TB-ICN: 233/2019

Seasonal Climate Change Scenarios for India: Impacts and Adaptation Strategies for Wheat and Rice

S Naresh Kumar, Adlul Islam, DN Swaroopa Rani, Shweta Panjwani, Khushboo Sharma, Neelesh K Lodhi, Subhash Chander, Parimal Sinha, Manoj Khanna, DK Singh and SK Bandyopadhyay

ICAR

NICRA

Centre for Environment Science and Climate Resilient Agriculture
ICAR-Indian Agricultural Research Institute
New Delhi-110012, India

Seasonal Climate Change Scenarios for India: Impacts and Adaptation Strategies for Wheat and Rice

Naresh Kumar S, Adlul Islam, DN Swaroopa Rani, Shweta Panjwani, Khushboo Sharma, Neelesh K Lodhi, Subhash Chander, Parimal Sinha, Manoj Khanna, DK Singh and SK Bandyopadhyay

Centre for Environment Science and Climate Resilient Agriculture
ICAR-Indian Agricultural Research Institute, New Delhi
New Delhi-110012

Correct citation:
Naresh Kumar S, Adlul Islam, DN Swaroopa Rani, Shweta Panjwani, Khushboo Sharma, Neelesh K Lodhi, Subhash Chander, Parimal Sinha, Manoj Khanna, DK Singh and SK Bandyopadhyay 2019. Seasonal Climate Change Scenarios for India: Impacts and Adaptation Strategies for Wheat and Rice. ICAR- IARI Pub. TB-ICN: 233/2019 p 56.

Year of Publication: December, 2019

Printed by:
M. S. Printers, C-108/1 Back Side, Naraina Industrial Area, Phase-1, New Delhi-110028
Mob: 7838075335, 9990785533, 9899355565, Tel.: 011-45104606
E-mail: msprinter1991@gmail.com

त्रिलोचन महापात्र, पीएच.डी.
एफ एन ए, एफ एन ए एस सी, एफ एन ए ए एस
सचिव एवं महानिदेशक

TRILOCHAN MOHAPATRA, Ph.D.
FNA, FNASc, FNAAS
SECRETARY & DIRECTOR GENERAL

भारत सरकार
कृषि अनुसंधान और शिक्षा विभाग एवं
भारतीय कृषि अनुसंधान परिषद
कृषि एवं किसान कल्याण मंत्रालय, कृषि भवन, नई दिल्ली 110 001

GOVERNMENT OF INDIA
DEPARTMENT OF AGRICULTURAL RESEARCH & EDUCATION
AND
INDIAN COUNCIL OF AGRICULTURAL RESEARCH
MINISTRY OF AGRICULTURE AND FARMERS WELFARE
KRISHI BHAVAN, NEW DELHI 110 001
Tel.: 23382629; 23386711 Fax: 91-11-23384773
E-mail: dg.icar@nic.in

Foreword

Climatic stress have been affecting the Indian agriculture and these stresses are reported to increase in future climates thus challenging the food security. Understanding the climate scenarios for agricultural seasons is imperative for delineating the climate change impacts on major crops and derive adaptation strategies to minimize negative impacts and maximize positive ones. The climate scenarios data derived from the Global Climate Models are known to have bias and correcting them before using them for impact and adaptation assessments. This compilation is thus important as it provides the bias corrected ensemble seasonal climate scenarios for India along with the impact assessments on wheat and rice crops. This area of research has been providing the vision for future production challenges and opportunities to make Indian agriculture resilient. It is hoped that the information provided in this book will be useful for researchers, development agencies and for policy support.

The study is conducted by the ICAR-Indian Agricultural Research Institute, under the 'National Innovations in Climate Resilient Agriculture' project. I congratulate Dr S. Naresh Kumar and his team for bringing out this publication.

(T. Mohapatra)

भा.कृ.अ.प. – भारतीय कृषि अनुसंधान संस्थान, नई दिल्ली–110012 (भारत)
ICAR - INDIAN AGRICULTURAL RESEARCH INSTITUTE
(A DEEMED TO BE UNIVERSITY UNDER SECTION 3 OF UGC ACT, 1956)
NEW DELHI - 110012 (INDIA)

डॉ. अशोक कुमार सिंह
उपमहानिदेशक (कृषि प्रसार) एवं
निदेशक, भा.कृ.अ.प.–भा.कृ.अ.सं. (अतिरिक्त प्रभार)

Dr. Ashok Kumar Singh
Deputy Director General (Ag. Extension) &
Director, ICAR-IARI (Additional Charge)

Phones : 011-2584 2367, 2584 3375
Fax : 011-2584 6420
E-mail : director@iari.res.in
Website : www.iari.res.in

Message

Understanding the climatic impacts on crops is important to identify the vulnerable areas and develop the adaptation technologies towards the climate resilient agriculture. The book presents the bias corrected ensemble climate change scenarios for agricultural seasons viz., kharif and rabi. In addition, the projected impacts of climate change on wheat and rice are presented along with the adaptation strategies at regional scale. Dissemination of such information will be of immense use for the researchers, development agencies, extension services and for policy support.

The Centre for Environment Science and Climate Resilient Agriculture has been carrying out the pioneering research in the area of modelling and climate change. The studies conducted so far have contributed significantly to policy support and provided information for prioritizing the research and development initiatives. This publication is intended to provide inputs for various stakeholders and for policy support. I congratulate Dr S. Naresh Kumar and his team for bringing out this publication.

(AK Singh)

Contents

Executive Summary

Significant achivements of modelling activities under NICRA at ICAR-IARI

Climate change projections for agricultural seasons

- Seasonal climate change projections for Indian region were derived from the bias corrected probabilistic ensemble of 33 global climate models. Based on the analysis it is projected that rise in minimum temperatures to be more than rise in maximum temperatures; rise in temperatures to be more during rabi than during kharif; variability in temperatures to increase; rise in temperatures are projected to be more in northern parts of India than in southern parts; rainfall projections, though less robust, indicate an increase during kharif and rabi seasons with increased variability. This analysis indicated a progressive climate change and variability in kharif and rabi seasons in India towards the end of the century.

Climate change impacts and adaptations: Wheat and rice

- Without adaptation, climate change is projected to affect the wheat productivity by about -3.2 to 5.3% in 2020 (2010-2039); -8.4 to -19.3% in 2050 (2040-2069); and -18.9 to -41% in 2080 (2070-2099) under different representative concentration pathways (RCPs). States like Bihar, Jharkhand, West Bengal are particularly vulnerable. More inter-annual variability in wheat yield is projected. Adaptation will improve the yield at state level in the range of 10 to 40% in major wheat growing states. However, many current management options may become unsuitable in future climates to sustain wheat yield. Developing short-duration heat tolerant varieties is important for sustaining wheat yield in central India.

- The irrigated rice yield during kharif season is projected to be affected by about -3% in 2020, -2 to 3.5% in 2050 and 2 to 5% in 2080 climate scenarios in all RCPs. The spatial variation indicated that in states such as Haryana, Karnataka, Kerala, Maharashtra, Tamil Nadu and West Bengal significant negative impacts are projected without adaptation. Growing short duration varieties with improved nutrient and water management can enhance the productivity upto 28% till 2050 climate scenarios but with significant interannual and spatial variations. Further, strategy of growing short duration varieties than the current ones in north-west India may not prove beneficial even in the near future.

- Rainfed rice productivity is projected to change in the range of 7 to -28% in 2020; 2 to -20% in 2050 and -10 to -47% in 2080 climate scenarios in different RCPs with significant spatial variation. It is projected that growing short duration stress tolerant high yielding varieties can improve the yield up to 28% in rainfed rice regions in India till 2050 scenario. But to sustain rainfed rice yield further, heat and water stress tolerant varieties with high yield may need to be developed. In addition, managing the water sources at field level will become crucial.

Disease and insect pest scenarios in changing climates

- Disease forecast models have been developed for spot blotch of wheat, leaf blast of rice. The climatic conditions in western zone are favourable for powdery mildew incidence in wheat only during March. The simulation analysis indicated that the disease is likely to be restricted to the western zone except a slight change in the eastern plains in future climates.

- Population dynamics simulation model of wheat aphids was coupled to InfoCrop-wheat model to simulate crop-pest interactions. The forewarning system of brown plant hopper is validated for Delhi region.

Integrated assessments for river basins: Ramganga and Brahmani

- In Ramganga river basin, maximum mean monthly water yield is projected to increase by 8 to 41 % in monsoon months except in RCP 4.5 (2050s) during the 2020s, 2050s and 2080s. However, in the months of March, October and December maximum decrease in mean monthly water yield by 1 to 59 % during the 2020s, 2050s and 2080s is projected except in RCP 8.5. InfoCrop wheat model based analysis indicated that wheat yield may improve in upper catchment areas even with current management conditions. But in middle and lower catchment areas, wheat yield is projected to reduce substantially. Irrigation water scarcity during December to affect wheat yield in middle and lower sub-basins.

- In Brahmani river basin, the simulation analysis projected an increase in stream flow in future climates. Crop simulation analysis indicated that during kharif season, application of one supplemental irrigation provides an opportunity to improve yield from 4.5 Mg ha^{-1} to 6 Mg ha^{-1} at a similar probability level of 40%.

- The Composite Hydrologic Indices (CHI) were developed for evaluating the recharge potential in the Betwa river basin. More than half of the basin area is dominated with high runoff potential zone and is suitable for selecting rainwater harvesting structure. The suitable sites for water harvesting structures in each Hydrologic Response Unit (HRU) have possibilities to increase the groundwater level.

Introduction

The global mean temperatures during 1951-2010 period increased by 0.6 to 0.7°C out of which natural variability contributed to ±0.1°C change in temperature, while 0.6°C increase is due to anthropogenic activities (AR 5 WG I, IPCC, 2013). In Indian region, the warming has been at a rate of 0.17 °C /10 years (for maximum temperatures) and 0.29 °C/10 years (for minimum temperatures) since 1970's (INCCA, 2010). During 1871-2019 period, India has faced 29 deficit and 20 excess monsoon years. Out of these, as many as 17 deficient monsoon years and 6 excess monsoon years fell in post 1960 period. All these have been affecting the Indian agriculture challenging food and nutritional security. Areas encompassed by climatic stresses and magnitude of loss have been increasing recently. For Indian region, the AR5 WGII (IPCC, 2014) report projects an increase in frequency of extreme temperature, rainfall, heat waves, flood and drought events and skewed monsoon years. Further, it projects an increased risk of drought related water and food shortage if agriculture is not adapted to changing climates. Thus, it is important to understand the climate change scenarios for India for agricultural seasons; to project the impacts and adaptation gains to prioritize the research and development efforts and to support the policy formulation towards climate resilient agriculture.

The integrated modelling activities under National Innovation on Climate Resilient Agriculture (NICRA) was initiated with the specific objectives to i) provide climate change impact assessments on crops/cropping systems and natural resources, and ii) derive adaptation strategies, identify adaptation domains and vulnerable regions. For this ICAR-Indian Agricultural Research Institute, New Delhi was given the lead role and ICAR-Natural Resource Management Division (NRM), New Delhi; ICAR-Central Research Institute for Dryland Agriculture (CRIDA), Hyderabad; Indian Institute of Soil and Water Conservation (IISWC), Dehradun; ICAR-Indian Institute of Soil Science (IISS), Bhopal; ICAR-Indian Institute of Farming Systems Research (IIFSR), Modipuram; ICAR-Central Potato Research Institute (CPRI), Shimla; ICAR-Indian Institute of Horticultural Research (IIHR), Bengaluru; Directorate of Onion and Garlic Research (DOGR), Rajguru Nagar; ICAR-Research Complex for Northeast Hill Region (RC-NEH) , Barapani; ICAR-Indian Institute of Water Management (IIWM), Bhubaneswar; ICAR-National Research Centre for Soybean (NRCS), Indore; ICAR-National Bureau of Soil Survey and Land Use Planning (NBSSLUP), Nagpur; ICAT-Central Institute on Brackish-water Aquaculture (CIBA), Chennai; ICAR-Central Marine Fisheries Research Institute (CMFRI), Kochi; ICAR-National Dairy Research Institute (NDRI), Karnal and Indian Institute of Technology (IIT)-Madras, Chennai as the collaborating Institutes.

The role of Indian Agricultural Research Institute (IARI) has been to derive the bias corrected seasonal climate scenarios from Global Climate Models (GCMs) and supply to the collaborating Institutions for their study region. In addition, the IARI had specific objectives to i) conduct integrated impact assessments and derive adaptation strategies per wheat and rice at regional level for near and long-term downscaled scenarios ii) derive the integrated assessments on impact of climate change on specific river basins and derive adaptation strategies to sustain crop productivity. Keeping these in view, the modelling team at IARI has conducted the simulation studies and the significant achievements are summarized in next sections.

Developing the bias corrected probabilistic ensemble seasonal scenarios for India

Climate change scenarios are continuously evolving over time. The IPCC Fifth Assessment Report (AR5) is based on representative concentration pathways (RCPs), which are based on greenhouse-gas concentration trajectories resulting from projections of radiative forcing. The Coupled Model Inter-comparison Project phase 5 (CMIP5) models include advances in parameterization of physical processes, representation of new physical processes, and increases in model resolution (IPCC 2013). The RCPs are improved version of scenarios over the earlier SRES based scenarios. The Special Report on Emission Scenarios (SRES) based scenarios do not account for natural forcing and they do not have the aerosol forcing. Moreover, the SRES scenarios viz., A1 (A1F, A1B, A1T), A2, B1 and B2 have the sequential approach. On the other hand the RCPs indicate the amount of radiative forcing due to the GHG load in the atmosphere. For example, RCP 2.6 means the GHG concentrations in the atmosphere have the radiative forcing of 2.6 W m^{-2}. Similarly the other RCPs are RCP 4.5 (4.5 W m^{-2}), RCP 6.0 (6.0 W m^{-2}) and RCP 8.5 (8.5 W m^{-2}). Thus the intermediate scenarios are possible. The RCP 2.6 represents the aggressive GHG mitigation scenario, while the RCP 4.5 and 6.0 represent GHG emission stabilization scenarios while the RCP 8.5 represents the business as usual scenario.

Testing the bias of GCMs for observed climatology over India

Thirty three Global Climate Models' (GCM) outputs were downloaded from ESGF website (Table 1).

The models' outputs for the baseline period (1980-2005) were compared with the gridded data of India Meterological Department. The GCM outputs were found to have significant cold bias for the northern region and hot bias in the southern region of India. The analysis compared the simulation performance of GCMs for temperatures and rainfall in past 26 years (1980-2005) over Indian region. For this, Priority Index from Fuzzy Analytic Hierarchy Process (FAHP) and Reliability Index were used and both methods were compared. Study revealed that models over estimated minimum and maximum temperatures in most regions of India, which resulted in hot bias especially in the southern region. However, models showed significant cold bias for the Himalayan region. In general, simulated rainfall was underestimated by many GCMs. The analysis indicated that FAHP method is good for shortlisting the GCMs based on their spatial and temporal performance in reproducing observed weather. Based on the Reliability Index (RI), Correlation Coefficient (CC), Agreement Index (AI) and Relative Mean Squared Error (RMSE), it was found that among 12 models tested, NORESM1 model has performed better in reproducing maximum temperatures. The IPSL-LR, FIO-ESM, GFDL-CM3, and MIROC5 models have performed better for minimum temperatures. In case of rainfall CSIRO, MIROC5, HADGEM2, GFDL-ESM 2 M and IPSL-LR have performed better as compared to other models (Shweta et al., 2018).

This underlines the importance of bias correction and use of climate model ensembles in climate change studies. Thus, the GCMs (Table 1) were bias corrected and probabilistic ensemble scenarios were developed.

Generation of Multi-Model Ensemble Climate Change Scenarios

The IPCC Fifth Assessment Report's climate change projections based on new emission scenarios called Representative Concentration Pathways were used in the present report. Bias corrected and spatially disaggregated

Table 1: Global Climate Model (GCM) projections used for generating bias corrected ensemble climate change scenarios

Modelling center or group, country	**Model name**	**Number of runs for RCP**			
		2.6	**4.5**	**6.0**	**8.5**
Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology (CSIRO-BOM), Australia	ACCESS1,0		1		1
Beijing Climate Center, China Meteorological Administration (BCC), China	BCC-CSM1.1	1	1	1	1
	BCC- CSM1.1(M)		1		1
College of Global Change and Earth System Science, Beijing Normal University (GCESS), China	BNU-ESM	1	1		1
Canadian Centre for Climate Modelling and Analysis (CCCma), Canada	CANESM2	5	5		,5
National Center for Atmospheric Research, USA	CCSM4	5	5	5	5
Community Earth System Model contributors, USA	CESM1-BGC		1		1
	CESM1-CAM5	3	3	2	3
Centro Euro-Mediterraneo per I Cambiamenti Climatici (CMCC), Italy	CMCC-CM		1		1
Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique (CNRM-CERFACS), France	CNRM-CM5		1		5
Commonwealth Scientific and Industrial Research Organization and Queensland Climate Change Centre of Excellence (CSIRO-QCCCE), Australia	CSIRO-MK3.6.0	10	10	10	10
EC-EARTH consortium	EC-EARTH	2	3		3
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University (LASG-CESS), China	FGOALS-G2	1	1		1
The First Institute of Oceanography, SOA, China	FIO-ESM	3	3	3	3
NOAA Geophysical Fluid Dynamics Laboratory (NOAA GFDL), USA	GFDL-CM3	1	1	1	1
	GFDL-ESM2G	1	1	1	1
	GFDL-ESM2M	1	1	1	1
NASA Goddard Institute for Space Studies (NASA GISS), USA	GISS-E2-H-CC		1		
	GISS-E2-R	1	5	1	1
	GISS-E2-R-CC		1		
National Institute of Meteorological Research/Korea Meteorological Administration (NIMR/KMA), South Korea	HADGEM2-AO	1	1	1	1
Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais) (MOHC/ INPE), UK	HADGEM2-ES	2	2	2	2
Institute for Numerical Mathematics (INM), Russia	INMCM4		1		1
Institut Pierre-Simon Laplace (IPSL), France	IPSL-CM5A-LR	3	4	1	4
	IPSL-CM5A-MR	1	1	1	1
	IPSL-CM5B-LR		1		1
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies (MIROC), Japan	MIROC-ESM	1	1	1	1
	MIROC5	1	1	1	1
	MIROC-ESM-CHEM	1	1	1	1
Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology) (MPI-M), Germany	MPI-ESM-LR	3			3
	MPI-ESM-MR	1			1
Meteorological Research Institute (MRI), Japan	MRI-CGCM3	1			1
Norwegian Climate Centre (NCC), Norway	NORESM1-M	1	1	1	1
Total models		24	30	17	31
Total runs		51	61	34	64

Fig 1: Spatial distribution of evaluation factors for maximum temperature

Reliability Index (RI), Correlation Coefficient (CC), Agreement Index (AI) and Relative Mean Squared Error (RMSE)

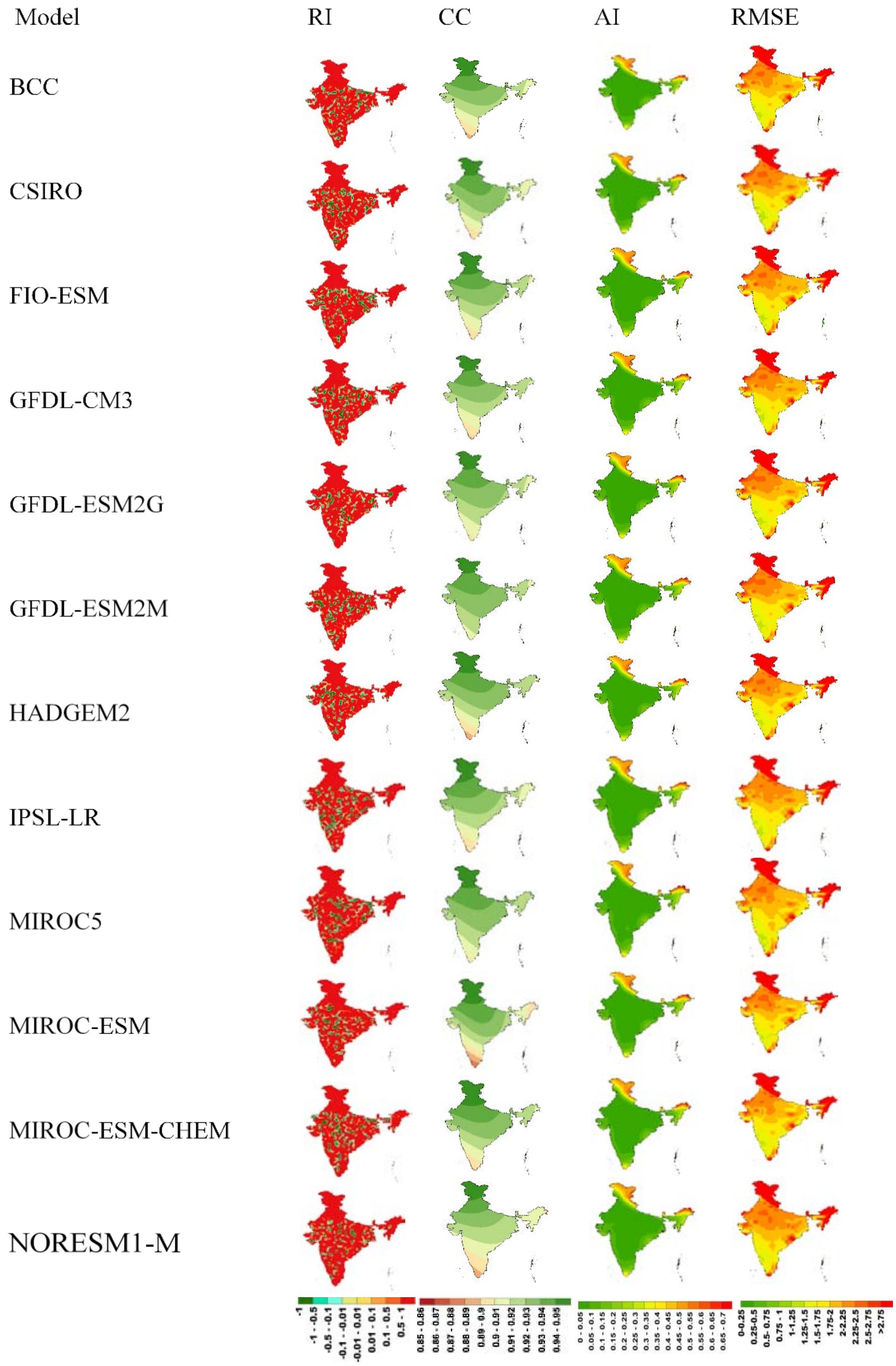


Fig 2: Spatial distribution of evaluation factors for minimum temperature

Reliability Index (RI), Correlation Coefficient (CC), Agreement Index (AI) and Relative Mean Squared Error (RMSE)

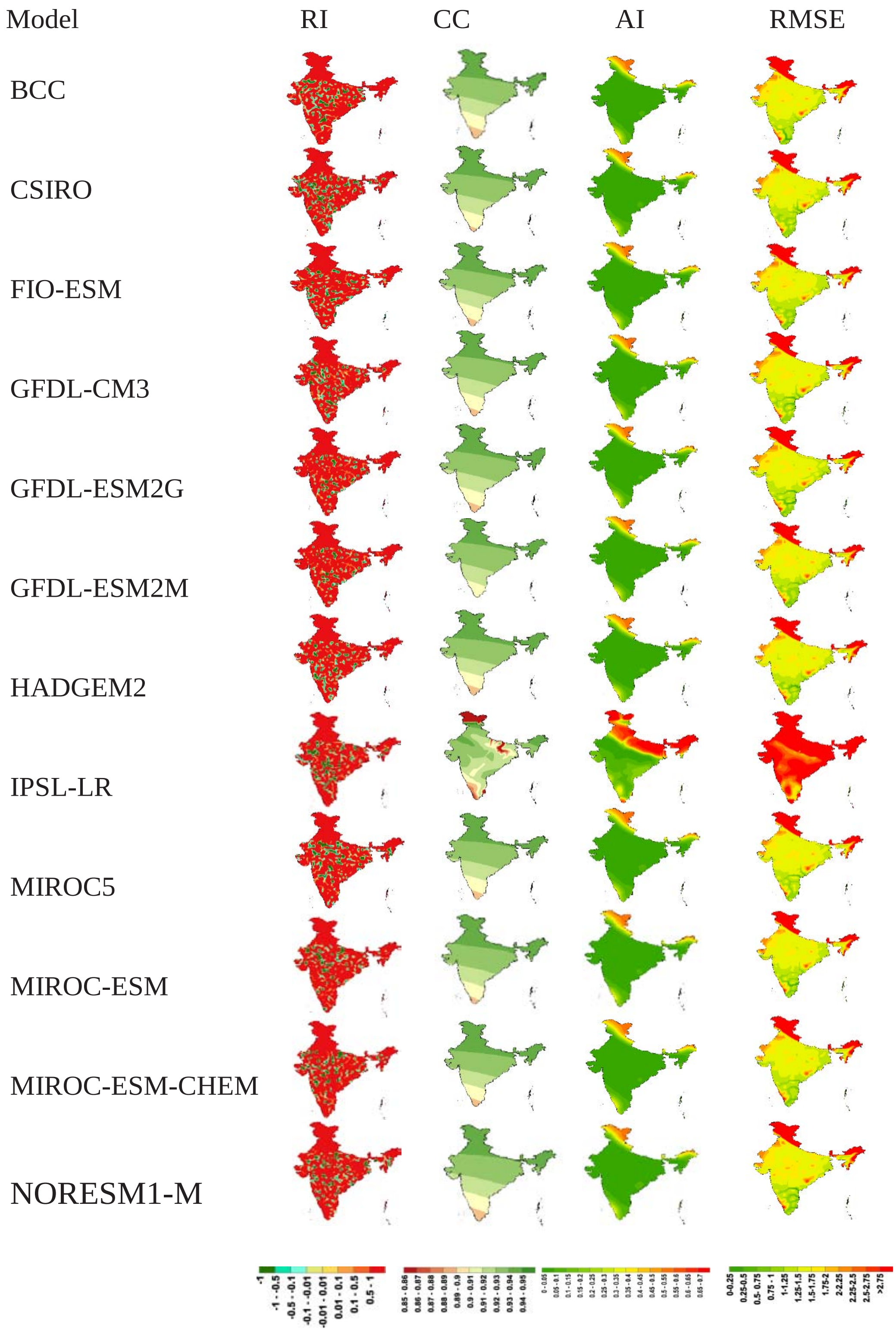


Fig 3: Spatial distribution of evaluation factors for summer monsoon rainfall

Reliability Index (RI), Correlation Coefficient (CC), Agreement Index (AI) and Relative Mean Squared Error (RMSE)

