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Climate Change Impact On Rice Productivity Using FAO AquaCrop Model: A Case Study in Lampung

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ABSTRACT

Climate change impacts global food productions, but its local effect on rice production, particularly on monsoon dominated regions remain less understood. Here, we assess climate change impact on rice production situated on Lampung Province, as one of the largest rice productions in Indonesia. The FAO AquaCrop model was used to predict rice productivity, incorporating climate projections from the CMIP5 model under medium (RCP 4.5) and high (RCP 8.5) emission scenarios. We simulated the model for fifteen locations representing districts in Lampung Province. Our results show that by 2050, the decreased rainfall is projected during the dry season and early rainy season, but the average monthly temperatures and evapotranspiration rates are expected to increase across all districts. AquaCrop simulated an increased rice productivity by +0.25 and +0.74 tons/ha for both scenarios in April planting season, but it decreased by -0.41 and -0.75 tons/ha in November planting season due to water stress. This research is important to provide a deeper understanding of the impact of climate change on rice productivity in Lampung Province. These findings highlight the need for adaptive strategies to sustain rice production under future climate conditions.

KEYWORDS
adaptation strategies, evapotranspiration, marksim weather generator, RCP 4.5, RCP 8.5

1. INTRODUCTION

Climate change significantly impacts agricultural yields, posing a risk of future food crises (Elsadek et al., 2024). With the global population projected to reach 9.6 billion by 2050, food demand may rise by 60% globally and 100% in developing countries (Yildiz, 2019). Lampung Province, as the sixth largest rice producers in Indonesia has a strategic role as a national food barn. Rice farming contributes to national food security, and supports the local and regional economy. However, changes in temperature and rainfall patterns due to climate change can affect rice production, thus threatening food security in this region.

In Lampung, climate change is marked by declining rainfall, and rising temperatures up to 0.7°C (Manik et al., 2014). Similar trend was reported based on historical and projection data (Kusumastuty et al., 2021). Previous research has shown that increased temperature affects rice plants by accelerate aging, and shorten the grain-filling period, ultimately reducing biomass production and rice yields (Saud et al., 2022; Tao et al., 2013). Additionally, decreased rainfall led to water scarcity, particularly in rainfed rice systems (Ansari et al., 2021).

Higher CO_2 concentrations level enhances the photosynthesis rate, which positively impacts biomass production and crop yields (Liu et al., 2020). With appropriate management, elevated CO_2 levels may help mitigate the negative effects of climate change

(Houma et al., 2021). However, the combined effects of increased CO_2 and rising air temperatures are not always additive, complicating predictions of rice productivity under climate change scenarios (Jing et al., 2016).

The AquaCrop model, developed by the Food and Agriculture Organization (FAO), is used to predict the impact of climate change on agricultural yields, including rice, by integrating climate variables such as temperature and rainfall to understand crop responses to environmental stress conditions (Alvar-Beltrán et al., 2022; Kang et al., 2021). AquaCrop simulations have shown a decline in rice productivity by 17% in Iran (Roshani et al., 2022). A similar finding was reported from Ecuador (Portalanza et al., 2022). In contrast, under high-emission scenarios rice yields might increase in the future (Xie et al., 2023).

To project future climate conditions, the Intergovernmental Panel on Climate Change (IPCC) introduced Representative Concentration Pathways (RCPs), as outlined in its Fifth Assessment Report (AR5) in 2014. These include four scenarios: RCP 2.6 (a strong mitigation pathway), RCP 4.5 and RCP 6.0 (intermediate stabilization pathways), and RCP 8.5 (a high-emission scenario) (Pachauri et al., 2015). This study investigates the potential impacts of climate change on evapotranspiration rates, water productivity, and rice yields in Lampung Province by the year 2050, using the RCP 4.5 and RCP 8.5 scenarios. The year 2050 was selected as it is a key reference point in many IPCC projections, reflecting the urgency of climate action and the anticipated consequences of emission trajectories (Parris et al., 2023).

