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Statistical downscaling and projections of relative humidity in the Bhima sub-basin, India using change factor method

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सार – यह अध्ययनभविष्य के सापेक्षिक आर्द्रतापरिदृश्य के विश्लेषण के ज़रिए कृषि, जल विज्ञान और सिंचाई प्रबंधन जैसे मुख्य क्षेत्रों पर जलवायुपरिवर्तन से संभावित प्रभावों की जांच करती है। "चेंज फैक्टर मेथड" का उपयोग करकेहम सांख्यिकीयरूप से कम किए गए वैश्विकजलवायु मॉडल अनुकरण के एक संगठन का उपयोग करके भीमा सब-बेसिन में रोज़ाना की औसत सापेक्षिक आर्द्रता को निम्न स्तरपर घटाया जाता है। हमारा केंद्र अलग-अलग रिप्रेजेंटेटिव कंसंट्रेशन पाथवे (RCP) परिदृश्य के तहत औसत दैनिक सापेक्षिक आर्द्रता में परिवर्तन का आकलन करने पर है। निष्कर्ष सभी RCP पाथवे में सापेक्षिक आर्द्रता में लगातार गिरावट दिखाते हैं, जिसमें RCP 6.0 और RCP 8.5 जैसे उच्च उत्सर्जन परिदृश्य में अधिक स्पष्ट कमी देखी गई है। इसके अलावा, यह अध्ययनभविष्य के अनुमानों में अनिश्चितताओं की उपस्थिति पर भी प्रकाश डालती है, जो पारितंत्र और जल संसाधनों पर संभावित प्रतिकूल प्रभावों को कम करने के लिए लगातार निगरानी और अनुकूल उपायों की आवश्यकता पर ज़ोर देती है। बॉक्स-एंड-व्हिस्कर प्लॉट का उपयोग करते हुएविश्लेषण समय के साथ बढ़ी हुई अनिश्चितता को रेखांकित करता है, जिसमें भविष्य की अवधियों के लिए असममित डेटा वितरण और तिरछे प्रतिरूप हैं, जो दूर के भविष्य (2081-2100) के अनुमानों की तुलना में निकट भविष्य (2021-2040) के अनुमानों में अधिक विश्वास का सुझाव देते हैं। प्रदान की गई जानकारी भीमा सब-बेसिन के भीतर प्राकृतिक संसाधन प्रबंधन और जलवायु परिवर्तन शमन से संबंधित मजबूत नीतियों के निर्माण के लिए महत्वपूर्ण जानकारी प्रदान करती है। ये निष्कर्ष स्थानीय अधिकारियों को क्षेत्र की अनूठी विशेषताओं के अनुरूप एक व्यापक नीतिगत ढांचा बनाने की दिशा में शिक्षित करने और निर्देशित करने में सहायक हैं।

ABSTRACT. This study investigates the anticipated impacts of climate change on key sectors such as agriculture, hydrology, and irrigation management through the analysis of future relative humidity scenarios. Employing the Change factor method, we downscale daily mean relative humidity across the Bhima sub-basin using an ensemble of statistically downscaled global climate model simulations. Our focus lies in assessing changes in average daily mean relative humidity under various Representative Concentration Pathway (RCP) scenarios. The findings reveal a consistent decline in relative humidity across all RCP pathways, with higher emission scenarios like RCP 6.0 and RCP 8.5 exhibiting more pronounced reductions. Furthermore, the study highlights the presence of uncertainties in future projections, emphasizing the need for continued monitoring and adaptive measures to mitigate potential adverse impacts on ecosystems and water resources. Utilizing a box-and-whisker plot, the analysis underscores heightened uncertainty over time, with asymmetrical data distributions and skewed patterns for future periods, suggesting greater confidence in nearer-term (2021-2040) projections compared to distant future (2081-2100) estimations. The insights provided furnish crucial information for the formulation of robust policies concerning natural resource management and climate change mitigation within the Bhima sub-basin. These findings are instrumental in enlightening and directing local authorities towards the creation of a comprehensive policy framework customized to the unique characteristics of the region.

Key words – Statistical downscaling, Change factor, Future projections, Relative humidity, RCPs scenarios, Bhima sub-basin.

1. Introduction

The amount of water vapour in the air relative to saturation is known as relative humidity (RH). Its prediction plays a crucial role in increasing the accuracy of weather forecasting as it is a key indicator of precipitation forecasting. The change in saturated vapour pressure, which is also influenced by variations in wind speed, solar radiation, pressure, temperature, and air moisture content, causes a change in the RH. In the scientific community, the RH is thought to be a sensitive parameter because it influences many aspects of biotic and abiotic entities. Human, animal, and plant health are influenced by RH fluctuations, affecting the spread of pests and diseases and can create environments that either foster or inhibit the proliferation of pathogens and pests, directly impacting the health of living organisms (Wu, X. *et al*., 2016, Godde *et al*., 2021).Variations in RH can lead to moisture-related issues in buildings, including mold growth, deterioration of building materials, compromised structural integrity, emphasizing the importance of considering RH in construction and building maintenance (Chowdhary *et al*., 2013, Berger *et al*., 2015).

Evaporation and transpiration processes are profoundly impacted by changes in RH. High RH levels can impede the evaporation of water from surfaces, affecting processes like drying and water cycle dynamics (Li, Z., *et al*., 2021). Additionally, RH levels influence transpiration rates in plants, impacting their water regulation and overall growth (Chia & Lim, 2022). Understanding and addressing the implications of RH variations across these diverse domains are crucial for various fields, including public health, architecture, environmental science, and agriculture. Incorporating effective RH management strategies can help mitigate potential risks and optimize conditions for human, animal, and plant well-being, as well as for sustainable structural design and environmental management.

Relative humidity can be linked to several dynamic processes, including advection, convection, and subsistence, which drive temperature variations. Additionally, RH is associated with diverse forms of diabatic heating, such as the absorption of radiation & the release of latent heat. The phase changes in the atmosphere, like cloud formation and precipitation, further contribute to these properties (Dinh & Fueglistaler, 2019). These inherent characteristics of RH explain its wide-spread application in various contexts: (*i*) its integration in mesoscale models to parameterize cloud radiative effects (Park *et al*., 2018); (*ii*) inclusion in crop simulation models, demonstrated by the Erosion Productivity Impact Calculator (EPIC) model (Wu, Y *et al*., 2021); (*iii*) utilization in estimating evapotranspiration, such as in the Penman-Monteith model (Moratiel *et al*., 2019); (iv) incorporation in climate change impact models (Javadinejad *et al*., 2020; Bourdin *et al*., 2021; Shad *et al*., 2022); (*v*) its role in modeling greenhouse gases ; (*vi*) application in analyzing urban environments (Kayes *et al*., 2019); and (*vii*) its relevance in hydrologic models (Ricard & Anctil, 2019). Therefore, it becomes imperative to evaluate the implications of climate change attributed to RH at both global and local scales, considering its significance across multiple scientific disciplines and its impact on various environmental processes.

For researchers and decision-makers evaluating the influence of climate change on aspects such as agriculture, hydrology, and irrigation management, it is essential to have access to future scenarios of relative humidity. According to Auer *et al*. (2021) scenarios enable a more comprehensive understanding of the potential impacts of climate change on various sectors and facilitate the development of appropriate adaptation and mitigation strategies to address the challenges posed by changing relative humidity conditions. The future is inherently unpredictable and difficult to foresee accurately. However, a scenario offers a credible depiction of potential future developments. To evaluate the uncertainty and gaps in knowledge linked to the future, a range of scenarios are employed. These scenarios help in understanding and planning for a spectrum of potential outcomes, allowing for more comprehensive and adaptable strategies to navigate the uncertainties ahead (IPCC 2018). Global climate models (GCMs) play a crucial role in formulating projections of future climate change based on predefined emission scenarios (Anandhi *et al*., 2009). However, the direct application of GCM output at a regional scale is hindered by the discrepancy in spatial resolutions between GCMs and local observations, as well as the requirements for conducting local impact assessments (Fowler *et al*., 2007). This necessitates the use of downscaling techniques to bridge the gap between the global scale represented by GCMs and the finer, localized scale needed for accurate regional impact assessments.

