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Assessing climate-driven phenological responses of tomato crops under future climate change trajectories: A Central India perspective

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ABSTRACT

Climate change poses a serious challenge to global agriculture, particularly by altering crop phenology and yield dynamics. This study investigates the phenological responses of tomato crops to anticipated climate scenarios by employing a Crop Simulation model, Decision Support System for Agrotechnology Transfer (DSSAT). Simulations were conducted for Central India under two Shared Socioeconomic Pathways (SSP 4.5 and SSP 8.5) across three temporal windows: near-century (2010–2039), mid-century (2040–2069), and far-century (2070–2099). Historical climate data and calibrated genetic coefficients were used to project shifts in flowering and fruiting stages under varying climate conditions. The study assessed the impacts of projected changes in temperature (T), solar radiation (Srad), and precipitation (PPT) patterns on phenological development. Climate input datasets were sourced from IMD, IPCC, and six CMIP6- Global Climate Models. Results revealed a distinct phenological advancement, characterised by a reduction in days to flowering and fruiting, along with a concurrent decline in tomato yield (Ton/ha) across all future timeframes. Increased growing season temperatures and marginal reductions in Srad were observed to accelerate crop development, while altered rainfall patterns influenced spatial variability in production. Notably, enhanced evapotranspiration demand driven by warming trends may be partially moderated by decreased radiation levels. Spatial rainfall analysis indicated intensified PPT in central zones, whereas western and northwestern regions may experience monsoonal weakening and prolonged dry spells. Model performance showed robust agreement with observed yields ($R = 0.78$), with validation metrics—MAE = 5.9, RMSE = 6.93, and Bias = -1.43—demonstrating consistent predictive accuracy with slight underestimation. The Nash–Sutcliffe Efficiency (NSE = 0.59) further affirms the model's applicability under future climate conditions. This research underscores the utility of process-based models in decoding climate–phenology–yield relationships and provides critical insights to inform climate-resilient agricultural strategies for sustainable tomato production in vulnerable agro-ecological regions.

1. Introduction

Tomato (*Solanum lycopersicum* L.) is one of the most widely cultivated vegetable crops worldwide and holds a pivotal role in global food and nutritional security. It is the second-most consumed vegetable after potatoes and ranks as the second-largest horticultural crop produced for human consumption [1]. In addition to its culinary versatility, tomato is a rich source of vitamins (notably vitamin C), minerals, and health-promoting antioxidants such as lycopene, which are associated with reduced risks of cardiovascular diseases and certain cancers [2,3]. India stands as the second-largest producer of tomatoes globally, following China and ahead of the United States and Turkey [4]. Among Indian states, Madhya Pradesh (MP) leads in production, yielding approximately 2970 thousand tonnes and accounting for 14.63 % of the national output [5]. Despite its economic and nutritional importance, tomato cultivation is increasingly vulnerable to the impacts of climate

Abbreviations: CC, Climate change; DSSAT, Decision Support System for Agrotechnology Transfer; IPCC, Intergovernmental Panel on Climate Change; CMIP6, Coupled Model Intercomparison Project 6; IMD, India Meteorological Department; CSMs, Crop Simulation Models; TT, Accumulated thermal time; LAI, Leaf Area Index; SSPs, Shared Socio-Economic Pathways; GIS, Geographic information systems; GCMs, General circulation models; MP, Madhya Pradesh; ACZs, Agro-climatic zones; PS, Phenological shifts; TAVG, Average temperature; T, Temperature; TS, Temperatures; PPT, Precipitation; SRAD, Solar Radiation.

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change (CC). The 21st century has seen a surge in global concerns over rising temperatures (Ts), erratic precipitation (PPT) patterns, and increased frequency of extreme weather events, which collectively threaten the sustainability of open-field horticultural systems [6]. Tomatoes, being sensitive to environmental cues, exhibit pronounced changes in phenology, fruit set, and yield under climatic stress [7]. Elevated Ts can shorten developmental phases, disrupt flowering and pollination processes, and heighten susceptibility to pests and diseases [8]. Consequently, there is an urgent need to develop robust adaptation and mitigation strategies, including the deployment of climate-resilient genotypes, predictive crop modeling tools, and data-driven agricultural practices [9,10].

Phenology—the study of periodic plant life cycle events such as flowering, fruiting, and maturation—is a vital indicator of how crops respond to environmental changes [11]. In climate-sensitive crops like tomato, phenological stages are tightly regulated by climatic variables such as temperature (T), PPT, and solar radiation (Srad) [12]. CC is disrupting these variables, causing observable phenological shifts (PS), including earlier or delayed flowering and fruiting, which impact synchronization with optimal growth conditions and reduce yield and quality [13,14]. Elevated T accelerates crop development, leading to early phenophases, but extreme heat, particularly above 30 °C during flowering, can impair fruit set and quality in tomato [15,16]. Likewise, irregular PPT patterns and water stress during critical stages such as flowering can reduce productivity, while excessive rainfall increases susceptibility to diseases [17]. Photoperiod sensitivity also plays a role in regulating reproductive stages, with deviations in day length influencing flowering and fruiting timing [18]. Furthermore, soil conditions—such as moisture and nutrient availability—modulate phenological responses, where early or delayed flowering can inform adjustments in irrigation, fertilization, or pest management [19]. These phenological and physiological disruptions underscore the vulnerability of tomato crops to ongoing climatic variability and highlight the need for adaptive management practices.

With ongoing CC, this kind of PS in crops like tomatoes is becoming increasingly significant [20]. Various climate scenarios, based on global socioeconomic developments and greenhouse gas emissions, help scientists predict how different crops will respond to these changes. Global Climate Models (GCMs), using frameworks such as Shared Socioeconomic Pathways (SSPs), predict how different socioeconomic and emissions trajectories will impact climate systems and crop phenology [21]. SSPs offer a broader perspective by incorporating not just emissions but also global development patterns, including technological advances, economic growth, and societal behaviours. For instance, under SSP1 (Sustainability Pathway), where global efforts are directed toward sustainable development and low emissions, tomato crops may experience mild PS. These shifts might include slightly earlier flowering and fruiting, with minimal disruptions to crop management. In contrast, under SSP3 (Regional Rivalry), where there is regional fragmentation, poor international cooperation, and high greenhouse gas emissions, the PS in tomato crops could be more extreme [22]. Tomatoes may flower and ripen much earlier, with extreme heat and water stress potentially reducing crop yields and fruit quality. By incorporating these climate scenarios based on SSPs, scientists and agricultural planners can better anticipate the effects of CC on tomato crop phenology and develop appropriate adaptation strategies for different regions and future climate conditions [23].

Numerous studies have explored the influence of climate change on crop phenology and productivity, including tomatoes, using both empirical observations and modeling approaches [24,25]. In the Indian context, research has predominantly focused on staple cereal crops such as rice and wheat, with relatively limited attention to horticultural crops like tomato. While recent efforts have examined the effects of T and water stress on tomato yield using observational or statistical approaches [26,27], these studies often lack the process-level detail needed to capture physiological responses under future climate conditions. To our knowledge, this study presents the first application of the DSSAT-CROPGRO-Tomato model to simulate and quantify climate-induced PS in tomato crops in Central India, a region highly susceptible to climatic variability. By integrating high-resolution climate projections with a process-based crop simulation model, the study aims to deliver a mechanistic understanding of how key climatic drivers—T, PPT and Srad influence tomato development and yield trajectories under future climate scenarios. This modeling approach enhances the precision of predictions and enables the design of location-specific, climate-resilient management strategies for tomato cultivation.

In purview of the above, this research examines the 1) phenological shifts in tomato harvests across several climatic projections i.e. near- (2010–2039), mid- (2040–2069), and far- (2070–2099), under two different scenarios—SSP2–4.5 (moderate emissions) and SSP5–8.5 (high emissions 2) Assess the impact of CC on Tomato Yield and Optimize Agricultural Practices for Future Climate Conditions 3) Develop a process-based crop model for tomato crops and validate its accuracy using historical and experimental data from Central India 4) To evaluate the phenological responses of tomato crops to various climate scenarios, providing essential insights for farmers, agricultural planners, and policymakers to alleviate the effects of CC on tomato output.

2. Study area

This research undertaken in the central part of India, MP, which is agriculturally diverse and prominently contributes to the nation's crop productivity, especially tomato production. MP is a centrally located state in India, known as the "Heart of India" due to its strategic position (Fig. 1). The entire province of MP, the 2nd largest state in India, has a vast amount of biodiversity and is included in the research study area. With a total size of 308,144 square kilometres, the state occupies 9.4 % of the nation's total land area (source: ncert.nic.in).

The area lies between 26.86°N and 21.07°N latitudes and 74.03°E and 82.81°E longitudes. MP experiences a predominantly tropical monsoon climate. Out of the 307.56 lakh hectares of the entire geographical area in the state, only 151.91 lakh hectares are arable [28]. There are currently 119 lakh hectares used for Rabi crops and 145 lakh hectares used for Kharif crops. Crops enclose 65.70 % of the state. This state encompasses various agroecological zones, ranging from the Narmada Valley in the south to the Malwa plateau and Bundelkhand region in the north. Because of the State's diverse climate, it is divided into 11 climatic zones and 5 crop regions (source: mpkrishi.mp.gov.in). The study's findings will help improve agricultural strategies and resilience in the tomato sector.

3. Datasets and methodology

Crop simulation models (CSMs) simulate the growth and yield of crops under varying environmental and management conditions by employing mathematical formulations and physiological algorithms. These models integrate multiple input variables—such as soil characteristics, T, PPT, Srad, and crop management practices—to estimate crop performance and predict yield outcomes [29,30]. Their application is critical in assessing crop responses to climate variability and in designing adaptive strategies for sustainable agriculture.

3.1. Climate data

The India Meteorological Department (IMD) released long-term observed daily meteorological data from 1980 to 2009 for a grid of 28 million pixels. The data was at a resolution of 0.5° × 0.5°, which was later upscaled to 1.0° × 1.0 °. The data included the highest T, the lowest T, and rainfall. The Hargreaves and Samani technique [31] was used to estimate the daily external solar radiation data in MJ/m^2/day units. The study utilised eight Global Climate Models (GCMs) to provide forecasts