Climate data were obtained from the MarkSim Weather Generator, which downscales outputs from General Circulation Models (GCMs). This study adopts an integrated modeling approach by incorporating RCP-based climate projections into the AquaCrop model, validated with observed local climate data. This method enables robust projections of future rice productivity in Lampung, contributing to the formulation of evidence-based adaptation strategies in the agricultural sector.

2. MATERIAL AND METHODS

2.1 Study Area

The study area was in 15 rice production areas in Lampung Province, which were selected based on the availability of completed rainfall data for 2011–2022. Lampung Province has a monsoonal rainfall pattern, characterized by a single peak rainy season and dry season, heavily influenced by the Asian and Australian monsoon wind circulations (Aldrian and Susanto, 2003).

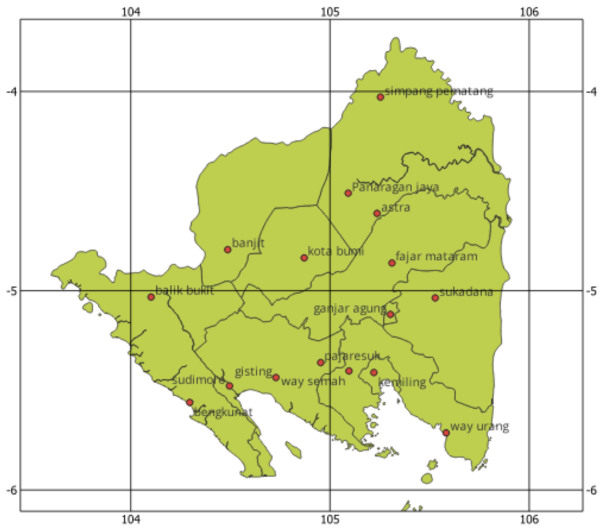

Figure 1. Map of Lampung Province

2.2 Datasets

The datasets used in this study include: (1) daily rainfall and air temperature (maximum and minimum) from 2011–2022 obtained from 15 rain gauge stations across Lampung Province (Figure 1), provided by the Lampung Climatology Station; (2) actual rice productivity data for the same period and locations from BPS Lampung; (3) modelled climate data (rainfall, temperature, and solar radiation) for the baseline and future scenarios (RCP 4.5 and RCP 8.5, year 2050) from the MarkSim Weather Generator using the CSIRO-Mk3-6-0 model; and (4) soil texture and physical property data from paddy field samples analyzed at the Lampung State Polytechnic Soil Laboratory.

2.3 Data Analysis

This study used AquaCrop software, a model developed by the FAO to simulate crop yields with water as the primary limiting factor. AquaCrop can simulate the effects of increased air temperature, CO_2 concentration, and changes in rainfall on crop water balance and productivity under climate change condition (Steduto et al., 2012). The core of AquaCrop is Equation (1), which links crop yield to the amount of water used by the plants.

$$\left(\frac{Y_x-Y_a}{Y_x}\right) = K_y\left(\frac{ET_x-ET_a}{ET_x}\right) \qquad (1)$$

Where Y_x and Y_a represent the maximum and actual crop yields, respectively, while ET_x and ET_a represent maximum and actual evapotranspiration. Ky is the proportionality factor that links relative yield loss to the relative reduction in evapotranspiration. This relationship is further extended in Equation (2), which encapsulates the crop growth mechanism concept in AquaCrop.

$$B = WP \times \sum Tr \qquad (2)$$

Where B is the biomass, WP is water productivity (biomass per unit of cumulative transpiration), and Tr is plant transpiration. These two equations represent expressions of the water dependent growth mechanism in the design of the crop growth model (Steduto et al., 2009).

The AquaCrop components, as shown in Figure 2, illustrate the key elements of the system that connects soil, plants, the atmosphere, and the factors influencing phenology, canopy cover, transpiration, biomass production, and yield. Solid lines represent direct relationships between variables and processes, while dashed lines indicate feedback loops (Steduto et al., 2012).

