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UNCERTAINTIES IN CLIMATE CHANGE SCENARIOS FOR DETERMINING TEMPERATURE AND RAINFALL PATTERNS IN REGIONS WITH MIXED CLIMATE CONDITIONS

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ABSTRACT

Aim of the study

This study aims to quantify uncertainty in assessing climate change impact on crop production by using all available climate models (GCMs) under both harsh and mild emission scenarios from 2020 to 2095, which has not yet been done in the studied region to date.

Material and methods

A comparative study was carried out for Ludhiana district, Punjab, India, in which Global Climate Model (GCM) outputs for daily maximum (T_{max}) and minimum temperature (T_{min}) and rainfall under A1B scenario concerning Mid Century (MC) (2020–2050) and End Century (EC) (2070–2095) were extracted from ECHam5-GCM and PRECIS model. DSSAT v.4.6.1 model and Papadakis method were used to study the climate change behavior under these two time-slices. In addition, climate data from RCP scenarios for the future were extracted from five randomly selected GCMs under scenarios RCP 4.5 and RCP 8.5 using the MarkSim DSSAT weather generator. These models were analyzed statistically for RMSE and NRMSE. One of the models, HAD GEM2-ES, was selected as having the least NRSME for the impact assessment studies.

Results and conclusions

The results showed that the annual minimum temperature would increase by 2.4°C and 2.45°C for EC using ECHAM5 and PRECIS models. In contrast, under RCPs 4.5 and 8.5 scenarios, the mean annual temperature would increase by 1.56°C in MC and 3.11°C in EC compared to that of the baseline period, and 2.75°C in MC and 5.46°C in EC compared to that of the baseline period, respectively. The corresponding likely decrease in annual RF under RCP 4.5 is 98 mm and 90 mm during MC and EC, respectively. The corresponding increase in annual RF under RCP 8.5 is 153 mm and 251 mm, respectively. Hence, our findings show that the uncertainty is prevalent even in relatively small regions, while selecting different climate change scenarios.

Keywords: Climate change, Global Climate Models, AIB scenarios, RCP Scenarios, DSSAT

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INTRODUCTION

Future climate projections and impact assessments are critical in evaluating the potential impacts of climate change and climate variability on crop production. Climate change impact assessment combined with the crop and climate models under different climate change scenarios is uncertain, and selecting an appropriate scenario is challenging.

Climate change is expected to increase the vulnerability of agricultural systems (Rosenzweig et al., 2014) by increasing temperature, changes in rainfall patterns, and the frequency of extreme weather events in most parts of the world (IPCC, 2014). Elevated CO_2 concentration (eCO_2) positively relates to crop growth, biomass, and yield by promoting photosynthesis and decreasing transpiration and stomatal conductance, and overall it enhances water use efficiency (Williams et al., 2015; Luo et al., 2016; Fahad et al., 2016a,b,c,d). However, more recent studies have shown that interactive effects of CO_2 projected an increase in temperature. Variability in precipitation in future climate scenarios could potentially offset the positive effect of CO_2 induced by doubling its concentration (Paz et al., 2012; Hatfield and Prueger, 2015; Nasim et al., 2016). More recently, downscaling of climate data has found wider application in hydro climatology for scenario construction and simulation/ prediction of (i) regional precipitation (Kim et al., 2004); (ii) low-frequency rainfall events (Wilby, 1998), (iii) mean, minimum and maximum air temperature (Kettle and Thompson, 2004); (iv) soil moisture (Georgakakos and Smith, 2001; Jasper et al., 2004); (v) runoff (Arnell et al., 2003) and stream flows (Cannon and Whitfield, 2002); (vi) groundwater levels (Bouraoui et al., 1999); (vii) transpiration (Misson et al., 2002), wind speed (Faucher et al., 1999) and potential evaporation rates (Weisse and Oestreicher, 2001); (viii) soil erosion and crop yield (Zhang et al., 2004); (ix) landslide occurrence (Buma and Dehn, 2000; Schmidt and Glade, 2003) and (x) water quality (Hassan et al., 1998). The approaches proposed for downscaling GCMs could be broadly classified into dynamic and statistical downscaling. In the dynamic downscaling approach, a Regional Climate Model (RCM) is embedded into GCM. The RCM is a numerical model in which GCMs are used to fix boundary conditions. The major drawback of RCM, which restricts its use in climate impact studies, is its complicated design and high computational cost. Moreover, RCM is inflexible because expanding the region or moving to a slightly different region requires redoing the entire experiment (Crane and Hewitson, 1998). Uncertainty in climate change impact projections is related to multiple factors, including climate model and greenhouse gas emission scenario selection, complexities in atmosphere modeling, downscaling methods, incomplete understanding of the processes included in climate models, and uncertainties in crop models (Wilby et al., 2009; Asseng, 2013; Challinor et al., 2013; Osborne et al., 2013; Uusitalo et al., 2015; Mason-D'Croz et al., 2016; Amin et al., 2017a). Most studies rely on only a few climate models and a single greenhouse gas (GHG) emission scenario; those were unable to characterize uncertainties in climate risk assessment (Meehl et al., 2007; Bassu et al., 2014; Tao et al., 2009; Rotter et al., 2011; Amin et al., 2017b). A more robust climate change impact assessment is based on multi-climate model (GCMs) projections and multiple scenarios (Tebaldi and Knutti, 2007; Kassie et al., 2015; Araya et al., 2015). Process-based dynamic crop models can be used for climate risk assessment (Ewert et al., 2015) but must be rigorously calibrated with growth and yield attribute data (Challinor et al., 2013; Adhikari et al., 2015; Bassu et al., 2014; Uusitalo et al., 2015; Kersebaum et al., 2015; Awais et al., 2017). As a result, models predict the expected impacts of uncertainties associated with climate change scenarios on the growth and yield of crops (Thorp et al., 2014; Rosenzweig et al., 2013, 2014; Ruane et al., 2013). Climate change impact assessment studies quantify uncertainties related to climate risks and provide decision support for more sustainable crop production. Crop model-derived yield predictions based on multiple GCMs and emission scenarios (RCPs) provide more reliable climate change impact assessments (Asseng, 2013; Rosenzweig et al., 2013; Ruane et al., 2013; Bhat et al., 2021). These studies can also be used to discover and assess the uncertainty in yield predictions and as well as to evaluate model performance (White et al., 2011; Challinor et al., 2013; Wajid et al., 2014; Mason-D'Croz et al., 2016). Climate change poses a significant threat to agrarian societies in tropical regions. In South Asia and India, warmer temperatures and increased variability in rainfall portend decreased yields and corresponding impacts on rural livelihood and national food security. Since the 1960s, several factors, such as high-yielding varieties of wheat and rice, higher use of fertilizers, expansion in irrigation, and increased cropping intensity, improved the resilience of India to the incidence of famine. The development of the national grain procurement, storage, and distribution system contributed significantly to the nation's food security. The success of these programs made it possible for a small state like Punjab, having just 1.52 percent of India's land area, to contribute around 50 percent to the national pool of food grains (GOP, 2010). Such a remarkable transition was facilitated initially by constructing a multi-purpose Bhakhra dam and canal system on Beas and Sutlej rivers to tap Himalayan snowmelt and rainfall. Today, given the widespread rural electrification, surface water (canal water) use is overshadowed by groundwater-based irrigation (Joshi et al., 2006). Echoing a policy used in other states of the country, the Punjab government offers free electricity to agriculture, contributing to a dramatic rise in the number of tube wells (Rodell et al., 2009) and a faster depletion in the groundwater, which has been termed as possibly the largest mining of water on earth based on the satellite images (Rodell et al., 2009). The farmers who used to pump groundwater from just 5-10 ft below the surface are drilling tube wells up to 300 ft. The remarkable increase in water usage in agriculture has resulted from the transition of Punjab's agriculture from traditional crops to rice-wheat monoculture occupying almost 80 percent of the cropped area, which ultimately leads to a dramatic rise in the water usage in comparison to the average annual water supply in the region (Singh and Sidhu, 2006). Such change in the farmers' behavior results from the targeted procurement of rice and wheat crops from this region by the Government of India at a guaranteed price, which is usually announced before the sowing of these crops (World Bank, 2010). Climate change is no longer a future phenomenon but has become a reality. A modest, long-term rise in summer temperature and rainfall, a relatively more pronounced increase in winter temperature, and a decline in winter precipitation showed a changing and variable climate in the country's northern region. The trends in the Punjab state are almost similar. The rise in minimum temperature is much sharper than the maximum temperature, which has serious implications for winter crops. The average precipitation has declined, and the mean temperature has risen. The practice of flood irrigation of rice being grown at more than 2.7 million ha has contributed to more humid conditions from June to September. The increase in relative humidity has created favorable conditions for the increased incidence of diseases and pest attacks. The recent trends attributed to weaker winter precipitation and warmer temperatures indicate declining wheat yields. An increase in variability of the summer monsoons will accentuate the negative impacts on rice through excessive flooding and increase the need for higher irrigation due to longer dry spells. It will eventually increase the cost of production. It will worsen the situation of the already dwindling groundwater resources in Punjab. Flood irrigation has led to increased water use and has also led to changes in the regional microclimate. Due to the rise in relative humidity, increased incidence of insect pests and disease attacks has favored higher use of agrochemicals and led to degradation of groundwater quality. Farm-level concerns on groundwater depletion and consequent water scarcity emerge from rising investments in deepening tube wells, increasing the cost of irrigation due to diesel usage, and expected yield and income losses translating into food and livelihood insecurity. The other climate factors emerge lower but are strongly associated with such concerns. Despite farmers' awareness of the contribution of climate and water factors to the recent rise in agricultural and livelihood risk, clear relationships have not been documented or are less visible. This study aims to quantify uncertainty in the assessment of climate change impact on crop production by using all available climate models (GCMs) under both harsh and mild emission scenarios from 2020 to 2095, which has not been done in the studied region to date. Existing studies are limited to old emission GHGs scenarios of IPCC (A2, B2, A1B, B1), and the very few GCMs are based in other parts of the world (Voloudakis et al., 2015; Gwimbi and Mundoga, 2010; Adhikari et al., 2015; Yang et al., 2014; Hebbar et al., 2013; Luo et al., 2016; Dar et al., 2017, 2018 and 2019) where climatic conditions are very different. Specifically, our goals are to 1) assess the potential impacts of future climate change and variability on crop production derived from the DSSAT crop simulation model, and 2) quantify the uncertainty in climate change impacts projections using ECHam5-GCM and PRECIS model and moderate and extreme RCPs scenarios (4.5 and 8.5) for early (1970–2015), mid-century (2020–2050) as well as end-century (2070–2095) periods.

