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Review Article

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Modeling Climate Change Impact; A Study on Different Procedures and Strategies: A Review

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ABSTRACT

The current challenges crop production faces in the context of required yield increases while reducing fertilizer, water and pesticide inputs have created an increasing demand for agronomic knowledge and enhanced decision support guidelines, which are difficult to obtain on spatial scales appropriate for use in a multitude of global cropping systems. Nowadays crop models are increasingly being used to improve cropping techniques and cropping systems. This trend results from a combination of mechanistic models designed by crop physiologists, soil scientists and meteorologists, and a growing awareness of the inadequacies of field experiments for responding to challenges like climate change. A general management decision to be made underlies the principle that a crop response to a certain input factor can only be expected if there is a physiological requirement and if other essential plant growth factors are in an optimum state. Hence, the challenge for a farmer is to determine how to use information with respect to the management decisions he has to make, in other words he has to find an efficient, relevant and accurate way how to evaluate data for specific management decisions to counteract challenges like climate change.

Key words: *GCMs, RCMs, Climate change Models, Bias Correction, DSSAT*

INTRODUCTION

Crop models enable researchers to speculate on the long-term consequences of changes in agricultural practices and cropping systems on the level of an agro-ecosystem. Models make it possible to identify very rapidly the adaptations required to enable cropping systems to respond to changes in the economic or regulatory context[102]. The following manuscript gives an overview on the current knowledge and use of crop models and addresses the problems associated with these methods. The discussion focuses on the currently available modeling techniques and addresses the necessary future research areas in this context. The climate change occurs due to interaction of atmosphere with the underlying surface–ocean, land and ice on the earth surface, and is assessed from the observed data and projected with the help of climate models.

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Climate parameters (precipitation, temperature and carbon dioxide levels) changes affect the demand for water as well as supply and have been the focus of several investigations over the past decade. Thus, the whole has been briefed under the following headings.

Climate change models

Crop simulation models

Climate change impacts studies

Climate change models

Climate models are mathematical representations of the climate system, expressed as computer codes and run on powerful computers. These models are based on established physical laws, such as conservation of mass, energy and momentum, along with a wealth of observations. The General Circulation Models (GCMs)/Regional Climate Models (RCMs), simulate/generate future and past weather data on temperature, precipitation (P_{cp}) and wind depending upon partially on the atmospheric concentration of GHGs, derived from "Emission scenarios", developed by inter government panel of climate change (IPCC) as well as on the model run (each run is different as weather is partly a stochastic phenomenon). Models are routinely and extensively assessed by comparing their simulations with observations of the atmosphere, ocean, cryosphere and land surface. The projections have to undergo downscaling either in the form of statistical downscaling or dynamic downscaling to incorporate local topological features and for assessing possible impacts on agriculture at regional level. The downscaled data still may have discrepancies in magnitude and time trends and need application of local bias correction methods.

Emission Scenarios

Emission scenarios describe the concentrations of GHGs, aerosols and other pollutants into the atmosphere from various sources–natural and manmade, to which climate is sensitive, along with information on land use and land cover. Over time, a variety of approaches to scenarios in climate research have been used, from stylized representations of annual percentage increases in global average concentrations of GHGs to advanced representations of emissions of many gases and particles affecting climate, derived from detailed socioeconomic and technology assumptions.

In 2000, the Intergovernmental Panel on Climate Change (IPCC) developed the global and regional emission pathways in its special report on emissions scenarios (SRES). It developed four families of emission pathways, namely A1, B1, A2 and B2 based on different socio-economic development assumptions. Global climate models or better known as IPCC climate models projected future climate change based on these emission pathways. The Fourth Assessment Report of IPCC used the SRES-based emission scenarios and climate projections from CMIP3 for characterizing future climate change and its impacts on society and ecosystems. In the past, climate projections for India have relied on the CMIP3 models. For instance[73] using CMIP3 multi-model data, provided projections of surface temperature and monsoon rainfall over India for the period 1901–2098. Global climate data from the Hadley Centre's Coupled Model (HadCM3), one of the models among the CMIP3 experiment, have been also downscaled by a high-resolution regional climate model for India under the 'Providing Regional Climate for Impact Studies (PRECIS)' project. Kumar *et al*[74] simulated the regional climate of India by using PRECIS for the baseline (1961–1990) as well as long-term climatology (2071–2100) for the SRES scenarios A2 and B2. Kumar *et al*[73] also used PRECIS model to simulate the regional climatology of India for the period 1961–2098 for the SRES scenario A1B. Three simulations from a 17-member perturbed physics ensemble from HadCM3 for quantifying uncertainty in model predictions (QUMP) project were used to drive PRECIS in that study for three time periods, i.e. short (2020s), medium (2050s) and long term (2080s). IPCC published the SRES scenarios in the year 2000 and the underlying economic and policy assumptions for these scenarios were fixed as early as by

