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Impressions of Coastal Communities on Climate Change and Livelihood: A Case Study of Coastal Maharashtra, India

Ravi Sharma*†, Shrishti Jagtap* and Prakash Rao*
*Symbiosis Institute of International Business (SIIB), Symbiosis International (Deemed University) (SIU), Pune-411057, India
†Corresponding author: Ravi Sharma; ravi.sharma@siib.ac.in

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ABSTRACT

The socio-economic and institutional systems of a developing country like India have a big role in the effects of perception on the choice of adapting capability. The study uses exploratory factor analysis to better understand these implications in a regional context (EFA). Therefore, survey research is carried out in Sindhudurg district of coastal Maharashtra, with 410 respondents, assessing perception. EFA leads to the unpacking of latent constructs evaluating the perception of climate change, which in turn affects adaptive capacity and livelihood resilience. These constructs are biophysical impact cognition, motivation to change, economic diversification, and adaptive skills, which together account for 50% of coastal fishermen's perception of climate change. Multivariate analysis of variance (MANOVA) revealed differences in the interpretation of these factors among coastal fishermen from various backgrounds (MANOVA). Overall, the research emphasizes the importance of perception in determining adaptive choices and resilience. According to the findings, developing adaptation-friendly infrastructural areas is recommended for society's resilient functioning.

INTRODUCTION

Climate change is a global phenomenon that affects all countries, but its impact and adaptive capacity differ largely depending upon the geographical and socio-cultural context (Adger et al. 2005). As evident from the climate change estimates, coastal ecosystems are the most impacted by the current climate altercations and are largely exposed to climate hazards (IPCC 2014, Checkley et al. 2017). Coastal ecosystems are mainly endangered due to sea-level rise, extreme weather patterns, temperature changes, and salt water erosion. Besides, coastal communities' ability to cope with these stressors is heavily influenced by the existing structural barriers (Salagrama 2012). Resource-dependent populations from such developing nations are more vulnerable to impacts (Chen 2020), with population, poverty, and illiteracy being prevailing challenges. To understand the local's perspectives, studying their perception is beneficial, which leads to the understanding of the underlying dimensions of the socio-cognitive construction process of climate change reality.

In diverse countries like India, there are differences in climate change perception and preference for adaptive behaviors. Therefore, to understand the region-specific cognitive patterns, relatively underexplored western coastal regions, particularly the coastal villages of Maharashtra state are explored for this research. According to the reports of Central Marine Fisheries Research Institute, Kochi, 1-m sea-level rise in the next 10-40 years, will deluge almost 75 villages of coastal Maharashtra (Vivekanandan 2011). Research using the Cumulative Vulnerability Index (CVI) to examine the vulnerability of the Sindhudurg district found that it is extremely vulnerable due to its proximity to the coastline (Krishnan et al. 2018). According to a vulnerability impact assessment, 32 percent of coastal Sindhudurg is extremely vulnerable to climate change (Krishnan et al. 2018). According to the same study, due to a lack of access to medical facilities, urban regions, and natural resources, there is a high level of economic sensitivity. Due to population density, it exhibits low social sensitivity. It's crucial to understand how these vulnerabilities are seen in different parts of the world.

Research conducted in India showed that the coastal communities are affected by the changes in coastal ecosystems (Pandey & Jha 2012) and that the existing socio-economic structures affect them even more. Perception of inadequacy in terms of one's coping capabilities subsequently influences the choice of adaptive response (Madhanagopal & Pattanaik 2019). Coastal fishermen's subjective perception towards climate change vulnerability, experience related to adaptation, and beliefs influence their behavioral response to climate change. Studies earlier have pointed out how the study of climate change perception can help foster eco-friendly adaptation practices (Hasan & Kumar 2019).

This study attempts to study perception by assessing the existing choice of adaptation strategies made by coastal fishermen and finding whether they are sustainable and resilient. Adaptation strategies are further often linked with resilience capacities, suggesting how building sustainable capacity and local empowerment decreases the impacts of adverse climate conditions (Pomeroy et al. 2006). By measuring these broader aspects of vulnerability, adaptive capacity, and livelihood resilience, the study undertakes to identify the region-specific underlying dimensions that mold the perception of the coastal fishermen community with varied socio-economic demographics.