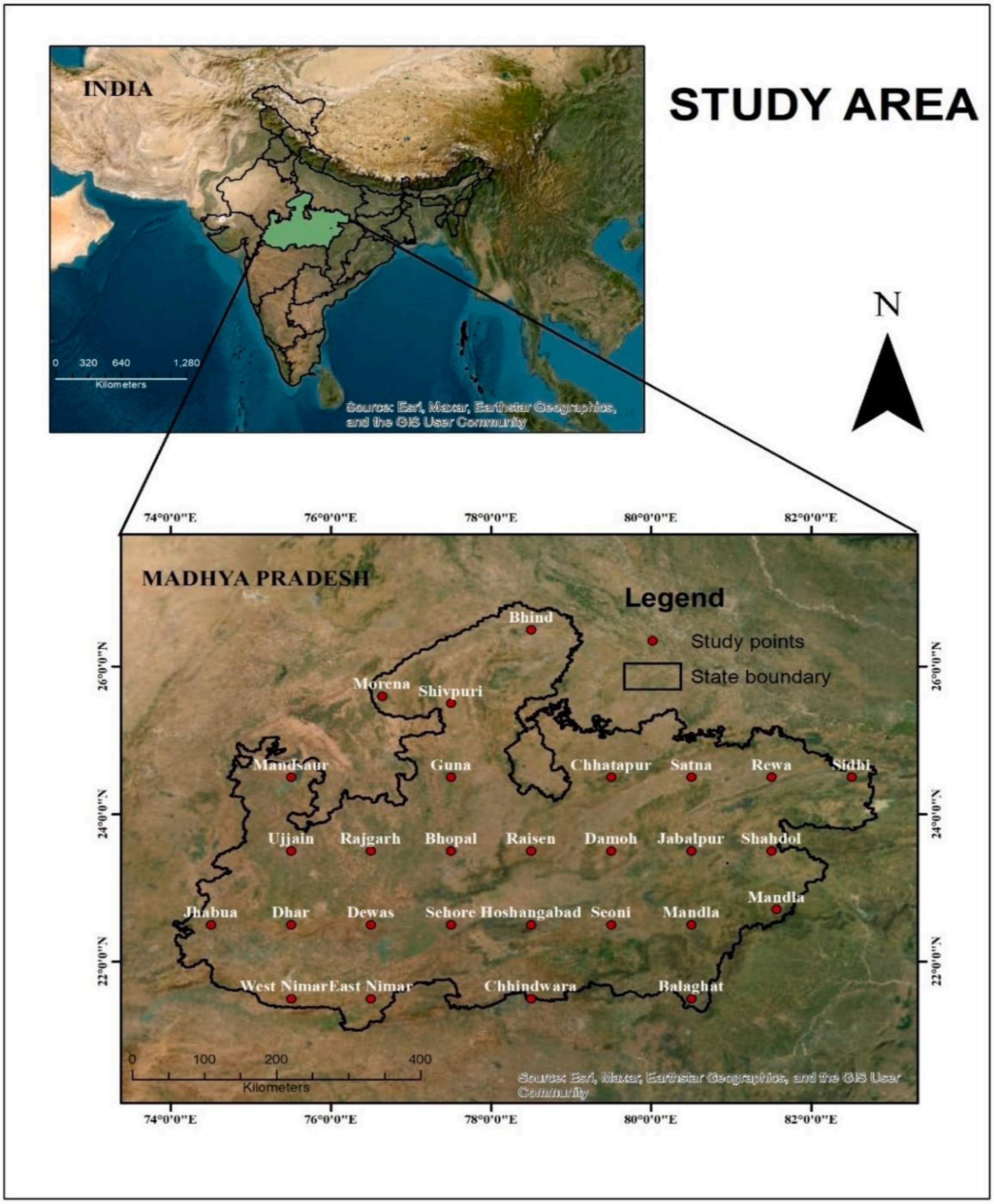


Fig. 1. A map illustrating the precise location of the study area.

of future climate conditions (Table 2). Data has been generated for each GCM across three distinct periods: 2010–2039 (near-future), 2040–2069 (mid-future), and 2070–2099 (far-future). This data corresponds to two environmental change scenarios: SSP2 (Middle of the road)-4.5 and SSP5 (Fossil-fuel Development)-8.5. All GCMs data that were used in this study were Bias-adjusted. This process is essential because raw climate model data often contains biases due to limitations in model resolution and representation of physical processes. The statistical bias correction method is efficient for large-scale climate data and helps make climate projections more reliable for impact assessments [32]. The Coupled Model Intercomparison Project (phase 6) (CMIP6) gathers multiple simulations of GCMs now employed for this investigation of future climate changes throughout three distinct periods: near-future, mid--future, and far-future. GCMs simulate the Earth's physical processes and atmosphere to replicate climate reactions and changes in land use [33]. The CMIP6 also offers estimates for novel situations known as shared socioeconomic pathways (SSPs). Hence, it is crucial to utilise the newly published CMIP- GCMs (Coupled Model Intercomparison Project Global Climate Models) for climate forecasts for Shared Socioeconomic Pathways (SSPs) to justify the vindication actions implemented based on earlier CMIP scenarios [34,35]. Multiple GCM outputs are utilised to determine the extent of uncertainty in assessing the lack of agreement between different models when assessing the effects of environmental change on crops (Table 1).

3.2. DSSAT model and functional architecture of DSSAT-CROPGRO

The DSSAT is an advanced computational framework designed to simulate crop growth, development, and yield under varying environmental and agronomic conditions. It integrates multiple components,

Table 1
GCMs CMIP6 considered in the research.

S. No.	Model	Institution/Country	Resolution	Period	References	Other Details
1	ACCESS-CM2	Australian Research Council Centre of Excellence for Climate System Science, Australia	1.25° × 1.875°	1950–2100	Smith et al. [36]	Focuses on Southern Hemisphere climate variations, coupled atmosphere-ocean model
2	NorESM2-LM	Norwegian Climate Centre, Norway	2° × 2°	1850–2100	Hansen et al. [37]	Includes detailed representation of ocean biogeochemistry
3	CMCC-ESM2	Euro-Mediterranean Centre on Climate Change, Italy	0.942° × 1.25°	1900–2100	Rossi et al. [38]	Emphasizes Mediterranean climate variability and regional extreme event simulations
4	FGOALS-g3	Chinese Academy of Sciences, China	2° × 2°	1960–2100	Li et al. [39]	Developed with a focus on Asia-Pacific climate, improved monsoon simulation
5	MIROC6	JAMSTEC, Kanagawa, Japan	1.4° × 1.4°	1850–2100	Watanabe et al. [40]	Accurate simulation of ocean currents and El Niño-Southern Oscillation (ENSO)
6	MPI-ESM1–2-HR	Max Planck Institute for Meteorology, Germany	0.94° × 0.94°	1850–2100	Mauritsen et al. [41]	High-resolution version; better atmospheric circulation simulation
7	MPI-ESM1–2-LR	Max Planck Institute for Meteorology, Germany	1.875° × 1.86°	1850–2100	Muller et al. [42]	Low-resolution version; focuses on long-term climate trends
8	MRI-ESM2–0	Meteorological Research Institute, Ibaraki, Japan	1.125° × 1.125°	1950–2100	Yukimoto et al. [43]	Improved tropical cyclone simulation, good for regional impact studies

including soil, plant, weather, and management practices, to provide a holistic understanding of crop-environment interactions (Fig. 2). The DSSAT-CSM incorporates structured data assimilation processes to translate environmental inputs into actionable agricultural insights [29]. One of the core modules within this system is DSSAT-CROPGRO, which is widely utilized in over 100 countries to evaluate agricultural systems, forecast crop behaviour, and assess climate adaptation strategies (source: dssat.net [44]). The CROPGRO-Tomato model, implemented in DSSAT v4.8.2, is specifically used to simulate tomato development and yield under diverse environmental and management circumstances (Fig. 3). This model has been extensively applied to optimize crop management strategies for improved productivity and sustainability [45,46].

➢ **Background of the CROPGRO-Tomato Model-** The CROPGRO-Tomato model within the DSSAT framework simulates crop growth, yield and phenological development through a series of mechanistic sub-models that represent key biophysical processes. The core equations governing these processes are outlined below through Eq. i-vi):

1) Phenological Development (Thermal Time Accumulation)

$$\mathbf{TT} = \Sigma\left(\mathbf{T}_{\text{avg}} - \mathbf{T}_{\text{base}}\right) \tag{i}$$

Where, TT: Accumulated thermal time (°C-days); T_{avg}: Daily average temperature = $(T_{max} + T_{min})/2$; and T_{base}: Base temperature (typically 10 °C for tomato). Each growth stage—from emergence to flowering and fruit maturity—is initiated once specific TT thresholds are met, making it a reliable predictor of crop progression under varying climatic

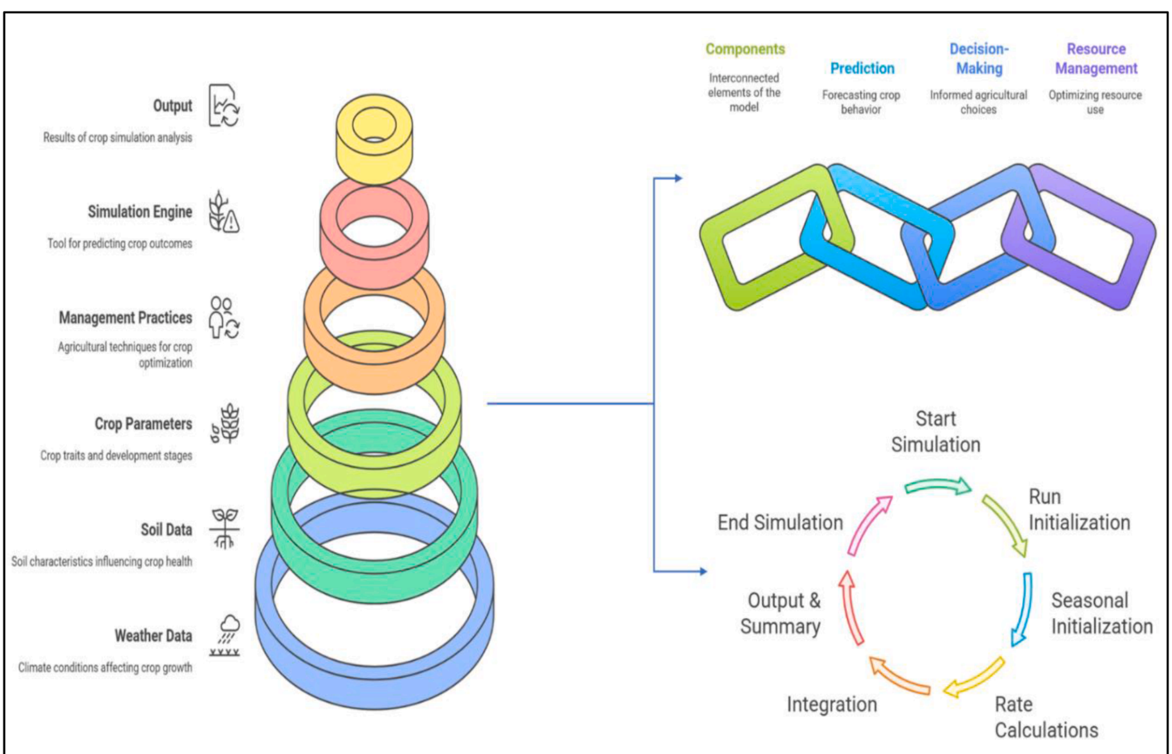


Fig. 2. From data to decisions: the synergistic flow of crop simulation models for smarter agriculture.