Researchers have adopted several approaches to develop future climate scenarios at a regional scale, namely, drawing analogies with distinct climatic zones or specific historical time periods (Degroot *et al*., 2022), utilizing global climate model data through straightforward adjustments of present climate observations - commonly known as the change factor methodology (Anandhi *et al*., 2011) & employing advanced statistical & dynamical downscaling techniques to derive more refined projections, as highlighted by studies such as Anandhi *et al*. (2011), Ghosh *et al*., (2012) and Ahmed & Kazi (2013). These methodologies enable

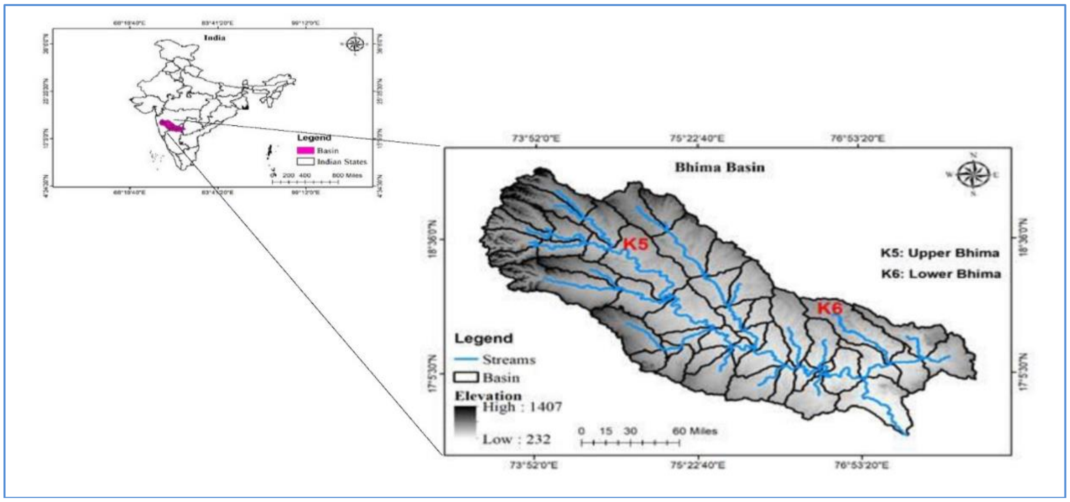

Fig. 1. Location map of the Bhima sub-basin; Upper Bhima (K5) and Lower Bhima (K6) (study area)

understanding of regional climate changes and help to generate more accurate and localized climate projections. The objective of this study is to evaluate the performance of the Change Factor (CF) method for statistically downscaling future scenarios of relative humidity.

2. Study area and data

2.1. *Study area*

The Bhima River originates in the rain shadow region of the Western Ghats in India and serves as a significant tributary of the Krishna River. The Bhima sub-basin (as shown in Fig. 1), covering an area of 70,263 km^2, is situated between latitudes 15° N to 20° N & longitude 73° E to 78° E. Flowing southeast through Maharashtra for approximately 750 kilometers, it shares the catchment basins of Karnataka and Telangana states. About two-thirds of the population in this basin depends on agriculture as a primary source of income & livelihood. Agricultural activities here consume a substantial amount of water & studies by Garg et al. (2011), Surinaidu (2013), Kumbhar, 2014 & Udmale *et al.* (2014) highlight potential impacts of climate change on the water resources sector, including prolonged droughts, reduced monsoon rainfall, environmental degradation ecosystem imbalances (Samal & Gedam, 2021). Hence, it is imperative that the local government is informed of the need for robust & resilient policies to manage natural resources & implement climate change mitigation measures in the Bhima sub-basin."

2.2. *Data*

Climate research offers a plausible depiction of the future and its progression, considering various inputs such as greenhouse gas emissions, socio-economic changes, technological advancements, and more. These inputs serve as crucial components for climate modeling. Consequently, the acquisition of climate data is essential for predicting climate-induced impacts on ecosystems (De Caceres *et al*., 2018). The Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report (AR5) identifies Representative Concentration Pathways (RCPs) as key scenarios for climate change studies. These pathways, including RCP8.5, RCP6, RCP4.5, & RCP2.6, serve as benchmarks for understanding potential future climate conditions. This research specifically focuses on downscaling relative humidity from Global Circulation Models (GCMs) using Representative Concentration Pathways (RCPs) such as RCP 2.6, 4.5, RCP 6.0, & RCP 8.5. GCMs enable the estimation of potential climate changes based on greenhouse gas concentrations and can simulate the climate system's reliability using mathematical functions (Nahar & Sharma, 2017).

Global Climate Models (GCMs) function at a coarse scale, creating a disparity between their capabilities & the hydrological needs required for impact studies. To bridge this gap, Wilby *et al*. (2004) devised statistical models that establish connections between the coarse-scale GCM outputs and regional hydrological variables, necessary for assessing the impacts of a changing climate, using observed datasets at a finer scale. This study considers the GCMs presented in Table 1, following the ranking proposed by Raju *et al*. (2018) for the Godavari & Krishna Basins in India, which include the Bhima sub-basin.

3. Methodology

Statistical downscaling, emphasized by Tripathi *et al*. (2006), is an efficient technique requiring less computational effort compared to dynamic downscaling

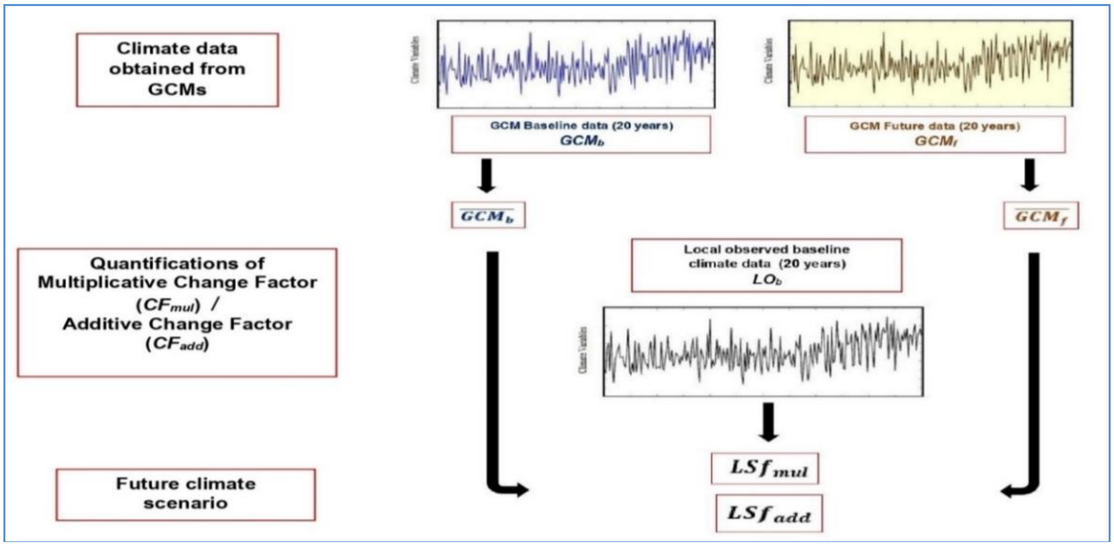

Fig. 2. Flowchart illustrating future scenario assessment with the change factor approach (Laddimath *et al.* 2021)

TABLE 1

List of General Circulation Models (GCMs) Utilized in the Research.

Sl. No.	Model Name	Model Centre
1	MIROCESM_ CHEM	Agency for Marine (Japan) - Earth Science and Technology, Atmosphere and Ocean research institute for environmental studies
2	MIROC5	
3	CSIRO-Mk3.6	Commonwealth Scientific and Industrial Research Organization
4	NorESM1 - M	Bjerknes Climate Research Centre, Norwegian Meteorological Institute Norway
5	GFDL-CM3	Geophysical Fluid Dynamics Laboratory USA

although it has certain limitations (Wangsoh *et al*., 2017). This method is widely used to study the impact of climate change on water resources in hydrological modelling. Particularly. the Change Factor (CF) approach is notable for its simplicity and efficiency in modeling multiple Global Climate Models (GCMs) and emission scenarios (Anandhi *et al*., 2011; Sunyer *et al*., 2015; Agilan and Umamahesh, 2016; Hosseinzadehtalaei *et al*., 2018; Van Uytven *et al*., 2020 and Vishnu *et al*., 2022).