MATERIALS AND METHODS

Research Statement

The research envisages understanding the perception of the fishermen's coastal community towards vulnerability due to climate change. As a resource-dependent coastal community, their perception towards livelihood resilience and adaptive capacity were also deciphered in the current research, providing a grass-root perspective in formulating multifaceted adaptive strategies.

Research Question and Hypothesis

RQ1: What are the inherent elements shaping the perception of the coastal fishermen regarding climate change, adaptive capacity, and livelihood resilience?

Hypothesis-1: Exploratory factor analysis will be unsuccessful in extracting simple factors underlying fishermen's perception of climate change.

RQ2: What are the differences in the deduced factors using EFA between respondents with varied socio-demographic backgrounds (i.e. age, socio-economic position, number of income sources, kind of fishing equipment)?

Hypothesis-2: There is no significant difference across respondents with a varied socio-economic and demographic background in terms of the factor scores derived.

Instrument Design and Development Process

The survey questionnaire mainly consists of two segments: the first access the socio-demographic information of the respondents, while the other part is to assess the perception of coastal fishermen communities through measuring vulnerability, adaptive capacity, and resilience.

Socio-Demographic Items

Socio-demographic items contain the age group, gender, socio-economic status, Number of other income sources (occupational multiplicity), and type of fishing equipment used (traditional or modern). Socio-economic status was calculated as a composite score from the revised version of the Kuppuswamy socioeconomic scale (Saleem 2020), which is scored on three parameters of the educational and occupational status of the family head and aggregate income of the family, yielding a composite score for further classification of the household into lower, upper-lower, lower-middle, upper-middle or upper class. For the current research, only three socio-economic categories were considered: upper-lower class, lower-middle-class, and upper-middle class.

Perception Items

The survey questionnaire was used to perform the perception study, which included aspects from multiple frameworks for assessing vulnerability, adaptive capacity, and livelihood resilience (Bonan & Doney 2018). The climate change impression of coastal fishermen communities to climate change is mainly studied in terms of vulnerability, adaptive capacity, and livelihood resilience. It contains a total of 50 items measured on a five-point Likert scale, based on "level of agreement" giving a score of '5' to 'Strongly Agree', '4' to 'Agree', '3' to 'Neither Agree or Disagree', '2' to 'Disagree' and '1' to 'Strongly Disagree'. Each sub-dimension is measured by two items (Appendix A).

Vulnerability is assessed with two sub-scales of exposure and sensitivity. Exposure assesses the perception of respondents towards their situation, infrastructure, housing, production capacities, and other tangible human assets that could be adversely affected. The sensitivity subscale assesses the threat perception levels of respondents at an extent to which human systems are affected by the exposure to risks.

Adaptive capacity assesses respondents' perception of whether their systems are capable of adapting to climate variability, mitigating potential damage, exploiting opportunities, and coping with consequences (Marshall & Marshall 2007).

Livelihood resilience assesses the individual and community's competency to mitigate stresses and disruption, consequently reorganizing themselves through gaining new skills for smooth functioning of the societal structure (Speranza et al. 2014).

Pilot testing was conducted with 70 respondents (excluded from the main research study), conducted in the Vengurla tehsil of Sindhudurg district. The Cronbach alpha of 0.87 was obtained, with the reliability of the individual 50 items ranging from 0.84 to 0.89, suggestive of high reliability. Content validity of the scale was indicated as suitable for professionals in the field.

Survey

Data collection was done from the coastal villages of the Sindhudurg district of Maharashtra. Data collection included socio-demographic details and perception of individuals on vulnerability, adaptive capacity, and livelihood resilience to climatic fluctuations. Data was collected in person from the household heads and participation in the study was entirely voluntary. The questionnaire was in the local dialect (Marathi and Hindi) for the convenience of the locals. Confidentiality of respondents' information was ensured.

Study Area

The study was conducted in the Sindhudurg district of western Maharashtra state. The coastal villages from the Devgad, Malvan, and Vengurla tehsil of Sindhudurg were selected for the study (total village=41).