1997[89] SRES scenarios are nearly 15 years old. Now, the scientific community has developed a set of new emission scenarios termed as representative concentration pathways (RCPs) In contrast to the forcing, not detailed socio-economic narratives or scenarios. Central to the process is the concept that any single radiative forcing pathway can result from a diverse range of socio-economic and technological development scenarios.

More recent to these scenarios are Representative Concentration Pathways (RCP). These are consistent sets of projections of only the components of radiative forcing (defined as the change in the balance between incoming and outgoing radiation to the atmosphere caused primarily by changes in atmospheric composition) that are meant to serve as input for climate modeling. Radiative forcing, measured in watts per square meter (Wm^{-2}), is the extra heat that the lower atmosphere will retain because of the presence of additional GHGs and aerosols. There are four RCP scenarios: RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. These scenarios are formulated such that they represent the full range of stabilization, mitigation and baseline emission scenarios available in the literature. (Table 2.1). New climate projections are being developed by different modelling groups based on these new RCP scenarios.

Table 2.1 Description of Representative Concentration Pathways (RCPs)

RCP	Description	Developed by
RCP 2.6	Its radiative forcing level first reaches a value around 3.1 W/m^2mid-centuries, returning to 2.6 W/m^2 by 2100. Under this scenario greenhouse gas emissions and emissions of air pollutants are reduced substantially over time	IMAGE modelling team of the Netherlands Environmental Assessment Agency
RCP 4.5	It is a stabilization scenario where total radiative forcing is stabilized before 2100 by employing a range of technologies and strategies for reducing greenhouse gas emissions	Mini CAM modelling team at the Pacific Northwest National Laboratory's Joint Global Change Research Institute
RCP 6.0	It is a stabilization scenario where total radiative forcing is stabilized after 2100 without overshoot by employing a range of technologies and strategies for reducing greenhouse gas emissions	AIM modelling team at the National Institute for Environmental Studies), Japan
RCP 8.5	It is characterized by increasing greenhouse gas emissions overtime representative of scenarios in the literature leading to high greenhouse gas concentration levels	MESSAGE modelling team and the IIASA Integrated Assessment Framework at the International Institute for Applied Systems Analysis (IIASA), Austria

General circulation models

Global Climate Models also known as General Circulation Models (GCMs) are the most complex of climate models, since they attempt to represent the main components of the climate system in three dimensions. GCMs are the tools used to perform climate change experiments from which climate change scenarios (possible representations of how the climate will evolve) can be constructed. Many research institutions around the world develop and maintain their own global climate models. Variables such as temperature, rainfall and wind are calculated over a three-dimensional array of grid cells covering the globe and spaced typically 100–400 km apart, with around 40 layers through the depth of the ocean and around 40 layers through the height of the atmosphere, depending on the model. While these models are similar in many ways, slight variations exist with respect to factors such as grid characteristics, spatial resolution, parameterization schemes and model sub–components (e.g. some models include a representation of atmospheric chemistry, while others do not), which means that climate simulations arising from these models differ.

Regional climate models

Global general circulation models (GCMs) for instance use grid spacings of more than 100 km which is often too coarse for catchment based hydrological investigations. Therefore, downscaling techniques have to be applied which generate horizontal distributions of climatic parameters based on the coarse GCM information but on a much finer scale. Besides statistical methods, regional climate models (RCMs) can be used for physically based dynamical downscaling. These models commonly use horizontal resolutions between 10 and 50 km and are able to dissolve important regional scale processes such as orographic lifting of air masses in complex terrain and the associated formation of clouds and precipitation. At their lateral boundaries, RCMs are either forced by GCM output or by global reanalyses. The simulated climate parameters (e.g. precipitation, near surface air temperature, specific humidity etc.) can subsequently be used as input for hydrological models (offline coupling). The nested regional modelling technique essentially originated from numerical weather prediction, and the use of RCMs for climate application was pioneered by[28,41] . The nested regional climate modelling technique consists of using initial conditions, time-dependent lateral meteorological conditions and surface boundary conditions to drive high-resolution RCMs. RCMs are now used in wide range of climate applications, from palaeoclimate[48] to anthropogenic climate change studies. They can provide high resolution (up to 10 to 20 km or less) and multi-decadal simulations and are capable of describing climate feedback mechanisms acting at the regional scale. More recently, RCMs have begun to couple atmospheric models with other climate process models, such as hydrology, ocean, sea-ice, chemistry/aerosol and land-biosphere models.

