Review of Literature

CHAPTER II

REVIEW OF LITERATURE

This chapter critically reviews various topics like climate, climate change, climate scenarios and climate models, crop simulation models, and how climate change impacts irrigation water requirement, yield, crop water productivity, and food security. Also specifically reviews various research conducted on the impact of climate change on the irrigation water requirement and crop water productivity of rice.

2.1. Climate, climate change and its causes

Climate refers to the long-term patterns and trends in weather conditions, including temperature, precipitation, wind, and other factors, in a specific region or worldwide. Climate is determined by complex interactions between the atmosphere, oceans, land, and ice. It is influenced by factors such as solar radiation, greenhouse gases, and natural variations in the Earth's systems (CCKP, 2021).

Climate change refers to the long-term shift in global or regional climate patterns, commonly associated with increased global temperatures since the mid-20th century (IPCC, 2021). It is characterized as altering climate patterns, primarily driven by releasing greenhouse gases from both natural processes and human actions. Human activities have already resulted in approximately 1.0 °C of global warming beyond pre-industrial levels, and this is projected to reach 1.5 °C between 2030 and 2052 if current emission rates continue. In 2018, the world witnessed 315 instances of natural disasters largely associated with climatic factors (Fawzy *et al.,* 2020).

Climate change has significant impacts on ecosystems, economies, and societies around the world. These impacts include more frequent and severe heatwaves, droughts, floods, storms, rising sea levels, loss of biodiversity, and changes in agriculture and food production. Addressing climate change requires a coordinated global effort to reduce greenhouse gas emissions and transition to a low-carbon economy, while adapting to the changing climate conditions (Xiao *et al.,* 2020).

Climate change exerts detrimental effects across various facets of human existence, posing a substantial threat to the global water supply (Kim *et al.,* 2016). Furthermore, climate change disrupts water-dependent sectors such as agriculture, hydropower, tourism, and navigation, with ramifications extending worldwide (Babel *et al.,* 2011).

Both natural and human activities cause climate change. Human activities, such as burning fossil fuels and deforestation, release greenhouse gases like carbon dioxide into the atmosphere, trapping heat and leading to global warming. Natural factors like volcanic eruptions also play a role. Agriculture, particularly the livestock sector, contributes significantly to greenhouse gas emissions. Understanding these factors is crucial for predicting and mitigating the impacts of climate change. Efforts to reduce emissions include improving crop management and reducing meat consumption (Kahrl *et al*., 2010, Popp *et al*., 2010, Montzka *et al*., 2011, Groenigen *et al*., 2011, O'Mara, 2011, Lesschen *et al*., 2011, Soltani *et al*., 2013, Stern and Kaufmann, 2014)

2.2.Effects of climate change

Climate change is causing a range of impacts on the Earth's natural systems and human societies. Li *et al*. (2022) reported that one of the most significant effects of climate change is rising temperatures (Fig. 2.1). As greenhouse gas concentrations continue to increase, it is expected that maximum temperatures will increase (Fig. 2.2a), while minimum temperatures will also rise (Fig. 2.2b), resulting in an overall increase in temperature variability. In terms of annual rainfall, many areas are expected to experience more frequent and intense rainfall events (Fig. 2.2c), leading to more flooding, while other areas may experience prolonged droughts due to changes in precipitation patterns. Additionally, the amount and intensity of solar radiation (Fig. 2.2d) reaching the Earth's surface may also be affected, with some areas potentially experiencing more intense heatwaves and solar radiation exposure (Ansari *et al.,* 2021). As the global temperature increases, the polar ice caps and glaciers are melting at an accelerated rate, leading to a rise in sea levels around the world (Fig. 2.3). Over the last century, sea levels have been on the rise, and in recent decades, this increase has accelerated. By 2016, the global sea level had exceeded the 1993 average by 3.2 inches (82 mm), marking the highest annual average recorded by satellites since 1993 (Lindsey, 2021). The rate of sea level rise is expected to accelerate in the coming decades, with projections suggesting that the global sea level could rise by several feet by the end of the century.

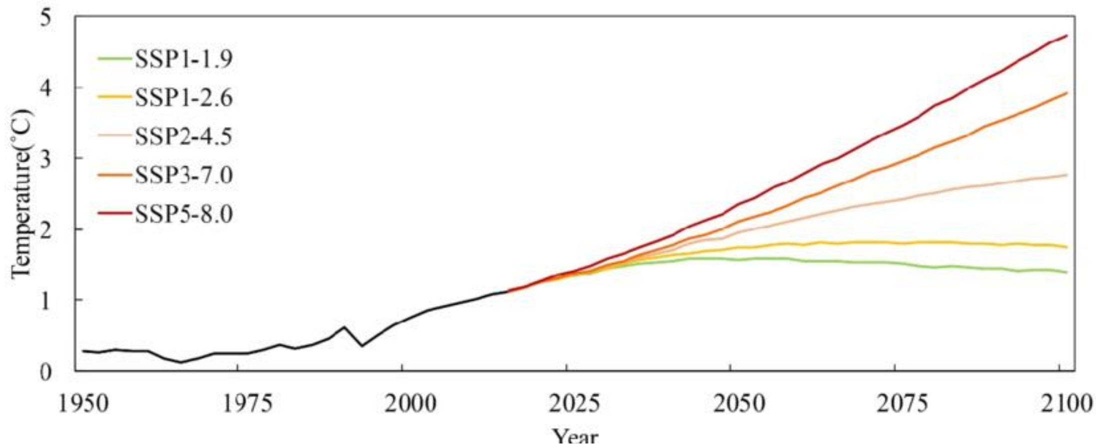

Fig. 2.1. Global surface temperature changes relative to 1850-1900 (Li *et al*,2022)

Additionally, climate change is also causing changes in the growing season and water availability, leading to food and water scarcity in some regions. Thawing permafrost is another significant consequence of climate change, as it releases large amounts of carbon dioxide and methane into the atmosphere. Furthermore, climate change is causing longer, more frequent and more intense fire seasons, exacerbating the loss of biodiversity and wildlife habitats. In summary, climate change is a global issue that requires immediate action to mitigate its impacts and reduce greenhouse gas emissions (Abbass *et al*., 2022).