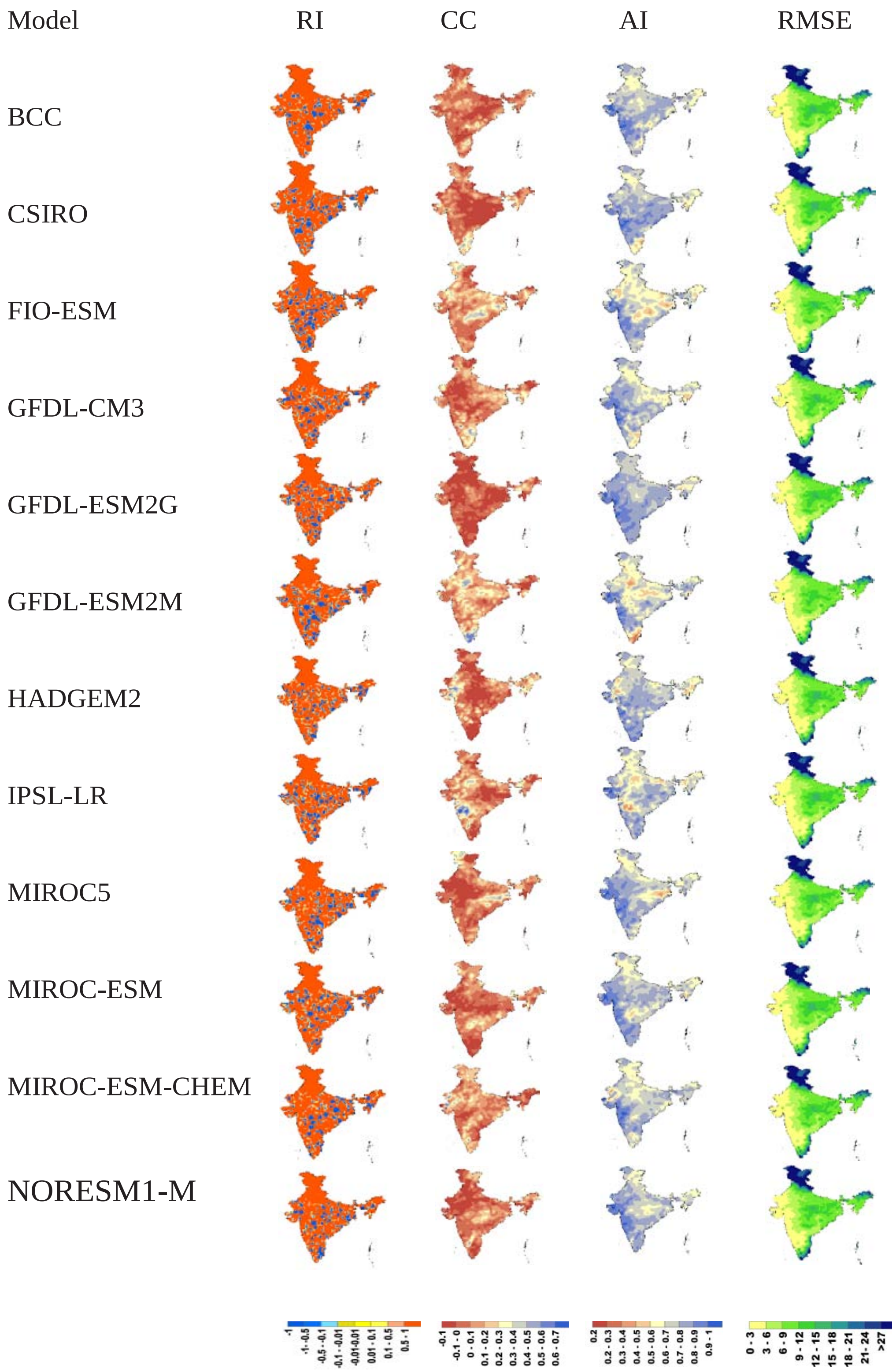
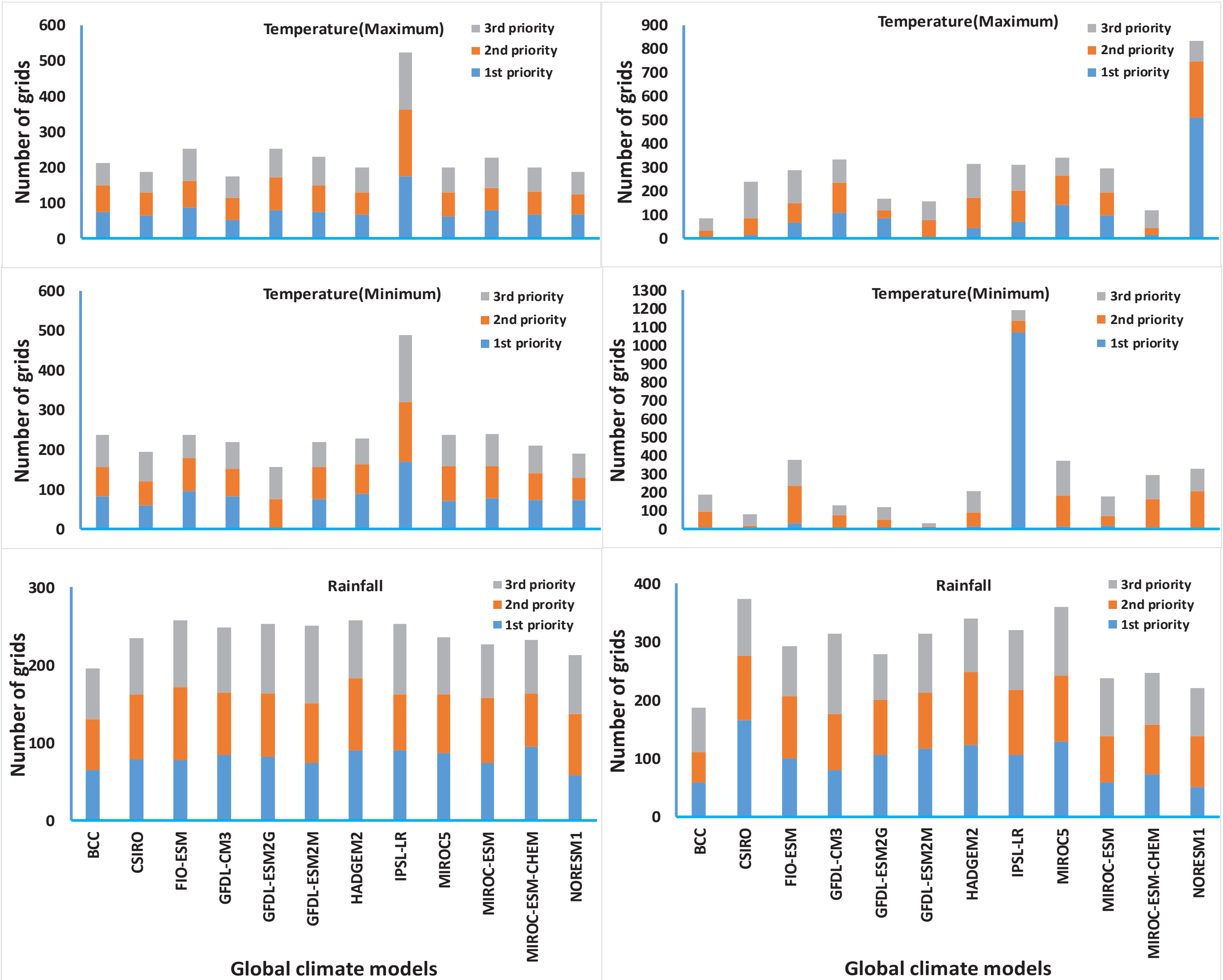


Figure 4. Model performance statistics on the basis of 1st, 2nd and 3rd priority. Number of grids counted based on 1st, 2nd and 3rd priority for every model based on Fuzzy AHP and Reliability Ensemble Average.

Fuzzy AHP **Reliability Ensemble Average**



(BCSD) monthly projections at 0.5×0.5° resolutions, were obtained from the World Climate Research Program's (WRCP's) Coupled Model Inter-comparison Project phase 5 (CMIP5) multi-model dataset for the period 1950–2099. As more than 20 modelling groups participated in CMIP5, climate projections were available from a number of GCMs and the number of runs (realizations) per model also varied. Further, climate projections were available for different simulation periods (near term - up to 2035 and long term -up to 2100) and variables (precipitation, Tmax, Tmin, Tav etc.). We selected models/projections with long term simulations (up to 2100) having precipitation, Tmax, Tmin data. Thus, we selected 51, 61, 34, and 64 projections (runs) for RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, respectively, for generating climate change scenarios (Table 1).

We used high resolution 0.25×0.25° India Meteorological Department (IMD) gridded rainfall and 1.0×1.0° resolution temperature data as observed time series data. As we used Coupled Model Inter-comparison Project phase 5 (CMIP5) bias corrected and spatially disaggregated monthly projections at 0.5×0.5° resolution, rainfall data corresponding to the CMIP5 BCSD grid points were extracted from 0.25×0.25° resolution IMD rainfall dataset. The IMD gridded temperature data available at 1×1° resolution were re-gridded at 0.5×0.5° resolutions to match the CMIP5 BCSD grid points.

The delta change method is the most commonly used method for generating future climate scenarios. But, this method does not consider variability or change in time series behaviour in the future. The hybrid-delta method, on the other hand, considers inter-annual variability for each month. In this study, the hybrid-delta ensemble method was used for generation of climate change scenarios from multiple GCM projections for four different RCPs. This method applies a different scaling factor to each month of the historic time series based on where it falls in the probability distribution function. In this method, BCSD monthly GCM data (historical as well as future) were first disaggregated into individual calendar months. The cumulative distribution functions (CDFs) were then developed for each month for historical and future time periods (2020s, 2050s, and 2080s). For creating an ensemble of multiple GCMs/runs, data from multiple GCMs/runs were used for developing historical and future CDFs. Similarly, the CDFs for the observed time series data (1976–2005) were also developed, and the non-exceedance probability for each of the observed data were computed. Quantile mapping was then applied to re-map the observations onto the bias-corrected GCM data (historical and future CDF) for each month to obtain the historic and future GCM projected data (rainfall and temperature) corresponding to the non-exceedance probability of observed data. This process is repeated for all the twelve months and for 1204 grid points at 0.5×0.5° resolution covering entire country. In this way, we generated the bias corrected probabilistic climate change projections of precipitation, maximum and minimum temperature for four different RCPs (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) and for three future periods of 2020s (2010-2039), 2050s (2040-2069) and 2080s (2070-2099).

Probabilistic ensemble scenarios for agricultural seasons over India

An analysis of ensemble probabilistic scenarios for India, derived from 33 CMIP5-GCMs data, for 2020, 2050 and 2080 in RCPs 2.6, 4.5, 6.0 and 8.5 at the Ecological Modelling lab, Centre for Environment Science and Climate Resilient Agriculture, ICAR-IARI, New Delhi indicated that

1) Rise in minimum temperatures is projected to be more than rise in maximum temperatures;

2) Rise in temperatures to be more during rabi than during kharif;

3) During kharif, minimum temperatures to increase in the range of 0.946 - 1.061 °C (2020), 1.345-2.42 °C (2050) and 1.358-4.067 °C (2080) in different RCPs, while the projected increase in rabi is 1.096-1.207 °C (2020), 1.542-2.759 °C (2050) and 1.546-4.652 °C (2080);

4) Maximum temperatures during kharif to increase in the range of 0.741 – 0.847 °C (2020), 1.145-2.004 °C (2050) and 1.265-3.533 °C (2080) in different RCPs while the projected increase in rabi is 0.882-0.947 °C (2020), 1.317-2.308 °C (2050) and 1. 389-4.01 °C (2080);

Fig 5. Spatial variation in seasonal mean and variability (coefficient of variation-CV) of maximum temperature, minimum temperature and rainfall in kharif season over India during baseline period (1976-2005).

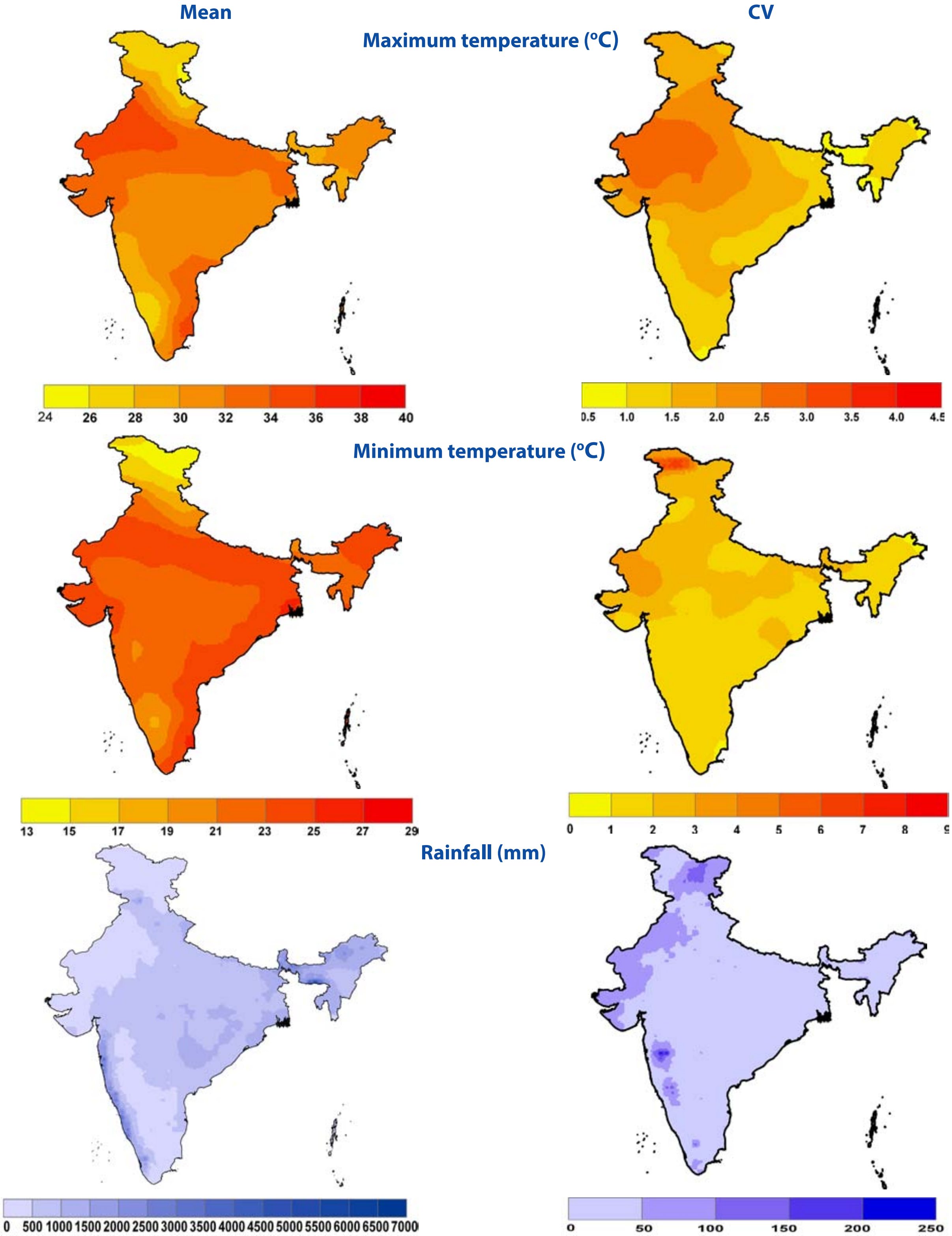


Fig 6. Spatial variation in seasonal mean and variability (coefficient of variation-CV) of maximum temperature, minimum temperature and rainfall in rabi season over India during baseline period (1976-2005).

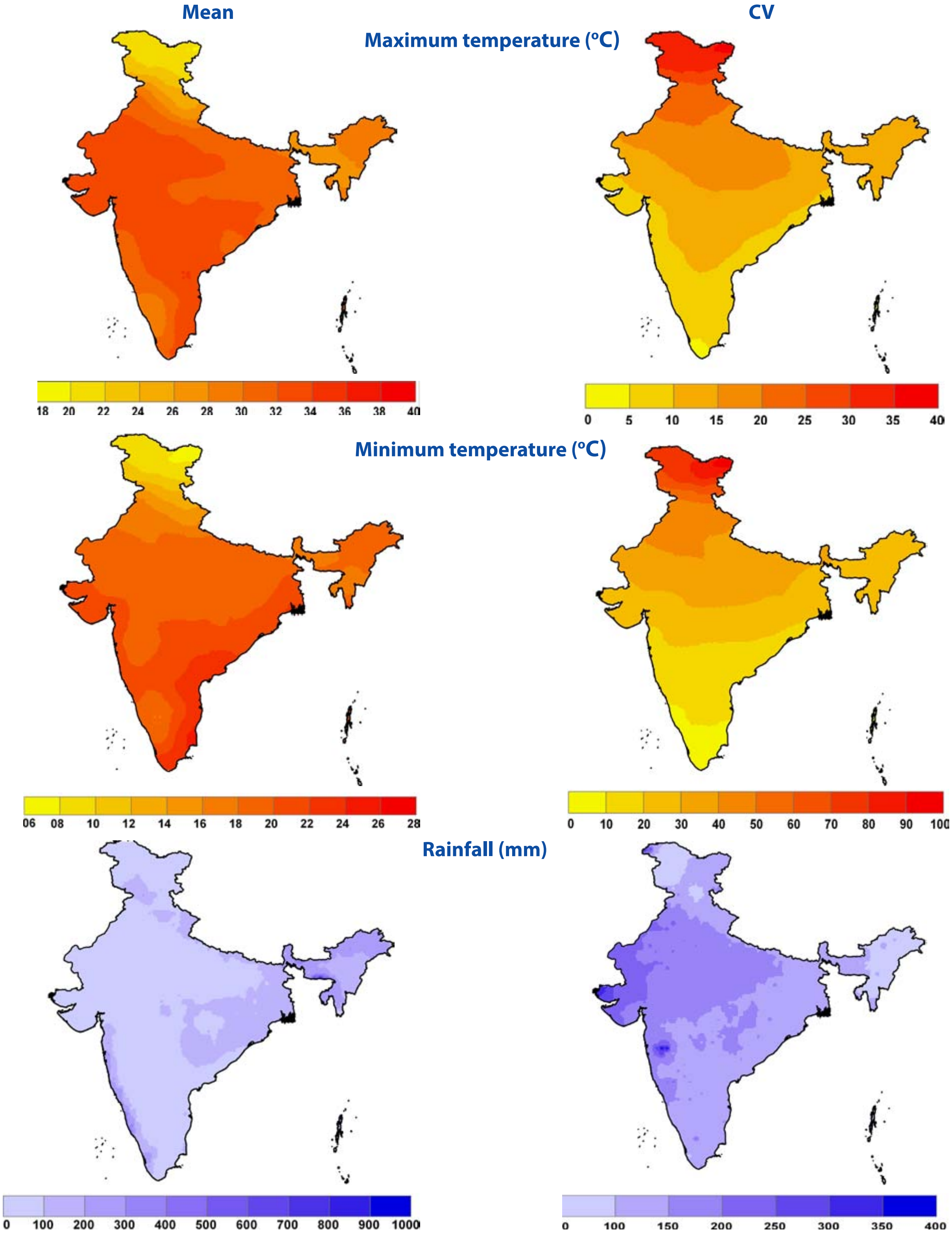


Fig 7. Spatial variation in projected seasonal mean maximum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2020 climate scenario (2010-2039).

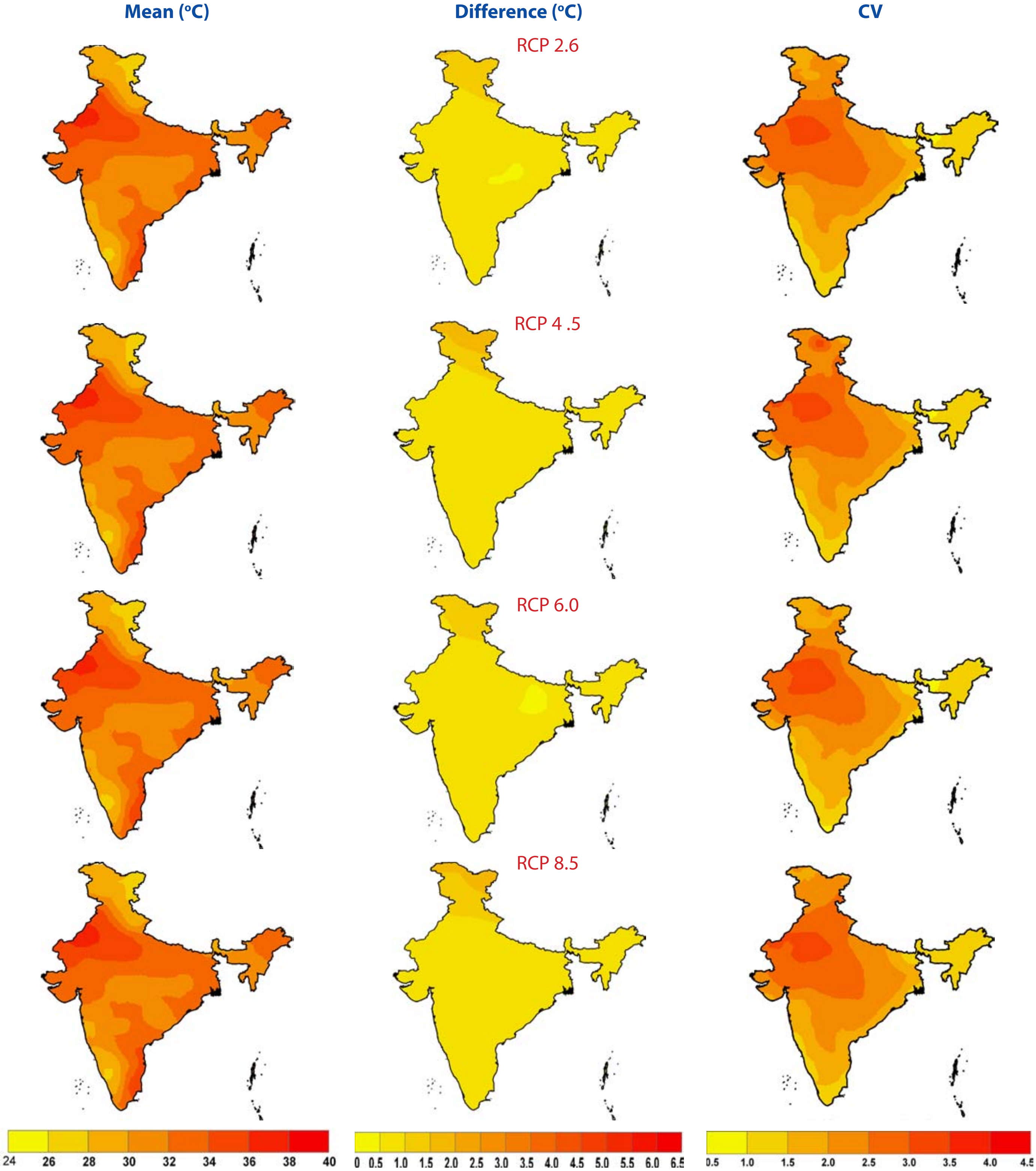


Fig 8. Spatial variation in projected seasonal mean maximum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2050 climate scenario (2040-2069).

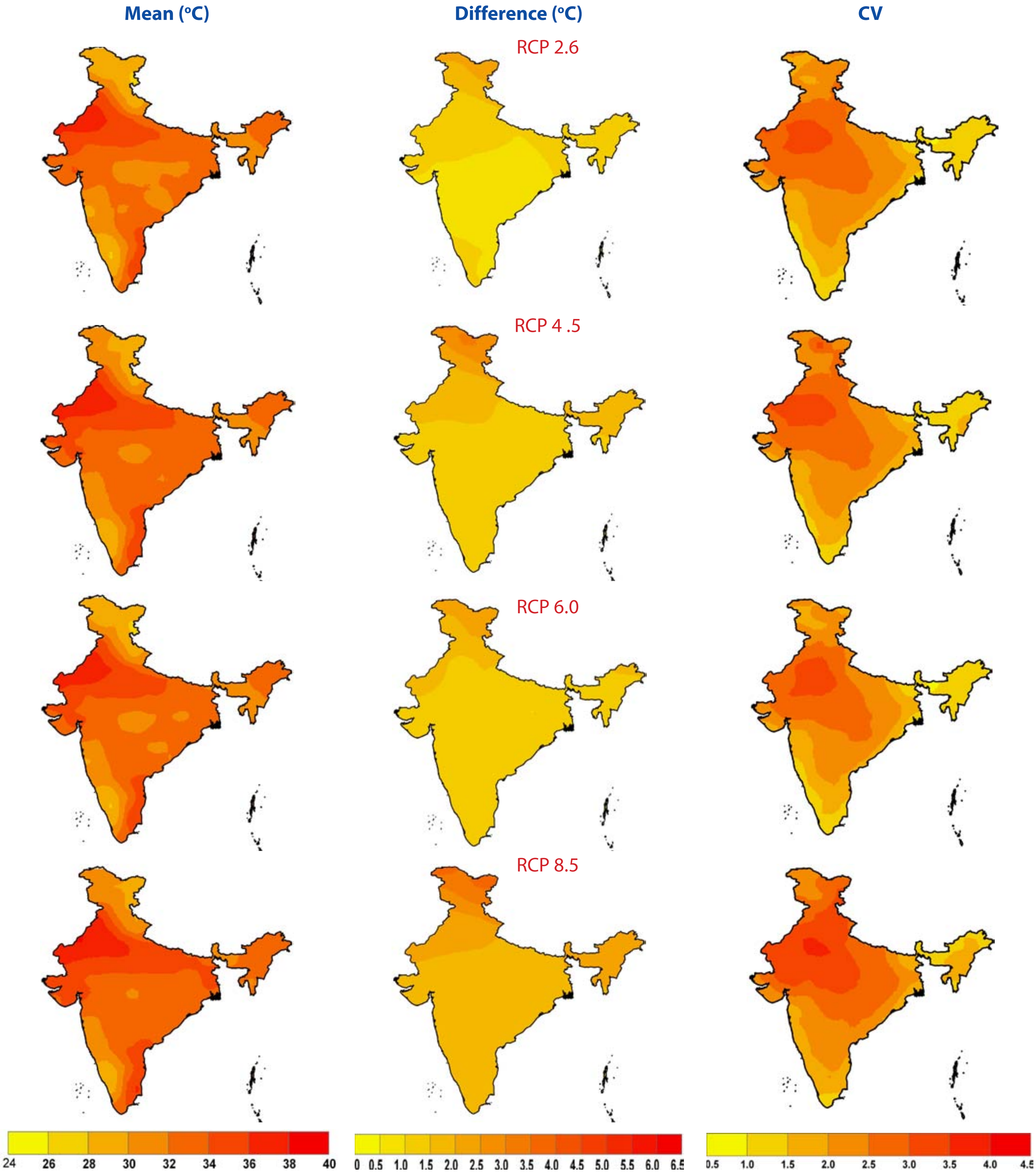


Fig 9. Spatial variation in projected seasonal mean maximum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2080 climate scenario (2070-2099).