MATERIALS AND METHODS

Environmental conditions of the site

The study was carried out for climate data of Ludhiana (Fig. 1) (75°52’ E longitude and 30°56′ N latitude) in the Punjab state (73°53’ to 76°55’ E longitude and 29°33’ to 32°31’ N latitude) of India. Ludhiana district falls in the central part of Punjab. The district is bounded between North latitude 30°33’ and 31°01’ and East longitude 75°25’ and 76°27’. The river Satluj forms the district’s border with Jalandhar and Hoshiarpur districts in the North. Ropar and Fatehgarhsahib districts mark the eastern and southeastern boundaries. The western border adjoins Moga and Ferozpur districts. The geographical area of the district is 3790 km^2. The climate of Ludhiana district can be classified as tropical steppe, hot and semi-arid, which is mainly dry with very hot summer and cold winter except during the monsoon season when moist air of oceanic origin penetrates the district.

The normal annual rainfall of the district is 680 mm, unevenly distributed over the area in 34 days. The southwest monsoon, which sets in from the last week of June and withdraws at the end of September, contributes about 78% of annual rainfall. July and August are the wettest months. The remaining 22% of rainfall is received during the non-monsoon period in the wake of western disturbances and thunderstorms. Generally, rainfall in the district increases from south-

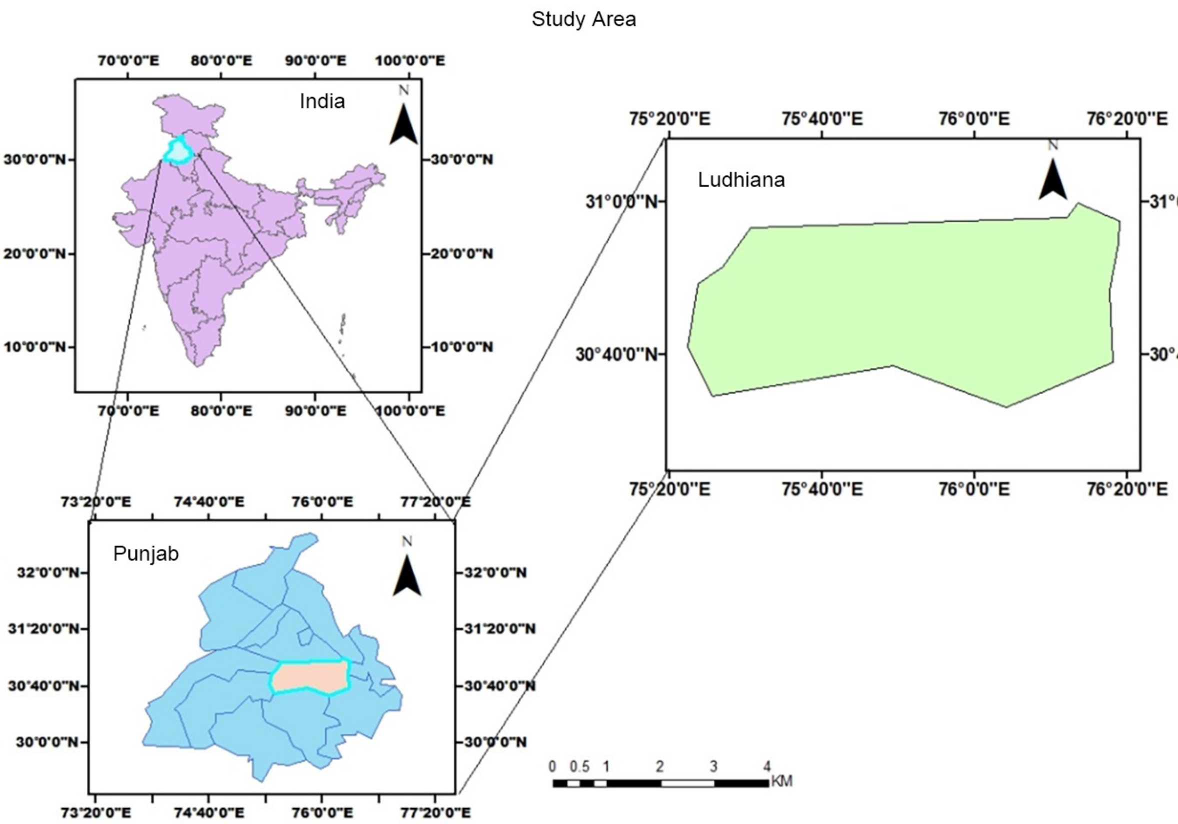

Fig. 1. Study location (source: own elaboration)

west to northeast. The district area is occupied by Indo-Gangetic alluvium.

Moreover, there are no surface features worth mentioning except the plain area. The major drains are Satluj and its tributaries and Budha Nala. The variations in soil profile characteristics are much more pronounced because of the regional climatic differences. The soil of this zone has developed under semi-arid conditions. The soil is sandy loam to clayey with a normal reaction (pH 7.8 to 8.5). This study used the past 46 years (1970–2015) of daily weather data on RF, T_{max}, and T_{min} recorded at meteorological observatories in the Ludhiana sub-district in .xlsx./.csv format.

Data collection

Climate change RCP 4.5 and RCP 8.5 scenario data for T_{max}, T_{min}, and RF were derived from HAD GEM2-ES. Under the A1B scenario for the Ludhiana district, data daily for midcentury (2020–2050) and end century (2070–2095) was extracted from the ECHam5-GCM and PRECIS model.

Leander and Buishand's 2007 approach was employed to bring the modeled data closer to the observed concerning time trends and magnitude.

Bias correction

There is often a clear bias from observations in the statistics of variables produced by GCMs, such as temperature and rainfall, due to limitations in, among others, the incorporation of local topography and non-stationary phenomena within the GCMs. We used the Linear scaling method in the present study for local bias correction of temperature and rainfall data.

Linear scaling method

The Linear scaling (LS) method aims to perfectly match the monthly mean of corrected values with that of observed ones (Lenderink et al., 2007). It operates with monthly correction values based on the differences between the observed and the raw data (raw GCM simulated data in this case). Precipitation is typically corrected with a multiplier and monthly temperature with an additive term.

The multipliers and additives are based on the formulas given under linear scaling, which are:

$$P_{cor,\,m,\,d} = P_{raw,\,m,\,d} \times \mu\,(P_{obs,\,m}) \,/\, \mu(P_{raw,\,m})$$

$$T_{cor,\,m,\,d} = T_{raw,\,m,\,d} + \mu(T_{obs,\,m}) - \mu(T_{raw,\,m})$$

Where P_{cor}, m, d and T_{cor}, m, d are corrected precipitation and temperature on the dth day of mth month, and P_{raw}, m, d and T_{raw}, m, d are the raw precipitation and temperature on the dth day of mth month. μ (...) represents the expectation operator (e.g., μ (P_{obs}, m) represents the mean value of observed precipitation at a given month (m).

