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Vulnerability of whiteleg shrimp production to climate change in coastal India: An indicator approach

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Abstract

Identification of spatial gradient in the vulnerability of white leg shrimp production to climate change is imperative in the formulation and implementation of suitable adaptive measures. A composite vulnerability index was computed by employing 36 variables pertaining to exposure (11), sensitivity (11) and adaptive capacity (14) dimensions to map the extent of vulnerability in white leg shrimp production across Indian states. Based on its magnitude, the vulnerability index was categorized into three groups, namely low, moderate and high. Results showed that the mean composite vulnerability index was 0.65 and ranged from 0.34 to 0.99 indicating that there was a strong spatial pattern. Among the nine states, Goa (0.99), Kerala (0.84) and Odisha (0.77) were highly vulnerable; Gujarat (0.75), Karnataka (0.57) and West Bengal (0.56) were moderately vulnerable; and Tamil Nadu (0.54), Andhra Pradesh (0.46) and Maharashtra (0.34) were less vulnerable to shrimp production. About one-fourth of the production and culture area of white leg shrimp were in moderate and highly vulnerable regions. The impact of climate change on shrimp production is diverse but can be reduced by implementing adaptive measures—suitable policies and investment plans—which should be region-specific.

KEYWORDS
adaptive capacity, climate change, shrimp farming, vulnerability index, whiteleg shrimp

1 | INTRODUCTION

Coastal ecosystems provide a diversity of goods and services (Costanza et al., 1997). Humans heavily rely on these services for their nutritious food security and livelihood. Globally, several anthropogenic activities are polluting coastal ecosystems and destroying aquatic habitats gradually (Crain et al., 2009; Doney et al., 2012). In addition to these, climate change threatens the very existence of life on earth (Gómez Murciano et al., 2021) and its intensity is expected to increase in coming years (IPCC, 2022a). Considering its seriousness, different mitigation and adaptive measures are being tried globally to reduce the magnitude of the negative impact of climate change in the future. However, the scarcity of resources for adaptation to climate change is hindering the aforesaid measures (IPCC, 2014), which leads to identifying the vulnerability of the region to climate change (Brooks et al., 2005; Samson et al., 2011). There are various approaches to studying the vulnerability generally measuring exposure (risk of exposure to a disturbance), sensitivity (sensitivity of the system to that disturbance) and adaptive capacity (capacity of the system to adapt to the disturbance) (IPCC, 2022b). These approaches tried in several countries have attempted to quantify the impact of climate change through the development of indices (Adger & Agnew, 2004; Ahsan & Warner, 2014; Brooks et al., 2005; Cardona, 2005; Lummen & Yamada, 2014).

Similar attempts have been tried in India also, as it is most susceptible to climate change due to its undulating topography that ranges from temperate to tropical (Sendhil et al., 2018). India with an extensive coastal length of 8129 km possesses a unique coastal ecosystem (157,000 ha area), which is largely conducive and harnessed for brackish water/coastal shrimp aquaculture activities (average production 100,000 metric tonnes y^{-1}). Particularly in the case of white leg shrimp, not only the culture area (283 to 108,526 ha) but also the production (1731 to 815,745 tonnes) has grown exponentially between 2009–10 and 2019–20 (MPEDA, 2021). In fact, the current Indian shrimp aquaculture industry is dominated by white leg shrimp culture as it constitutes more than 75% of the total shrimp production. Therefore, any kind of damage to this sector will greatly affect India's seafood export industry in terms of foreign exchange.

Like all the other food production sectors, shrimp production and its relevant economic benefit can be affected by variability in precipitation, flooding or salinity inundation (Cabral et al., 2017; Zsamboky et al., 2011). The ebb and flow of precipitation and rising flood frequency were observed in different states of India. A study has already reported that changes in temperature and precipitation have reduced shrimp production by about 20–50%, whereas the cyclones have demolished the same (Muralidharan et al., 2013). This condition is only going to worsen further as the temperature of India has been projected to increase by 1.7–2.0°C by 2030 and 3.3–4.8°C by 2080. The vulnerability of shrimp production not only depends on the impact of exposure but also relies on the sensitivity and adaptive capacity of the shrimp production ecosystem (IPCC, 2007). Vulnerability assessment in different sectors is commonly reported (Das et al., 2016), but no studies are available using multidimensional indicators or addressing a single farmed species, that is white leg shrimp. Here, we aim to assess the degree of vulnerability and address the anticipated consequences that change in climate may like to inflict on white leg shrimp production in India. We also believe that the study helps to accomplish the sustainable developmental Goal 12—responsible consumption and production (ensure sustainable consumption and production patterns) and Goal 13—climate action (take urgent action to combat climate change and its impacts).

2 | MATERIALS AND METHODS

2.1 | Study area and data source

In the year 2020, white leg shrimp was produced in 100,206 ha which falls in about nine states (Andhra Pradesh, Goa, Gujarat, Karnataka, Kerala, Maharashtra, Odisha, Tamil Nadu and West Bengal), predominantly covering the southern part of India. All nine coastal states were chosen in this study to construct the composite vulnerability index considering data availability (Andhra Pradesh includes Telangana, similarly Tamil Nadu includes Puducherry) under different parameters of white leg shrimp farming. The study used secondary data published by various Government of India organizations dealing with fisheries and climate change. The specific data sources are given in Table 1 under different sub-headings (Figure 1).

2.2 | Selection of indicators for vulnerability index

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, 2022a). Vulnerability in shrimp production can be delineated as the degree to which extent shrimp production is susceptible or unable to cope with adverse change in climate events (IPCC, 2001). The Intergovernmental Panel on Climate Change (IPCC) defined that vulnerability consists of three main components, namely exposure, sensitivity and adaptive capacity (IPCC, 2007).

2.2.1 | Exposure

Exposure is the nature and degree to which a system is exposed to significant climate variation. Shrimp production could be adversely affected by exposure to short-term and long-term abnormal climatic events. This effect can be captured by selective indicators based on the combination of inputs from literature review and experts' opinions (see Table 1 for further details). In the present study, minimum temperature, maximum temperature, precipitation and extent of the flood-prone areas have been used to find the extent of shrimp production exposure to climate change. Elevated water temperature can alter the physical changes in an aquatic habitat like shift in dissolved oxygen that produce more algal blooms and increase the incidence of disease (Karvonen et al., 2010). Toxic substance present in water augment toxicity at higher water temperature leads to mass mortality (Rijnsdorp et al., 2009). Low water temperature during winter season also causes mortality of shrimp. Low precipitation decreases the water availability resulting salt intrusion into groundwater (Herbert et al., 2015). During high precipitation, there is a possibility of flood which may affect the culture area of shrimp, since it is mainly practised in coastal regions (Akankali & Jamabo, 2012).