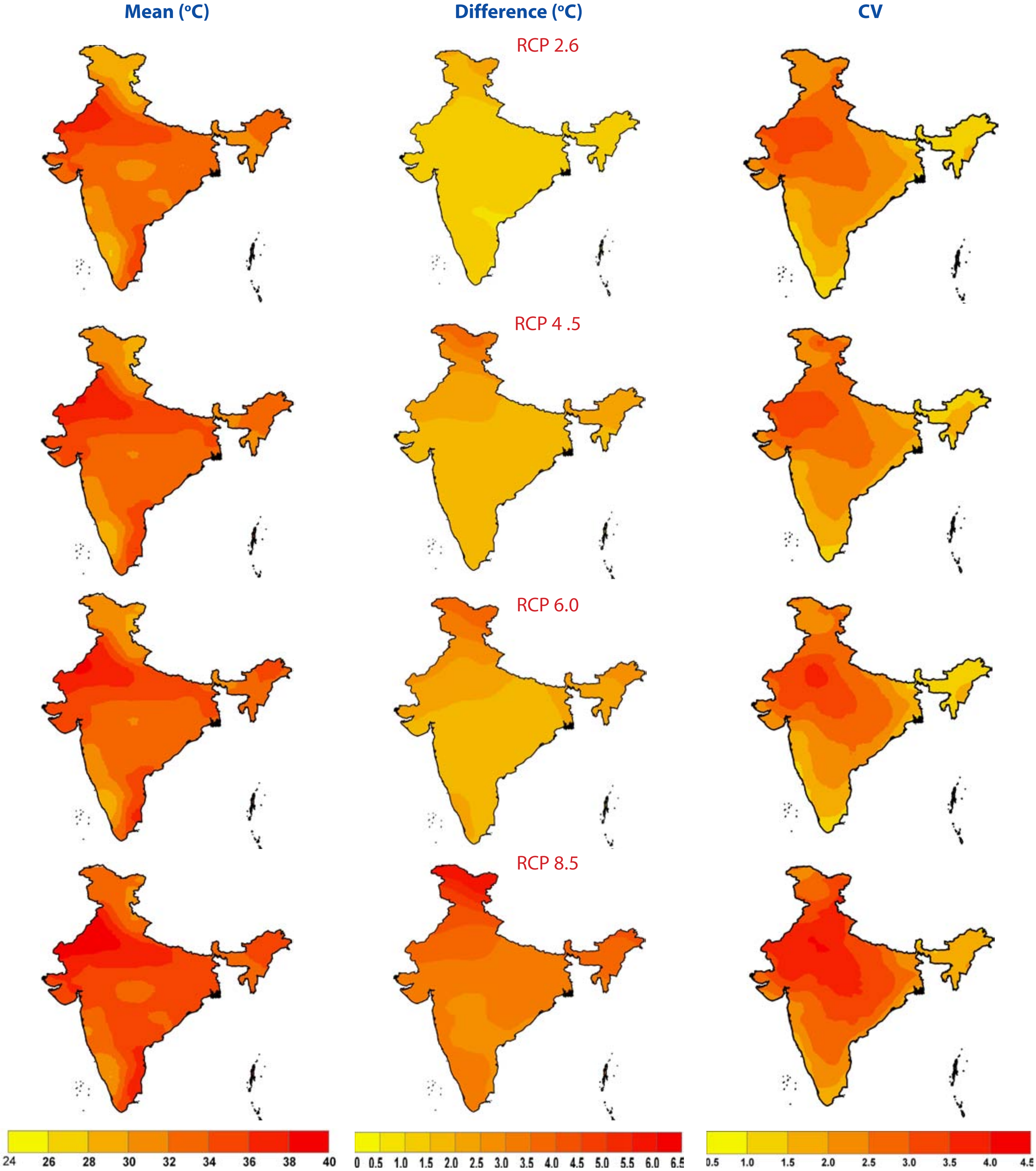


Fig 10. Spatial variation in projected seasonal mean minimum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2020 climate scenario (2010-2039).

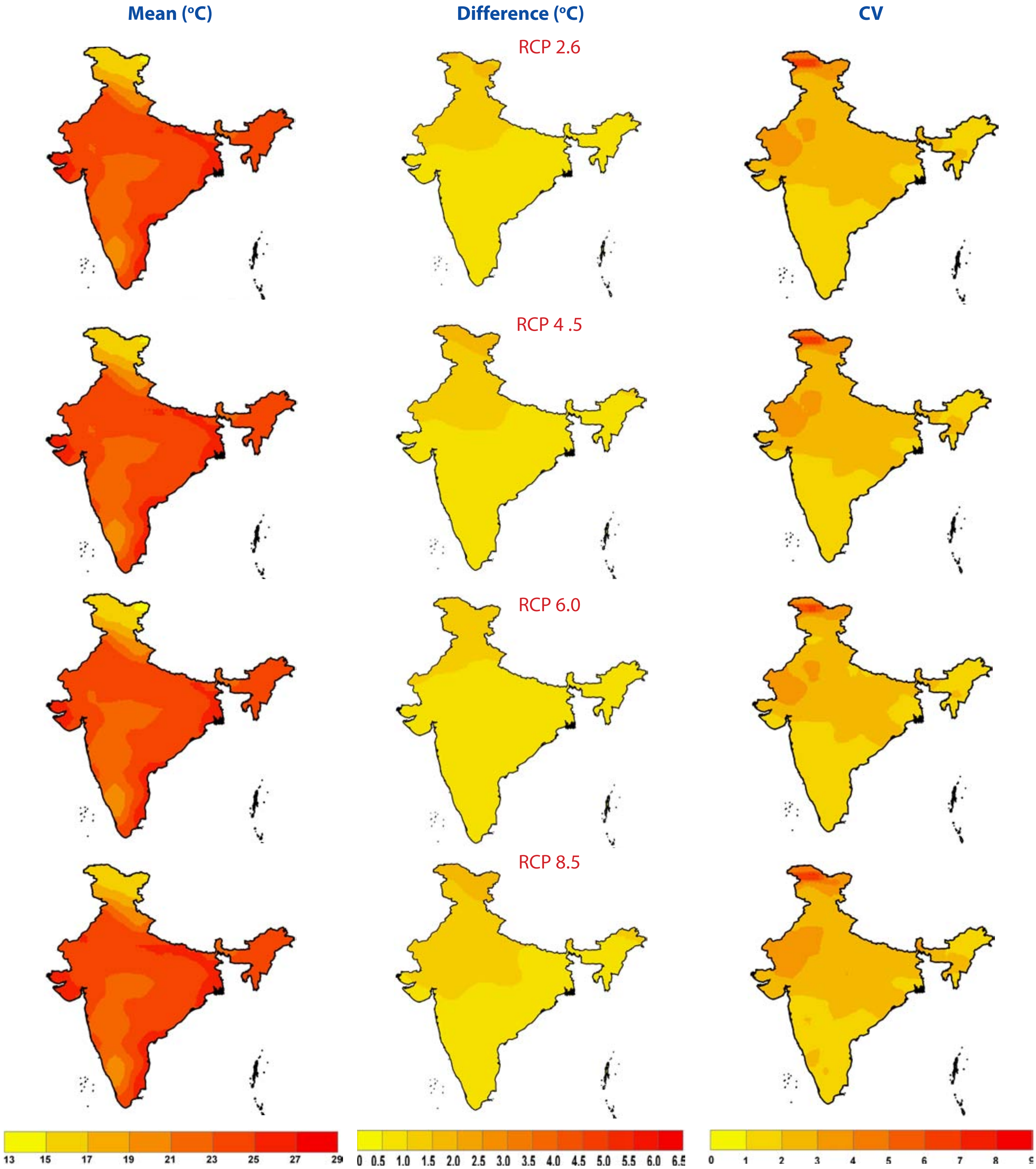


Fig 11. Spatial variation in projected seasonal mean minimum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2050 climate scenario (2040-2069).

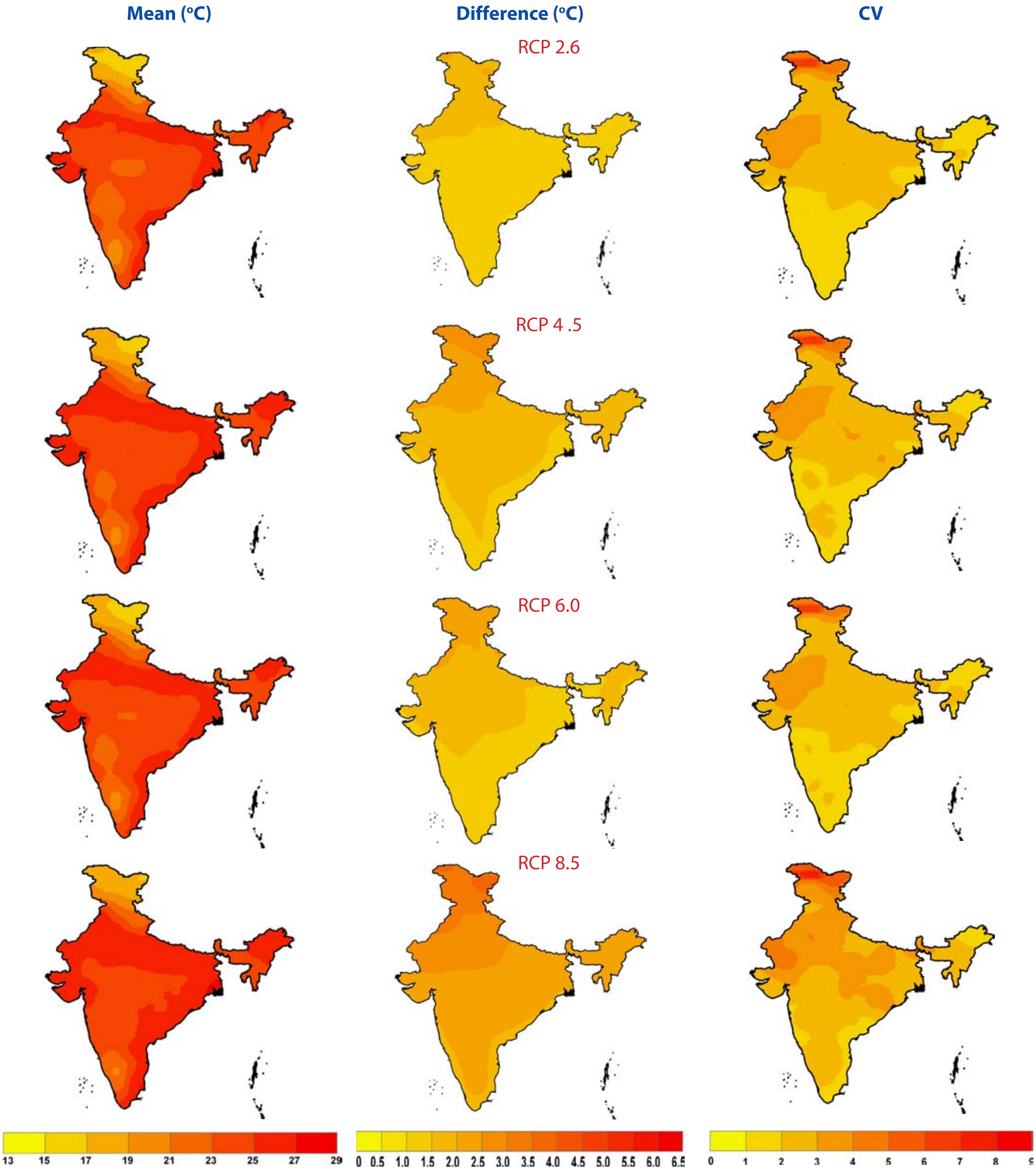


Fig 12. Spatial variation in projected seasonal mean minimum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2080 climate scenario (2070-2099).

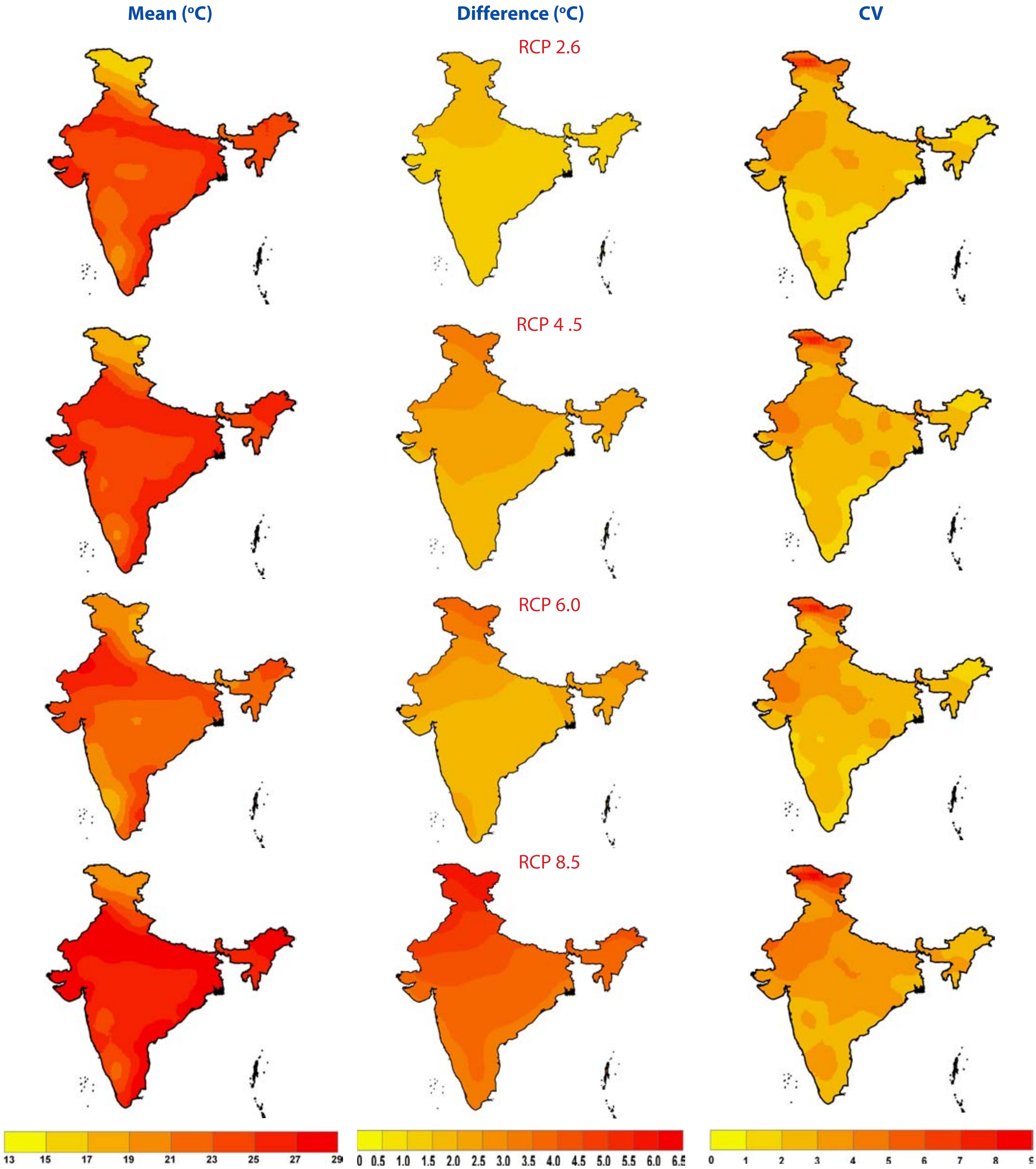


Fig 13. Spatial variation in projected seasonal rainfall, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2020 climate scenario (2010-2039).

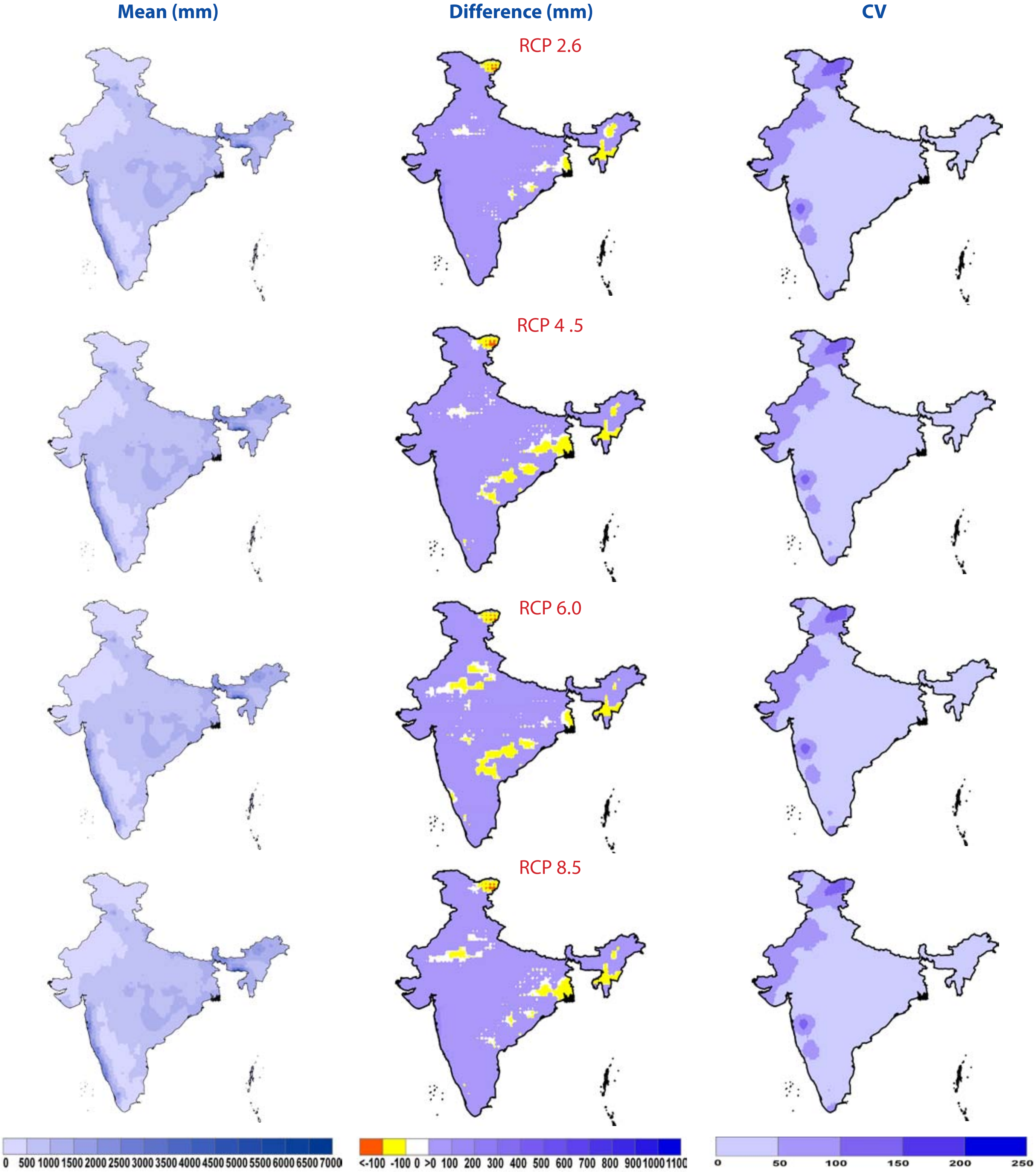


Fig 14. Spatial variation in projected seasonal rainfall, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2050 climate scenario (2040-2069).

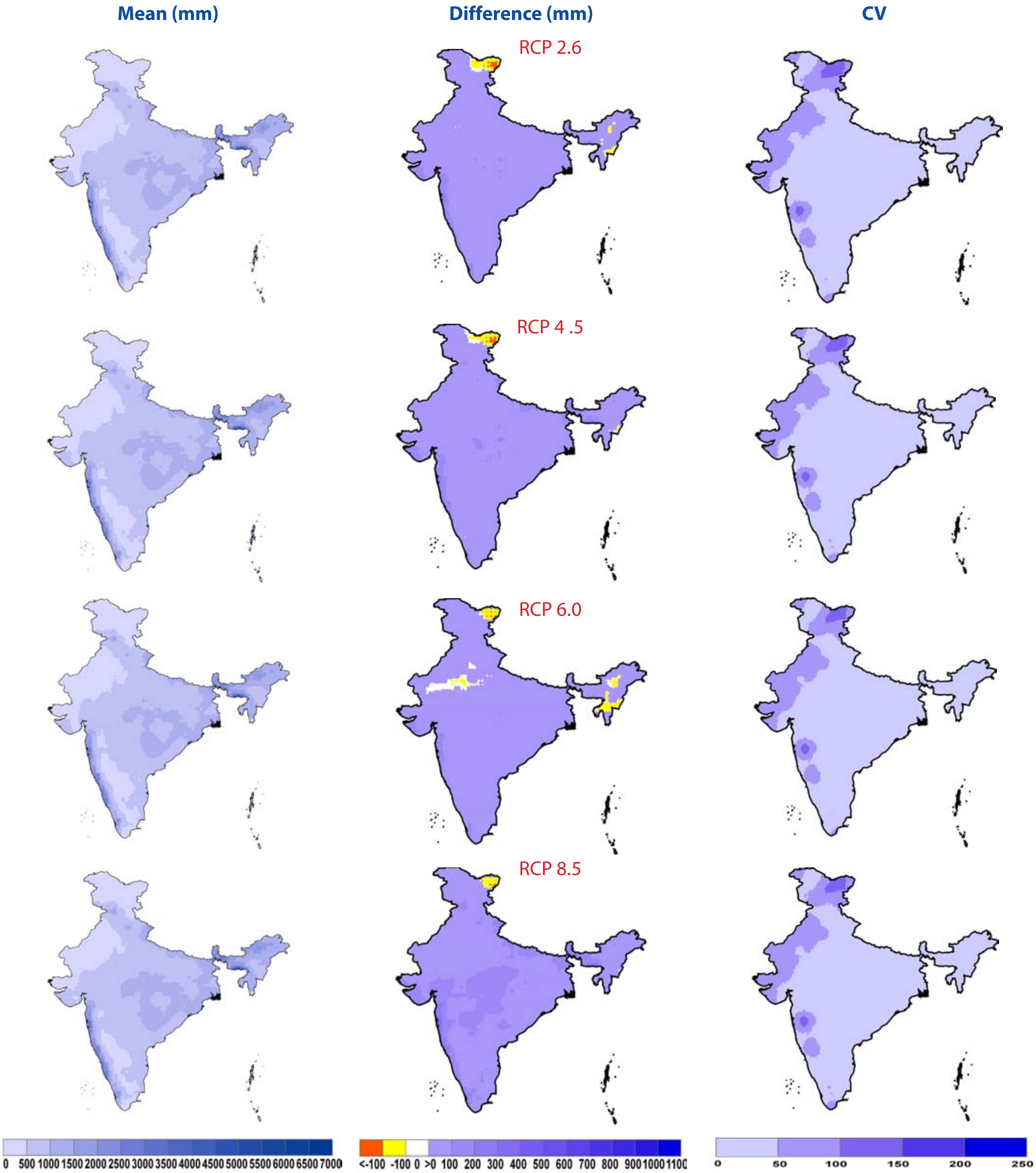


Fig 15. Spatial variation in projected seasonal rainfall, change from baseline (difference) and variability (coefficient of variation-CV) in kharif season over India in different Representative Concentration Pathways (RCPs) of 2080 climate scenario (2070-2099).