Target Population

For this research, coastal fishermen communities were the targeted population (*N=410*). Data from household heads with the primary or secondary occupation of fishery was collected. Respondents differed across demographic, socio-economic status, and type of equipment used.

Sampling Method

The multistage stratified random sampling method was to collect responses from the coastal fishermen community. Devgad, Malvan, and Vengurla Tehsil were identified for the study in the first stage and then 41 coastal villages from these tehsils by establishing the criteria of 2 km from the coastline and having coastal communities' habitats as per the Population Census 2011. Using the priori statistical analysis, the sample size of 368 was targeted and an actual sample size of 410 was collected.

Data Analysis

Principal axis factoring (PAF) and oblimin rotation were used to evaluate the data. The skewness and kurtosis values were checked for univariate normality, and values between ±2 were found to be acceptable. The scale's overall dependability was 0.89, which is higher than the allowed level of 0.7. (Fabrigar et al. 1999). In the initial stage of EFA, data was screened for sampling adequacy using Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (>0.5) and Bartlett's test of sphericity ($p< 0.05$). KMO, Bartlett's tests, and determinant of correlation matrix were again examined during the final stage of the EFA process as validation checks. The scree plot and parallel analysis were used to predetermine the number of extracted factors and Communalities > 0.2 were acceptable. The general linear model of Multivariate analysis of variance (MANOVA) was also used, with discriminant function analysis (DFA) as a *post-adhoc* measure, to measure the perceived differences across respondents with varied

Table 1: Socio-demographic features of the coastal fishermen (N=410).

Socio-demographic factors	Frequency	Percentage
Age group		
21 to 30	16	3.9
31 to 40	143	34.9
41 to 50	195	47.6
51 to 60	48	11.7
61 to 70	8	2
Socio-economic Status		
upperlc	104	25.4
lowermc	302	73.7
uppermc	4	1
Occupational Multiplicity		
single	367	89.5
multiple	43	10.5
Fishing Equipment Used		
traditional	266	64.9
modern	144	35.1
Total	410	100

socio-demographic characteristics. Besides correlational analysis using Pearson product-moment correlation was also conducted. The statistical analysis is done using IBM SPSS V26.0, and R- statistical software version 4.0.5.

RESULTS AND DISCUSSION

Respondents Socio-Demographic Profile

This study included 410 coastal fishermen from various socioeconomic backgrounds, age groups, types of fishing equipment used, and a number of household livelihood sources (Table 1).

Data Screening

The raw data was cleaned, coded, and classified into suitable categories for ease of statistical analysis. Negative items were reverse coded. There was no missing data in the current research. Univariate analysis of 50 variables was done and mean, standard deviation (S.D), skewness, and kurtosis of the sample data were examined. The total mean was 3.38 (S.D = 1.22) ranging from 2.18 to 4.14, with an S.D ranging from 0.92 to 1.50. Histogram, box plots, and QQ plots were also examined suggesting normality. The skewness (< ± 2) ranged from - 1.40 to 0.58. The kurtosis ranges from (< ± 2) ranging from -1.42 to 1.14. Shapiro-Wilk's test indicated significant univariate normality W (410) = 0.8712, p< 0.01.

EFA

EFA was performed on the data collected (n=410), using the PAF, rotation method being direct oblimin. A correlation matrix was generated based on Pearson product-moment correlation coefficients (Fig. 1). Firstly, the correlation matrix was examined, with a sizable number of variables having correlation exceeding ± 0.3 and no variable having inter-correlation exceeding ± 0.8, suggesting factorability of the data. Second, the KMO measure of sampling adequacy