The daily climate variables used in the AquaCrop simulation include rainfall, maximum and minimum air temperature, solar radiation, and CO_2 concentration. The rice planting schedule follows the main cropping season, starting on November 1, and the second cropping season (gadu) on April 1 (Andono, 2017). The selected rice variety is Ciherang, one of the most commonly grown varieties by farmers in Lampung Province.

AquaCrop was calibrated by adjusting crop parameter values to match field conditions. Adjustments included a maximum canopy cover of 55 days, senescence at 85 days, a yield of 8 tons/ha, and a growth duration of 120 days, based on the "*Buku Deskripsi Varietas Unggul Tanaman Padi*" (Thamrin et al., 2023). The soil type used was clay, with a composition of 18.2% sand, 45% clay, and 36.8% silt, based on soil sample analysis conducted in a soil laboratory. The irrigation system applied was rainfed, and land management involved the use of rice field bunds, a characteristic feature in fields that helps retain surface water (Steduto et al., 2009).

The model was validated using historical climate data from 2011 to 2022. We simulated rice productivity to validate the AquaCrop model by comparing model outputs with actual productivity data. The Relative Root Mean Square Error (RRMSE) analysis was applied to validate the model (Chai and Draxler, 2014). Subsequently, the AquaCrop simulation was conducted using climate data from the MarkSim Weather Generator, including baseline data and projections for RCP 4.5 and RCP 8.5 scenarios for the year 2050.

The limitations of the AquaCrop model lie in its dependence on the quality of input data. AquaCrop requires detailed information about climate, soil, and crop management practices, which may not always be available or accurate (Luciani et al., 2019). Additionally, this model may not fully account for other important factors affecting rice production under climate change, such as pest and disease dynamics, soil fertility changes, and socio-economic factors influencing agricultural practices (Yersaw et al., 2024). Another limitation is related to the climate change scenarios from the General Circulation Model (GCM), where GCMs often struggle to accurately simulate extreme events (Hidayat and Taufik, 2025), which are expected to become more frequent and intense due to climate change (Morley et al., 2018).

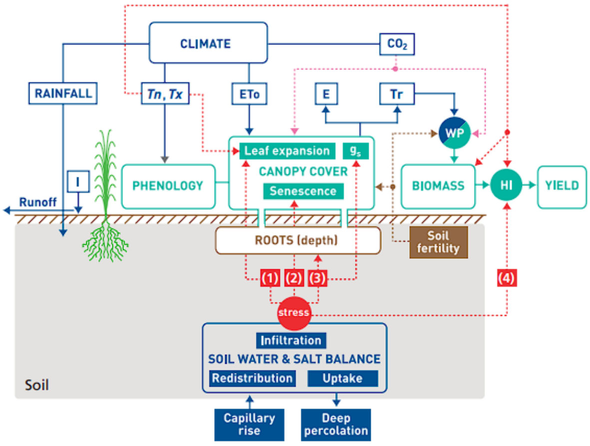

Figure 2. AquaCrop Component Chart

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3. RESULTS AND DISCUSSION

3.1 Model Evaluation

The AquaCrop model was run using climate and crop parameters from 2011 to 2022 to compare actual rice productivity with model predictions. The simulation results indicated that the productivity predicted by the AquaCrop model varied across the study sites. Table 1 presents the RRMSE values, ranging from 6% to 26%. In general, the performance of model was good at northern Lampung regions, such as Mesuji, Tulang Bawang, and North Lampung, (RRMSE values 6% to 11%), while the model performance in Southern Lampung regions, such as Pesawaran, South Lampung