"The CF method' s reliability is due to its adaptability, which allows for the direct scaling of local data based on projected changes from GCM models. In this approach, factors that represent the 'difference' or 'ratio' of each GCM for specific scenarios are computed. These factors are then applied to observed historical climate data (baseline period: 1986-2005) to project future climate variables (long-term monthly average data for future periods, such as 2021-2040, 2041-2060, *etc*.). Comprehensive details on downscaling climate variables using the CF method can be found in studies by Anandhi *et al*. (2011), Sunyer *et al*. (2015), and Agilan and Umamahesh (2016). Additionally, a brief discussion provided below:

The Additive Change Factor (ACF) and Multiplicative Change Factor (MCF) methods are used for scaling climate variables. The ACF method calculates the difference between future and current GCM simulations (Equation 1), while the MCF method calculates their ratio (Equation 2). Future values are then scaled using these factors, as shown in Equations 3 and 4. Fig. 2 describes the procedure for assessment of future scenarios using CF.

$$CF_{add} = (\overline{GCM_f} - \overline{GCM_b}) \quad (1)$$

$$CF_{mul} = (\overline{GCM_f})/(\overline{GCM_b}) \quad (2)$$

$$LSf_{add,i} = LOb_i + CF_{add} \quad (3)$$

$$LSf_{mul,i} = LOb_i \text{ x } CF_{mul} \quad (4)$$

4. Results and discussion

4.1. *Assessment of Downscaled Relative Humidity Results*

Historical values serve as references to compare and contrast present and future climate conditions. A spatial map of the historical era (1986-2005) shown in Fig. 3 illustrates the variation in daily mean relative humidity as a percentage across the Bhima sub-basin, derived from NCEP/NCAR data. This map highlights the spatial distribution and patterns of relative humidity, providing a baseline for assessing changes over time. By examining

TABLE 2

Average change (%) in relative humidity over the basin derived from the ensemble average of projections from five GCMs

Scenario(s)	Month Time Series	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
RCP2.6	2021-2040	0.8917	-7.8887	-16.785	-14.123	-1.1144	3.8976	1.0748	2.1975	-0.077	2.6965	3.2296	1.2677
	2041-2060	3.1854	-6.5742	-13.124	-14.616	-6.9262	2.3553	2.2494	2.6462	0.3395	1.6325	1.9313	4.2085
	2061-2080	2.6111	-11.126	-16.511	-19.168	0.4679	3.8705	1.2704	2.2756	-1.2058	0.5901	3.4957	0.667
	2081-2100	1.1573	-11.067	-15.636	-18.333	0.8745	4.9994	2.31	1.6628	-0.8979	1.7004	2.8114	0.7102
RCP4.5	2021-2040	-0.1412	-12.019	-13.993	-13.822	-4.051	2.1303	1.9159	3.4683	0.045	1.7273	3.3887	3.0993
	2041-2060	0.923	-7.8528	-11.721	-12.17	-0.9728	1.2822	2.2561	2.842	-0.2253	1.9957	1.7563	-0.6179
	2061-2080	0.8461	-8.211	-12.775	-13.742	2.7883	7.4722	3.5385	2.9032	0.6287	2.5146	4.0032	-0.1538
	2081-2100	-1.3983	-15.503	-19.92	-19.466	-1.9299	3.6556	3.0791	2.4374	-1.0647	1.0488	1.9383	-2.0644
RCP6.0	2021-2040	1.0574	-10.356	-16.697	-19.661	-5.5808	4.419	2.2122	2.5641	-0.3602	1.2167	3.4427	1.1777
	2041-2060	0.2551	-11.664	-17.915	-20.436	-3.9845	1.7085	0.9348	1.6392	-1.4638	0.6118	3.7601	2.732
	2061-2080	-5.2801	-18.143	-17.715	-13.192	0.8045	3.8461	1.0787	0.8225	-3.5964	-1.6478	0.0586	-3.6799
	2081-2100	-13.914	-27.534	-30.126	-25.043	-7.6125	1.0956	-0.8293	-0.8313	-4.6586	-4.777	-2.3178	-11.094
RCP8.5	2021-2040	4.4582	-5.744	-11.994	-15.265	-2.0816	1.2757	1.1739	2.6695	-0.3575	1.9524	2.8715	4.0986
	2041-2060	2.5455	-8.0595	-12.37	-13.663	-2.8678	3.7274	2.2855	3.2702	-0.0348	2.563	5.6103	4.4525
	2061-2080	-4.7727	-19.594	-27.34	-23.837	-6.6166	0.044	1.4333	2.2867	-1.295	-0.3286	0.2377	-2.7837
	2081-2100	-3.8087	-18.043	-29.229	-23.359	-5.2111	1.4579	-0.0533	1.3844	-1.1825	-0.3839	-1.091	-4.897

these historical trends, one can identify areas of significant deviation and better understand the impacts of climate variability on the region. This analysis is crucial for developing adaptive strategies & enhancing the resilience of water resources management in the Bhima sub-basin.

4.2. *Projection of future changes of downscaled relative humidity*

The percentage (%) change in daily mean relative humidity is calculated utilizing equation 5 as outlined below. Spatial maps and histograms depicting the percentage change in the average daily mean relative humidity, estimated from ensemble averages in RCP 2.6, 4.5, 6.0, and 8.5 scenarios, are presented in Figures 4, 5, 6, and 7 respectively.

$$\%\,\Delta = \frac{T_2 - T_1}{T_1} \times 100 \qquad (5)$$

T_1 and T_2 represent historical and future periods respectively.

According to the ensemble average for the RCP 2.6 scenario, the anticipated relative humidity shows a declining trend in comparison to historical values, with values of -1.0%, -0.85%, -1.85%, and -1.8% for each of the 20 years intervals from 2021 to 2100 (*i.e.* 2021-40; 2041-60; 2061-80 & 2081-2100). About 12 grid sites in the basin show considerably larger variations in forecasts of mean decreasing relative humidity from 2061 to 2080. According to the RCP 4.5 scenario, relative humidity will decrease between 2021 and 2100 by -1.05%, -1.0%, +0.1%, and -2.5% compared to historical values. About 11 grid sites in the basin show considerably larger changes in relative humidity forecasts from 2081 to 2100.

From 2021 through 2100, the RCP6.0 scenario indicates declining trends in relative humidity with -1.8%, -2.1%, -4.0% and -9.0% reductions from historical values. From 2081 to 2100, around ten grid sites in the basin show comparatively larger variations in relative humidity forecasts. The RCP 8.5 scenario also indicates declining trends in relative humidity from 2021 to 2100, with -0.5%, -0.1%, -5.0% and -5.0% reductions from historical values. From 2081 to 2100, around 13 grid sites in the basin show considerably larger variations in relative humidity forecasts. Table 2 shows the month-by-month average percentage (%) changes in basin relative humidity based on the ensemble average of estimates from five GCMs.