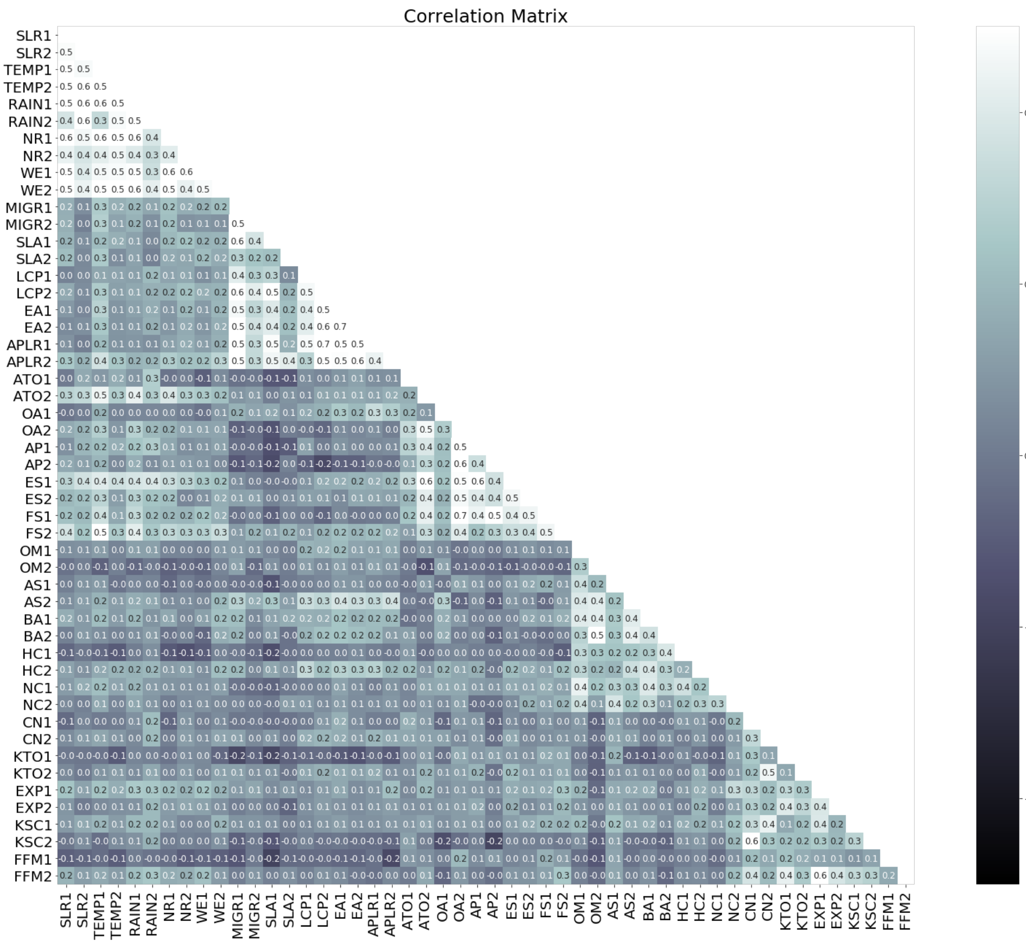

Fig.1: Pearson correlation matrix of 50 variables.

was found to be 0.87, which is 'meritorious'. Bartlett's test of sphericity was ($\chi 2$ (1225) = 9452.57, p < .001), indicating the correlation matrix is significantly different from the identity matrix, hence factorable.

The exploratory factor was run on 50 variables using the principal axis factoring technique. The initial analysis yielded a 12-factor solution. Items NR2, SLA2, EA1 cross-loaded significantly on more than one factor, whereas OA2 and FFM1 didn't load significantly on any factor, therefore they were deleted and the EFA was again repeated. The same process was repeated 5 times, and items RAIN2, ATO2, AP1, ES1, HC1, SLA2, AS2, BA1, HC2, ATO1, KTO2, CN2, EXP1, KTO1, EXP2, FFM2, and NC2 were removed due to cross-loading, absence of loading on any factor, less than 3 variables with loadings < 0.4. After many iterative steps and elimination of the above variables, a total of 24 variables were retained for final factor analysis. A final validation check was run on the 24 variables, yielding a meritorious KMO value of 0.87, and Bartlett's test of sphericity ($\chi 2$ (276) =4354.86, p< .01) was also significant. The determinant of the correlation matrix was 0.000019 (higher than the critical value of 0.00001). In the final factor analysis stage, PAF with an oblimin rotation was used. The decision regarding the number of factors to be extracted was taken using a Scree plot and parallel analysis. Scree plot suggested a total of four factors (Fig. 2). From the parallel analysis, adjusted eigenvalues greater than 1 are retained, also suggesting four factors. Further using the oblimin method of rotation, a theoretically meaningful four-factor solution emerged (Table 2).