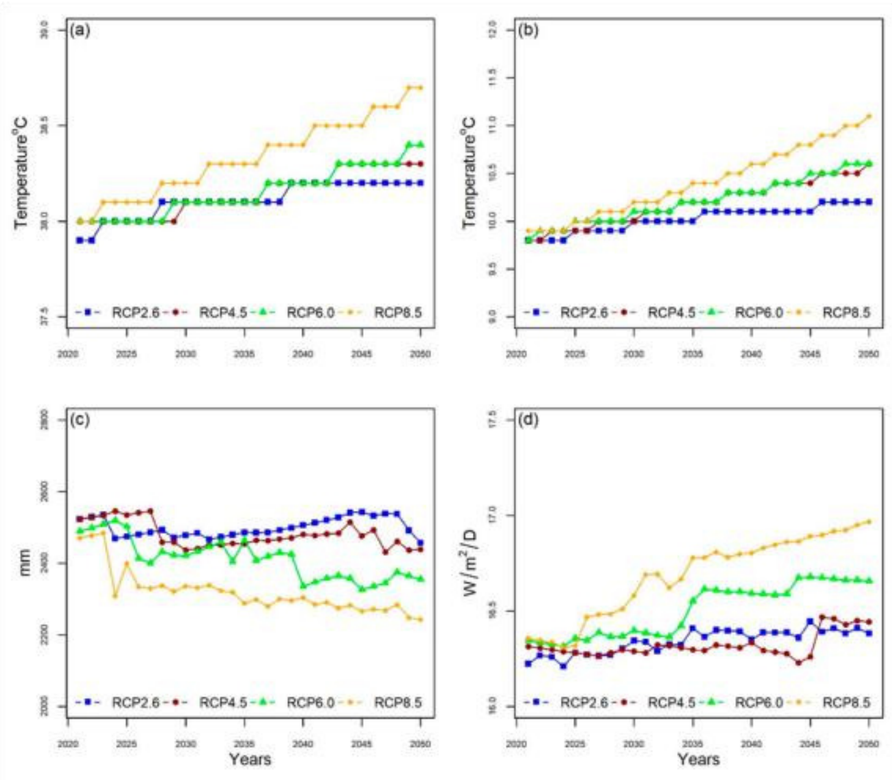

Fig. 2.2. Future climate predictions under different scenarios for (a) maximum temperature, (b) minimum temperature, (c) annual rainfall, and (d) solar radiation (Kundu *et al*., 2017)

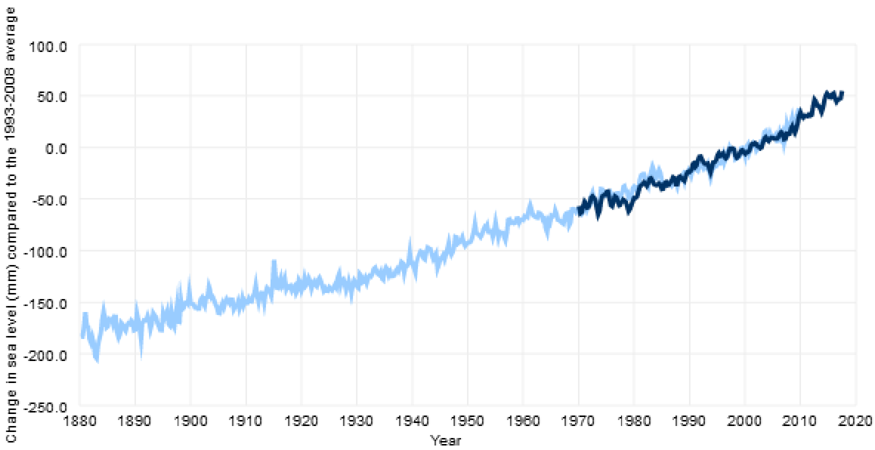

Fig. 2.3 Global sea level change since 1880 (Hogarth *et al*., 2021)

2.3. Climate models

Climate models are essential tools for studying and simulating climate behavior and their complex interactions. These models come in various types, with the most intricate ones being atmosphere–ocean general circulation models. These models consist of components replicating the interactions of the atmosphere, land, sea, and ocean ice. They divide the environment into numerous matrix cells and incorporate biophysical and land-surface processes. Regional climate models, on the other hand, utilize higher resolution to provide more precise insights into specific geographical areas, often as small as subcontinents. These models can be combined with various integrated assessment models, serving a valuable role in exploring significant vulnerabilities (Moss *et al.,* 2010).

Various climate models exist, among them are Earth System Models (ESMs), are advanced computer models designed to replicate the interactions between the earth's atmosphere, oceans, land surface, cryosphere, and biogeochemical cycles (Flato, 2011). In the last hundred years, climate modeling has improved by adding more scientific knowledge about how the earth's climate works into these models. Fig. 2.4 depicts the timeline of when different climate system components became routinely integrated into global climate model simulations (Bellenger *et al.,* 2014).

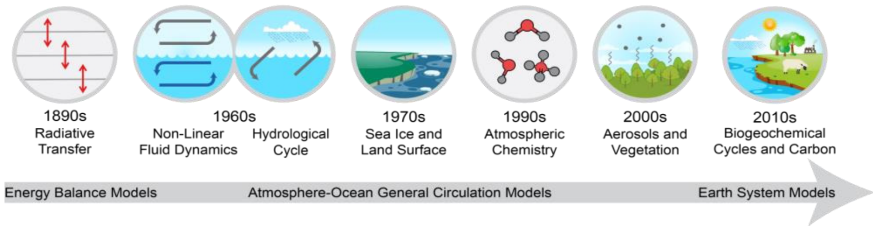

Fig. 2.4 A climate modeling time line (Hayhoe *et al.,* 2017)

2.3.1. Global climate models

Global Climate Models (GCMs) often named as General Circulation Models, are advanced tools currently available to depict the physical processes occurring within the atmosphere, ocean, cryosphere, and on land. These models are employed to make virtual projections of environmental changes for future periods (IPCC, 2014) and are used to forecast future climate scenarios based on potential anthropogenic activities using equations of motion. GCMs can simulate climate alterations resulting from minor variations in specific conditions, such as changes in the solar constant or physical parameters like greenhouse gas concentrations (Subramanian *et al*., 2023). These models are grounded in the scientific principles of the Navier-Stokes Equation, which describes oceanic and atmospheric processes from a thermodynamic perspective. Previously, Atmospheric GCMs (AGCMs) focus on climate and land components, while Oceanic GCMs (OGCMs) addressed oceanic aspects. A more recent approach to atmospheric modeling involves combining AGCMs and OGCMs to create Atmospheric Oceanic GCMs (AOGCMs). GCMs are recognized as the most reliable instruments for predicting the pace of climate change. However, their primary limitations include poor resolution, insufficient detailing of atmospheric and oceanic processes, an inability to represent the environment fully, and incapacity to simulate cloud mechanisms (Krishnan *et al.,* 2007). Some of the GCMs used in India (Raju and Kumar, 2015) and their details are shown in Table 2.1.

