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Farmer perceptions and adaptation to agricultural water scarcity in Kondagaon district, Chhattisgarh, rural India

Nuru Hasan[1], Raji Pushpalatha[1]✉ & Natalia Magnani[2]

Water scarcity is rapidly intensifying due to climate change and other related factors. In India, over 60% of wheat and rice cultivation faces significant water scarcity. Thus, it is important to understand farmers' perspectives and adaptation responses through the application of model for private proactive adaptation to climate change MPPACC. However, there is limited empirical application of the MPPACC model in rural micro-level contexts within the Indian subcontinent, leaving its relevance for understanding farmers' adaptation to water scarcity underexplored. The study aimed to examines farmers' perceptions and adaptation to agricultural water scarcity using MPPACC in Kondagaon district, India. Quantitative approach using cross-sectional research design was employed. Data was collected from 146 farmers via survey questionnaires. Structural equation modelling (SEM) used to assess the predictive ability of MPPACC in explaining farmers' adaptation intentions and strategies. The finding indicates that MPPACC explained 43.8–46.2% of the variation in farmers' adaptation intention and strategies against agricultural water scarcity. The model only moderately predicts variations in farmers' perceptions and adaptation strategies, indicating missing components that warrant refinement through additional relevant variables. Hence, the study offers valuable information for agricultural practitioners, policymakers, and other stakeholders to develop appropriate strategies for effective farmers adaptation strategies.

Keywords Water scarcity, Farmers' perceptions and adaptation, MPPACC, Structural equation modelling

Globally, water insecurity is a daunting challenge that affecting billions of people. Nearly 4.0 billion people grapple with water scarcity for at least one month annually, while a staggering 733 million individuals confront severe water shortages annually[1–3]. By 2030, due to the current state of climate change, nearly half of the global population will reside in regions experiencing significant water stress[4]. Furthermore, alarming forecasts suggest a staggering 20% decline in water resources by 2070, coupled with an expected surge in water-stressed areas from 19 to 35% due to climate change's effects[5,6]. In agriculture, water scarcity has become more concerning in recent years, with around 40% of worldwide croplands experiencing water scarcity and this scenario is anticipated to worsen, jeopardising the future sustainability of agriculture[6,7].

The Indian subcontinent includes a nation classified as water-stressed, with annual per capita water availability falling below 1400 cubic meters, a notable decrease from 1800 cubic meters two decades ago[8]. Agriculture, which presently constitutes almost 80% of the nation's overall water usage has significant challenges due to water scarcity[9,10]. According to the National Institution for Transforming India, about 74% of the land under wheat cultivation and 65% of the land under rice cultivation has faced significant water scarcity[11].

At the state level, several states, including Andhra Pradesh, Tamil Nadu, Gujarat, Karnataka, and Maharashtra, grapple with severe water scarcity issues[12]. Chhattisgarh, the state chosen for this study, reports moderate water scarcity[12]. Nevertheless, some areas in the state continue to face severe water scarcity. The study area experiences water scarcity, notably exacerbated during the summer months from March to May, which may affect agricultural activities essential to the community's economy.

While several studies at the global, national, and regional levels examined water scarcity broadly, most of them fail to incorporate community perceptions and behavioral responses into the analysis of water scarcity[13–17].

[1]Amrita School for Sustainable Futures, Amrita Vishwa Vidyapeetham, Amritapuri 690525, Kollam, India. [2]Department of Sociology and Social Research, University of Trento, 38122 Trento, Italy. ✉email: rajip@am.amrita.edu

Many of these studies focused on hydrological and meteorological analyses, they largely overlook how local communities, particularly farmers, experience, interpret, and adapt to water-related stress. They were primarily concentrated on a broader geographical scope, leaving a gap in micro-level examination of water scarcity perception and adaptation mechanisms. In addition, there is a limited body of research that has applied the MPPACC in the context of the Indian subcontinent. Although a few studies in India have applied the MPPACC framework, they were either purely qualitative or did not statistically assess the model's predictive power[18,19]. Existing applications also failed to examine how individual components such as perceived probability or perceived severity influence farmers' adaptation intentions and strategies. This gap highlights the need for further investigation into how this model can inform and enhance adaptation strategies at the micro-level in rural India. Thus, the study's novelty resides in its emphasis on the local environment, a domain frequently neglected by existing literature, especially how local people perceive and respond to water scarcity.

Therefore, the current study aimed to examine how farmers perceive and respond to agricultural water scarcity using the model for private proactive adaptation to climate change (MPPACC). This research can augment the current literature by broadening the limited application of MPPACC, thereby providing further evidence of the model's applicability even in very remote and micro area.

Theoretical framework

Several theories have been employed to identify the psychological and cognitive factors influencing adaptive behaviours under different types of calamities worldwide and India in particular. For instance, Protection Motivation Theory (PMT) was utilised to analyse how individuals convert disaster information into protective measures to improve preparedness against cyclones in West Bengal[21]. In addition, Theory of Planned Behaviour (TPB) and Value-Belief-Norm (VBN) theory applied to predict the climate change mitigation and adaption behaviours in agriculture production in the Kashmir Valley[22]. Similarly, the social and psychological factors of climate change adaptation among rural women in Uttarakhand was investigated using TPB[23].

Furthermore, MPPACC was also used to explore farmers' climate change adaptation in South and North India[18,19,20]. MPPACC is the extension of protection motivation theory (PMT), which is widely used in the field of health risk research[24,25]. PMT involves three main elements: the event's magnitude, the probability of its occurrence, and the efficacy of responses to the events[25]. However, MPPACC includes additional components to PMT, such as social discussions on climate change risks and adaptation, evaluation of risk experiences, reliance on public adaptation, cognitive biases and heuristics, motivations or incentives for adaptation, and objective adaptive capacity[24]. MPPACC delineates two core cognitive appraisal processes within individuals' decision-making for self-protection.