DSSAT model

The DSSAT/CSM (Decision Support System for Agro technology Transfer or Crop simulation Model) simulates the growth, development, and yield of a crop growing on a uniform area of land under prescribed or simulated management as well as the changes in soil water, carbon, and nitrogen that take place under the cropping system over time. The DSSAT-CSM is structured using the modular approach described by (Jones et al., 2001) and (Porter et al., 2000).

Papadakis method

The method created by Papadakis (1966) categorizes climates according to their suitability for agriculture. This categorization uses complex criteria and extreme values instead of direct average characteristics to accurately depict heat and humidity regimes (Verheye, 2008). Papadakis' method considers winter severity, summer thermal stress, and water availability throughout the year to characterize climates regarding crop ecophysiology at a specific location. It uses extreme temperatures, variations in temperature and rainfall within seasons, and soil water balance.

RESULTS AND DISCUSSION

Climate Change under different scenarios Using ECHAM 5 and PRECIS model

Global Climate Model (GCM) output on maximum and minimum temperature and rainfall under A1B scenario for Ludhiana district daily for mid-century (2020–2050) and end century (2070–2095) was extracted from ECHam5-GCM and PRECIS model. Leander and Buishand's 2007 approach was employed to bring the modeled data closer to the observed data, concerning time trends and magnitude. ECHAM5 and PRECIS indicated an increase in rainfall under the A1B scenario during the mid and end century. However, there is significant variation in the magnitude of change in rainfall in both models. The average annual increase in rainfall during MC was computed as 181 and 311 mm by ECHAM5 and PRECIS, respectively. The corresponding increase in EC was 328 and 389 mm, respectively (Fig. 2).

The annual maximum temperature would increase by 1.2°C and 2.45°C during MC using ECHAM 5 and PRECIS models, respectively (Fig. 3). The maximum temperature would decrease in March and April under the PRECIS scenario during the mid-century. The corresponding increase in EC was 6.5 and 5.0°C using the PRECIS model. The increase in maximum temperature will be more than 6.5°C in March, April, May, and June in ECHAM5. In contrast, a more than 6.5°C increase in maximum temperature was predicted in September, October, November, and December by the PRECIS model (Fig. 3). Bal et al. (2016) in his study projected that the maximum temperature throughout India from six ensemble models over the period between 1970–2100 showed an increasing trend within the range of 2.5°C to 4.4°C by the end of the century, concerning the present-day climate simulations using PRECIS model under AIB scenario.

The annual minimum temperature would increase by 2.4°C and 2.45°C during EC using ECHAM5 and PRECIS models. During the mid-century, the minimum temperature would decrease in October under the ECHAM5 scenario. The corresponding increase in EC was 5.4 and 5.0°C using ECHAM5 and PRECIS models, respectively. The increase in minimum temperature will be more than 7°C in March, April, May, June, and September in ECHAM5. In contrast, a more than 7°C increase in minimum temperature was predicted in July, August September by the PRECIS model (Fig. 4). Kaur

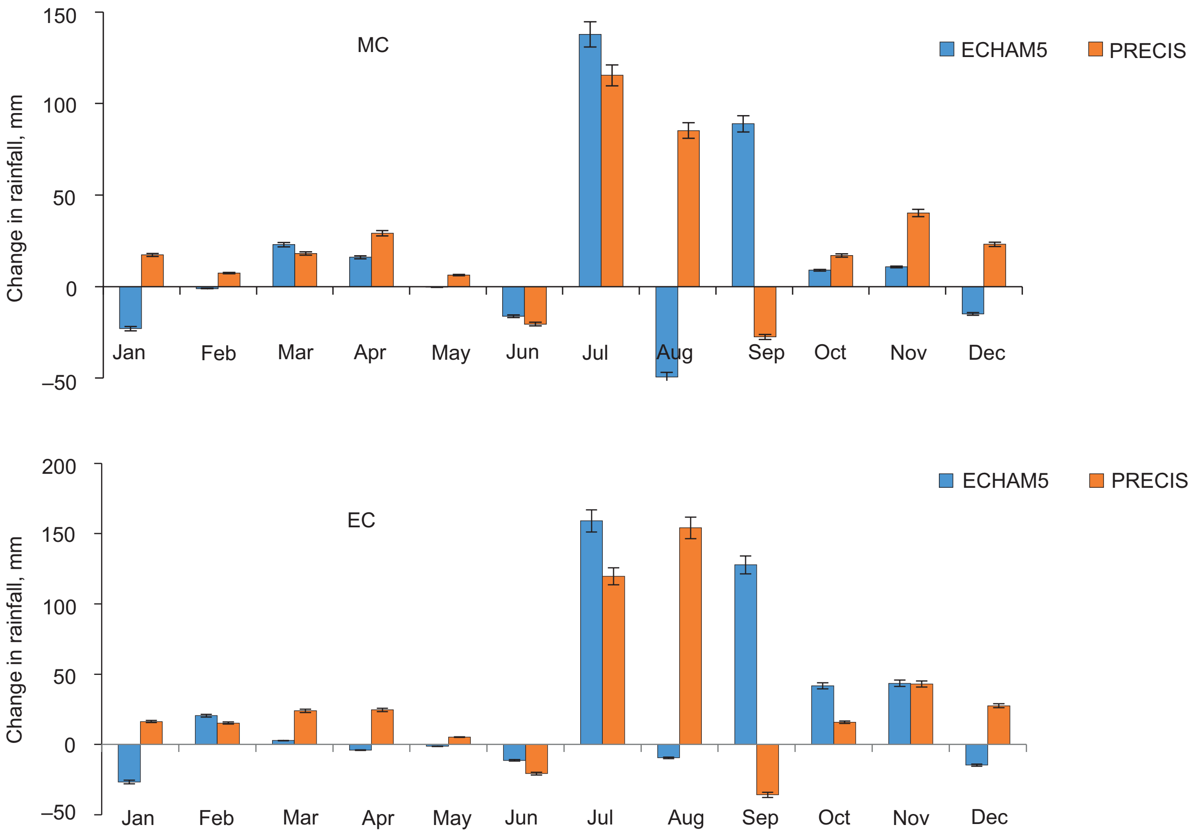

Fig. 2. Change in rainfall (mm) under A1B scenario during mid and end century using ECHAM5 and PRECIS model (source: own elaboration)

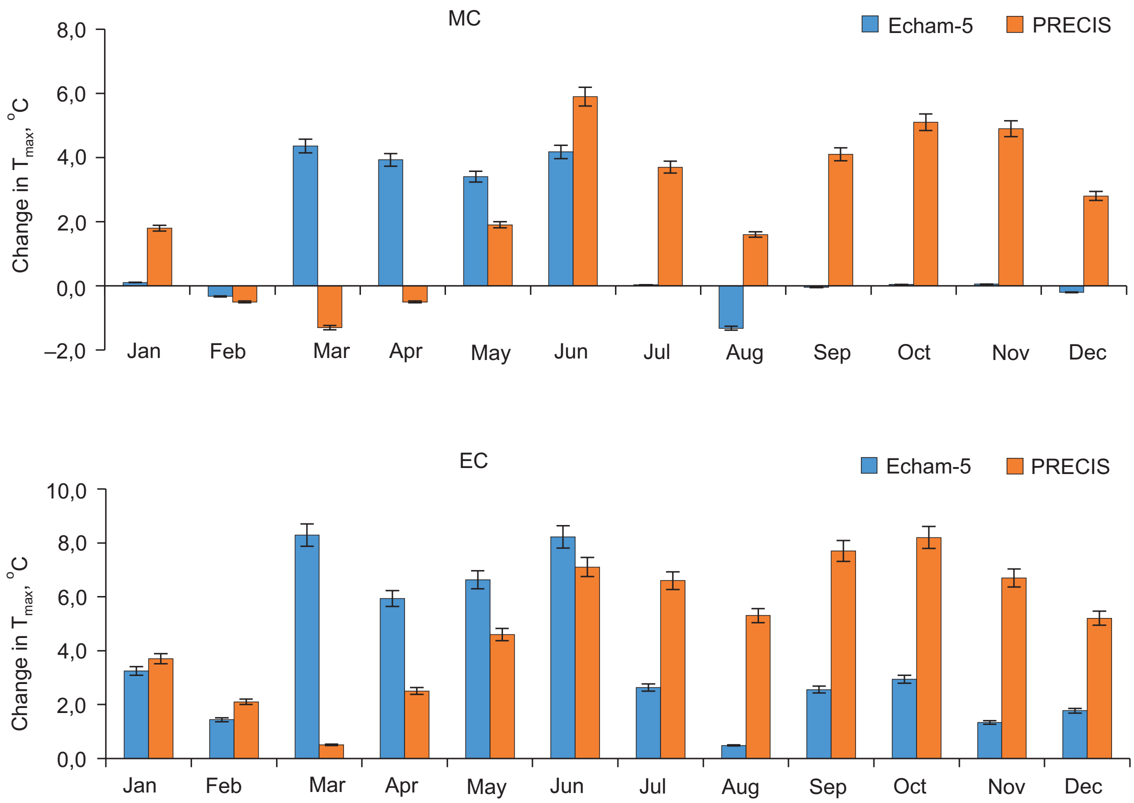

Fig. 3. Change in maximum temperature under A1B scenario during mid and end century using ECHAM5 and PRECIS model (source: own elaboration)

et al. (2017) predicted that the maximum and minimum temperature and rainfall would increase by 2.0 to 2.2°C, 3.3 to 5.4°C and 33% to 66% respectively in one of the agroclimatic zones of Punjab under the changing climate scenarios of AIB using PRECIS model.

