Original Research Article

Developmentand Standardization of a Climate Vulnerability Index to Measure the Vulnerability Indices of Paddy Growers

ABSTRACT

India is prominently recognized as the foremost producer of paddy, cultivating this crop over 47.83 million hectares and generating 135.75 million tonnes of paddy, thus playing a substantial role in the worldwide paddy output. However, there is an anticipated decline in paddy production yields due to the projected effects of climate change, estimated to range from 10% to 30% by 2030. The assessment of vulnerability will give a comprehensive picture of current and future climate change risks with more stress factors to be anticipated. It will help identify opportunities arising from climate change, and provide information on how to assess adaptive capacity and cope with uncertainty. Adaptation cannot be planned based on the climate projections; information on risk and vulnerabilities is also needed to determine how the climate interacts with socio-economic issues. Against this backdrop, the proposed research seeks to fill this crucial knowledge gap by developing and constructing vulnerability indices tailored specifically for paddy growers in India. Based on review of literature and discussion with experts, three dimensions along with indicators and sub-indicators by adopting the indicator approach method under the vulnerability indices of paddy growers due to climate change were identified. The relevancy rating score was obtained from 50 experts in the concerned area. Based on the relevancy score, 17 indicators and 65 sub-indicators of 0.80 and above were considered for inclusion in the vulnerability index. To compute the index values for each of the identified dimensions, their relative importance in the vulnerability was worked out by assignment of weights to indicators and sub-indicators under each dimension through Principal component analysis (PCA) and the findings revealed that sensitivity was observed to be in the top position (8.36), followed by exposure (8.28) and adaptive capacity (5.61) in assessing the climate vulnerability of paddy growers.

Keywords: Climate change; exposure; sensitivity; adaptive capacity; vulnerability index; paddy growers; principal component analysis.

INTRODUCTION

India is prominently recognized as the foremost producer of paddy, cultivating this crop over 47.83 million hectares and generating 135.75 million tonnes of paddy, thus playing a substantial role in the worldwide paddy output (MoA&FW, 2023). However, there is an anticipated decline in paddy production yields due to the projected effects of climate change, estimated to range from 10% to 30% by 2030 (IPCC, 2023). There is 13.27 per cent less area under paddy in 2022, compared to last year, even as the sowing of paddy was completed by the end of July in most parts of the country due to the failure of monsoon and paddy is one of the main food grains grown in the kharif season that starts in June and ends in October (MoA&FW, 2022). The forecast by the US Department of Agriculture anticipated a 3% decline in Indian rice production during the kharif season of 2023 due to below normal rainfall. Initially disregarded by both experts and the government, this prediction has now been validated as the government released its kharif crop estimates, acknowledging a 3.76% decrease in paddy production despite an expansion in acreage across India in 2023.

The sixth assessment synthesis report of Inter-governmental Panel on Climate Change found that the southern parts of India, there will be a more severe increase in rainfall, accompanied by rising snowline elevations and declining glacier volumes. Projections suggest that monsoon precipitation will increase in the mid-to-long term across South Asia, leading to an overall rise in annual mean precipitation. Specifically, rainfall is anticipated to surge by approximately 20% along the southwest coast. India, being one of the most vulnerable countries, is expected to experience a heightened frequency and severity of hot extremes. Climate change, coupled with increasing demand, forecasts that around 40% of India's population will face water scarcity by 2050, up from the current 33%. Furthermore, both the Ganges and Brahmaputra River basins are expected to suffer from flooding due to climate change, particularly if temperatures surpass a 1.5-degree Celsius increase. (IPCC, 2023). Tropical cyclones in India are primarily the result of the ENSO phenomenon. In India, tropical cyclones primarily occur between November and May (Singh *et al.*, 2000). Various studies show that the warming of oceans causes sea levels to rise, causing thermal-hydro expansion, which intensifies the strength and frequency of cyclones in the coastal regions of India (Mimura N., 2013). A total of 283 cyclones hit the Indian coastline between 1877 and 2005; as many as 106 of these were extreme cyclonic events that affected a 50 km–long strip on the east coast of India, and 35 hit the west coast (ADRC, 2012).Natural disasters are a common occurrence worldwide, with Asia experiencing the most frequent occurrences compared to other regions and there is a risk to food and water security due to increased temperature extremes, rainfall variability and drought (IPCC, 2022). These extreme weather events caused paddy crop damage across lakh of hectares and yield loss.

The onset of human-induced global warming, signified by a rise of 1.1 degrees Celsius, has ushered in unprecedented changes in Earth's climate (IPCC, 2023). Climate change has become an important area of concern for India to ensure food and nutritional security for growing population. In India, significant negative impact has been implied with medium-term (2010-2039) climate change, predicted to reduce yields by 4.5-9%, depending on the magnitude and distribution of warming. Since agriculture makes up roughly 16% of India’s GDP, a 4.5-9% negative impact on production implies a cost of climate change to be roughly up to 1.5% of GDP per year (Venkateswarlu et al., 2013). Furthermore, India's rank as the 7th most exposed and vulnerable nation in the Global Climate Risk Index Report-2021 underscores the urgency of understanding and mitigating the specific challenges faced by its agricultural sector.

The maximum temperature and low rainfall conditions have been identified as key factors impacting Indian rice yields, subsequently affecting the nation's economy (Ashkra et al., 2023). Climate change compounds these challenges, posing a significant threat to Indian agriculture in general, influencing food security, and hindering efforts to meet Sustainable Development Goals (IPCC, 2023).

In terms of vulnerability to extreme weather events, India stands as the seventh most vulnerable nation globally. A temperature increases of just one degree Celsius may result in a 3-7% reduction in yields of major food crops, with rice production anticipated to decrease significantly under higher temperature scenarios. Paddy farmers, already contending with heavy rainfall, low temperatures, and other climate-induced stressors, face a multitude of challenges, leading to reduced yields and variations in crop prices.

The assessment of vulnerability will give a comprehensive picture of current and future climate change risks with more stress factors to be anticipated. It will help identify opportunities arising from climate change, and provide information on how to assess adaptive capacity and cope with uncertainty. Adaptation cannot be planned based on the climate projections; information on risk and vulnerabilities is also needed to determine how the climate interacts with socio-economic issues.

The ongoing El Niño year in India, coupled with expected disruptions in monsoons, further heightens the vulnerability of paddy growers, presenting potential threats to food security and exacerbating existing challenges. Despite the critical importance of understanding and mitigating these vulnerabilities, the estimation of climate change vulnerability in the specific context of paddy cultivation is still a relatively nascent field of study.

Against this backdrop, the proposed research seeks to fill this crucial knowledge gap by developing and constructing vulnerability indices tailored specifically for paddy growers in India. These indices will encompass a comprehensive set of parameters, considering factors such as temperature variations, precipitation patterns, and the overall climatic conditions impacting rice production. By adopting a multidimensional approach, this research aims to provide nuanced insights into the vulnerabilities faced by paddy growers, facilitating targeted policy interventions, sustainable agricultural practices, and enhanced climate resilience in this vital sector. The resulting indices will not only contribute to academic scholarship but also serve as practical tools for policymakers, researchers, and stakeholders striving to address the complex challenges posed by climate change in Indian agriculture.

Importance of agriculture in India

India is agriculture dependent country and more than two-third of its population depends upon agriculture for their survival and it contributes approximately 18.3% to India's GDP (MoSPI, 2024). Of the total holdings, 86 per cent are in marginal and small farm categories of less than 2 ha (GOI, 2015-16). It has diverse seasons mean diverse crops and farming systems. There is a high dependency of agriculture on the monsoon rains approximately 67.79 million hectares out of India's total agricultural land of 180 million hectares lack irrigation, constituting 40% of the nation's agriculture, which relies on increasingly variable rainfall patterns and a close link exists between climate and water resources (MoA& FW, 2022). In this climate change era, agriculture is the most threatened sector because its dependence on local weather conditions. The effects of change in climate are global, but countries like India are more vulnerable in view of the high population depending on agriculture.

Paddy is the third most important cereal crop in the world after maize, wheat and is widely grown across 115 countries with a total production of 517.60 million tonnes which is the cornerstone of food security (FAO, 2023). It is estimated that about 90 per cent of rice production is achieved in Asia, where about 60 per cent of the world population lives (Pazhanisamy*et al*., 2020). About 3 billion people around the world consume rice as staple food (Jayapriya *et al*., 2016). India is the second largest rice producing country after China contributing about 26% of total rice production of the world (USDA, 2024). In India, about

43 per cent of total food grain production comes from rice and constitutes about 46 per cent of total cereal production of the country. India contributes about 26.7 and 23.5 per cent of total global rice area and production, respectively and continues to play a vital role in the national food and livelihood security. Rice contributes around 10 per cent of the agricultural GDP and its production generates 3.5-billion-man days of employment in India (Ahmad, *et al*. 2017, Kumar *et al*., 2018). Consumption of rice as a staple food by a large proportion of people, its contribution in agricultural GDP and generation of employment highlights its role in national food security, income and employment generation in India (Ahmad *et al*., 2019).