Table 1. Metric evaluation of RMSE and R2 between actual data (BPS) and AquaCrop

Regency	Average actual productivity from BPS (ton/ha)	Average Productivity of the model from AquaCrop (ton/ha)	Relative RMSE
Mesuji	4.70	4.68	6%
Tulang Bawang	4.48	4.53	9%
Lampung Utara	4.68	4.62	11%
Way Kanan	4.70	4.81	12%
Pesisir Barat	4.98	4.38	15%
Lampung Timur	5.02	4.42	15%
Tulang Bawang Barat	4.77	4.69	17%
Tanggamus	5.51	4.76	18%
Metro	5.33	4.53	19%
Lampung Tengah	5.19	4.44	20%
Pringsewu	5.53	4.50	20%
Bandar Lampung	5.52	4.43	21%
Lampung Barat	4.81	5.94	25%
Lampung Selatan	5.64	4.38	23%
Pesawaran	5.39	4.16	26%

and Bandar Lampung, was poor (RRMSE values 25% to 26%).

Previous studies showed the RRMSE value between 10%-12.4%, as reported from simulating grain yield of paddy rice under different irrigation regimes (Pirmoradian et al., 2020). The discrepancy between model and actual productivity is due to the AquaCrop model using a rainfed irrigation system, while the actual data used a mixed irrigation system combining both irrigation and rainfed methods. The model's productivity output was also sensitive to short-term droughts occurring during the simulation. Overall, based on historical data, AquaCrop can be considered reliable for predicting rice productivity.

3.2 Changes in Rainfall, Temperature, and Evapotranspiration

Based on MarkSim Weather Generator projections (Figure 3), rainfall in Lampung Province is expected to decline from June to December by 2050 under both RCP 4.5 and RCP 8.5 scenarios, with no significant change observed from January to May. This indicates a drier dry season (April to October) and reduced rainfall during the early rainy season (September to December). These findings align with Achyadi et al. (2019), who reported that several GCM models (e.g., Access 1.0 and MRI.GCM3) project a similar dry season decline in the Barito Kuala region, South Kalimantan, for the 2041–2060 period.

Figure 3b shows that air temperature is projected to increase by 2050, with a rise of approximately +1.6°C under RCP 4.5 and +1.9°C under RCP 8.5, relative to the baseline. This 0.3°C difference highlights a stronger warming trend under the high-emission scenario. Global warming had already reached around +1°C above pre-industrial levels during 2006–2015 (IPCC, 2015), and under both RCPs, Lampung is projected to exceed the 2°C threshold targeted by the Paris Agreement by 2050 (Pachauri et al., 2015).

Increased temperatures are closely linked to higher evapotranspiration rates. Based on AquaCrop simulation results (Figure 3c), evapotranspiration is projected to rise from June to January under both RCPs, with maximum increases of +24 mm/month (RCP 4.5) and +26 mm/month (RCP 8.5). In contrast, evapotranspiration remains unchanged in March and May, and decreases in February by −24 mm/month (RCP 4.5) and −26 mm/month (RCP 8.5). The rise in evapotranspiration under RCP 8.5 is mainly driven by increased temperatures, which intensify atmospheric moisture demand (Hordofa et al., 2021). Climate variability, particularly temperature, plays a critical role in altering evapotranspiration, influencing water loss across different environments (Liu et al., 2020).

3.3 Changes in Crop Water Productivity in 2050

Climate change is projected to reduce rice crop water productivity, with average declines of −0.3 kg/m^3 under RCP 4.5 and −0.4 kg/m^3 under RCP 8.5 compared to the baseline (Figure 4a). This decline occurred across all districts except Pesisir Barat, where an increase was observed. Overall, the reduction was more pronounced