Table. 2.1 List of Global Circulation Models

Model Name	Institution and Country	Resolution
BCC-CSM2-MR	Beijing Climate Centre (BCC) and China Meteorological Administration (CMA), China	1.1° × 1.1°
CanESM5	Canadian Earth System Model, Canada	2.81° × 2.81°
ACCESS-ESM1-5	Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the Australian Bureau of Meteorology (BoM) Earth System Model	1.88° × 1.88°
CNRM-CM6_HR	Centre National de Recherches Météorologiques-Centre Européen de Recherches et de Formation Avancée en Calcul Scientifique, France	0.5° × 0.5°
FGOALS-g3	Flexible Global Ocean-Atmosphere-Land System model Grid-point version 3	2° × 2.3°
INM-CM5-0	Numerical Mathematics, Russian Academy of Science, Moscow 119991, Russia	2° × 1.5°
IPSL-CM6A-LR	Institut Pierre-Simon Laplace, France	2.5° × 1.3°

MPI-ESM1-2-LR	Max Planck Institute for Meteorology, Low Resolution, Germany	0.9° × 0.9°
MPI-ESM1-2-HR	Max Planck Institute for Meteorology, High Resolution, Germany	1.9° × 1.9°
TaiESM	Research Centre for Environmental Changes, Taiwan	1.3° × 1°

2.3.2. Regional Climate Models (RCMs)

Unlike GCMs, which simulate the entire earth's climate system, RCMs focus on modeling climate processes at a regional scale. They provide more detailed information about climate variables such as temperature, precipitation, and wind patterns for specific regions, typically at higher spatial resolutions than GCMs. RCMs are often used to downscale global climate model output to provide more localized climate projections, making them valuable tools for assessing climate impacts on smaller scales, such as individual countries, regions, or river basins (Feser *et al.,* 2011).

Rajib and Rahman (2012) conducted a study using the Regional Climate Model (RCM) called PRECIS to develop future surface temperature projections for Bangladesh from 2011 to 2100. PRECIS is a grid point model with 19 levels and can downscale to a 25 km resolution. Hence, a high-resolution limited area Regional Climate Model (RCM) can produce reasonably appropriate projections for climate-scenario generation on a country scale. If the domain is too large, the model's flow may deviate from the driving dataset. At the same time, a domain that is too small may limit the model's ability to generate accurate responses to local climate conditions.

2.4.Downscaling of climate models

Downscaling is a technique to derive high-resolution climate information for specific regions from the low-resolution output of global climate models (GCMs). This is because GCMs operate at a coarse resolution of several hundred kilometers (100-300 km × 100-300 km), which cannot capture local and regional climate variability. Many impact models require data of finer scales 50 kms or less.

There are two main types of downscaling techniques: statistical and dynamical downscaling. Statistical downscaling involves developing empirical relationships between the large-scale climate variables simulated by GCMs and the local/regional climate variables of interest based on observed historical data. This technique is relatively simple and computationally efficient. Still, it assumes that the relationships between the large-scale and local/regional variables will remain unchanged in the future, which may not be true under changing climate conditions (Zhou *et al.,* 2023, Tang *et al.,* 2016).

Dynamical downscaling develops finer regional climate models (RCMs) within coarser resolution GCMs. On the other hand, uses RCMs to simulate the finer-scale processes that are not resolved by GCMs, such as local topography, land cover, and atmospheric dynamics. RCMs are driven by the boundary conditions provided by GCMs and simulate the interaction between the large-scale climate processes and the local/regional processes, producing high-resolution climate projections for specific regions (Tang *et al.,* 2016). This technique is computationally expensive and requires detailed input data. Still, it is more physically realistic and can capture the local/regional variability and extreme events that are important for impact assessments and adaptation planning (Walton *et al.,* 2020).

2.5.Bias Correction of climate model output

Bias correction methods are used to correct systematic errors or biases in climate model output. These biases can arise due to various reasons, such as the coarse resolution of the model, inaccurate parameterizations, or errors in the input data. Biases in climate model output can lead to incorrect conclusions when analyzing the impact of climate change on a specific region or sector.

The lack of reliable information on geophysical processes gives rise to assumptions in developing GCMs in terms of parameters and experimental formulations. Consequently, GCMs are not devoid of inaccuracies and fail to precisely replicate climatic factors due to the disparities between observed and simulated climatic variables across all GCMs. This divergence is commonly referred to as bias. Eliminating bias from GCM outcomes is crucial for enhancing the accuracy of predicting future hydrologic and climatic conditions (Salvi *et al.,* 2011). Bias is the systematic distortion of statistical results from the expected value (Teng *et al.,* 2015).

Challenges, such as the unavailability of daily climate data at sufficiently high spatial resolution for future studies, create impediments for comprehensive small-scale analyses of climate change impacts. The utilization of GCM outputs in regional impact assessments is hindered by biases inherent in GCMs. Therefore, correcting biases becomes crucial to validate the meaningful applications of these GCM outputs (Murphy, 2000). Statistical methods have been identified as a straightforward approach to bias correction (Hayhoe *et al.,* 2007). Moreover, this correction reduces the average error and minimizes the maximum error in simulated daily or monthly mean values.

The five types of bias correction methods are Quantile mapping, Delta change, Linear scaling, Local intensity scaling, and Power transformation (Smitha *et al.,* 2018)

Quantile mapping: This method involves adjusting the model data distribution to match the observed data distribution. The mapping function is typically determined by comparing the cumulative distribution functions of the modeled and observed data over a reference period. This method is effective for correcting biases in precipitation data (Thrasher, *et al.,* 2012, Enayati *et al.,* 2021 and Grillakis and Koutroulis, 2017)

Delta change: This method involves adding or subtracting a constant value (delta) to the model output to match the observed data. The delta value is typically determined by comparing the mean or median of the modeled and observed data over a reference period. This method is useful for correcting biases in temperature data (Raty *et al.,* 2014).

Linear scaling: This method involves scaling the modeled data using a linear function to match the observed data. The scaling factors are typically determined by comparing the mean or median of the modeled and observed data over a reference period. This method is useful for correcting biases in temperature and precipitation data (Shrestha *et al.,* 2017; Aqilah, 2018).

Local intensity scaling: This method involves scaling the modeled data using a non-linear function to match the observed data. The scaling factors are typically determined by comparing the frequency and intensity of extreme events in the modeled and observed data over a reference period. This method is useful for correcting biases in extreme precipitation events transformation (Smitha *et al.,* 2018).

Power transformation: This method involves applying a power transformation to the modeled data to match the observed data. The transformation function is typically determined by comparing the probability distribution functions of the modeled and observed data over a reference period. This method is useful for correcting biases in precipitation data transformation (Smitha *et al.,* 2018).