Bias Correction

The raw outputs of the climatic parameters from GCM/RCM models often suffer from systematic errors which may prevent their direct application for the analysis of the behavior of the climate system, its eventual changes and their local impacts. The errors in modelled daily rainfall and temperature may afflict the monthly or annual time trends and magnitude. Andreasson *et al*[6] pointed out that these biases are particularly pronounced for P_{cp} than temperature. Downscaling approaches, either physical process based dynamic downscaling or statistically based ones, are required to remove systematic biases in models and transform simulated climate patterns at coarse grid to a finer spatial resolution of local interest[87] . The dynamic approach uses limited area models or high-resolution GCMs to simulate physical processes at fine scales with boundary conditions given by the coarse resolution GCMs. The statistical approach transforms coarse scale climate projections to a finer scale through trained transfer functions that connect the climate at the two spatial resolutions. To capture the anthropogenic climate change signal, the choice of predictor variables is a critical step[45]. Two important considerations are that (1) the selected predictors should reflect the primary circulation dynamics of the atmosphere reasonably well and (2) there is a physical connection to the predictant. There are also statistical downscaling methods primarily for the purpose of bias correction which involve some form of transfer function derived from cumulative distribution functions (CDFs) of observations and model simulations[50,94]. The advantages and disadvantages of both approaches have been thoroughly documented[39] . The key advantage of the statistical approach is the lower computational requirement compared to the dynamical model–based alternative, and thus, statistical downscaling approaches are widely used in climate impact–related research work.

Statistical and dynamic downscaling methods are available to correct GCM predictions relative to climatology at a local, sub-grid scale . Statistical downscaling approaches are generally applied to aggregate rather than daily time scales. When they are applied at a daily time scale, the perfect prognosis assumption required makes them quite susceptible to GCM biases. One approach to addressing the problem of distortion of daily variability is to aggregate GCM predictions into seasonal or sub seasonal (e.g. monthly) means, then use a stochastic weather model to disaggregate in time to produce synthetic daily weather that is conditioned on the predictions[35,44].

A few studies have used daily GCM outputs directly for crop simulation studies. Mavromatis and Jones[88] used daily outputs from the HadCM2 GCM as input to CERES-Wheat for studying potential impacts of climate change on regional winter wheat production in France. Yields simulated with GCM weather data approximated mean yields simulated with observed weather during the past century, and captured a yield trend associated with the recent trend in observed temperature. They concluded, however, that daily GCM outputs were not useful for estimating future agricultural risk because they did not represent year-to year variability adequately. Challinor *et al*[19] have also explored the use of daily GCM outputs for forecasting groundnut yields in western India. Because of GCM biases, the crop model required calibration to observed district yields in order to obtain good predictions.

Crop simulation models

The current challenges crop production faces in the context of required yield increases while reducing fertilizer, water and pesticide inputs have created an increasing demand for agronomic knowledge and enhanced decision support guidelines, which are difficult to obtain on spatial scales appropriate for use in a multitude of global cropping systems. Nowadays crop models are increasingly being used to improve cropping techniques and cropping systems[13,93,120] . This trend results from a combination of mechanistic models designed by crop physiologists, soil scientists and meteorologists, and a growing awareness of the inadequacies of field experiments for responding to challenges like climate change. A general management decision to be made underlies the principle that a crop response to a certain input factor can only be expected if there is a physiological requirement and if other essential plant growth factors are in an optimum state. Hence, the challenge for a farmer is to determine how to use information with respect to the management decisions he has to make, in other words he has to find an efficient, relevant and accurate way how to evaluate data for specific management decisions. Crop models enable researchers to speculate on the long-term consequences of changes in agricultural practices and cropping systems on the level of an agro-ecosystem. Finally, models make it possible to identify very rapidly the adaptations required to enable cropping systems to respond to changes in the economic or regulatory context[102].