Total four factors emerged from the analysis which explained 50 % of the total variance. The first factor consists of 8 items: SLR1, SLR2, TEMP1, TEMP2, RAIN1, NR1, WE1, and WE2, explaining 35% of the variance. The second group of factors consists of 8 items: MIGR1, MIGR2, SLA1, LCP1, LCP2, EA2, APLR1, and APLR2, explaining 34 % total variance. The third group of factors consists of four items: OA2, AP2, ES2, and FS1, explaining 19 % of the variance. The final fourth group of factors consists of four items: OM1, OM2, BA2, and NC1, explaining 12% of the variance. The first factor was labeled as *"biophysical impact cognition"*. The 2nd factor was labeled as "*Motivation to change"*. The 3rd factor was labeled as *"Diversification"*. The 4th factor was labeled as *"Adaptive skills"* according to the item relations within these groups as supported by the literature. Correlations between factors ranged from -0.02 to 0.33. Finally, the reliability analysis was also conducted for each factor using Cronbach's alpha, with all the factors having reliability $\geq$ 0.7 which is considered good (biophysical impact cognition= 0.9, Motivation to change= 0.88, diversification= 0.81, and Adaptive skills= 0.7). The values for

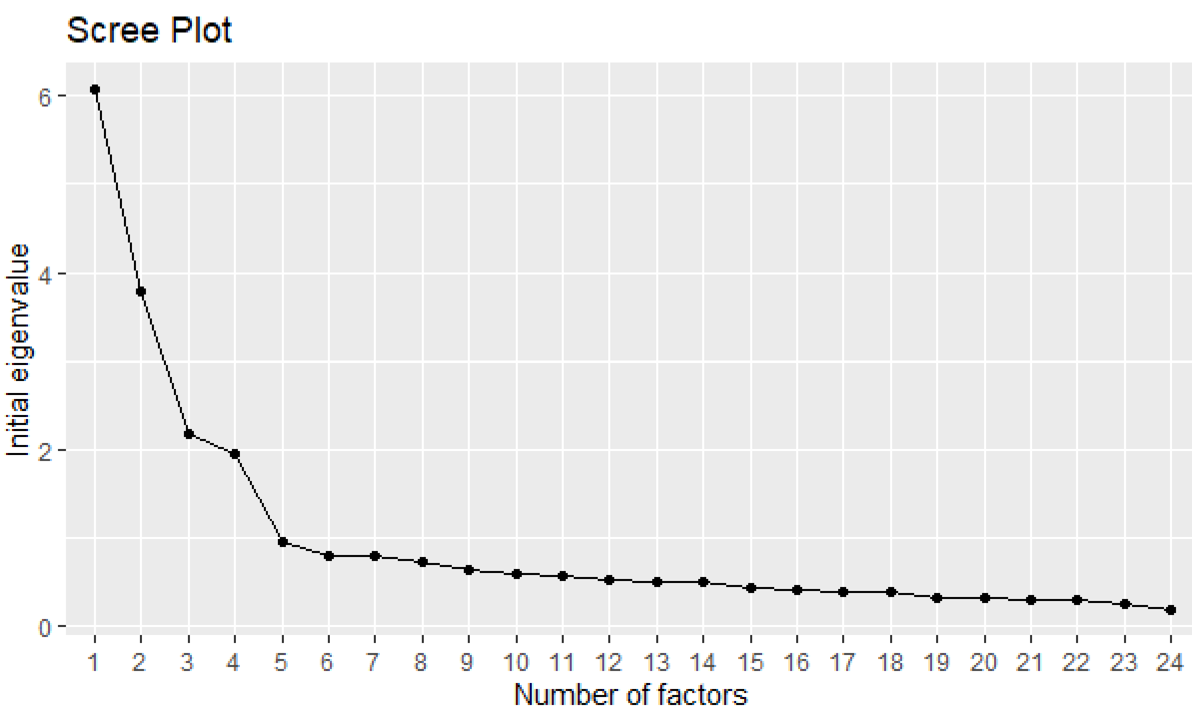

Fig. 2: Scree plot for the number of factors to be extracted.