4.3. *Decadal changes in relative humidity*

Based on the Table 2, which showcases the average change (%) over the basin in relative humidity based on the ensemble average of projections from five GCMs, the following inferences can be drawn:

RCP 2.6: The relative humidity shows a mixed pattern of increase and decrease over the basin across different months and time series. While some periods

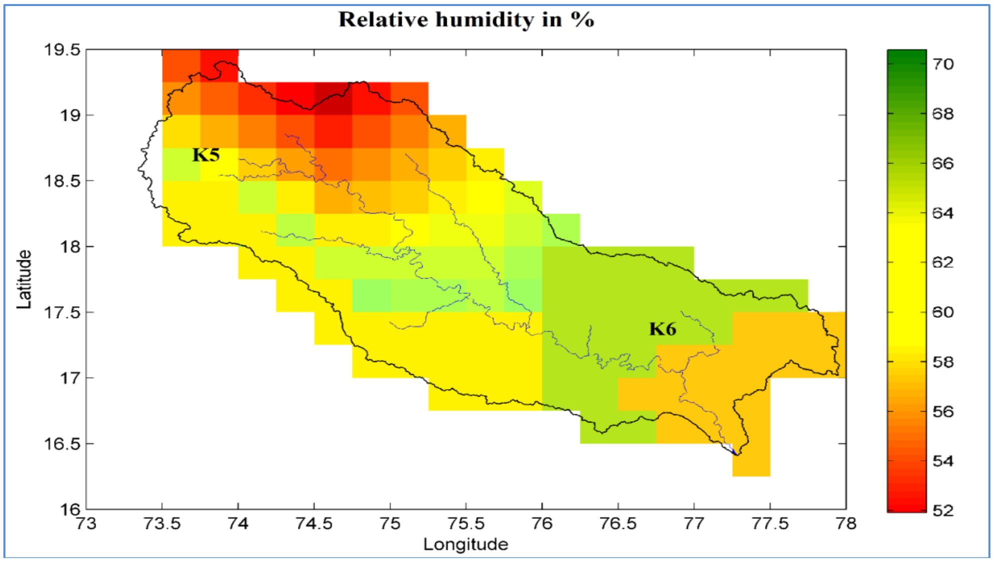

Fig. 3. Average daily mean relative humidity (%) over the basin during 1986 -2005

TABLE 3

Variations in the Average Mean Relative Humidity (%) across the Bhima Sub-Basin Considering GCM and Scenario Uncertainties

Period	Max.	Mean	Min.	Max. % change	Mean % change	Min. % Change
2021-2040	63	60.63	58.75	2.02	-1.81	-4.86
2041-2060	63.08	60.88	58.04	2.15	-1.41	-6.01
2061-2080	62.78	60.66	56.38	1.67	-1.77	-8.7
2081-2100	62.76	59.69	52.76	1.64	-3.34	-14.56

Note: The average mean relative humidity over the basin during 1986-2005 is 61.75%

exhibit a significant increase, such as in June and November during 2021-2040 and 2041-2060, there are instances of significant decrease as well, particularly in March and April.

RCP 4.5: The relative humidity demonstrates a fluctuating pattern, with both positive and negative changes across different months and time periods. Notably, the months of February, March, and April experience a decrease in relative humidity in the latter half of the century (2081-2100).

RCP 6.0: Relative humidity experiences a notable decrease over the basin, especially in the latter time periods (2061-2080 and 2081-2100) for most months, with the most significant reductions seen in the months February, March, and April.

RCP 8.5: The relative humidity displays a consistent decreasing trend throughout the future time periods across all months and time series. Particularly substantial reductions are observed in the months of February, March, and April, especially in the latter half of the century (2081-2100).

These inferences suggest that different RCP scenarios have varying impacts on the relative humidity over the basin, with RCP8.5 indicating the most significant and consistent decrease, followed by RCP6.0, RCP4.5, and RCP2.6, in that order.

4.4. *Quantification of uncertainty in statistical downscaling*

Statistical downscaling helps provide detailed information at finer resolutions for understanding regional impacts and adapting to changes. Thus, it's crucial to measure the uncertainty linked with climate change impacts. This study evaluates results from General Circulation Models (GCMs) using four different Representative Concentration Pathway (RCP) scenarios to understand the level of climate change, considering both

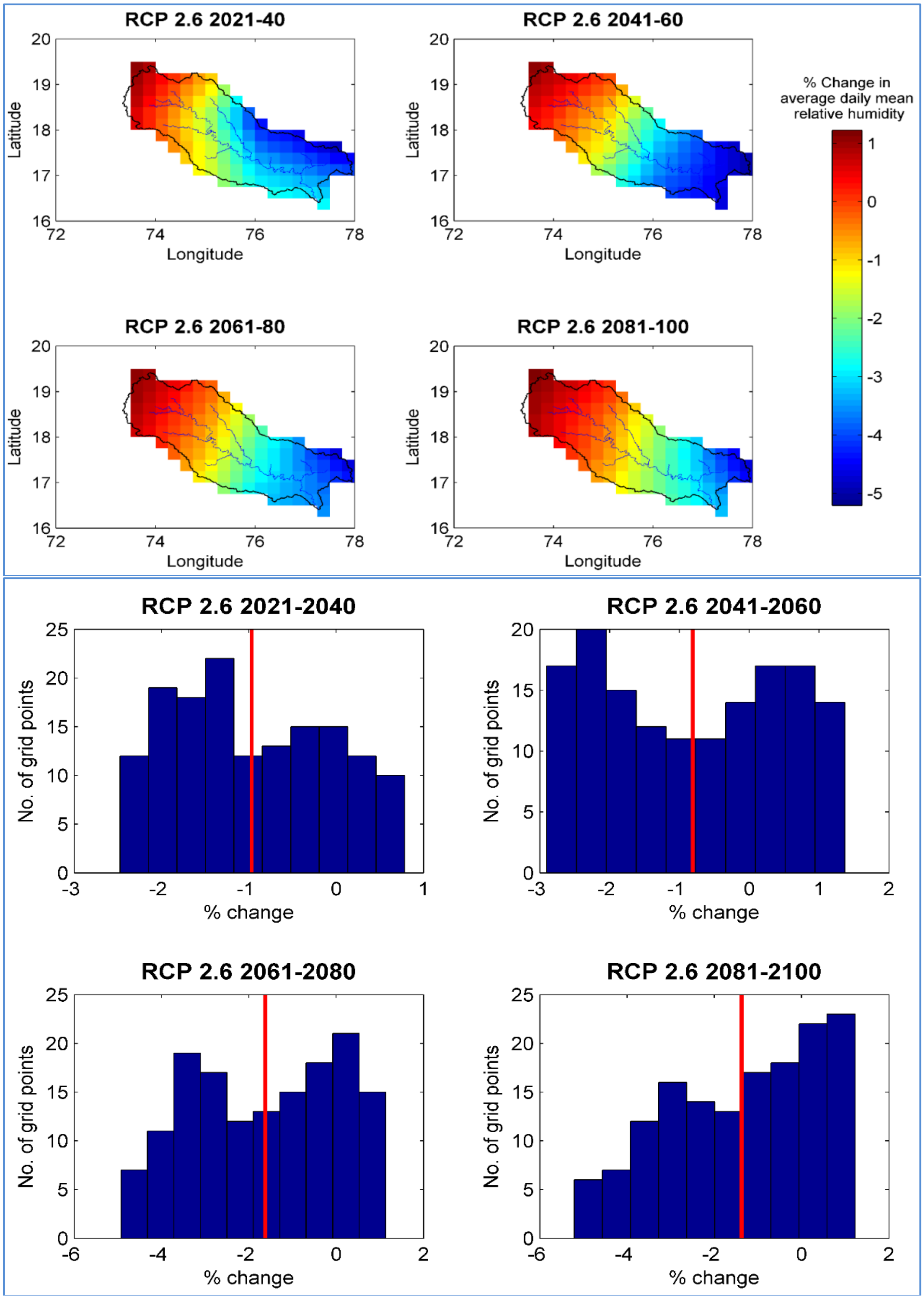

Fig. 4. Spatial maps (top 4 panels) and histograms (bottom 4 panels) showing the percentage change in average daily mean relative humidity projected from ensemble averages in the RCP 2.6 scenario. The red line in the histograms denotes the mean percentage change