The initial process, termed 'risk appraisal,' involves evaluating the likelihood and potential harm of a threat to one's valued possessions[24,26]. Higher risk appraisal generally increases the motivation to consider adaptation options. The second process is called 'adaptation appraisal,' which refers to the capacity of an individual to take action to address or minimise the threat while considering the cost related to the adaptation effort[24]. Adaptation appraisal determines whether perceived risk is required to converted into adaptation intention. Hence, each of these components also has its own elements. For example, risk appraisal involves two key variables: perceived probability and perceived severity[24,26,27]. Perceived probability refers to the possibility of facing a certain threat, whereas perceived severity denotes the extent of the threat, especially when it's materialised[26].

Following risk appraisal, adaptation appraisal starts when the threat surpasses a certain level of threshold[18,26]. Perceived adaptation efficacy, perceived self-efficacy, and perceived costs are the three primary components of adaptation appraisal[19,24]. For instance, perceived adaptation efficacy denotes the belief in the efficiency of adaptation approaches, whereas perceived self-efficacy pertains to an individual's confidence in their capacity to execute those approaches[18,19,27]. Perceived adaptation cost, on the other hand, is the expenses (e.g., money, time, effort, social or psychological issues) individuals anticipate incurring to implement changes[19,26]. High perceived adaptation efficacy and self-efficacy combined with manageable costs increase adaptation intention, while high costs may weaken it.

Furthermore, an individual responds to a risk by demonstrating two categories of behaviours contingent upon the results of risk and adaptation evaluations[24]. These responses are called adaptive and avoidant maladaptation[26–27]. Adaptive responses seek to prevent harm and are undertaken when both risk perception and perceived adaptive capabilities are significant[28]. Adaptive responses follow a strong risk appraisal and a favourable adaptation appraisal. On the other hand, avoidant maladaptation is behaviour such as denial, wishful thinking, and fatalism, and wrong adaptation that may even worsen the situation[24–26]. Thus, avoidant maladaptation responses reduce the likelihood of forming adaptation intentions. Consequently, when individuals opt for adaptive responses, their initial step is to formulate an adaptation intention, the execution of which is contingent upon objective adaptive capability, including resources such as time, financial means, expertise, and social and institutional support[24–27]. Adaptation intention leads to actual adaptation strategies when objective adaptive capacity is sufficient.

Therefore, for the current study, the following seven hypotheses were formulated:

H1 *Risk appraisal positively influences farmers' adaptation intentions and adaptation strategies.*

H2 *Adaptation appraisal has positive effect on adaptation intentions and adaptation strategies.*

H3 *Social discourse positively affects farmers' adaptation intentions and adaptation strategies.*

H4 *Climate change perception positively influences adaptation intentions and adaptation strategies.*

H5 *Maladaptive responses negatively affect adaptation intentions and adaptation strategies.*

H6 *Objective adaptive capacity positively influences adaptation intentions and adaptation strategies.*

H7 *Adaptation intention positively influences adaptation strategies.*

To investigate these research questions, the MPPACC framework was adapted following a comprehensive review of existing literature. However, the current study did not include all components of the MPPACC model, such as reliance on public adaptation, and adaptation incentives which may require additional information regarding public adaptation programs. For example, reliance on public adaptation refers to individuals' perceived dependence on governmental or administrative measures to manage risks, which may reduce the perceived need for private precautionary or adaptive actions and requires detailed information on the presence and functioning of formal adaptation programmes[24,28]. Although explicit justification is limited, many of the existing literature on MPPAC have partially or fully omitted the aforementioned variables from their empirical analyses[18,19,26,28]. The selected MPPACC components used to test the study hypotheses are illustrated in Fig. 1, and the corresponding measurement items are presented in Table 3.

Materials and methods

Study area

The current study is undertaken in Malgaon, located in the Kondagaon district of Chhattisgarh, central India (Fig. 2). Positioned approximately 250 km away from the state capital, Raipur, and about 25–28 km from the district headquarters. The village is situated at geographical coordinates of 19°61″58′° N latitude and 81′ 88″ 42′3″ E longitude. Regarding climate, the average annual temperature and precipitation of Malgaon is 24.93 °C and 1325.81 mm, respectively. The village encompasses approximately 1598.08 hectares of land, with 1134.83 hectares designated as forested areas and 463.25 hectares designated for agricultural and residential use. Agriculture serves as the main source of livelihood, complemented by livestock rearing and the collection of forest products. Predominant crops cultivated include paddy, maize, urad dal, and various vegetables. The village's agricultural practices are predominantly reliant on rainwater, notably during the monsoon season, with irrigation utilised in the dry season. Malgaon is home to a population of 1743. Demographically, the majority of the residents belong to the scheduled tribes (ST), while some of the dwellers belong to other backward caste (OBC), and General caste. The primary languages spoken in the village are Halbi and Hind.

The village was purposely selected as a catchment area of Amrita University's Live-in-Labs® program. The Live-in-Labs® program was launched in 2013 by Mata Amritanadamayi Math (UN-recognized humanitarian) to transform rural Indian villages into self-reliant villages[29,30]. As of now, the Live-in-Labs program is active in more than 22 states and over 250 villages across India. The Live-in-Lab program is a multidisciplinary initiative that applies theory to practice by developing sustainable solutions for rural challenges in India[31]. Researchers from diverse fields reside in designated rural communities to gain a comprehensive understanding of challenges across nine thematic domains: agriculture, water and sanitation, health and well-being, education, gender equality, energy, livelihoods, environment, and climate and disaster risk reduction[29,32].