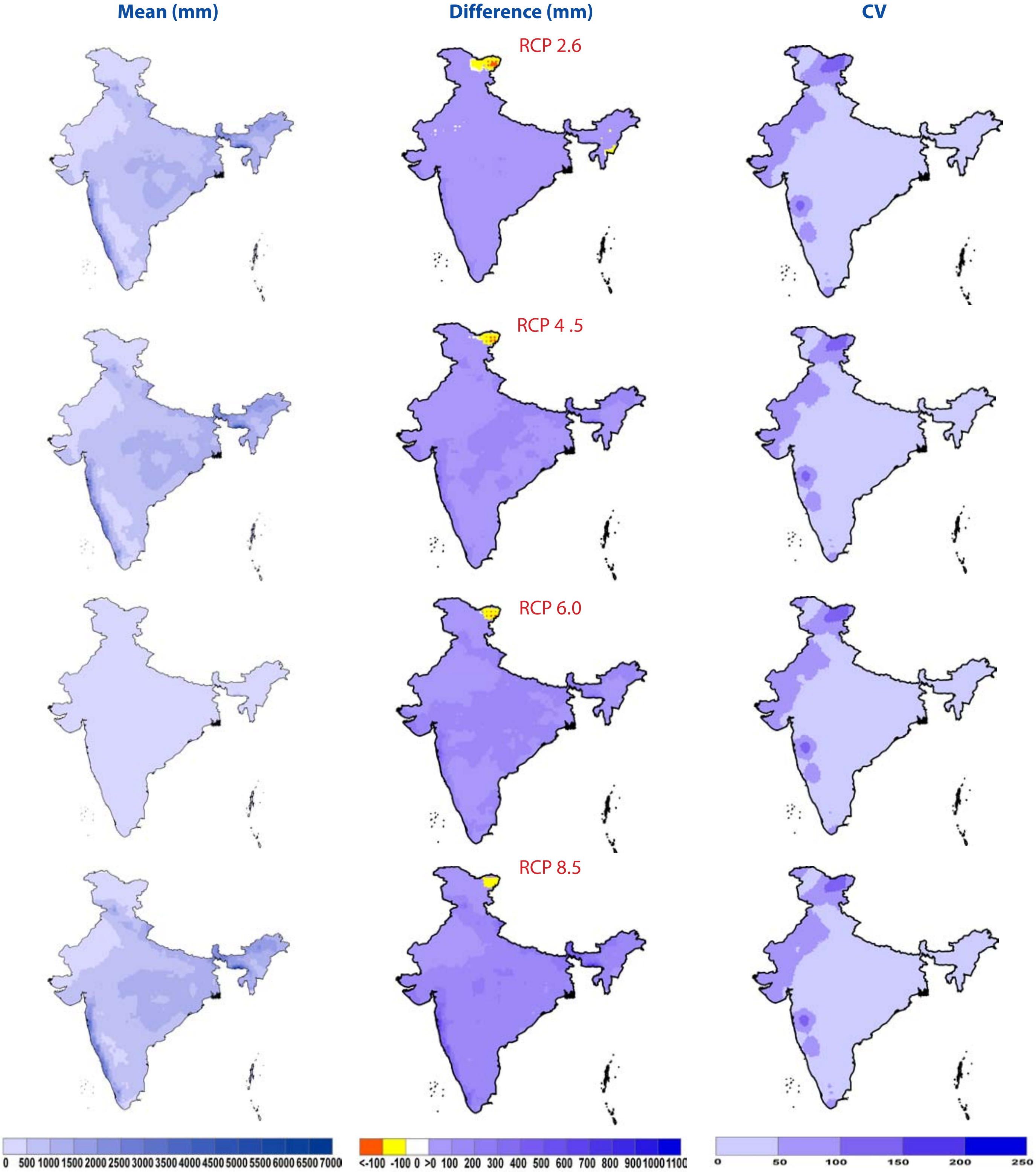


Fig 16. Spatial variation in projected seasonal mean maximum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2020 climate scenario (2010-2039).

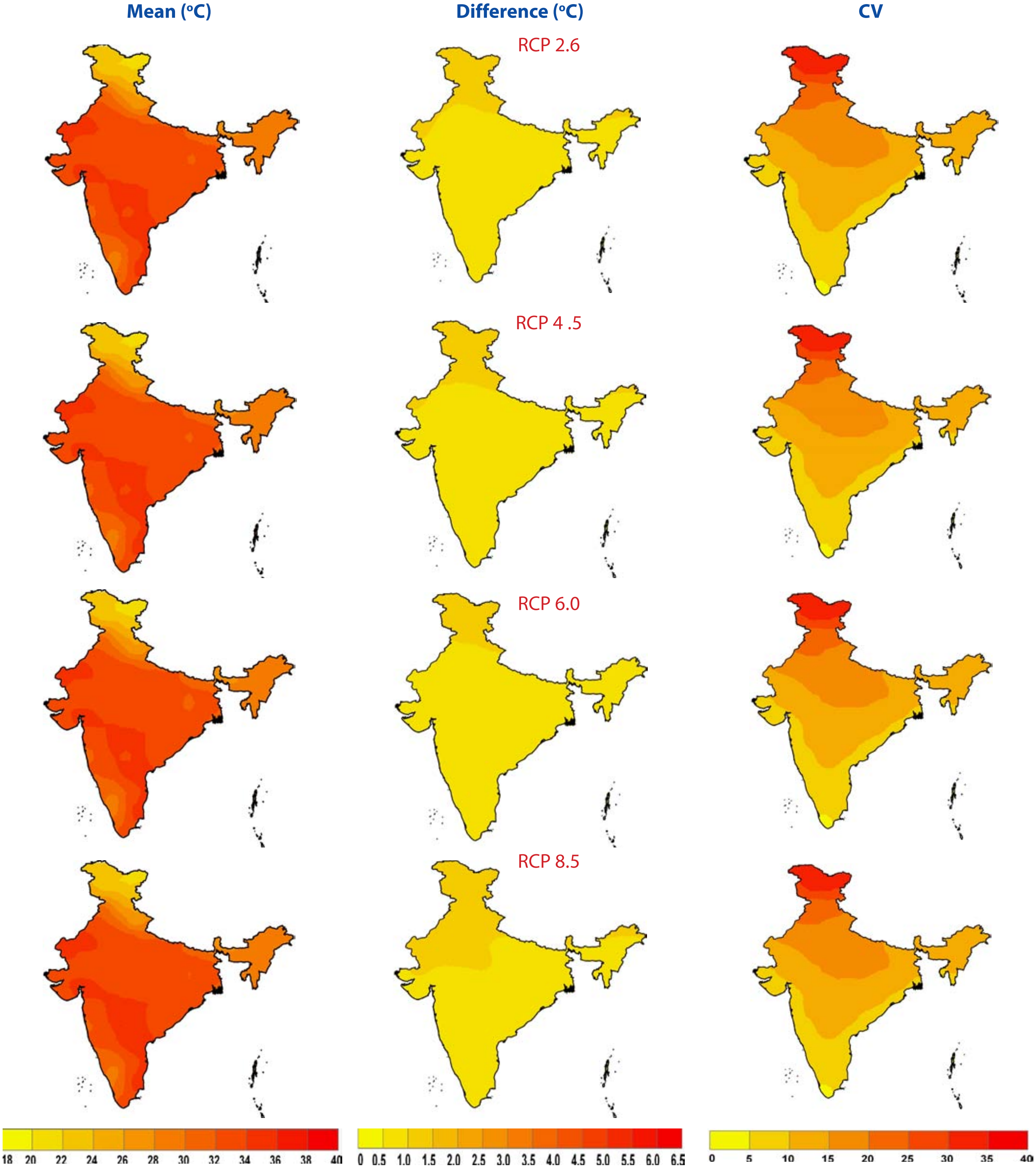


Fig 17. Spatial variation in projected seasonal mean maximum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2050 climate scenario (2040-2069).

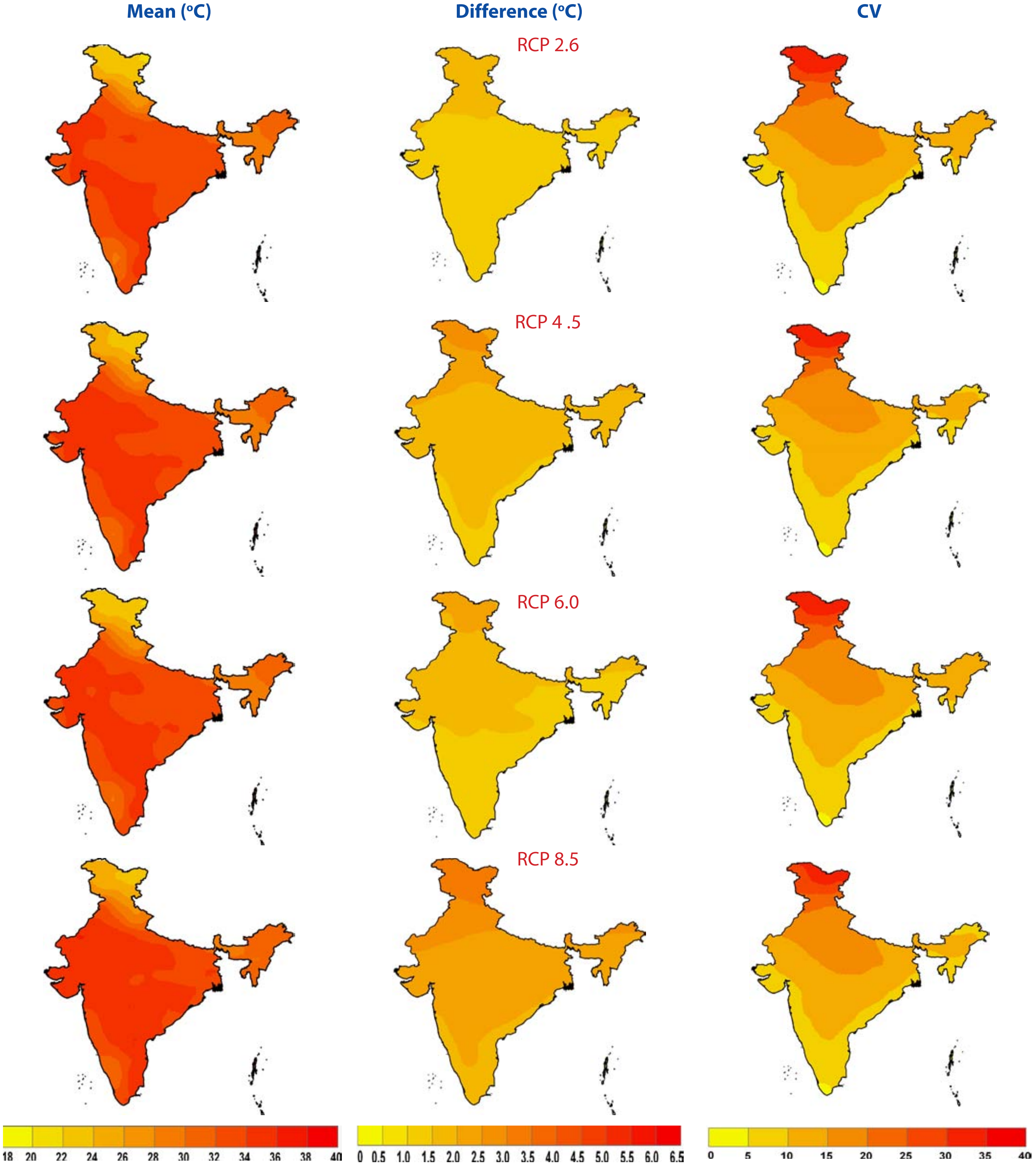


Fig 18. Spatial variation in projected seasonal mean maximum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2080 climate scenario (2070-2099).

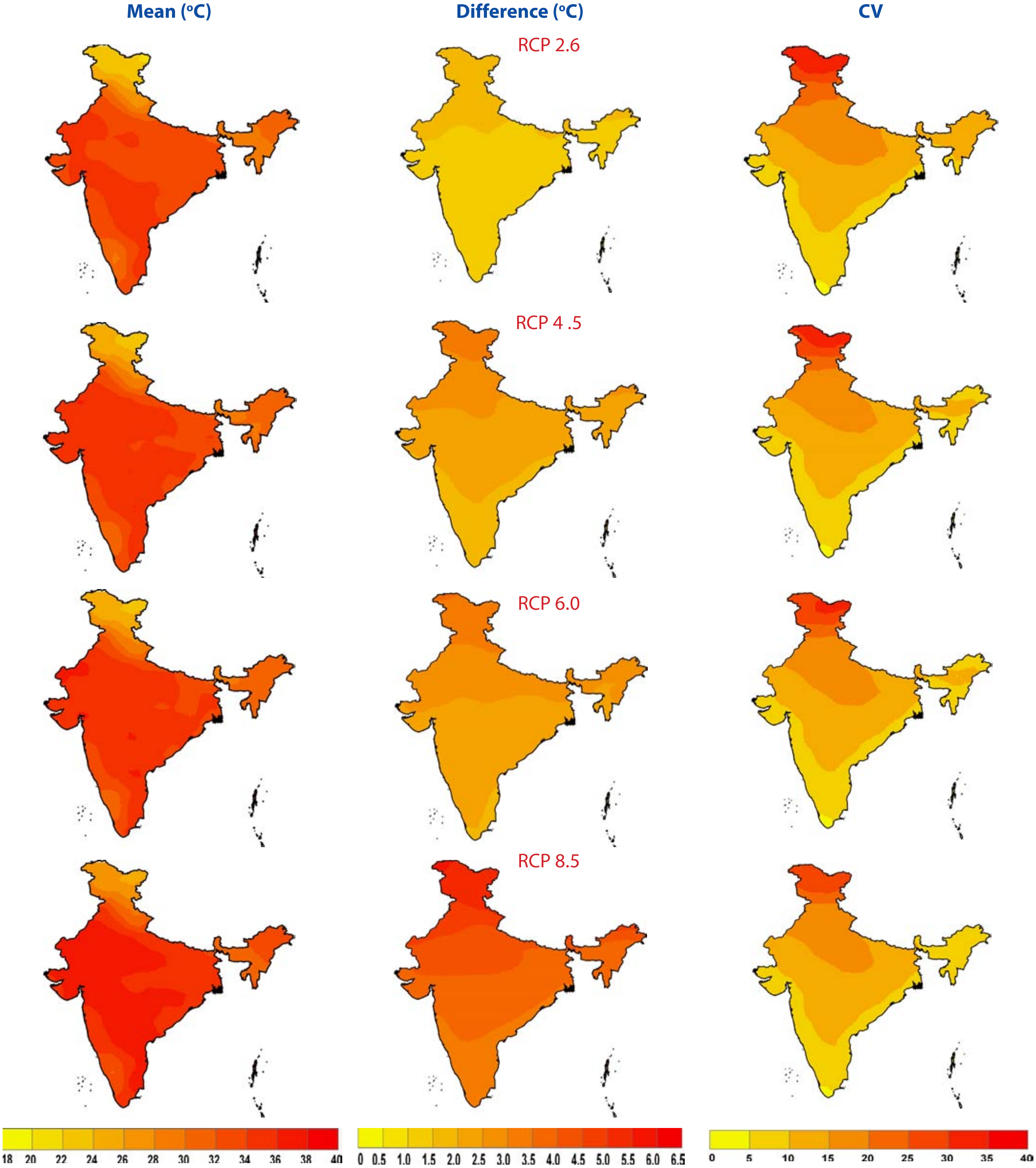


Fig 19. Spatial variation in projected seasonal mean minimum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2020 climate scenario (2010-2039).

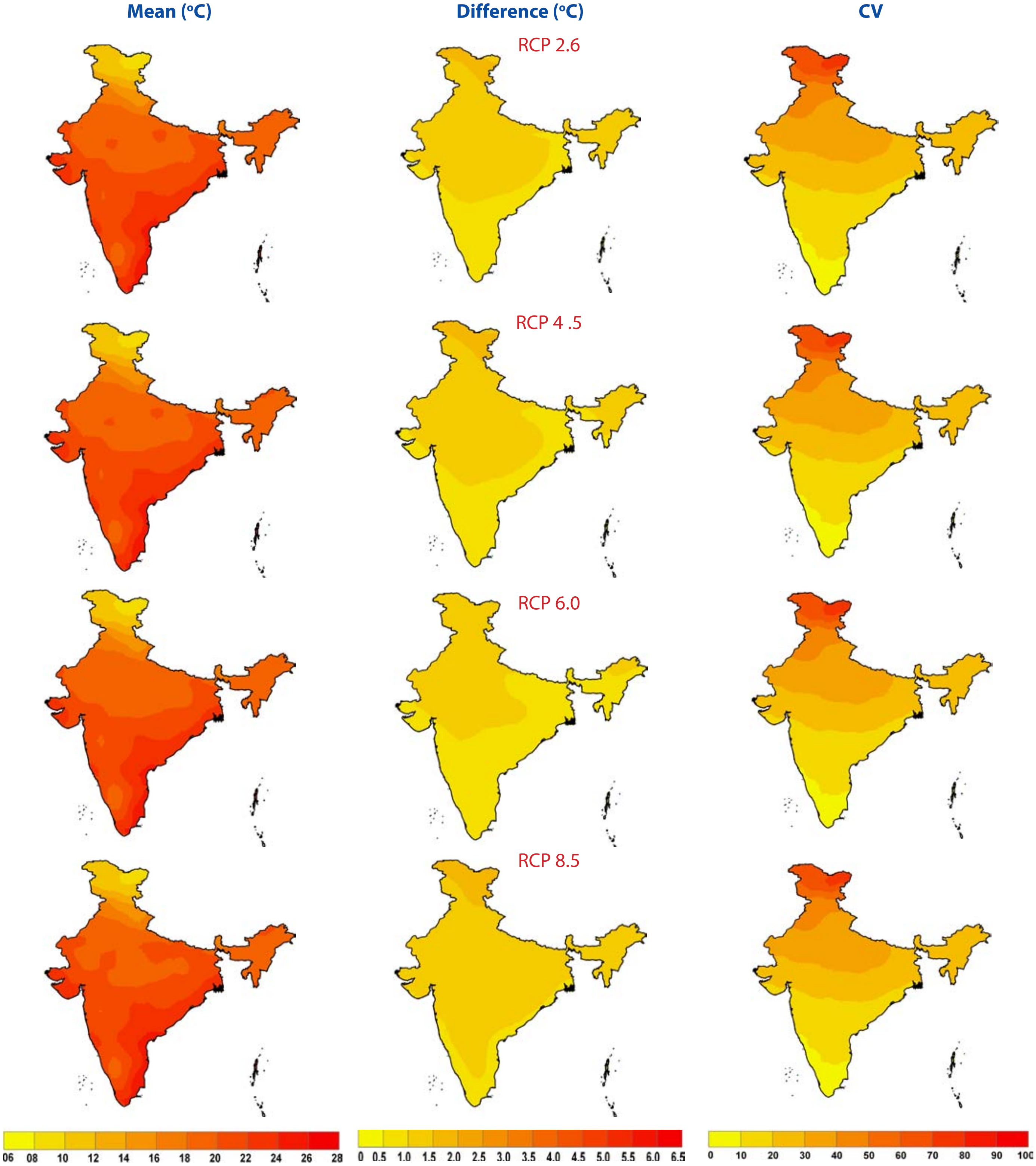


Fig 20. Spatial variation in projected seasonal mean minimum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2050 climate scenario (2040-2069).

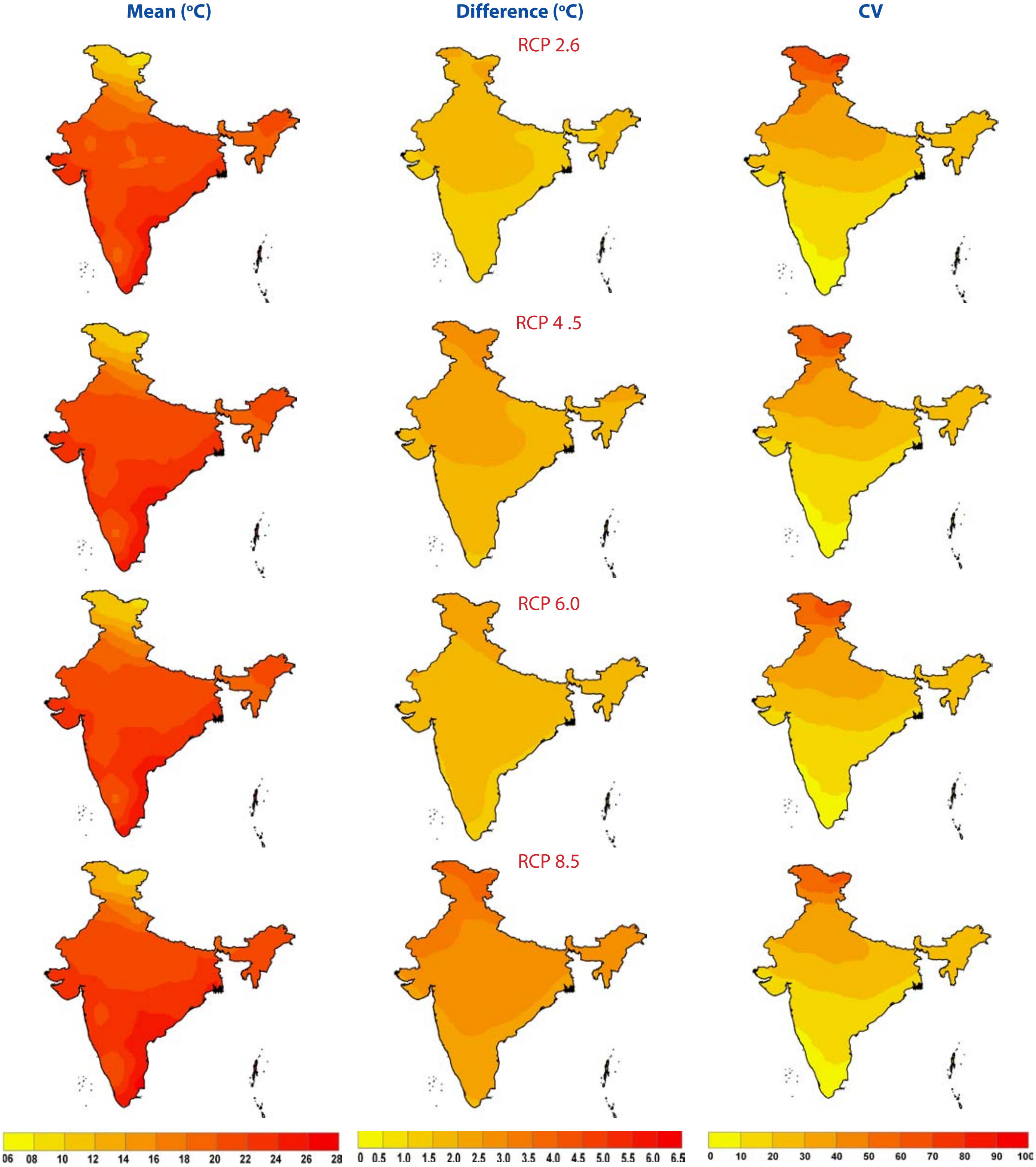


Fig 21. Spatial variation in projected seasonal mean minimum temperatures, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2080 climate scenario (2070-2099).

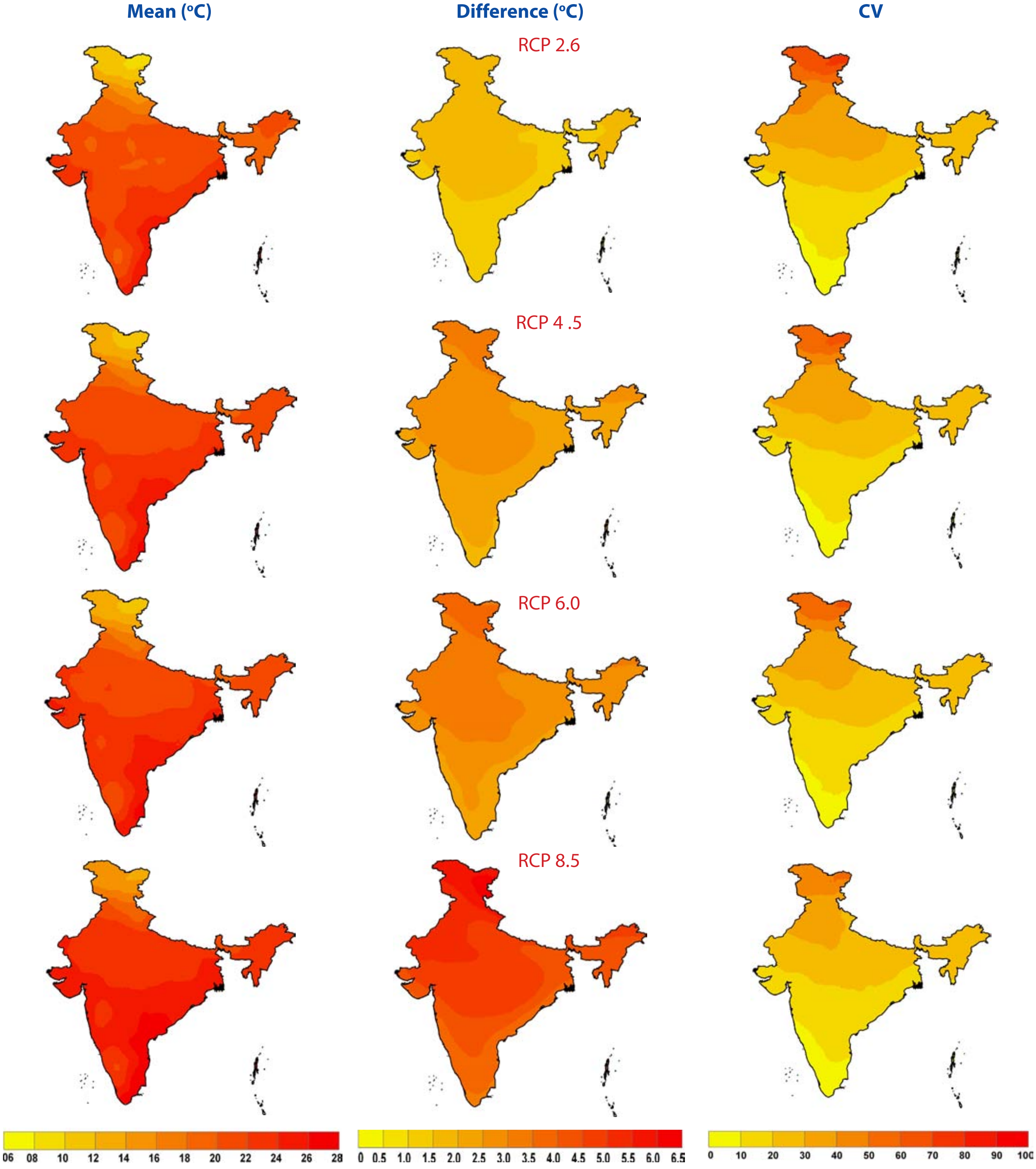


Fig 22. Spatial variation in projected seasonal rainfall, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2020 climate scenario (2010-2039).