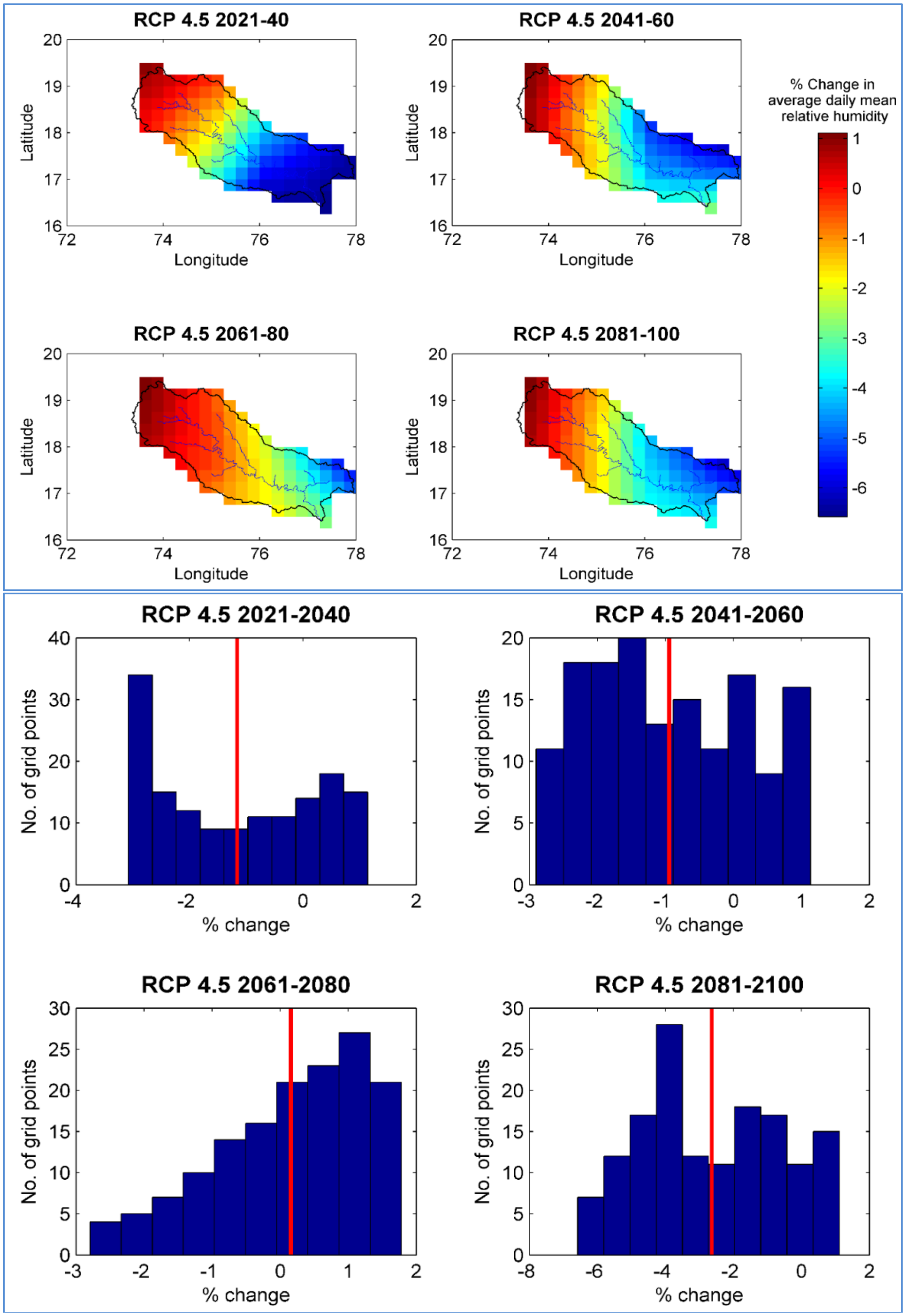

Fig. 5. Spatial maps and histograms showing the percentage change in average daily mean relative humidity projected from ensemble averages in the RCP 4.5 scenario

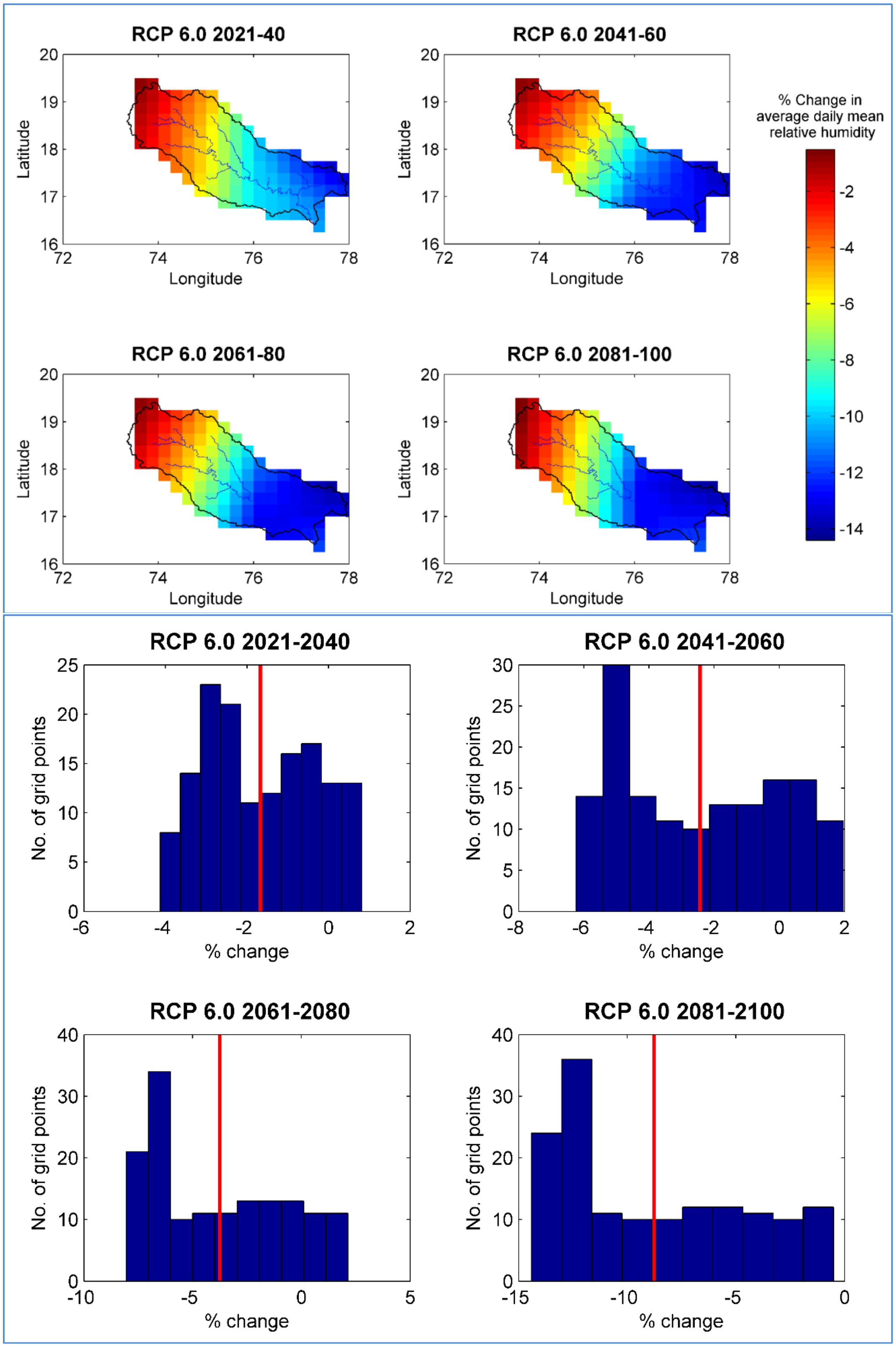

Fig. 6. Spatial maps and histograms showing the percentage change in average daily mean relative humidity projected from ensemble averages in the RCP 6.0 scenario