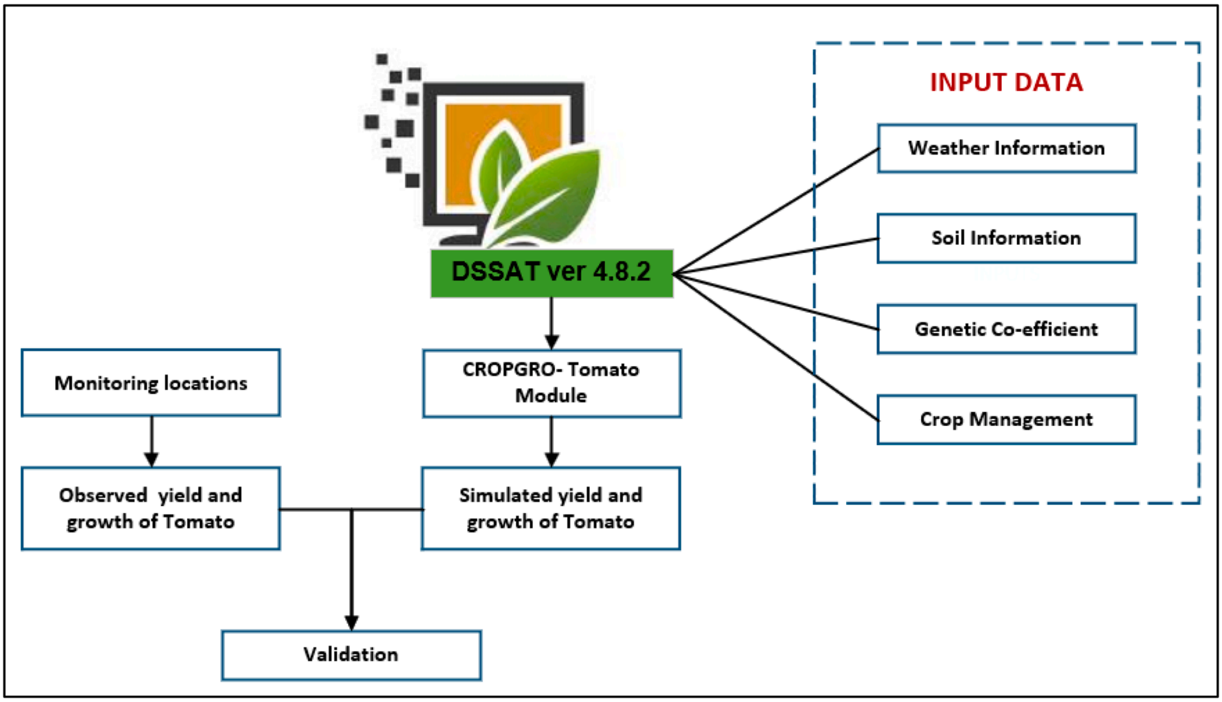


Fig. 3. Outline of the general methodology of the DSSAT- CROPGRO- Tomato model.

conditions [29]. While TT directly governs phenology, it also influences yield by controlling the duration of photosynthetically active periods, particularly the reproductive phase. Accelerated TT accumulation due to elevated temperatures can shorten the fruit development window, limiting assimilate translocation and reducing final yield (Boote et al., 2010).

2) Biomass Accumulation via Radiation Use Efficiency

$$\boldsymbol{\Delta W} = \mathbf{RUE} \times \mathbf{IPAR} \qquad \text{(ii)}$$

Where, ΔW: Daily increase in biomass (g/m^2); RUE: Radiation use efficiency (g/MJ); and IPAR: Intercepted photosynthetically active radiation (MJ/m^2). Biomass accumulation is essential for supporting fruit growth. Reductions in IPAR due to poor canopy development or environmental stress can suppress yield potential by limiting source strength [47].

3) Leaf Area Index (LAI)

$$\mathbf{LAI} = \mathbf{SLA} \times \mathbf{W_{leaf}} \qquad \text{(iii)}$$

Where, LAI: (m^2 leaf/m^2 ground); SLA: Specific Leaf Area (m^2/g); and W_{leaf}: Leaf dry weight (g/m^2). LAI is pivotal for both phenology and yield, as it regulates intercepted solar radiation and influences photosynthesis. It also shapes canopy microclimate (light, temperature, humidity), which affects developmental timing [29]. Optimal LAI supports effective source–sink dynamics, while suboptimal values under stress can reduce yield and delay or disrupt flowering and fruit maturation [30].

4) Fruit Dry Matter Allocation

$$\textbf{Fruit Dry Weight} = \textbf{Total Biomass} \times \textbf{Fruit Partitioning Fraction} \qquad \text{(iv)}$$

This equation determines the fraction of total assimilated biomass allocated to fruit. Fruit yield is inherently sensitive to the amount and duration of biomass availability during the reproductive phase [47].

5) Conversion to Fresh Yield

$$\textbf{Yieldfresh} = \textbf{Fruit Dry Weight} \times [100 / (100 - \%\textbf{Water})] \qquad \text{(v)}$$

Tomato fruits typically contain 90–94 % water. This equation allows conversion of simulated fruit dry matter into fresh yield values suitable for field validation and comparison with harvest data [29].

6) Environmental Stress Modulation

$$\mathbf{SF_{actual}} = \mathbf{min}\ (\mathbf{SF_{water}}, \mathbf{SF_{nitrogen}}, \mathbf{SF_{temperature}}) \qquad \text{(vi)}$$

Each stress scalar ranges from 0 (complete stress) to 1 (no stress), dynamically scaling growth and development rates. This adjustment affects photosynthesis, biomass accumulation, and phenology. For example, heat or nitrogen stress can accelerate phenological progression or impair reproductive development, resulting in lower yield [48,49].

3.3. Operational framework and calibration of the DSSAT-CROPGRO-Tomato model for climate-responsive yield simulation

The DSSAT-CROPGRO-Tomato model requires multiple input variables to simulate crop growth and yield accurately. These include climate data, which encompasses daily meteorological parameters such as T, PPT, and Srad, recorded at a specific geographic location over the crop-growing period. Soil data is another crucial input, providing information on soil properties like texture, organic matter content, and pH, all of which influence water retention, nutrient availability, and root development. Additionally, crop parameters, including genetic coefficients, govern key aspects of crop phenology, growth stages, and yield potential. Management practices such as planting dates, irrigation schedules, fertilization regimes, and pest control strategies also play a significant role in defining the crop's response under various environmental conditions (Fig. 2) [50]. These elements are systematically processed within the DSSAT-CROPGRO simulation engine, which models daily crop growth dynamics, water balance, and nutrient uptake. The model operates through an iterative computational sequence, beginning with run initialization, where it sets up predefined conditions [51]. This is followed by seasonal parameterization, establishing environmental settings for each simulation cycle. Subsequently, the model executes daily rate calculations, integrating physiological responses over time to simulate plant development and resource utilization. The final outputs include yield predictions, phenological shifts, and resource-use efficiency metrics, which undergo post-processing for validation and refinement [29]. The DSSAT-CSM is designed with a modular structure, enabling the seamless integration of multiple crop models within a unified computational framework (Fig. 3). This architecture allows all crop models to share common soil process components and management modules, ensuring consistency across different cropping systems. Such an approach is particularly beneficial for simulating crop rotations, as it facilitates the continuous operation of soil processes, nutrient cycling, and field management activities across multiple growing seasons [52]. By maintaining the interactions between soil and crops over time, this design enhances the accuracy of long-term agricultural assessments and improves predictions of productivity under varying environmental conditions [53,54].

To ensure reliable performance, the CROPGRO-Tomato model was calibrated using an iterative parameter adjustment approach, following the methodology outlined by Hunt et al. [46] and Godwin et al. [46,55]. This calibration process involved trial-and-error modifications to refine model outputs, aligning simulated crop phenology and yield with observed field data. By accurately representing tomato growth under different environmental conditions, the model serves as a valuable tool for optimizing crop management strategies. Through field-based simulations, growers, researchers, and policymakers can develop site-specific agricultural practices tailored to local climatic and soil conditions, improving decision-making for sustainable crop production. The DSSAT-CROPGRO framework provides a robust decision-support tool for enhancing precision agriculture and resource management [56]. By integrating diverse agronomic, climatic, and management factors, it enables comprehensive evaluations of crop performance, facilitating improved adaptation strategies under changing climatic scenarios. This predictive capability strengthens efforts toward sustainable food production, efficient resource utilization, and climate-resilient farming systems [29].

3.4. Crop data and variety

Using an increased amount of CO_2 {per IPCC-6th AR and [57]} to the baseline CO_2 measurement of 380 ppm (by default value) for every environmental scenario and timeframe, the CROPGRO-Tomato model was employed to simulate tomato phenology and yield. One of the input parameters that the module uses is climate data. The tomato cultivar used in this study, Narendra Tomato-4 (NDT-4), is normally planted in September or October and harvested 60–80 days after transplantation [58]. Based on secondary data collected for MP, the initial field conditions were given [51,59]. In this study, the DSSAT-CROPGRO-Tomato model was calibrated to simulate the growth and phenology of the tomato cultivar NDT-4. The model initially utilized genetic coefficients previously developed and validated by Yadav et al. [60] for tomato simulation in northern Indian conditions. However, to ensure model accuracy and regional applicability under current climatic and experimental conditions, further refinement was carried out. Calibration of genotype-specific parameters was conducted using a combination of the Genotype Coefficient Calculator (GENCALC) and the Generalized Likelihood Uncertainty Estimation (GLUE) method. These tools enabled iterative adjustment of genetic coefficients to minimize discrepancies between observed and simulated yield attributes. The parameters were tuned within physiologically plausible limits based on literature values and expert knowledge. The final set of calibrated coefficients for the NDT-4 cultivar is presented in Table 2. This calibration process was critical to improving the model's predictive capacity under future climate scenarios in Central India (MP).

To determine how phenological stages (flowering and fruiting) responded to weather factors like T, Srad and CO_2 change, simulations were run at the potential level. This implies that during the simulations, neither water stress nor nutritional stress was considered. Running the DSSAT-CROPGRO model potentially provides a foundation for developing targeted interventions to improve crop resilience and productivity in the face of changing climatic conditions [61]. However, this can lead to overestimation of yields, as actual field conditions often involve varying degrees of water and nutrient limitations or other stress factors. An analysis of the uncertainty around the degree of change in tomato performance led to the creation of 48 climate scenarios, comprising 8 models, 2 scenarios, and 3 time periods. As we all know, CMIP6 started in 2015, by incorporating historical data into the 2010–2014 period, the near-term projections (2010–2039) are transformed into a hybrid dataset that commences with observed data and progresses to modeled projections, thereby enabling the analysis of a continuous time series (carbonbrief.org).

3.5. Statistical evaluation and model assessment

The efficacy of the DSSAT CROPGRO-Tomato model was evaluated by comparing simulated tomato yields with observed yields over five consecutive cropping years: 2019–2020, 2020–2021, 2021–2022, 2022–2023, and 2023–2024. Observed yield data were obtained from the Horticulture Area Production Information System (HAPIS) portal, which provides district-level yield statistics for horticultural crops across India (Department of Agriculture and Farmers Welfare, n.d.[5]). To ensure spatial consistency with the model simulations, district-level yields were aggregated and spatially averaged across 28 grid points

Table 2
Calibrated genetic coefficients for CROPGRO-Tomato Model (Cultivar NDT-4).

Genetic Coefficient	Description	Calibrated Range	Final Value
EM-FL	Time from emergence to flowering (R1) [photothermal days]	8–20	10.0
FL-SH	Time from flowering to first pod (R3) [photothermal days]	5–15	6.0
FL-SD	Time from flowering to first seed (R5) [photothermal days]	10–18	12.0
SD-PM	Time from first seed to physiological maturity (R7) [photothermal days]	30–50	40.0
FL-LF	First flower to end of leaf expansion [photothermal days]	30–50	40.0
LFMAX	Peak photosynthetic rate [mg CO_2 m^{-2} s^{-1}]	1.0–1.5	1.160
SLAVR	Specific leaf area [cm^2 g^{-1}]	300–400	350
SIZLF	Maximum size of a full leaf (three leaflets) [cm^2]	250–350	300
XFRT	Maximum fraction of daily fruit growth	0.8–1.0	1.0
WTPSD	Maximum weight per seed [g]	0.003–0.005	0.004
SFDUR	Seed filling duration [photothermal days]	20–30	25.0
SDPDV	Average number of seeds per pod	300–500	400
PODUR	Time to reach final pod load [photothermal days]	30–45	40.0
THRSH	Threshing percentage [%]	8–10	9.0
SDPRO	Protein fraction in seed [g/g]	0.25–0.35	0.300
SDLIP	Oil fraction in seed [g/g]	0.000–0.01	0.000

representing the study area (Fig. 1). These grid points served as the spatial framework for both model execution and yield validation, allowing for direct comparison between simulated and observed data. Model performance was quantitatively evaluated using standard statistical indicators (Eq. vii-xii), including Root Mean Square Error (RMSE), Bias, Mean Absolute Error (MAE), Nash–Sutcliffe Efficiency (NSE), Pearson's correlation coefficient (r), and the Coefficient of Determination (R^2). The validation method of the yield output generated by the DSSAT-CROPGRO Tomato model often involves juxtaposing the model's projected outcomes with observed data gathered from diverse locations and conditions. The technique may involve iterative modifications of parameters, including genetic coefficients, soil properties, and climatic conditions, succeeded by comparisons of the results with empirical data for each of the 28 grids. This repeated process persists until a satisfactory alignment is achieved.