This work has been recognised by the UN as one of the programs that making an impact at the grassroots level to transform rural communities across India. Of the aforementioned thematic areas, the author has been working in the agriculture thematic area. Although the purposive selection of the study area may influence the

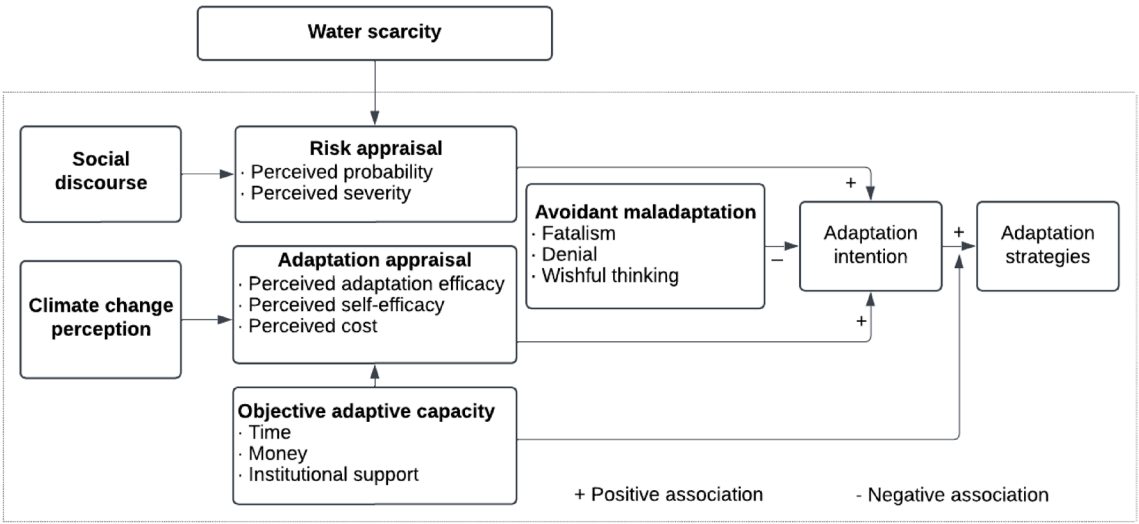


Fig. 1. Theoretical framework of the study. The figure displays the structure of the MPPACC theoretical framework adapted from[24].

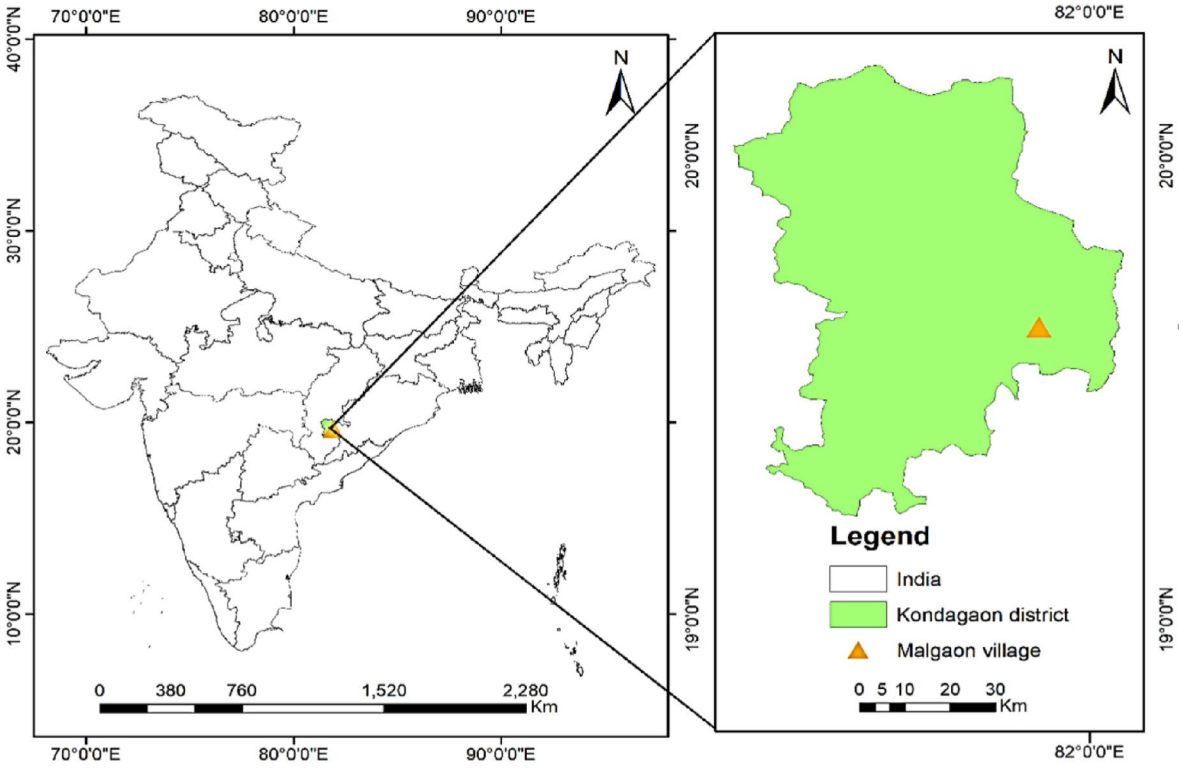


Fig. 2. Map of the study area. The map was created by the authors using the administrative boundary shapefile obtained from the Survey of India (https://onlinemaps.surveyofindia.gov.in/Product_NewSpecification.aspx) and was digitized using ArcGIS Pro (version 3.1) under the institutional license of Amrita Vishwa Vidyapeetham.

generalizability and external validity of the findings, the sampled farmers represent substantial diversity in socio-economic conditions, livelihoods, landholding patterns, and the typical characteristics of smallholder farming in rural India. This heterogeneity strengthens the analytic robustness and external validity of the findings, especially in understanding the behavioral responses of farmers to agricultural water scarcity and supports the meaningful extrapolation of insights to other water-scarce rural settings across central India.