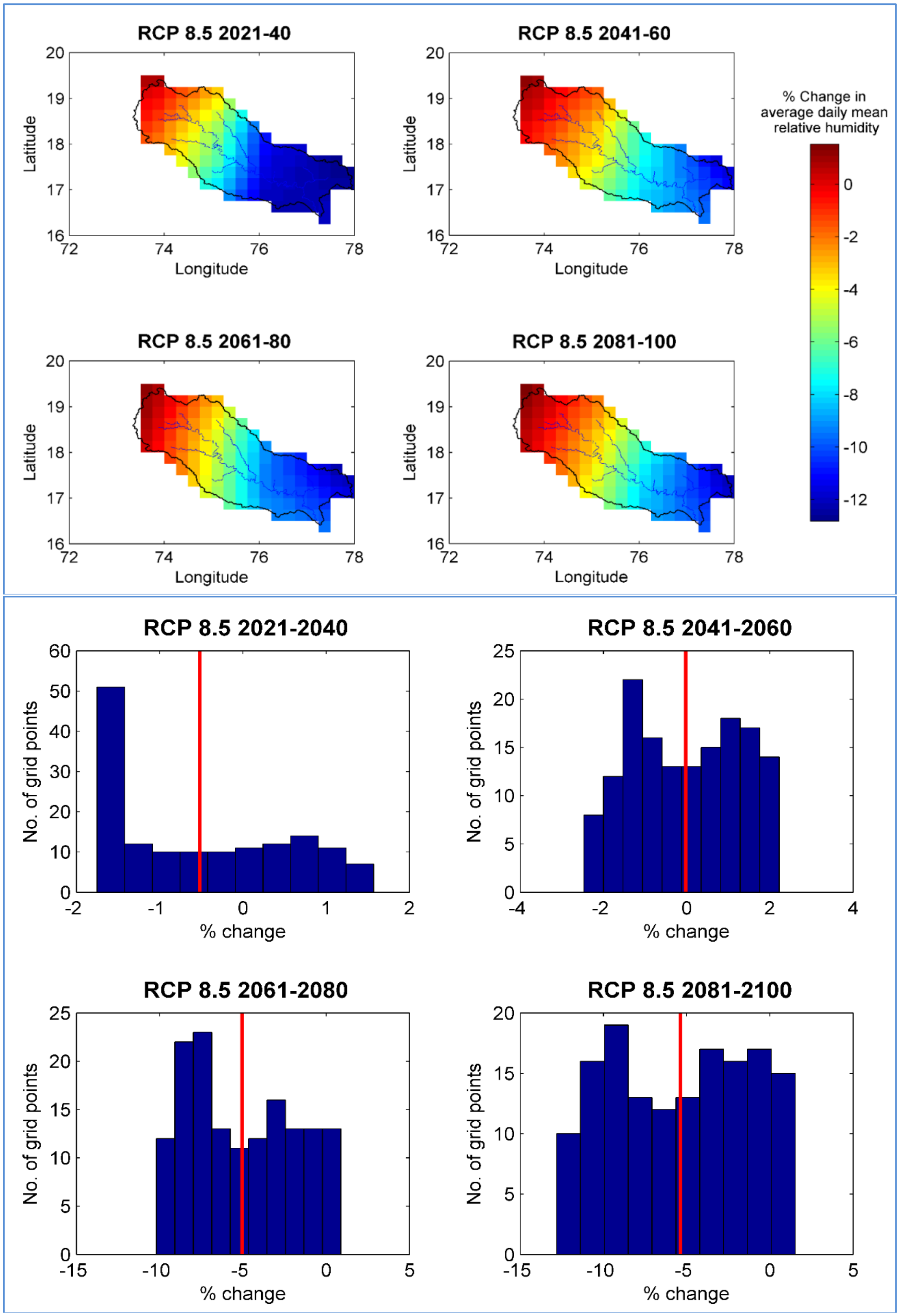

Fig. 7. Spatial maps and histograms showing the percentage change in average daily mean relative humidity projected from ensemble averages in the RCP 8.5 scenario

TABLE 4

Fluctuations in Average Mean Relative Humidity (%) across the Bhima Sub-Basin (Scenario Uncertainty)

Period	Max.	Mean	Min.	Max. % change	Mean % change	Min. % Change
RCP 2.6						
2021-2040	62.99	60.891	58.791	2.42	-0.99	-4.4
2041-2060	62.55	60.947	60.347	1.7	-0.9	-1.88
2061-2080	61.43	60.332	59.832	-0.11	-1.9	-2.71
2081-2100	61.49	60.393	59.693	-0.01	-1.8	-2.94
RCP 4.5						
2021-2040	62.36	60.762	60.162	1.4	-1.2	-2.18
2041-2060	62.89	60.891	59.741	2.26	-0.99	-2.86
2061-2080	62.81	61.562	60.412	2.13	0.1	-1.77
2081-2100	62.25	60.147	58.547	1.21	-2.2	-4.8
RCP 6.0						
2021-2040	63.33	60.332	58.332	2.98	-1.9	-5.15
2041-2060	64.21	60.209	58.209	4.4	-2.1	-5.35
2061-2080	63.42	58.917	56.417	3.12	-4.2	-8.27
2081-2100	61.47	55.965	51.465	-0.06	-9	-16.32
RCP 8.5						
2021-2040	62.99	61.193	60.093	2.43	-0.5	-2.29
2041-2060	63.54	61.039	59.439	3.31	-0.1	-3.35
2061-2080	61.83	59.125	55.725	0.53	-5	-9.39
2081-2100	61.56	58.864	56.064	0.1	-5.1	-8.84

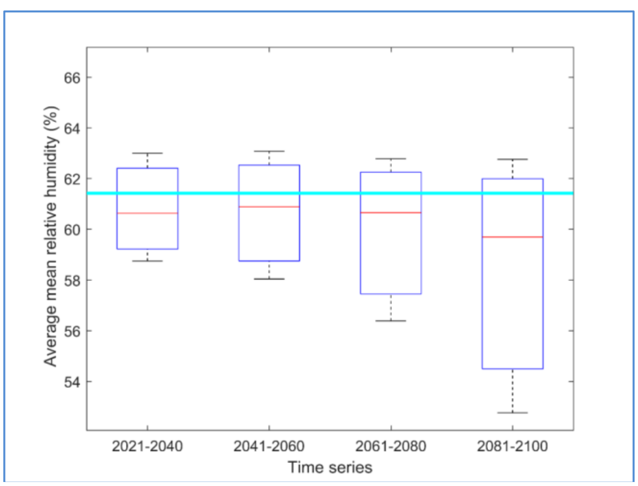

Fig. 8. Representation of GCM and Scenario Uncertainty in Climate Change Impact on Average Mean Relative Humidity over the Bhima Sub-Basin

GCM and scenario uncertainties. To simplify, we averaged data across the basin rather than analyzing every grid in the IMD. Figs. 8-9 and Tables 3-4 show the expected changes in climate variables from 2021 to 2100 compared to the historical period (1986-2005). We used a box-and-whisker plot to understand the data patterns and identify uncertainty levels.

Looking at Table 3 and Fig. 8, we see a decrease in the average percentage change for relative humidity over time. The box plot for 2041-2060 shows a balanced distribution, while projections for 2021-2040, 2061-2080, and 2081-2100 have skewed distributions, indicating higher uncertainty, especially in later years.

To gain a comprehensive understanding of the spatial variability of uncertainty propagation, our analysis focused on the GCM, incorporating scenario uncertainty in climate change impacts on average mean relative humidity. Table 4 delineates alterations in the average mean relative humidity. In Fig. 9, scenario uncertainty for the average mean relative humidity is illustrated through skewed box plots for projections during the 2061-2080 and 2081-2100 time periods for RCP 2.6, RCP 6.0, and RCP 8.5. Their median values deviate within the range of -1.18% to -5.1% from the historical observed value. Moreover, relatively less uncertain projections are discernible in the symmetric box plots for the 2041-2060 time slots.