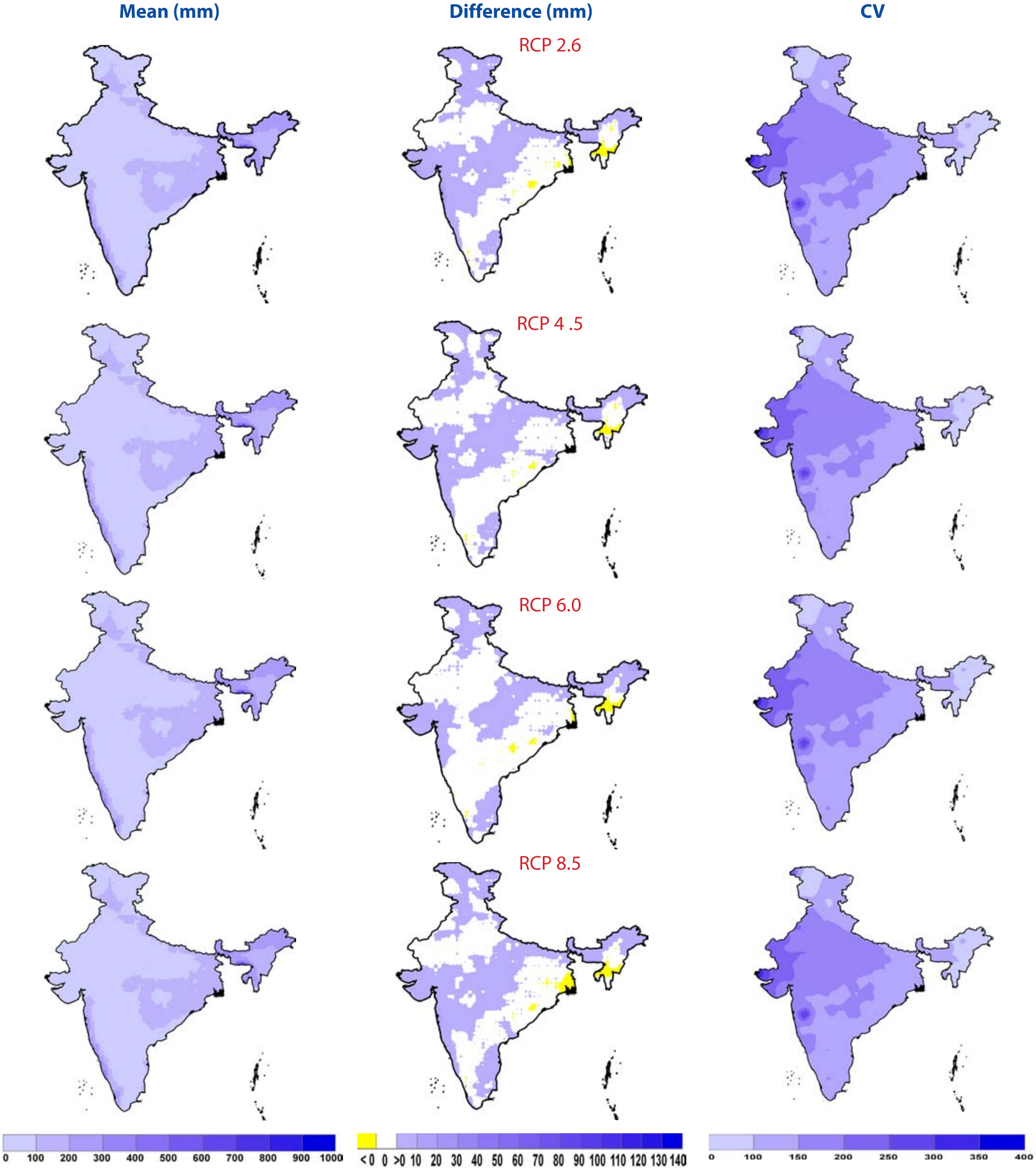


Fig 23. Spatial variation in projected seasonal rainfall, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2050 climate scenario (2040-2069).

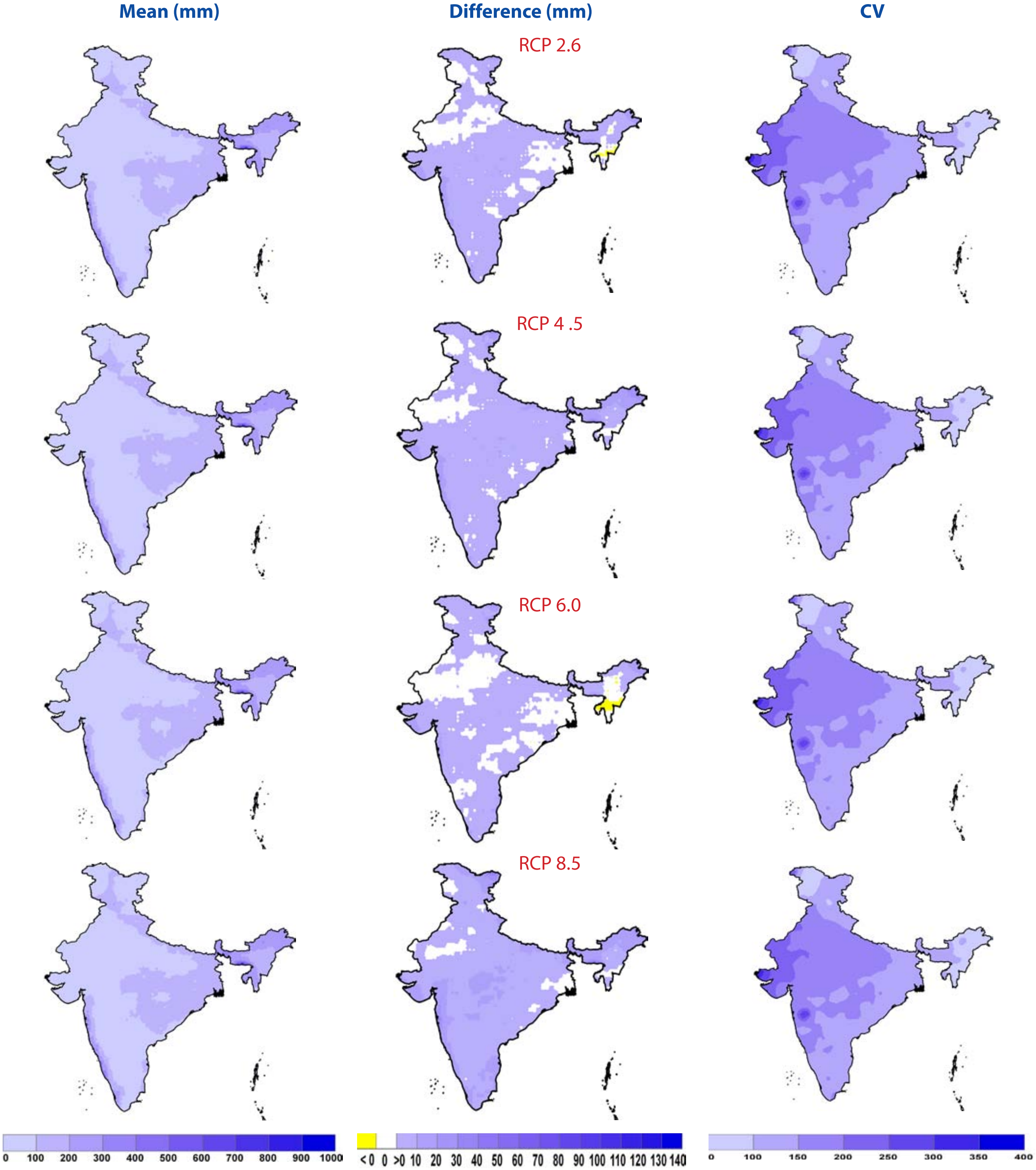
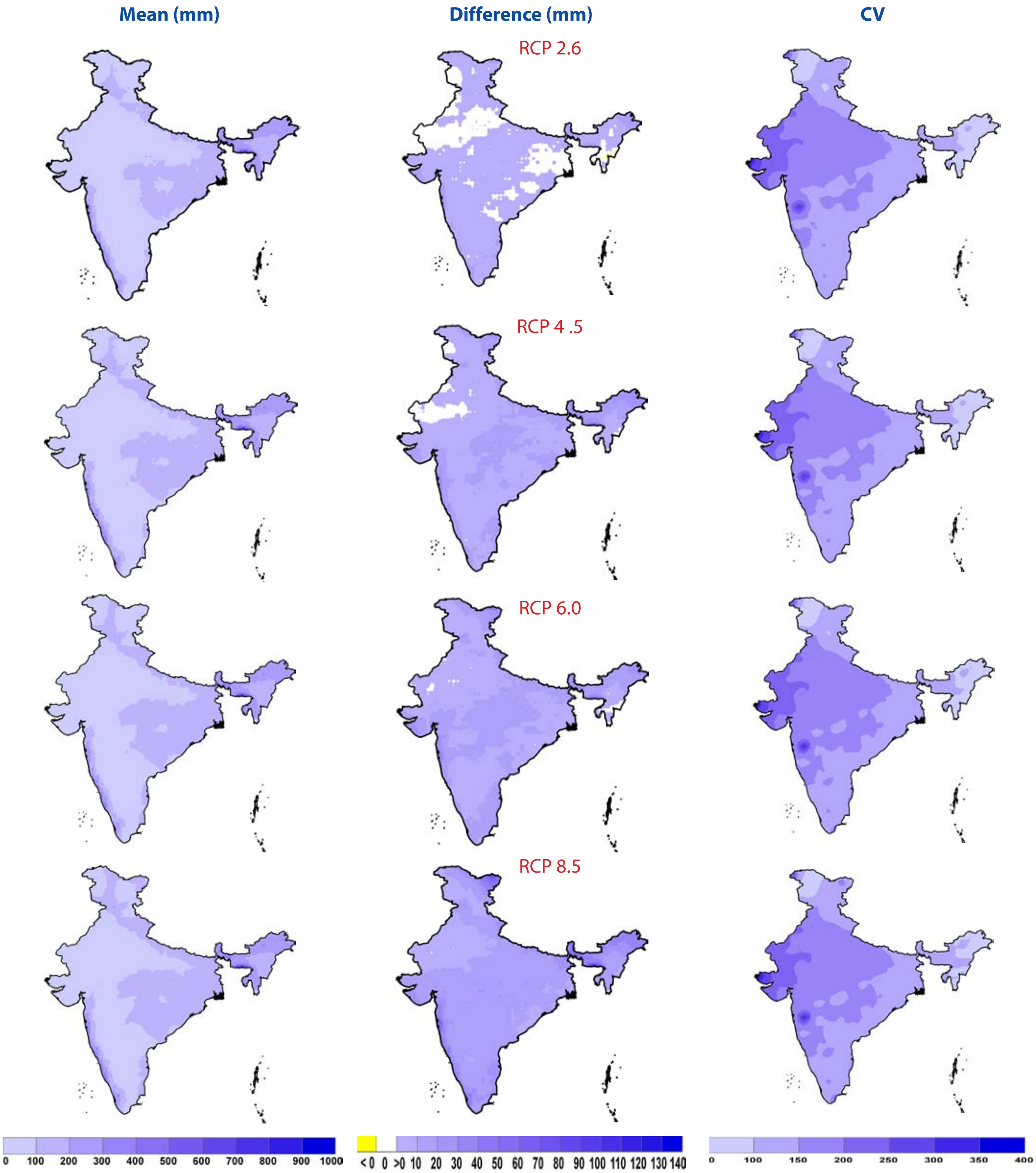


Fig 24. Spatial variation in projected seasonal rainfall, change from baseline (difference) and variability (coefficient of variation-CV) in rabi season over India in different Representative Concentration Pathways (RCPs) of 2080 climate scenario (2070-2099).



5) Rise in temperatures are projected to be more in the northern regions of India than in the southern region;

6) Rainfall projections, though less robust, indicate an increase during kharif and rabi seasons;

7) Kharif rainfall is projected to increase in the range of 2.3-3.3% (2020), 4.9-10.1% (2050) and 5.5-18.9% (2080), while rabi rainfall is projected to increase in the range of 12% (2020), 12-17% (2050) and 13-26% (2080);

8) Rainfall increase (%) is projected to be more during rabi than increase during kharif but the variability is projected to increase significantly in both seasons.

9) Variability in terms of coefficient of variation for minimum and maximum temperatures is more during rabi than during kharif.

10) The variability for maximum temperatures is projected to rise during both seasons

11) The variability for minimum temperatures to rise in kharif; while it may remain high in rabi season

This analysis indicated a progressive climate change and increase in variability during kharif and rabi seasons in India towards the end of the century.

The bias corrected probabilistic ensemble GCM scenarios at a spatial resolution of 0.5×0.5^{o} and at daily temporal resolution for 2010-2099 period, CO_2 concentrations along with IMD daily gridded data for 1976-2005 period were supplied to the partner Institutes under modelling group of NICRA to conduct the impact, adaptation and vulnerability studies for target crops/ river basins.

Impact and adaptation assessment methodology framework

The IARI has conducted the impact and adaptation studies on rice and wheat crops as well as on three river basins using the bias corrected probabilistic ensemble GCM scenarios. For conducting these studies, the models used included InfoCrop, DSSAT and APSIM (all crop models), SWAT and PRMS (hydrological models) and InfoCrop pest models. The generic methodological framework for regional impacts and adaptation gain assessments for crops as well as the integrated assessments for selected river basins are given below.

Fig 25: Generic methodological framework for impacts and adaptation gain assessments for crops

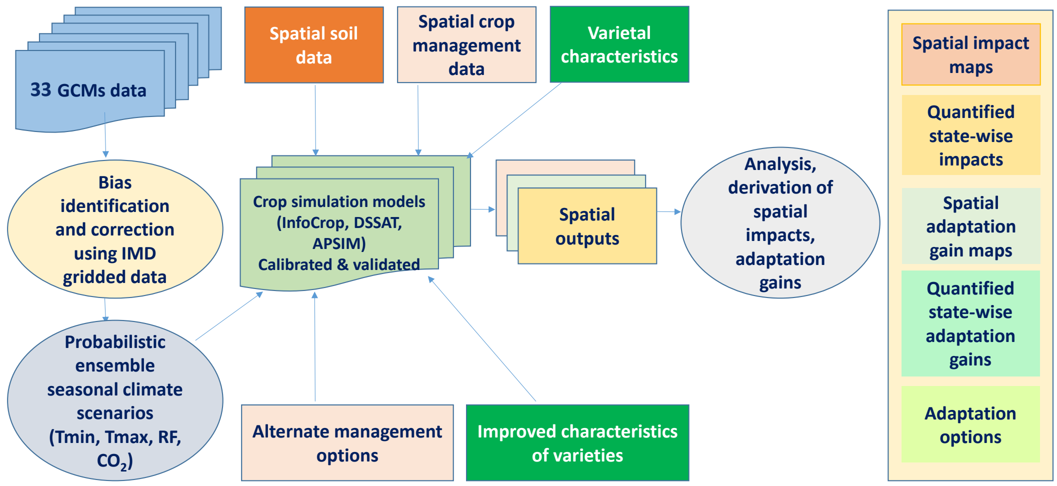
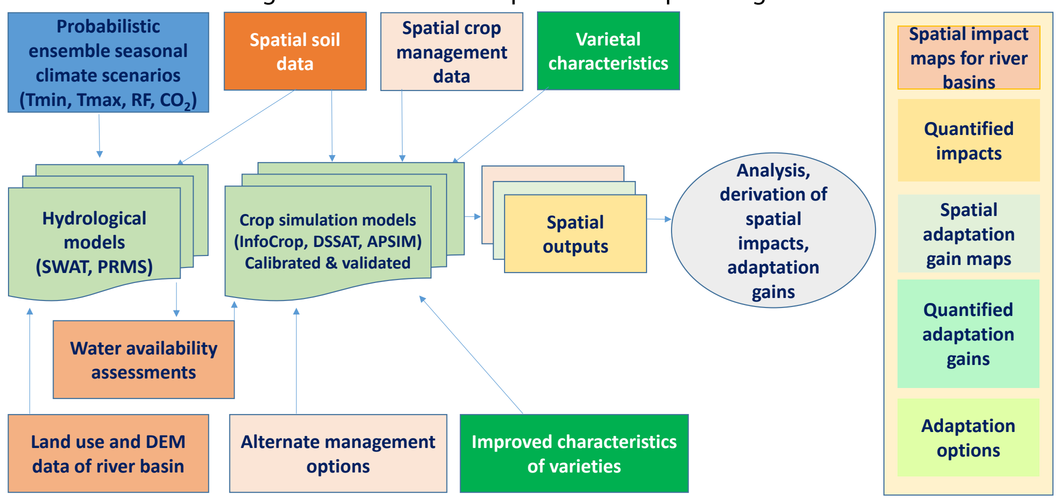


Fig 26: Generic methodological framework for impacts and adaptation gain assessments for river basins



The results thus obtained are presented in brief in the following sections.

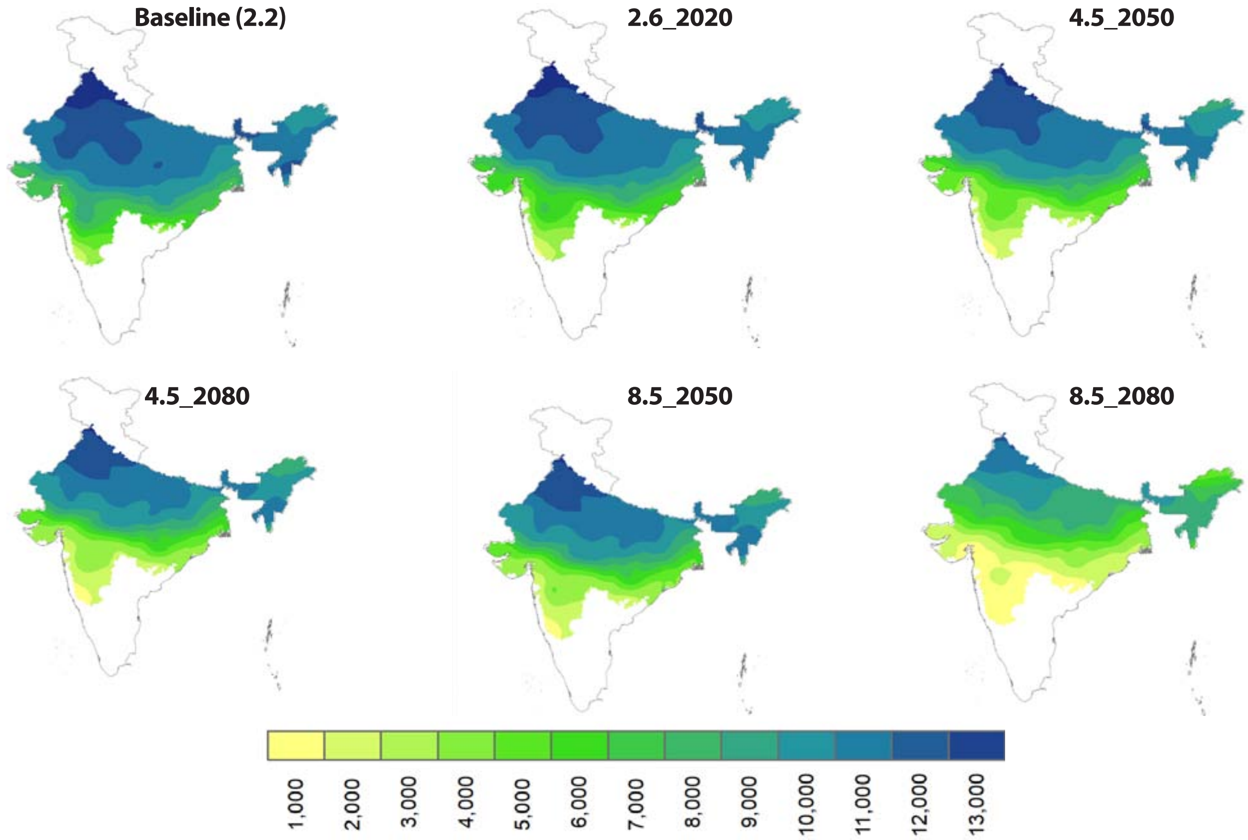
Climate change and wheat productivity in India

The simulation analysis was carried out on wheat crop to delineate the impacts of climate change and to derive the adaptation strategies. For this, three crop simulation models (InfoCrop, DSSAT and APSIM) were used. The simulation setup for this entire analysis on wheat consisted of 2.36 billion simulations. The 288 combinations consisting of varieties and management (sowing time, nitrogen, irrigation, organic matter) were simulated for each grid. Apart from these, the potental yield of wheat in climate change scenarios without nutrient or water stress were simulated.

Impact of climate change on potential yield of wheat in India

Potential yield of current wheat varieties in India ranged from 6-12.5 Mg/ha in major wheat growing areas in India. North-west India has the highest potential yield while central India has less potential for obtaining high yield in wheat. The potential yield is projected to reduce in future climates towards the year 2100. Reduction in potential yield is projected to be more in high GHG emission scenario (RCP 8.5) as compared to the stabilization scenario (RCP 4.5), though the yield potental is projected not to change significantly in 2020 under all RCP scenarios. Area with high yield potential is also projected to shrink and high yield potential regions are projected to confine towards northern latitudes.

Fig 27: Projected potential yield (kg ha^{-1}) of wheat in future climates



Climate change impacts on wheat productivity in India

Without adaptation, climate change is projected to affect the wheat productivity by -3.2 to 5.3% in 2020 (2010-2039); -8.4 to -19.3% in 2050 (2040-2069); and -18.9 to -41% in 2080 (2070-2099) climate scenarios under different Representative Concentration Pathways.

Fig 28: Projected impact of climate change on wheat productivity in India in future climates

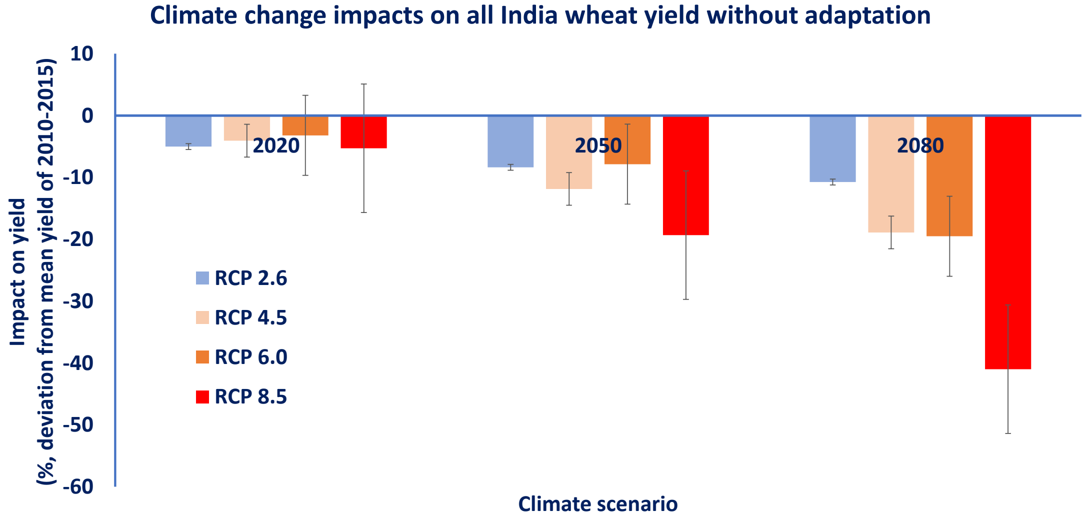
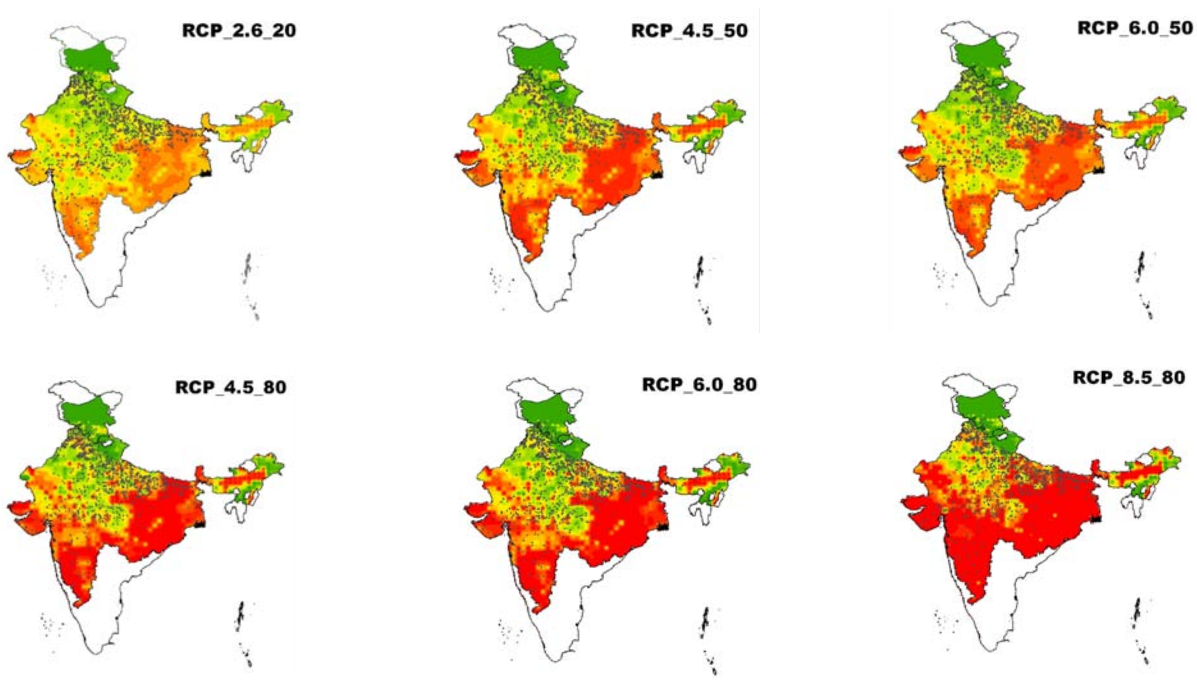
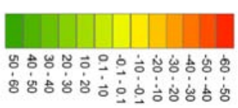


Fig 29: Spatial variation in projected impact of climate change on wheat productivity in India without adaptation under different representative concentration pathways (RCPs) in 2020, 2050 and 2080 climate scenarios.