Using RCP Scenarios

Under RCP scenarios, the future climate data was extracted for five randomly selected GCMs under scenarios RCP 4.5 and RCP 8.5 using the MarkSim DSSAT weather generator. The GCMs were BCC-CSM1-1, CSIRO-Mk3-0, GFDL-ESM -2M, GISS-E2-R, and HAD GEM2-ES. These models were analyzed statistically for RMSE and NRMSE. One of the models, HAD GEM2-ES, was selected as having the least NRSME (Table 1) for the impact assessment studies. The Linear scaling approach was used to remove biases in future data. The predictions are presented in Table 2 and Table 3.

In the baseline, the average ± standard deviation of RF was 759.79 ± 227.1 mm, which decreased to 662.24 ± 49.7 mm in MC and 670.10 ±39.3 mm in EC in RCP 4.5. Under RCP 8.5, the average ± standard deviation of rainfall is 759.79 ± 227.1 mm, which is likely to increase to 912.48 ± 146.45 mm in MC and 1010.95 ± 65.06 mm in EC. In the case of T_{max}, it was 29.73 ± 0.5°C for the baseline of the century, and rose to 31.08± 0.4°C in MC and 33.08± 0.3°C in EC under RCP 4.5. Under RCP 8.5 average annual T_{max} of 29.73 ± 0.5°C for the baseline would increase to 33.14± 0.45°C in MC and 35.87± 0.7°C in EC. Correspondingly, T_{min} of 16.64 ±0.8°C of baseline would increase to 18.40 ± 0.3°C in MC and 19.51 ± 0.2°C in EC under RCP 4.5, and would increase to 18.73 ± 0.5°C in MC and 21.41 ± 0.6°C in EC under RCP 8.5. This indicated that under RCPs 4.5 and 8.5, scenarios mean annual temperature would increase by 1.56°C in MC and 3.11°C in EC compared to that of the baseline period

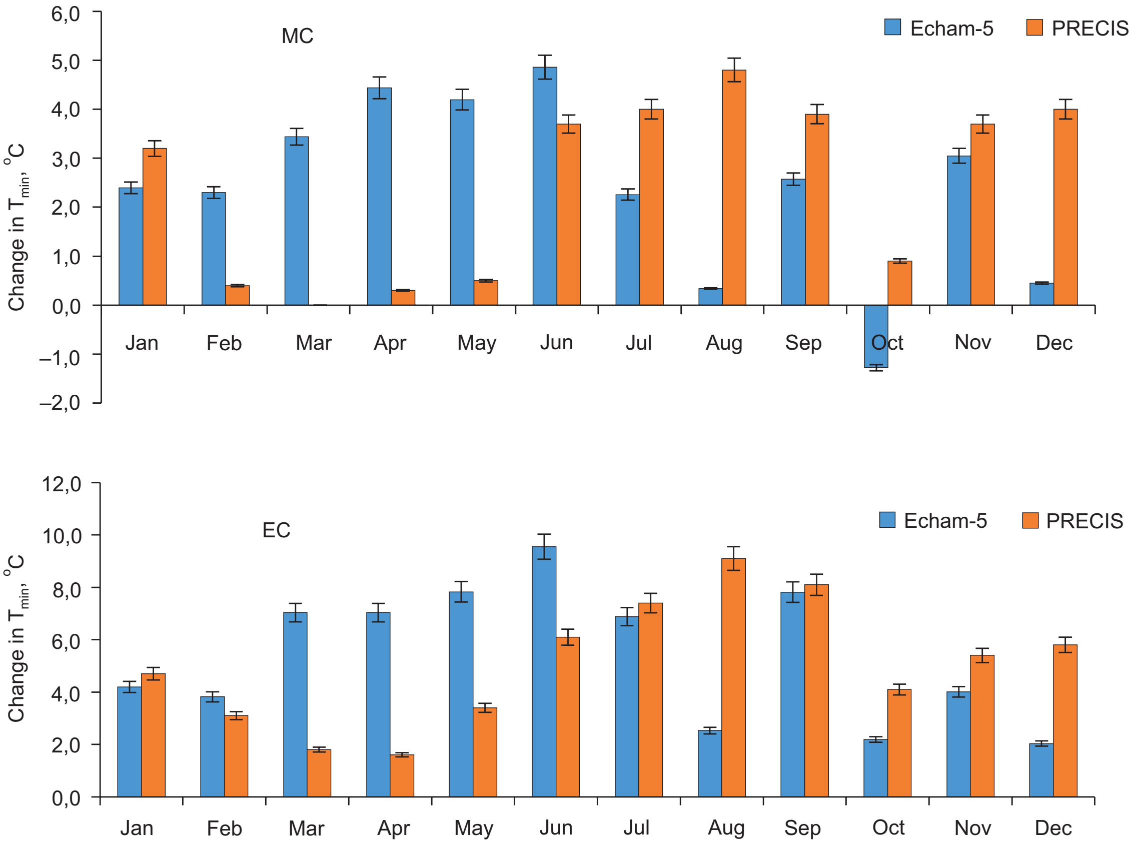

Fig. 4. Change in minimum temperature under A1B scenario during mid and end century using ECHAM5 and PRECIS model (source: own elaboration)

Table 1. RMSE and NRSME values of different models were selected for the study area (source: Dar et al., 2017)

Models	RMSE value	NRMSE value
BCC-CSM1-1	4.67	0.284
CSIRO-Mk3-0	4.87	0.296
GFDL-ESM -2M	5.13	0.313
GISS-E2-R	4.92	0.299
HAD GEM2-ES	4.51	0.274

Table 2. The average annual climate of the Ludhiana district during Baseline, MC, and EC under RCP 4.5 (source: Dar et al., 2017).

Temperature (°C)	Baseline (1970–2015)	MC (2020–2050)	EC (2060–2090)
Tmax	29.73	31.08	33.08
Tmin	16.64	18.40	19.51
Mean	23.18	24.74	26.29
Rain	759.79	662.24	670.10

Table 3. The average annual climate of the Ludhiana district during Baseline, MC, and EC under RCP is 8.5 (source: Dar et al., 2017).

Temperature	Baseline (1970–2015)	MC (2020–2050)	EC (2060–2090)
Annual Tmax	29.73	33.14	35.87
Annual Tmin	16.64	18.73	21.41
Mean	23.18	25.93	28.64
Rain	759.79	912.48	1010.95

and 2.75°C in MC and 5.46°C in EC compared to that the baseline period, respectively. The corresponding likely decrease in annual RF under RCP 4.5 is 98 mm and 90 mm, respectively. In contrast, the corresponding increase under RCP 8.5 is 153 mm and 251mm, respectively. From three different models and under different scenarios, there is wide variation in predictions; however, we can conclude that in central Indian Punjab, the temperature will increase by 1.56°C to 2.5°C in mid-century, and by 3.11°C to 5.1°C at the end of the 21st century under different scenarios and models. Chaturvedi et al. (2012) predicted that under RCP 6.0 and 8.5 scenarios, the mean temperature in India is likely to be in the range of 1.7 to 2°C by 2030s and 3.3 to 4.8°C by 2080s relative to pre-industrial times, whereas the precipitation is projected to increase in the range from 4 to 5% by 2030s and 6 to 14% towards the end of the century (2080s) when compared to the 1961 to 1990 baseline period. Montenegro et al. (2022) predicted that the high-risk warming calculated from the CMIP5 models for all stations under RCP 8.5 scenario is expected to grow from 0.6°C to 1.4°C and 1.8°C to 4.6°C for 2010–2040 and 2041–2070, respectively

Impact of Futuristic Climatic Scenario on Crop Water Requirement for Rice-Wheat System (GCM model) for Central Punjab

Using Papadakis method

Increasing temperature, evapotranspiration, variable rainfall patterns, and interactions with other meteorological parameters may negatively affect crop water requirement (CWR). To better manage available resources and agricultural production, it is important to understand crop water requirements, the current level of water supplies, and the possible effects of climate change in the future. Based on the ECHAM5 model, it was concluded that the evapotranspiration losses would be reduced by 13.5 and 9.4 percent in the *Kharif* season during the mid-century and at the end century. However, the evapotranspiration losses would increase by 21.3 percent during the *Rabi* season. However, the PRECIS outputs indicated that evapotranspiration losses would increase by 13.1 and 24.7 percent in the *Kharif* season during the mid and end centuries. During the *Rabi* season, the evapotranspiration losses would reduce by 2.0 percent in the mid-century and increase by 11.3 percent during the end century. Based on the results, it is suggested that in both the mid and end century, the rice-wheat cropping system would be best for the rice to be transplanted on 6th July and wheat to be sown on 2nd December as ET loss would be least for these dates of sowing (Table 4).