2.6.Climate Scenarios

Global warming is caused primarily due to increase in carbon dioxide emission into the atmosphere from fossil fuel burning and deforestation activity. The increase or decrease in carbon dioxide concentration in the atmosphere might influence the global and local climatic conditions. Future GHG emissions are the product of very complex dynamic systems, determined by driving forces such as demographic development, socioeconomic development, and technological change (IPCC, 2000). Their future evolution is highly uncertain. Scenarios are alternative images of how the future might unfold an area and appropriate tool with which to analyze how driving forces may influence future emission outcomes and to assess associated uncertainties (IPCC. 2000). These scenarios are projections of future climate conditions based on assumptions about greenhouse gas emissions, atmospheric concentrations, and other factors. Analysts use these scenarios to assess future vulnerability to climate change and help to inform decisions about adaptation and mitigation strategies. Thus, IPCC produces climate scenarios and projections in their assessment reports, which policymakers, researchers, and stakeholders widely use. The SRES scenarios were developed in 2000 and used in the IPCC's Fourth Assessment Report in 2007, while the RCPs were developed in 2014 and used in the IPCC's Fifth Assessment Report in 2014 and 2015. The SSP scenarios were developed in 2016 and used in the IPCC's Sixth Assessment Report in 2021.

According to the fifth Assessment Report (AR5) in 2014, IPCC introduced four greenhouse gas concentration trajectories known as Representative Concentration Pathways (RCPs). These pathways replaced the Special Report on Emissions Scenarios (SRES) from 2000 onwards. The four RCPs, namely RCP-2.6, RCP-4.5, RCP-6.0, and RCP-8.5, encompass a broad spectrum of potential changes in future anthropogenic (human-induced) greenhouse gas (GHG) emissions. Their primary objective is to depict the atmospheric concentrations of these gases over time. Each RCP follows a distinct trajectory. RCP 2.6 indicates the highest global annual GHG emissions (measured in CO_2-equivalents) between 2010 and 2020, with a substantial decrease in emissions thereafter. In RCP 4.5, emissions peak around 2040 and subsequently decline. RCP 6 exhibits the highest emissions approximately in 2080, followed by a reduction. Conversely, RCP 8.5 foresees a continual increase in emissions throughout the 21st century (Meinshausen *et al.,* 2011).

IPCC, in the sixth assessment report, has developed a new set of scenarios called the Shared Socioeconomic Pathways (SSPs), which combine assumptions about greenhouse gas emissions and socioeconomic factors such as population growth, economic development, and technological change. Shared Socioeconomic Pathways (SSPs), developed collaboratively by an international team of climate scientists, economists, and energy systems modelers, serve as a toolkit for the climate change research community, enabling integrated, multi-disciplinary analysis. These pathways outline conceivable global developments that could pose different challenges for climate change mitigation and adaptation in the future (Van Vuuren et al., 2011). They are based on five narratives depicting alternative socio-economic developments, including sustainable development, regional rivalry, inequality, fossil-fueled development, and middle-of-the-road development (Riahi *et al.*, 2017). The SSPs provide a range of scenarios for future socioeconomic and environmental conditions and are used in conjunction with the RCPs to project future climate change impacts.

SSPs are detailed frameworks used in climate change studies, as highlighted by Auer *et al*., 2021. They describe socioeconomic and environmental trends globally and in major world regions throughout the 21st century. These pathways include both qualitative and quantitative information, allowing us to distinguish between different SSPs in terms of their challenges for reducing emissions and adapting to climate change. Additionally, SSPs incorporate key data used as input by global models that predict energy, economy, land use, and climate impacts, as noted by Riahi *et al*., 2017. They consider factors like future population growth, economic development, and global connectivity. It's important to note that SSPs don't specify exact technological solutions or emissions scenarios. They also don't include policies directly aimed at addressing climate change or their effects on other factors, as explained by Kriegler *et al*., 2014.

Table 2.2 Overview of RCP scenarios by Van Vuuren *et al.* (2011)

Scenarios	Radiative Forcing	CO_2 Equiv (ppm)	Temperature Anomaly (C)	Pathway	SRES Temperature Anomaly Equivalent
RCP 8.5	Rising Radiative Forcing Pathway leading to 8.5 W/m2 in 2100	1370	4.9	Rising	SRES A1F1
RCP 6.0	Stabilization without overshoot pathway to 6.0 W/m2 at stabilisation after 2100	850	3.0	Stabilisation without overshoot	SRES B2

RCP 4.5	Stabilization without overshoot pathway to 4.5 W/m2 at stabilisation after 2100	650	2.4	Stabilisation without overshoot	SRES B1
RCP 2.6	Peak in Radiative Forcing at ~3 W/m2 before stabilisation and decline	490	1.5	Peak and decline	None

Table 2.3 Overview of SSP scenarios by Leimbach *et al.* (2023)

SSP Scenario	Description
SSP1 (Sustainability)	Emphasizes sustainability, equality, and environmental protection. Assumes rapid economic growth, low population growth, and increased emphasis on social equality.
SSP2 (Middle of the Road)	Represents a world where current trends continue with no major shifts toward sustainability or inequality. Assumes medium population growth, moderate economic development, and fragmented governance.
SSP3 (Regional Rivalry)	Envisions a fragmented world with high regional disparities, limited international cooperation, and unsustainable resource use. Assumes high population growth, slow economic development, and conflict-prone governance.
SSP4 (Inequality)	Focuses on a highly unequal world with fragmented governance and limited global cooperation. Assumes rapid

	economic growth in some regions and stagnation or decline in others, leading to high income inequality.
SSP5 (Fossil-Fueled Development)	Assumes high emissions and limited climate action, resulting in a world where fossil fuels remain dominant. Envisions rapid economic growth, high population growth, and weak environmental policies.

2.7.Crop growth simulation models

Crop simulation models are used to evaluate the impact of climate change on crop productivity, grain yield and water productivity. Several models are available for this purpose, which includes AquaCrop, DSSAT, STICS, APSIM, and INFOCROP. These models use a combination of climate and soil data, crop management information, and physiological parameters to simulate crop growth and yield under different environmental conditions. They allow researchers and farmers to explore different scenarios, such as changes in temperature, rainfall, and irrigation, and evaluate how these changes might affect crop production (Rauff. and Bello, 2015).

