I. Energ. Convers. Manag. 43 (16), 2275–2286. https://doi.org/10.1016/S0196-8904(01)00161-3.

Stanley, T.D., Jarrell, S.B., 2005. Meta-regression analysis: a quantitative method of literature surveys. J. Econ. Surv. 19 (3), 299–308. https://doi.org/10.1111/j.0950-0804.2005.00249.x.

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. BULL. Am. Meteorol. Soc. 93 (4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1.

Thompson, S.G., Higgins, J.P., 2002. How should meta-regression analyses be undertaken and interpreted? Stat. Med. 21 (11), 1559–1573. https://doi.org/10.1002/sim.1187.

Tian, X., Engel, B.A., Qian, H., Hua, E., Sun, S., Wang, Y., 2021. Will reaching the maximum achievable yield potential meet future global food demand? J. Clean. Prod. 294, 126285 https://doi.org/10.1016/j.jclepro.2021.126285.

Timsina, J., Humphreys, E., 2006. Performance of CERES-Rice and CERES-wheat models in rice–wheat systems: a review. Agr. Syst. 90 (1–3), 5–31. https://doi.org/10.1016/j.agsy.2005.11.007.

ur Rahman, M.H., Ahmad, A., Wang, X., Wajid, A., Nasim, W., Hussain, M., Hoogenboom, G., 2018. Multi-model projections of future climate and climate change impacts uncertainty assessment for cotton production in Pakistan. Agr. For. Meteorol. 253, 94–113. https://doi.org/10.1016/j.agrformet.2018.02.008.

van Dijk, M., Morley, T., Rau, M.L., Saghai, Y., 2021. A meta-analysis of projected global food demand and population at risk of hunger for the period 2010–2050. Nat. Food 2 (7), 494–501. https://doi.org/10.1038/s43016-021-00322-9.

Wichelns, D., 2017. The water-energy-food nexus: is the increasing attention warranted, from either a research or policy perspective? Environ. Sci. Policy 69, 113–123. https://doi.org/10.1016/j.envsci.2016.12.018.

Wilcox, J., Makowski, D., 2014. A meta-analysis of the predicted effects of climate change on wheat yields using simulation studies. Field Crop. Res. 156, 180–190. https://doi.org/10.1016/j.fcr.2013.11.008.

Winter, J.M., Lopez, J.R., Ruane, A.C., Young, C.A., Scanlon, B.R., Rosenzweig, C., 2017. Representing water scarcity in future agricultural assessments. Anthropocene 18, 15–26. https://doi.org/10.1016/j.ancene.2017.05.002.

Zeleke, K., 2021. Simulating agronomic adaptation strategies to mitigate the impacts of climate change on wheat yield in south-eastern australia. Agron 11 (2), 337. https://doi.org/10.3390/agronomy11020337.

Zhao, Q., Liu, J., Khabarov, N., Obersteiner, M., Westphal, M., 2014. Impacts of climate change on virtual water content of crops in China. Ecol. Inform. 19, 26–34. https://doi.org/10.1016/j.ecoinf.2013.12.005.