Table 2: Pattern matrix of the factors derived from EFA

Item code	1	2	3	4	h2
SLR1	0.76				0.57
SLR2	0.69				0.47
TEMP1	0.61				0.58
TEMP2	0.76				0.53
RAIN1	0.74				0.62
NR1	0.76				0.6
WE1	0.68				0.46
WE2	0.7				0.51
MIGR1		0.77			0.63
MIGR2		0.55			0.31
SLA1		0.66			0.49
LCP1		0.54			0.31
LCP2		0.82			0.68
EA2		0.74			0.54
APLR1		0.76			0.57
APLR2		0.59			0.45
OA2			0.89		0.78
AP2			0.64		0.43
ES2			0.55		0.35
FS1			0.8		0.68
OM1				0.51	0.29
OM2				0.59	0.36
BA2				0.66	0.48
NC1				0.56	0.35
SS loadings	4.27	3.95	2.34	1.48	
Proportion Explained	0.35	0.33	0.19	0.12	
Cumulative Variance	0.18	0.34	0.44	0.50	
Cumulative Proportion	0.35	0.68	0.88	1	
Cronbach's alpha	0.9	0.88	0.81	0.7	

h^2 = communalities

variables in the community were all > 0.2, thus they were not eliminated. There were also roughly 11% non-redundant residuals ($p > 0.05$), which was much below the crucial levels and hence acceptable. Four-factor solutions were obtained from the EFA. As a result, our null hypothesis is rejected.

MANOVA

MANOVA is conducted depending on the factors that emerged from the EFA. The factors scores were derived using a refined regression method. Age, socioeconomic status, and the number of income sources are the independent variables with many levels, whereas these regression component scores are employed as dependent variables. DFA was used as a post hoc approach to identify dependent variables that are linearly connected to grouping variables.

Age and Factor Scores

Age variable was divided into five age groups, with 21 to 30 years of age group (n=16), 31 to 40 years (n=143), 41 to 50 years (n=195), 51 to 60 years (n=48) and 61 to 70 years (n=8). Box's test was significant (Box's M=82.165, p.05), indicating that dependent variable covariance is not equal across groups. As a result, the Pilla's Trace criterion was applied, revealing a significant difference in factor scores across age groups (V=.35, F[16, 1220]=9.64, p< 0.01). After MANOVA, the DFA was used as a post hoc test. The first function explained 95.1% of the variation, the second 4.2%, the third function 0.6% of the variance, and the fourth function 0.1% of the variance, with canonical R^2 values 0.57, 0.14, 0.05, and 0.02 respectively. When all the functions are tested in combination, Wilk's λ has the value .660(χ2(16)=167.99, p=0.000), which indicates that all the functions in combination significantly discriminate between the age groups. Removing 1 function did not significantly discriminate between age groups (λ = .98, χ2(9)=9.81, p=.366). Further removing the 2nd function also produced non-significant results (λ=.98, χ2 (4)=1.28, p=.867) and same with removing 3rd function (λ=1, χ2(1)=.14, p=.71). Biophysical impact cognition loaded fairly high on the 1st (r=.75) and 2nd (-.53) functions than on 3rd (r=.18) and 4th (r= -.37) functions. Motivation to change loaded significantly on the 2nd function (r =.644). The 2nd function (r =.644) was heavily loaded with motivation to change. The first function discriminated participants in the age groups 21- 30 and 31- 40 from respondents in the age groups 41- 50, 51- 60, and 61- 70, according to the discriminant functions estimated at group means. The second function discriminated respondents aged 31 to 40 and 41 to 50 from those aged 21 to 30, 51 to 60, and 61 to 70. The third function discriminated the age groups of 21- 30 and 41- 50 from those of 31- 40, 51- 60, and 61- 70. The fourth function, on the other hand, discriminated 51- 60 from 21- 30, 31- 40, 41- 50, and 61- 70.