Using DSSAT Model

Under RCP scenarios, simulated crop yields and water balance components of rice and wheat crops in the Baseline, MC, and EC for four soil series using the DSSAT model are presented in (Table 5).

At baseline, the resultant simulated yield averaged across soils and years was 6419 kg ha^{-1} in rice and 5772 kg ha^{-1} in wheat. Under RCP 4.5, averaged across soil series, rice yield in MC and EC was reduced by 197 kg ha^{-1} and 103 kg ha^{-1}, respectively, then in the baseline. The wheat yield in MC and EC was reduced by 110 kg ha^{-1} and 680 kg ha^{-1}, respectively, then baseline. Similarly, under RCP 8.5 averaged across soil series, the yield of rice in MC would be increased by 1.09 t/ha (17.13%), and in EC, yield is reduced by 855.5 kg/ha (13.32%), respectively from the baseline, similar results were observed by (Chun et al., 2015). The wheat yield in MC and EC would

Table 4. Impact of climate change on the Evapotranspiration requirements under A1B scenario (source: own elaboration)

Crop	Date	Present ET	Mid-Century (change)		End Century (change)	
			ECHAM5	PRECIS	ECHAM5	PRECIS
Wheat	28th October	412.5	388.0(–1.4)	421.9(32)	474.3(84.9)	480.8.3(91.4)
	4th November	389.4	371.2(–18.2)	392.0(2.5)	455.5(66.1)	441.9(52.5)
	25th November	369.0	376.5(–12.9)	349.4(–40)	466.9(77.5)	396.5(7.1)
	2nd December	350.2	361.2(–28.2)	327.5(–61.9)	448.4(59.0)	373.5(–15.9)
Rice	6th June	696.9	630.2(69.9)	811.7(251.7)	696.7 (136.4)	873.8(313.8)
	16th June	560.3	494.1(–69.0)	628.7(68.4)	532.5(–27.8)	681.8(121.5)
	26th June	639.9	538.2(–22.0)	716.6(156.3)	546.9(–13.4)	805.4(245.1)
	6th July	572.1	471.3(–89.0)	631.7(71.4)	468.2(–97.5)	718.6(158.3)

Table 5. Simulated yield, water balance components, and water-use efficiency of rice and wheat crops as influenced by different time slices of the 21st century under RCP 4.5 and RCP 8.5 (source: Dar et al., 2017)

Time slice	Soil	Yield (kg ha^{-1})	ET (mm)	Irr (mm)	RF (mm)	D (mm)	WUE (kgm^{-3})
				Rice			
Baseline	RCP 4.5	6419	550.3	1495.3	595.61	1164.88	1.16
	RCP 8.5	6419	550.3	1494.9	595.61	1164.88	1.16
Mid-century	RCP 4.5	6222	541.2	1367.2	541.5	949.55	1.15
	RCP 8.5	7519	737.3	1289.6	744.58	1019.04	1.01
End century	RCP 4.5	6316	592.9	1385.1	582.77	947.06	1.06
	RCP 8.5	5564	802.2	1305	829.49	987.96	0.69
				Wheat			
Baseline	RCP 4.5	5772	431.9	297.9	121.74	-	1.33
	RCP 8.5	5604	449	306.9	121.83	-	1.24
Mid-century	RCP 4.5	5661	449.6	370.6	72.36	-	1.25
	RCP 8.5	3940	424.3	390.2	43.51	-	0.92
End century	RCP 4.5	5092	464.7	426.4	32.01	-	1.09
	RCP 8.5	3002	427	401.1	28.89	-	0.7

be reduced by 1.6 t/ha (29.6%) and 2.6 t//ha (46.4%), respectively, from 5772 kg/ha in the baseline. When averaged across soil series, the resultant crop duration was shortened by five days and seven days in rice, and six days and nine days in wheat in MC and EC, respectively, under RCP 4.5. Under RCP 8.5, in MC and EC (averaged over soil series), crop duration would be shortened by five days and four days in rice, and six days and 11 days in wheat, respectively. Rice yield in MC and EC decreased in almost all the years compared to the baseline. The wheat yield decreased in fewer years in both MC and EC. Though wheat yield decreased in fewer years, the magnitude of the decrease was more than in rice, especially in EC. For example, the lowest simulated yield in wheat was 4885 kg ha^{-1} in 2090, and in rice, it was 5741 kg ha^{-1} in 2032. Kaur et al. (2022) predicted the impact of climate change on the water use efficiency and yield of maize for three different sowing dates in the Punjab region of India. The results indicated that the water use efficiency of maize was higher in D_2 (second week of June) concerning grain yield when compared with D_3 (first week of July) and D_1 (third week of May). They also predicted that with an increase in temperature, the water productivity of maize would decrease, which would be compensated for with an increase in CO_2 using DSSAT and CROPWAT models. These results show that inter-year rotation information on crop yields in MC and EC can only be obtained using HAD GEM2-ES and like models, which provide daily weather data.

In the MC and EC, water balance components were changed as the crop duration was shortened, and RF was decreased under RCP 4.5 compared to the baseline. In MC, the RF was decreased by 54 mm during rice and 49 mm during wheat crops. The corresponding values in EC were 13 mm and 90 mm, respectively. Similarly, under RCP 8.5, in MC, the RF was increased by 149 mm during rice and decreased by 78 mm during wheat crops. The corresponding values in EC were 234 mm and 93 mm, respectively.

Because of fluctuating behavior of rainfall, under these two scenarios, the irrigation requirement (averaged over soils) in MC and EC was decreased by 128 and 110 mm in rice, and increased by 73 and 129 mm in wheat, respectively. In RCP 8.5, MC and EC irrigation decreased by 205 and 190 mm in rice, and increased by 83 and 94 mm in wheat, respectively. Under RCP 4.5, ET was decreased by nine in MC and EC and increased by 43 mm in rice, and 18 and 33 mm in wheat, respectively. Similarly, under RCP 8.5, in MC and EC, ET was increased by 187 and 252 mm in rice, and decreased by 25 and 22 mm in wheat, respectively. Under elevated temperatures, a decrease in ET due to the shortening of crop duration has also been reported by Buttar et al. (2012). The drainage component of water balance in MC and EC was decreased by 215 and 218 mm in rice. In contrast, no drainage was computed by the model for wheat crops under RCP 4.5. Under RCP, 8.5 decreases in drainage components for MC and EC were computed as 146 and 177 mm for rice crops, and zero drainage was computed for the wheat crop.

Water use efficiency in rice decreased from (1.16 ± 0.05 kg m^{-3}) in the baseline to 1.15kg m^{-3} in MC and 1.06 kg m^{-3} in EC (Table 5). However, in wheat, the water efficiency of (1.33 ± 0.12 kg m^{-3}) in the baseline was decreased by 0.08 kg m^{-3} in MC and 0.24 kg m^{-3}in EC. Similarly, under RCP 8.5, water use efficiency in rice was decreased from (1.16 ± 0.05 kg m^{-3}) to 1.01kg m^{-3} in MC and 0.69kg m^{-3} in EC. However, water use efficiency decreased in the wheat crop from (1.24 ± 0.27 kg m^{-3}) to 0.92 kg m^{-3} in MC and 0.70 kg m^{-3} in EC (Table 5). Jalota et al. (2013) predicted the impact of climate change on rice wheat system yield and water use efficiency in Indian Punjab using the CropSyst model. The results indicated that there would be a reduction in crop yields associated with the shortening of growth periods. They also predicted that the evapotranspiration and water use efficiency decrease. They hypothesized that postponing the planting dates of rice and wheat by 15–21 days can mitigate the impact of climate change. Zhao et al. (2022) studied the impact of climate change on the rice-wheat system yield and water balance components in China using the APSIM model. The results showed that the WUE of the rice-wheat system was negatively correlated with temperature but positively correlated with CO_2. They concluded that climate change seriously threatens crop growth processes, yield, and water consumption.