Review of literature

Bahri *et al*. (2024) revealed that the Livelihood Vulnerability Index can be succinctly divided into three distinct categories along with main and sub-components under each category: exposure, adaptive capability, and sensitivity. The results of this study indicated that based on the vulnerability index derived from LVI-IPCC calculations, Aceh Utara farming households were more susceptible to climate change than Aceh Besar. Regarding exposure, Aceh Besar exhibited a higher susceptibility to drought than Aceh Utara. The primary climatic phenomenon that significantly affected agricultural activities for paddy farmers was the increased frequency of periods of drought on agricultural land. Overall vulnerability of paddy farming households in North Aceh was more vulnerable to climate change compared to Aceh Besar because the vulnerability value of paddy farming households in Aceh Besar was 0.44 and North Aceh was 0.45. Shankara *et al*. (2023) revealed that the exposure of farmers to climate change, rainfall and temperature were selected and the majority of farmers were severely exposed (0.822) and sensitive (0.894) to climate change with lower adaptive capacity (0.576) between the year 2013-2017. It showed that, 0.186, 0.226, 0.224, 0.220 and 0.241 was the Climate Vulnerability Index (CVI) of Arsikere, Kadur, Tiptur, Chiknayakanahalli and Challakere *taluk*, respectively. The overall CVI value of all taluks was 0.218. As per the result, all *taluks* were severely vulnerable to climate change. Akanbi *et al*. (2022)found that the vulnerability assessment index was 0.3001 (a measure of the exposure, susceptibility and resilience/capacities of rice farmers) indicated that the study area was prone to the adverse effect of climate; this could be adduced to the problem of constant flooding occasioned by proximity to the river Niger. This high value had a negative effect on their livelihood as their livelihood was threatened. The high value might be because they were highly exposed and susceptible to climatic induced hazards coupled with low adaptive capacity. For this reason, the study empirically underscores the need for farmers to adopt and adapt the planting of drought tolerant and/or early maturing varieties of rice. Importantly, the capacities of the local communities need to be strengthened vis-à-vis the relationship between climate change and crop production. Arifah*et al*. (2022) revealed that the livelihood vulnerability index (LVI) framework and livelihood vulnerability index-Intergovernmental Panel on Climate Change (LVI-IPCC) approach were applied by selecting geographic and socio-demographic indicators that affected the farmer households, included 8 major components and 26 sub-components and found that the vulnerability of natural disasters and climate variability in both regions were moderately vulnerable (0.52 and 0.35, respectively). The sub-component of the number of droughts showed that the downstream area had high vulnerability (0.83). The increase in pest attacks contributed to moderate vulnerability in both areas, with a score of 0.51 in the downstream and 0.50 in the upstream. The index values in the upstream area were 0.15 and 0.27 in the downstream area, indicating that the two study locations were not vulnerable to flooding. Farmers experienced a decrease in rice production with a vulnerability score of 0.59 in the downstream and 0.29 in the upstream. The result of this study indicated that drought, pest attacks, and flooding all have an impact on lowland rice productivity. They found that the downstream area was more exposed to climate change impacts (0.52) than the upstream area (0.35) and in terms of adaptive capacity, the downstream and upstream areas were in the moderate vulnerability range (0.46 and 0.47, respectively. The sensitivity and exposure components in the downstream area had a higher vulnerability index than the adaptive capacity.Kus *et al.* (2022) revealed that there was a geographical division of vulnerability in Konya, in that the northern part was the most vulnerable, whereas the southern part was the least vulnerable. Common features of the highly vulnerable districts were their high exposure and sensitivity figures and low adaptive capacities. The main causes of high sensitivity were low precipitation and limited water resources, which increased the percentage of rain-fed agricultural land and reduced crop diversity. Low adaptive capacity occurred mainly owing to low agricultural insurance issuance and partly owing to lack of road infrastructure.Loi *et al.* (2022) found that the combination of three components i.e., exposure, sensitivity, and adaptive capacity according to IPCC to assess agricultural vulnerability was found like quite reliable. Climate change has a profound effect on agriculture in Ha Tinh province, causing negative impacts on the economy, society, and the environment. The results also showed that adaptive capacity is inversely proportional to vulnerability, greatly influencing other components. This indicated that the more adaptive capacity areas were the less vulnerable. In addition, low education levels and poor infrastructure in mountainous areas also make the vulnerability to agriculture higher.

Loria *et al* (2015) revealed that the indicators of vulnerability are weighted using Principal Component Analysis. In the low-hill zone, frequency of drought events, share of non-natural resources-based income and human assets registered highest weights of 0.68, 0.98 and 0.89 among the indicators of exposure, sensitivity and adaptive capacity, respectively. Mbakahya and Ndiema (2015) indicated that the indicator approach is a method that could be used to measure vulnerability This method was based on developing a range of indicators and selecting some of them through expert judgment, principal component analysis, or correlation with past disaster events. Mallari and Ezra (2016) considered rainfall volume, average typhoon wind speed, and plant growth stage during typhoon as the sensitivity indicators for the vulnerability assessment. Affected production areas, affected farmers, damaged farmer equipment/houses/infrastructure, and frequency of typhoons are the chosen exposure indicators. Access to crop insurance, access to typhoon forecasting information, and access to planting calendar bulletins are the chosen adaptive capacity indicators. Further, they described the vulnerability index, which was derived from the weighted summations of sensitivity, exposure and adaptive capacity ratings, shows that all barangays with agricultural areas in Mabalacat City have vulnerability ratings classified as “High”, except for Bundagul, Cacutud, Camachiles, Mamatitang, Mawaque, Sapang Biabas with vulnerability ratings classified as “Very High”. Kumar et al., (2014) in their study considered the relevance of indicators to study area and availability of data, indicators were selected to measure all the three dimensions of vulnerability index. Following the methodology used by, the selected indicators were first normalized to make the indicators units free. The functional relationships between the indicators and exposure or sensitivity or adaptive capacity were established before the normalization of indicators.BCCI-K (2011) reported Vulnerability status by using a composite index (based on demographic, social, occupational, agricultural and climatic indicators) where they estimated that Gulbarga district is the most vulnerable district and Dakshin Kannada is the least vulnerable district in Karnataka.

Theoretical Background of the study

Vulnerability is a multidimensional concept which varies across temporal and spatial scales and depends on economic, social, geographic, demographic, cultural, institutional, governance and environmental factors (Thornton et al., 2006; Piya et al., 2012). Vulnerability is defined as the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt (IPCC, 2022). Vulnerability to climate change is defined as the degree to which a system issusceptible toand unable to cope up with the adverse effects of climate changeincluding climate variability and extremes. Vulnerability is a function or magnitude andrate of climate change and variation to which a system is exposed, its sensitivity, and itsadaptive capacity(IPCC, 2007).

Exposure is "the degree to which a system is exposed tosignificant climatic variations". Sensitivity to climate change is defined as "the degreeto which a system is affected, either adversely or beneficially, by climate variability".Adaptive capacity is "the ability of a system to adjust to climate change to moderatepotential damages or to take advantage of opportunities, or to cope with theconsequences"(IPCC, 2007).

Operationalization of Vulnerability indices of paddy growers:

Vulnerability indices of paddy growers due to climate change is operationally defined as the degree to which paddy growers are susceptible to or unable to cope with adverse effects of climate change. It takes into account the exposure of paddy growers to climate-related hazards, their sensitivity to these hazards, and their adaptive capacity.

(a) **Exposure of paddy growers to climate variability** is operationally defined as degree ofclimate variability that farmers experiences over a period of time in cultivation of paddy.
(b) Sensitivity of paddy growersto climate change is operationally defined as the degree to which paddy growers and their farming practices are adversely affected due to the changes in climate. It takes into account how various climatic factors such as precipitation, temperature and extreme weather events can influence farming practices, yield, income and overall agricultural productivity.
(c) Adaptive Capacity of paddy growersto climate change is operationally defined as ability of farmers to adjust themselves to climate change and its potential damages caused on agriculture or to take up advantage of opportunities created or to cope up with its consequences.

METHODOLOGY

Vulnerability index was developed by following the procedure as given below:

Step1: Identification of Dimensions

The vulnerability indicesof paddy growers due to climate change was identified as adependent variable. Based on a thorough review of literature related to vulnerability toclimate change, three dimensions were identified viz.,

• Exposure of paddy growers,

• Sensitivity of paddy growers and

• Adaptive capacity of paddy growers.

Further the different indicators and sub-indicators were framed under each dimension by adopting the ‘indicator approach method’ and those sub-indicators are the variables for the research study.

Step 2: Collection of indicators and sub-indicators

A large number of draft indicators and sub-indicators on each dimension of vulnerability indices of paddy growers due to climatechange were collected based on review of literature, discussion with concerned specialists.These indicators and sub-indicators were carefully edited, revised and restructured in google forms.

The Google forms were mailed to 100 experts in the agricultural extension and other related fields of ICAR Institutes and SAUs to critically evaluate the relevancy of each indicator and sub-indicators in the three-point continuum viz., Relevant (R), Somewhat Relevant (SWR) and Not Relevant (NR) with the score of 3, 2 and 1 respectively. They were also requested to add other indicators that they find relevant to measure vulnerability indices of paddy growers. A total of 50experts returned thequestionnaires duly completed andconsidered for further processing. From thedata gathered, Relevancy Rating Scorewas worked out for all the indicators and sub-indicators by using the formula

$$\textbf{Relevancy Rating Score} = \frac{\mathbf{R \times 3 \ + \ SWR \times 2 \ + \ NR \times 1}}{\textbf{No. of judges responded} \ \times \textbf{Maximum score}}$$

Taking into consideration the overall values which was given by thejudges, the items having relevancy rating score of equal and more than 0.80 were considered for the inclusion infurther analysis. Thus, indicators andsub-indicators were considered for further processing and suitablymodified as per the comments of experts wherever applicable. The indicators that have passed the criteria arepresented in Table 2.

The indicators and sub-indicators were chosen for studying climate vulnerability covered various aspects that affected how communities and ecosystems coped with climate change. Factors like unpredictable monsoons, changes in rainfall, extreme weather events like storms and floods, and rising temperatures were important to consider. We also looked at how these changes affected agriculture, including when crops were planted and harvested, and the spread of pests and diseases. Financial stability, access to water, and how well communities were prepared for emergencies were also crucial. Understanding these factors helped us figure out who was most at risk and how we could help them prepare and adapt to the changing climate. By studying these indicators, we could develop better strategies to protect people and the environment from the impacts of climate change.