Short-term variation of annual precipitation, annual minimum temperature, annual maximum temperature (Monterroso et al., 2014) of triennium ending (TE 2020) was considered (Sendhil et al., 2018) because shrimp is usually cultured as two crops, that is in two seasons. The coefficient of variation was applied to capture the long-term trend in time series data, but it overestimates the level of variation (Kumar et al., 2005). Therefore, experts (14 researchers, 6 policy makers and 10 academicians) suggested to apply the Mann–Kendall's test to capture the long-term trend coefficient, which is z statistic, and magnitude of the trend as indicated by the Sen's slope (Jain & Kumar, 2012; Radhakrishnan et al., 2017). The z statistic and Sen's slope of annual precipitation, minimum temperature and maximum temperature of shrimp-producing states were estimated using long-term (1970–2020) data. The natural disaster like floods may damage the shrimp culture area that affects production of shrimp (Monterroso

TABLE 1 Indicators and their functional relationship for assessment of the composite vulnerability of shrimp production, India

Indicator	Variables	Unit	Time span	Functional relationship	Data source	References
Exposure	Annual rainfall	mm	2017–2020	Positive	IMD, 2021	Allison et al. (2009); Das et al. (2016); Monterroso et al. (2014); UNDP and FAO (2021)
	Temperature maximum in °C	°C	2017–2020	Positive	IMD, 2021	Allison et al. (2009); Das et al. (2016); Handisyde et al. (2006); UNDP and FAO (2021)
	Temperature minimum in °C	°C	2017–2020	Positive	IMD, 2021	Allison et al. (2009); Das et al. (2016); Handisyde et al. (2006); UNDP and FAO (2021)
	Sen's slope of annual rainfall	unit free	1970–2020	Positive	IMD, 2021	Authors' inclusion based on experts' opinion
	Sen's slope of temperature maximum	unit free	1970–2020	Positive	IMD, 2021	Authors' inclusion based on experts' opinion
	Sen's slope of temperature minimum	unit free	1970–2020	Positive	IMD, 2021	Authors' inclusion based on experts' opinion
	z. statistic annual rainfall	unit free	1970–2020	Positive	IMD, 2021	Authors' inclusion based on experts' opinion
	z. statistic of temperature maximum	unit free	1970–2020	Positive	IMD, 2021	Authors' inclusion based on experts' opinion
	z. statistic of temperature minimum	unit free	1970–2020	Positive	IMD, 2021	Authors' inclusion based on experts' opinion
	Area liable to floods	million ha	2015	Positive	MHA, 2015	Allison et al. (2009); Das et al. (2016); Handisyde et al. (2006); Monterroso et al. (2014); Seekao and Pharino (2018)
	Area liable to flood	%	2015	Positive	MHA, 2015	Authors' inclusion based on experts' opinion
Sensitivity	Culture area of whiteleg shrimp	ha	2017–2020	Negative	MPEDA, 2021	Islam et al. (2019); UNDP and FAO (2021)
	Production of whiteleg shrimp	tons	2017–2020	Negative	MPEDA, 2021	Das et al. (2016); Islam et al. (2019); Nagothu et al. (2012); UNDP and FAO (2021)
	Productivity of whiteleg shrimp	tons ha^{-1}	2017–2020	Negative	MPEDA, 2021	Balaganesh et al. (2020); Palanisami et al. (2009)
	Inland fish production	'000 tons	2017–2020	Negative	DOF, 2021	Allison et al. (2009); Das et al. (2016); Handisyde et al. (2006); UNDP and FAO (2021)
	Fish seed production	millions fry	2017–2020		DOF, 2021	Allison et al. (2009); Das et al. (2016); Handisyde et al. (2006); UNDP and FAO (2021)
	CV of whiteleg shrimp culture area	%	2009–2020	Positive	MPEDA, 2021	Sendhil et al. (2018)
	CV of whiteleg shrimp production	%	2009–2020	Positive	MPEDA, 2021	Sendhil et al. (2018)
	CV of whiteleg shrimp productivity	%	2009–2020	Positive	MPEDA, 2021	Sendhil et al. (2018)
	CV of Inland fish production	%	2011–2019	Positive	MPEDA, 2021	Sendhil et al. (2018)
	CV of fish seed production	%	1999–2019	Positive	MPEDA, 2021	Sendhil et al. (2018)
	Population density	per square km	2011	Positive	Census, 2011	Allison et al. (2009); Das et al. (2016)

TABLE 1 (Continued)

Indicator	Variables	Unit	Time span	Functional relationship	Data source	References
Adaptive capacity	Inland fishers	number	2019–20	Positive	DOF, 2021	Allison et al. (2009); Das et al. (2016); Sendhil et al. (2018)
	Rivers and canals	km	2019–2020	Positive	DOF, 2021	Authors' inclusion based on experts' opinion
	Reservoir/ tanks and other water bodies	ha	2019–2020	Positive	DOF, 2021	Authors' inclusion based on experts' opinion
	Brackish water	ha	2019–2020	Positive	DOF, 2021	Authors' inclusion based on experts' opinion
	Per capita fish consumption	per capita/ kg/year	2019–2020	Positive	DOF, 2021	Das et al. (2016)
	Infant mortality	per thousand numbers	2018z	Negative	Census, 2011	Abson et al. (2012); Das et al. (2016); Jones (2001)
	Poverty rate	%	2011–12	Negative	Census, 2011	Abson et al. (2012); Islam et al. (2019); Monterroso et al. (2014)
	Length of road	km	2017	Positive	RBI, 2021	Islam et al. (2019)
	Per capita net state domestic product	USD	2018–19	Positive	RBI, 2021	Balaganesh et al. (2020); Das et al. (2016); Jones (2001); Monterroso et al. (2014); Sendhil et al. (2018)
	Credit to agricultural	million USD	2019	Positive	RBI, 2021	Monterroso et al. (2014)
	Internet user	Number	2011	Positive	Census, 2011	Authors' inclusion based on experts' opinion
	Mobile user	Number	2011	Positive	Census, 2011	Authors' inclusion based on experts' opinion
	Effective literacy rate	%	2011	Positive	Census, 2011	Allison et al. (2009); Das et al. (2016); Islam et al. (2019); Monterroso et al. (2014); Palanisami et al. (2009); Sendhil et al. (2018)
	Fund released fisheries development	million USD	2017–2020	Positive	DOF, 2021	Authors' inclusion based on experts' opinion