CONCLUSIONS

The future climatic predictions by the GCM model for the Ludhiana district (ECHam5) through the A1B scenario showed that maximum temperature would rise by 1.2 and 5.0 °C during the *Kharif* season and 1.5 and 4.2 °C during the *Rabi* season in mid-century and end century, respectively. Similarly, the minimum temperature during *Kharif* and *Rabi* seasons will rise by 2.6 and 7.3 °C, and 2.9 and 5.1 °C during the mid- and end century. The *Kharif* rainfall will increase by 4.2 and 7.1 mm while the *Rabi* rainfall will decrease by 61.2 and 97.3 mm during the mid- and end century. In central Indian Punjab, the temperature would increase by 1.56°C to 2.5°C in mid-century, and by 3.11°C to 5.1°C at the end of the 21st century under two scenarios and different models. Because of fluctuating behavior of rainfall, under RCP 4.5, the irrigation requirement (averaged over soils) in MC and EC would decrease by 128 and 110 mm in rice, whereas it would increase by 73 and 129 mm in wheat, respectively. In RCP 8.5, MC and EC irrigation would decrease by 205 and 190 mm in rice, and it would increase by 83 and 94 mm in wheat, respectively. The crop water requirement will be less when rice and wheat crops are sown on 6^{th} July and 2^{nd} December (832.5 and 916.6 mm) for the rice-wheat cropping system during the mid- and end century. Therefore, a comprehensive understanding of such models will help in better predictions of climate behaviors, and thorough further research is needed to understand the uncertainties in the predictions of such models.

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AUTHORS' CONTRIBUTIONS

Rajan Aggarwal, Samanpreet Kaur, Mehraj U Din Dar, Alban Kuriqi: Conceptualization, Methodology, Investigation, Formal analysis, Data curation. **Rajan Aggarwal, Samanpreet Kaur, Mehraj U Din Dar, Alban Kuriqi:** Visualization, writing – original draft, Writing – review and editing, Resources. **Rajan Aggarwal, Alban Kuriqi**: Supervision.

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REFERENCES

Adhikari, P., Ale, S., Bordovsky, J.P., Thorp, K.R., Modala, N.R., Rajan, N., Barnes, E.M. (2015). Simulating future climate change impacts on seed cotton yield in the Texas high plains using the CSM-CROPGRO-cotton model. Agric. Water Manag. 164, 317–330. DOI: http://dx.doi.org/10.1016/j.agwat.2015.10.011

Amin, A., Nasim, W., Mubeen, M., Ahmad, A., Nadeem, M., Urich, P., Fahad, S., Ahmad, S., Wajid, A., Tabassum, F., Hammad, H.M., Sultana, S.R., Anwar, S., Baloch, S.K., Wahid, A., Wilkerson, C.J., Hoogenboom, G. (2017a). Simulated CSM-CROPGRO cotton yield under projected future climate by SimCLIM for southern Punjab. Pak. Agric. Syst. DOI: http://dx.doi.org/10.1016/j.agsy.2017.05.010

Amin, A., Nasim, W., Mubeen, M., Kazmi, D.H., Lin, Z., Wahid, A., Sultana, S.R., Gibbs, J., Fahad, S. (2017b). Comparison of future and base precipitation anomalies by SimCLIM statistical projection through ensemble approach in Pakistan. Atmos. Res., 194

Araya, A., Hoogenboom, G., Luedeling, E., Hadgu, K.M., Kisekka, I., Martorano, L.G. (2015). Assessment of maize growth and yield using crop models under present and future climate in Southwestern Ethiopia. Agric. For. Meteorol, 214–215, 252–265.

Arnell, N.W., Hudson, D.A., Jones, R.G. (2003). Climate change scenarios from a regional climate model: Estimating change in runoff in southern Africa. Journal of Geophysical Research – Atmospheres, 108 (D16), AR 4519.

Asseng, S. (2013). Uncertainty in simulating wheat yields under climate change. Nat. Clim. Change 3, 627–632. DOI: http://dx.doi.org/10.1038/ncliamte1916

Awais, M., Wajid, A., Nasim, W., Ahmad, A., Saleem, M.F., SammarRaza, M.A., Bashir, M.U., Habib-ur-Rahman, M., Saeed, U., Hussain, J., Arshad, N., Hoogenboom, G. (2017). Modeling the water and nitrogen productivity of sunflower using OILCROPSUN model in Pakistan. Field Crops Res., 205, 67–77. DOI: http://dx.doi.org/10.1016/j.fcr.2017.01.013

Bassu, S., Brisson, N., Durand, J.L., Boote, K., Lizaso, J., Jones, J.W., Rosenzweig, C., Ruane, A.C., Adam, M., Baron, C., Basso, B., Biernath, C., Boogaard, H., Conijn, S., Corbeels, M., Deryng, D., De Sanctis, G., Gayler, S., Grassini, P., Hatfield, J., Hoek, S., Izaurralde, C., Jongschaap, R., Kemanian, A.R., Kersebaum, K.C., Kim, S.H., Kumar, N.S., Makowski, D., Müller, C., Nendel, C., Priesack, E., Pravia, M.V., Sau, F., Shcherbak, I., Tao, F., Teixeira, E., Timlin, D., Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors? Glob. Change Biol., 20, 2301–2320. DOI: http://dx.doi.org/10.1111/gcb.12520

Bal, P.K., Ramachandran, A., Palanivelu, K., Thirumurugan, P., Geetha, R., Bhaskaran, B. (2016). Climate change projections over India by a downscaling approach using PRECIS. Asia-Pacific Journal of Atmospheric Sciences, 52, 353–369.

Bhat, S.A., Bashir, O., Bilal, M., Ishaq, A., Dar, M.U.D., Kumar, R., Sher, F. (2021). Impact of COVID-related lockdowns on environmental and climate change scenarios. Environmental Research, 195, 110839.

Bouraoui, F., Vachaud, G., Li, L.Z.X., Le Treut, H., Chen, T., (1999). Evaluation of the impact of climate changes on water storage and groundwater recharge at the watershed scale. Climate Dynamics, 15, 153–161.

Buma, J., Dehn, M. (2000). Impact of climate change on a landslide in South East France, simulated using different GCM scenarios and downscaling methods for local precipitation. Climate Research, 15 (1), 69–81.

Buttar, G.S., Jalota, S.K., Sood, A., Bhushan, B. (2012). Yield and water productivity of Bt cotton (Gossypiumhirsutum) as influenced by temperature under semi-arid conditions of north-western India: Field and simulation study. Indian Journal of Agricultural Sciences, 82(1), 44.

Cannon, A.J., Whitfield, P.H. (2002). Downscaling recent streamflow conditions in British Columbia, Canada using ensemble neural network models. Journal of Hydrology, 259 (1), 136–151.

Challinor, A.J., Smith, M.S., Thornton, P. (2013). Use of agro-climate ensembles for quantifying uncertainty and informing adaptation. Agric. For. Meteorol., 170, 2–7. DOI: http://dx.doi.org/10.1016/j.agrformet.2012.09.007

Challinor, A.J., Smith, M.S., Thornton, P. (2013). Use of agro-climate ensembles for quantifying uncertainty and informing adaptation. Agric. For. Meteorol., 170, 2–7. DOI: http://dx.doi.org/10.1016/j.agrformet.2012.09.007

Chaturvedi, R.K., Joshi, J., Jayaraman, M., Bala, G., Ravindranath, N.H. (2012). Multi-model climate change projections for India under representative concentration pathways. Current Science, 791–802.

Crane, R.G., Hewitson, B.C. (1998). Doubled CO_2 precipitation changes for the Susquehanna Basin: Down-Scaling from the Genesis General Circulation Model. International Journal of Climatology, 18, 65–76.

Dar, M.U.D., Aggarwal, R., Kaur, S. (2017). Effect of climate change scenarios on yield and water balance components in ricewheat cropping system in Central Punjab, India. Journal of Agrometeorology, 19(3), 226–229.

Dar, M.U.D., Aggarwal, R., Kaur, S. (2018). Comparing bias correction methods in downscaling meteorological variables for climate change impact study in Ludhiana, Punjab. Journal of Agrometeorology, 20(2), 126–130.

Dar, M.U.D., Aggarwal, R., Kaur, S. (2019). Climate predictions for Ludhiana District of Indian Punjab under RCP 4.5 and RCP 8.5.Int J Environ Clim Chang, 9, 128–141.