Crop growth models have been used since the 1970s[47]. The first crop growth models were based on approaches of simulating industrial processes (Forrester 1961). Brouwer and De Wit[14,] and De Wit *et al*[25] developed some of the early crop growth models in a program called BACROS. Many models now exist for predicting how crops respond to climate, nutrients, water, light, and other conditions. The most commonly used models are the Environmental Policy Integrated Climate (EPIC) model Decision Support System for Agro-Technology Transfer (DSSAT) model[58,60,100] , CROPSyst[115], CROPWAT model[112] and APSIM[67] While all models have achieved various degrees of success in application, they all have their weakness and fail under certain circumstances, wherefore authors of models should clarify the limitations of their models and ranges of applications[82].

One of the most widely used modeling systems across the world is the DSSAT model (Decision Support System for Agro technology Transfer). It was initially developed under the auspices of the International Benchmark Sites Network for Agro technology Transfer[47]. Currently, the DSSAT shell is able to incorporate models of 27 different crops, including several cereal grains, grain legumes, and root crops[47]. The models are process-oriented and are designed to work independent of location, season, crop cultivar, and management system. The models simulate the effects of weather, soil water, genotype, and soil and crop N dynamics on crop growth and yield[58]. The models predict daily plant growth based on daily weather data and soil, management and genetic information. Growth is computed based on light interception and the daily photosynthesis, which can be reduced by temperature, water and N stress. Furthermore, crop models offer the possibility to aggregate knowledge on and over different scales. Linking the models with a GIS offers a mechanism to integrate many scales of data developed in and for agricultural research. Data access and final management decision can be expanded to a decision support system, which uses a mix of process oriented models and biophysical data at different temporal and spatial scales (e.g. growing season, climate characteristics, soils). Thus, a need exists for an integrated GIS system which combines the different available information (e.g. soil map, yield, weather, management) to allow agricultural producers as well as policy makers to know the impact of differences between input and output spatially from one place or region to another to improve management, productivity and profitability. Other different crop models used by different scientists from time to time are discussed as. Attia *et al*[9] worked on winter wheat (Triticum aestivum L.) being a major crop in the semi-arid Texas High Plains, using the DSSAT-CERES-Wheat model. Results of simulations using historical weather data for 32 years (1980–2012) showed that a single irrigation of 100 mm at jointing or booting had 35% higher grain yield than dryland while 140 mm at anthesis or grain filling produced 68% higher grain yield compared to dryland. Simulation of biomass yield showed significant advantage of irrigating 100 mm at jointing or booting stage compared to 140 mm at anthesis or grain filling. Irrigation of 100 mm at jointing and 140 mm at anthesis (240 mm in total) was found to produce similar grain and biomass yields as full irrigation (400 mm). Deficit irrigation at grain filling significantly increased WUE compared to full irrigation. These results showed the importance of irrigation timing in winter wheat production under water-limited conditions in the Texas High Plains.

The EPIC model had been used in estimating soil moisture, crop water requirements and crop evapotranspiration for the last three decades. Numerous studies on the use of EPIC model in different geographical locations and in various agro-environmental conditions[15,23,40,70103] have been reported in the literature. Ko *et al*[70] used the EPIC model to simulate the variability in crop yields under different irrigation regimes for managing the irrigated cotton and maize in South Texas.

Singh *et al*[111] modeled the effects of soil and water management practices on the water balance and performance of rice field study using the modified SAWAH model. This study demonstrated that intermittent irrigation coupled with increased puddling intensity and shift of transplanting date towards low evaporativity period may help to check decline in water table and make the system energy-efficient.

Kuo *et al*[75] used CROPWAT model for simulating the complicated on-farm “crop-soil-climate” phenomena to facilitate the estimation of the crop evapotranspiration and irrigation schedule, of different cropping patterns for irrigation planning. The results showed that in paddy fields, the crop water requirements and deep percolation are respectively 962 mm and 295 mm for the first rice crop, and 1,114 mm and 296 mm for the second rice crop. The research showed that the irrigation management model can effectively and efficiently estimate the crop water requirements.