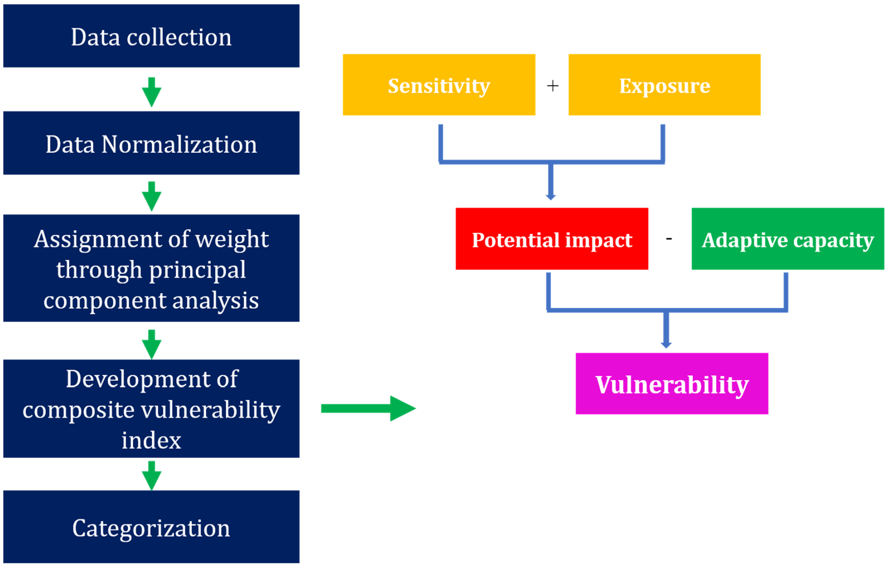

FIGURE 1 Framework for the assessment of composite vulnerability index.

et al., 2014; Seekao & Pharino, 2018); therefore, here we included the area liable to floods and its percentage of the area liable to floods.

2.2.2 | Sensitivity

The sensitivity is the extent, shrimp production responds to changes in climate. The white leg shrimp culture area, production and productivity for the TE 2019–20 indicated the short-term changes. We considered the inland fish production and fish seed production under sensitivity since they also fall in the same geographical regions. Exclusion of these may not be able to provide the index comprehensively; therefore, inland fish production and fish seed production were included (UNDP and FAO, 2021). The beneficial stimuli against the change in climate show a negative relationship with culture area, production and productivity (IPCC, 2007; Sendhil et al., 2018). The coefficient of variation in white leg shrimp culture area, production and productivity indicates the long-term (2009 to 2020) changes in white leg shrimp-producing states of India, as it exhibits a positive association with sensitivity and also it would be useful to capture whether there existed a significant regional disparity (Sendhil et al., 2018). The population density was considered under sensitivity since they strive for resources in a particular area; furthermore, it exacerbates under extreme climate events.

2.2.3 | Adaptive capacity

The variables, which improve the potential of the shrimp-producing states to better adapt to the change in climate events, have been selected. Several variables—resources, health status, infrastructure facilities, technological advancement and investment (Abeygunawardena et al., 2003; Gómez Murciano et al., 2021)—that influence the adaptive capacity of the shrimp production are presented in Table 1. People working in the same field share their knowledge and experiences with other people which leads to improving their adaptive capacity. Access to Internet could improve the performance of shrimp farming by accessing knowledge and facilitating faster communication with other farmers to improve adaptive capacity, when there are adequate resources, that is brackish water could be used to cope with adverse climate events and other similar resources like rivers/canals, reservoir/tanks could be used for other alternative diversified livelihood activities—that is fish farming and integrated farming practices.

Credit given by the commercial banks to agricultural and allied activities was considered (Monterroso et al., 2014) as a proxy for credit to fisheries since no information was exclusively available for fisheries as it is considered as one of the allied sectors of agriculture in India. Such credit access helps to improve the adaptive capacity of fishers. Per capita net state domestic product indicates the wealthiness of the state, higher the value, better the adaptive capacity. Effective literacy rate significantly influenced the production activities (Das et al., 2016; Monterroso et al., 2014; Sendhil et al., 2018), and improved education gives insights into knowledge on shrimp production and coping mechanisms to change in climate. The funds invested for development of fisheries sector improved the infrastructure facilities, and advancement in technologies is directly proportional to adaptive capacity. The length of the road (availability of proper road facilities) not only ensures access for quality inputs but also helps for timely delivery of these highly perishable foods. All the aforesaid variables were found to positively influence the adaptive capacity of shrimp production, but infant mortality and poverty rate (Monterroso et al., 2014; Sendhil et al., 2018) negatively affect the adaptive capacity.

2.3 | Normalization of data

Data on variables used to estimate the vulnerability index were normalized to make them unit and scale free for comparison. When the variables have positive relationship in relation to indicators, normalization was done using the formula given below:

$$\text{Normalization} = \frac{\text{Actual value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}}$$

When the variables have negative relationship in relation to indicators, normalization was done as given below.

$$\text{Normalization} = \frac{\text{Maximum value} - \text{Actual value}}{\text{Maximum value} - \text{Minimum value}}$$

To compute the composite index, weights have been assigned to the normalized values (0 to 1) of the respective variables.

2.4 | Assigning weights to variables

In general, to assign weights for the variables, expert opinion (Brooks et al., 2005), equal weightage (Lucas & Hilderink, 2005; O'Brien et al., 2004) and statistical methods such as principal component analysis (PCA) or factor analysis (Cutter et al., 2003; Thornton et al., 2006) are used. The expert opinion is usually considered to be subjective and limited to availability of experts, number of variables and research time to get the response; Equal weights may undermine or overestimate some variable that stimulate the index disproportionately; advantage of PCA over other two methods is the technique used to extract the linear combination that best captures the information from large group of variables.