Relative yield change (%) from 2010-2015 mean yield



The impact of climate change on wheat yield is projected to be not siginificant in north-west India and also in states like Madhya Pradesh and Rajasthan at least till 2050s. But in the middle and lower Gangetic plains, the major wheat producing states like Bihar, Jharkhand, West Bengal are particularly vulnerable to climate change. Similarly, wheat yield in Gujarat and Maharashtra are projected to be affected without adaptation. The impacts on these states are projected to vary between -8 to -25% in 2020; -11to -61% in 2050 and -19 to-70% in 2080 scenarios under different RCPs.

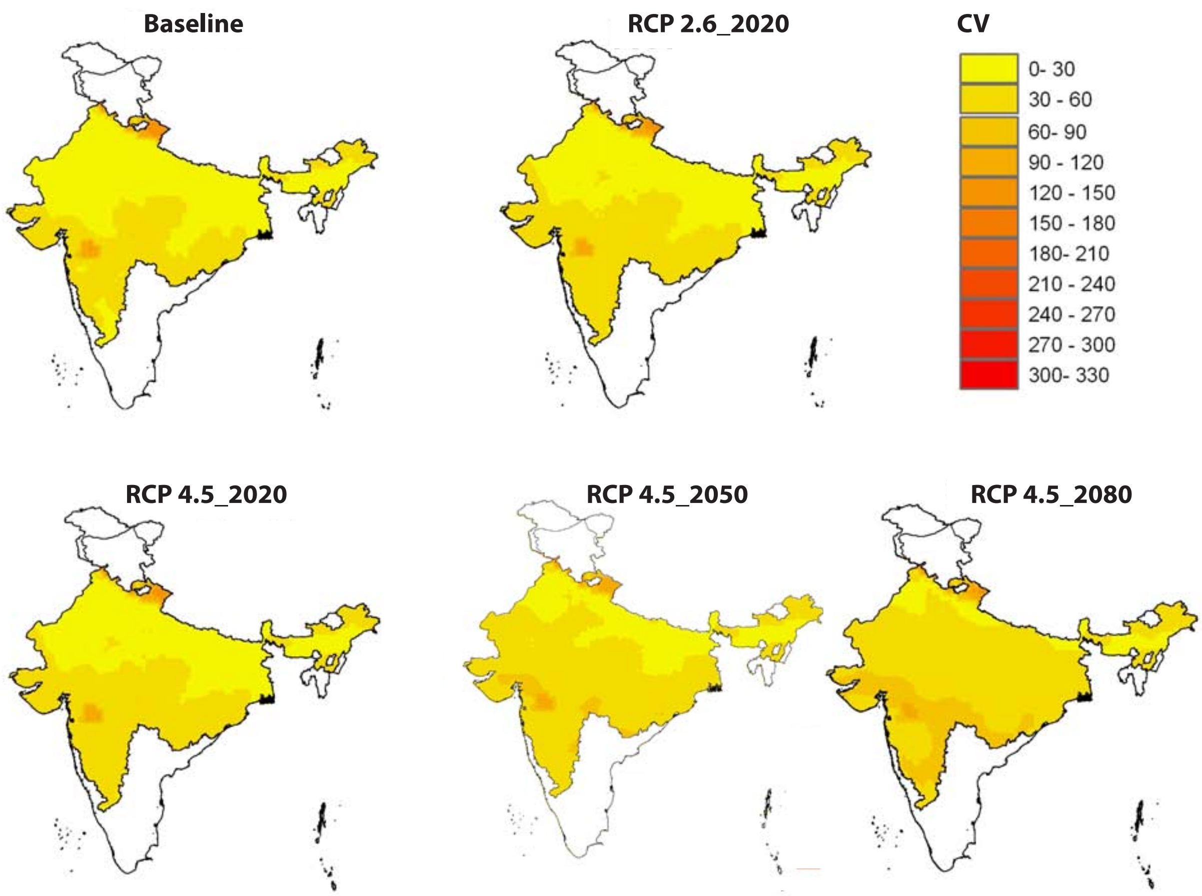
Impact of climate change on yield stability of wheat in future climates

In addition to quantifiying the impact of climate change on wheat yield, this study, for the first time quantifies the inter-annual variation in wheat yield in current and future climates. Results indicated that the inter-annual variation, is more in central India as compared to that in north India. However, in climate change scenarios, the inter-annual variation is projected to increase in northern regions as well. Thus the study indicated an increase in inter-annual variation in wheat yield in future climates under different RCPs.

A rise of 1 $^{\circ}$C in temperature in vegetative phase and grain filling period can cause yield loss of 360 kg ha^{-1} and 265 kg ha^{-1}, respectively. Farmer's choice of variety and management determine the direction and magnitude of

Fig 30: Spatial variation in projected inter-annual variation in wheat productivity in India without adaptation in climate scenarios

Inter-annual variation in wheat yield is projected to increase: spatial variation



impact. Further analysis indicated that wheat yield in about 300 districts will be affected due to climate change if no adaptation strategy is followed. The adaptation thus becomes important for sustaining wheat yield in these vulnerable regions

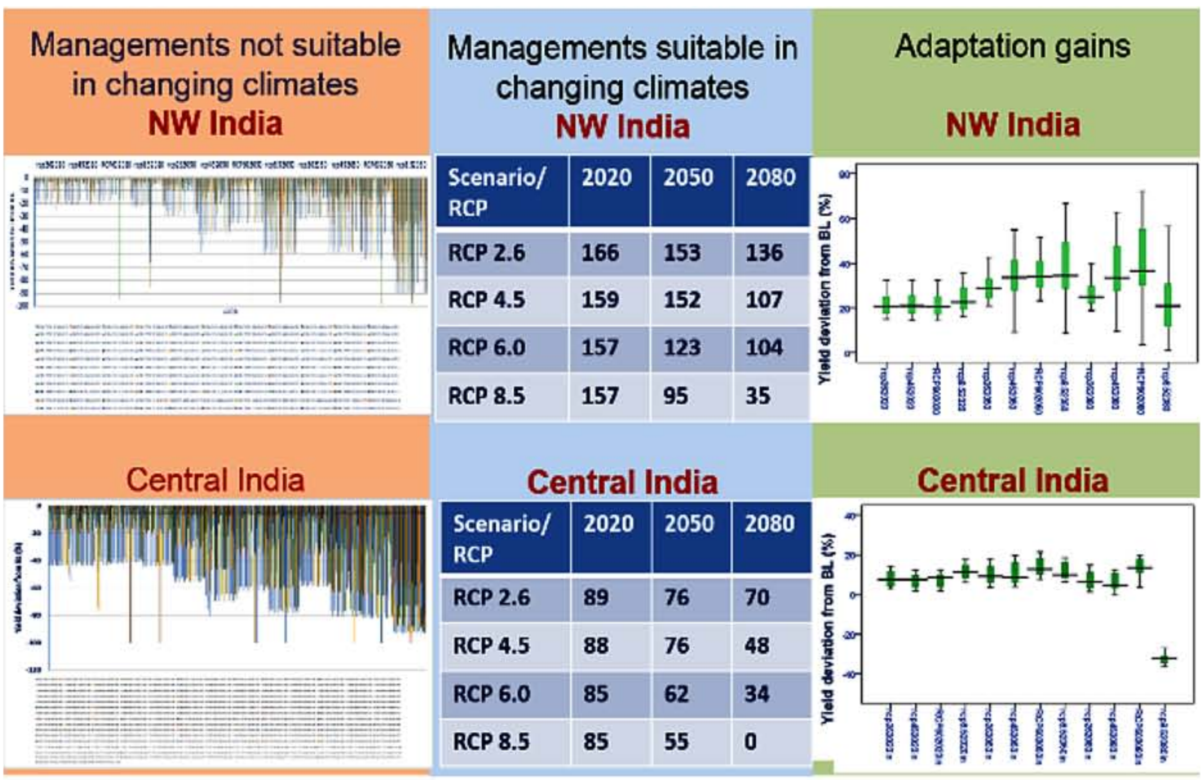
This study implies that i) there is a need for developing varieties with stress tolerance and high yield potential and ii) also to develop the crop management strategies to minimize the impact of climate change and inter-annual variation in wheat in future climates. Simulations were further setup to develop the adaptation strategies and map adaptation niche areas.

Adaptation strategies for improving wheat productivity in climate change scenarios

Adaptation strategies and adaptation gains were quantified for wheat crop. The simulation analysis indicated that adaptation gains have significant spatial and temporal variation. Out of 288 combinations of management and varieties, 166 management and variety combinations were found to be suitable for atleast maintaining current yield levels in future climates. This number of options is projected to reduce in future climates with 136 combinations suitable in 2020 scenario in RCP 2.6 to just 35 combinations in RCP 8.5 2080 scenario in north-west India. In this region, adaptation niche options include long duration varieties, organic matter addition and irrigation scheduling to improve yield. The results indicated that November first fortnight sowing may help in reducing the inter-annual variability. Further, the analysis indicated that short duration varieties, and late- or very late- sown in low input

Fig 31: Adaptation gains and number of managements that may sustain wheat productivity in India in climate change scenarios.

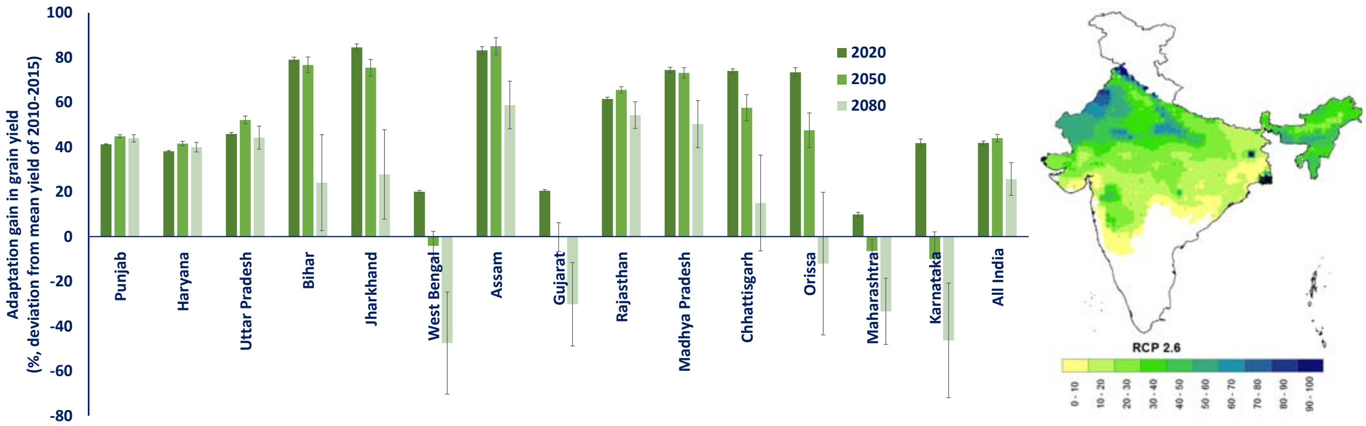
Adaptation to improve wheat productivity in future climates



Scenario/ RCP	2020	2050	2080
RCP 2.6	166	153	136
RCP 4.5	159	152	107
RCP 6.0	157	123	104
RCP 8.5	157	95	35

Scenario/ RCP	2020	2050	2080
RCP 2.6	89	76	70
RCP 4.5	88	76	48
RCP 6.0	85	62	34
RCP 8.5	85	55	0

Fig 32: Spatial variation in adaptation gains due to currently available best adaptation option in wheat



farms have highest inter-annual variability and are highly vulnerable. However, short and medium duration varieties sown in December will have low yield variability. For central India, out of 288 management combinations just 85-89 are suitable in 2020 scenario and these numbers are projected to reduce to about 34-48 in RCP 4.5 and RCP 6.0 in 2080 climate scenario. For central India, short duration varieties, organic matter addition and shifting (delay by fortnight) sowing time will give improved yield in future climates. In this region, growing long duration varieties, early sowing, and low-input farms are projected to have reduced yield due to shrink in climate-suitability window for wheat crop.

Thus, the adaptation is a must and improved management and varieties can significantly improve the wheat yield across India in 2020 scenario. But beyond 2040 as the climatic stresses increase further, the current available technologies may not help to sustain wheat productivity in states like West Bengal, Gujarat, Maharashtra and Karnataka. Hence development of new technologies (varieties, agronomic management) may be prioritized for central India. Adaptation will improve the yield at state level in the range of 10 to 40% in major wheat growing states. The gains may be even up to 80% in states where current yield levels are very low.

Climate change and rice productivity in India

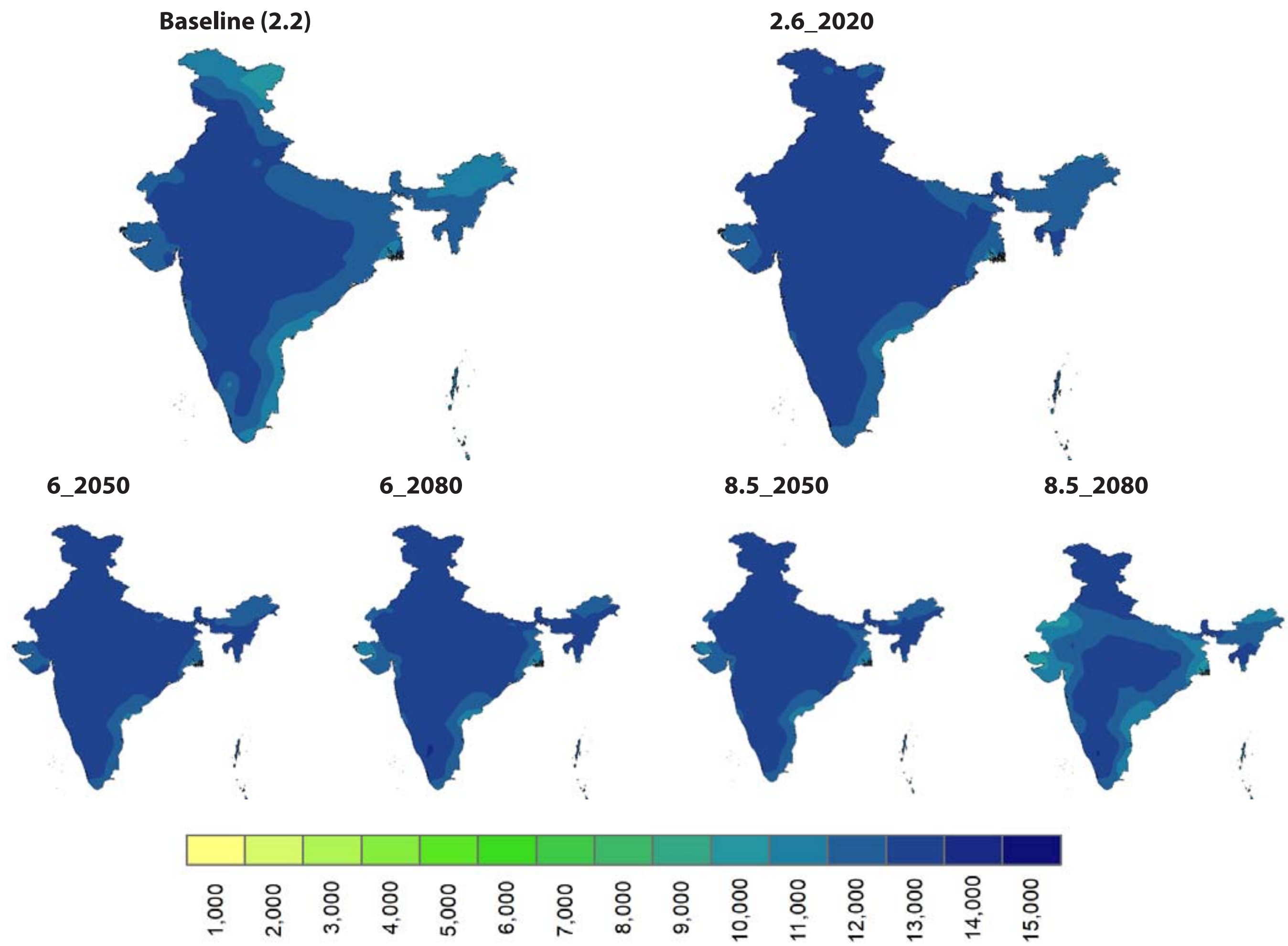
A simulation analysis for estimating rice yield in baseline (1976-2005) and climate scenarios of RCP 2.6, 4.5, 6 and 8.5 (in 2020, 2050 and 2080 periods) under various management regimes was carried out. Overall rice simulation setup involved 6.225 billion simulations consisting of various varieties, management, sowing/ transplanting time for direct seeded and transplanted rice for various rice growing regions in India.

Rice yield potential in climate change scenarios

Results indicated that the climate potential (nutrients and irrigation are not limiting) for rice yield will not change significantly in future. However, significant reduction in climate potential of current varieties' yield is projected in RCP 8.5 scenario, which is an extremely high GHG emission scenario.

Fig 33: Spatial variation in potential yield (kg h^{-1}) of rice in future climates

Potential yield of kharif rice is projected to reduce in extreme climate change scenario



Climate change impacts on irrigated rice productivity during kharif season in India

The simulation analysis indicated that the irrigated rice yield will be affected due to climate change. The irrigated rice yield during kharif season is projected to be affected by about -3% in 2020, -2 to 3.5% in 2050 and -2 to -5% in 2080 climate scenarios in all RCPs. The impacts will have significant spatial variation. It indicated a marginal

Fig 34: Impact of climate change on irrigated rice productivity during kharif season in India in 2020, 2050 and 2080 climate scenarios of various emission scenarios

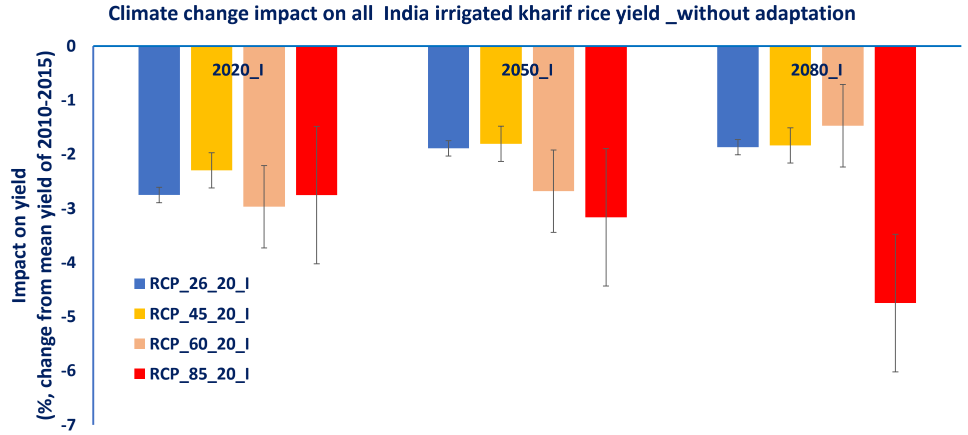
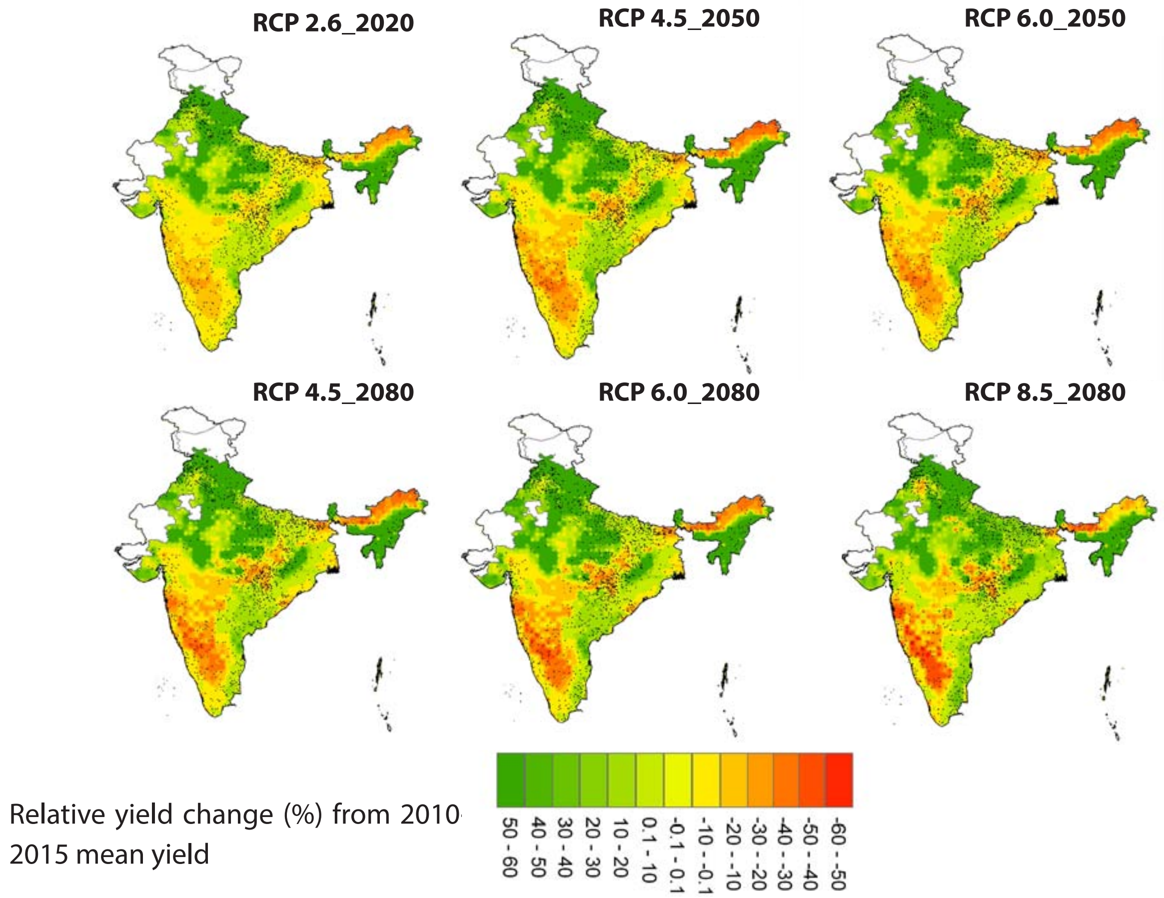


Fig 35: Spatial variation in projected impact of climate change on kharif season irrigated rice productivity in India without adaptation under different representative concentration pathways (RCPs) in 2020, 2050 and 2080 climate scenarios.

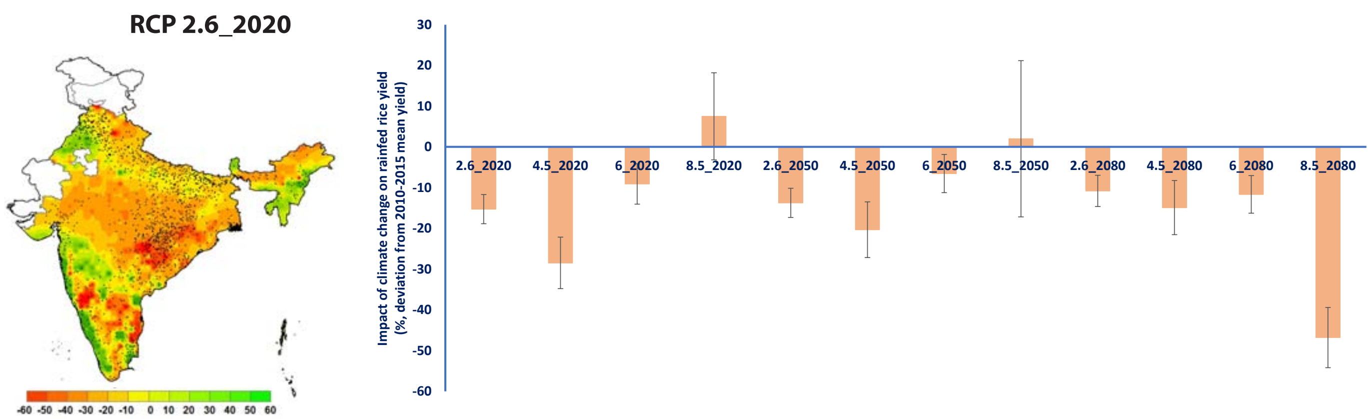


positive impact on irrigated rice yield in states like Andhra Pradesh, Jharkhand, Odisha and Gujarat even with current management. But in other states such as Haryana, Karnataka, Kerala, Maharashtra, Tamil Nadu and West Bengal significant negative impacts are projected without adaptation.

Climate change impacts on rainfed rice productivity during kharif season in India

Rainfed rice is projected to be impacted by the climate change. The productivity is projected to change in the range of 7 to -28% in 2020; 2 to -20% in 2050 and -10 to -47% in 2080 climate scenarios in different RCPs. The analysis on impact of climate change on rainfed rice yield in different management conditions indicated that the magnitude and direction of impacts have high spatial variation. If no adaptation is followed, the rainfed rice yield may reduce in some regions. The low-input rice farms are projected to be vulnerable in terms of yield in changing climates.