Sampling frame

The village was purposely selected as the catchment area for the Amrita Vishwa Vidyapeetham Live-in-Labs® program. The research employed a cross-sectional approach, focussing on farmers within the study village. Taro Yamane method was employed to determine the sample size of the current study (Yamane 1967). Taro Yamane technique is a simplified method for determining the sample size when the target population are known. Accordingly, the village has 349 households, some of which are not involved in farming activities, and in some cases, more than one family lives in one household. To maintain an equal representation of each farming household, we took only one farmer per household. Therefore, we took 300 as an approximate number to determine the sample size for the study. Accordingly, the sample size of the current study was 171. However, 151 responses were collected from the randomly selected farmers. This is because the data was collected between May and June, which was a busy time for harvesting summer crops and soil preparation for monsoon crops, so we were not able to collect all 171-sample size. Before analyzing the results, outliers were assessed using both univariate and multivariate criteria. Univariate outliers were identified using standardized z-scores ($z > 3$), while multivariate outliers were detected via the Mahalanobis distance method in AMOS. After removing outliers, 146 survey responses were used for final analysis out of 151 surveys collected.

Data analysis

Five-point Likert scale with " 1 strongly disagree " to "5 strongly agree," were applied to measure farmers' perception and adaptation to agricultural water scarcity through MPPACC model. The assessment comprises 29 items across 11 domains (Table 3). Structural equation modelling (SEM) in SPSS-AMOS free trail was employed to analyses the collected responses. The model is capable of assessing measurement error and path coefficients. SEM has two phases where the initial phase involves confirmatory factor analysis (CFA) to assess the appropriateness of the measurement model, followed by the application of SEM itself. Convergent and discriminant validity as well as reliability test are mainly evaluated during the CFA phase. Average variance extracted (AVE), composite reliability (CR), Cronbach's alpha (α), and t statistics are commonly employed to gauge the reliability of the research model. The threshold for AVE is 0.5, while 0.7 for α, and CR[26,33].

Furthermore, goodness of fit indicators was employed to assess the validity of the measurement model. In SEM, the model goodness of fit is classified into three categories: absolute, incremental, and parsimonious[34,35]. To deem a measurement model valid, the Parsimony Normed Fixed Index (PNFI), Parsimony Comparative Fit Index (PCFI), and relative chi-square (CMIN/df) must be below five[26,34,35]. Adjusted goodness-of-fit index (AGFI), goodness-of-fit index (GFI), normed fit index (NFI), Tucker–Lewis index (TLI), Incremental fit index (IFI), and comparative fit index (CFI) is 0.9[36,37]. However, it is considered if it is between 0.75 and 0.90 due to sample size influences[26,34]. Furthermore, the Root Mean Square Error of Approximation (RMSEA) and standardised Root Mean Square Residual (SRMR) must be below 0.08 for the model to be deemed an acceptable fit[38,39].

Result

Demographic profile of the respondents

The surveyed farmers were between 19 and 76 years old, with an average age of 44.37 ± 12.7 years. Household composition was typical of rural settings, averaging 3 children and 6 members. Farming experience was high, with respondents reporting an average of 30 years of involvement in agriculture. Farm sizes ranged from small holdings of 1 acre to larger plots of 12 acres, with a mean of 3.7 ± 2.02 acres. The farmers were predominantly married (96.5%) and largely represented by Scheduled Tribes (86.3%). Educational levels were modest, as nearly one-third were illiterate, while most had only elementary or secondary schooling.

Results of measurement model

In the first phase of SEM, the measurement model was evaluated using confirmatory factor analysis (CFA). Factor loadings indicate that all constructs are well measured by their respective indicators (Fig. 3). Moreover, convergent and discriminant validity assessments of the present study. The composite reliability (CR) and average variance extracted (AVE) values for most constructs are above the recommended thresholds of 0.7 and 0.5 respectively, indicating good convergent validity (Table 1). Similarly, the square root of the AVE for each construct is greater than the correlations between that construct and other constructs, suggesting adequate discriminant validity. In short, the results suggest the measures used in the study have good convergent and discriminant validity, supporting the reliability and construct validity of the research.

Table 2 provides the model goodness of the test result of the current study along with recommended values. Absolute fit indices such as CMIN/DF, RMSEA, and SRMR values for both MM and SM indicate good model fit, while GFI, and AGFI are close to the recommended threshold of > 0.90, suggesting an acceptable fit. Incremental fit indices such as CFI and IFI values for both MM and SM suggest good model fit, whereas TLI and NFI values