In the present study, PCA is applied due to the use of multidimensional data to calculate the weight of each variable. Some of the studies used only the first component of factor loading to assign the weight (Kumar et al., 2016; Monterroso et al., 2014), but a majority selected the components with eigen value more than one which account for maximum variation in the data (Kaiser, 1960; Kale et al., 2016; Sendhil et al., 2018). Therefore, to show maximum data variation, the following framework with the component (eigen value more than one) was used in the present study:

$$X_t = \Lambda_t F_t + e_t$$

where, X_t is the N-dimensional vector of variables influencing vulnerability, Λ_t is the r×1 common factor, F_t is the factor loading, and e_t is the associated idiosyncratic error-term of order N×1.

Weight was calculated as mentioned in the below-given formula:

$$W_i = \sum | L_{ij} | E_j$$

Here, W_i is the weight of i^{th} variable, E_j is the eigen value of j^{th} factor and L_{ij} is the loading value of i^{th} variable on j^{th} factor.

Expressing the above-calculated weights for each variable for all the shrimp-producing states in the following formula will provide a composite index value for each state:

$$\text{Index} = \frac{\sum_{i=1}^{n} X_i W_i}{\sum_{i=1}^{j} W_i}$$

Here, X_i is the normalized value of i^{th} variable, and W_i is the weight of i^{th} variable.

2.5 | Composite vulnerability index and its classification

Two—additive and multiplicative—can be used to establish the composite vulnerability index (Allison et al., 2009). Exposure and sensitivity are weighed one quarter each, and adaptive capacity is weighed one half of the vulnerability score in multiplicative method. Comparing to the multiplicative approach, the final vulnerability value arrived through additive approach relies equally on all the three—exposure, sensitivity and adaptive capacity (Hajkowicz, 2006). To avoid the curbing nature of multiplicative method in robust weighing, we applied the following formula of additive method in the present study to arrive the composite vulnerability index:

$$\text{Vulnerability} = [(\text{Exposure} + \text{Sensitivity}) - \text{Adaptive capacity}]$$

The composite vulnerability of shrimp-producing states are classified into three categories namely low, moderate and high that relies on the distribution of composite index value (Ayyoob et al., 2013; Kale et al., 2016).

$$\text{Low} = \text{Index} < (\overline{X} - 0.5\,\sigma)$$

$$\text{Moderate} = (\overline{X} - 0.5\sigma) \le \text{Index} \le (\overline{X} + 0.5\,\sigma)$$

$$\text{High} = \text{Index} > (\overline{X} - 0.5\,\sigma)$$

3 | RESULTS

3.1 | Principal component analysis

The results of principal component analysis for the exposure are presented in Table 2. Three principal components were retained in PCA for the analysis of shrimp-producing states. Together, these first three principal components accounted for 84.93% of the variation in 11 variables that were analysed. Table 3 shows the loading of each sensitivity variable for the retained principal components and the first three components accounted for 90.20% of the variation. The assigned weight for the sensitivity variables ranged from 3.33 (CV of Inland fish

TABLE 2 Component matrix and weights for variables under exposure dimension

Variables	Component 1	Component 2	Component 3	Weight
Annual rainfall in mm	0.18	−0.39	0.87	3.38
Temperature maximum in °C	0.57	0.35	−0.64	4.96
Temperature minimum in °C	0.34	0.56	0.22	3.42
Sen's slope of annual rainfall	0.78	−0.27	0.35	5.43
Sen's slope of temperature maximum	0.79	0.50	0.16	5.64
Sen's slope of temperature minimum	−0.53	0.74	0.14	4.73
z. statistic annual rainfall	0.90	−0.14	−0.29	5.66
z. statistic of temperature maximum	0.85	0.34	0.33	5.88
z. statistic of temperature minimum	−0.58	0.75	0.25	5.21
Area liable to floods in million ha	−0.85	−0.12	−0.22	5.25
Area liable to flood in %	−0.92	−0.07	0.27	5.56
% of Variance	49.06	19.84	16.03	
Cumulative %	49.06	68.90	84.93	
Eigen values	5.40	2.18	1.76	

production) to 5.75 (CV of white leg shrimp productivity). The component matrix of the adaptive capacity reveals that the first four components alone explained about 88.10% of the total variation for the analysed 14 adaptive capacity variables (Table 4). The eigen values were 5.48 (component one), 3.47 (component two), 2.16 (component three) and 1.22 (component four). The per capita fish consumption had the lowest weight (3.06), and brackish water had the highest weight (6.53) to establish adaptive capacity index.

3.2 | Vulnerability index

The exposure index, sensitivity index and adaptive capacity index for nine shrimp-producing states in India are presented in Table 5. The mean exposure index was observed as 0.52 with a standard deviation of 0.10; similarly, the mean was 0.54 with a standard deviation of 0.18 for sensitivity index and the mean was 0.41 with a standard deviation of 0.11 for adaptive capacity index. The index of exposure, sensitivity and adaptive capacity for all the shrimp-producing states is presented in Figure 2. Four states had a low exposure index, two states had a

TABLE 3 Component matrix and weights for variables under sensitivity dimension

	Component			
Variables	1	2	3	Weight
Culture area of whiteleg shrimp in ha	0.89	−0.05	−0.45	5.50
Production of whiteleg shrimp in tons	0.88	−0.05	−0.45	5.48
Productivity of whiteleg shrimp in tons ha^{-1}	0.70	0.52	0.06	5.11
Inland fish production in ‘000 tons	0.76	0.04	0.57	5.08
Fish seed production in millions fry	0.74	−0.03	0.62	5.05
CV of whiteleg shrimp culture area in %	0.76	0.31	0.41	5.52
CV of whiteleg shrimp production in %	0.75	0.21	−0.59	5.55
CV of whiteleg shrimp productivity in %	−0.69	0.55	0.36	5.75
CV of Inland fish production in %	−0.08	0.89	−0.17	3.33
CV of fish seed production in %	0.14	0.94	0.18	3.79
Population density per square km	0.47	−0.72	0.41	5.28
% of Variance	45.70	26.39	18.11	
Cumulative %	45.70	72.09	90.20	
Eigen values	5.03	2.90	1.99	

TABLE 4 Component matrix and weights for variables under adaptive capacity dimension