Step 4:Operationalization and Functional relationship of indicators and sub-indicators to climate vulnerability

The indicators and sub-indicators are operationalized in this step as given below:

Table 1.Functional Relationship of the indicators to the climate vulnerability

Dimensions	**Indicators**	**Sub-indicators**	**FR[a]**	**Description of the sub-indicator**
Exposure of paddy growers to climate variability	Monsoon Variability	Changes in pre-monsoon rainfall	↑	Farmers who perceived alterations in rainfall patterns occurring before the onset of the monsoon season
		Changes in the onset and duration of South-West Monsoon	↑	Farmers who had a perspective on shifts in the timing and length of the primary monsoon season.
		Changes in post-monsoon rains	↑	Farmers who viewed variations in rainfall patterns following the monsoon season
		Changes in Winter season	↑	Farmers who observed alterations in temperature and weather conditions during the winter months
	Precipitation Variability	Delay in onset of rainfall	↑	Farmers who experienced delays in the arrival of seasonal rainfall.
		More number of rainy days	↑	Farmers who encountered an increased number of rainy days
		More dry spells during crop season	↑	Farmers who experienced prolonged periods of limited rainfall within the crop growing season
		Rainfall aberrations during crop growth period	↑	Farmers who observed irregular or unexpected rainfall patterns occurring during critical stages of crop growth
		Erratic rainfall throughout the season	↑	Farmers who perceived unpredictable fluctuations in rainfall amounts and distribution over the entire cropping season
		Low number of rainy days/Untimely winter rainfall	↑	Farmers who reported a decrease in the frequency of rainy days or rainfall occurring at inappropriate times during the winter season
	Climate Hazard	Occurrence of floods	↑	Farmers who experienced sudden inundation of land areas due to excessive rainfall or river overflow.
		Occurrence of cyclones	↑	Farmers who reported an increase in frequency and incidence of Cyclones
		Heavy rains	↑	Farmers who encountered heavy rainfall events over a period of time
		Unseasonal rains	↑	Farmers who experienced rainfall occurring outside the typical monsoon season or at irregular intervals.
		Extended dry spells	↑	Farmers who experienced prolonged

				periods of limited rainfall
		Hailstorms/Thunderstorms and Lightning	↑	Farmers who faced hailstorms, thunderstorms, and lightning perceived significant impacts on their crop damage and yield loss.
	Temperature	Rising Temperatures	↑	Farmers who observed maximum temperatures over time
		Heat waves during crop season	↑	Farmers who experienced heat waves during the crop season
		Low Temperature	↑	Farmers who encountered low temperatures
Sensitivity of paddy growers to climate variability	Crop phenology	Delay in planting nursery/sowing	↑	Farmers who experienced delays in planting nursery or sowing due to unfavourable weather conditions
		Change in timing of planting	↑	Farmers who observed alterations in the usual timing of planting activities influenced by climate variations.
		Change in scheduling irrigation	↑	Farmers who noted modifications in the timing and frequency of irrigation
		Change in scheduling pesticide inputs	↑	Farmers who reported adjustments in the timing of pesticide applications to manage pest due to climate-related factors
		Change in scheduling of post-harvest activities	↑	Farmers who experienced alterations in the timing of post-harvest activities such as harvesting, drying, and storage influenced by climate variations
	Pest and Disease Dynamics	Susceptibility to pests-BPH, yellow stem borer, leaf folder, rodents due to climate change	↑	Farmers who reported an increase in the incidence of pest/insect attack due to climate change
		Susceptibility to diseases- Blast, sheath blight, bacterial blight due to climate change	↑	Farmers who reported an increase in the incidence of diseases attack due to climate change
		Inability to take plant protection activities	↑	Farmers who faced challenges in implementing plant protection activities against pest/disease attack due to climate-related factors
	Economic vulnerability	Augmented climate-induced cultivation costs	↑	Farmers who believed climate-led risk had increased the cost of rice cultivation
		Climate-induced market challenges	↑	Farmers who encountered disruptions or difficulties in accessing markets and selling their produce due to climate change impacts.

		Hefty labour costs	↑	Farmers who faced an increased expenses associated with labour for agricultural activities
		Price fluctuations	↑	Farmers who observed unpredictable changes in commodity prices influenced by climate variations
		Income instability	↑	Farmers who experienced fluctuations or uncertainty in income levels over time due to climate change
		Debt vulnerability	↑	Farmers who reported susceptibility to financial indebtedness or an inability to repay loans.
		Weather triggered input expenses	↑	Farmers who believed additional input expenses incurred in response to weather-related risks or uncertainties.
	Water sensitivity	Delayed/Limited release of canal water for irrigation	↑	Farmers who experienced delays or limited release of canal water for irrigation due to climate-related factors
		Low yields due to non-availability of irrigation	↑	Farmers who believed low yields due to non-availability of irrigation water influenced by climate variability
		Non-availability of water during planting	↑	Farmers who encountered non-availability of water during planting seasons due to climate-related factors
		Non-availability of water during grain formation	↑	Farmers who experienced non-availability of water during grain formation stages influenced by climate variability
	Extreme weather sensitivity	Crop failure due to floods/cyclones	↑	Farmers who faced crop failure due to floods or cyclones driven by climate variability.
		Affecting fodder production	↑	Farmers who observed adverse impacts on fodder production influenced by climate variability
		Low quality of harvested rice grain	↑	Farmers who encountered low quality of harvested rice grain due to climate change
		Reduction in crop yield	↑	Farmers who experienced reductions in crop yield influenced by climate variability.
Adaptive capacity of paddy growers to climate variability	Socio-Demographic	Education	↓	Farmers' average years of schooling
		Farming Experience	↓	Number of years
		Membership in community level organisations/farmer-based organisation	↓	Farmers who were members of community-level organizations or farmer-based organizations
	Knowledge Acquisition	Awareness of climate information	↓	Farmers who were aware of climate information and early warning

		and early warning system		systems shared their perceptions.
		Awareness of climate change impacts on paddy farming	↓	Farmers who were aware of climate change impacts on paddy farming
		Understanding of climate resilient practices and climate-informed inputs	↓	Farmers who had an understanding of climate resilient practices and climate-informed inputs
	Preparedness	Access to early warning system/climate information	↓	Farmers who had access to early warning systems or climate information services
		Utilization of mobile apps and online portals for monitoring weather and pest conditions	↓	Farmers who utilized mobile apps and online portals for monitoring weather and pest conditions
	Weather-Responsive Planning	Flexibility in farming schedules based on weather changes	↓	Farmers who demonstrated flexibility in farming schedules based on weather changes
		Rescheduling planting and harvesting dates based on weather forecast	↓	Farmers who rescheduled planting and harvesting dates based on weather forecasts
		Utilization of climate forecasts to anticipate and manage yield variability	↓	Farmers who utilized climate forecasts to anticipate and manage yield variability
	Social Networking	Participation in farmer groups, cooperatives and networks	↓	Farmers who participated in farmer groups, cooperatives, and networks shared their experiences
		Exchange of climate related information and best practices	↓	Farmers who exchanged climate-related information and best practices expressed varied opinions
	Capacity Building	Participation in workshops/training sessions on climate resilient practices	↓	Farmers who participated in workshops or training sessions on climate-resilient practices shared their perspectives.
		Access to Agricultural Extension services	↓	Farmers who had access to Agricultural Extension services
	Financial resilience	Access to agricultural credit	↓	Farmers who had access to agricultural credit and loans

		and loans		
		Access to non-formal credit	↓	Farmers who had access to non-formal credit
		Access to crop insurance	↓	Farmers who had access to crop insurance
		Access to market	↓	Farmers who had access to markets
	Infrastructural Preparedness	Rainwater harvesting	↓	Farmers who practiced collection and storage of rainwater for agricultural use
		Elevated pathways for drainage of water	↓	Farmers who utilized and construction of raised pathways to facilitate drainage and prevent waterlogging.
		Access to mechanized equipment	↓	Farmers who had access to availability of machinery for agricultural operations.
		Grain storage silos	↓	Farmers who utilized facilities for storing and preserving harvested grains

[a] Functional relationship of the indicators to the vulnerability

Step 5: Normalization of Indicators and sub-indicators

The indicators and sub-indicators that passed the criteria of relevancy rating scores were selected for inclusion in the index. Consequently, the scores of all indicators and sub-indicators were normalized using the provided formula.

$$U_{ij} = \frac{Y_{ij} - Min_{yj}}{Max_{ij} - Min_{yj}}$$

Where,

U_{ij} = Unit score of the ith respondents on thejth component

Y_{ij} = Value of ith respondent on the jth component

Max_{ij} = Maximum score on the jth component

Min_{yj} = Minimum score on the jth component

Step 7: Validity Test:

In the present investigation,Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericitywas adopted to compute the validity of the Vulnerability Index and it was established by the expert’sjudgement.The variance proportion can be interpreted as per the following table

Table 2.The KMO Value Interpretation Criteria

KMO Value	**Interpretation of sampling adequacy**
1 to 0.9	Very Good
0.8 to 0.9	Good

0.7 to 0.8	Medium
0.6 to 0.7	Reasonable
0.5 to 0.6	Acceptable
< 0.5	Unacceptable

Prior to assigning weights to indicators and sub-indicators under each dimension via Principal Component Analysis, the normalized data underwent analysis with KMO and Bartlett's Test to assess the validity of items for measuring sampling adequacy, utilizing SPSS software (version 20).

Step 6: Assignment of weights to indicators and sub-indicators under each dimension through Principal component analysis(PCA)

After normalization, factor analysis for each data set of 17 indicators and 65 sub-indicators under each dimension of vulnerability index was runchoosing Principal Component Analysis (PCA) for extraction and varimax method forrotation of factors using SPSS software (version20).Then, the method followed by Feroz et al.,2010; Maiti et al., 2015 adopted to assign the weight to the indicators sub-indicators under each dimension.

The initial Eigen values above were recognized. Based on the number of Eigen values exceeding 1, an equivalent number of rotated components were extracted for each sub-indicator, as depicted in the rotational component matrix. Subsequently, the extracted rotated component matrix was multiplied by the Eigen values, with the first values being multiplied by the first extracted component column and the second Eigen value being multiplied by the second extracted component column. The resulting values were then aggregated for each indicator to determine their respective weights. Similarly, the same process was carried out to derive weights for other indicators. Convert the obtained values into absolute values and calculate the sum of each row for all the indicators to obtain weightage values.