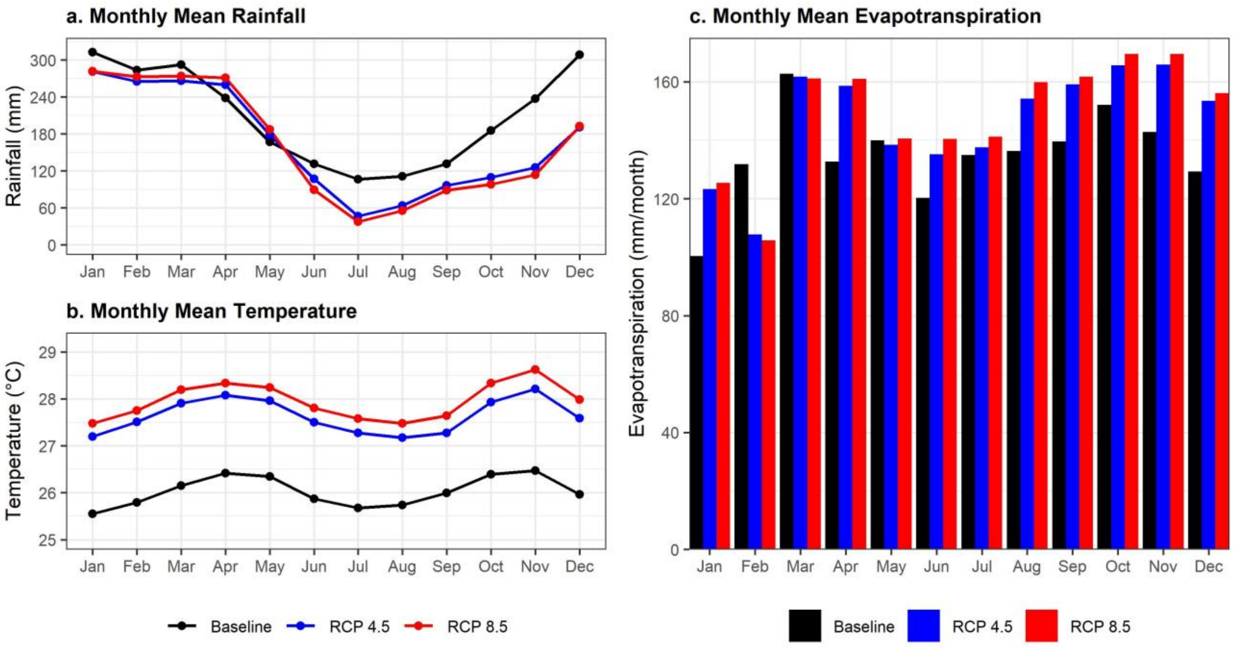

Figure 3. Mean climatological of (a) rainfall; (b) temperature; and (c) evapotranspiration relative to baseline (2011-2022)

under RCP 8.5, except in Tulang Bawang and Lampung Selatan, where RCP 4.5 showed a slightly greater decline. The decrease in water productivity is attributed to increased water use and reduced yield. Similarly, a decrease in rainfed rice water productivity in Thailand, with reductions of 32% under RCP 4.5 and 29% under RCP 8.5 (Boonwichai et al., 2018).

However, future projections suggest that rice water productivity can improve with the implementation of efficient and proper irrigation systems (Houma et al., 2021). In regions with limited water availability, optimized irrigation, such as precision water management and deficit irrigation can increase water use efficiency and improve crop resilience (Adenan et al., 2015; Kumar et al., 2023).

3.4 Changes in Rice Productivity in 2050

Climate change is projected to alter rice productivity in Lampung Province during both the April and November planting seasons by 2050 under RCP 4.5 and RCP 8.5 scenarios (Figure 4b–c). In the April season, rice productivity generally increases compared to the baseline. Under RCP 4.5, productivity rises in districts such as Pesawaran, Lampung Timur, Pesisir Barat, Pringsewu, Lampung Selatan, Lampung Barat, and Lampung Tengah, while it declines in Tulang Bawang, Metro, Bandar Lampung, Mesuji, Way Kanan, Tulang Bawang Barat, and Lampung Utara. Tanggamus shows minimal change. Under RCP 8.5, nearly all regions exhibit increased productivity, except Tanggamus, Tulang Bawang, Way Kanan, and Bandar Lampung, which show slight declines. On average, the projected productivity increase in April is +0.25 tons/ha under RCP 4.5 and +0.74 tons/ha under RCP 8.5.