	Component				
Variables	1	2	3	4	Weight
Inland fishers in number	−0.62	0.00	−0.42	−0.05	4.36
Rivers and canals in km	−0.64	0.51	0.05	0.33	5.76
Reservoir/tanks and other water bodies in ha	−0.24	0.88	−0.29	0.24	5.25
Brackish water in ha	−0.71	−0.55	0.17	0.31	6.53
Per capita fish consumption in kg/year	0.06	−0.11	0.92	0.30	3.06
Infant mortality per thousand in number	0.89	0.23	−0.19	0.14	6.24
Poverty rate (%)	0.89	0.09	−0.11	−0.27	5.71
Length of road in km	−0.51	0.79	0.01	0.22	5.81
Per capita net state domestic product	−0.24	0.89	0.04	−0.11	4.62
Credit to agricultural (million USD)	0.04	0.73	0.42	−0.51	4.27
Internet user in number	0.80	0.05	−0.45	0.26	5.81
Mobile user in number	0.95	0.25	0.06	−0.02	6.22
Effective literacy rate in %	0.71	0.16	−0.03	0.62	5.26
Fund released fisheries development (million USD)	0.45	0.18	0.78	0.06	4.85
% of variance	39.16	24.79	15.45	8.70	
Cumulative %	39.16	63.95	79.40	88.10	
Eigen values	5.48	3.47	2.16	1.22	

TABLE 5 Exposure, sensitivity and adaptive capacity for whiteleg shrimp-producing states in India

State	Exposure index		Sensitivity index		Adaptive capacity	
Andhra Pradesh	0.57	Moderate	0.21	Low	0.32	Low
Goa	0.59	High	0.78	High	0.38	Moderate
Gujarat	0.65	High	0.44	Low	0.34	Moderate
Karnataka	0.46	Low	0.49	Moderate	0.39	Moderate
Kerala	0.60	High	0.79	High	0.55	High
Maharashtra	0.45	Low	0.49	Moderate	0.59	High
Odisha	0.40	Low	0.66	High	0.29	Low
Tamil Nadu	0.57	Moderate	0.46	Moderate	0.49	High
West Bengal	0.37	Low	0.51	Moderate	0.32	Low
Mean	0.52		0.54		0.41	
Standard deviation	0.10		0.18		0.11	

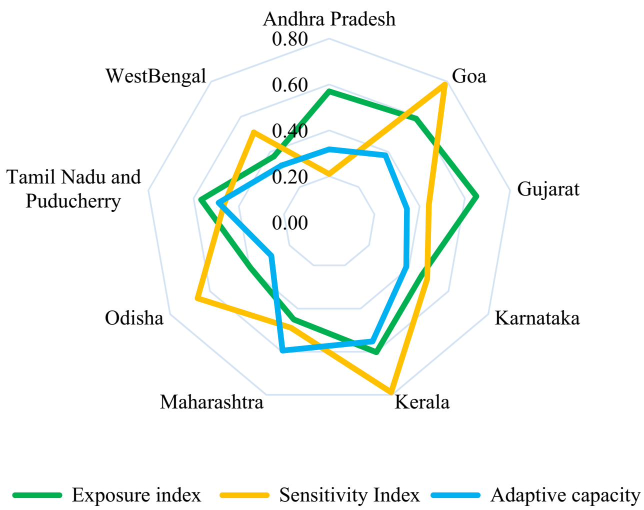

FIGURE 2 Radar chart of the exposure, sensitivity and adaptive capacity indices of shrimp-producing states of India.

moderate exposure index, and three states had high exposure index. In the case of sensitivity index, two states had low, four states had moderate, and three states had high indices. However, in the case of adaptive capacity index, the nine states, fell equally as three per category. Figure 3 portrays the composite vulnerability index of all the shrimp-producing states of India ranging between 0.34 and 0.99 (Figure 4). The estimated mean composite vulnerability index was 0.65 with a standard deviation of 0.20. Similar to adaptive capacity; the studied nine states fell equally as three per category in the case of composite vulnerability index.

3.3 | Quantification of culture area and production from various vulnerability degree

We quantified the extent of culture area and production of shrimp in each category of vulnerability (Table 6). In the case of shrimp culture area, 73.05% was in low vulnerable region and 16.19% was in moderate vulnerable region and the remaining 10.77% was in highly vulnerable region. Similarly, in the case of shrimp production, 78.81% was in low vulnerable region and 14.91% was in moderate vulnerable region and the remaining 6.28% was in highly vulnerable region. Among the nine states, Andhra Pradesh and Tamil Nadu together hold the major culture area (71.72%) and shrimp production (78.02%) fell under low vulnerable region in the analysis. This was the reason for the result to indicate that the major white leg shrimp production is happening in low vulnerable region (Figure 4). Furthermore, we also observed that the shrimp production from the low, moderate and highly vulnerable regions was 7.7 tons ha^{-1} year^{-1}, 6.5 tons ha^{-1} year^{-1} and 4.1 tons ha^{-1} year^{-1} respectively (Figure 5).

4 | DISCUSSION

Indian aquaculture is highly sensitive to climate change as it has potential to affect food security and livelihood. Shrimp production's susceptibility to climate change was measured by vulnerability index which relies on to what extent the climate events affect the shrimp production. In addition, adaptive capacity of the particular region plays a significant role in reducing the vulnerability of shrimp-producing states in terms of climate change. The study's result revealed that around one-fourth of the shrimp culture area and production was in moderate and highly vulnerable regions.

4.1 | Principal component analysis (PCA)

The PCA approach, through its robust analytical strength, provides a small number of independent variables that can be easily interpreted to define the context of a specific aspect of vulnerability that concerns a specific geographical location (Abson et al., 2012). The factor loading value from the PCA supplement helps to understand the detailed relationship between different indicators of exposure, sensitivity and adaptive capacity. Exposure variables such as temperature maximum, Sen's slope of annual rainfall, Sen's slope of temperature maximum, z. statistic annual rainfall and z. statistic of temperature maximum positively influenced in component one, whereas Sen's slope of temperature minimum, z. statistic of temperature minimum,