Step 8: Reliability of the Vulnerability Index:

Internal consistency reliability method via Cronbach alpha was adopted to testthe reliability using SPSS software version 20. The standard Cronbach Alpha coefficient valueof equal or more than 0.70, which indicatesgood internal consistency of items and considered for further inclusion in the index.

RESULTS

Selection of indicators for inclusion in the index: The responses were quantified and presented in the Table 3.

Table 3: Relevant Rating Scoreof Indicators

Indicator	RRS
Monsoon Variability	0.85
Precipitation Variability	0.86
Climate Hazard	0.87
Temperature	0.91
Crop phenology	0.89
Pest and Disease Dynamics	0.91

Financial resilience	0.88
Water sensitivity	0.83
Extreme weather sensitivity	0.84
Socio-Demographic	0.83
Knowledge Acquisition	0.85
Preparedness	0.82
Weather-Responsive Planning	0.87
Social Networking	0.84
Capacity Building	0.92
Economic Vulnerability	0.89
Infrastructural Preparedness	0.84

The table 3 displayed the Relevant Rating Scores (RRS) for various indicators used to create a vulnerability index assessing the impact of climate change on paddy growers. Scores ranged from 0.81 to 0.92, with higher scores indicating greater relevance. Factors like temperature, pest and disease dynamics, and capacity building received exceptionally high scores, while others like financial resilience and weather planning scored moderately high. Indicators with RRS above 0.80 were chosen for the index, resulting in 17 selected indicators covering climatic, agricultural, socio-economic, and preparedness aspects. This rigorous selection ensures that the index accurately captures the complex vulnerabilities of paddy growers, facilitating effective climate adaptation and mitigation strategies.

Selection of sub-indicators: The table 4 presented the Relevancy Rating Scores (RRS) for various sub-indicators considered in creating an index to assess the vulnerability of paddy growers to climate change. These scores, ranging from 0.80 to 0.93, were calculated by dividing the actual score obtained for each sub-indicator by the maximum score possible. Ultimately, 65 sub-indicators were selected for inclusion in the index, each representing different aspects of vulnerability. Noteworthy findings included high scores for sub-indicators like changes in monsoon patterns, extreme weather events, economic vulnerability, and capacity building, indicating their significant impact on paddy growers' vulnerability to climate change. Conversely, factors such as non-availability of irrigation water and limited access to credit received relatively lower scores but were still crucial considerations for understanding vulnerability. These selected sub-indicators collectively provided a comprehensive framework for evaluating and addressing the complex challenges faced by paddy growers in adapting to climate change impacts.

Table 4. Relevancy Rating Score of Sub-indicators

Indicator	Sub-indicator	RRS
Monsoon Variability	Changes in pre-monsoon rainfall	0.84
	Changes in the onset and duration of South-West Monsoon	0.92
	Changes in post-monsoon rains	0.84
	Changes in Winter season	0.83
Precipitation Variability	Delay in onset of rainfall	0.83
	More number of rainy days	0.85
	More dry spells during crop season	0.87
	Rainfall aberrations during crop growth period	0.89

	Erratic rainfall throughout the season	0.90
	Low number of rainy days/Untimely winter rainfall	0.86
Climate Hazard	Occurrence of floods	0.87
	Occurrence of cyclones	0.89
	Heavy rains	0.85
	Unseasonal rains	0.89
	Extended dry spells	0.90
	Hailstorms/Thunderstorms and Lightning	0.84
Temperature	Rising Temperatures	0.91
	Heat waves during crop season	0.85
	Low Temperature	0.85
Crop phenology	Delay in planting nursery/sowing	0.89
	Change in time of planting	0.87
	Change in scheduling irrigation	0.87
	Change in scheduling pesticide sprays	0.83
	Change in scheduling of post-harvest activities	0.82
Pest and Disease Dynamics	Susceptibility to pests-BPH, yellow stem borer, leaf folder, leaf mite and rodents due to climate change	0.89
	Susceptibility to diseases- Blast, sheath blight, bacterial leaf blight due to climate change	0.92
	Inability to take plant protection activities	0.91
Economic Vulnerability	Augmented climate-induced cultivation costs	0.89
	Climate-induced market challenges	0.92
	Hefty labour costs	0.90
	Price fluctuations	0.88
	Income instability	0.92
	Debt vulnerability	0.89
	Weather triggered input expenses	0.83
Water sensitivity	Delayed/Limited release of canal water for irrigation	0.80
	Low yields due to non-availability of irrigation	0.81
	Non-availability of water during planting	0.82
	Non-availability of water during grain formation	0.90
Extreme weather sensitivity	Crop failure due to floods/cyclones	0.81
	Affecting fodder production	0.81
	Low quality of harvested rice grain	0.89
	Reduction in crop yield	0.85
Socio-Demographic	Education	0.86
	Farming Experience	0.89
	Membership in community level organisations/farmer-based organisation	0.81
Knowledge Acquisition	Awareness of climate information and early warning system	0.80
	Awareness of climate change impacts on paddy farming	0.82
	Understanding of climate resilient practices	0.86

	and climate-informed inputs	
Preparedness	Access to early warning system/climate information	0.82
	Utilization of mobile apps and online portals for monitoring weather and pest conditions	0.85
Weather-Responsive Planning	Flexibility in farming schedules based on weather changes	0.81
	Rescheduling planting and harvesting dates based on weather forecast	0.90
	Utilization of climate forecasts to anticipate and manage yield variability	0.85
Social Network	Participation in farmer groups, cooperatives and networks	0.82
	Exchange of climate related information and best practices	0.86
Capacity Building	Participation in workshops/training sessions on climate resilient practices	0.93
	Access to Agricultural Extension services	0.91
Financial resilience	Access to formal credit	0.85
	Access to non-formal credit	0.80
	Access to crop insurance	0.82
	Access to market	0.83
Infrastructural Preparedness	Rainwater harvesting	0.87
	Elevated pathways for drainage of water	0.81
	Access to mechanized equipment	0.84
	Grain storage silos	0.85

Validity and Computation of assigning weightsto indicators and sub-indicators under each dimension through Principal Component Analysis:

Dimension 1: Exposure of paddy growers to climate variability

Table 5: KMO and Bartlett's Test Value for exposure of paddy growers to climate variability

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.567
Bartlett's Test of Sphericity	Approx. Chi-Square	383.706
	Df	171
	Sig.	0.000

The validity of indicators and sub-indicators under the dimension of exposure to climate variability for paddy growers was assessed using Principal Component Analysis (PCA), with the results presented in Table 5. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was found to be 0.567, indicating an acceptable level of adequacy. This value suggested that the correlations among the variables were sufficiently strong to proceed with factor analysis. Essentially, it implies that the selected indicators and sub-indicators effectively capture the variability in exposure to climate variability among paddy growers.Moreover, Bartlett's Test of Sphericity yielded a significant result, with an Approx. Chi-Square value of 383.706 and a significance value (p) of 0.000. This result indicated that the correlation matrix was not an identity matrix, implying a strong relationship among the variables. Consequently, factor analysis was considered appropriate for this dataset, further validating the selection of indicators and sub-indicators.In simpler terms, these results suggest that the indicators and sub-indicators chosen to assess the exposure of paddy growers to climate variability are statistically valid and reliable. The significant relationships among the variables indicate that they collectively contribute to understanding the vulnerability of paddy growers to climate change impacts. This analysis provides a robust foundation for identifying key factors influencing vulnerability and guiding the development of targeted adaptation strategies for paddy growers.

Table 6: Eigen values for exposure of paddy growers to climate variability

Total Variance Explained					
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	4.120	21.687	21.687	4.120	21.687
2	3.571	18.797	40.483	3.571	18.797
3	1.476	7.766	48.250	1.476	7.766
4	1.371	7.215	55.465	1.371	7.215
5	1.242	6.538	62.003	1.242	6.538
6	1.048	5.517	67.520	1.048	5.517
7	0.994	5.232	72.752		
8	0.931	4.902	77.653		
9	0.770	4.050	81.703		
10	0.692	3.644	85.347		
11	0.638	3.359	88.706		
12	0.511	2.690	91.396		
13	0.408	2.147	93.543		
14	0.386	2.032	95.574		
15	0.213	1.119	96.694		
16	0.200	1.053	97.747		
17	0.188	0.989	98.736		
18	0.154	0.813	99.549		
19	0.086	0.451	100.000		

Extraction Method: Principal Component Analysis.

Table 6 provided insights into the Eigen values for assessing the exposure of paddy growers to climate variability. Eigen values represent the variance explained by each principal component extracted through Principal Component Analysis (PCA).In this analysis, six components were chosen based on having Eigen values greater than one. These six components collectively accounted for 67.52% of the total variance in exposing paddy growers to climate vulnerability. This implies that these six factors capture a significant portion of the variability in how paddy growers are exposed to climate variability.Eigen values were crucial as they help to identify which components were most influential in explaining the variation in the dataset. In this case, the six components with Eigen values greater than one were considered meaningful in understanding the exposure of paddy growers to climate variability. This analysis aids in prioritizing and focusing on key factors that contribute most significantly to the vulnerability of paddy growers to climate change impacts.