Marsela and Spiro[86] evaluated the performance of Aqua Crop in simulating sugar-beet production under three irrigation levels (100%, 75% and 50 % of water requirement) in a semi-arid environment in Korea region (south eastern Albania). Their results showed that Aqua Crop is able to accurately simulate soil water content of root zone, crop biomass, tuber yield and Eta (actual evapotranspiration) with normalized root mean square error (NRMSE) less than 10%. Soil water simulated by Aqua Crop tends to follow closely the trend in the measured data, but with slight underestimations for full irrigation treatment and significant overestimations for deficit treatments. Statistical indicators in the model’s evaluation such as RMSE and Willmot’s d-statistics for tuber yield, biomass, and ETa and soil water content suggested that the model can be used to highly reliably assess yield and irrigation water use efficiency.

Climate change impact studies

The changes in crop production related climatic variables will possibly have major influences on regional as well as global food production[1]. Climate change impacts on crop yield are different in various areas, in some regions it will increase, in others it will decrease which is concerned with the latitude of the area and irrigation application. The positive effects of climate change on agriculture are concerned with the CO_2 concentration augment, crop growth period increases in higher latitudes and montane ecosystems; the negative effects include the increasing incidence of pests and diseases, and soil degradation owing to temperature change[76].

The likely impacts of climate change on crop yield can be determined either by experimental data or by crop growth simulation models. To predict future impacts on crop yields, crop models present valuable approaches. A number of crop simulation models, such as CERES-Maize (Crop Environment Resource Synthesis), CERES-Wheat, SWAP (soil water atmosphere plant), and Info Crop [2] have been widely used to evaluate the possible impacts of climate variability on crop production, especially to analyze crop yield-climate sensitivity under different climate scenarios.

Anwar *et al*[7] used CropSyst version-4 to predict climate change impacts on wheat yield in south-eastern Australia, and their results showed that the elevated CO_2 level can reduce the median wheat yield by about 25%. Eitzinger *et al*[32] utilized the CERES-wheat model to assess climate change impacts on wheat production under four climate scenarios, and the results showed that the CO_2 effect maintains a great responsibility for increasing crop yield in the research area. Luo *et al*[80] discussed climate change impacts on wheat production with DSSAT 3.5 (Decision Support System for Agro technology Transfer) CERES-Wheat models under all CO_2 levels in Southern Australia for 2080s, and the result showed that wheat yield will increase under all CO_2 levels, and the drier sites are more suitable for wheat production but are likely to have lower wheat quality.

Krishnan *et al*[72] analyzed the impacts of elevated CO_2 and temperature on irrigated rice yield in eastern India by ORYZAI and Info Crop-rice models, and the result showed that increased CO_2 concentration can increase the rice yield, which is concerned with the sterility of rice spikelets at higher temperature, the sowing time and the selection of genotypes. Yao analyzed CO_2 level impacts on rice yield with the CERES-Rice model in Chinese main rice production areas, which shows that rice yield will increase with CO_2 effect, otherwise it will decrease. Challinor and Wheeler[20] used the GLAM (general large-area model) to analyze climate uncertainty impacts on peanut yield, and the result is that the yield can rise by 10–30% with fixed-duration simulation. Parry *et al*[92] used the IBSNAT-ICASA (International Benchmark Sites Network for Agro technology Transfer) dynamic crop model to estimate climate potential changes in the major grain cereals and soybean crop yield, the result of which is that climate change will increase yields at high and mid-latitudes and decrease yields at lower latitudes. Reddy and Pachepsky[98] validated soybean yield prediction based on the GCMs and soybean crop simulator, GLYCIM in Mississippi Delta, providing a practical method to derive the general relationship between crop yields and climate change including temperature, precipitation and CO_2 concentration.

Water availability is also under threat from changing climate because of possible precipitation decrease in some regions of the world. In the light of the uncertainties of climate variability, water demand and socio-economic environmental effects, it is urgent to take some measures to use the limited water efficiently and develop some new water resources. If water availability is reduced in the future, soil of high water holding capacity will be better to reduce the frequency of drought and improve the crop yield[95].

Thomas[116] studied the effects of climate change on irrigation requirements for crop production in China using a high-resolution (0.25°, monthly time series for temperature, precipitation and potential evapotranspiration) gridded climate data set that specifically allows for the effects of topography on climate was integrated with digital soil data in a GIS. Future scenarios indicated a varied pattern of generally increasing irrigation demand and an enlargement of the subtropical cropping zone rather than a general northward drift of all zones as predicted by GCM models. Clazedilla *et al*[16] studied the potential impacts of climate change and CO_2 fertilization on global agriculture using e GTAP-W model. Their results showed that global food production, welfare and GDP fall in the two time periods and SRES scenarios. Higher food prices are expected. Independently of the SRES scenario, expected losses in welfare are marked in the long term. They are larger under the SRES A2 scenario for the 2020s and under the SRES A1B scenario for the 2050s. The results showed that countries are not only influenced by regional climate change, but also by climate-induced changes in competitiveness.