AquaCrop, for example, is a model designed to simulate crop water use and yield under water-limited conditions, making it particularly useful for arid and semi-arid regions. DSSAT is a widely used model that can simulate the growth, development, and yield of over 40 crops. STICS is a model that can simulate the impact of climate change on crops, soil, and water, while APSIM can simulate the interactions between crops, soil, water, and nutrients (Kherif *et al.*, 2022). INFOCROP is another model that can simulate the growth, development, and yield of various crops under different environmental conditions (Aggarwal *et al.*, 2006). These models provide valuable insights into the potential impact of climate change on crop productivity and can help inform decision-making related to agricultural management practices, including crop selection, irrigation strategies, and fertilizer application (Gul *et al.*, 2020).

2.7.1. AquaCrop Model

AquaCrop is a crop growth simulation model developed and supported by the Food and Agriculture Organization (FAO). Based on biophysical processes

(Steduto *et al*., 2009), the AquaCrop model takes into account a continuous structure of plants, soil, and atmosphere (Raes *et al*., 2018). It has a user-friendly interface and requires limited data. AquaCrop is designed to simulate the effects of water stress on crop growth and yield, with a focus on climate change, water, and crop yield (Raes *et al.,* 2009).

AquaCrop simulates the potential yields of herbaceous crops by considering the amount of water transpired (Steduto *et al.,* 2012). The inputs to AquaCrop include climate data, soil properties, crop management practices, and crop characteristics, such as variety, planting date, and planting density. The model also requires information on the initial soil water content and the irrigation schedule, if applicable (Zhang *et al*., 2022).

The outputs of AquaCrop include estimates of crop yield, biomass production, evapotranspiration, soil moisture, and water use efficiency. The model can also provide information on the timing and severity of water stress, which can be used to evaluate the effectiveness of different irrigation strategies and water management practices (Hsiao *et al.,* 2009). AquaCrop also calculates the water balance of the crop-soil system, taking into account precipitation, irrigation, evapotranspiration, and runoff. The model simulates the growth of different crops, including cereals, vegetables, fruits, and forage crops, considering different growth stages such as germination, vegetative growth, and reproductive growth (Feng *et al*., 2022).

In addition, AquaCrop simulates the response of crops to water stress, considering different levels of stress and the timing of stress. The model can be used to evaluate the effects of different irrigation strategies and water management practices on crop yields and water use efficiency. It is a field-scale model that calculates irrigation water requirements (IWR) by water balance (Raes *et al*., 2014).

2.7.2. Application of AquaCrop model in crop yield simulation studies

AquaCrop is a model for predicting grain yield and biomass response to water stress in various field crops, requiring fewer input data than other models. Studies have affirmed the model's ability to accurately simulate crop grain yield and biomass across diverse global locations, enhancing its usability at different sites (Deb *et al.,* 2015; Shrestha *et al.,* 2016).

Abedinpour *et al*. (2012) conducted a study to evaluate the performance of the AquaCrop model for maize cultivation in a semi-arid environment in India. The study involved experiments with different irrigation and nitrogen fertilizer regimes. Calibration and validation of AquaCrop were conducted using experimental data from 2009 and 2010. The results showed that AquaCrop's performance closely matched the experimental data, particularly under full irrigation and 25% deficit irrigation with normal nitrogen fertilizer.

Zeleke and Nendel (2020) conducted a field experiment in Wagga Wagga, Australia, for two years (2013 and 2014), in two spring wheat varieties (EGA Gregory and Livingston) and two soil water regimes (rainfed and supplemental irrigation) using FAOs AquaCrop model version 4.0. The model was calibrated and validated for various parameters, including crop canopy cover, biomass, soil water content, and grain yield. The root-mean-square error (RMSE) for grain yield and biomass was 0.293 and 2.2 t ha^{-1}, respectively, while the RMSE for rootzone soil water content was 25 mm. The validated model was used to analyze the impact of sowing dates and irrigation timings on grain yield and water productivity. Grain yield and water productivity decreased with delayed sowing dates, and the application of supplemental irrigation to mid-May sown wheat resulted in higher yields than mid-April and mid-June sowings. Additionally, applying irrigation in both September and October improved yield and water productivity compared to applying irrigation only in October. Off-season practices like mulching and pre-irrigation had a 68% greater impact on yield in low-rainfall years than in wet years.

Zhang *et al.* (2021) conducted research on evaluation of saline water irrigation on cotton growth and yield using the AquaCrop crop simulation model. The study focused on evaluating the feasibility of using brackish water for irrigation to address freshwater shortages and sustain food production, specifically for cotton crops in Hebei's lowland plain. Four years of experiments from 2012 to 2015 tested various salinity levels in irrigation water. The AquaCrop model can simulate cotton growth and salinity dynamics under saline water irrigation and accurately simulate crop parameters like canopy cover, soil moisture, and biomass under saline water irrigation. Scenario simulations revealed that high and normal rainfall years facilitated salt drainage from the soil, while salt accumulation occurred in low rainfall years. The study concluded that soil salinization poses a real risk to cotton production under saline water irrigation.

The study conducted by Stričević *et al.*, 2023 evaluates the performance of the AquaCrop model in simulating yield, biomass, and water requirements of common beans under various irrigation treatments and sowing periods to achieve high yield productivity. The model was calibrated using two years of experimental data from the Syrmia region in Serbia, considering three sowing periods and three irrigation levels and the results indicate that the model accurately predicts common bean yield, biomass, canopy cover, and water requirements, with statistical indices for yield and biomass indicating good model performance. The model effectively predicted irrigation requirements for full and deficit irrigation scenarios when testing different irrigation strategies. Specifically, it accurately estimated the irrigation water needs for full and two deficit irrigation strategies, performing well in predicting irrigated yield under varying sowing periods and irrigation strategies.

2.7.3. Application of AquaCrop in crop water productivity

The Aquacrop model enables the simulation of water management effects on yield, offering insights to implement strategies that enhance overall water productivity (Saad *et al.,* 2014). The study by Mansour *et al.*(2020) aimed to assess the impact of pulse drip irrigation on maize growth using the AquaCrop model. They tested two discharge rates (6 lph and 10 lph) and different water stress levels (80%, 65%, 50% of evapotranspiration) during the 2018 growing season in Egypt. Results showed that the efficiency of the irrigation system was higher with a discharge rate of 6 lph, and by decreasing the discharge rate, overall efficiency was improved. Grain and biomass yields were high, with a discharge rate of 10 lph and a water stress level of 50%. Water productivity was also high with a discharge rate of 6 lph and a water stress level of 80%. Hence, using a water stress level of 50% is recommended to conserve water under pulse drip irrigation with a discharge rate of 6 lph.