Socio-Economic Status and Factor Scores

Respondents were divided into three socio-economic categories that are upper lower class (n=104), lower middle class (n=302), upper-middle-class (n=4), whereas none of the respondents fitted in the upper class and lower-class categories. Box's test was significant, violating the assumption of covariance equality across categories (Box's M=30.38, p=0.001). Pilla's Trace criterion showed a significant difference in factor scores across socio-economic categories (V=.524, F[8, 810]=35.98, p=0.00). With DFA two functions were identified, with the first explaining 99.6% of the variance, and the second explaining 0.4%, with canonical R^2 of .72 and .07 respectively. When all the functions are tested in combination, Wilk's λ has the value .478 (χ299.29=(8)2, p=.000) which indicates that all the functions in combination do significantly discriminate between the socio-economic categories. Removing the 1st function did not significantly discriminate between socio-economic categories (λ=.995, χ2 (3)=1.85, p=.604). Biophysical impact cognition (r=0.66) and motivation to change (r=.37) loaded significantly on 1st function while diversification (r=.804) and adaptive skills (r=-.63) loaded significantly on 2nd function. The discriminant function analysis shows that 1st function discriminates Upper-lower class from lower-middle-class and upper-middle-class, whereas 2nd function discriminates lower-middle class from upper-lower class and upper-middle class.

Occupational Multiplicity and Factor Scores

Respondents were divided into two categories of occupational multiplicity: a single source of income (n=367) and multiple/ alternative sources of income (n=43). Box's test was non-significant assuming equality of covariance (Box's M=13.35, p=0.231). Pilla's Trace criterion showed a significant difference between socio-economic categories (V=.030, F[4, 405]=3.094, p=0.016). One function was identified using DFA, explaining 100% variance and canonical R^2 of .17. Wilk's λ has a value of .970(χ2(4)=12.22, p=.016) which indicates that the function does significantly discriminate between the occupational multiplicity categories. Biophysical impact cognition (r=0.74), motivation to change (r=.69), diversification (r=.44) and adaptive skills (r=.42) loaded significantly on 1st function. The discriminant function analysis shows that 1st function discriminates between single and multiple sources of income.

Fishing Equipment Used and Derived Factors

Respondents were divided into two categories based on the type of fishing equipment they used: traditional (n=266) and modern (n=144). Box's test was significant, rejecting the hypothesis of covariance equality across groups (Box's M=7.82, p=0.65). Pilla's Trace criterion showed no significant difference across fishing equipment (V=.003, F[4, 405]=0.267, p=0.899). DFA was not conducted as there was no significant difference between the categories.

CONCLUSION

From the EFA conducted, four factors emerged: biophysical impact cognition, motivation to change, diversification, and adaptive skills. The factor biophysical impact cognition indicates the importance of cognition in the perceptual process. It helps to understand the individual's and community's construal of climate variability. The motivation to change factor indicates that risk perception and accurate representation of reality motivates adaptive behavior. Diversification of the economy aids resource-dependent communities in adapting to climate change. The development of adaptation skill components emphasizes their role in the interpretation of climatic variations. In keeping with earlier research, this study finds considerable variances among age groups, socioeconomic situations, and a variety of employment sources (Haq & Ahmad 2017). The emergence of elements underpinning coastal fishermen's perceptions, which provide a theoretical framework for assessing their perceptions, properly addresses research questions. Null hypotheses are rejected based on the above findings.

These derived factors are perceived differently by coastal fishermen with different backgrounds. Besides these factors have strong relationships with various dimension aspects of adaptive capacity, highlighting the importance of perception in adaptive behaviors. This study assesses the factors influencing the current perception, which shadows its sensory and temporal nature, which is largely subject to biases. Therefore, in future longitudinal studies assessing the perception over a time span, specifically before and after extreme climate events and examining the biases in perceptual processes should be addressed. Generating a sustainable adaptive response requires communities to gain profound cognizance of climate variations, as opposed to the heuristic perception of the complex issue. It is critical to educate community members to assist them in adapting. To attain these goals, further study should be conducted on how to lower the barriers to achieving adaptive capacity and what coping skills should be instilled in coastal communities.