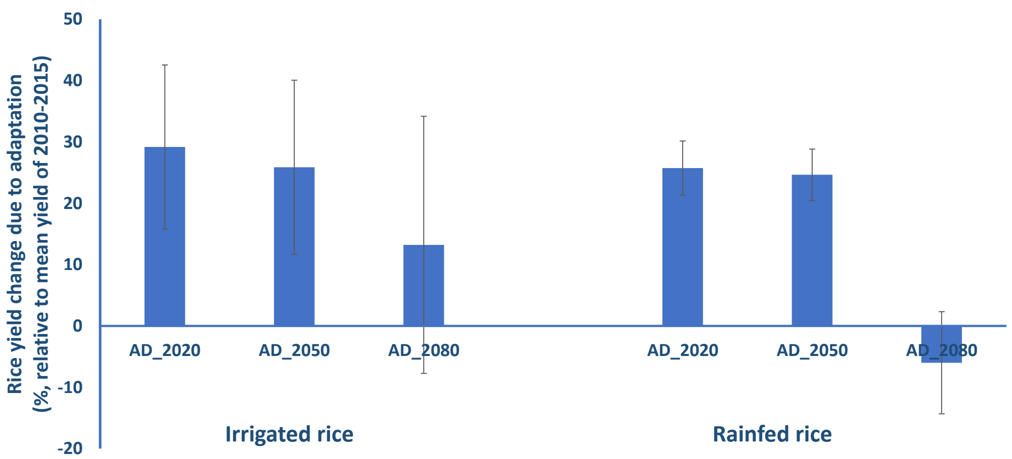
Fig 36: Spatial variation in impact of climate change on rainfed rice yield. Yield change (%) is relative to 2010-2015 mean yield



Adaptation strategies for improving rice yield in climate change scenarios

The simulation analysis indicated that short-duration varieties with improved management can significantly enhance the yields despite climate change. In case of irrigated rice, the yield improvement can be achieved by

Fig 37: Adaptation gains for irrigated and rainfed rice yield at all India level under climate change scenarios



sowing short duration high yielding and heat tolerant varieties. Growing improved short duration varieties with improved nutrient and water management can enhance the irrigated rice productivity even upto 28% till 2050 climate scenario. But in 2080 scenario, these adaptation options will not be sufficient to sustain the yield. The yield gains are projected to have significant inter-annual variations and spatial variations. The analysis further indicated that the strategy of growing shorter duration varieties than the current ones in north-west India may not prove beneficial even in near future.

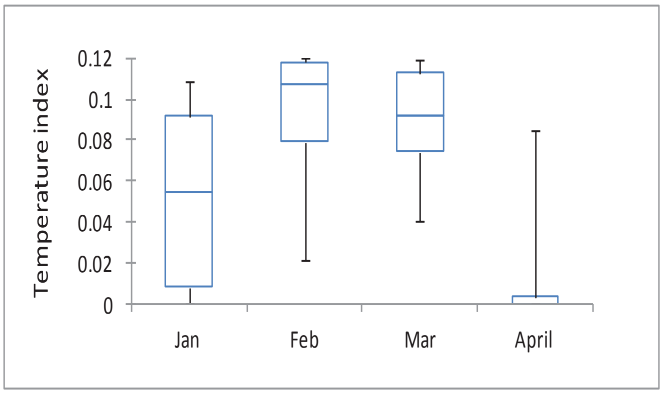
In rainfed conditions, it is projected that growing short duration stress tolerant high yielding varieties can improve the yield up to 28% in rainfed rice regions in India. However, in 2080 scenario the impacts can not be offset by the adaptation options considered. Hence more heat and water stress tolerant varieties with high yield may need to be developed for sustaining the rainfed rice yield. In addition, managing the water sources at field level will become crucial.

Simulating the climate change impacts on diseases and insect pests

Climatic indicator for monitoring powdery mildew in wheat in north western India

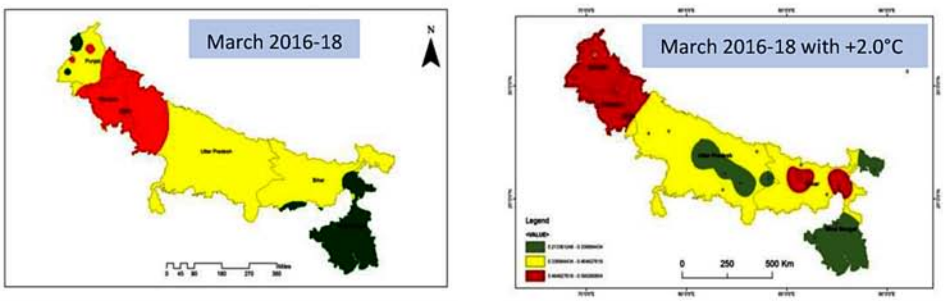
Based on the temperature index for powdery mildew development (mildew development rate = $0.005*[(26-Temp)/8][(Temp-8)/10]^{1.25}$), a daily index of 0.06 for 7-10 consecutive days derived from daily maximum and minimum temperatures can be considered as the threshold for management decision. The disease risk period could be monitored for deploying control measures to minimize the damage.

Fig 38. Powdery mildew development index for Madhopur, Jallandhar Punjab during 2016-18



Box plot for index

Fig 39. Spatio-temporal distribution of powdery mildew in the Indo-Gangetic plains



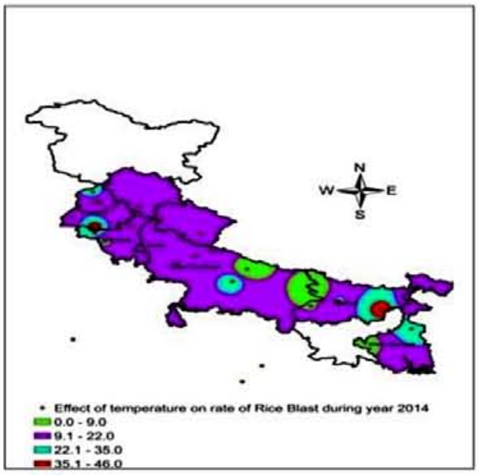
Based on spatio-temporal dynamics, it was found that climatic conditions in western zone is favourable only during March and it matches with powdery mildew incidence in the region. The model allowed for extrapolation of 2.0°C rise over the ambient to simulate climate change scenario. The simulation analysis indicated that the disease is likely to be restricted to the western zone only except a slight change in the eastern plains.

Effect of temperature rise on rice leaf blast

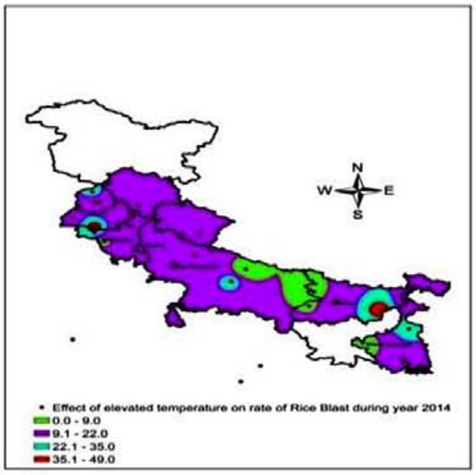
Kharif rice throughout the Indo-Gangetic Plains (IGP) is grown during July –October when prevalent temperatures are between 25-38°C. The analysis indicated no change in generation rate of pathogen causing leaf blast in rice.

Spatio-temporal pattern for leaf blast scenario, simulated based on current hourly temperature ($D_{current} = \sum r[T(t)]\,dt$), and observed leaf blast incidence pattern (past and current) indicated no remarkable change in pattern throughout the IGP. Similarly, spatio-temporal pattern, generated for climate change scenario (($D_{1.5°C\ rise} = \sum r[T(t)]\,dt$, adding 1.5°C to current hourly temperature data) across the Indo-Gangetic plains, did not show significant deviation in pattern during kharif rice (July-October) compared to the ground truth data on blast incidence with 2014 as the base year.

Fig 40. Leaf blast scenario in kharif rice throughout the Indo-Gangetic plains with 2014 as the base year



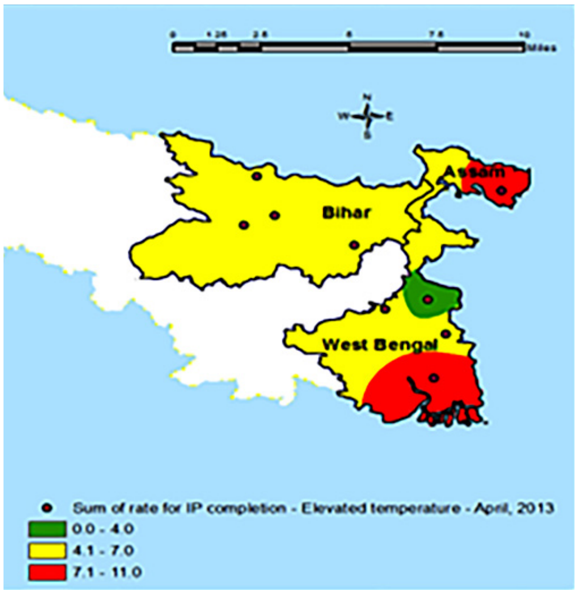
A: current



B: With +1.5°C

However, a similar analysis reflected a slight increase in leaf blast pattern in boro rice grown during December to March in the eastern part of the IGP. Ground truth for blast incidence during 2014-16 did indicate a notable increase in blast incidence pattern especially in some districts of West Bengal such as Barddhaman, Hooghly, Nadia, North and South 24 Parganas and Medinipore.

Fig 41 Leaf blast scenario in boro rice in eastern Gangetic plains and Brahmaputra basin.



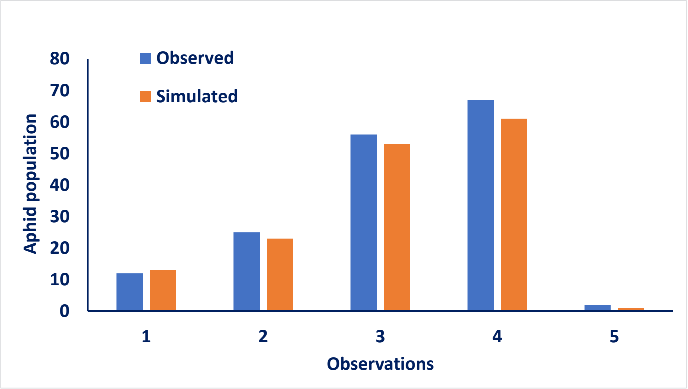
Monitoring criteria for Aschochyta blight in chickpea

For monitoring of *Aschochyta* blight, a temperature-dependent infection threshold was adopted as blight development rate =[1-exp(-2.6*LWD)]* 0.007576*[(30-T)/10][(T-5)/10]$^{1.5}$, where T is air temperature (°C). This model was tested for Indo-Gangetic plains. Threshold for blight development is occasionally fulfilled except in Himachal Pradesh as leaf wetness duration or high RH hours requirement for infection was not satisfied.

Validation of population simulation model of wheat aphid

A population simulation model of wheat aphids was developed earlier based on thermal constant (128 DD), development threshold (5.3°C) and biotic and abiotic mortalities. The model was satisfactorily validated with field data on aphid infestation during rabi 2017-18. The population model was coupled with InfoCrop-wheat model at appropriate plant growth processes and is applied to simulate climate change impact on aphid population as well as to simulate the crop-pest interactions.

Fig 42. Validation of population simulation model of wheat aphid



Simulation of damage of wheat aphids and development of decision support tools

The damage due to wheat aphids in cultivars- HD3059 and HD3086 was simulated with InfoCrop-wheat model using crop management, pest population and yield data. Various levels of aphid infestation were created with differential application frequency of imidacloprid 17.8SL @0.006%. The different pest levels resulted in different infestation levels. The yield and infestation data were used to satisfactorily validate the damage mechanisms of wheat aphids. In terms of pest damage mechanisms, aphids acted as assimilate sapper and light stealers. The validated model was used to simulate Economic Injury Levels (EILs) of wheat aphids for different scenarios of control expenditures and market price of wheat.

Fig. 43 Validation of damage mechanisms of wheat aphids

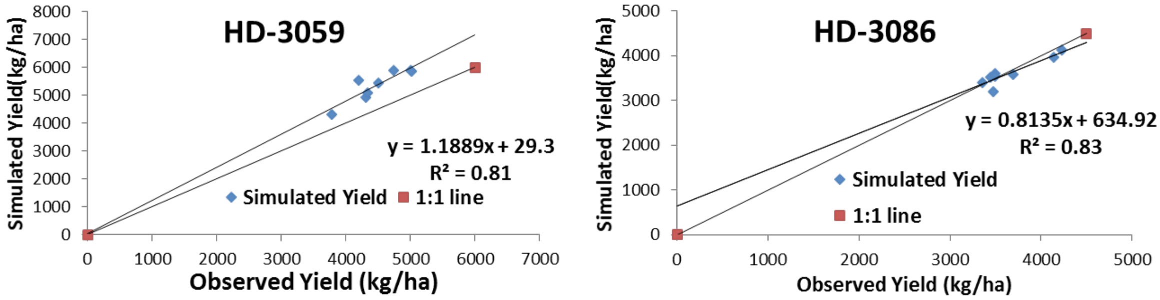
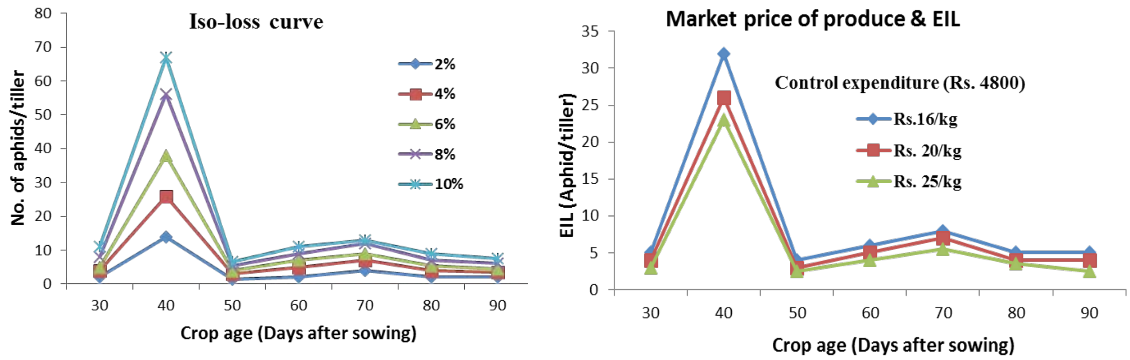


Fig 44. Simulated economic injury levels and iso-loss curves of wheat aphids

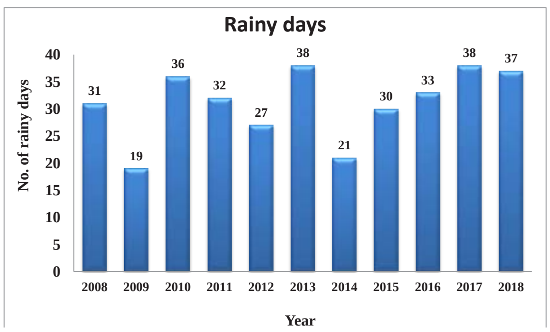


The simulated EILs ranged between 5-40 aphids/tillers for various combinations of control expenditure, market values of produce and crop age. Likewise, isoloss curves were also derived which reflected various combinations of aphid population and crop age that resulted in similar yield loss. These decision support tools will be helpful in deciding the need and timing of control interventions.

Validation of forewarning of brown plant hopper of rice

Brown Plant Hopper (BPH) has become an important pest of rice in north India during last decade. The first major outbreak of this pest in north India occurred in 2008 and subsequent outbreaks of this pest have been witnessed during 2010, 2013, 2016, 2017 and 2018. Weather data from 1999-2013 were analyzed to determine the likely causes of BPH outbreak.

Fig 45. Number of rainy days between June-September during different years



The analysis of 15-year weather 1999-2013 revealed that more frequent rains during June-September months (>30 days) might have a role in BPH outbreaks. Higher rainfall accompanied with cloudy weather and lower sunshine hours results in favourable temperature and relative humidity for BPH development. The pest as a result attains higher population. The thumb rule was validated during 2014, 2015, 2016, 2017 and 2018. The pest outbreaks were observed during 2016, 2017 and 2018, when number of rainy days happened to be 33, 38 and 37, respectively during June-September. On the other hand, the pest outbreak did not occur during 2014 and 2015 when 21 and 30 rainy days respectively were recorded during the same period. Out of seven years with >30 rainy days between 2008 and 2017, the BPH outbreaks have occurred during 5 years. Rain forecast may thus provide a clue about likely BPH incidence and thereby help in timely management of the pest. Regular monitoring is essential for effective management of BPH.

Integrated modelling for selected river basins

Integrated modelling for selected river basins: Ramganga river basin

Modelling of climate change impact on water resources availability and crop yield in Ramganga river basin in the Indo-Gangetic Plains

Impact of climate change on water availability in Ramganga river basin in Indo-Gangetic plains was studied using Soil and Water Assessment Tool (SWAT) model. Historical long-term stream flow data were collected from the Central Water Commission (CWC), Government of India. The long-term gridded weather data (rainfall, temperature) for the period 1976-2005 was used for the study.

Fig 46 Geographical location of Ramganga river basin and sub-basin catchment area

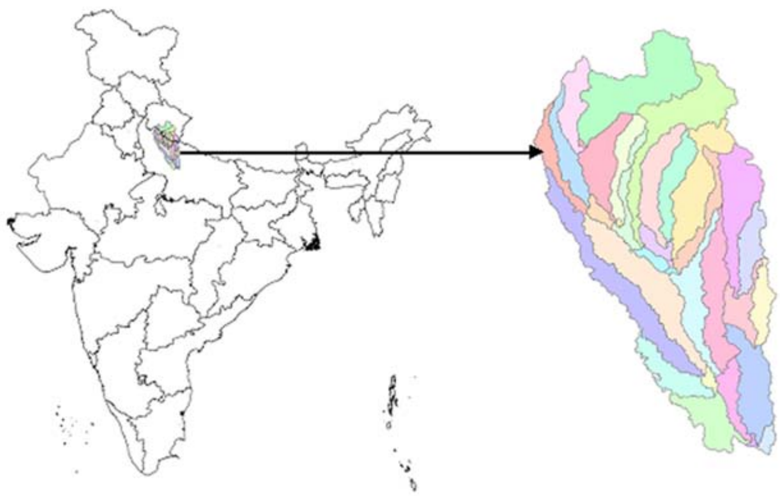
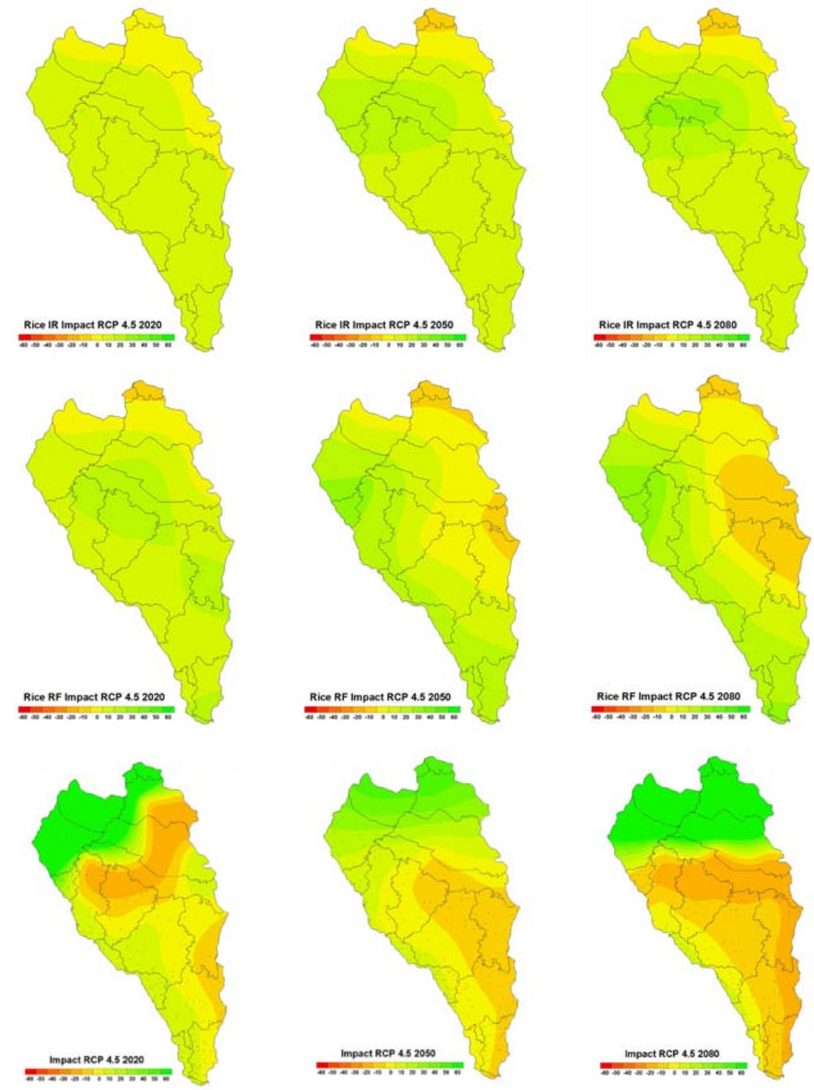


Table 2: Projected impact of climate change on surface water resources for RCP 2.6 (2020) as compared to Baseline

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Moradabad	19.5	7.6	12.8	14.8	9.5	3.3	-0.2	1.0	10.6	10.0	0.6	0.4
Dabari	36.9	11.5	5.9	46.2	28.2	-18.1	-1.7	3.7	2.5	9.8	5.3	6.8
Bareilly	20.8	2.1	6.4	25.8	10.4	-6.2	0.5	6.0	5.4	5.5	0.2	-1.1
Rampur	31.3	29.8	16.5	38.2	18.4	8.8	30.4	-6.3	40.5	24.6	1.8	-6.0

Digital elevation model (DEM) was taken from SRTM (90m resolution) data, while soil data of Harmonized World Soil Database at 1: 50,000 scale was used for the soil classification and physical properties. Land use land cover data was collected from USGS at 1:50,000 scale for land use classification. The river basin was divided into Hydrologic Response Units (HRUs) based on land use and land cover records. Ramganga River basin was sub divided into 33 sub-basins using SWAT watershed delineation process and sub-basin discretization. It was further divided into 1644 HRUs. The model was parameterized for stream flow at five spatially distributed gauging stations of Bareilly,

Fig. 47 Impact of climate change on irrigated rice (top panels), rainfed rice (middle panels) and wheat (bottom panels) yield in Ramganga river basin in RCP 4.5 2020, 2050 and 2080 scenarios. The scale indicates yield change (%) from mean yield of 2010-2015 period.



Moradabad, Rampur, Fatehgunj and Dabari using their observed monthly average stream flow data. The SWAT simulation used initial three years data (1981-1983) to stabilize the initial conditions of the model. Ten years (1981-1991) observed data at gauging station were used to calibrate the model and another next ten years (1992-2001) data were used to validate the model. Most sensitive model parameters were also identified through calibration. Out of 17 hydrological parameters, 14 were identified as the most sensitive flow parameters and were used for calibration. The calibrated and validated SWAT model was used for future analysis with RCP (2020, 2050, and 2080) data. Water yield (surface water resources) was projected for each of the sub basins. The per cent change in mean monthly water yield under climate change (RCP 2.6, 4.5, 6.0, and 8.5) scenarios of 2020, 2050, and 2080 was calculated over the baseline. The analysis indicated that maximum mean monthly water yield to increase by 8 to 41 % in monsoon months except in RCP 4.5 (2050) during the 2020, 2050 and 2080 scenarios. However, in the month of March, October and December maximum decrease is projected in mean monthly water yield to the tune of -1 to -59 % during the 2020, 2050 and 2080, except in RCP 8.5. Water yield information for RCP 2.6

for 2020, 2050s and 2080s for each sub basin was further analyzed with respect to agricultural, domestic and industrial demand in each sub basin. Demand-side and supply-side adaptation measures are required to minimize the impact of climate change on water availability.

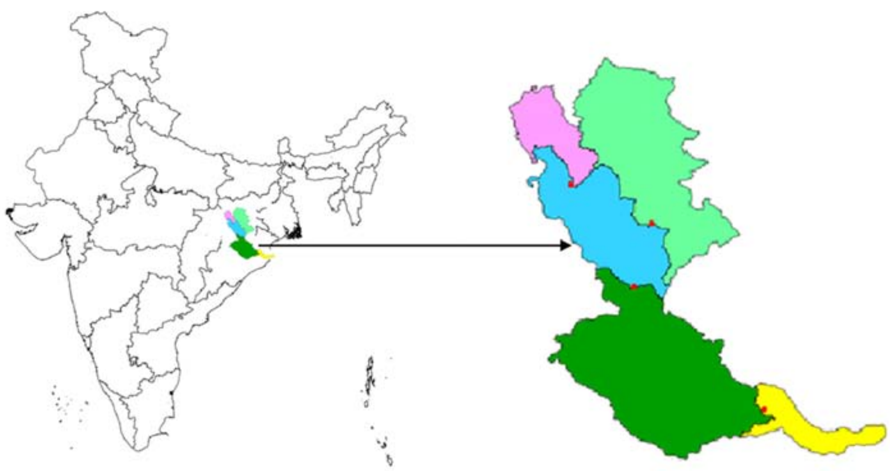
Under integrated modelling for assessing the impacts of climate change on crops in Ramganga river basin, InfoCrop wheat model was used to study the impacts in 2020, 2050 and 2080 climate scenarios in RCP 2.6, 4.5, 6.0 and 8.5 emission scenarios. The analysis indicated that climate change impacts on irrigated rice in this river basin are marginally beneficial. Wheat yield also may improve in upper catchment areas even with current management conditions. But in middle and lower catchment areas, wheat yield is projected to reduce substantially. Irrigation water scarcity in December will affect wheat productivity in middle and lower sub-basins. Additional irrigation sources need to be developed for meeting the crop water requirement in these regions in future climate scenarios.

Integrated modelling for selected river basins: Brahmani river basin

Modelling climate change impact on streamflow in Brahmani river basin

The Brahmani river basin is located in the eastern part of India and is situated within the latitudes of 20°30′10″ and 23°36′42″N and the longitudes of 83°52′55″and 87°00′38″E. Rainfed agriculture is predominant in the region except in the lower deltaic parts where irrigation plays a major role. Flood is recurring feature in the delta region. The problem of water scarcity as well as flood like situation may further aggravate under the changing climate scenarios. Hence, understanding the impact of future climate change in basin hydrology is essential for developing suitable water management adaptation plans.