Adeboye *et al*. (2020) investigated the modeling of evapotranspiration, soil water storage, and water productivity of rainfed soybeans under different nitrogen fertilizer levels in Nigeria using the FAO AquaCrop model. Field experiments were conducted during the 2015 and 2016 rainy seasons, with five nitrogen levels and two soybean varieties. AquaCrop was calibrated using 2015 data and validated using 2016 data. The model accurately simulated canopy cover, soil water storage, evapotranspiration, and seed yield, with low error rates. Despite overestimating aboveground biomass, the model reliably predicted seed yields under various nitrogen levels. This suggested the suitability of AquaCrop model for predicting soybean productivity and optimizing resource use in tropical farming systems.

The study by Pirmoradian *et al*. (2020) aimed to simulate the water productivity of paddy using the AquaCrop model in both humid and semiarid regions of Iran, which is crucial for optimizing irrigation management and enhancing water productivity in rice production. Field experiments were conducted with different rice cultivars and irrigation treatments for two consecutive years, one in a semi-arid climate (Kooshkak) and the other in a humid climate (Rasht). The simulation results showed a relative root mean square error (RRMSE) of grain yield simulation ranging from 2.28% to 15.09%. Water productivity based on transpiration (WPT) and water productivity based on evapotranspiration (WPET) varied significantly with irrigation treatments, with greater ranges observed in the dry climate compared to the wet climate. Continuous flooding resulted in higher WPT and WPET averages in both humid (1.21 kg m^{-3} and 0.82 kg m^{-3}, respectively) and dry (1.26 kg m^{-3} and 0.76 kg m^{-3}, respectively) climates, highlighting the impact of evaporation losses on decreasing water productivity in dry climates. Notably, continuous flooding treatments exhibited the highest evapotranspiration (ET), with evaporation rates 88% higher in dry than in humid climates.

Zhang *et al*. (2022) conducted a study that focused on understanding how irrigation affects crop yield and water productivity for winter wheat over 60 years of weather data (1961—2020). The study used AquaCrop model to simulate different irrigation scenarios. Results showed that reference evapotranspiration

(ET_0) remained stable, but seasonal precipitation during the wheat growing cycle decreased, and the risk of drought increased. Despite this, crop yield and water productivity increased steadily with higher temperatures. Irrigation significantly improved yield and water productivity compared to rainfed conditions. The study demonstrated AquaCrop model's reliability in simulating crop growth and production under water deficit conditions and provided guidance for optimizing irrigation schedules.

2.8. Climate change impact on agriculture

Rising temperatures, changes in precipitation patterns, and extreme weather events affect crop yields, soil health, and water availability. In some regions, climate change is leading to increased frequency and severity of droughts, floods, and heatwaves, damaging crops and disrupting food systems. Additionally, climate change is causing the spread of new pests and diseases, which threaten crops and livestock (Malhi *et al*., 2021).

2.8.1. Climate change impact on water availability

According to a study by Lehner *et al. (2018),* climate change is likely to reduce water availability in the regions of the Mediterranean, Southern Africa, Middle East, North Africa, South Asia, Southern Europe, and the southwestern United States in the coming years. Udall *et al*. (2018) projected a 6-7% reduction in streamflow by 2050 in the Colorado River Basin, indicating the anticipated impact of climate change. This reduction in water availability will have significant consequences for agriculture, ecosystems, and human communities that rely on the Colorado river for their water supply.

Konapala *et al*. (2020) explored the impact of climate change on water availability by analyzing seasonal hydroclimatic patterns using a non-parametric statistical approach. They classified global land regions into nine regimes based on late 20th-century precipitation means and seasonality. Their analysis revealed that four regimes exhibited increased precipitation variation, while five showed decreased evaporation variation alongside rising mean precipitation and evaporation levels. The study projected increased seasonal precipitation variation in already "highly variable regimes" leading to a trend of "seasonally variable regimes” becoming more variable. Conversely, regions with low precipitation seasonality experienced heightened wet-season precipitation. These findings highlight the complex interplay between seasonal and annual precipitation and evaporation patterns, shedding light on potential shifts in water availability due to climate change.

2.8.2 Climate change impacts on irrigation water requirement

Climate change can increase irrigation water demand in most regions of the world, particularly in South Asia, North Africa, and the Middle East. By 2050, due to climate change, irrigation water demand could increase by 11-14% globally (Wada *et al.,* 2017). By 2050, global food demand is expected to increase by 60%, which will put significant pressure on irrigation water resources, particularly in water-stressed regions (FAO, 2017). Climate change will likely reduce the productivity of key crops, including rice, wheat, and maize, which could increase the land and water needed to produce the same amount of food (Zhao *et al.,* 2018). Climate change is expected to increase irrigation water demand by up to 20% in some regions of the country, including California. Agriculture accounts for around 70% of global freshwater withdrawals, and as climate change alters precipitation patterns, irrigation water availability could become more unpredictable (UN, 2021).

Boonwichai *et al*. (2018) studied how climate change affects irrigation water requirement (IWR), rice yield, and crop water productivity (CWP) for Thai Jasmine rice in Thailand's Songkhram River Basin. They used the DSSAT crop simulation model with five Regional Circulation Models (RCMs) under RCP4.5 and RCP8.5 scenarios. The findings indicate that maximum and minimum temperatures are projected to increase by 1.9°C under RCP8.5 by the 2080s. Rainfall may decrease in the 2030s and increase in the 2055s and 2080s, but rainfall during the rice reproductive phase could decrease. Changes in rainfall may affect rice yield rather than temperature, potentially causing water stress. Rising temperatures could increase crop water usage, and high rainfall alone might not be enough. IWR is expected to rise in the future. By the 2080s, rainfed rice yield could decrease by 14% under RCP4.5 and 10% under RCP8.5. Due to increased water use and reduced yield, CWP could decrease by 32% under RCP4.5 and 29% under RCP8.5 by 2080s. These findings were useful for planning adaptation strategies to address water stress and enhance rice yield and CWP in the basin under climate change.

2.8.3 Climate change impacts on crop yield

Bhuwaneswari *et al*. (2014) investigated the impact of climate change on rice crops and developed adaptation strategies for the western zone of Tamil Nadu. The CERES-Rice model in the DSSAT was used to assess the impact of climate change on rice and develop adaptation strategies to sustain rice production. The model results showed that there was a reduction in yield with an increase in temperature. To manage the water crisis under changing climatic conditions, different methods of cultivation viz., Transplanted Rice Conventional (TRC) method, Direct Sown Rice (DSR), Alternate Wetting and Drying Method (AWD), System of Rice Intensification (SRI) and Aerobic Rice Cultivation (ARC) were simulated and adaptation strategies were developed.