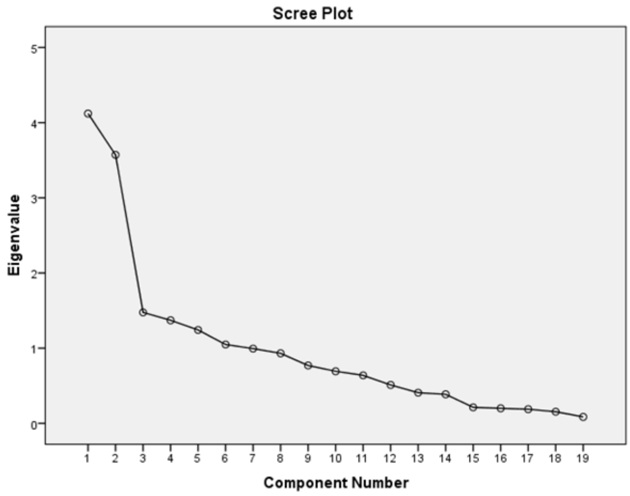

Figure 1: Scree plot for exposure of paddy growers to climate variability

Figure 1, presented above, displayed a scree plot representing the eigenvalues of all components, offering a visual representation of the variance explained by each component. The Y-axis of the graph indicated 'Eigenvalues,' ranged from 0 to 5, derived from the 'Total' column in Table 6. Each eigenvalue was plotted as a point on the curve of the scree plot. On the X-axis, labelled 'Component Number,' values from 1 to 19 were depicted, obtained from the 'Component' column in Table 6.Upon examining Figure 1, it was observed that the curve in the scree plot started to level off between component 6 and component 7. This suggested a diminishing marginal contribution of additional components to explaining the variance in exposing paddy growers to climate variability. Furthermore, eigenvalues for components 1 to 6 exceeded 1, indicating that these components captured a significant portion of the variance. In contrast, eigenvalues for components 7 to 19 were less than 1, implying a lower explanatory power.Therefore, based on the scree plot, it was decided to retain only the first six components, as they accounted for the majority of the variance in the dataset. This decision ensures a more parsimonious model while still capturing the essential factors influencing the exposure of paddy growers to climate variability.

Table 7. Rotated Component Matrix for exposure of paddy growers to climate variability

Rotated Component Matrix[a]						
Sub-indicators	Component					
	1	2	3	4	5	6
Changes in Winter season	0.781					
Changes in post-monsoon rains	0.749					
Changes in pre-monsoon rainfall	0.742					
Delay in onset of rainfall	0.673					
Extended dry spells		0.737				
Unseasonal rains		0.718				

Low number of rainy days/Untimely winter rainfall		0.697				
Occurrence of cyclones		0.514				
Rainfall aberrations during crop growth period			0.853			
Changes in the onset and duration of South-West Monsoon			0.694			
More dry spells during crop season			0.593	0.501		
Low Temperature			0.553			
Erratic rainfall throughout the season			0.550			
More number of rainy days				0.733		
Heat waves during crop season				0.628		
Rising Temperatures				0.620		
Heavy rains					0.817	
Hailstorms/Thunderstorms and Lightning						0.869
Occurrence of floods				0.532		-0.583
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]						
a. Rotation converged in 8 iterations.						

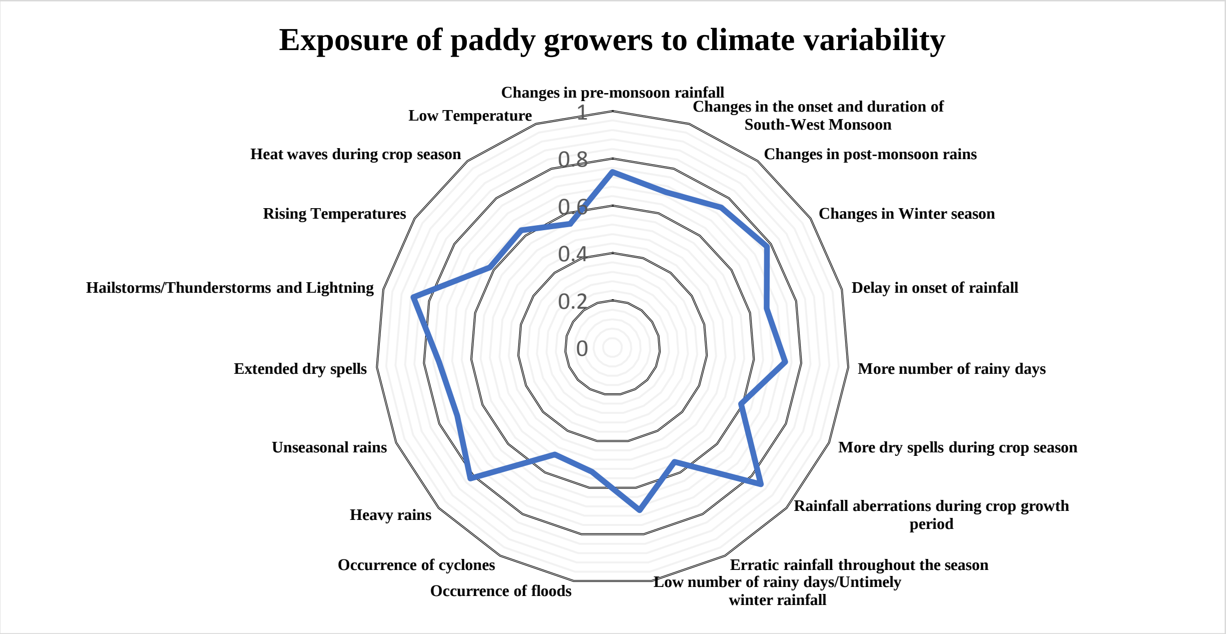

Figure-2 Factor loadings of exposure of paddy growers to climate variability sub-indicators

Table 7 and Figure 2 presented the rotated component matrix for exposure of paddy growers to climate variability. This matrix displayed the correlation between the sub-indicators and the identified factors extracted through principal component analysis. Each factor column represented a distinct dimension of exposure to climate variability.

Upon analyzing the table, it was evident that certain sub-indicators exhibit strong correlations with specific factors. For instance, sub-indicators such as "Rainfall aberrations during crop growth period", "Heavy rains" and "Hailstorms/Thunderstorms and Lightning" demonstrated high factor loadings (>0.80) on Factor 3, 5 and 6, indicated a strong association with this dimension of climate variability which was also depicted in figure 2. Similarly, sub-indicators like "Changes in Winter season", "Changes in post-monsoon rains", "Changes in pre-monsoon rainfall", "Extended dry spells", "unseasonal rains" and "More number of rainy days" exhibited high factor loadings (>0.70), indicated asignificant correlation with Factor 1, 2 and 4 which was also shown in figure 2. Furthermore, sub-indicators with factor loadings exceeding 0.50 are considered to have substantial relationships with the corresponding factors. For instance,"Delay in onset of rainfall" display notable correlation with Factor 1, represented changes in seasonal rainfall patterns.

Overall, Table 7 highlights the key sub-indicators contributing to each dimension of exposure to climate variability among paddy growers. By identifying these significant correlations, policymakers and agricultural stakeholders can prioritize interventions and strategies to mitigate the impacts of specific climate-related challenges on paddy cultivation.

Dimension 2: Sensitivity of paddy growers

Table 8: KMO and Bartlett's Test Value for sensitivity of paddy growers to climate change

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.581
Bartlett's Test of Sphericity	Approx. Chi-Square	443.672
	Df	253
	Sig.	.000

Table 8 presented the results of the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests conducted to assess the sampling adequacy and sphericity, respectively, for the sensitivity of paddy growers to climate change. The KMO value obtained was 0.581, indicated an acceptable level of sampling adequacy. This value suggested that the correlations among variables were sufficiently strong to proceed with factor analysis, with 58.1% of the variance in the variables accounted for by common factors.

Furthermore, Bartlett's Test of Sphericity yielded an Approx. Chi-Square value of 443.672, with a significance value (p) of 0.000. The significance of the chi-square test indicated that there was a significant relationship among the variables, supporting the suitability of conducting factor analysis on the dataset.

Overall, the results from Table 8 affirmed the appropriateness of utilizing factor analysis to explore the sensitivity of paddy growers to climate change. The significant KMO value and Bartlett's test results provide confidence in the validity of the dataset for identifying underlying factors associated with the sensitivity of paddy cultivation to climate variability.

Table 9:Eigen values for sensitivity of paddy growers to climate change

Total Variance Explained		
Component	Initial Eigenvalues	Extraction Sums of Squared Loadings

	Total	% of Variance	Cumulative %	Total	% of Variance
1	4.480	19.476	19.476	4.480	19.476
2	3.700	16.089	35.565	3.700	16.089
3	1.812	7.879	43.444	1.812	7.879
4	1.589	6.908	50.352	1.589	6.908
5	1.301	5.654	56.006	1.301	5.654
6	1.235	5.369	61.375	1.235	5.369
7	1.105	4.806	66.181	1.105	4.806
8	1.029	4.473	70.654	1.029	4.473
9	0.967	4.204	74.858		
10	0.851	3.702	78.560		
11	0.762	3.312	81.872		
12	0.671	2.918	84.790		
13	0.640	2.783	87.573		
14	0.519	2.257	89.830		
15	0.487	2.118	91.947		
16	0.432	1.877	93.824		
17	0.350	1.520	95.345		
18	0.310	1.348	96.693		
19	0.202	0.877	97.570		
20	0.185	0.805	98.375		
21	0.163	0.709	99.084		
22	0.133	0.579	99.663		
23	0.078	0.337	100.000		
Extraction Method: Principal Component Analysis.					

Table 9 provided the Eigenvalues and the percentage of variance explained by each component for the sensitivity of paddy growers to climate change. The table illustrated that the initial Eigenvalues ranged from 4.480 to 0.078, with corresponding percentages of variance ranging from 19.476% to 0.337%. These values represent the amount of variability captured by each component.

In total, eight components with Eigenvalues greater than one were selected, explaining a cumulative variance of 70.65%. This indicated that these eight factors collectively accounted for 70.65% of the variability observed in the sensitivity of paddy growers to climate change. The extraction sums of squared loadings further confirm the variance explained by each component.

Overall, Table 9 highlighted the significance of these eight factors in understanding the sensitivity of paddy growers to climate change. By capturing a substantial portion of the variance, these factors provided valuable insights into the various dimensions of sensitivity among paddy growers, enabling targeted interventions and adaptive strategies to mitigate the impacts of climate change on paddy cultivation.