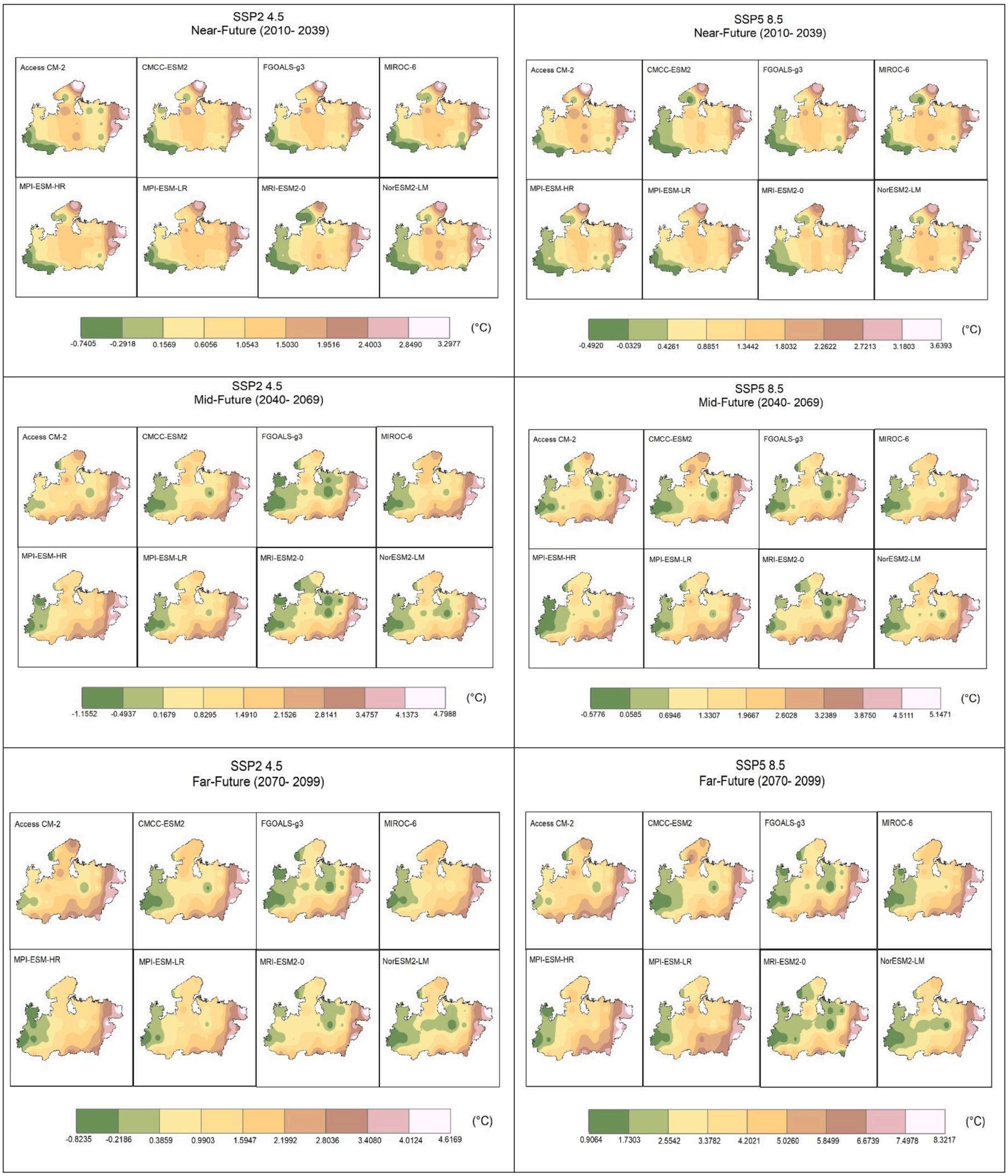


Fig. 4. Spatial distribution of change in average temperature (°C) from the reference period (1980–2009) and make projections across different CMIP6 models under SSP2-4.5 and SSP5-8.5 scenarios for near (2010–2039), mid (2040–2069), and far future (2070–2099).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}} \tag{vii}$$

$$\mathrm{Bias} = \frac{1}{n}\sum |\mathrm{P_i} - \mathrm{O_i}| \tag{viii}$$

$$\mathrm{MAE} = \frac{1}{n}\sum |\mathrm{O_i} - \mathrm{P_i}| \tag{ix}$$

$$\mathrm{NSE} = 1 - \frac{\sum (\mathrm{O_i} - \mathrm{P_i})^2}{\sum \left(\mathrm{O_i} - \bar{\mathrm{O}}\right)^2} \tag{x}$$

$$r = \sum \left(\frac{X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum (X_i - \overline{X})^2 \sum (Y_i - \overline{Y})^2}} \tag{xi}$$

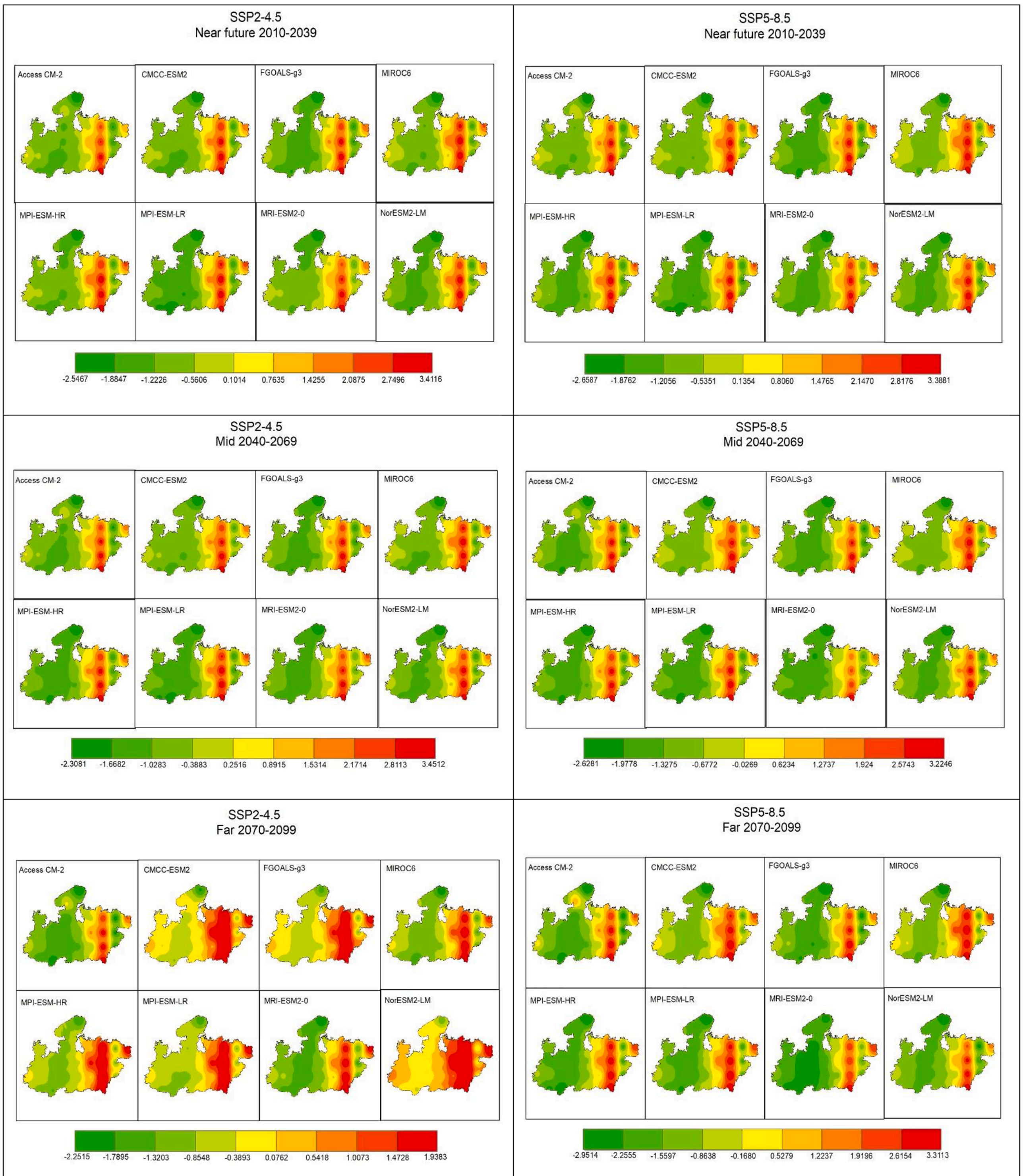


Fig. 5. Spatial distribution of change in solar radiation (Srad) (in MJ/ (m^2.d)) from reference period (1980–2009) and make projections across different CMIP6 models under SSP2-4.5 and SSP5-8.5 scenarios for near (2010–2039), mid (2040–2069), and far future (2070–2099).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} \left(O_i - \bar{O}\right)^2} \tag{xii}$$

To validate the model's conclusions, we utilised five years (2019–2023) of observed tomato yield data (in ton/ha) for each grid across the MP region. The model demonstrates a moderate to good level of accuracy in forecasting tomato yields for each grid and considered year. The correlations frequently exhibit a high magnitude, suggesting a robust linear association between observed and projected yields. MAE and RMSE values are comparatively low, indicating that the model's predictions are, on average, near the observed values. The Bias scores indicate a minor underestimation of yields across years. The NSE values indicate moderate model efficiency, with opportunities for further refinement. The R^2 values indicate that the model accounts for a substantial fraction of the variability in the reported yields.