Koch *et al*[71] studied that changing climate conditions in the Jordan river region are likely to have adverse effects on irrigated crop yields and, as a result, increase the demand for irrigation area based on A1B scenario. They applied a regional version of the dynamic land-use change model LandSHIFT to quantify the effect of climate change on the demand for irrigation area needed to maintain a constant production of irrigated crops. Their simulation results showed that climate change may cause an expansion of irrigation area by about 25%, whereas different climate projections only lead to minor variability in the simulated irrigation area demands. By comparison, an increase in crop demand could result in an expansion of irrigation area by about 71%.

Shahid[107] studied to estimate the change of irrigation water demand in dry-season *Boro* rice field in northwest Bangladesh in the context of global climate change. The study showed that there will be no appreciable changes in total irrigation water requirement due to climate change. However, there will be an increase in daily use of water for irrigation. As groundwater is the main source of irrigation in northwest Bangladesh, higher daily pumping rate in dry season may aggravate the situation of groundwater scarcity in the region.

Vishal assessed the potential effects of climate change and adaptive management on irrigation water supply in the Cache Creek watershed in California using the Water Evaluation And Planning (WEAP) system. They examined three adaptation scenarios to 2099: (1) changes in cropping patterns based on econometric forecasts, (2) a shift toward a more diversified and water-efficient cropping patterns, and (3) a combination of irrigation technology improvements and changes in cropping patterns. Results showed that irrigation demand increased by 26% and 32% under B1 and A2 baseline climate scenarios respectively in the latter part of the century under baseline climate scenarios. Increases in demand from climate change alone exceed applied water reductions from changing cropping patterns by an order of magnitude. Maximum applied water savings occur by combining a diversified water-efficient cropping pattern with irrigation technology improvements, which decreased demand to levels 12% below the historical mean, thereby also reducing groundwater pumping.

Long and Huang[79] studied the impact on irrigation water by climate change in Taoyuan in northern Taiwan. Projected rainfall and temperature during 2046–2065 were adopted from five downscaled general circulation models. Based on a five year return period, the future irrigation requirement was 7.1% more than the present in the first cropping season, but it was insignificantly less (2.1%) than the present in the second cropping season.

Chun *et al* [22] studied Rice (Oryza sativa L.) used multi-scale crop modeling approach to assess the impacts of climate change on future rice yields in South east Asia. Climate variables collected from the coordinated Regional climate Downscaling

Experiment (CORDEX)-East Asia were used as inputs to run the GLAM-Rice and CERES-Rice crop models. Simulations produced by the GLAM-Rice model identified Cambodia as the country in Southeast Asia where the reduction in rice yields under climate change will be the largest (a decrease of approximately 45% in the 2080s under RCP 8.5, relative to the baseline period 1991–2000) without adequate adaptation. The results of the model simulations considering the CO_2 fertilization effect showed that improved irrigation will largely increase rice yields (up to 8.2–42.7%, with the greatest increases in yields in Cambodia and Thailand) in the 2080s under RCP 8.5 compared to a scenario without irrigation. In addition, the grid cell that will benefit the most (12.6 °N and 103.8 °E) was identified through further investigation of the spatial distribution of the effects of irrigation for Cambodia. For this grid cell, the CERES-Rice model was used to develop the best combination of adaptation measures. The results showed that while a doubled application rate of nitrogen fertilizer (100 kg N ha^{-1}) will increase rice yields by 3.9% in the 2080s under the RCP 4.5 scenario for the Sen Pidao cultivar, a decrease in rice yield was projected for the Phka Rumduol cultivar under RCP 4.5. For both cultivars, the results showed that additional adaptation strategies besides the 100 kg N ha^{-1} fertilizer application rate and planting adjustment should be applied in order to offset all of the negative projected impacts of climate change on rice yields in the 2080s under RCP 8.5.