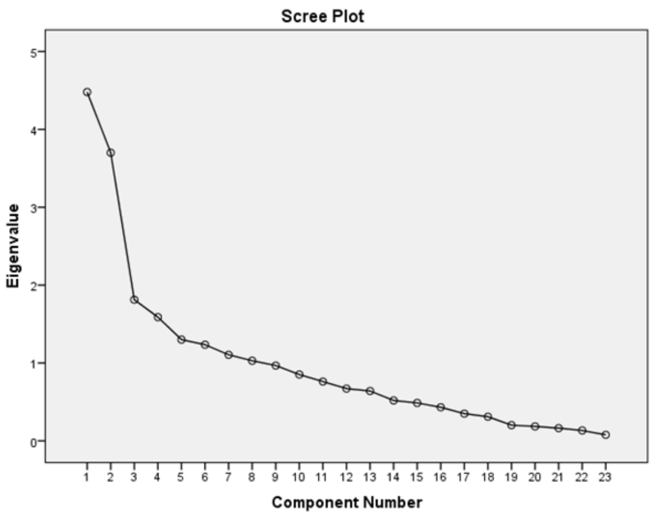

Figure 3: Scree plot for sensitivity of paddy growers to climate change

Figure 3, shown above, provided a visual representation of the eigenvalues of all components through a scree plot. This plot served to illustrated the variance explained by each component, aiding in the determination of the optimal number of factors to retain. The Y-axis of the graph represented the eigenvalues, ranged from 0 to 5, with the maximum of 8 components derived from the 'Total' column in Table 9. These eigenvalues were plotted as points on the curve of the scree plot. On the X-axis, the 'Component Number' ranged from 1 to 23, obtained from the corresponding column in Table 9. Analysis of Figure 2 indicated that the curve of the scree plot started to level off between components 8 and 9. Additionally, it was observed that the eigenvalues for components 1 to 8 exceeded 1, suggested their significance in explaining the variance in sensitivity of paddy growers to climate change. Conversely, for components 9 to 23, the eigenvalues were less than 1, indicated less explanatory power. Therefore, based on the scree plot, it was determined that retaining 8 factors would sufficiently capture the variability in the dataset.

Table 10. Rotated Component Matrix for sensitivity of paddy growers to climate change

Rotated Component Matrix[a]								
Sub-indicators	Component							
	1	2	3	4	5	6	7	8
Reduction in crop yield	0.759							
Crop failure due to floods/cyclones	0.754							
Low quality of harvested rice grain	0.736							
Delayed/Limited release of canal water for irrigation	0.686							0.548
Non-availability of water during grain formation		0.807						
Non-availability of water during planting		0.710						
Affecting fodder production		0.694						

Change in scheduling pesticide inputs		0.581						
Augmented climate-induced cultivation costs		0.557				0.512		
Weather triggered input expenses			.780					
Debt vulnerability			.664					
Price fluctuations			.610					
Low yields due to non-availability of irrigation				0.703				
Hefty labour costs				0.608			-0.507	
Change in scheduling irrigation				0.594				
Change in timing of planting				0.590				
Inability to take plant protection activities					0.776			
Susceptibility to pests- BPH, yellow stem borer, leaf folder, rodents due to climate change					0.724			
Susceptibility to diseases- Blast, sheath blight, bacterial blight due to climate change					-0.613			
Income instability						0.788		
Delay in planting nursery/sowing							0.808	
Change in scheduling of post-harvest activities			0.781					
Climate-induced market challenges								0.775

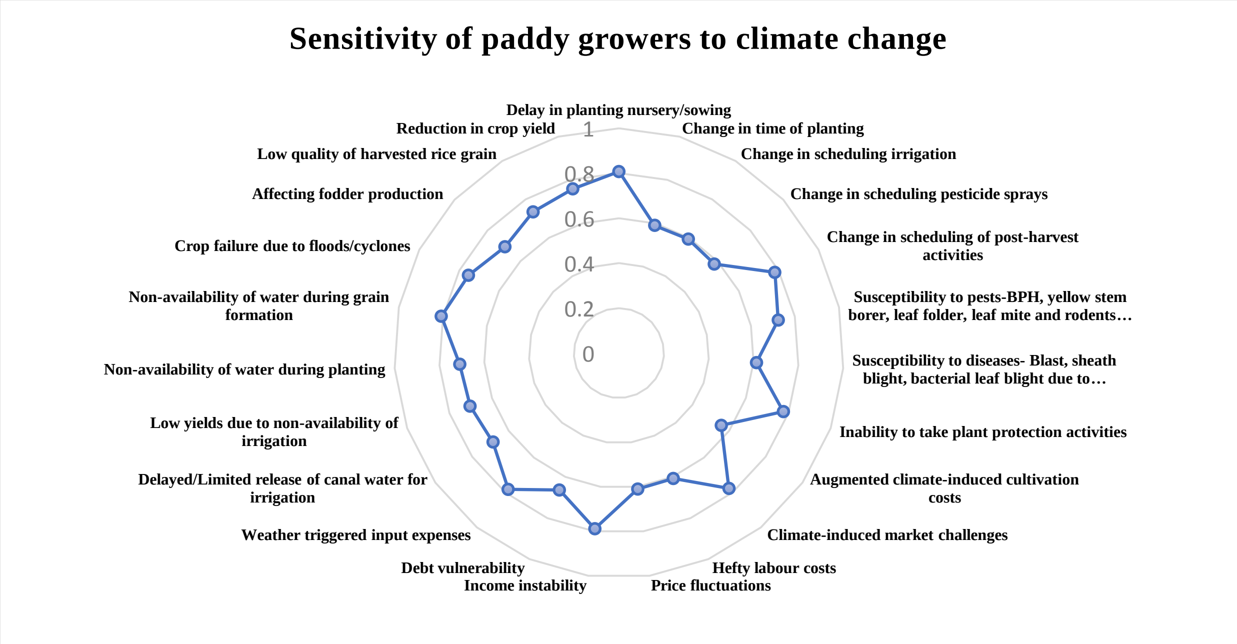

Figure-4 Factor loadings of sensitivity of paddy growers to climate change sub-indicators

Table 10 and figure 4 presented the Rotated Component Matrix for the sensitivity of paddy growers to climate change. Each column represented a factor, and the values within the table were factor loadings indicated the correlation between each sub-indicator and the corresponding factor.

Factor analysis had been conducted to identify underlying variables that explained the pattern of correlation within the observed sub-indicators. The rotated component matrix had revealed which sub-indicators were more strongly associated with each factor. For instance, under Factor 7, sub-indicator like delay in planting nursery/sowing and factor 2, sub-indicator like non-availability of water during grain formation had high factor loadings (>0.80),Factor 1, sub-indicators like reduction in crop yield, crop failure due to floods/cyclones, and low quality of harvested rice grain had shown high factor loadings (>0.70), indicated their strong correlation with this factor depicted in figure 4. Similarly, other factors had captured different aspects of sensitivity to climate change, such as water availability, input costs, labour expenses, pest and disease susceptibility, and market challenges.

By examined the factor loadings, researchers had been able to identify the key factors driving the sensitivity of paddy growers to climate change. Sub-indicators with higher factor loadings (typically above 0.50) had been considered more strongly correlated with the corresponding factor and had thus played a more significant role in determining sensitivity. This information had helped prioritize adaptation and mitigation strategies, focusing on areas where paddy growers had been most vulnerable to climate change impacts.

Dimension 3: Adaptive Capacity of paddy growers to climate change

Table 11: KMO and Bartlett's Test Value forAdaptive Capacity of paddy growers to climate change

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.534
Bartlett's Test of Sphericity	Approx. Chi-Square	447.140
	Df	253

	Sig.	.000

Table 11 presented the output of KMO and Bartlett's test, which assessed the validity of the indicators in the dataset. The Kaiser-Meyer-Olkin (KMO) value obtained was 0.534, indicated an acceptable value. This suggested that the sum of partial correlations was not significant compared to the sum of correlations, accounting for 53.4% of the analysis indicators. Therefore, the dataset demonstrated a coherent correlation pattern suitable for factor analysis. Consequently, reliable and distinct factors could be derived from this data, enhancing the validity of the subsequent analysis.

Additionally, Bartlett's Test of Sphericity yielded significant results, with an Approx. Chi-Square value of 447.140 and a significance value (p) of 0.000, indicating a robust relationship among the variables. This supported the suitability of factor analysis for the dataset, further confirming its applicability.

Overall, the results of KMO and Bartlett's test provided confidence in the validity of the dataset and justified the use of factor analysis to derive meaningful insights from the data. These findings laid the groundwork for subsequent analyses aimed at understanding the underlying factors influencing the phenomenon under investigation.

Table 12:Eigen values for Adaptive capacity of paddy growers to climate change

Total Variance Explained					
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	4.074	17.712	17.712	4.074	17.712
2	3.718	16.165	33.877	3.718	16.165
3	1.840	8.000	41.877	1.840	8.000
4	1.681	7.308	49.185	1.681	7.308
5	1.522	6.616	55.801	1.522	6.616
6	1.352	5.878	61.679	1.352	5.878
7	1.219	5.298	66.977	1.219	5.298
8	0.989	4.300	71.278		
9	0.945	4.111	75.388		
10	0.890	3.870	79.258		
11	0.805	3.498	82.756		
12	0.623	2.709	85.465		
13	0.603	2.623	88.088		
14	0.537	2.335	90.423		
15	0.411	1.787	92.210		
16	0.385	1.672	93.883		
17	0.345	1.500	95.382		
18	0.290	1.262	96.644		
19	0.249	1.082	97.726		
20	0.173	0.752	98.478		
21	0.146	0.633	99.111		
22	0.118	0.514	99.626		
23	0.086	0.374	100.000		
Extraction Method: Principal Component Analysis.					