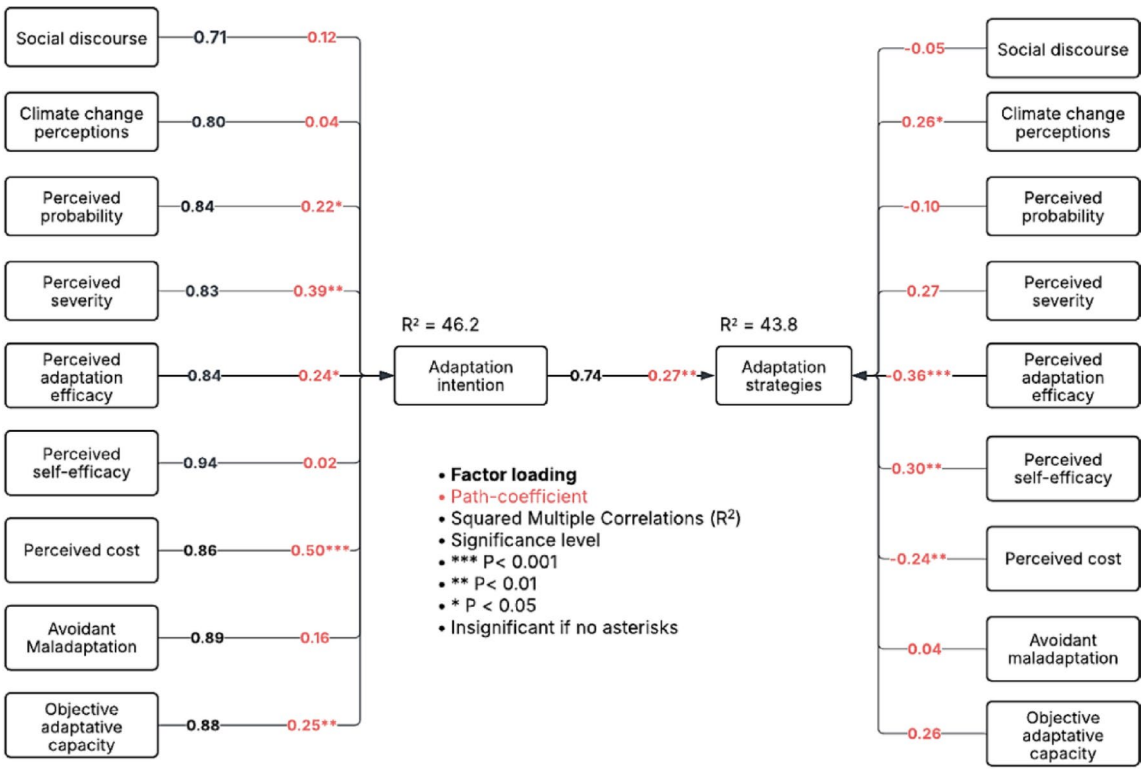


Fig. 3. Structural equation model showing factor loadings, path coefficients, and significance levels for the latent variables. Factor loading values are presented only in the left side of the figure to avoid repetition, as similar constructs used to measure the dependent variables.

	CR	AVE	SD	CCP	PP	PC	MD	AI	AS	OAC	PS	PAE	PSE
SD	0.75	0.51	0.71										
CCP	0.85	0.66	0.10	**0.81**									
PP	0.83	0.71	−0.07	0.20*	**0.85**								
PC	0.90	0.77	0.08	0.58***	0.31**	**0.87**							
MD	0.83	0.73	−0.05	−0.007	0.07	−0.03	**0.85**						
AI	0.79	0.56	−0.09	0.32**	0.35***	0.37***	0.16	**0.75**					
AS	0.71	0.38	−0.02	0.16	−0.02	0.04	0.05	0.35**	**0.62**				
OAC	0.88	0.78	−0.07	−0.12	0.10	−0.23*	−0.06	0.11	0.28*	**0.88**			
PS	0.82	0.70	−0.39**	0.08	−0.02	−0.15	0.06	0.32**	0.09	−0.05	**0.83**		
PAE	0.92	0.70	−0.24*	−0.26*	−0.13	−0.55***	0.00	0.04	−0.2*	−0.03	0.36***	**0.84**	
PSE	0.94	0.89	0.12	−0.08	0.17	0.19*	0.12	0.05	0.17	0.05	−0.32**	−0.08	**0.94**

Table 1. Convergent and discriminant validity test results. CR, composite reliability; AVE, average variance extracted; SD, social discourse; CCP, climate change perceptions; PP, perceived probability; PS, perceived severity; PAE perceived adaptation efficacy; PSE, perceived self, efficacy; PC, perceived cost; MD, avoidant maladaptation; AI, adaptation intention; OAC, objective adaptative capacity; AS, adaptation strategies.

Indices	Recommended value	MM values of current study	SM values of current study	Fit categories	References
CMIN/DF	< 5.0	1.578	1.562	Absolute	26,34,35
GFI	> 0.90	0.827	0.828		36,37
RMSEA	< 0.08	0.063	0.062		38,39
AGFI	> 0.90	0.762	0.764		36,37
SRMR	< 0.08	0.064	0.064		38,39
CFI	> 0.90	0.917	0.918	Incremental	36,37
TLI	> 0.90	0.894	0.896		26,34,35
NFI	> 0.90	0.809	0.809		26,34,35
IFI	> 0.90	0.921	0.922		
PNFI	> 0.5	0.632	0.631	Parsimonious	
PCFI	> 0.5	0.716	0.717		34

Table 2. Goodness of fit indices. MM stands for measurement model and SM is structural model.

are close to or slightly below recommended thresholds of > 0.90, indicating acceptable fit. PNFI and PCFI of the parsimonious fit indices for both MM and SM are within recommended ranges, indicating parsimonious fit.

Descriptive result on farmers' water scarcity perception

The study sheds light on farmers' perceptions and adaptations to agricultural water scarcity (Table 3). Farmers acknowledge the existence of water scarcity, with mean values for the perceived probability of water scarcity ranging from 4.14 ± 0.45 to 4.16 ± 0.59. They attributed this scarcity to climate change, believing that rainfall patterns are decreasing and water availability in streams, ponds, and wells has reduced. This perception is indicated in their climate change awareness, with mean values ranging from 4.06 ± 0.50 to 4.07 ± 0.43. The average value of perceived severity ranges from 4.02 ± 0.49 to 4.02 ± 0.56, reflecting farmers' belief in the effect of water scarcity.

However, the mean scores for social discourse (ranging from 1.88 ± 0.54 to 1.90 ± 0.53) suggest that farmers have less engagement in discourses about water scarcity with their friends and neighbours. Their access to media such as radio and television is also limited. Similarly, the results indicate that farmers' engagement with agricultural extensions services is relatively low. Moreover, while farmers believe that adaptation activities can protect their crops and minimize severe damage, with mean values of perceived adaptation efficacy ranging from 3.99 ± 0.52 to 4.01 ± 0.41, the comparatively low mean values of perceived self-efficacy (2.59 ± 1.00 and 2.59 ± 1.02) indicate that farmers are inadequately equipped with the necessary knowledge and skills to execute effective adaptation strategies. In addition, farmers believe that adaptation strategies are costly, require high effort, and are labour-intensive. The mean value of perceived cost ranges from 4.18 ± 0.48 to 4.21 ± 0.50.