The crop yield can be increased with irrigation application and precipitation increase during the crop growth; meanwhile, crop yield is more sensitive to the precipitation than temperature. Ortiz *et al*[91] discussed how wheat can adapt to climate change in Indo-Gangetic Plains for 2050s and suggested that global warming is beneficial for wheat crop production in some regions, but may reduce productivity in critical temperature areas, so it is urgent to develop some heat-tolerant wheat germplasm to mitigate climate change. With climate change, the growing period will reduce, and the planting date also needs to change for higher crop production. Climate change can decrease the crop rotation period, so farmers need to consider crop varieties, sowing dates, crop densities and fertilization levels when planting crops[24]. Xu assessed the climate change impact, the carbon dioxide (CO_2) fertilization effect, and the adaptation strategy effectiveness on rice yields during future periods (2011–2099) under the newly released Representative Concentration Pathway (RCP) 4.5 scenario in the Sichuan Basin of China using CERES-Rice model. The modeling results indicated a continuing rice reduction in the future periods. Compared to that without incorporating of increased CO_2 concentration, a CO_2 fertilization effect could mitigate but still not totally offset the negative climate change impacts on rice yields. Three adaptive measures, including advancing planting dates, switching to current high temperature tolerant varieties, and breeding new varieties, could effectively offset the negative climate change impacts with various degrees.

Yamei applied CERES-Rice model to assess the impacts of climate change and carbon dioxide (CO_2) fertilization on rice yield, as well as the effectiveness of two popularly adopted adaptive measures in Hunan Province, the main rice production location in China. The simulation spanned 30 years of baseline (1981-2010) as well as three future periods (2011-2040, 2041-2070 and 2071-2099) with climate data generated by five general circulation models (GCMs) under the newly developed Representative Concentration Pathway (RCP) 4.5 and 8.5 scenarios. The simulation showed that compared with average rice yield during the baseline (1981-2010) the ensemble average yield of all cultivars during the 2020s, 2050s and 2080s would decrease under both RCPs without CO_2 fertilization effects. The ensemble average yield reduction during the 2080s was alleviated under both RCPs if CO_2 fertilization effects were accounted for. Adaptation simulations indicated that two adaptive measures (switching cultivars and changing planting dates) could mitigate the adverse effect to different extents.

Shrestha *et al*[109] in their study analyzed the impacts of climate change on irrigation water requirement (IWR) and yield for rain fed rice and irrigated paddy, respectively, at Ngamoeyeik Irrigation Project in Myanmar. Climate projections from two General Circulation Models, namely ECHAM5 and HadCM3 were derived for 2020s, 2050s, and 2080s. The climate variables were downscaled to basin level by using Statistical Downscaling Model. The Aqua Crop model was used to simulate the yield and IWR under future climate. The analysis showed a decreasing trend in maximum temperature for three scenarios and three time windows considered; however, an increasing trend was observed for minimum temperature for all cases. The analysis on precipitation also suggested that rainfall in wet season is expected to vary largely from -29 to +21.9% relative to the baseline period. A higher variation was observed for the rainfall in dry season ranging from -42% for 2080s, and +96% in case of 2020s. A decreasing trend of IWR was observed for irrigated paddy under the three scenarios indicating that small irrigation schemes were suitable to meet the requirements. An increasing trend in the yield of rain fed paddy was estimated under climate change demonstrating increased food security in the region.

Rehana and Mujumdar[99] used statistical downscaled general circulation model (GCM) output with the A1B scenario, to assess the likely changes in irrigation demands for paddy, sugarcane, permanent garden and semi dry crops over the command area of Bhadra reservoir, India. The irrigation requirements were projected to increase, in most cases, suggesting that the effect of projected increase in rainfall on the irrigation demands is offset by the effect due to projected increase or change in other meteorological variables (viz. T_{max} and T_{min}, solar radiation, RH and U2). The irrigation demand assessment study carried out at a river basin would be useful for future irrigation management systems.