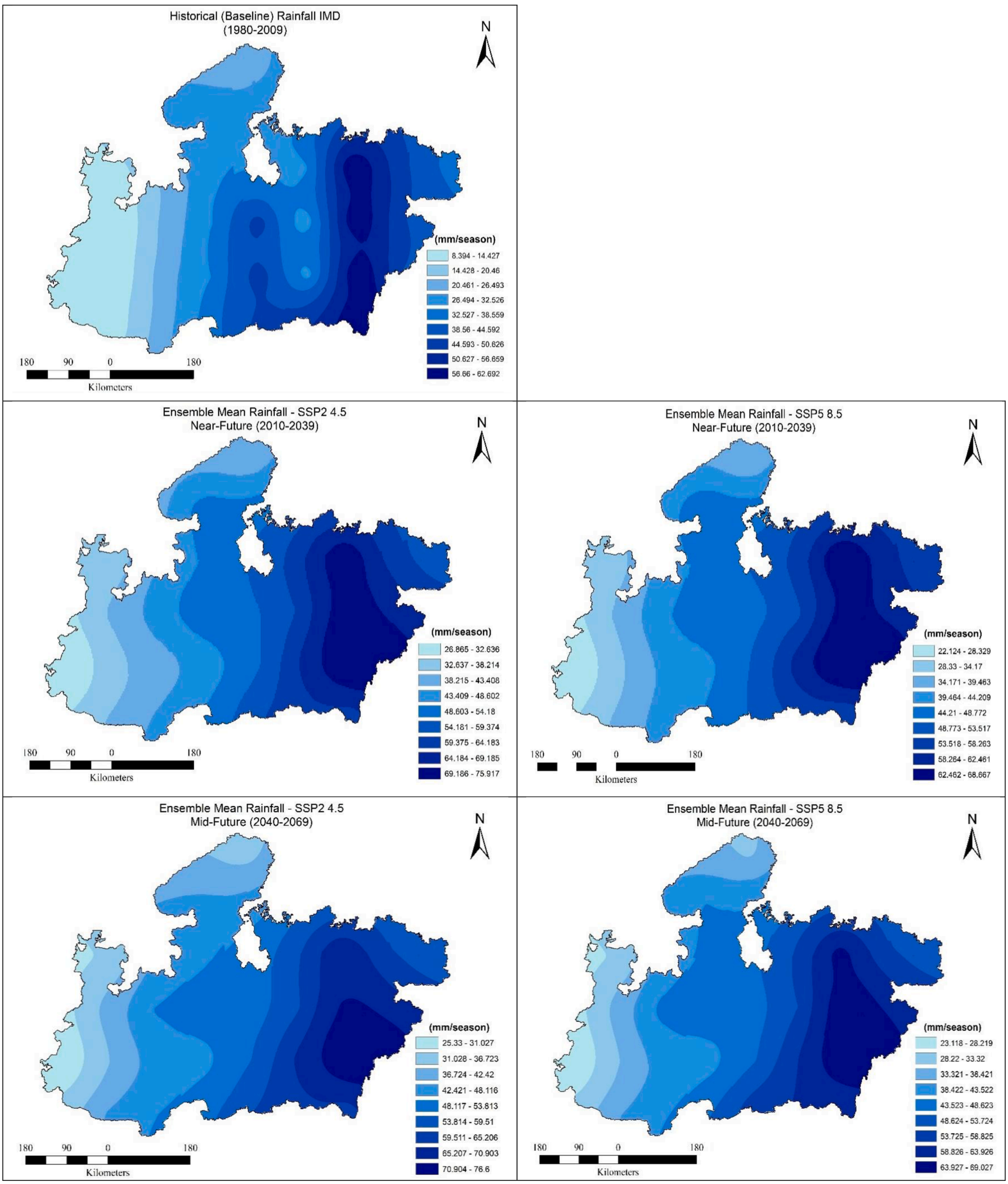


Fig. 6. Spatial distribution of historical (1980–2009) and projected rainfall (mm/season) under SSP2-4.5 and SSP5-8.5 scenarios for near (2010–2039), mid (2040–2069), and far future (2070–2099).

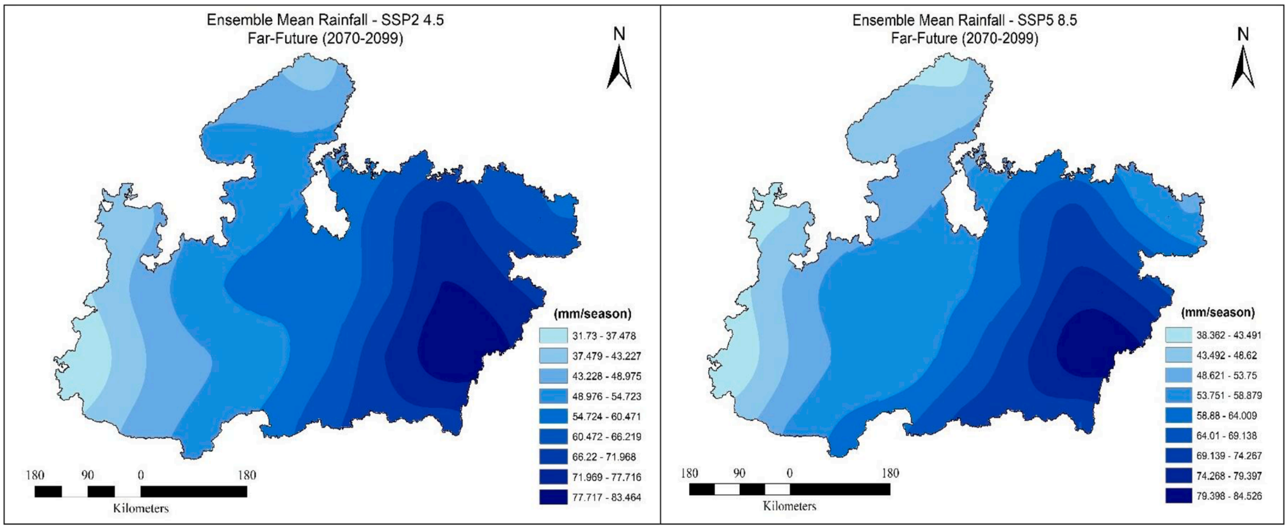


Fig. 6. (*continued*).

4. Results & discussion

4.1. Simulated yield responses to projected hydro-climatic variability

The spatiotemporal analysis of hydro-climatic variables across MP (Figs. 4–6) highlights projected shifts in key environmental drivers—T, PPT, and Srad—under future climate scenarios. Although these figures illustrate climate model outputs, their implications for tomato productivity are interpreted through their integration as input drivers within the DSSAT-CROPGRO-Tomato model, which simulates yield responses under seasonal and region-specific conditions. As the present study focuses on winter-season tomato cultivation, model simulations demonstrate that even modest increases in average T—especially during critical growth phases such as flowering and fruit set—can lead to reduced yield potential. Tomato plants grown during winter typically perform optimally within a T range of 15 °C to 25 °C. Deviations beyond this can impair floral development, fruit set, and photosynthetic efficiency [62]. Moreover, increased Ts may accelerate evapotranspiration, intensify soil moisture stress and shorten phenological stages, both of which negatively impact yield formation. Simulated yield declines are also influenced by PPT patterns, where prolonged dry spells lead to inadequate moisture availability during flowering, and excessive rainfall increases the risk of nutrient leaching and root diseases. Srad, an essential driver of photosynthesis, plays a pivotal role during the relatively short winter photoperiod. Reduced Srad may lead to delayed fruit development and lower biomass accumulation [63]. While elevated CO_2 concentrations may enhance photosynthesis and water-use efficiency, their positive effects are often negated by concurrent thermal and hydric stresses [17,64]. Thus, the projected spatiotemporal trends in hydro-climatic variables are mechanistically linked to the simulated yield responses in our study, underlining the complex interplay between climate change and tomato crop productivity across Central India.

4.1.1. Change in the seasonal average temperature

Across all scenarios and timeframes, the SSP5-8.5 pathway consistently predicts greater average temperature (Tavg) increases compared to SSP2-4.5, highlighting the impact of higher greenhouse gas emissions. This section examines the change in Tavg from the reference period of 1980–2009 to future projections for different timeframes: the near future (2010–2039), mid-future (2040–2069), and far future (2070–2099) (Fig. 4). The annual T deviations from the reference period indicate an overall increase in Tavg across the entire state of MP, with a few exceptions in the southwestern districts, including Jhabua, Dhar, and Mandsaur, under both the SSP2-4.5 and SSP5-8.5 scenarios for the mid and far future. Regions such as Sidhi, Mandla, and Bhind experience rising Ts, while Jhabua and the entire Nimar region show a slight decrease in Tavg from the reference period in the near future under both scenarios. In the mid- and long-term future, peak Tavg variations present a clearer picture. There is a notable increase in Tavg over the northern and eastern Agro-Climatic Zones (ACZs), while the southwestern ACZs show a decrease. In the distant future, SSP5-8.5 projects significant warming for Mandla and Sidhi, with Tavg increases exceeding 8 °C in certain areas. Central and northeastern zones are particularly affected, indicating a drastic rise in Tavg under high-emission scenarios. Both SSP2-4.5 and SSP5-8.5 climatic scenarios indicate that the cm2 model consistently overestimates Tavg, while the MIROC6 model steadily underestimates them across all conditions (Fig. 4).

The Tavg has a direct effect on the growth and development of crops and has the potential to substantially alter plant phenology [65]. These are frequently disregarded components of plant ecology, yet they have substantial implications for agricultural productivity [66,67]. MP is one of India's largest states (by area), and the majority of it is a jutting plateau; thus, it is extremely vulnerable to Tavg fluctuations in terms of health, agriculture and economic implications. Elevated Ts can significantly impact the phenology and yield of tomato crops. Exposure to high temperatures, particularly during the reproductive phase, can disrupt flowering, fruit set, and ripening processes. Previous studies suggest that even a 1- 2 °C increase in Tavg can reduce crop yield and alter phenological stages [68,8]. Furthermore, warming trends during the winter season could impact vernalization-dependent crops, altering their growth cycles [69]. To alleviate the detrimental impacts of increasing Tavg, it is imperative to employ adaptive tactics, such as modifying planting schedules, choosing heat-resistant tomato cultivars, and adopting effective watering techniques [70].

4.1.2. Variability in solar radiation

The model ensembles indicate a decline in Srad for both the SSP2-4.5 and SSP5-8.5 scenarios, except for the near future (2010–2039) under SSP2-4.5. In the central and western regions of MP, the models ACCESS CM2, MPI ESM HR, FGOALS g3, MPI ESM LR, MRI ESM2.0, and MIROC6 project a decline in Srad. The only exceptions are the models NorESM2-LM and CMCC ESM2, which show different results under both the SSP2-4.5 and SSP5-8.5 scenarios for the mid-future (2040–2069) and far future (2070–2099). For near-term projections, almost all models, except for ACCESS CM2 and MRI ESM2.0, predict an increase in Srad for both climate change scenarios (SSP2-4.5 and SSP5-8.5). Regions such as Balaghat, Mandla, and Seoni exhibit an increase in Srad compared to the reference period (1980–2009) across all three time periods under both climate scenarios (Fig. 5). The greatest increase in Srad during the near-future SSP5-8.5 scenario is observed in Mandla, with a rise of 2.93 MJ/(m^2·d), while Balaghat shows an increase of 3.68 MJ/(m^2·d). In contrast, the most significant decrease in Srad in the far-future SSP5-8.5 scenario occurs in East Nimar (Burhanpur) and the Bhind region, with declines of −2.48 and −2.95 MJ/(m^2·d), respectively. Models like CMCC ESM2, MIROC6, MPI ESM HR, MPI ESM LR, and FGOALS g3 show slight variations in Srad between the two scenarios across the three-time frames. According to the reference period (1980–2009), the model NorESM2-LM predicts a maximum increase in Srad of approximately 3.65 MJ/(m^2·d) at Mandla for the SSP2-4.5 scenario in the distant future, while the model ACCESS CM2 forecasts a maximum decrease of about −2.95 MJ/(m^2·d) at Bhind for the SSP5-8.5 scenario in the far future. Overall, for nearly all periods evaluated, the climate models NorESM2-LM and ACCESS CM2 exhibit exaggerated and understated forecasts, respectively, under the SSP2-4.5 and SSP5-8.5 climate change scenarios (Fig. 5).