This shows that the adoption of adaptation strategies is significantly influenced by resources availability. The investigation of objective adaptative capacity, with the mean values of 2.47 ± 1.43 and 2.51 ± 1.47, further shows that financial setbacks and limited government support significant barriers to farmers adaptation strategies. Finally, mean values for adaptation strategies range from 2.17 ± 1.11 to 3.72 ± 1.28, highlighting that while some farmers engage in water conservation practices such as rainwater harvesting as well as utilizing boreholes and ponds for irrigation, the adoption of more advanced irrigation methods remains limited. The lower mean scores

No	Items	Mean	SD	FL	T-value	References
	Social discourse (α = 0.747)					
1.	My friends and neighbours discuss the threat of water shortage and adaptation strategies.	1.90	0.53	0.78	6.49	24,26
2.	I get information on the possibility of water shortage and adaptation techniques from radio and television.	1.99	0.72	0.68	6.32	
3.	I get information on water scarcity threats and adaptation techniques from agricultural extension professionals.	1.88	0.54	0.67	1*	
	Climate change perception (α = 0.851)					
4.	I contend that rainfall is occurring less often than in previous years.	4.07	0.43	0.69	9.06	18,19, 40
5.	I contend that the water levels of streams, ponds, and wells have diminished compared to previous levels.	4.10	0.46	0.88	11.53	
6.	I believe that there is less water for cultivating my crops	4.06	0.50	0.84	1*	
	Perceived probability (α = 0.810)					
7.	I believe my crops are prone to water scarcity	4.14	0.45	0.77	6.03	24,26
8.	I believe a high likelihood of water scarcity causing damage to crop yields	4.16	0.59	0.91	1*	
	Perceived severity (α = 0.811)					
9.	I believe my crops severely damaged due to water scarcity.	4.02	0.56	0.90	7.66	41,42
10.	I have incurred financial losses due to a decline in my crop resulting from water scarcity	4.02	0.49	0.76	1*	
	Perceived adaptation efficacy (α = 0.808)					
11.	Performing adaptation activity in response to water scarcity protects my crops	4.01	0.41	0.78	8.99	19,24,26
12.	Performing adaptation activity in response to water scarcity minimize severe damage	3.99	0.52	0.88	1*	
	Perceived self-efficacy (α = 0.943)					
13.	I possess the knowledge and skills necessary to address the challenge of water shortage on my farm.	2.59	1.00	0.95	11.57	42
14.	I feel confident in my capacity of handling water scarcity.	2.59	1.02	0.93	1*	
	Perceived cost (α = 0.897)					
15.	Adaptive measures are very expensive	4.21	0.50	0.69	10.64	41,42
16.	Adaptive measures are time consuming	4.18	0.51	0.96	23.96	
17.	Significant effort is required to adjust my farm to water scarcity.	4.18	0.48	0.95	1*	
	Avoidant maladaptation (α = 0.880)					
18.	Everything including water shortage, are determined by fate and destiny.	1.90	0.56	0.97	3.8	24,26
19.	God will protect my farm, so no need to worry about water scarcity	1.92	0.51	0.81	1*	
	Adaptation intention (α = 0.754)					
20.	To lessen the likelihood of water shortage, I intend to implement contemporary irrigation techniques in the coming year.	3.65	0.94	0.78	1*	41,43
21.	In an effort to play a greater role in water conservation, I will do my best.	3.64	0.83	0.84	9.13	
22.	Modern methods of water saving and irrigation are something I would be interested in learning more about.	3.97	0.44	0.61	6.94	
	Objective adaptive capacity (α = 0.706)					
23	I have enough money to implement adaptation strategy	2.47	1.43	0.88	6.89	26
25	Government provide support to implement adaptation strategy	2.51	1.47	0.89	1*	
	Adaptation strategies (α = 0.707)					
26.	I actively engage in rainwater harvesting as response to water scarcity	2.45	1.35	0.68	1*	26,43,44
27.	I utilize boreholes, wells, or ponds for water conservation	3.72	1.28	0.69	6.07	
28.	I employ various irrigation methods such as deficit, drip, sprinkler, alternate wetting and drying, etc., to alleviate the effects of water scarcity.	2.17	1.11	0.55	5.21	
29.	I cultivate drought-resistant crops to mitigate the impact of water scarcity	3.14	1.37	0.55	5.2	

Table 3. Constructs used for the current study with their mean, standard deviation, factor loading, and t-value. The asterisks 1* indicate reference items whose factor loadings were fixed at 1.0 to set the scale of the construct to control construct variance; therefore, their t-values were not estimated. The selection of measurement items in this study was guided by the adapted MPPACC framework and the specific objective of explaining individual farmers' perceptions, intentions, and adaptation strategies in response to agricultural water scarcity. The items were adopted from previously validated studies and widely used empirical applications of MPPACC-based models to ensure consistency.

(2.17 ± 1.11) for irrigation techniques such as the deficit irrigation, drip, sprinkler, alternate wetting, and drying, indicate limited adoption of water-efficient agricultural technologies.

Results of the structural model

The results of the structural model for the dependent and independent variables used in this investigation are shown in Table 4. Adaptation intention and adaptation strategies were served as the dependent variables, while the other nine variables acted as independent variables to investigate farmers agricultural water scarcity perceptions and adaptations. The result of structural model discussed in the following section.

Hypothesis			URW	SRW (β)	SE	CR	*P*	Label
Social discourse	→	Adaptation_intention	0.22	0.11	0.21	1.0	0.29	Rej
Climate change perception	→	Adaptation_intention	0.06	0.03	0.19	0.29	0.77	Rej
Perceived probability	→	Adaptation_intention	0.31	0.23	0.13	2.4	0.02	Sup
Perceived severity	→	Adaptation_intention	0.73	0.38	0.22	3.2	00	Sup
Perceived adaptation efficacy	→	Adaptation_intention	0.43	0.27	0.19	2.2	0.02	Sup
Perceived self-efficacy	→	Adaptation_intention	0.01	0.01	0.07	0.14	0.88	Rej
Perceived cost	→	Adaptation_intention	0.83	0.53	0.23	3.6	***	Sup
Avoidant maladaptation	→	Adaptation_intention	0.23	0.14	0.15	1.7	0.08	Rej
Objective adaptive capacity	→	Adaptation_intention	0.13	0.24	0.05	2.6	0.00	Sup
Social discourse	→	Adaptation_strategies	− 0.28	− 0.11	0.31	− 0.90	0.37	Rej
Climate change perception	→	Adaptation_strategies	0.57	0.26	0.29	1.9	0.04	Sup
Perceived probability	→	Adaptation_strategies	− 0.38	− 0.22	0.20	− 1.9	0.06	Rej
Perceived severity	→	Adaptation_strategies	0.13	0.05	0.35	0.39	0.69	Rej
Perceived adaptation efficacy	→	Adaptation_strategies	− 1.08	− 0.55	0.33	− 3.3	***	Sup
Perceived self-efficacy	→	Adaptation_strategies	0.29	0.29	0.10	2.7	0.00	Sup
Perceived cost	→	Adaptation_strategies	− 1.10	− 0.55	0.39	− 2.8	0.00	Sup
Avoidant maladaptation	→	Adaptation_strategies	− 0.08	− 0.03	0.22	− 0.37	0.71	Rej
Objective adaptive capacity	→	Adaptation_strategies	0.09	0.13	0.07	1.1	0.24	Rej
Adaptation intention	→	Adaptation_strategies	0.65	0.52	0.20	3.2	00	Sup