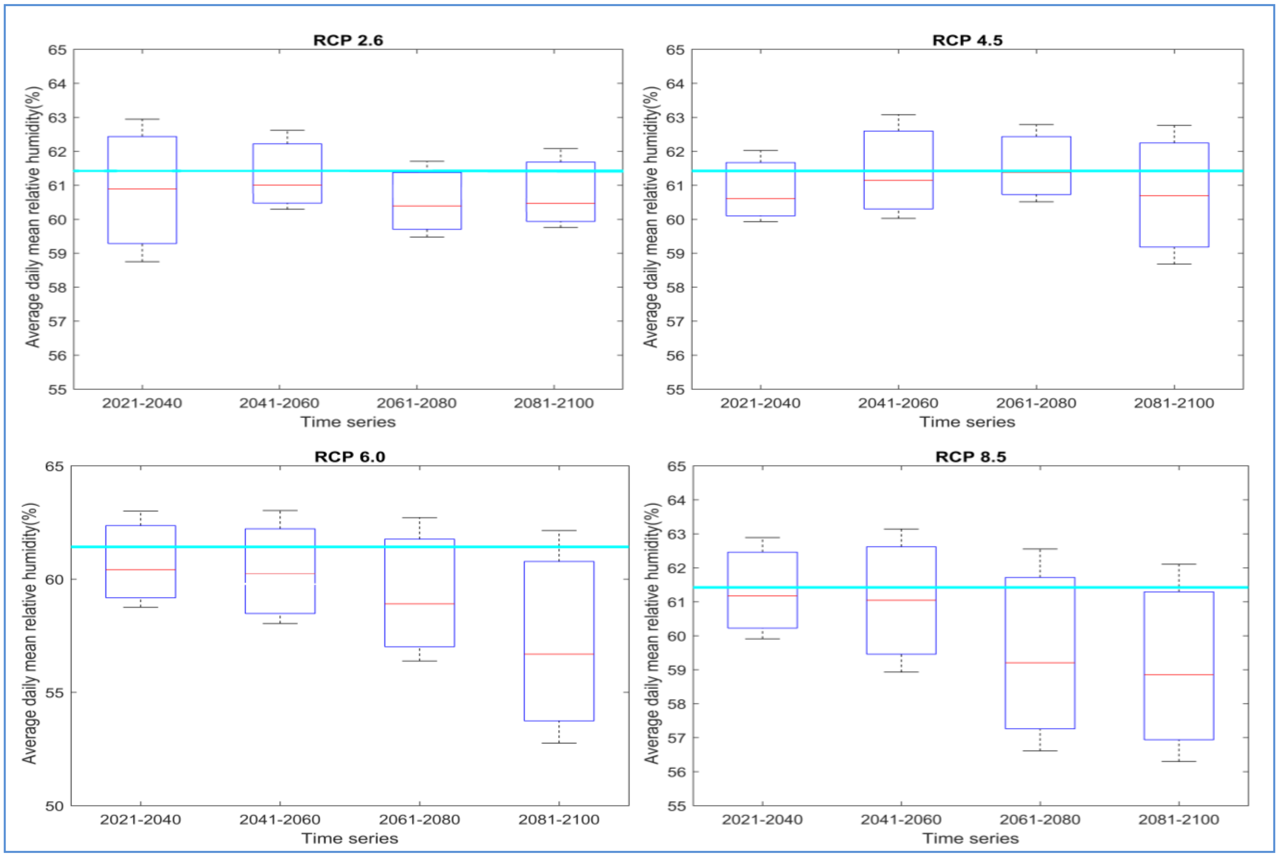

Fig. 9. Depiction of Scenario Uncertainty in Climate Change Impact on Average Daily Mean Relative Humidity Across All Four RCP Scenarios

5. Summery and conclusion

The study examines the changes in average daily mean relative humidity over Bhima sub-basin under different Representative Concentration Pathway (RCP) scenarios. The analysis demonstrates a consistent decline in average daily mean relative humidity across all RCP scenarios, suggesting a potential drying trend in the concerned sub-basins. The results underline the significance of considering various climate change scenarios, especially the higher emission pathways like RCP 6.0 and RCP 8.5, which exhibit more drastic declines in relative humidity. The presence of unusual occurrences in certain time periods emphasizes the need for continued monitoring and adaptive measures to mitigate potential adverse impacts on ecosystems and water resources in the sub-basins.

While many previous studies have attempted to comprehend the climate system and enhance its simulation, the reduction of uncertainties in future projections remains limited. The investigations concerning climate change impact assessment, accomplished through downscaled General Circulation Model (GCM) outputs, are constrained by a range of uncertainties associated with the GCM utilized and scenario variability. Employing a box-and-whisker plot in this analysis revealed trends in data projections, indicating a heightened uncertainty over time. Specifically, the data distributions in the 2061-2080 and 2081-2100 time slots displayed asymmetrical box plots and skewed patterns. As a result, the study expresses a greater degree of confidence in the projections for the nearer future (*i.e.*, 2021-2040) due to the symmetric data distribution, compared to those for the distant future (2081-2100). These findings offer valuable insights for evaluating the evolving climate conditions, facilitating the formulation of robust and resilient policies for natural resource management and climate change mitigation in the Bhima sub-basin. These insights can be effectively communicated to local authorities through a comprehensive policy document.

Competing Interests

The authors declare no competing interests.

Conflict of interest

The author declares that the publishing of this manuscript does not constitute a conflict of interest.

Authors' Contributions

Dr. Rajashekhar S. Laddimath: Responsible for overseeing the entire project, including analytic computations, conceptualization, data curation, formal analysis, and drafting the original manuscript.
Dr. Nagraj S. Patil: Provided supervision throughout the study and ensured the accuracy of the analytical methods. (email-nspatil@vtu.ac.in).
Dr. Sharad G. Joshi: Contributed by proofreading the manuscript, suggesting corrections, and assisting in the conceptualization of the work. (email-gsharadjoshi@gmail.com).

All authors have read, understood, and have complied as applicable with the statement on Ethical responsibilities of Authors" as found in the Instructions for Authors.

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References

Agilan, V. and Umamahesh, N. V., 2016, "Is the covariate based non-stationary rainfall IDF curve capable of encompassing future rainfall changes? In *Journal of Hydrology*", **541**, 1441-1455, Elsevier BV. https://doi.org/10.1016/j.jhydrol.2016.08.052

Ahmed, Kazi Farzan, 2013, "Statistical Downscaling and Bias Correction of Climate Model Outputs for Climate Change Impact Assessment in the U.S. Northeast." *Global and Planetary Change* **100**, 2013, 320-32. http://dx.doi.org/10.1016/j.gloplacha.2012.11.003.

Anandhi, A., Frei, A., Pierson, D. C., Schneiderman, E. M., Zion, M. S., Lounsbury, D., and Matonse, A. H., 2011, Examination of change factor methodologies for climate change impact assessment. In Water Resources Research, **47**, 3, *American Geophysical Union* (AGU). https://doi.org/10.1029/2010wr009104.

Anandhi, A., Srinivas, V., Kumar, D.N. and Nanjundiah, R.S., 2009, "Role of predictors in downscaling surface temperature to river basin in India for IPCC SRES scenarios using support vector machine", *Int. J. Climatol*. **29**, 4, 583–603.

Auer, C., Kriegler, E., Carlsen, H., Kok, K., Pedde, S., Krey, V. and Müller, B., 2021, "Climate change scenario services: From science to facilitating action", *In One Earth*, **4**, **8**, 1074–1082. Elsevier BV. https://doi.org/10.1016/j.oneear.2021.07.015.

Berger, J., Guernouti, S., Woloszyn, M. and Buhe, C., 2015, "Factors governing the development of moisture disorders for integration into building performance simulation", *In Journal of Building Engineering*, **3**, 1–15, Elsevier BV. https://doi.org/10.1016/j.jobe.2015.04.008.

Bourdin, S., Kluft, L. and Stevens, B., 2021, "Dependence of climate sensitivity on the given distribution of relative humidity. *Geophysical Research Letters*, **48**, 8, e2021GL092462.

Chia, S. Y. and Lim, M. W., 2022, "A critical review on the influence of humidity for plant growth forecasting. In IOP Conference Series: Materials Science and Engineering, **1257**, 1, 012001). IOP Publishing. https://doi.org/10.1088/1757-899x/1257/1/012001.

Chowdhary, P. and Sharma, R. K., 2013, "Effect of relative humidity on creep-shrinkage behaviour of composite tall buildings", *In Latin American Journal of Solids and Structures*,**10**, 3, 571–584). FapUNIFESP (SciELO). https://doi.org/10.1590/s1679-78252013000300007.

De Caceres, M., Martin-StPaul, N., Turco, M., Cabon, A. and Granda, V., 2018, "Estimating daily meteorological data and downscaling climate models over landscapes" *Environmental Modelling & Software*, **108**, 186-196.