Tomato crops use Srad as their principal energy source for photosynthesis. The amount of intercepted radiation controls the rate of photosynthesis, which causes differences in biomass accumulation [71]. The variability in Srad caused by climatic changes and air circumstances can substantially impact the physiological and phenological development of tomatoes. Reduced Srad from cloud cover, aerosol concentration, or higher humidity may limit carbon assimilation, reducing dry matter buildup in leaves, stems, and fruits [72]. Several studies have found that variations in incoming Srad directly affect tomato output. A 10–15 % reduction in sun radiation during important phenological stages (flowering and fruit set) has been linked to decreased fruit set and smaller fruit size [73]. The impact of Srad on tomato crops is also region-specific, varying across ACZs. Additionally, decreased Srad can endorse the growth of herbaceous plants with shallow root systems by decreasing surface soil evaporation and increasing soil moisture retention [74]. In central India, agriculture is a critical component of the economy, and shifts in Srad could have substantial effects on crop yields, stressing food supplies (source: climatechange.mp.gov.in).

4.1.3. Variation in mean rainfall

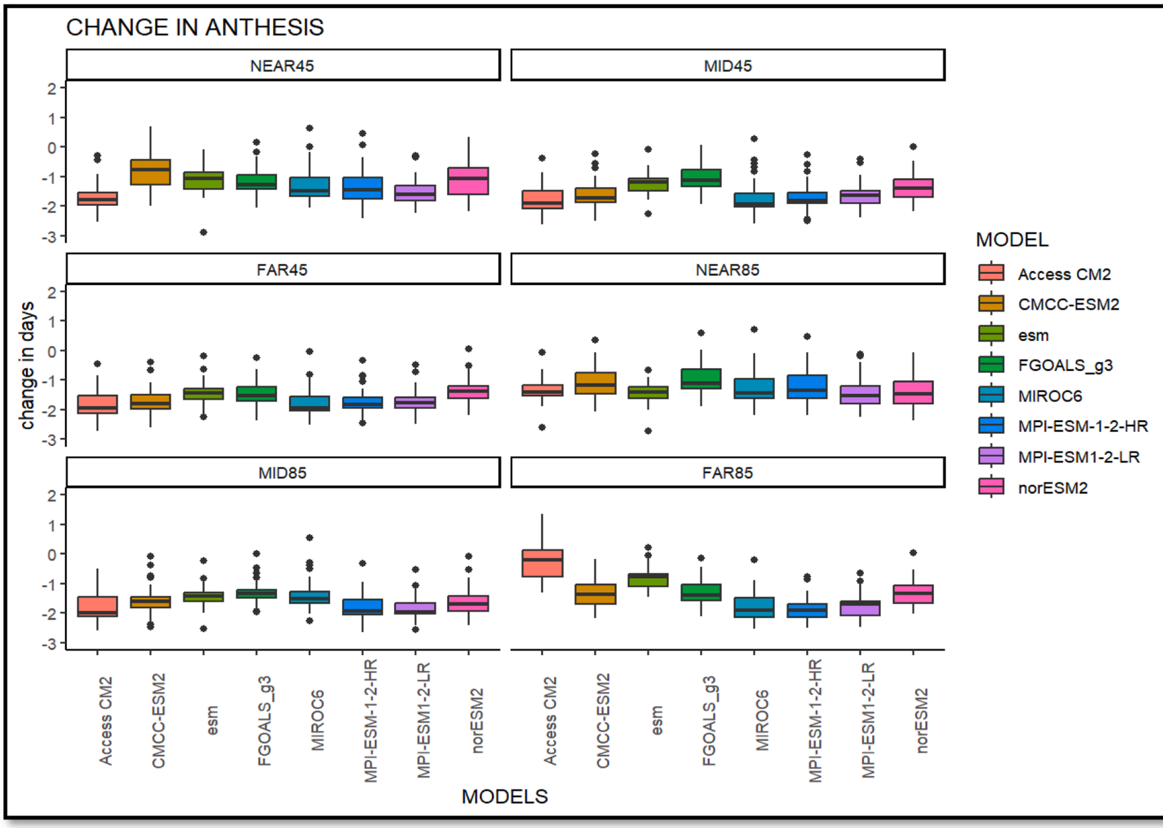
Variations in PPT patterns markedly impact tomato crop yield by directly influencing soil moisture availability and nutrient absorption efficiency. Analysis of rainfall distribution over various grids in MP indicates that areas with unpredictable PPT—marked by extended dry periods succeeded by heavy rainfall—demonstrate a significant reduction in tomato output. Moreover, documented data reveal that fluctuations in patterns of rainfall cause phenological changes in tomato crops, especially during the vital flowering and fruiting phases, which may result in diminished productivity and overall yield inconsistency [75].

The spatial distribution of historical (1980–2009) and projected rainfall (mm/season) under different scenarios (SSP2-4.5 and SSP5-8.5) for near (2010–2039), mid (2040–2069), and far future (2070–2099) unveils significant shifts in PPT regimes across MP, India. The historical precipitation data from IMD (1980–2009) exhibit pronounced spatial heterogeneity, with lower rainfall recorded in western and central MP and elevated PPT observed in the eastern and southeastern regions (Fig. 6). The baseline seasonal rainfall from October to March ranged from 8.39 mm to 62.69 mm. For the near future (2010–2039), under the SSP2-4.5 scenario, seasonal rainfall is projected to increase to 75.91 mm, while under SSP5-8.5, it is expected to reach 68.66 mm. This suggests a rising trend in off-season PPT, which may be beneficial for maintaining adequate soil moisture during the early vegetative and flowering stages of winter tomatoes. However, the western and northern regions remain susceptible to rainfall deficits, exacerbating drought conditions and increasing irrigation demands. Additionally, excessive rainfall could elevate the risk of fungal infections, such as early and late blight, potentially compromising fruit quality and yield [76]. In the mid-future (2040–2069), rainfall projections indicate a near-stabilization under SSP2-4.5 (25.33–76.60 mm) and a slight decline under SSP5-8.5 (23.11–69.02 mm). The spatial distribution of PPT suggests a potential shift in rainfall zones, with increased rainfall concentration in central regions. Conversely, the western and northwestern areas exhibit a persistent decline in seasonal PPT, which could prolong dry spells and reduce crop water availability (Fig. 6). For winter tomato cultivation, additional reliance on supplemental irrigation may be necessary to prevent moisture stress during fruit maturation. Moreover, improved disease management strategies could be essential to reduce outbreaks of waterborne pathogens linked to excessive soil moisture [77]. For the distant future (2070–2099), substantial increases in PPT are projected, with rainfall reaching 83.46 mm under SSP2-4.5 and 84.52 mm under SSP5-8.5. The increased rainfall during the October–March period may enhance soil moisture retention and groundwater recharge, reducing dependency on irrigation. However, excessive moisture could lead to waterlogging, delayed fruit ripening, and increased post-harvest losses due to heightened humidity, thereby negatively affecting both yield and market quality [78]. In all future projections, Jhabua records the lowest rainfall due to its rain-shadow effect from the Aravalli and Vindhya ranges, limiting moisture-laden winds. Conversely, Mandla receives the highest rainfall, benefiting from orographic PPT influenced by the Satpura and Maikal ranges and higher forest cover aiding local PPT cycles [79]. The increasing variability in rainfall patterns may pose significant challenges for tomato crop development, particularly in aligning phenological stages with optimal soil moisture availability.

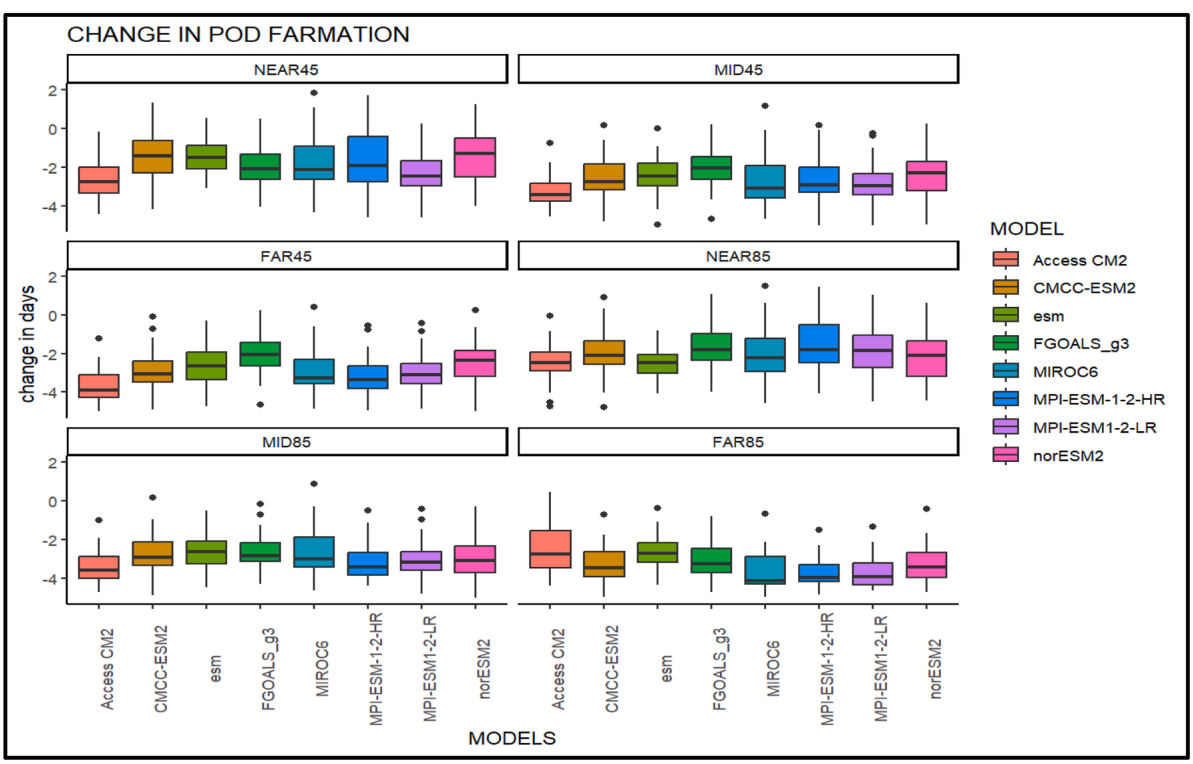
4.2. Change in days of Anthesis (Flowering) and pod (Fruits) formation

The climate models group shows a decrease (in days) in phenological stages, such as (a) change in days of Anthesis and (b) change in Pod formation, compared with baseline in both of the SSP2-4.5 and SSP5-8.5, change in the climate scenarios for different time frames (Fig. 7). The findings demonstrate that, though to varying degrees, days of its anthesis and pod development decrease in every circumstance. The variation across different models suggests that temperature and radiation changes influence the phenological response differently depending on the climate projection used. In the case of pod formation, the highest decrease was observed through MIROC6 (−6.06 days) and then via Access CM-2 (−6.00 days) of far future under scenario SSP5-8.5 and SSP2 4.5 at the Mandla region of M.P. The Bhind region experienced the greatest reduction in days of anthesis under SSP2-4.5 climate change scenarios, as evidenced by MRI ESM2 0 (−2.89 days) for the future and MPI-ESM-1-2-HR (−2.63 days) for the mid-future (Fig. 7). When compared to the reference period across the entire M.P., certain models, such as FGOALS_g3, ESM, and norESM-2, exhibit the lowest average change or reduction in days of anthesis and pod development under both scenarios over the entire time frame. The environment model Access CM-2 is an exception; it exhibits a minor increase in anthesis up to 1.34 days under scenario SSP5-8.5 at a far time horizon as compared to the baseline era at the M.P. region's Jhabua. Some models indicate that the number of days of anthesis in the Morena, Jhabua, and Balaghat regions for the far future under the SSP5-8.5 scenario will increase from the baseline period. Similarly, some models, such as CMCC ESM2, norESM-2, and MIROC6, indicate that the number of pod formation days will increase in the Morena and Jhabua regions shortly under the SSP2-4.5 climate change scenarios.