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APPENDIX A

Perception Study Indicators and coding

Exposure Indicator	Items(code)
Sea level rise	When the sea level rises, my occupation suffers (SLR1)
	The sea-level rise does not affect my occupation (SLR2)
Temperature	When temperature changes, my occupation gets affected (TEMP1)
	The work was smoothly carried out independent of temperature (TEMP2)
Rainfall	Rainfall changes affect my occupation. (RAIN1)
	occupation doesn't get affected by rainfall (RAIN2)
Natural Resource	completely dependent on the natural resources for livelihood (NR1)
	My family members perceive that NR are in abundance (NR2)

Cont....

Exposure Indicator	Items(code)
Weather Events	Extreme weather in last few years, either it's too hot or too cold (WE1)
	weather events are seasonal and not too extreme (WE2)
Sensitivity Indicator	
Migration to the non-coastal area	I am very attached to my place (MIGR1)
	The present area of living is highly sensitive to climatic changes; therefore planning to shift away from coastal areas (MIGR2)
Supplemental livelihood activities	Engaged with other occupations along with my current (SLA1)
	need to switch to different occupations due to changes in climate (SLA2)
Local Conservation Planning	interested in participating in the planning and execution of adaptation measures locally (LCP1)
	find it very difficult to adopt conservation measures (LCP2)
Environmental Awareness	Do not have access to multiple channels and schemes on environmental initiatives by Govt (EA1)
	I am not aware of any environmental institution in our region (EA2)
Adaptive Capacity Indicator	
Ability to plan, learn, reorganize	have knowledge of all the requirements needed for my current occupation (APR1)
	If any abrupt change in my job, don't have any immediate plan to handle it. (APLR2)
Attachment to occupation	I cannot imagine myself suitable to get fitted in any other job (ATO1)
	Compared to others, I am more likely to adapt to the environmental change and my occupation (ATO2)
Occupational adaptability/flexibility	I am satisfied with my current job, and no plan to change my occupation (OA1)
	For business decisions, I always seek professional advice (OA2)
Attachment to place	I plan to be a long-term resident of this community (AP1)
	I will leave my current place if get a better opportunity elsewhere (AP2)
Employment Security	If there are any more changes, I won't survive much longer in this work (ES1)
	If I decide to leave my job, I have many options available to me(ES2)
Financial security	financially secured my current occupation in case of natural calamity (FS1)
	have financial arrangements already planned to execute interesting ideas to make my work more sustainable (FS2)

Cont....

Exposure Indicator	Items(code)
Occupational Mobility	In the last five years, the voluntary change observed in occupational patterns in my area. (OM1)
	I'd be nervous to try something else than what I'm doing now (OM2)
Access to services	prefer to use different and newer technologies in my job (AS1)
	Good basic education is far from my area (AS2)
Business approach	Skilled to build my own business rather than my current occupation (BA1)
	Not skilled to start a new business (BA2)
Livelihood Resilience Indicator	
Human Capital	live very close to the available nearby health facility (HC1)
	the average period of occupation reduces when there is a natural calamity (HC2)
Natural Capital	I can make full use of natural resources as per my skills (NC1)
	availability of natural resources during the peak season of a year (NC2)
Cooperation & Area Networks	support from local organizations and networks (CN1)
	groups and their decisions are often not much fruitful (CN2)
Knowledge of threats and opportunities	ability to analyze threats and the potential to adapt to the risks (KTO1)
	I recognize threats when they are very closer (KTO2)
Experimentation	I always have the zeal to learn new methods and skills for my job (EXP1)
	I am unable to think of any innovative ideas to improve my work conditions (EXP2)
Knowledge sharing capacity	learned new methods of carrying out my work from the community (KSC1)
	not able to share my skills with others (KSC2)
Functioning feedback mechanisms	Community member frequent contact with local institutions and learning new ideas (FFM1)
	community members help me to understand the current changes and through management response (FFM2)

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