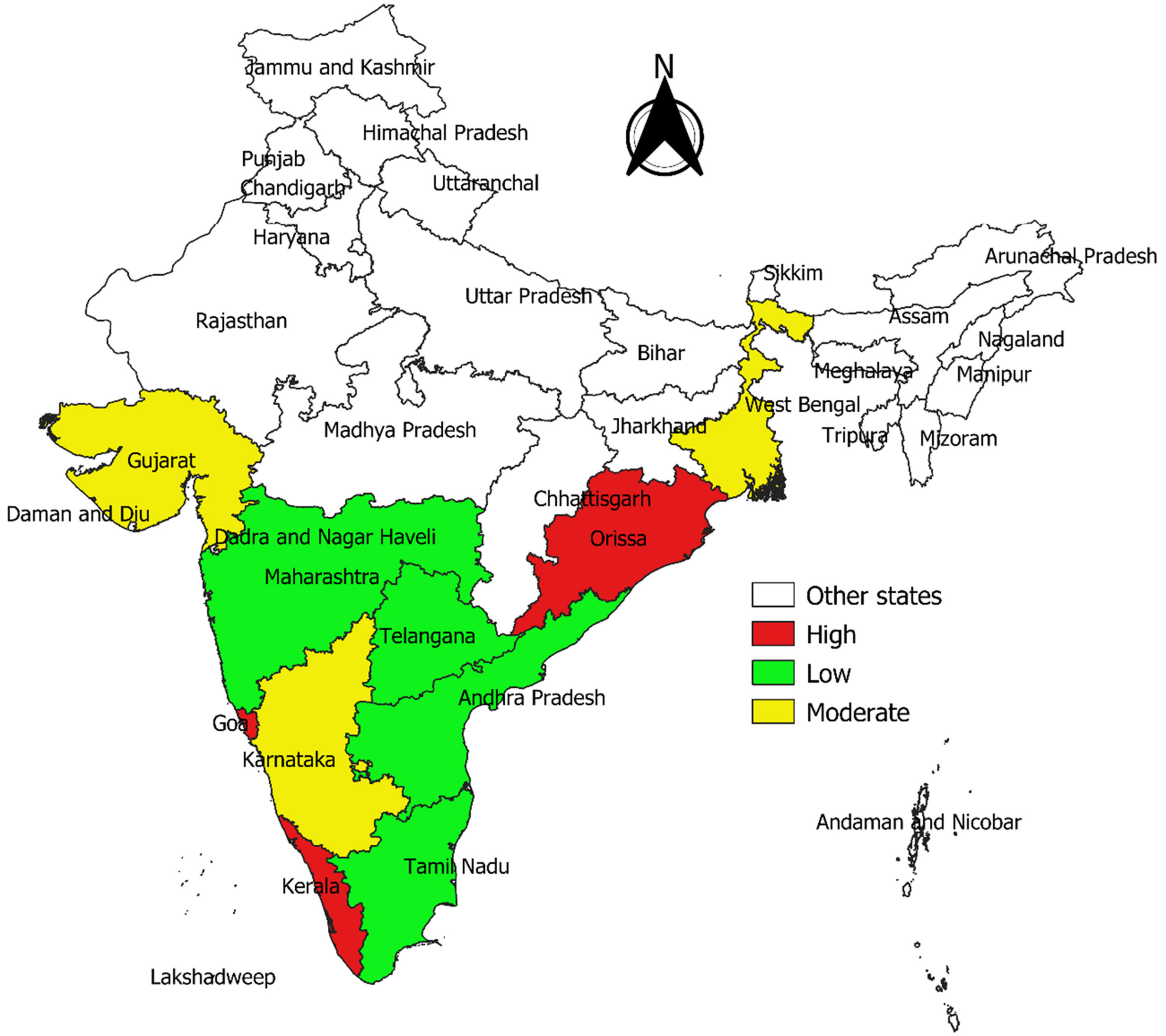

FIGURE 3 Map of the composite vulnerability index for shrimp-producing states in India (Andhra Pradesh includes Telangana and Tamil Nadu includes Puducherry for the construction of the composite vulnerability index due to the non-availability of white leg shrimp production data).

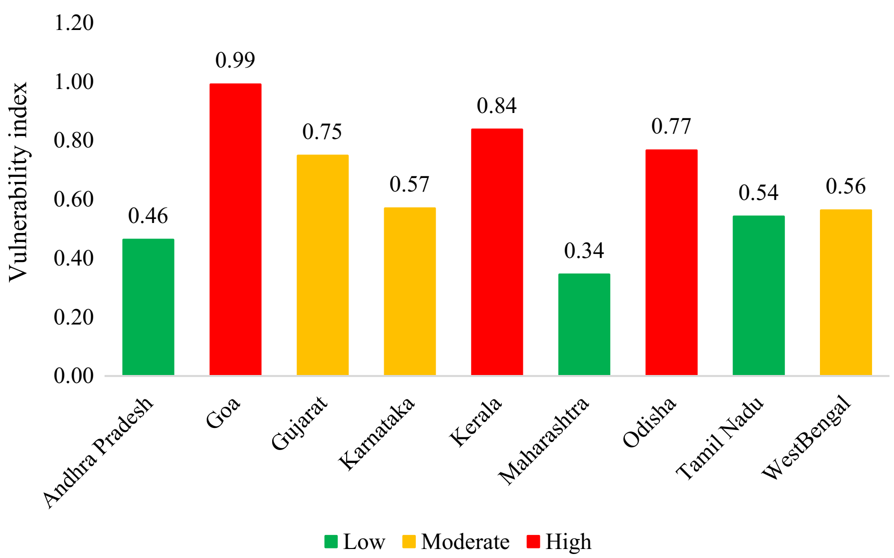

FIGURE 4 Composite vulnerability index of shrimp-producing states in India.