This improvement is linked to relatively stable rainfall conditions during the April planting through June harvest period, despite higher evapotranspiration and slight rainfall decreases in June. Moreover, the CO_2 concentration rise from 369 ppm (baseline) to 474 ppm under RCP 4.5 and 541 ppm under RCP 8.5, enhances photosynthesis and crop growth. However, fertilization can improve yields under certain conditions and could rise by 15% at 550 ppm (Pingale et al., 2017), although it may not fully offset climate risk (Wang et al., 2017).

In contrast, during the November planting season, most districts experience a decline in productivity. Areas affected include Lampung Selatan, Pesawaran, Bandar Lampung, Metro, Tanggamus, Lampung Tengah, Lampung Timur, Lampung Barat, and Way Kanan. Only Tulang Bawang, Tulang Bawang Barat, and Pesisir Barat show increased productivity. On average, productivity is projected to decline by −0.41 tons/ha under RCP 4.5 and −0.75 tons/ha under RCP 8.5. This reduction linked to the increased evapotranspiration and reduced rainfall during the late-year growing period, which diminishes water availability for crop development.

The decline in rainfall during November, combined with rising temperatures and increased evapotranspiration, contributes to water deficits for rice crops. This leads to water stress during the early growth stages. particularly the first month after planting, hindering canopy development and ultimately reducing yields.