Ewert, F., Rötter, R.P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K.C., Olesen, J.E., van Ittersum, M.K., Janssen, S., Rivington, M., Semenov, M.A., Wallach, D., Porter, J.R., Stewart, D., erhagen, J., Gaiser, T., Palosuo, T., Tao, F., Nendel, C., Roggero, P.P., Bartošová, L., Asseng, S. (2015). Crop modelling for integrated assessment of risk to food production from climate change. Environ. Model. Softw., 72, 287–303. DOI: http:// dx.doi.org/10.1016/j.envsoft.2014.12.003

Fahad, S., Hussain, S., Saud, S., Hassan, S., Chauhan, B.S., Khan, F., et al. (2016a). Responses of rapid visco analyzer profile and other rice grain qualities to exogenously applied plant growth regulators under high day and high night temperatures. PLoS One, 11(7), e0159590. DOI: http://dx.doi.org/10.1371/journal.pone.0159590

Fahad, S., Hussain, S., Saud, S., Hassan, S., Ihsan, Z., Shah, A.N., Wu, C., Yousaf, M., Nasim, W., Alharby, H., Alghabari, F., Huang, J. (2016c). Exogenously applied plant growth regulators enhance the morpho physiological growth and yield of rice under high temperature. Front. Plant Sci., 7, 1250. DOI: http://dx.doi.org/10.3389/fpls.2016.01250

Fahad, S., Hussain, S., Saud, S., Hassan, S., Tanveer, M., Ihsan, M.Z., Shah, A.N., Ullah, A., Nasrullah, K.F., Ullah, S., Alharby, H., Wu, C., Huang, J. (2016d). A combined application of biochar and phosphorus alleviates heat-induced adversities on physiological, agronomical and quality attributes of rice. Plant. Physiol. Biochem., 103, 191–198.

Fahad, S., Hussain, S., Saud, S., Khan, F., Hassan Jr, S., Amanullah, Nasim, W., Arif, M., Wang, F., Huang, J. (2016b). Exogenously applied plant growth regulators affect heat stressed rice pollens. J. Agron. Crop. Sci., 202, 139–150.

Faucher, M., Burrows, W.R., Pandolfo, L. (1999). Empirical-statistical reconstruction of surface marine winds along the western coast of Canada. Climate Research, 11(3), 173–190.

Georgakakos, K.P., Smith, D.E. (2001). Soil moisture tendencies into the next century for the conterminous United States. Journal of Geophysical Research – Atmospheres, 106(D21), 27367–27382.

Government of Punjab (2010). Statistical Abstract of Punjab, Economic Advisor to Government of Punjab, Chandigarh.

Gwimbi, P., Mundoga, T. (2010). Impact of climate change on cotton production under rainfed conditions: Case of Gokwe. J. Sustain. Dev. Afr. 12, 59–69.

Hassan, H., Hanaki, K., Matsuo, T. (1998). A modeling approach to simulate impact of climate change in lake water quality: Phytoplankton growth rate assessment. Water Science and Technology, 37 (2), 177–185.

Hatfield, J.L., Prueger, J.H. (2015). Temperature extremes: effect on plant growth and development. Weather Clim. Extremes, 10, 4–10. DOI: http://dx.doi.org/10.1016/j.wace.2015.08.001

Hebbar, K.B., Venugopalan, M.V., Prakash, A.H., Aggarwal, P.K. (2013). Simulating the impacts of climate change on cotton production in India. Clim. Change, 118, 701–713. DOI: http://dx.doi.org/10.1007/s10584-012-06734

IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland.

Jasper, K., Calanca, P., Gyalistras, D., Fuhrer, J. (2004). Differential impacts of climate change on the hydrology of two alpine river basins. Climate Research, 26(2), 113–129.

Jalota, S.K., Kaur, H., Kaur, S., Vashisht, B.B. (2013). Impact of climate change scenarios on yield, water and nitrogen-balance and-use efficiency of rice–wheat cropping system. Agricultural Water Management, 116, 29–38.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T. (2003). The DSSAT cropping system model. European Journal of Agronomy, 18(3–4), 235–265.

Joshi, A.S., Singh S., Sharma V.K., Kingra H.S. (2006). Income and Consumption Pattern of Farmers in Punjab. Annual Research Report, Department of Economics and Sociology, Punjab Agricultural University, Ludhiana.

Kassie, B.T., Asseng, S., Rotter, R.P., Hengsdijk, H., Ruane, A.C., Van Ittersum, M.K. (2015). Exploring climate change impacts and adaptation options for maize production in the Central Rift Valley of Ethiopia using different climate change scenarios and crop models. Clim. Change, 129, 145–158. DOI: http://dx.doi.org/10.1007/s10584-014-1322-x

Kaur, P., Kaur, N., Singh, H. (2017). PRECIS-model simulated changes in climatic parameters under various scenarios in different agro-climatic zones of Punjab. Mausam, 68(1), 139–148.

Kaur, H., Kingra, P.K., Singh, R., Kaur, S., Singh, S. (2022). Simulation of climate change impact on water productivity of maize in central Punjab. MAUSAM, 73(3), 673–682.

Kersebaum, K.C., Boote, K.J., Jorgenson, J.S., Nendel, C., Bindi, M., Frühauf, C., Gaiser,T., Hoogenboom, G., Kollas, C., Olesen, J.E., Rötter, R.P., Ruget, F., Thorburn, P.J., Trnka, M., Wegehenkel, M. (2015). Analysis and classification of data sets for calibration and validation of agro-ecosystem models. Environ. Model. Softw., 72, 402–417. DOI: http://dx.doi.org/10.1016/j.envsoft.2015.05.009

Kettle, H., Thompson, R. (2004). Statistical downscaling in European mountains: Verification of reconstructed air temperature. Climate Research, 26 (2), 97–112.

Kim, M.K., Kang, I.S., Park, C.K., Kim, K.M. (2004). Superensemble prediction of regional precipitation over Korea. International Journal of Climatology, 24 (6), 777–790.

Leander R., Buishand, T. (2007) Resampling of regional climate model output for the simulation of extreme river flows. J Hydrol, 332, 487–496.

Lenderink, G., Buishand, A., Van Deursen, W. (2007). Estimates of future discharges of the river Rhine using two scenario methodologies: Direct versus delta approach. Hydrology and Earth System Sciences, 11(3), 1145–1159.

Luo, Q., Bange, M., Braunack, M., Johnston, D. (2016). Effectiveness of agronomic practices in dealing with climate change impacts in the Australian cotton industry – a simulation study. Agric. Syst., 147, 1–9. DOI: http://dx.doi.org/10.1016/j.agsy.2016.05.006

Mason-D'Croz, D., Vervoort, J., Palazzo, A., Islam, S., Lord, S., Helfgott, A., Havlík, P., Peou, R., Sassen, M., Veeger, M., van Soesbergen, A., Arnell, A.P., Stuch, B., Arslan, A., Lipper, L. (2016). Multi-factor, multi-state, multi-model scenarios: exploring food and climate futures for Southeast Asia. Environ. Model.Softw., 83, 255–270. DOI: http://dx.doi.org/10.1016/j.envsoft.2016.05.008

Meehl, G.A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J.F.B., Stouffer, R.J., Taylor, K.E. (2007). The WCRP CMIP3 multi model dataset: A new era in climatic change research. Bull. Am. Meteorol. Soc., 88, 1383–1394. DOI: http://dx.doi.org/10.1175/BAMS-88-9-1383

Misson, L., Rasse, D.P., Vincke, C., Aubinet, M., Francois, L. (2002). Predicting transpiration from forest stands in Belgium for the 21st century. Agricultural and Forest Meteorology, 111 (4), 265– 282.

Montenegro, M., Campozano, L., Urdiales-Flores, D., Maisincho, L., Serrano-Vincenti, S., Borbor-Cordova, M.J. (2022). Assessment of the impact of higher temperatures due to climate change on the mortality risk indexes in ecuador until 2070. Frontiers in Earth Science, 9, 1340.

Nasim, W., Ahmad, A., Belhouchette, H., Fahad, S., Hoogenboom, G. (2016). Evaluation of the OILCROP-SUN model for sunflower hybrids under different agro-meteorological conditions of Punjab-Pakistan. Field Crops Res., 188, 17–30.

Osborne, T., Rose, G., Wheeler, T. (2013). Variation in the global-scale impacts of climate change on crop productivity due to climate model uncertainty and adaptation. Agric. For. Meteorol., 170, 183–194.

Papadakis, J. (1966). Climates of the world and their agricultural potentialities. Buenos Aires: Eigenverl. d. Verf.

Paz, J.O., Woli, P., Garcia y Garcia, A., Hoogenboom, G. (2012). Cotton yields as influenced by ENSO at different planting dates and spatial aggregation levels. Agric. Syst., 111, 45–52.

Porter, C.H., Jones, J.W., Adiku, S., Gijsman, A.J., Gargiulo, O., Naab, J.B. (2010). Modeling organic carbon and carbon-mediated soil processes in DSSAT v4.5. Operational Research, 10, 247–278.

Rodell, M., Velicogna, I., Famiglietti, J.S. (2009). Sattelite-based estimates of groundwater depletion in India. Nature, 460, 999–1002.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model inter comparison. Proc. Natl. Acad. Sci. U.S.A., 111, 3268–3273.