In a study conducted by Goswami *et al*. (2016), the specific repercussions of climate change on rice yield variability in the Jorhat district of Assam were investigated across various Representative Concentration Pathways (RCPs). The findings revealed that the anticipated variations in grain yield, compared to the observed mean yield from 2009 to 2013, ranged from -12.7% to -43.4% across all scenarios and transplanting dates considered. Ding *et al*. (2020) emphasized the efficacy of adjusting sowing dates as a more effective strategy in mitigating the effects of climate change in China.

A recent study by Aswathi *et al.* (2022) found that rice crops have shown a continuous decrease in yield during the near, mid, and end centuries of the 21st century due to climate change, as projected under two different greenhouse gas emissions scenarios (RCP 4.5 and RCP 8.5). This highlights the urgent need for adaptation measures, such as the development of climate-resilient crops and sustainable farming practices to mitigate the negative impact of climate change on crop yields and ensure food security in the future.

Lotfi *et al*. (2022) investigated the impact of climate change on the yield and length of dryland wheat phenological stages in western Iran, focusing on rainfed cultivation management. Two downscaling models, SDSM and LarsWG, were employed to simulate climate conditions over the next 30 years. AquaCrop and DSSAT models were utilized to model performance and phenological stages, considering three RCP climate scenarios (2.6, 4.5, and 8.5). Results indicated that the AquaCrop model outperformed DSSAT, demonstrating higher coefficient of determination values and lower root mean square error (RMSE) values. Specifically, AquaCrop exhibited coefficient of determination values of 0.86, 0.64, and 0.89 in Kermanshah, Sanandaj, and Ilam stations, respectively, with corresponding RMSE values of 198.6, 274.6, and 192 kg/ha. In contrast, DSSAT showed coefficient of determination values of 0.90, 0.11, and 0.82, with RMSE values of 219.9, 288.1, and 238 kg/ha, respectively. Generally, the results indicated lower yields in scenarios of rising temperature and carbon dioxide levels. The SDSM downscale model showed the highest dryland wheat yields mainly in scenarios 4.5 and 8.5, whereas the LarsWG model indicated the lowest yields in these scenarios. These findings underscore the significance of downscaling and crop model selection in determining climate change impact on agricultural yields.

2.8.4 Climate change impacts on crop water productivity

Climate change can have a significant impact on crop water productivity, which is a measure of how efficiently crops convert water into yield. Higher temperatures, changes in precipitation patterns, and extreme weather events can all affect crop water productivity (FAO, 2020).

One of the ways in which higher temperatures can impact crop water productivity is by increasing the water requirements for crops. As temperatures rise, crops need more water to maintain their growth and development. This increased water demand can result in water stress, where the crops do not receive enough water to grow and yield optimally. This, in turn, can reduce crop water productivity.

In addition to increased water demand, higher temperatures can also lead to reduced crop yields, further reducing crop water productivity. Extreme heat can cause heat stress in crops, which can reduce their growth and development. This, in turn, can lead to reduced yields and lower crop water productivity.

Changes in precipitation patterns can also impact crop water productivity. Too much or too little precipitation can lead to reduced crop yields and lower crop water productivity. For example, if there is too much precipitation, it can cause soil erosion and nutrient leaching, which can negatively affect crop growth and development. Too little precipitation can cause water stress, where crops do not receive enough water to grow and yield optimally, leading to reduced yields and lower crop water productivity.

The impact of climate change on crop water productivity is a global concern, with studies predicting significant declines in yields and water productivity for major crops in different regions of the world. For instance, a recent study by Lobell *et al.* (2021) found that global maize yields are expected to decline by 7.4% on average by 2040 due to climate change, resulting in a 6.4% decrease in crop water productivity. Similarly, Azeem *et al.,* (2020) projected that climate change could decrease the water productivity of rice, wheat, and maize crops in South Asia by 8.7%, 5.5%, and 6.5%, respectively, by 2050. In the Midwest United States, Ojha *et al*. (2019) predicted a decrease in crop water productivity of maize, soybean, and wheat crops by 4.4%, 4.1%, and 3.1%, respectively, by the end of the century. Likewise, Silva *et al*. (2018) estimated that climate change could reduce the crop water productivity of maize and soybean crops in Brazil by 3.3% and 2.2%, respectively, by 2050. These findings highlight the urgent need for adaptation measures to maintain or improve crop water productivity and ensure sustainable food production in the face of climate change.

Shrestha and Shrestha (2017) investigated the effects of climate change on crop yield and irrigation water requirement of two major cereal crops (rice and wheat) in Bhaktapur district, Nepal. The yield simulation model, AquaCrop, was used to simulate the crop yield with reasonable accuracy. Crop yield simulations, based on HadCM3Q0 projection, indicated decreased yield, while ECHAM5 projection indicated increased yield for monsoon rice in the A1B scenario and rather stable yield for winter wheat in both projections. Simulation results for management strategies indicated that the crop yield was mainly constrained by water scarcity and low fertility. A suitable deficit irrigation method was also discovered to be useful for stabilising wheat yield during the dry season.

2.9.Potential Adaptation and Mitigation Strategies

Adaptation to climate change, as defined by the IPCC in 2007, involves the modification of natural and human systems in response to observed or anticipated climate change and its associated impacts, with the aim of safeguarding valuable opportunities. Agriculture, being highly sensitive to climate conditions, is particularly vulnerable to the hazards and influences of climate change. Consequently, adaptation involves both the development and implementation of capacity (IPCC, 2007). Adaptation measures can be categorized into various types, including anticipatory and responsive adaptations, private and public adaptations, as well as autonomous and planned adaptations (Orlove, 2022).

Adaptation and mitigation strategies can play a critical role in reducing the impact of climate change on crop water productivity and food security. Implementing water-saving irrigation techniques, increasing water storage capacity, and improving water use efficiency can help to optimize water resources and reduce waste (Kang *et al.*, 2021). Similarly, making crops more resilient to drought, heat stress, and other climate-related challenges can help to maintain crop yields and ensure food security (Amoak *et al.*, 2022). Innovative technologies, such as remote sensing and GPS, can help to optimize water and fertilizer use, reduce waste, and increase yields (Khanal *et al.*, 2020). Conservation agriculture and agroforestry can also contribute to improving soil health, increasing carbon sequestration, and enhancing the resilience of ecosystems to climate change (Khan *et al.*, 2021).

Mitigation strategies, such as transitioning to renewable energy sources, increasing energy efficiency, and reducing emissions from transportation and industry, can help to reduce the impact of climate change on food security (Rial, 2024). Changes in the timing of planting and harvesting may also impact food security, as the availability and affordability of food may vary throughout the year. Investing in water storage and distribution systems can ensure that water is available for irrigation during times of drought or other extreme weather events (Mwadzingeni, 2022). Moreover, preparedness for extreme weather events, such as floods, droughts, and heat waves, can help to reduce the impact of these events on food production and distribution.