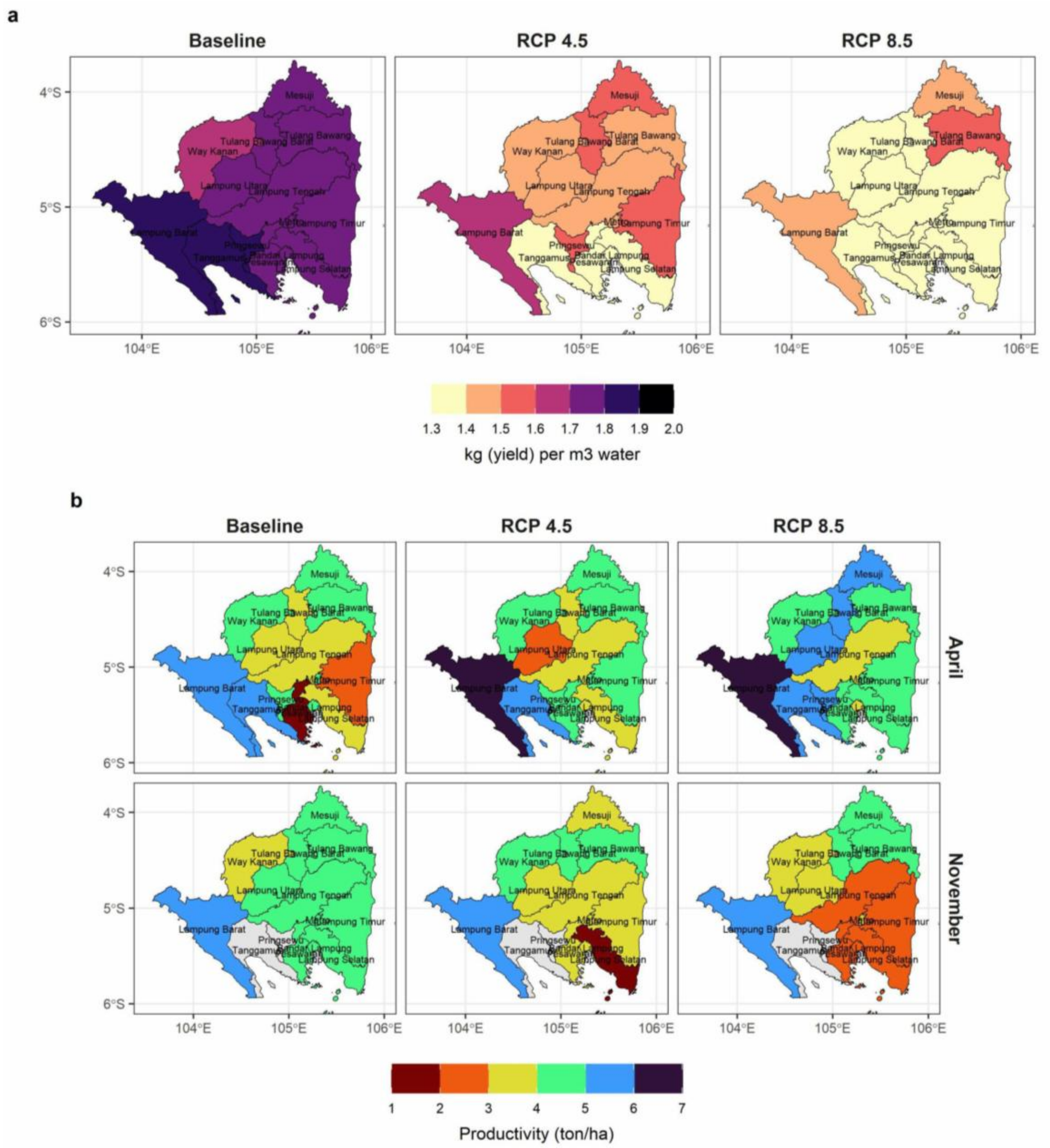

Figure 4. Changes in (a) water productivity and (b) rice productivity per district relative to baseline level under RCP 4.5 and RCP 8.5

Water stress at this stage significantly limits plant height and leaf area expansion, both critical for photosynthesis and biomass accumulation (Rajasivaranjan et al., 2022). Moreover, stress during the vegetative phase negatively affects root development, essential for nutrient uptake and plant stability, and often results in greater yield losses than stress during the reproductive phase.

This is consistent with previous studies, which project significant reductions in rainfed rice yields under future climate scenarios, ranging from 14.7% to as high as 40% due to increased temperature, water stress, and shifting rainfall patterns (Khan et al., 2020; Sonko et al., 2019). Despite these risks, effective adaptation strategies, particularly improved irrigation practices are critical to reducing the vulnerability of rice systems to climate-induced water stress.

While this study offers important insights into the potential impacts of climate change on rice productivity in Lampung Province, several limitations must be acknowledged. First, the AquaCrop simulations were conducted under rainfed conditions, whereas actual field conditions often involve a mix of irrigation practices, possibly leading to discrepancies between modeled and observed productivity.

Additionally, the model may be sensitive to short-term droughts and may not fully capture the influence of extreme weather events, which are increasingly common and impactful under climate change. The simulations also do not account for socioeconomic factors, pest and disease pressures, or technological advancements, all of which could significantly alter future rice productivity. Lastly, model calibration was limited by the availability of site-specific field parameters, which may affect the accuracy of projected crop responses.

4. CONCLUSION

The climate projection data based on RCP 4.5 and 8.5 scenarios generated by the MarkSim Weather Generator and simulated using AquaCrop provides crucial insights into the future condition of rice productivity in Lampung Province by 2050. Threats to rice productivity become more apparent with increasing evapotranspiration rates, decreasing rainfall, and delayed rainy seasons, despite rising CO_2 concentrations. AquaCrop simulations utilizing data from the MarkSim Weather Generator serve as an effective and user-friendly tool for understanding the impact of climate change on future rice productivity.

For future studies, it is recommended to use the latest scenarios, such as the Shared Socioeconomic Pathways (SSPs) which provides a comprehensive and integrated framework for understanding the interactions between climate change and socio-economic factors. Additionally, AquaCrop calibration should be carried out using more field based parameters to improve the accuracy of crop simulations and ensure results that closely align with actual data.

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