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J.M. (2013). The agricultural model inter comparison and improvement project (AgMIP): Protocols and pilot studies. Agric. For. Meteorol., 170, 166–182. DOI: http://dx.doi.org/10.1016/j.agrformet.2012.09.011

Rotter, R.P., Carter, T.R., Olesen, J.E., Porter J.R. (2011). Crop–climate models need an overhaul. Nat. Clim. Change, 1, 175–177. DOI: http://dx.doi.org/10.1038/nclimate1152

Ruane, A.C., Cecil, L.D., Horton, R.M., Gordón, R., McCollum, R., Brown, D., Killough, B., Goldberg, R., Greeley, A.P., Rosenzweig, C. (2013). Climate change impact uncertainties for maize in Panama: Farm information, climate projections, and yield sensitivities. Agric. For. Meteorol., 170, 132–145.

Schmidt, M., Glade, T. (2003). Linking global circulation model outputs to regional geomorphic models: A case study of landslide activity in New Zealand. Climate Research, 25 (2), 135–150.

Singh, J., Sidhu, R.S. (2006). Accounting for impact of environmental degradation in agriculture of Indian Punjab. Agricultural Economics Research Review, 19, 37–48.

Tao, F., Yokozawa, M., Zhang, Z. (2009). Modelling the impacts of weather and climate variability on crop productivity over a large area: a new process-based model development, optimization, and uncertainties analysis. Agric. For. Meteorol., 149, 831–850. DOI: http://dx.doi.org/10.1016/j.agrformet.2008.11.004

Tebaldi, C., Knutti, R. (2007). The use of the multi-model ensemble in probabilistic climate projections. Philos. Trans. R. Soc. A Math. Phys. Eng. Sci., 365, 2053–2075. DOI: http://dx.doi.org/10.1098/rsta.2007.2076

Thorp, K.R., Ale, S., Bange, M.P., Barnes, E.M., Hoogenboom, G., Lascano, R.J., McCarthy, A.C., Nair, S., Paz, J.O., Rajan, N., Reddy, K.R., Wall, G.W., White, J.W. (2014). Development and application of process-based simulation models for cotton production: A review of past, present, and future directions. J. Cotton Sci., 18, 10–47.

Uusitalo, L., Lehikoinen, A., Helle, I., Myrberg, K. (2015). An overview of methods to evaluate uncertainty of deterministic models in decision support. Environ. Model. Softw., 63, 24–31. DOI: http://dx.doi.org/10.1016/j.envsoft.2014.09.017

Voloudakis, D., Karamanos, A., Economou, G., Kalivas, D., Vahamidis, P., Kotoulas, V., Kapsomenakis, J., Zerefos, C. (2015). Prediction of climate change impacts on cotton yields in Greece under eight climatic models using the Aqua Crop crop simulation model and discriminant function analysis. Agric. Water Manag., 147, 116–128. DOI: http://dx.doi.org/10.1016/j.agwat.2014.07.028

Verheye, W. (2008). Agro-climate based land evaluation systems. In: W. Verheye (Ed.), Land use Land Cover and Soil Sciences,. UNESCO-EOLSS Publ., Oxford, UK.

Wajid, A., Ahmad, A., Hussain, M., Rahman, M.H.U., Khaliq, T., Mubeen, M., Rasul, F., Bashir, U., Awais, M., Iqbal, J., Sultana, S.R., Hoogenboom, G. (2014). Modeling growth, development and seed-cotton yield for varying nitrogen increments and planting dates using DSSAT. Pak. J. Agric. Sci., 51, 641–650.

Weisse, R., Oestreicher, R. (2001). Reconstruction of potential evaporation for water balance studies. Climate Research, 16 (2), 123–131.

White, J.W., Hoogenboom, G., Kimball, B.A., Wall, G.W. (2011). Methodologies for simulating impacts of climate change on crop production. Field Crops Research, 124, 357–368. DOI: http://dx.doi.org/10.1016/j.fcr.2011.07.001

Wilby, R.L., 1998. Modelling low-frequency rainfall events using airflow indices, weather patterns and frontal frequencies. Journal of Hydrology, 213 (1–4), 380–392.

Wilby, R.L., Troni, J., Biot, Y., Tedd, L., Hewitson, B.C., Smith, D.M., Sutton, R.T. (2009). A review of climate risk information for adaptation and development planning. Int. J. Climatol., 29, 1193–1215. DOI: http://dx.doi.org/10.1002/joc.1839

Williams, A., White, N., Mushtaq, S., Cockfield, G., Power, B., Kouadio, L. (2015). Quantifying the response of cotton production in Eastern Australia to climate change. Clim. Change, 129, 183–196. DOI: http://dx.doi.org/10.1007/s10584-014-1305-y

World Bank (2010). Deep wells and prudence: Towards pragmatic action for addressing groundwater overexploitation in India. Washington, D.C., U.S.A.: The World Bank.

Yang, Y., Yang, Y., Han, S., Macadam, I., Liu, D.L. (2014). Prediction of cotton yield and water demand under climate change and future adaptation measures. Agric. Water Manag., 144, 42–53.

Zhang, X.C., Nearing, M.A., Garbrecht, J.D., Steiner, J.L. (2004). Downscaling monthly forecasts to simulate impacts of climate change on soil erosion and wheat production. Soil Science Society of America Journal, 68 (4), 1376– 1385.

Zhao, Y., Xiao, D., Bai, H., Liu, D.L., Tang, J., Qi, Y., Shen, Y. (2022). Climate change impact on yield and water use of rice – Wheat rotation system in the Huang-Huai-Hai Plain, China. Biology, 11(9), 1265.

NIEPEWNOŚĆ W SCENARIUSZACH ZMIAN KLIMATU W KONTEKŚCIE OKREŚLANIA WZORCÓW TEMPERATURY I OPADÓW W REGIONACH O MIESZANYCH WARUNKACH KLIMATYCZNYCH

ABSTRAKT

Cel badań

Niniejsze badania mają na celu ilościowe określenie niepewności w ocenie wpływu zmian klimatu na produkcję roślinną przy użyciu wszystkich dostępnych modeli klimatycznych (GCM) zarówno w przypadku ekstremalnych, jak i łagodnych scenariuszy emisji w latach 2020–2095. W omawianym regionie są to pierwsze badania nad tym zagadnieniem.

Materiał i metody

W tym celu przeprowadzono badanie porównawcze dla regionu Ludhiana w stanie Pendżab w Indiach. Dane wyjściowe globalnego modelu klimatu (GCM) dla dziennej maksymalnej temperatury (T_{max}) i dziennej minimalnej temperatury (T_{min}) oraz opadów w scenariuszu A1B dotyczącym połowy wieku (MC) (2020–2050) i końca wieku (EC) (2070–2095) zostały wyodrębnione z modelu ECHam5-GCM i PRECIS. Zostały one wykorzystane do zbadania zachowania zmian klimatu. W tych dwukrotnych przekrojach zastosowano następnie Model DSSAT v.4.6.1. oraz metodę Papadakisa. Ponadto dane klimatyczne ze scenariuszy RCP na przyszłość zostały wyodrębnione z pięciu losowo wybranych GCM w ramach scenariuszy RCP 4.5 i RCP 8.5 przy użyciu generatora pogodowego MarkSim DSSAT. Modele te poddano analizie statystycznej dla RMSE i NRMSE. Jeden z modeli, HAD GEM2-ES, został wybrany do badań oceny skutków jako posiadający najmniej NRSME.

Wyniki i wnioski

Z badań wynika, że na koniec wieku (EC) roczna minimalna temperatura wzrosłaby o 2,4°C i 2,45°C przy użyciu modeli ECHAM5 i PRECIS. Natomiast w scenariuszach RCP 4.5 i 8.5 średnia roczna temperatura wzrosłaby odpowiednio o 1,56°C w połowie wieku (MC) i o 3,11°C na koniec wieku (EC) w porównaniu z okresem bazowym oraz o 2,75°C w połowie wieku (MC) i 5,46°C na koniec wieku (EC) w porównaniu z okresem bazowym. Odpowiedni prawdopodobny spadek rocznego RF, jeśli przyjmiemy scenariusz RCP 4.5, wynosi odpowiednio 98 mm i 90 mm w połowie (MC) i na koniec wieku (EC). Z kolei przyjmując scenariusz RCP 8.5, otrzymamy wzrost rocznego RF odpowiednio o 153 mm i 251 mm. Nasze ustalenia pokazują zatem, że przy wyborze różnych scenariuszy zmian klimatycznych niepewność występuje nawet w stosunkowo małych regionach.

Słowa kluczowe: zmiany klimatyczne, globalne modele klimatyczne, scenariusze AIB, scenariusze RCP, DSSAT