Food assistance programs and cash transfers can also help to ensure that vulnerable populations have access to food during times of food insecurity. Finally, reducing food waste can help to reduce the impact of climate change on food security by ensuring that food resources are used efficiently. Overall, implementing a combination of adaptation and mitigation strategies can help to build a more resilient food system that can cope with the challenges of climate change and ensure sustainable food production for future generations.

2.9.1. Adaptation by changing cropping calander

An adaptation measure to climate variability involves modifying cropping techniques by adjusting the timing of farm activities in response to changes in climate conditions. This adaptation strategy encompasses alterations in sowing dates, the provision of irrigation, and the selection of crop cultivars with varying phenology, taking into account the patterns of ozone pollution concentration (Teixeira *et al.,* 2011).

The study by Truong (2020) focuses on how changing the timing of planting rice crops can help cope with the challenges of climate change in the Long Xuyen Quadrilateral region of Vietnam. With climate change affecting rice paddies and leading to lower crop yields, the research aims to find the best times to plant rice to counter these effects. Using a crop model called FAO-AquaCrop, the study simulates rice yields under different planting schedules. The results show that delaying the planting schedule by 7 to 14 days can increase rice yields by around 5% to 6% in different seasons. This suggests that changing the planting calendar for rice crops could be a practical way to reduce the harmful effects of changing weather patterns and boost rice production. This research highlights the importance of adapting farming practices to climate change, which can be crucial for ensuring food security in the region.

2.9.2. Adaptations in management of irrigation water

The management of irrigation water is expected to confront significant challenges in the upcoming decades, primarily centered around ensuring the safety of water supplies and coping with the depletion of water resources (Bird *et al*., 2016). Structural options such as the construction of ponds, dams, or utilization of groundwater may be implemented to address these challenges. Enhancing the management of surface storage reservoirs and mitigating leakage losses will prove beneficial in the context of climate change (Wang *et al*., 2016, Islam *et al*., 2022). Implementing appropriate agricultural practices for water consumption, the lining of canals and watercourses, as well as the efficient operation and maintenance of irrigation networks, will play a crucial role in adapting to the increased variability in water resources induced by climate change (Iglesias and Garrote, 2015).

The study by Iglesias and Garrote (2015) sheds light on the pressing need for adaptation strategies in agricultural water management amidst climate change in Europe. By analyzing a substantial body of literature, the research underscores the intensified risks posed by climate change, particularly in regions already grappling with water scarcity, while also highlighting emerging opportunities in certain areas. Through a comprehensive review of over 168 publications spanning 15 years, the study provides insights into the diverse adaptation strategies proposed to date, aiming to address regional challenges and enhance the resilience of agricultural water management systems. The findings emphasize the importance of understanding the current technological landscape and the need for proactive measures to bolster adaptive capacity, including policy reforms, farmer training initiatives, and financial support mechanisms. These insights serve as valuable guidance for stakeholders as they navigate the complexities of climate change adaptation and work towards developing robust strategies to safeguard the agricultural sector against future uncertainties.

The study by Zhao and Boll (2022) underscores the critical role of adaptive water management strategies in addressing the challenges posed by climate change, particularly in the context of irrigation water management. Focusing on the Yakima River Basin (YRB) in Washington State, USA, the research emphasizes the importance of implementing adaptations in the management of irrigation water to mitigate the impacts of drought on agricultural production. By enhancing an integrated water resource management tool, the study evaluates various adaptation methods aimed at enhancing the resilience and sustainability of agricultural systems. These adaptations include strategies such as managed aquifer recharge, greenhouses, optimized crop planting times, and water-efficient irrigation technologies. Through their analysis, the researchers highlight the necessity of adopting a comprehensive approach that integrates multiple adaptation methods to effectively alleviate future drought impacts on agriculture. This research contributes significantly to the understanding of adaptive water management strategies and their crucial role in ensuring the long-term viability of agricultural water resources in changing climate conditions.

2.9.3. Adaptation strategies specific to Aquacrop Model.

AquaCrop offers a range of potential adaptation strategies to enhance both yield and biomass. Strategies that align with climatic trends and simulate natural adaptation include adjusting the sowing date and opting for no mulching or using either organic or synthetic mulches (Bird *et al*., 2015, Islam *et al*., 2022). Additionally, modifying irrigation management practices can be effective, whether through surface irrigation methods like basin, border, and furrow techniques or by employing sprinkler or drip irrigation methods (Shrestha *et al*., 2016, Islam *et al*., 2022). AquaCrop also provides the option to incorporate bunds as a field practice and assess the impact of shifting from full to deficit irrigation strategies (Bird *et al*., 2015).

The study conducted by Bird *et al*. (2015) employed AquaCrop's versatile functionalities to assess the impacts of climate change on agriculture in Sardinia and Tunisia, while also exploring potential adaptation strategies. By utilizing AquaCrop's options for variable sowing dates based on rainfall patterns and the inclusion of mulching as a field practice, the researchers investigated how adjusting agricultural practices could mitigate the adverse effects of climate change on crop yields. Mulching, with default parameters resulting in a 50% reduction in soil evaporation, was identified as a potential adaptation measure to conserve soil moisture and enhance water productivity. Although bunds were tested as a field practice, their limited impact on crop yields and water requirements was attributed to default soil curve characteristics, suggesting the need for more detailed soil runoff information for bunds to become a viable adaptation strategy. Additionally, AquaCrop's capability to calculate net irrigation requirements under deficit irrigation management was utilized to explore future irrigation needs and inform adaptive strategies to maximize water-use efficiency while minimizing crop water stress. By integrating these AquaCrop features, the study provides valuable insights into how agricultural management practices can be optimized to sustain crop productivity in changing climate conditions, contributing significantly to climate change adaptation in agriculture.

The study by Islam *et al*. (2022) provides valuable insights into the challenges and potential adaptation strategies for enhancing water productivity in wheat cultivation, particularly in the Dinajpur region of Bangladesh, amidst changing climatic conditions. By utilizing the AquaCrop model and considering future climate projections, the research underscores the anticipated reduction in water productivity of wheat due to climate change, with potential decreases of up to 33%. However, the study offers optimism by identifying adaptation measures such as altering sowing dates and introducing heat-tolerant wheat varieties, which could mitigate these adverse impacts and enhance water productivity. These findings contribute significantly to the existing literature by highlighting actionable strategies for policymakers and stakeholders to address the dual challenges of food and water security in the context of climate change, particularly in regions highly dependent on wheat cultivation, like northwestern Bangladesh.