TABLE 6 Quantification of vulnerability degree in shrimp acreage and production for 2019–20

Degree of vulnerability	Culture area		Production	
	Ha	%	Tons	%
Low	73196.31	73.05	560886.10	78.81
Moderate	16219.97	16.19	106110.10	14.91
High	10789.54	10.77	44677.70	6.28

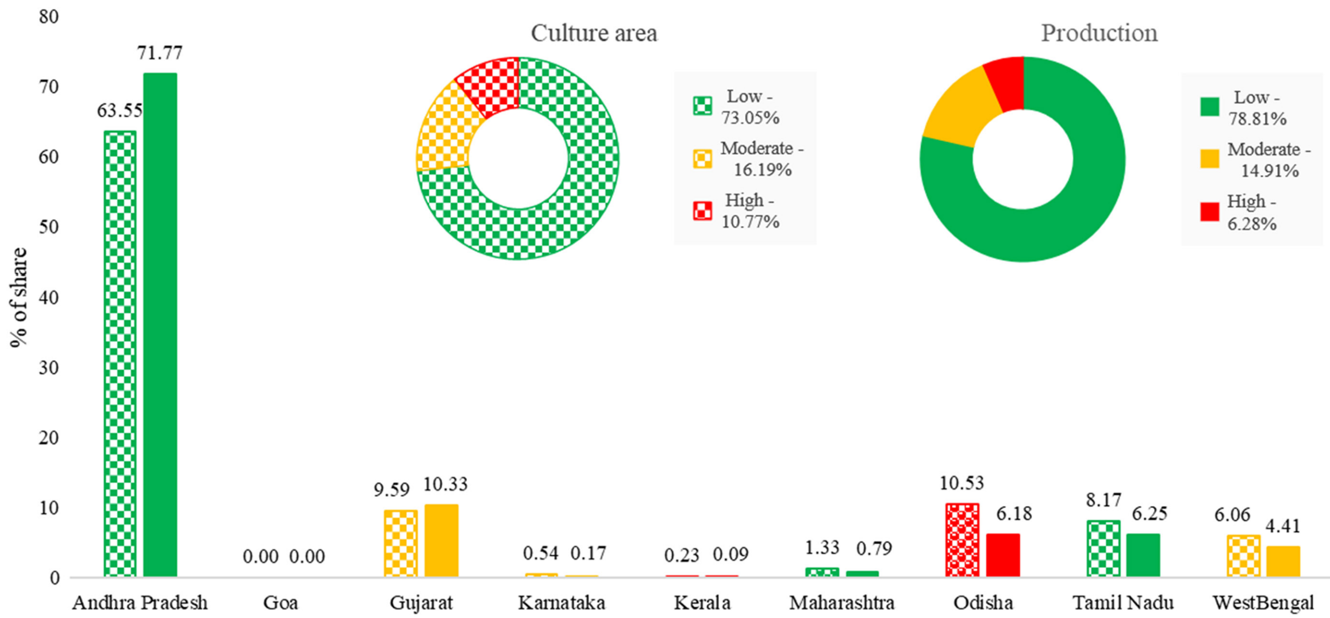

FIGURE 5 State-wise vulnerability in terms of culture area and production share in India for the year 2020.

area liable to floods and percentage of area liable to flood negatively influenced in component one that explained 49.06% of the total variances. The Sen's slope and z. statistic of temperature minimum were the major variables explaining component two which showed 19.84% of the total variance. In the case of component three, it showed 16.03% of the total variance and annual rainfall was influenced positively while the maximum temperature was influenced negatively.

Under sensitivity, shrimp culture area, shrimp production, shrimp productivity, inland fish production, fish seed production, and CV of shrimp culture area and shrimp production registered positive factor loading, and CV of productivity alone had significantly negative factor loading in component one and these all together explained 45.70% of the total variances. In component two, the shrimp productivity, CV of shrimp productivity, inland fish production and seed production had remarkable positive factor loading and the population density had negative factor loading, and all these together explained 26.39% of the total variance.

Under adaptive capacity, infant mortality, poverty rate, internet user, mobile user and effective literacy rate had positive factor loading but the resources and inland fishers had negative factor loading that explained 39.16% of the variance in component one. The components two, three and four explained 24.79%, 15.45% and 8.70% of the total variance respectively. The factor loadings indicate the context in which specific drivers were important factors in determining aggregate vulnerability indices. The socio-ecological vulnerability mapping in Southern Africa using PCA showed that infant mortality, poverty, agricultural constraints and malnutrition were heavily loaded in component one; the human appropriated net primary productivity, soil degradation and irrigation were in component two. Component three was loaded on available net primary production per capita, infrastructure poverty and travel time, and the component four on precipitation cv, malnutrition and aridity. These four components showed 63.5% of the variation by analysing 12 variables (Abson et al., 2012).

4.2 | Vulnerability index

4.2.1 | Exposure

While analysing the exposure of shrimp growing states of India to different meteorological variables, it was observed that Gujarat had the highest exposure index (0.65) and West Bengal had the lowest exposure index (0.37). The inconsistency of the exposure indices was 0.28 which indicates that there is disparity in short-term and long-term changes in precipitation, temperature minimum and temperature maximum, and their z static and Sen's slope. In terms of exposure, three states (Goa, Gujarat and Kerala) had high index, two states (Andhra Pradesh and Tamil Nadu) had moderate index and the remaining four states (Karnataka, Maharashtra, Odisha and West Bengal) had a low index. The temperature maximum of 33.23°C was observed for Gujarat, followed by Andhra Pradesh (33.07°C) and Maharashtra (33.02°C). The lowest annual precipitation (828 mm) was in Tamil Nadu and highest annual precipitation (4261 mm) was in Goa.

Environmental temperature has profound effect on metabolic rate of the shrimp; every 1°C decline in water temperature may reduce the feed consumption resulting in 10% (dry weight) loss of body weight. Rains may lower the water temperature, which can reduce the feed consumption that leads to cessation of shrimp growth and high mortality in subtropical regions (Kumlu & Kır, 2005). The high temperature can increase the pH level and water salinity. The lower water availability decreases the growth rate (Ariadi et al., 2019; Asean, 1978; Boyd, 2004; Boyd & Tucker, 2012; Islam et al., 2018) and increases the culture costs and culture period of shrimp; ultimately, shrimp mortality will take place up to 90% loss. Due to increasing water temperature, the production loss of 10–20% and economic loss of USD $ 65–75 year^{-1} was observed in India (Muralidhar et al., 2012). Lowering water temperature due to high precipitation also makes an unsuitable condition for post-larvae of shrimp (Kumlu & Kır, 2005). Floods can increase water pollution and viral infections and also may cause, stock escape from the pond to wild by damaging farm dykes. An estimated production loss of 220–400 kg and economic loss of USD$ 1200–1400 was observed in shrimp farms of Andhra Pradesh due to flood (Muralidhar et al., 2012).