Table 12 showcased the Eigen value specifications and the percentage of variance explained by the components for the adaptive capacity of paddy growers to climate change. The table revealed that seven factors were extracted from the seven components, collectively explaining a total variance of 66.97 percent.The Eigen values indicated the amount of variance accounted for by each component. Components with Eigen values greater than one were considered significant and were chosen for further analysis. These seven selected factors contributed to explaining 66.97 percent of the variability in the adaptive capacity of paddy growers to climate change.Understanding the variance explained by each factor was crucial for assessing the relative importance of different components in influencing adaptive capacity. In this case, the factors derived from the Eigen values shed light on the key dimensions contributed to the adaptive capacity of paddy growers. This information could guide policymakers and stakeholders in prioritizing interventions aimed at enhancing the adaptive capacity of paddy growers in response to climate change challenges.

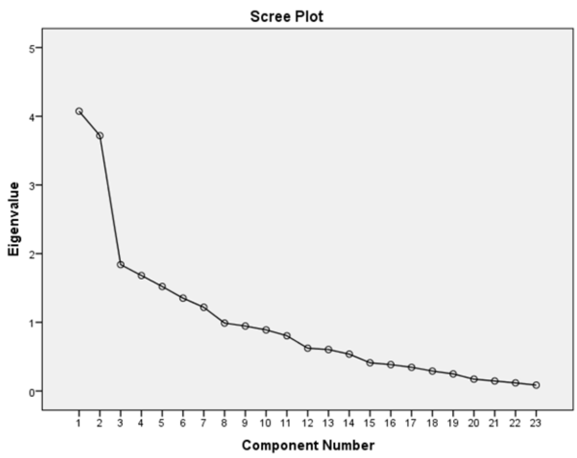

Figure 5: Scree plot for Adaptive capacity of paddy growers to climate change

Figure 3 provided a visual representation of the eigenvalues of all components, served as a scree plot for the adaptive capacity of paddy growers to climate change. The graph depicted the eigenvalues plotted against the component number.The scree plot helped in identifying the significant components to retain for further analysis. Eigenvalues greater than one were considered substantial and indicative of the variance explained by each component. As observed, the curve in the scree plot began to level off between component 7 and component 8, suggested a diminishing return in explaining additional variance beyond the seventh component.Components 1 to 7 had eigenvalues exceeding 1, implying their importance in explaining the variability in the adaptive capacity of paddy growers. Conversely, components 8 to 23 had eigenvalues less than 1, indicated less significant contributions to the overall variance shown in table 12.By retained the first seven components, which captured the most substantial amount of variance, the analysis focused on the key dimensions influenced the adaptive capacity of paddy growers to climate change. This decision facilitated a more concise and targeted understanding of the factors driving adaptive capacity, aiding in the formulation of effective strategies and interventions to enhance resilience in paddy farming practices.

Table 13. Rotated Component Matrix for Adaptive capacity of paddy growers to climate change

Sub-indicators	Rotated Component Matrix[a]						
		Component					
	1	2	3	4	5	6	7
Participation in farmer groups, cooperatives and networks	0.812						
Awareness of climate information and early warning system	0.809						
Education	0.748						
Membership in community level organisations/farmer-based organisation	0.723						
Access to market	0.532						
Access to non-formal credit	0.513						
Access to mechanized equipment	0.500						
Access to Agricultural Extension services		0.858					
Access to agricultural credit and loans		0.687					
Participation in workshops/training sessions on climate resilient practices		0.650	0.522				
Utilization of climate forecasts to anticipate and manage yield variability		0.633					
Farming Experience		0.513					
Exchange of climate related information and best practices			0.705				
Flexibility in farming schedules based on weather changes			0.549				
Rainwater harvesting			0.516				
Utilization of mobile apps and online portals for monitoring weather and pest conditions				-0.803			
Grain storage silos					-0.787		

Access to crop insurance			0.527		0.623		
Access to early warning system/climate information					0.622	0.540	
Rescheduling planting and harvesting dates based on weather forecast						0.705	
Understanding of climate resilient practices and climate-informed inputs							0.688
Elevated pathways for drainage of water							0.606
Awareness of climate change impacts on paddy farming							-0.557
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]							
a. Rotation converged in 13 iterations.							

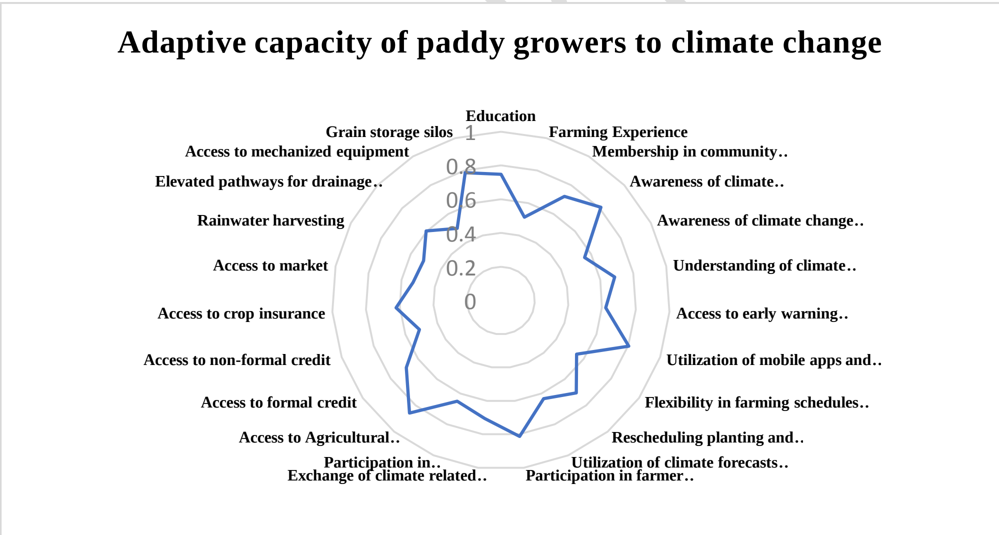

Figure 6: Factor loadings of Adaptive capacity of paddy growers to climate change sub-indicators

Table 13 and figure 6 presented the Rotated Component Matrix for the adaptive capacity of paddy growers to climate change. This matrix illustrated the correlation between each sub-indicator and the seven identified factors influencing adaptive capacity.

Factor analysis was conducted to uncover underlying variables that explain the observed correlations among the sub-indicators. The rotated component matrix revealed which sub-indicators were most strongly associated with each factor, aiding in identified key aspects contributing to the adaptive capacity of paddy growers.

For instance, under Factor 1, sub-indicators such as participation in farmer groups, awareness of climate information and early warning systems, education level, and membership in community-level organizations showed high factor loadings which was also illustrated in figure 6. This indicated that these factors play a crucial role in enhancing the adaptive capacity of paddy growers to climate change.

Similarly, other factors capture different dimensions of adaptive capacity, included access to agricultural extension services, utilization of climate forecasts, flexibility in farming schedules, adoption of technology, and understanding climate-resilient practices.

By examined the factor loadings, we could discern the key factors driving the adaptive capacity of paddy growers to climate change. Sub-indicators with higher factor loadings (typically above 0.50) were considered more strongly correlated with the corresponding factor and thus played a more significant role in enhancing adaptive capacity.

This information is valuable for policymakers, agricultural extension workers, and stakeholders involved in designing interventions and strategies aimed at bolstering the adaptive capacity of paddy growers. By focusing on enhancing the identified factors, stakeholders can effectively support paddy growers in mitigating the impacts of climate change and ensuring the sustainability of paddy farming practices.

Table 14. Assignment of weights to the sub-indicators

Indicator	**Sub-indicator**	**Factor Loadings**	**Weight obtained through PCA**
I. Exposure of paddy growers to climate variability			
Monsoon Variability	Changes in pre-monsoon rainfall	0.742	3.057
	Changes in the onset and duration of South-West Monsoon	0.694	1.024
	Changes in post-monsoon rains	0.749	3.086
	Changes in Winter season	0.781	3.218
Precipitation Variability	Delay in onset of rainfall	0.673	2.773
	More number of rainy days	0.733	1.005
	More dry spells during crop season	0.593	1.562
	Rainfall aberrations during crop growth period	0.853	1.259
	Erratic rainfall throughout the season	0.550	0.812
	Low number of rainy days/Untimely winter rainfall	0.697	2.489
Climate Hazard	Occurrence of floods	0.532	1.340
	Occurrence of cyclones	0.514	1.835
	Heavy rains	0.817	1.015
	Unseasonal rains	0.718	2.564
	Extended dry spells	0.737	2.632
	Hailstorms/Thunderstorms and Lightning	0.869	0.910
Temperature	Rising Temperatures	0.620	0.850
	Heat waves during crop season	0.628	0.861
	Low Temperature	0.553	0.816
II. Sensitivity of paddy growers to climate change			
Crop	Delay in planting nursery/sowing	0.808	0.893

phenology	Change in time of planting	0.590	0.938
	Change in scheduling irrigation	0.594	0.944
	Change in scheduling pesticide sprays	0.581	2.149
	Change in scheduling of post-harvest activities	0.781	1.415
Pest and Disease Dynamics	Susceptibility to pests-BPH, yellow stem borer, leaf folder, leaf mite and rodents due to climate change	0.724	0.942
	Susceptibility to diseases- Blast, sheath blight, bacterial leaf blight due to climate change	0.613	0.798
	Inability to take plant protection activities	0.776	1.009
Economic Vulnerability	Augmented climate-induced cultivation costs	0.557	2.693
	Climate-induced market challenges	0.775	0.798
	Hefty labour costs	0.608	1.526
	Price fluctuations	0.610	1.105
	Income instability	0.788	0.973
	Debt vulnerability	0.664	1.203
	Weather triggered input expenses	0.780	1.413
Water sensitivity	Delayed/Limited release of canal water for irrigation	0.686	3.637
	Low yields due to non-availability of irrigation	0.703	1.117
	Non-availability of water during planting	0.710	2.627
	Non-availability of water during grain formation	0.807	2.986
Extreme weather sensitivity	Crop failure due to floods/cyclones	0.754	3.377
	Affecting fodder production	0.694	2.567
	Low quality of harvested rice grain	0.736	3.297
	Reduction in crop yield	0.759	3.400
III. Adaptive capacity of paddy growers to climate change			
Socio-Demographic	Education	0.748	3.047
	Farming Experience	0.513	1.907
	Membership in community level organisations/farmer-based organisation	0.723	2.945
Knowledge Acquisition	Awareness of climate information and early warning system	0.809	3.296
	Awareness of climate change impacts on paddy farming	0.557	0.679
	Understanding of climate resilient practices and climate-informed inputs	0.688	0.839
Preparedness	Access to early warning system/climate information	0.622	1.677
	Utilization of mobile apps and online portals for monitoring weather and pest conditions	0.803	1.349
Weather-Responsive Planning	Flexibility in farming schedules based on weather changes	0.549	1.010
	Rescheduling planting and harvesting dates based on weather forecast	0.705	0.953