The process of grain filling and settling begins at anthesis, also known as blossoming. Morning anthesis occurs between 9:00 and 10:00 AM. On the first day of anthesis, pollen fertility is at its highest. As the flowers open during anthesis, the reproductive organs—the pistil and stamen—become visible, facilitating pollination [80]. The tomato fruit, which develops from the flower's ovary, is consumed by humans. In the case of tomatoes, this ovary produces a fruit commonly referred to as a pod, or more broadly, a tomato. Once the ovules inside the pod become seeds, the pod begins to grow and change. During the transition from the anthesis process to fruit development, several stages occur, including cell division, enlargement, and differentiation. The rate and effectiveness of these processes can be affected by factors such as plant health,



(a)



(b)

Fig. 7. Using various climate models for MP, India, we simulated changes in phenological stages under SSP2 4.5 and SSP5 8.5 for the near future (2010–2039), mid-future (2040–2069), and far future (2070–2099). We compared these changes to the reference point (1980–2009).

the success of pollination, and environmental conditions [81]. As climacteric fruits, tomatoes experience significant metabolic changes during their development. Sometimes, tomato plants may produce many flowers but fail to set fruit [82]. The reduction in anthesis and pod formation observed in our study can be attributed to multiple physiological and environmental factors, primarily governed by sink strength, hormonal regulation, and climatic influences. Gibberellins (GA1) and auxins (IAA) exhibit a dynamic interplay in regulating floral development, influencing anthesis timing and pod set efficiency. Reduced gibberellin biosynthesis or impaired signal transduction pathways have been linked to delayed floral induction, as seen in crops like wheat and sugar beet. Additionally, auxin-mediated upregulation of GA biosynthesis is essential for ensuring optimal pod formation, and any disruptions in this hormonal balance may adversely affect reproductive success [83]. Sink strength, which defines the capacity of developing pods to attract and utilize assimilates, plays a crucial role in pod setting. A weaker sink results in reduced translocation of photosynthates, leading to compromised pod development. This aligns with previous findings where pod carbon import was directly linked to dry matter accumulation and pod load [84].

Beyond intrinsic physiological factors, environmental conditions such as photoperiod and temperature further modulate anthesis and pod formation. Vernalization and specific light-duration responses have been shown to trigger flowering, suggesting that suboptimal temperature and day-length conditions might contribute to delayed anthesis and reduced pod setting. Collectively, these insights emphasize the intricate coordination between biochemical pathways and environmental cues in governing reproductive success in crops. Optimizing hormonal dynamics and managing environmental variables could serve as viable strategies to mitigate anthesis delays and enhance pod formation under changing climatic scenarios [84]. Elevated Ts accelerate the crop growth cycle, expediting anthesis by shortening the vegetative phase and hastening reproductive transitions. The advancement in pod formation timing under climate change conditions indicates a compressed reproductive window, potentially altering fruit development dynamics and jeopardizing yield stability [85]. While raised temperatures enhance pod and fruit development rates, they concurrently exacerbate floral abscission, diminish pollen viability, and degrade fruit quality. These phenological shifts pose significant risks to tomato yield and quality, potentially disrupting synchrony with pollinators, intensifying heat stress during crucial developmental stages, and misaligning water availability with crop demand [86]. To counteract these challenges, adaptive strategies—such as optimized sowing schedules, deployment of heat-resilient cultivars, and precision irrigation—will be imperative in sustaining tomato productivity under evolving climatic conditions.

4.3. *Evaluation and validation of the DSSAT-CROPGRO-Tomato model*

The yield prediction model's performance was rigorously evaluated by analyzing observed versus predicted yield values across five years (2019–20 to 2023–24) (Fig. 8). A combination of scatter plots and key statistical metrics—including the R, R^2, MAE, RMSE, bias, and NSE—provided a comprehensive assessment of the model's predictive accuracy and reliability.

The model demonstrated a strong correlation between observed and predicted yield values across all years, with R values ranging from 0.76 to 0.80. The R^2 values varied between 0.57 and 0.63, indicating that the model explained 57 % to 63 % of the variance in yield predictions. Although these values suggest a reasonably good fit, there is potential for improvement, especially in reducing prediction errors. The MAE ranged from 5.73 to 6.15, while the RMSE fluctuated between 6.75 and 7.15, reflecting consistent errors over the years (Fig. 8). A slight upward trend in RMSE for the years 2021–22 and 2022–23 suggests a minor decrease in prediction accuracy, which may be attributed to climatic

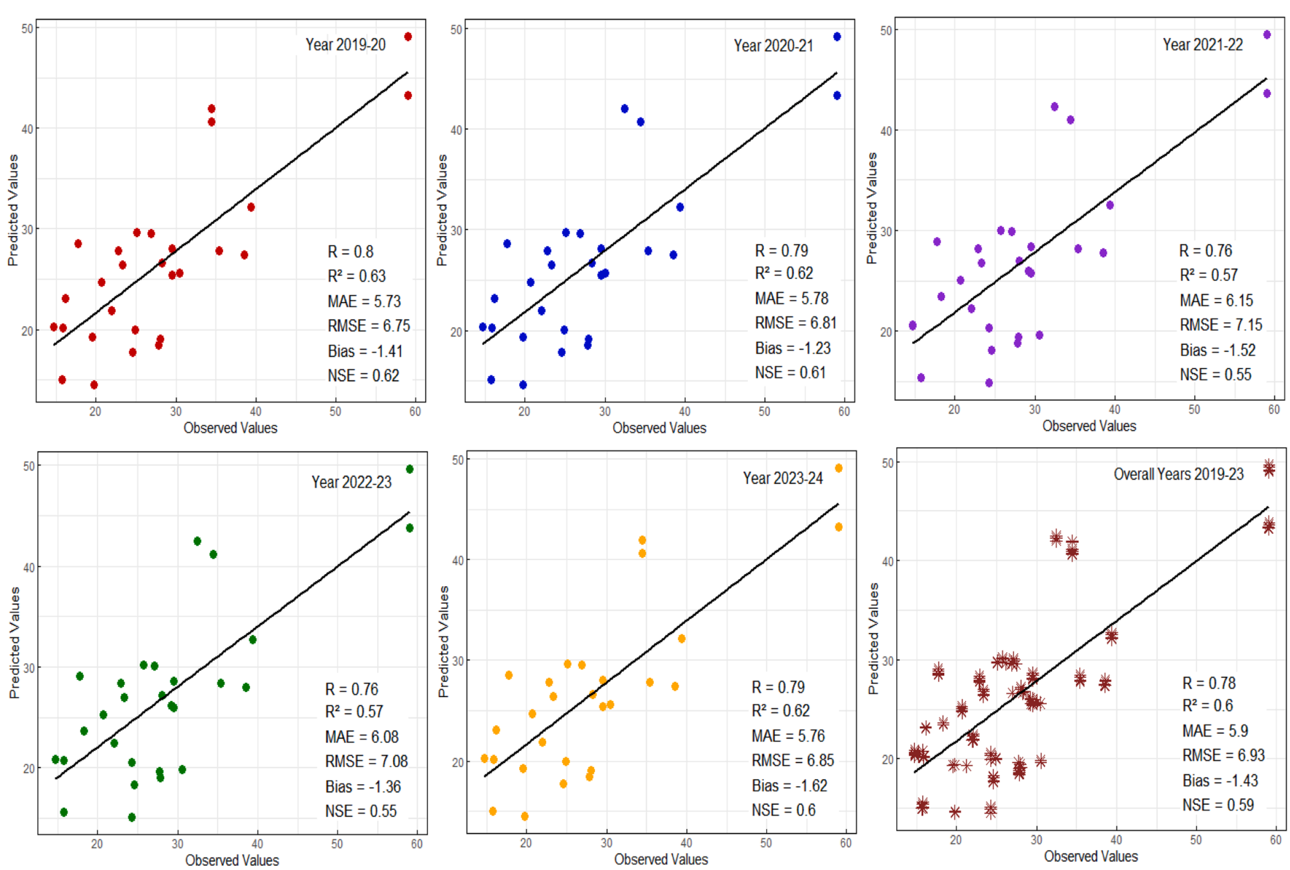


Fig. 8. Temporal validation of tomato yield prediction model CSMs (2019–20 to 2023–24) using observed vs. predicted scatter analysis.

variations or uncertainties in the input data. Additionally, the model exhibited a consistent negative bias, with values between −1.23 and −1.62, indicating a systematic underestimation of yield values. The least biased year was 2020–21, with a bias of −1.23, while 2023–24 had the most significant underestimation at −1.62 (Fig. 8). These outcomes suggest that the model parameters may require further calibration to minimize this systematic deviation. The NSE values ranged from 0.55 to 0.62, indicating moderate to good performance. A value closer to 1 would represent an ideal predictive model. While the NSE values are satisfactory, they underscore areas where the model could be refined. The year-wise performance analysis indicates that 2019–20 exhibited the best model performance with the highest R (0.8) and R^2 (0.63), lowest RMSE (6.75), and NSE (0.62), suggesting strong predictive accuracy. 2020–21 followed closely with $R = 0.79$ and $R^2 = 0.62$, and the lowest bias (−1.23), indicating reduced underestimation, though RMSE (6.81) slightly increased. In 2021–22 and 2022–23, model performance declined slightly, with R dropping to 0.76 and R^2 to 0.57, while RMSE increased beyond 7.0, and bias also worsened, suggesting growing prediction uncertainty, possibly due to climatic variations or input dataset limitations. 2023–24 showed a slight recovery, with $R = 0.79$ and $R^2 = 0.62$, although bias (−1.62) reached its highest, indicating the strongest underestimation of yield. The results indicate that the model successfully predicts tomato crop yield, although further improvements are necessary to enhance its accuracy. The final overall year plot represents the cumulative predictive performance of the DSSAT-CROPGRO model using combined datasets from the years 2019–2023. A strong correlation coefficient ($R = 0.78$) and a coefficient of determination ($R^2 = 0.60$) indicate that the model captures a substantial proportion of the variability in observed tomato yields. The error metrics—MAE = 5.9, RMSE = 6.93, and Bias = −1.43—highlight the model's consistent accuracy and slight underestimation tendency. The Nash–Sutcliffe Efficiency (NSE = 0.59) further confirms the model's robustness and its applicability in real-world scenarios (Fig. 8). To improve yield predictions in the context of changing climatic conditions, it may be beneficial to incorporate climate resilience factors and fine-tune the DSSAT model with updated climate projections. Future work should focus on adjusting model parameters or including additional factors such as fertilizer application rates, pest influences, or microclimatic conditions [87].

4.4. Analysis of simulated yield changes

The projected yield changes for tomato crops under different climate models and future timeframes were analyzed for two scenarios (SSP2 4.5 and SSP5 8.5) relative to the baseline period (1980–2009). The findings indicate significant declines in yield across all climate models and future time horizons, with the magnitude of decline varying based on the scenario and timeframe.