Fig 48 Geographical location of Brahmani river basin and sub-basin catchment area



The US Geological Survey's Precipitation Runoff Modelling System (PRMS), a physical process based, distributed parameter modelling system was used for this study. The basin was delineated into 66 spatially distributed HRUs. The PRMS model was calibrated and validated using observed daily meteorological data (precipitation, maximum and minimum temperature) and daily streamflow data for the years 1980–1992. One-year data for the period 1979 – 1980 was used as a model warm- up period. Daily streamflow data were used to calibrate the annual water balance and daily runoff at the basin outlet, whereas estimated monthly potential evapotranspiration data were used to optimize PRMS evapotranspiration related parameters.

Climate change impact on streamflow in Brahmani river basin

Comparison of simulated hydrograph for different time horizons (2020, 2050 and 2080) with the baseline period showed an increase in streamflow for most of the projected climate change scenarios. Simulation results showed increase in stream flow in the basin under all the four RCPs during all the three future periods. The increase in streamflow varied from 1.4 to 2.4%, 8.0 to 13.2%, and 7.0 to 21.3% during 2020, 2050, and 2080 climate scenarios, respectively. In general, there is an increase in annual streamflow in the basin and it is in consistent with the increase in rainfall. Though there is an increase in temperature in the basin, changes in rainfall have greater effect on streamflow as compared to the change in temperature since the basin is located in sub-humid climatic condition (Islam *et al.*, 2012)

Fig 49. Changes in annual streamflow in the basin under different RCPs.

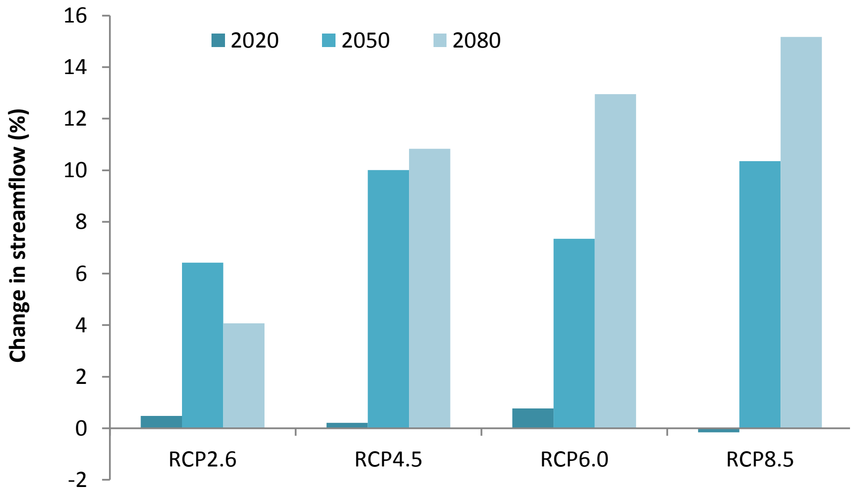
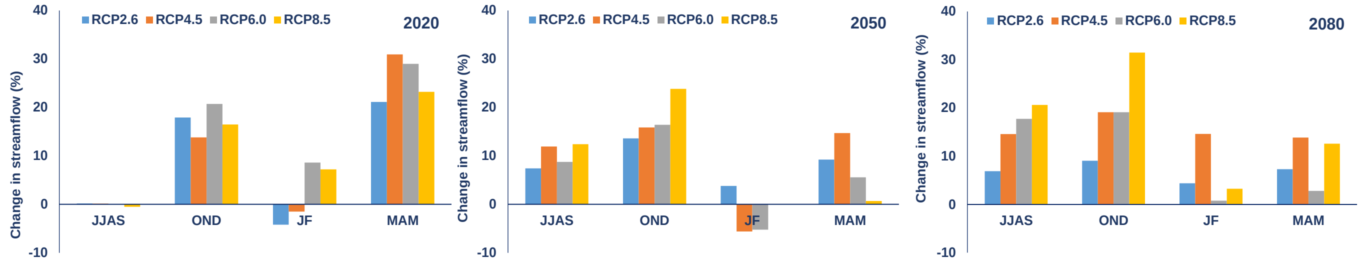


Fig 50. Changes in seasonal streamflow in the basin under different RCPs



Based on the analysis, it is projected that seasonal stream flow to increase during most of the seasons except during winter season (January and February) during 2020 and 2050. During monsoon (JJAS) season, projected increase in streamflow during 2020 is negligible (-0.5 to 0.2%), whereas during 2050 and 2080 the increase in streamflow is projected to range from 7.4 to 12.4% and 6.9 to 20.6%, respectively. During post-monsoon (OND) season, increase in streamflow is projected under all the four RCPs and during all the three future periods. The projected increase in post-monsoon season streamflow vary from 13.8 to 20.7%, 13.6 to 23.8% and 9.0 to 31.5% during 2020, 2050 and 2080, respectively.

Climate change impact on high and low flows in Brahmani river basin

For studying climate change impact on flow regimes ranging from high to low flows, Flow Duration Curves (FDC) were constructed for the baseline period and for each of the RCPs for the future periods of 2020, 2050 and 2080. We used Q5 and Q10 as high flow indices, and Q90 and Q95 as low flow indices for evaluating changes in high and low flow characteristics in the basin.

Fig 51 Changes in high flows during 2020, 2050 and 2080 in the Brahmani river basin

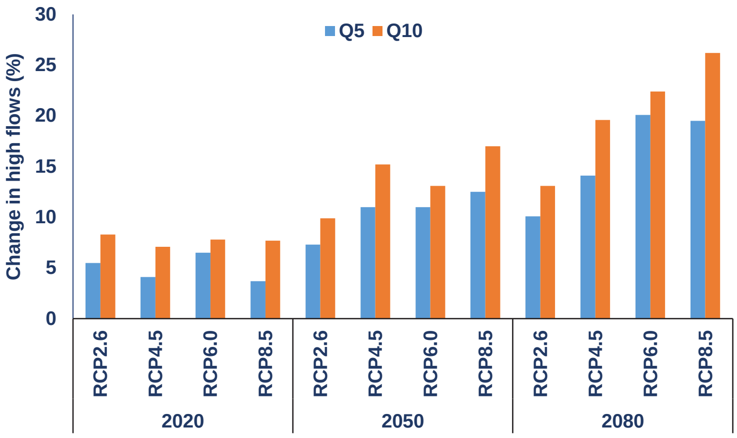
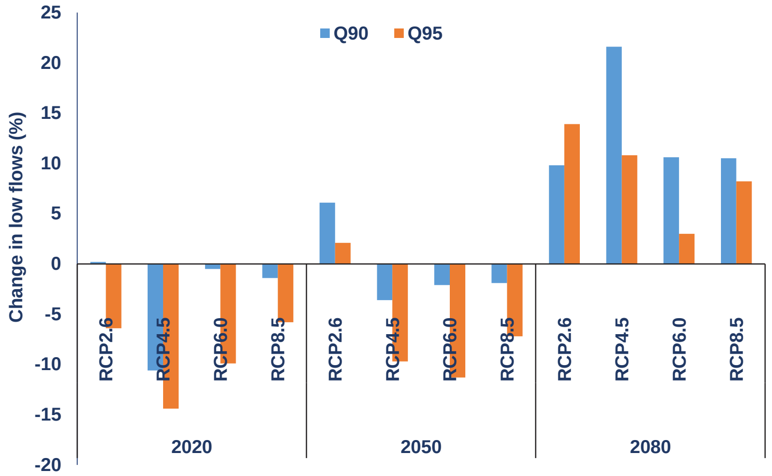


Fig 52 Changes in low flows during 2020, 2050 and 2080 in the Brahmani river basin



The results indicate an increase in high flows under all the RCPs during all the three future periods. The increase in Q5 ranged from 3.7 to 5.5%, 7.3 to 12.5%, and 10.1 to 19.5% during 2020, 2050 and 2080 scenarios. Similarly, the increase in Q10 is projected to range from 7.1 to 8.3%, 9.9 to 17.0%, and 13.1 to 26.2% during 2020, 2050 and 2080 scenarios. In 2020 scenario increase in high flows are projected to be lower under RCP 8.5 as compared to other RCPs, but during 2080 the increase in high flows is projected to be comparatively greater under RCP 8.5. Analysis of low flow indices indicated a decrease in the low flows in the basin during 2020 and 2050 under all the RCPs expect RCP 2.6 during 2050, and the decrease in low flows vary in the range of 0.5 to 14.4%, and 1.9 to 11.3% during 2020, and 2050, respectively. During 2080, increase in low flows are projected in the range from 3.0 to 21.6%

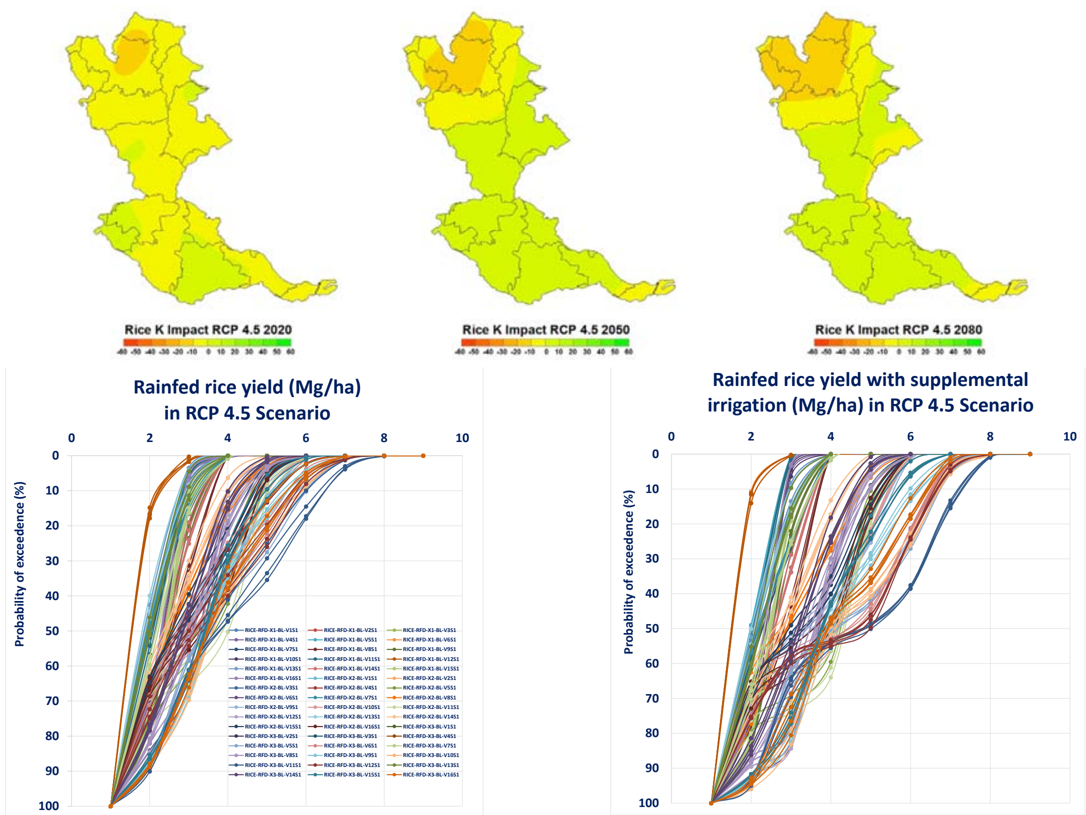
in all the four RCPs. The study thus revealed an increase in magnitude of flood flows while there is a reduction in magnitude of low flows under all scenarios during future periods. The water availability in the basin is dominated by monsoonal flows with low flows during the non-monsoon periods. This implies that greater attention might be needed to maintain environmental flows and developing drought management strategies in the basin. As the flood as well as water scarcity during non-monsoon period are causes of concern in the basin, water harvesting and storing excess water during monsoon and post-monsoon season as an adaptation strategy will help, not only to provide irrigation during rabi season but will also help to attenuate the flood peak during monsoon season. Further, temporal variation in the streamflow in the basin suggests the need for developing different irrigation water management adaptation strategies for crop planning.

Impact and adaptation assessment for rice crop

For integrated assessment of climate change impact, we run the PRMS and InfoCrop models in a loosely coupled mode. Simulation was further done after recalibrating the PRMS model matching InfoCrop simulated PET. After recalibrating the PRMS model with InfoCrop PET, simulation results showed slight decrease in change in annual stream flow. The annual streamflow varied from -0.2 to 0.8, 6.4 to 10.4, and 4.0 to 15.2% during 2020s, 2050s, and 2080s, respectively. This change is mainly due to higher consumptive use due to land use change in the basin.

In Brahmani river basin, InfoCrop based simulation analysis indicated that during kharif season the rice productivity is projected to have an increased inter-annual variability. Application of one supplemental irrigation provides opportunity to improve the rice yield from 4.5 Mg/ha to 6 Mg/ha at a similar probability level of 40%.

Fig. 53 Impact of climate change on rice yield in RCP 4.5 2020, 2050 and 2080 scenario in Brahmani river basin with and without supplemental irrigation. The scale indicates yield change (%) from mean yield of 2010-2015 period.



Composite hydrologic index for groundwater recharge in Betwa river basin

The Composite hydrologic indices (CHI) were developed for evaluating the recharge potential in the Betwa river basin. The prospect of groundwater recharge was assessed in relation to soil type, slope, R/P ratio and evapotranspiration. The Soil and Water Assssment Tool (SWAT) model was used to simulate the hydrologic response of the various Hydrologic Response Units (HRU) in Betwa basin. Groundwater recharge potential zones were divided into very good, good, moderate and low based on the four factors that affect groundwater recharge. Very good groundwater recharge is concentrated in the mixed forest region due to the distribution of sandy clay loam soil with high infiltration ability than clay and clay loam soil. The composite hydrologic index (CHI) for the study area was found to vary between 0.01 and 1. The upstream region is less important for groundwater recharge as most of water runoffs to lower region. However, in upstream region good groundwater recharge potential is possible because maximum region is under forest cover. More than half of the basin area is dominated with high runoff potential zone and is suitable for selecting rainwater harvesting structure. The suitable sites for water harvesting structures in each HRU having possibilities to increase the groundwater level are identified and mapped.

Fig 54 Geographical location of Betwa river basin and suitable sites for water harvesting structure

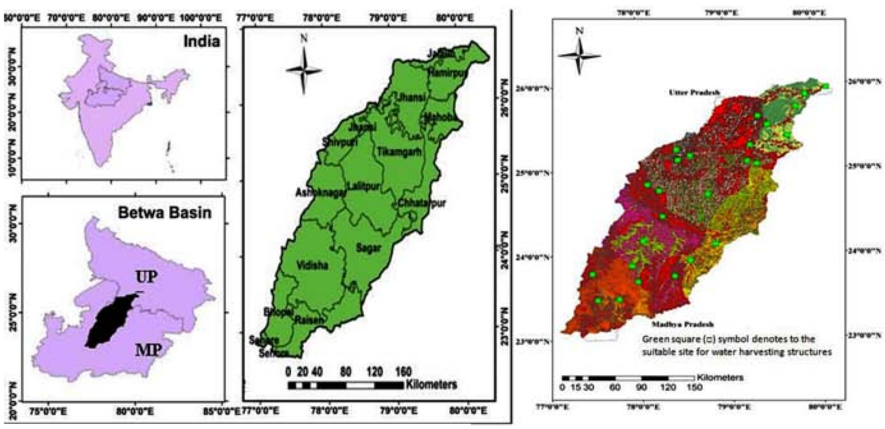


Table 3: Projected impact of climate change on mean annual water balance from baseline

	Per cent change in mean annual water balance from baseline		
Scenario	**RCP 2.6 (2020)**	**RCP 2.6 (2050)**	**RCP 2.6 (2080)**
Rain (mm)	-2.9	9.2	10.8
Surface Q (mm)	-9.7	29.1	33.9
Water Yield (mm)	-10.0	45.1	34.9
Scenario	RCP 4.5(2020)	RCP 4.5(2050)	RCP 4.5(2080)
Rain (mm)	2.1	-0.4	11.0
Surface Q (mm)	4.5	-3.8	30.0
Water Yield (mm)	4.5	-4.2	30.5
Scenario	RCP 6(2020)	RCP 6(2050)	RCP 6(2080)
Rain (mm)	0.00	5.9	5.8
Surface Q (mm)	-4.7	13.9	12.2
Water Yield (mm)	-4.9	14.7	42.2
Scenario	RCP 8.5 (2020)	RCP 8.5 (2050)	RCP 8.5 (2080)
Rain (mm)	-3.2	4.6	15.4
Surface Q (mm)	-12.4	15.3	48.9
Water Yield (mm)	-12.8	15.5	50.4

Publications (for 2017-2019 period)

1. Shweta Panjwani, S., Naresh Kumar, L. Ahuja and Adlul Islam. 2019. Prioritization of Global Climate Models Using Fuzzy Analytic Hierarchy Process and Reliability Index. Theoretical and Applied Climatology. https://doi.org/10.1007/s00704-018-2707-y (NAAS Rating 8.32)

2. Panjwani S,Naresh Kumar S,Ahuja L,Islam A (2019)"Evaluation of selected global climate models for extreme temperature events over India", Theoretical and applied Climatology.(under final revision) (NAAS Rating 8.32)

3. Mina,U., T.K. Chandrashekara, S. Naresh Kumar, M.C. Meena, S. Yadav, S. Tiwari, Deepak Singh, Pranav Kumar, Ram Kumar (2018). Impact of particulate matter on basmati rice varieties grown in Indo-Gangetic Plains of India: Growth, biochemical, physiological and yield attributes. Atmospheric Environment. https://doi.org/10.1016/j.atmosenv.2018.06.015 (NAAS rating 9.629)

4. Enli Wang, Pierre Martre, Zhigan Zhao, Frank Ewert, Andrea Maiorano, Reimund Rötter, Bruce Kimball, Michael Ottman, G. Wall, Jeffrey White, M. Reynolds, Phillip Alderman, Pramod Aggarwal, Jakarat Anothai, Bruno Basso, Christian Biernath, Davide Cammarano, Andrew Challinor, Giacomo De Sanctis, Jordi Doltra, E. Fereres, Margarita Garcia-Vila, Sebastian Gayler, Gerrit Hoogenboom, Leslie A Hunt, Roberto Izaurralde, Mohamed Jabloun, Curtis Jones, Kurt Kersebaum, Ann-Kristin Koehler, Leilei Liu, Christoph Müller, S Naresh Kumar, Claas Nendel, Garry O'Leary, Jorgen Olesen, Taru Palosuo, Eckart Priesack, Ehsan Rezaei, Dominique Ripoche, Alex Ruane, Mikhail Semenov, I. Shcherbak, Claudio Stöckle, Pierre Stratonovitch, Thilo Streck, I Supit, Fulu Tao, Peter Thorburn, Katharina Waha, Daniel Wallach, Zhimin Wang, Joost Wolf, Zhu Yan and Senthold Asseng (2017). The uncertainty of crop yield projections is reduced by improved temperature response functions" by Nature Plants. 3, 17102 (2017). DOI: 10.1038/nplants.2017.102 (NAAS Rating 17.47)

5. Har Vir Singh, S Naresh Kumar, G C Srivastava, R C Harit (2017). Recovery potential and yield of selected wheat (*Triticum aestivum*) varieties exposed to unseasonal rainfall stress. Ind J Agril Sci. Vol 87, No 4. 555–558 (NAAS Rating 6.23)

6. Har Vir Singh, S. Naresh Kumar, Naleeni Ramawat and R. C. Harit. 2017. Response of wheat varieties to heat stress under elevated temperature environments. Journal of Agrometeorology 19 (1): 17-22. (NAAS Rating 6.56)

7. Nitin Sharma, Archana Yadav, Sangeeta Khetarpal, Anjali Anand, Lekshmy Sathee, Ranjeet Ranjan Kumar, Bhupinder Singh, Naresh Kumar Soora, Suchitra Pushkar. 2017. High day–night transition temperature alters nocturnal starch metabolism in rice (*Oryza sativa* L.). Acta Physiologiae Plantarum, 39 (3), 74. (NAAS Rating 7.44)

8. Viswanath, K., P Sinha, S Naresh Kumar, Shalini Saxena, Taru Sharma, Shweta Panjwani, H Pathak and Shallu Shukla Mishra (2017). Simulation of leaf blast infection in tropical rice agro-ecology under climate change scenario. Climatic Change 142: 155-167; (NAAS Rating 9.54)

9. Ali Viani, P Sinha, Taru Sharma, L M Bhar (2017). A model for forecasting spot blotch disease in wheat. Australasian Plant Pathology 46: 601-609. (NAAS Rating 7.01)

10. Madhusudhan P, Sinha P, Rajput LS, Bhattacharya M, Sharma T, Bhuvaneshwari V, Gaikwad K, Krishnan SG, Singh AK (2019). Effect of temperature on Pi54-mediated leaf blast resistance in rice. World J Microbiol Biotechnol. 35(10):148. doi: 10.1007/s11274-019-2724-8. (NAAS Rating 8.10)

11. Dubey A, Sinha P, Baranwal V K, Mishra R, Saritha R K (2019). Temperature influence on leaf crinkle disease expression in urdbean (*Vigna mungo* (L.) Hepper) and potential distribution of the disease in India. Crop Pro-

tection DOI: 10.1016/j.cropro.2019.01.011. (NAAS Rating 7.68)

12. Viswanath, K., Taru Sharma, Shalini Saxena, P. Nagamani and P. Sinha (2017). Temperature influenced regulation of adenosine 30, 50 – cyclic monophosphate dependent protein kinase A in Magnaporthe grisea (T.T. Hebert), M. E. Barr. Proc. Natl. Acad. Sci., India, Sect. B Biol. Sci. DOI 10.1007/s40011-017-0845-0 (online February 6, 2017). (NAAS Rating 5.68)

13. L S Rajput, Taru Sharma, P Madhusudhan and P Sinha (2017). Effect of Temperature on Growth and Sporulation of Rice Leaf Blast Pathogen Magnaporthe oryzae. Int. J. Curr. Microbiol. App. Sci 6(3): dx.doi.org/10.20546/ijcmas. (NAAS Rating 5.38)

14. Rajput L S, Sharma T, Madhusudhan P, Kumar Sanjeev, and Sinha P. (2019). Role of various signalling pathways for glycerol synthesis in appressoria of Magnaporthe oryzae under climate change scenario. Res J Biotechnol 14: (accepted). (NAAS Rating 6.00)

15. Gurupirasanna PG., Chander S., Madan Pal, Soumia PS. 2018. Impact of elevated CO_2 on *Oryza sativa* phenology and brown planthopper, *Nilaparvata lugens* (Hemiptera: Delphacidae) population. Current Science 114:1767-1777. (NAAS Rating 6.84)

16. Pandi G. Guru Pirasanna1, Chander Subhash, Singh MP, Soumia P. S., Sujithra M. 2019. Imidacloprid efficacy against brown planthopper, *Nilaparvata lugens* under elevated carbon dioxide and temperature. Current Science 117(7):1194-1199. (NAAS Rating 6.84)

17. Dharavath V, Chander S., Sagar D. 2018. Impact of elevated carbon dioxide on the Protective enzymes in Brown Planthopper (BPH) and infested rice plants". Indian Journal of Agricultural Sciences 88 (9):1366-1370 (NAAS Rating 6.23)

18. Sagar D., Nebapure S., Chander S. 2017. Weather based prediction model for Helicoverpa armigera in chickpea. Journal of Agrometeorology 19(4): 328-333 (NAAS Rating 6.40)

19. Nebapure SM, Sagar D, Chander S. 2018. Population dynamics of insect pests on short duration pigeon pea in relation to weather parameters. Journal of Agrometeorology *20 (3): 234-237 (NAAS Rating 6.40)*

Book chapter

1. Naresh Kumar S. 2017. Improving Crop Adaptations to Climate Change: Contextualizing the Strategy. In Abiotic Stress Management for Resilient Agriculture (Eds Minhas, Paramjit, Rane, Jagadish, Pasala, Ratna Kumar). Pp Springer Pub. 277-298

2. Panjwani S,Naresh Kumar S,Ahuja L (2016). "Comparative study of classification techniques for weather data, ICACDS: First International Conference on Advances in computing and data sciences. https://www.springer.com/in/book/9789811054266

3. Panjwani S,Naresh Kumar S,Ahuja L (2019). "Multi-criteria decision making and its Application" Published in IJITEE through CONSILIO: International Conference on Smart and Intelligent Learning for Information Optimization .https://www.ijitee.org/download/volume-8-issue-9s4/

4. Panjwani S,Naresh Kumar S,Ahuja L (2019). "Bias Correction of GCM data using Quantile Mapping Technique", ICCCT : 2nd International Conference on Communication and Computational Technologies

5. L. S. Rajput, P. Madhusudhan and P. Sinha (2017). Epidemiology of seed borne diseases. In Seed Borne Diseases of Agricultural Crops: Detection, Diagnosis & Management (for Springer).

6. Chander S. 2018. Integrated Pest Management in Crops. In: Improved Agriculture and Allied Technologies for Farmers, (eds. Singh BK, Sharma Nishi). New India Publishing Agency, New Delhi.

7. Chander S. 2018. Integrated pest management practices for quality food under ICM approach, pp. 104-112. In: (eds. Chaudhary AK, Bana RS, Pooniya V.) Integrated crop management practices for enhancing roductivity, resource-use efficiency, soil health and livelihood security. ICAR-IARI, New Delhi, 217pp.

Students trained

Six PhD students were trained during the course of this study.

Acknowledgements

The authors sincerely acknowledge the financial support provided by the National Innovations in Climate Resilient Agriculture (NICRA) project. Sincere thanks are also to the Director, Indian Agricultural Research Institute (IARI), Joint Director (Research), IARI; ADG (AAF and CC), DDG (NRM), Director, CRIDA, PI, NICRA; DG, ICAR; Expert Committee Members, NICRA for their constant encouragement and support. The authors sincerely thank all others who directly or indirectly helped in this study.