Table 4. Assessment of the structural model. URW, unstandardised regression weight; SRW (β), standardised regression weight; SE, standard error, CR, critical ratio; *P*, *p* value.

Determinants of adaptation intention

Adaptation intention was significantly influenced by several key variables. Adaptation intentions were shown to be strongly predicted by perceived severity (β = 0.38, CR = 3.2, $p < 0.001$), suggesting that farmers are more inclined to intend to adjust if they see the implications of water shortage as more severe. Likewise, the likelihood that a crop would be severely affected by water shortage is a strong motivator for farmers to develop adaptation intention behaviour (β = 0.23, CR = 2.4, $p < 0.02$). Perceived adaptation efficacy also significantly influences adaptation intention (β = 0.27, CR = 2.2, $p < 0.02$), suggesting that confidence in adaptation activities drives farmers' intentions. Objective adaptive capacity was another significant predictor (β = 0.24, CR = 2.6, $p < 0.001$), emphasizing that tangible resources such as financial means and institutional support play a vital role in fostering adaptation intentions. Perceived cost strongly influenced adaptation intention (β = 0.53, CR = 3.6, $p < 0.0001$), highlighting the importance of financial considerations in shaping adaptation behaviour.

Conversely, social discourse (β = 0.11, CR = 1.1, $p < 0.27$), climate change perception (β = 0.03, CR = 0.24, $p > 0.80$), avoidant maladaptation (β = 0. 14, CR = 1.7 $p > 0.08$), and perceived self-efficacy (β = 0.00, CR = 0.04, $p > 0.97$) were not showed significant influence on adaptation intention in the current study.

Determinants of adaptation strategies

Several variables such as social discourse, climate change perception, avoidant maladaptation, and perceived self-efficacy did not show significant influence on adaptation intention in the current study. However, some of these variables were found to influence actual adaptation strategies. For instance, climate change perception was a positive predictor of adaptation strategies (β = 0.26, CR = 1.9, $p = 0.04$), indicating that awareness of changing climate may encourage the adoption of adaptation measures. Perceived self-efficacy also positively predicted adaptation strategies (β = 0.29, CR = 2.7, $p < 0.001$), showing that confidence in one's ability to adapt plays a key role in implementing strategies. Most notably, adaptation intention itself predicted adaptation strategies (β = 0.52, CR = 3.2, $p < 0.001$), demonstrating that once intention is formulated, irrespective of its underlying motivations, it is likely to result in practical adaptive behaviour.

In contrast, perceived adaptation efficacy had a negative relationship with adaptation strategies (β = − 0.55, CR = − 3.3, $p < 0.0001$), suggesting a potential mismatch between farmers' belief in the effectiveness of adaptation measures and their actual implementation. Perceived cost also negatively influenced adaptation strategies (β = -0.55, CR = − 2.8, $p < 0.001$), reaffirming that financial constraints remain a significant barrier to action.

However, several factors did not show significant relationships. Social discourse (β = -0.11, CR = − 0.90, $p > 0.37$) was not a significant predictor, indicating that discussions within social networks do not directly influence adaptation measures. Similarly, perceived probability (β = − 0.22, CR = − 1.8, $p > 0.06$), perceived severity (β = 0.05, CR = 0.40, $p > 0.68$), and avoidant maladaptation (β = − 0.06, CR = − 0.69, $p > 0.48$) did not significantly predict adaptation strategies. Overall, the study model predicted 46.2% of the variation in adaptation intention and 43.8% of the variance in adaptation strategies (Fig. 3).

Discussion

The MPPACC theoretical framework was used to examine how farmers perceive and respond to agricultural water scarcity. The study pointed out the important role of both risk appraisal, such as perceived probability and

perceived severity, and adaptation appraisal, such as perceived adaptation efficacy, perceived cost and perceived self-efficacy, in shaping farmers' decisions. The study found that risk appraisal did not directly translate into action but rather influenced adaptation intention, which in turn affected adaptation strategy. The SEM results indicate that MPPACC provides a reasonable prediction of farmers' adaptation intentions and adaptation strategies, with a variance of 46.2% and 43.8%, respectively, signifying the moderate predictive strengths of the framework.

The moderate predictive power of the MPPACC has important theoretical implications for understanding farmers' adaptation to water scarcity. While the model captures the influence of risk and adaptation appraisals on adaptation intention and adaptation strategies, its ability to predict variations in dependent variables is moderate in Malgaon village, suggesting that key components may be missing. This discrepancy might be because of certain excluded constructs of the MPPACC models such as public adaptation and adaptation incentives. In addition, contextual factors such as institutional support, trust, indigenous knowledge systems, and community coping norms might shape adaptation intention, and adaptation strategy may override individual cognitive biases[46–48]. In fact, previous studies applying the MPPACC framework have reported relatively similar, moderate predictive power, indicating that while the model explains a meaningful share of variance in adaptation behaviour, some relevant components may not be fully captured within the framework[26,27].