Yadav in their study used Decision Support System for Agro technology Transfer (DSSAT v4.5) Cropping System Model (CSM) to study the impact of climate change and variability on productivity of different *kharif* (rice, maize, *jowar* and *bajra*) and *rabi* crops (wheat and barley) at Varanasi. Keeping in view the observed trends in climate variability, productivity of different *kharif* and *rabi* crops were simulated under plausible synthetic climatic scenarios of changes in temperature, solar radiation and carbon dioxide. Productivity of *kharif* crops *viz*. rice, maize, *jowar* and *bajra* and *rabi* crops *viz*. wheat, and barley decreased with an increase in temperature or a decrease in solar radiation above normal. However, productivity of different *kharif* and *rabi* crops increased under expected enhanced CO_2 concentrations. Highest productivity decreased in barley crop (40.7%) of *rabi* season and minimum in rice crop (5%) of *kharif* season with an increase of 3.0 $^{\circ}$C in temperature from normal. Whereas, maximum productivity decreased in barley crop (5.0%) of *rabi* season and minimum in *jowar* crop (1.8%) of *kharif* season with a decrease of 2.5 per cent in solar radiation from normal. Highest productivity increase in barley crop (58.2%) of *rabi* season and lowest in *jowar* crop (4.2%) of *kharif* season were simulated under expected enhanced CO_2 concentration of 660 ppm. The maximum decrease in productivity of barley crop (45%) in *rabi* season and minimum in rice crop (7%) in *kharif* season were simulated when a decrease in temperature by 3 $^{\circ}$C and solar radiation by 2.5 per cent from normal. Highest counter-balance on productivity of rice crop (13%) in *kharif* season and lowest in *bajra* crop (-23%) of *kharif* season were simulated when an increase in temperature by 3 $^{\circ}$C from normal under expected enhanced CO_2 concentration of 660 ppm.

In Punjab context, various researchers have used crop simulation models for assessing and mitigating climate change impacts. Jalota *et al*[52,53,54] in their study took climate data recorded for the last 40 years (1971–2010) at meteorological station of Punjab Agricultural University, Ludhiana (Central Indian Punjab) and future changes in climate data derived from three General Circulation Models (GCMs), viz. HadCM3, CSIRO-Mk2 and CCCMA-CGCM2, and were analyzed. Averaged across GCMs and scenarios, CropSyst model simulated crop yields of rice–wheat System showed 7%, 15% and 25% decrease in rice and 10%, 20% and 34% in wheat for the years 2020, 2050 and 2080 respectively.

Jalota *et al*[57] in another study assessed the impact of location specific climate change scenario on crop duration, yield, water and nitrogen-balance and-use efficiency of rice–wheat system and found that in midcentury (MC) and end century (EC) time slice of the 21st century, rainfall and temperature would increase; crop yields (simulated with cropping systems simulation model) would decrease owing to shortening of crop duration. In MC (2021–2050) and EC (2071–2098), evapotranspiration, transpiration, drainage and irrigation requirement would decrease and soil water evaporation would increase. However, their magnitudes would vary with the location. Delaying transplanting of rice by 15 days in MC; and of wheat by 15–21 days in MC and EC emerged as the best adaptation measures to sustain yield of rice–wheat system at all locations.

Kaur *et al*[66] studied the effect of climate change on crop yield, crop duration, water and balance of rice–wheat cropping system using CropSyst model. Model simulations predicted reduction in crop yields in future associated with shortening of growth period due to increased temperature. Yield reduction was more with increase in maximum temperature than minimum; and in finer- than coarser textured soil. Increased rainfall in future would decrease irrigation water requirement of crops but would not offset the adverse effect of increased temperature.

Climate change impacts on crop yield are often integrated with its effects on water productivity and soil water balance. Khan *et al*[68] reviewed water management and crop production for food security in China, who pointed out that it, is necessary to integrate climate, energy, food, environment and population together to discuss future food security in China and in the world as well. This is because climate change has many uncertainties in water management and other water-related issues. Food security is increasingly important for human beings all over the world. Food availability and food quality still are the big challenges for scientists due to changing climate. Food security is always studied with CO_2 effects under changing climate scenarios. Further research on food security needs to integrate population, crop production, climate change and water availability, consequently, to evaluate food security completely and systematically.

CONCLUSION

In summary, climate change is likely to have an impact on future irrigation water requirements. Quantifying the impact is difficult, however, and is subject to uncertainties present in the future climate predictions. Simulations based on general circulation models (GCMs) have yielded mixed and conflicting results, raising questions about their reliability in predicting future hydrologic conditions. Irrigation water requirements are influenced not only by hydrologic processes, but also by the physical characteristics of the land surface and soil profile. Many climate change studies have focused on modelling the temporal changes in the hydrologic processes and ignored the spatial variability of physical properties across the study area. Long-term water resource planning requires both spatial and temporal information on irrigation water requirements in order to properly manage not only water use and exploitation, but also land use allocation and development. Studies concerned with climate change should therefore also consider the spatial changes in irrigation water requirement and demand for irrigation.

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