Degroot, D., Anchukaitis, K. J., Tierney, J. E., Riede, F., Manica, A., Moesswilde, E. and Gauthier, N., 2022, "The history of climate and society: a review of the influence of climate change on the human past", *In Environmental Research Letters*, **17**, 10, p. 103001). IOP Publishing. https://doi.org/10.1088/1748-9326/ac8faa

Dinh, T. and Fueglistaler, S., 2019, "On the Causal Relationship Between the Moist Diabatic Circulation and Cloud Rapid Adjustment to Increasing CO2", *In Journal of Advances in Modeling Earth Systems*, **11**, 11,3836–3851). American Geophysical Union (AGU). https://doi.org/10.1029/2019ms001853.

Fowler, H J, S Blenkinsop, and C Tebaldi. 2007, "Linking Climate Change Modelling to Impacts Studies: Recent Advances in Downscaling Techniques for Hydrological." 1578(September): 1547–78.

Garg, K. K., Bharati, L., Gaur, A., George, B., Acharya, S., Jella, K., 2012, "Spatial mapping of agricultural water productivity using the SWAT model in Upper Bhima Catchment, India", *Irrigation and Drainage*, **61**, 1, 60–79.

Ghosh, S., and Katkar, S., 2012, "Modeling uncertainty resulting from multiple downscaling methods in assessing hydrological impacts of climate change", *Water resources management*, **26**, 12, 3559-3579.

Godde, C. M., Mason-D'Croz, D., Mayberry, D. E., Thornton, P. K. and Herrero, M., 2021, "Impacts of climate change on the livestock food supply chain; a review of the evidence", *In Global Food Security*, **28**, p. 100488. Elsevier BV. https://doi.org/10.1016/j.gfs.2020.100488.

IPCC., 2022, "Global Warming of 1.5°C", Cambridge University Press. https://doi.org/10.1017/9781009157940.

Javadinejad, S., Dara, R. and Jafary, F., 2020, "Potential impact of climate change on temperature and humidity related human health effects during extreme condition", *Safety in Extreme Environments*, **2**, 189-195.

Kayes, I., Shahriar, S. A., Hasan, K., Akhter, M., Kabir, M. M. and Salam, M. A., 2019, "The relationships between meteorological parameters and air pollutants in an urban environment", *Global Journal of Environmental Science and Management*, **5**, 3, 265-278.

Kumbhar, V., Choudhury, S., Sen, A. and Singh, T. P., 2014, Assessment of Irrigation and Agriculture Potential Using

Geospatial Techniques: A Case Study of "Bhima-Ujjani" Project. In Procedia - Social and Behavioral Sciences, **157**, 277–284. Elsevier BV.

Laddimath, R. S., Patil, N. S., Rao, P. S. and Nagendra, 2021, "Assessing the impacts of climate change on drought-prone regions in Bhima sub-basin (India) using the Standard Precipitation Index", *In Journal of Water and Climate Change*. IWA Publishing.

Li, Z., Xu, Y., Li, R., Jia, M., Wang, Q., Chen, Y., Cai, R., and Han, Z. 2021, "Impact of the water evaporation on the heat and moisture transfer in a high-temperature underground roadway", *In Case Studies in Thermal Engineering*, **28**, p. 101551, Elsevier BV. https://doi.org/10.1016/ j.csite.2021.101551.

Moratiel, R., Bravo, R., Saa, A., Tarquis, A. M., and Almorox, J., 2019, "Estimation of evapotranspiration by FAO Penman–Monteith Temperature and Hargreaves–Samani models under temporal and spatial criteria", *A case study in Duero Basin (Spain*). Copernicus GmbH. https://doi.org/10.5194/nhess-2019-250.

Nahar, J., Johnson, F. and Sharma, A., 2017, "Assessing the extent of nonstationary biases in GCMs", *Journal of Hydrology*, **549**, 148–162.

Park, S. Y., Lee, H. J., Kang, J. E., Lee, T. and Kim, C. H., 2018, "Aerosol radiative effects on mesoscale cloud–precipitation variables over Northeast Asia during the MAPS-Seoul 2015 campaign", *Atmospheric environment*, **172**, 109-123.

Raju, K. S., Kumar, D. N. and Babu I, N., 2016, "Ranking of Global Climate Models for Godavari and Krishna River Basins, India, Using Compromise Programming. In Sustainable Water Resources Planning and Management Under Climate Change 87–100, *Springer Singapore*. https://doi.org/10.1007/978-981-10-2051-3_4.

Ricard, S. and Anctil, F., 2019, "Forcing the penman-montheith formulation with humidity, radiation, and wind speed taken from reanalyses, for hydrologic modeling. *Water,* **11**, 6, 1214.

Samal, D. R. and Gedam, S., 2021, "Assessing the impacts of land use and land cover change on water resources in the Upper Bhima river basin, India", In Environmental Challenges, **5**, p. 100251. Elsevier BV. https://doi.org/10.1016/j.envc.2021.100251.

Shad, M., Sharma, Y.D. and Singh, A. 2022, "Forecasting of monthly relative humidity in Delhi, India, using SARIMA and ANN models. Model", *Earth Syst. Environ*. **8**, 4843–4851. https://doi.org/10.1007/s40808-022-01385-8.

Sunyer, M. A., Hundecha, Y., Lawrence, D., Madsen, H., Willems, P., Martinkova, M., Vormoor, K., Bürger, G., Hanel, M., Kriaučiūnienė, J., Loukas, A., Osuch, M., and Yücel, I. 2015, "Inter-comparison of statistical downscaling methods for projection of extreme precipitation in Europe", *Hydrol. Earth Syst. Sci.*, **19**, 1827–1847, https://doi.org/10.5194/hess-19-1827-2015, 2015.

Surinaidu, L., Bacon, C. G. D. and Pavelic, P., 2013, "Agricultural groundwater management in the Upper Bhima Basin, India: current status and future scenarios", *Hydrology and Earth System Sciences*, **17**, 2, 507–517. https://doi.org/10.5194/ hess-17-507-2013.

Tripathi S, Srinivas VV, Nanjundiah RS. 2006, "Downscaling of precipitation for climate change scenarios: a support vector machine approach", *J. Hydrol*. **330**, 621– 640.

Udmale, Parmeshwar & Ichikawa, Yutaka & Kiem, Anthony and Panda, Sudhindra, 2014, "Drought Impacts and Adaptation Strategies for Agriculture and Rural Livelihood in the Maharashtra State of India", *The Open Agriculture Journal*. **8**. 41-47.

Van Uytven, E., Wampers, E., Wolfs, V. and Willems, P., 2020, "Evaluation of change factor-based statistical downscaling methods for impact analysis in urban hydrology", *In Urban Water Journal*, **17**, 9, 785–794. Informa UK Limited. https://doi.org/10.1080/1573062x.2020.1828497.

VishnuPriya, M. S. and Agilan, V., 2022, "Evaluation of change factor methods in downscaling extreme precipitation over India", *In Journal of Hydrology*, **614**, p.128531, Elsevier BV. https://doi.org/10.1016/j.jhydrol.2022.128531.

Wangsoh, N., Wathayu, W. and Sukawat, D., 2017, "A hybrid climate model for rainfall forecasting based on combination of self-organizing map and analog method", Sains Malays, **46**, 12, 2541-2547.

Wilby, R. L., Charles, S. P., Zorita, E., Timbal, B., Whetton, P. and Mearns, L. O., 2004, "Guidelines for use of climate scenarios developed from statistical downscaling methods. Supporting material of the Intergovernmental Panel on Climate Change, available from the DDC of IPCC TGCIA, 27.

Wu, X., Lu, Y., Zhou, S., Chen, L. and Xu, B., 2016, "Impact of climate change on human infectious diseases: Empirical evidence and human adaptation", In Environment International, **86**, 14–23. Elsevier BV. https://doi.org/10.1016/j. envint.2015.09.007.

Wu, Y., Guo, H., Zhang, A. and Wang, J., 2021, "Establishment and characteristics analysis of a crop–drought vulnerability curve: a case study of European winter wheat", *In Natural Hazards and Earth System Sciences*, **21**, 4, 1209–1228. Copernicus GmbH. https://doi.org/10.5194/nhess-21-1209-2021.