Under the SSP2–4.5 scenario, all climate models consistently project a declining trend in tomato yield across the near (2010–2039), mid (2040–2069), and far future (2070–2099) periods. The most pronounced reductions occur in the near term, with models such as MPI-ESM-1–2-HR and ACCESS-CM2 estimating losses exceeding 44 %. Although the decline persists into the mid- and far-future periods, models like FGOALS_g3 and ESM project relatively lower reductions, suggesting a potential stabilization in yield losses under moderate-emission conditions. In the far future, yield changes range from −16.11 % (ESM) to −34.11 % (MIROC6), indicating some degree of model-predicted resilience (Fig. 9a). In contrast, the SSP5–8.5 scenario presents a more severe impact across all timeframes. Near-future projections show yield declines between −36.03 % (CMCC-ESM2) and −48.23 % (ACCESS-CM2), largely driven by intensified heat and water stress during critical phenophases. This pattern continues through mid-century, with MPI-ESM-1–2-HR and ACCESS-CM2 projecting sustained losses above 40 %. Interestingly, a few models (e.g., CMCC-ESM2 at −6.35 % and ESM at −5.21 %) simulate attenuated yield losses in the far future, possibly reflecting physiological acclimation or the fertilization effect of elevated atmospheric CO_2 [88]. However, substantial reductions persist in models like MPI-ESM-1–2-HR (−24.37 %) and MIROC6 (−31.07 %), suggesting that extreme temperatures, altered precipitation regimes, and moisture stress will likely offset any potential CO_2-related gains (Fig. 9b).

Regionally, yield losses are most pronounced in the eastern and northern ACZs during the mid- and far-future periods, where Ts frequently exceed optimal thresholds for flowering and fruit set (>30–35 °C), PPT becomes increasingly erratic, and Srad declines [16,63,68]. These combined stressors accelerate crop development, shorten reproductive duration, and reduce assimilate translocation, ultimately impairing yield formation. Conversely, central and western MP show relatively stable yield trends in the near term under SSP2–4.5, benefitting from more favorable thermal and hydrological conditions. Although some far-future simulations under SSP5–8.5 indicate reduced losses, the extent to which CO_2 fertilization may counterbalance climatic stress remains uncertain and requires further field-based validation [89].

Inclusive, these findings underscore the critical need for spatially targeted adaptation strategies, including optimized sowing dates, deployment of heat- and drought-tolerant cultivars, precision irrigation, and improved nutrient management. Furthermore, the substantial variation across climate models highlights the importance of ensemble-based approaches for robust impact assessments. Integrating machine learning with multi-model simulations may further enhance predictive accuracy and support informed decision-making for climate-resilient tomato production [7].

4.5. Adaptation strategies and recommendations for climate-resilient tomato cultivation

Based on the simulated PS and yield responses under future climate scenarios, several evidence-based adaptation strategies are recommended to mitigate the adverse effects of climate change on tomato production in Central India (MP).

1. **Optimal Planting Window Adjustment**: The advancement or delay of key phenophases under warming scenarios suggests that adjusting sowing dates could help avoid exposure to high-T stress during sensitive stages like flowering and fruit set ([7,90]). Simulation results indicate that shifting the planting window 2–3 weeks earlier in high-risk zones may preserve yield potential under SSP5–8.5.
2. **Climate-Resilient Variety Selection**: Introducing heat-tolerant and drought-resistant tomato cultivars, particularly for regions projected to experience increased thermal and moisture stress, is essential. Cultivars with enhanced pollen viability at higher Ts and longer reproductive durations could buffer against premature senescence [16,18].
3. **Water and Nutrient Management**: Strategic irrigation management, including drip irrigation and mulching, can improve water-use efficiency and reduce evapotranspiration losses. Supplementary nutrient applications, especially potassium, may enhance stress tolerance and fruit quality under elevated CO_2 and T regimes [17].
4. **Policy and Institutional Support**: Region-specific agro-advisories, phenology monitoring systems, and climate-smart subsidies for infrastructure (e.g., protected cultivation, soil moisture sensors) should be integrated into state-level agricultural policies. Investments in climate-resilient extension services can empower farmers to implement adaptive practices effectively [91,92].

These strategies, based on model-simulated yield responses to projected climate scenarios, offer actionable ways to strengthen the resilience of tomato production systems in Central India. Rooted in the outputs of the DSSAT-CROPGRO-Tomato model, they provide specific interventions to maintain productivity amid increasing climate variability, especially in the near- and mid-term futures.

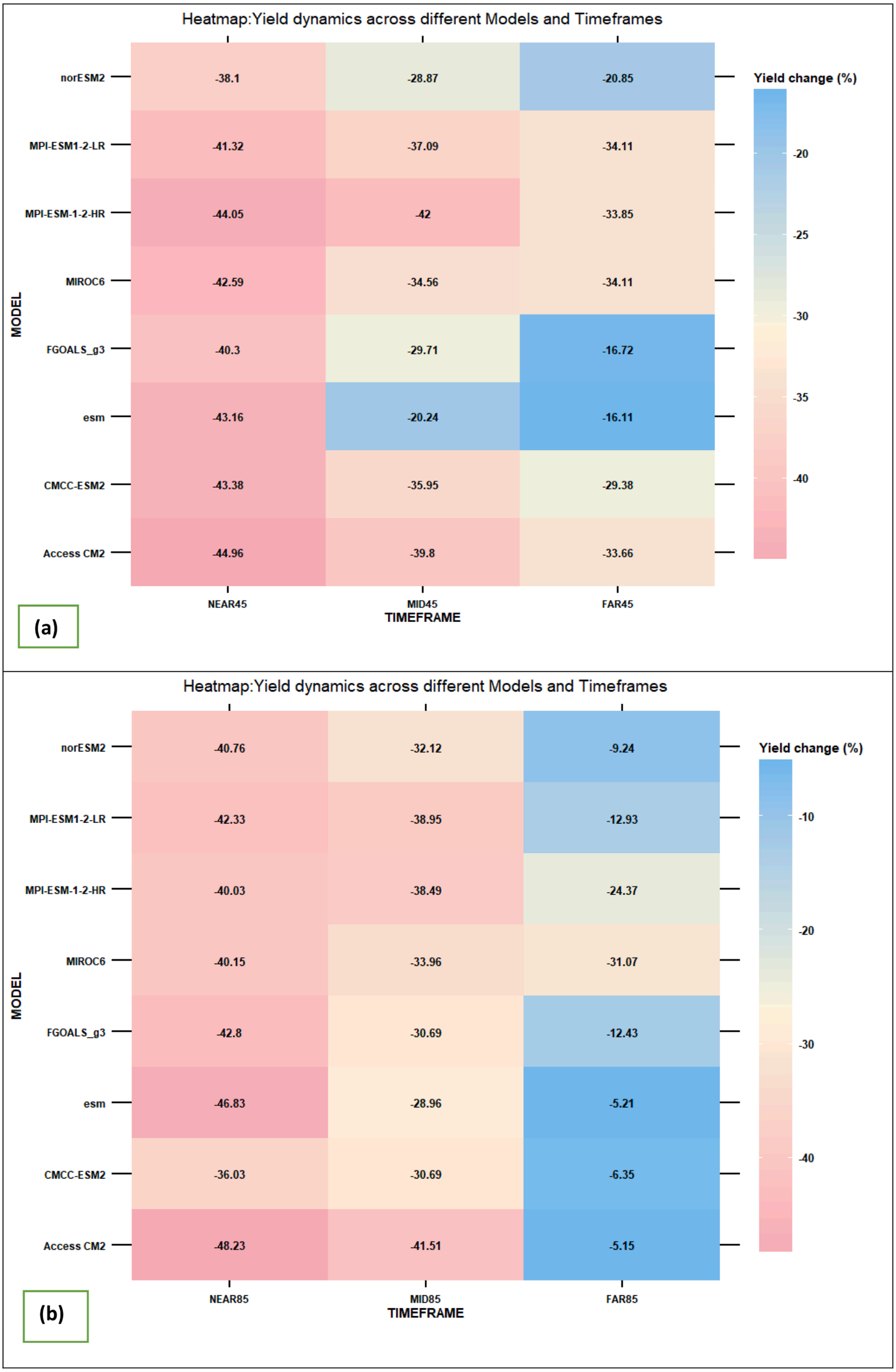


Fig. 9. Changes in Projected Tomato Yields (%) Across Various Climate Models and Timeframes Under (a) SSP2 4.5 and (b) SSP5 8.5 Scenarios, Highlighting the Effects of Climate Variability from the Near Future (2010–2039) to the Distant Future (2070–2099) Relative to the Baseline (1980–2009).

5. Conclusion

This research revealed distinct and substantial phenological shifts in tomato crops predominantly influenced by elevated Ts, modified Srad, and varying PPT patterns under forecasted climatic scenarios. Elevated temperatures expedited essential developmental phases, including blooming and fruiting, thereby abbreviating crop cycles and perhaps diminishing production potential. Seasonal Tavg deviations demonstrated a notable increase under SSP2–4.5 and SSP5–8.5 scenarios for both mid and distant futures, mainly impacting places such as Sidhi and Mandla. However, minor temperature reductions were recorded in Jhabua and Nimar in the near future. Fluctuations in Srad affected plant growth rates and photosynthetic efficiency, while alterations in rainfall distribution significantly altered water availability, hence exacerbating agricultural performance and production. Srad demonstrated considerable geographical disparity, with Mandla and Balaghat witnessing substantial rises, whereas East Nimar (Burhanpur) and Bhind encountered dramatic declines. Rainfall patterns indicated that Jhabua is the driest area due to rain-shadow effects, in contrast to Mandla, which benefited from orographic precipitation. These climate changes significantly impacted tomato phenology, hastening critical developmental stages of Tomato crop such as anthesis (flowering) and pod (fruit) formation. The discrepancies across several models indicate that alterations in temperature and radiation affect phenological responses differently based on the climate projection used. The results demonstrate that tomato crop productivity will be considerably influenced by forthcoming climate scenarios, with the SSP5 8.5 scenario posing a greater risk of yield reductions due to severe climatic circumstances. The model demonstrated a robust connection between observed and anticipated yields, with R values ranging from 0.76 to 0.80 and R^2 values between 0.57 and 0.63, signifying substantial concordance. The MAE and RMSE values indicate satisfactory prediction errors. NSE values varied from 0.55 to 0.62, indicating moderate to good performance. These findings emphasise the need for specific adaptation methods, including the development of heat-tolerant varieties, enhancement of irrigation management, and modification of planting schedules to correspond with expected climate changes. Incorporating simulation models such as DSSAT into agricultural planning can markedly improve the resilience and sustainability of tomato production systems, hence securing food availability in the face of changing climatic conditions. Ongoing research centred on localised climate modeling and validation via comprehensive field trials will be essential for enhancing predictions and formulating effective adaptive strategies. By analyzing the timing of key growth stages in response to projected climate variability, this study provides essential insights that can be used to enhance management practices. While the findings are regionally focused on Central India—an agriculturally significant zone for tomato production; however, the insights and adaptive strategies proposed in this study have broader applicability to other tomato-growing regions facing similar climate-induced challenges worldwide.

Ethics statement

Not applicable: This manuscript does not include human or animal research.

CRediT authorship contribution statement

Pashupati Nath Singh: Writing – original draft, Software, Methodology, Investigation, Formal analysis. **Prashant K. Srivastava:** Writing – review & editing, Supervision, Project administration, Investigation, Conceptualization. **Bhawana Sharma:** Writing – review & editing, Validation, Methodology, Data curation. **R.K. Mall:** Writing – review & editing, Supervision, Resources, Conceptualization.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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