Furthermore, the findings from the current study partially corroborate and partially contradict the findings of the existing literature. For instance, several studies report that risk perception motivates adaptation behaviours[18.19.24.26] which is consistent with the current study. In addition, other authors were also found that adaptation intention is determined by structural capacities such as resource availability and social and institutional support[24.45]. This indicates that integrating extrinsic factors alongside intrinsic psychological variables is essential to refine behavioural models, particularly for rural settings like central India, where socio-cultural realities and community-based coping mechanisms might play a substantial role in shaping adaptation behaviour.

In consistency with the current study, a previous study found that farmers' self-belief and awareness about climate change are crucial in shaping the adaptation strategies of the farmers[26.49]. However, the gap emerged in terms of actual implementation, which was indicated by a negative association between perceived adaptation efficacy and adaptation strategies in the current study ($p < 0.001$). Though farmers acknowledge the importance of adaptation strategies, their practical application is often hindered by several factors, such as financial setbacks, lack of access to resources, and limited institutional support. For instance, perceived cost negatively influenced adaptation strategies ($p < 0.001$), confirming farmers' view of adaptation as expensive and time-consuming and requiring significant effort, which are major barriers consistent with previous studies[18,19.26].

Some of the findings from the current study contradict existing literature. For instance, a study by[24,26,42] found that adaptation intentions and strategies are negatively influenced by avoidant maladaptive behaviours such as wishful thinking, denial, and fatalism. However, this variable did not show either negative or positive influence on both adaptation intention and adaptation strategies under the current study. This indicates that the influence of some of the psychological determinants on individual adaptation may vary depending on the socioeconomic and cultural context of a particular area. It also indicates that variables like institutional support and trust, indigenous or localised knowledge systems, and community coping mechanisms, or norms, might override individual cognitive biases. Moreover, this study differs from the findings of previous research, which reported that adaptive strategies are directly influenced by perceived severity and perceived probability[26,42]. In contrast, the current study shows that these constructs do not directly influence adaptation strategies ($p > 0.05$); instead, they significantly predict adaptation intentions ($p < 0.001$ and $p < 0.02$), which in turn influence adaptive strategies ($p < 0.001$).

From a practical perspective, the findings elucidate significant behavioural and structural constraints that influence farmers' adaptive responses. Even when farmers perceive water scarcity, their adaptation behaviour is determined by perceived costs and objective adaptive capacity, such as money, time, and institutional support. This mismatch reflects widespread resource limitation in the face of recurring seasonal agricultural water scarcity and persistent gaps in extension outreach, all of which weaken the translation of intention into actual adaptation strategies. Although no severe droughts have been reported so far, seasonal water scarcity, especially during the summer months, is now extending into the monsoon period, particularly affecting the early and late stages of crop growth, as reported by the farmers.

Addressing these challenges requires integrated approaches that emphasise both behavioural change by improving self-awareness and self-efficacy and structural factors, like financial assistance, access to credit, water infrastructure, and timely agricultural advice. In addition, demonstrations, training, and peer-learning platforms can help improve farmers' confidence, which can lead to the use of locally relevant practices such as crop diversification, switching to less water-intensive crops, mixed cropping, or efficient irrigation.

Despite these insights, this study has several limitations. First, the study was conducted in Malgaon village, Kondagaon district, Chhattisgarh, with 146 farmers, making it difficult to generalize the findings to all agricultural regions. Second, the current study does not account for potential variations in adaptive behaviours based on gender, landholding size, or socio-economic status. Third, the study relied on cross-sectional survey data, meaning that farmers' responses were captured at a single point in time, while adaptation decisions are inherently dynamic, evolving across seasons.

Future studies could include larger and more diverse samples to improve representativeness and examine differential behavioural responses across social groups. Conducting longitudinal studies across multiple agricultural seasons would also provide deeper insights into how adaptation decisions evolve. Incorporating missing elements of MPPACC, such as adaptation incentives, reliance on public adaptation, and cognitive biases, along with other variables drawn from the Indian knowledge system, may further strengthen its theoretical

validation in the sub-continent of India. Additionally, integrating qualitative approaches could shed light on why certain psychological variables, such as avoidant maladaptation, behave differently in specific cultural contexts.

Conclusion

The current study employed MPPACC model to assess farmers' perceptions and responses to agricultural water scarcity. Some elements of this model significantly influence adaptation intention and adaptation strategies of the farmers. For example, perceived severity, perceived probability, adaptation efficacy, cost, and objective adaptive capacity significantly shaped adaptation intention, while adaptation strategies were further influenced by climate change perception, perceived self-efficacy, and adaptation intention. However, resource limitations and insufficient institutional support constrained the implementation of adaptation measures, resulting in a gap between intention and action.

The current study contributes to the existing body of knowledge by expanding the applicability of MPPACC theoretical framework in agricultural water scarcity adaptation research, especially in the Indian subcontinent, where limited studies on this model are available. This study demonstrates the model's usefulness in understanding farmers' adaptation behaviour in response to water scarcity. However, the model's ability to predict the variations in the dependent variables is moderate, suggesting that some important components may be missing from the theoretical framework and should be explored further through the inclusion of additional relevant variables.

Data availability

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions

N.H.-Conceptualization, Methodology, Data collection, writing original draft, Visualization; R.P.-Supervising, reviewing, and editing; N.M.-Supervising, reviewing, and editing. The final text has been reviewed and approved by all authors.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
Prior to data collection, the researcher received approval from the Institutional Human Ethics Committee (IHEC) of Amrita Vishwa Vidyapeetham, which approved the study protocol with registration number IHEC Ref No.: IHEC/2024/02/19. The study was conducted in accordance with all relevant guidelines and regulations of the research protocol.

Consent to participate
Written informed consent was obtained from all participants prior to the study.

Consent for publication
The authors granted the journal complete authorisation to publish this work.

Additional information
Correspondence and requests for materials should be addressed to R.P.

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