	Utilization of climate forecasts to anticipate and manage yield variability	0.633	2.353
Social Network	Participation in farmer groups, cooperatives and networks	0.812	3.308
	Exchange of climate related information and best practices	0.705	1.297
Capacity Building	Participation in workshops/training sessions on climate resilient practices	0.650	3.377
	Access to Agricultural Extension services	0.858	3.190
Financial resilience	Access to formal credit	0.687	2.554
	Access to non-formal credit	0.513	2.089
	Access to crop insurance	0.623	1.918
	Access to market	0.532	2.167
Infrastructural Preparedness	Rainwater harvesting	0.516	0.949
	Elevated pathways for drainage of water	0.606	0.738
	Access to mechanized equipment	0.500	2.037
	Grain storage silos	0.787	1.198

Table 14 provided the assignment of weights to the sub-indicators across three dimensions of vulnerability indices for paddy growers: exposure to climate variability, sensitivity to climate change, and adaptive capacity to climate change.

These weights were determined through Principal Component Analysis (PCA) and were derived from the factor loadings obtained from the rotated component matrix. Factor loadings exceeding 0.5 were considered significant and were multiplied by eigenvalues exceeding 1 for all the sub-indicators.

For each dimension, the weights represented the relative importance of each sub-indicator in contributing to the overall vulnerability index. Higher weights indicated a stronger influence of the corresponding sub-indicator on the vulnerability of paddy growers within that dimension.

For example, under the dimension of exposure to climate variability, sub-indicators such as changes in pre-monsoon rainfall, changes in post-monsoon rains, and changes in the winter season received relatively higher weights, indicated their greater contribution to the overall exposure of paddy growers to climate variability.

Similarly, in the sensitivity to climate change dimension, sub-indicators such as crop failure due to floods/cyclones, reduction in crop yield, and economic vulnerability received higher weights, highlighting their significant impact on the sensitivity of paddy growers to climate change.

In the adaptive capacity dimension, sub-indicators such as participation in farmer groups, awareness of climate information, access to agricultural extension services, and participation in workshops/training sessions on climate-resilient practices obtained higher weights, underscored their importance in enhancing the adaptive capacity of paddy growers to climate change.

Overall, these weighted values provide valuable insights for policymakers and stakeholders, enabling them to prioritize interventions and allocate resources effectively to address the most critical vulnerabilities faced by paddy growers in the context of climate change.

Table 15: Assignment of weights to the indicators

Indicator	Weight obtained through PCA
Monsoon Variability	10.385
Precipitation Variability	9.899
Climate Hazard	10.297
Temperature	2.527
Crop phenology	6.339
Pest and Disease Dynamics	2.749
Financial resilience	9.712
Water sensitivity	10.367
Extreme weather sensitivity	12.643
Socio-Demographic	7.900
Knowledge Acquisition	4.813
Preparedness	3.026
Weather-Responsive Planning	4.316
Social Networking	4.605
Capacity Building	6.567
Economic Vulnerability	8.729
Infrastructural Preparedness	4.922

Table 15 provided the assignment of weights to the various indicators based on the weighted values obtained from the sub-indicators of vulnerability indices for paddy growers.These weights represented the overall importance of each indicator in assessing the vulnerability of paddy growers to climate change. They were derived by summing up the weighted values of all sub-indicators corresponding to each indicator.For instance, the indicator "Monsoon Variability" obtained a weight of 10.385, indicated its significant contribution to the overall vulnerability of paddy growers. This suggested that factors related to changes in monsoon patterns, such as pre-monsoon rainfall, post-monsoon rains, and winter season changes, collectively exert a substantial influence on the vulnerability of paddy growers to climate variability.

Similarly, "Extreme Weather Sensitivity" received the highest weight of 12.643, emphasizing the critical role of extreme weather events such as floods, cyclones, droughts, and heatwaves in determining the vulnerability of paddy growers. These events can severely impact crop yields, livelihoods, and agricultural infrastructure, necessitating targeted adaptation and resilience-building efforts.

On the other hand, indicators like "Temperature" and "Pest and Disease Dynamics" obtained relatively lower weights, indicated a comparatively lesser but still significant impact on the vulnerability of paddy growers. While temperature fluctuations can affect crop growth and development, pest and disease outbreaks can lead to yield losses and economic instability.

Overall, the assignment of weights to these indicators provides a comprehensive understanding of the key drivers of vulnerability among paddy growers to climate change. This information was essential for policymakers, researchers, and practitioners to develop effective strategies and interventions aimed at enhancing the resilience of paddy farming communities in the face of ongoing climate challenges.

Testing for Reliability of vulnerability indices of paddy growers: The reliability of vulnerability indices for paddy growers was assessed using the Internal Consistency Reliability method via Cronbach's alpha, conducted with SPSS software version 20.
The Cronbach's alpha coefficient obtained was 0.90, surpassing the standard threshold of 0.70. This high value indicated a strong level of reliability and excellent internal consistency within the vulnerability index presented in Table 16.
The reliability coefficient of 0.90 suggested that the items (indicators and sub-indicators) comprised the vulnerability indices exhibited strong correlation and consistency with each other. In other words, the variables included in the vulnerability assessment framework were reliably measuring the underlying construct of vulnerability among paddy growers to climate change.
This robust reliability indicated that the vulnerability index could be considered a dependable tool for assessing and monitoring the vulnerability of paddy growers over time. Policymakers, researchers, and practitioners had confidence in the accuracy and consistency of the index's measurements when designing and implementing interventions to address the identified vulnerabilities in paddy farming communities.

Table 16: Reliability Statistics of vulnerability indices

Cronbach's Alpha	No. of Items
0.903	65

Computation of index values to the dimensions of vulnerability indices of paddy growers

To calculate the index values for each identified dimension, based on the sum of weights acquired through PCA for all indicators as displayed in Table 15, the vulnerability indices of paddy growers were determined.

Table 17. Index values of climate vulnerability indices of paddy growers

S.No.	Dimensions	Index values	Ranks
1.	Exposure of paddy growers	8.28	II
2	Sensitivity of paddy growers	8.36	I
3	Adaptive capacity of paddy growers	5.61	III

Table 17 presented the index values of climate vulnerability for paddy growers across different dimensions, namely exposure, sensitivity, and adaptive capacity.

The index values indicated the relative vulnerability levels of paddy growers within each dimension. Sensitivity, with an index value of 8.36, was ranked first, suggested that paddy growers were highly sensitive to climate change impacts. This implies that they were particularly susceptible to changes in climatic conditions, such as variations in temperature, precipitation patterns, and extreme weather events.

Exposure, with an index value of 8.28, ranked second. This indicated that paddy growers were significantly exposed to various climate-related hazards and risks, including floods, cyclones, erratic rainfall, and temperature fluctuations. Exposure highlighted the extent to which paddy growers were directly affected by climate variability and change.

Adaptive capacity, with an index value of 5.61, ranked third. Although paddy growers exhibited a degree of ability to adjust to climate change, the index value implied that there was potential for enhancement. Adaptive capacity reflected the ability of paddy growers to cope with and respond effectively to climate-related challenges through strategies such as knowledge acquisition, infrastructure development, and social networking.

These index values provided insights into the overall vulnerability profile of paddy growers to climate change. By understanding the relative importance of each dimension, policymakers and stakeholders could prioritize interventions and strategies to enhance the resilience of paddy farming communities. Addressing the identified vulnerabilities could help build more sustainable and climate-resilient agricultural systems, ensuring the long-term livelihood security of paddy growers.

Measurement procedures of indicators

As the index developed was composite in nature, the indicator measures include both quantitative and qualitative procedures. Under each indicator, suitable sub indicatorsand variables were identified and levels of measurement were fixed for variables.

Schedule development

For all the indicators, a schedule was prepared to elicit appropriate variability forvulnerability indices of paddy growers. A pilot study was conducted among 60 respondents in non-sample to test the reliability and validity of index

Calculation of the vulnerability index

The normalized indicators are then multiplied with the assigned weights to construct the indices separately for each component of vulnerability viz. exposure, sensitivity and adaptive capacity separately. Finally, vulnerability index of paddy growers is calculated as:

$$VI = (EI + SI) - AI$$

Where,

VI is the Vulnerability Index,

EI is the Exposure Index,

SI is the sensitivity Index and

AI is the Adaptive Capacity Index

CONCLUSION

The study's index for measuring vulnerability among paddy growers presented a valuable tool for addressing contemporary challenges facing agriculture, particularly in the context of climate change and environmental concerns. By offering a comprehensive means of assessing vulnerability across three dimensions, this index fills a critical research gap in understanding the specific challenges faced by paddy growers. Stakeholders, including researchers, policymakers, and agricultural administrators, can leverage this index to gain insights into the vulnerability levels of paddy growers and tailor interventions accordingly. For researchers, the index provides a structured framework for conducting further studies on climate vulnerability among paddy growers, thereby advancing our understanding of this complex issue. Policymakers and administrators can utilize the index values to inform targeted strategies aimed at mitigating vulnerabilities and enhancing resilience within paddy farming communities. By bridging the current research gap and offering practical insights, the index developed in this study contributes to more effective decision-making and sustainable agricultural development.

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