4.2.2 | Sensitivity

The standard deviation (0.18) explicitly showed that there was disparity in the index of sensitivity due to its wide range. In the case of sensitivity, three states (Goa, Kerala and Odisha) were highly sensitive, four states (Karnataka, Maharashtra, Tamil Nadu and West Bengal) were moderately sensitive, and two states (Andhra Pradesh and Gujarat) low sensitive to white leg shrimp production. Andhra Pradesh and Gujarat together contributing above 75% of the national production are consistent performers of white leg shrimp production with less instability in shrimp culture area, high shrimp production and shrimp productivity (7.7 tons ha^{-1} year^{-1}). This can be attributed to the comparatively lower human population density per square km that made their shrimp production low sensitive to climate change.

4.2.3 | Adaptive capacity

Andhra Pradesh, Odisha and West Bengal were found to have low adaptive capacity to climate change. Similarly, Goa, Gujarat and Karnataka have moderate adaptive capacity, whereas Kerala, Maharashtra and Tamil Nadu have high adaptive capacity. Odisha had the lowest (0.29) and Maharashtra had the highest (0.59) adaptive capacity; this divergence (of 0.30) explicitly indicated that there is a huge disparity in adaptive capacity among the major shrimp-producing states of India. The principal component analysis showed that brackish water culture area had the highest weightage (6.53) and per capita fish consumption had the lowest weightage (3.06). The infant mortality and mobile user had the second (6.24) and third (6.22) highest weightage in adaptive capacity respectively. The rivers/canals, reservoir/tanks, poverty rate, length of road, per capita net state domestic product and effective literacy rate had weightage score above 5. The very low adaptive capacity of Odisha can be attributed to its comparatively higher infant mortality (40 individual per thousand), higher poverty rate (32.6%), lower per capita net state domestic product (USD$ 515,842), less mobile users (38%) and lower effective literacy rate (73.45%) than other states like Kerala, Maharashtra and Tamil Nadu.

4.3 | Composite vulnerability

PCA-based vulnerability index could be used by policymakers and development aid donors, especially for the highly vulnerable region (Liu et al., 2008). There was a strong spatial pattern observed in vulnerability of white leg shrimp-producing states in India. Among the nine states, Goa, Kerala and Odisha were highly vulnerable; Gujarat, Karnataka and West Bengal were moderate vulnerable; Andhra Pradesh, Maharashtra and Tamil Nadu were less vulnerable to shrimp production in India. The coastal regions are more vulnerable compared with inland regions because they are highly exposed to climatic hazards—cyclones, floods, riverbank erosion and salinity problems (Gosling et al., 2011; Minar et al., 2013; Zsamboky et al., 2011). Most of the funding agencies and government interventions concentrate more on coastal areas for resilience and development comfortably excluding the inland aquaculture areas. Globally, inland aquaculture areas are equally or sometimes more vulnerable than coastal aquaculture (Islam et al., 2019). Tamil Nadu and Maharashtra had low vulnerability mainly due to its higher adaptive capacity—availability of better agricultural credit facilities to farmers, higher information and communication technology (Internet and mobile user) usage, more effective literacy rate, adequate investment for fisheries development (Census, 2011). Despite higher adaptive capacity of Kerala, the state was highly vulnerable to climate change due to undulating climatic events and its responses to shrimp production.

4.4 | Quantification of culture area and production through categorized vulnerability

A majority of the shrimp were produced from the low vulnerable region, especially from Andhra Pradesh (71.77%) and Tamil Nadu (6.25%). Almost 6.28% of the shrimps were produced from highly vulnerable region, that is Odisha (6.18%), Kerala (0.09%) and Goa

(0.00%). Of the moderate vulnerable region, Gujarat accounted 10.33%, followed by West Bengal (4.41%) and Karnataka (0.17%).

5 | CONCLUSION

Finally, our finding sounds the alarm that three white leg shrimp-producing states were highly vulnerable and three were moderately vulnerable to climate change. In essence, this result shows that one-fourth of the culture area (26.05%) and production (21.19%) (representing six states of India) were vulnerable to climate change. Since white leg shrimp is a highly demanded exportable commodity, policy initiatives for climate change mitigation and resilience may be given priority not only based on the current production but also on envisaging future production potential. The policy initiatives should be supported by evidence-based research and development mainly focusing on the highly vulnerable regions. The present study recommends the following four initiatives to strengthen the adaptive capacity of the highly vulnerable regions:

a. Conducting large-scale awareness programmes to sensitize the stakeholders of shrimp farming about the lethal effects of climate change over the sector
b. Organizing exclusive capacity-building programmes to the stakeholders on climate resilient culture practices ('more crop per drop' technologies like Recirculatory Aquaculture System etc.,) including the rearing of alternate species (native species can be given priority)
c. Strengthening farmers network by harnessing the advantages of advanced Information and Communication Technology (ICT) tools to share knowledge among them, especially about the application of disruptive technologies (Internet of things, blockchain technology, artificial intelligence, etc.) in shrimp production
d. Enabling the legislative provisions for improving the capital investment on fisheries, infrastructure and social capital, to manage the climate change and harness of the potential of shrimp production

6 | LIMITATION OF THE STUDY

Even within a State, the shrimp production varies between districts/blocks (equivalent to a county/municipal of USA) level due to topographic and climatic variation. Therefore, to know the actual impact due to climatic change, studies have to be conducted at the aforesaid district/block level, which is currently hindered due to insufficient data on shrimp production, fish production, fish seeds, fisheries resources (rivers and canals, reservoir/ tanks, brackish water and other water bodies) and funds released for fisheries development at district/block level. Estimation of vulnerability for shrimp production at district/block level may provide better insights into adaptation measures against climate change rather than state-level analysis, which is the limitation of the current study.

AUTHOR CONTRIBUTIONS

Kalidoss Radhakrishnan, C. Lloyd Chrispin, J. Amali Infantina, R. Sendhil and Ankhita Chutia conceived and designed the experiment. Kalidoss Radhakrishnan, C. Lloyd Chrispin, R. Sendhil, Sandip Shil, M. Krishnan, A. Karthy and J. Amali Infantina performed and analysed the data. Kalidoss Radhakrishnan, R. Sendhil, Sandip Shil and Swadesh Prakash materials/analysis tools. Kalidoss Radhakrishnan, C. Lloyd Chrispin and A. Karthy wrote the paper. R. Sendhil, Sandip Shil, M. Krishnan, J. Amali Infantina, Ankhita Chutia and Swadesh Prakash review and edit the paper.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

The authors confirm that the ethical policies of the journal, as noted on the journal's author guidelines page, have been adhered to. No ethical approval was required as this is a research article with secondary data and analyses.

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